FOOTHILLS RESEARCH INSTITUTE
GRIZZLY BEAR PROGRAM
2013 ANNUAL REPORT

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DISCLAIMER

This report presents preliminary findings from the 2013 research program within the Foothills Research Institute (FRI) Grizzly Bear Program. It must be stressed that these data are preliminary in nature and all findings must be interpreted with caution. Opinions presented are those of the authors and collaborating scientists and are subject to revision based on the ongoing findings over the course of these studies.

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TABLE OF CONTENTS

REPORT A: RESEARCH TO SUPPORT RECOVERY AND LONG TERM CONSERVATION OF GRIZZLY BEARS IN ALBERTA 12

Chapter A.1. Summary of 2013 Capture Program 14

Introduction 14

Method 14

Study Areas 14

Capture Protocol 15

Results 16

Grizzly Bear Captures 16

Black Bear Captures 16

Sex and Age Characteristics 17

GPS Radio-Telemetry Data 17

Grizzly Bear Health Evaluation 18

Modification of Anesthetic Protocol for Foothills Research Institute Grizzly Bear Project 18

Chapter A.2. An Evaluation Of Reproductive Activity In Grizzly Bears, And How It Is Influenced By Stress, Based On The Measurement Of Hormones In Hair 20

Executive Summary 20

Background 21

Objectives and Hypotheses 22

Detection and Measurement of Steroid Hormones 25

Detection and Measurement of Peptide Hormones 25

New Insights into the Measurement of Hormones in Hair 26

Validation Study 1 26

Validation Study 2 28

Plans for Year Three 30

Chapter A.3. Understanding Seasonal Variation In Leptin And Adiponectin Production, Adipose Function, And Whether Either Hormone Can Be Used To Estimate Body Fat Content In Brown Bears 33

Methods..35

Current Results 36

Serum leptin-adiponectin content relative to body fat content 36

Effect of centrally administered leptin on food intake..37

Plans for Year 2 40

Leptin-adiponectin studies 40

Hair reproduction studies..40

Chapter A.4. Population Recovery Targets For Grizzly Bears In Alberta 42

Executive Summary 42

Background..43

Methods..45

Available energy (nutritional landscape)..45

Modeling (mapping) spatial variation in food supply (digestible energy)..45

Bioenergetic estimates of total energy expenditure (demands)..47

Energetic model for grizzly bears 47

Simulated scenarios (reproductive classes and diets) 48

Results..49

Food supply and digestible energy estimates for buffaloberry and ungulates 49

Bioenergetic demands..50

Relationship between ungulate meat, buffaloberry fruit, and grizzly bear abundance..50

Discussion and next steps..51

Appendix A.4.1. Estimating Ungulate Biomass in the Yellowhead Grizzly Bear Population Unit..63

Objectives 63

Ungulate Surveys 63

Analysis Scale and Environmental Predictors 64

Abundance Models 65
Biomass Maps 66

Chapter A.5. Future of Alberta's Forests for Grizzly Bears Disturbance Evaluation and LiDAR Habitat Classification 72

Executive summary 72
A.5.1. STAARCH Continuation, 2013 and beyond. 75
Introduction 75
Results 75
A.5.2. Characterizing a Decade of Disturbance Events using Landsat and MODIS Satellite Imagery in Western Alberta, Canada for Grizzly Bear Management 78
Introduction 78
Methods 81
Study Area 81
Data 82
Disturbance Detection 82
Disturbance Attribution 83
Grizzly Bear Habitat States 85
Data Analysis 86
Results 86
Western Alberta Disturbance Attribution 86
Habitat State Attribution 91
Discussion 93
Conclusion 96
A.5.3. LiDAR forest metrics abstraction and habitat mapping 97
Results 99
A.5.4. Understory Species distribution modelling using LiDAR -Fine-Spatial Scale Predictions of Understory Species Using Climate and LiDAR-Derived Terrain and Canopy Metrics. 101
Introduction 101
Methods 104
Study area 104
Plant distribution data 105
Environmental Covariates 105
Modelling: Boosted Regression Trees 107

Table of Contents

Results........108

Discussion........114

A.5.5. Advanced landcover classification using LiDAR and LandsatIntegrating optical satellite data and Airborne Laser Scanning in habitat classification for wildlife management........116

Introduction........116

Methods........119

Wetland areas:........119

Alpine areas:........120

Forest-cover density:........120

Study area........120

Data sources........121

Evaluation data........121

Classification scheme........121

Filling the gaps........123

Results........123

Discussion........125

A.5.6. Phenocam Field of view comparison, broad v.s. narrow........126

Introduction........126

Materials and methods........127

Study Area........127

Digital Camera Network........128

Image Analysis........129

Phenophase Validation........130

Statistical Analyses between Fields of View........130

Results........131

Individual species responses:........132

Discussion........134

A.5.7. Phenocam bear foods detection 2013, Heracleum lanatum........135

Field Visits........135

Cameras........136

Data........136

Camera 1, edge (incomplete)........137

Camera 3, closed canopy........137

Camera 4, open canopy........137

Camera 5, edge 138

Camera 6, closed canopy 138

A.5.8. Field Campaign to update forest structure and habitat 139
Study Site 139

Field Crew 139

Field Campaign Summary 140

A.5.9. Implementation of the LANDIS-II Dynamic Forest Landscape Model and the Mechanistic Fire Sub-model 142
Introduction 142

Methods 144

Results 157

A.5.10. Modeling Tree Species Regeneration Niche Response to Climate Change 164
Introduction 164

Methods 171

Results 177

Analysis 180

A.5.Appendix: Comparing Climate Normal and Daily Weather Inputs 186

REPORT B: GRIZZLY BEARS AND PIPELINES: RESPONSE TO UNIQUE LINEAR FEATURES 199

Executive Summary 201

Chapter B.1. Background, Study Area, And Research Objectives 202

Background 202

Study Area 204

Research objectives 205

Chapter B.2. Grizzly Bear Habitat Selection Patterns On Pipeline Right-Of-Ways 206

Introduction 206

Methods 206

Grizzly bear location data: 206

Linear feature datasets: 208

Analysis: 210
Results...211
Discussion 214

Chapter B.3. Parameters Influencing The Use Of Pipeline Right-Of-Ways. 219

Introduction 219
Methods..219
Location data: 219
Factors influencing pipeline use: 219
Analysis: 221
Results...223
Discussion 230

Chapter B.4. Food Availability On Pipeline Right-Of-Ways. 233

Introduction 233
Methods..233
Study site selection: 233
Field methods: 234
Analysis: 234
Results...236
Discussion 240

Chapter B.5. Linear Features And Predation. 242

Introduction 242
Methods..243
Grizzly bear location data and study site generation: 243
Field data: 244
Analysis: 245
Results...246
Discussion 253

Chapter B.6. Mortality Risk Factors 254

B.6.1. Sightability of grizzly bears on pipeline RoWs. 254
  Introduction 254
  Methods...255
    Site selection: 255
    Field methods: 255
    Analysis: 256
  Results..257
  Discussion 264
B.6.2. Levels of human and wildlife use on pipeline RoWs. 266
  Introduction 266
  Methods...266
    Photo processing: 266
  Results..267
  Discussion 272

Chapter B.7. Final Conclusions 273

REPORT C: EVALUATING GRIZZLY BEAR HABITAT USE AND RESPONSE TO NEW APPROACHES TO FOREST MANAGEMENT, HARVESTING, AND ACCESS PLANNING IN CORE GRIZZLY BEAR CONSERVATION AREAS – ARE NEW APPROACHES POSSIBLE TO SUPPORT RECOVERY EFFORTS? 282

  Introduction 283
  Methods...284
    Study Area 284
    Grizzly Bear Capture 285
    DNA Population Inventory...285
    Scat DNA sampling...285
  Results..286
    Grizzly Bear Capture 286

DNA Population Inventory 286
Scat DNA and Grizzly Bear Food Quantification 287
Summary and Work Planned for 2014 (Year 2) 287

REPORT D: RESEARCH AND APPLIED TOOLS TO ENHANCE FOREST MANAGEMENT LINKAGES TO GRIZZLY BEAR CONSERVATION AND RECOVERY IN ALBERTA 298

Executive Summary 299

Key Research Finding: 300
Recommended Management Actions/Considerations 300
Background 303

Chapter D.1. Grizzly Bear Response To The Edge And Interior Of Forestry Cutblocks 305

Introduction 305
Methods 306
Study Area 306
Grizzly Bear Capture and Monitoring 307
Forested Habitat and Edge Classification 307
Grizzly Bear Home Ranges and Random Locations 308
Variable Processing 308
Statistical Analysis 309
Results 310
Discussion 311
Management Implications 312

Chapter D.2. Grizzly Bear Selection Of Forestry Cutblock Edges 319

Introduction 319
Methods 320
Grizzly Bear GPS and Random Locations 320

- Environmental Conditions and Mortality Risk 321
- Statistical Analysis 321

Results 322

Discussion 323

Management Implications 325

Chapter D.3. Do Grizzly Bears Respond To Varying Levels Of Green Tree Retention Within Cutblocks? 331

Introduction 331

Methods 332

Results 334

Discussion 335

Management Implications 336

Chapter D.4. Are Berries More Abundant At Forestry Cutblock Edges? 341

Introduction 341

Methods 342

Results 346

Discussion 346

Management Implications 347

Chapter D.5. Does Silviculture Influence Food Availability And The Behavior Of Grizzly Bears? 353

Introduction 353

Methods 355

Results 359

Discussion 360

Management Implications 361

Chapter D.6. Gis-Based Planning Tools 367

Background 367

Tools and Application 369

Caribou & Grizzly Bear Planning Tool. 369
Road Reclamation Tool for Grizzly Bear 373
Visibility Tool for Grizzly Bear 374
Appendix D.1.: Grizzly Bear Activity 384
Appendix D.2.: Outline of the GBtools folder 388
Appendix D.3. GBTools User Interface 389

REPORT E: A SUMMARY OF EIGHT YEARS OF ANTHROPOGENIC DISTURBANCE IN THE YELLOWHEAD POPULATION UNIT 2004-2012 392

Introduction 392
Study Area 392
Methods 393
Disturbance types 394
Results 396
Discussion 397

REPORT F: NEW GIS TOOLS FOR LIDAR-BASED MAPPING AND ANALYSIS OF SEISMIC CUTLINES IN NORTHERN ALBERTA 399

Executive summary 399
Introduction 400
METHODS 403
Study area 403
Process 404
Update of Lidar canopy surface 404
Spatial adjustment of digitized line features to follow the disturbance corridor 405
Delineation of disturbance corridor 406
Extraction of topographic and vegetation metrics along the trail 407
Measurement of tree heights adjacent to the corridor 409
Discussion 410

Table of Contents

REPORT G: MODELING THE SEQUENCE AND INTERANNUAL TEMPORAL VARIATION OF CANADIAN BUFFALOBERRY (*SHEPHERDIA CANADENSIS*) USING BROAD-SCALE CLIMATE PROXIES. 413

Introduction 413
Methods 415
  Study Area 415
  Phenological Data 415
  Climate Data 417
  Shepherdia canadensis Phenology Models 417
  Interannual Phenological Variability 419
  Validation 420
Results 420
  Phenology Models 420
  Interannual Phenological Variability 423
  Validation results 424
Discussion 425
Conclusion 427
APPENDIX E: LIST OF PROGRAM PARTNERS (1999 – 2013) 432
APPENDIX F: LIST OF PROGRAM PARTNERS (2014) 433
APPENDIX G: LIST OF REPORTS, THESES AND PUBLISHED PAPERS. 434

List of Tables

REPORT A: RESEARCH TO SUPPORT RECOVERY AND LONG TERM CONSERVATION OF GRIZZLY BEARS IN ALBERTA

CHAPTER A.1. Summary of 2013 Capture Program

Table 1. Details of the grizzly (G) and black bear (bb) captures. 16

CHAPTER A.4. Population Recovery Targets For Grizzly Bears In Alberta

Table 1: Support for ordered logistic regression models explaining local abundance in grizzly bears as a function of sampling design (session number for DNA hair-snagging in 2004), local road density (anthropogenic impacts on bears), and nutritional landscapes surrounding hair snag sites for two critical food items: buffaloberry and ungulate meat. Akaike's Information Criteria (AIC) is used to rank support for models. Note that the null landscape model is included in all models except for the null intercept model. 55

Table 2: Ordered logistic regression model parameters (β and SE) for the AIC-selected landscape, fruit, and meat model explaining local abundance of grizzly bears in the Yellowhead population unit during the 2004 DNA hair-snag mark-recapture population survey. Odds ratios (e^β) and standardized coefficients (e^βStdX) are provided to assess strength of relationship per one unit change in variable (e^β) or one standard deviation change in the variable (e^βStdX). 56

Appendix A.4.1. Estimating Ungulate Biomass in the Yellowhead Grizzly Bear Population Unit

Table 1. Variables used to predict ungulate densities across the Yellowhead Grizzly Bear Population Unit. 70

Table2. Species specific regression coefficients estimated using Generalized Linear Models. Coefficients are representative of averaged values using Akaike weights and multimodel inference. 71

List of Tables

CHAPTER A.5. Future of Alberta's Forests for Grizzly Bears Disturbance Evaluation and LiDAR Habitat Classification

Table 1: Summary Statistics for the detected STAARCH disturbances. 76

Table 2: the location and the date of acquisition of the Landsat images used in the research analysis, obtained from the USGS GLOVIS archive....84

Table 3: description of the FRAGSTATS metrics used in the decision tree model to identify type of disturbance (McGarigal et al. 2012) 85

Table 4: Focus understory plant species.... 105

Table 5. Environmental covariates utilised in Boosted Regression Tree Modelling.... 107

Table 6: Model results 109

Table 7: Proposed classification scheme:.... 122

Table 8: Proposed classification decision rules:.... 123

Table 9: Confusion matrix for 12 classes with comparision to the currently available habitat map and EOSD.... 124

Table 10. Characteristics of the camera plot locations 128

Table 11. Inter-site length of season analysis for all species presences..... 131

REPORT B: GRIZZLY BEARS AND PIPELINES: RESPONSE TO UNIQUE LINEAR FEATURES

Chapter B.2. Grizzly Bear Habitat Selection Patterns On Pipeline Right-Of-Ways

Table 1: Buffers applied to linear features in the Kakwa study area, based on widths measured in the field or using a GIS..... 210

Table 2. Seasonal model coefficients, standard errors, and 95% confidence limits for female grizzly bear habitat selection of linear features. Results in bold indicate that use was significantly different than expected based on habitat availability..... 212

List of Tables

Table 3. Seasonal model coefficients, standard errors, and 95% confidence limits for male grizzly bear habitat selection of linear features. All results are significantly different than expected based on habitat availability........ 213

Table 4. Matrix of comparisons of female grizzly bear use of linear feature types. Seasonal model coefficients, standard errors, and 95% confidence limits indicate the likelihood of use of the linear feature type on the left as compared to the linear feature type across the top of the table. Confidence intervals were corrected using the Bonferonni adjustment for comparison across multiple habitat types. Results in bold indicate statistically significant differences. 215

Table 5. Matrix of comparisons of male grizzly bear use of linear feature types. Seasonal model coefficients, standard errors, and 95% confidence limits indicate the likelihood of use of the linear feature type on the left as compared to the linear feature type across the top of the table. Confidence intervals were corrected using the Bonferonni adjustment for comparison across multiple habitat types. Results in bold indicate statistically significant differences. 216

Chapter B.3. Parameters Influencing The Use Of Pipeline Right-Of-Ways

Table 1. Candidate models. 222

Table 2. Pipeline RoW candidate models and AICc values for pipeline parameters*. Top models are in bold, and superscripts indicate top models for: 1) Spring, 2) Summer, 3a) and 3b) Fall. Variables include age-sex class (AS), disturbance age (DA), multi-pass (MP), pipeline density (PD), and land cover (LC). 225

Table 3. Pipeline-road RoW candidate models and AIC_c values for pipeline parameters*. Top models are in bold, and superscripts indicate top models for: 1)a and 1)b Spring, 2) Summer, 3) Fall. Variables include age-sex class (AS), original pipeline age (PA), multi-pass (MP), pipeline density (PD), road density (RD), and landcover (LC). 227

Chapter B.4. Food Availability On Pipeline Right-Of-Ways.

Table 1. Bear foods used in analysis. 235

List of Tables

Table 2. Frequency of occurrence (percentage of plots with bear food present) of bear foods by habitat type. 237

Tables 3a. and 3b. Comparison of probability of occurrence of bear foods at pipeline RoWs compared to coniferous forest, deciduous/mixed forest, and regenerating forest (cutblocks). Significant differences are in bold. 238

Tables 4a. and 4b. Comparison of probability of occurrence of bear foods at pipeline edges compared to coniferous forest, deciduous/mixed forest, and regenerating forest (cutblocks). Significant differences are in bold. 239

Chapter B.5. Linear Features And Predation.

Table 1. Average distance to linear feature for individual grizzly bears, by use points (GPS collar locations), available points (random locations), confirmed predation sites (killsites), and confirmed non-predation use sites. Mean values with significant differences are in bold, and contrasts between comparison groups are indicated by a) significant differences between use and available, and b) significant difference between killsites and available. 248

Table 2. Coefficients and confidence intervals by individual grizzly bear for analysis of distance to nearest road for: 1) use versus available locations, 2) killsites versus available locations, and 3) killsite versus non-killsite use locations. Significant results are in bold. 249

Table 3. Coefficients and confidence intervals by individual grizzly bear for analysis of distance to nearest seismic line for: 1) use versus available locations, 2) killsites versus available locations, and 3) killsite versus non-killsite use locations. Significant results are in bold. . 250

Table 4. Coefficients and confidence intervals by individual grizzly bear for analysis of distance to nearest pipeline for: 1) use versus available locations, 2) killsites versus available locations, and 3) killsite versus non-killsite use locations. Significant results are in bold. . 251

Table 5. Coefficients and confidence intervals by individual grizzly bear for analysis of distance to nearest pipeline-road RoW for: 1) use versus available locations, 2) killsites versus available locations, and 3) killsite versus non-killsite use locations. Significant results are in bold. 252

List of Tables

Chapter B.6. Mortality Risk Factors

B.6.1. Sightability of grizzly bears on pipeline RoWs.

Table 1. Percent cover classes used to estimate forbs/grass and shrubs > 25 cm tall and tree canopy cover on pipelines. 256

Table 2. Explanatory variables used for assessing maximum line-of-sight down pipelines at road intersections in the Kakwa study area. 262

Table 3. A priori candidate models used to describe the maximum line-of-sight down pipelines at road intersections in the Kakwa study area. 263

Table 4. AICc-selected models for predicting the maximum line-of-sight down pipelines at road intersections in the Kakwa study area. The model with the highest AIC weight is in bold. 264

B.6.2. Levels of human and wildlife use on pipeline RoWs

Table 1. Count of photos by photo subject across the 6 camera sites. *Miscellaneous includes one photo each of an elk, mule deer, gray jay, and lynx. 269

REPORT C: EVALUATING GRIZZLY BEAR HABITAT USE AND RESPONSE TO NEW APPROACHES TO FOREST MANAGEMENT, HARVESTING, AND ACCESS PLANNING IN CORE GRIZZLY BEAR CONSERVATION AREAS – ARE NEW APPROACHES POSSIBLE TO SUPPORT RECOVERY EFFORTS

Table 1. Grizzly bears captured by the Foothills Research Institute Grizzly Bear Program in 2013. 289

Table 2. Grizzly bear detections on the 2013 DNA grid within the Yellowhead BMA. The total number of hair samples collected per session includes both grizzly bear and black bear samples but detections refer strictly to grizzly bear detections. Known bears are bears that have been previously identified through capture efforts or past DNA projects. First detection refers to the number of individual bears first detected in that session. 290

Table 3. Individual grizzly bears identified per session by DNA hair snag methods during the 2013 grizzly bear population inventory project. A colour scheme is used to indicate what session the bear was first detected in. 291

REPORT D: RESEARCH AND APPLIED TOOLS TO ENHANCE FOREST MANAGEMENT LINKAGES TO GRIZZLY BEAR CONSERVATION AND RECOVERY IN ALBERTA

Chapter D.2. Grizzly Bear Selection Of Forestry Cutblock Edges

Table 1. Population averaged response, selection (+), neutral (/), and avoidance (-), and the number of individual grizzly bears showing positive selection for a habitat variable. Sample size for male bears in the summer (n=12) differed from the fall (n=9), but was the same for females (n=12). 328

Table 2. The proportion of use (grizzly bear) and the proportion of available (random) locations in relation to habitat variables by season and gender. 328

Table 3. Model parameters, sample size (n), and AIC output from generalized linear models explaining seasonal variation in grizzly bear selection of edge habitat (Uncut Edge, Pine Edge, Cutblock Pine, and High Risk). 329

Chapter D.3. Do Grizzly Bears Respond To Varying Levels Of Green Tree Retention Within Cutblocks?

Table 1. The proportion of male and female grizzly bear GPS locations (habitat use) relative to high levels of retention patch amount (sum area, mean size, standard deviations in size, and total number of patches) by season. 339

Chapter D.4. Are Berries More Abundant At Forestry Cutblock Edges?

Table 1. QIC output from generalized estimating equation models describing shrub (Vaccinium myrtilloides) abundance as a function of model variables 351

Table 2. QIC output from generalized estimating equation models describing shrub (Vaccinium myrtilloides) fruit abundance as a function of model variables. We used a squared term for our distance variable (Tdist) to explain the non-linear response. 351

Chapter D.5. Does Silviculture Influence Food Availability And The Behavior Of Grizzly Bears?

Table 1. AIC output of logistic regression, generalized linear model, and ordered logistic regression explaining the distribution and abundance of shrubs and fruits in relation to a priori seleced models. 365

Table 1. Matrix of grizzly bear and caribou RSF model values. 378

Chapter D.6. Gis-Based Planning Tools

Table 1. Summary statistics (edge distance) of grizzly bear (n=6) activities by forest age (years) class. 386

Table 2. AIC_i table of competing logistic regression models explaining variation in the probability of a grizzly bear bed site. 386

Table 3. AIC_i table of competing logistic regression models explaining variation in the probability of a grizzly bear kill site. 387

Table 4. AIC_i table of competing logistic regression models explaining variation in the probability of a grizzly bear herbaceous feeding site. 387

Table 5. AIC_i table of competing logistic regression models explaining variation in the probability of a grizzly bear berry foraging site. 387

Appendix D.2.: Outline of the GBtools folder

Table 1. Dataset name, description, and folder path within GBtools. 388

List of Tables

REPORT E: A SUMMARY OF EIGHT YEARS OF ANTHROPOGENIC DISTURBANCE IN THE YELLOWHEAD POPULATION UNIT 2004-2012

Table 1: Reference images……………………………………………………………………………393
Table 2: Annual change by disturbance type………………………………………………………395

REPORT G: MODELING THE SEQUENCE AND INTERANNUAL TEMPORAL VARIATION OF CANADIAN BUFFALOBERRY (*SHEPHERDIA CANADENSIS*) USING BROAD-SCALE CLIMATE PROXIES

Table 1. Phenophase codes for *Shepherdia canadensis* and other deciduous shrubs. Dierschke 1972).. 415

Table 2. Explanatory variables used for modeling the phenological sequence of *S. canadensis*.. 418

Table 3. Model performance for AIC-selected generalized linear models for the prediction of vegetative green-up timing in *S. canadensis* (Phenophases 0-6). Model rank was assessed through AIC values (Δ_i) and weights (w_i) which describe model likelihood. Model complexity, the number of parameters, is symbolized by K_i......................... 420

Table 4. Model performance for AIC-selected generalized linear models for the prediction of late-season vegetative senescence timing in *S. canadensis* (Phenophases 6-10).................... 420

Table 5. Model performance for AIC-selected generalized linear models for the prediction of reproductive phenophase timing in *S. canadensis* 421

Table 6. Estimated model parameters for top-ranked AIC models of *S. canadensis* phenological timing. Raw coefficients and Standard errors (in parentheses) are presented by model.....421

Table 7. Green-up, senescence, and reproductive model prediction RMSE validation.. 423

List of Figures

REPORT A: RESEARCH TO SUPPORT RECOVERY AND LONG TERM CONSERVATION OF GRIZZLY BEARS IN ALBERTA

CHAPTER A.1. Summary of 2013 Capture Program

Figure 1: Study area boundaries for the 2013 capture season showing grizzly bear capture locations........15

CHAPTER A.2. An Evaluation Of Reproductive Activity In Grizzly Bears, And How It Is Influenced By Stress, Based On The Measurement Of Hormones In Hair

Figure 1. Hypothesized hormone profiles in hair samples collected from grizzly bears of different sex, age, and reproductive classes. The graphs depict the relative concentrations of three steroid hormones, progesterone (P), estradiol (E), and testosterone (T). The three scale markers on the vertical axis indicate relative levels of low, moderate, and high. The circled numbers refer to our nine research hypotheses. 24

Figure 2. Comparison of mean hair cortisol concentration (HCC) among female and male grizzly bears (*n* = 486) sampled by barbwire hair snagging (barbwire) or by clipping hair following capture by either remote drug delivery from helicopter (helicopter), leg-hold snare (snare), or culvert trap (culvert). Mean HCC values are adjusted for year of capture = 2005. 28

Figure 3. Comparisons of cortisol concentrations between methanol- and isopropanol-washed guard hair, and between methanol or isopropanol washes used to clean the grizzly hair samples (*n* = 4). Mean values are presented as points with the standard errors represented by vertical bars. 29

Figure 4: Comparison of mean cortisol concentrations between two commercial enzyme immunoassay (EIA) kits (Oxford and Salimetrics) in subsamples of bear hair (*n* = 16), and in the solvent (wash) used to clean hair samples. Mean values are presented as points with the standard errors represented by vertical bars........30

List of Figures

CHAPTER A.3. Understanding Seasonal Variation In Leptin And Adiponectin Production, Adipose Function, And Whether Either Hormone Can Be Used To Estimate Body Fat Content In Brown Bears

Figure 1. Changes in body fat content and serum leptin and adiponectin concentrations in four captive bears during the active season. 36

Figure 2. The relationship between body fat content and leptin concentrations in four captive brown bears during the active season. 37

Figure 3. The relationship between serum adiponectin and body fat content as affected by type of dietary fat. 38

Figure 4. A. The effect of centrally administered leptin or the carrier (i.e., control) on food intake in bears at two times of the year (Aug and Oct). B. Annual serum leptin profile of WSU grizzly bears (n = 6-12 for each point, collected from 2008–2014). Arrows indicate times that central leptin was administered to bears shown in panel A, and the dashed line represents the detection limit. Note the extremely narrow window for leptin production. 39

CHAPTER A.4. Population Recovery Targets For Grizzly Bears In Alberta

Figure 1: Nutritional landscape pattern of total available ungulate meat (log10 kcal; Dig E) and associated local abundance of grizzly bears during the 2004 hair-snag DNA population survey. 57

Figure 2: Nutritional landscape pattern of buffaloberry fruit (log10 kcal; Dig E) and associated local abundance of grizzly bears during the 2004 hair-snag DNA population survey. 58

Figure 3: Patterns in road density (7440 m radius) and local abundance of bears within the 2004 Yellowhead hair-snag DNA survey for grizzly bears. 59

Figure 4: Total energy cost for grizzly bears in the Foothill and Mountain ecosystems of Alberta. Energy cost is expressed in kcal/active period. Maintenance cost (black), Mass gain (dark grey), Movement (light grey), and Lactation (white) are illustrated. 60

Figure 5: Total fresh intake of food (in tons) for grizzly bears during the active period in the Foothill and Mountain ecosystems of west-central Alberta. 60

List of Figures

Figure 6: DNA hair-snag mark-recapture survey sites collected during the 2004 population survey for the Yellowhead population of grizzly bears in west-central Alberta. Elevation is shown for reference and the location of defined 7x7 km grid used for allocating sample efforts.......61

Figure 7: Contour plots illustrating the predicted probability (AIC-selected model) of detecting either zero bears (a) or 3 or more bears (b) at a DNA hair-snag sites in the Yellowhead ecosystem as a function of local available digestible energy in ungulates (x-axis) and buffaloberry fruit (y-axis). Road density and sample session number are set in this example to a value of 0.......62

CHAPTER A.5. Future of Alberta's Forests for Grizzly Bears Disturbance Evaluation and LiDAR Habitat Classification

Figure 1 Landsat Tiles with last year STAARCH update.......76

Figure 2 overview of disturbances over the whole study area.......77

Figure 3: Study area in Alberta showing the foothills area with observed Grizzly bear habitat states.......81

Figure 4: STAARCH output for the Grizzly bear study area classified by the type of disturbance from 2001-2011.......87

Figure 5: Total disturbed area (square kilometers) classified by type of disturbance (a) and by month of acquisition over the ten year study period (b) for western Alberta.......89

Figure 6: (A) Percent of individual disturbance events, and (B) as fraction of the area in Grizzly bear study area from 2001 to 2011.......90

Figure 7: Total disturbed area (square kilometers) classified by type and habitat state from 2001-2011.......91

Figure 8: Total disturbed area (square kilometers) classified by year, for individual habitat states (primary habitat, secondary habitat, primary sink, secondary sink and non-critical habitat) from 2001-2011.......92

List of Figures

Figure 9: Scatterplot of Field and LiDAR derived data for plot locations (green points in canopy cover are areas with maximum canopy heights < 10m). 98

Figure 10: Scatterplot of Percent Conifer model (R^2 = 0.56, p < 0.0001), green points are fore areas with canopy height < 4m. 98

Figure 11: Quick look map of Canopy Conifer Cover 99

Figure 12: Quick look map of Canopy Height........ 100

Figure 13: Quick look map of Percent Conifer........ 100

Figure 14: Overview of the study area and plot locations. Subset shows area displayed in species figures below. 104

Figure 15: Probability of occurrence maps based on Climate (left), Climate + forest cover (middle), and Climate + Lidar (right) data *for E.arvense, H.alpinum, T.officinale*, *and V.vitis-idea*........ 111

Figure 16: Top three variables selected in model development for the three model suites........ 112

Figure 17: Response graphs if the first three most important variables for the Climate + Lidar model for E.arvense, H.alpinum, T.officinale and V.vitis-idea. 113

Figure 18: Change in Variables selected by models when incorporating fine scale site and canopy LiDAR derived information........ 114

Figure 19. Example area for the habitat classification 124

Figure 20: Geometry of images 129

Figure 21. Comparison between estimations of phenological event dates (i.e., Begining of Season, End of Season) as estimated by field observations and values derived from the broad- (2a) and narrow- (2b) field of view imagery. Species for which both field data and imagery was available included H. alpinum, L. ochroleucus, S. canadensis, and A. uva-ursi. When broad and narrow fields of view were taken together, R^2 = 0.82 (n=18). Grey line represents 1:1. A. uva-ursi was excluded from correlation due to its being an outlier........ 132

List of Figures

Figure 22. Splines fits to 2G-RBi daily values through the growing season for H. alpinum, Castilleja spp., A. uva-ursi, Salix spp., Camas spp., and S. canadenisis. Raw and Narrow field of views are compared 133

Figure 23. Deviation 2G-RBi plots (broad – Narrow) by species. 133

Figure 24. Locations of cameras set-up to moniter the phenology of *Heracleum* in the Kakwa study area 135

Figure 25. Example of camera frames at each of the study sites 138

Figure 26: Plot Locations (on Landsat TM, RGB=543). 139

Figure 27: Histograms of Canopy Height, Canopy Cover, and Basal Area 140

Figure 28: Scatterplots of Canopy Height, Cover, and Basal Area 141

Figure 29. Simulation Framework 145

Figure 30. Performance of Iterative Linear Transformation for Fire Parameter Optimization 154

Figure 31. Area Burned by Natural Region and Natural Subregion, 1923-2012 159

Figure 32. Frequency of fires relative to foliar moisture content (FMC) 160

Figure 33. Species establishment by Natural Subregion and time period 161

Figure 34. Forest structural change for the simulated time period 1923-1953, showing model spin-up effects 163

Figure 35. The ZELIG model framework (Urban 1990) 166

Figure 36. The TACA-EM model framework (Nitschke and Innes 2008) 168

Figure 37. The TACA-GEM model framework (Nitschke et al. 2012) 170

Figure 38. NOAA GHCN-Daily Weather Stations in the Proximity of Natural Subregions within the Phase 7 Study Area 172

Figure 39. Sum of Station Individual Parameter Metrics by Natural Subregion 173

Figure 40. Constructive and destructive interference produced by summing two waves (image adapted from Georgia State University HyperPhysics) 176

Figure 41: Change in Species Establishment with Extreme Events, 1923-1952 to 1983-2012. 178

Figure 42. Treeline Elevation Change by Genus, Handölan Valley, Sweden (in Brubaker 1986) 181

Appendix A.5. TACA-GEM Model Results Comparing Input Weather Data Types in Three Natural Subregions a)Central Mixedwood; b) Foothills Fescue; and c) Montane. 188

REPORT B: GRIZZLY BEARS AND PIPELINES: RESPONSE TO UNIQUE LINEAR FEATURES

Chapter B.1. Background, Study Area, And Research Objectives.

Figure 1: Kakwa study area 204

Chapter B.3. Parameters Influencing The Use Of Pipeline Right-Of-Ways

Figure 1. Predicted probability of pipeline use by age-sex class and season. Age-sex classes include females with cubs of the year (Fcoy), adult females (AF), adult males (AM), subadult males (SaM), and subadult females (SaF) 226

Figure 2. Mean disturbance age for available and used pipeline sites, summer and fall. 226

Figure 3. Predicted probability of pipeline-road RoW use by age-sex class and season. Age-sex classes include females with cubs of the year (Fcoy), adult females (AF), adult males (AM), subadult males (SaM), and subadult females (SaF) 228

Figure 4. Mean pipeline age for available and used pipeline-road RoW sites, by season 229

Figure 5. Mean pipeline densities for available and used pipeline-road RoW sites, by season. 229

Figure 6. Mean road densities for available and used pipeline-road RoW sites, by season. 230

Chapter B.5. Linear Features And Predation.

Figure 1. Mean distances to roads, seismic lines, pipeline-road RoWs and pipelines, by location type. 247

Chapter B.6. Mortality Risk Factors

B.6.1. Sightability of grizzly bears on pipeline RoWs.

Figure 1. Frequency of maximum line-of-sight distances down pipelines from road intersections in the Kakwa Study area. 258

Figure 2. The maximum line-of-sight obstruction types at 66 pipeline-road intersections in the Kakwa study area. 259

Figure 3. Average percent of a "grizzly bear" visible in 50m increments down a pipeline from a road intersection at different location pairs for a total of 504 "bear" locations. Standard error bars are shown..... 260

Figure 4. Count of obstruction type by distance (m) down pipelines at road-pipeline intersections at 504 "bear" locations. 261

B.6.2. Levels of human and wildlife use on pipeline RoWs

Figure 1. Remote camera picture of a grizzly bear event from the Pine Ridge site. One of these bears is an adult male grizzly bear (G270) wearing a GPS collar. 270

Figure 2. Events/100 camera days across sites by photo subject..... 271

REPORT C: EVALUATING GRIZZLY BEAR HABITAT USE AND RESPONSE TO NEW APPROACHES TO FOREST MANAGEMENT, HARVESTING, AND ACCESS PLANNING IN CORE GRIZZLY BEAR CONSERVATION AREAS – ARE NEW APPROACHES POSSIBLE TO SUPPORT RECOVERY EFFORTS

Figure 1. Grizzly bear DNA population inventory grid, DNA sites, grizzly bear capture locations, and Forest Management Areas (FMAs) located within the Yellowhead study area. The DNA grid is comprised of 50 7×7-km cells with one hair snag site per cell..... 292

Figure 2. Methods for the capture and handling of grizzly bears includes: A) free-range, B) culvert trap, and C) helicopter. 293

Figure 3. A typical DNA hair snag site used in the grizzly bear DNA population inventory........ 294

Figure 4. Grizzly bear minimum convex polygons (2013) in relation to the DNA hair snag grid and planned harvest cutblocks. Five of these bears (G129, G150, G151, G152, and G153) were detected on the DNA grid during the grizzly bear DNA population inventory in 2013. 295

Figure 5. GPS collar data of eight bears captured within the Yellowhead Population Unit by the Foothills Research Institute Grizzly Bear Program in 2013. 296

Figure 6. Grizzly bear detections in 2004 (red) and 2013 (black) in relation to estimated grizzly bear resource selection (i.e. the probability of use of an area by a grizzly bear). Grizzly bear capture locations in 2013 are also shown. 297

REPORT D: RESEARCH AND APPLIED TOOLS TO ENHANCE FOREST MANAGEMENT LINKAGES TO GRIZZLY BEAR CONSERVATION AND RECOVERY IN ALBERTA

Chapter D.1. Grizzly Bear Response To The Edge And Interior Of Forestry Cutblocks

Figure 1.. Natural Sub Regions within Weyerhaeuser Grande Prairie Forest Management Agreement area, Alberta, Canada........ 316

Figure 2. Predicted mean distance to edge and 95% confidence intervals of male and female grizzly bear and random locations among four forest age classes. 317

Figure 3. Grizzly bear selection of interior and edge habitat by season, sex and reproductive class, and forest age (years). 318

Chapter D.2. Grizzly Bear Selection Of Forestry Cutblock Edges

Figure 1. Grizzly bear selection (odds ratio) of cutblock edge types by season and gender. Edge type refers to cutblock edges classified (=1) as pine leading in cutblock, adjacent stand uncut, adjacent stand pine leading, and high mortality risk........ 330

List of Figures

Chapter D.3. Do Grizzly Bears Respond To Varying Levels Of Green Tree Retention Within Cutblocks?

Figure 1. Male and female selection (odds ratio) of high levels of retention patch amount (sum area, mean size, standard deviations in size, and total number of patches) by season. Error bars represent standard errors 340

Chapter D.4. Are Berries More Abundant At Forestry Cutblock Edges?

Figure 1. Probability of *Vaccinium myrtilloides* fruit being present by habitat as a function of edge distance estimated using a generalized estimating equation model. 352

Figure 2. Predicted berry count of *Vaccinium myrtilloides* by habitat as a function of edge distance estimated using a generalized estimating equation model. 352

Chapter D.5. Does Silviculture Influence Food Availability And The Behavior Of Grizzly Bears?

Figure 1. The seasonal population averaged response (odds ratio) of male and female grizzly bears to cutblocks harvested in winter, and where site preparation or herbicide treatments occurred. 366

Chapter D.6. Gis-Based Planning Tools

Figure 1. Caribou Grizzly RSF tool User interface. 379

Figure 2. Caribou RSF (left), grizzly bear RSF (center), and the interaction matrix (right). 380

Figure 3. Road Reclamation tool: user interface. 381

Figure 4. Watershed (highlighted) and road selected for reclamation (dashed), and the regenerated Habitat State model (left) with road removed (right). 381

Figure 5. Viewshed calculator: user interface. 382

Figure 6. Sightlines (green) from roadside (dashed) with timber visual buffers (right) and without (left). 383

Appendix D.3. GBTools User Interface

Figure 1. GIS tools in ArcToolbox. 390

Figure 2. ArcCatalog layers. 391

Figure 3. Model extent. 391

REPORT E: A SUMMARY OF EIGHT YEARS OF ANTHROPOGENIC DISTURBANCE IN THE YELLOWHEAD POPULATION UNIT 2004-2012

Figure 1: Study area 390

Figure 2: Annual change by disturbance type 390

Figure 3: New roads constructed in study area after 2004. 390

REPORT F: NEW GIS TOOLS FOR LIDAR-BASED MAPPING AND ANALYSIS OF SEISMIC CUTLINES IN NORTHERN ALBERTA

Figure 1: Seismic cutline 390

Figure 2: OHV trail (yellow) and regenerating trees (green) within cutline corridor 402

Figure 3: Areas where seismic lines have been delineated using Lidar surfaces 403

Figure 4: Original (left) and updated (right) Full Feature Lidar surface 404

Figure 5: Manually digitized (red) and adjusted seismic line (yellow) 405

Figure 6: Disturbance corridor 406

Figure 7: Vegetation height along Least-cost path 407

Figure 8: Steep trail bypassed by detour 407

Figure 9: Line-blocking, left; trees heights derived from cluster analysis, right 409

Figure 10: Seismic cutlines: original line feature (dotted black); adjusted line (blue-green); corridor edge (yellow); heights of adjacent trees color-coded green to red 410

REPORT G: MODELING THE SEQUENCE AND INTERANNUAL TEMPORAL VARIATION OF CANADIAN BUFFALOBERRY (*SHEPHERDIA CANADENSIS*) USING BROAD-SCALE CLIMATE PROXIES

Figure 1. Study Area and observation sites 2008-2010.. 415

Figure 2. *Shepherdia canadensis* bearing ripe fruit. 416

Figure 3. Stacked green-up and senescence S. canadensis vegetative models predicting interannual phenological variability based on the minimum, maximum, and neutral MEI values occurring during the study period. 423

Figure 4. *S. canadensis* reproductive model predicting interannual phenological variability based on the minimum, maximum and average MAT values occurring during the study period. 424

Figure 5. Variability of MEI and PDO index values throughout the study period with the most phenologically influential periods highlighted 425

REPORT A: RESEARCH TO SUPPORT RECOVERY AND LONG TERM CONSERVATION OF GRIZZLY BEARS IN ALBERTA

Year Two

Prepared for: Alberta Innovates Biosolutions and fRI Grizzly Bear Program Partners

fRI Grizzly Bear Program

Editors: Gordon B. Stenhouse and Karen Graham

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The materials and conclusions presented in this report should be viewed as preliminary in nature and citations of this work should not be made without the written consent of the appropriate authors.

CHAPTER A.1. Summary of 2013 Capture Program

Prepared by

Gordon Stenhouse, Karen Graham and Terry Larsen

Introduction

In 2013, the Foothills Research Institute's (FRI) Grizzly Bear Program (GBP) focused its capture and collaring efforts in areas where forestry and oil and gas activities were occurring. The purpose was to collect grizzly bear location data to examine habitat use and movement with respect to resource extraction. At the same time, we continued to collect information on health parameters of all grizzly bears handled.

Although capture efforts were focused on acquiring data for FRI projects, we also provided capture and handling assistance for a study being conducted by the University of Alberta (U of A) in association with Alberta Tourism, Parks and Recreation looking at human interactions and grizzly bears.

Method

Study Areas

We captured and sampled grizzly bears in three distinct study areas in 2013 (Figure 1). Seven bears were captured between Grande Prairie and Grande Cache, known as the Kakwa study area. One grizzly bear was caught within the Kakwa Wildland Provincial Park. Three grizzly bears were captured south of highway 16 and east of Jasper National Park, known as the U of A study area (Human Interaction study) and 5 grizzly bears and 3 black bears were captured in the Nordegg study area north of highway 11.

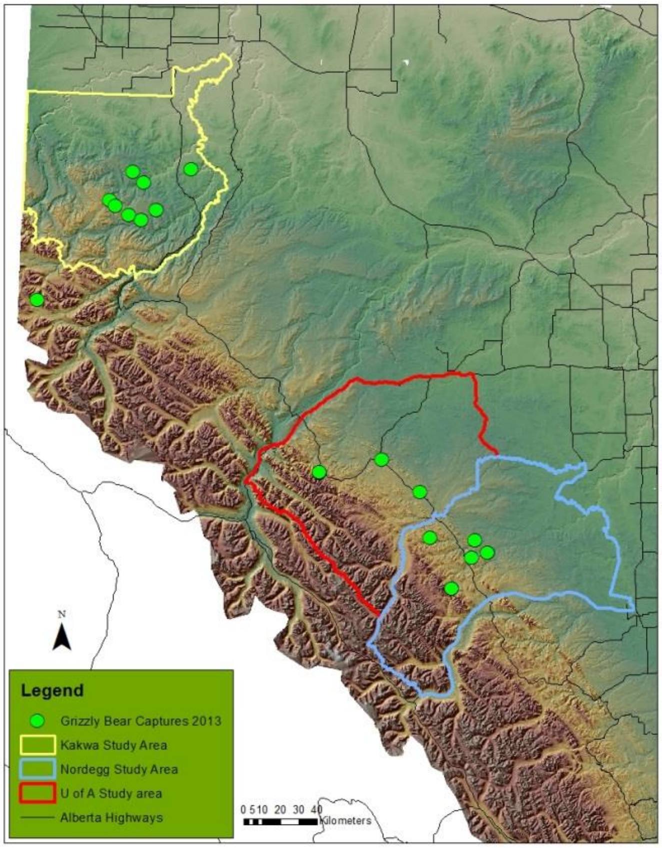

Figure 1: Study area boundaries for the 2013 capture season showing grizzly bear capture locations.

Capture Protocol

The capture crew consisted of biologists and veterinarians with experience in grizzly bear capture and handling. Grizzly bears were captured via helidarting, culvert traps, or free-range (ground) darting from a vehicle. All traps were established along existing industrial access roads, and each trap was equipt with a satellite alarm system. No snaring of grizzly bears occurred.

Capture efforts began in early May in the Kakwa and U of A study areas and mid June for the Nordegg study area. Captures occurred throughout the spring, summer and fall. Helicopter capture was used primarily to target specific bears for recapture and collar replacement, but was also employed to capture in open habitats where possible (e.g. alpine, cutblocks). One bear in the Nordegg study area was ground darted while the remaining captures involved culvert traps (Table 1).

Results

Grizzly Bear Captures

In total, we caught 16 grizzly bears in our 2013 field season (Table 1) from 17 capture events (1 bear was caught twice). Eight bears were captured in the Kakwa study area, one was captured in the Kakwa Wildlands Provincial Park (under permit 13-050), 3 were captured in the U of A study area south of Hinton and 5 were captured in the Nordegg study area. Three black bears were also captured in the Nordegg study area. No other non-target species were captured. No capture related mortalites occurred during the 2013 field season.

Black Bear Captures

Three black bears were captured and two were collared (females) for a project intiated by Ann Hubbs of ESRD in the Nordegg Study area. The goal was to capture female black bears to obtain detailed movement information and determine survival.

Table 1. Details of the grizzly (G) and black bear (bb) captures.

Name	Date	Recap	Sex	Age Class	Population Unit	Capture Method
BB145	18-Jun-13	no	F	adult	Yellowhead	culvert trap
BB146	18-Jun-13	no	M	subadult	Yellowhead	culvert trap
BB147	29-Jun-13	no	F	subadult	Yellowhead	culvert trap
G111	09-Jun-13	yes	F	adult	Yellowhead	heli dart
G127	17-May-13	no	M	subadult	Yellowhead	heli dart
G128	05-Oct-13	no	M	subadult	Yellowhead	culvert trap
G129	08-Oct-13	no	M	subadult	Yellowhead	culvert trap
G150	14-Jun-13	no	M	subadult	Yellowhead	ground dart
G150	03-Jul-13	yes	M	subadult	Yellowhead	culvert trap
G151	17-Jun-13	no	M	adult	Yellowhead	culvert trap
G152	04-Jul-13	unk	M	adult	Yellowhead	culvert trap
G153	09-Sep-13	no	F	subadult	Yellowhead	culvert trap
G260	28-Aug-13	yes	F	adult	Grande Cache	heli dart
G270	16-May-13	yes	M	adult	Grande Cache	culvert trap
G275	23-Aug-13	yes	F	adult	Grande Cache	heli dart
G280	22-Aug-13	yes	F	subadult	Grande Cache	heli dart
G284	22-Aug-13	yes	M	subadult	Grande Cache	heli dart
G286	13-May-13	no	M	adult	Grande Cache	culvert trap
G287	27-May-13	no	M	subadult	Grande Cache	culvert trap
G288	28-Aug-13	no	F	adult	Grande Cache	heli dart

We anaesthetized 9 grizzly bears and 3 black bears using a combination of xylazine and Telazol and 8 bears using a combination of Medetomidine-hydromorphine-telazol; both administered by remote drug delivery, e.g., dart rifle or jab pole. Once immobilized, grizzly bears were weighed, and measured (chest girth, zoological length, and straight-line length). Samples were collected (blood, hair, skin biopsy, and tooth). Radio-collar and ear tag transmitters were attached. A transponder (microchip) was also inserted beneath the skin for future identification purposes. Vital functions and blood-oxygen levels were monitored throughout the handling period. Following handling, we administered atipamezole to reverse the effects of anaesthesia and monitored the bears until they showed imminent signs of recovery. We checked all bears within 24 hours of capture to ensure they had recovered fully from immobilization. All details of capture operations conformed to both provincial and national standards on the capture and handling of ursids.

Sex and Age Characteristics

There was a 50/50 split between captured adult and subadult grizzy bears. Males were caught more often (10 bears; 63%) than females (6 bears; 37%). Subadult males were captured most often (38%), adult males and adult females were caught similarly (25% each) and subadult females were caught the least (12%) (Table 1). No cubs of the year were caught.

Black bears that were captured included one adult female, one subadult female and one subadult male (Table 1).

GPS Radio-Telemetry Data

We deployed a Global Positioning System (GPS) radio-collar and (VHF) ear-tag transmitter (attached to the collar) on 16 grizzly bears. All radio-collars have an integrated remote release mechanism in addition to a rot-off system as a backup in case of electronic failure. Radio-collars deployed consisted of Follow-it Tellus Iridium collars. Data from these collars can be acquired from a website so data upload flights were not necessary. Collars collect locations on the following schedule:

- April 1 to November 31 - 1 location/ hour.
- December 1 to March 31 - 1 location/day

We collected over 40,000 GPS location points from these collars in 2013.

Grizzly Bear Health Evaluation

We gathered health information from all 16 grizzly bears as part of our research activities. The data from these bears include data on physical and physiological measurements recorded at capture as well as results from subsequent laboratory analyses of blood serum, skin, and hair. All health data for 2013 will be entered into our project health database.

Modification of Anesthetic Protocol for Foothills Research Institute Grizzly Bear Project

Beginning in the spring of 2012, we began to incrementally replace the immobilizing drug combination of xylazine-zolazepam-tiletamine (XZT), which has been utilized by our research team for the past 12 years, with the combination of medetomidine-zolazepam-tiletamine (MZT). The use of MZT has been used for many years by our colleagues in Sweden and allows the administration of smaller drug volumes, due to the greater potency of medetomidine, which potentially can facilitate improved accuracy and reduced injury by remote drug delivery. Furthermore, the anesthetic effects of MZT are more readily reversed with the antagonist drug atipamezole than are the effects of XZT. Thus, increased reliability with the reversal procedure will allow us to better ensure that captured bears recover (mobility) as soon as possible following handling.

In the 2013 capture season we used the following dosages: medetomidine at 60-75 ug/kg IM, Telazol (zolazepam-tiletamine) at 2.1-2.6 mg/kg IM, and atipamezole at 240-300 ug/kg IM. This protocol has been adapted for use with Alberta grizzly bears from a similar protocol used by the Scandinavian Brown Bear Project (SBBP) over the past 15 years(1 In the spring of 2012, we tested MZT and atipamezole at the dosages listed above to anesthetize and reverse four grizzly bears captured by culvert trap. Albeit a small number of animals, induction was smooth and relatively quick (≤5 min), anesthesia was stable over a 45-60 min handling/sampling period, and reversal was also smooth and relatively quick (10-20 min). The 2013 field season allowed further work with this drug combination in both aerial and ground capture situations.

Relevent Literature

(1) Painer J, Zedrosser A, Arnemo JM, Fahlman Å, Brunberg S, Segerstrøm P, and Swenson JE. (2012). Effects of different doses of medetomidine and tiletamine-zolazepam on the duration of

induction and immobilization in free-ranging yearling brown bears (*Ursus arctos*). Canadian Journal of Zoology 90(6):753–757.

(2) Cattet MR, Caulkett NA, Polischuk SC, Ramsay MA. (1997). Reversible immobilization of free-ranging polar bears with medetomidine-zolazepam-tiletamine and atipamezole. Journal of Wildlife Diseases 33(3):611–617.

CHAPTER A.2. An Evaluation Of Reproductive Activity In Grizzly Bears, And How It Is Influenced By Stress, Based On The Measurement Of Hormones In Hair

Prepared by
Marc Cattet and David Janz

Executive Summary

Over the past two years, we have been developing and validating laboratory techniques to measure several hormones, indicative of reproductive function, in the hair of grizzly bears in a reliable and feasible manner that can be readily included as a wildlife health assessment component in a recovery and conservation action plan. We are now able to measure several hormones, broadly known as steroid hormones, which play key roles in mammalian reproduction; these are estradiol, progesterone, and testosterone. This past year, we also attempted to measure another class of hormones, the peptide hormones (e.g., prolactin, leptin), in hair but detection of these hormones requires the application of techniques that are too expensive for routine use in monitoring for recovery and conservation programs. Nonetheless, despite this setback, we should still be able to distinguish bears of different sex, age, and reproductive classes on the basis of steroid hormone profiles measured in their hair samples.

We also conducted two validation studies this past year that have important implications for our overall research program. In one study, we provide evidence to show that capture and handling may rapidly increase the cortisol concentration of hair even after it has ceased growing. These findings are incongruent with the popular assumption that the hormone concentration in determined solely by passive diffusion from the vascular supply to the follicular cells that produce the hair, and suggested the presence of other mechanisms that also influenced hormone levels. In another study, we used several different laboratory methodologies that have been described in the

peer-reviewed literature to measure the cortisol concentration of hair, and identified large differences in cortisol concentrations among subsamples of hair from the same grizzly bears. With these findings, we concluded that results cannot be meaningfully compared between studies if different methodologies were used to determine cortisol concentrations.

For the third and final year of this program supported by Alberta Innovates Biosolutions, we will: (i) characterize hormone profiles in hair samples collected from bears of different sex, age, and reproductive classes; (ii) measure hair cortisol levels to investigate the effects of stress on reproduction; and (iii) develop multi-state models to identify dynamic relationships between reproductive function, long-term stress, environmental covariates, and demographic metrics.

Background

To support the recovery and long-term conservation of grizzly bears (*Ursus arctos*) in Alberta, we have been developing and validating non-invasive techniques to improve our understanding of, and ability to monitor, grizzly bear reproduction. More specifically, we have been determining how to measure several hormones, indicative of reproductive function, in the hair of grizzly bears in a reliable and feasible manner that will eventually allow these procedures to be integrated into a recovery and conservation action plan.

The collection and analysis of hair offers several advantages when compared to using other biological samples, e.g., blood serum. It can be collected from animals without capturing them, e.g., with the use of hair traps (Woods *et al*., 1999). This allows researchers to circumvent the potentially confounding influence of stress caused by capture and handling, it reduces the likelihood of adversely affecting the welfare and fitness of study animals, and it enables cost-effective collection from large numbers of animals over large areas. Hair samples are also easy and inexpensive to prepare for storage; simply air-dry, seal in paper envelopes, and store at indoor ambient temperature (Macbeth *et al*., 2010). Samples can also be assigned to individual animals through DNA extraction and analysis (Proctor *et al*., 2010). Finally, because hormones incorporated into the hair matrix do not degrade appreciably over time or after exposure to the environment (Macbeth *et al*., 2010), it opens the possibility of conducting analyses using archived samples including museum specimens.

Although potential exists to evaluate a range of physiological functions through the analysis of hormones in hair (Stalder and Kirschbaum, 2012), our primary focus has been reproduction because it is an important attribute of health (i.e., reproduction may cease when health is poor) and biological fitness in individual animals (Eberhardt, 2002; Zedrosser *et al*., 2013), and because it is required as a measurement to estimate reproductive rates at the population level (Garshelis *et al*., 2005). We are investigating potential indicators of reproductive activity (or the lack of) in juvenile and adult, female and male bears, but our efforts are weighted more toward adult females because, unlike in adult males, the outcome of successful reproduction (i.e., viable offspring) can be inferred by hormone levels. We have also been evaluating hair-based physiological indicators of stress and energy balance because these functions may affect reproduction (Dickens *et al*., 2010; Robbins *et al*., 2012), and because these functions may also serve as important links between human-caused environmental change and depressed reproductive output (Acevedo-Whitehouse and Duffus, 2009; Semeniuk *et al*., 2012).

Herein, we review progress made during the second year of a 3-year program supported by Alberta Innovates Biosolutions. We start by reviewing our research objectives and hypotheses, of which the latter have been modified from year one to reflect methodical limitations identified this past year (for details, see the section on detection and measurement of peptide hormones). This is followed by summaries of steps forward in three areas, (i) the detection and measurement of steroid hormones, (ii) the detection and measurement of peptide hormones, and (iii) new insights into the measurement of hormones in hair. Finally, we outline the research activities planned for the third and final year of the program.

Objectives and Hypotheses

In our initial proposal to Alberta Innovates Biosolutions, we identified three objectives to support attainment of our research goal which is to develop and validate non-invasive techniques to improve our understanding of, and ability to monitor, grizzly bear reproduction. These are as follows:

1. To develop and validate non-invasive biomarkers of reproductive state that can be measured in grizzly bear hair;
2. To investigate effect(s) of long-term stress on reproduction; and
3. To develop multi-state models to identify dynamic relationships between reproductive function, long-term stress, environmental covariates, and demographic metrics

The completion of objectives 2) and 3) is contingent upon our success with addressing the first objective. In other words, we cannot begin to tackle these latter two objectives until we have completed objective one. Further, the time required to develop and validate biomarkers is substantial and, consequently, remains a primary focus of our efforts even today. In contrast, the completion of objectives 2) and 3) will occur in parallel over a much shorter time frame during the final year of the program.

We have revised our research hypotheses during year two as follows below (Fig. 1). As an aside, it should be pointed out that these hypotheses speak directly to objectives 1) and 2). In contrast, the completion of objective 3) will require the use of multiple data sources owned by the Foothills Research Institute Grizzly Bear Program, in addition to the hair hormone levels produced by this study, to develop predictive models rather than test specific hypotheses.

1) The estradiol concentration in hair is higher in adult female grizzly bears than in adult male bears.
2) The estradiol concentration in hair is higher in adult female grizzly bears than in juvenile (reproductively immature) female bears.
3) The testosterone concentration in hair is higher in adult male grizzly bears than in adult female grizzly bears.
4) The testosterone concentration in hair is higher in adult male grizzly bears than in juvenile (reproductively immature) male bears.
5) The progesterone concentration in hair is lower in non-pregnant grizzly bears than in pregnant bears or bears undergoing false pregnancy (pseudo-pregnancy).
6) Whereas the progesterone concentration in hair is elevated in both pregnant and pseudo-pregnant grizzly bears, the testosterone concentration in hair is elevated only in pseudo-pregnant bears.
7) The concentration of progesterone (a biomarker of pregnancy) in the hair of adult females is inversely associated with the hair cortisol concentration (a biomarker of stress).
8) The concentration of testosterone (a biomarker of libido) in the hair of adult males is inversely associated with the hair cortisol concentration (a biomarker of stress).
9) The hair cortisol concentrations of adult females and their yearling offspring are directly associated.

It was necessary to revise our hypotheses this past year after concluding that we were unable to feasibly measure peptide hormones in hair (for details, see the section on detection and measurement of peptide hormones). The consequences of this limitation are two-fold. First, we will not be able to ascertain a bear's energy balance through the analysis of its hair because the two biomarkers of energy status (leptin and adiponectin) that we were considering are both peptide hormones. Further, we are not aware of any other energy status biomarkers that could potentially be found in hair. Second, it is unlikely that we will be able to determine if a bear is lactating by the analysis of its hair because the two primary biomarkers of lactation (prolactin and oxytocin) are both peptide hormones. Nonetheless, the possibility remains, albeit slim, that we may be able to distinguish lactating females from non-lactating adult females and juvenile females on the basis of differences in their steroid hormones levels (progesterone, estradiol, testeosterone), which is why lactating females are still included in Figure 1.

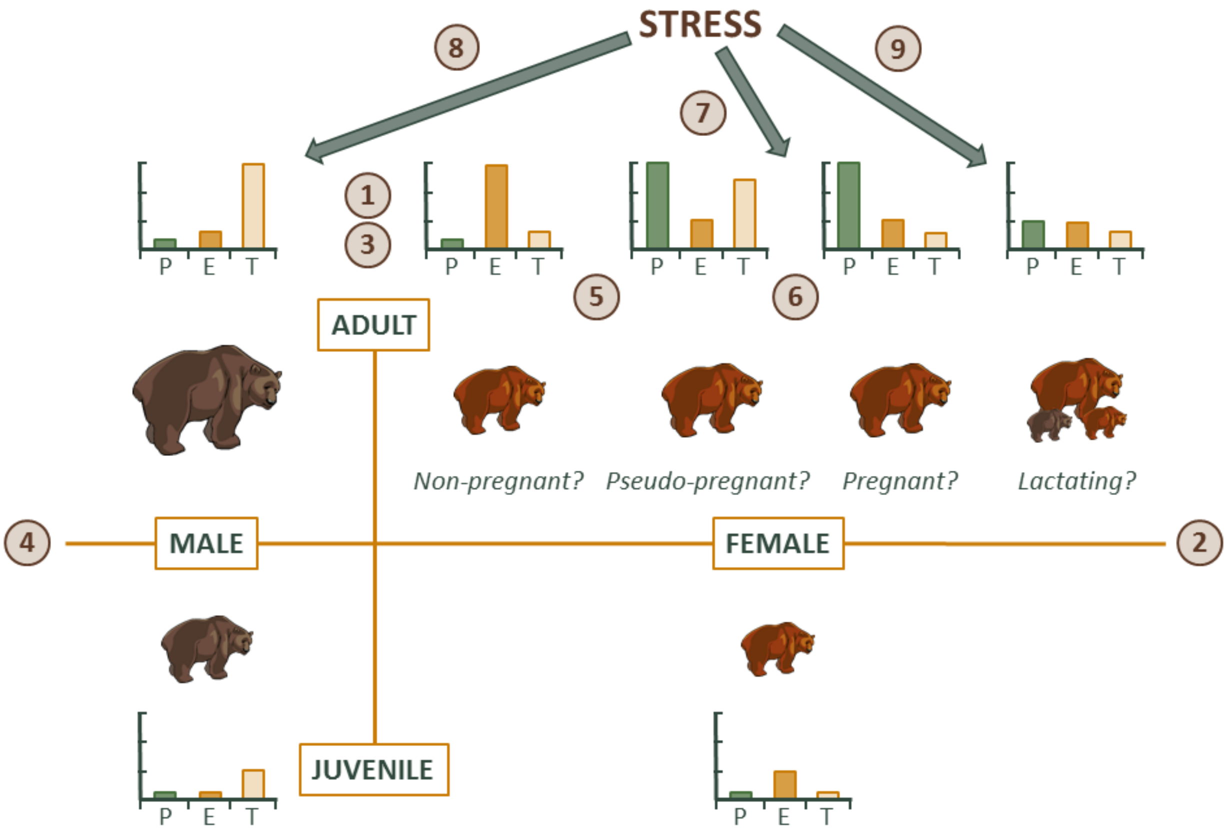

Figure 1. Hypothesized hormone profiles in hair samples collected from grizzly bears of different sex, age, and reproductive classes. The graphs depict the relative concentrations of three steroid hormones, progesterone (P), estradiol (E), and testosterone (T). The three scale markers on the vertical axis indicate relative levels of low, moderate, and high. The circled numbers refer to our nine research hypotheses.

Detection and Measurement of Steroid Hormones

Our main focus has been on validating techniques to measure sex steroid hormones in hair. This was due to the success we have had determining the steroid hormone cortisol in small quantities of hair such as that obtained from barbwire snags. Specific hormones being evaluated include the female sex steroids estradiol and progesterone, and the male sex steroid testosterone. To date, using the same extraction procedure used for cortisol, we have validated progesterone and testosterone in grizzly bear hair for their accuracy and precision in the laboratory. Importantly, we can measure these hormones in similarly small quantities of hair compared to cortisol (i.e., < 50 mg hair). Estradiol in hair has proven to be more challenging, since it required the development of a new method testing a variety of extraction solvents and related modifications to the technique. We have successfully developed this technique for hair estradiol (using tert-butyl methyl ether as extraction solvent). However, in the samples analyzed to date, estradiol levels in hair are very low (even in adult females) compared to the other steroid hormones. It does not appear that we will be able to measure estradiol in small hair quantities as with cortisol, testosterone and progesterone. Ongoing work with the sex steroids is determining these hormones in hair samples obtained from bears with known life history status (i.e., adult females with differing pregnancy and offspring status, adult males, juvenile females, and juvenile males).

Detection and Measurement of Peptide Hormones

We spent approximately 9 months in year 2 trying to detect peptide hormones in grizzly bear hair. We focused on leptin and prolactin, hormones involved in energy balance and lactation, respectively. We initially focused on these hormones because they are relatively small peptides, which should allow for diffusion into the hair shaft, and because they are periodically abundant in circulation. We first tried our standard hair grinding procedure used for steroids, followed by extraction into aqueous buffer, but were not able to detect the hormones. We then adapted a technique used to isolate keratin isoforms from hair, which involved digestion of hair in 8M urea, followed by dialysis to remove the urea and then ultrafiltration of the resulting fractions. We then ran Coomassie-stained gels and were able to detect proteins in the appropriate molecular mass range of the peptides of interest, but subsequent immunoblotting (using canine antibodies against leptin and prolactin) did not detect either peptide in the purified fractions. The last attempt was with 200 mg of hair, and we still were unable to detect the peptides. Given that we were trying to develop a technique to detect peptides in much smaller masses of hair (<50mg), we decided to stop this work. The best approach would likely be to use two-dimensional gel electrophoresis and mass spectrometry, but we do not have the infrastructure or resources to follow this path.

New Insights into the Measurement of Hormones in Hair

The measurement of hormones, especially glucocorticoids (cortisol and corticosterone), in the hair and feathers of free-ranging wildlife has accelerated in recent years as reflected through a notable increase in peer-reviewed articles; twenty-four articles have been published over the past 3 years compared to ten articles in the preceding 9 years starting with the first report by Koren *et al.* in 2002 (Wildlife and Ecology Studies Worldwide Database, 2014 EBSCO Industries, Inc., Ipswich, MA, USA). Unfortunately, in some of these studies, it appears that application of these measurements to address ecology and conservation-related questions has gone ahead without the necessary validation studies to confirm that hair hormone levels in the species of interest are indeed accurate and consistent indicators of physiological function. This raises questions about the validity of results and their interpretation because the measurement of hair hormone values can be confounded by the influence of other variables that were not considered. To illustrate this concern, and to underscore the importance of validation studies, we summarize below the findings of two studies that we conducted this past year. Although these studies do not fall within the scope of the 3-year program supported by Alberta Innovates Biosolutions, the results of these studies have clear implications for this research program.

Validation Study 1

Capture and handling may rapidly increase the cortisol concentration of hair even after it has ceased growing (Cattet et al. 2014. – submitted to Conservation Physiology in February 2014)

The measurement of cortisol in hair is becoming important in studying the role of stress in the life history, health, and ecology of wild mammals. The hair cortisol concentration (HCC) is generally believed to be a reliable indicator of long-term stress that can reflect frequent or prolonged activation of the hypothalamic-pituitary-adrenal axis over weeks-to-months through passive diffusion from the vascular supply to the follicular cells that produce the hair. Nonetheless, this mechanism as the sole determinant of HCC has not been confirmed. In this study, we report on a range of factors that are associated with, and possibly influence, cortisol concentrations in the hair of free-ranging grizzly bears. Through two levels of analyses that differed in sample sizes and availability of predictor variables, we identified the presence or absence of capture, restraint, and handling, as well as different methods of capture (remote drug delivery by helicopter, leg-hold snare, culvert trap), as significant factors that influenced HCC in a time-frame that was too short (minutes-to-hours) to be explained by passive diffusion alone (Fig. 2). Further, our results suggest that HCC was altered after hair growth had ceased and its blood supply was essentially cut-off. We also confirmed that HCC was influenced by long-term stress, insofar as this measure was inversely associated with brown bear body condition and was, therefore, responsive to diminished food availability/quality and possibly other long-term stressors that affect body condition. However, our findings should caution against the broad application of HCC as an indicator of long-term stress until further validation of the mechanisms of cortisol accumulation in hair and the influence of stressors on these mechanisms.

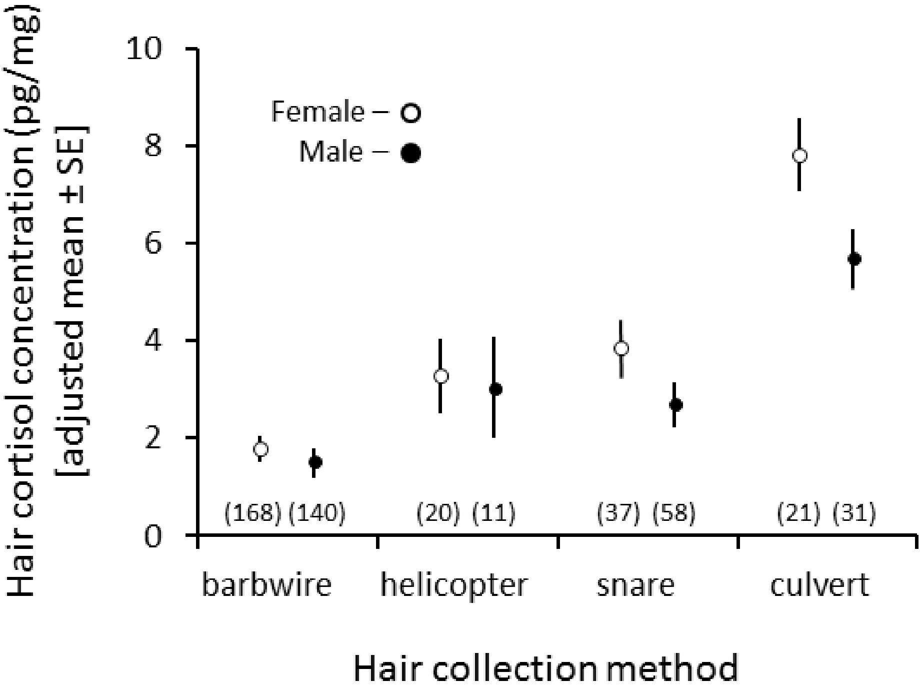

Figure 2. Comparison of mean hair cortisol concentration (HCC) among female and male grizzly bears (*n* = 486) sampled by barbwire hair snagging (barbwire) or by clipping hair following capture by either remote drug delivery from helicopter (helicopter), leg-hold snare (snare), or culvert trap (culvert). Mean HCC values are adjusted for year of capture = 2005.

Validation Study 2

A comparison of laboratory methodologies used in the detection and measurement of cortisol in hair (Kroshko et al. 2014. – to be submitted in the near future to General and Comparative Endocrinology)

Over the past decade, the measurement of HCC has shown increasing promise as an indicator of long-term stress in humans and wildlife. However, the methodologies used to measure HCC have varied considerably across studies, which could make comparisons of results across studies difficult, if not impossible. We compared HCC values from subsamples of hair from four grizzly bears that were determined using different laboratory methodologies that are frequently described in the peer-reviewed literature. More specifically, we used two solvents (methanol and isopropanol) to wash cortisol from the external surface of hair, and two commercial enzyme immunoassay (EIA) kits (the Oxford EA-65 cortisol EIA Kit and the Salimetrics cortisol salivary EIA kit) to measure cortisol within both washes and hair samples, to determine if the cortisol concentrations in the solvents and/or hair were affected by the methods used. We found that repeated washes of grizzly hair with methanol and with isopropanol yielded significantly different results with higher concentrations of cortisol in both hair and wash consistently occurring with isopropanol (Fig. 3). We also found that cortisol concentrations determined using the Salimetrics kit were 10-15 times greater than the concentrations determined using the Oxford kit, irrespective of wash solvent used (Fig. 4). With these findings, we conclude that HCC results cannot be meaningfully compared between studies if different solvents and/or different EIA kits were used to determine cortisol concentrations.

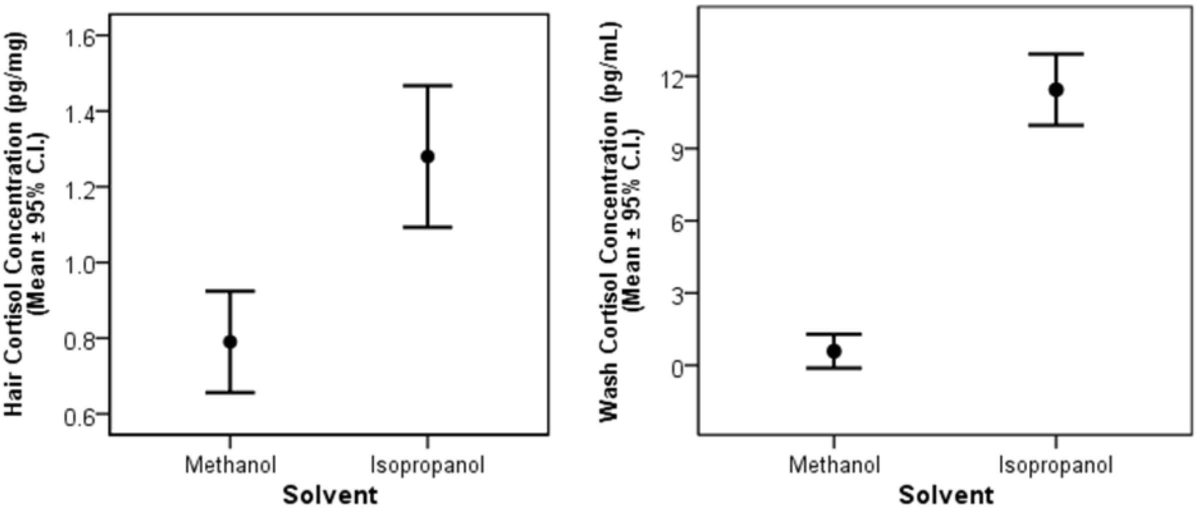

Figure 3. Comparisons of cortisol concentrations between methanol- and isopropanol-washed guard hair, and between methanol or isopropanol washes used to clean the grizzly hair samples (*n* = 4). Mean values are presented as points with the standard errors represented by vertical bars.

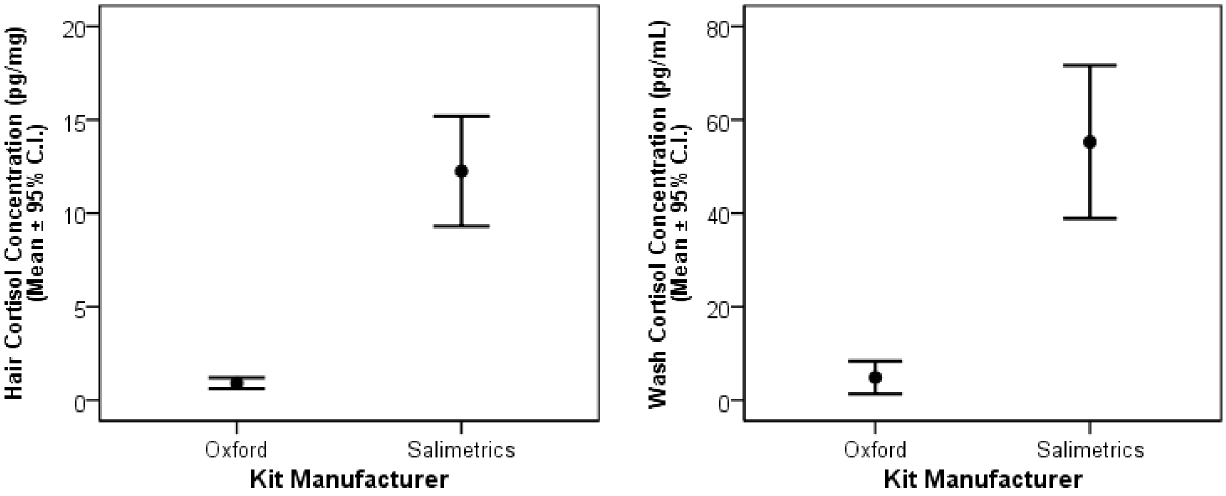

Figure 4: Comparison of mean cortisol concentrations between two commercial enzyme immunoassay (EIA) kits (Oxford and Salimetrics) in subsamples of bear hair (*n* = 16), and in the solvent (wash) used to clean hair samples. Mean values are presented as points with the standard errors represented by vertical bars.

Plans for Year Three

We are near to completing the development of techniques to measure sex steroid hormones (estradiol, progesterone, and testosterone) in hair, and will soon start to characterize hormone profiles in hair samples collected from bears of different sex, age, and reproductive classes, as illustrated in Figure 1. For this, we are using hair samples collected from three sources, the Foothills Research Institute Grizzly Bear Program (FRIGBP; free-ranging bears in Alberta), the Scandinavian Brown Bear Research Project (SBBRP; free-ranging brown bears in Sweden), and the Washington State University Bear Research, Education, and Conservation Program (WSUBRECP; captive bears housed in research facilities at Washington State University). These research collaborations, between the FRIGBP and the SBBRP, and between the FRIGBP and WSUBRECP were described in detail in our initial proposal to Alberta Innovates Biosolutions, as well as in our progress report from year one.

Hair samples from free-ranging bears that were previously captured have been archived over many years, since 1999 for the FRIGBP and since 1984 for the SBBRP, and provide a rich source of samples from bears with known identity and history. Researchers with both projects will also continue to collect hair for our program during the coming year. In addition to using these samples to characterize hormone profiles from bears of different sex, age, and reproductive classes, we will also measure hair cortisol levels in select samples to investigate the effects of stress on reproduction.

Hair samples from WSUBRECP are being collected monthly, except during hibernation from November to March, from twelve captive grizzly bears (six adult females, two adult males, four juvenile males). This includes two adult females that will be bred in May 2014 and sampled throughout pregnancy and the first year of lactation. The multiple hair samples collected over time with regular frequency will enable us to determine if there are characteristic changes in hormone levels of individual bears, and if these changes are consistent between bears, as they develop through different reproductive stages, i.e., maturation, estrus, pregnancy, etc. These hormone data will be essential to validating hormone levels measured in the hair of free-ranging bears.

Our final objective, the development of multi-state models to identify dynamic relationships between reproductive function, long-term stress, environmental covariates, and demographic metrics will be carried out at the end of year three and will be based ideally on data collected by the FRIGBP. However, the complexity of models to be developed may be constrained by sample size, such that additional sampling may be required beyond year three to develop Alberta grizzly bear-specific models. If this is the case, we may explore the possibility of using more extensive dataset of the SBBRP to at least evaluate the utility of multi-state analyses to address the complex relationships and sampling biases that arise from linking grizzly bear health to dynamic environments. If this approach is deemed feasible, we will apply it to FRIGBP data on an annual basis with a goal of increasing model complexity and goodness-of-fit (Boulanger *et al.*, 2013).

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CHAPTER A.3. Understanding Seasonal Variation In Leptin And Adiponectin Production, Adipose Function, And Whether Either Hormone Can Be Used To Estimate Body Fat Content In Brown Bears

Prepared by:

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In this study, we wished to elucidate the relationships between adipose function, adipose hormones, and the relationship between those hormones and body fat content in brown (grizzly) bears. One need of field biologists interested in understanding how productivity varies between individuals and populations is to accurately estimate body fat content. While several systems have been developed for estimating body fat content (e.g., water dilution, BIA, and mass and morphometric measures), additional indices would be useful. For example, blood samples are frequently taken during capture programs, and hair samples are often taken remotely at barbed-wire hair snares. Blood contains at least two hormones (leptin and adiponectin) that are produced by fat. In many species, the concentration of leptin is proportional to body fat content and is used to regulate intake and energy balance. Leptin was correlated to body fat content in American black bears (*U. americanus*), although there were separate regressions for captive and free-ranging bears which suggests that other factors may be involved (Spady et al. 2009).

However, based on preliminary studies, we hypothesize that many of the systems that other animals use to sense energy status (e.g., leptin) will be turned off in bears during the active, feeding time of the year. In our preliminary studies with brown bears as well as in more extensive studies with Japanese black bears (*U. thibetanus japonicus*), serum leptin concentrations are near zero from March to September (Tsubota et al. 2008), but then leptin concentrations rise very rapidly and generally peak in October or November before falling back to near zero for the rest of hibernation.

While most animals optimize fat accumulation, brown bears and polar bears maximize fat accumulation (Robbins et al. 2012). Fatter females produce larger cubs that have a better chance of survival than do leaner females and their cubs (Derocher and Stirling 1996, Dahle et al. 2006). Thus, there is heavy selection for large appetites and almost unlimited fat accumulation that produces “morbidly obese” bears by human standards. Surprisingly, such bears are completely healthy with no detectable circulatory, respiratory, or other pathologies, perhaps due to long-term evolutionary pressures for seasonal adiposity.

Our initial hypotheses included:

1. Bear adipose exhibits seasonal variation in metabolic efficiency and leptin/adiponectin production. Specifically, fall fat is optimized for lipogenesis while winter fat is optimized for lipolysis.

2. Serum leptin/adiponectin levels rise during the fall and may be directly related to body fat content. The major purpose for the fall spikes in leptin and adiponectin production may be to initialize the hibernation processes, including when to begin hibernating, when to implant developing embryos, and how much milk to produce.

3. The genetic and physiological pathways for producing leptin are turned off during much of the active portion of the year, which is reflected in the need for species that hibernate to accumulate large amounts of fat. Adiponectin is produced throughout the year, which may reflect its larger role in maintaining healthy tissues throughout the body.

4. While serum leptin and adiponection are unlikely to be useful in estimating bear body fat content because of the extremely transitory nature of their fall peak (leptin and adioponectin) or the very low levels during most of the year (leptin), hair leptin/adiponectin may be very useful. This will depend on whether 1) leptin/adiponectin enter the hair during its growth, particularly during the fall peak 2) whether those hormones remain chemically stable in the hair shaft, and 3) whether the concentration in the hair shaft is proportional to the concentration in the blood and, therefore, body fat content.

5. Unlike serum analyses, hair leptin/adiponectin measures may be useful in understanding productivity of wild bear populations by providing an accurate estimate of female fall body fat

content and thereby her ability to produce cubs. We hypothesize that food conditions that lead to fatter females in the fall will result in increased cub production and survival.

Methods

In previous studies of leptin and adiponectin, we used blood samples that were collected as part of other studies and were summarized on a monthly basis. However, we recognized that while there was little change in at least leptin during much of the year, there appeared to be a very sharp spike during October that could only be quantified with weekly samples. Thus, we took one sample per month from May to August, but then weekly samples during September and October. Four bears trained for blood sampling were used so that anesthetic drugs would not be a confounding factor. However, because the bears were being used in studies involving differing sources of dietary fats, we were able to test if the type of fat (i.e., saturated versus unsaturated) affected the relationships between leptin or adiponectin production and body fat content. Two of the bears consumed a diet high in unsaturated fats (i.e., salmon and salmon oil) while two others consumed a diet high in saturated fats (hamburger, beef fat, and cheddar cheese). The amounts of saturated and unsaturated fats contained in both diets far exceeded what would occur in a wild bear's diet. Thus, these are the extremes in diets that can be used to test the hypothesis that type of dietary fat may affect either serum leptin or adiponectin concentrations. Body fat contents were determined at the same time by water dilution (Hilderbrand et al. 1998). Leptin and adiponectin were analyzed by commercial ELISA kits validated for use in bears.

Leptin is a major fat-borne appetite regulator in most species. For an animal needing to maximize fat mass and then enter a prolonged period of fasting, we hypothesized that the bear would be an ideal model to test seasonal changes in central (brain) leptin sensitivity. Specifically, we hypothesized that bears would 1) be insensitive to leptin during the active season when they are either not producing leptin or at least minimal amounts, which results in minimal to no constraint by leptin on their food intake during the spring through early fall, whereas 2) they would be sensitive to leptin prior to hibernation at a time when they are normally producing large amounts of leptin and presumably getting ready to suppress appetite and enter hibernation. To test these hypotheses, we injected bears into the cisterna magna (i.e., spinal tap) with human recombinant leptin or the carrier (i.e., control) and measured food intake over several days.

Current Results

Serum leptin-adiponectin content relative to body fat content

Leptin concentrations remained low from May through September, but peaked in mid to late-October (Figs. 1, 4). Leptin levels were not correlated with body fat content during any interval (Fig. 2). Adiponectin tracked body fat content better than did leptin (Fig. 1). However, there appears to be major differences in the adiponectin-body fat relationship depending on the type of fat being consumed. For example, the relationship between adiponectin and body fat content for bears consuming unsaturated fats was very good, but there was no relationship for bears consuming saturated fats (Fig. 3).

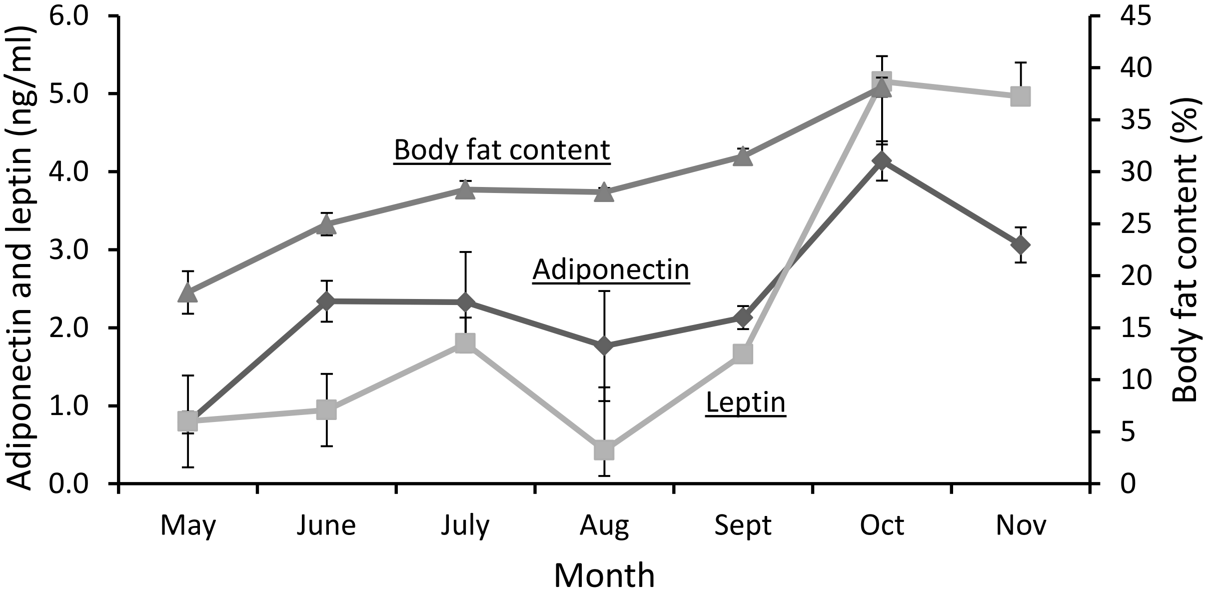

Figure 1. Changes in body fat content and serum leptin and adiponectin concentrations in four captive bears during the active season.

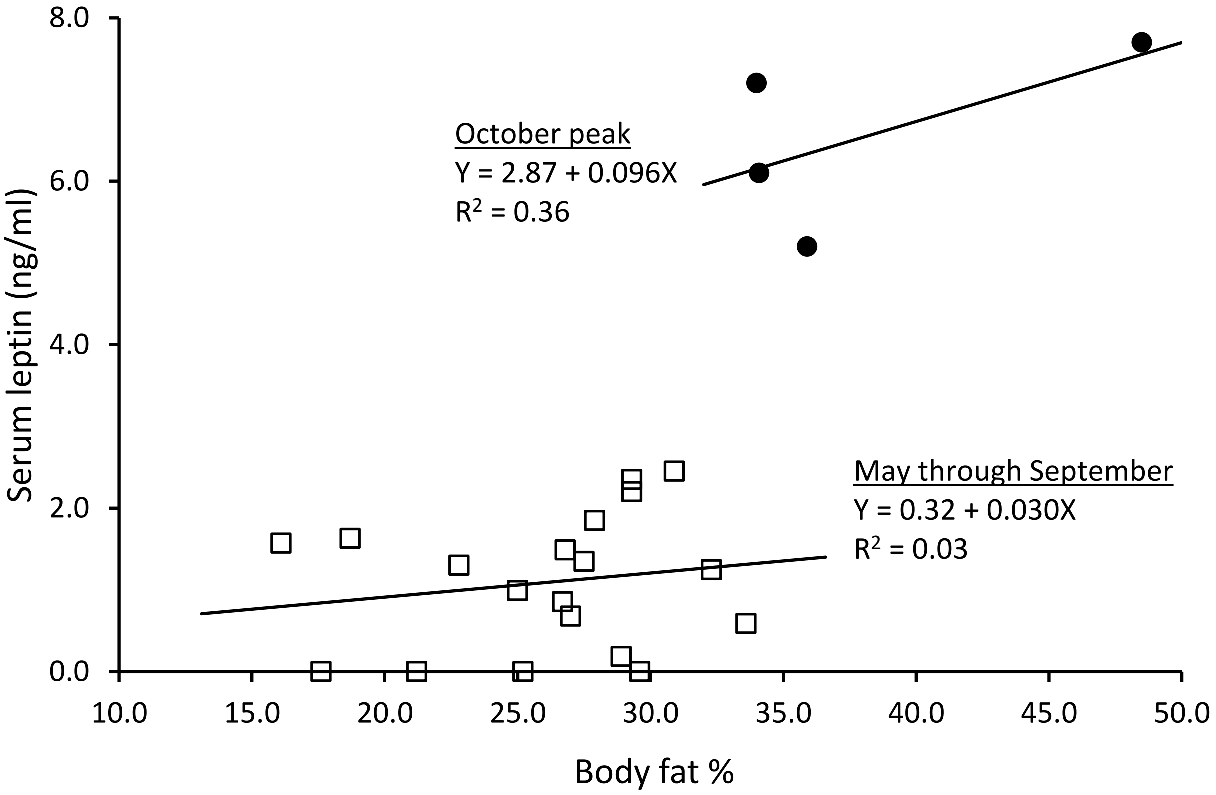

Figure 2. The relationship between body fat content and leptin concentrations in four captive brown bears during the active season.

Effect of centrally administered leptin on food intake

Our preliminary findings from 4 bears tested in August reveal that the increase in appetite that normally is expressed beginning in August was not suppressed by centrally-injected leptin. However, appetite was suppressed in October. Thus, the inhibitory ability of leptin on food intake is season-specific and reflective of both immediate physiological changes occurring in the bear and long-term evolutionary process that maximize intake in the fall, but ultimately reduce intake once the bears are fat enough to enter hibernation. Indeed, during October prior to hibernation, leptin suppressed the bears' food intake by approximately 40% (Fig. 4). We plan to repeat this experiment in 2014.

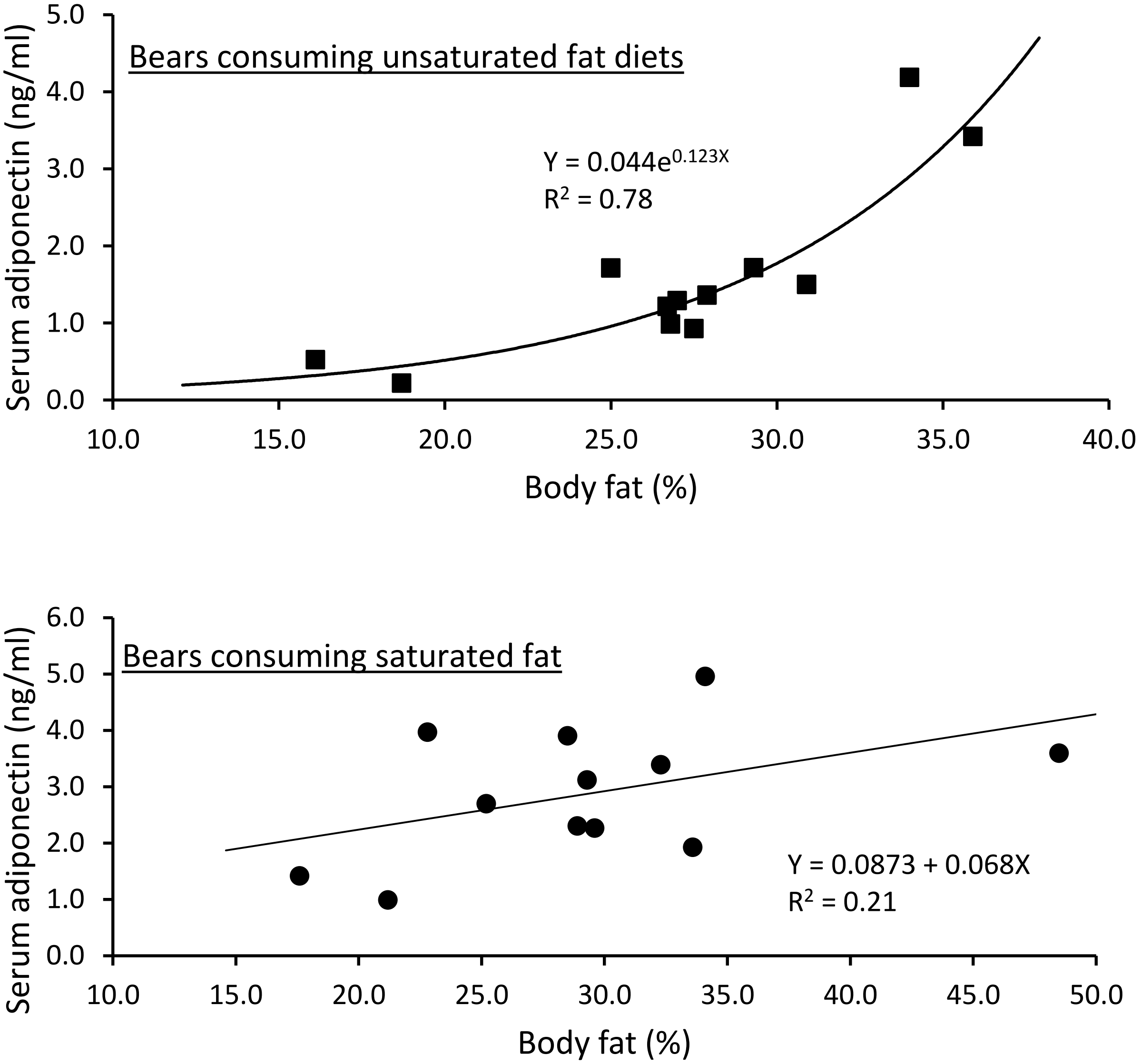

Figure 3. The relationship between serum adiponectin and body fat content as affected by type of dietary fat.

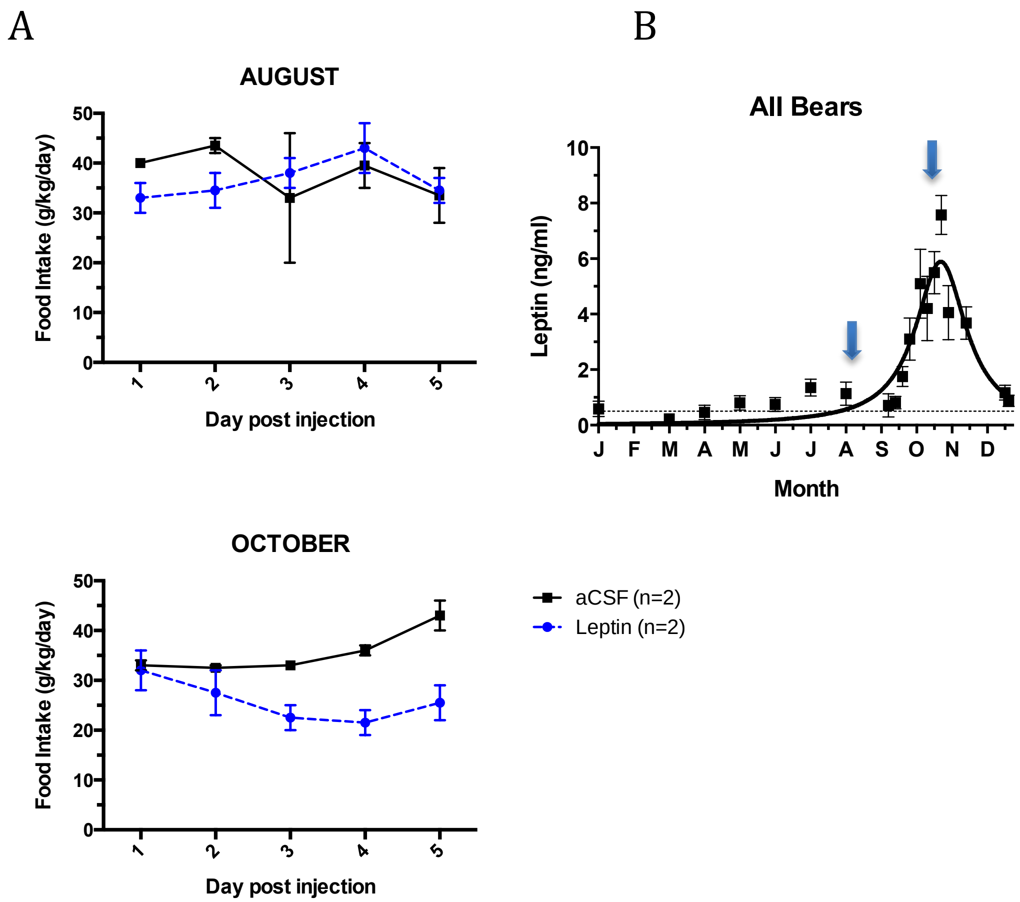

Figure 4. A. The effect of centrally administered leptin or the carrier (i.e., control) on food intake in bears at two times of the year (Aug and Oct). B. Annual serum leptin profile of WSU grizzly bears (n = 6-12 for each point, collected from 2008–2014). Arrows indicate times that central leptin was administered to bears shown in panel A, and the dashed line represents the detection limit. Note the extremely narrow window for leptin production.

Plans for Year 2

Leptin-adiponectin studies

Plans are continuing to develop, but currently we want to further test some of the ideas that developed in Year 1. For example, the typical explanation for the October surge in serum leptin is that represents a large gain in weight and corresponding fat accumulation that has occurred in the fall. Thus, we plan to take our 4 trained bears and hold their weights constant from April to November (i.e., probably at ± 22% body fat) and determine if that October leptin surge occurs in the absence of seasonal weight and fat gain and if the October peak in serum leptin varies with body fat content. We hypothesize that the surge will continue to occur in the absence of seasonal weight gain because it is a signal that indicates adequate body fat for hibernation and, thereby, initializes a series of subsequent hibernation processes, such as embryo implantation. We are also discussing what diet to use based on the dramatic differences in adiponectin production due to type of dietary fat. The good relationship between adiponectin and body fat content when bears consume diets containing primarily unsaturated fats is an important observation in that plants and fish contain predominantly unsaturated fats. While ruminant fat is predominantly saturated fat, we suspect that far more unsaturated fats are consumed by wild bears because of the limited amount of fat available from wild ruminants. Thus, we plan to feed the four bears a commercial bear chow that is largely plant based to determine if the relationship between serum adiponectin and bear body fat content remains the same as during the previous year.

Hair reproduction studies

We will collect hair samples from 2 adult breeding males and 2 adult breeding females for David Janz and Marc Cattet. The current plan would be to collect those in late October just prior to hibernation. We will collect and send other samples as determined by the research team.

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CHAPTER A.4. Population Recovery Targets For Grizzly Bears In Alberta

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Executive Summary

In 2010, grizzly bears (*Ursus arctos*) were listed as a threatened species in Alberta. There is, however, no agreed upon recovery target or approach for defining recovery success. Monitoring human-bear conflict rates, translocations of problem bears, and known mortalities provide initial metrics for bear management, but ultimately knowledge of population size and trends with respect to established targets will be needed to support changes in status (recovery) of grizzly bears. This report (year 2 of 3) outlines research supported by Alberta Innovates – BioSolutions and industry partners on better understanding and predicting biologically-based carrying capacities (*K*) for grizzly bears. This information can be used to inform population targets for recovery within the context of social carrying capacity and thus guide decision-making around the population status of grizzly bears within a region. The basic approach is to map (empirically model) habitat (food) supply for grizzlies across a region based on field data measures of food resources and estimates of energetic costs of bears to determine local carrying capacity (density). This removes any effect of human-caused mortalities that may reduce populations below *K*.

In year 2 we extended our prior analyses from year 1 by: (1) further developing energetic models to describe energy and protein requirements of grizzlies in the area; (2) testing relationships between predicted spatial patterns in food supply (digestible energy) within the Yellowhead population to observed patterns in local abundance of grizzly bears at hair-snag sites;

and (3) developing initial food supply models for the reference population of the Willmore Wilderness Area. Here we report on the outcome of the first two objectives with the third objective in progress and to be completed in year 3 (2014-15) of the grant.

Energetic models provide minimum energy and protein requirements for reproductive female and male bears in the Yellowhead ecosystem. Together with the use of food habits and nutritional information, energetic models illustrate that grizzly bear populations are limited by nutritional conditions. Low nutritional environments not only restrict carrying capacity, but also affect individual reproductive rates and thus without immigration rates of population recovery.

A strong additive relationship between ungulate and buffaloberry food supply explained local variation in abundance of bears in the Yellowhead population. This food supply-bear abundance relationship was observed after accounting for sampling methods and the negative effects of roads on bear populations (lower survival), supporting the connection between 'bottom-up' definitions of habitats and populations in bears. Food resource models for the Willmore Wilderness Area, a region where grizzly bear populations are presumably at carrying capacity due to lack of human disturbances, are being used to directly relate food supply to actual densities of bears (vs. indices from hair-snag sites). This information will be used to relate food-density relationships to biologically-based (bottom-up) estimates of *K* for other nearby management units including the Yellowhead population.

Background

Alberta listed grizzly bears (*Ursus arctos*) as a threatened species in 2010. This designation came following population estimates of 691 bears for the majority of currently occupied habitat with approximately half of population at breeding age (Alberta Sustainable Resource Development and Alberta Conservation Association 2010). This estimate is far fewer than the IUCN and Alberta Conservation Committee's criterion of 1,000 breeding animals defining a secure population of a species. While grizzly bears in Alberta are connected to populations in Montana and British Columbia that would as a whole exceed 1,000 breeding individuals, the Alberta population is managed and regulated under the Wildlife Act and these areas are outside provincial jurisdiction.

Much effort is now placed on recovering grizzly bear populations in Alberta, although no explicit recovery targets have been suggested beyond the initial IUCN benchmark of 1,000 breeding animals (~2000 bears) and suggestions for documenting stable population trends and demonstrating low documented numbers of mortalities. Two populations appear to be secure or increasing in Alberta (Grande Cache and Castle population units), but others continue to be considered quite low in number. Reliance on trend analyses of populations like grizzly bears necessitates substantial resources and time and may not indicate recovery for existing small populations like the Yellowhead population which was estimated to be fewer than 50 bears (Boulanger et al. 2005), a number typically considered in conservation biology to be a minimum viable population. Likewise, mortality rates may decrease due to two causes: (1) actual reductions in mortality rates (rates aren't, however, known in counts of 'known' mortalities); or (2) population declines which provide fewer bears for mortalities. Without knowledge of population size and number of unknown mortalities, reliance on these metric alone for recovery will be insufficient to guide recovery decisions.

An alternative, or complementary approach, to trend monitoring is to directly estimate recovery benchmarks (population targets) using habitat-based carrying capacity measures and using population size estimates from periodic DNA mark-recapture surveys to determine whether populations meet a defined recovery target. Such information would provide an important source of information for assessing effectiveness of management actions and decision-making on grizzly bear recovery, especially if those targets suggest that 1000 breeding animals is unlikely to be supported in Alberta's habitats which are naturally much poorer in food resources than coastal populations that can be 100-fold higher than populations observed in Alberta, or even interior populations in adjacent Montana and British Columbia that can be up to 10-fold higher than populations in Alberta.

Here we outline an approach for estimating habitat (food supply) in units (kcal) that are biologically relevant to measuring populations. This approach assumes that populations of bears are limited not only be low survival (top-down regulation), but also by food resource supply (bottom-up regulation). We also examine energetics of bears to determine resource needs for successful reproduction and test relationships between spatial patterns in food supply for two critical resources (ungulate matter and buffaloberry fruit) with local patterns in grizzly bear abundance. This is done for the Yellowhead ecosystem south of Hinton, Alberta were food supply maps and DNA hair-snag information is available.

Methods

Available energy (nutritional landscape)

Modeling (mapping) spatial variation in food supply (digestible energy)

In the prior report by Nielsen *et al*. (2013) we estimated available landscape digestible energy in kcal based on 17 different food resources commonly used by bears. Subsequent exploration of these data suggested that two of these resources — buffaloberries (*Shepherdia canadensis*) and ungulates (moose, elk, bighorn sheep, white-tailed deer, and mule deer) — were particularly important in explaining local patterns in abundance of bears based on DNA hair-snag information collected in the 2004 population survey. We subsequently focused on these two items and their relationship to local abundance of bears in year 2 of this grant. Below we describe the two resources, ongoing bioenergetic modeling work that will be used again in year 3 of the grant, and the analysis between the two main resources and local abundance of bears.

Buffaloberry food supply (kcal of digestible energy)

As explained previously in Nielsen *et al*. (2013), we used a multi-stage statistical modeling approach to estimate resource distribution (presence) of buffaloberry, abundance (shrub density where present), and fruit abundance where present using generalized linear models (GLMs) with the response variable representing field data from plots collected throughout the region and environmental predictors derived from a GIS. Predictor variables included: land cover, climate, terrain, soils, and forest stand measures, which were previously found to be important predictor of buffaloberry distribution (Nielsen *et al*. 2003; 2004a; 2010; Roberts *in press*). Models were predicted in a GIS to map distribution, shrub density, and fruit abundance. Average fruit per unit area (900 m^2 pixel) was then converted to biomass based on average dry fruit weights of buffaloberries (Coogan 2012). See Nielsen *et al*. (2013) for more details on methods of mapping buffaloberry resources, along with spatial predictions for the Yellowhead ecosystem. Based on the fruit abundance to dry biomass model, fruit was converted from biomass to available digestible energy (Dig E; kcal/kg) using the biomass to digestible energy conversions of:

Eqn. 1: Gross energy * % Digestible energy

Parameters for gross energy and percent digestible energy were estimated in the lab based on fruit samples collected in the Yellowhead ecosystem south of Hinton (see Coogan 2012). Gross energy of buffaloberry fruit was estimated as 4,310 kcal/kg, while percent digestible energy was estimated as 64.5% (Coogan 2012) resulting in 2,780 kcal Dig E/kg or on a per gram basis of 2.8 kcal Dig E/g.

Ungulate food supply (kcal of digestible energy)

For ungulates, models of local abundance (population density) were estimated across the study area for five common ungulate species: moose, elk, bighorn sheep, white-tailed deer, and mule deer. Aerial survey data were collected for a sample of the area (selected survey blocks) by Alberta Environment and Sustainable Resource Development. These data were provided to us and used to model local density of ungulates across the entire area using generalized linear models (GLMs) fit to observed abundance of individual ungulate species based on aerial survey data (sampled blocks) and a set of environmental predictors (land cover, land use, and terrain). See Nielsen *et al*. (2013) for more details on abundance modeling for ungulates and predicted maps.

After population density was estimated for all 'blocks' in the area, conversions to total biomass were estimated for each species, including neonates, based on a literature review of body sizes. Digestible energy (Dig E; kcal/kg) estimates for ungulates were based on regional ungulate biomass (kg) estimates (see Nielsen *et al*. 2013), whole ungulate (moose, *Alces alces*) percent body composition minus hide and injesta (IFB mass; Hundertmark *et al*. 1997), and digestible energy (kcal/kg) estimates for meat (Pritchard and Robins 1990) using the following equation:

Eqn. 2: Whole ungulate biomass (kg) × % IFB mass × % dry matter IFB × % ash free IFB × digestible energy (kcal/kg)

Specifically, percent IFB mass was 88.1, percent dry matter of IFB mass was 34.8, percent ash-free content IFB was 94.9% (100-5.1% ash), and digestible energy was taken as 6,920 kcal/kg.

Because of high grizzly bear mortalities associated with distance to roads (Nielsen *et al.* 2004b; Nielsen 2011), we included estimates of average road density (7,440-m radius moving window) as a covariate within spatial models relating food supply to bear density. Additionally, time of hair-snag sampling (session number) in the 2004 DNA hair-snag survey was included as a 'noise' covariate in the model in order to account for differences in 'capture rates' between sessions.

Bioenergetic estimates of total energy expenditure (demands)

Energetic model for grizzly bears

We used an energetic model for grizzly bears (López-Alfaro *et al*. 2013; López-Alfaro 2014) to estimate the energy (kcal) and protein (kg) requirements of individual bears in the Foothill and Mountain ecosystems of the Yellowhead population in west-central Alberta. The model simulates the body mass dynamics (loss/gain, kg) of bears from the beginning of hibernation to the end of the active period. The model operates in a daily time step for 365 days. Day 1 is den entry at the start of the hibernation and the final day 365 days later is again the start of hibernation (den entry). We assumed a hibernation period of 180 days and thus an active period of 185 days.

Body mass (kg) was separated into lean and fat mass (kg). The energetic model assessed the loss or gain of fat and lean mass based on the balance of the energy and protein intake minus energy and protein requirements. The model integrates key metabolic mechanisms to assess maintenance, mass gain, reproduction, and movement cost. Energy and protein intake were based on the nutritional quality of the diet and total food intake. Diet information was based on prior information from the area (Munro *et al*. 2006) and synthesized for the energetic model in López-Alfaro (2014). Model outputs included daily fat mass, body mass gain/loss per day, and food intake.

Hibernation phase energetics

During the hibernation phase the model simulated body fat and lean mass loss based on maintenance and reproductive costs. Maintenance cost was based on body mass and it was assumed that no protein requirements were needed for maintenance (Barbosa *et al*. 1997; Tøien *et al*. 2011). Lactation cost includes fetus development and the lactation cost itself (Farley and Robbins 1995; López-Alfaro *et al*. 2013).

Active phase energetics

During the active period, the model simulated lean and fat mass dynamics (i.e., gain or loss) based on energy and protein costs of maintenance, mass gain, lactation and movement relative to gains occurred from foraging. Maintenance energy and protein cost is based on the individual body mass, and the dietary energy and protein content (Robbins 1993; Erlenbach *et al*. 2014; López-Alfaro 2014).

Mass gain cost was based on the target body mass (see section on *initial conditions* below) and the energy and protein content of fat and lean mass. Energy content of fat mass was assumed to be 9.1 kcal/g; lean mass: 1.2 kcal/g; and the protein content of the lean mass: 0.221 gr/g (Blaxter 1989). Lactation cost is based on those estimated in Farley and Robbins (1995).

To estimate energy cost of movement, we created a movement module in the energetic model that is based on the individual body mass (BM) measured in kg and the daily movement distance of bears measured in km based on work by Taylor *et al.* (1982) and shown as equation 3 below. Daily movement rates for bears used in the model were estimated randomly from a distribution ranging from 3.5 km to 12 km for females and from 4.5 km to 9.5 km for males as reported in McKay *et al*. (2011).

Eqn. 3: $\mathrm{Kcal/kg/km} = 2.57 \times \mathrm{BM}^{-0.316}$

Simulated scenarios (reproductive classes and diets)

We simulated different scenarios depending on the sex (male and female), three reproductive classes for females and two bear diets. Total energy (kcal) and protein (kg) requirements were estimated for all scenarios. The three reproductive conditions for female bears were: (1) non-lactating; (2) pregnant; and (3) lactating. Non-lactating bears were barren through hibernation and the following active period. Pregnant bears were barren through hibernation and during the active period, but will mate and attempt to achieve a target body mass to give birth during the following season. Lactating bears gave birth to two cubs 106 days into hibernation and then lactated for the rest of the active period.

Diets resemble bear food habits in the Foothill and Mountain ecosystem based on Munro *et al*. (2006) and they are characterized for their dry matter, dry matter digestibility, energy content, protein content, and digestibility (López-Alfaro 2014).

Initial conditions

For each reproductive class and sex we assumed an initial body mass (lean and fat content) and target body mass (López-Alfaro *et al*. 2013; López-Alfaro 2014). Initial lean and fat mass determines available body resources to support hibernation (maintenance and reproduction). Due to the low nutritional conditions of the bear food habits in Alberta, lactating bears need to use body reserves to support lactation, even during their active period (López-Alfaro 2014). We therefore assumed an initial denning body fat content (initial conditions) that allows bears to emerge from the den with body reserves sufficient to support lactation.

Target lean and fat mass correspond to the body mass at the end of simulations. Because simulations end when individuals start a second hibernation period, target body mass was also defined as the minimum body reserves necessary to support hibernation.

Initial conditions used for the three reproductive classes of females included a lean mass and target body lean mass was 100 kg for the 3 reproductive classes and 160 kg for males. From this lean mass, 30% were to be used as energetic resources to provide energy or protein. For males, initial fat content and target body fat was taken to be 30%, while for non-lactating females, initial fat content and target body fat was 22%. For pregnant females, initial fat content was 22% and target body fat was 45%. Lactating females had an initial fat content of 45% and a target body fat of 22%.

Results

Food supply and digestible energy estimates for buffaloberry and ungulates

High concentrations of digestible energy from ungulate meat were predicted to be within the mountainous western region of the Yellowhead population unit bordering Jasper National Park. The highest concentrations of ungulate resources occurred around the reclaimed Greg River mine and surrounding areas (Figure 1). Available digestible ungulate-based energy was generally lower in the eastern foothills where elk and sheep were absent (sheep) or less abundant (elk). DNA hair-snag sites recorded areas of high local bear abundance (>2 animals or 'hits') in areas predicted to have relatively high amounts of digestible energy from ungulates.

Spatial patterns of digestible energy from buffaloberry was more varied than for ungulates, having areas of high energy predicted for areas in both the mountains and foothills and often following valley bottoms (Figure 2). DNA hair-snag sites recording grizzly bear 'hits' were found either within or close to areas providing a relatively high amount of digestible energy from buffaloberry with exceptions to that rule generally being in areas with higher road density (Figure 3).

Bioenergetic demands

Energy cost for females range from 1.3 to 3.0 kcal x 10^6. As expected, energy requirements were higher for lactating females, followed for pregnant and barren females (Figure 1). For males, energy cost was estimated at ~2.3 kcal x 10^6 (Figure 4).

Protein requirements for non-lactating and pregnant females were ~6 kg/active period. For lactating females protein requirements were ~ 67 kg of protein per active period. Total protein requirements for males were ~ 12.0 kg per active period. Total fresh food intake ranged from ~3.0 to 5.7 tons of fresh food per active period, depending on the sex and reproductive class of females (Figure 5).

Energetic results are being incorporated in year 3 of the grant for estimates of carrying capacity in the Yellowhead ecosystem.

Relationship between ungulate meat, buffaloberry fruit, and grizzly bear abundance

AIC comparisons of models explaining local patterns of grizzly bear abundance at DNA hair-snag sites (Figure 6) as a function of ungulate and buffaloberry food supply, road density (factor associated with reductions in local abundance of bears), and DNA hair-snag survey session number, supported a model that suggested additive effects between ungulate and buffaloberry food supply (kcal Dig E) after accounting for session (sampling method) and surrounding road density (Table 1). Multiplicative (interactive) effects between ungulate and buffaloberry food supply had the second most supported model, but overall with much less support than a simple additive relationship (Table 1).

Ordered logistic regression parameters demonstrated a negative effect between road density and observed local abundance in grizzly bears (Table 2; Figure 3) with each per unit increase in road density resulting in a 93.8% decrease (odds ratio of 0.516) in local abundance (probability of ordinal ranks). Road density was highest in the north and eastern areas of the Yellowhead population unit, with an additional area of high density found in the southeast (Figure 3). Areas of low road density were, on the other hand, found in the central and western regions adjacent to the Rocky Mountains. There was a negative effect on session number with a 43.9% decrease in odds per session (Table 2).

Relationships between food supply and local abundance of bears predicted that for each 10-fold increase in buffaloberry food supply ($\log_{10}$[kcal of fruit]), local abundance of bears increased (probability of increasing rank order) by a factor of 2 (Odds ratio [e^β] = 2.1). Each 10-fold increase in ungulate food supply ($\log_{10}$[kcal of ungulate meat]), on the other hand, increased local abundance of bears by a factor of 59 (Odds ratio [e^β] = 59). Standardized coefficients (e^βStdX) suggested, however, that on a per one unit standard deviation change, both ungulate and buffaloberry food supply were similar in their effect on local grizzly bear abundance (Table 2). This suggests a much greater variation in fruit supply than in in the supply of ungulate meat. Regardless on a per kcal basis, ungulate matter was 29 times more important than buffaloberry in explaining local variation in bear abundance. Figure 7 illustrates the additive relationship between ungulate matter and buffaloberry fruit on predicted probability of either no bears being observed at a hair-snag site (Figure 7a) or conversely a large count of bears at a hair-snag site (Figure 7b).

Discussion and next steps

In year 2 of the grant we demonstrated that spatial patterns in digestible energy of two key grizzly bear food resources predict local variation in bear abundance. This supports our original working hypothesis (critiqued by others in year 1) that bottom-up factors can be related to local abundance of bears and thus useful for informing population recovery targets of grizzly bears in a region. Energetic models further illustrated demands (energetic costs) required by grizzly bears in the area, including for hibernation and successful female reproduction. These models illustrate the nutritional restrictions faced by grizzly populations in the Yellowhead area which may result in slower than anticipated population recovery relative to other recovering or recovered populations like the Greater Yellowstone Ecosystem or southwest Alberta. The Yellowhead population is also more isolated from a western immigration source of bears (British Columbia) given the naturally large barrier of the Columbia Icefields directly to the west of the Yellowhead ecosystem. This limits a western rescue effect on populations and may help explain current low populations densities in the area (D = 5 bears/1000 km^2), although a small rescue effect from adjacent Jasper populations (immigration) likely contributes to populations on adjacent crown lands in the Yellowhead ecosystem. Prior analyses suggest that the Yellowhead population is well below carrying capacity, although re-parameterization of this estimate is needed (Nielsen *et al*. 2013) and is the current focus of our work. In year 3 of the project we will estimate biological carrying capacity for the Yellowhead population unit helping inform population recovery target setting for the area.

We will work on the following tasks in year 3 of the grant (2014-15) to accomplish these goals:

- Examine patterns in body size and potentially reproductive indices as a function of spatial patterns in digestible energy within the home range or habitat use (GPS locations) of bears
- Examine effects of temporal variation in energy supply, particularly inter-annual variation in fruit production and competition for that fruit (potential consumption rates)
- Complete analysis for a population at carrying capacity (Willmore Wilderness) to estimate bears per unit energy
- Estimate carrying capacity for the Yellowhead unit

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Table 1: Support for ordered logistic regression models explaining local abundance in grizzly bears as a function of sampling design (session number for DNA hair-snagging in 2004), local road density (anthropogenic impacts on bears), and nutritional landscapes surrounding hair snag sites for two critical food items: buffaloberry and ungulate meat. Akaike's Information Criteria (AIC) is used to rank support for models. Note that the null landscape model is included in all models except for the null intercept model.

Model description	**LogLik**	**K**	**AIC**	**Δ AIC**	**w_i AIC**
null model	-407.02	3	820.04	105.99	0.00
null landscape (session + road density)	-376.84	5	763.68	49.63	0.00
landscape + fruit	-368.88	6	749.77	35.71	0.00
landscape + meat	-355.49	6	722.97	8.92	0.01
landscape + fruit + meat	**-350.03**	**7**	**714.05**	**0**	**0.72**
landscape + fruit + meat + fruit*meat	-350.00	8	716.00	1.95	0.27

Table 2: Ordered logistic regression model parameters (β and SE) for the AIC-selected landscape, fruit, and meat model explaining local abundance of grizzly bears in the Yellowhead population unit during the 2004 DNA hair-snag mark-recapture population survey. Odds ratios (e^β) and standardized coefficients (e^βStdX) are provided to assess strength of relationship per one unit change in variable (e^β) or one standard deviation change in the variable (e^βStdX).

Variable	**β**	**SE**	**e^β**	**e^βStdX**
Session	-0.364	0.111	0.695	0.688
Road density (7440 m radius)	-0.662	0.420	0.516	0.761
$\log_{10}$(buffaloberry kcal w/in 1690 m)	0.754	0.273	2.125	1.994
$\log_{10}$(ungulate kcal w/in 7440 m)	4.080	0.520	59.12	1.998

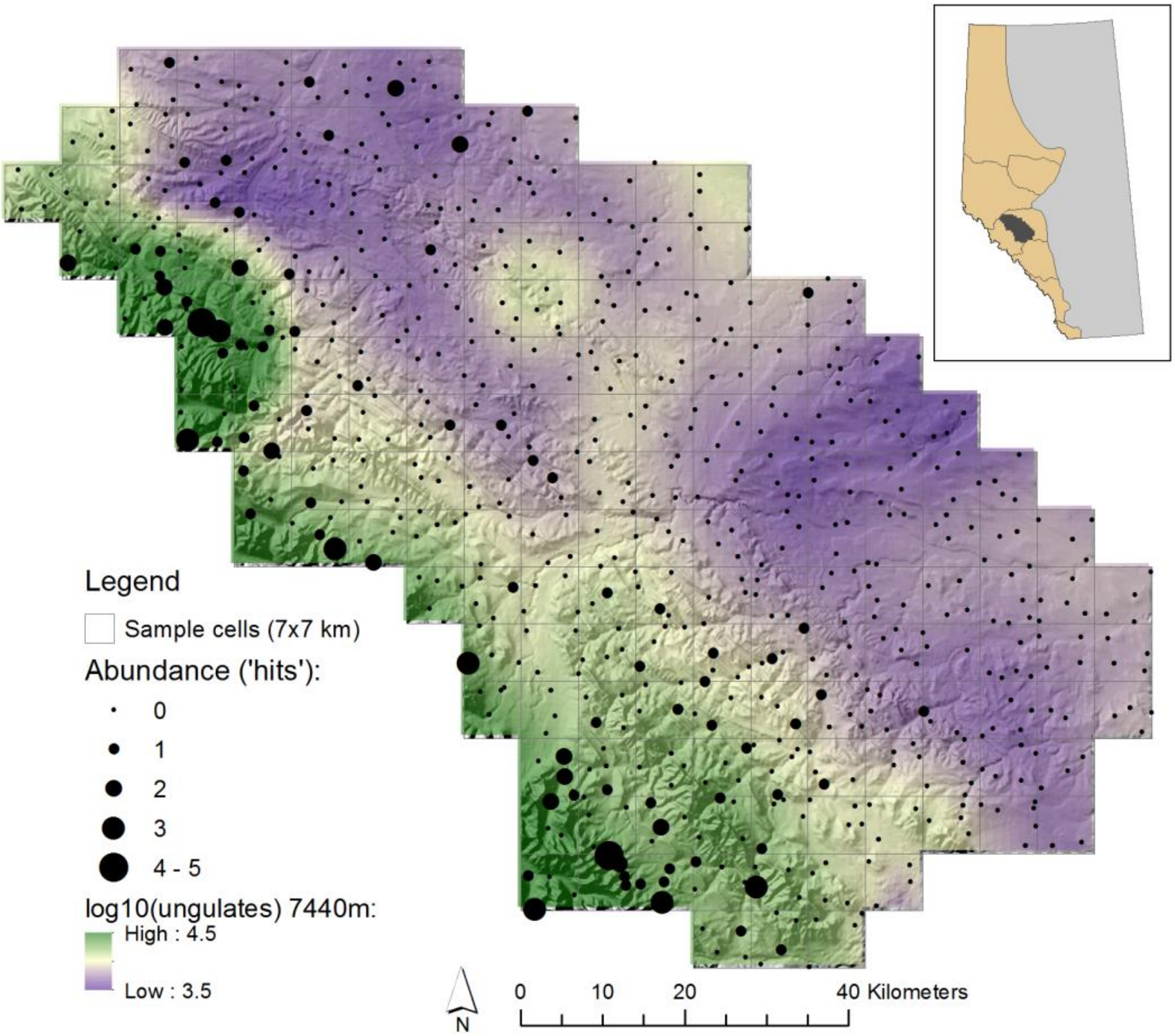

Figure 1: Nutritional landscape pattern of total available ungulate meat (log10 kcal; Dig E) and associated local abundance of grizzly bears during the 2004 hair-snag DNA population survey.

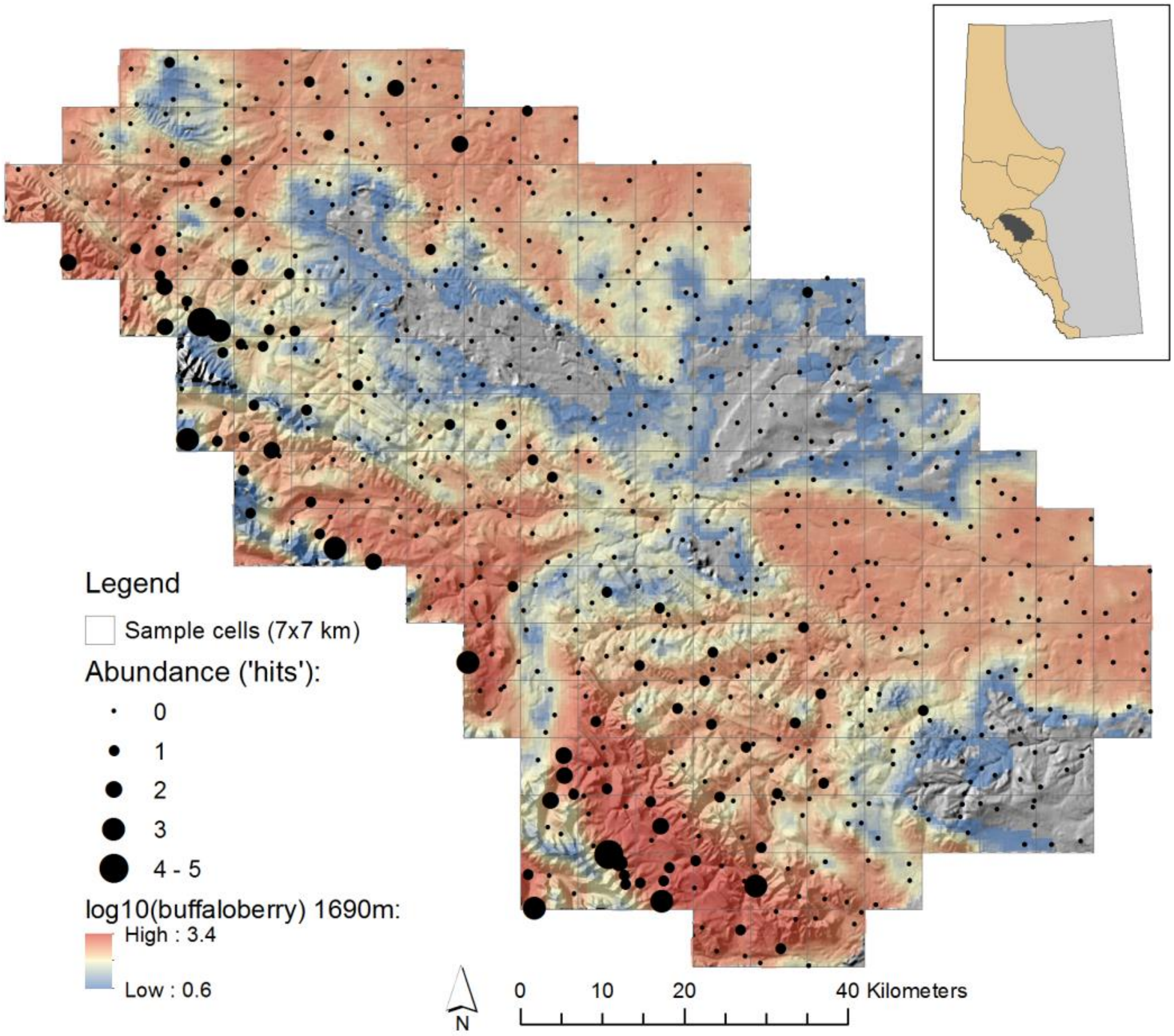

Figure 2: Nutritional landscape pattern of buffaloberry fruit (log10 kcal; Dig E) and associated local abundance of grizzly bears during the 2004 hair-snag DNA population survey.

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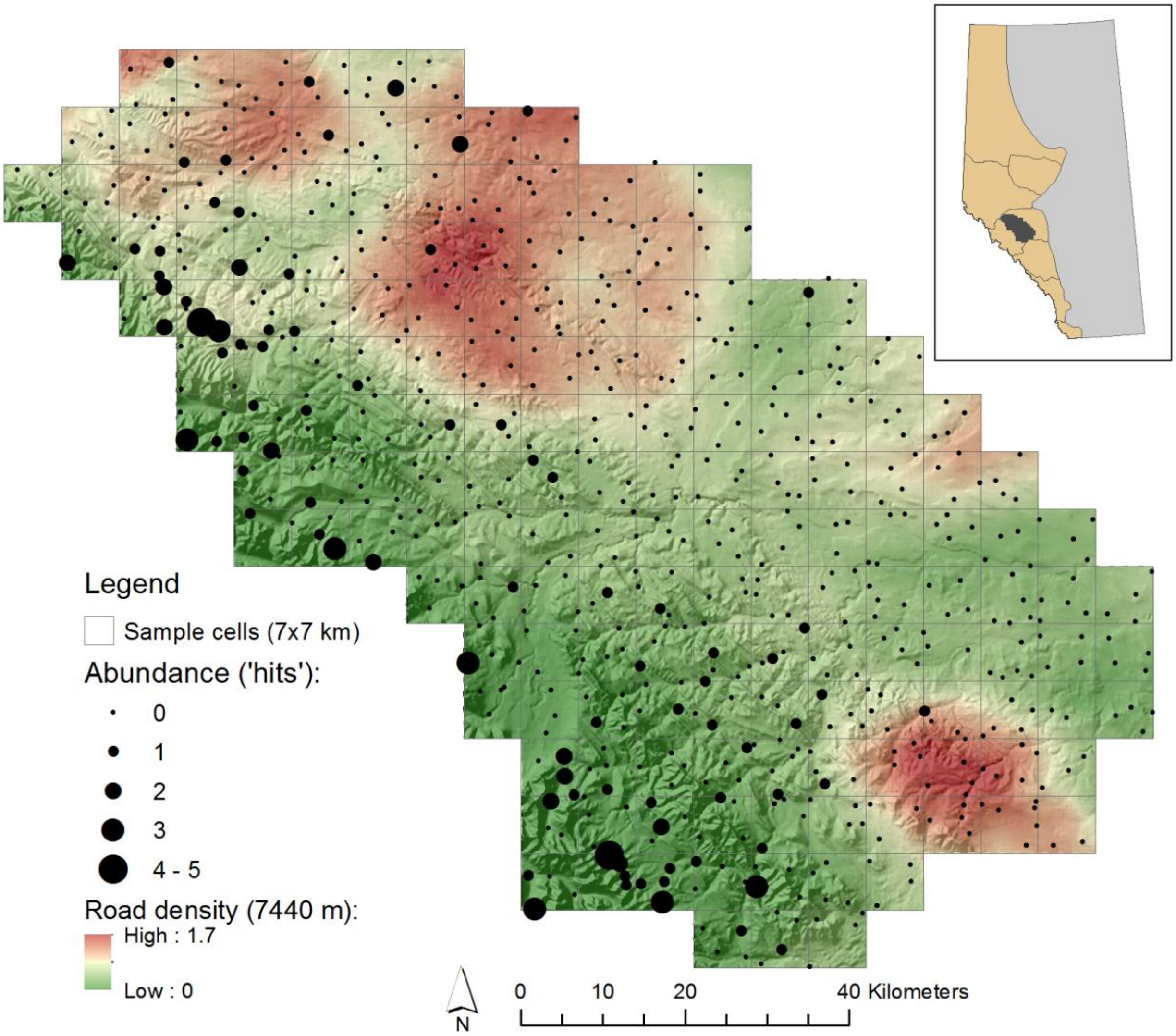

Figure 3: Patterns in road density (7440 m radius) and local abundance of bears within the 2004 Yellowhead hair-snag DNA survey for grizzly bears.

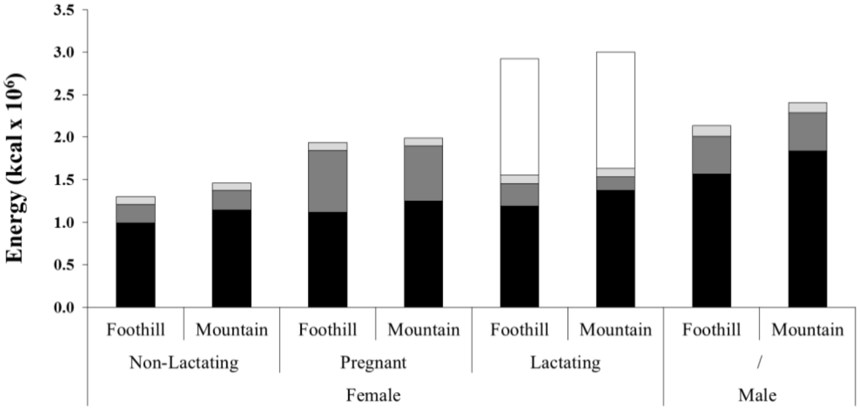

Figure 4: Total energy cost for grizzly bears in the Foothill and Mountain ecosystems of Alberta. Energy cost is expressed in kcal/active period. Maintenance cost (black), Mass gain (dark grey), Movement (light grey), and Lactation (white) are illustrated.

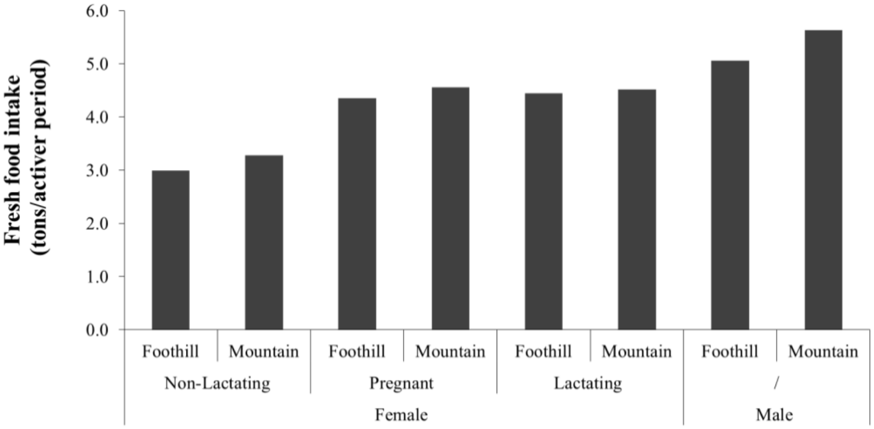

Figure 5: Total fresh intake of food (in tons) for grizzly bears during the active period in the Foothill and Mountain ecosystems of west-central Alberta.

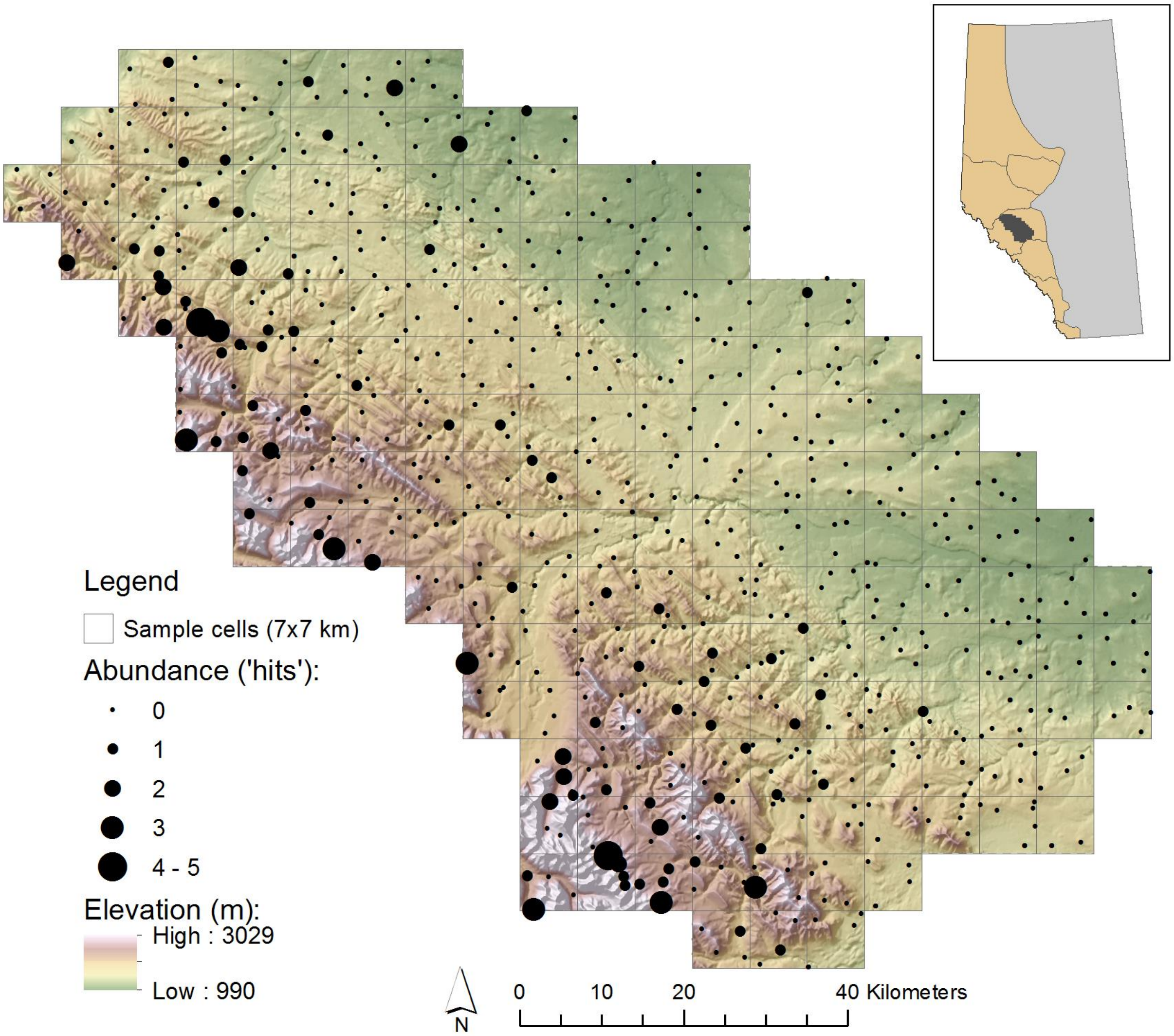

Figure 6: DNA hair-snag mark-recapture survey sites collected during the 2004 population survey for the Yellowhead population of grizzly bears in west-central Alberta. Elevation is shown for reference and the location of defined 7x7 km grid used for allocating sample efforts.

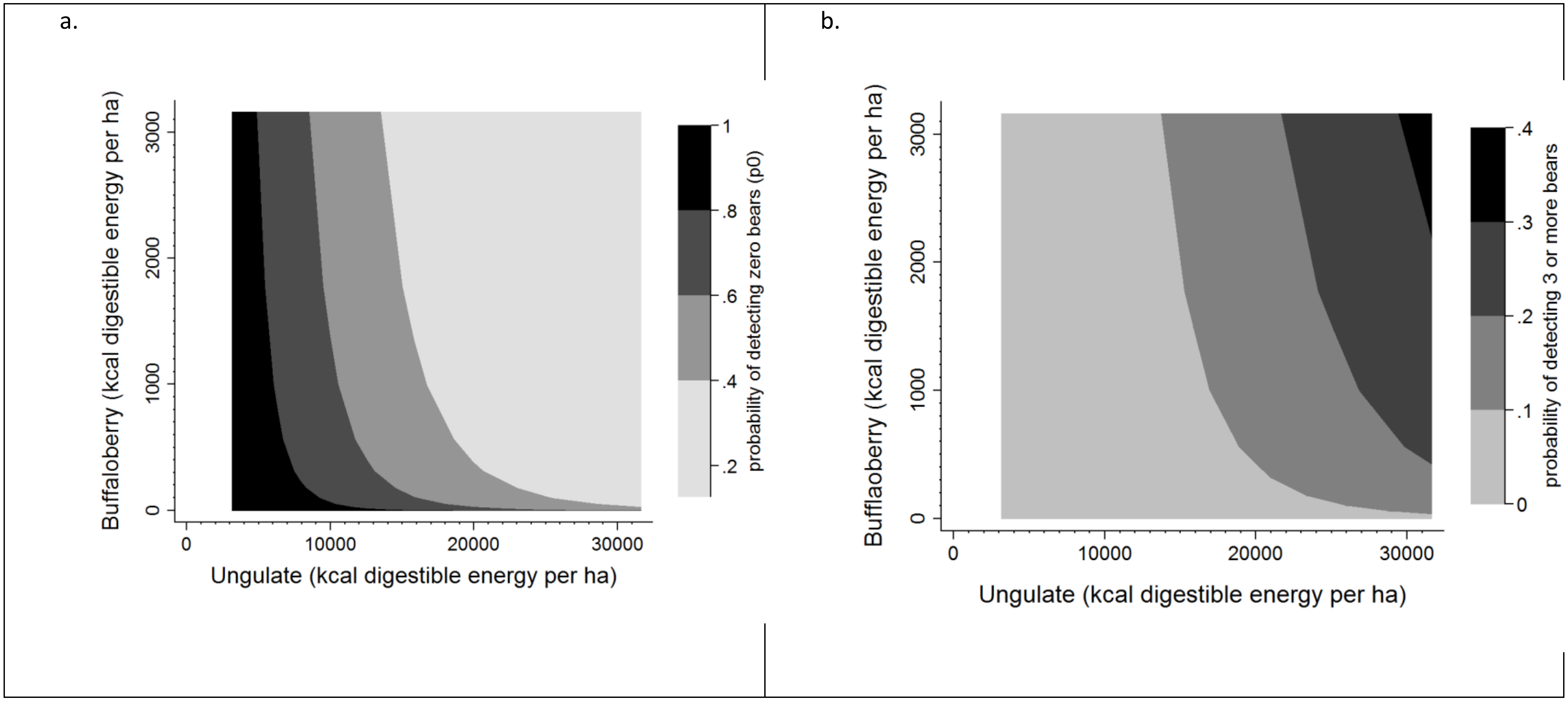

Figure 7: Contour plots illustrating the predicted probability (AIC-selected model) of detecting either zero bears (a) or 3 or more bears (b) at a DNA hair-snag sites in the Yellowhead ecosystem as a function of local available digestible energy in ungulates (x-axis) and buffaloberry fruit (y-axis). Road density and sample session number are set in this example to a value of 0.

Appendix A.4.1. Estimating Ungulate Biomass in the Yellowhead Grizzly Bear Population Unit

Prepared by Terry Larsen

Objectives

Our objectives were to: 1) develop species specific abundance models (density) for moose (*Alces alces*), Rocky Mountain elk (*Cervus elaphus*), white-tailed deer (*Odocoileus virginianus*), mule deer (*Odocoileus hemionus*), and bighorn sheep (*Ovis Canadensis*) by relating aerial and ground-based survey data (counts) to local environmental predictors; 2) map ungulate densities across the Yellowhead Population Unit; and 3) convert mapped density estimates of ungulates to biomass (kg/km^2).

Ungulate Surveys

We obtained winter aerial moose survey data collected by Alberta Environment and Sustainable Resource Development (AESRD) for WMUs 338 (2009), 339 (2011), and 340 (2010). The most recent survey year was used in our study since ungulate populations are dynamic and may change over time due to predation, disease, climate (snowfall, temperature), or hunting (Edwards, 1956; Rolley and Keith, 1980; Post and Stenseth, 1998; Ferguson et al., 1999; DeCesare and Pletscher, 2006; Hebblewhite et al., 2006; Dekker, 2009; Boyce et al., 2012). Aerial surveys followed a modified random survey block design (Gasaway et al. 1986). First, a fixed-wing aircraft was used to fly east-west transects at an interval of 1' latitude. Observers scanned 300-500m from the aircraft, counting and recording the locations of moose with a hand-held Global Positioning System (GPS) unit. Moose density (low, medium, and high) was then determined for each survey block (5' latitude x 5' longitude, or 3' latitude x 5' longitude), and a rotary-winged aircraft was used to intensively (400 m intervals) survey five of each density category selected at random. We also acquired winter bighorn sheep survey data collected by AESRD for WMUs 436-446, excluding 445 (2011). The survey was a comprehensive inventory of sheep winter range; mountain complexes where animals typically concentrate. Using a rotary-winged aircraft, mountain contours were flown in a counter-clockwise direction and at a height above ground where open slopes and ridges could be observed. Although efforts were made to count all ungulate species observed, only moose and sheep were classified (sex, age class).

We obtained winter aerial and ground-based ungulate survey data from Teck Coal Ltd. and Bighorn Wildlife Technologies Ltd. Surveys occurred on the Gregg River, Luscar, Cheviot, and Coal Valley open pit coal mine sites. AESRDs aerial sheep survey (2011) was complemented by a ground survey of the Gregg River, Luscar, and Cheviot mine sites. The systematic ground survey covered the entirety of each mine site by walking, driving, and viewing ungulates from strategic vantage points. Additional winter aerial surveys were conducted by rotary-winged aircraft on the Cheviot (2005) and Coal Valley (RobbTrend – 2008; RobbWest – 2011) mines sites. These surveys consisted of flying pre-determined transects orientated NW-SE, approximately 800m apart. However, when animals were concentrated through observations of tracks and cratering in the snow, the helicopter circled to increase efficiency. Because elk tended to be difficult to count, tracks were followed off transect to locate the animals. All ungulate species were counted, classified where possible, and the location coordinates recorded using a GPS.

To minimize biases associated with aerial surveys, crew members consisted of experienced observers, the aircrafts speed and height above ground were consistent albeit dependent on terrain ruggedness, and surveys occurred when weather conditions were ideal – adequate snow cover, little cloud cover, and low winds. Although surveys typically occurred within 3-5 days, AESRDs sheep survey (2011) was prolonged because of high winds. We assumed that the count data from the sheep survey were representative regardless of the sampling period as there tends to be little animal movement between mountain complexes in winter.

Analysis Scale and Environmental Predictors

We used the survey block sizes 3' x 5' for WMU 339 and 5' x 5' for WMUs 338 and 340 to define the analysis scale for moose survey data. In doing so, search effort could be accounted for explicitly in abundance models. We defined the analysis scale for all other survey data (line transect, 'complete' coverage) by extending the 5' x 5' survey grid, which assumes that search effort was adequately represented in each survey block. Although this approach allows for the investigation of habitat relationships at a common scale, we recognize the potential weakness of inference derived at a single scale. Ungulates may respond to local environmental conditions at specific scales (Maier et al., 2005), ungulate densities may vary locally as animals alter their habitat use and movement patterns to cope with reduced food availability and snow depth (Telfer, 1978; Parker et al., 1984; Poole and Mowat, 2005), and individual animals may migrate long distances from summer to winter ranges (Nicholson et al., 1997; Hebblewhite et al., 2006). While our approach does not address the potential issue of changing densities associated with ungulate migration, we believe that the relatively large area (~52 km^2) of survey blocks accounted for local changes in ungulate density associated with seasonal habitat use since mountain tops and valley bottoms would be captured in a single survey block.

We chose abiotic variables that mirrored those used in previous studies of ungulate distribution and abundance. These variables were grouped into unique categories reflecting broad differences in habitat composition associated with vegetation (landcover), forest composition (leading tree species) and structure (canopy cover, stand age), topography, water, and anthropogenic land use (Table 1.).

Landcover was represented by a 10 class raster (30 x 30m) map that distinguished vegetated from non-vegetated habitats (McDermid, 2005). Anthropogenic features including well-sites, pipelines, powerlines, railways, and roads were buffered according to the width of each feature visually estimated from Landsat (30 x 30m pixel) imagery. All anthropogenic features were grouped into a single feature class. We rasterized (30 x 30m pixel) anthropogenic features along with vector data to identify cutblocks and reclaimed mine footprint. We then created a final habitat layer by replacing landcover values with the rasterized layers. In doing so, herb, shrub, and barren landcover classes would be representative of naturally occurring meadow or alpine habitats. Attributes were retained to distinguish anthropogenic features from cutblocks and the Gregg River/Luscar and Coal Valley mines. We discriminated between the two mine sites because sheep were not found on the Coal Valley mine.

Forest attributes were represented by raster layers of canopy closure, leading tree species, and stand age, which were perfectly aligned with pixels classified as treed in the final landcover layer. We reclassified the continuous leading species raster to identify conifer (≥50% conifer) dominant pixels. A digital elevation model raster (30 x 30m pixel) was used to create slope and aspect grids. The aspect grid was scaled so that values between 0 and +180 were westerly, 0 and -180 were easterly, and 0 was south (Keating et al., 2007). To identify escape terrain for sheep, we created a four class raster layer to identify slopes greater than 27° and where contiguous patches were greater than 7000 m^2 (DeCesare and Pletscher, 2006). Streams (AltaLIS, 2008) were separated in two different types based on order (Strahler, 1957). The first type (order 1-2) includes headwater streams that were relatively small in size and that may flow intermittently or permanently, while the second type (order 3-5) were streams relatively large in size, permanently flowing, and include major river valleys. All forms of naturally occurring standing water such as ponds and lakes were identified as water bodies (AltaLIS, 2008).

For each survey block, we calculated the proportion of each landcover class, anthropogenic, conifer and deciduous forest, escape cover, escape cover greater than 7000 m^2 in size, and waterbodies. We also calculated the total length (m) of each stream order class, the average and standard deviations of canopy closure, stand age, slope, and aspect as well as the average distance (m) to escape cover and escape cover greater than 7000 m^2 in size. For canopy closure and forest age, we calculated average and standard deviations by coding other non-forested habitats as no data or as zero. We used standard deviations in addition to averaged values as habitat heterogeneity tends to be an important factor influencing animal distribution and health (Mysterud, et al., 2001; Kie et al., 2002; Boyce et al., 2003). Geographical Information System (GIS) manipulations were performed using ArcGIS 10.1 and the Spatial Analyst extension (ESRI, 2012).

Abundance Models

We summed counts of ungulates by species, sex, and age class (adult and unclassified) excluding neonates for each survey block (sample unit). Summed counts were then linked to underlying habitat associated with each survey block. Our preliminary evaluation suggested that species level counts including male and female moose were not correlated, however, counts of male and female sheep were highly correlated (Pearson's $|r| = 0.91$). After considering sample size (number of survey blocks) and correlations amongst the count data, models were developed for adult male (n=54) and female (n=84) moose, elk (n=26), white-tailed deer (n=50), mule deer (n=21), and sheep (n=26).

We created additional continuous variables to group herb and shrub landcover classes and stream order, and to also investigate non-linear relationships using squared terms. We created binary variables to differentiate small from large survey blocks (AREAc) as well as and the presence or absence of escape terrain and reclaimed coal mine area. Large survey blocks were distinguished from small ones according to the smallest 5' x 5' grid size (>51180952m^2).

Prior to model fitting, we used graphical plots to identify potential outliers relative to our explanatory variables, and we determined whether or not explanatory variables were correlated (Pearson's $|r| \geq 0.6$) (Zuur et al., 2009). Because our goal was to create models based on the principal of parsimony (Burnham and Anderson, 2002), we used Akaike's information criterion (AIC) scores, adjusted for small sample size (AIC_c), to select variables that would be included in the final candidate model sets. For each broad habitat class (e.g., anthropogenic vs. terrain), we retained variables where ΔAIC_c scores were > 2 units from an intercept only model or where the inclusion of a squared term further reduced ΔAIC_c scores when compared to the linear variable. For those variables that were not correlated, we considered all possible variable combinations (all-subset approach) between the habitat types as biologically plausible candidate models. However, we excluded models where multicollinearity was an issue. Multicollinearity was deemed influential if variance inflation factors exceeded 3 (Zuur et al., 2009). Although an all-subset approach to model selection is not advised (Burnham and Anderson, 2002), because there is limited information regarding ungulate habitat-density relationships in the Yellowhead Population Unit, our approach was exploratory in nature. Ultimately, we aimed to not simply develop the best fit model with the fewest parameters, but to test for the effect of different broad habitat classes in explaining variation in ungulate densities.

We only considered non-zero observations thereby eliminating issues of zero inflation or false-zeroes (Martin et al., 2005). To ensure homogeneity of variance and to meet the assumption of normal residuals, response variables were transformed by taking the natural log of the count. Species level models were then fit using a Generalize Linear Model with a gaussian error distribution and identity link (McCullaugh and Nelder, 1989). We calculated AIC_c scores, ΔAIC_c, and Akaike weights (W_i) to compare competing models. Because no 'best' model could be identified (W_i >0.9), we used multimodel inference (Burnham and Anderson, 2002). In this case, the 'best' model was represented by a weighted average of the regression coefficients from the full candidate model set using Akaike weights (Burnham and Anderson, 2002) (Table 2.).

Biomass Maps

We applied the averaged species level model coefficients to the Yellowhead Population Unit area based on the underlying habitat within each 5' x 5' grid cell. However, for sheep we limited our inference to those grid cells that overlapped with the Rocky Mountain Natural Region and where elevation values were above a specific cutoff point (ELEVx >= 1488 and ELEVsd >= 100). Below these cutoff points, sheep were not present according to the survey data. Because extrapolated estimates would in some cases result in over prediction, we recoded specific environmental predictors on the grid to their maximum value for male (SLPsd = 13) and female (AGEsdND = 82) moose, elk (ELEVsd = 242, AGExND = 126), and white-tailed deer (ELEVsd = 109).

Abundance estimates were back transformed by taking the exponent of each grid cell prediction. We determined the proportion of female to male elk (0.85), white-tailed (0.85) and mule (0.79) deer, and sheep (0.55) for each grid cell. Male to female ratios were determined from the raw survey data, but only where animals were classified to sex. We then calculated the number of neonates per adult female (> 1 year old) moose (0.78; Schwartz, 1992), elk (0.78; Hegel, 2003), white-tailed deer (1.0; Alberta, 1995), mule deer (0.85; Alberta, 1989), and sheep (0.91; Gaillard et al., 2002). However, sheep were only considered adults after 2 years (Jorgensen et al., 1993). To account for this, sheep counts were multiplied by the proportion of adult females (0.93) according to the proportion of female yearlings (0.07) observed on the Gregg River and Luscar mines. We also calculated the number of twins expected per female moose (0.15; Schwartz, 1992), white-tailed (2.08; Alberta, 1995) and mule (1.6; Alberta, 1989) deer as elk rarely have twins and sheep, not at all. Finally, we calculated biomass (kg/km^2) of adult males, adult females (including yearlings for sheep), and neonates by multiplying abundance estimates in each grid cell by fall (October – December) live body mass (kg) per unit area. We obtained from the literature, body mass values (averaged or predicted) for moose (male = 442; female = 401; neonate = 184; Lynch et al., 1995), elk (male = 327; female = 230; neonate = 122; Bender et al., 2003), white-tailed deer (male/female averaged = 87; neonate = 28; Kuzyk et al., 2009), mule deer (male/female averaged = 110; neonate = 28; Renecker, 1991), and sheep (male = 89; female = 67; neonate=32; Festa-Bianchet et al., 1996).

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Table 1. Variables used to predict ungulate densities across the Yellowhead Grizzly Bear Population Unit.

Habitat Class	Habitat Type	Variable	Description
Landcover	Upland Tree	UT	(>5% tree cover by crown closure; mesic or dry moisture regime)
	Wetland Tree	WT	(>5% tree cover by crown closure; wet or aquatic moisture regime)
	Upland Herb	UH	(>5% herbaceous cover; mesic or dry moisture regime)
	Wetland Herb	WH	(>5% herbaceous cover; wet or aquatic moisture regime)
	Shrubs	SHR	(>5% shrub cover; any moisture regime)
		SHRHRB	UH+WH+SHR
	Water	WAT	(<5% vegetated; aquatic moisture regime)
	Barren	BAR	(<5% vegetated; mesic or dry moisture regime)
	Agriculture	AGR	Agricultural mask
Forest Attributes	Conifer	CON	Conifer dominated (>50% conifer)
	Deciduous	DEC	Deciduous dominated (≤50% conifer)
	Canopy closure	CCx	Average canopy closure (other 'open' habitats set to nodata)
		CCndx	Average canopy closure (other 'open' habitats set to zero)
		CCsd	Standard deviations in canopy closure (other 'open' habitats set to nodata)
		CCndsd	Standard deviations in closure (other 'open' habitats set to zero)
	Stand age	AGEx	Average stand age (other non-forested habitats set to nodata)
		AGEndx	Average stand age (other non-forested habitats set to zero)
		AGEsd	Standard deviations in stand age (other non-forested habitats set to nodata)
		AGEndsd	Standard deviations in stand age (other non-forested habitats set to zero)
Terrain	Slope	SLPx	Average slope
		SLPsd	Standard deviation of slope
	Escape terrain	ESCP1	Amount of slopes >27°; patch size >7000m^2
		ESCP01	Amount of slopes >27°
		ESCP1_1	Presence/absence of ESCP1
		ESCP01_1	Presence/absence of ESCP01
		ESCPx1	Average distance to slopes >27°; patch size >7000m^2
		ESCPx01	Average distance to slopes >27°
	Aspect	ASPx	Average aspect scaled (-180, +180)
		ASPsd	Standard deviation of aspect
	Elevation	ELEVx	Average elevation
		ELEVsd	Standard deviation of elevation
Lakes/Rivers	Rivers	ORD0	Stream length (Strahler order 1 and 2)
		ORD1	Stream length (Strahler order 3 - 5)
		ORD01	ORD0 + ORD01
	Waterbody	WATB	Waterbodies
Anthropogenic	Well-sites	ANT	Buffered by 70m
	Pipelines		Buffered by 20m
	Powerlines		Buffered by 30m
	Roads		Buffered by 30m
	Railway		Buffered by 30m
	Cut-blocks	BLK	Forestry cutblocks
	Coal Mine	Cmine	Reclaimed Cardinal/Gregg River open pit coal mine
		Rmine	Reclaimed Coal Valley open pit coal mine
		Cmine1	Presence/absence of Cmine
		Rmine1	Presence/absence of Rmine

Table2. Species specific regression coefficients estimated using Generalized Linear Models. Coefficients are representative of averaged values using Akaike weights and multimodel inference.

Variable	Moose - male	Moose - female	Elk	White-tailed deer	Mule deer	Sheep
AREAc	0.27		1.37			
WT		1.38				
CON		-0.34				
DEC	1.18	0.15		5.46		
AGEndx			0.03			
AGEsd		-0.02				
CCx	0.02					
CCndsd					0.06	
ELEVsd			4.69E-03	0.02		
SLPsd	0.08					
DESCP01x	5.45E-05	4.90E-05				
DESCP01x^2	-5.64E-10	-3.71E-10				
ORD01		5.25E-06				
BLK			-0.88	-0.92		
Cmine			1.65			11.61
Rmine				1.29	0.91	
Constant	-0.71	1.24	-0.69	0.44	0.39	2.74

CHAPTER A.5. Future of Alberta's Forests for Grizzly Bears Disturbance Evaluation and LiDAR Habitat Classification

Participants:

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Executive summary

This annual report describes the continuing remote sensing research on Alberta's grizzly bear habitat and the opportunities and threats of habitat change to grizzly bear populations. The research includes provisions to map and monitor landscape changes associated with pests, human activities, harvesting and resource extraction, and to develop predictive models capable of forecasting the impacts of habitat management and change through time. The overall goal of the remote sensing team is to provide resource managers with the knowledge and planning tools necessary to inform on the linkages between grizzly bears, habitat, harvesting operations, fire occurrence, and climate change. The research is concentrated in four thematic areas:

1. Continuation of disturbance monitoring and creating updates of base map products: canopy cover and land cover.
2. Refining classification of important bear habitats, e.g. alpine areas and open canopy forests by means of including LiDAR data

3. Monitoring of plant phenology for important food species and collection of field data to support thems 1 and 2.
4. Implementing the LANDIS-II dynamic forest landscape model , validating LANDIS-II's mechanistic fire model, and improving regeneration niche modeling with germination processes

Disturbance Monitoring

We continue our derivation of high-spatial (30m) and -temporal (bi-weekly) resolution geospatial predictions of disturbance generated by the Spatial Temporal Adaptive Algorithm for mapping Reflectance Change (STAARCH). The STAARCH procedures were adapted to use the newly available Landsat 8 data, and 11 out of 14 tiles are updated to 2013. We re-analysed the existing decade of data from 2001-2011 and used a decision tree model and fire data to attribute disturbances to different causes like fire, harvest, roads, or wellsites. Results are summarized by grizzly habitat states.

Forest Structure and Habitat Classification

The Province of Alberta in cooperation with industry partners have recently compiled a large collection of LiDAR data, which provide more direct measurements of forest structural characteristics than traditional optical remote sensing data. Following on the creation of canopy metrics at resolutions relevant to habitat processes, we use the LiDAR data in the prediction of understory forage species distribution, refined habitat classification, and creation of continues fields of canopy characteristics like height and density.

Field data and Plant Phenology

The available phenology cameras were employed in the Kakwa area overseeing *Heracleum lanatum* plants under various types of forest cover. The objective of the 2013 observation program is to compare phenological patterns and food availability throughout the growing season between areas with full canopy cover, recent clear cuts and edge habitat. A second project involves re-analysis of 2010 data, which was specifically aimed at comparing close vs. wide view images. In conjunction with the retreival of the cameras after the growing season we have collected data on 102 variable radius plots to use as reference data towards our habitat mapping and forest metrics calculation efforts.

LANDIS-II Runs, Mechanistic Fire Model Validation, and Regeneration Niche Modeling

We improved our tree species regeneration niche modeling through the implementation of Tree an Climate Assessment Germination and Establishment Model (TACA-GEM), which includes the latest germination sub-model. We adjusted the temporal resolution of climate inputs, based on early results indicating the importance of using daily-resolution weather data. This finding is supported by the literature on plant phenology, whereby plants are fine-tuned to changes in climate and photoperiod (Saxe et al. 2001; Badeck et al. 2004). We included the latest revisions to the germination sub-model in this work. We created new climate data tools in the R programming language to facilitate this change, which will be released as part of the *rnoaa* package. Using daily-resolution weather data, we modeled changes to tree species germination and establishment across Natural Subregions within western Alberta, under four different historical time period conditions. In addition, we conducted our final LANDIS-II simulations using the base-level succession and fire models, changed to an annual resolution to improve model performance. We also parameterized and ran the LANDIS-II Dynamic Fuels and Fire System, an advanced mechanistic fire model for four historical time periods. Fire model validation and improvement is underway through collaboration with the model developers at U.S. Forest Service.

A.5.1. STAARCH Continuation, 2013 and beyond.

Introduction

As part of disturbance mapping program in Grizzly Bear habitat from optical satellite data using high spatial and temporal resolution data, we have derived disturbance information from combined Landsat TM-5 and MODIS imagery since 2000 . We use the Spatial Temporal Adaptive Algortihm for mapping Reflectance Change (STAARCH) (Hilker *et al*. 2009)which was developed as an extended version of STARFM to allow the detection of disturbance events at spatial scales of the Landsat pixel (30m) and the temporal resolution of MODIS (16 day cloud free composites), through the generation of a spatial change mask derived from Landsat and an image sequence recording the temporal evolution of disturbance events.

Due to the malfunction in Landsat-7 Scan Line Corrector and the decommissioning of Landsat-5 there no new, high quality image data was acquired since for for 2013. The newly launched Landsat 8 satellite became operational in 2013, and generates compatible image data for the STAARCH routine. We were able to obtain data for 11 out of the 14 scenes that cover the FP7 area and have generaterd an updated STAARCH disturbance layer for the FP7 region. To enable the use of the new Landsat 8 data, as well as the updated products that are made available by the USGS for the Landsat archive, the image pre processing procedures have been upgrade. Our STAARCH processing script can now seamlessly integrate data from Landsat 5, 7 and 8 for the detection of stand replacing disturbances.

Results

The new STAARCh layer has updated disturbance statistics for all years after 2010. A summary is shown in Table 1. The complete STAARCH disturbance layer is deliverd as shapefile for distribution to all project partners. Figure 1 shows the last year of updata for each Landsat tile, and Figure 2. has a quick look of of the disturbances in the FP7 area. The areas with no suitable data in 2013 will receive updates as soon as data becomes available, this will be in the summer of 2014.

Table 1: Summary Statistics for the detected STAARCH disturbances.

Year	Number of disturbances	Area [ha]
2010	40101	1181615
2011	28994	94544
2012	19774	63648
2013 (until summer)	16030	61063

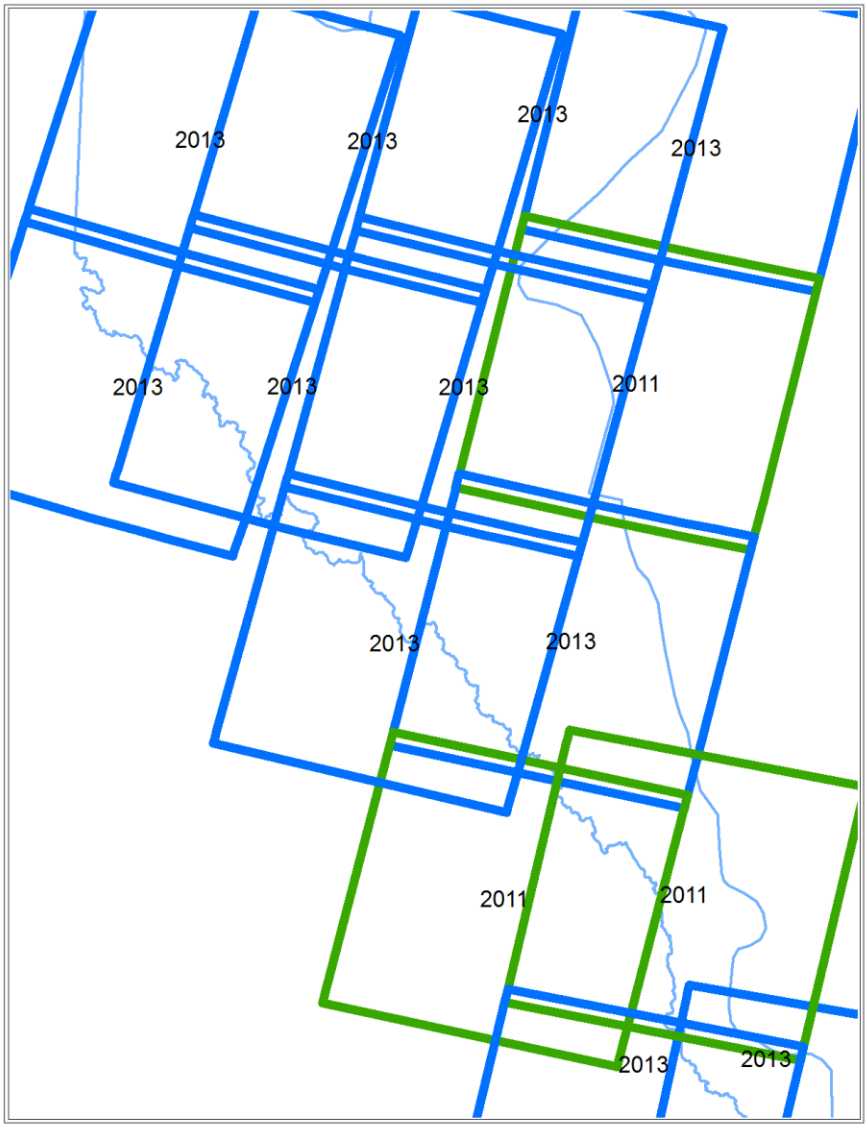

Figure 1 Landsat Tiles with last year STAARCH update

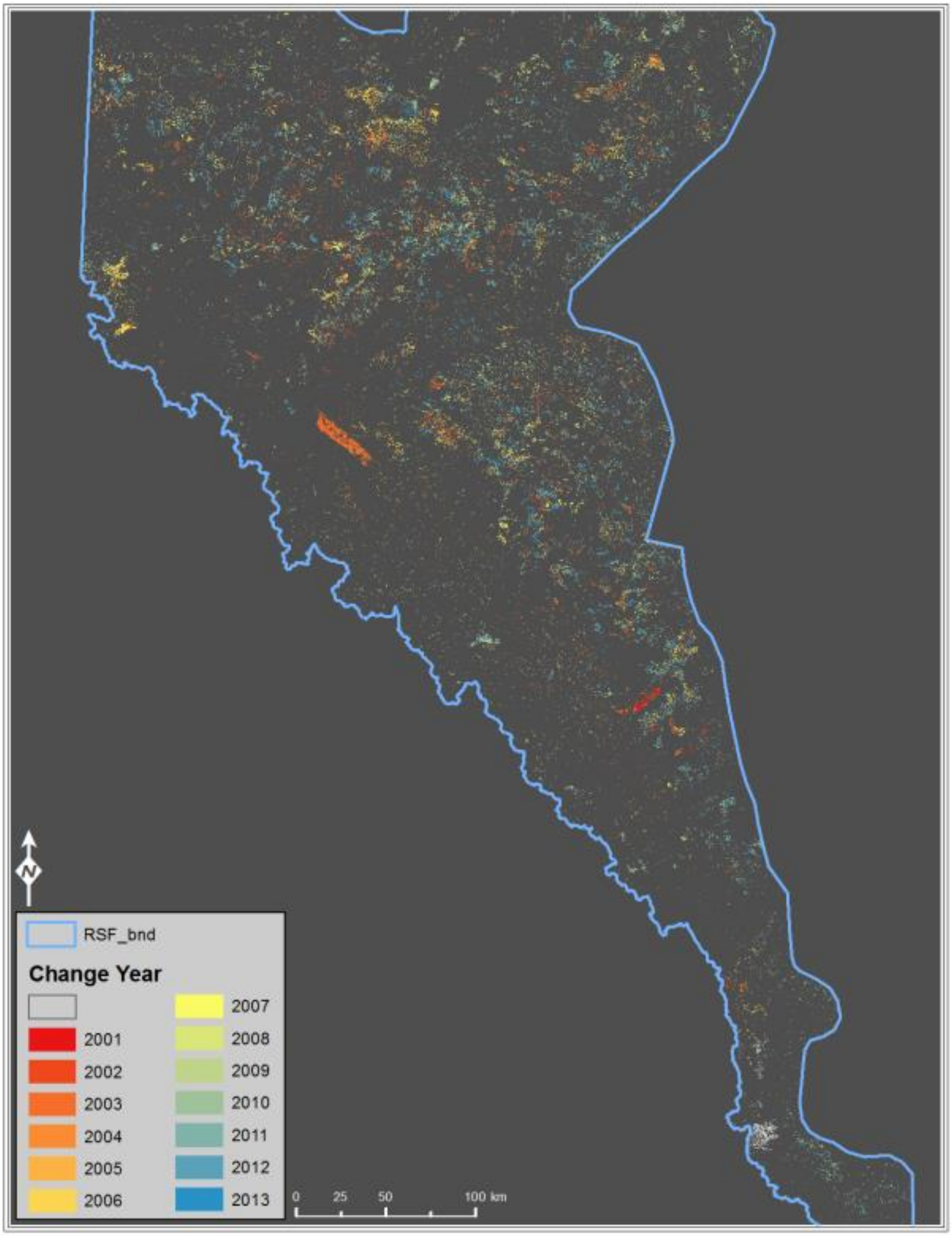

Figure 2 overview of disturbances over the whole study area.

A.5.2. Characterizing a Decade of Disturbance Events using Landsat and MODIS Satellite Imagery in Western Alberta, Canada for Grizzly Bear Management

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Introduction

Sustainable forest management aims to maintain biodiversity, ecosystem structure, and ecosystem services (Amoroso et al. 2011) while allowing persistence of renewable resources for future yield. Forested ecosystems are highly dynamic and often are subject to a wide range of disturbances which can include both biological (e.g., disease, insects) and non-biological (e.g., fire, wind throw) events as well as anthropogenic disturbances including mining, forest harvest, road building and infrastructure development (Nielsen et al. 2004a). Fire and forest harvest, given time, will return back to a natural state, whereas roads or well sites represent more permanent changes in the environment and are often viewed as habitat loss (Roever et al. 2008). Disturbances can cause mortality to organisms and alter the spatial fragmentation of the landscape, with potentially significant impacts on wildlife habitat (Gardner 1998, Nielsen et al. 2004b). The amount and extent of fragmentation, available and edge habitat quality, and resource availability are closely related to disturbance regimes and influence forest productivity and biodiversity (Berland et al. 2008; Linke et al. 2005).

Western Alberta Canada is a dynamic area with widespread occurrence of resource extraction activities (Roever et al. 2008). Increased coal, oil, gas, and timber extraction, in addition to local population growth and subsequent urban expansion and development, impacts biodiversity through habitat loss and fragmentation (Schneider et al. 2003). Western Alberta represents the eastern limit of grizzly bear (*Ursus arctos*) habitat in southern Canada and the last of its historic range in the province (Nielsen et al. 2009). Grizzly bear within the area occur at low densities due to their extensive habitat demands. On the east side of the rocky mountain massif, grizzly diet consists mainly of plant resources (*Equistem* spp*.,Trifolium, Vaccinium* spp*., Rubus* spp., etc.) with a small proportion of ungulate protein and insects, varying amongst populations (Munro et al. 2006). The size of individual home ranges is determined by sex (Gau, 1998; McLoughlin et al. 1999), age, reproductive status, and resource availability (McLoughlin et al. 2000). Grizzly bear have low reproduction rates, caused by the age at which they reach reproductive maturity, number of offspring produced, high dependency of cubs on the mother for resources and protection, and long intervals between litters (Alberta Grizzly Bear Recovery Plan, 2008). Based on population inventory data (2004-2008) for most of Alberta grizzly bear range and concerns over habitat alteration and loss the status of this species was changed to “threatened” in 2010Resource extraction in western Alberta increases the area of habitat alteration and the number of grizzly human-bear interactions, which is the greatest cause of mortality for bears (Nielsen et al. 2009). Grizzly bear require a mosaic of landscapes that had been historically maintained by wild fires. Because of effective fire suppression and increased resource extraction, anthropogenic disturbances have partly replaced the role of fire in providing this variation in habitat (Bratkovich, 1986, Hillis, 1986; Nielsen et al. 2004b, c). Forest regeneration and edge habitats provide a range of herbaceous plants and shrubs that are important forage for grizzly bear (Nielsen et al. 2004a) and thus can, depending on the time since disturbance, provide beneficial habitat for bears. However roads, connecting industries to the resources themselves, create increased probabilities for bear–human interactions (Berland et al. 2008, Nielsen et al. 2004a, 2008), and are therefore a major factor in bear mortality. Comprehensive management plans therefore need to recognize and map natural and anthropogenic disturbance while at the same time minimizing human bear interactions. One possible method of mapping disturbances in a timely and spatially comprehensive way is through satellite remote sensing. Remote sensing offers potential to detect and attribute disturbance events across large areas. For instance, the Landsat series of satellites have proven capable of observing land cover change at 30 m spatial resolution for over 40 years. However, Landsat has a revisit time of 16 days which, together with frequent cloud cover, limits timely attribution of disturbances (Wulder et al. 2008a), although increasingly numerous approaches for mitigating cloud cover have emerged (Wulder et al. 2011; Griffiths et al. 2013). One potential approach to mitigate this limitation is by fusing Landsat imagery with other satellite data having a shorter revisit time, such as the data blending approach of Gao et al. (2006). We use the Spatial Temporal Adaptive Algorithm for mapping Reflectance Change (STAARCH) (Hilker et al. 2009) to derive disturbance patches based on biweekly surface reflectance data at 30m spatial resolution. STAARCH uses combined Tasseled Cap Transformations (TCT) of Landsat Thematic Mapper (TM)/ Enhanced Thematic Mapper Plus (ETM+) and Moderate Resolution Imaging Spectrometer (MODIS) imagery. While this technique has been successfully applied to map disturbances across large areas, remotely sensed disturbance maps may also be used for disturbance attribution. One possible way to attribute disturbance patches is by their shape and time of occurrence. That is, anthropogenic disturbance patches can be characterized by their regularity in shape and limited spatial extent, whereas non-anthropogenic disturbances tend to be more irregular or variable in shape (Stewart et al. 2009). A simple way of defining patches is by using any contiguous disturbed area. The patches are then used to calculate area and shape specific parameters including area/density/edge metrics, shape metrics, core metrics, isolation/proximity metrics, contrast metrics, contagion/interspersion metrics, connectivity metrics, and diversity metrics (Su et al 2011).

In this resaerch we apply the STAARCH data fusion method (Hilker et al. 2009) to detect fine spatial resolution disturbance events across western Alberta over the past decade (2001 – 2011). We ask the question: How much disturbance has occurred over the Alberta foothills in the past decade? A decision tree approach was then applied to attribute disturbance events based on both spatial and temporal characteristics allowing us to assess how much of this disturbance is anthropogenic or non-anthropogenic in nature. We distinguished between forest harvest, resource exploration and installations, and road development, as well as fire disturbance based upon polygons from the national fire database. Classifying disturbance by type allows anthropogenic change to be quantified and the persistence of cover change to be calculated. We examine disturbance regimes across the entire region, by season and by type. Lastly, to demonstrate how these data can be used, we compare disturbance events with Grizzly bear habitat states (Nielsen et al. 2005) to observe spatial patterns of disturbance with safe harbor and attractive sink habitats. Our observations aim to provide an indication of how these datasets can be used to fill missing elements to grizzly bear comprehensive management strategies, which is quantifying habitat loss and bear-disturbance interactions that can be applied over large areas.

Methods

Study Area

The foothills region of Alberta, Canada, is a transition zone between the Rocky Mountains and Prairies, with elevations ranging from 700-1700m above sea level. The 130,727 km^2 study area (Figure 3) is typified by a wide range of temperature conditions (average temperature -12 to 15 ° C). Forests in the lower elevations in the foothills region are deciduous or mixed wood and common tree species include aspen (*Populus* spp.), balsam poplar (*Populus balsamifera*), white birch (*Betula papyifera*), lodgepole pine (*Pinus contorta*), white spruce (*Picea glauca*) and black spruce (*Picea Mariana*). The upper elevations in the foothills region is characterized by a distinct change in tree species dominance from mixed or deciduous to closed conifer forests of primarily lodgepole pine (Natural Regions Committee 2006). The region has been sub divided into five Grizzly bear habitat states: non-critical, primary sink, secondary sink, primary and secondary habitats (Nielsen et al. 2006).

Figure 3: Study area in Alberta showing the foothills area with observed Grizzly bear habitat states

Data

Disturbance Detection

The STAARCH algorithm relates biweekly change in forest cover at 30m spatial resolution (Hilker et al. 2009). In brief, the algorithm utilizes a minimum of two Landsat observations of the same location at the start and end of the study period, in addition to a sequence of MODIS 250 m images at a biweekly interval (Gao et al. 2006). First, the spatial extent of disturbances occurring from one Landsat observation to the next is mapped using two or more cloud filtered (Irish et al. 2006) scenes. Disturbances are mapped using a spectral disturbance index (Healy et al. 2005) based on the brightness, greenness, and wetness indices following calculation of the TCT (Kauth and Thomas, 1976). Second, a time series of MODIS imagery is used to determine the time of disturbance at biweekly time steps. To do so, the MODIS based disturbance index is computed based on the MODIS land bands and compared to identify significant changes in the time series of bi-weekly observations. The STAARCH algorithm has been applied and validated in previous research within the same study area (Hilker et al., 2009). This work demonstrated the accuracy and applicability of the STAARCH based disturbance detection technique, for identifying and categorizing disturbance based on spatial and temporal metrics. Hilker et al., (2009) found the STAARCH approach had an accuracy rate for correctly identifying disturbances in the correct year of 87%, 87% and 89% in 2002, 2003 and 2005 respectively, based on an independently derived disturbance mapping dataset derived from aerial photography. The spatial accuracy of the detection area itself was 93% when compared to the validation dataset. Areas where the algorithm had poorer accuracy were wetter sites, and as a result, disturbances within flood plains and bogs, may be more poorly represented. Similarly successful disturbance detection is dependent on cloud free viewing, so in some cases there was an 8-day delay in time attribution due to cloud obscured MODIS data. Overall however, we are confident in the accuracy of the approach and its applicability for assessing and attributing disturbances in this region. As persistent cloud and snow cover makes delineation of disturbance events extremely difficult in winter, the STAARCH methodology is applied only to growing season images (March to October). As a result, areas disturbed in winter will appear in the first image in the growing season of the following year (Hilker et al., 2009).

For this project a total of 64 Landsat 5 TM scenes covering an area of 16 path/rows (Table 2), acquired between July 2001 and August 2011 were obtained free of charge and ready for analysis (Woodcock et al. 2008) from the USGS GLOVIS archive (http://glovis.usgs.gov/). Images were selected to minimize cloud cover (where possible to below 30%) as well as the temporal separation between adjacent scenes across the study area. All images were expressed as top of atmosphere reflectance and corrected using a dark object subtraction (Song et al. 2001) technique. Land cover data was obtained from the Landsat 7 land cover classification of Canada that was produced for the Earth Observation for Sustainable Development of forests (EOSD) initiative (Wulder et al. 2008b) representing circa year 2000 conditions.

Disturbance Attribution

Prior to attribution, any disturbance patches which had adjacent disturbance patches detected at the same date were merged by Date of Disturbance (DOD), and expanded until no more adjacent polygons exist. Patches less than one hectare in size were removed based on Hilker et al. (2011). Fragstats, a landscape ecology tool that calculates intra- and interpatch metrics, was used to obtain the necessary spatial analytics (McGarigal et al. 2012). Patches are defined as groups of pixels surrounded by null space. Three sets of metrics were calculated for each patch including area, perimeter, contiguity and perimeter-area ratio. Core area and core area index, were also calculated and can be used to quantify the area that is not under edge influence. Lastly, isolation and proximity metrics calculate the distances between nearby patches (Hilker et al 2011).

A decision tree model previously developed by Hilker et al (2009) was then applied using the patch characteristics to identify disturbance type. Decision trees use data mining approaches to find the most accurate predictive method based on patterns within large datasets. As described in Hilker et al (2009), the key patch metrics identified as the most important variables in disturbance prediction were date of disturbance (DOD), core area (Core m^2), patch area (Area m^2), core area index (CAI), and contiguity index (Contig), described in Table 3.

Table 2: the location and the date of acquisition of the Landsat images used in the research analysis, obtained from the USGS GLOVIS archive

Path	**Row**	**2001**	**2004**	**2008**	**2011**
41	26	2001-10-03	2004-06-21	2008-09-20	2011-09-29
42	24	2001-09-08	2004-07-14	2008-07-25	2011-08-10
42	25	2001-09-08	2004-07-14	2008-07-25	2011-09-04
42	26	2001-09-08	2004-07-14	2008-07-25	2011-09-04
43	22	2001-09-15	2004-06-19	2007-09-16	2011-09-27
43	23	2001-09-15	2004-06-19	2008-08-17	2011-08-26
43	24	2001-09-15	2004-06-19	2008-08-17	2011-08-26
43	25	2001-09-15	2004-06-19	2008-08-17	2010-07-29
44	22	2001-07-04	2004-08-13	2008-08-08	2010-10-01
44	23	2001-07-04	2004-08-13	2008-10-11	2010-10-01
44	24	2001-07-04	2004-08-13	2008-06-21	2011-08-17
45	22	2001-08-12	2004-06-17	2009-08-27	2011-09-09
45	23	2001-08-12	2004-06-17	2008-09-16	2010-07-27
46	22	2001-09-20	2004-08-11	2008-08-06	2010-07-27
46	23	2001-09-04	2004-08-11	2008-08-06	2011-08-31
47	22	2001-08-10	2004-08-18	2008-09-14	2011-09-07

Patch characteristics combined with the DOD were used to classify well sites, roads, and forest harvest between 2001 and 2011 using decision tree analysis. In addition to the automatic attribution of the polygons, we utilized the Canadian National Fire Database and the Alberta ESRD Historical Wildfire Perimeter Data. The two datasets provide perimeter data for the outer limits of individual fires within Alberta, based on satellite imagery. Data completeness varies between year and collection agency, and the methods of different mapping techniques. Fire polygons were used to dictate the fire attribution of intersecting STAARCH polygons with the remainder classified as either well site, road, fire, or forest harvest.

Table 3: description of the FRAGSTATS metrics used in the decision tree model to identify type of disturbance (McGarigal et al. 2012)

Metric Name	Description
DoD	Date that change was detected from the STAARCH algorithm
Core	Area within individual patches that is greater than 30m from the patch edge
Area	Area of individual patches within the landscape
CAI	Core area divided by the total patch area multiplied by 100
Contig	Average contiguity value for cells - sum of cell values divided by number of pixels in the patch minus one, divided by the sum of the template values minus one

Grizzly Bear Habitat States

The habitat states for the study area were created from the methods derived in Nielsen et al. 2006, which combined the relative probability of adult female occupancy (based on environmental variables and telemetry data (Nielsen et al. 2005), and risk of human caused mortality (based on bear mortality data) (Nielsen et al. 2004a) models. From these models Nielsen et al., (2004a) then derived sink (Delibes et al. 2001, Naves et al. 2003) and safe-harbor (source) areas and extended them across the complete study area of western Alberta. Attractive sinks are areas where grizzly bears were likely to occur, but are at higher risk of human-caused mortality. Safe-harbor sites are areas where grizzly bears are likely to occur, with a lower risk of human-caused mortality. Habitat states were divided into five separate groups calculated from the above methods; primary and secondary habitat (sources), primary and secondary sink (sinks) and non-critical habitat (Nielsen et al. 2006).

Data Analysis

Our processing methodology was as follows: First the STAARCH algorithm was applied to identify disturbance patches. These patches were input into FRAGSTATS to calculate the required metrics for use in the decision tree developed by Hilker et al. (2011) to attribute each patch as either well site, road or forest harvest. The fire disturbance layer was then overlaid with the patch identification layer produced from STAARCH and the decision tree, and patches identified as fire by the fire database had their attribution changed to fire, regardless of the decision tree attribution. Polygons attributed as fire by the decision tree, but not contained within the fire polygons, were attributed to forest harvest. Disturbance polygons were then analyzed temporally (monthly and annual), for the distribution of anthropogenic and natural disturbance events. Secondly, disturbance polygons were overlaid with the grizzly bear habitat states to observe disturbance by type on known Grizzly bear habitat.

Results

Western Alberta Disturbance Attribution

Over the decade of 2001 – 2011 a total of 4,603 km^2 of disturbances covering 3.5% of the study area were detected. Figure 4 shows the disturbances from 2001 – 2011 and disturbance type (well-site, road, fire, or forest harvest). The results show an east–west trend across the area with the Rocky Mountain region to the west having fewer disturbances than the foothills region in the east. Forest harvest accounts for most of the disturbed area between 2001 and 2011 (Figure 5). Well sites and roads were frequent, but have relatively small spatial extents (0.03 and 0.02 km^2 respectively). Fires, while more infrequent, are larger (0.26km^2) than the other disturbance types, and dominate the spatial patterns in some areas. Forest harvest occurs across the study area at differing densities and patch sizes (as related to the cut block size).

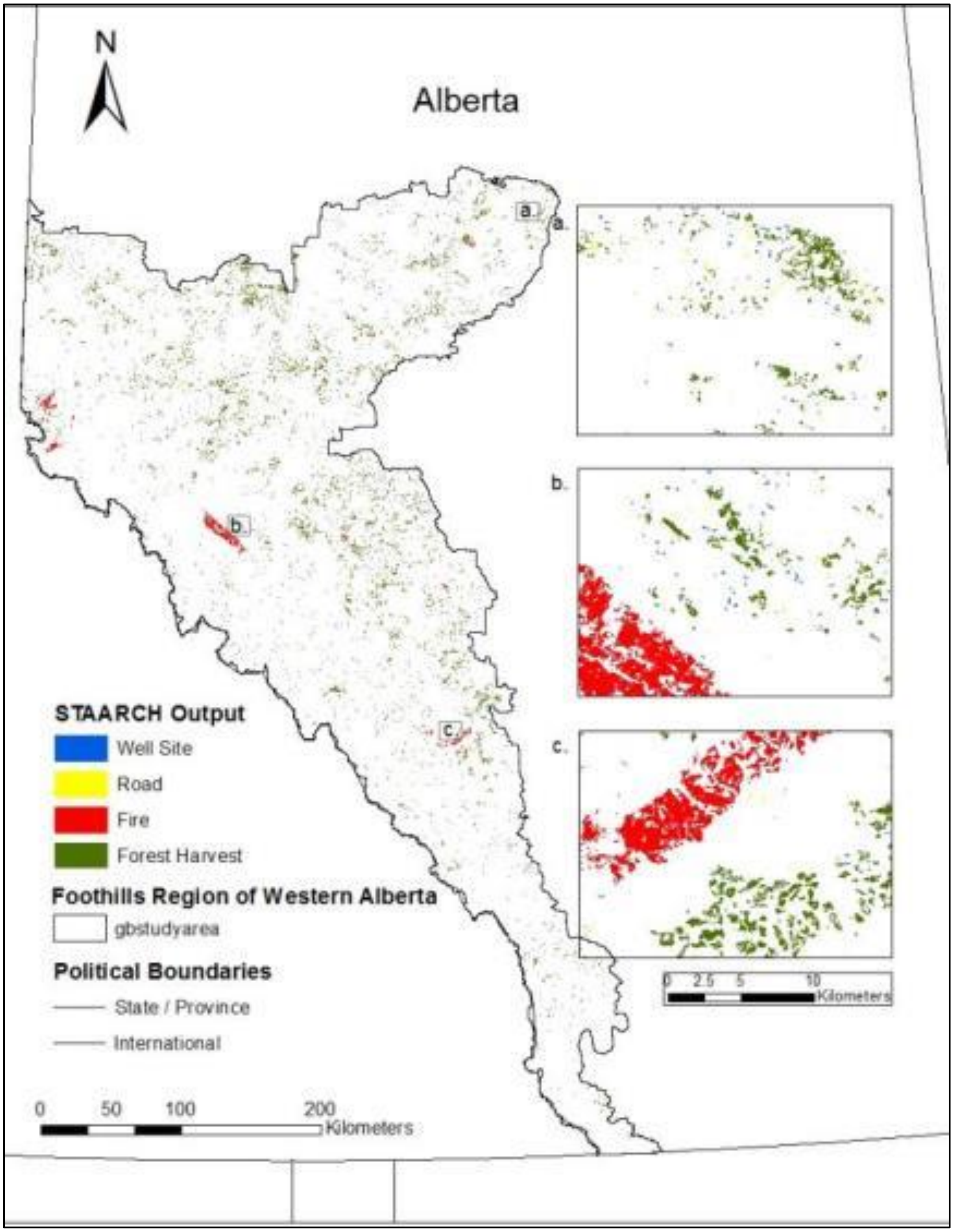

Figure 4: STAARCH output for the Grizzly bear study area classified by the type of disturbance from 2001-2011.

Summer (July and August) and fall (September and October) periods accounted for most of the disturbance area. The summer and fall months (July to October) have the highest proportion of forest harvesting, although sometimes decreases temporarily during dry periods due to fire risk. Road construction remained relatively consistent throughout the year; well site construction was comparatively less from June to August, and forest fires account for a variable portion of disturbance during the detection period, peaking in late summer, and early fall (Figure 5b). Generally, September observed the highest amount of forest disturbance through the decade, accounting for 1,032 km^2 of disturbance (22 %), with forest harvesting accounting for 63.5% of that change.

Well sites and roads have the smallest footprint in disturbance area, averaging 0.03 and 0.02 km^2 respectively, followed by forest harvest (0.13 km^2) and fire disturbance (0.26 km^2). Non-anthropogenic disturbance (fire) has 2% of the number of disturbance events (Figure 6a) yet 9% of the total area observed (Figure 6b). Well sites and roads compose 63% of the disturbance events (35% and 28% respectively), although composed only 22% of the total disturbed area (13% and 9% respectively). Forest harvest is 35% of the total disturbance events and occupies 69% of the disturbed area in the study area.

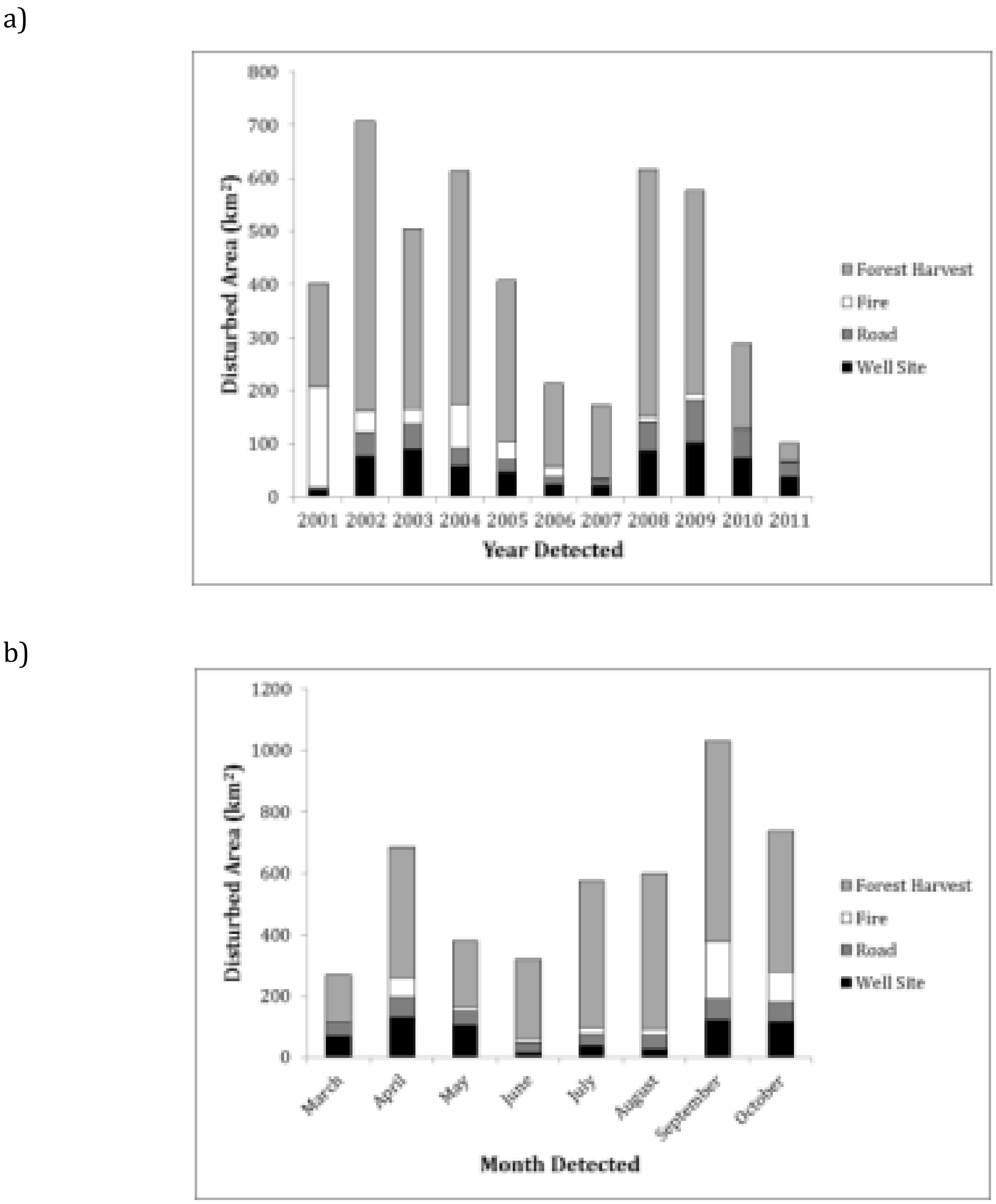

Figure 5: Total disturbed area (square kilometers) classified by type of disturbance (a) and by month of acquisition over the ten year study period (b) for western Alberta.

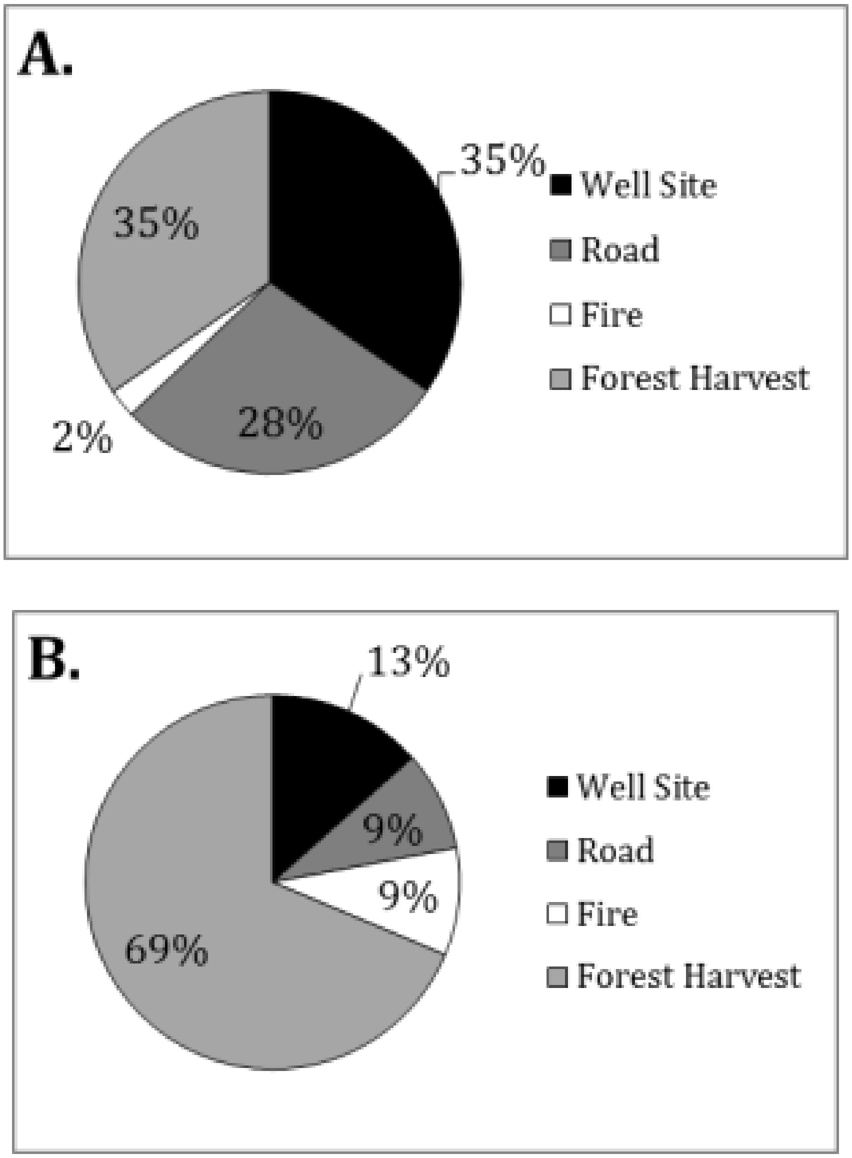

Figure 6: (A) Percent of individual disturbance events, and (B) as fraction of the area in Grizzly bear study area from 2001 to 2011.

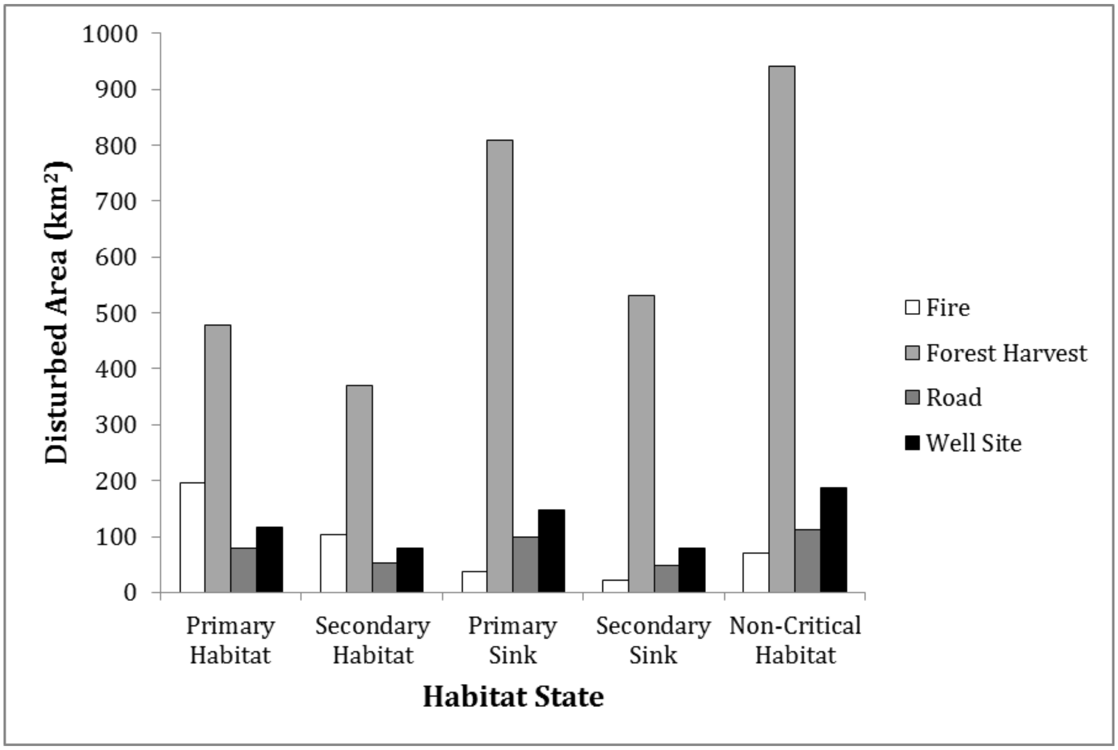

Figure 7: Total disturbed area (square kilometers) classified by type and habitat state from 2001-2011.

Habitat State Attribution

Grizzly bear source (primary and secondary) areas had lower total disturbed area than did sink areas or non-critical habitat (Figure 7). Primary habitat areas had a total of 672 km^2 of anthropogenic disturbance, and 195 km^2 of non-anthropogenic disturbance (2.9% and 0.9% of the area respectively). Secondary habitat areas had a total of 501 km^2 of anthropogenic disturbance and 104 km^2 of non-anthropogenic disturbance (2.7 and 0.6 km^2). Primary sink areas had a total of 1,055 km^2 of anthropogenic disturbance (5.9% of the area), and secondary sink areas had a total of 658 km^2 of anthropogenic disturbance (5.3% of the area). Anthropogenic disturbance is responsible for 97% of the disturbance in both primary and secondary sink habitats, and 95% in non-critical habitats. Figure 8 shows the annual area disturbed in each individual grizzly bear habitat state. Primary and secondary habitat and primary sinks, showed declining trends in disturbance area from 2001-2011, except in years 2008 and 2009 which were the highest years of total disturbance, behind 2002. Between the years of 2001-2005 total disturbed area of both primary and secondary habitat was 933km², compared with 539km² from 2006-2011. Total disturbed area for both primary and secondary sink areas from 2001-2005 was 1092km², and from 2006-2011 was 680km². Both source and sink areas show a decline in the amount of disturbed area from 2001-2011.

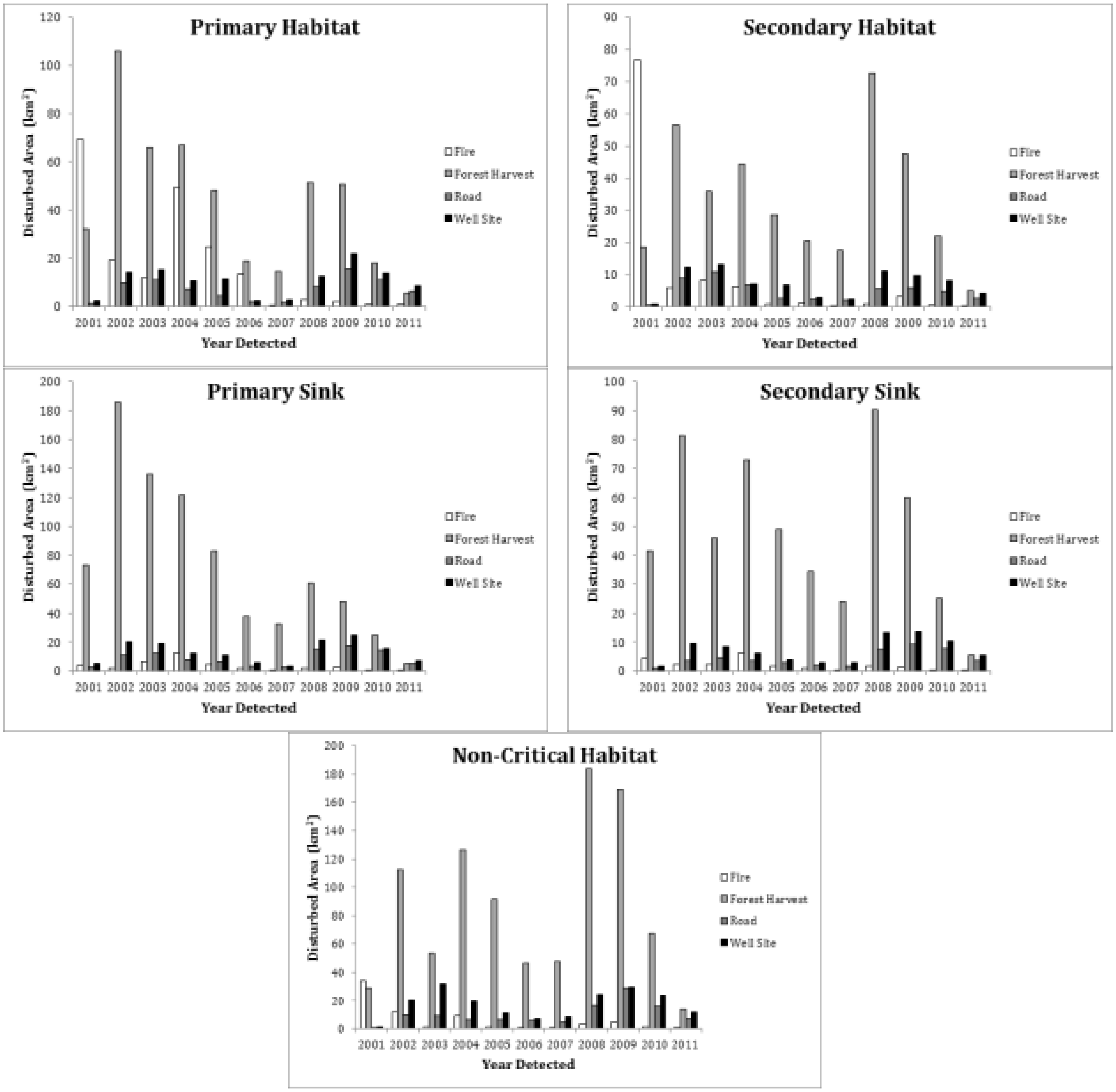

Figure 8: Total disturbed area (square kilometers) classified by year, for individual habitat states (primary habitat, secondary habitat, primary sink, secondary sink and non-critical habitat) from 2001-2011.

Discussion

In this paper we analyzed a decade (2001-2011) of forest disturbances in western Alberta as detected by the STAARCH algorithm for fusion of Landsat TM and MODIS satellite data. A decision tree classifier was used to attribute individual disturbances to forest harvest, fire, well sites, or roads and consequently the spatial and temporal patterns of disturbances within the context of grizzly bear home ranges were examined. While we analyzed a decade of data, 2001 and 2011 were incomplete data sets. 2001 included two time stamps, September 22 and October 8, and 2011 included time steps from the beginning of the study period until July 28.This likely reduced the total amount of area detected in these years, as well as impacting the monthly proportions over the entire study period.

Our analysis aimed to detect both anthropogenic and non-anthropogenic disturbances for western Alberta, as there is no timely, publicly available, comprehensive data source for the region on well sites, road building and forest harvest activities, derived in a consistent and transparent manner. The Canadian National Fire Database has publicly accessible historical fire polygons and these were used to allocate fire attribution on the intersecting STAARCH polygons, regardless of the decision tree results. Well sites, roads, fires and forest harvests were selected as the critical disturbance types for observation, as they represent the most common and spatially unique disturbances in the region. We applied an existing model to attribute the detected disturbances which used a unique combination of time of disturbance, as well as spatial features of the detected patch. The use of an automated change detection and attribution framework is an important goal both for remote sensing scientists as well as natural resource managers as it reduces subjectivity and improves the timeliness of change data (Stewart et al. 2009). The use of shape and contextual attributes adds additional dimensions to disturbance patches and evidence from a number of papers supports the use of shape-based and reflectance-based attributes (Stewart et al. 2009). Our approach which incorporates the temporal dimension of when the disturbance event occurred throughout the year is novel. Surface or open pit mining, pipelines, and seismic lines, also exist although these were omitted from our analysis as mines account for a small proportion of the study area only (0.55 ha/km^2; Linke and McDermid 2012). Pipelines and seismic lines were also omitted as they have a narrow disturbance footprint (Stewart et al. 2009) which cannot be reliably detected in our data fusion approach.

Gaulton et al (2011) observed 22% of disturbance events in the first two time stamps of each year using the STAARCH approach, compared with 23.4 % in this research. This may be a result of disturbances occurring outside of the study period (November-February) being recorded in the next cloud free day in the following year. Disturbance peaked in August and September, corresponding to the driest months of the year making it ideal for resource extraction (Gaulton et al. 2011). Our results peaked from September to October, with fire disturbance reaching its maximum in September. Stocks et al. (2003) found that the largest fires in Canada burned in the months of June and July. The majority of the fires have low value-at-risk and do not require intensive fire suppression, allowing for large burn areas. However, our research observed a limited area and did not cover large unsuppressed northern fires (Stocks et al. 2003).

Well sites and roads are subject to omission, due to their small area. STAARCH polygons less than one hectare in size were not included in the study, as they have a high potential for misclassification (Hilker et al. 2011) and as a result the number of events and disturbed area is likely under observed. Expanding the STAARCH polygons to join neighboring polygons resulted in an increased size of individual disturbance events. Our mean disturbance area was 0.068km^2, compared with 0.034 km^2 found by Gaulton et al. (2011) for the same study area. The overall rate of disturbance was not impacted; we observed 0.35% of disturbed land per year, compared to 0.4% in Gaulton et al. (2011).

Understanding life history traits and habitat interactions is necessary for creating comprehensive management plans for species of conservation concern (Franklin et al. 2000). Grizzly bear represent a long-lived species with expansive home ranges and low reproductive rates, with high demand for detailed management plans (Nielsen et al. 2006). We analyze habitat states to examine if our observations were in line with the model framework and general trends in disturbance rates. Our findings support the conservation habitat model as a higher percentage of anthropogenic disturbance occurs in sink habitats than in source habitats. High disturbance occurence results in increased probability of human-bear interactions, and subsequent mortality (Nielsen et al. 2004c, 2006, 2008). The overall disturbed area of quality Grizzly bear habitat per year has declined over the past decade, but resource extraction is likely to expand further into core habitat areas (Schnieder et al. 2003)making human-bear interactions more likely (Nielsen et al. 2004a, 2006). Although anthropogenic disturbance was higher in sink rather than source areas as expected, sink areas still represent high quality habitat, but with increased risk of mortality. As the majority of grizzly bear mortality is human-caused (McLellan et al. 1999, Benn and Herrero 2002), ease of access to quality habitat areas must be reduced. Disturbances can have lasting impacts on habitats decades after the disturbance event occurs (Nielsen et al. 2004a) and some anthropogenic land cover changes (well sites and roads) represent more permanent fixtures on the landscape (Roever et al. 2008). Decommissioning of resource roads is a management objective that may have the most positive influence on grizzly bear persistence in AlbertaUnderstanding the impact of anthropogenically derived forest edges is anothermajor issue given their attraction to grizzly bear, in particular in relation to food resources. A number of studies have compared grizzly bear telemetry data and edges extracted from a combination of satellite-derived land cover data and conventional vector datasets (roads, pipelines, and forest harvests). Results have demonstrated that in general female bears selected anthropogenic edges, whereas males selected natural edges and both sexes selected the natural transition of shrub to conifer (Stewart et al., 2013). Edge metrics could relatively easily be extracted from remote sensing (Wulder et al., 2009) such as in this decadal dataset, to provide fine spatial scale information for improving management of edge features and ultimately minimizing human-bear conflicts (Stewart et al., 2013). The combined use of Landsat and MODIS imagery can provide both broad scale assessment of disturbance within the major conservation zones, as well as at the stand scale for edge detection. The overall approach contributes to identifying areas of grizzly bear conservation concern, and whether or not management practices can be implemented to reduce attractive sink areas.

The STAARCH disturbance detection and attribution represents a tool for land managers to observe changes in habitat area, identify disturbance type and identify areas of conservation concern for grizzly bears. The ability to identify anthropogenic and non-anthropogenic disturbances is important for bear conservation. Anthropogenic disturbances increase the number of human-bear interactions, by creating access from resource roads into core habitat areas. Human caused mortality accounts for about 90% of bear mortality in the Rocky Mountains (Benn 1998, Craighead et al. 1988, McLellan et al 1999), therefore identifying anthropogenic disturbances can aid in bear management (Nielsen et al. 2004c, Nielsen et al. 2008). Our decade study period has the potential to be extended to observe Grizzly bear disturbance interaction over long periods. This would provide land managers with information for making better informed decisions on grizzly bear protection in Alberta.

Conclusion

In this paper we demonstrate the ability to map and attribute disturbances as detected by the STAARCH algorithm across the foothills of western Alberta. This is made possible by fusing fine spatial resolution of Landsat images(30m) with the high temporal resolution of MODIS (bi-weekly) images, which have lower spatial resolution of 250m. Anthropogenic disturbances (forest harvest, well sites and road construction) are the most influential disturbances on the landscape of south western Alberta, in terms of number and area affected. This disturbance has both positive (increased forage) and negative (increased human-bear interactions) implications on important grizzly bear habitat. Our research represents a viable monitoring tool for land managers through quantification the disturbed area while also characterizing the type of disturbance.

A.5.3. LiDAR forest metrics abstraction and habitat mapping

Widespread LiDAR data coverage from GOA is now available over the grizzly research area. This allows the creation of detailed layers describing land form, forest structure and linear features. We have created a suite of canopy metrics based on the LiDAR data and made them available in a 25*25m raster format, to facilitate habitat modeling and landscape classification efforts.

Some basic metrics like canopy height can be readily derived from the LiDAR data using available relations. More detailed structural metrics will be empirically modeled using available and newly acquired field data. The products are based on the currently available 1m gridded LiDAR product and are created at 25m resolution. To create the most effective canopy metrics we use field data from 102 plot collected in October 2013, a more detailed description of the campaign can be found in section 3.3 of this report. At this point we deliver three base layers for the forested areas in the Grade Cache and Yellowhead region, two from the LiDAR (Canopy Height and Canopy Cover), and one from Tassled Cap Transformed Landsat data (Percent Conifer)

The relationship between canopy estimates from LiDAR and the field were 1:1 based multiple linear regression models for the percent conifer model. Scatterplos are shown in Figures 9 and 10. The derived models are only valid for the forested range in our study area, so in the final products areas with canopy height < 4m are excluded.

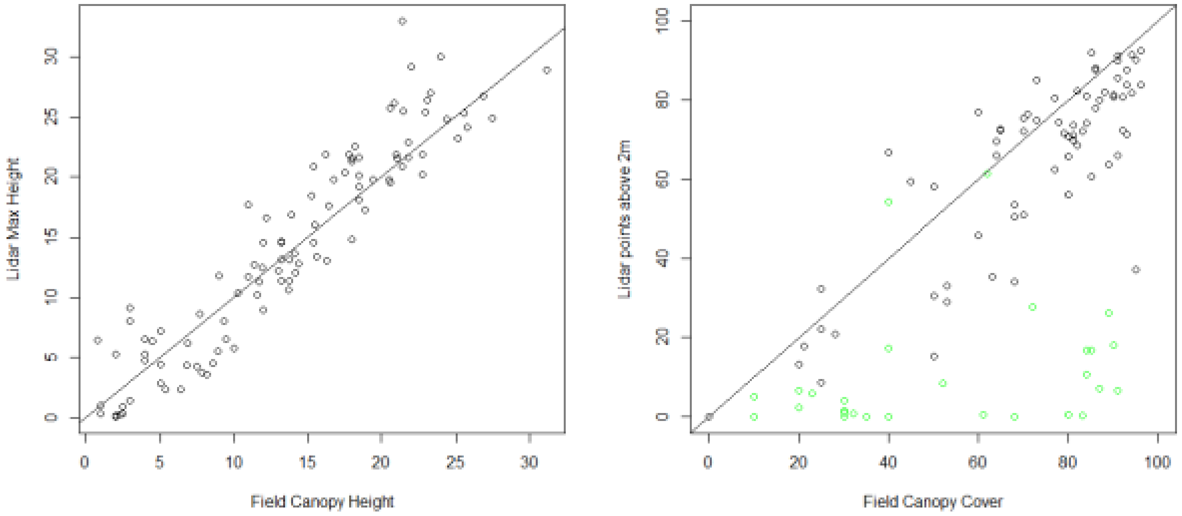

Figure 9: Scatterplot of Field and LiDAR derived data for plot locations (green points in canopy cover are areas with maximum canopy heights < 10m).

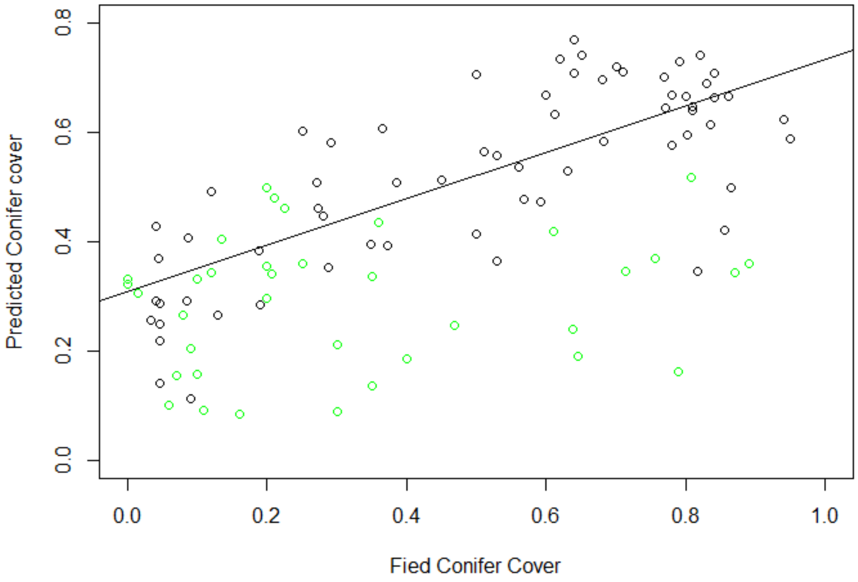

Figure 10: Scatterplot of Percent Conifer model ($R^2 = 0.56$, $p < 0.0001$), green points are fore areas with canopy height < 4m.

Results

The figures 11 to 13 show quick looks of the created raster layers. All layers are deliverd in standard geolocated raster format in 25 meter resolution.

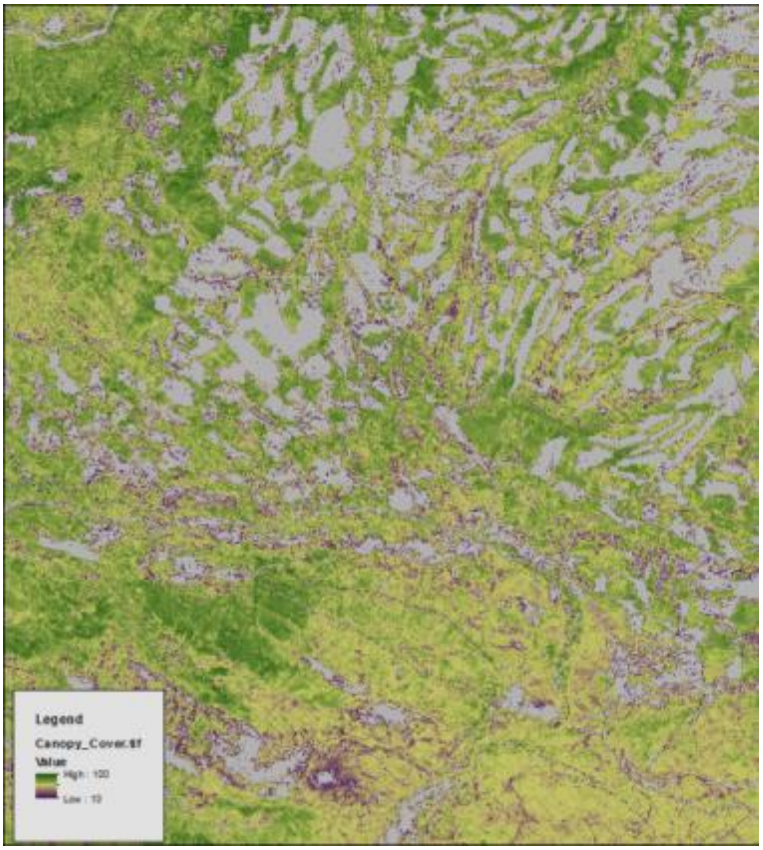

Figure 11: Quick look map of Canopy Conifer Cover

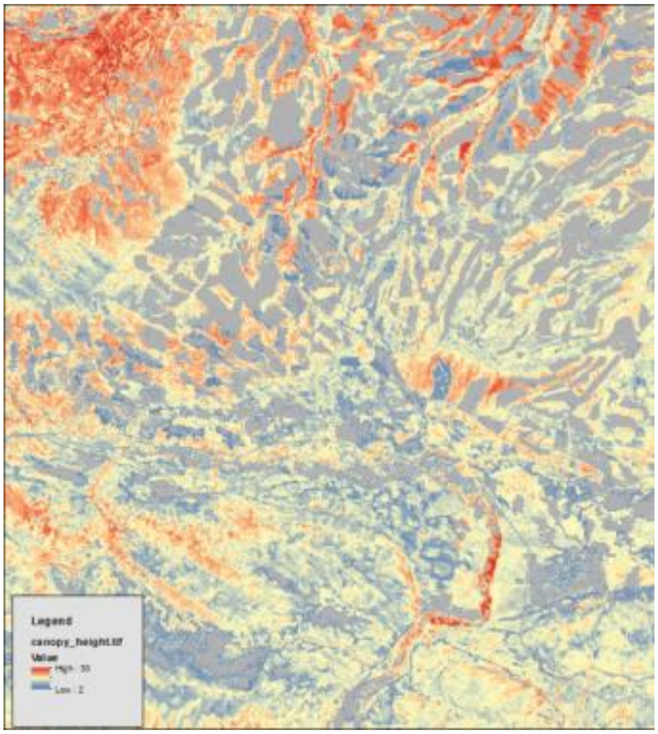

Figure 12: Quick look map of Canopy Height

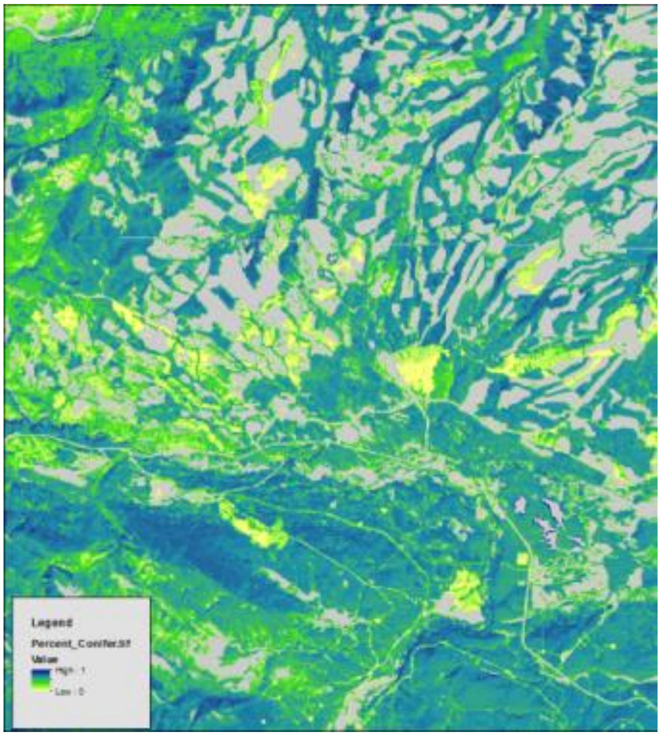

Figure 13: Quick look map of Percent Conifer

A.5.4. Understory Species distribution modelling using LiDAR -Fine-Spatial Scale Predictions of Understory Species Using Climate and LiDAR-Derived Terrain and Canopy Metrics.

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Introduction

Developing a comprehensive understanding of food and habitat resource use for large mammals is a critical component for their conservation and management, as well as for assessing cumulative effects of human impacts and estimating habitat-based carrying capacities for species of management concern (Gordon et al 2004). This is particularly true for grizzly bear (*Ursus arctos*) populations in western Alberta, Canada where resource extraction is expanding (e.g., forestry, exploration and mining, and urban expansion) along with human use of the landscape, resulting in concern for the long term survival of the species in this region (Clark et al., 1996; Nielsen et al., 2004a, 2006, 2008).

Grizzly bears are considered habitat generalists (Schwartz at al. 2003) with diverse, seasonal diet and habitat requirements. Within this region, optimal habitat is a mosaic of forested and non-forested areas (Nielsen et al., 2004b). Large gaps within forest stands, alpine meadows, and areas regenerating after fire offer bears an abundance of understory species, including seasonal fruits, ants, ungulates, green herbaceous vegetation, roots, other subterranean foods, and grasses which can form a major part of the species diet for at least some part of the year (Martin, 1983; Zager et al., 1983; Munro et al., 2006). Forest harvesting can provide similar habitat, as regenerating stands share many understory species. As a result, forest cutblocks provide an alternate habitat resource to otherwise open areas (Benn and Herrero, 2002; Nielsen et al., 2004a).

However, ongoing forestry and resource extraction activity is also a threat to grizzly bears; management agencies within Alberta are actively trying to balance economic development needs with the conservation needs of the species (Alberta Sustainable Resource Development, 2008). Key to this conservation priority is a comprehensive understanding of how food resource availability and abundance may vary in response to forest management, where the ultimate goal is to better understand the observed habitat use of bears in western-central Alberta, Canada (Nielsen et al., 2004b).

Grizzly bears have three distinct foraging seasons: hypophagia, early hyperphagia, and late hyperphagia (Nielsen et al., 2006). During hypophagia, grizzly bears un our study area feed on the roots of *Hedysarum* spp. (sweetvetch) and other early herbaceous material. During early hyperphagia, their diet extends to green herbaceous material such as *Heracleum lanatum* (cow-parsnip) and *Equisetum* spp. (horsetail), while in the later season berries such as *Shepherdia canadensis* (buffalo berry) and *Vaccinium* spp*.* (huckleberry, blueberry, and lingonberry) make up the majority of their diet. As fruit availability declines in the fall, grizzly bears once again dig for sweetvetch roots (Nielsen, 2005; Nielsen et al., 2006; Munro et al., 2006; Nielsen et al., 2010). While animal matter and insects are an important food resource for grizzly bears during spring and early summer, the variety of vegetable matter (including roots, forbs, and fruit) makes up the majority of their diet between late June and early October.

A comprehensive understanding of the horizontal distribution of understory flora is required to accurately predict wildlife-habitat relationships (MacArthur and MacArthur, 1961; Lindzey and Meslow, 1977; Roughgarden et al., 1991; Linderman et al., 2005). Neglecting to consider the influence of understory vegetation in broad-scale habitat studies has limited the connection of fine-scale monitoring (e.g., radio collar movement data) with opportunities provided by remote sensing for accurate conservation and management planning (Linderman et al., 2005).

The distribution of these plant species is influenced by local landscape conditions and canopy structure (Nielsen et al., 2004b). For example, many berry species have higher yields in open canopies, while plant species (e.g., clover and dandelions) thrive in recently opened areas such as forest clearings associated with anthropogenic disturbance. The most common approaches to species abundance and occurrence modelling rely on empirical correlations with environmental variables to develop “niche” or “bioclimatic envelope” models (Austin, 1985; Iverson and Prasad, 1998; McKenzie et al., 2003; Thuiller et al., 2008). These models usually empirically relate presence / absence data to environmental variables, most often with climate (but sometimes including soil and physiographic features), using an array of statistical methods including multiple regression techniques, neural networks, and regression tree analysis (Iverson and Prasad, 2001). Climate surfaces are effective predictors of broad scale patterns and a number of studies have linked climate and land cover information derived from optical remote sensing data (Nielsen et al., 2003, 2010), such as forest cover classes derived from Landsat Thematic Mapper (McDermid, 2005). Land cover attributes derived from optical remote sensing have been shown to increase the predictive power of models, but they are still unable to fully represent the fine scale processes related to stand and canopy conditions, particularity in areas where forest management regularly changes the structure of the forest.

Light detection and ranging (LiDAR), is an increasingly well understood and established remote sensing technology which is able to detect both topographic and canopy features within forest ecosystems at previously unavailable levels of accuracy (Wulder et al., 2008c). Airborne LiDAR systems function by emitting and receiving laser energy that measure distance to target surfaces. Laser systems, when combined with Global Positioning Systems (GPS) and orientation systems (e.g., Inertial Navigation Systems), allow the location of surfaces intercepted by the beam to be precisely computed (Gaveau and Hill, 2003) with vertical and horizontal accuracies approximately within 40 cm (Davenport et al., 2004). Especially for understory applications, a key advantage of LiDAR over conventional optical remote sensing imagery (such as Landsat, or high spatial resolution imagery, like Quickbird and Worldview) is the ability to describe the canopy structure in three dimensions including information on areas otherwise obscured by the tree canopy.

LiDAR data has shown promise in estimating understory structural attributes despite there being a limited number of studies of which most are associated with fire fuel prediction. Seielstad and Queen (2003) investigated the potential of using LiDAR data to quantify fuel for a widely applied fuel model. Riaño et al. (2003) used cluster analysis, based on the minimum Euclidean distance, to distinguish understory from overstory returns in a mixed conifer and deciduous two-tiered forest. Maltamo et al. (2005) applied regression models to estimate the number and mean height of suppressed understory trees in a boreal forest using LiDAR data with r^2 values of 0.87 and 0.76, respectively.

In this study we assess the effectiveness of using LiDAR remote sensing data to predict species occurrence for 14 understorey plant species relevant to bear habitat and food. We compare these to more conventional climate- and land cover-based models of species occurrence to evaluate whether

LiDAR data improves our understanding of the local distribution of bear foods. To do so, we compiled, and derived a number of topographic and canopy metrics from airborne LiDAR data, and combined them with climate and land cover data, to model the distribution of 14 key plant species in the Alberta foothills region. Model performance and spatial patterns of the three sets of models were compared. In addition we assessed variable importance within the models to increase our understanding of the main environmental drivers on plant distribution in the study area.

Methods

Study area

The study area is situated in the Rocky Mountains and Foothills area in western Alberta stretching from the North Saskatchewan River (Highway 11) in the south to Grande Prairie in the north, with elevations ranging between 600m and 3300m. Variations in climate and topography generate a vegetation species gradient from the south west to the north east. Higher elevation and rugged, conifer-dominated forests of the Subalpine and Upper Foothills transitions to a lower elevation, gently rolling terrain that is characteristic of the Lower Foothills and Central Mixedwood subregions.

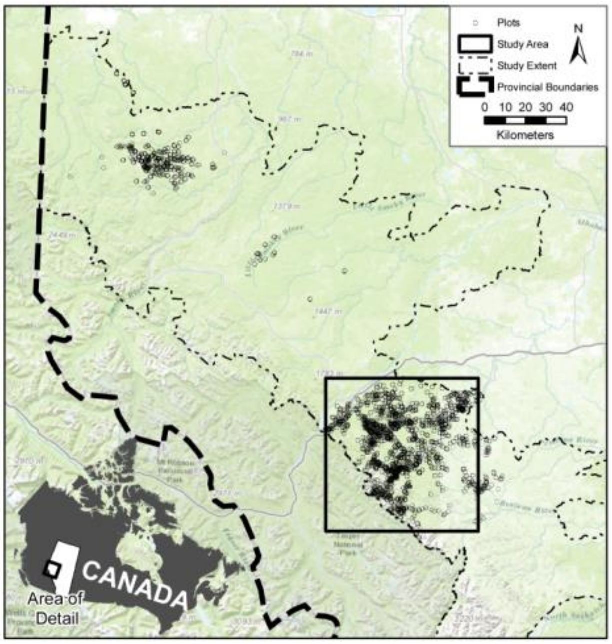

Figure 14: Overview of the study area and plot locations. Subset shows area displayed in species figures below.

Plant distribution data

Field data was collected between the years 2001 and 2008 as part of the Foothills Research Institute Grizzly Bear Project (Figure 14). In total, 1,941 plots were sampled as described in detail by Nielsen et al. (2010), within a study area of 4435 km^2. To avoid issues with plots having been sampled prior to a subsequent disturbance, we utilised a Landsat-derived disturbance layer (Gaulton et al., 2011) which provided information on recent harvest and fire events within the region. Fourteen species formed the basis of the analysis including species important for root digging, herbivory, and fruiting (Table 4).

Table 4: Focus understory plant species

Scientific name	**Common name**	**Plots Present**
Root digging		
Hedysarum alpinum	alpine sweetvetch	7.6%
Lathyrus ochroleucus	creamy peavine	5.9%
Herbivory		
Equisetum arvense	Horsetail	21.3%
Heracleum lanatum	cow-parsnip	6.2%
Taraxacum officinale	Dandelion	18.2%
Frugivory		
Arctostaphylos uva-ursi	Bearberry	12.9%
Fragaria virginiana	wild strawberry	38.3%
Rosa acicularis	prickly rose	32.5%
Rubus idaeus	wild red raspberry	13.5%
Rubus pedatus	five leaf bramble	9.4%
Shepherdia Canadensis	Buffaloberry	8.7%
Vaccinium caespitosum	dwarf blueberry	24.4%
Vaccinium vitis-idaea	lingonberry	38.8%
Viburnum edule	highbush cranberry	8.8%

Environmental Covariates

Climate: Spatial predictors of the region included a number of seasonal and annual climate variables which were derived from long term (1961-1990) climate records, using the CLIMATE-

WNA (Wang et al., 2010) which uses a PRISM down-sampling (Daly et al., 1994) approach to create surfaces at a 500*500m resolution. These included mean maximum and minimum temperature, growing degree days (base 0°C), frost free period, mean annual precipitation during the growing season, and summer moisture index (Table 5).

Land and Forest Cover: Landsat-derived land cover information was available for the study region and included information on land cover, canopy cover (%), and percent of pixel dominated by conifer overstory species (McDermid et al., 2009). The products were based on Landsat images acquired between 2005 and 2009 and have a 30*30m resolution.

LiDAR Data: LiDAR data were provided by the Alberta Environment and Sustainable Resource Department (AESRD), who compiled a variety of LiDAR datasets acquired from 2003 – 2008. The data were collected over a number of years to a pre-defined set of outcome specifications. To meet the specification, the data collecting agencies had latitude to use slightly differing sensor configurations. To minimise the impact of different survey configurations and acquisition dates (e.g., hit density, or leaf-on/off), the data was thinned to produce a consistent 1m spacing dataset, which, despite being lower than many typical LiDAR datasets (Wulder et al., 2008c), ensured consistent density and coverage over the entire 4435 km^2 study area. From the thinned LiDAR point cloud, a bare Earth DEM (Digital Elevation Model) and a canopy height model was provided. From the bare Earth DEM, slope aspect and elevation were extracted for each plot location. A suite of forest canopy metrics were then developed for each 25*25m pixel, including a calculation of percentiles from 0 to the 100th, where a given height percentile was calculated as the height greater than a given percentage of LiDAR first returns (Means et al., 2000). Mean height, cover higher than 2m, relative height ratio, skewness of the percentile height, and standard deviation of heights were also computed for each plot. In addition to the canopy and topographic metrics, information on the annual radiation regime for the bare Earth DEM, canopy height, and terrain and canopy elevation for each plot was calculated from the LiDAR data using a hemispherical viewshed algorithm (Rich et al., 1994; Fu and Rich, 2002), which incorporates extraterrestrial solar flux, the relative optical path (determined by the solar zenith angle and elevation above sea level), the duration of a defined time interval, and the effect of the surface orientation (Garner and Ohmura, 1968). Lastly, a Wet-Areas Mapping (WAM) layer was available, providing an estimate of depth to water table using the shape and orientation of the terrain (White et al., 2012). Input variables used for the models are listed in Table 5.

Table 5. Environmental covariates utilised in Boosted Regression Tree Modelling

	Range		**unit**
Climate			
max mean maximum monthly temp.	10.3	22.6	°C
min mean minimum monthly temp.	-18.9	-16.1	°C
degree days base 0°C	1134.0	2014.0	days * °C
frost free period	46.4	101.4	days
growing season precipitation	377.5	532.7	mm
mean annual precipitation	516.9	965.9	mm
summer moisture index	0.2	3.0	–
Forest			
landcover class (14 classes)	0	13	categorical
regenerating forest mask	0	1	binary
canopy cover	0.0	95.0	%
percent conifers	0.0	99.0	%
Lidar			
Max height above ground	0.1	35.1	meter
Mean height above ground	0.0	17.7	meter
05th percentile	-0.6	0.9	meter
50th percentile	0.0	21.0	meter
95th percentile	0.0	27.7	meter
fraction points above 2m	0.0	94.1	%
relative height ratio	0.0	0.7	–
Skewness	-2.2	21.4	–
standard deviation	0.0	11.2	meter
Elevation	858.9	2266.6	meter
Slope	0.1	40.3	degrees
Aspect	0.0	360.0	degrees
terrain solar index	0.9	2.0	–
canopy solar index	1935.0	2618.0	–
canopy and terrain solar index	2218.0	3810.0	–
Wet Area Map	0.0	257.0	meter

Modelling: Boosted Regression Trees

Distribution models were built for the 14 plant species using Boosted Regression Trees using R statistical software (R Development Core Team, 2012). Boosted Regression Tree modelling is a relatively new technique which is gaining popularity in the distribution modelling community (Elith et al., 2008) with benefits including flexibility in combining different types of variables (e.g., continuous, categorical, nominal), flexibility in statistical distributions, and demonstrate high predictive power (Elith et al. 2008). Up to 1500 individual trees were fit with a 5 level tree depth and a learning rate of 0.005 to avoid over fitting of collinear variables. The optimum number of trees was selected using a 10 fold cross validation within the training data. To verify the selected model, we made a random 80-20 split of all plot data before the model building and calculated model fit using the separated 20% of the plots. Model performance was assessed using the “Area under the Receiver-Operator Characteristic Curve" (AUC) (Jiménez-Valverde, 2011) with values ranging from 0.5 to 0.7 generally viewed as ‘low’ model accuracy, values between 0.7 and 0.9 considered ‘good’, and values greater than 0.9 considered ‘high’ model accuracy (Swets, 1988; Manel et al., 2001). The kappa coefficient also was calculated, having been recommended as a metric to assess the accuracy of the developed models and being useful particularly in ecological research (see review by Monserud and Leemans, 1992). This statistic calculates the proportion of specific agreement across presence and absent classes.

Results

Overviews of the three sets of models developed for the individual species in Table 6 show a wide variety of model accuracy. Model AUC values ranged from 0.70 – 0.85, while K statistic values ranged between 0.09 and 0.48 (i.e., poor to moderate, based on Landis and Koch’s (1977) thresholds for the K statistic). The most accurately predicted species was *Hedysarum alpinum* (sweet vetch) while the poorest was *Equisetum arvense* (horsetail). *Hedysarum alpinum* is a critical spring root-digging resource for bears, whereas horsetail produces a high-protein, succulent and herbaceous food resource at green-up (Table 6).

Overall, 8 of the 14 most accurate species models were developed using a combination of climate and LiDAR-derived variables, with an average increase in AUC of 5% and the greatest model improvement of up to 12% for *Arctostaphylos uva-ursi* (bearberry). For three species, the most accurate model derived was from climate and broader scale land and forest cover information, and three were equally supported.

Table 6: Model results

	Training AUC	Validation AUC	Validation Kappa	Variable Importance		
				1 st	2nd	3rd
Arctostaphylos uva-ursi						
Climate	0.87	0.67	0.15	Growing season Precip.	Mean annual Precip.	Frost free period
Climate + Forest cover	0.89	0.69	0.26	Growing season Precip.	Frost free period	Degree days base 0
Climate + LiDAR	0.95	0.79	0.34	Terrain Solar	Growing season Precip.	Mean annual Precip.
Equisetum arvense						
Climate	0.80	0.69	0.20	Growing season Precip.	Mean annual Precip.	Frost free period
Climate + Forest cover	0.78	0.67	0.15	Mean annual Precip.	Growing season Precip.	Frost free period
Climate + LiDAR	0.81	0.69	0.19	Wet Area	Elevation	Mean annual Precip.
Fragaria virginiana						
Climate	0.77	0.67	0.24	Mean annual Precip.	Degree days base 0	Growing season Precip.
Climate + Forest cover	0.81	0.67	0.21	Mean annual Precip.	Degree days base 0	Frost free period
Climate + LiDAR	0.84	0.74	0.30	Mean annual Precip.	Degree days base 0	Wet Area
Hedysarum alpinum						
Climate	0.94	0.88	0.47	Degree days base 0	Frost free period	Mean annual Precip.
Climate + Forest cover	0.94	0.89	0.46	Degree days base 0	Frost free period	Mean annual Precip.
Climate + LiDAR	0.96	0.91	0.48	Degree days base 0	Frost free period	Mean annual Precip.
Heracleum lanatum						
Climate	0.87	0.71	0.10	Mean annual Precip.	Frost free period	Growing season Precip.
Climate + Forest cover	0.88	0.70	0.09	Mean annual Precip.	Growing season Precip.	Frost free period
Climate + LiDAR	0.92	0.80	0.15	Wet Area	Mean annual Precip.	Slope
Lathyrus ochroleucus						
Climate	0.82	0.73	0.10	Mean annual Precip.	Frost free period	Summer moisture index
Climate + Forest cover	0.84	0.76	0.11	Mean annual Precip.	Frost free period	Degree days base 0
Climate + LiDAR	0.94	0.76	0.21	Mean annual Precip.	Terrain Solar	top of canopy Solar
Rosa acicularis						
Climate	0.77	0.69	0.26	Mean annual Precip.	Degree days base 0	Summer moisture index
Climate + Forest cover	0.79	0.71	0.23	Mean annual Precip.	Frost free period	Degree days base 0
Climate + LiDAR	0.84	0.75	0.32	Terrain Solar	Mean annual Precip.	Elevation
Rubus idaeus						
Climate	0.85	0.74	0.16	Frost free period	Mean annual Precip.	Degree days base 0
Climate + Forest cover	0.88	0.79	0.26	Frost free period	Mean annual Precip.	Degree days base 0
Climate + LiDAR	0.91	0.81	0.30	Wet Area	Frost free period	Maximum Height
Rubus pedatus						
Climate	0.84	0.79	0.20	Mean annual Precip.	Growing season Precip.	Degree days base 0
Climate + Forest cover	0.87	0.84	0.27	Growing season Precip.	Mean annual Precip.	Degree days base 0
Climate + LiDAR	0.91	0.87	0.29	Terrain Solar	Growing season Precip.	Mean annual Precip.
Shepherdia canadensis						
Climate	0.92	0.76	0.19	Degree days base 0	Mean annual Precip.	Summer moisture index
Climate + Forest cover	0.92	0.78	0.26	Degree days base 0	Frost free period	Growing season Precip.
Climate + LiDAR	0.94	0.76	0.25	Degree days base 0	Terrain Solar	Mean annual Precip.
Taraxacum officinale						
Climate	0.79	0.64	0.10	Mean annual Precip.	Frost free period	Growing season Precip.
Climate + Forest cover	0.85	0.73	0.24	Frost free period	Mean annual Precip.	Growing season Precip.
Climate + LiDAR	0.88	0.72	0.17	Frost free period	Mean Height	Wet Area
Vaccinium caespitosum						
Climate	0.80	0.67	0.16	Frost free period	Mean annual Precip.	Degree days base 0
Climate + Forest cover	0.83	0.72	0.24	Frost free period	Mean annual Precip.	Degree days base 0
Climate + LiDAR	0.87	0.73	0.32	Wet Area	5th percentile	Frost free period
Vaccinium vitis-idaea						
Climate	0.83	0.75	0.35	Frost free period	Degree days base 0	Summer moisture index
Climate + Forest cover	0.86	0.77	0.37	Frost free period	percent conifers	Degree days base 0
Climate + LiDAR	0.89	0.77	0.38	Frost free period	Minimum monthly temp.	Elevation
Viburnum edule						
Climate	0.92	0.80	0.21	Frost free period	Mean annual Precip.	Degree days base 0
Climate + Forest cover	0.93	0.85	0.31	Frost free period	Mean annual Precip.	Degree days base 0
Climate + LiDAR	0.93	0.82	0.19	standard deviation	canopy Solar	Mean annual Precip.

Examining the spatial predictions of the species models, the differences in the spatial resolution of the input parameters was apparent. Figure 15 shows the probability of occurrence for a number of species for subset of the study area (*E.arvense* (horsetail), *H.alpinum* (sweet vetch), *T.officinale* (dandelion), and *V.vitis-idea* (loganberry) based on the 3 different sets of variables. Overall, the coarser nature of the climate data (500m) results in a coarse model output which is unable to reflect changes in forest patterns associated with management or fine scale topographic features across the landscape. In contrast, models developed using either the 30m Landsat-derived land cover or the LiDAR-derived canopy and terrain information were much finer, allowing management and topographic variation to be represented in greater spatial detail.

Examining variable importance (Figure 16) for the climate-only models, mean annual precipitation and frost free period were selected as the most critical variables predicting species occurrence for most species, followed by degree days, growing season precipitation, and summer moisture index. No other climate variables were selected as important in the climate-only model predictions. When forest and land cover variables were added into the models, their overall effect was minor; only percent conifers were additionally selected as an important variable for a single species model. This result implies that the addition of Landsat-scale variables on land cover and forest cover do not add significant power to the understory models in this area. When LiDAR-derived canopy and terrain attributes were added to the models, variable selection changes markedly. A large number of LiDAR-derived variables were selected as important in model prediction. Wet area information, derived from the LiDAR DEM, was the most common variable added into the models, selected in 6 of the 14 species models. This was followed by the annual terrain-intercepted radiation (which is indicative of radiation regimes imposed by terrain) and then elevation. The addition of these three variables indicates the importance of higher spatial resolution in terrain patterns as it affected species distribution models. In response to these additions related to terrain attributes, there was a reduction in the importance of climate variables including frost free period and degree days while annual precipitation remained critical to model predictions. Of the LiDAR-derived canopy attributes, height and the solar regime of the canopy (i.e., shading of sites based on canopy cover and canopy gaps) were selected most often.

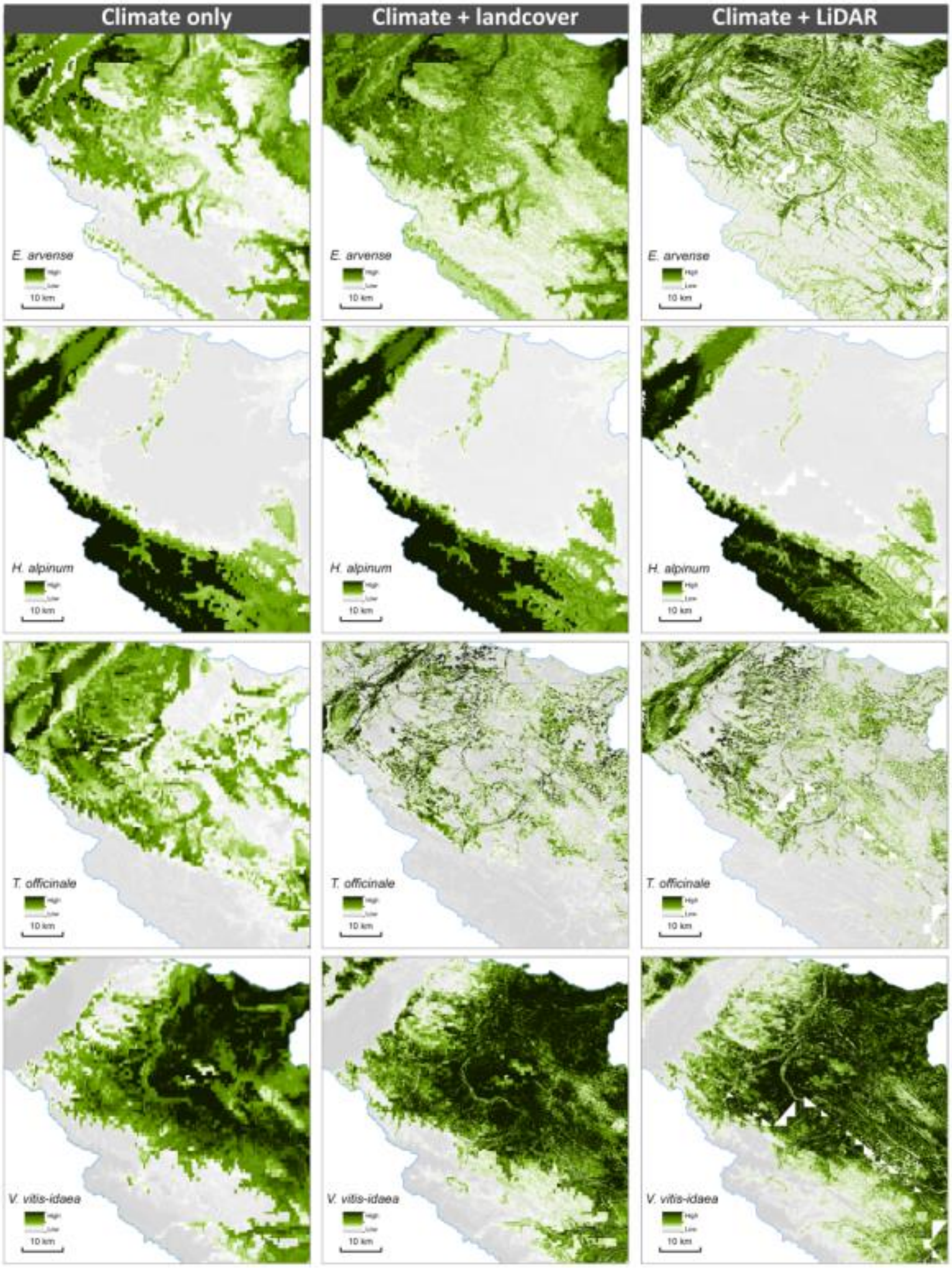

Figure 15: Probability of occurrence maps based on Climate (left), Climate + forest cover (middle), and Climate + Lidar (right) data *for E.arvense, H.alpinum, T.officinale*, *and V.vitis-idea*

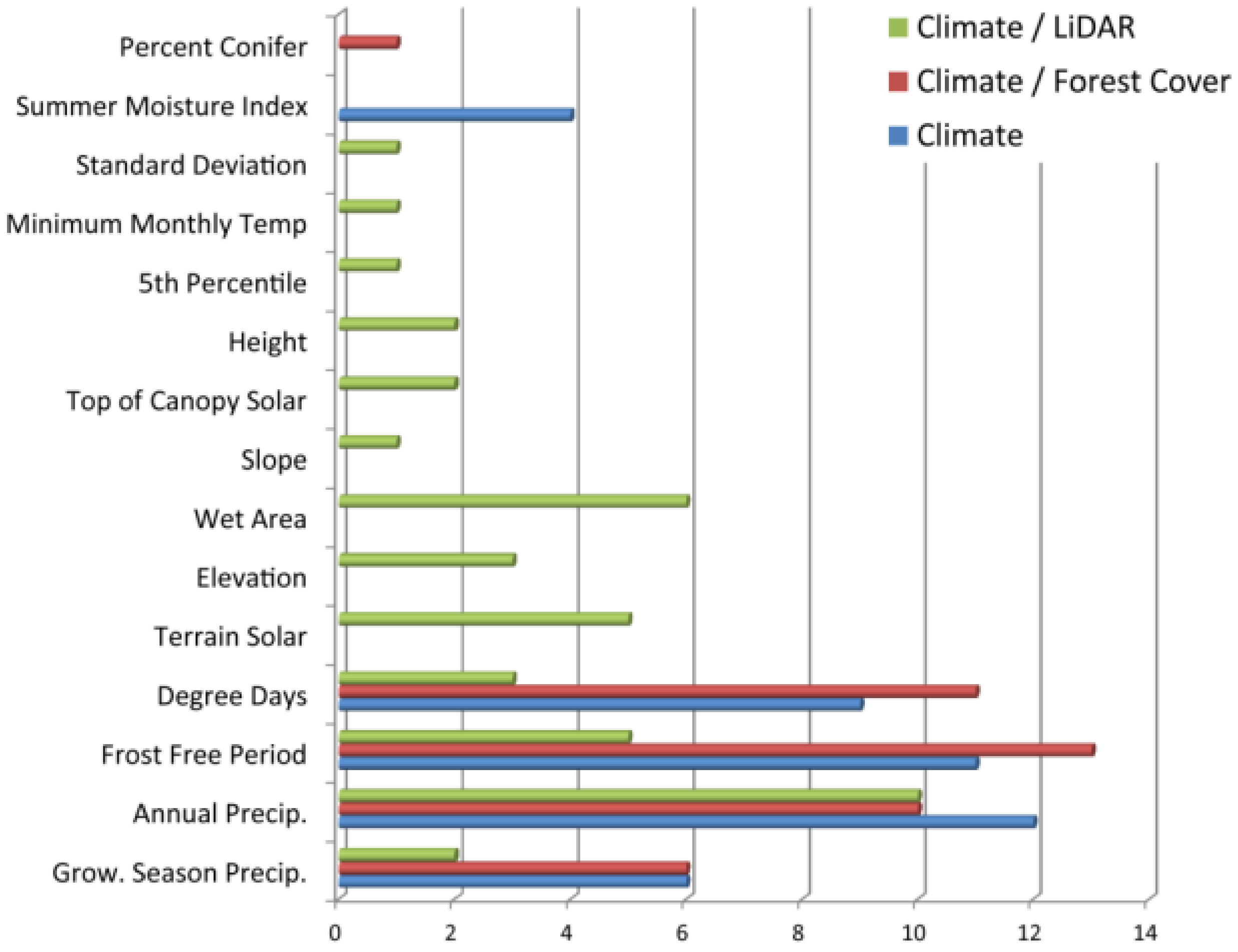

Figure 16: Top three variables selected in model development for the three model suites

The individual response graphs of the most important variables of the combined models for 4 species are shown in Figure 17 and indicate the relationship between species occurrence and environmental drivers. For *E. arvense,* it is apparent that species occurrence is driven by presence of wet areas within the landscape at lower elevations. The *H. alpinum* model did not incorporate any LiDAR-derived terrain or canopy information and had a bi-modal response for degree days, reflecting its occurrence in cold, high elevation meadows, and warmer low elevation sites in stream valleys. *T. officinale* is predicted to occur in sites with longer frost free periods and lower mean canopy height, predominantly in sites having vegetation cover less than 5m in height. Lastly, *V. vitis-idea* occurs in sites with intermediate frost free period lengths and in cooler, lower elevation sites.

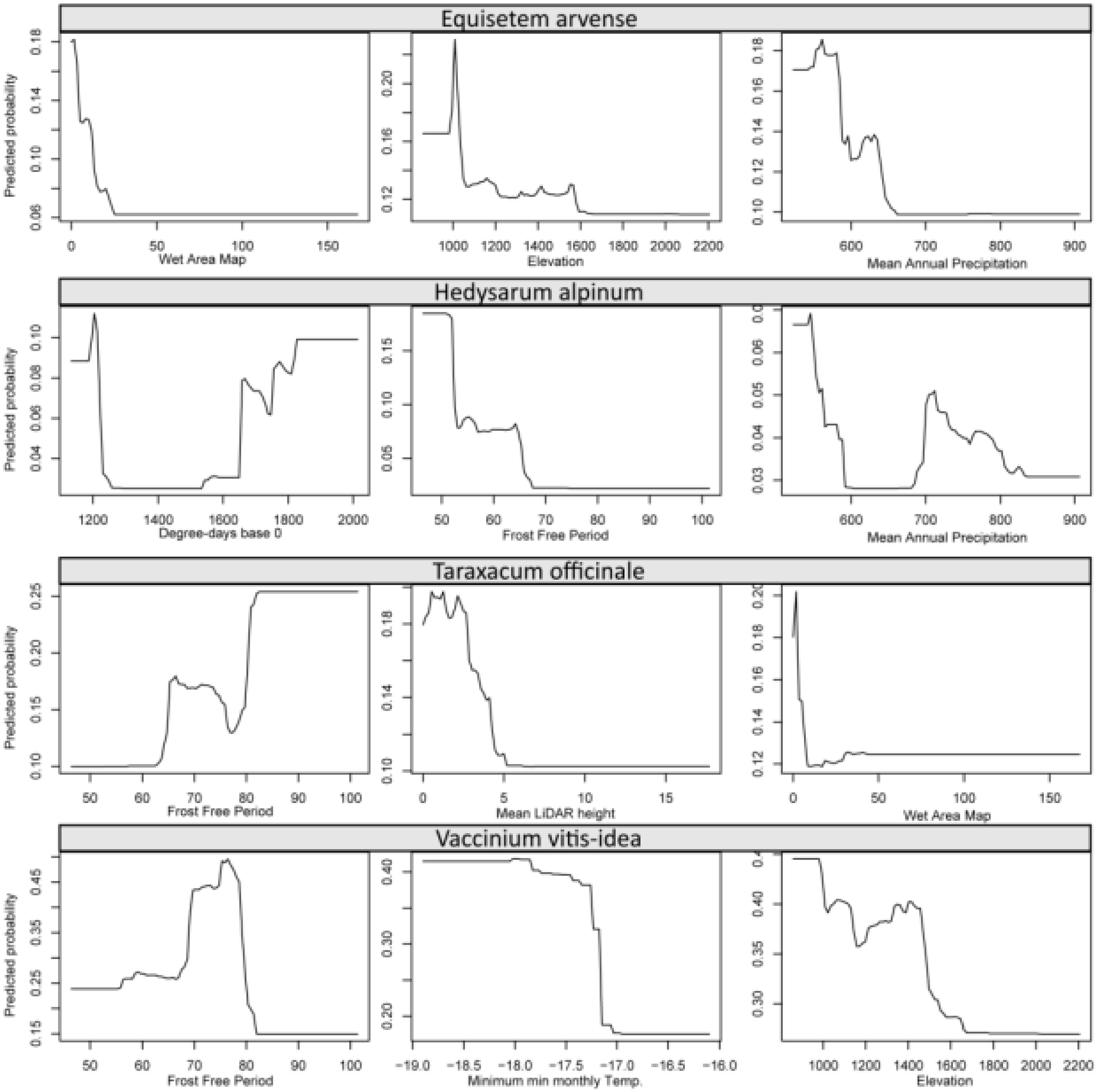

Figure 17: Response graphs if the first three most important variables for the Climate + Lidar model for E.arvense, H.alpinum, T.officinale and V.vitis-idea.

Discussion

In this study we investigated the added benefit of incorporating LiDAR-derived terrain and forest canopy information into understory species models relevant for grizzly bear species habitat modelling. The results demonstrate that models developed with a combination of both broad-scale climate data, as well as with LiDAR-derived terrain and canopy information, provided the best overall performance, capturing more fine scale spatial variation than models using climate data alone. The inclusion of the LiDAR attributes suggest that these variables provide a more detailed explanation of the fine scale site conditions, such as access to water, solar radiation regime at the site caused by terrain shading, in addition to overall site elevation and slope (White et al., 2012). Information on canopy height, gaps, shading, and height variations also appear to affect distributions for some species but to a lesser degree than the finer site condition measured by LiDAR (Figure 18). The inclusion of site level measures from LiDAR resulted in a reduction of importance of growing degree days and frost free periods. This shift implies that the inclusion of LiDAR data allows a more comprehensive description of the thermal and radiation regimes of individual sites, replacing the need for broader scale descriptions of the thermal load of each site.

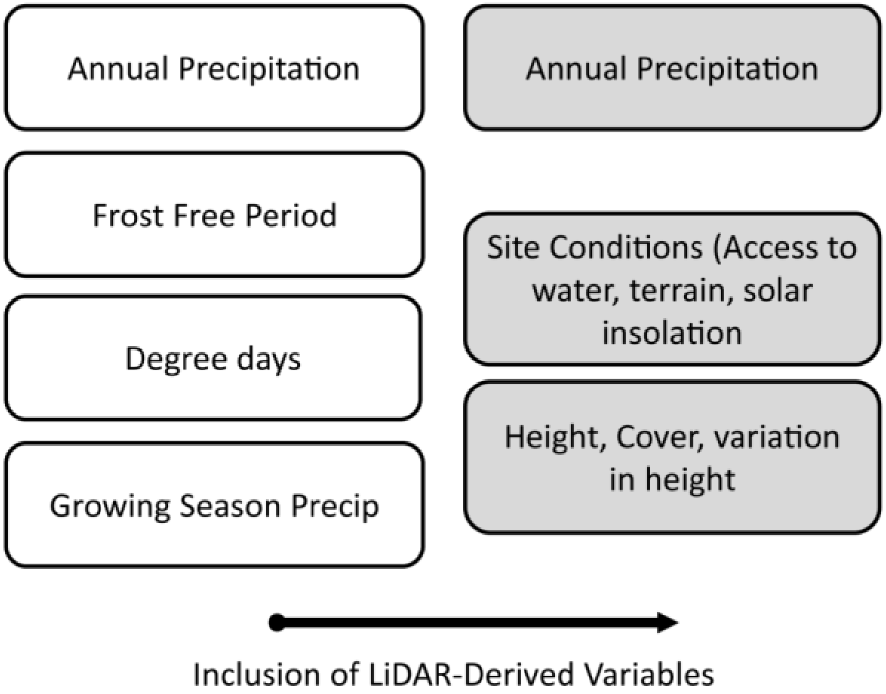

Figure 18: Change in Variables selected by models when incorporating fine scale site and canopy LiDAR derived information

Our use of boosted regression trees for model development enabled the combination of multiple data types as well as the inclusion of complex relationships which are often not possible to represent within standard linear models. Boosted regression trees allow representation of the main variables used in the developed models, as well as response graphs between individual plant occurrence and the most important variables. The past five years has seen these models increasingly selected in ecological research because of a number of features, including an ability to deal with collinear datasets, to exclude insignificant variables, and to allow for asymmetrical distribution of samples (De'ath 2002; Schwalm et al. 2006; Melendez et al. 2006). We recognize that a limitation of boosted regression approaches is that many observations are required for reliable model building, making model development of rare and more localised understory species more problematic, and should be undertaken with caution (Coops et al., 2011).

In addition, we are cognisant of potential issues surrounding the quality of both LiDAR and plot observation data given that both datasets were collected over multiple years. Using disturbance data on fire, harvesting, and resource extraction, we were able to highlight sites which have had significant disturbance over the 8 year study period, and removed these sites from the analysis (Hilker et al 2009). However, some issues may remain with LiDAR and field observations not directly coinciding.

A.5.5. Advanced landcover classification using LiDAR and LandsatIntegrating optical satellite data and Airborne Laser Scanning in habitat classification for wildlife management

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Introduction

Wildlife responds to a large number of factors when selecting habitat, involving complex behavioral decisions which are made at multiple spatial scales (Johnson et al. 2002; Ciarniello et al 2007; Herfindal et al. 2009). Broad scale spatial variation in biodiversity is thought to respond to three major drivers; climatic stability, productivity, and habitat structure (MaxArthur, 1972) – with empirical evidence demonstrating the importance of each of these variables (Coops et al., 2008). Bioclimatic models are often applied to estimate the broad scale distribution of species (Guisan & Zimmermann 2000; Rahbek & Graves 2001; Willis & Whittaker 2002). At finer spatial scales drivers such as land cover, disturbance, and habitat heterogeneity are more important for habitat selection (Iverson & Prasad 1998; Thuiller *et al.* 2004).

The vertical and horizontal structure of vegetation plays a critical role in defining suitable wildlife habitat and can do so in a variety of ways. For certain species, vegetation structure drives food quality, diversity, and availability (Johnson et al. 2002; Månsson et al. 2007; Hamer and Herrero 1987). Access to high quality forage in early successional stage forest stands, deciduous overstorey stands, or open areas, like understorey grass, forb, herb and berry species (Allen et al. 1987; Dussault et al., 2005; Munro et al 2006), decrease energy required for foraging and digestion, and thus maximise energy intake (White 1983). Vegetation structure also provides protection and/or cover for species which can protect species from heat stress when ambient temperature exceeds optimal levels (Schwab and Pitt 1991), or during winter refuge against increasing snow depth; with snow accumulation often adversely impacting species mobility and food intake, and thus the survival and reproduction rates (Mech et al. 1987; Cederlund et al. 1991; Post and Stenseth 1998). Vegetation structure is also inextricably linked to disturbances, especially fire, harvesting and insect defoliation. As a result, habitat disturbances potentially increase habitat suitability in the following years (Rempel et al. 1997, Nielsen et al, 2004). Heterogeneity in vegetation structure also provides access to forest edges, where forage and protection is often amplified, known as the cover-food edge which is a key habitat type selected by many species (Courtois et al. 2002;Dussault et al. 2005;Dussault et al. 2006b).

Over the past 40 years, since the launch of the first Earth observation satellites, satellite-based image classification techniques have been used to map species habitat and has become an important tool in large area mapping for habitat and wildlife management (McDermid et al 2005; Wang et al 2009). The Landsat series of sensors in particular have set the standard for regional classification projects because of its combination of spatial and spectral resolution, consistent long term record, and excellent data availability (Franklin & Wulder 2002, Cohen & Goward 2004, Leimgruber et al 2005). However, considerable limitations exist in the application of optical satellite imagery specifically involving the detection of detailed forest structural characteristics beyond initial canopy closure (Wang et al, 2009; Franklin et al, 2003). The issue of signal saturation on optical remote sensing imagery with increasing leaf area is well known, with many studies both theoretically and practically demonstrating that estimation of canopy parameters can be difficult beyond a leaf area index of 3 – 5 (Baret and Guyot 1991; Turner et al., 1999, Song 2012) and that canopy parameter estimation also varies between conifer and deciduous canopy types (Song 2012). As a result while classification schemes often recognize the importance of forest structure in the class definition (McDermid et al, 2009; Wulder et al, 2009; Franklin et al, 2003), they are often generalized or have considerable uncertainty in forest density classes caused by the inherent limitations of the optical sensor system.

Many have tried to bridge the gap between the need for structural information and the inability of direct optical classification to provide this information. Solutions may use ancillary data, texture information, object based analysis, post classification procedures, or other remotely sensed data like Radar (Lu & Weng 2007, Roberts et al. 2007). The most common source of ancillary data is elevation models (McDermid et al 2009, Johnson et al. 2003, Franklin et al. 2002) and derivatives like slope and aspect. Texture information is used in the form of gray-level co-occurrence matrices (Franklin et al 2003), spatial autocorrelation (Magnussen et al 2004), or variogram functions (Zhang et al 2010), based on homogeneity assumptions within forest stand and the information content of shaded vs sunlit parts in the canopy. In post classification methods the fine scale patterning of simple land-cover types (e.g. treed, herb, bare) or vegetation indices is used to define habitat classes (Sluiter et al. 2004). Radar is able to partially penetrate vegetation canopies, but the efficacy in detecting structure is highly dependent on the used wavelength, vegetation height and moisture content (Imhoff et al, 1997). All of the above discussed methods provide improved classification results in certain cases, but are often laborious, or require extensive training data or manual steps which may lead to interpreter related differences.

Airborne Laser Scanning (ALS) uses discrete return small footprint airborne LiDAR map the elevation of the ground surface and canopy elements. ALS gives a high accuracy account of canopy heights and density through the separation of the terrain model from canopy returns. The potential of ALS to detect structural forest characteristics has been shown in many studies, and it has quickly become the new golden standard for estimation of forest height, structure etc in local studies (Wulder et al, 2008c; Lim et al 2008). Habitat studies increasingly use LiDAR for canopy characterisation, structural diversity mapping (Lefsky et al 2002, Melin et al 2012) and the modelling of canopy light transmission (Lee et al. 2009)

In regional projects application of ALS is often still limited by data availability, but large area acquisitions are increasingly common. The province of Alberta together with industry partners has created a near wall to wall covering ALS dataset over the forested range of the foothills area. With this data we can fully integrate ALS data in a habitat classification for wildlife management. The integration of ALS and Optical Satellite data means we can use the strength of both datasets in the classification system and use a fully rule based, heuristic classifier that provide consistent, reproducible result over large areas with little localized training or interpreter choices needed

Western Alberta, Canada is a dynamic region where ecosystem values co-occur with widespread resources extraction from the forestry and fossil fuels industries (Roever et al. 2008). Coal, oil, gas, and timber extraction, in addition to related population growth, urban development and expanding demands for outdoor recreation impact biodiversity habitat alteration and fragmentation (Schneider et al. 2003). Western Alberta represents the eastern limit of grizzly bear (*Ursus arctos*) habitat in southern Canada (Nielsen et al. 2009) and has an important population of woodland caribou (*Tarandus rangifer)* (Festa-Bianchet et al 2011, Bradshaw and Herbert 1994). Effective management of wildlife habitat is of paramount importance for sustainable support of both ecological values and resource extraction in the region. To support wildlife and habitat management we need a detailed account of habitat status and a thorough understanding of the demands different key species have for their environment. The availability of accurate habitat maps is crucial for both.

In this research we introduce Airborne Laser Scanning and multispectral satellite images for use in a new heuristic wildlife habitat classifier for western Alberta. The classifier is based on established ecological knowledge and presents a step forward both in structural detail and accuracy. We evaluate the accuracy of the different decision layers and compare the classification results against existing Landsat based classifiers. Based on our results we look at implications of increased ALS availability for habitat mapping and wildlife management, and make recommendations the application of ALS in regional habitat mapping studies.

Methods

ALS data can support habitat classification in many aspects, especially those related to small scale topographical features and vertical vegetation structure which are hard to detect using classic optical imaging. Improvements are also possible in classes that are expressed for a large part in the understory but with a similar canopy cover and thus non-unique spectral signature. Here we discuss some specific habitat classes the contribution of ALS data to improved separation.

Wetland areas:

Wetland areas are often not spectrally unique from drier forests or herbal vegetation and depending on tree cover inseparable from these dry vegetation types. However, understory cover and associated resources for animals are fundamentally different. The terrain detail ALS data provides enables accurate mapping of topographically wet areas and separates them from other habitat types.

Alpine areas:

Alpine meadows and barren terrain are indifferent form lower barren or herbal areas, but have a different faith and function to animals. Lowland areas with no forest cover are usually transient and result from disturbances, while alpine areas have a more stable vegetation cover. The LiDAR derived elevation model can be used to separate alpine areas by threshold, or using an automated tree line finding algorithm (Coops et al., 2013)

Forest-cover density:

Canopy closure is a crucial habitat driver as it relates to understory composition and shielding from adverse climate and snowfall. Optical methods struggle beyond leaf areas of 3-5 m2/m2 and may have ambiguous results depending on different species compositions. ALS cover measures are consistent over both deciduous and coniferous species and do not saturate at densities found in temperate or boreal forests. ALS therefore allows for the more detailed and consistent separation of canopy density classes.

ALS has limited potential for the classification of specific species or the separation of coniferous vs. deciduous vegetation cover, neither do the commonly used height data separate well between low herbaceous vegetation and barren areas. Luckily these classes are already reliably detected in multispectral images as are water bodies. Integrating both ALS and optical data sources, a complete heuristic habitat classification scheme is within range.

Study area

The Study area is in the western Rocky Mountains in Alberta, Canada and is mostly contained by the Upper and Lower foothills Natural subregions, with the higher elevations in the Alpine natural subregion (Natural Regions Committee, 2006). Elevations range from 700 to 3000m asl with the with steep montane topography in the west, transitioning to a gently rolling landscape in the eastern parts of the area. The natural vegetation in the sub-alpine areas is forested with logepole pine, white spruce, and trembling aspen as the main tree species. The area has extensive resource extraction in underground resources and forest harvest, resulting in a varied mosaicked landscape of mature forest, regrowth forest and barren or recovering areas.

Data sources

ALS data for the study area was collected between 2003 and 2009, with the main volumes collected in 2007 and 2008. The data from different acquisitions is collected, thinned, and distributed as 1*1 meter gridded products including a bare earth layer, and a full feature (top of canopy) layer. For the classification the 1m products were generalized to 25*25m grid metrics in FUSION (McGaughey 2014), with metrics including Max canopy height, Percentiles, points above 2 m, and base statistics like mean and standard deviation. The bare earth product was used to create a 25m DEM and derivatives (slope, aspect, curvature). In addition to these ALS products, we also included depth to groundwater table as created by the UWaterloo based on the same ALS data using a hydrological modelling process (White et al., 2012).

For the optical data we used Landsat TM5 data from the 2010 GLS dataset. All scenes were processed to surface reflectance by the USGS using their standard image preprocessing procedures (Masek 2006; usgs cdsr product guide 2013).

Evaluation data

Evaluation data was collected during a field campaign in 2013. During the campaign we established 102 variable radius plots and noted among other things: habitat class, canopy height, cover, soil wetness, and canopy species composition.

Classification scheme

The new classification is designed to be backwards compatible with the existing scheme as defined by McDermid (2006), but there are some additional classes we wish to include because they are currently omitted but still significant towards the habitat use of grizzly bear. These classes are not necessarily spectrally different but are derived based on the inclusion of ancillary datasets. We also use the included ALS data in our analysis improving the ability to discriminate between forest cover and density types. Because of the ALS data we have more direct data on vegetation height and crown closure and thus can use a heuristic classifier that is less reliant on spectral data. We propose to use the improved classification scheme in Table 7.

Table 7: Proposed classification scheme:

Class label	description
Dense coniferous forest	>75% crown closure; >80% conifer based on stem count; 'dry' or 'mesic' moisture regime
Moderate coniferous forest	40-75% crown closure; >80% conifer based on stem count; 'dry' or 'mesic' moisture regime
Open coniferous forest	6-40% crown closure; >80% conifer based on stem count; 'dry' or 'mesic' moisture regime
Closed broadleaf forest	>50% crown closure; >80% broadleaf based on stem count; 'dry' or 'mesic' moisture regime
Open broadleaf forest	6–49% crown closure; >80% broadleaf based on stem count; 'dry' or 'mesic' moisture regime
Closed mixedwood forest	>50% crown closure; 26–79% broadleaf by count; 'dry' or 'mesic' moisture regime
Open mixedwood forest	6–49% crown closure; 26–79% broadleaf by count; 'dry' or 'mesic' moisture regime
shrubs	>25% shrub cover; <6% tree cover; 'dry' or 'mesic' moisture regime
herbaceous	<25% shrub cover; <6% tree cover; 'dry' or 'mesic' moisture regime
Alpine Bare	<6% vegetation cover, Alpine Elevations\subregion
Alpine Meadow	<25% shrub cover; <6% tree cover; Alpine Elevations\subregion
Wetland Treed	>10% crown closure; 'wet' or 'aquatic' moisture regime
Wetland Open	<10% crown closure; 'wet' or 'aquatic' moisture regime
Water	>6% standing or flowing water
Barren Land	<6% vegetation cover
Agriculture	Landuse agriculture, crops, pasture etc.

The Actual classification will be rule based, using a broad Spectral classification, Percent Conifer model, ALS data, and ancillary data. We propose to use classification rules shown in Table 8. The Spectral classifier will separate water, bare, and vegetated classes which will be further divided based on height and density measures.

Table 8: Proposed classification decision rules:

Class	Decision Rules
Dense coniferous forest	p95 > 4m; above2m < 75%; >80% conifer
Moderate coniferous forest	p95 > 4m; above2m < 50%; >80% conifer
Open coniferous forest	p95 > 4m; above2m < 50%; >80% conifer
Closed broadleaf forest	p95 > 4m; above2m > 50%; <25% conifer
Open broadleaf forest	p95 > 4m; above2m < 50%; <25% conifer
Closed mixedwood forest	p95 > 4m; above2m > 50%; 25-80% conifer
Open mixedwood forest	p95 > 4m; above2m < 50%; 25-80% conifer
shrubs	p95 < 4m, spectral
herbacious	p75 < 2m , spectral
Alpine Bare	Region\Elevation == Alpine, Spectral
Alpine Meadow	Region\Elevation == Alpine, Spectral, p75 < 2m

Filling the gaps

LiDAR has some gaps, and has insufficient return time to deal with changes. Here we use Landsat data only and a maxlike classifier trained on a random sample of unchanged original data.

Results

The new classification shows a considerable improvement over currently available classification products. Some confusion remains in the species composition, between the mixed and pure classed, but the class boundaries are somewhat arbitrary here. Decision rules for this are based on Landsat Tasseled cap bands. Confusions are mainly in recovering blocks after harvest where deciduous understory shrubs are visible through the closing canopy and newly growing pines have a lighter spectral signature than full grown coniferous trees.

Our results are considerably better than the other classifications that have more confusion (Table 9). An example of the spatial detail is shown in Figure 19. The Habitat classification is delivered as 25 meter resolution geolocated raster for the Grande Cache and Yelowhead regions.

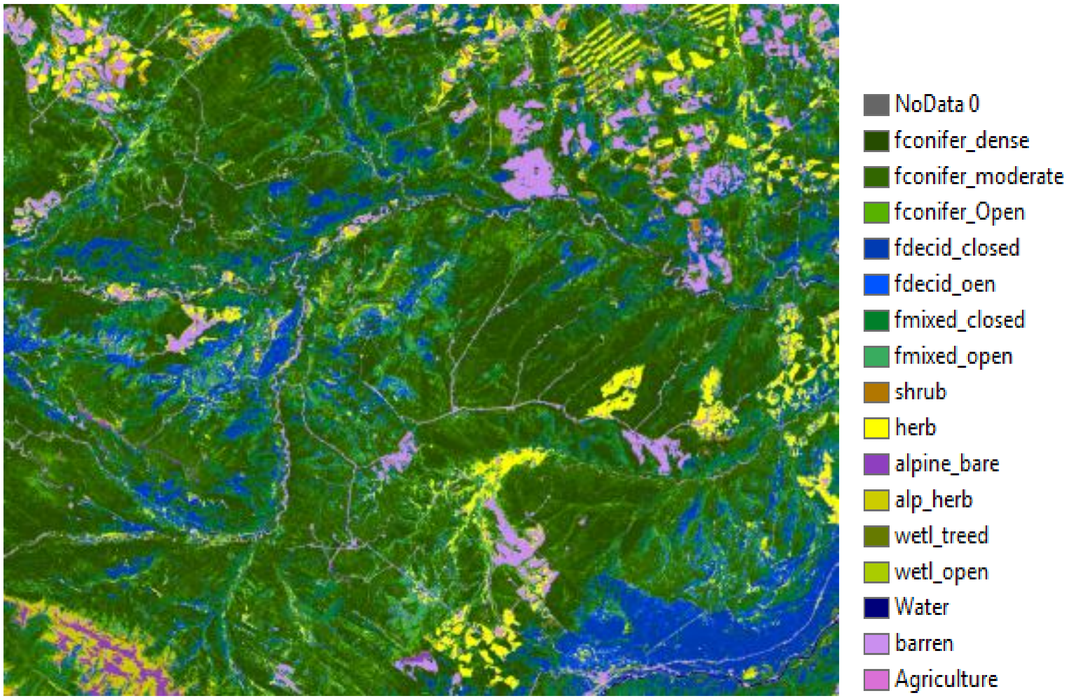

Figure 19. Example area for the habitat classification

Table 9: Confusion matrix for 12 classes with comparision to the currently available habitat map and EOSD

Reference																		
Prediction	conifer close	conifer open	deciduous closed	deciduous open	mixed closed	mixed open	shrub	herb	wetland treed	wetland open	water	barren					FRI_14	EOSD
conifer close	**21**	1			3									**0.68**	25		**0.35**	**0.81**
conifer open	2									1				**0.00**	3		**0.00**	**0.00**
deciduous closed	1		**4**	1	4		1							**0.50**	11		**0.13**	**0.75**
deciduous open		2		**1**						1				**0.50**	4		**0.00**	**0.50**
mixed closed	6	1	3		**7**				1					**0.44**	18		**0.63**	**0.06**
mixed open					1	**2**			2					**1.00**	5		**0.00**	**0.00**
shrub	1						**2**							**0.50**	3		**0.50**	**0.25**
herb		1			1		1	**12**		1				**1.00**	16		**0.17**	**0.33**
wetland treed									**4**					**0.57**	4		**0.00**	**0.00**
wetland open										**6**				**0.67**	6		**0.00**	**0.56**
water											**10**			**1.00**	10		**1.00**	**1.00**
barren			1									**6**		**1.00**	7		**0.17**	**0.00**
	0.84	**0.00**	**0.36**	**0.25**	**0.39**	**0.40**	**0.67**	**0.75**	**1.00**	**1.00**	**1.00**	**0.86**						
	31	5	8	2	16	2	4	12	7	9	10	6			**0.67**		**0.47**	**0.33**
														Kappa	0.6209		0.3795	0.2356

Discussion

The change from a classical spectral classifier relies on training data (for supervised classifications) or the discretion of the interpreter (for labeling unsupervised clustering) and heavily favors classes that are spectrally different. In the case of a combination of forest density and species composition spectral classification are often quite ambiguous as no unique relation exists in a multispectral variable space like Landsat images. By adding ancillary data sources such as DEMs, stratifying datasets, or including the spatial domain in classifiers it is possible to improve the classification accuracy, but these techniques are also laborious.

The availability of ALS data makes that we can use direct information on vegetation structure in the classification which corresponds to the original definition of many classification systems designed for habitat evaluation and wildlife management. By using ALS data in combination with optical data we have direct information on all key vegetation characteristic and we can use a direct, rule based classifier that directly employs the class definitions as set based on the management information needs. Our results show a considerable accuracy improvement over the existing Landsat based classification and we were able to also increase the class resolution.

A.5.6. Phenocam Field of view comparison, broad v.s. narrow

Assessing the Impact of Field Of View on Monitoring Understorey and Overstorey Phenology Using Digital Repeat Photography

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Introduction

Information on the timing of seasonal or recurring biological events are important indicators of phenology (Morisette et al., 2009) and key signals relating inter-annual climatic variations (Reed et al. 1994, White et al. 2003, Xiao et al. 2004). The effects of a changing climate on phenology poses challenges to resource managers (Morisette et al., 2009; Schwartz et al., 2006; Walther et al., 2002), especially at northern latitudes, where increases in growing season length and vegetative productivity (Myneni et al., 1997) and decreases in seasonality (Xu et al., 2013) are expected (Myneni et al., 1997). Changes in phenology may have impacts on species composition and discrete seasonal events such as flowering, leaf emergence, senescence and other characteristics (Coops et al., 2011). The phenological cycle of vegetation is also a critical driver of food availability and animal habitat usage for a wide range of species, such as the grizzly bear (Ursus arctos L.) whose foraging activities are known to be highly seasonal (Munro et al. 2006, Nielsen et al. 2010) or Caribou (Rangifer tarandus L.) who migrate over large distances following forage availability (Thomas et al., 2011).

In a remote sensing context, variations in the reflectance of vegetation cover can be used as indicators of phenological changes (Badeck et al., 2004) and, as a result, data from a number of instruments and sensor types are used to monitor vegetation changes at both local and global scales. At the stand level, the increasing popularity and use of inexpensive visible spectrum digital cameras has offered a new source of information for the monitoring and measurement of phenological events at the local scale (Woebbecke et al. 1995, Graham et al. 2006, Ide 2010, Graham et al. 2010, Nijland et al. 2014). Repeat photography allows a very fine temporal sampling, often at daily or hourly intervals, for monitoring vegetation phenology (Bater et al., 2011a, 2011b; Nijland et al., 2013; Graham et al., 2010; Richardson et al., 2010). This type of near remote sensing system has a number of benefits, includings high temporal frequency data acquisition and cost-effectiveness. However, as novel techniques proliferate, comparisons between approaches are not often undertaken, resulting in a wide variety of methods with little examination of issues such as field of view or scene extent and the associated trade-offs. In this communication we examine the impact of field of view on the capacity of imagery, acquired from a digital camera network, to detect changes in phenology of selected plant species. To do so we examine a series of oblique images acquired at narrow and broad fields of view. Identical plants were located on both sets of images, with the start and end of season's phenological indicators derived for individual plants, from each scene, and compared by species. Phenological events were also recorded in the field and statistically compared to both the narrow and broad field of view estimates. We conclude with recommendations on appropriate fields of view for vegetation monitoring.

Materials and methods

Study Area

Camera units were positioned at three plots near the communities of Robb and Cadomin, Alberta, Canada (53.2°N, 177.0°W) representing native vegetation (i.e., arboreal and understorey) and a range of elevations (Table 10). The study area is within the Upper Foothills Natural Subregion (UFNS) flanking the Rocky Mountains in western Alberta. Together with the Lower Foothills Natural Subregion, the UNFS extends along the eastern Rocky Mountains between Grand Prairie in the north and the Bow River Valley in the south (Natural Regions Committee, 2006). In contrast to its lower-elevation counterpart, the UNFS favors conifer over deciduous species due to its short, wet summers and cold, snowy winters. Closed-canopy conifer stands comprising Pinus contorta (lodgepole pine), Picea mariana (black spruce), and Picea glauca (white spruce) are present on all aspects throughout the UNFS.

Table 10. Characteristics of the camera plot locations

Plot	Coordinates [UTM 11N]	Elevation [m]	Vegetation Type
Drinnan Creek	N5894401 ; E465076	1356	Spruce and pine forest
Folding Mountain	N5900474 ; E447823	1139	Spruce forest
Cardinal Divide	N5860769 ; E483439	2025	Alpine meadow

Digital Camera Network

Six digital camera units were installed (Harbortonics, Fort Collins, CO, USA) at three study locations in western Alberta (Table 10 and Table 11). The primary component of each camera unit was a Pentax K100D digital SLR (Pentax Corporation, Tokyo, Japan) installed with lithium ion batteries and supplemented by a solar panel for power throughout the study period. Five images were acquired between noon and 13h local time for each day of the study in JPEG format (3008 x 2008 pixels), and stored on memory cards, retrieved at the completion of data collection. At each location, for the duration of the study period (late April to early October 2010), two cameras were positioned on suitable trees in order to collect both broad and narrow field of view oblique images (see Figure 20). The field of view of an image is a function of the camera focal length, image sensor size (in the case of a digital camera, the CCD array) and the distance between the lens and the object distance. In this case, given the cameras were identical, the field of view is principally a function of the distance between the camera and the vegetation. All cameras were positioned facing north, with the broader field of view images acquiring data over a greater spatial range than the narrow field of view cameras. The motivation and discussion of the network is provided by Bater et al., (2010).

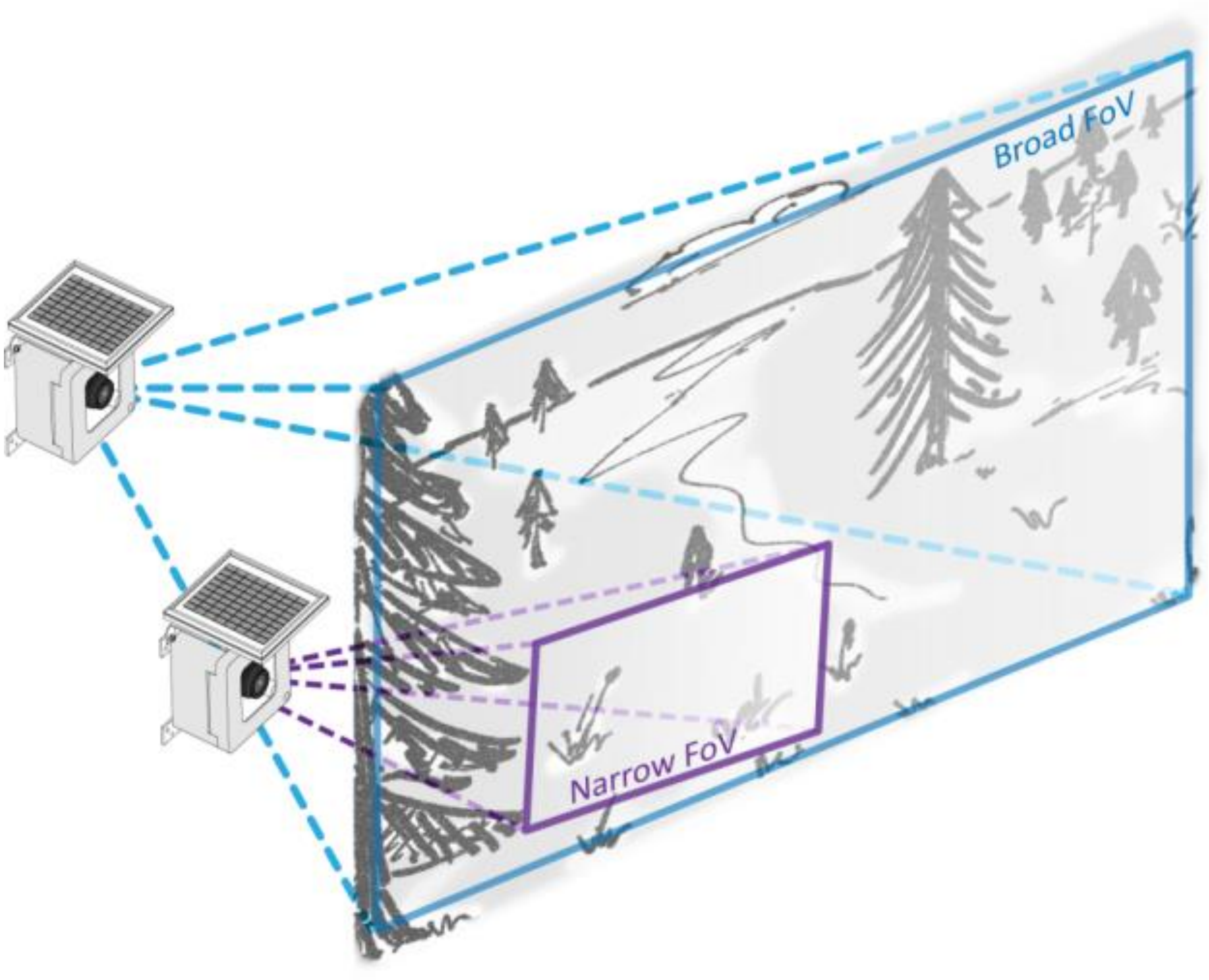


Figure 20: Geometry of images

Image Analysis

Images were processes and analyzed in the R programming environment (R Development Core Team, 2012) to obtain the start and end of the growing season. To do so, we located individual plants per frame in both the broad and narrow field of view images, delineated pixel coordinates, and extracted average RBG values per individual. RGB values were then used to calculate the 2G-RB index (Richardson et al., 2007) to minimize light intensity differences between averaged daily images:

$$2G\text{-}RBi = 2\mu G - (\mu R + \mu B)$$

Where μ is the is the image digital numbers in bands R: red, G: green, and B: blue.

Beginning of season (Begining of season) and end of season (EoS) dates were calculated from the temporal sequence of 2G-RBi values using the half-maximum method which has been used both in local phenological monitoring as well as larger scale investigations (Richardson et al., 2009; Bater et al., 2011; Schwartz et al., 2002). Beginning of season was defined as the first day above the derived half-maximum value, and end of season as the first day below. To ensure integrity of the derived values, images recording excessive rain or snow were removed from analysis and values normalized by the 10 and 90 percentiles to remove outliers from the remaining data (i.e., the lowest and highest 10% of data points were removed) (Nijland et al, 2013). Lastly deviance plots were produced for each species and field of view.

Phenophase Validation

Fortnightly visits to the three study plots provided phenophase validation data according to the codes formulated by Dierschke (1972). Codes 4 ("Leaf unfolding up to 50%"), 5 ("Leaf unfolding up to 75%"), 9 ("Yellowing over 50%"), and 10 ("Dead") were used to determine phenological events of selected species within selected fields of view. In total 11 individual understorey plants were sampled over all locations: Hedysarum alpinum (Alpine sweetvetch) across all study locations; Shepherdia canadensis (buffalo-berry) at Folding Mountain; Lathyrus ochroleucus (cream pea) at Drinnan Creek; and Arctostaphylos uva-ursi (bear-berry) at Drinnan Creek.

Statistical Analyses between Fields of View

The impact of recording imagery with narrow and broad fields of view was assessed in a number of ways. First t-tests were undertaken to assess if differences existed between the broad and narrow fields of view, beginning of season, and end of season estimates where compared to the field data. Using t-tests and correlation analysis, we then assessed, if the broad and narrow field of view estimates beginning of season and end of season differed from each other.

Results

Each camera acquired between 800 - 880 images per site with a few data breaks due to power or storage failures. In total, 11 individuals from eight species were identified across all images, and differences in phenology were compared across the three key stages of the annual vegetation development, the greening phase, approximately comprising the first third of the curve; the peak and/or flowering phase, comprising the middle third; and the yellowing or senescing phase, approximately comprising the last third, as well as the beginning and end of season estimates.

When compared to the field observed phenological stage, results indicated no significant difference between the broad or narrow fields of view with field measured beginning of season values ($p > 0.05$). In contrast, end of season validation data was found to be significantly different ($p < 0.003$) to both the broad and fine field of view images with differences of 14 and 21 days respectively, suggesting that 2G-RBi is not as effective at determining end of season compared to the beginning. When comparing the broad and fine field of view estimates to each other, both the beginning and end of season estimates were not statistically different, with mean differences on average by all species of between 0.75 and 2.71 days, respectively (Figure 21).

Table 11. Inter-site length of season analysis for all species presences.

Scientific Name	**Common Name**	**Vegetation Type**	**Location**	**Field of View**	**Season Start**	**Season End**	**Length of Season**	**Elevation (m)**	**n**
Hedysarum alpinum	Sweet vetch	Herbaceous	C. Divide	Broad	178	243	65	2025	5
				Narrow	173	243	70	2025	5
			D. Creek	Broad	186	249	63	1356	3
				Narrow	178	234	56	1356	6
			F. Mountain	Broad	157	252	95	1139	5
				Narrow	149	249	100	1139	3
Salix spp.	Willow	Woody Shrub	C. Divide	Broad	175	249	74	2025	6
				Narrow	174	249	75	2025	4
			D. Creek	Broad	178	253	75	1356	4
Shepherdia canadensis	Buffaloberry	Woody Shrub	F. Mountain	Broad	153	254	101	1139	5
				Narrow	159	254	95	1139	5
			C. Divide	Narrow	173	243	70	2025	6
Camassia spp.	Camas	Herbaceous	C. Divide	Broad	177	243	66	2025	5
				Narrow	176	243	67	2025	5
Arctostaphylos uva-ursi	Bearberry	Evergreen	D. Creek	Broad	137	238	101	1356	5
				Narrow	143	249	106	1356	13
Castilleja spp.	Indian Paintbrush	Herbaceous	F. Mountain	Broad	152	250	98	1139	6
				Narrow	157	249	92	1139	5
Lathyrus ochroleucus	Cream pea	Herbaceous	D. Creek	Narrow	182	256	74	1356	8

Individual species responses:

H. alpinum was the only species visible in the both the narrow and broad field of views across all study locations. Examination of the fitted splines indicates the narrow and broad fields of view phenological curves deviated more in the greening and flowering periods than for the senescing period. Similar trends were also found with A. uva-ursi. Species where the splines were more closely included Camassia spp. and Salix spp, which both exhibited only minimal differences in 2G-RBi for much of their duration (Figure 22, 23).

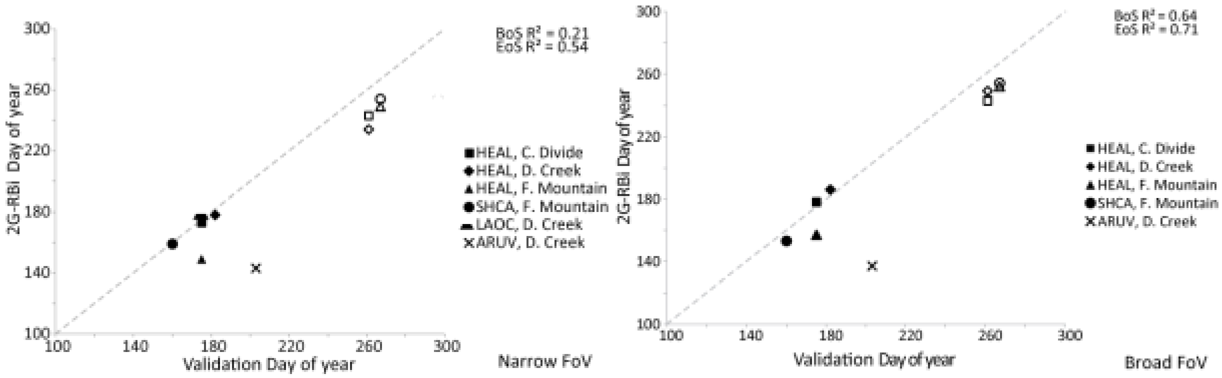


Figure 21. Comparison between estimations of phenological event dates (i.e., Begining of Season, End of Season) as estimated by field observations and values derived from the broad- (2a) and narrow- (2b) field of view imagery. Species for which both field data and imagery was available included H. alpinum, L. ochroleucus, S. canadensis, and A. uva-ursi. When broad and narrow fields of view were taken together, $R^2 = 0.82$ (n=18). Grey line represents 1:1. A. uva-ursi was excluded from correlation due to its being an outlier.

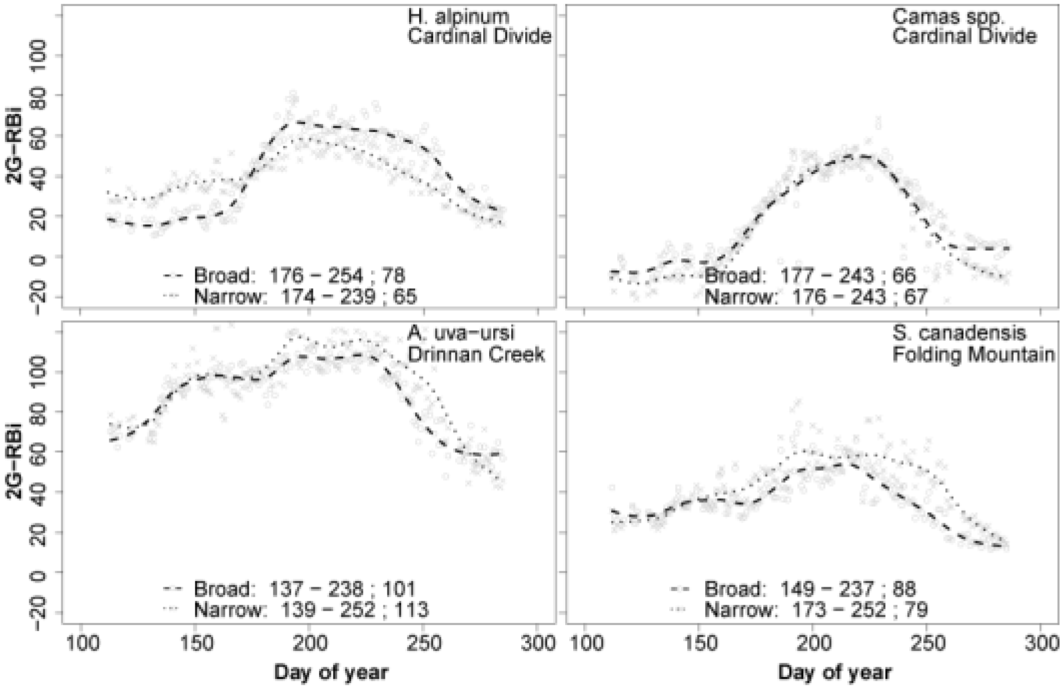


Figure 22. Splines fits to 2G-RBi daily values through the growing season for H. alpinum, Castilleja spp., A. uva-ursi, Salix spp., Camas spp., and S. canadenisis. Raw and Narrow field of views are compared.

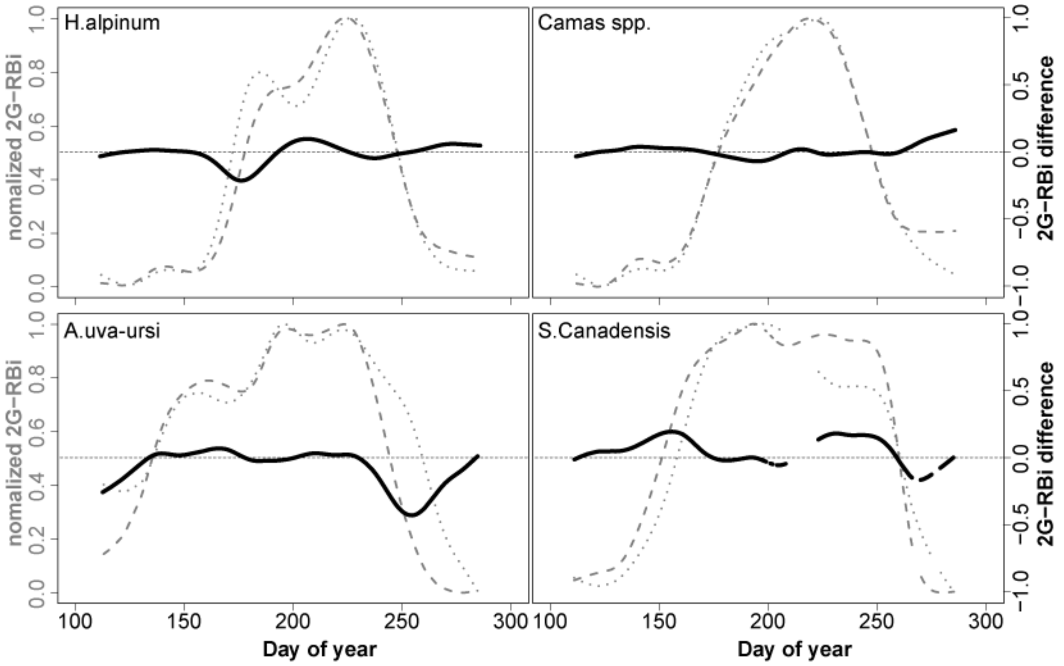


Figure 23. Deviation 2G-RBi plots (broad – Narrow) by species.

Discussion

In this study we evaluate broad and narrow field of view images to detect changes in phenology in forest understorey plant species. Bater et al. (2011) proposed that proximity may play a role in event monitoring efficacy; that is, images which contain more spatial detail may be able to collect more accurate species-specific phenological information, and further, that the need for validation field visits would be reduced if species-specific events could clearly be discerned on the time-series imagery. Likewise, Nijland et al. (2012) highlighted other potential advantages offered by close proximity phenological monitoring, including an amelioration of perspective issues and increased spatial resolution. In contrast to these expectations, the results of this analysis suggest that broad field of view images perform in a similar manner when compared to images captured using a narrow field of view.

This result is advantageous to environmental model studies. By virtue of the broader field of view, larger areas can be sampled and phenological status of an increased number of individuals is possible using broad field of view data, in turn allowing for more efficient data collection. We suggest that, with no statistically significant difference between the broad and narrow fields of view, the use of the broad field of view is a viable option for phenological analysis.

To date, most studies investigating the role of digital camera imagery for environmental monitoring have used cameras with a broad field of view (Richardson et al., 2007; Graham et al., 2010). In this study we found that broad scale image series area as accurate in detecting phenological events as closer placed, fine scale images. Installing cameras with a wider field of view is more cost effective when the phenology of multiple species can be detected in the same image. Furthermore our results support the investigation towards the use of readily available camera stations that have been installed for other purposes like traffic monitoring or tourism to monitor phenology. The field of view is often broad and highly oblique, but will likely still be suitable for accurate extraction of the main vegetation phenophases

A.5.7. Phenocam bear foods detection 2013, Heracleum lanatum

We employed the available phenology cameras in the Kakwa area (Figure 24) overseeing *Heracleum lanatum* plants under various forest cover and structural configurations. The objective is to compare phenological patterns and food availability throughout the growing season across stands subject to a range of management activities.

Field Visits

Three field visits were made for the camera work: 1) in May to install the cameras; 2) late June to download the data and check for progress or defects, and 3) October to retrieve the cameras and data. The field crews included Wiebe Nijland (all visits), Adam Erickson (May and Oct), 'Bean' Yahao Lu (May), Michell Vartanian (June), Paul Pickell (June), and Ilia Parshakov (Oct). The October visit was combined with the collection of additional plot data on forest structure and habitat for the development of the new land cover map. Site selection was supported by Karen Graham and Terry Larsen.

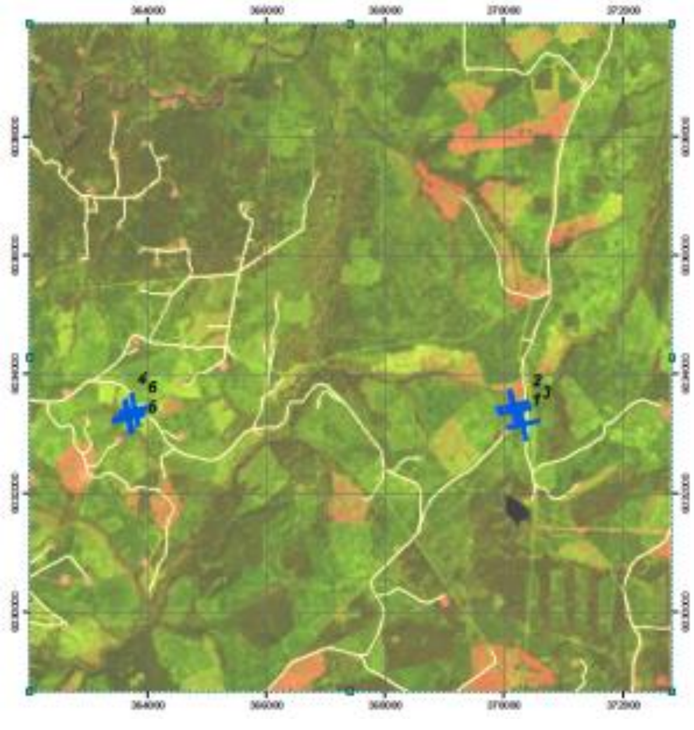


Figure 24.   Locations of cameras set-up to moniter the phenology of *Heracleum* in the Kakwa study area.

Cameras

Six RGB cameras were available at the time of installation, and installed in paired locations, representing open, edge, and closed canopy conditions. The sites were selected for presence of *Heracleum lanatum* within the field of view (Fig 24).

On the June field visit we found camera 2 had severe problems and was taken down. Camera 1 had some issues and was re-activated. Later we found out the problems were not resolved successfully.

Data

Four cameras generated a complete photo record from May 22nd to October 18th. In total 2803 Photos were taken.

A quick exploration of the images (Figure 25) shows *Heracleum lanatum* leaves at all of the sites. Cameras 4 and 6 (in open and edge canopy) have flowers present, Cameras 3 and 5 (closed canopy) did not flower in 2013, but flower stalks from the year before were observed at installation. Flowering dates were similar in all images with the main flowering in the first week of July.

Camera 1, edge (incomplete)

Camera 3, closed canopy

Camera 4, open canopy

Figure 25. Continued…

Camera 5, edge

Camera 6, closed canopy

Figure 25. Example of camera frames at each of the study sites

A.5.8. Field Campaign to update forest structure and habitat

To create robust base data products training and validation data is required. The currently available plot datasets were acquired over 10 years ago and require an update as well as well as refining to meet the needs of the new land cover classification system. We therefore held a short field campaign in fall 2013 to acquire field data to be used our forest structure and habitat work.

Study Site

Grizzly FP7 area, Focused around the Hinton-Kakwa region.

Field Crew

Wiebe Nijland, Adam Erickson, Ilia Parshakov

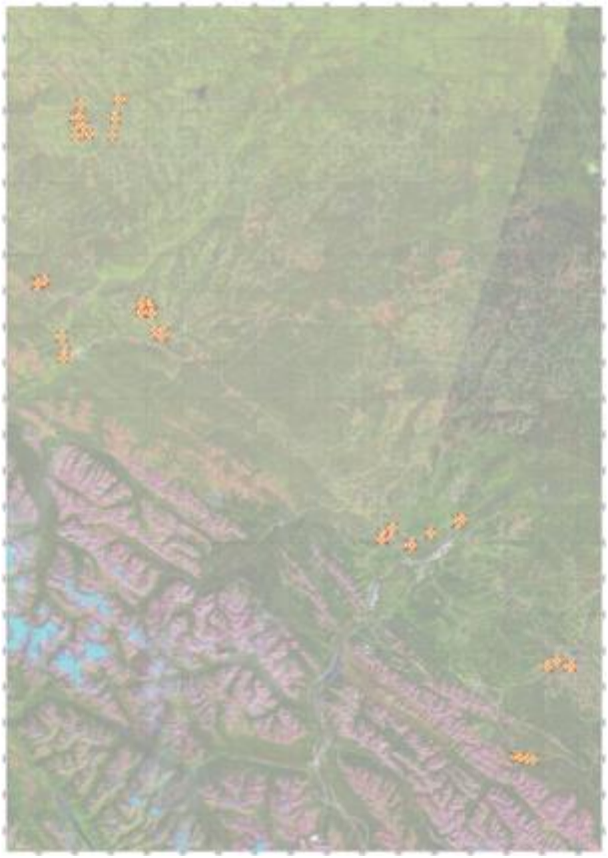


Figure 26: Plot Locations (on Landsat TM, RGB=543).

Field Campaign Summary

During the week long field campaign we collected ground truth information on the occurrence of habitat types and forest structure (canopy structure and understory cover) for 102 Sites (Fig 26). The campaign was combined with retrieving the phenology cameras in the Kakwa area

The Field data is pre-processed and has passed initial quality control for unexplained outliers, positional accuracy. On each plot we recorded the following information:

Basic: Date, time, plot_nr, Coord_X, Coord_Y, GPS_Elevation, Slope, Aspect.
Structure: Can_Height, Can_Cover,, LAI, Groundcover 0-50cm, Understory cover 50-250cm, Understory cover 250-500cm, BasalArea, Last Harvest Estimate.
Soil, Wetness
Habitat
Percent Species Cover:
Spruce, Pine, Fir, Trembling Aspen, Willow, Alder, Larix, Total Deciduous, Total Conifer

Plot locations were selected purposefully to get a good cross section through the forest types in the study area. On a micro level the plot centers were chosen randomly to avoid bias towards heavy canopies or avoidance of stems etc. Exploratory analysis shows an even coverage of height and density classes of the forest (Fig 27 and 28)

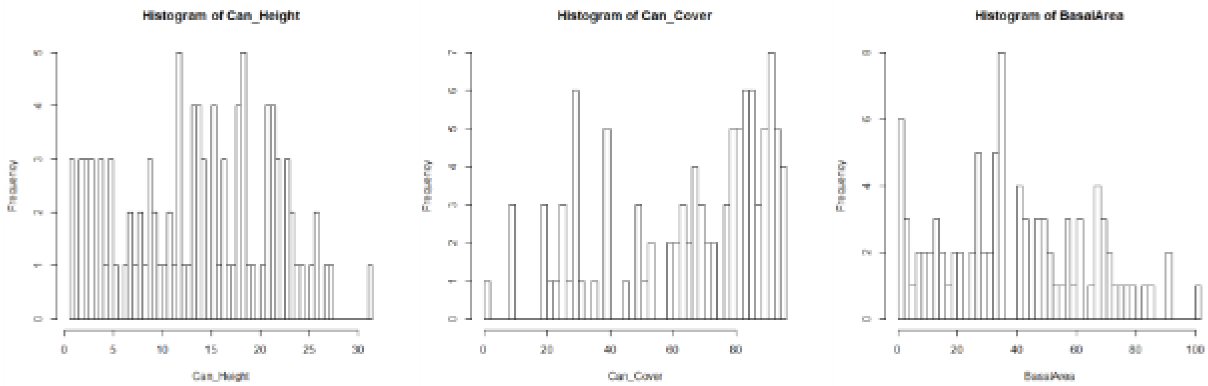


Figure 27: Histograms of Canopy Height, Canopy Cover, and Basal Area

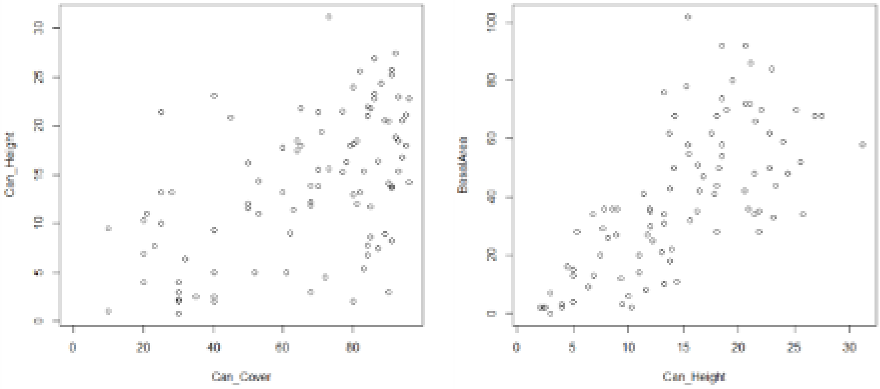


Figure 28: Scatterplots of Canopy Height, Cover, and Basal Area

A.5.9. Implementation of the LANDIS-II Dynamic Forest Landscape Model and the Mechanistic Fire Sub-model

Introduction

Western Alberta's forests are vital to the conservation of remaining grizzly bears (*Ursus arctos*) and woodland caribou (*Rangifer tarandus*). Intensive extractive industry activity in the form of forestry, oil and gas exploration, and mining are extensively practiced throughout the region's forests (Nielsen et al., 2013). Prior to European settlement, Alberta's forests were largely shaped by the coupled effects of climate and fire, typical of boreal forest ecosystems (Tymstra et al., 2007). While human pressure is at the highest level in recorded history, the future implications of intensifying human activities remain widely unknown.

The importance of modelling coupled dynamics is evidenced by the lagging of tree species distributions behind climatic optima, whereby disturbances initiate state transitions toward directional climatic forcing. The widespread prevalence of climatic lagging, or disequilibria dynamics, is related to the long-lived organismal nature of trees, whereby climatic change rarely produces direct mortality. Rather, climate-related mortality is driven by extreme events such as drought and wind (Martínez-Vilalta et al., 2012). The increased velocity of climatic change may increase the frequency of such climate-related disturbances. However, while providing directional change along broader temporal scales, climatic change is not the only factor impacting forests in an era of widespread management. The indirect effects of climate, such as altered fire regimes, are critical to the near-term state of forests. Over longer temporal scales, fire may also act as a climate-stabilizing negative feedback, decreasing fire severity and terrestrial carbon emissions while improving wildlife habitat (Li et al., 2000).

While historical vegetation distributional changes were strongly correlated to long-term climatic gradients, the persistence of this coupling given widespread human management is uncertain. Analyses of past vegetational communities show the prevalence of species assemblages with no present day analogue (Bertrand et al., 2011), even during climate conditions similar to today. These phenomena indicate that climate is not the only factor driving species distributions, though it may act as a slow vacuum. Statistical equilibrium models are therefore inappropriate for addressing the complex dynamics of forest change, due to their fundamentally static and correlative nature.

Dynamic forest landscape models signify a major advancement in scientists' ability to represent complex forest ecosystem dynamics (Kimmins et al., 2010). This class of models addresses a growing imperative to embed ecological forecasting within forest management activities (Luo et al., 2011). Forest ecosystems are complex adaptive systems, characterized by processes interacting at different frequencies, durations, magnitudes, and scales, producing a vast phase space of potential system states. The advantage of hybrid models lies in their ability to represent system complexity in a computationally efficient manner.

Complex patterns in ecology are often the product of self-organization and emergence, two hallmarks of complex adaptive systems, whereby relatively simple local dynamics extended over time can produce non-linear dynamics at the landscape scale. Designed to model self-replicating systems, cellular automata offer insights into the nature of complex systems (Bak et al., 1989). These insights stem from parallels in model design and system dynamics. Though supercomputers may enable fully mechanistic modeling, these models are often cumbersome to use (Grimm et al., 2005)and suffer from slow model development (Levins, 1966). Furthermore, the cost of supercomputers is prohibitive for many researchers and managers.

In this study, we employ a dynamic forest landscape model to simulate landscape-scale forest ecosystems under four coupled historical climate-fire periods. We focus on climate and fire, which together have historically driven natural selection and diversity in boreal and montane forests (Rowe & Scotter, 1973). Our work builds on suggestions in the literature to divide "...the study area into compartments to capture regional variations in the fire environment and climate change" (Tymstra, Flannigan, Armitage, & Logan, 2007, p. 159). We hypothesize that historical climate, fire, and management changes related to increasing global human activity are already strongly impacting forest ecosystems in the region. We estimate that parameterizing simulations with empirical data, thereby focusing on measurable trajectories, can serve to reduce the uncertainty of model scenarios. Finally, we demonstrate novel methods of parameterizing and optimizing dynamic forest landscape models, Canada-wide and globally, respectively.

Methods

We utilize a hybrid modelling approach by fusing the Tree and Climate Assessment Establishment Model (TACA-EM) tree establishment model (Nitschke & Innes, 2008) with the Landscape Disturbance and Succession model, or LANDIS-II (Scheller et al., 2007), to model succession and disturbance dynamics in western Alberta. Though highly specialized recent adaptations, each model descends from the general lineage of forest gap models (Bugmann, 2001), which grew from forest dynamics research (Oliver & Larson, 1996). The TACA-EM model is a probabilistic phenology model of tree species establishment, which is a function of species' unique biophysical space in relation to regional climatic and edaphic conditions. The TACA-EM model was design to assess climate change impacts on tree species' regeneration niche – the most sensitive niche to climatic change (Nitschke & Innes, 2008). Phenology is an important driver of species distributions (Chuine & Beaubien, 2001), as it is a critical driver of plant fitness (Chuine, 2010), necessitating its inclusion in forecasting forest ecosystems.

The LANDIS-II model is designed to operate at a forest stand resolution (~one hectare) and a landscape scale (~106 hectares). Functionally, the LANDIS-II model fuses Monte Carlo methods and cellular automata. The model contains many parametric sub-models and specialized extensions, which can be empirical, mechanistic, probabilistic, stochastic, or logical. By coupling TACA-EM with LANDIS-II, we are able to model succession and disturbance dynamics critical to forecasting landscape-scale forests in an era of global change.

We conducted LANDIS-II simulations within the broadest grizzly bear habitat area utilized for conservation efforts in the region. In western Alberta, grizzly bears are provincially 'threatened' and a national 'species of special concern.' We selected a broadest area to include diverse forest types, habitat critical to remaining grizzly bear populations, and neighbourhood effects such as fire spread and seed dispersal vectors. The area is 25 million hectares in size, with 18 million hectares of the area containing active grid cells, after masking for human settlements and agricultural regions. Our work represents the largest LANDIS-II simulation – and the largest dynamic forest landscape model simulation – conducted to date. The region represents the transition between Montane Cordillera, Boreal Plains, and Prairies under Canada's terrestrial ecozones framework, or the transition between Boreal Forest, Subalpine Forest, Montane Forest, Grasslands, and Tundra under Canada's forest regions framework.

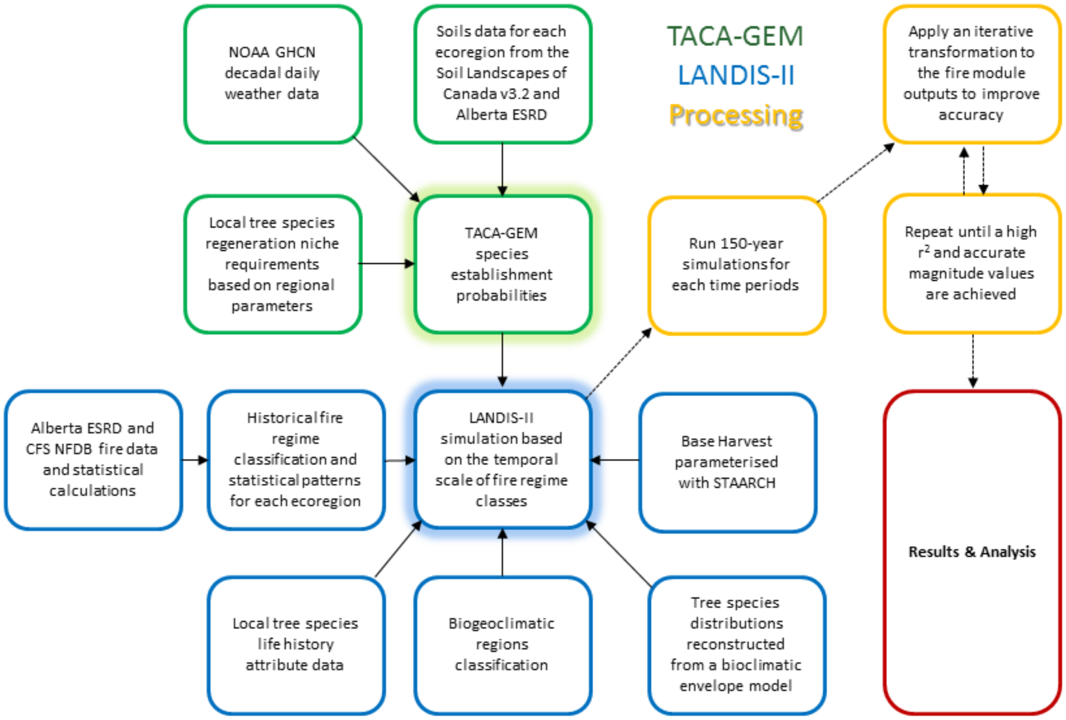


Figure 29. Simulation Framework

To conduct an analysis of historical fire regimes, we used the latest Canadian Forest Service National Fire Database fire perimeter data (Canadian Forest Service, 2013). The national fire perimeter data represents the best available data for mapping historical fires in the region. While remote sensing disturbance detection may produce more precise fire size estimates, the classification of disturbance types currently contains an unacceptable level of uncertainty for use in long-term simulations. The national fire perimeter data was created through a joint provincial-federal government disturbance mapping effort, using high-resolution historical orthorectified aerial photographs and Landsat scenes combined with expert-based manual fire delineations.

We fused the fire perimeter data with NASA Shuttle RADAR Topography Mission (SRTM3) v2 data, processed using standard correction techniques (Reuter et al., 2007), and Natural Subregions of Alberta spatial data (Natural Regions Committee, 2006), to analyze historical regional fire distributions in relation to biogeoclimatic regions and topography. The 30-year temporal scale of the climate-fire scenarios was selected to align with historical changes to fire management, as well as the widespread use of 30-year climate average data. To analyze historical fire regime shifts related to management, we focus on known changes to management, as well as annual fire frequency and area burned change points relative to 30-year time periods, described in detail below. Our expert-based temporal classification method is similar in spirit to fuzzy logic change point detection, though more qualitative in nature.

I. TACA-EM

a. Model Overview

The TACA-EM model probabilistically models species response to climatic and edaphic conditions as a function of their fundamental-establishment niche space. TACA-EM is a phenological establishment model that relies upon empirically derived biophysical relationships. TACA-EM is driven by the climatic-edaphic regeneration niche space of tree species. The model relies on empirical biophysical species parameters for growing degree days, temperature thresholds, chilling requirements, bud break, drought, and frost. The model utilizes a modifier-based decision tree approach to produce probability distributions of tree species establishment.

a. Model Requirements

For each scenario, TACA-EM requires climatic, edaphic, and solar radiation parameters for each site modeled. The parameters are decadal-scale daily-resolution temperature minima and maxima, precipitation, soil moisture regime, soil texture, rooting zone depth, coarse fragment percent, percolation rate, an optional nitrogen modifier class for productivity, and latitude. From the parameters, TACA-EM calculates solar radiation (W/m^2/day) based on Waring and Running (1998), evapotranspiration, soil available water storage capacity, and annual heat moisture index using equations, in order to incorporate the effects of vapor pressure deficit. Available water storage capacity is the key soils variable; when it falls to zero, the soil is assumed to be at the permanent wilting point, or below the minimum amount of soil moisture required to prevent permanent turgor loss through wilting. Using this information, TACA-EM produces a drought index as a function of the actual evapotranspiration-potential evapotranspiration ratio through a soil moisture submodel. Importantly, TACA-EM is not limited to modeling the effects of soil moisture and nutrients, as it also models species-, population-, or genera-specific phenological responses to climate, such as bud break, winter hardening, and frost kill.

b. Model Parameterization

TACA-EM model implementation is typically restricted to individual sites with soil sample data and in situ weather station measurements. Due to the large scale of our study area, we created a TACA-EM parameterization technique that calculates the mean daily resolution weather station measurements across biogeoclimatic regions for maximum temperature, minimum temperature, and precipitation, required by TACA-EM. We wrote R functions to download and process NOAA Global Historical Climate Network-Daily (GHCN-Daily) data, which will be incorporated into the upcoming ROpenSci *rnoaa* package. We designed the approach after a preliminary analysis showed markedly different results in TACA-EM when using ClimateWNA monthly 30-year climate averages compared to daily resolution weather station data. The results are logical given the daily resolution of TACA-EM model processes.

Our algorithm outputs daily resolution mean climate data for all stations within regions for any defined temporal scale, useful in the analysis of climatic oscillations with varying frequencies and wavelengths. Our algorithm performs another useful function in that it can also be used to impute missing observations for a period based on values from observations in adjacent time periods, important given the paucity of continuous weather station data at high latitudes in North America. However, we used the expectation-maximization (EM) algorithm to impute missing data in this work, implemented through the R FastImputation package.

We used the National Soil Database Soil Landscapes of Canada (SLC) v3.2 (Soil Landscapes of Canada Working Group, 2010) to produce soil parameters for Natural Subregions of Alberta. We appended SLC attribute tables to calculate the necessary parameters for TACA-EM. We calculated the dominant soil type for each Natural Subregion, based on a soil type histogram. Soil texture, rooting zone depth, coarse fragment percent, and available water soil capacity were then derived from the SLC database. We used a standard USDA soil texture classification triangle to classify soils into textural types based on percentages of sand, silt, and clay for each dominant soil type. We derived percolation rates for each textural class from the literature. The Central Mixedwood Natural Subregion, classified as Sandy Clay Loam in soil texture, was converted to the TACA class Organic, based on a provincial description of the subregion. Elevational and latitudinal information were derived from a provincial report (Natural Regions Committee, 2006). The new method enables the parameterization of TACA-EM soils across Canada, addressing a key model parameterization challenge.

II. LANDIS-II

a. Model Overview

The LANDIS-II model is a spatially explicit dynamic forest landscape model based on the JABOWA-FORET genre of gap models and LANDSIM (Mladenoff & He, 1999). LANDIS-II is simplified from fully mechanistic physical models, such as coupled atmosphere-fire models, and aspatial physiological growth models, in order to operate efficiently at the landscape scale. The LANDIS-II model core is the central hub of a modular system that allows users to specify varying succession, disturbance, and biogeochemical cycle extensions at user-defined time-steps. The open-source design of LANDIS-II facilitates rapid model development. The strengths of the model rest in its combination of computational efficiency and modular open-source design.

The model design of LANDIS-II reduces complexity by aggregating forest dynamics along assumptions supported at the landscape scale; simple rules are often used in place of complex mechanistic algorithms. Each grid cell or stand is comprised of horizontally homogeneous species-age cohort classes, whereby stands have zero structural and compositional variation internally. The simulation landscape can be spatially divided into distinct biogeoclimatic and disturbance regions, allowing regional parameterization schemes through remote sensing and geographic information system techniques. Where empirical data is available, basic spatial analysis is often all that is required to parameterize the simpler extensions. In our work, we utilize two key extensions: Age-Only Succession and Base Fire.

We employ the Age-Only Succession extension to model light, reproduction, aging, senescence, seed dispersal, and site-level interspecific competition for successional dynamics. Light is modeled as a function of the maximum shade tolerance for sexually mature species present at a site, whereby the presence of highly shade tolerance species that often fare poorly in open stands relative to pioneer species are used as a proxy for diminished light conditions. Reproduction is limited by propagule presence and light availability while establishment is modeled by probability distributions output by TACA-EM. Fire disturbance directly interacts with species reproduction through resprouting and serotiny.

Cohort mortality is a function of species maximum age, with an increasing probability of random mortality once a species has reached 80% of its maximum age. Seed dispersal is modeled by a two-part negative exponential probability distribution with a leptokurtic dispersal kernel, based on a long-tailed solution to Reid's paradox of rapid plant migration. Interspecific competition occurs through the spatiotemporal intersection of species life history attributes, species establishment probabilities, and local disturbance patterns, extended across the matrix landscape. The model design is consistent with complex adaptive systems theory, whereby simple rules can extend to produce non-linear dynamics, as well as self-organization and emergence.

We employ and compare the Base Fire and the Dynamic Fuels and Fire System extensions for modeling wildfire patterns in western Alberta. Here, elevational gradient-driven climatic and edaphic patterns produce differences in disturbance and soil moisture regimes that are estimated to drive vegetational patterns through selection pressure. The two fire models are markedly different in design; Base Fire is an empirical or scenario model representing fire entirely through statistical distributions and stochasticity, while the Dynamic Fuels and Fire

System is a mechanistic fire growth model that incorporates topography, fuels, and fire weather. The Dynamic Fuels and Fire System is functionally parallel to Prometheus and FARSITE; the models are two-dimensional fire growth models rooted in the Canadian Forest Fire Behaviour Prediction (FBP) System and the US Fire Behavior prediction and Fuel Modeling (BEHAVE) System, respectively. Each model also follows a similar surface fire spread model design. In both LANDIS-II fire models, fires begin through separate ignition and initiation events. Mean fire return intervals are used to model regional fire frequency.

The Base Fire model consists of empirical, probabilistic, and stochastic processes. Fire ignition frequency follows a Poisson distribution while fire initiation is based on Bernoulli trials where the ignition probability is a function of time-since-last-fire. Fire sizes are drawn from a log-normal distribution. Fire shape is a product of a stochastic percolation algorithm representing wind direction, comprised of a random wind vector that iterates through each of eight neighboring cell cardinal directions. Inactive cells may act as fire breaks, stopping fire spread before reaching its target size, drawn from a log-normal distribution. Smaller fires occur more frequently, supported in our historical fire regime analysis. If fire spreads to a new region, the fire is stopped in the original region and a new fire initiation is tested before a target size is drawn from a fire size distribution. Fire severity is determined by fuel and wind curves, representing fuel buildup and decay, and is a function of time-since-last-fire. Fire is a bottom-up disturbance in LANDIS-II, whereby the youngest cohorts generally have the highest probability of mortality, though species-specific tolerances are used.

The Dynamic Fuels and Fire System utilizes a mechanistic representation of fire growth. This class of fire model represents the best available approach for modeling fire at the landscape scale without requiring supercomputing computational resources. Similar to Base Fire, fire events are hierarchically bifurcated into ignition and initiation. Fire ignition frequency similarly follows a Poisson distribution, with cells in each fire region selected stochastically for ignition. Unlike Base Fire, fire initiation is modeled probabilistically based on cell fuel conditions, calculated using the FBP and Fire Weather Index (FWI) Systems. Fire sizes are drawn from a log-normal distribution. Fire shape is modeled using rate-of-spread equations adopted and a modified minimal travel time method. Fire spread has two main components: wind bias and fuel-based spread. Wind bias has an ellipsoidal shape with the length and width based on a wind speed vector. Fuel-based spread is a function of fuel class, wind speed, and topography. A cost surface is created using the inverse rate-of-spread to calculate minimum travel time, with cumulative minimum travel time and a predefined fire size determining the overall fire shape.

The minimum travel time method implemented in Dynamic Fire is functionally equivalent to Huygens' principle of wave propagation, used in Prometheus and FARSITE, but improves computational efficiency (Finney, 2002). Five fire size bins are defined based on the probability of fire sizes being drawn from a distribution. Five fire weather bins are related to the fire size bins, under the assumption that larger fires occur during more favorable fire weather conditions, typically created by classifying Fire Weather Index values. Fire seasons are represented probabilistically, defining the leaf status for a fire event.

b. Model Requirements

The LANDIS-II core requires a species list with life history attributes for species present in the landscape, including longevity, sexual maturity age, shade tolerance, fire tolerance, seed dispersal, vegetative reproduction, and post-fire regeneration. The model core requires an initial communities raster consisting of the spatial distribution of user-defined species-age cohort classes. A biogeoclimatic regions raster is required to represent regional differences in species climatic and edaphic suitability, modeled by establishment probabilities.

The Base Fire model requires historical or expected fire regime distribution data for each of the fire regions, typically set to the same raster used for the biogeoclimatic regions for consistency. Base Fire requires fire region data for mean, minimum, and maximum event size, ignition probability (the Poisson distribution rate parameter), and *k*, functionally equivalent to the mean fire rotation period, or FRP. The Base Fire model requires optimization to reproduce desired fire distributions, typically achieved by manual approximation of the ignition probability and FRP parameters. To improve model accuracy, we developed an automated transformation optimization technique based on Monte Carlo methods in signal processing, discussed in detail below.

Due to its mechanistic nature, the Dynamic Fuels and Fire System requires greater parameterization. Fire regions are similarly designated with raster image and corresponding lookup table, typically set to biogeoclimatic regions. The Dynamic Fire model requires the expected mean, standard deviation, and maximum log-normally distributed fire size, seasonal foliar moisture content (FMC) low-high averages and proportion of fires during high FMC conditions, open fuels class designation, and the annual frequency of fire initiation for each of the fire regions. The model further requires a seasons table with leaf status, proportion of fires, percent curing, and fire day length proportion. The model requires a fuel-type table based on FBP System classes, consisting of values for base type, surface type, initiation probability, three fuel type-specific rate-of-spread constants, the buildup index (BUI in the FBP System), maximum buildup effect (q in the FBP System), and crown base height, used to modify the initial spread index.

The Dynamic Fire model's fire damage table requires parameters for upper bound of cohort age range and the minimum difference between fire severity and tolerance for mortality to occur. An initial weather database is also required, or one year of daily-resolution fire weather station calculations for fine fuel moisture code, buildup index, wind speed velocity, fire weather index, fire weather index bin, season, and ecoregion. To model topographic effects on fire shape, users may input percent slope and upslope azimuth raster images, which we performed. The Dynamic Fuels model requires a fuel coefficient for each species and maximum site percent hardwood to be considered a coniferous fuel group. The fuels models requires a fuel type classification table to reclassify sites following succession and disturbance, with parameters for base fuel type, age range, and species present or absent. A disturbance conversion table can optionally be used to allow other disturbance types to modify the fuel type.

III. Model Parameterization

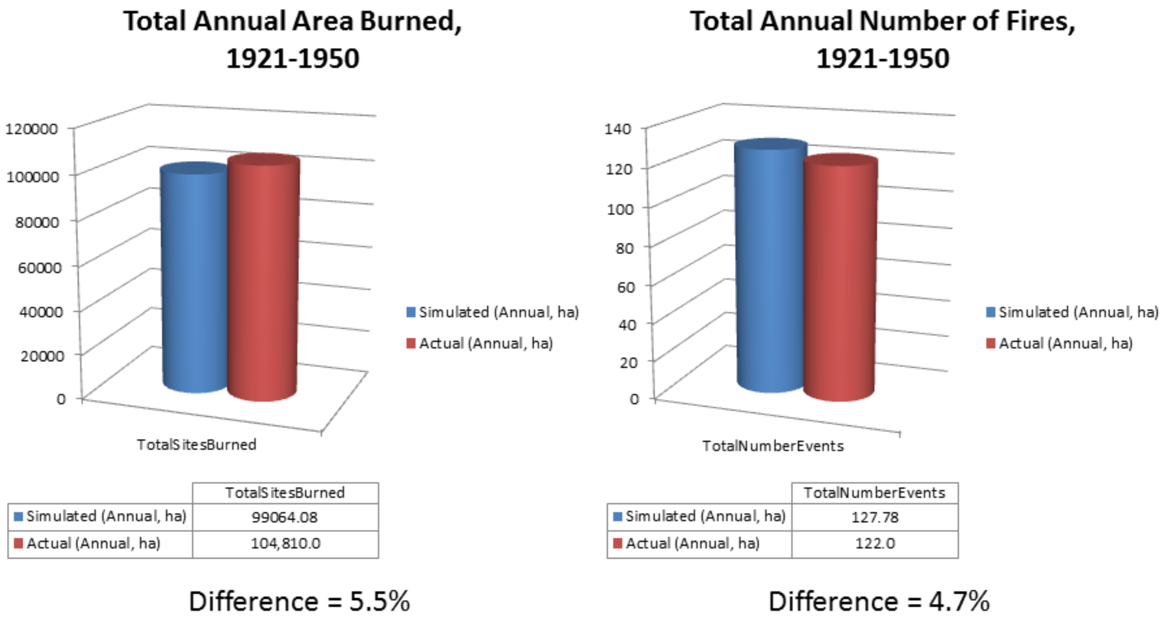
To parameterize the LANDIS-II model core, we used local species parameters where possible to incorporate local variability, otherwise deferring to two commonly used North

American silvicultural references (Burns & Honkala, 1990; Farrar & Canadian Forest Service., 1995). For more information on species parameters, see Appendix A. We used Brendan Ward`s double exponential model of seed dispersal (Ward et al., 2004). To parameterise species-age cohort initial communities, we conducted a rules-based classification of recent species distribution model outputs for western North America (Roberts & Hamann, 2012). While bioclimatic envelope model outputs may be less suitable for projecting future forest states, model results showed high accuracy in predicting current species distributions, a parameter currently unavailable through remote sensing products. While spatially interpolating plot data is common, bioclimatic envelope models may offer more accurate estimates of current species distributions (ibid). However, bioclimatic envelope models predating direct measurement techniques, often suffer from variable interdependence, due to use of pollen record for both interpolating species distributions and estimating climatic patterns.

We classified modeled species frequency values into known current vegetation assemblages from the Canadian Forest Fire Behaviour Prediction System. The fuel types used were Aspen (D-1), Boreal Spruce (C-2), Lodgepole or Jack Pine (C-3/C-4), Douglas-fir (C-7), and Boreal Mixedwood (M-1/M-2). For the age class distributions, we set each site to a homogeneous 0, 30, 60, and 90 year old age classes for each species, using 20-year model spin-up to replicate historical age class distributions. We used climate and fire patterns to reconstruct the initial landscape state, inferred to be the largest drivers of age classes and thus forest structure in northern forests. For biogeoclimatic regions, we utilized the Natural Subregions of Alberta.

We then used a fusion and reclassification of the Landcover for Agricultural Regions of Canada and the joint Canadian Forest Service-Canadian Space Agency Earth Observation for Sustainable Development of Forests, circa 2000 conditions, to mask our initial communities parameterisation. Using landcover fusion data, we defined three base cell states in LANDIS-II: active-treed, active-open, and inactive. We clipped the initial communities map to active-treed cells, defined by the presence of forests in the EOSD classes. Herb, grassland, and shrubland, and were set to active-open while agriculture, annual cropland, perennial crops and pasture, wetland, water, exposed land, snow/ice, rock/rubble, and built-up cells were all set to inactive. Forested sites were represented within their range and could expand into open natural areas with suitable conditions, but not into developed or resource-limited sites.

For Base Fire, we utilized historical fire distribution data from the Canadian National Wildfire Database for 1923 to 2012. For the fire region map, we used the Natural Subregions of Alberta. We used the default fuel curve table to represent five fire severity levels. We wrote custom R functions to calculate the mean, minimum, and maximum fire size, ignition probability, and FRP for each Natural Subregion. Since optimizing the stochastic Base Fire extension typically involves trial-and-error, we developed an automated iterative linear transformation method, based on Monte Carlo method signal processing, whereby simulations are run at low resolution for long durations in order to derive the signal for a given parameter space. Following each simulation, the fire parameters for each region are multiplied by a coefficient equal to the actual fire size divided by the simulated fire size. The performance of our parameter optimization approach is shown in Figure 30.



	TotalSitesBurned
🟦 Simulated (Annual, ha)	99064.08
🟥 Actual (Annual, ha)	104,810.0

Difference = 5.5%

	TotalNumberEvents
🟦 Simulated (Annual, ha)	127.78
🟥 Actual (Annual, ha)	122.0

Difference = 4.7%

Figure 30. Performance of Iterative Linear Transformation for Fire Parameter Optimization

First, the ignition probability is adjusted linearly for each region, until the simulated fire frequency is within 1% of the target range. Next, the same operation is applied to k values. The ignition probability adjustment can typically be performed in a single long annual time-step simulation, whereas the k adjustment may require a few iterations. The resulting improvement is often drastic. The method can produce a fire frequency well within 1% of the target, with R2 values over 0.99 for the simulated area burned in fire regions, compared to initial parameterization values approximately 20% and 0.75, respectively. The iterative linear transformation process is simple and efficient. However, if the fire regime for a given area deviates largely from the typical log-normal distribution modeled, Base Fire will be limited in its ability to reproduce the fire distribution.

For Dynamic Fire, we wrote custom R scripts to calculate the expected mean, standard deviation, maximum fire size, and annual fire frequency for each biogeoclimatic region and period. We wrote R functions derived from the FBP System to calculate seasonal FMC values for each region. We first calculated the regional minimum MFC date based on the latitude, longitude and elevation, before calculating the median seasonal FMC based on ordinal dates for the vernal equinox, summer solstice, autumnal equinox, and winter solstice. We then used this output to calculate the corresponding proportion of fire occurring during the high FMC period. Low and high FMC period cut-offs were set to 25% and 75% of the maximum, respectively, based on the mean. We used Natural Subregions as the fire regions map. For percent ground slope and uphill azimuth, we downloaded SRTM version 2 data from NASA JPL and processed it using ENVI. We used standard interpolation techniques for filling low RADAR backscatter voids in mountainous regions, before calculating ground slope percent and uphill slope azimuth. For the fire seasons table, we set the leaf status for spring, summer, and fall to leaf off, leaf on, and leaf off, respectively. We calculated the proportion of fires during each season by using a subset of the fire database with date information available, converted to ordinal date and then season. The percent curing values were calculated as a function of FMC value, using a grassland curing index equation (Dilley et al., 2004), using the mean curing index value for each season. Day length proportion for fires was set to one.

An initial fire weather database was calculated based on values derived from Alberta Agriculture and Rural Development's historical fire weather station data. We selected fire weather stations the closest to the center within each Natural Subregion. We used daily resolution decadal scale fire weather data for the April 2012 through March 2013 fire weather season for each of the Natural Subregions to represent the most recent conditions. The daily metrics downloaded for each station include precipitation, mean temperature, mean humidity, wind speed at 10m above ground, and wind direction at 10m above ground. We first used the R mtsdi time-series imputation package to impute missing values for the period, using the default EM algorithm and splines method. We then used the R fwi.fbp package to calculate daily values for fine fuel moisture content, build-up index, and fire weather index with standard equations (Van Wagner, 1987). We create five different fire weather index bins using the R Hmisc package, binning continuous variables into five quantile groups. We maintained original values for wind speed and direction at 10m above ground, adding values for season and Natural Subregion.

To parameterize the fuel type table, we used standard FBP System fuel classes and parameters (Forestry Canada Fire Danger Group, 1992). The parameters include base type, surface type, initiation probability, a, b, and c rate-of-spread parameters, a q depth dryness parameter, build-up index, maximum build-up effect, and crown base height. We set the fuel types not currently present in the landscape to inactive. We used a standard fire damage table, whereby the likelihood of a cohort being killed decreases it ages, based on species-specific fire tolerances, with transitions at 20%, 50%, 85% and 100% age percent of longevity.

We used the optional Dynamic Fuels extension, whereby the landscape is classified into fuels groups following the completion of each simulation year. This way, fire patterns realistically change as the landscape fuels are altered by succession and disturbance. To parameterize the fuels model, we assigned every species present in the landscape with a fuel reclassification coefficient of 1.0, so that they are equally weighted. We set the hardwood maximum composition for conifer stands to 10%. We based the fuel type reclassification table on the FBP System, utilizing its definitions for species composition and age class ranges.

IV. Scenario Runs

We ran simulations based on four 30-year historical time periods at annual resolution. The periods used for TACA-EM and LANDIS-II parameterization consisted of 1923-1952, 1953-1982, 1983-2012, and 2003-2012, with fire weather based on the 2012-

2013 season. The simulations were designed to model the continuation of historical fire and climate patterns thirty years ahead from the present, by running models for fifty years and dedicating the first twenty years to model spin-up. We focus on changes to fire, as a preliminary analysis of weather station data indicated a mild linear warning trend across the full 1923-2012 time period. The 1923-1952 period represents pre-suppression era fire regimes, 1953-1982 represents early suppression, 1983-2012 represents intensive anthropogenic activity, and 2003-2012 represents the recent spike in fire frequency and milder increase in area burned. For each scenario, we analysed changes to biogeoclimatic region fire regimes, relative species abundance, species richness, and age class richness. We focused on outputs important for long-term forest dynamics and grizzly bear habitat across the study area.

Results

I. Historical Fire Regime Analysis

The results of our historical fire regime analysis indicated three distinct 30-year fire regime periods corresponding to known changes in management. Changes to fire frequency, total area burned, and mean annual area burned are evident. The three scenario periods are 1923-1952, 1953-1982, and 1983-2012. We included the 2003-2012 period to model the continuation of recent trends showing a marked increase in fire frequency and decline in mean fire size. These changes to fire regimes are anticipated to correspond to coupled anthropogenic-climatic change. Warming is evident throughout the period from instrument-adjusted direct weather station measurements and proxies, including changes in fire season initiation and length.

The advent of fire suppression is clearly discernible mid-century, following the Chinchaga wildfire of 1950. Thereafter, mean fire size steadily declined even as warming produced more favourable fire conditions. The area burned followed a similar trend, rising in 1998 at the beginning of a rapid increase in fire frequency. An increase in fire suppression corresponds to an increasing human presence in forested regions, as Alberta's population grew roughly seven-fold from 1923-2011 (Statistics Canada, 2011). While most large fires remain caused by lightning, an overall increase in the number of human-caused fires is indicative of greater anthropogenic activity.

The ratio of human- to lightning-caused fires grew from 1.10 during 1923-2003 to 1.69 during 2003-2012. The results indicate that increased anthropogenic activity explains most the increase in frequency of small fires, though warming is known to increase the frequency of cloud-to-ground lightning strikes (Saunders, 1993) and favourability of fire weather conditions. A visual confirmation using point data from the Canadian National Fire Database indicates that, an increasing amount of small fires occurred near human hotspots in recent years, typically concentrated around roads. This finding is supported by the literature, which show a non-linear U-shaped relationship between anthropogenic activity and fire ignition probability. Due to the generally greater remoteness of Alberta's burnable land compared to that of California, the relationship appears much more linear in our study area. A comprehensive study of fire suppression efficacy indicates that suppression activities were successful (Cumming, 2005), accounting for the steady decline in mean area burned and a relatively small increase in total area burned in recent years, given a marked rise in fire frequency. The persistence of successful suppression under novel climatic conditions and still-increasing anthropogenic activity is uncertain, while the cost of suppression is likely to increase (ibid). Across the full period, the fire season began earlier and ended later in the year, indicative of lengthened fire seasons, a phenomenon that has troubled managers in recent years (Tymstra et al., 2007).

The fire season length increase matches previous predictions (Wotton & Flannigan, 1993). In contrast, the anticipated increase in area burned is counter to our empirical analysis, which shows only a recent rise in total area burned, even though climate warming extended across the full period. It is evident that human factors are also driving fire regimes in an era of widespread anthropogenic activity.The largest fires and annual area burned occurred in the boreal forest, followed distantly by the foothills and Rocky Mountain regions. Within the boreal, the mixedwood zone experienced more area burned than the highlands.

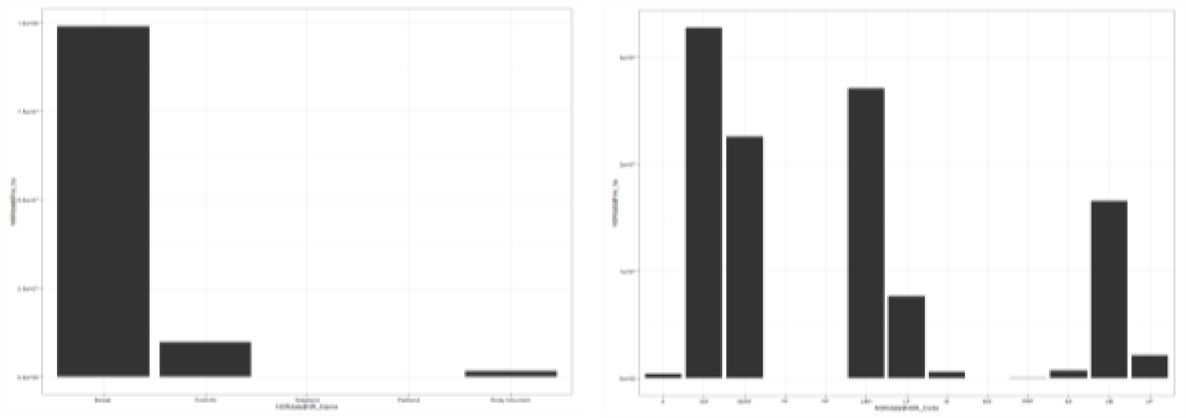


Figure 31. Area Burned by Natural Region and Natural Subregion, 1923-2012

The prevalence of large fires in the boreal is supported by previous studies (Flannigan, Logan, Amiro, Skinner, & Stocks, 2005; Tymstra et al., 2007). However, these studies fail to note empirical evidence of increasingly small boreal fires, counter to climate-based correlative predictions of larger and more intense fires. We estimate that the reduced size of boreal fires is attributable to two factors: (1) reduced fuel loads resulting from increased anthropogenic-source fire frequency, and (2) an increase in suppression resources. In addition, we found that most fires occurred at the cusp of the modeled spring dip in foliar moisture content, rather than at the base, where they would be expected to occur (Figure 32). This finding implies that the foliar moisture content model used in the Canadian Fire Behaviour Prediction System may require regional adjustment.

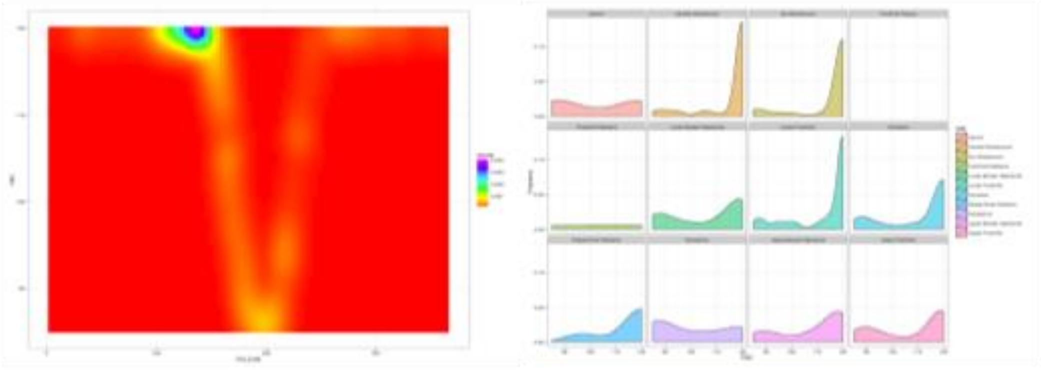


Figure 32. Frequency of fires relative to foliar moisture content (FMC)

II. TACA-EM

Our TACA-EM model results indicate that the realized niche of tree species are increasingly under suboptimal phenological establishment conditions, compared to historical periods (Figure 33). Species responses differ interregionally, but exhibit a high degree of interspecific agreement intraregionally. As previously shown in empirical studies (Kullman, 2001), higher elevations are experiencing improved suitability as temperatures rise. Precipitation patterns have also been shown to drive distributions downward in regions, due to a changing water balance (Crimmins et al., 2011). However, many of the lowland areas of western Alberta are characterized by loam soils and morainal parent material, related to a glacial and fluvial history (Cathcart et al., 2008), with high porosity and infiltration rates producing low pore pressure, field capacity, and available soil water capacity. In western Alberta, the differences in response across the four time periods indicate that climatic warming is diminishing establishment suitability across lowland areas, where coarse aeolian deposits and glacial till soils drain water rapidly and produce an increased incidence of drought. Drought limitations related to generally coarse soils also appear to be limiting subalpine and montane region suitability. Here, TACA-EM could be improved by approximating snow accumulation and melt using existing weather time-series parameters.

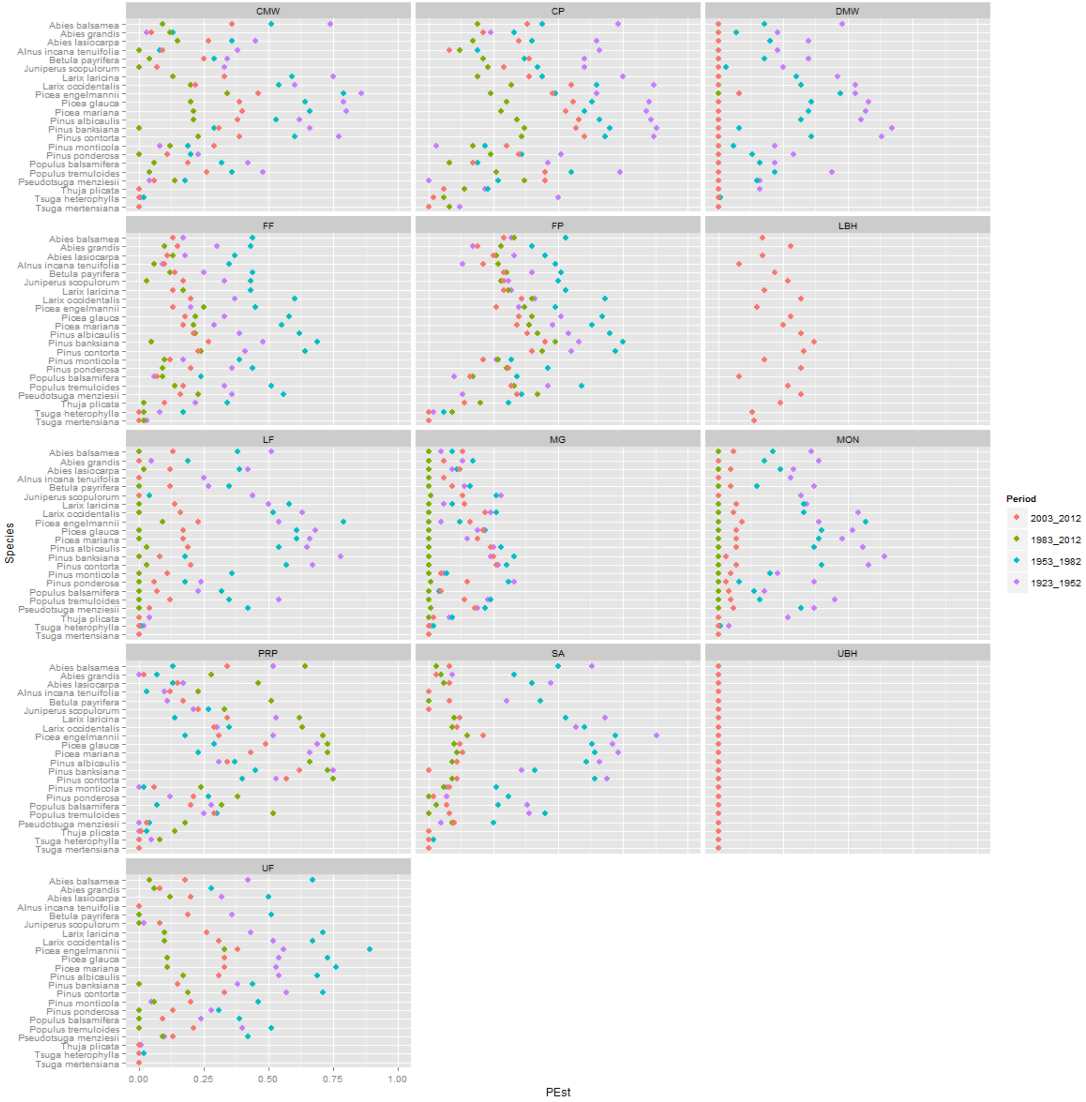


Figure 33. Species establishment by Natural Subregion and time period

III. LANDIS-II

We utilized LANDIS-II to simulate the coupled effects of changing fire regimes and species establishment. Our results show clear differences in forest composition and structure stemming from coupled changes to climate and fire. Under the persistence of large historical fires that characterized the boreal forest in the pre-suppression era, selection pressure was fire-driven, reflected in the continued prevalence of pyrogenic species such as pine and aspen. Fires were less frequent, but larger than during other time periods, creating a landscape composed of spatially distant heterogeneous patches, reflecting reduced age class distribution entropy. The LANDIS-II model results showed clearly different implications for continued historical coupled climate-fire patterns. The modeled changes to fire frequency and area burned show distinct patterns across the different time periods.

As the climate warmed, evidenced by weather station measurements and TACA-EM outputs, fire sizes decreased while frequency increased. We found that coupled climate-fire changes markedly increased species-age class diffusion across the landscape, transitioning from large homogeneous mosaics into Gaussian noise-like patterns, related to the stochastic fire site algorithm combined with small fire sizes. Concurrently, tree species and fire regimes migrated upland. The incidence of drought appears most related to high percentages of sand and till in soils, and low percentages of clay and silt, related to increased infiltration rates and reduced available soil water capacity. These soil properties were shared by high elevation and some low elevation areas, related to a history of glaciation, fluvial processes, and aeolian deposition.

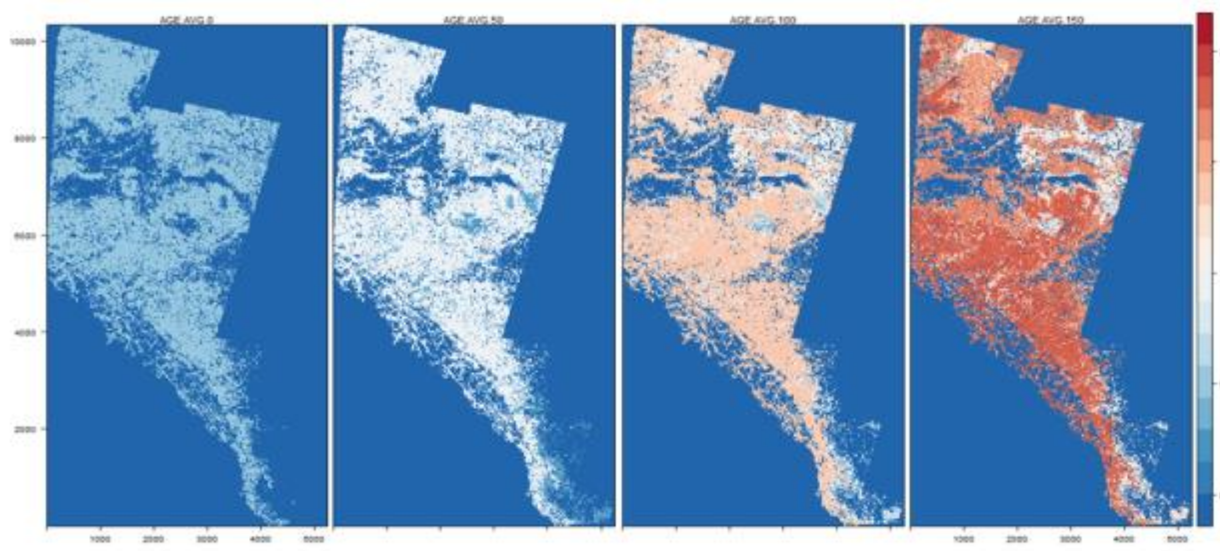


Figure 34. Forest structural change for the simulated time period 1923-1953, showing model spin-up effects

Forest change was generally more structural than compositional, as our simulations were 50 years in overall duration, including approximately 10 years of model spin-up. Temporally extended, the prevalence of many small fires in later years is likely to facilitate faster compositional changes by making available many pockets of suitable habitat for disbursed seeds from neighboring stands. While large fires also create suitable habitat for pioneer species, the reduced fire frequency and relative isolation of sites both serve to slow species migrations, compounded when combined. Changes to species relative abundance reflects coupled climate-fire dynamics for each of the time periods, through changing establishment probabilities, fire frequency, fire severity, and fire sizes, altering the species-specific reach and success of dispersal vectors. Within these species-specific changes in landscape composition, we find patterns of genera-specific responses related to shared species life history attributed and biophysical phenological responses. We find that historical fire periods comprised of lower frequency but larger fires supports much greater landscape compositional and age class stability. Changing fire regimes in the 1983-2012 and recent 2003-2012 period clearly indicate that tranistions in species compositions are likely to occur at a much more rapid pace than previously in history.

A.5.10. Modeling Tree Species Regeneration Niche Response to Climate Change

Introduction

There are three commonly deployed types of models applied to forests: individual tree models, forest landscape models, and gap models. Individual tree models simulate forests at an arboreal organismal scale, from greatly simplified to intricate in spatiotemporal and biophysical detail. Confusingly, individual tree models such as FOREST and SORTIE, are often classified as gap models, as they are designed to function at the stand scale (Bugmann, 2001). Forest landscape models simulate changes to forests in aggregate at the landscape-scale and are thus generally greatly simplified, involving numerous scale-related assumptions. Gap models, based on the theory of gap or patch dynamics, typically simulate tree dynamics at the stand, rather than individual or landscape, scale. The scale for stands typically ranges from 100 m^2, as in the original JABOWA model, to 1000 m^2 stands, effective for high-latitude forests with narrow-crowned trees, as is the case in Alberta. Gap models have been shown to accurately predict forest dynamics at the stand scale. Trees within stands are represented either individually or in aggregate as cohorts or height classes. Some gap models track the location of individual trees within patches, while others are horizontally homogeneous, whereby within-patch tree position is ignored. Gap models are the most widely applied group of mechanistic models used to analyze forest response to climatic change.

While early gap models focused mostly on stand-scale dynamics of tree growth (e.g., ZELIG), reflecting a long history of empirical growth and yield models, recent gap models have expanded to simulate stand-scale establishment (e.g., TACA-GEM) and landscape-scale disturbance (e.g., LANDIS-II), dynamics previously neglected. Gap models grew in development parallel to the study of landscape ecology, where gap models are useful for forming and testing hypotheses about long-term processes difficult to measure, due to the long-lived nature of arboreal organisms. A noteworthy gap model improvement for high latitudes was the change from modeling tree crowns as two-dimensional disks to three-dimensional cylinders. The cylindrical crown model developed in the FORSKA family of models greatly improved the accuracy of insolation modeling in Sweden (Prentice & Leemans, 1990), with implications for other regions that experience low solar altitudes. The more recent ZELIG family of models, originally developed for use in the Pacific Northwest of the United States, utilize this improvement. The TACA-EM model, a specialized ZELIG family model, ignores tree crowns altogether to focus on the regeneration niche and establishment.

Gap models employ scale- and process-dependent assumptions to reduce complexity, addressing logistical modeling challenges while maintaining realism and precision. Within gap models, growth sub-models are generally biophysical in basis, though model assumptions vary. Biophysically based models are estimated to produce a robust representation of environment-vegetation relationships given novel environmental conditions, while correlative statistical relationships have the potential to uncouple, yielding greater uncertainty. Simple models may outperform more complex models, but only when there is an absence of data for model parameterization (Mikkelson, 2001). Though biophysically based models are generally complex, there exist a number of model simplifications. The strength of hybrid models is that they represent biophysical relationships both mathematically and empirically, simplifying some processes while maintaining realism in others less sensitive to the stand scale. Biophysical models often do not incorporate processes related to population genetics or phenotype plasticity, let alone fine-scale atomic or molecular processes governed by quantum mechanics, as increased complexity poses many challenges. A strength of biophysically based models is that they are typically modular in design, enabling the addition of novel processes through mathematical sub-models and related coefficients.

The relevance of biophysical processes to ecological models depends on the scale of analysis. The TACA-GEM model is primarily designed to function aspatially and does not include growth, allometric-based biomass, or mortality equations, unlike its predecessor ZELIG++. Similar to bioclimatic envelope models that can perform calculations for a single site or across matrices, the site-level scale of TACA-GEM can be extrapolated to the landscape-scale, given spatial climate, soils, and species data. The key constraint to applying TACA-GEM at the landscape-scale is currently logistical, as it is built within Excel and requires manual inputs, which does not require programming skills, but is markedly inefficient compared to a C++ implementation. Currently, TACA-GEM must be applied at individual sites, or its results extrapolated across relatively homogeneous classes of regions, which we perform in this work. Advancements in remote sensing and in the processing of ground-level data continue to increase the extent of applicability of TACA-GEM, 3-PGS, and related biophysically based models.

For our comparative analysis, we consider only the ZELIG family of models, further including ZELIG++ (Burton & Cumming, 1995), TACA-EM, and TACA-GEM, which, excluding the latter, have been applied in or adjacent to western Alberta. Both ZELIG++ and TACA-EM are based on the individual forest stand (gap or patch) model approach of JABOWA (Botkin et al., 1972) and FORET (Shugart, 1984; Urban et al., 1991), collectively known as the JABOWA-FORET gap model genre, or simply gap models. Most gap models simulate mortality and regeneration stochastically while growth is modeled deterministically. Tree growth is often modeled parametrically using sum of growing degree-days, soil moisture availability, and solar radiation, with species-specific growth constraints for each parameter. In ZELIG (Figure 35) and subsequent models, soil moisture is estimated as a function of temperature, or potential evapotranspiration. Thus, climate is an extrinsic driver in ZELIG (Urban et al., 1993). The ZELIG family of gap models was also the first gap model to include spatial interactions, building on a rich history of cellular automata that began with John von Neumann at Los Alamos National Laboratory in the late 1940s (von Neumann, 1966).

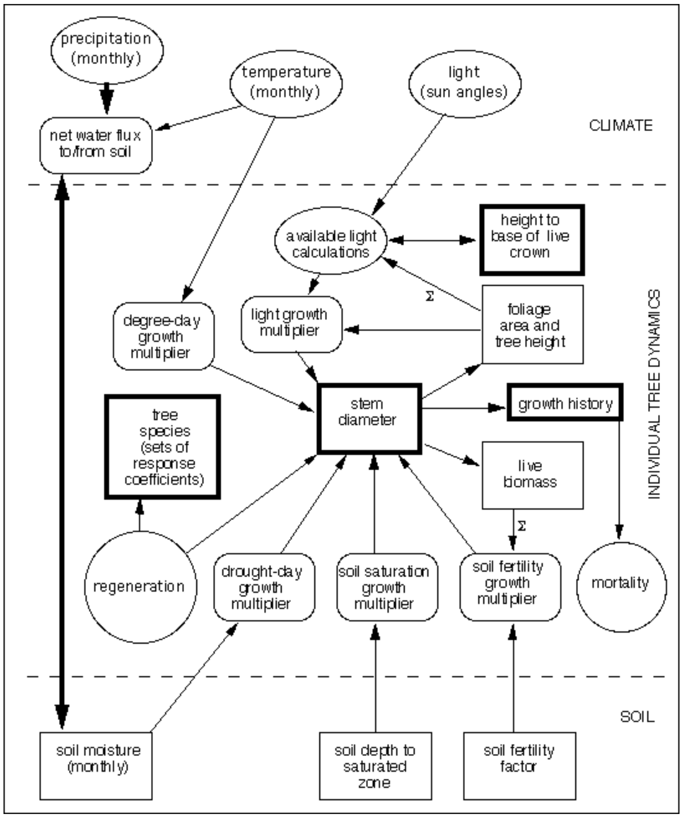


Figure 35. The ZELIG model framework (Urban 1990)

The ZELIG++ model improved the original ZELIG model by incorporating phenological event-based temperature response, rather than traditional gap model heat sum curves, and by implementing the model in the more efficient C++ programming language. The improved ZELIG++ model is otherwise fundamentally similar to the ZELIG model, shown in Figure 35. The incorporation of phenological events (i.e., bud-break, growing season, chilling requirement, frost hardiness, killing frosts, and early frosts) and species-specific responses in ZELIG++ improved model accuracy in predicting species distributions in British Columbia compared to ZELIG. Soil water deficit was the primary growth constraint shown in the simulations. The TACA-EM model is similar to the ZELIG++ model, upon which it is based, including utilizing phenological temperature response. However, TACA-EM does not include any spatial, growth, volumetric, or mortality equations. The TACA-EM model instead specializes in modeling the regeneration niche of species, as it is estimated to be the most venerable to climatic change (ibid). The TACA-EM model was created specifically to simulate the impact of climatic change on tree populations by placing a unique emphasis on phenology within an aspatial biophysically based gap model focusing on species establishment.

Similar to ZELIG++, TACA-EM's driving variables are growing degree-days, species-specific threshold temperature, minimum temperature, chilling requirement, bud break, drought, and frost. Since TACA-EM (Figure 36) does not model growth, frost events are instead used to modify species establishment coefficients, with more frequent events leading to lower establishment values. Frost events are used because species are most susceptible to frost damage in the regeneration phase, becoming at greater risk of pathogens. The TACA-EM model assumes a species absent if its chilling requirements are not met. Similar to ZELIG++, TACA-EM uses a ratio of actual evapotranspiration to potential evapotranspiration based on the Thornwaite-Mather equations (Thornthwaite & Mather, 1955, 1957) to calculate drought, using temperature. If a species-specific drought tolerance threshold is exceeded, the species is assumed to be absent.

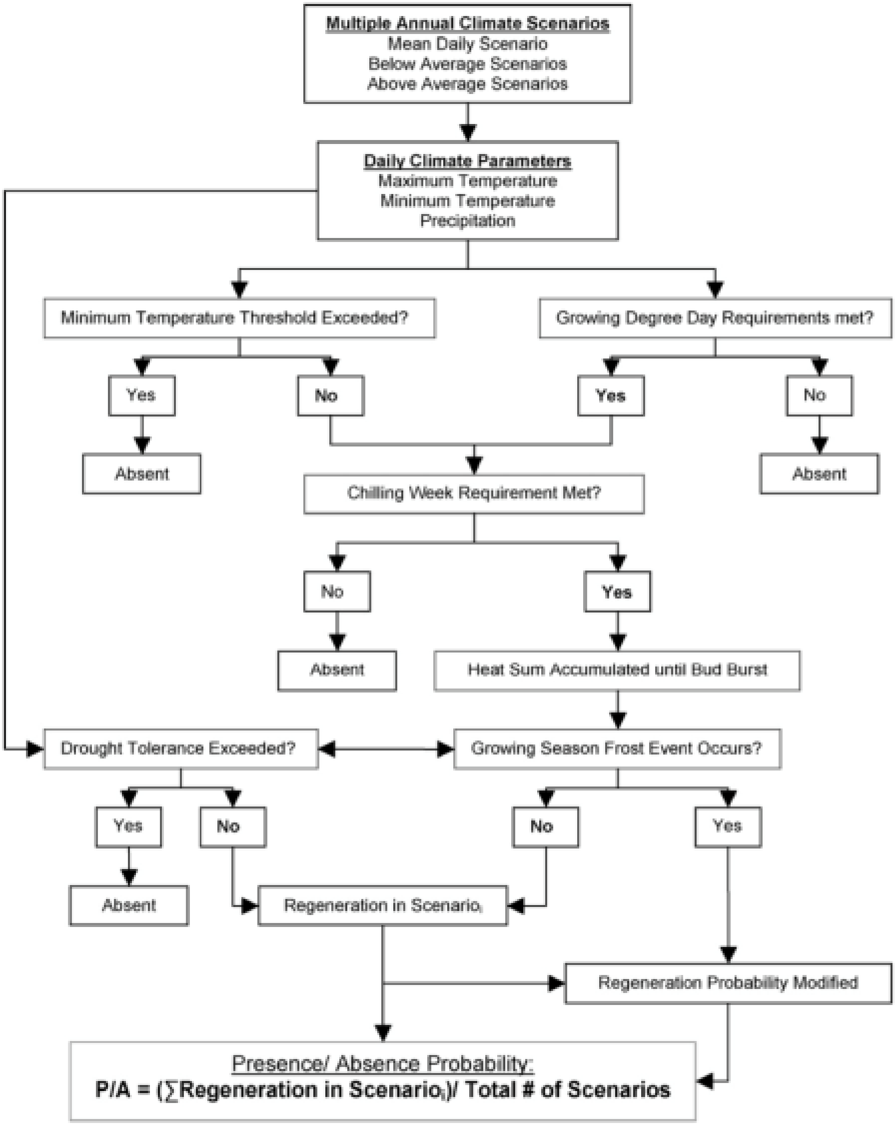


Figure 36. The TACA-EM model framework (Nitschke and Innes 2008)

The TACA-GEM model (Mok et al., 2012) advances the TACA-EM model (Figure 37a) by adding an optional germination sub-model (Figure 37b). The germination sub-model combines species phenology and germination processes related to temperature, soil moisture, and frost, using species-specific functions for dormancy, heat sum, and frost modifiers. The germination sub-model is empirical rather than mathematical in design, and is intended to simulate the effects of climatic change on germination processes. TACA-GEM operates on the assumptions of ample light and substrate for regeneration, as well as sufficient availability of viable seed – assumptions that must be addressed outside of the model for a give site. TACA-GEM does not currently account for vapor pressure deficit, successive droughts, extreme climatic events, or species interactions, though it does indirectly model phenotype plasticity. A weakness noted in TACA-GEM is the lack of species competition and spatial interactions, which are important drivers of change. While TACA-GEM results can be extrapolated across landscape matrices, they can also be used more effectively as establishment inputs in cellular automata hybrid models that already simulate important spatial and aspatial processes (e.g., within LANDIS-II succession extensions).

Here, we fuse outputs from an aspatial stand-scale hybrid (mathematical-empirical) model specializing in germination and establishment, TACA-GEM, with a spatially explicit landscape-scale hybrid model, LANDIS-II. In doing so, we couple aspatial germination and establishment model processes with spatially explicit and interspecific model processes for a more realistic representation of forest ecosystems in western Alberta. Combined models are sometimes referred to as meta-models, a term loosely borrowed from computer science, approximating to a higher-order model, or a model of models. A more precise term would be a coupled-model approach, as the TACA-GEM and LANDIS-II models are bound through establishment parameters iteratively called at every simulation time-step, compounding over time in effect.

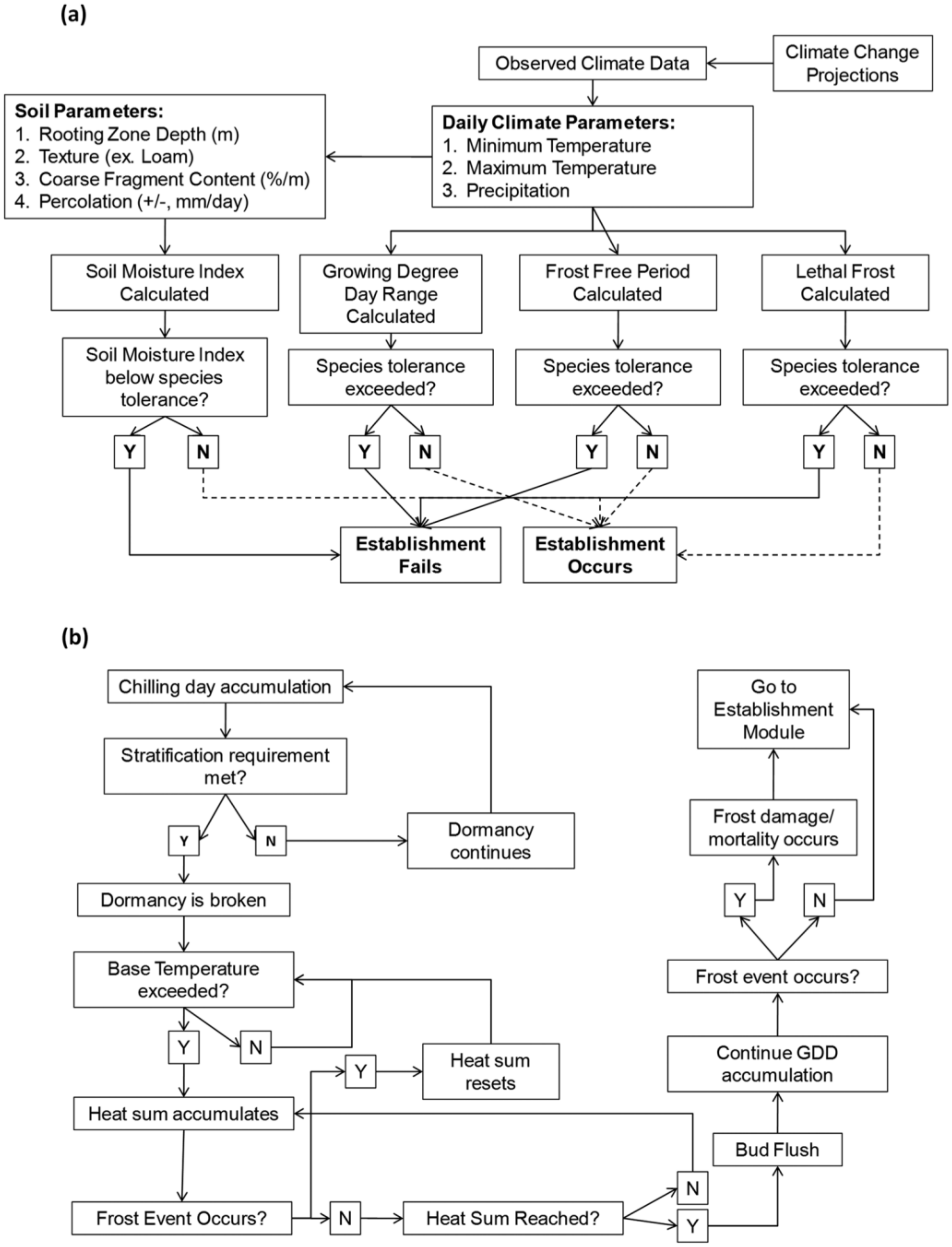


Figure 37. The TACA-GEM model framework (Nitschke et al. 2012)

Bioclimatic envelope models, commonly called species distribution models, fundamentally differ in that they are statistical rather than mechanistic models. Statistical models are also known as equilibrium models, as they assume a fixed correlative relationship between climate and vegetation. Bioclimatic envelope models are omitted from this analysis, as they do not explicitly describe the mechanisms that drive species response to change, but are instead based on the assumed static statistical correlation of environmental data with the realized niche of species. While statistical models may do well within the scope of historical climatic ranges, by which most statistical models are fundamentally constrained, the absence of an empirical basis markedly reduces predictive power given novel environmental conditions. Though bioclimatic envelope models have proven accurate for predicting past or current species distributions in western Canada, their ability to forward-project environment-vegetation relationships is unsupported (Urban et al., 2011). Bioclimatic envelope models sacrifice realism to generality and precision.

Methods

Climate data used to parameterize the Tree and Climate Assessment Germination and Establishment Model (TACA-GEM) model were derived from the latest National Oceanic and Atmospheric Administration (NOAA) Global Historical Climate Network (GHCN) Daily dataset version 3.11, maintained at NOAA's National Climatic Data Center (NCDC). The latest GHCN-Daily dataset provides a suite of 133 climate metrics for 86,738 weather stations in 180 countries, compiled from numerous sources and subjected to uniform quality assurance reviews. Two-thirds of the weather stations report precipitation data only, while a limited number of stations report metrics other than the main three: precipitation, maximum temperature, and minimum temperature. The benefit of using the NOAA GHCN-Daily data set is that it routinely undergoes quality check-quality assurance and it has global coverage at a daily time step. The raw global historical weather station data was downloaded and processed using custom scripts written in the R programming language. We collected and formatted descriptive weather station data for the global dataset, which contains information about each weather station, including the metrics and years of data availability for each station. We subset the descriptive weather station information by the Federal Information Processing Standards (FIPS) country code for Canada, producing weather station information for the country. We used a custom spatial clipping function to extract and classify descriptive weather station data for each Alberta Natural Subregion falling within the Foothills Research Institute Grizzly Bear Program's Phase 7 Study Area boundary (Figure 38).

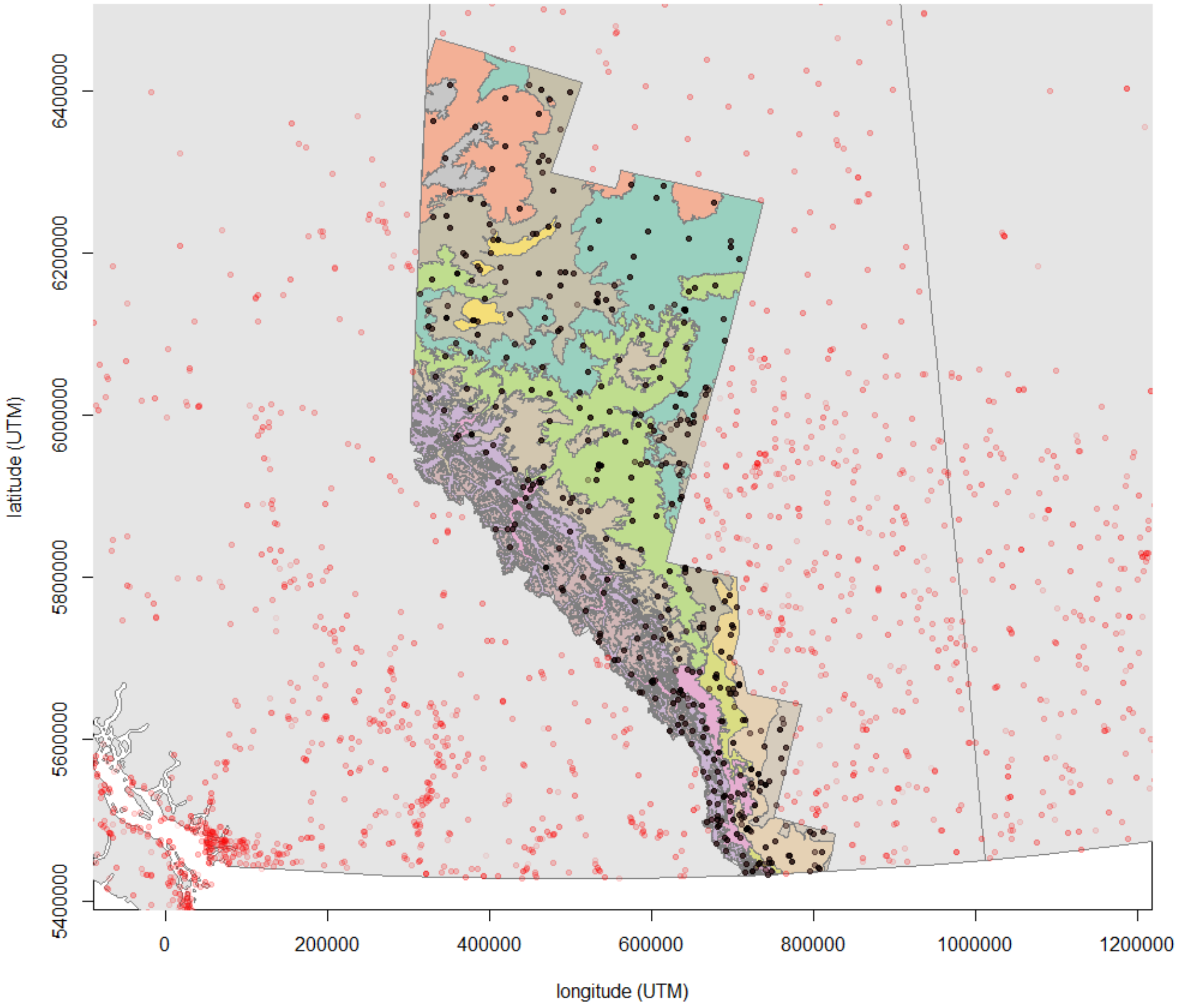


Figure 38. NOAA GHCN-Daily Weather Stations in the Proximity of Natural Subregions within the Phase 7 Study Area

The spatial subsetting function includes the automated mapping of weather station locations within the study area, binding the Natural Subregion class information to each of the weather station spatial data frames. Using this method, we can quickly and simply extract weather station data for single or multiple user-defined spatial classes anywhere in the world by adding a single ESRI shapefile file path parameter to the function call. The function pulls the projection information from the user-provided shapefile and uses it to re-project the WGS84-projected latitude and longitude information contained within the descriptive station information data. We can thereby map stations by location using symbology based on a suite of descriptors appended to the attribute table during the subsetting process. We used this spatial subset of the descriptive weather station data to filter and download raw historical weather station data for each weather station falling within each class in the study area. We added another parameter to this function call to subset for stations that provide the desired climatic variables and year range of interest.

Our scripts are deliberately designed to subset the descriptive weather station information to the highest degree possible before downloading the raw weather station data, in order to reduce the amount of processing and downloading overhead and thus speeding operation. After downloading the raw individual weather station data for the study area, we automatically formatted and exported the data by class with a separate custom function that reduces the data frames to the elements of interest. To parameterize TACA-GEM, we filtered the raw weather station files to include only stations that have at least partial coverage of maximum temperature, minimum temperature, and precipitation. The NOAA GHCN-Daily dataset is an excellent resource for gathering these three climatic metrics at a daily time-step on a global scale. Other variables within the NOAA GHCN-Daily dataset are comparatively sparse. Figure 39 summarizes the number of stations available in each of the Natural Subregion Classes.

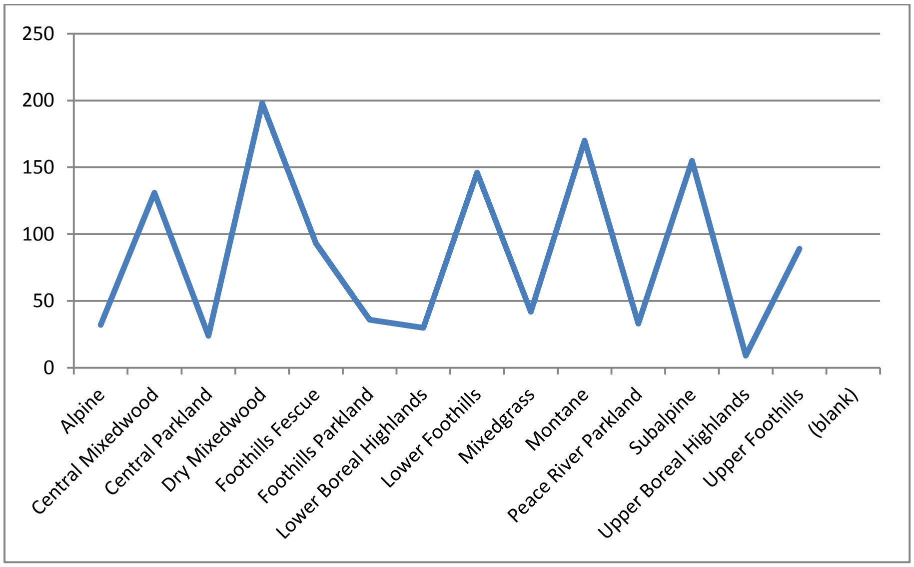


Figure 39. Sum of Station Individual Parameter Metrics by Natural Subregion

Once we downloaded and formatted all of the individual weather station historical data for each Alberta Natural Subregion within the Phase 7 Study Area, we applied a novel method of summarizing data across weather stations by Natural Subregion at a daily time step. This method iteratively reads in all of the weather stations for a class and binds them together by row for each desired metric in order to calculate a daily average for the region across the full temporal scale. The function first constructs a table of all of the weather station identification codes and corresponding Natural Subregion classes. In order to again improve memory efficiency, the code is designed to iteratively load classes of weather station data. The code utilizes loop parallelization and C wrappers with binary search where possible to improve memory efficiency and computation time.

We additionally produced methods of computing decadal-scale daily resolution weather data summarized by region, required for our TACA-GEM model iterations. We also produced a novel method of creating decadal-scale daily weather regional summaries in a way that reflects broader temporal trends of climatic change. A straightforward method of including the effects of three decades of climatic data in TACA-GEM, which requires daily scale data for individual decades, is to model each of the decades separately and average the results for the supra-decadal scale (e.g., 30-year periods in our case). Given logistical model challenges, concerns over the loss of decadal climatic variability, and substantial temporal gaps in weather station data, we produced a new method of climate data summarization that addresses each of these challenges. Paired with the NOAA GHCN-Daily dataset, this solution is well attuned to parameterizing TACA-GEM to summarize the effects of climatic change.

As TACA-GEM model inception involved transferring the ZELIG++ model from the highly efficient C++ programming language to Microsoft Excel in order to facilitate improved access for practicing forest managers, TACA-GEM can be time-inefficient to parameterize for multiple iterations and/or classes. We required a method that would give us comparable results to the aforementioned approach without suffering from as many shortcomings. We employ a novel method comprised of a simple vector math function that averages adjacent positive and negative temporal scale multiples before averaging these multiples with the median temporal range values. We term this approach scale-multiple neighborhood averaging.

Simply calculating the mean daily element values for a decadal scale (our user-defined time period) at a daily resolution (the resolution required within TACA-GEM) would dampen any apparent cross-decadal climatic variability related to the Pacific Decadal Oscillation and/or decadal variability relate to the Quasi-Decadal Oscillation. In effect, any climatic cycles or forcings beyond the decadal scale or out of phase with the decade of interest would likely be averaged into an unrealistically flat and simplified waveform. Thus, we created methods that better maintain the inhomogeneous waveform nature of distinct climatic periods. Such decadal changes to waveform are estimated to be of marked importance to mechanistic species distribution models, particularly those that include germination. Although our method still suffers from some of the same shortcomings, it does so to a far lesser degree. Averaging along neighborhood scales before averaging with the median period of interest effectively weights the median values to retain more of the original waveform.

Daily scale decadal climatic variability is believed to be of vital importance to the phenological and biophysical regeneration niche processes TACA-GEM is designed to model. The TACA-GEM model produces a probability distribution of species presence/absence based on the following seven driving variables: growing degree-day thresholds, species-specific threshold temperature, minimum temperature, chilling requirement, bud break, drought, and frost. We desired to include broader 30-year trends in species response to climatic change in order to directly overlap our analysis of species response to climatic and edaphic conditions with historical trends in wildfire regimes. Using this method, we can connect changing species responses to climatic and edaphic conditions to trends in fire regimes to determine coupled effects difficult to discern by disparate analyses. The results of our TACA-GEM model runs and historical fire regime analysis will be fused through parameterizing the LANDIS-II landscape-scale forest ecosystem simulation program in order to analyze the potential effects of coupled processes of change. Similar to constructive and destructive interference resulting from the phase of two waves in summation, the coupling of these two temporally distinct dynamics may combine to amplify or attenuate landscape-scale vegetational change (Figure 40). Of particular interest to our work is how these processes may combine to alter the distribution and abundance of grizzly bear (*Ursus arctos*) foods.

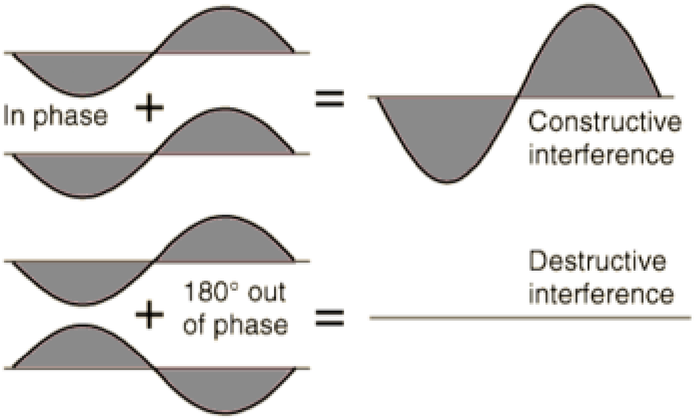


Figure 40. Constructive and destructive interference produced by summing two waves (image adapted from Georgia State University HyperPhysics)

Whether we utilize scale-multiple neighborhood averaging or simply calculate the class climatic variable averages for each day, missing values are imputed using a multivariate model based on Amelia-II, which assumes multivariate distribution normality. The method of imputation used utilizes a training dataset to speed the imputation process, producing results consistent with the Amelia-II algorithm. We used this function to impute missing values for maximum temperature, minimum temperature, and precipitation for each of the three ten-year time periods of interest (1921-1950, 1951-1980, 1981-2010). The full summary of our TACA-GEM parameterisations, using both ClimateWNA 30-year monthly resolution climate averages and NOAA GHCN daily resolution data, is shown in Appendix A.5.10. The establishment probabilities for each species, Natural Subregion, and climate scenario are used to parameterise species response to environmental conditions within succession extensions of LANDIS-II.

Results

We applied the TACA-GEM model (Mok et al. 2012), including its new germination submodel, to Natural Subregions (NSRs) within the Foothills Research Institute's Phase 7 Study Area of western Alberta. The NSRs represent biogeoclimatically homogeneous zones, similar to the BEC system in British Columbia. In addition to developing novel processes for NOAA GHCN-Daily weather data, we created a novel method that allows us to use the Soil Landscapes of Canada (SLC) version 3.2 to parameterize mode soil type for each of the NSRs for use in TACA-GEM. As previously described, this method is unique in its applicability Canada-wide. Combined with the NOAA GHCN-Daily dataset and a few conversions inferred from additional sources, we were able to successfully parameterize TACA-GEM for each of the Natural Subregions. The only persistent challenge is creating biophysical species parameters for two species within the study area, for which there was no readily available data. To account for the two species' realized niche space, we averaged biophysical properties for biogeoclimatically and physiologically near species, explicitly assuming continued spatial autocorrelation of currently proximate species. Our work modeling tree species regeneration niche in TACA-GEM, or how each species is estimated to respond to changing climatic and edaphic conditions, culminated in probability distributions for each biogeoclimatic region.

Individual species response to climatic change, inferred from changes to establishment probabilities in Figure 41, indicate that species tend to respond similarly to climatic change within regions. The finding is surprising given that one would expect the unique autecology of species, formed through its evolutionary history, to produce a less homogeneous response. In our model outputs, some regions are shown to be generally less suitable for all species, while others are generally more suitable. These values represent absolute change in establishment values rather than relative change; species that fail to establish in both scenarios or whose values are cancelled out appear unchanged. There are clear differences in species response in the Central Mixedwood NSR, discernible in the variability in establishment change values for a region (variance or standard deviation of change in establishment probability would thus be an appropriate metric). The Central Mixedwood NSR is one of the few lowland forested regions, theoretically more likely to experience a higher variability of response (Bertrand et al., 2011). Contrastingly, the Mixedgrass NSR exhibits the least amount of variability, due to consistently unsuitable conditions across scenarios related to soil moisture constraints. In essence, the homogeneous response of species within regions may be explained by patterns of species realised niche related to the autecology of cold weather-adapted species along latitudinal and elevational gradients.

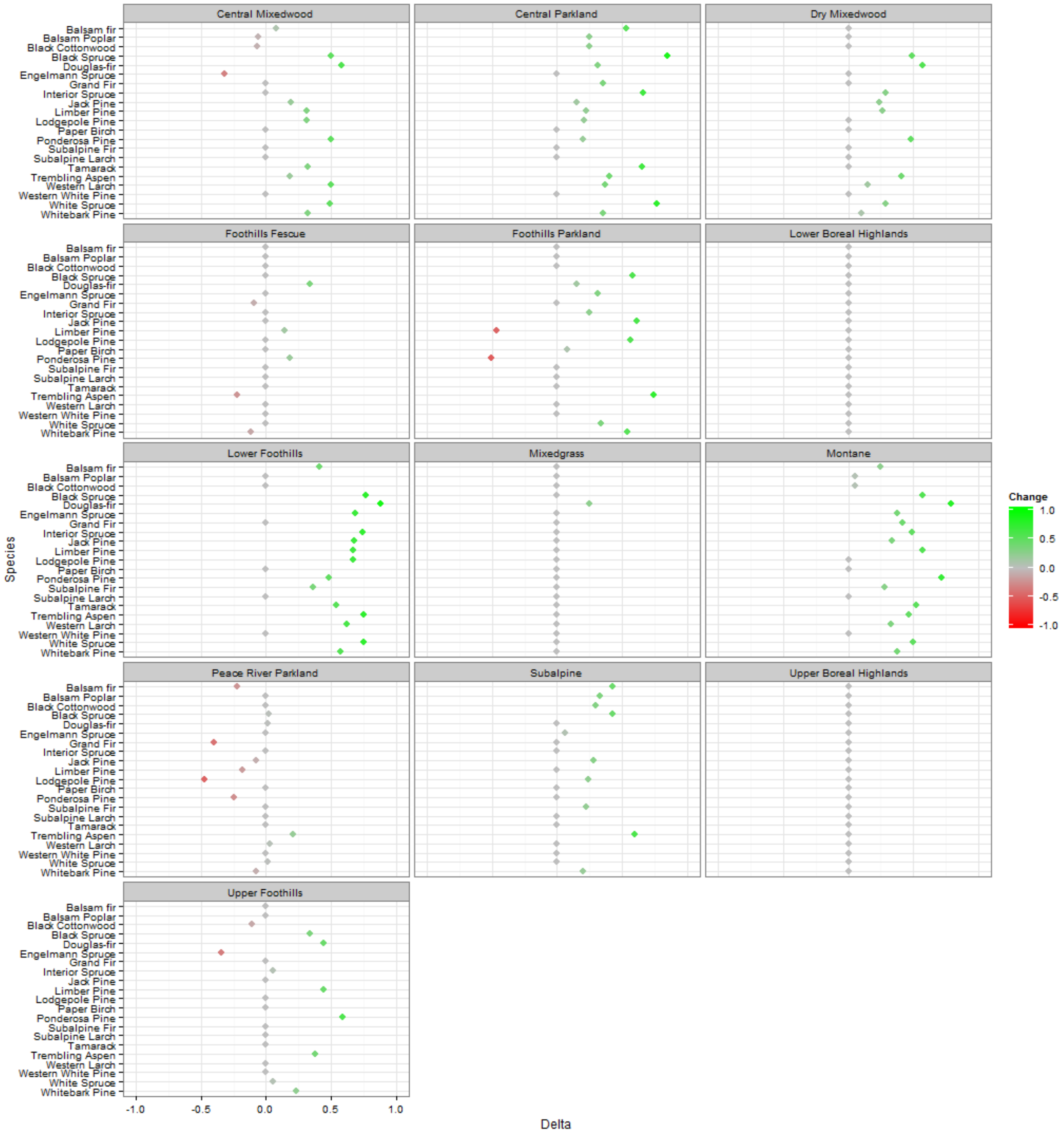


Figure 41: Change in Species Establishment with Extreme Events, 1923-1952 to 1983-2012.

The Phase 7 Study Area contains a number of cold weather- and poor site-adapted species at latitudinal and elevational limits. Modeled species at the southern limits of their realised niche, or current distribution, include white spruce (*Picea glauca*), black spruce (*Picea mariana*), jack pine (*Pinus banksiana*), paper birch (*Betula papyrifera*), tamarack (*Larix laricina*), and balsam fir (*Abies balsamea*). Modeled species at their lower elevational limits include subalpine fir (*Abies lasiocarpa*), Engelmann spruce (*Picea engelmannii*), western larch (*Larix occidentalis*), aspen (*Populus tremuloides*), Rocky Mountain juniper (*Juniperus scopulorum*), and whitebark pine (*Pinus albicaulis*). We conclude that Figure 41 exhibits the effects of warming on cold weather- and poor site condition-adapted species, at both latitudinal and elevational limits, theoretically producing a homogeneous response due to a bifurcated similarity in species autecology.

The above TACA-GEM results are generally supported by the literature, which shows the greatest change in distribution tends to be at the maxima and minima edges of species limits, producing ill-understood disequilibrium dynamics (Svenning & Sandel, 2013). While lowland forests are shown to be in the greatest amount of disequilibrium (Bertrand et al., 2011), owing to an increased 'velocity' of climatic change related to topographic effects (Loarie et al., 2009), species respond with greater vagility at elevational and latitudinal edges. The accelerated rate of migration may also reflect the narrow realised niche of high latitude and elevation specialists, well adapted to cold, poor nutrient sites, but ill adapted at interspecific competition in more productive lowland regions. Areas at the most extreme climatic edges of tree distributions also offer relatively accessible sites for expansion compared to fragmented lowland areas with dispersal limitation (Bertrand et al., 2011). However, it is important to note that TACA-GEM values merely represent changes to climatic suitability related to mechanistic germination and establishment processes, and do not account for competitive effects or spatial processes inherent to species migration and realised niche. We conclude from Figure 41 that differences in species realised niche are more related to interspecific competition and spatial processes, such as dispersal and disturbance, than species autecology. While climatic and edaphic suitability remain a requisite for establishment, other processes are estimated to be more important in determining species realised niche.

We can also infer from Figure 41 that climatic change is already affecting species germination and establishment in western Alberta, even viewed conservatively. The TACA-GEM model results reflect empirical ecological evidence of climatic change, including the observed poleward and upland migration of species and resultant disequilibria related to the difference between the fundamental and realised niches. It is important to note that TACA-GEM is a parametric mechanistic model representing germination and establishment at a relatively fixed point in space and time. We assume that the effects of evolutionary adaptive capacity will be negligible at most for sub-millennial timescales, insignificant at the 150-year timescale employed.

One of the many useful things about the TACA-GEM model is that it demonstrates how close a species is to equilibrium in its biophysical space, defined herein as a single dynamic point or tuple of points of a given moment in n-dimensional space for a species, where establishment processes are maximized. When species is distant in a Euclidean sense from this point or tuple of points, it is said to be in disequilibrium. By adjusting the parameters or degrees of freedom of the system that combine to make an n-dimensional array or space, the TACA-GEM has the potential to produce the biophysical phase space of modeled species, wherein each possible state is represented as a point in space – in this case, a probability distribution – with climatic change representing a phase space trajectory. It is important to remember that these findings do not yet incorporate important spatial processes, such as coupled or compounded disturbance interactions, which can act as catalysts of ecosystem change (Flannigan et al., 2000).

Analysis

Ecological modeling results must be compared to empirical evidence, validation data (if the model is not yet validated in a biogeoclimatically similar region), and ecological theory in order to determine the plausibility of model results given climatic change. We compare our results to past studies that have analyzed nearby regions using similar biophysically based mechanistic models, in addition to previous works in theoretical ecology. Kimmins and Lavender (1992) discussed potential ecosystem responses to climate change in British Columbia, estimating that warming would interact with the physiology of trees in the following ways: increased spring frost damage, reduced seed production, increased pathogens (they correctly predicted the recent bark beetle epidemic), increased fire severity, and in coastal regions, a failure to meet chilling requirements. They hypothesized a bifurcated response based on soil water availability: a topographic shift of vegetation in mountainous regions where soil water availability is limited, with far more pronounced change in regions with less topographic relief and theoretically fewer limitations on soil water availability (ibid).

Utilizing empirical evidence and ecological theory, the researchers predicted a general species niche movement of 300 to 600 kilometers northward and 300 to 600 meters upslope, given a warming scenario of 2 to 5 degrees Celsius (Kimmins & Lavender, 1992); they were not the first to offer such a hypothesis. Others estimated that tree species would respond to climatic change by migrating to higher elevations and latitudes, based on previous research (van der Kamp & Worrall, 1990). Initial support for the elevational-latitudinal gradient migration hypothesis was based on empirical observations of tree line shifts in undisturbed forests in Sweden (Figure 42 by Kullman in Brubaker 1986) and Quebec, and post-disturbance failed species reestablishment in Washington state (Brubaker, 1986). Shugart (1985) concluded that the timing of such population migrations is fundamentally species-dependent. Research has also shown that climatic change is likely to produce "no-analogue" communities, or novel vegetational communities, making it difficult to assess ecosystem change at the community level. Such "no-analogue" communities are shown to have existed in the past (Davis & Shaw, 2001). Thus, assessing climatic change impacts based on individual species responses, rather than extant vegetation community assemblages, is supported by both theoretical and empirical evidence.

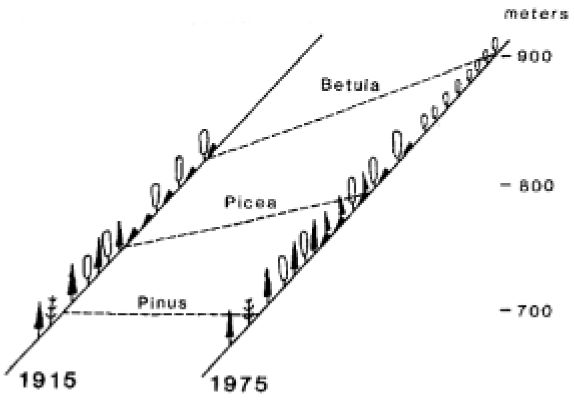


Figure 42. Treeline Elevation Change by Genus, Handölan Valley, Sweden (in Brubaker 1986)

Kimmins and Lavender (1992) described ecological and spatial constraints to species migrations, in terms of changes to their fundamental niche. Chief among constraints were pathogens, fire, and competition – processes simulated by LANDIS-II. They estimated a heterogeneous impact of climatic change on different ecological zones. In terms of ecosystem- and species-level responses to climatic and edaphic change, they note two key biophysical factors constraining tree species: fall and spring early killing frosts, and a failure to meet winter chilling requirements. The authors anticipate that mortality of reproductive buds, which are more sensitive to changes in temperature than other vegetative buds, may lead to a broad decline in the natural regeneration of tree species. This hypothesis is supported by evidence from van der Kamp and Worrall (1990) and Cannell (1984), the latter of which similarly estimated that the earliest effects of climatic change on northern conifers would be an increased incidence of frost damage (Cannell & Smith, 1984).

Based on a review of the literature, we conclude that it is essential that biophysical modeling efforts assessing tree response to climatic change in Canada include phenological processes representing frost kill and chilling requirements. Frost damage and chilling requirements are important to biophysical processes in the TACA-GEM model, albeit at a reproduction level related to germination and establishment, rather than a tree level. Although seed production is not explicitly modeled (a critical missing component in current models), as the model does not represent existing trees in a stand, TACA-GEM's germination sub-model reduces the establishment probability to null in the occurrence of frost kill events in the daily resolution decadal weather data. In effect, the germination model can be used as a kind of synthetic modifier or analogue for tree mortality or reduced seed production by altering species establishment probabilities and thus long-term occurrence, related to the unique phenology of tree species or population genetics.

The TACA-GEM model thus adds an important and novel contribution to assessing the impact of climatic change by including germination processes, particularly when combined with competition and disturbance processes modeled within LANDIS-II. TACA-GEM combines three of the most important climatic change processes estimated to alter the distribution of trees: phenological hardening and frost events, and soil water availability based on a common actual evapotranspiration (AET) to potential evapotranspiration (PET) ratio model (AET:PET), using climate as a driver. The simplistic climate-driven approach to modeling soil water availability, widely used in gap models, is another area for improvement, potentially mitigated by the application of remote sensing technologies such as LiDAR topography and shortwave infrared imagery.

As the first researchers to apply TACA-GEM in western Canada, we must compare our results with previous applications of models from the ZELIG family, necessitating the above discussion of model design. The ZELIG++ model was first applied to forests of western Canada in 1995 and then British Columbia in 1996. Burton and Cumming (1995) used an ensemble of four general circulation model projections to model the effects of climate change with ZELIG++. Given the ensemble climate projection, ZELIG++ model results for Engelmann Spruce-Subalpine Fir forests showed the rapid loss of subalpine fir (*Abies lasiocarpa*), the decline of both Engelmann-white spruce hybrids (*Picea engelmannii x glauca*) and white spruce (*Picea glauca*), and a large increase in western larch (*Larix occidentalis*), Douglas fir (*Pseudotsuga menziesii var. glauca*), and grand fir (*Abies grandis*). Our application of TACA-GEM to the Subalpine NSR using historical climate periods somewhat contrastingly showed a widespread decline in species, likely due to a combination of inadequate soil water and seasonal hardening, while the Montane NSR showed a complete flat-line across species estimated to relate to the same limiting factors.

Interior Cedar-Hemlock forests of south-central British Columbia, outside our study area, were projected to stay fairly stable, with an increase in grand fir and a large increase in western hemlock (*Tsuga heterophylla*). Boreal spruce forests in northeastern British Columbia were projected to experience a rapid loss of white and black spruce, a marked increase in Jack-lodgepole pine hybrids (*Pinus banksiana x contorta*), and an increase of trembling aspen (*Populus tremuloides*) (Burton and Cumming 1995). Our results for the Lower Boreal Highlands NSR show a marked increase in the habitat suitability for all species modeled, likely due to a decreased incidence of killing frosts and temperature constraints to germination, as the photoperiod is not currently modeled and is fixed by a latitude surrogate.

In Alberta, ZELIG++ model results suggested that no trees would persist in the dry subregion of the Boreal Mixedwood zone, estimated to result from the widespread presence of trembling aspen paired with an inadequate representation of soil water balance (Burton and Cumming 1995). As shown above, our application of TACA-GEM shows identical results as the previous study, likely due to incorporation of the same model assumptions. We also find the results overstated, given the patchy nature of the Dry Mixedwood NSR. The modeling of soil water balance is particularly important in the boreal region, as numerous glacial geological depressions exist, creating numerous small pockets of lacustrine and bog ecosystems, often feeding into large river systems. The results may be improved by including more soil types to represent the region, averaging the results rather than using the most abundant type. The ZELIG++ model showed that the wet subregion of the Boreal Mixedwood is expected to remain dominated by Pinus species, while our results for the Central Mixedwood NSR show a dominance of Picea and hardwood species relative to others. We estimate that this dissimilarity is due to chilling requirements of the different species, or another species phenology attribute.

Cumming and Burton (1996) again applies the ZELIG++ model to British Columbia. Model results suggested that the Engelmann Spruce-Subalpine Fir zone, high elevation interior forests with ample snow, would gradually transition to a canopy of amabilis fir and western hemlock, favored over subalpine fir by the lengthened growing season. Interior Douglas-fir was estimated to be prevented from invasion by persistent frosts during the growing season, though disturbances may enable establishment (ibid). For both the Interior Douglas-fir zone and the Interior Cedar-Hemlock zone, no significant change was shown in species composition. For the Sub-Boreal Spruce zone in central British Columbia, the model predicted spruce forests with lodgepole pine, typically dominated by Engelmann-white spruce hybrids. All four of the GCMs predicted a transition to Douglas-fir dominance here due primarily to a decline in frosts, an increased growing season, and reduced light competition. For the Boreal White and Black Spruce zone, the model showed an existing climate more suitable to Douglas-fir, lodgepole pine, white spruce, and balsam poplar, all of which were currently abundant with the exception of Douglas-fir, which fared well in the simulations due to its high growth rate and drought tolerance attributes (ibid). Under climate change, western larch increased in abundance here, becoming dominant between simulation years 200-350. White spruce quickly declined due to drought stress, which was also associated with declines in Douglas-fir and lodgepole pine (Cumming & Burton, 1996). Although this work was outside our study area, a comparison of these results with TACA-EM can provide a basis for model comprehension.

Nitsche and Innes (2008) describe the development and application of the TACA-EM model to the North Okanogan region of the Interior Douglas-fir zone in British Columbia. They selected this region to apply TACA-EM due to its very hot and dry climate, with frequent drought and frost events. Douglas-fir, lodgepole pine, and ponderosa pine represent key species in differing regions based on available water, with spruce, larch, fir, pine, cedar, alder, birch, cottonwood, and aspen existing on sites with adequate moisture. Model results suggested that the current number of growing degree exceeds the maximum threshold for 41% of the species, climbing to 88% by 2085. The probability of failing to meet species chilling requirements will similarly shift from a current 0% to 38% by 2085. Frost damage probability increased from 32% at current to 51% by 2055, while the probability of exceeding species drought thresholds increased from 71% at current to 94% of species by 2085. Model validation showed species presence prediction accuracy over 90%, with more omission error than commission. Overall study results suggested that by 2085, the Interior Douglas-fir zone would transition to ponderosa pine, currently the hottest and driest forest zone in British Columbia. The authors note the similarity of TACA-EM to ZELIG++ in use of a daily time step, differing from the monthly average values used by ZELIG and modern bioclimatic envelope models, though TACA-EM uses multiple weather scenarios while ZELIG++ uses daily averages. These improvements in temporal resolution and variability lend to greater precision in modeling phenological events (Nitscke and Innes 2008).

Nitscke et al. (2012) conducted work similar to this research, combining output from an improved version of TACA-EM to the SORTIE-BC hybrid model (Nitschke et al., 2012). As part of this work, they applied an enhanced version of TACA-EM to the Sub-Boreal Spruce zone of British Columbia, modeling lodgepole pine, interior spruce, subalpine fir, western hemlock, trembling aspen, and black cottonwood. The AET:PET ratio soil moisture function of TACA-EM was modified to include the commonly used Hargreaves evapotranspiration model (Hargreaves & Samani, 1985), and a daily solar radiation model based on Bristow and Campbell (1984) and Duarte et al. (2006), apparently later replaced by estimates from Waring and Running (1998) (Bristow & Campbell, 1984; Waring & Running, 1998; Duarte et al., 2006). The soils component of TACA-EM was also expanded to allow for three new soil parameters, combining to represent improved soils heterogeneity. The TACA-GEM model version we used incorporates the above improvements.

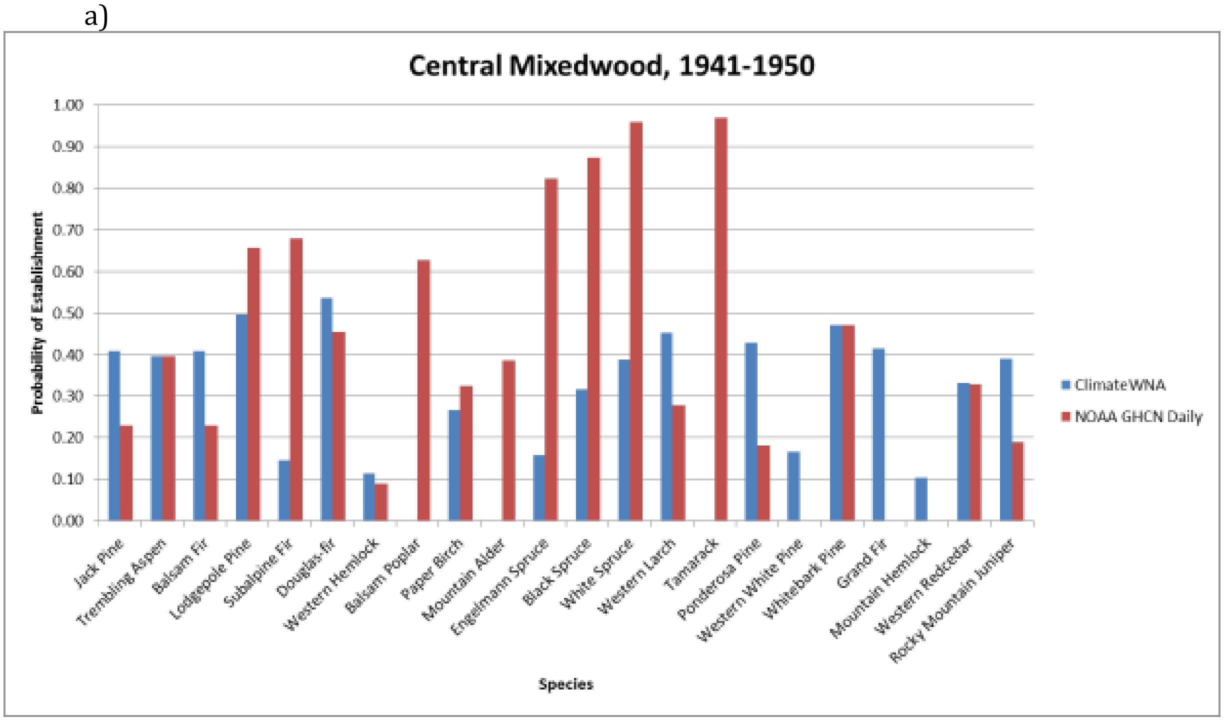
The TACA-EM model results in Nitscke et al. (2012) show strong persistence of lodgepole pine and trembling aspen across site types and climate scenarios, both declining markedly only under climate change on the poorest sites. Interior spruce and subalpine fir greatly decline under climate change across sites, both performing best on rich-moist sites. Western hemlock and black cottonwood both show low regeneration probabilities, but hemlock expands under climate change while cottonwood essentially disappears. These results are consistent with the previous results for ZELIG++ and TACA-EM for British Columbia forests. In general, the models show a decline of cold weather species with low drought tolerance, with other species improving in response to the increased number of growing degree days. Even though ZELIG++ is a spatial growth model while TACA-EM and TACA-GEM are aspatial and only consider the regeneration niche, model results are surprisingly consistent and therefore exhibit general model robustness.

A.5.Appendix: Comparing Climate Normal and Daily Weather Inputs

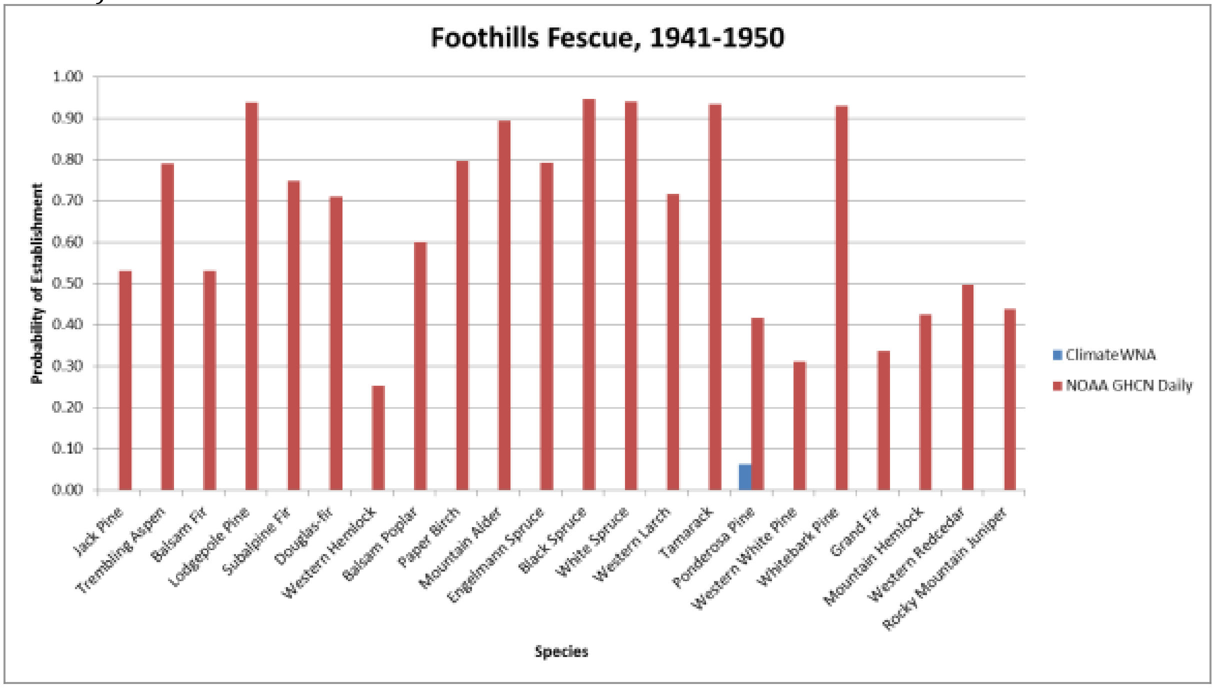
As the following graphs show for the period from 1941 to 1950 for three Natural Subregions in the Phase 7 Study Area, we found a strong difference in TACA-GEM outputs dependent upon the type of climate data used. The two types of climate data prepared for the single decade were daily resolution climate data and monthly resolution 30-year climate averages. For daily resolution data, we used weather station data from NOAA GHCN-Daily while for monthly resolution data, we used ClimateWNA. For the TACA-GEM model runs, all variables outside of the weather data inputs were held fixed as control variables to focus on the effects of changing weather input types. We also enabled the new TACA-GEM germination submodel.

We found the most drastic differences in species response to weather data type in lower elevations that often experience greater climate variability and more frequent drought conditions. The change in modeled species response, though generally directional across all species, also showed interspecific heterogeneity, particularly in the Central Mixedwood region. We infer that the changes in response values are a result of species biophysical traits, soil conditions, and local climatic patterns. We believe these results are expected given the phenology and germination focus of the TACA-GEM model – processes that rely on weather variability at relatively fine temporal resolutions. Based on the below results (Appendix A5), we used NOAA GHCN-Daily weather data for our final model runs.

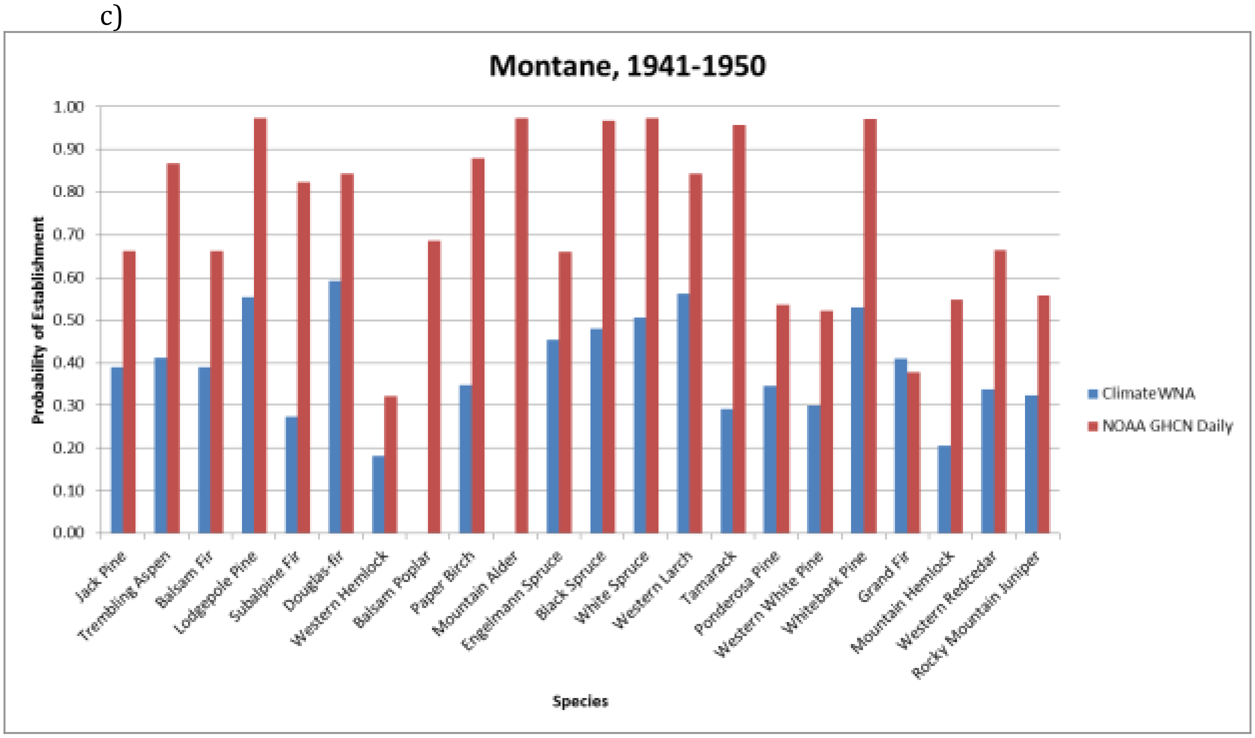
a)


Central Mixedwood, 1941-1950
Probability of Establishment
1.00
0.90
0.80
0.70
0.60
0.50
0.40
0.30
0.20
0.10
0.00
Jack Pine
Trembling Aspen
Balsam Fir
Lodgepole Pine
Subalpine Fir
Douglas-fir
Western Hemlock
Balsam Poplar
Paper Birch
Mountain Alder
Engelmann Spruce
Black Spruce
White Spruce
Western Larch
Tamarack
Ponderosa Pine
Western White Pine
Whitebark Pine
Grand Fir
Mountain Hemlock
Western Redcedar
Rocky Mountain Juniper
Species
ClimateWNA
NOAA GHCN Daily

b)


Foothills Fescue, 1941-1950
Probability of Establishment
1.00
0.90
0.80
0.70
0.60
0.50
0.40
0.30
0.20
0.10
0.00
Jack Pine
Trembling Aspen
Balsam Fir
Lodgepole Pine
Subalpine Fir
Douglas-fir
Western Hemlock
Balsam Poplar
Paper Birch
Mountain Alder
Engelmann Spruce
Black Spruce
White Spruce
Western Larch
Tamarack
Ponderosa Pine
Western White Pine
Whitebark Pine
Grand Fir
Mountain Hemlock
Western Redcedar
Rocky Mountain Juniper
Species
ClimateWNA
NOAA GHCN Daily

c)



Appendix A.5. TACA-GEM Model Results Comparing Input Weather Data Types in Three Natural Subregions a)Central Mixedwood; b) Foothills Fescue; and c) Montane.

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REPORT B: GRIZZLY BEARS AND PIPELINES: RESPONSE TO UNIQUE LINEAR FEATURES

Final Report for Alberta Upstream Petroleum Research Fund

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Executive Summary

This report includes results from two years of research investigating grizzly bear response to oil and gas pipelines in the Kakwa region of west-central Alberta. We investigated grizzly bear habitat selection patterns on pipeline RoWs and other linear features, parameters influencing the use of pipeline Rows, bear food occurrence on pipelines, the spatial relationship between grizzly bear predation and linear features, and factors that influence grizzly bear mortality risk on pipelines.

Grizzly bears used pipelines, pipeline-road right-of-ways, and roads significantly more than expected based on availability. Male bears also used seismic lines more than expected, while female bears appeared to avoid seismic lines during spring and fall. A number of bear foods were more common on pipeline RoWs and edges than in other available habitats, including dandelion, clover and ants, known to be important bear foods in our region. There were differences between age-sex classes in use of pipeline habitat, with some sexual segregation of habitat use. Bears were more likely to use younger pipelines (mean age ~ 7 years) and pipelines in areas of lower pipeline and road densities. Our spatial analysis of grizzly bear predation sites did not find evidence that predation events occurred close to linear features.

Analysis of factors influencing grizzly bear mortality risk on pipelines indicated that sightability of bears from pipeline-road intersections was most influenced by topography and shrub cover. All pipelines investigated in our study were used by people and by grizzly bears, suggesting that bear-human encounters could occur on pipeline RoWs.

Chapter B.1. Background, Study Area, And Research Objectives.

Background

Approximately 350,000 km of oil and gas transmission pipelines have been constructed on the Alberta landscape (Alberta Environment and Sustainable Resource Development 2013). Understanding grizzly bear habitat use and response to these linear features is important for effective conservation, management, and recovery of this threatened species. This information may also be useful for mitigation actions related to pipeline development planning. Other wildlife species such as woodland caribou (*Rangifer tarandus*) are reported to avoid linear features (James & Stuart-Smith 2000, Dyer et al. 2001). Previous research has also shown that wolves may use linear corridors as travel routes (Thurber et al. 1994, Musiani et al. 1998, James & Stuart-Smith 2000, Whittington et al. 2005, McKenzie et al. 2012). Despite the fact that pipelines have been a part of the Alberta landscape for several decades, there has been limited research published regarding the response of grizzly bears to pipelines in North America. Labaree et al. (2014) reported that grizzly bears in the Kakwa area were not farther than expected from pipelines during the spring, while response during other seasons depended on age-sex class and time of day. Grizzly bear use of the edges created by pipelines has also been reported in the Kakwa region (Stewart et al. 2013). However, grizzly bear habitat use and movement at the small spatial scale of linear feature RoWs has not been previously published.

The Foothills Research Institute Grizzly Bear Program (FRIGBP) has been working in the Kakwa region of west central Alberta since 2005 (Figure 1). Grizzly bear location data along with the presence of extensive linear features in this region provide an opportunity to investigate grizzly bear response to pipelines. In 2012, the FRIGBP initiated an AUPRF-funded study to address the knowledge gap regarding grizzly bears and pipelines, and this research was continued into a second year (2013). This report constitutes the final summary of this two year project.

In the first year of this project (2012), we focused on the primary knowledge gaps around grizzly bears and pipelines, including habitat selection patterns, grizzly bear activities, and movement patterns. Preliminary results from the first year of this study suggested that some grizzly bears may use pipelines and other linear feature RoWs more than expected based on habitat availability. Analysis of field data from the first year of this study also indicated that bears were using pipeline RoWs for a range of foraging activities, with anting as the most common activity. An analysis of movement rates in the first year showed that grizzly bears traveled significantly faster on road RoWs, road-pipeline RoWs, pipeline RoWs, and seismic RoWs as compared to in non-linear habitat, suggesting that linear feature RoWs may serve as movement corridors for grizzly bears in our study area.

Research objectives in 2012 and 2013 were addressed by utilizing and expanding upon our existing grizzly bear GPS location dataset in the Kakwa study area. GIS analyses of existing data were supplemented by fieldwork in 2012 and 2013 at selected sites within the region. Based on preliminary results suggesting that bears may use pipelines, in the second year of this project (2013) we were interested in determining what parameters may predict grizzly bear use of pipelines, including: pipeline attributes, the characteristics of the surrounding landscape, and bear food availability on pipeline RoWs compared to the surrounding habitat. In addition, based on evidence that grizzly bears may be using RoWs for movement, we investigated whether bears may be using RoWs for access to ungulate prey.

Linear corridors also provide human access into remote grizzly bear habitat. Pipeline RoWs may be used for a variety of human activities, including ATV travel, hunting, and general recreation. In addition, pipelines are often constructed next to roads, and frequently intersect with roads. Human-caused mortality is considered to be the primary limiting factor for grizzly bears in Alberta (Alberta Sustainable Resource Development [ASRD] 2008), and areas with a higher level of human access are associated with an increased risk of human-caused grizzly bear mortalities and lower survival rates (Jalkotzy et al. 1997, Benn 1998, Nielsen et al. 2004a, Boulanger et al. 2013). Grizzly bear use of pipelines has the potential to increase their exposure to humans and subsequently increase the risk of human-caused grizzly bear mortality. In the second year of this project, we also investigated factors associated with pipeline RoWs that could increase the probability of bear-human encounters, including the visibility of bears on pipelines from roads and the actual levels of human use on RoWs.

Study Area

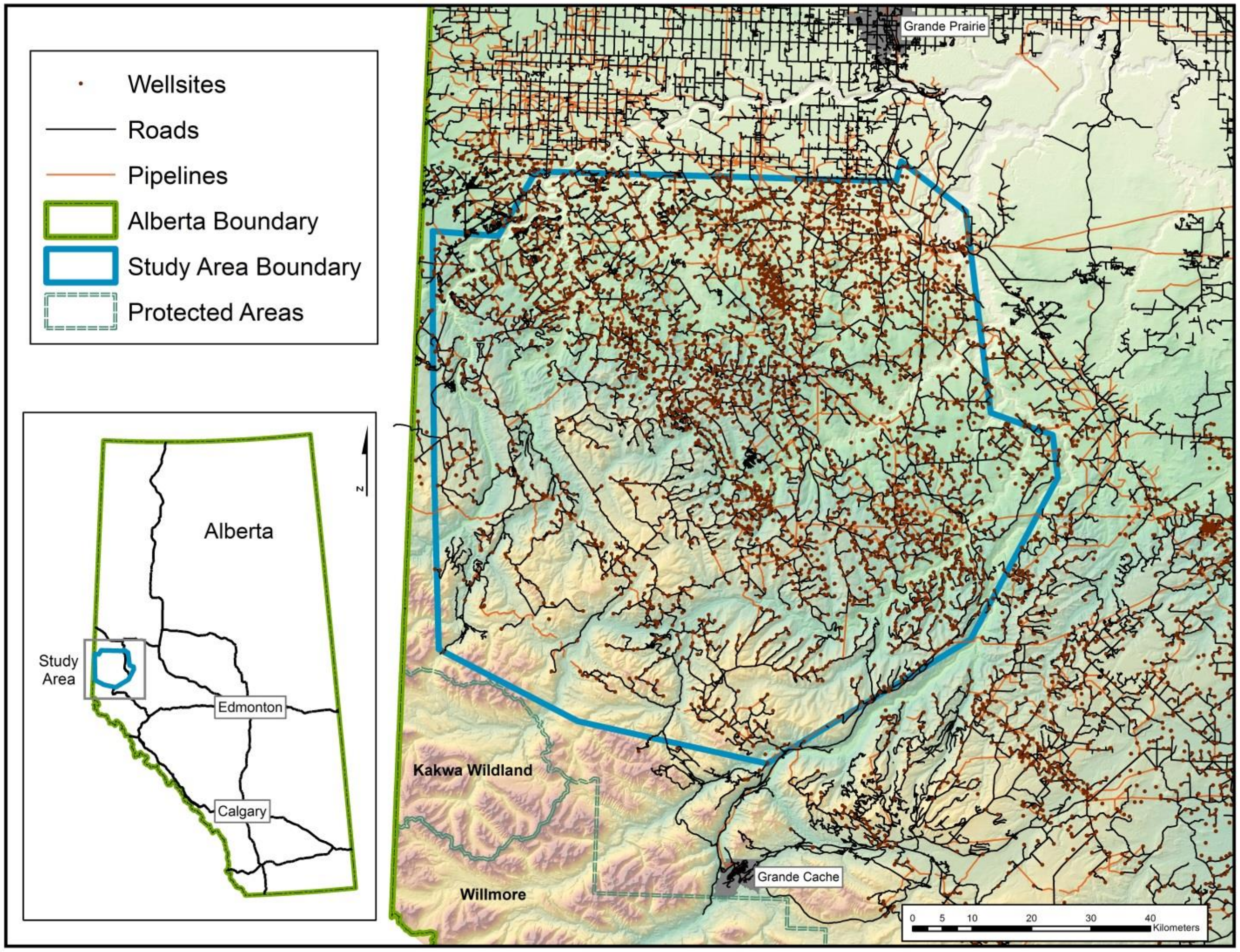

Figure 1: Kakwa study area.

Research objectives

Objectives in the second year of this project expand on knowledge gained in the first year, and incorporate additional data obtained in 2013 into the initial (first year) habitat use analysis:

I. Analysis of grizzly bear habitat selection patterns on pipeline RoWs:
   a. Do grizzly bears use pipelines and other linear features more, less, or no differently than expected?
   b. How do selection patterns compare between linear feature types?

II. Determination of parameters influencing use of RoWs:
   a. Is grizzly bear use of pipeline RoWs influenced by pipeline characteristics and/or adjacent habitat and/or other landscape characteristics?
   b. Is grizzly bear use of pipelines influenced by food availability on RoWs?

III. Investigation of the use of RoWs for predation:
   a. What is the spatial relationship between linear features and grizzly bear predation sites?

IV. Evaluation of factors that might influence grizzly bear mortality risk on pipelines:
   a. What is the sightability of grizzly bears on RoWs from current road access features?
   b. What parameters predict sightability of grizzly bears on pipeline RoWs?
   c. What is the level of human use along pipeline RoWs, what are the types of use (i.e. recreational, pipeline maintenance, hunting), and are there seasonal differences?

Chapter B.2. Grizzly Bear Habitat Selection Patterns On Pipeline Right-Of-Ways

Introduction

Within west-central Alberta, researchers have reported that grizzly bears select for cutblocks (Nielsen et al. 2004b, Stewart et al. 2012), wellsites (Sahlen 2010, McKay et al. 2011) and roads (Roever et al. 2008a, Graham et al. 2010). Other authors have reported grizzly bear use of pipeline edges (Stewart et al. 2013), and Labaree et al. (2014) reported that grizzly bears were not farther than expected from pipelines during the spring. However, patterns of grizzly bear habitat use directly at linear feature RoWs have not been previously reported.

The main objective of our analysis was to determine how grizzly bears respond to pipeline right of ways. However, in investigating grizzly bear use of pipeline RoWs, it is also important to acknowledge the presence of many other linear features on the landscape. Therefore, we also investigated how use of pipelines differs from grizzly bear selection patterns of other linear features such as roads and seismic lines. Habitat selection can vary with age-sex class and season (Nielsen 2005, Berland et al. 2008, Graham et al. 2010, Roever et al. 2010) and these factors were also considered in our analysis of grizzly bear use of linear features. Building on results from Year 1 of this study, we expanded our dataset in Year 2 to include data from 2013.

Methods

Grizzly bear location data:

Location data were obtained from collared grizzly bears within the Kakwa study area during 2006-2013. Aerial darting, leg-hold snaring, and culvert traps were used to capture grizzly bears; all trapping and collaring efforts met or exceeded the standards of the Canadian Council of Animal Welfare (animal use protocol number 20010016, G. Stenhouse, pers. comm.). Capture procedures are described in Cattet et al. (2003a, 2003b). The capture of bears using leg hold snares was stopped in 2008, following results indicating long term effects with this capture technique (Cattet et al. 2008).

Bears were fitted with Televilt (Followit) or Telemetry Solutions GPS collars. Data from collars were collected remotely using monthly Very High Frequency (VHF) data upload equipment during fixed-wing aircraft flights during 2006 to 2012, and/or via satellite transmissions during 2011 to 2013. Across the years of data collection, collars were programed for a range of GPS acquisition schedules, including hourly fixes, every two hours, 4 hour fixes, and 6 hour fixes. We also observed variation across the collars with regards to the success rate of obtaining fixes. Missed GPS fixes or low fix rates have the potential to introduce bias in habitat selection analysis (Frair et al. 2004). To reduce GPS fix rate bias (Friar et al. 2004), we limited our dataset to collars that obtained ≥4 fixes per day.

Televilt collars average 18m and 265m error distances for 3D and 2D locations respectively (Sager-Fradkin et al. 2007), and Telemetry Solutions collars are assumed to have similar accuracy. Due to the small spatial scale of linear features in our analysis, we removed 2D locations from our dataset to reduce the potential for location errors.

To define the area available to an animal, we determined annual home ranges as Minimum Convex Polygons (MCPs) (Nielsen et al. 2004b, Roever et al. 2008a). MCPs were generated in a Geographic Information System (ArcGIS) using ACCRU tools. The ACCRU tool runs a Python script in ArcInfo, and draws a line around the outermost points in the dataset (personal communication, Charlene Nielsen, University of Alberta).

To standardize sampling intensity for random (available) locations, we generated random locations at a density of five points per square kilometer within each MCP, based on the area of the home range for each bear (Nielsen et al. 2004b, Roever et al. 2008a). For MCPs that extended outside of the Kakwa study area, only use and available points that fell within the study area boundary were used in analysis. Den entry and exit dates were determined for each bear, based on when GPS collars stopped collecting data in the fall, and started successfully obtaining fixes again in the spring. Only non-denning locations were retained in the final dataset. Use locations were separated by established foraging seasons for our area, including hypophagia (spring; May 1st to June 15th), early hyperphagia (summer; June 16th to July 31st), and late hyperphagia (fall; August 1st to October 31st) (Nielsen 2005). For each season, we restricted our analysis to bears with GPS collar locations that included at least half of that season. Based on previous knowledge that habitat selection can vary between the sexes, data were grouped by sex class, but only two classes were included (i.e. females and males), as age-sex class/reproductive status were included as a variable in our investigation of parameters influencing the use of pipelines.

Linear feature datasets:

Linear pipeline data (updated to 2013) were obtained from Alberta Energy; these data were originally provided to Alberta Energy by pipeline operators in the Kakwa area. Roads data were obtained from Alberta Environment and Sustainable Resource Development (AESRD), and were manually updated on an annual basis by FRIGBP staff. Power transmission lines (powerlines) and seismic line data were also provided by AESRD. Seismic line data were last updated in 2008; however, the vast majority of seismic lines built after 2008 were low-impact seismic. Tigner et al. (2013) found that black bear use of seismic lines ≤2m wide was not different than habitat use of undisturbed forest. Low-impact seismic lines in our study area are meandering, narrow in width (≤ 3m), and difficult to discern in remote sensing imagery. Therefore, we did not consider low-impact seismic lines as significant linear features for the purpose of our analysis, and we used only conventional seismic lines constructed prior to 2008.

A construction date was provided for the majority of the pipeline segments. For those pipelines without a construction date, a construction year was determined using satellite imagery. For multi-pass pipelines, we applied the earliest construction date, to represent the year the RoW first appeared on the landscape. Other linear feature datasets were limited in accuracy with regards to construction dates. Roads data included a “built before” year, while powerlines and seismic lines could be assigned an approximate construction period.

Based on the limitations in the data regarding, assigning a specific construction date (i.e. month and day) or season to the linear feature segments was not appropriate; therefore, we generated annual linear feature datasets. Pipeline data that originally included a construction date were assigned to annual datasets as follows: construction dates prior to August 1st for a given year were considered to be present on the landscape during that year and any subsequent years. Pipelines with a minimum construction date on or after August 1st were only considered present on the landscape during subsequent years. The cutoff of August 1st was selected to maintain consistency with other linear feature datasets; SPOT imagery used to confirm construction years was usually captured in early August, therefore this date corresponded with the dates used to designate built-before years for roads. The majority of pipeline segments built during 2006-2013 were constructed during January to April (before den exit) or November and December (after den entry); therefore, this cutoff date was applied to a relatively small number of pipeline segments.

All linear feature data were initially represented as line segments; therefore, we needed to generate a dataset that represented the actual areas of the features on the ground. We calculated the median RoW width for pipelines as measured at over 300 RoWs in the field. To determine median RoW widths for the various road classes, powerlines, and seismic lines, random locations were generated along the linear features and overlaid on LiDAR imagery in a GIS. LiDAR imagery was generated by subtracting 0.5 m heights from bare earth, making road and vegetated right-of-ways discernible. The width of the linear feature was measured at each random point using the GIS measuring tool. Median widths for all linear features were divided by half for use as a buffer along each side of the linear feature line segment. The relatively narrow footprint of linear features also makes them sensitive to collar location errors. To account for collar error, we added 18m (3D collar error distance, see above) on each side of a linear feature polygon. McKenzie et al. (2009, 2012) applied a similar approach in their investigation of wolf movements on seismic lines, buffering their line data by the average seismic RoW width plus estimated collar error.

The final median widths and buffers applied to each linear feature class are summarized in Table 1. In the case of overlapping adjacent buffers (e.g. a pipeline next to a road), pipeline or powerline buffers that overlapped with road buffers were identified as a unique linear feature, and were subsequently classified as road-pipeline or road-powerline combined RoWs. In areas where linear features intersected, precedence was given to the feature with the largest RoW width, followed by the feature with the highest level of human disturbance (e.g. roads versus pipelines). Features with higher precedence replaced those with lower precedence if they coincided on the landscape. Powerlines took precedence over pipelines (individually and in combined RoWs). For roads, paved roads took precedence over gravel, which took precedence over unimproved roads. As the smallest features, seismic lines took the lowest priority, and were overridden by any other linear feature. The end result was a polygon dataset representing the approximate areas of each class of linear feature on the ground.

Table 1: Buffers applied to linear features in the Kakwa study area, based on widths measured in the field or using a GIS.

Linear Feature Class	Sample Size	Median/2 (m)	Collar Error (m)	Final buffer width (m) (applied to both sides of line segment)
Pipeline	322	10	18	28
Roads: unimproved	27	8	18	26
Roads: one and two lane gravel	29	18	18	36
Roads: paved	5	38	18	56
Power transmission lines	5	35	18	53
Seismic lines	20	3	18	21

Using the polygons generated by the above buffers, habitat within the Kakwa study area was classified into five groups: pipeline RoWs, pipeline-road combined RoWs, roads, seismic lines, and the remaining non-linear habitat.

Analysis:

Methods used for the habitat analysis in the first year of this study were based on selection ratios. The assumptions of the Chi-square test used in calculation of selection ratios are not met if expected values are less than five, and standard errors and confidence limits are not reliable if observed values are less than five (Manly et al. 2002). A number bear location datasets did not meet these criteria, and were excluded from our sample in Year 1. In the current analysis, we applied a different technique, and maintained a larger sample size for the analysis. It is expected that results may differ slightly between the two analyses.

For each year of data, use and available locations for each bear were intersected with the annual linear feature dataset for that year. We compared bear locations (use) with random (available) locations to assess the probability of habitat selection for pipelines, roads, pipeline-road RoWs, and seismic lines versus expected habitat use based on availability. We calculated a random effect resource selection function (RSF) model at the population level for each season (spring, summer, and fall) using a generalized linear mixed-effects logit model (gllamm) in Stata 12.1™ (StataCorp, Texas, U.S.A). Use and available were defined by individual bear ("design III", Manly et al. 2002), and individual bear was included as the random effect (random intercept) to account for the unbalanced sample among bears. To allow the estimation of a resource selection probability function where each of the habitat categories has a different probability of use (Manly et al. 2002), indicator variables with 0/1 values were created corresponding with the five habitat categories (pipelines, roads, pipeline-road RoWs, seismic lines, non-linear habitat). Results for each habitat class were reported as coefficients with 95% confidence intervals, interpreted as the use of each habitat class compared to that expected based on habitat availability, with a significance level set at p=0.05.

We also compared habitat selection between the different linear feature types. Each use and available point was assigned a habitat class from 1 to 5, with non-linear habitat as the reference category. We ran a random effects logit model (xtlogit) in Stata 12.1™ (StataCorp, Texas, U.S.A) for each season (spring, summer, and fall) with individual bear as the random intercept. For each seasonal model for females and males, pairwise comparisons of marginal linear predictions were generated to contrast habitat selection between the different linear feature types. Bonferroni corrections were applied to 95% confidence intervals for pairwise comparisons to adjust for multiple comparisons across habitat classes, with an overall significance level set at p=0.05.

Results

During 2006 to 2013, a total of 125,624 collar locations were collected from 30 individual grizzly bears, including 15 females and 15 males. Spring, summer, and fall datasets included 20, 29, and 22 bears, respectively.

In the spring, female bears used pipelines, pipeline-road RoWs, and roads significantly more than expected based on habitat availability, but seismic lines were used significantly less than expected (Table 2). During summer, females again used pipelines, pipeline-road RoWs, and roads more than expected, while use of seismic lines was not significantly different than expected (p=0.13). The pattern in the fall was the same as the spring, with use of pipelines, pipeline-road RoWs, and roads significantly greater than expected, and use of seismic lines significantly less than expected (Table 2).

Table 2. Seasonal model coefficients, standard errors, and 95% confidence limits for female grizzly bear habitat selection of linear features. Results in bold indicate that use was significantly different than expected based on habitat availability.

					95% CI	
	Linear feature	**β**	**SE**	**p**	**Lower**	**Upper**
Spring	Pipeline	**0.389**	**0.078**	**<0.001**	**0.237**	**0.542**
	Pipeline-road RoW	**0.445**	**0.046**	**<0.001**	**0.355**	**0.535**
	Road	**0.262**	**0.053**	**<0.001**	**0.159**	**0.365**
	Seismic line	**-0.226**	**0.045**	**<0.001**	**-0.314**	**-0.138**
Summer	Pipeline	**0.889**	**0.060**	**<0.001**	**0.772**	**1.007**
	Pipeline-road RoW	**0.989**	**0.036**	**<0.001**	**0.919**	**1.059**
	Road	**0.684**	**0.042**	**<0.001**	**0.602**	**0.766**
	Seismic line	0.056	0.037	0.129	-0.016	0.129
Fall	Pipeline	**0.644**	**0.055**	**<0.001**	**0.538**	**0.751**
	Pipeline-road RoW	**0.650**	**0.034**	**<0.001**	**0.583**	**0.716**
	Road	**0.487**	**0.039**	**<0.001**	**0.410**	**0.565**
	Seismic line	**-0.165**	**0.033**	**<0.001**	**-0.230**	**-0.100**

For male bears, pipelines, pipeline-road RoWs, roads, and seismic lines were all used more than expected based on availability in the spring, summer, and fall (Table 3).

Table 3. Seasonal model coefficients, standard errors, and 95% confidence limits for male grizzly bear habitat selection of linear features. All results are significantly different than expected based on habitat availability.

					95% CI	
	Linear feature	**β**	**SE**	**p**	**Lower**	**Upper**
Spring	Pipeline	0.431	0.112	<0.001	0.211	0.651
	Pipeline-road RoW	0.377	0.069	<0.001	0.241	0.513
	Road	0.352	0.086	<0.001	0.183	0.521
	Seismic line	0.293	0.057	<0.001	0.181	0.405
Summer	Pipeline	0.683	0.071	<0.001	0.543	0.823
	Pipeline-road RoW	0.655	0.044	<0.001	0.568	0.742
	Road	0.592	0.053	<0.001	0.488	0.696
	Seismic line	0.257	0.040	<0.001	0.178	0.336
Fall	Pipeline	0.981	0.071	<0.001	0.842	1.120
	Pipeline-road RoW	0.550	0.049	<0.001	0.453	0.646
	Road	0.489	0.060	<0.001	0.373	0.606
	Seismic line	0.754	0.038	<0.001	0.680	0.827

In comparing probability of use of the different linear features, females used seismic lines significantly less than all other linear features in the spring, summer, and fall (Table 4). In the summer, females also used roads less than pipelines and pipeline-road RoWs. During fall, females again used roads less than pipeline-road RoWs, but use of roads was not significantly different from use of pipelines (p=0.099). There were no significant differences in use between pipelines and pipeline-road RoWs in any season.

For males, there were no significant differences in use of linear features in the spring. However, similar to females, males used seismic lines less than all other linear features in the summer (p<0.001). In the fall, the pattern of use changed, with seismic lines used more than pipeline-road RoWs and roads, and pipelines used more than all other linear features (Table 5).

Discussion

Determining grizzly bear habitat response to pipeline RoWs is the first critical step in investigating how pipelines may affect bears in Alberta. Both males and females in our study used pipelines, pipeline-road RoWs, and roads more than expected by availability, across all seasons. Results from this analysis differ somewhat from results previously reported in Year 1 of this study. Methods used in the first year of this study involved calculation of selection ratios, which resulted in more limited sample sizes due to restrictions imposed by the assumptions of the method. The RSF approach in this analysis incorporated a larger sample size, with more even representation among the age-sex classes, potentially providing a clearer picture of grizzly bear selection patterns around linear features.

Table 4. Matrix of comparisons of female grizzly bear use of linear feature types. Seasonal model coefficients, standard errors, and 95% confidence limits indicate the likelihood of use of the linear feature type on the left as compared to the linear feature type across the top of the table. Confidence intervals were corrected using the Bonferonni adjustment for comparison across multiple habitat types. Results in bold indicate statistically significant differences.

		Pipeline					**Pipeline-road**					**Road**				
					95% CI					95% CI					95% CI	
		β	SE	p	Lower	Upper	β	SE	p	Lower	Upper	β	SE	p	Lower	Upper
Spring	Pipeline-road	0.05	0.09	1.000	-0.21	0.30										
	Road	-0.12	0.09	1.000	-0.38	0.14	-0.17	0.07	0.151	-0.36	0.03					
	Seismic	**-0.62**	**0.09**	**<0.001**	**-0.87**	**-0.37**	**-0.66**	**0.06**	**<0.001**	**-0.84**	**-0.49**	**-0.50**	**0.07**	**<0.001**	**-0.69**	**-0.31**
Summer	Pipeline-road	0.10	0.07	1.000	-0.09	0.30										
	Road	-0.20	0.07	0.047	-0.41	-0.001	-0.31	0.05	<0.001	-0.46	-0.15					
	Seismic	**-0.83**	**0.07**	**<0.001**	**-1.02**	**-0.63**	**-0.93**	**0.05**	**<0.001**	**-1.07**	**-0.79**	**-0.62**	**0.05**	**<0.001**	**-0.78**	**-0.47**
Fall	Pipeline-road	-0.01	0.06	1.000	-0.19	0.17										
	Road	-0.17	0.07	0.099	-0.36	0.02	**-0.16**	**0.05**	**0.019**	**-0.30**	**-0.015**					
	Seismic	**-0.82**	**0.06**	**<0.001**	**-1.00**	**-0.64**	**-0.80**	**0.05**	**<0.001**	**-0.94**	**-0.67**	**-0.64**	**0.05**	**<0.001**	**-0.79**	**-0.50**

Table 5. Matrix of comparisons of male grizzly bear use of linear feature types. Seasonal model coefficients, standard errors, and 95% confidence limits indicate the likelihood of use of the linear feature type on the left as compared to the linear feature type across the top of the table. Confidence intervals were corrected using the Bonferonni adjustment for comparison across multiple habitat types. Results in bold indicate statistically significant differences.

		Pipeline					**Pipeline-road**					**Road**				
					95% CI					95% CI					95% CI	
		β	SE	p	Lower	Upper	β	SE	p	Lower	Upper	β	SE	p	Lower	Upper
Spring	Pipeline-road	-0.06	0.13	1.000	-0.43	0.30										
	Road	-0.09	0.14	1.000	-0.47	0.31	-0.02	0.11	1.000	-0.32	0.29					
	Seismic	-0.14	0.12	1.000	-0.49	0.21	-0.08	0.09	1.000	-0.33	0.17	-0.06	0.10	1.000	-0.35	0.22
Summer	Pipeline-road	-0.01	0.08	1.000	-0.25	0.22										
	Road	-0.08	0.09	1.000	-0.33	0.17	-0.07	0.07	1.000	-0.26	0.12					
	Seismic	**-0.42**	**0.08**	**<0.001**	**-0.65**	**-0.20**	**-0.41**	**0.06**	**<0.001**	**-0.57**	**0.24**	**-0.34**	**0.06**	**<0.001**	**-0.52**	**-0.16**
Fall	Pipeline-road	**-0.42**	**0.09**	**<0.001**	**-0.66**	**-0.18**										
	Road	**-0.48**	**0.09**	**<0.001**	**-0.73**	**-0.22**	**-0.05**	**0.08**	**1.000**	**-0.27**	**0.16**					
	Seismic	**-0.24**	**0.08**	**0.026**	**-0.46**	**-0.02**	**0.18**	**0.06**	**0.023**	**0.01**	**0.35**	**0.24**	**0.07**	**0.005**	**0.04**	**0.43**

A number of other authors have reported grizzly bear use of anthropogenic features in west-central Alberta. Nielsen et al. (2004b) reported that grizzly bears selected for harvested areas more than expected during the summer, Roever et al. (2008a) showed that grizzly bears selected habitats close to roads in spring and early summer, and Graham et al. (2010) found that females with cubs were within 200m of roads more than expected in spring. McKay et al. (in review) reported that female bears used wellsites more than expected across all seasons, while males used wellsites more than expected in summer and fall. Stewart et al. (2013) also reported grizzly bear use of edge habitat created by cutblocks, roads, and pipelines. The use of anthropogenic openings by grizzly bears has been attributed to the presence of bear foods growing along edges and within young or deforested habitats (Nielsen et al. 2004c, Munro et al. 2006, Roever et al. 2008b, Larsen 2012, Stewart et al. 2013). Similar to other anthropogenic disturbances, pipelines provide edges and openings that could also support the growth of bear foods; a comparison of bear food distribution on pipelines is included in Chapter 4 of this report. Results from the first year of this study indicated that bears in the Kakwa region use pipelines for a range of foraging activities. Analysis of movement rates in the first year also showed that grizzly bears traveled significantly faster on pipelines, pipeline-road RoWs, roads, and seismic lines as compared to non-linear habitat, suggesting that linear features may serve as movement corridors for grizzly bears in our study area.

While previous research reported that grizzly bears were not farther than expected from pipelines during the spring (Labaree et al. 2014), to our knowledge, there is no previously published research regarding habitat use directly at linear feature RoWs. Linear corridors are relatively narrow features on the landscape. It can be difficult to detect effects at such a small spatial scale, particularly with hourly GPS data; the timing of a GPS collar location may not exactly coincide with a bear location in a narrow right-of-way. However, analyses of this type provide direct information regarding grizzly bear use of these features, building on information obtained from larger landscape scale analyses. In spite of the relatively narrow areas of linear features, we detected significant differences in habitat use between linear features and non-linear habitat in our analysis, with both male and female grizzly bears using pipelines, pipeline-road RoWs, and roads more than expected based on availability.

Tigner et al. (2013) reported that black bears used conventional seismic lines more than forest interiors, but the analysis was based on camera data, and was not analyzed by sex class. In our study, male bears used seismic lines more than expected in all seasons, while females appeared to avoid seismic lines in the spring and fall. Other authors have reported sexual segregation of habitat use in grizzly bears (Rode et al. 2006). Females in our study area may be avoiding seismic lines in order to avoid male bears. Steyaert et al. (2013) reported spatiotemporal segregation in habitat selection between females with cubs-of-the-year and adult males during the mating season (spring). Our habitat analysis did not separate habitat selection patterns of females with cubs from females without young. Further investigation of grizzly bear use of seismic lines is beyond the scope of this report, but could contribute more knowledge to sexual segregation of habitat use by grizzly bears. Male grizzly bear use of seismic lines may also have implications for caribou, as it has been shown that seismic lines may facilitate predator access to caribou (Whittington et al. 2011, McKenzie et al. 2012).

It is important to note that although grizzly bears used these linear features more than expected based on availability, grizzly bears spend the majority of their time within nonlinear habitat. Pipelines are relatively narrow disturbances compared to other anthropogenic disturbances (e.g. forest cutblocks), and in our study it appears that these features are not causing avoidance or displacement of grizzly bears. However, the primary limiting factor for grizzly bears in Alberta is human-caused mortality (ASRD 2008). Greater use of these features than expected based on availability suggests that bears are attracted to linear features. The presence of bears on linear features has the potential to increase their exposure to humans, and subsequently increase the risk of human-caused grizzly bear mortality. Mortality risk factors including sightability of bears on pipelines and levels of human use on pipeline RoWs in the Kakwa region are discussed in Chapter 6 of this report.

Chapter B.3. Parameters Influencing The Use Of Pipeline Right-Of-Ways.

Introduction

Our habitat selection analysis suggests that grizzly bears are using pipeline right-of-ways. Based on these selection patterns, we wanted to gain a more detailed understanding of what parameters may influence bear use of pipelines. A number of ecological and landscape factors could affect whether individual grizzly bears use or avoid particular pipelines, including grizzly bear age-sex class, reproductive status of bears, pipeline characteristics, and the characteristics of the surrounding habitat. Grizzly bear use of wellsites has been attributed to disturbance age and characteristics of the surrounding area (McKay et al. in review), while use of cutblocks has been related to disturbance age, cutblock shape, and site preparation methods (Nielsen et al. 2004b). Information regarding parameters influencing use of pipelines may provide a better understanding of the mechanisms behind grizzly bear use of these features, and could help predict which pipelines are more likely to be used by bears in the Kakwa region.

Methods

Location data:

Location data were obtained from collared grizzly bears within the Kakwa study area during 2006-2013, and we generated random (available) locations within home ranges at a standard density of five points per square kilometre (see Chapter 2, Grizzly bear location data). For each year of data, use and available locations for each bear were intersected with the annual linear feature dataset for that year (see Chapter 2, Linear feature datasets). Use and available locations from the habitat analysis in Chapter 2 were carried forward into this analysis of parameters influencing use of pipelines if they intersected with pipelines or pipeline-road combined RoWs.

Factors influencing pipeline use:

We investigated the influence of pipeline characteristics, grizzly bear age class and reproductive status, surrounding habitat and forest cover, and surrounding anthropogenic disturbance on grizzly bear use of pipelines.

During pipeline construction, a right-of-way (RoW) is cleared through the existing habitat. Following the construction phase, re-vegetation occurs along the RoW, but the RoW may also be disturbed at a later date for pipeline repairs or the addition of another pipe within the RoW. Pipeline age (i.e. years since clearing) may be an indicator of plant succession and abundance of bear foods on the RoW. Therefore, we hypothesized that potential differences in grizzly bear use of pipelines could be influenced by the number of years since pipeline construction or clearing. Two different parameters were extracted for vegetation succession on pipelines, including 1) the number of years since the pipeline was first cleared for construction (original pipeline age), and 2) the number of years since the most recent construction (disturbance age). These parameters were based on approximate construction dates provided in the original dataset. Each pipeline location was also classified as to whether it was a single pass pipeline (only one pipeline constructed within the RoW) or multi-pass pipeline (RoW disturbed more than once). For single pass pipelines, the most recent construction was the original clearing, and these dates were identical.

Behavioral responses to anthropogenic features have been shown to differ by grizzly bear age-sex class and reproductive status (Darling 1987, Rode et al. 2006, Nellemann et al. 2007, Elfström and Swenson 2009), and we included reproductive status as a variable in our model of parameters influencing pipeline use. Grizzly bears ≥ 5 years old were considered adults. Bears were classified as subadults if they were <5 years old, > 2 years old, and independent from their mother. Age determination was completed using cementum analysis of a pre-molar tooth extracted at capture. Female bears were classified as females with cubs of the year if it could be confirmed by sightings that they were accompanied with one or more cubs of the year. To maintain sample sizes across age-sex classes, females with yearlings or two year olds were grouped into the adult female class along with females without young. This grouping was based on preliminary analysis in this study indicating similar patterns within these groups of females, previous habitat analysis results (McKay et al. in review), and previous research indicating that the largest differences between home range size and movement patterns are between females with cubs of the year and the other age-sex classes (Graham et al. in press). Due to the fact that females may lose their cubs over the course of the year, reproductive status was specific to season (spring, summer, and fall) for each year. Data from female bears with unconfirmed reproductive status were not included in our models. Final age-sex classes included: 1) females with cubs of the year, 2) adult females (with yearlings, two year olds, or no cubs), 3) adult males, 4) subadult males, and 5) subadult females.

Characteristics in the region surrounding a pipeline were calculated within a 400m radius of the use and available pipeline locations, based on the average hourly travel distance for male grizzly bears in our study area. Adjacent habitat has the potential to influence foraging decisions and small scale habitat use on features such as RoWs. To describe available adjacent habitat, we used landcover classes originally derived from Landsat7 imagery (McDermid 2005). Landcover classes were grouped as herbaceous habitat, shrublands, forest, and cutblocks classified by forest age (0 to 20 years, and greater than 20 years since clearing). For each use and random location, adjacent landcover was defined as the dominant landcover within a 400m radius. Adjacent canopy cover (hiding cover) was defined as the average percent canopy cover within a 400m radius of each use and random location.

The Kakwa study area is a highly altered landscape, including both forestry and oil and gas development. The density of anthropogenic features varies across the study area, with different levels of habitat alteration and human presence. On a section of pipeline RoW, there is potential for the surrounding disturbance to influence grizzly bear use of that anthropogenic feature. We considered road densities and pipeline densities as indicators of the level of disturbance and human use in the area surrounding each pipeline location. We calculated road and pipeline densities (km/km^2) in a 400m radius around each use and random location. Distance to the nearest road (km) was also investigated as an index of human disturbance in the area.

Analysis:

Pipeline RoWs and pipeline-road combined RoWs were considered as separate habitat types, and were modeled separately. For both RoW types, we generated a set of *a priori* logistic regression models for each season, for a total of six model sets. Models were created by grouping parameters according to areas of ecological relevance, including: bear-specific factors, pipeline-specific factors, surrounding level of anthropogenic disturbance, habitat/food-related factors, and combinations of these groups (Table 1). Model combinations were focused around bear specific factors (age-sex class), based on previous data suggesting that habitat selection patterns differ by age-sex class. Interaction factors were also limited to age-sex class and human disturbance parameters, as the response to human features is the main focus of our investigation.

Parameters were checked for correlation and collinearity using Pearson's correlation coefficients, variance inflation factors, and regression of independent variables against each other.

Variables with a correlation coefficient ≥0.6, VIF >1.5, or highly significant regression coefficients were considered to be correlated, and were not included together in any candidate models. Distance to the nearest road and road density were correlated (r=0.6). In preliminary analyses, road density explained more variation in the data, and therefore distance to road was not included in the models. Landcover class is closely related to tree cover, and landcover class and canopy cover were also correlated. We chose to exclude canopy cover and include landcover in our models, as landcover provides both information on habitat type and indirect information regarding hiding cover. The original pipeline age and disturbance age were also highly correlated. Pipeline age variables were assessed separately for each of the six model sets, with further candidate models including the age that explained the most variation in the data for that RoW type/season.

Table 1. Candidate models.

Model	Description	Parameters
1	Bear specific factors	Age-sex class (including female reproductive status) (AS3)
2	Pipeline specific factors	Original pipeline age or disturbance age, multipass/single pass, and surrounding pipeline density
3	Level of human disturbance in area	Road density and pipeline density
4	Food availability (vegetation succession) and habitat	Original pipeline age or disturbance age, landcover class
5	Bear specific and disturbance	Age-sex class, road density, pipeline density
6	Bear specific and disturbance with interactions	Age-sex class, road density, pipeline density, interaction factors
7	Bear specific and food availability	Age-sex class, pipeline age
8	Bear specific, food availability, disturbance	Age-sex class, pipeline age, road density, pipeline density
	Global model	Age-sex class, pipeline age, multipass/single pass, landcover, road density, pipeline density, interaction factors

We used random intercept mixed-effects logit models (xtlogit) in Stata 12.1™ (StataCorp, Texas, U.S.A) with individual bear as the random effect. Model selection was based on comparing differences in Akaike's Information Criterion corrected for small sample sizes (ΔAIC_C). We used conventional AIC methods for model selection rather than the conditional AICs sometimes applied to random effects models, because we were interested in inferences to the population of grizzly bears in our area rather than to individuals (Vaida & Blanchard 2005, Hebblewhite & Merrill 2008). Controversy exists regarding appropriate cutoffs for selecting and/or averaging top models, with recommended ΔAIC values ranging from 2 to 6 and beyond (Burnham & Anderson 2002, Richards 2008, Arnold 2010). However, the addition of a single parameter to a model can result in a model with ΔAIC ≤2 even if the additional parameter does not have any explanatory ability, since a one unit increase in the number of parameters will only increase AIC by 2, and the selection of models with larger ΔAIC values often results in retention of uninformative parameters (Guthery et al. 2005, Arnold 2010). We chose an approach that included careful consideration of model weights and ΔAIC values along with a review of the parameters that were retained in each of the top models. For each season, we reviewed the models with the highest AIC weights and ΔAIC≤ 2, and verified that models with ΔAIC~2 were not simply the result of adding one more parameter to the top model (Richards 2008, Arnold 2010). If applicable, we carried out model averaging to calculate parameter estimates. Coefficient values and confidence intervals were taken into account in interpretation of model results. To contrast effects of categorical variables, pairwise comparisons of marginal linear predictions were calculated after model generation. Bonferroni corrections were applied to 95% confidence intervals for pairwise comparisons to adjust for multiple comparisons across categories, with an overall significance level set at p=0.05.

Results

For pipeline RoWs, the top model in the spring retained the variable of age-sex class, and accounted for 0.693 of the total AIC_c weight (AIC_cW) (Table 2). Pairwise comparisons of age-sex class indicated that adult females were more likely to use pipelines than females with cubs of the year (p=0.043), but no other significant differences were observed between age-sex classes in spring (Figure 1).

For summer, age-sex class and disturbance age (years since most recent clearing) were both retained in the top model, with an AIC_cW=0.77. Females with cubs were more likely to use pipelines than subadult males, and subadult females were more likely to use pipelines than subadult males (Figure 1). Disturbance age had a negative influence on use of pipelines, with the probability of use decreasing with increasing pipeline age (Figure 2). The mean disturbance age of used pipelines was 5.7 years, versus 7.7 years for available pipelines.

The top model for the fall included the variables of age-sex class and disturbance age ($AIC_cW=0.66$). The second ranked model in the fall also included the variables of road density and pipeline density ($AIC_cW= 0.31$, $\Delta AIC_c = 1.54$) and this model was included in model averaging and calculation of coefficients for fall. There were a number of significant differences in the probability of pipeline use between age-sex classes in the fall (Figure 1). Females with cubs were more likely to use pipelines than adult females, subadult males, and subadult females. Subadult females were less likely to use pipelines than adult females and adult males, and subadult males were less likely to use pipelines than adult males. Again, disturbance age had a negative influence on use of pipelines (Figure 2); mean disturbance age of used pipelines was 5.7 years and 7.3 years for available pipelines. Surrounding pipeline density and road density also had a negative influence on use of pipelines, with the probability of use decreasing with increasing densities.

For pipeline-road RoWs, the top model for spring included age-sex class, road density, and pipeline density, with $AIC_cW=0.52$ (Table 3). The second ranked model also included the variable of original pipeline age ($\Delta AIC_c = 0.17$, $AIC_cW=0.47$); both models were used for inference. These same four variables (age-sex class, road density, pipeline density, and original pipeline age were all retained in the top model for summer ($AIC_cW =1.00$), and for the two top models for fall (Table 3).

Table 2. Pipeline RoW candidate models and AICc values for pipeline parameters*. Top models are in bold, and superscripts indicate top models for: 1) Spring, 2) Summer, 3a) and 3b) Fall. Variables include age-sex class (AS), disturbance age (DA), multi-pass (MP), pipeline density (PD), and land cover (LC).

			Spring					Summer					Fall			
Model	Parameters	K	LL	AICc	**ΔAIC_c**	**AIC_cW**		**LL**	**AIC_c**	**ΔAIC_c**	**AIC_cW**		**LL**	**AIC_c**	**ΔAIC_c**	**AIC_cW**
Null		1	-732.43	1467.08	5.93	0.036		-1315.43	2633.02	22.33	0.000		-1436.12	2874.45	82.06	0.000
1	AS	5	**-723.43**	**1461.15**	**0.00**	**0.693**		-1307.93	2628.60	17.90	0.000		-1392.63	2799.01	6.62	0.024
2	DA + MP + PD	4	-730.79	1472.24	11.09	0.003		-1303.67	2617.07	6.38	0.032		-1428.71	2867.77	75.38	0.000
3	RD + PD	3	-731.80	1471.09	9.95	0.005		-1314.03	2635.05	24.36	0.000		-1433.49	2874.31	81.92	0.000
4	LC + DA	5	-727.56	1469.40	8.25	0.011		-1301.20	2615.13	4.43	0.084		-1417.81	2849.37	56.98	0.000
5	AS + RD + PD	7	-722.85	1469.04	7.89	0.013		-1306.43	2632.46	21.77	0.000		-1389.36	2800.72	8.33	0.010
6	AS + RD + PD + AS*RD + AS*PD	15	-721.68	1555.37	94.22	0.000		-1298.60	2657.50	46.81	0.000		-1370.59	2829.17	36.78	0.000
7	**AS +DA**	6	-722.41	1463.29	2.14	0.238		**-1297.35**	**2610.69**	**0.00**	**0.768**		**-1387.4**	**2792.39**	**0.00**	**0.660**
8	**AS + RD + PD + DA**	8	-721.88	1472.85	11.70	0.002		-1295.45	2614.47	3.78	0.116		**-1383.43**	**2793.93**	**1.54**	**0.306**
Global	AS + DA + MP + RD + PD + LC4 + AS*RD	19	-716.97	2153.94	692.79	0.000		-1283.71	2700.41	89.72	0.000		-1354.24	3126.47	334.08	0.000

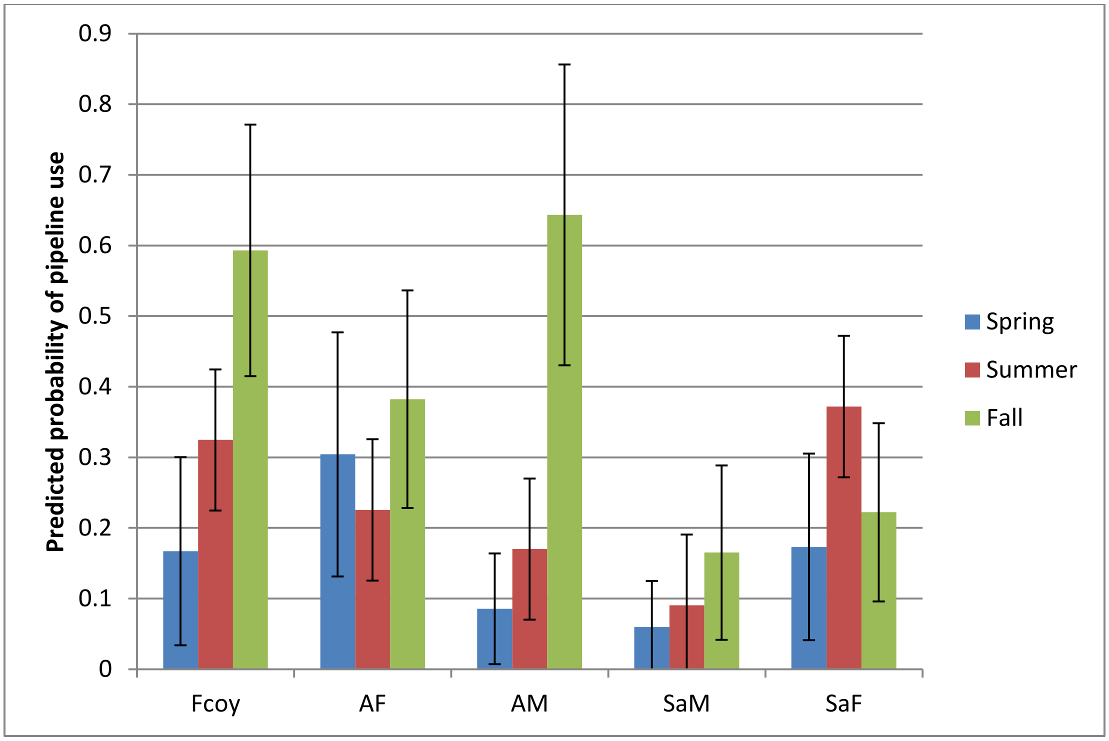

Figure 1. Predicted probability of pipeline use by age-sex class and season. Age-sex classes include females with cubs of the year (Fcoy), adult females (AF), adult males (AM), subadult males (SaM), and subadult females (SaF).

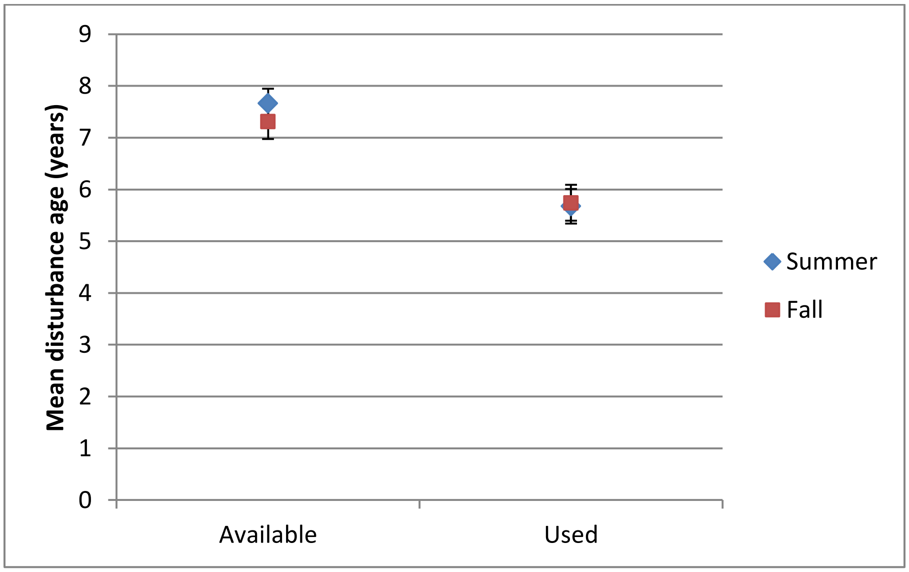

Figure 2. Mean disturbance age for available and used pipeline sites, summer and fall.

Table 3. Pipeline-road RoW candidate models and AIC_c values for pipeline parameters*. Top models are in bold, and superscripts indicate top models for: 1)a and 1)b Spring, 2) Summer, 3) Fall. Variables include age-sex class (AS), original pipeline age (PA), multi-pass (MP), pipeline density (PD), road density (RD), and landcover (LC).

			Spring				**Summer**				**Fall**			
Model	**Parameters**	**K**	**LL**	**AIC_c**	**ΔAIC_c**	**AIC_cW**	**LL**	**AIC_c**	**ΔAIC_c**	**AIC_cW**	**LL**	**AIC_c**	**ΔAIC_c**	**AIC_cW**
Null		1	-2019.86	4041.94	75.23	0.000	-3738.21	7478.56	299.84	0.000	-3679.61	7361.41	130.49	0.000
1	AS	5	-1987.13	3988.55	21.85	0.000	-3673.95	7360.51	181.79	0.000	-3634.83	7283.41	52.49	0.000
2	PA + MP + PD	4	-2007.23	4025.13	58.43	0.000	-3648.16	7305.98	127.26	0.000	-3636.44	7283.23	52.31	0.000
3	RD + PD	3	-1999.23	4005.96	39.26	0.000	-3686.82	7380.61	201.88	0.000	-3664.85	7337.04	106.12	0.000
4	LC + PA	5	-2012.30	4038.89	72.19	0.000	-3661.21	7335.02	156.30	0.000	-3652.76	7319.27	88.35	0.000
5	**AS + RD + PD^{1a}**	**7**	**-1971.69**	**3966.70**	**0.00**	**0.520**	-3668.78	7356.90	178.17	0.000	-3624.05	7270.11	39.19	0.000
6	AS + RD + PD + AS*RD + AS*PD	14	-1968.23	4048.45	81.75	0.000	-3624.75	7307.50	128.77	0.000	-3606.83	7301.66	70.74	0.000
7	AS + PA	6	-1981.44	3981.34	14.63	0.000	-3605.41	7226.64	47.92	0.000	-3608.38	7234.35	3.43	0.152
8	**AS + RD + PD + PA^{1b,2,3}**	**8**	**-1968.89**	**3966.87**	**0.17**	**0.479**	**-3577.76**	**7178.73**	**0.00**	**1.000**	**-3601.92**	**7230.92**	**0.00**	**0.848**
Global	AS + PA + MP + RD + PD + LC + AS*RD +AS*PD	19	-1962.35	4644.71	678.00	0.000	-3562.70	7247.84	69.11	0.000	-3570.84	7559.68	328.76	0.000

Similar to results for pipeline RoWs, adult females were more likely to use pipeline-road RoWs in the spring than females with coy (p=0.001). Both subadult males and subadult females were less likely to used pipeline-road RoWs than adult males, and the probability of use for subadult males was also lower than for all adult females (Figure 3). The pattern of use shifted in the summer, with adult females and adult males less likely to use pipeline-road RoWs than females with cubs. The probability of use for subadult males was lower than for all other age-sex classes in summer, and this pattern continued in the fall. Adult females also used pipeline-road RoWs less than females with coy in the fall.

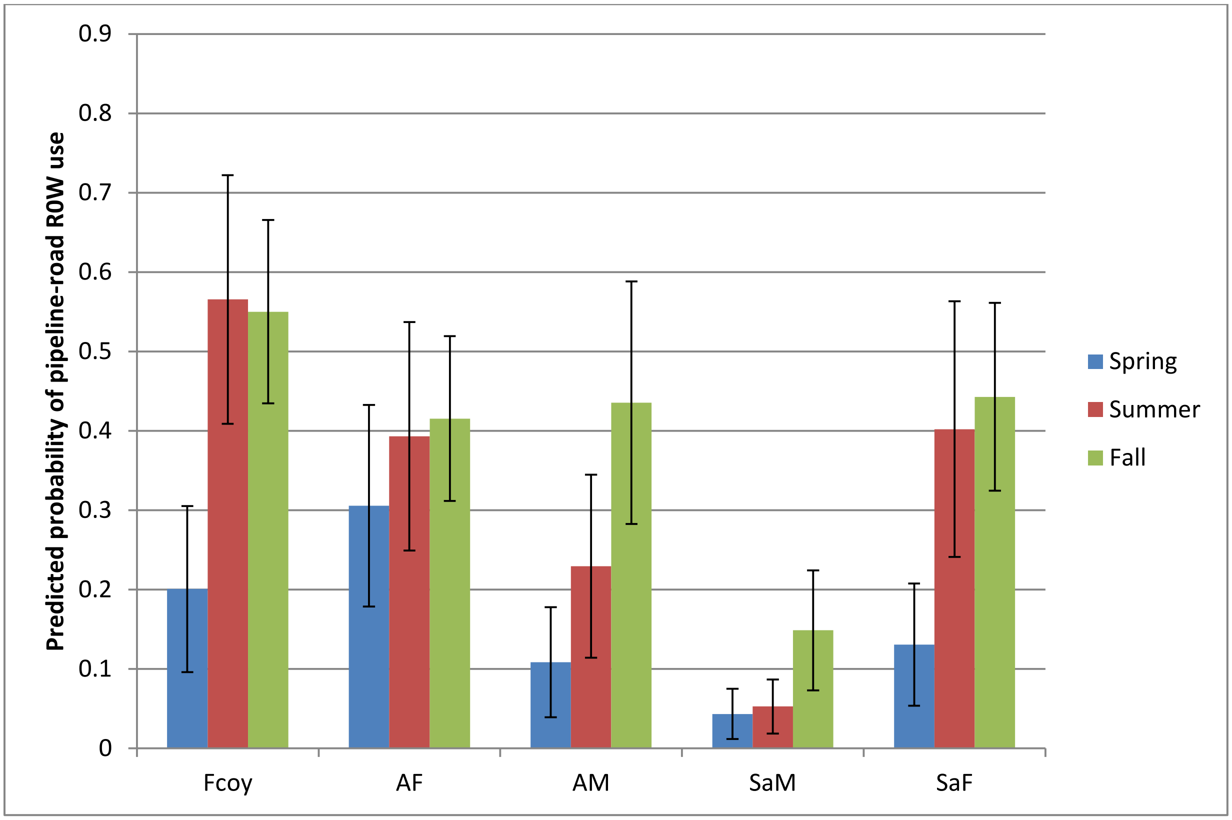

Figure 3. Predicted probability of pipeline-road RoW use by age-sex class and season. Age-sex classes include females with cubs of the year (Fcoy), adult females (AF), adult males (AM), subadult males (SaM), and subadult females (SaF).

For all three seasons, original pipeline age had a negative influence on pipeline-road RoW use, with the probability of use decreasing as pipeline age increased (Figure 4). Across seasons, mean pipeline age was consistently lower for used pipelines (overall mean=7.4 years) versus those available (mean =9.1 years). Surrounding pipeline and road density also had a negative influence on selection of pipeline-road RoWs across all seasons, with the probability of use decreasing with increasing pipeline and road densities (Figures 5 and 6).

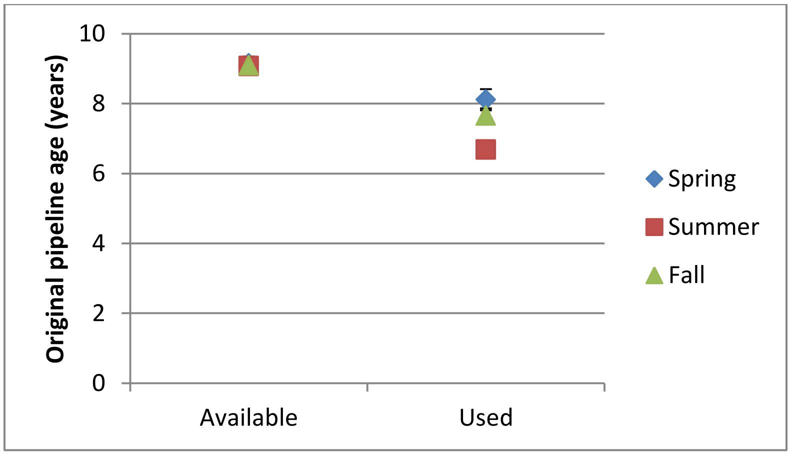

Figure 4. Mean pipeline age for available and used pipeline-road RoW sites, by season.

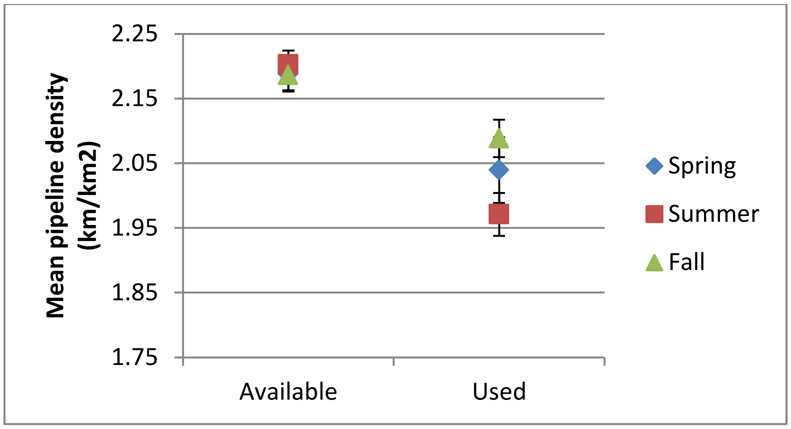

Figure 5. Mean pipeline densities for available and used pipeline-road RoW sites, by season.

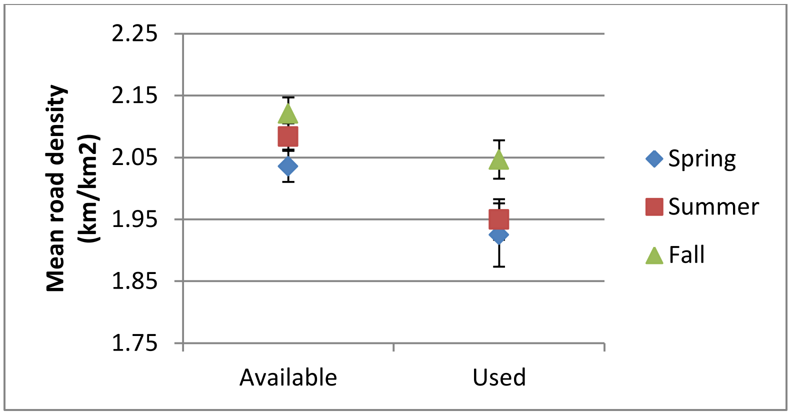

Figure 6. Mean road densities for available and used pipeline-road RoW sites, by season.

Discussion

In the spring, females with cubs of the year were less likely to use both pipelines and pipeline-road RoWs than adult females without cubs. This pattern shifted completely in the summer, when females with cubs were more likely to use pipeline-road RoWs than single females, and in the fall, females with cubs were more likely to use both pipelines and pipeline-road RoWs than adult females. We did not detect significant differences in pipeline use between females with cubs and adult males, although females with cubs were observed to use pipeline-road RoWs more than adult males in the summer. In Sweden, Steyaert et al. (2013) reported a strong pattern of spatiotemporal segregation in habitat selection between female brown bears with cubs-of-the-year and adult males during the mating season. Females with cubs selected for areas closer to buildings, but generally avoided areas close to roads and trails. The authors also noted a shift in habitat selection after the mating season, when females with cubs followed a pattern more similar to other female bears (Steyaert et al. 2013). Other authors have also reported sexual segregation of habitat use in grizzly bears, and suggested that females with cubs may perceive the risk of male grizzly bears as greater than the risk of humans (Rode et al. 2006). Previous work in Alberta has found that females used areas near roads more than males (Graham et al. 2010), females with cubs used habitat near roads more than other bears in British Columbia (McLellan & Shackleton 1988), and females with cubs in the Kakwa region were more likely to use wellsites than male bears (McKay et al. in review), similar to findings for other populations. We also observed that subadult males and subadult females displayed different selection patterns than adult bears, and subadult males in particular used pipelines and pipeline-road RoWs less than other age-sex classes. While differences between age-sex classes varied across seasons, it appears that some sexual segregation of habitat use could be taking place on pipelines.

Disturbance age (years since most recent disturbance) and original pipeline age (years since original pipeline construction) were predictors of the use of pipelines and pipeline-road RoWs, respectively. Both parameters serve as an index of vegetation succession, and potentially of bear food availability. Disturbance age and original pipeline age both had a negative influence on use of pipelines/pipeline-road RoWs, with the probability of use decreasing as pipeline age increased. In spite of a relatively small difference in average age of pipelines between used and available (e.g. 7.4 and 9.1 years, respectively), this relationship was consistent for both pipelines and pipeline-road RoWs, with a strong effect for age across all seasons for pipeline-road RoWs. These results are in contrast to the response reported for wellsites in our area (McKay et al. in review), where bears were more likely to select older wellsites rather than recently cleared wellsites. Pipelines are narrow features, and may grow in more quickly than larger openings such as wellsites or cutblocks. Early colonizing bear food species such as clover and dandelion may peak a few years after a pipeline is cleared, and as a result of vegetation succession, the pipeline may become overtaken by grass, alder, willow, and other non-berry producing shrubs. If grizzly bears are mostly using pipeline RoWs to access clover and other colonizing species, they may select for those pipelines in the earlier stages of succession. Preliminary analysis in this study indicated that there was a higher occurrence of clover at pipeline use sites than at pipeline random locations, suggesting that bears are targeting clover on pipeline RoWs. Previous results from year 1 of this study also indicated that bears use pipelines for travel, and a pipeline may become less suitable for fast movement as vegetation and shrub cover increases.

Surrounding pipeline and road density had a negative influence on use of pipelines in the fall and pipeline-road RoWs across all seasons. With increasing pipeline and road densities in the 400m surrounding pipelines/pipeline-road Rows, the probability of use decreased. These results are analogous to the grizzly bear response to wellsites in the Kakwa region reported by McKay et al. (in review). The authors reported that with increasing wellsite and road densities in the surrounding area, the probability of grizzly bear use of a wellsite decreased. In a working landscape such as the Kakwa, wellsite, pipeline, and road densities reflect the level of resource extraction and human activity in the area. Although bears appear to be selecting for pipelines, these results suggest that they may prefer habitat in areas of lower overall human presence. Other research has suggested that anthropogenic features may not directly cause disturbance effects (i.e. avoidance), but the associated human activities may have an impact on bears (Swenson et al. 1996, Jalkotzy et al. 1997, Olson et al. 1998, Ordiz et al. 2011). Boulanger and Stenhouse (in review) found that grizzly bear survival was related to road density, and identified threshold levels at which population levels would decline. While bears in our study area appear to show a positive selection for pipelines, they may be compensating by using pipelines in areas with a lower risk of encountering humans. There may be a threshold for pipeline and road density above which bears avoid pipelines, resulting in an effective overall loss of habitat. This is an important consideration for grizzly bear habitat in the Kakwa region, as oil and gas development continues in this area.

Chapter B.4. Food Availability On Pipeline Right-Of-Ways.

Introduction

Our habitat selection analysis suggests that grizzly bears are using pipeline right-of-ways, and bears have also been reported to use pipeline edges in the Kakwa region (Stewart et al. 2013). Based on these selection patterns, we wanted to gain a more detailed understanding of what may influence bear use of pipeline RoWs. Research suggests grizzly bear use of anthropogenic openings is related to the presence of bear foods growing along edges and within the early successional habitats created by disturbance (Nielsen et al. 2004c, Roever et al. 2008b, Larsen 2012, Stewart et al. 2013). Similar to other anthropogenic disturbances, pipelines provide edges and openings that could also support the growth of bear foods. Other authors have reported that both roadsides and cutblocks have a higher frequency of some bear foods than nearby forest habitat (Nielsen et al. 2004c, Roever et al. 2008b). During pipeline construction, a right-of-way (RoW) is cleared through the existing habitat. Following the construction phase, early colonizing species move in to the disturbed area along the RoW. Dandelion, clover, and *Equisetum* species are frequent colonizers of disturbed areas, and these plants are known to be important bear foods grizzly bears in west-central Alberta (Munro et al. 2006). Based on the assumption that differences in the availability of food could have a strong influence on grizzly bear use of pipelines, our research objective was to determine whether the distribution of bear foods on pipeline RoWs and in pipeline RoW edges were different from that of other available habitat types.

Methods

Study site selection:

In 2012/2013, prior to the field season, random locations were generated within the study area using a GIS, stratified by habitat type, and randomly subsampled to generate field sites for vegetation sampling. Habitat types used in the analysis included conifer forest (≥80% conifer), broadleaf and mixed forests (<80% conifer), regenerating forest (cutblocks of various age), pipeline RoWs, and pipeline edges. Random locations within pipeline RoWs were also stratified according to pipeline age, in order to capture a range of vegetation succession on RoWs. The FRIGBP also conducted extensive fieldwork in the Kakwa area during 2006 and 2007 for a previous study, and these data were incorporated into our analysis. During 2006 and 2007, random points were paired with use sites for bears from those years, and were generated based on a random cardinal direction and a distance of 300m from bear use points. Based on this method of point generation, the locations were not entirely random on the landscape. However, vegetation cover was not compared between use and random points, spatial distribution of study sites was consistent across the study area, and the number of points within each habitat type was similar. Therefore, data from 2006 and 2007 study sites were included in the vegetation analysis.

Field methods:

Field crews visited sampling sites in the Kakwa study area during 2006-2007 and 2012-2013. Field protocols and data collection were consistent between the two sampling periods, allowing for use of the previously collected 2006-2007 data in the current study. Personnel navigated to within 2 metres of the coordinates of the sampling site location using a hand held GPS unit. For pipeline sites, plots were centered on the RoW, each plot was 30m long, and included the width of the RoW plus 5 metres into the forest edge on each side. For non-pipeline sites, the GPS coordinate for the sampling site was plot centre, and each plot was 30m by 30m.

At each plot, we recorded the presence/absence and abundance of all plant species known to be common bear foods in west-central Alberta (Munro et al. 2006). Plots were also searched for the presence of ants (mounds or woody debris) and for the presence of ungulate pellets. Ungulate pellets were not considered as an index of ungulate abundance, rather as an indicator of ungulate presence/absence (Nielsen et al. 2004c), and all ungulate species were grouped together. At pipeline plots, food presence was recorded separately for the RoW and each edge plot, and these plots were considered as separate habitat types.

Analysis:

Out of the 29 bear foods recorded at our sampling sites, we chose to focus on 14 bear foods for our analysis (Table 1), based on common foods specifically identified in scat from bears within the Kakwa area (Larsen & Pigeon 2006), foods commonly found in disturbed areas (Roever et al. 2008b), and berry shrubs commonly observed at pipeline sites in our study area. *Hedysarum alpinum*, an important bear food in west-central Alberta (Munro et al. 2006) was essentially detected only at use sites, and therefore was not common enough to include in occurrence models for our study area.

Table 1. Bear foods used in analysis.

Food	Common name/description
Ants	Hills/mounds or woody debris, confirmed presence of ants/anting
Equisetum sp.	Horsetail species
Heracleum lanatum	Cow parsnip
Lonicera involucrata	Honeysuckle
Ribes sp.	Currant/Gooseberry species
Rubus sp.	Raspberry species
Shepherdia canadensis	Buffalo berry
Taraxacum officinale	Dandelion
Trifolium sp.	Clover
Ungulates	Presence of pellets: deer, moose, elk
Vaccinium caespitosum	Dwarf blueberry
Vaccinium membranaceum	Huckleberry
Vaccinium myrtilloides	Wild blueberry
Vaccinium vitis-idaea	Lingonberry

We used logistic regression to compare the occurrence of each bear food at random locations between coniferous forest, mixed/deciduous forest, cutblocks, pipeline RoWs, and pipeline edges. Each food model was run in Stata 12.1™ (StataCorp, Texas, U.S.A), with conifer forest as the reference habitat category. Chi-square likelihood ratios were used to determine the significance of individual food models. We used pairwise comparisons of marginal linear predictions to contrast the probability of bear food occurrence between habitat types. Bonferroni corrections were applied to 95% confidence intervals for pairwise comparisons to adjust for multiple comparisons across categories, with an overall significance level set at p=0.05. Results are reported as odds ratios, interpreted as the probability of bear food occurrence versus the probability of bear food occurrence in the comparison habitat. Pairwise comparisons of habitat types were completed for significant food models. As the focus of our investigation was to compare food occurrence on pipelines to other habitats, odds ratios and p values for pairwise comparisons are reported only if significant differences were detected between pipeline and other habitat categories. Contrasts between pipeline RoWs and pipeline edge plots are not reported in our analysis, since these plots were not considered independent.

Results

Field crews visited 366 use points and 101 random points on pipelines during 2012 and 2013, and 14 non-pipeline random study sites in 2013. An additional 110 non-pipeline random and 197 use sites were visited in the Kakwa area during 2006 and 2007, and included directly comparable bear food data. In total, field crews visited 54 sites in coniferous forest, 60 sites in broadleaf and mixed forests, 85 sites in regenerating forest, 87 sites on pipeline RoWs, and 172 plots on pipeline edges.

Individual food models showed significant prediction of bear food presence for ants, *Equisetum sp., Heracleum lanatum, Lonicera involucrata, Taraxacum officinale, Trifolium sp.,* Ungulates, *Vaccinium membranaceum,* and *Vaccinium vitis-idaea.* Food models for *Shepherdia canadensis, Vaccinium caespitosum,* and *Vaccinium myrtilloides* were not significant, indicating that habitat type was not a significant predictor of occurrence for these species in our study area. The frequency of occurrence of bear foods in each habitat type and model significance for each bear food are summarized in Table 2.

Table 2. Frequency of occurrence (percentage of plots with bear food present) of bear foods by habitat type.

Food item	**Coniferous forest**	**Mixed or deciduous**	**Cutblocks**	**Pipeline RoW**	**Pipeline Edge**	**Model significance**
Ants	1.9	3.3	3.5	39.1	5.2	<0.0001
Equisetum sp.	79.6	73.3	91.8	97.7	79.7	<0.0001
Heracleum lanatum	27.8	43.3	35.3	43.7	25.0	0.0105
Lonicera involucrata	44.4	28.3	36.5	60.9	51.7	0.0003
Ribes sp.	44.4	81.7	62.4	57.5	43.0	<0.0001
Rubus sp.	14.8	53.3	52.9	94.3	68.0	<0.0001
Shepherdia canadensis	14.8	36.7	21.2	24.1	20.9	0.0726
Taraxacum officinale	1.9	5.0	28.2	88.5	35.5	<0.0001
Trifolium sp.	1.9	3.3	17.6	88.5	41.3	<0.0001
Ungulates	64.8	68.3	68.2	19.5	8.1	<0.0001
Vaccinium caespitosum	25.9	20.0	24.7	20.7	18.6	0.7227
Vaccinium membranaceum	48.1	6.7	47.1	28.7	20.9	<0.0001
Vaccinium myrtilloides	37.0	16.7	28.2	27.6	23.8	0.1408
Vaccinium vitis-idaea	72.2	11.7	58.8	26.4	34.9	0.0001
Vaccinium sp.	88.9	28.3	76.5	55.2	50.6	<0.0001
Number of plots	54	60	85	87	172	

Tables 3a. and 3b. Comparison of probability of occurrence of bear foods at pipeline RoWs compared to coniferous forest, deciduous/mixed forest, and regenerating forest (cutblocks). Significant differences are in bold.

Pipeline RoW versus comparison group

	Ants		*Equisetum sp.*		*Lonicera involucrata*		*Ribes sp.*		*Rubus sp.*	
Comparison group:	Odds ratio	p	Odds ratio	p	Odds ratio	p	Odds ratio	p	Odds ratio	p
Coniferous forest	**34.0**	**0.006**	**10.9**	**0.026**	1.95	0.574	1.69	1.000	**94.3**	**<0.001**
Deciduous/mixed forest	**18.6**	**0.001**	**15.5**	**0.004**	**3.94**	**0.001**	**0.303**	**0.027**	**14.4**	**<0.001**
Cutblocks	**17.5**	**<0.001**	3.8	1.000	**2.71**	**0.015**	0.816	1.000	**14.6**	**<0.001**

Pipeline RoW versus comparison group

	Taraxacum		*Trifolium sp.*		Ungulates		*Vaccinium membranaceum*		*Vaccinium vitis-idaea*	
Comparison group:	Odds	p	Odds ratio	p	Odds ratio	p	Odds ratio	p	Odds ratio	p
Coniferous forest	**408**	**<0.001**	**408**	**<0.001**	**0.13**	**<0.001**	0.43	0.208	**0.14**	**<0.001**
Deciduous/mixed forest	**146**	**<0.001**	**223**	**<0.001**	**0.11**	**<0.001**	**5.65**	**0.024**	2.72	0.332
Cutblocks	**19.6**	**<0.001**	**35.9**	**<0.001**	**0.11**	**<0.001**	0.453	0.139	**0.25**	**<0.001**

Tables 4a. and 4b. Comparison of probability of occurrence of bear foods at pipeline edges compared to coniferous forest, deciduous/mixed forest, and regenerating forest (cutblocks). Significant differences are in bold.

Pipeline edge versus comparison group

	Lonicera involucrata		*Ribes sp.*		*Rubus sp.*		*Taraxacum*	
Comparison group:	Odds ratio	p	Odds ratio	p	Odds ratio	p	Odds ratio	p
Coniferous forest	0.70	0.571	0.944	1.00	**12.2**	**<0.0001**	**29.1**	**0.010**
Deciduous/Mixed forest	**0.08**	**0.013**	**0.170**	**<0.0001**	1.83	0.424	**10.4**	**0.001**
Cutblocks	0.80	0.703	**0.456**	**0.038**	1.89	0.191	1.40	1.000

Pipeline edge versus comparison group

	Trifolium sp.		Ungulates		*Vaccinium membranaceum*		*Vaccinium vitis-idaea*	
Comparison group:	Odds ratio	p	Odds ratio	p	Odds ratio	P	Odds ratio	p
Coniferous forest	**37.2**	**0.004**	**0.048**	**<0.001**	**0.29**	**0.001**	**0.21**	**<0.001**
Deciduous/Mixed forest	**20.4**	**<0.001**	**0.041**	**<0.001**	3.70	0.173	4.06	0.012
Cutblocks	**3.28**	**0.002**	**0.041**	**<0.001**	**0.30**	**<0.001**	0.38	0.003

A number of bear foods had a higher probability of occurrence on pipeline RoWs than in other habitats. Ants, *Rubus sp., Taraxacum sp.* and *Trifolium sp.* had a significantly higher probability of occurrence on RoWs than in all other habitat types. In particular, odds ratios for *Taraxacum sp.* and *Trifolium sp.* at RoWs versus coniferous forest were extremely high (Tables 3a and 3b); these species were present at 88.5% of RoW plots visited, versus less than 2% in coniferous forest (Table 2). For *Equisetum* species, RoWs had a higher occurrence than either forest type, but the probability of occurrence was not different from cutblocks. Ungulate pellets were less likely to occur on pipeline RoWs than any other habitat type. Occurrence patterns for *Lonicera, Ribes* species, and *Vaccinium* species were variable.

For pipeline edges, *Trifolium sp.* also had a significantly higher probability of occurrence than in all other habitat types, *Taraxacum officinale* was more likely to occur in pipeline edges than in either forest type, and *Rubus sp*. were more likely to occur in pipeline edges than in coniferous forest (Table 4a). As for pipeline RoWs, ungulates were less likely to occur in edges than in all other habitat types. Again, occurrence patterns for *Lonicera, Ribes* species, and *Vaccinium* species were varied, but in all cases where significant differences were detected, these berry shrubs were less likely to occur in pipeline edges than in other habitat types.

Discussion

Our results indicate that a number of bear foods are more common on pipeline RoWs and edges than in other available habitats. In particular, dandelion and clover had a much higher probability of occurrence on pipelines than in other habitat types. These species are common to recently disturbed areas (Haeussler et al. 1999; Roberts and Zhu 2002), and known to be commonly used bear foods in our study area (Larsen & Pigeon 2006). Nielsen et al. (2004c) and Roever et al. (2008b) also reported a higher occurrence of dandelion and clover in cutblocks and roadsides, respectively. Ants were also more common on pipeline RoWs than in other available habitats. These results are consistent with the analysis from year 1 of this study, when anting was observed at approximately 25% of grizzly bear use sites on pipelines. Other authors have also reported a higher occurrence of ants in disturbed areas (Nielsen et al. 2004c, Roever et al. 2008b). Ants are an important source of protein in west-central Alberta (Munro et al. 2006). The high occurrence of dandelion, clover, and ants on RoWs may serve as an attractant to pipelines.

A number of authors have reported grizzly bear use of edge habitat (Blanchard 1983, Larsen 2012, Stewart et al. 2013). It has been suggested that bears use edges because food is more abundant (Nielsen et al. 2008). In our analysis, berry shrubs (*Lonicera, Ribes species,* and *Vaccinium* species) were not more likely to occur in pipeline edges than in forest habitat. Other research in the Kakwa area found that *Vaccinium* species and other berry shrubs were observed to be relatively abundant in wellsite edges (T. McKay, unpublished data), and Vaccinium berry abundance was highest in close proximity to forestry cutblock edges (~1m) and declined rapidly within 10m (T. Larsen, unpublished data). Harper et al. (2003) also reported that *Vaccinium myrtilloides* was more abundant in forest edges compared to interior black spruce boreal forests in Quebec. Harper and Macdonald (2002) reported a decrease in some berry shrubs (*Ribes oxycanthoides, Rubus idaeas,* and *Lonicera involucrata*) and an increase in others (*Amelanchier alnifolia* and *Prunus pensylvanica*) near the forest edge in mixed wood forest in Alberta. However, to our knowledge, previous research has not been completed regarding the distribution and abundance of berry shrubs in pipeline edges. Other research suggests that *Vaccinium* species abundance is related to elevation, soil moisture, and forest stand composition (Larsen 2012); these factors were not investigated in our analysis. Further work on characterizing pipeline edge and the relationship between bear food presence/abundance, adjacent habit, and other factors could provide a clearer picture of bear food availability in pipeline edges. Regardless, it is possible that due to the narrower width of RoWs, pipelines do not allow as much light to penetrate the forest edge, so pipeline edges may not function in the same way as edges of other anthropogenic features for grizzly bear food availability.

Based on the high occurrence of some important bear foods at pipelines, pipeline RoWs could provide good grizzly bear foraging habitat. However, while bears may be attracted to pipelines, the potential increase in mortality risk could counteract the direct positive effect of higher food abundances in these areas.

Chapter B.5. Linear Features And Predation.

Introduction

The habitat analysis from this study (Chapter 2) indicates that bears are using pipelines, and field evidence (see Chapters 4 and 6) also indicates that ungulates use pipelines in our study area; therefore, encounters could occur between bears and ungulates on pipelines. Results from the first year of this study also showed that grizzly bears in the Kakwa area use pipelines for travel, which could influence encounter rates with prey. Thus grizzly bear use of linear features could have impacts for ungulate prey species, including caribou populations where they overlap with grizzly bear range.

Previous research has shown that wolves use linear corridors, potentially increasing encounter rates and predation risk for ungulates. It has been reported that wolves use areas near linear features such as roads, trails, railway lines, pipelines, and seismic lines (James & Stuart-Smith 2000, Whittington et al. 2005, Neufeld 2006, Latham et al. 2011), and that travel speeds are faster along these features (Musiani et al., 1998, McKenzie et al. 2012). Use of linear features by wolves has been well demonstrated; however, to our knowledge, no research has been published directly connecting linear features with grizzly bear predation events in Alberta.

Location cluster analysis has been previously used in predation research for grizzly bears and other species (Anderson & Lindsey 2003, Webb et al. 2008, Krofel et al. 2013, Merrill et al. 2013), and has the potential to decrease the amount of fieldwork required for kill-site data collection by targeting locations with a higher probability of predation (Rauset et al. 2012). We generated location clusters from GPS collared bears and visited these clusters in the field to determine whether or not predation events occurred. These sites were modeled with linear feature data (pipelines, pipeline-road RoWs, roads, and seismic lines) to determine the spatial relationship between grizzly bear predation sites and linear features.

Methods

Grizzly bear location data and study site generation:

Bears were fitted with Followit or Telemetry Solutions GPS collars or GPS satellite collars. Data from GPS collars were collected monthly using Very High Frequency (VHF) data upload equipment from a fixed-wing aircraft during 2006 and 2007, and data from GPS satellite collars were collected via satellite transmission in 2013. To maximize sample size, three sources of field data were combined: previous FRI data (2006 and 2007), data collected by FRI staff during 2012 and 2013, and data collected by University of Calgary researchers for a thesis project in 2013. As a result, three different methods of sampling site generation were used.

FRI sampling sites during 2006 and 2007 were generated after each monthly VHF data acquisition. GPS collar locations were separated by time of day (day, night, and crepuscular periods) and randomly subsampled to obtain an equal number of points for each bear for each time period to assess habitat use, activity, and diet. Although, the goal of data collection during 2006 and 2007 was not to maximize detection of killsites, we were able to use this data for this predation analysis, due to similar field data collection methods.

During the two field seasons of this research project (2012 and 2013) collar data were downloaded via satellite every two weeks, with a goal of maximizing the probability of detecting killsites. Collar data were processed using a Python script in ArcGIS, and clusters of three or more consecutive points less than or equal to 100m apart in space and less than or equal to 2 hours apart in time were generated. We screened these initial location clusters using criteria similar to those in Rauset et al. (2012), including the time period (total time) of the cluster and the number of daily activity periods. Daily activity periods are defined by the diurnal patterns of grizzly bear activity, separated into two periods of higher activity (morning/evening) and two periods of inactivity (afternoon/night). Inclusion of both a low and high activity period reduces the probability that a group of points is a bedding cluster. Final sampling sites to be visited in the field included only location clusters that spanned more than one activity period, with a cluster time period of greater than or equal to 8 hours.

One of the goals of the research initiated by the University of Calgary was to develop a predictive killsite model for application to historic GPS data. For this project, location clusters were generated using a space-time statistical clustering approach (Kulldorff 2001, Webb et al. 2008), stratified by cluster size (number of points), and sampling sites were selected from an even distribution of cluster sizes (Kermish-Wells, pers. comm.).

The application of different methods to select sampling sites has the potential to influence results. We classified field data into three types based on the above methods of sampling site generation, and included field data type as a parameter in our analysis to account for these potential differences.

We determined annual home ranges for each collared bear using Minimum Convex Polygons (MCPs) (see Chapter 2, Grizzly bear location data). To standardize sampling intensity for random (available) locations, we generated random locations at a density of five points per square kilometer within each MCP, based on the area of the home range for each bear (Nielsen et al. 2004b, Roever et al. 2008a). Use and available points that fell within the Kakwa study area boundary were used in the analysis. Only non-denning locations were retained in the final dataset (see Chapter 2, Grizzly bear location data).

Field data:

During 2006, 2007, and 2012 field crews visited bear use points within one month of the location date. In 2013, we visited cluster sites within two weeks of the location date whenever possible, but at least 7 days after the last point in the cluster, in order to avoid encountering bears at killsites. During 2006/2007, field crews navigated to the use point and searched for any bear activities within a 30mx30m plot centered at the use location. In 2013, field crews navigated to the centre of the cluster (as determined by the mean UTMs of the cluster points) and searched outwards in a spiral pattern for any evidence of bear activities or signs of a kill. Sites were searched outward to a 50m radius from the centre point.

In all years, study sites were confirmed as a predation site if a carcass, or parts thereof, was located. Crews identified the prey species based on observation of hooves, legs, antlers, other body parts, hair, and/or hide. When possible, the age class of the prey species was classified as calf, yearling, or adult based on body size, jaw size, presence of antlers, and the eruption pattern of teeth. To gain information about what species killed the prey (i.e. grizzly bear, wolves, coyotes, or cougar), crews recorded the presence/absence of other predator sign (tracks or scat) and additional information including whether or not a carcass was buried, if the hide was present or absent, if the carcass was disarticulated, cracked femurs, and presence of hair piles. However, it was often difficult to confirm whether a grizzly bear killed the animal, or if the animal was previously killed by other predators and subsequently scavenged by the bear. Any other bear activities or sign were also recorded, including evidence of bedding, anting, berry feeding, foraging, digging, scat, or tracks.

Analysis:

We used a GIS to measure the distance from each random location, killsite location, non-killsite use location (field-confirmed), and GPS collar location to the nearest pipeline, pipeline-road combined RoW, road, and seismic line, using disturbance datasets specific for each year (see Chapter 2, Linear feature datasets).

Similar to the methods of James and Stuart-Smith (2000), we compared the distance to the nearest linear feature between: 1) use locations and available (random) locations, 2) random locations and killsites, and 3) killsites and non-killsite use locations. Based on our results indicating that grizzly bears use most linear features more than expected based on availability (Chapter 2), we hypothesized that grizzly bear use sites and/or killsites may also be closer than expected to linear features than random locations. The interpretation of distance from killsites to linear features could be confounded by the fact that non-killsite use locations might also be closer to than expected to pipelines; therefore, we wanted to also compare killsite locations to grizzly bear use locations. However, not all GPS collar locations were visited in the field, and it was not possible to confirm whether all locations were killsites or not. We used only field-confirmed grizzly bear killsite and non-killsite use locations for our comparison of killsites versus non-killsites. Based on previous research suggesting that predation behaviour differs between individual bears (Cristescu et al. 2011, K.Graham unpublished data), analysis of all three comparison groups were run for each individual bear using logistic regression. Distance to the nearest pipeline, pipeline-road RoW, road, and seismic line were included as predictor variables. For the comparison of killsite versus non-killsite use points (field data), an effect was included for field data type.

Distance variables were checked for correlation and collinearity using Pearson's correlation coefficients and variance inflation factors (VIF), respectively. VIF values were relatively low (≤1.6), but distance to pipelines and distance to pipeline-road RoWs were correlated ($r \sim 0.6$). Therefore, these variables were included in separate models with the other distance to linear feature variables (distance to road and distance to seismic). For each bear, coefficients were reported from each model for distance to pipeline and distance to pipeline-road RoW, and averaged between the two models for distance to road and distance to seismic lines.

Results

Our final dataset included hourly GPS collar data and killsite data for one bear from 2006, two bears from 2007, and five bears in the 2013 season. FRIGBP field crews visited 300 use sites in 2006/2007, 12 clusters in 2012, and 25 clusters in 2013. University of Calgary researchers visited an additional 158 cluster sites in 2013. The final field dataset included 489 field sites at grizzly bear use locations, and 58 of these were confirmed predation sites (Table 1). The number of killsites visited per individual bear ranged from 3 to 14 (Table 1).

In general, use locations (GPS collar data, killsites, and non-killsite use) were closer to linear features than available locations (Figure 1). Some differences were observed between mean values between killsite locations, random locations, and non-killsite use locations, but these differences were not consistent or statistically significant. Mean distances to linear features by individual bear are in Table 1, and coefficients and p values from regression analyses are included in Tables 2 through 5. Grizzly bear predation sites were not significantly closer to linear features than non-predation grizzly bear use sites, and were not closer to linear features than expected based on availability.

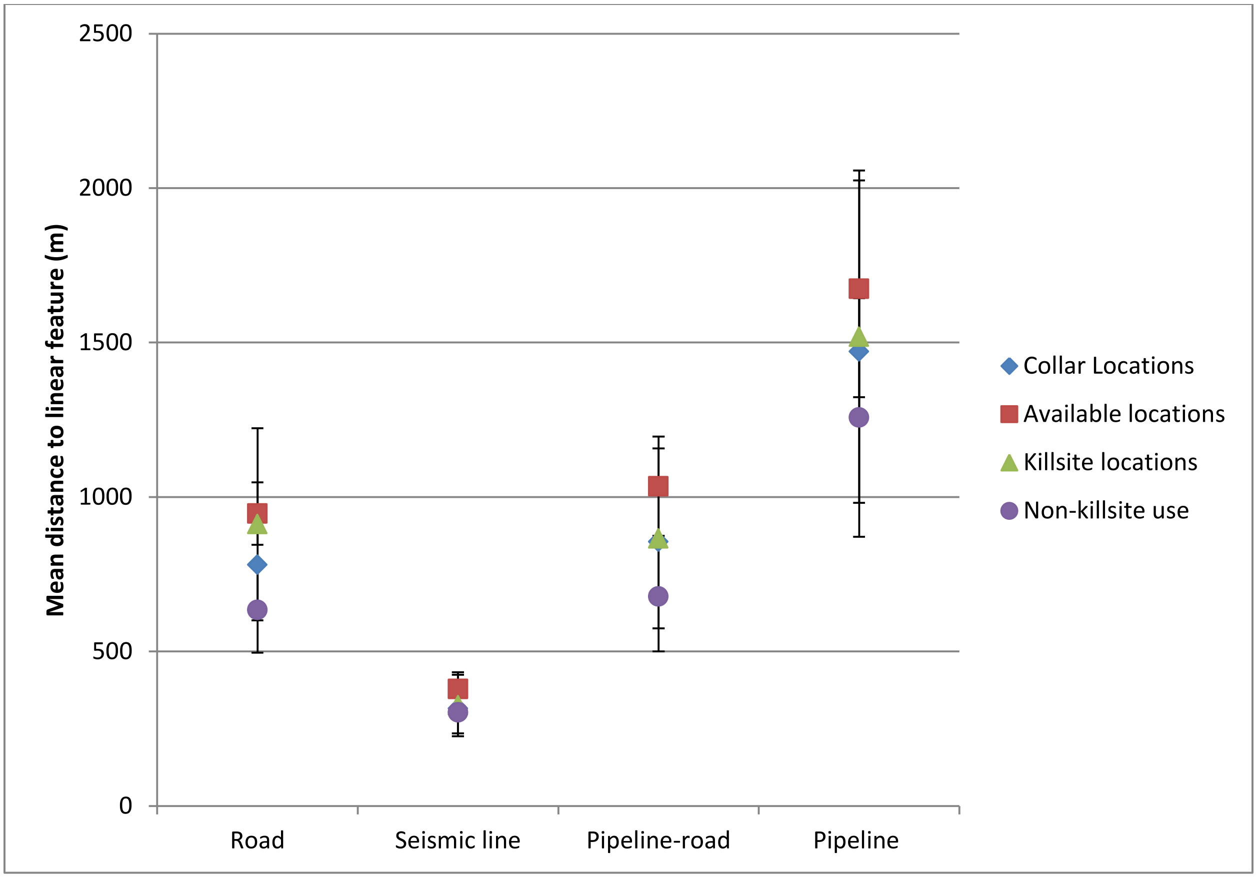

Figure 1. Mean distances to roads, seismic lines, pipeline-road RoWs and pipelines, by location type.

Table 1. Average distance to linear feature for individual grizzly bears, by use points (GPS collar locations), available points (random locations), confirmed predation sites (killsites), and confirmed non-predation use sites. Mean values with significant differences are in bold, and contrasts between comparison groups are indicated by a) significant differences between use and available, and b) significant difference between killsites and available.

		Use(GPS collar locations)		**Available (random locations)**		**Killsites**		**Non-predation use sites**	
Bear	**Linear feature**	**N**	**Mean**	**N**	**Mean**	**N**	**Mean**	**N**	**Mean**
G223	Road	2763	**688**[a]	2897	791	3	884	29	615
	Seismic		**278**[a]		304		228		224
	Pipeline-Road		**959**[a]		831		317		639
	Pipeline		**1171**[a]		1283		780		889
G236	Road	2400	**691**[a]	5241	639	3	871	88	654
	Seismic		**369**[a]		305		413		419
	Pipeline-Road		**846**[a]		685		537		927
	Pipeline		**1043**[a]		942		1198		1071
G238	Road	2120	**634**[a]	5618	879	6	390	60	576
	Seismic		**343**[a]		370		362		284
	Pipeline-Road		1174		1201		1071		593
	Pipeline		**2317**[a]		2108		1671		2200
G260	Road	4647	**722**[a]	5593	835	10	564	127	481
	Seismic		**302**[a]		305		266		259
	Pipeline-Road		**569**[a]		824		819		533
	Pipeline		**1002**[a]		1229		1004		1034
G270	Road	3740	**876**[a]	7840	1065	14	**1290**[b]	58	812
	Seismic		**331**[a]		464		326		270
	Pipeline-Road		**887**[a]		1458		673		682
	Pipeline		**1850**[a]		2476		1796		1399
G280	Road	2704	**734**[a]	2067	902	7	1099	19	735
	Seismic		**347**[a]		482		462		256
	Pipeline-Road		1080		1247		1524		865
	Pipeline		**1935**[a]		2000		2745		1395
G284	Road	2338	892	7007	828	10	712	7	499
	Seismic		**200**[a]		237		150		136
	Pipeline-Road		**888**[a]		724		655		862
	Pipeline		**1371**[a]		964		805		1103
G287	Road	1664	**629**[a]	14007	1003	5	504	24	674
	Seismic		**297**[a]		357		250		340
	Pipeline-Road		**653**[a]		1019		299		344
	Pipeline		**997**[a]		1671		804		587

Table 2. Coefficients and confidence intervals by individual grizzly bear for analysis of distance to nearest road for: 1) use versus available locations, 2) killsites versus available locations, and 3) killsite versus non-killsite use locations. Significant results are in bold.

	Use versus available				**Killsites versus available**				**Killsites versus non-killsite use**			
			95% CI				95% CI				95% CI	
Bear	β	p	Lower	Upper	β	p	Lower	Upper	β	p	Lower	Upper
G223	**-0.00025**	**0.000**	**-0.00033**	**-0.00016**	0.00034	0.672	-0.00123	0.00191	0.00143	0.350	-0.00155	0.00441
G236	**0.00014**	**0.041**	**0.00003**	**0.00025**	0.00101	0.387	-0.00126	0.00328	0.00133	0.332	-0.00135	0.00400
G238	**-0.00055**	**0.000**	**-0.00063**	**-0.00047**	-0.00169	0.131	-0.00387	0.00050	-0.00101	0.414	-0.00343	0.00141
G260	**-0.00013**	**0.000**	**-0.00019**	**-0.00008**	-0.00069	0.272	-0.00193	0.00054	0.00040	0.505	-0.00076	0.00157
G270	**-0.00011**	**0.002**	**-0.00016**	**-0.00006**	0.00051	0.083	-0.00004	0.00107	0.00045	0.176	-0.00020	0.00110
G280	**-0.00033**	**0.000**	**-0.00041**	**-0.00024**	0.00021	0.616	-0.00061	0.00103	-0.00081	0.533	-0.00334	0.00172
G284	0.00009	0.088	0.00001	0.00017	-0.00031	0.604	-0.00148	0.00086	0.00270	0.228	-0.00165	0.00705
G287	**-0.00063**	**0.000**	**-0.00072**	**-0.00053**	-0.00101	0.316	-0.00299	0.00096	-0.00083	0.409	-0.00280	0.00114

Table 3. Coefficients and confidence intervals by individual grizzly bear for analysis of distance to nearest seismic line for: 1) use versus available locations, 2) killsites versus available locations, and 3) killsite versus non-killsite use locations. Significant results are in bold.

	Use versus available				**Killsites versus available**				**Killsites versus non-killsite use**			
Bear			95% CI				95% CI				95% CI	
Bear	β	p	Lower	Upper	β	p	Lower	Upper	β	p	Lower	Upper
G223	**-0.00033**	**0.023**	**-0.00054**	**-0.00012**	-0.00098	0.719	-0.00633	0.00437	-0.00150	0.674	-0.00848	0.00549
G236	**0.00086**	**0.000**	**0.00068**	**0.00103**	0.00130	0.483	-0.00234	0.00495	-0.00001	0.939	-0.00405	0.00403
G238	**-0.00025**	**0.010**	**-0.00040**	**-0.00009**	0.00021	0.864	-0.00221	0.00263	0.00121	0.480	-0.00192	0.00435
G260	**0.00028**	**0.001**	**0.00013**	**0.00042**	-0.00033	0.795	-0.00281	0.00216	0.00013	0.935	-0.00292	0.00317
G270	**-0.00071**	**0.000**	**-0.00083**	**-0.00059**	-0.00080	0.373	-0.00254	0.00094	0.00112	0.356	-0.00123	0.00347
G280	**-0.00108**	**0.000**	**-0.00126**	**-0.00090**	-0.00042	0.667	-0.00235	0.00151	0.00259	0.311	-0.00237	0.00756
G284	**-0.00101**	**0.000**	**-0.00125**	**-0.00077**	-0.00266	0.231	-0.00702	0.00170	-0.00675	0.373	-0.02140	0.00791
G287	**-0.00039**	**0.001**	**-0.00058**	**-0.00019**	-0.00088	0.665	-0.00489	0.00312	-0.00165	0.353	-0.00514	0.00184

Table 4. Coefficients and confidence intervals by individual grizzly bear for analysis of distance to nearest pipeline for: 1) use versus available locations, 2) killsites versus available locations, and 3) killsite versus non-killsite use locations. Significant results are in bold.

	Use versus available				**Killsites versus available**				**Killsites versus non-killsite use**			
			95% CI				95% CI				95% CI	
Bear	β	p	Lower	Upper	β	p	Lower	Upper	β	p	Lower	Upper
G223	**-0.00011**	**<0.001**	**-0.00017**	**-0.00006**	-0.00073	0.414	-0.00247	0.00102	-0.00022	0.838	-0.00235	0.00191
G236	**0.00014**	**<0.001**	**0.00008**	**0.00020**	0.00026	0.677	-0.00096	0.00147	0.00012	0.830	-0.00093	0.00116
G238	**0.00011**	**<0.001**	**0.00008**	**0.00014**	-0.00010	0.739	-0.00066	0.00047	-0.00024	0.410	-0.00080	0.00033
G260	**-0.00026**	**<0.001**	**-0.00030**	**-0.00021**	-0.00017	0.641	-0.00090	0.00055	-0.00005	0.885	-0.00080	0.00069
G270	**-0.00010**	**<0.001**	**-0.00013**	**-0.00008**	-0.00021	0.213	-0.00054	0.00012	0.00023	0.321	-0.00023	0.00069
G280	**0.00005**	**0.019**	**0.00001**	**0.00009**	0.00032	0.165	-0.00013	0.00078	0.00064	0.132	-0.00019	0.00148
G284	**0.00052**	**<0.001**	**0.00047**	**0.00057**	-0.00019	0.664	-0.00106	0.00068	-0.00305	0.098	-0.00667	0.00056
G287	**-0.00029**	**<0.001**	**-0.00034**	**-0.00024**	-0.00050	0.396	-0.00165	0.00065	0.00116	0.271	-0.00091	0.00323

Table 5. Coefficients and confidence intervals by individual grizzly bear for analysis of distance to nearest pipeline-road RoW for: 1) use versus available locations, 2) killsites versus available locations, and 3) killsite versus non-killsite use locations. Significant results are in bold.

	Use versus available				**Killsites versus available**				**Killsites versus non-killsite use**			
			95% CI				95% CI				95% CI	
Bear	β	p	Lower	Upper	β	p	Lower	Upper	β	p	Lower	Upper
G223	**0.00026**	**<0.001**	**0.00019**	**0.00033**	-0.00232	0.212	-0.00597	0.00133	-0.00223	0.366	-0.00705	0.00260
G236	**0.00034**	**<0.001**	**0.00026**	**0.00041**	-0.00068	0.576	-0.00308	0.00172	-0.00099	0.422	-0.00340	0.00143
G238	0.00002	0.386	-0.00003	0.00007	-0.00006	0.881	-0.00090	0.00077	0.00049	0.336	-0.00051	0.00149
G260	**-0.00064**	**<0.001**	**-0.00071**	**-0.00057**	0.00016	0.729	-0.00075	0.00107	0.00071	0.122	-0.00019	0.00161
G270	**-0.00034**	**<0.001**	**-0.00038**	**-0.00030**	**-0.00093**	**0.022**	**-0.00172**	**-0.00014**	0.00035	0.634	-0.00108	0.00177
G280	0.00005	0.169	-0.00002	0.00011	0.00021	0.559	-0.00049	0.00090	0.00043	0.472	-4.94887	2.29020
G284	**0.00035**	**<0.001**	**0.00029**	**0.00042**	-0.00007	0.896	-0.00109	0.00095	-0.00058	0.680	-0.00336	0.00219
G287	**-0.00039**	**<0.001**	**-0.00047**	**-0.00031**	-0.00217	0.140	-0.00506	0.00071	-0.00124	0.896	-2.76339	2.41860

Discussion

Models using wolf and caribou telemetry data have predicted that encounter rates would be significantly higher between predators and prey in areas of high seismic density (McKenzie et al. 2012) and in proximity to other linear features (Whittington et al. 2011). However, limited research is available regarding the occurrence of confirmed predation events on or near linear features. James and Stuart-Smith (2000) found that wolves were closer than expected to linear corridors, but predation sites were not significantly closer than random locations or telemetry locations. Results from our analysis suggest that grizzly bear predation events in our study area did not occur closer to linear features than that expected based on availability. However, previous results from the Kakwa area indicated that grizzly bears are using linear features for travel, similar to predator movement patterns in other areas of the province (Musiani et al. 1998, McKenzie et al. 2012).

Sample sizes for killsites were low in our study, possibly limiting the power to detect significant differences. Research planned in the Kakwa area during 2014 includes further investigation of grizzly bear predation in caribou range. The outcomes of the study will include: spatial and temporal models describing grizzly bear use and movement relative to linear features within the summer range of mountain caribou herds, estimates of caribou kill rates by grizzly bears from this area, and new predictive models of grizzly bear predation identifying anthropogenic and other factors influencing the distribution of caribou mortalities. This study will also include the development of new techniques (stable isotope analysis from bear hair and/or scat) which could be used to monitor caribou consumption by grizzly bears and other predators found within all caribou ranges in Alberta and across Canada. The use of isotope analysis has the potential to reduce the amount of field data necessary for predation studies.

Predator use of linear features has the potential to increase kill rates of large ungulates (Webb et al. 2008, McKenzie et al. 2009). Based on our current analysis, we have no evidence to suggest that this pattern occurs with grizzly bears, ungulate prey species, and pipeline RoWs in our study area. Movement along linear features in our study area has the potential to increase grizzly bear access to prey; however, based on our distance to linear feature analysis, it is uncertain whether bears traveled on linear features prior to predation events. We anticipate that results from research in 2014 will aid in understanding the complexity of grizzly bear predation behaviour in the boreal forest.

Chapter B.6. Mortality Risk Factors

B.6.1. Sightability of grizzly bears on pipeline RoWs.

Introduction

Human-caused mortality is considered to be the primary limiting factor for Alberta grizzly bears (ASRD 2008), and areas with a high level of human access are associated with an increased risk of mortality (Jalkotzy et al. 1997, Benn 1998, Nielsen et al. 2004a, Boulanger et al. 2013). The use of linear features by grizzly bears for travel and/or foraging may put them at a higher risk of human-caused mortality, but this risk may be partially dependent on the visibility of bears at road/pipeline intersections

A number of authors have previously measured hiding cover and the visibility of bears and other species, including the distance at which a simulated animal is detected, the amount of "animal" that is visible, and the maximum distance visible along a linear feature, or line-of-sight distance (Sunde et al. 1998; Switalski &Nelson 2011; Kjellander et al. 2012). Sunde et al. (1998) found that the tolerance of lynx to human presence depended on cover, and Switalski and Nelson (2011) reported that the frequency of black bears photographed along roads in Montana was negatively correlated with line-of-sight distance, and positively correlated with hiding cover.

Based on the potential for mortality risk, we were interested in investigating the visibility on pipelines from a road. We examined visibility of grizzly bears at varying distances and collected data on factors that may affect visibility. A variety of equipment and methods have been applied to measure visibility (Collins & Becker 2001; Ordiz et al. 2009), and we adapted these techniques to measure visibility of grizzly bears at pipeline-road intersections in the Kakwa area. We proposed that visibility of bears may depend on vegetation, pipeline age, adjacent habitat, presence of a trail, and topography (e.g. slopes, depressions). Using knowledge gained in the examination of these factors, a spatial model would be developed to predict which pipelines in the Kakwa study area had high visibility and therefore grizzly bears would have a high risk of human-caused mortality on these sections of pipelines. This visibility Information will provide an indication of their vulnerability to human-caused mortality (illegal killing) while on pipelines.

Methods

Site selection:

A Geographic Information System (GIS) was used to determine locations of pipeline and road intersections. Pipelines parallel to roads were not included as part of this analysis. The intersections were stratified by age class of pipeline and randomly subsampled to generate field sites for data collection.

Field methods:

Based on the average height and length of grizzly bears in our area, we constructed a rectangle out of brown cloth, approximately 1m tall (based on shoulder height) and 1.5m wide. The rectangular section of cloth was mounted on stakes to allow it to be displayed in the field, and marked into four quarters to assist with estimating the percent visible. With one person stationed on the road at a randomly generated distance from the pipeline edge, the second person walked 50m up the edge of the pipeline, traversed out onto the pipeline at a different randomly generated distance from the edge, and held out the cloth "bear". The person at the road estimated the percent of "bear" visible, and recorded any obstruction, including grass/forbs, shrubs, trees, hill, depression, corner, and "other", (e.g. infrastructure or logging debris). We called this a road random-pipe random paired locations measure. If wildlife or an off-highway vehicle (OHV) trail was present down the pipeline from the road, three additional paired location visibility estimates were taken. The person at the 50m distance on the pipeline would move across the pipeline to the trail and visibility of the "bear" on the trail was assessed by the person at the random location on the road (road random –pipe trail paired locations). The person on the road then moved along the road to look down the trail and estimated % of the "bear" visible down the trail (road trail-pipe trail paired locations) and lastly the person at the 50m mark moved back to the 50m random location and the person standing at the road-trail junction did a forth visibility estimate (road trail – pipe random paired locations). Tree, shrub and grass/forb cover > 25 cm tall were visually estimated using cover classes (Table 1) for the entire 50 m length of pipeline, and height of vegetation was measured at the random pipeline location and the trail location. Adjacent habitat on both sides of the pipeline was classified to conifer species (lodgepole pine, white spruce or black spruce) and canopy cover (open, moderate or dense), other habitat types (mixed forest, broadleaf forest, open wetland, treed wetland, shrubs, herbaceous or water) or anthropogenic habitat (cutblock or wellsite).

Table 1. Percent cover classes used to estimate forbs/grass and shrubs > 25 cm tall and tree canopy cover on pipelines.

Grass/Forb and Shrub Cover Class	Percent Grass/Forb or Shrub Cover	Midpoint value used in analysis	Tree Canopy Class	Percent Tree Canopy Cover	Midpoint value used in analysis
+	< 1	0.5	1	1-10	5.5
2	< 5	2.5	2	11-30	20.5
3	5-25	15	3	31-50	40.5
4	26-50	38	4	51-70	60.5
5	51-75	63	5	71-90	80.5
6	76-100	88	6	91-100	95.5

Measurements were repeated at 100m, 150m, and 200m distances down the pipeline, or until 0% of the bear was visible. At that point it was assumed that the visibility of the "bear" would continue to be zero up until 200m.

The maximum line-of-sight down the pipeline from the road intersection was measured using a rangefinder. Maximum line-of-sight was measured to the furthest point at which >0% of a bear would be visible. Pipeline RoW width and the presence/absence of a belt of shrubs or trees next to the road were also recorded.

Analysis:

We completed exploratory summaries of the data. We tested for differences in the percentage of bear visible among the location pairs (RdRandom-PipeRandom, RdRandom_PipeTrail, RdTrail-PipeRandom and RdTrail-PipeTrail) and the 4 distances (50m, 100m, 150m, 200m). We used an ordinal logistic regression because of the large number of 0% visibility values. Percent visible values were categorized into 4 visibility classes (0-25%, 26-50%, 51-75%, and 76-100%).

We conducted a generalized linear model (GLM) analysis to determine the important factors in predicting maximum line-of-sight down a pipeline from a road intersection. Age of pipeline was obtained in a Geographic Information System (GIS) based on pipeline construction dates provided by Alberta Energy. Pipelines with more than one construction date (i.e. a second or additional pipeline had been construction down the same pipeline right-of-way at a later date) were removed from the GLM analysis because field data collection did not distinguish between vegetation estimates from the older and recent portions of the pipeline; therefore, dates could not be confidently matched to vegetation estimates. A Terrain Ruggedness Index (TRI) and a Compound Topographic Index (CTI) were extracted at each pipeline-road intersection visited. Terrain Ruggedness index (TRI) provided a measure of the unevenness of the terrain at a 30m scale, as averaged across the 8 surrounding 30m pixels (Riley et al. 1999), based on a Digital Elevation Model (DEM). The CTI provided a measure of moisture in a 150m radius at each pipeline-road intersection. We log-transformed the maximum line-of-sight distance (m) to improve normality, and tested for collinearity using variance inflation factors (VIF) among all the variables prior to the analysis.

Results

Field crews collected data from 66 pipelines in 2013, twenty (30%) of which had trails present. Eighty percent of trails were classed as OHV, and 20% were classed as a wildlife trail. The average maximum line-of-sight down a pipeline from a road intersection was 164.5m, with a range of 2-900m and a median of 112.5m. Forty-eight percent of pipelines had a maximum line-of-sight < 100m; 3% had a maximum line-of-sight > 500m (Figure 1).

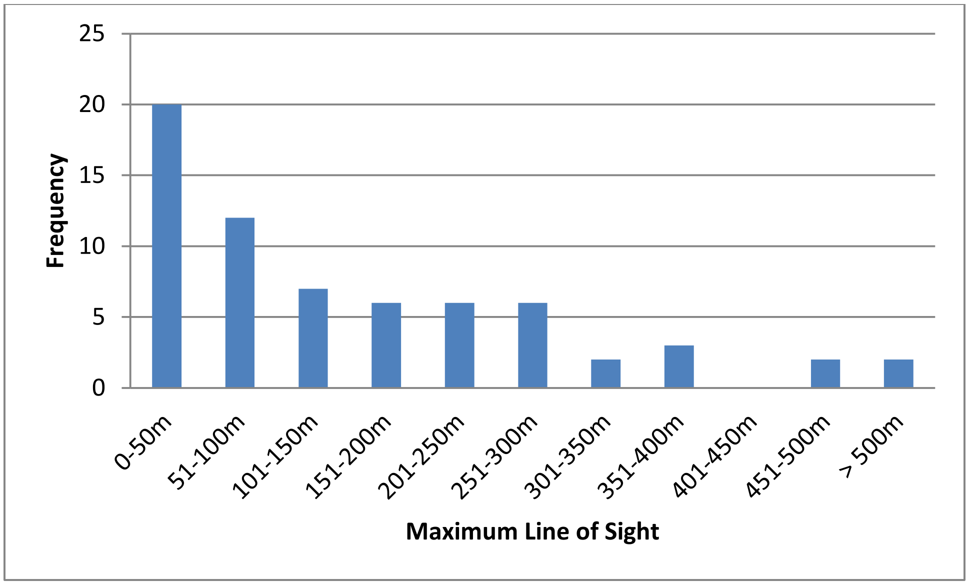

Figure 1. Frequency of maximum line-of-sight distances down pipelines from road intersections in the Kakwa Study area.

Sites with shrubs or trees recorded as the obstruction were pooled into a shrub/tree obstruction class due to small sample sizes. A vegetation belt at the pipeline-road intersection occurred at only 2 sites, and these were also pooled with the shrub/tree obstruction class. Sites with a hill, berm, or depression as the obstruction were also pooled to create a topography obstruction class.

Topography was the main cause of obstruction of maximum line-of-sight at over 50% of the sites, followed by pipeline corners, shrubs, and grass/forbs (Figure 2).

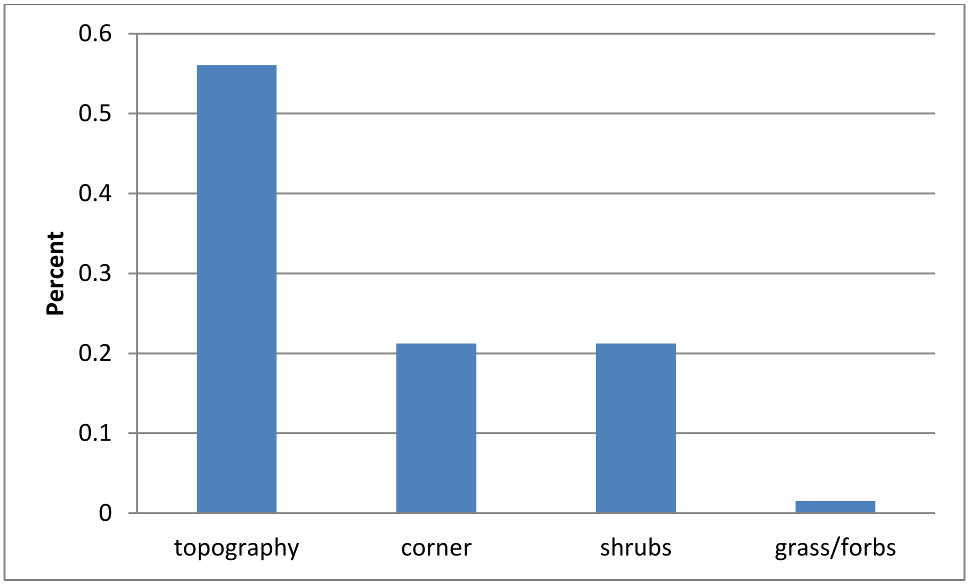

Figure 2. The maximum line-of-sight obstruction types at 66 pipeline-road intersections in the Kakwa study area.

At 50m distance from the road, on average 20% of the "bear" was visible when looking from the road to a random pipeline location (n= 66); compared to 34% visible when looking down a trail with the "bear" on the trail (n=20; Figure 2). At the 200m distance, 7-8 % of the bear was visible regardless of whether the "bear" was on a trail. Mean height of vegetation at random pipeline locations (mean=77.4 cm, n=40) was significantly different than on trails (mean = 53.4 cm, n=40; paired t-test: t =2.94; df=39; P = 0.005).

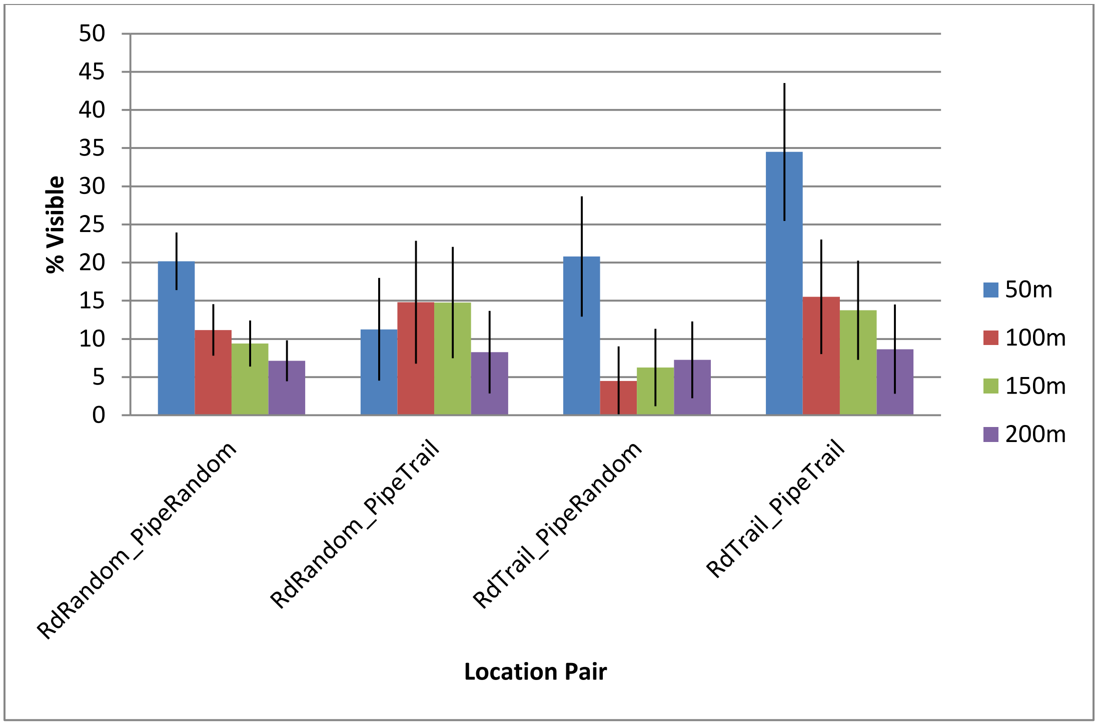

Figure 3. Average percent of a "grizzly bear" visible in 50m increments down a pipeline from a road intersection at different location pairs for a total of 504 "bear" locations. Standard error bars are shown.

The ordinal logistic regression looking at location pairs and distance from a road down a pipeline found distance from road was a significant predictor of visibility (z = -3.32, P = 0.001), but the 4 location pairs was not (P > 0.05; Figure 3).

Visibility was reduced most often by shrubs/trees (42% of the 504 "bear" locations), followed by topography (37.5%), grass/forbs (8%), corners (7%), and other (1%; Figure 3). Shrubs/trees and topography were important obstructions at all 4 distances, while grass/forb and "other" were more important at the 50m distance. Pipeline corners were most important at 150m and 200m distances (Figure 4).

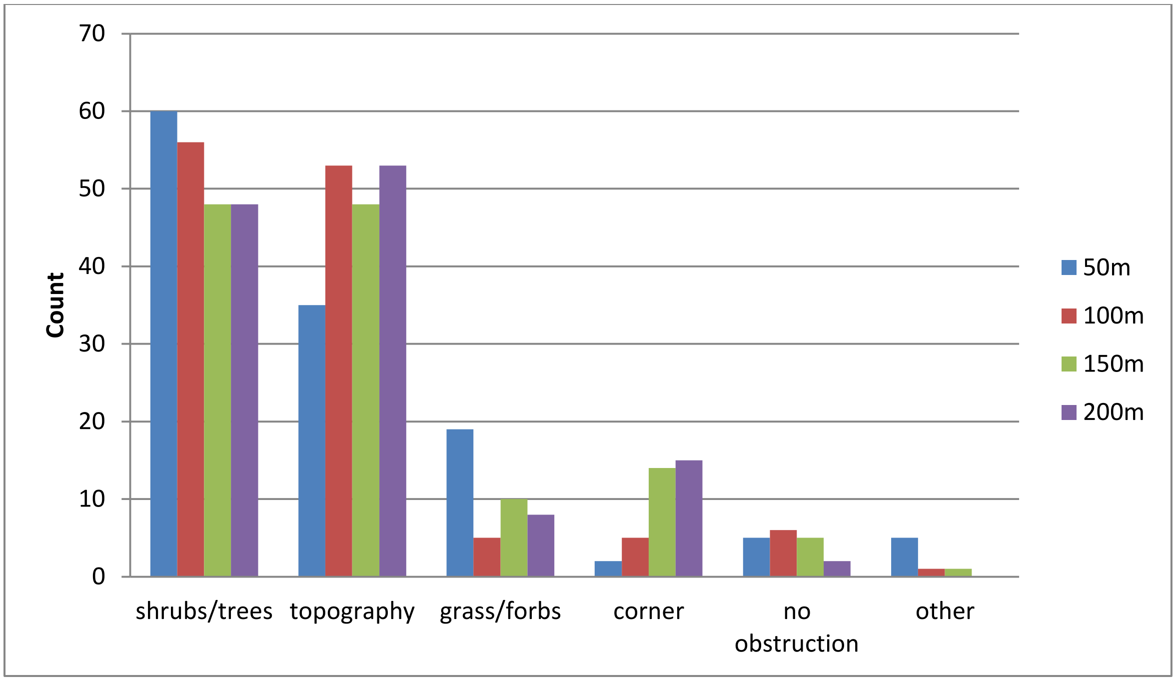

Figure 4. Count of obstruction type by distance (m) down pipelines at road-pipeline intersections at 504 “bear” locations.

Of the 66 pipelines visited, we excluded 16 due to missed data or multiple construction years. Based on our exploratory examination, we developed three *a priori* models based on vegetation, terrain or pipeline attributes to explain maximum line-of-sight (Tables 2 and 3). We used elevation as a surrogate for tree species in the adjacent habitat. Elevations ranged from 695m to 1314m. Forested sites below 1050m consisted mainly of deciduous tree species (89%), while sites above 1050m were mainly coniferous species (86%). There was no collinearity among the parameters in Table 2 with all variance inflation factors (VIF) < 1.99. The model with the most AIC support was the vegetation model, which included shrub cover and vegetation height, and explained 90% of the variability (Table 4).

Table 2. Explanatory variables used for assessing maximum line-of-sight down pipelines at road intersections in the Kakwa study area.

Variable	Source	Description	Range
ShrubTCover	Field measure	Average shrub/tree cover (%) on a pipeline using midpoint of cover classes (Table 1)	0-63 %
VegHeight	Field measure	Average vegetation height (cm) on a pipeline	0-202 cm
Elevation	GIS Raster	Elevation of location based on a 30 m Digital Elevation Model (DEM)	695-1314m
Year	Alberta Energy	Construction Year of pipeline	1981-2012
width	Field measure	Width of pipeline (m)	9-60m
CTI	GIS Raster	Compound Topographic (wetness) Index– at a 150m scale	6-11
TRI	GIS Raster	Terrain Ruggedness Index – at a 90m scale	0-15

Table 3. A priori candidate models used to describe the maximum line-of-sight down pipelines at road intersections in the Kakwa study area.

Model Number	**Model Name**	**Parameters**	**Number of observations**
	Null (logdistance)	none	50
1	Vegetation	Shrub cover, vegetation height	50
2	Terrain	Elevation, TRI, CTI	50
3	Pipeline	Year, RoW width	50
4	Global	Shrub cover, vegetation height, CTI, elevation, TRI, year, RoW width	50

Table 4. AICc-selected models for predicting the maximum line-of-sight down pipelines at road intersections in the Kakwa study area. The model with the highest AIC weight is in bold.

Model Number	Log Likelihood	K	AiCc	Δ_i	w_i
Null	-37.001	1	76.08533	6.757594	0.030666
1	**-31.403**	**3**	**69.32774**	**0**	**0.899606**
2	-36.666	4	82.22089	12.89315	0.001427
3	-34.463	3	75.44774	6.12	0.042180
4	-28.447	8	76.4062	7.078456	0.026121

We examined whether shrub/tree cover or vegetation height were associated with construction year or CTI. We found no relationship between construction year and shrub/tree cover (t = 1.65; P > 0.05) or vegetation height (t = 0.05; P > 0.05). Similarly there was no relationship between CTI and shrub/tree cover (t = -0.27; P > 0.05) or vegetation height (t = -0.76; P> 0.05).

Discussion

At the start of this research, our intention was to create a model that could be applied to the entire study area, in order to highlight pipelines with the farthest sightability (maximum line-of-sight) at road intersections. These intersections would present the highest grizzly bear mortality risk and could therefore be targeted for mitigation. This analysis required GIS layers that were potential predictors of maximum line-of-light for our study area. Our exploratory analysis and GLM indicated that shrub cover and/or vegetation height were important predictors, but a GIS layer including vegetation information for all pipelines in the study area was not available. Therefore, we examined whether construction year or CTI could be used as a surrogate for these vegetation parameters, but found no relationship. In addition, the index of topography (TRI) used in the GLM analysis was a poor predictor of maximum line-of-sight; in spite exploratory work indicating that topography was the most important obstruction of sight lines. We suspect that the TRI was not at the right spatial scale to detect the small hills and depressions that could hide a grizzly bear. Without suitable GIS layers for model development and testing, we did not pursue this analysis further.

We had expected that construction year would predict our shrub cover estimates or vegetation heights; however, this was not the case. It is possible that the pipeline construction year did not accurately represent when the last disturbance event occurred, as it is unknown whether pipelines were cleared again after their initial construction date. It is also plausible that shrub growth is related to many other factors other than last disturbance date, such as light intensity and duration, soil seed bank, soil type etc. These factors were not investigated in our analysis.

Over half of our sites had a maximum line-of-sight of > 100m down the pipeline from a road intersection. Topography blocked maximum line-of-sight at over 50% of our plots, and was also important in reducing bear visibility at 50-200m down a pipeline. Shrubs were less important in determining maximum line of sight compared with topography, but were important in reducing bear visibility at 50-200m down a pipeline. Based on these results, creating an earth berm along road intersections and/or encouraging shrub growth within the first 50m of a road intersection could help to reduce grizzly bear mortality risk on pipelines at road intersections.

The presence of a trail, although not significant in affecting visibility of a "bear" compared to random locations, did result in more of the "bear" being seen, especially at the 50m distance. If a trail is required on a pipeline, the trail-road junction could be hidden by shrubs or a berm to reduce visibility while still allowing workers to travel on the pipelines.

Although maximum line-of-sight was often > 100m, this is the distance when a bear was presumed to be completely hidden. At a 50 m distance from the majority of road intersections, 10-35% of a "bear" was visible. This suggests that many pipelines have topography, curves or shrub cover that partially hide a grizzly bear from the view of passing vehicles. Our sightability results also suggest that workers or recreationists using pipelines for travel may not be able to see a grizzly bear on a pipeline from long distances. We recommend that pipeline workers be trained in bear awareness and safety when working in bear habitat. We examine the human use of pipelines in the next section (6B).

B.6.2. Levels of human and wildlife use on pipeline RoWs.

Introduction

It is well known that human access is associated with an increased risk of human-caused grizzly bear mortalities (Jalkotzy et al. 1997, Benn 1998, Nielsen et al. 2004a, Roever et al. 2008a, Boulanger et al. 2013). However, while the risk of mortalities can be predicted, the actual occurrence of mortality events depends on human-bear encounters and the attitudes and behaviours of the people encountering bears. We set out to examine levels of human use of pipelines within the Kakwa study area, and to assess the probability of these encounters taking place.

Methods

Previous work by our staff in this study area suggested an overall low level of human presence on pipelines; therefore, we decided to situate cameras to maximize the probability of detecting any use of pipelines by humans. We installed cameras just prior to and during the hunting season in the fall. Camera locations were subjectively determined based on observations of human use on pipelines, the configuration of the pipeline across the landscape, and the distance to the nearest road. Potential sites were mapped in a GIS. Sites were selected within 100m of a main gravel road that either: a) spanned a large distance across the study area, in which case cameras were placed at different entry points, or b) were on a short pipeline but provided entry to areas where road access was limited.

The cameras installed for this data collection included Bushnell Trophy Cams, Cuddyback No Flash, and Cuddyback AttackIRs. At each site, cameras were locked inside protective metal cases and attached to a tree with screws at a height of between 0.75-1.5 m, depending on the height of the terrain in front of the camera. Tall grass, forbs and shrubs were cleared from the camera field of view.

Photo processing:

Each photo was visually assessed, and photo date, time, photo subject, and direction of travel were entered into a database. Wildlife species were recorded as well as human use. An event was defined as a sequence of photos within 5 minutes of each other triggered by the same animal or person. We also identified "linked" events, when two events of the (presumed) same individual (based on physical characteristics) occurred within the same day. Most of these linked events were of people with distinguishable features such as ATV or clothing. For grizzly bear sightings, we used data to confirm whether a collared bear was at a location at different times of the day. We used colour and size to determine if it was the same uncollared bear, but only if the events occurred within the same hour, in order to minimize misidentification of individuals. Antlers and size of animal helped to determine the unique identity of male ungulates, however, it was not possible to determine the unique identity for coyotes, lynx or female ungulates.

Each photo subject was identified to species whenever possible. Observations of ATVs were classified as work-related, recreational, or unknown. Although it was not possible to confirm peoples' activities, we used the presence of coveralls, cruise vests, or equipment strapped to the ATV as evidence of work-related activities. ATV-unknown included photos with poor visibility of the vehicle and/or people. For each camera site, we standardized the frequency of photos by photo subject per 100 camera-days.

Results

Seven cameras were installed between 31 July and 1 Aug 2013 (Figure 1). One camera (Ridge) failed immediately after deployment, and another camera (Comeau) was removed after 20 days due to nearby construction of a pipeline. The Camp camera missed 20 days in early September as a result of hundreds of misfires that filled the SD card. Cameras were removed from between 10-15 Oct 2013. The Comeau site collected pictures for 20 days, the Camp camera for 55 days, and the remaining 4 sites collected pictures for 72-76 days.

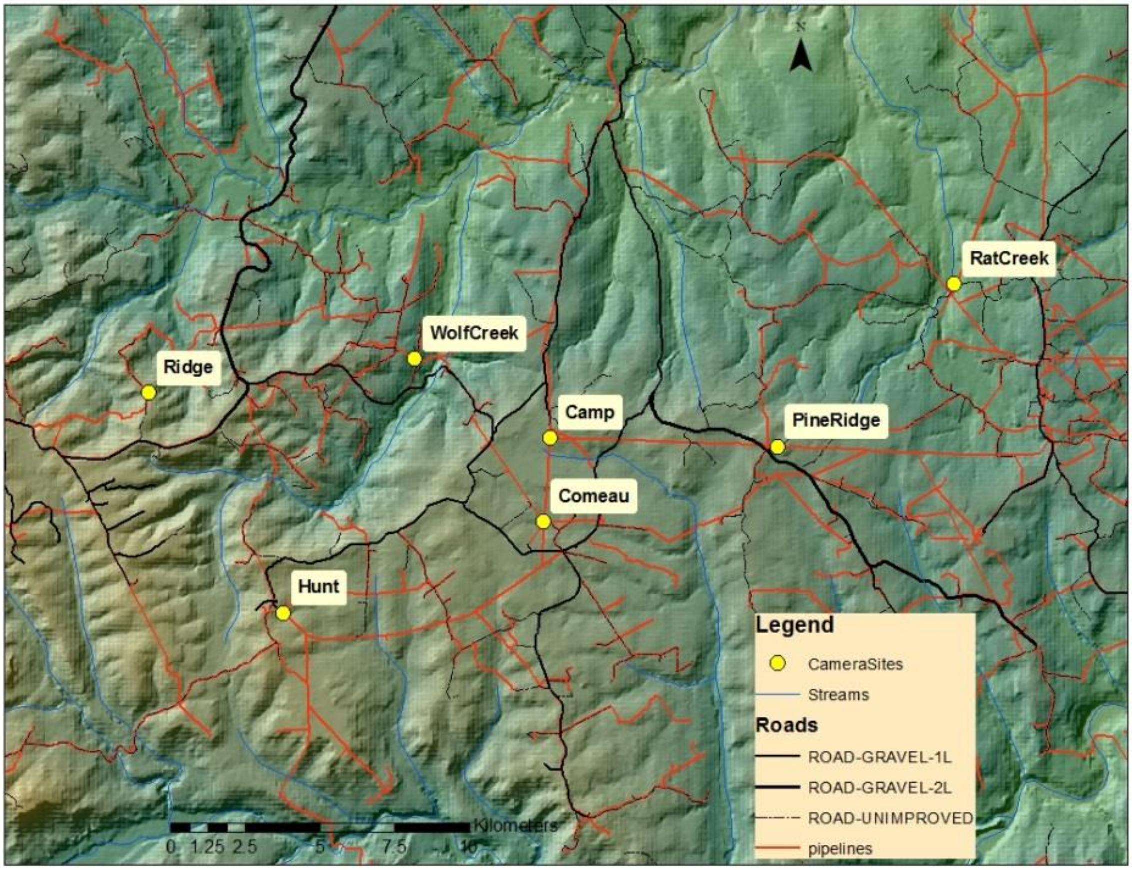

Figure 1. Locations of 7 cameras located on pipelines within the Kakwa study area.

A total of 1280 photos were obtained from six cameras, with 345 photos (27%) attributed to an observable photo subject (person or animal), for a total of 144 events. The remaining 935 photos (93%) did not have a person or animal detected. It appeared that the wind may have resulted in misfires, and some photos may have been triggered by an animal too small or moving too fast for the camera to capture.

Table 1 shows counts for each photo subject by camera site. Species observed only once were pooled into a miscellaneous group including elk, gray jay, lynx, and mule deer. Of the 144 events, 38% were ATVs (including quads and side-by-sides), followed by grizzly bears at 19%, white-tailed deer at 19%, coyote and moose at 5%, people on foot or helicopter at 4%, deer at 3%, miscellaneous at 3% and bears of unknown species and unknown animals both at 2%.

ATVs were detected at all six camera sites. Of the ATV events, 65% appeared to be work related, 9% may have been recreational, and 26% were unknown. In addition, 59% of ATV sightings were linked to one or more events in the same day, typically observed going in one direction in the first photo and in the opposite direction in the linked photo. All human detections occurred during daylight hours. A firearm was seen in 28% of the ATV photos, all of which came from one site and likely the same individual.

Table 1. Count of photos by photo subject across the 6 camera sites. *Miscellaneous includes one photo each of an elk, mule deer, gray jay, and lynx.

Camera Site	ATV	Grizzly Bear	White-tailed Deer	Coyote	Moose	Persons on foot or heli	Deer Sp.	Misc. *	Bear Sp.	Unk	Grand Total
Camp	6	16	3	6		3	1	1	3	2	41
Comeau	2		1		2						5
Hunt	34		1		1	2	1	1			40
PineRidge	3	10	8	1	2		2			1	27
RatCreek	2	2	5			1	1	1			12
WolfCreek	7		9		2			1			19
Grand Total	**54**	**28**	**27**	**7**	**7**	**6**	**5**	**4**	**3**	**3**	**144**

Grizzly bears were detected at 3 of the camera sites, with two of the sites providing 93% of the detections. Of the 28 events, 18% were linked and all linked events occurred at the Camp site. Forty-seven percent of grizzly bear detections occurred at night (Figure 1), followed by day (40%), dusk (9%) and dawn (4%). White-tailed deer were the most ubiquitous species; detected at all 6 sites with 52% detections occurring at night, 44% during the day and 4% at dusk.

Figure 1. Remote camera picture of a grizzly bear event from the Pine Ridge site. One of these bears is an adult male grizzly bear (G270) wearing a GPS collar.

Using standardized values for each camera site and only the first event for linked events, all six sites had an average of 9.1 ATV events/100 camera days (SD=8.9). The Hunt site had the highest (26.3 ATV events/100 camera days) and the Rat Creek and Pine Ridge sites the lowest (2.6 ATV events/100 camera days, Figure 2). Grizzly bears were detected at the Camp site most often at 20 events/100 camera days, followed by the Pine Ridge site at 13 events/100 camera days and lastly at the Rat Creek Site at 2.7 events/100 camera days.

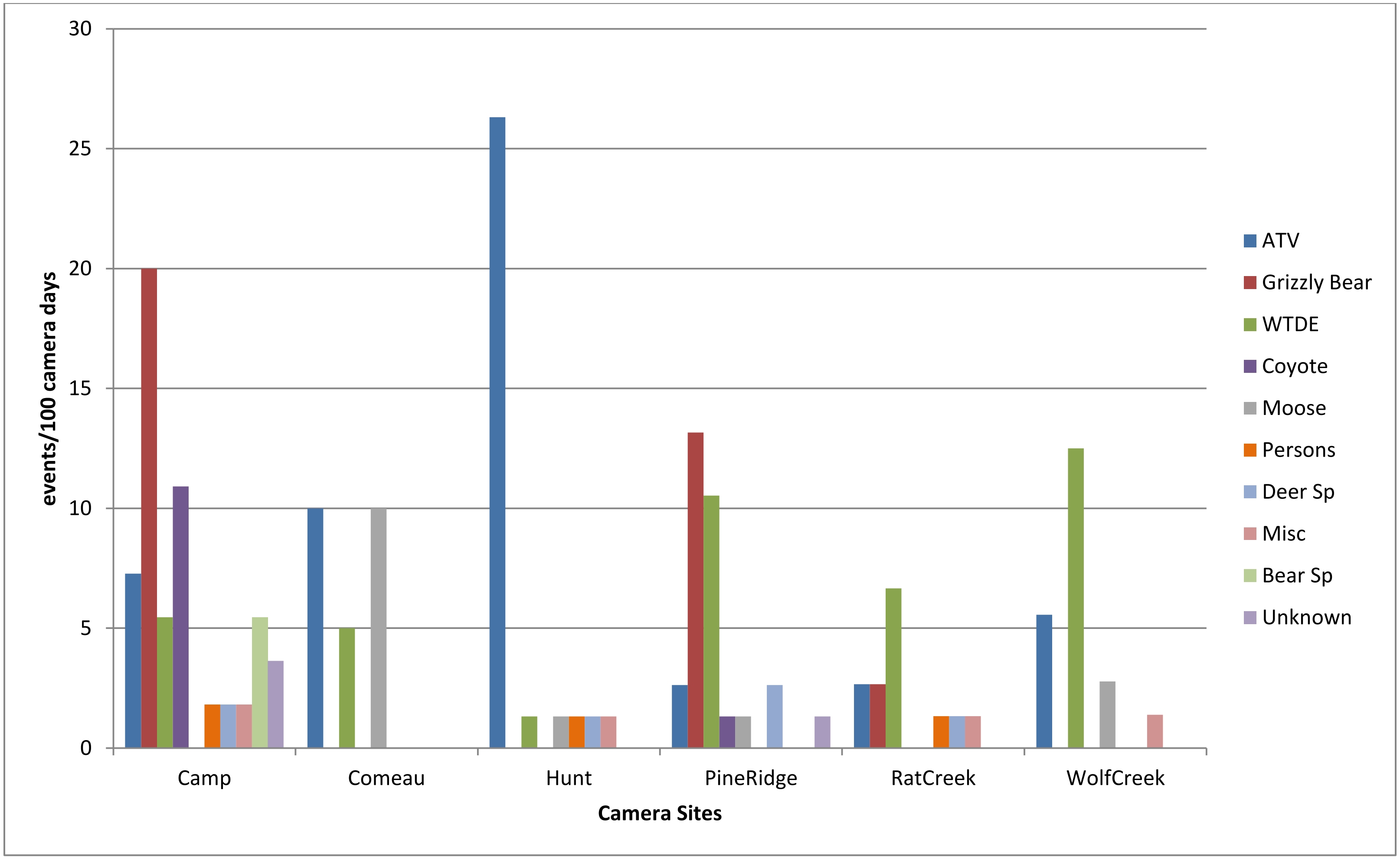

Figure 2. Events/100 camera days across sites by photo subject.

Discussion

Cameras were an efficient method to quantify human use, although frequent checks were needed to determine whether SD cards were full, batteries were dead, cameras had malfunctioned, or events (e.g. construction) near the camera could put the camera at risk of being damaged or removed. Over 90% of the pictures did not detect anything, suggesting problems with camera sensitivity.

All pipelines monitored were used by people, always during the day, and often while driving off-highway vehicles for what appeared to be work-related activities. Pipelines were also used during the day by grizzly bears, which points to the possibility that bear-human encounters could occur on pipelines in the Kakwa study area. Further, as we found in Chapter 6A, topography and shrubs on pipelines can reduce visibility of a grizzly bear to < 50m. It is hoped that industry workers are trained in grizzly bear safety, awareness, and behaviours. It is recommended that bear spray be provided to all field workers with appropriate training in its use, as evidence has shown that bear spray is an effective deterrent against grizzly bears (Smith et al. 2008) and has advantages over a gun (Floyd 1999, Smith et al. 2012).

Reducing human-caused mortality by reducing access development and use is the first recommendation in the Alberta Grizzly Bear Recovery Plan (ASRD 2008). Up to thirty-five percent of human detections on the pipelines may have involved recreational activities. Minimizing the use of pipelines to the public would lower the risk of human-bear encounters and possibly human-caused mortalities. As suggested in Chapter 6A, creating a shrub or berm visibility shield at pipeline-road intersections could potentially hide trails used by workers, and reduce the number of recreationists using pipelines.

Chapter B.7. Final Conclusions

The main objective of this two-year research project was to address the knowledge gap regarding grizzly bear habitat use, foraging patterns, and movement patterns on pipelines, along with the possible mechanisms behind patterns of grizzly bear use of pipelines. Investigation of grizzly bear use of pipeline RoWs in our study area also required consideration of other linear features present on the landscape, including roads and seismic lines.

In the first year of this project (2012), we focused on habitat selection patterns, grizzly bear activities, and movement patterns. Research objectives in the second year of this project (2013) expanded to investigate grizzly bear use of pipelines in more detail, including parameters that may predict use of pipelines, and the spatial relationship between grizzly bear predation sites and linear features. We also investigated pipeline factors that could increase the probability of bear-human encounters, and therefore influence the risk of human-caused grizzly bear mortality. These factors include the visibility of bears on pipelines from roads, and levels of human use on RoWs.

Results from our habitat analyses indicate that grizzly bears used pipelines, road-pipeline right-of-ways, and roads significantly more than expected based on availability. Male bears also used seismic lines more than expected, while female bears appeared to avoid seismic lines during spring and fall. It appears that grizzly bears in the Kakwa study area are not generally avoiding linear features. Our analysis of bear food availability on pipelines indicated that a number of bear foods are more common on pipeline RoWs and edges than in other available habitats; in particular, dandelion, clover and ants had a much higher occurrence on pipelines than in forested habitat. These species are known to be important bear foods in our study area, and bears may be attracted to pipelines due to the occurrence of these foods. Field data collected during both years of this study indicated that bears were using pipeline RoWs for a range of foraging activities, with anting as the most common activity. For small and threatened populations like the grizzly bear population in west-central Alberta, pipelines could function as habitat sinks.

An analysis of movement rates in the first year showed that grizzly bears traveled significantly faster on road RoWs, road-pipeline RoWs, pipeline RoWs, and seismic RoWs as compared to in non-linear habitat, suggesting that linear feature RoWs may serve as movement corridors for grizzly bears in our study area. However, grizzly bear predation events in our study area did not occur closer to linear features than expected based on availability, or as compared to other use sites.

Based on our current analysis, we have no evidence to suggest that grizzly bears used linear features to access ungulate prey species; however, grizzly bear movement patterns prior to predation events are still unclear. Research activities planned for 2014 will provide more information regarding grizzly bear predation patterns and the relationship with anthropogenic features.

Based on the combined results from the analyses of habitat selection, bear activities, movement rates, and bear food occurrence on pipelines, it is likely that grizzly bears in our study area use pipeline RoWs for a combination of foraging and travel. Whether for foraging or movement, the presence of bears on linear features has the potential to increase their exposure to humans, and subsequently increase the risk of human-caused grizzly bear mortality. All pipelines monitored in our study were used by people, suggesting that bear-human encounters on pipelines in this area are a real possibility. In our analysis, surrounding pipeline and road density had a negative influence on use of pipelines and pipeline-road RoWs. Although bears appear to be selecting for pipelines, these results suggest that they may prefer habitat in areas of lower overall human presence. Our sightability analysis indicated that many pipelines had topography, curves or shrub cover that would partially hide a grizzly bear from the view of passing vehicles. These findings provide potential mitigation options to reduce grizzly bear mortality risk at pipeline-road intersections.

Results from this research project address the knowledge gap regarding grizzly bear response to oil and gas pipelines. We believe this new knowledge will play an important role in grizzly bear recovery efforts and resource management in Alberta.

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REPORT C: EVALUATING GRIZZLY BEAR HABITAT USE AND RESPONSE TO NEW APPROACHES TO FOREST MANAGEMENT, HARVESTING, AND ACCESS PLANNING IN CORE GRIZZLY BEAR CONSERVATION AREAS – ARE NEW APPROACHES POSSIBLE TO SUPPORT RECOVERY EFFORTS?

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Introduction

Grizzly bears are a forest resource that has a high value among the public of Alberta and also at National and International levels. Grizzly bears are also widely recognized as an umbrella species and as an indicator of forest ecosystem health; thus, maintaining healthy grizzly populations may be in an important component of maintaining other species and their habitat. Unfortunately, grizzly bears are a threatened species in Alberta and continue to experience high levels of human caused mortality, largely a result of increased human activity and access within grizzly bear habitat. In Alberta, human activities in grizzly bear habitat include forestry, oil and gas exploration, mining, hunting, and recreation, including off highway vehicles (OHV). Because of accompanying road developments, these activities lead to higher mortality risk for grizzly bears. On the other hand, activities such as forest harvesting also creates early seral habitat that may support an abundance and diversity of bear foods. Research has shown a favorable response by grizzly bears to a matrix of different forest seral stages with high use of forest edge habitat. In most cases opening the forest canopy, with adjacent older age stands has a positive effect on maintaining grizzly bear habitat over time. However, the combination of high resource value associated with food coupled with high mortality risk means that these areas can become ecological traps or sink habitat – habitat that grizzly bears are attracted to, but that they are also likely to die in. However, with access and resource management, the mortality risk of these habitats can be reduced or minimized allowing bears to exist within a multi-use landscape.

Maintaining this important wildlife species, in conjunction with the wise and sustained use of other forest resources such as pulp, lumber, oil and gas, will demonstrate to Albertans – and all user and stakeholder groups – that the use of forest resources is indeed possible and being actively pursued. There is clear evidence within the forest product marketplace that consumers are concerned about sustainable forestry practices when making purchasing decisions. Today, the forestry sector (and all resource extraction companies) is facing pressures related to operational practices in provincial grizzly bear recovery zones where the land management focus has been on maintaining open road densities below target thresholds. This can be challenging for forestry operations as it relates to both access and forest harvest planning. There remains ongoing concern on how forest management and harvesting operations can proceed in identified core grizzly bear zones in Alberta. The focus to date has been to maintain open road densities in core zones below 0.6km/km^2. To date, no attempt has been made to evaluate if new approaches to road construction and management might be possible in terms of maintaining habitat use while minimizing the risk of human caused grizzly bear mortalities. In addition, new approaches to forest harvesting (block sizes) have not been investigated to determine what impacts these might have on the movements and habitat use of resident grizzly bears.

This project moves us beyond what is currently known about grizzly bear response to forestry activities to investigate change in response over longer time frames and how new forestry approaches might influence bear response. The evaluation of new suggested prescriptions have not been tested or evaluated relative to either habitat use/response or bear numbers. Thus, this research effort is focused on assessing new forest management approaches to address access planning and forest harvest design to support continued use by grizzly bears and to limit/reduce human caused grizzly bear mortality risk. Additionally, this work allows the use of historic data (1999-2003) to current data sets when comparing different harvesting and road management strategies to the traditional two pass systems with open road networks. The ability to build on existing data sets gathered over a 15 year period (and supported by both FRIAA funding and member companies during this time period) provides a valuable opportunity to assist the forestry sector in Alberta in understanding how their management activities can be better integrated with the ecological needs of grizzly bears and if new approaches can assist in provincial grizzly bear recovery efforts.

The work presented in this report focuses on improving our understanding of current grizzly bear habitat use and movements in three provincial grizzly bear watershed units that occur in core grizzly bear conservation units within the Yellowhead BMA within portions of the Weyerhaeuser and West Fraser FMA's. By supporting this research program, FRIAA and member companies will work towards further integration of forest management with species at risk management in an adaptive management framework that will support grizzly bear conservation and recovery in Alberta. In this way, FRIAA and its member companies will continue to show leadership and commitment to sustainable forest management in this province.

Methods

FRI Grizzly Bear Research Field activities in 2013 were focused within two provincial Bear Management Areas (BMA's) in the province that included portions of the Weyerhaeuser Grand Prairie, Weyerhaeuser Drayton Valley, and West Fraser Forest Management Areas. Our field work in these areas involved capturing and collaring grizzly bears, conducting grizzly bear population inventory sampling using DNA hair snags within specified watershed units. These activities are in support of projects associated with an existing grants from the Forest Resources Improvement Association of Alberta (FRIAA) and collaborations with Weyerhaeuser, West Fraser, University of Alberta (Andrew Ladle), and Washington State University (Heiko Jansen).

Study Area

Although FRI research activities spanned two BMA's, the DNA population inventory work and a significant portion of the capture effort was located near Nordegg, Alberta (Figure 1). This area thus represents the focus of the FRI research activities in 2013 and includes portions of the Weyerhaeuser Drayton Valley Forest Management Areas and three (Edson, Hinton, and Sundre) West Fraser Forest Management Areas (Figure 1). The specific areas within the Weyerhaeuser FMA include the Canyon Creek, Wawa Creek, and Rapid Creek working circles and harvesting planned in the Rodney Creek area (Figure 1). Elevation ranges from 800 m to 3360 m within the study area. Vegetation consists of mixed forests of spruce (*Picea* spp.), lodgepole pine (*Pinus contorta*), aspen (*Populus tremuloides)*, and tamarack (*Larix laricina*). Important bear foods such as alpine sweet vetch (*Hedysarum alpinum*)*,* buffaloberry (*Shepherdia canadensis*)*,* cow parsnip (*Heracleum lanatum*)*,* and various blueberry species (*Vaccinum spp.*) are found here. Human activities in the study area include forestry, oil and gas exploration, and recreation (including the use of ATVs). Several communities were located near the southeast portion of the study area.

Grizzly Bear Capture

Grizzly bears were captured within three Forest Management Agreement (FMA) areas including Weyerhaeuser Grande Prairie, Weyerhaeuser Drayton Valley – Pembina Operations, and West Fraser - Hinton. Primarily, we captured grizzly bears using culvert traps supplemented with helicopter darting (Figure 2). On occasion and where conditions permitted, free-range darting of animals from a truck was also employed. Although the biological and movement data gathered from captured animals will be used to meet project objectives, ultimately the information gathered contributes to a larger ongoing long term database that will be used for other research initiatives. Biological samples from all bears captured within this research program are now being analyzed: pre-molar tooth (age); hair (DNA and cortisol stress levels), blood (general health assessment) and tissue (stress protein levels).

DNA Population Inventory

Abundance and distribution of grizzly bears were sampled using 50 fixed hair snags (1 per 7×7-km cell) surveyed over five 14-day sampling sessions from June 4th to August 22nd (Figure 1). Hair snag locations were determined based on historic 2004 DNA sites that were selected using expert opinion and grizzly bear resource selection function models, to allow for comparisons with 2004 data sets. Hair snags consisted of approximately 30-m length of barbed wire encircling 4-6 trees at a height of 50-cm above the ground (Figure 3). A scent lure – a 2-L mixture of aged cattle blood and canola oil – was poured on woody debris piled in the center of the barb wire corral and was refreshed at each visit. Hair samples were collected at each site visit (every 10 days) and stored in paper envelopes and all hair snag sites were dismantled and removed following the last sampling session. Following collection, hair samples were sent for genetic analysis at the Wildlife Genetics Lab in Nelson, BC. Using multilocus genotyping, hair samples were genotyped to 8 loci (7 microsatellites and gender) for individual identification.

Scat DNA sampling

The intent of scat DNA collection was two-fold: sampling would help to further develop/refine both laboratory and field techniques to successfully extract bear DNA from scats and at the same time identify animals that may not have been inventoried with the barbwire hair snags. Within the Nordegg and Rodney Creek areas, bear scats were collected opportunistically for DNA analysis while conducting capture operations. In most cases, scats were collected on roads while driving between trap sites both on and off of the DNA grid. Bear scats were also opportunistically collected at hair snag sites by the DNA field crew and by Weyerhaeuser personnel. Genetic analysis of the scat samples is currently in progress at the Norwegian Genetics Lab.

Results

Grizzly Bear Capture

Yellowhead Population Unit – Capture spanned three different areas (Hinton-south, Nordegg, and Rodney Creek) within this BMA and occurred between June 4th and October 11th. Over 58 days, eight bears were captured in total (Table 1); five in culvert traps, 2 via aerial darting, and one free-range capture. In the Hinton-south area, a male and a female bear was captured in support of Andrew Ladle's (PhD candidate) ongoing research at the University of Alberta. The female was fit with an Actiwatch unit. In Nordegg (Weyerhaeuser - Pembina), three males and one female bear was captured in proximity to areas where forestry cutblocks were planned to occur – Marshy Bank, Rapid, and Wawa. The goal was to gather detailed habitat use and movement data in relation to harvested cutblocks, and at the same time, distribute collars within two watersheds where DNA based methods were being used to inventory the grizzly bear population. Because of local stakeholder interest, the Weyerhaeuser – Pembina project was expanded to include a portion of West Fraser's FMA. As a result, two additional animals were captured further north and outside of the Nordegg DNA grid, but in proximity to the harvest blocks planned for Rodney Creek. It is important to emphasize that all bears captured have large home ranges that may encompass portions of the specific watersheds of interest related to the specific research questions (Figure 4). G150 was found killed on an active well-site. Cause of death was confirmed to be human caused (shot). Habitat use by grizzly bears in the Yellowhead Population Unit is shown using the GPS collar data collected in 2013 (Figure 5).

DNA Population Inventory

In total, 788 hair samples were collected and 302 samples were sent for genetic analysis. Following genetic analysis, grizzly bears were detected at 18 of 50 sites (36%) (Figure 6). Seven bears were detected in sessions one, two and three; and four bears were detected in sessions four and five (Table 2). Seven bears were first detected in session 1, four bears in session 2, three bears in session 3, two bears in session 4, and no new bears were detected in session 5 (Table 2). Genetic analysis of the hair samples revealed the identification of 16 grizzly bears (11 males, 5 females) (Table 3). Of these 16 bears, five bears were collared research bears (4 males, 1 female) and three bears (2 males, 1 female) were recaptures from previous projects, resulting in 8 newly identified individuals. The minimum convex polygons of seven bears known to occur in and around the study area are shown in Figure 4, five of whom were detected on the DNA grid during the grizzly bear DNA population inventory in 2013.

Based on these results, the minimum count of grizzly bears occurring on the DNA grid is 16 bears. This number provides pre harvest data on the minimum number and gender of grizzly bears in the study area. In 2004 within these same grid cells, the minimum count of grizzly bears occurring on the same grid was 4 bears (3 males, 1 female) detected at 10 sites (Figure 6).

Scat DNA and Grizzly Bear Food Quantification

Within the Nordegg and Rodney Creek areas, bear scats were collected opportunistically for DNA analysis (n=30) while conducting capture operations. Bear scats (n=9) were also opportunistically collected at hair snag sites by the DNA field crew. Genetic analysis of scat samples is in progress.

Summary and Work Planned for 2014 (Year 2)

In 2013, eight bears were collared in the Yellowhead Population unit (6 male, 2 female). This sample of radio collared grizzly bears will be used to understand current movement paths of bears in relation to various forest harvest stages (i.e. pre harvest, recent harvest, 5-7 years harvested, 7-10 years harvested and 10-15 years harvested). We plan to increase this sample size to 10 bears in 2014. GPS collar data indicates that grizzly bears frequently occur within a significant portion of the Forest Management Areas and the 2013 DNA grid. Their movements are also wide-ranging, likely in response to seasonal resource availability, including the resources found on forestry cutblocks. Such wide-ranging movement can also increase the mortality risk to grizzly bears. In fact, collar data indicates that several bears frequently occur near Highway 40 (Forestry Trunk Road) in addition to numerous other roads that exist within the study area (but were not shown). New access management strategies in relation to forestry and oil and gas activities could have dramatic impacts to grizzly bear numbers, movement, and habitat selection.

Between May to August of 2013, 18 of 50 DNA sites detected a grizzly bear. Genetic analysis revealed 16 individuals (11 males, 5 females) – eight bears (6 males, 2 females) were previously known to researchers and eight bears (5 males, 3 females) are newly identified individuals. In comparison, four bears (3 males, 1 female) were detected at 10 sites on the same grid in 2004. In addition to the increase in the number of bears detected, bears were also detected further east in 2013 than in 2004. The increase in the number of bears could be a result of an increasing bear population or it could represent a change in bear density and distribution related to landscape change or human use of this area. Further analysis is needed to assess the trends in abundance and distribution between 2004 and 2013.

The number of bears detected decreased in sessions four and five and no new bears were detected in session 5, which suggests a high recapture rate. Similarly, the total number of hair samples collected peaked in session 2 and then declined. Together, this information is valuable for ensuring cost effective study designs – i.e. maximizing detection while minimizing costs.

With additional funding from the Government of Alberta and West Fraser Ltd, the DNA population inventory study area will expand in 2014 to include 100% of the 2004 DNA grid with additional sampling to occur in Jasper National Park. This is a unique opportunity to conduct cost effective grizzly bear population monitoring in forested landscapes in Alberta where we are managing for both sustainable development and sustainable wildlife populations. Results from the 2013 population inventory and 2011 research (Rovang 2012[1]) will guide study design and site selection of the 2014 DNA grid. Population results from 2014 will then be compared to the 2004 population estimate to assess regional trends in abundance in distribution, which will be important for understanding the changes in the number and distribution of grizzly bears observed on the 2013 DNA grid.

Overall, the data collected in 2013 provides important pre-harvest data of grizzly bear movement, distribution, and abundance. Work planned for 2014 will evaluate the numerical response (DNA, movement patterns and habitat use (GPS data) of grizzly bears in habitats created by the forest harvesting stages listed above. Future work will also evaluate how new access management strategies associated with forest planning and oil and gas activities may alter movements or habitat use of grizzly bears on an individual and population level . This will be done by comparing 2013, 2014, and historic data sets of grizzly bear movement, distribution, and abundance. New food model data sets, annual landscape change data, and human use data are currently being developed and will further supplement this work. Once complete, DNA extraction from scat may also provide additional information on grizzly bear abundance and distribution.

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[1] Rovang, S.R. (2012). Factors affecting the detectability and eastern distribution of grizzly bears in Alberta, Canada. Thesis, University of Alberta, Alberta, Canada.

Table 1. Grizzly bears captured by the Foothills Research Institute Grizzly Bear Program in 2013.

Bear Name	Captured	Recapture	Population Unit	Sex	Known Age (2013)	Estimated Age	Status
G286	13-May		Grande Cache	M		Adult	Dropped collar
G270	16-May	Yes	Grande Cache	M	Adult (7 yrs)		Collar working
G127	17-May		Yellowhead	M		Sub-adult	Collar failed
G287	27-May		Grande Cache	M		Sub-adult	Collar working
G150	14-Jun		Yellowhead	M		Sub-adult	Dead bear
G151	17-Jun		Yellowhead	M		Sub-adult	Collar working
G111	19-Jun	Yes	Yellowhead	F	Adult (9 yrs)		Collar working
G152	4-Jul		Yellowhead	M		Sub-adult	Collar working
G284	22-Aug	Yes	Grande Cache	M	Sub-adult (4 yrs)		Collar working
G280	22-Aug	Yes	Grande Cache	F	Sub-adult (3 yrs)		Collar working
G275	23-Aug	Yes	Grande Cache	F	Adult (5 yrs)		Collar working
G288	28-Aug	Yes	Grande Cache	F		Adult	Collar working
G260	28-Aug	Yes	Grande Cache	F	Adult (11yrs)		Dead bear
G153	19-Sep		Yellowhead	F		Sub-adult	Collar working
G128	5-Oct		Yellowhead	M		Sub-adult	Collar working
G129	8-Oct		Yellowhead	M		Sub-adult	Collar working

Table 2. Grizzly bear detections on the 2013 DNA grid within the Yellowhead BMA. The total number of hair samples collected per session includes both grizzly bear and black bear samples but detections refer strictly to grizzly bear detections. Known bears are bears that have been previously identified through capture efforts or past DNA projects. First detection refers to the number of individual bears first detected in that session.

Session	Hair Samples	Detections	Known Bears	First Detection
1	182	7	4	7
2	269	7	4	4
3	160	7	3	3
4	93	4	4	2
5	94	4	2	0

Table 3. Individual grizzly bears identified per session by DNA hair snag methods during the 2013 grizzly bear population inventory project. A colour scheme is used to indicate what session the bear was first detected in.

Session	**Individual**	**Sex**	**Detection History**
1	11905Ba1	M	Redetection
1	410-1A-1	F	
1	440-5B-1	M	
1	464-1A-1	F	
1	G129	M	Captured 2013
1	G150	M	Captured 2013
1	G153	F	Captured 2013
2	11905Ba1	M	Redetection
2	378-6B-2	M	
2	411-6C-2	M	
2	G152	M	Captured 2013
2	93-2b-2	M	Redetection
2	G150	M	Captured 2013
2	G153	F	Captured 2013
3	410-1A-1	F	
3	435-1A-3	F	
3	438-1A-3	M	
3	463-1A-3	M	
3	G152	M	Captured 2013
3	G150	M	Captured 2013
3	G153	F	Captured 2013
4	11166Ta1	F	Redetection
4	G152	M	Captured 2013
4	G150	M	Captured 2013
4	G151	M	Captured 2013
5	11166Ta1	F	Redetection
5	378-6B-2	M	
5	410-1A-1	F	
5	G152	M	Captured 2013
Legend	First detected in session 1		
	First detected in session 2		
	First detected in session 3		
	First detected in session 4		

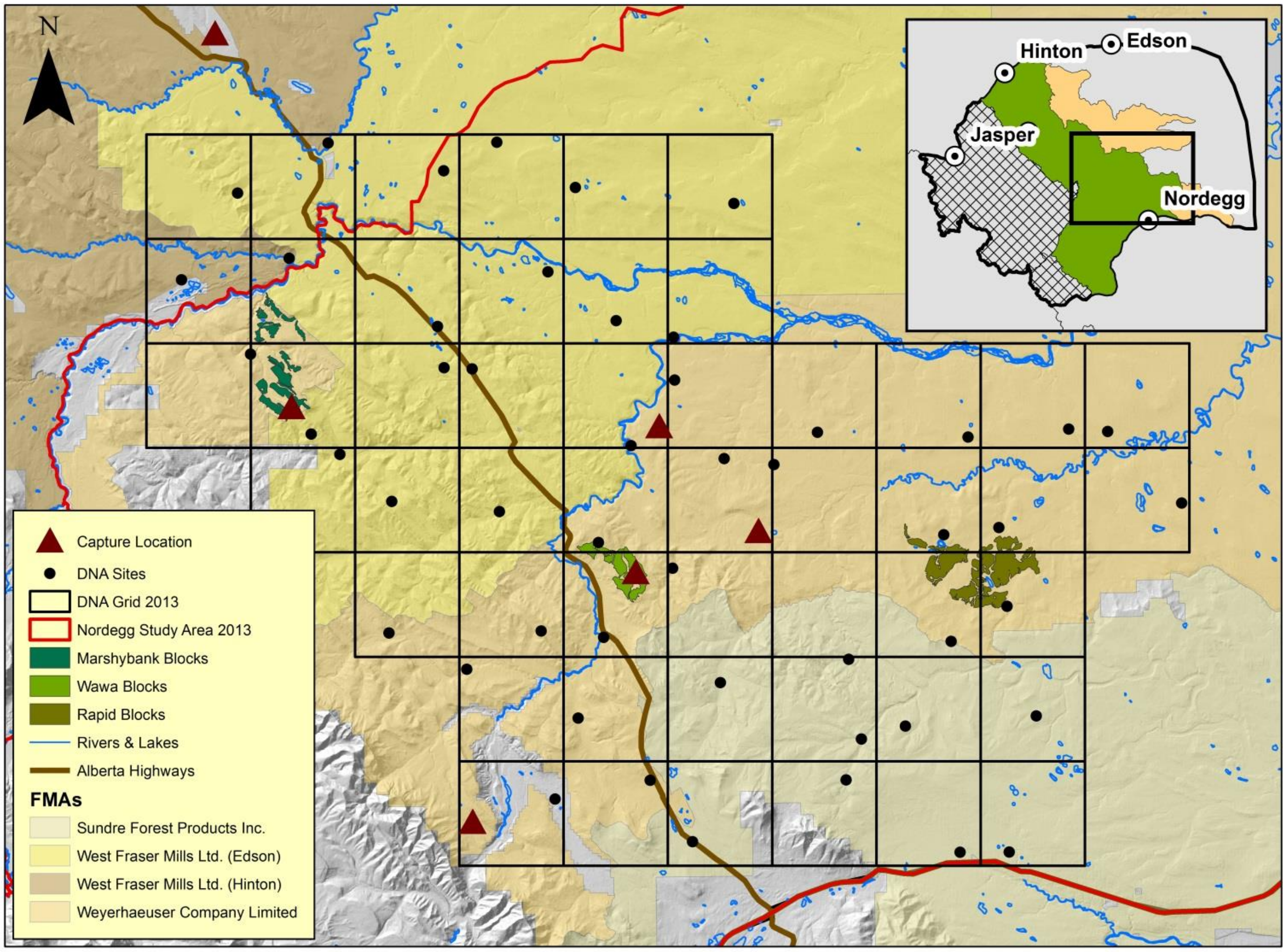

Figure 1. Grizzly bear DNA population inventory grid, DNA sites, grizzly bear capture locations, and Forest Management Areas (FMAs) located within the Yellowhead study area. The DNA grid is comprised of 50 7×7-km cells with one hair snag site per cell.

Figure 2. Methods for the capture and handling of grizzly bears includes: A) free-range, B) culvert trap, and C) helicopter.

Figure 3. A typical DNA hair snag site used in the grizzly bear DNA population inventory.

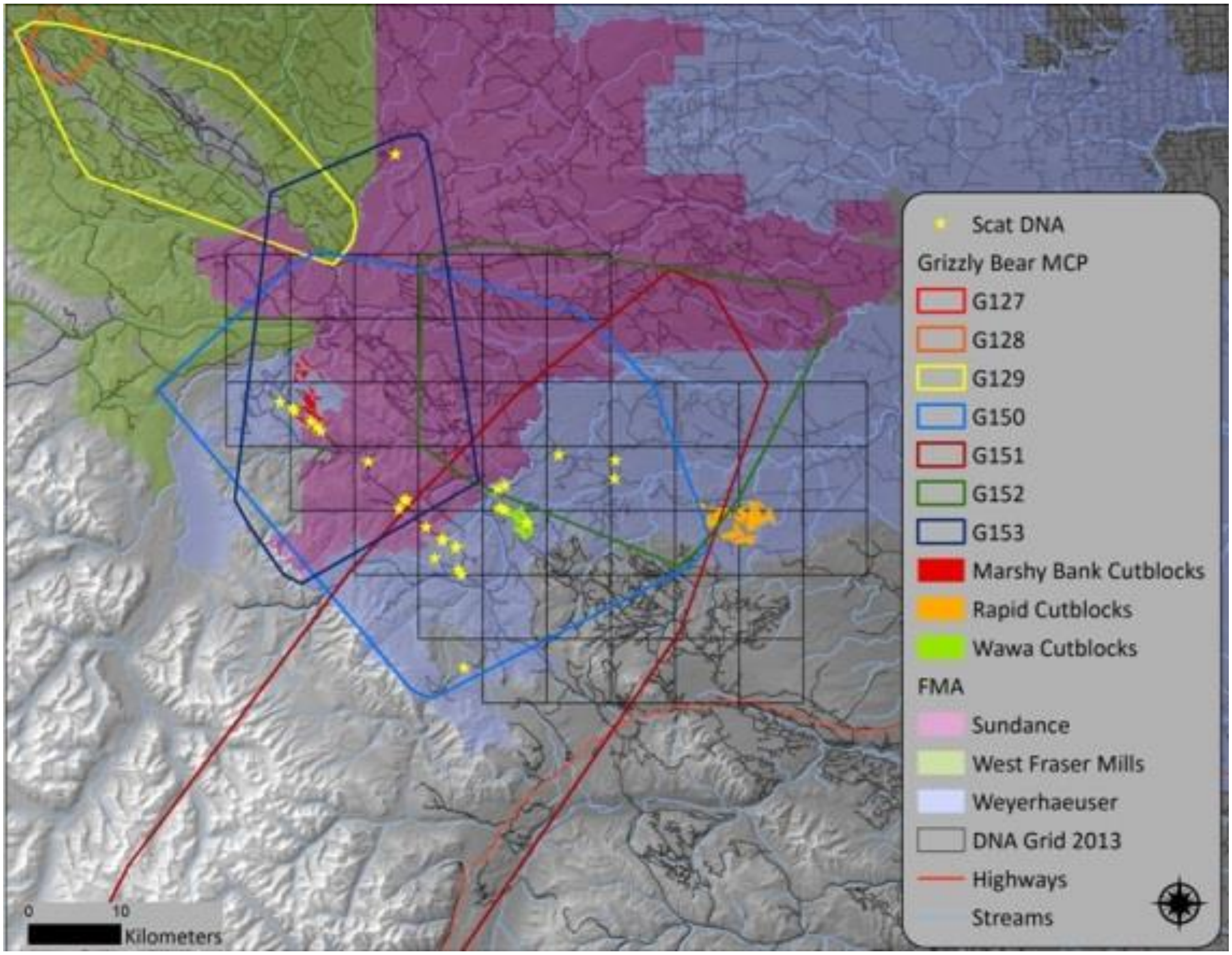

Figure 4. Grizzly bear minimum convex polygons (2013) in relation to the DNA hair snag grid and planned harvest cutblocks. Five of these bears (G129, G150, G151, G152, and G153) were detected on the DNA grid during the grizzly bear DNA population inventory in 2013.

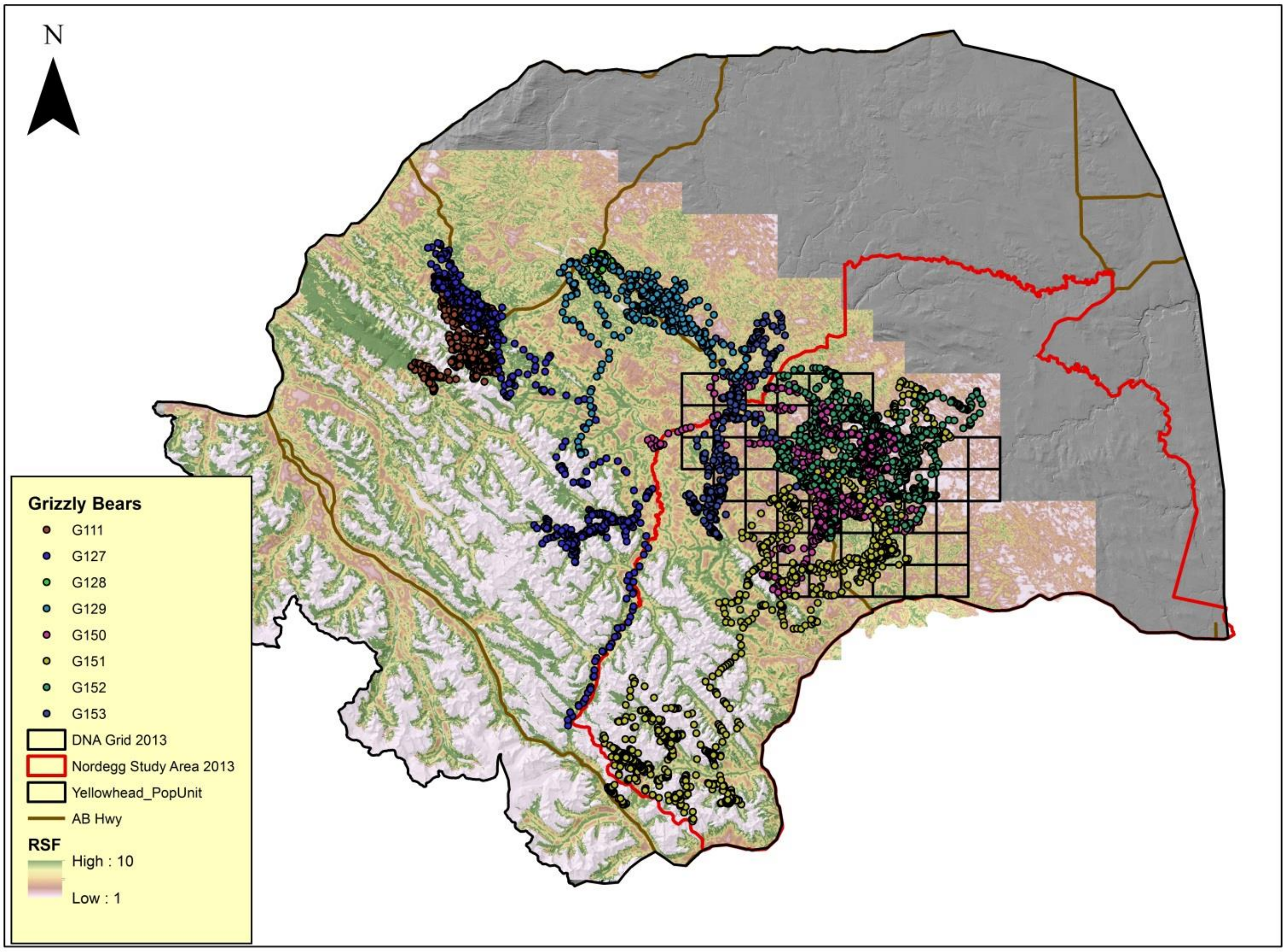

Figure 5. GPS collar data of eight bears captured within the Yellowhead Population Unit by the Foothills Research Institute Grizzly Bear Program in 2013.

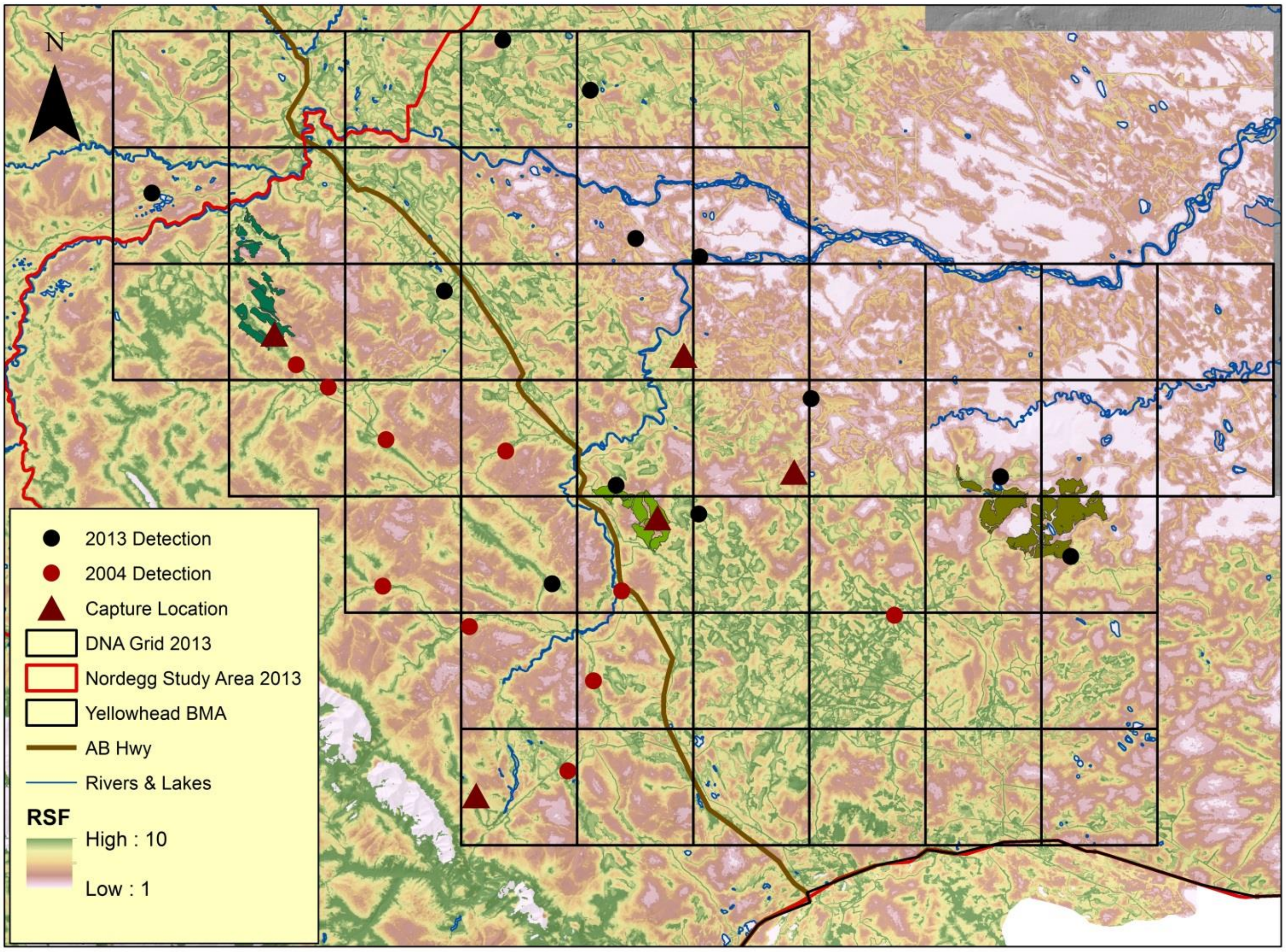

Figure 6. Grizzly bear detections in 2004 (red) and 2013 (black) in relation to estimated grizzly bear resource selection (i.e. the probability of use of an area by a grizzly bear). Grizzly bear capture locations in 2013 are also shown.

REPORT D: RESEARCH AND APPLIED TOOLS TO ENHANCE FOREST MANAGEMENT LINKAGES TO GRIZZLY BEAR CONSERVATION AND RECOVERY IN ALBERTA

Final Report for the Forest Resource Improvement Association of Alberta (FRIAA)

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Executive Summary

Grizzly bears (*Ursus arctos*) are a threatened species highly valued by the Alberta public both from a recreational perspective and as an indicator of ecosystem integrity. Conservation of this species, in conjunction with the development of forest resources, will demonstrate to the public and stakeholder groups that sustainable forest management is possible and is being actively pursued. Our research program supported by FRIAA and member companies have invested in new knowledge and planning tools to support grizzly bear conservation and recovery in Alberta, while showing leadership and commitment for sustainable forest management.

This FRIAA project was undertaken to build upon existing data sets and knowledge acquired over the past 12 years within the Foothills Research Institute Grizzly Bear Program. Acquiring this information would not be possible without the commitment from over 60 program partners including significant financial support from FRIAA during this time period. The results of this research presented in this report have been supported by seven FRIAA member companies.

During the first year of this two year project, we focused on two species at risk in the province; grizzly bear (*Ursus arctos*) and woodland caribou (*Rangifer tarandus*). We present three GIS applications (Chapter 6) that allows end-users to 1) simultaneously evaluate changes in habitat conditions for grizzly bear and caribou associated with forest harvesting, 2) quantify changes in grizzly bear habitat security following road reclamation, and 3) identify areas within forestry cutblocks that are visible from roads to enhance habitat security for grizzly bears. In the second year of this project, we focused on analyzing both historical data and data gathered during this project to aid in our understanding of changing habitat conditions for grizzly bears in relation to forest structure and silvicultural practices associated with forest harvesting. Our objective was to develop quantitative models to explain variation in grizzly bear habitat selection and food availability associated with 1) habitat edge and edge distance; 2) retention patch amount and size; and 3) harvesting in winter vs. summer, site preparation and herbicide treatment.

Key Research Finding:

- Male and female (single or with cubs older than 1yr of age) grizzly bears do not avoid the interior of cutblocks based on current landscape conditions.
- Unlike male and female bears that avoided the interior of uncut forests, females with cubs of the year selected uncut forest interior and suggests forest interiors provide important security cover.
- Uncut forest adjacent to young (≤20yrs) cutblocks appeared to be important fall habitats for grizzly bears, albeit dependent on forest composition and environmental gradients.
- Use of young cutblock edges by grizzly bears resulted in elevated risk of human-caused mortality, particularly during the summer.
- Grizzly bears were positively associated with variation in retention patch size.
- Fruit production of an important grizzly bear food (*Vaccinium myrtilloides*) was most abundant within 10m of cutblock edges.
- Fruit production was highest in young cutblocks, similar in uncut edges and retention patches, and lowest in older (>20yrs) cutblocks.
- Grizzly bears were attracted to cutblocks harvested in winter and where herbicide treatments were undertaken, whereas cutblocks with site preparation tended to elucidate a negative response, particularly by females.
- Cutblocks harvested in winter were associated with higher fruit production in (*Vaccinium myrtilloides*).

Recommended Management Actions/Considerations

Forest harvesting strategies that increase the amount of uncut forest adjacent to young cutblocks is likely to benefit grizzly bears because of the increase in quality of fall habitat. However, harvesting during the winter should be a priority, particularly where important fruit producing shrub populations are known to occur. Although we did not find a negative response of grizzly bears to the interior of cutblocks under current conditions, further assessment is required since bears may avoid cutblock interiors where edge distance is large. Future research should examine bear response to a range of interior habitat areas. At the same time, managers should understand that increasing the availability of young cutblocks and edges may benefit male and female grizzly bears, but a reduction in the amount of uncut forest could have a negative effect on cub survival due to a decrease in secure habitat. Given that the short-term goal of the surge cut for mountain pine beetle management is to reduce the amount of mature pine stands, the availability of important fall grizzly bear habitat over the long-term may be reduced.

ACKNOWLEDGEMENTS

First and foremost, we would like to thank Wendy Crosina and Weyerhaeuser Grande Prairie who made this project possible and for their continued support of the Foothills Research Institute Grizzly Bear Program. We would like to thank the other six FRIAA member companies for their support including: Alberta Newsprint; West Fraser Ltd; ***Daishowa-Marubeni International*** Ltd; Canfor; Tolko; and Millar Western. Thank you to Alberta Environment and Sustainable Resource Development for use of the Kakwa field camp, and to John Stadt of the Forest Management Branch. We would also thank Steve Wotton of Peregrine Helicopters and numerous field crews that helped with grizzly bear capture and the collection of important field data.

Background

Grizzly bears (*Ursus arctos*) are threatened in the province of Alberta and a recovery plan is in place to address concerns regarding population viability. The focus of management actions to date regarding grizzly bear population recovery has been directed towards resolving issues of survival (human-caused mortality risk) associated with roads and access with no emphasis placed on habitat conservation or enhancement. Recovery at the provincial level remains a formidable management challenge given that industrial development and human activity on public land continues to increase within grizzly bear range. Although it is undisputed that addressing the issue of survival is essential to the recovery and conservation of grizzly bears, there is also a need to maintain or enhance essential resources such as food and cover. Recent research suggests that grizzly bear density is limited by bottom-up processes linked to the availability of food resources. Because forestry cutblocks accounts for a relatively large proportion of the total anthropogenic footprint within grizzly bear range, forest management plays a fundamental role in shaping current and future habitat conditions for bears and could have implications for provincial recovery. This is particularly relevant today given that there has been a fundamental shift from traditional forestry practices (two-pass forestry) towards one that is geared towards emulating patterns of natural disturbance. In addition, Alberta is experiencing unprecedented levels of forest harvesting surrounding mountain pine beetle (*Dendroctonus ponderosae*) mitigation. Understanding grizzly bear response and changes in food availability associated with current forestry practices is an essential component of sustainable forest management and the conservation and recovery of this species in Alberta.

This document is the final report for FRIAA project entitled; *Research and applied tools to enhance forest management linkages to grizzly bear conservation and recovery in Alberta*, and was undertaken from 2012-2013. This research was focused on the following topics:

1. Assessing grizzly bear use of cutblock edge, silviculture treatment, and patch retention.
2. Creation of a planning tool to simultaneously evaluate the effect of forest harvesting on caribou and grizzly bear habitat within a shared landscape.
3. Development of a GIS application to calculate the effect of road reclamation on grizzly bear habitat security within conservation areas.

4. Development of a GIS application to calculate the proportion of planned cutblock area visible from roadsides to enhance grizzly bear survival.

This report is prepared in chapter format related to the aforementioned research topics.

Chapter D.1. Grizzly Bear Response To The Edge And Interior Of Forestry Cutblocks

Introduction

For grizzly bear populations without access to salmon (*Salmo* spp.), foraging habitats are typically associated with natural openings (avalanche chutes, meadows) amongst a mosaic of seral stages following disturbances such as fire. In forested environments that lack natural openings and where there has been a long history of fire suppression, reduced foraging opportunities can be offset through the creation of forestry cutblocks associated with an increase in the availability of food resources (Hamer and Herrero 1987; Nielsen et al., 2004b; Larsen, 2012). Previous research suggests that grizzly bears respond positively (selection) to cutblocks, but selection patterns vary and often depend on parameters such as biological factors (gender, reproductive status), local environmental conditions (moisture, climate), and stand age. But, research has also demonstrated that grizzly bears display strong selection for the cutblock edge (proximity)(Nielsen et al., 2004a). Although future forest harvesting in Alberta is likely to improve habitat conditions for grizzly bears associated with early seral forest conditions and habitat edge, there is concern that large block size following natural disturbance based forestry may reduce foraging opportunities because bears may avoid the interior of these cutblocks. Studies have shown that foraging activities tend to be near (<100m) forested edges, presumably because both food and security cover are readily available (Blanchard, 1983; Mattson, 1997; Nielsen et al., 2004a). We suspect that reduced foraging opportunities for grizzly bears would be associated with early successional forests, where security cover would be lower due to tree height in the absence of green tree retention. A better understanding of how grizzly bears respond to edge and interior habitats could help guide management decisions surrounding harvesting design and the condition of future forests.

Here we use a GPS locations dataset from radio collared grizzly bears to assess the spatial (edge distance) and temporal (habitat selection) response of bears to the edge and interior of forestry cutblocks. Our specific research objectives were to:

1. Quantify how far grizzly bears are from cutblock edges in relation to forest age, and determine if distance to edge differs from random.
2. Assess the response of grizzly bears to different age classes of edge and interior forested habitats.
3. Determine if 1 and 2 differ due to seasonality and/or sex and reproductive status.

In support of the hypothesis that grizzly bears select forested edges because of some perceived security risk associated with open habitats, we predict that grizzly bears would be closer to cutblock edges and avoid the interior of the youngest regenerating age class (1-10yrs) compared to stands (11-20yrs) with more vertical tree growth and security cover, but where food resource availability appears to be similar (Larsen, 2012).

Methods

Study Area

The study area encompasses the southern portion of the Weyerhaeuser (Grande Prairie) Forest Management Agreement (FMA) area (9192 km^2; Figure 1.1). The area is bound by the Smoky River in the east, British Columbia to the west, and private lands (agriculture) to the north. There is a prominent elevation gradient from the south-west to the north-east. Higher elevations in the south-west are rugged and dominated by coniferous tree species characteristic of the Sub-alpine and Upper Foothills Natural Subregion (NSR) (Natural Regions Committee, 2006). The transition to lower elevations and the Lower Foothills NSR consists of gently rolling terrain with forests comprised of mixed coniferous and deciduous species (Natural Regions Committee, 2006). Although forest harvesting has occurred since the early 1970's, resulting in a mosaic of regenerating cutblock age classes, the land base is dominated by mature (~120 years) fire origin stands of lodgepole pine (*Pinus contorta*). Development from the energy sector has created a network of seismic lines, pipelines, powerlines, and wellsites accessed through road networks that tie into those associated with forest harvesting. In the interest of maintaining habitat for the Red Rock/Prairie Creek Caribou Herd, caribou zones to the west and higher elevations to the south and west have minimal human footprint as areas are managed to maintain contiguous tracts of mature forest. Other forms of human activity occur on the landbase such as Off Highway Vehicle use, hunting and fishing.

Grizzly Bear Capture and Monitoring

We captured grizzly bears (2005-2012) via helicopter, leg hold snare, or culvert trap. After 2009, leg hold snares were phased out since capture by this method was more likely to cause significant muscle injury compared to the other techniques (Cattet *et al*., 2008). Animals were fit with Televilt Tellus GPS collars or Followit GPS satellite radio-collars (Followit®, formerly Televilt® TVP Positioning AB, Lindesberg, Sweden). Collars were programmed to collect locations at 20 minute or hourly intervals during the non-denning period. Each collar was equipped with a VHF transmitter and a mechanical drop-off system. Bears received an Advanced Telemetry System VHF ear tag transmitter (ATS®) used primarily as a backup in the event of collar malfunction or failure. Cub survival was monitored through repeated visual observations of females during monthly telemetry flights using fixed or rotary wing aircraft (Skymaster 337, Bell 206 Jet Ranger). Aerial counts were supplemented with ground observations.

Forested Habitat and Edge Classification

We used Alberta Vegetation Inventory (AVI; polygon database) provided by Weyerhaeuser Grande Prairie to define grizzly bear habitat. Polygons were stratified into habitat represented by forest stands (cutblock, uncut forest), natural openings, and other (i.e., anthropogenic features, water bodies). Polygons were aggregated according to leading tree species (lodgepole pine; ≥60%) and stand origin year. Cutblocks were distinguished from other cutblocks as distinct patches where age differed by at least 1 year of age. We removed in-block retention patches from the cutblock layer. Some of the natural openings identified as a non-forested vegetated class (herb, shrub) were actually cutblocks and subsequently updated. We considered only areas within 1025m (max distance) of a cutblock edge in uncut forest in our analysis to have a similar comparison of interior area.

For each year of bear data, habitat layers were created to account for forest succession and the anthropogenic footprint. Starting with a base habitat layer (2005), new disturbances (roads, well sites, and harvested cutblocks) were accounted for by digitizing features from Landsat imagery (path 46 row 22). Although cloud or scan line errors reduced the effectiveness in 4 of the 8 images, attempts were made to match the Landsat image, creating a synoptic representation of a continuously changing landscape. We removed anthropogenic (4%; excluding seismic lines) and non-vegetated features (i.e., water bodies) including oil and gas well sites (60m buffer), power lines

(60m buffer), roads and pipelines (20m buffer) from our habitat layer. Remaining boundaries (edges) between habitats were represented by polylines defined by the habitat strata.

Because we found that natural openings were relatively rare (2% available) and their use by grizzly bears was relatively low (3%) in our preliminary evaluation, we focused exclusively on forestry cutblock edges. However, Stewart et al. (2013) showed that using a landcover map, natural openings between different forest types were more common and grizzly bears responded to their availability.

Grizzly Bear Home Ranges and Random Locations

We assessed bear response at the home range level (3rd order selection; Johnson, 1980) since land management decisions typically occur at this scale (Nielsen et al., 2004a). For each bear, home ranges were delineated across seasons and years using minimum convex polygons (MCP). We used Geospatial Modeling Environment© (Beyer, 2012) to generate 1 random location for every 1ha of MCP within the habitat strata. GPS locations were intersected with each corresponding habitat layer by bear year, and for random locations the most recent bear year. Distance to the nearest cutblock edge was determined. All GIS manipulations were conducted in ArcGIS 10.1 (ESRI® Redlands, CA).

Variable Processing

We coded GPS locations as summer (June 16 to 31 July) and fall (August 1 to October 15), which generally corresponds to the hyperphagic period when food resource levels are highest (Nielsen et al., 2010) and a major dietary shift from protein to carbohydrate (fruit) rich foods occurs for grizzly bears (Munro et al., 2006). During hyperphagia, compared to other times of the year, bears forage voraciously on available food resources, which is particularly important for growing individuals and lactating females given their high energetic demands (Farley and Robbins, 1995, Robbins et al., 2007), but also for bears to build adequate fat reserves for hibernation (McLellan *et al.*, 2011). For pregnant females, body fat (~20%) gained through foraging translates into the ability to have cubs (Robbins *et al.*, 2012).

We considered three sex and reproductive classes; males, females, and females with cubs of the year (COY) since previous research suggests there are differences in home range size, movement, and habitat selection (Graham and Stenhouse, *in press*; Nielsen *et al.*, *in prep*). Class assignment was changed for females with COY that lost their entire litter in any given season. We created a four class categorical variable to distinguish between three stages of tree regeneration (cutblock) and uncut forest: 1) 1-10yr age class represents the tree establishment stage and open canopy conditions (Larsen, 2012); 2) 11-20yr age class is indicative of the 'free to grow' period when a stand reaches the minimum height requirements before the adjacent stand can be harvested; 3) >20yrs, the canopy is well developed. In this system, fruit production is similar in stands ≤20 years of age, however, production declines in cutblocks after about 20 years, likely associated with canopy closure, whereas forbs tend to be more abundant (Larsen, 2012); and 4) uncut forest. A final variable was created to identify the edge and interior (>90m; 1.2.6 *Edge Proximity Analysis*) within cutblocks and uncut forested habitat.

<u>**Statistical Analysis**</u>

Edge Proximity – For each grizzly bear (sample unit) according to sex and reproductive class and season, we calculated the mean edge distance for each forest age class using the GPS and random locations. We used a generalized linear model (GLM; McCullagh and Nelder, 1989) with a Gaussian error term distribution and a log link, to estimate regression coefficients with robust estimates of variance for our response variable edge distance (Hanley et al., 2003). We tested if competing models with individual effects for sex (ignoring females with COY), season, forest age, or interactions amongst these variables, fit better than an intercept only (null) model. Pearson's correlation coefficient (|r|>0.6) and Variance Inflation Factors (VIF>3) were used to assess correlations between covariate combinations prior to model fitting. Support for the best fit model was determined using Akaike weights (Burnham and Anderson, 2002), but we considered that models may contain uninformative parameters (Arnold, 2010). Using the random locations dataset, we also fit a GLM model with a single covariate (forest age) to explain variation in edge distance. Bear was used as a cluster variable to appropriately adjust standard errors of parameter estimates. When comparing grizzly bear and random locations, statistically significant differences in the means were confirmed when confidence intervals (95%) did not overlap.

Edge vs. Interior Habitat Selection – We estimated habitat selection ratios for each bear by sex and reproductive class and season where habitat availability exceeded 5% and animals had more than 50 GPS locations (Manly *et al*., 2002) relative to edge and interior habitats and forest age. Population level selection or avoidance of habitat was determined from a one-sample *t*-test against a hypothesized mean of 1.0 (use=availability). We defined habitat availability the same in each season to allow us to detect changes in habitat use.

Results

Edge Proximity - We used GPS locations (61289) from male (n=15) and female (n=15) grizzly bears to model edge distance. The best model explaining grizzly bear edge proximity included the additive effects of forest age and sex (Akaike weight=0.6). Although there was support for a model with a sex and forest age interaction effect (Akaike weight=0.3; Coef=0.18, SE=0.12, z=1.57, p=0.12), we concluded that this was an uninformative parameter because the Δ AIC$_i$ was not more than two units from the best model (Arnold, 2010). Overall, males were further from edges than females, but confidence intervals were overlapping. When compared to a random point distribution, edge distance in grizzly bears did not differ in young regenerating stands (≤20 years) for males or females (Figure 1.2). For males, edge distance was comparable to random considering older cutblocks (>20 years) and uncut forest. Conversely, females were significantly closer to edge when using older cutblocks and uncut forest (Figure 1.2). On average, grizzly bears were about 84m from the edge when using cutblocks and 272m from the edge in uncut forest.

Edge and Interior Habitat Selection – To determine summer and fall selection of grizzly bears, we used GPS locations from male (n=14), female (n=15), and females with COY (n=4). At the population level, selection of edge and interior habitats varied amongst the sex and reproductive classes, by season and forest age (Figure 1.3). In summer, male and female bears showed similar responses since they either selected or used at availability, the interior of cutblocks older than 10 years of age. This pattern changed in the fall when male bears selected for the interior of 1-10yr old cutblocks and avoided other regenerating age classes. On the other hand, females were neutral (use=available) in their response to the 1-10yr age class and selected the interior of cutblocks between 11 and 20 years of age. Male and female bears selected the interior of older (>20 years) cutblocks in the summer and avoided them in the fall. Grizzly bears selected for cutblock edges, yet patterns of edge use coincided with either a neutral or positive response to the same age class in any given season. Although males and females consistently avoided the interior of uncut forest, unlike males, females selected the uncut forested edge. Females with COY, had no GPS locations in the 1-10yr regenerating age class and selected for the interior of cutblocks older than 10 years of age. Similar to females, females with COY selected the uncut edge, but unlike male and females, they selected the uncut interior.

Discussion

Our findings support the contention that the use of cutblocks by male and female (single bears and with cubs older than 1yr) grizzly bears associated with the edge and interior of habitat appears to be related to food resources rather than security cover associated with tree regeneration. This is because male and female bears were not closer to the edge in the youngest and most open regenerating age class (1-10yrs) and either selected or used these stands at availability. Although, grizzly bears may simply adjust their temporal habitat use patterns to reduce risk such as using cutblocks during crepuscular/nocturnal time periods (Nielsen et al., 2004a), bears in this system are known to rest predominantly at night (Larsen, 2012). Conversely, patterns of habitat use in females with COY appeared to be related to security cover rather than food availability, since they avoided young regenerating stands completely (no GPS locations associated with this age class). Females with COY may be segregating themselves from other bears, particularly infanticidal males, by using different habitats that are thought to have fewer (uncut interior) food resources (Nielsen et al., 2004b; Larsen, 2012; Nielsen et al., in prep), or where resources might be higher (uncut edge), but escape (security) cover (trees) is available (Nielsen et al., in prep). Other studies suggest that females tend to forage close to the forested edge to provide escape cover for their young (Jonkel and Cowan, 1971; Lindsey and Meslow, 1977).

Although our analysis found that females tended to be closer to edges, which is consistent with other research (Stewart *et al*., 2013), we found that male and female grizzly bears showed similar patterns of edge and interior use of cutblock habitat in the summer, which could be related to the availability of herbaceous foods (Appendix A). This pattern changed in the fall and this change may reflect dietary differences and the spatial distribution of food resources (Nielsen et al., 2004b; Larsen et al, 2012). Females are likely to consume more fruit and gain weight (fat) given their relatively small body size, and fruit production in certain species (*Vaccinium myrtilloides*) may be higher on the edge (Larsen, 2012). Consistent selection of edges, particularly uncut stands in female bears, suggests novel habitat conditions associated with the juxtaposition between forest age classes (Harper and Macdonald, 2001; Boutin and Hebert, 2002; Harper and Macdonald, 2002; Redding *et al*., 2003) and the potential for lasting ecotone effects that enhance food. While edge use may be associated with foraging, other activities such as tree rubbing or movement may also explain edge use (Green and Mattson, 2003). The implication is that bears may use edges for a variety of purposes, which at times may be associated with specific foraging activities. For females with COY, foraging and traveling along the forest cutblock edge interface may represent a strategy to maximize the availability of food while providing escape (security) cover for cubs.

Management Implications

Nielsen et al. (2008) suggested that large cutblocks may be more detrimental to grizzly bears because of less edge habitat and less heterogeneity in forest age classes at the home range level. Although we did not demonstrate interior cutblock avoidance in the range of cutblock sizes we studied, this could change if cutblock size increases following natural disturbance based forestry (Nielsen *et al.,* 2008) or mountain pine beetle management (Stewart *et al*., 2013). Recently, Nielsen et al. (*in prep*) showed that males selected larger cutblocks than females and females with COY. However, size in this context does not account for large cutblocks that might have more interior habitat. If block size increases, in-block retention patches could create the desired edge/interior habitat conditions, and could offset the potential negative effects of forestry activities on grizzly bears. Understanding whether or not grizzly bears respond positively to in-block retention patches would be an important first step before using this approach (see findings presented in Chapter 2).

The fall season is recognized as the critical foraging period when bears gain body fat. Our results showed that female grizzly bears were attracted to uncut stands and avoided older regenerating edges, 2nd pass harvesting may reduce the availability of important seasonal food resources such as berries that may influence body fat content and reproduction (Robbins et al., 2012; McLellan, 2011). This is particularly relevant today as many of the stands being harvested for mountain pine beetle management are associated with second pass harvesting. Whether or not edge use by grizzly bears in young cutblocks is related to the adjacent habitat type (1st vs. 2nd pass harvest) is addressed in Chapter 2.

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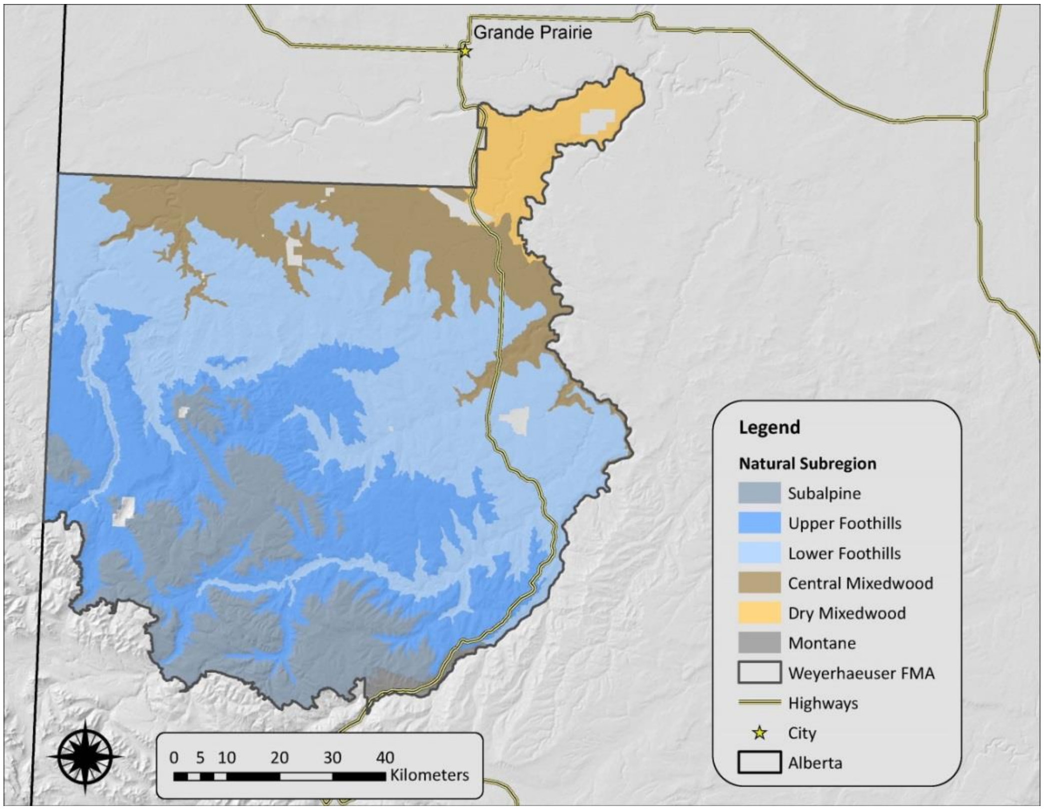

Figure 1.. Natural Sub Regions within Weyerhaeuser Grande Prairie Forest Management Agreement area, Alberta, Canada.

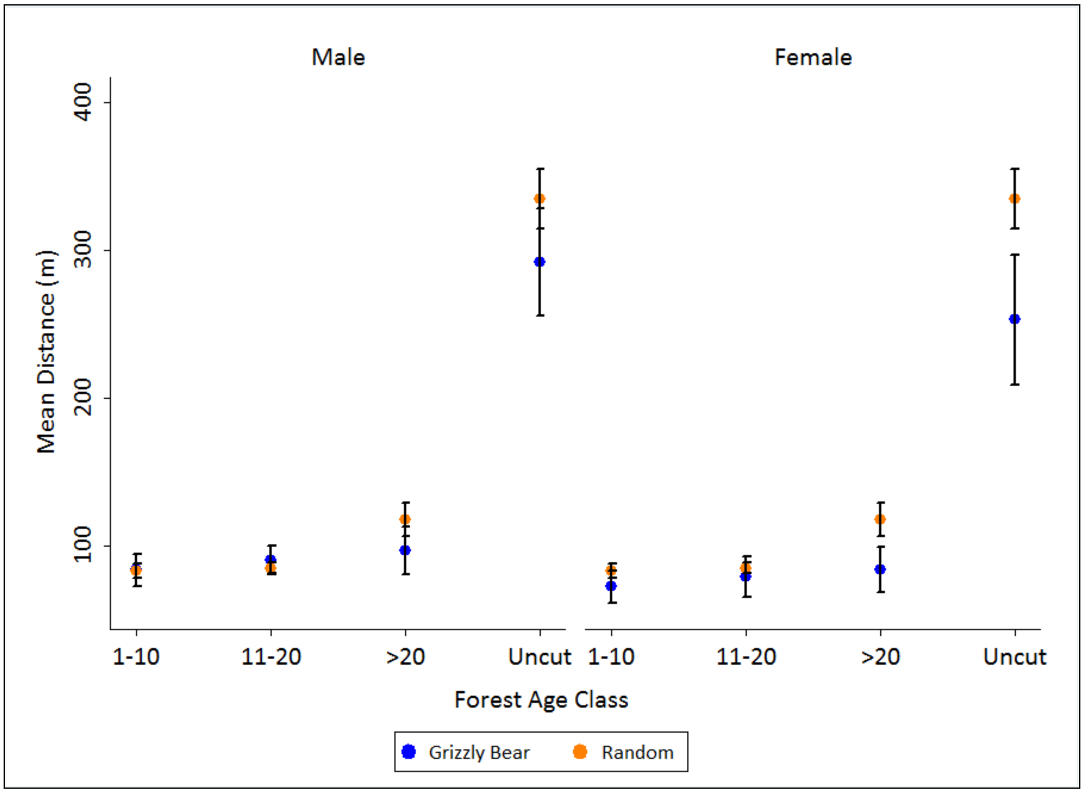

Figure 2. Predicted mean distance to edge and 95% confidence intervals of male and female grizzly bear and random locations among four forest age classes.

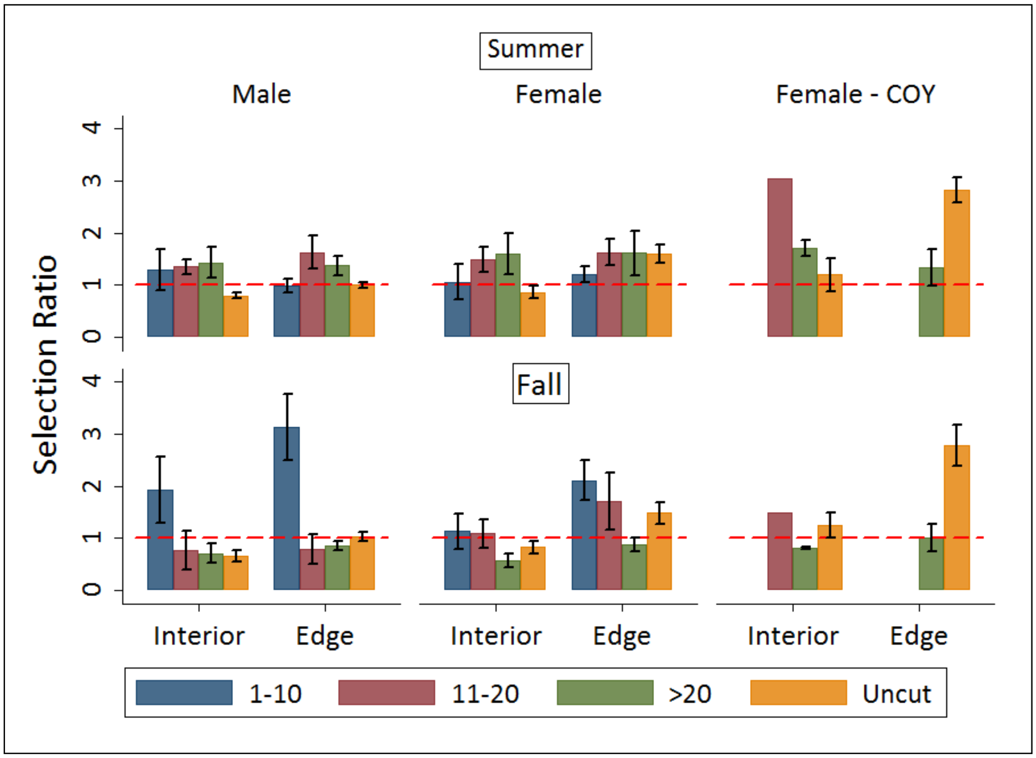

Figure 3. Grizzly bear selection of interior and edge habitat by season, sex and reproductive class, and forest age (years).

Chapter D.2. Grizzly Bear Selection Of Forestry Cutblock Edges

Introduction

In forested environments that lack natural openings due to fire suppression, habitat disturbance associated with forest harvesting is likely to improve habitat conditions (food supply) for grizzly bears (*Ursus arctos*) due to an increase in early seral forests, and the creation of habitat edge (Nielsen et al., 2008). Because forestry cutblocks have the potential to increase food availability for grizzly bears (Nielsen et al., 2004c; Larsen, 2012), bears that used regenerating habitats had higher indices of body condition (Boulanger et al., 2013). This relationship is important because larger females and those that are in better body condition, may produce faster growing cubs that are more likely to survive to adulthood (Robbins et al., 2007 and references therein). However, there is a trade-off in that higher body condition from bears using regenerating forests are also exposed to lower survival potential given the inherent risk of human-caused mortality associated with roads and habitat edge (Nielsen et al., 2004b; Boulanger et al., 2013).

In Chapter 1, we showed that grizzly bears, particularly females during the fall, are attracted to young cutblock edges (≤20yrs), as well as to the edge of uncut forest, whereas all bears avoided the edge of older cutblocks (>20yrs). Larsen (2012) found that fruit production in lodgepole pine (*Pinus contorta*) stands was higher in young cutblocks and mature stands when compared to intermediate regenerating forest age classes. Because the amount of older cutblocks within grizzly bear range is expected to increase with forest harvesting over the long-term (Larsen, 2012), habitat quality for grizzly bears may decline where uncut stands adjacent to young cutblocks are harvested following a two-pass harvesting system. However, it remains unclear whether or not grizzly bear selection for young cutblock edge is functionally related to the characteristics of the adjacent stand (age and/or composition), or if selection can be attributed to the local environmental conditions (moisture, elevation) of the cutblock. It is also not known if the selection of cutblock edge is dependent on habitat availability (i.e., functional responses) (Mysterud and Ims, 1998). Understanding what types of edges influence grizzly bear distribution (habitat selection) will provide information to help guide management decisions surrounding future cutblock design and forest conditions. At the same time, it is important that steps are taken to mitigate human-caused mortality risk where management decisions may enhance grizzly bear habitat (Nielsen et al., 2008), which has been a recommended management action in provincial grizzly bear recovery efforts.

In Chapter 2, we use GPS locations of grizzly bears to assess bear response to cutblock edge habitat. We focus our analysis on male and female bears because data for females with cubs of year were sparse (Chapter 1), and tended to be associated with the edge and interior uncut forests (Chapter 1). As grizzly bears tend to be relatively close to cutblock edges (Chapter 1), we focus our attention to areas within 90m of the cutblock edge interface. This was the average distance bears were from the edge of young cutblocks. In addition to our assessment of site-specific factors (habitat adjacency, forest composition, environmental gradients), we explore differences in cutblock edge selection that could be attributed to seasonality and gender. We also determine whether edge selection results in a higher risk of mortality. Our specific research objectives were to:

1. Determine if stand composition (leading species) or environmental conditions (moisture, climate) of cutblocks influences habitat selection.
2. Determine if the type (cut vs. uncut) or composition (leading species) of the adjacent habitat influences habitat selection.
3. Assess whether or not edge selection leads to higher levels of mortality risk.
4. Determine if selection of cutblock edges is functionally related to their availability.
5. Examine variation in 1-3 in relation to seasonality and gender.

Methods

Grizzly Bear GPS and Random Locations

We used summer and fall grizzly bear GPS locations that were within 90m of young (<20 years) cutblock edges (Chapter 1.). For our available sample, we generated 10 random locations for each 1ha of grizzly bear home range (Minimum Convex Polygon) that was within 90m of young cutblock edges using Geospatial Modeling Environment (Beyer, 2012). We used the most recent bear year to define available habitat for each animal. Annual landscape condition maps were prepared from remote sensing imagery to ensure that forest conditions matched the GPS location data for each year. For use and random locations, we identified the nearest cutblock edge (Chapter 1), and then created binary variables to represent 1) cutblocks as leading pine; 2) adjacent edge (stand) as leading pine; 3) adjacent edge as uncut forest.

Environmental Conditions and Mortality Risk

To represent gradients in environmental conditions known to influence grizzly bear food supply (Nielsen et al, 2004c; Nielsen et al., 2010; Larsen, 2012), we used a Compound Topographic Index (CTI) indicative of terrain related differences in moisture conditions and soils, and we used a Digital Elevation Model (25x25m pixel) as a proxy for climatic variation (e.g., temperature, moisture). We obtained mortality risk values that corresponded to each bear year to account for changes in landscape conditions (Nielsen et al., 2004b). We treated CTI and elevation as continuous variables, and we created a binary variable to identify areas of high (≥8 out of 10 - 50th percentile) mortality risk. We used ArcGIS 10.1 for Geographical Information System processing (ESRI® Redlands, CA).

Statistical Analysis

At the scale of a grizzly bear home range (3rd order selection - Johnson 1980) we used resource selection function (RSF) models to quantify selection of edge habitat for individual animals by season and sex. Using a two stage approach to RSF modelling (Aebischer et al., 1983; Manly et al., 2002), we first fit individual logistic regression models of the exponential form (logistic discriminant function) to estimate regression coefficients of our binary and continuous variables (squared term) chosen *a priori*. Second, we used a meta-analytical approach where regression coefficients were weighted by the inverse variance to obtain population averaged estimates of the mean and standard error. This approach accounts for differences in sample size between bears by giving more weight to regression coefficients that have more locations (Sutton et al., 2000). All statistics were performed in Stata 12.1 (StataCorp, 2011).

Odds ratios were used to interpret bear response at the population level. We deemed habitats to be selected or avoided when the odds ratio of any given variable was above or below 1 and the standard errors did not overlap (α=0.05). Otherwise, our interpretation was random use of habitat (neutral; use=availability). We then calculated, by season and sex, the number of bears that showed positive selection for our binary variables. We used a generalized linear model (GLM; McCullagh and Nelder, 1989) and an information theoretic approach (AIC_c) to test a series of candidate models selected *a priori* (Burnham and Anderson, 2002). These models consisted of individual effects for sex and habitat availability (proportion) against models with these variables as additive or interactive effects. We identified the best model, after considering potential uninformative paramaters (Arnold, 2010), as having the highest Akaike weight and that was greater than two ΔAIC units from a null (intercept only) model. Prior to model fitting we identified potential sources of correlation (Pearson $|r|>0.6$) and multi-collinearity (Variance Inflation Factor; VIF>3) amongst our predictor variables (Zuur et al., 2009). Following model fitting, routine diagnostics (residuals) were performed to ensure model validity and to identify influential observations and outliers (Zuur et al., 2009). Finally, for each season and sex, we calculated summary statistics (mean, min, and max) for GPS locations (use) amongst our binary habitat classes.

Results

Comparing our seasonal RSF models, selection for cutblock edges differed for males and females. In summer, males avoided and females (single and with cubs older than 1 yr of age) used at availability leading pine regeneration, whereas in the fall males (8 of 9) and females (9 of 12) showed strong selection (Figure 1 and Table 1). The use (% of GPS locations) of pine edges by grizzly bears was relatively high (72%) overall and highest in the fall (Table 2). Our top AIC selected model (Akaike weight) associated with leading pine edges included a single term for availability (Table 2). Selection of leading pine edges by grizzly bears was positively related to their availability, and the effect on the mean was more pronounced in the summer (coef=3.00, se=0.82, z=3.67, $p<0.01$) than in the fall (coef=3.75, se=1.28, z=2.92, $p<0.01$).

Although selection of cutblock edges was positive on average where the adjacent forested stand was uncut, population level estimates suggested a neutral response by grizzly bears (Figure 2.1). However, grizzly bear use of uncut edge was relatively high (83%) and was consistently high regardless of season and gender (Table 2). After consideration of uninformative parameters, our AIC model with the most support (Akaike weight) included a single term for habitat availability. Selection of cutblock edges was positively related to the availability of adjacent uncut forest, and the effect on the mean was slightly greater in the fall (coef=4.12, se=1.86, z=2.2, p=0.02) compared to the summer (coef=3.65, se=1.74, z=2.1, p=0.04).

Male grizzly bears selected for cutblock edges in the fall (6 of 9) where the adjacent edge was leading pine, otherwise habitat use was equal to availability with about half of the individuals showing positive selection (Figure 1 and Table 1). On average, grizzly bears spent about 57% of their time using cutblock edges where the adjacent stand was leading pine (Table 2).

Grizzly bears generally selected for cutblock edges despite high mortality risk in these areas. Male bears selected for edges where mortality risk was high in the summer (9 of 12) and the fall (8 of 12), whereas females selected edges with high mortality risk in the summer (9 of 12), but not during the fall (Figure 1 and Table 1). Compared to females, male grizzly bears spent more time along cutblock edges with higher values of mortality risk (Table 2).

Patterns of cutblock edge selection associated with site-specific environmental conditions differed between male and female grizzly bears. In the summer, male bears selected for wet (high CTI values) cutblock edges and in the fall males selected for edges that were mesic to wet (intermediate to high CTI values) (Table 2). Females selected for cutblock edges where moisture conditions were mesic to wet in the summer and in the fall. Grizzly bears appeared to select for intermediate to high elevations (non-linear response), however, the only significant population level response could be attributed to females during the fall as they selected for intermediate to high elevations (Table 2).

Discussion

We demonstrated that the use of young (≤ 20yrs) cutblocks by grizzly bears differed seasonally and was influenced by site-specific factors such as forest composition (leading pine) of the regenerating stand, as well as moisture and climate (elevation). Similar to other studies of grizzly bear habitat selection, food resource availability was likely playing a major role influencing bear behavior (Nielsen et al., 2004ac; Nielsen et al., 2010). Grizzly bears selected pine leading cutblock edges in the fall, when bears tend to feed on berries (Munro et al., 2006), which is consistent with greater fruit production in pine forests (Larsen, 2012). However, the fact that we found this pattern in males is somewhat inconsistent with previous research as male bears tend to eat less vegetation and more meat due to foraging constraints associated with body size (Robbins et al., 2007). We suspect that the availability of alternative foods such as ants, ungulates, or forbs could explain this finding.

Despite our finding that grizzly bears spent substantially more time using cutblock edges where the nearest edge was uncut forest, we did not find population level selection for this edge type. We suspect that this could be related to habitat availability as high levels of habitat use can yield negative responses when habitats are common (Beyer et al., 2010). However, when we considered habitat selection in the context of landscape level availability (home ranges), selection was positively related to the availability of cutblock edges where the adjacent habitat was uncut forest, which is indicative of a functional response in habitat selection (Mysterud and Ims, 1998). Our interpretation is that fewer uncut forested edges associated with 1st pass cutblocks results in a decrease in grizzly bear habitat selection, and suggests a potential reduction in high quality fall habitat related to a decline in fruit production (Larsen, 2012). The juxtaposition of habitat types is an important facet of understanding edge effects, as intermediate characteristics of the contrasting habitats may be present which can result in differential environmental conditions, and consequently vegetation structure and composition (Ries et al., 2004; Harper et al., 2005). Therefore, contrasting edge types may enhance grizzly bear habitat through an increase in the accessibility of food resources that would otherwise be spatially separated (Ries et al., 2004). In Chapter 4, we quantify the distribution and abundance of berries along cutblock edges, and determine the effect of habitat adjacency to address this knowledge gap.

Previous research suggests that there is an inherent risk of grizzly bear mortality associated with cutblock edges (Nielsen et al., 2004b), we showed that male (summer and fall) and female (summer) bears selected cutblock edges where mortality risk was the highest. It is plausible that elevated mortality risk could be explained by grizzly bears using cutblock edges that are close to roads, thus, cutblock edge use could be more related to accessing alternative food resources associated with roads such as clover rather than foods associated with cutblock edges (Roever et al., 2008). Stewart et al. (2013) found that edge selection associated with roads increased in the fall. Although this contrasts with our results which found that females did not select high risk cutblock edges in the fall, we suspect that this difference is related to foraging behavior and the spatial distribution of food resources. Females may forage on fruit when using cutblock edges that could be both near and far from roads.

Management Implications

Our study highlights the need to evaluate habitat selection at the landscape level, and suggests that habitat contrast is a key component of determining the quality of cutblock edges. This is particularly important and relevant to forest management today as fire origin (uncut) stands still dominate the landscape within grizzly bear range. Therefore, maintaining the availability of cutblock edges where the adjacent habitat type is an uncut forested stand is important. We suggest that forest planners and managers should consider retaining a portion of uncut edges as retention structure. Although this is a departure from current forest harvesting strategies, by increasing the accessibility of spatially separated resources we suspect that this approach could enhance habitat quality over the long-term, which, in turn, could reduce the length of time to recover provincial grizzly bear populations.

Anthropogenic disturbances leads to a trade-off situation in that increased food availability results in an increased risk of human-caused bear mortality and attractive sink dynamics (Nielsen et al., 2008; Boulanger et al, 2013). Because the potential for human caused mortality appears to be particularly high, albeit dependent on site-specific environmental conditions and the contrasting edge habitat, we emphasize the need to decommission or eliminate access in these areas as young cutblock edges in proximity to roads may be particularly attractive to grizzly bears.

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Table 1. Population averaged response, selection (+), neutral (/), and avoidance (-), and the number of individual grizzly bears showing positive selection for a habitat variable. Sample size for male bears in the summer (n=12) differed from the fall (n=9), but was the same for females (n=12).

		Summer		**Fall**	
Class	**Variable**	**Population**	**Individual**	**Population**	**Individual**
Male	Pine Cutblock	-	5	+	8
	Uncut Edge	/	5	/	6
	Pine Edge	/	6	+	6
	High Risk	+	9	+	8
	CTI	/	8	+	9
	CTI^2	+	4	-	0
	Elev	/	9	/	8
	$Elev^2$	/	3	/	2
Female	Pine Cutblock	/	7	+	9
	Uncut Edge	/	8	/	8
	Pine Edge	/	4	/	7
	High Risk	+	9	/	6
	CTI	+	11	+	9
	CTI^2	/	1	/	2
	Elev	/	10	+	12
	$Elev^2$	/	2	/	0

Table 2. The proportion of use (grizzly bear) and the proportion of available (random) locations in relation to habitat variables by season and gender.

			Male			**Female**		
Measure	**Variable**	**Season**	**mean**	**min**	**max**	**mean**	**min**	**max**
Use	Pine Cutblock	Summer	0.64	0.18	0.89	0.71	0.07	0.94
		Fall	0.76	0.12	0.99	0.77	0.02	0.98
Available			0.66	0.47	0.82	0.72	0.23	0.87
Use	Uncut Edge	Summer	0.83	0.63	0.99	0.82	0.63	0.99
		Fall	0.87	0.70	1.00	0.80	0.38	0.99
Available			0.85	0.76	0.93	0.83	0.67	0.96
Use	Pine Edge	Summer	0.56	0.39	0.75	0.54	0.08	0.89
		Fall	0.58	0.09	0.85	0.58	0.08	0.81
Available			0.50	0.40	0.60	0.54	0.17	0.63
Use	High Risk	Summer	0.68	0.38	0.90	0.56	0.09	0.95
		Fall	0.69	0.30	0.89	0.53	0.03	0.91
Available			0.60	0.25	0.88	0.49	0.09	0.78

Table 3. Model parameters, sample size (n), and AIC output from generalized linear models explaining seasonal variation in grizzly bear selection of edge habitat (Uncut Edge, Pine Edge, Cutblock Pine, and High Risk).

			Uncut Edge					Pine Edge				
Season	**Model**	**n**	**$\log(L_i)$**	k	**AIC_i**	**Δ_i (AIC)**	W_i	**$\log(L_i)$**	k	**AIC_i**	**Δ_i (AIC)**	W_i
Summer	Null	24	-27.97	1	57.9	1.44	0.20	-15.72	1	33.4	0.00	0.47
	Female	24	-27.85	2	59.7	3.19	0.09	-15.62	2	35.2	1.81	0.19
	Available	24	-26.25	2	56.5	0.00	0.42	-15.55	2	35.1	1.67	0.20
	Female + Available	24	-25.94	3	57.9	1.37	0.21	-15.49	3	37.0	3.55	0.08
	Female*Available	24	-25.93	4	59.9	3.36	0.08	-14.82	4	37.6	4.20	0.06
Fall	Null	21	-23.04	1	48.1	2.85	0.13	-16.57	1	35.1	0.00	0.33
	Female	21	-23.03	2	50.1	4.84	0.05	-16.13	2	36.3	1.13	0.19
	Available	21	-20.62	2	45.2	0.00	0.54	-16.47	2	36.9	1.81	0.13
	Female + Available	21	-20.61	3	47.2	1.98	0.20	-15.90	3	37.8	2.68	0.09
	Female*Available	21	-20.60	4	49.2	3.98	0.07	-13.80	4	35.6	0.46	0.26

			Cutblock Pine					High Risk				
Season	**Model**	**n**	**$\log(L_i)$**	k	**AIC_i**	**Δ_i (AIC)**	W_i	**$\log(L_i)$**	k	**AIC_i**	**Δ_i (AIC)**	W_i
Summer	Null	24	-28.85	1	59.7	6.02	0.03	-20.61	1	43.2	0.03	0.27
	Female	24	-28.37	2	60.7	7.06	0.02	-20.52	2	45.0	1.84	0.11
	Available	24	-24.84	2	53.7	0.00	0.59	-19.60	2	43.2	0.00	0.27
	Female + Available	24	-24.63	3	55.3	1.58	0.27	-19.28	3	44.6	1.38	0.14
	Female*Available	24	-24.58	4	57.2	3.47	0.10	-17.81	4	43.6	0.43	0.22
Fall	Null	21	-33.82	1	69.6	2.74	0.11	-22.58	1	47.2	0.00	0.43
	Female	21	-33.10	2	70.2	3.30	0.08	-22.19	2	48.4	1.22	0.23
	Available	21	-32.05	2	68.1	1.19	0.23	-22.50	2	49.0	1.83	0.17
	Female + Available	21	-30.45	3	66.9	0.00	0.42	-21.96	3	49.9	2.76	0.11
	Female*Available	21	-30.43	4	68.9	1.95	0.16	-21.62	4	51.2	4.08	0.06

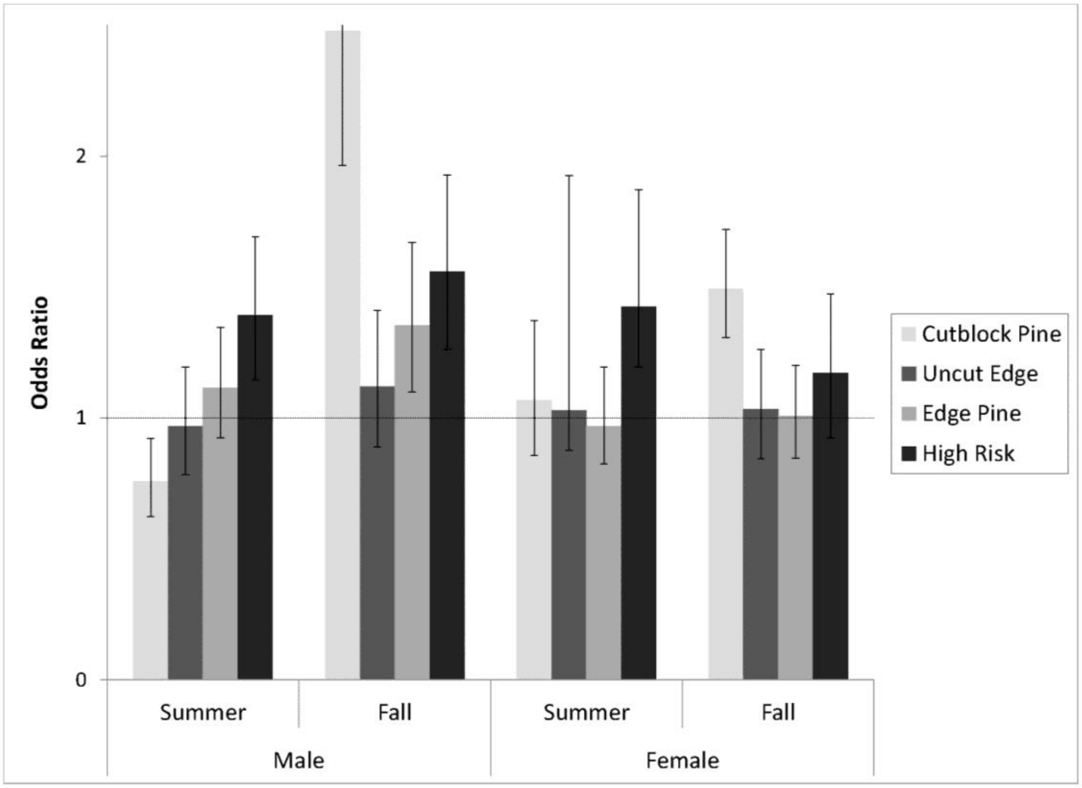

Figure 1. Grizzly bear selection (odds ratio) of cutblock edge types by season and gender. Edge type refers to cutblock edges classified (=1) as pine leading in cutblock, adjacent stand uncut, adjacent stand pine leading, and high mortality risk.

Chapter D.3. Do Grizzly Bears Respond To Varying Levels Of Green Tree Retention Within Cutblocks?

Introduction

Emulating patterns of natural disturbance such as fire has become main stream in North American forest management as a means of maintaining forest ecosystem function and biodiversity (Long, 2009). As part of this paradigm shift, the retention of forest structure (green trees, snags and woody debris) following timber harvest has become an important component for replicating characteristics of future forests that follow natural disturbance events. In Alberta, this is a key component of forest management planning. Grizzly bears are a species generalist well suited to habitat disturbance and are likely to benefit from green tree retention in cutblocks given their affinity for habitat edge associated with young (≤20yrs) cutblocks, particularly if cutblock size increases resulting in more interior cutblock area (Chapter 2).

Where harvesting occurs, there is an In-Block Retention Strategy that aims to leave 2.5% conifer and 3% deciduous merchantable volume on the land base (Weyerhaeuser, 2011). However, retention amounts in cutblocks can vary, and this can differ on a regional basis. Certain cutblocks may have no retention while others can have greater than 25% tree cover remaining. Maintaining heterogeneous conditions in cutblocks through the creation of different sized patches (natural range of variability) is likely to conserve biodiversity over the long-term, particularly for interior or mature forest dependent species. It is also likely that grizzly bears will respond positively to such structural heterogeneity associated with retention patches in cutblocks because available resources (food, cover) are enhanced. However, the benefits of structural retention for grizzly bears have not been studied in Alberta. Understanding whether grizzly bears respond to current retention strategies will help forest managers make planning decisions that considers the habitat needs of grizzly bears when designing harvesting strategies.

To evaluate the response of grizzly bears to in-block retention, we use GPS locations of collared grizzly bears in combination with a cutblock database where retention patches were mapped. Our objective was to determine if grizzly bears responded positively to different measures of patch retention amounts: 1) total retention patch area; 2) mean retention patch area; 3) standard deviations in patch area; and 4) counts of patch retention. In support of our hypothesis that resources (food, cover) for grizzly bears are enhanced with retention patch heterogeneity, we predicted that irrespective of seasonality and gender, grizzly bears would respond positively to heterogeneity in retention patch size by selecting for cutblocks with higher standard deviations in retention patch area. In Chapter 4, we assess food distribution and abundance in retention patches as a possible mechanism to explain observed bear response.

Methods

In-block Retention Patch Mapping

We defined in-block retention as single trees (dispersed) or clusters of trees (patch) excluded from harvesting and completely surrounded by the cutblock edge. Patches touching the edge were assumed to be functionally connected to the adjacent forest. We used three data sources to represent green tree in-block retention. Although data sources did not encompass all cutblocks available to grizzly bears, for certain cutblocks multiple data sources were available. We utilized the data sources that we viewed to be the most accurate from visual examinations of cutblocks with high resolution orthophotos. In order of accuracy, these included: 1) Weyerhaeuser - digitized single trees and patches for cutblocks with an origin year between 2006 and 2010; 2) Alberta Vegetation Inventory (AVI) - digitized patches for cutblocks prior to 2006; and 3) Light Detection and Ranging (Lidar) for all other cutblocks where Lidar was available. Because Lidar data was not available for cutblocks more recent than 2010, and since it was difficult to differentiate retention from post-harvest regeneration for cutblocks older than 1990 we excluded these blocks from our analysis. The difference between 1) and 2) reflects a greater effort to precisely identify single trees and outline patches in 1).

The following steps were taken to blend the three data sources into a single dataset. First, point features (single trees) from 1) were buffered by 3m to approximate 6m wide crowns and then merged where patches overlapped. Second, cutblock inner features from 3), were buffered by 20m to eliminate pixels next to the cutblock edge, and then converted to a raster (4m pixel) and used to clip the Lidar canopy height model (Full feature surface minus Bare Earth surface). Pixel values greater than 10m (vegetation height) were converted to point features, buffered by 6m to approximate tree crowns, and merged with overlapping patches. The 10m cutoff was used to distinguish regenerating trees from residual uncut mature timber. A buffer distance of 6m, rather than 3m, was used to eliminate gaps between clusters of single trees that in 1) were digitized as patches. Finally, layers 1) – 3) were merged into a single dataset, and the area (ha) of individual non-overlapping patches was calculated. We summarized the following attributes for each cutblock as our measures of retention patch amount: 1) total amount (sum); 2) mean size (; 3) standard deviations in size; and 4) number of patches (counts).

Grizzly Bear and Random Locations

We used GPS locations (2005-2012) of collared grizzly bears (habitat use) that corresponded with cutblocks that had mapped retention patches. Grizzly bears with fewer than 85 GPS locations were removed leaving 22,061 locations from male (n=13) and female (n=13; single or with cubs older than 1yr of age) bears for our analysis. We removed animals with few locations as they would have little influence on population level estimates following our meta-analysis approach (Chapter 2). We generated grizzly bear home ranges and random locations (1/ha^{-1} of home range) following methods outlined in Chapter 2. For each use and random location, we extracted retention patch attribute values from cutblocks.

Habitat Selection Analysis

From the random location sample, we determined what the 50th percentile was for each retention measure: 1) sum>0.9; 2) mean>0.03; 3) standard deviation>0.03; and 4) count>17. We then created binary variables for use and random locations representing the 50th percentile cut-off for each retention measure. Thus, binary variables equal to 1 were indicative of high amounts of retention area, larger average patch size, heterogeneity in patch size, and more retention patches given current conditions and what was available to grizzly bears.

To assess variation in grizzly bear response to our measures of retention patch amount for each season (summer and fall) and according to gender (male and female), we used a resource selection function (RSF) model and the model building strategy outlined in Chapter 2. Pearson's correlation coefficient confirmed that model variables were not correlated (|r|>0.6). Our interpretation of grizzly bear response (population level) to retention patch amount was based on a weighted average (analytical weights) of individual model coefficients and standard errors (Sutton et al., 2000). This approach adjusts estimates to give more weight to animals with a larger sample size to account for differences in the precision of variable estimates. Exponentiated coefficients and standard errors were used to assess grizzly bear selection or avoidance of different measures of retention amount when standard errors did not overlap 1 (neutral; use=availability). We also determined the time grizzly bears spent (proportion) within each measure of retention patch amount to aid in our interpretation.

Results

Male grizzly bears responded positively to cutblocks with more retention patches and showed strong selection in the summer (Figure 3.1). For females, although standard errors overlapped 1, their response was negative in both seasons. The reduction in odds ratios of male and female bears from summer to fall corresponded to lower overall habitat use proportions, particularly for females (Table 1).

Grizzly bears tended to use cutblocks that contained larger retention patches relative to their availability, but in the fall both male and females showed significant avoidance (Figure 3.1). Habitat use proportions were similar overall, but revealed that the use of larger retention patches was higher in the fall for males and in the summer for females (Table 1).

Across seasons, male and female grizzly bears responded positively to cutblocks with higher standard deviations in retention patch area (Figure 1). Females showed strong selection in the summer and fall while for male bears, selection occurred in the fall. Although habitat use proportions were similar, male grizzly bears spent more time in cutblocks with higher standard deviations in patch size in the fall, but for females use was highest in the summer (Table 1).

Male and female grizzly bears showed a similar response to cutblocks that contained more retention patches. Responses were positive in the summer and negative in the fall, which was consistent with habitat use proportions (Figure 1 and Table 1).

Discussion

Our findings support our prediction that grizzly bears are attracted to cutblocks where the heterogeneity in retention patch size is greater. This supports our hypothesis that resources (food, cover) may be enhanced in cutblocks for grizzly bears under current conditions. A wide range of retention patch sizes would increase habitat edge (food) and could increase grizzly bear access to spatially separated food resources. At the same time, more tree cover could promote grizzly bear foraging behaviour in cutblocks through increased foraging opportunities related to the proximity of security cover. Serrouya et al. (2011) showed that grizzly bear selection of the best avalanche chutes (food) was associated with treed retention buffers adjacent to the chutes. Retention may be particularly important in larger cutblocks where distance to escape cover could be higher (Zager et al., 1983). Mealey et al. (1977) found that grizzly bears used smaller cutblocks with leave trees, but not larger ones without leave trees. However, bear response (positive or negative) to open habitat conditions may be related to human activity (Cristescu et al, 2013). The availability of retention patches of varying size may also promote bear activities other than foraging. Because grizzly bears tend to rest (day beds) in older (>20yrs) cutblocks and mature uncut forest (Appendix A), larger retention patches in cutblocks may provide bears with important thermal cover for resting as moisture and temperature gradients tend to be more similar to interior forest conditions (Redding et al., 2003). Zager et al. (1983) found that bears used uncut timber between harvested areas for travelling and resting.

Our results suggest that cutblocks with larger retention patches on average tend to be avoided by grizzly bears during the fall when bears, particularly females, forage intensively on available fruit (Munro et al., 2006). This is similar to other studies where retention buffer width had little measurable influence on grizzly bear habitat use (Serrouya et al., 2011). Because fruit production could be lower on a per unit area basis in cutblocks with larger retention patches, foraging efficiency may be reduced leading to avoidance behavior by grizzly bears (Serrouya et al., 2011). This supports previous research that suggests grizzly bears avoid uncut forests (Waller and Mace, 1997; Nielsen et al., 2004a), presumably because fruit production (*Vaccinium myrtilloides*) tends to be lower in uncut forest compared to young cutblocks (Larsen, 2012).

Management Implications

Although there are no universally applicable recommendations regarding structural retention for wildlife because species responses can be highly variable, it is advised that a variety of retention levels and associated patterns should be implemented across the landscape (Serrouya and D'Eon, 2004). The results of our research support the contention that managers should promote heterogeneous habitat conditions in cutblocks by increasing the variation of retention patch size. Retention strategies such as this would not only offer benefits from the perspective of biodiversity conservation in the face of future uncertainty, but this approach could also enhance resources for species at risk (Rosenvald and Lohmus, 2008). The grizzly bear is threatened in the province and improving habitat conditions through variable patch retention would support grizzly bear population recovery.

Even though larger retention patches may not be favoured by grizzly bears, other species associated with interior old forest conditions would likely benefit (Bradbury, 2004; Nelson and Halpern, 2005; Otto and Roloff, 2012). It is plausible that the value of larger retention patches, and retention patches in general, could be improved if food resources were purposefully retained during the harvesting process. For example, higher elevations in our study area are known to contain certain berry species and/or associated with mature pine forests (e.g., *Vaccinium membranaceum*, *Vaccinium vitis-idaea*). Ensuring that retention patches contain important fruit producing species could be important to maintain fall habitat quality for grizzly bears at these higher elevations since young cutblocks tend to have lower fruit production. This would require additional work during the block layout stage of forest harvesting to identify important bear foods that could be integrated into retention patch design. In Chapter 4, we quantify the abundance of food resources for grizzly bears in retention patches compared to uncut forests to determine the potential for habitat enhancements.

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Table 1. The proportion of male and female grizzly bear GPS locations (habitat use) relative to high levels of retention patch amount (sum area, mean size, standard deviations in size, and total number of patches) by season.

		Sum Area			Mean Area			SD Area			Count		
Gender	**Season**	**Mean**	**Min**	**Max**	**Mean**	**Min**	**Max**	**Mean**	**Min**	**Max**	**Mean**	**Min**	**Max**
Male	Summer	0.60	0.30	0.88	0.43	0.19	0.78	0.49	0.27	0.78	0.57	0.25	0.76
	Fall	0.58	0.17	0.85	0.49	0.05	0.92	0.52	0.02	0.90	0.46	0.07	0.82
Female	Summer	0.52	0.18	0.98	0.43	0.23	0.91	0.47	0.23	0.97	0.57	0.26	0.95
	Fall	0.44	0.10	0.96	0.39	0.02	0.67	0.44	0.09	0.66	0.45	0.16	0.97

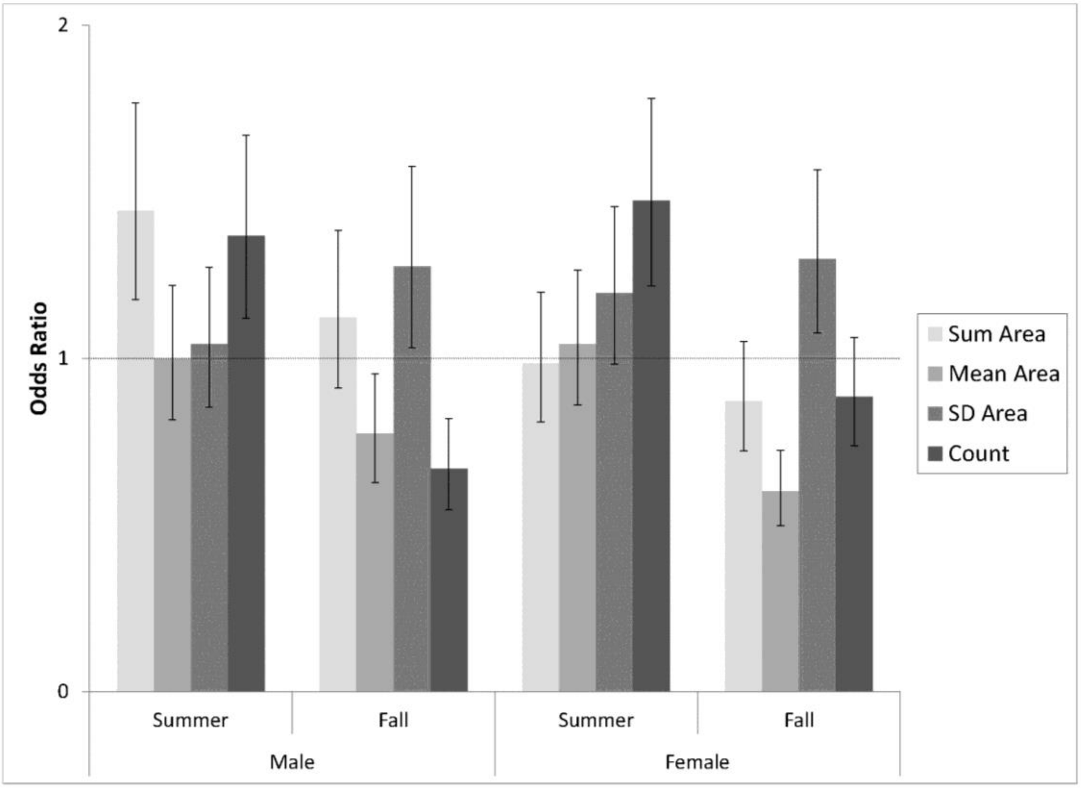

Figure 1. Male and female selection (odds ratio) of high levels of retention patch amount (sum area, mean size, standard deviations in size, and total number of patches) by season. Error bars represent standard errors

Chapter D.4. Are Berries More Abundant At Forestry Cutblock Edges?

Introduction

Understanding mechanisms that influence the distribution or abundance of wildlife is central to ecology and is an important part of sustainable forest management. For grizzly bears, it is likely that both distribution and abundance is related to the accessibility of available food resources within and among habitats (Nielsen et al., 2004; Nielsen et al., 2010; Larsen, 2012). In Alberta, grizzly bears, particularly females, are known to select young cutblock edges in the fall because of the availability (e.g., distribution/abundance, energy) of seasonally critical foods such as fruit (Chapter 2). Fruit availability is important for bears generally to gain the necessary fat reserves for winter denning, and is particularly important for females to meet requirements for reproduction (20% body fat) as well as provide for growing cubs (Farley and Robbins, 1995; Robbins et al., 2012). However, it is not known if fruit production is higher at cutblock edges of different ages, nor is it understood what distance into the interior of habitats this effect might be. The effect of forest age and edge distance is important to understand as changes that occur over time through forest harvesting (i.e., second pass harvesting) and natural succession may alter this food supply, and thus influence the ability of bears, particularly females, to overwinter and reproduce. A reduction in fecundity may have population level implications that could influence grizzly bear recovery. A recent study showed that the availability of fruit, in addition to ungulates, explains bear distribution and abundance derived from DNA based estimates from hair snags (Nielsen et al., 2013). However, other research in British Columbia suggests fruit alone may explain regional differences in grizzly bear density (McLellan, 2011).

Previous research examining grizzly bear response to cutblock edge suggests that fruit production would increase due to changes in vegetation (canopy cover – light), particularly at the interface between young cutblocks (≤20yrs) and uncut stands (1st pass) compared to the edge interface when cutblocks are adjacent (2nd pass) (Larsen, 2012). If this is the case, green tree retention may benefit grizzly bears as food resources would be enhanced both within cutblocks, as well as at the cutblock edge (Chapter 3). At the same time, young cutblocks may be less attractive to grizzly bears where the adjacent stand is another cutblock because of reduced foraging opportunities associated with spatially separated resources (Chapter 2). Because fruit production is affected by forest harvesting and its influence on forest age (Nielsen et al., 2004; Nielsen et al., 2010; Larsen, 2012), and since fruiting species used by bears may vary spatially across the landscape due to gradients in environmental conditions (climate, moisture) (McLellan and Hovey, 2001; Nielsen et al., 2010; Larsen, 2012), that in turn are linked to disturbance history (fire) (Hamer and Herrero, 1987a; Hamer and Herrero, 1987b; Hamer, 1996), local studies are necessary to help inform management at a regional level. Understanding how forestry practices influence food availability would provide important information to forest managers relative to designing future cutblocks to benefit grizzly bear populations.

We collected data on a number of bear foods in this study. However, for this report we assess the response of *Vaccinium myrtilloides* (VAMY) to habitat edge created through forestry practices within a conifer dominated landscape. Previous research suggests this is an important fall food source for grizzly bears in this system (Larsen and Pigeon, 2006; Larsen, 2012). We use vegetation survey data to quantify changes in the distribution and abundance of VAMY along cutblock edges and within retention patches. More specifically, we modelled the effect of edge distance and forest age on shrub and fruit occurrence and abundance. We hypothesized that VAMY shrubs and fruits would be more likely to occur and would be more abundant in close proximity to cutblock edges (<10m), and that the occurrence and abundance of VAMY would be lowest in older cutblocks.

Methods

Edge and Retention Patch Stratification

We used a spatial cutblock database (Chapter 1) to identify forested stands (patches) within the Subalpine and Upper Foothills Natural Region (Natural Regions Committee, 2006). We defined cutblock edge as the continuous perimeter (polyline) of each harvested area boundary where the age of origin (skid clear date for cutblocks) between adjacent habitat patches exceeded one year. We determined cutblock age by subtracting 2013 from the skid clear date, and then stratified cutblocks as young (2-10yrs), moderate (11-20yrs), or old (21-43yrs). We then stratified edges by type: 1) where cutblock edge was adjacent to uncut (>43yrs) forest (1st pass); and 2) where cutblock edge was adjacent to another cutblock (2nd pass).

We stratified mapped retention patches (Chapter 3) by size (ha). For each data source (1 – Weyerhaeuser; 2 – AVI; and 3 – LiDAR), we classified retention patches as A) small, B) medium, or C) large (≥0.5ha). To discern between small and medium patches, we used equal intervals to determine the cut-off point. Large patches signified the point where observers could identify (digitization) retention patches with some level of certainty as those that were smaller were difficult if not impossible to detect (Nash, 2009). ArcGIS 10.1 was used for data processing (ESRI® Redlands, CA).

Random Sampling

Using a hand held GPS unit, we navigated to 1st pass edges (n=72), 2nd pass edges (n=18), and retention patches (n=34) selected from a random point distribution. Random locations were drawn from a sample of edges that were further than 120 meters from roads, wellsites, pipelines, seismic lines, or powerlines. This was to ensure that we avoided other potential anthropogenic edge effects. Retention patches were paired with a 1st pass edge from the same cutblock. We attempted to balance sampling effort amongst our cutblock (age, edge type) and patch retention (source, size) stratifications.

Transect Sampling

To determine the starting point for our line transects, we located the nearest edge or retention patch tree (≥5cm @ 1.3m) using a range finder with 1m accuracy. At cutblock edges, we ran 2-60m transects perpendicular to, and on opposite sides, of the edge. Transects began at the base and on either side (cutblock/interior) of the nearest edge tree. Similarly, at retention patch edges, we located the nearest edge tree and ran a single 60m transect perpendicular to the cutblock edge and through the retention patch. Along each transect, we established 10-1m^2 and 8-10m^2 subplots (using a peg and string), at different sampling intervals (1m^2: 0.56, 2.5, 5, 7.5, 10, 20…60m; 10m^2: 1.7m, 5, 10, 20…60m). Our rationale for using two subplot sizes was to capture differences in the spatial growth patterns of plant species – for example distributed (*Vaccinium spp.*) vs. clumped (*Shepherdia canadensis*). We sampled vegetation more frequently with 10m from the edge to obtain a better estimate of the mean since responses were expected to change abruptly as distance from the edge increased. Because our goal was to capture changes in the distribution and abundance of vegetation associated with edge distance, transects were established where the systematic spacing of each subplot would be greater than the distance to the nearest edge tree. If maintaining this edge distance was not possible, or if any anthropogenic feature was within 60m of a transect we moved the start point in a random direction along the edge (30m increments). However, this rule was not used for retention transects as our goal was to capture variation associated with the interaction of multiple edges given that patches tend to be small.

At each subplots we occularly estimated the percent cover (0-100) and counted berries based on their status (unripe, ripe, and overripe) for a number of bear foods. Competing vegetation and other environmental factors such as downed and hanging trees were also measured. We picked berries using a per unit time constraint (1 minute/subplot), which allowed for more rapid counts (abundance). For each berry species and status, we weighted berries to the nearest decimal place using a spring scale (Pesola ©). We weighed berries the sample to allow for energetics (digestible energy) to be calculated more precisely.

Using a range finder, we located the nearest (≤60m) three trees (≥5cm @ 1.3m diameter-at-breast height (DBH) at each subplot, and recorded the distance, species, DBH, and other attributes (alive vs. dead; broken or not). Within cutblocks and where the nearest tree was part of a retention patch, we distinguished single trees from a patch (≥3 trees). We defined patches as 'islands' of continuous tree cover where mechanical damage appeared to be absent. When sampling transects within retention patches, when a subplot was closer to a different edge tree than the starting edge tree, we also recorded the distance. Due to the variable size of retention patches many were smaller than the 60m transect. When this occurred we also noted when subplots fell outside the retention patch and/or fell within the cutblock-edge interface.

Data collected on other bear foods, competing vegetation, other environmental factors, and the attributes of the three nearest trees will be incorporated into a comprehensive analysis for a peer reviewed publication.

Variable Coding for Analysis

We created a categorical variable to represent transect habitat: 0) young (2-20 yrs) cutblock; 1) old (21-43 yrs) cutblock; 2) uncut (>43 yrs); and 3) uncut retention. For retention transect subplots where the area landed completely within the cutblock, we re-coded the age/type categorical variable accordingly. Distance to edge was treated as a continuous variable.

Distribution and Abundance Models

We used generalized estimating equations (GEE) to model the distribution and abundance of VAMY shrubs and berries with robust estimates of variance (Williams, 2000). We used GEE over a mixed model since we were interested in the population level average response of our predictor variables, and since we could specify both binomial (presence/absence, percent cover) and negative binomial (counts) error term distributions. We choose exchangeable correlation structure, which assumes that within transect observations (subplots) were correlated. In this case, transect was treated as a cluster variable (sample unit), allowing for the correct estimation of standard errors (Hanley et al., 2003). We fit a null (intercept only) model and models with variables representing forest age/type, edge distance, and the interaction between these variables. Prior to model fitting, we used generalized additive models (GAM; Hastie and Tibshirani, 1990) to determine non-linearity amongst our response variables as a function of edge distance. For applicable models, we used a squared term to represent potential non-linear effects. Regression diagnostics were used to assess the validity of models and identify potential outliers (Zuur et al., 2009). Pearson correlation coefficient ($|r|>0.6$) and variance inflation factors (VIF; >3) were used to assess potential correlations and multi-collinearity amongst our predictor variables (Zuur et al., 2009).

We used a quasi-likelihood information criterion (QIC) approach to model selection and inference that was based on a modification of the Akaike (AIC) approach (Pan, 2001). Unlike generalized linear models (GLM) that utilize maximium likelihood estimation (McCullagh and Nelder, 1989), GEE is based on quasi-likelihood theory (Wedderburn, 1974) where no assumptions are made about the distribution of the response variable. Similar to AIC (Burnham and Anderson, 2002), we calculated QIC model weights that can be interpreted as the probability of support for competing models. We report the model with the highest model weight and discuss competing models.

Results

The top models explaining variation in the distribution and abundance of VAMY shrubs included a single variable for habitat (Table 1 & 2). Although there was also support for models with an additional variable for edge distance (Tdist), we concluded that this variable was uninformative since the ΔQIC value was within 2 units. Model weights suggested overwhelming support for a model that contained the additive effects of habitat and edge distance on our distribution (0.98) and abundance (0.98) models.

The distribution and abundance of VAMY fruit differed by habitat and edge distance (Figure 1 & 2). Compared to young cutblock edges, the probability of a VAMY shrub occurring in older regenerating stand edges was reduced by 58%, while the abundance of fruit decreased by 85%. When young cutblock edge was compared to uncut forested edge, the occurrence probability and abundance of berries was lowered by 37 and 76%, respectively. In retention patches, the probability of VAMY fruit was reduced by 75%, whereas berry abundance within retention patch edges was 79% less when compared to young edges. The relationship between berry abundance and edge distance was non-linear (Figure 4.2). Within the first 10m of young cutblock edges, the probability of VAMY fruit occurring was reduced by 31% and the abundance of berries by 41%.

Discussion

Our findings support the hypothesis that the effect of edge on increasing VAMY fruit abundance occurred only in close proximity to the cutblock edge. Within 10m from the cutblock edge, berry abundance dropped precipitously. Although some authors report vegetation responses that extend beyond this distance to as much as 40m, others suggest that edge effects may only extend up to 5m (Harper and Macdonald, 2001; Harper et al., 2004). Edge effects are known to be highly variable, and also tend to be species specific. Responses of fruit to edges can be positive or negative, and the magnitude of edge effect on the mean can differ (Ries et al., 2004). These differences are believed to be associated with changes in microclimatic conditions at the edge, which in turn is dependent on contrasts between adjacent habitats (Burton, 2002; Harper et al., 2005; Kowal and Cartar, 2012).

The results of our analysis suggest that shrub distribution and abundance does not vary to any great extent due to forest age, nor in relation to edge distance. However, we found substantial differences in fruit occurrence and abundance associated with forest age and edge distance. In habitats where canopy cover was expected to be higher such as in uncut, retention and older cutblock edges, berry production was dramatically reduced (~80%) compared to young cutblocks. Previous research suggests that fruit production is functionally related to the rate of overstory regeneration (Zager et al., 1983; Martin, 1983; Hamer et al., 1996). However, this does not explain why fruit production did not increase as a function of edge distance. It is plausible that the condition of VAMY shrubs along the edge of cutblocks was better, resulting in greater fruit production at cutblocks edges when compared to the interior of cutblocks. This may be explained by mechanical damage to interior VAMY shrubs during harvest, or during post-harvest site preparation, which in turn could reduce fruit production in cutblock interiors (Zager et al., 1983; Martin, 1983). Alternatively, intermediate canopy cover or partial shading near the edge of cutblocks could enhance fruit production; however this hypothesis contrasts with previous research, which suggested that open canopy conditions are more conducive to higher levels of fruit production in this species (Moola and Mallik, 1998). In Chapter 5, we test the hypothesis that fruit production is enhanced in cutblocks through silvicultural practices that reduce damage to shrubs, and that grizzly bears respond positively to this variation.

Management Implications

If we assume that the fruit production/edge relationship within young cutblocks is consistent, which tends to be the case under similar habitat conditions (Ries et al., 2004), retention patches within cutblocks may replicate the edge effect on fruit production that we observed in this study. Thus, increasing retention patches could boost fruit production in cutblocks. Regardless, if fruit does not increase within the patch itself, the presence of retention patches, particularly smaller more dynamic patches, will increase the amount of habitat edge within cutblocks, which in turn could drive increased berry production across the landscape. At the same time, we observed higher predicted berry counts of VAMY as distance from the cutblock edge increased. This variation could be explained by differences in shrub quality associated with silvicultural prescriptions. Research suggests that greater mechanical damage due to soil disturbance tends to be higher when harvesting occurs in the summer or where high impact site preparation techniques are used to expose mineral soil (Martin 1983; Coxson and Marsh, 2001). Therefore, management practices that involve both harvesting during the winter months combined with low impact site preparation will result in less mechanical damage to rhizomes and potentially result in greater berry yields, which we believe would be beneficial for grizzly bears.

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Table 1. QIC output from generalized estimating equation models describing shrub (Vaccinium myrtilloides) abundance as a function of model variables.

Shrub		**Distribution**			**Abundance**		
Species	**Model**	**QIC**	**Δ QIC**	***w***	**QIC**	**Δ QIC**	***w***
Vaccinium myrtilloides	Null	1187.1	12.95	0.00	332.8	5.62	0.03
	Tdist	1188.4	14.28	0.00	332.2	5.10	0.03
	Hab	1174.3	0.10	0.42	328.3	1.12	0.25
	Tdist + Hab	1174.2	0.00	0.44	328.3	1.16	0.25
	Tdist * Hab	1176.4	2.26	0.14	327.1	0.00	0.44

Table 2. QIC output from generalized estimating equation models describing shrub (Vaccinium myrtilloides) fruit abundance as a function of model variables. We used a squared term for our distance variable (Tdist) to explain the non-linear response.

Fruit		**Distribution**			**Abundance**		
Species	**Model**	**QIC**	**Δ QIC**	***w***	**QIC**	**Δ QIC**	***w***
Vaccinium myrtilloides	Null	782.8	22.9	0.00	6853.6	586.0	0.00
	[1]Tdist	776.7	16.7	0.00	6878.0	610.4	0.00
	Hab	768.3	8.4	0.02	6361.5	93.9	0.00
	[1]Tdist + Hab	760.0	0.0	0.98	6267.6	0.0	0.98
	[1]Tdist * Hab	771.4	11.5	0.00	6275.7	8.1	0.02

[1] Squared term (Tdist) for distribution and abundance models.

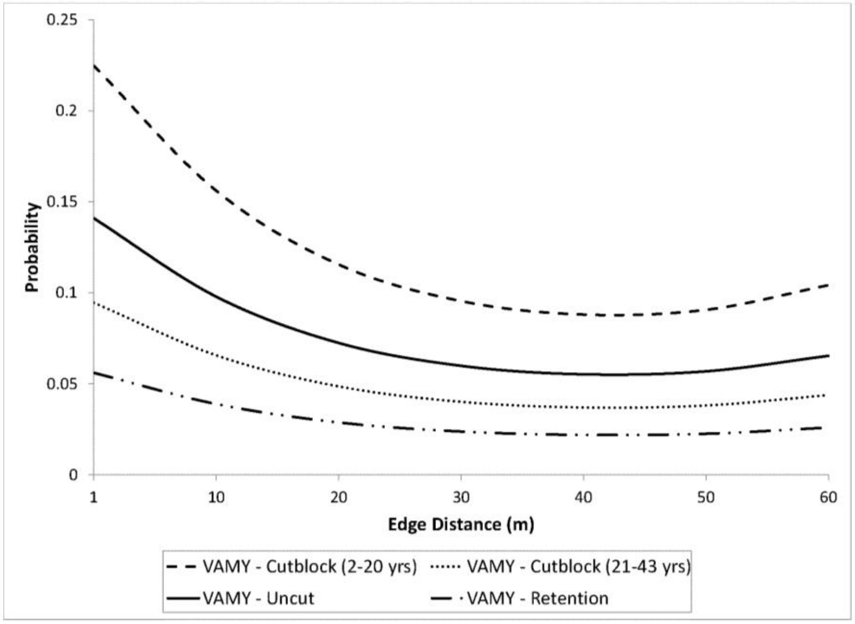

Figure 1. Probability of *Vaccinium myrtilloides* fruit being present by habitat as a function of edge distance estimated using a generalized estimating equation model.

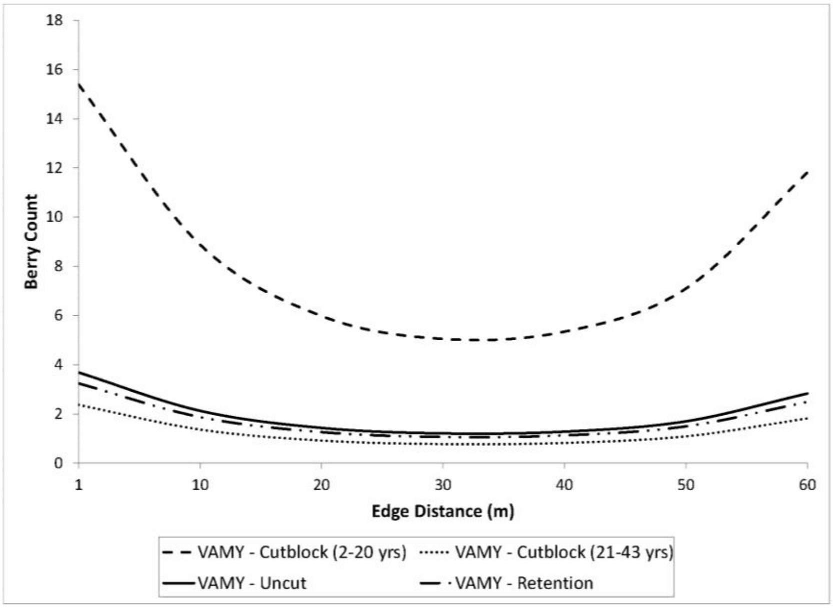

Figure 2. Predicted berry count of *Vaccinium myrtilloides* by habitat as a function of edge distance estimated using a generalized estimating equation model.

Chapter D.5. Does Silviculture Influence Food Availability And The Behavior Of Grizzly Bears?

Introduction

Silviculture is the practice of controlling the establishment, growth, composition, and vigor of regenerating forests following timber harvest. Although silviculture is often and mistakenly viewed solely as a means to improve timber production, the intent is also to maintain other forest values such as wildlife habitat. Increasingly, silviculture has become a fundamental component of sustainable forestry, especially in landscapes where managers are faced with maintaining important habitat for species at risk. However, in many cases there is little information on which to base management decisions that support conservation. To manage wildlife habitat over the long-term, there is a need to better understand how past silvicultural practices have affected the current state of forested landscapes. In doing so, silvicultural prescriptions can be tailored at the stand level, which in turn would allow more effective wildlife habitat management regionally and at the provincial level.

Along the eastern slopes of Alberta, much of the forested land base outside of parks and protected areas are managed for commercial timber production. At the same time these areas are also considered important grizzly bear habitat. Because forest harvesting accounts for a relatively large amount of what is considered the industrial footprint, the future conditions of grizzly bear habitat will, to a large extent, be dictated by forestry practices (Nielsen et al., 2004a). This is an important consideration as grizzly bears are a threatened species in the province, and augmenting the population is vital to recovery (Alberta Grizzly Bear Recovery Plan, 2008-2013, 2008). Previous research suggests that in the absence of human-caused mortality risk associated with forestry roads (Nielsen et al., 2008), cutblocks may be beneficial to grizzly bears as they often contain seasonally important food resources (Nielsen et al., 2004b; Larsen, 2012). However, it has also been suggested that the availability of certain foods (e.g., fruit) may have a disproportionate effect on population level processes that influence grizzly bear densities (McLellan, 2011; Nielsen et al., 2013). Therefore, ensuring that forestry practices through silviculture maintain or enhance critical food resources for bears could be important to recovery efforts and in the conservation of this species.

In Alberta, regeneration strategies for cutblocks are diverse and dependent on broad differences in climate (Natural Subregion), as well as local factors associated with eco-site (Weyerhaeuser, 2011). For example, depending on the moisture regime, drag scarification (mesic) or mounding (wet) may be used to promote conifer regeneration by exposing mineral soil, whereas in other areas (dry) natural regeneration techniques (seed) could be utilized (Weyerhaeuser, 2011). Although this approach allows for silvicultural treatments (site preparation, herbicide) to be site specific, and improve conditions for tree growth (Weyerhaeuser, 2011), it also provides the opportunity to make modifications at the local scale that could enhance grizzly bear habitat.

Soil disturbance associated with forest harvesting and site preparation alters nutrient availability and the conditions of soils (temperature, moisture) (Frey, 2003; Schmidt et al., 1996). Certain herbaceous species, particularly exotics (e.g., *Trifolium* spp., *Taraxacum* spp.), shrubs, and graminoids tend to increase with soil disturbance as they are able to rapidly colonize disturbed areas via seed and vegetative propagation (Bock and Van Rees, 2002; Lieffers and Macdonald, 1993; Haeussler et al., 2004; Redburn and Strong, 2008). Others species such as those that reproduce from rhizomes can be negatively affected (Martin, 1983; Zager et al., 1983; Haeussler et al., 1999; Nielsen et al., 2004b). Herbicide (glyphosate) treatments can also result in positive or negative effects to vegetation (Hamilton, 1991; Moola et al., 1998; Lautenschlager and Sullivan, 2002). Although silvicultural strategies are used to ameliorate site conditions (competition) conducive to the survival and growth of seedlings to meet regeneration standards and specific management objectives (Haeussler et al., 2004; Boateng et al., 2000), steps can be taken to reduce soil disturbance by harvesting in the winter or implementing low impact site preparation techniques (Coxson and Marsh, 2001; Berger et al., 2004). However, the potential impacts of silviculture on the availability of grizzly bear foods, particularly fruit production, and the response of grizzly bears to variation in treatments are not well documented (but see Nielsen et al., 2004b). Understanding these relationships and providing this information to managers may identify opportunities to enhance grizzly bear habitat where appropriate and to support of provincial grizzly bear recovery efforts.

Here we use GPS locations from collared male and female grizzly bears, vegetation surveys, and a cutblock database to determine bear response, and examine changes in vegetation, associated with silviculture. More specifically, we assess the seasonal habitat selection of grizzly bears and quantify the distribution and abundance of *Vaccinium myrtilloides* (VAMY) shrubs and fruits in relation to the timing of harvest (summer vs. winter) and whether or not cutblocks were treated using mechanical site preparation or herbicide. We focus on VAMY for this report because previous research suggests that it is an important food in the system (Chapter 4). However, the results of our comprehensive analysis that included a number of other bears foods are the subject of ongoing analysis and will be provided in a future publication. We hypothesized that winter harvest and no site preparation or herbicide would result in more VAMY shrubs and higher fruit production, and that grizzly bears would respond positively to cutblocks with these treatments.

Methods

Silviculture Treatment

We used a historical cutblock database (Chapter 1) with attributes describing the year and month of harvest (skid clear date), and whether or not mechanical site preparation and the application of herbicide occurred. Cutblocks were classified as winter if harvesting occurred between November 1st and April 30th. This followed the classifications used by Weyerhaeuser Grande Prairie and generally corresponds to the period when snow cover would be the greatest and when the ground is frozen. Although we did have information regarding treatment area, we did not know spatially within cutblocks where site preparation and herbicide treatments occurred. Thus, cutblocks were classified as either treated or not.

Grizzly Bear and Random Locations

We used the GPS locations (33,056) of male (n=15) and female (n=14; single or with cubs older than 1yr of age) grizzly bears from Chapter 1 that overlapped with our cutblock database. Methods for home range delineation and random point generation (1/ha^{-1} home range) to define habitat availability followed Chapter 2. For each use and random location, we extracted cutblock attributes describing the timing of harvest and silvicultural treatments.

Vegetation Sampling

To model the distribution and abundance of VAMY shrubs and berries, we used data from three different studies that occurred predominantly within the Upper Foothills Natural Region (Natural Regions Committee, 2006) and that corresponded generally to the distribution of our collared grizzly bears.

Vegetation data obtained from the first source was originally gathered to examine grizzly bear food availability at activity (Appendix A) and random locations in a paired design, which were subsequently collected over a two year period (2006, 2007). At grizzly bear activity and random locations in cutblocks (n=197), a 30m transect was established south to north. Random locations were established 300m from paired activity locations in 1 of 4 cardinal directions selected at random. Within a 30x30m area, plot center was positioned either at the nearest bear sign. When grizzly bear sign was not present and for random locations, the point nearest to the GPS coordinate with the lowest GPS error was determined to be plot center. Along each transect, five subplots (1x1m) were established every six meters in 2006, whereas in 2007 three subplots (1x1m) were equally spaced by 15m. The percent cover of VAMY was occularly estimated and all berries were counted within each subplot.

The second data source consisted of vegetation surveys conducted to understand grizzly bear food availability in lodgepole pine (*Pinus contorta*) stands (Larsen, 2012). Using a stratified random design, 30x30m plots (n=148) were established in cutblocks according to age of origin (skid clear date; 5yr interval) from June to October over 2 years (2008, 2009). Twenty-five subplots (1x1m) were aligned south to north and equally spaced along five 30m transects. The percent cover of VAMY was occularly estimated at each subplot and all berries were counted.

The third source consisted of vegetation data collected for this project (Chapter 4). However, included only those subplots along transects that occurred in cutblocks (n=48) and that were ≥20m from cutblock edges or retention patches. We did not consider subplots within 10m of the cutbock edge because fruit production in VAMY was significantly higher than areas further away.

Resource Selection Models

For grizzly bear GPS and random locations, we created binary variables to identify (=1) cutblocks harvested in winter, and where mechanical site preparation or herbicide treatment occurred. Using a two stage modeling approach (Chapter 2), we used logistic regression of the exponential form (logistic discriminant) to build resource selection function models (RSF; Manly et al., 2002) and estimate regression coefficients with standard errors relative to our three cutblock treatments. The reference category was set to no treatment and each model contained the three explanatory variables since we confirmed that there was no evidence of correlation ($r \geq |0.6|$). We developed seasonal RSF models (summer and fall) for individual male and female grizzly bears. For each season and cutblock treatment, we obtained population level estimates of means and variance using a meta-analytical procedure (Chapter 2). In doing so, we account (precision of estimates) for differences in the number of GPS locations for individual grizzly bears by giving more weight (analytical weights) to regression coefficients for those animals with more data. Our interpretation of population level selection (>1) or avoidance (<1) of habitats was determined by exponentiating our averaged point estimates. When standard errors (α=0.05) overlapped 1, we assumed random use of habitat or a neutral response (use=availability) by grizzly bears.

Distribution and Abundance Models

We used logistic regression (shrub distribution/abundance), generalized linear models (shrub abundance), and ordered logistic regression (fruit abundance) to explain variation in the distribution and abundance of VAMY shrubs and berries with robust estimates of variance. Our four response variables included values obtained at the transect level (sample unit): 1) presence/absence of VAMY shrubs; 2) average proportion of VAMY shrubs; 3) presence/absence of VAMY berries; and 4) summed counts of VAMY berries. Because berry counts tend to be highly variable often resulting in over dispersion and estimates with exceptionally high variation, we coded our berry counts as an ordered variable: 0 (none); 1 (low); and 2 (high). We distinguished low from high by taking the 50th percentile (61) of counts greater than 1.

For our explanatory variables we extracted cutblock attribute data by overlaying the location of vegetation plots with the cutblock database. First, we created a binary variable to differentiate young (1-20yrs) from old (21-38yrs) cutblocks. Because forest age has been shown to have a considerable effect on the abundance of VAMY fruit (Larsen, 2012), we wanted to control for this effect in our models. At the same time, because of sample size, and since we assume that older cutblocks would contain legacy effects from past silvicultural treatments, we included these data in our analysis even though young cutblocks are of interest relative to assessing fall grizzly bear habitat conditions. We then created binary variables to code (=1) vegetation plots identifying cutblocks that were harvested in winter, and for plots where mechanical site preparation or herbicide had occurred. Finally, because data collection differed between studies we also generated a categorical variable (source) to account for the potential differences in the mean.

We used an information theoretic approach (AIC) to model selection and inference that considered uninformative parameters (Burnham and Anderson, 2002; Arnold, 2010). For each response variable, we fit models with individual effects winter harvest (winter), site preparation (site), and herbicide (herb). We also fit an additional model containing the interaction between winter and site preparation. The interaction variable was to test for the compounding effects of both summer harvest and site preparation on VAMY. We included source in all models because it was deemed highly influential on the predicted mean. All variable combinations were deemed biologically plausible *a priori* and were compared to a null (intercept only) model to ensure results were not spurious. Prior to model fitting, we used Pearsons' correlation coefficient ($r \geq |0.6|$) and variance inflation factors (VIF>3) to determine no collinearity or multicollinearity amongst our covariate combinations (Zuur et al., 2009). The validity of our models including the potential effects of influential observations was assessed following regression diagnostic procedures (Zuur et al., 2009; Hosmer and Lemshow, 2000). For each model, we used the percent deviations from the null to assess model fit (variation explained). Likelihood ratio and brant tests confirmed (not significant) that ordered the logistic regression model met the assumption of proportional odds. Alpha (statistical significance) was set to 0.05.

All GIS manipulations were done using ArcGIS 10.1 (ESRI® Redlands, CA). Statistical analyses were completed in Stata 12.1 (StataCorp., 2011).

Results

Habitat Selection

Seasonal patterns in habitat selection were apparent between male and female grizzly bears (Figure 5.1). Male bears in the summer showed a positive response to cutblocks that were harvested in winter and treated with mechanical site preparation and herbicide. However, standard errors overlapped 1 and suggested individual animal responses were variable, and at the population level males were using these habitats at random. Female grizzly bears showed different patterns of habitat selection. In the summer, females selected for cutblocks treated with herbicide, otherwise they showed a neutral response, albeit negative, to cutblocks harvested in the winter and that were treated with site preparation.

In the fall patterns of habitat selection changed and tended to be more similar between male and female grizzly bears. Males selected for cutblocks that had received herbicide treatment and that were harvested in the winter. However, cutblocks with mechanical site preparation were used at availability. Female bears also selected for herbicide and winter harvested cutblocks, however, the effect of herbicide was less pronounced (lower odds ratio) compared to site preparation (higher odds ratio) than it was for males. Unlike males, females showed a negative response to cutblocks that received mechanical site preparation, but standard errors overlapped 1.

Distribution and Abundance Models

Variation from the three studies (source) explained a substantial amount of the observed variation in the data with very little explained by our explanatory variables of interest (~1%) (Table 1). However, despite this short coming, our top AIC selected models were at least 2 Δ AIC units from the model containing the variable source. The distribution of VAMY shrubs was best explained by a model containing herbicide (herb) while variation in shrub abundance was only attributed to the data source. However, we found support in both cases for models containing the effect of winter harvest on the distribution and abundance of VAMY fruit.

Once we accounted for the effect of the three data sources, winter harvesting (coef=0.75, p=0.34, z=2.23, p=0.03) was positively correlated with VAMY fruit occurrence. Marginal probabilities where the variable source was held at its mean value showed that fruit occurrence was higher in winter (0.1) vs. summer (0.05) cutblocks. Again, after accounting for the differences between data sources, the effect of winter harvesting (coef=0.71, SE=0.34, z=2.09, p=0.04) on the abundance of VAMY berries was significant. In terms of odds ratios, our interpretation of this relationship was that a 1 unit increase in winter harvesting corresponds to an increase in low or high berry yields by 2.03 times. Marginal means showed that the probability of a zero outcome was higher in cutblocks harvested in summer (0.95) vs. the winter (0.9).

Discussion

Our findings do not support the hypothesis that mechanical site preparation and herbicide treatments reduced the abundance of VAMY shrubs and fruits, a result which would in turn influence grizzly bear behavior. Although research suggests fruit production may decline following glyphosate application, this tends to only occur when there are multiple treatments (Moola et al., 1998). Other research suggests that fruit production can actually increase after herbicide application (Hamilton, 1991). This could explain the strong response by male and female bears in the fall to herbicide treated cutblocks. While females tended to show a negative response to site preparation both in the summer and fall. Nielsen et al. (2004) showed that foods (ants, roots) other than fruit producing shrubs may be negatively influenced by site preparation. This suggests that site preparation as defined it here may negatively influence food availability for grizzly bears more generally. However, we assess in our comprehensive analysis differences that can attributed to the different types of site preparation and equipment used, which will be reported in a manuscript to follow.

We did find support for part of our hypothesis. VAMY fruit was more abundant in winter harvested cutblocks, which explained the significant positive response by grizzly bears in the fall; particularly females. Because of their small body size, females tend to be less carnivorous than males, thus can profit (gain body mass) by foraging on seasonal fruit (Mowat and Heard, 2006; Robbins et al., 2007). Our result that VAMY was not negatively influenced by mechanical damage (soil disturbance) contradicts other research which has shown a negative effect of summer harvesting and mechanical site preparation on VAMY (Haeusseler et al., 1999; Coxson and Marsh, 2001). This could be explained by sampling relatively few cutblocks (Coxson and Marsh, 2001), and limiting sampling to a single age class (Haeussler et al., 1999). It is plausible that in our study area, VAMY could have recovered to the point where on average there was no negative effect. Regardless, we suspect that soil disturbance has influenced fruit production. Snow cover and frozen soil associated with winter harvesting tends to cause less soil disturbance and results in a shift in the dominance and composition of understory species (Berger et al., 2004). Moola and Mallik (1998) showed that heavy shading in harvested areas influenced fruit production (light availability), and that there was no statistical difference in shrub abundance between complete and partial cutting techniques.

Compared to cutblocks where site preparation occurred, herbicide treated cutblocks elucidated a greater response by grizzly bears in the summer and the fall. We postulated that the strong response of grizzly bears in the fall could be related to fruit production (Hamilton, 1991). At the same time, herbicide treatments may also increase the availability of herbaceous foods for grizzly bears associated with a reduction in tall shrubs (e.g., *Alnus* spp., *Salix* spp.) that tend to be strong competitors (Lautenschlager and Sullivan, 2002). Previous research suggests that herbicide treatments often results in an increase in other shrubs and herbaceous species associated with soil disturbance (Boateng et al., 2000; Haeussler et al., 2004), which could explain the strong selection by females during the summer and selection of herbicide cutblocks in general. This increase in shrub and herb diversity and abundance associated with herbicide may influence the distribution of ungulates that could explain grizzly bear selection, particularly males that depend on protein sources from meat because of their larger body size (Robbins et al., 2007).

Management Implications

Winter harvesting results in higher VAMY fruit production and grizzly bears respond positively to the availability of these cutblocks during the critical foraging season. This is important because the availability of fruit can influence population vital rates which could have implications for provincial grizzly bear recovery. This is of concern if the surge cut associated with forest harvesting strategies for mountain pine beetle management results in more frequent harvesting during the summer to meet pine reduction targets. Previous research suggests that VAMY occurs at lower elevations and is most abundant in pine stands (Larsen, 2012). Unfortunately, this is where mountain pine beetle control harvesting is most likely to occur. Given that harvesting has the potential to boost fruit production in the system, future efforts should be made to have winter harvesting take place in areas that are most likely to support populations of fruit producing shrubs.

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Table 1. AIC output of logistic regression, generalized linear model, and ordered logistic regression explaining the distribution and abundance of shrubs and fruits in relation to a priori seleced models.

Response Variable		**Model**	**LL**	***k***	**AIC**	**ΔAIC**	***w***	**% Dev**
Shrub	Distribution	Null	-251.51	1	505.0	112.8	0.00	-
		Source	-195.24	3	396.5	4.2	0.04	0.22
		Source + Herb	-192.14	4	392.3	0.0	0.32	0.24
		Source + Winter	-195.23	4	398.5	6.2	0.01	0.22
		Source + Site	-193.89	4	395.8	3.5	0.06	0.23
		Source + Herb + Winter	-192.05	5	394.1	1.8	0.13	0.24
		Source + Herb + Site	-191.35	5	392.7	0.4	0.26	0.24
		Source + Winter + Site	-193.82	5	397.6	5.4	0.02	0.23
		Source + Winter * Site	-193.75	6	399.5	7.2	0.01	0.23
		Source + Herb + Winter + Site	-191.20	6	394.4	2.1	0.11	0.24
		Source + Herb + Winter * Site	-191.20	7	396.4	4.1	0.04	0.24
Shrub	Abundance	Null	-28.71	1	59.4	0.8	0.19	-
		Source	-26.32	3	58.6	0.0	0.29	0.08
		Source + Herb	-26.14	4	60.3	1.6	0.13	0.09
		Source + Winter	-26.29	4	60.6	1.9	0.11	0.08
		Source + Site	-26.31	4	60.6	2.0	0.11	0.08
		Source + Herb + Winter	-26.10	5	62.2	3.6	0.05	0.09
		Source + Herb + Site	-26.12	5	62.2	3.6	0.05	0.09
		Source + Winter + Site	-26.29	5	62.6	3.9	0.04	0.08
		Source + Winter * Site	-26.08	6	64.2	5.5	0.02	0.09
		Source + Herb + Winter + Site	-26.09	6	64.2	5.5	0.02	0.09
		Source + Herb + Winter * Site	-25.93	7	65.9	7.2	0.01	0.10
Fruit	Distribution	Null	-188.64	1	379.3	90.1	0.00	-
		Source	-143.20	3	292.4	3.2	0.08	0.24
		Source + Herb	-143.00	4	294.0	4.8	0.03	0.24
		Source + Winter	-140.60	4	289.2	0.0	0.38	0.25
		Source + Site	-143.20	4	294.4	5.2	0.03	0.24
		Source + Herb + Winter	-140.47	5	290.9	1.7	0.16	0.26
		Source + Herb + Site	-143.00	5	296.0	6.8	0.01	0.24
		Source + Winter + Site	-140.53	5	291.1	1.9	0.15	0.26
		Source + Winter * Site	-140.49	6	293.0	3.8	0.06	0.26
		Source + Herb + Winter + Site	-140.36	6	292.7	3.5	0.07	0.26
		Source + Herb + Winter * Site	-140.29	7	294.6	5.4	0.03	0.26
Fruit	Abundance	Null	-239.23	2	482.5	89.8	0.00	-
		Source	-193.69	4	395.4	2.7	0.10	0.19
		Source + Herb	-193.48	5	397.0	4.3	0.04	0.19
		Source + Winter	-191.32	5	392.6	0.0	0.38	0.20
		Source + Site	-193.66	5	397.3	4.7	0.04	0.19
		Source + Herb + Winter	-191.20	6	394.4	1.7	0.16	0.20
		Source + Herb + Site	-193.47	6	398.9	6.3	0.02	0.19
		Source + Winter + Site	-191.32	6	394.6	2.0	0.14	0.20
		Source + Winter * Site	-191.25	7	396.5	3.9	0.05	0.20
		Source + Herb + Winter + Site	-191.18	7	396.4	3.7	0.06	0.20
		Source + Herb + Winter * Site	-191.08	8	398.2	5.5	0.02	0.20

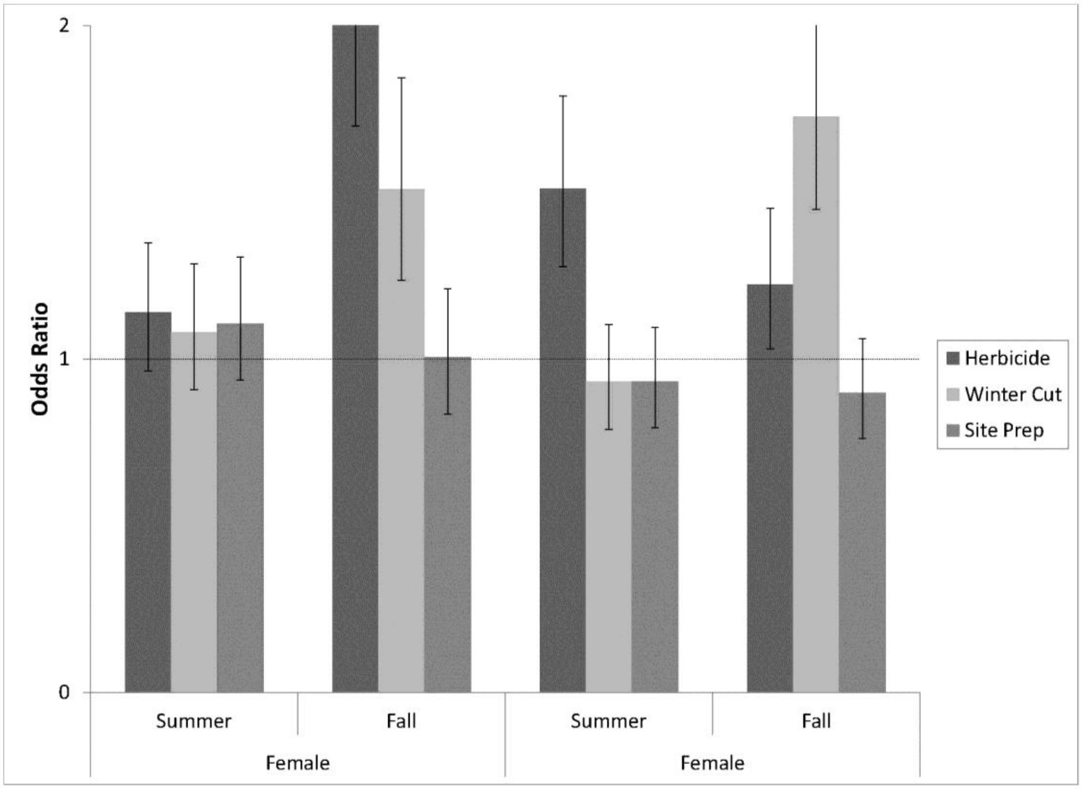

Figure 1. The seasonal population averaged response (odds ratio) of male and female grizzly bears to cutblocks harvested in winter, and where site preparation or herbicide treatments occurred.

Chapter D.6. Gis-Based Planning Tools

Background

To manage the forested landscape while considering wildlife values, managers are in need of quantitative tools to assist with the land use planning process. Resource selection function models (RSF; Manly et al., 2002) developed from animal location data in combination with Geographic Information System (GIS) maps of habitat provides a powerful framework for developing spatio-temporal models of species distributions. RSF approaches have been widely used in natural resource management and conservation, and to evaluate wildlife responses to novel habitat conditions associated with environmental gradients and changing landscapes. Understanding such wildlife-habitat relationships is paramount given the need for cumulative effects assessment, determination of population viability, making predictions about climate change, or even identifying movement corridors (Boyce et al., 2002).

Caribou (*Rangifer tarandus*) and grizzly bear (*Ursus arctos*) are threatened in the province of Alberta and population recovery is the focus of management actions. Managing these species, however, is a formidable challenge for land use planners. Not only because of fundamental differences in habitat requirements, but because of their resiliency to environmental perturbation. Caribou are considered habitat specialists as they are thought to require large tracts of contiguous mature forest with a lichen understory (low productivity) for survival, whereas grizzly bear are a habitat generalist that are well suited to habitat disturbances both natural and anthropogenic (Nielsen et al, 2009). Previous research has focused on understanding the ecology of caribou (DeCesare, 2012) and grizzly bear (Nielsen et al., 2009) to better manage habitat in the face of industrial development. In theory, these models provide the foundation for the concurrent management of caribou and grizzly bear on a common landscape. A model that simultaneous evaluates changes and trade-offs in habitat conditions for caribou and grizzly bear associated with proposed forest harvesting scenarios would be beneficial to forest and land use planners.

Reducing human-caused grizzly bear mortality is essential to successful recovery of this species. Within the recovery plan for Alberta (Alberta Grizzly Bear Recovery Plan 2008-2013, 2008), road density thresholds were set for conservation areas within grizzly bear range (core and secondary conservation areas) identified as high quality in terms of having high resource availability and low mortality risk (Nielsen et al, 2009). However, within certain watersheds, road density thresholds have already been exceeded, thus, there is a need to begin a process of reclamation (road removal/motorized access restrictions) to meet open road density recovery targets. A GIS based tool that calculates the effect of road removal on mortality risk would allow for the reclamation process to be streamlined and focused in areas of high resource value for bears. In doing so, the regulator (AESRD and AER) working with companies could then achieve the greatest return (reduction in grizzly bear mortality risk) on their investment. Although restricting motorized road access is fundamental to reducing mortality risk for bears, reducing sight lines into open habitats such as cutblocks that bears are attracted to (Nielsen et al., 2004a), might also have a positive effect on survival. A GIS tool that calculates sightability from road access would provide opportunities for companies to alter cutblock design and incorporate green tree retention during the planning stage as these sightlines are directly linked to vegetation height and terrain.

Here, we discuss the development and application of three tools. The tools forecast potential changes in grizzly bear and caribou habitat condition associated with forest management activities (timber harvest and road reclamation), defined by RSF and habitat security models (Nielsen et al., 2004b and 2009). An outline of the application toolbox (GBTools folder) as well as a guide to the user interface is provided in Appendices D.2 (Table 1) and D.3.

Objectives:

Caribou & Grizzly Bear Planning Tool **-** Create a planning tool to simultaneously evaluate the potential effect of forest harvesting on caribou and grizzly bear habitat where they co-occur.

Road Reclamation Tool for Grizzly Bear **-** Develop a GIS application to calculate the effect of road reclamation on grizzly bear habitat security.

Visibility Tool for Grizzly Bear **-** Develop a GIS application that calculates the proportion of planned cutblock visible from roadsides.

Tools and Application

Caribou & Grizzly Bear Planning Tool.

Data Layers & Models **-** This tool generates Resource Selection Function (RSF) surfaces for both caribou and grizzly bears, and summarizes their values. Optionally, the user may input a timber harvest scenario, consisting of a block layer attributed with stand age, similar to those produced by timber supply models such as Patchworks or Woodstock/Stanley. The regenerated RSF models will reflect the change in resource selection by both species under these different landscape configurations.

The grizzly bear RSF models used to create this application were developed by Dr. Scott Nielsen (University of Alberta) and are specific to the five population management units south of the Peace River (Grande Cache, Yellowhead, Swan Hills, Clearwater, Livingstone, and Castle). Models are representative of three different seasons: spring (May 1 – June 15), summer (June 16 – 31 July), and fall (Aug. 1 – Oct. 15).

The caribou RSF models developed by Nick DeCesare (DeCesare, 2012), are specific to three caribou herds in Alberta (A La Peche, Little Smoky, and Redrock/Prairie Creek) across two seasons: summer (May 16 – Oct. 16) and winter (Oct. 17 – May 15).

To ensure spatial and temporal consistency between RSF models for the two species, the summer caribou RSF model was used in conjunction with a combined spring/summer/fall grizzly bear RSF. However, the extent of the interaction model was limited to where caribou herds overlap with grizzly bear populations and in areas subject to forest harvest. The application generates the summer RSF for three west-central Alberta caribou herds (Redrock, A La Peche, and Little Smoky) as well as the seasonal composite grizzly bear RSF for the Grande Cache population unit.

To represent the interaction between grizzly bear and caribou, the RSF for each species was reclassified into categories of high, medium, and low. Categories were combined in a matrix of nine possible combinations. By comparing current RSF values with forecast values across the planning unit, forest managers can better understand the trade-offs of different harvest scenarios on RSF values.

Note that this application is Version 1 and may be revised following ongoing peer review. A demonstration analysis was performed in September 2012 for Canadian Forest Products Ltd. (Canfor). The script was modified to incorporate long-term (up to 50 years) timber supply scenarios generated by Patchworks timber supply modeling software (Phase 2 of Activity 3). In this demonstration, 3rd-order summer and winter RSFs for the Little Smoky herd were regenerated for the Caribou Special Management Zone (710 sq km2) in the Canfor FMA, based on 5 different timber harvest scenarios. Methodology and output for this sample analysis was distributed to 14 expert reviewers representing federal and provincial government, universities, and forest industry partners. A number of modifications to the initial application were made in response to comments from the reviewers, including: regenerating 1st-order, 2nd-order, and scale-integrated RSFs; changing the upper age limit for cutblocks from 40 to 50 years; generating RSFs for the A La Peche and Redrock herds; and incorporating a 20-year delay in removal (ie, reforestation) of seismic lines following harvest.

A workshop will be held in May 2013 with the program partners to review this version of the application, and to determine future development and revisions.

User Interface - The inputs (Figure 5.1) to the CaribouGrizzly application are:

1) **Area of interest** (AOI) (Required): A polygon shapefile or feature class representing an analysis area such as a watershed, operating compartment, or other planning unit.

2) **Herd** (Required): The user has a choice of regenerating RSFs for one of three herds: the Little Smoky, A La Peche, or Redrock.

3) **Timber Harvest Scenario** (Optional): This is a geodatabase polygon feature class representing harvested areas, and can be output by timber supply models such as Patchworks or Woodstock/Stanley.

Note: The feature class must contain an integer attribute field named [STANDAGE], with values representative of stand age at the time of the forecast scenario.

4) **Output scenario name** (Required): This is a string, up to 9 characters long, that names the output caribou and grizzly RSFs, and the interaction matrix.

Process Description - The polygon feature layer entered as the first parameter is first clipped by the model boundary, and the result is converted to a 30m raster. This is used to extract portions of the grizzly RSF (seasonal maximum) and caribou RSFs (1st-order, 2nd-order, and 3rd-order) for the herd chosen in the 2nd parameter.

If no timber harvest scenario is entered in parameter 3, the grizzly RSF is reclassified into high, medium, and low classes. The 3 caribou RSFs are multiplied together in a MapAlgebra expression to create the scale-integrated RSF (srsf). The srsf is also reclassified into high, medium, and low classes. The reclassified grizzly and caribou final RSFs are multiplied together to form a matrix of unique combinations (Table 1)

If a timber harvest scenario is entered as a third parameter, the grizzly and caribou RSFs are regenerated from base layers for the AOI. The timber supply scenario consists of a block layer, clipped to the AOI, with a field for stand age. This layer represents all harvested areas at the time of the scenario and is used to generate 3 different block layers, dependent on stand age:

- ALL blocks are less than 50 years old. These are burned into the existing 11-class landcover layer for caribou. This layer is used to recalculate cutblock density at three different scales (12k, 5km, and 70m search radii), as a predictor for caribou RSF. Crown closure values are assigned to each block based on stand age.
- OLD blocks are blocks >50 yrs old in the scenario. These areas revert to the original landcover class (assumed to be closed conifer).
- MED blocks are blocks that existed in 2012 but are >20 yrs old in the scenario. These are used to erase seismic lines with the assumption that seismic lines are reforested following harvest and a 20-year regeneration delay. Seismic line density is then recalculated at three different scales (12k, 5km, and 70m search radii).

The assumption underlying this process is that all areas that are not harvested will remain unchanged. Although this assumption is not very realistic because given the construction of new roads, pipelines, and other features, or due to natural changes associated with wildfire or MPB kill, the purpose of this tool is to compare the effect of different harvest scenarios alone.

Predictor variables for the caribou and grizzly RSFs consisted of variables for terrain and climate (e.g., snow cover and NDVI), while others were included to account for forest disturbance. Each of these variables are multiplied by their respective coefficient and summed in a Spatial Analyst MapAlgebra expression. The update variables are:

Grizzly:

- Wet tree Landcover classes
- Shrub Landcover classes
- Wet herb Landcover classes
- Upland herb Landcover classes
- Non-vegetated (barren) Landcover classes
- Regen (regenerating forest, <50 years stand age)
- Crown closure in regen areas
- Crown closure in forested areas
- Percent conifer in upland tree areas
- Distance to forest edge inside upland tree class
- Distance to forest edge inside wetland tree class
- Distance to forest edge inside upland tree class
- Distance to forest edge inside upland herb class
- Distance to forest edge inside regen
- Distance to forest edge inside non-vegetated class
- Range (occupancy) factor
- non-habitat mask

Caribou:

- Cutblock density
- Seismic line density
- Open conifer landcover class
- Mixed conifer/deciduous landcover class
- Muskeg landcover class
- Shrub landcover class
- Herbaceous landcover class
- Alpine vegetated landcover class
- Rock/ice landcover class
- Cutblock landcover class
- Burn landcover class

Predictions (Figure 5.2) for each of these variables are made for all areas harvested in a timber supply scenario. Regenerating forest is treated as its own landcover class in both the grizzly and caribou land covers. When a block is more than 50 years old, it reverts to closed conifer class in the caribou landcover, which is then updated to the upland tree class in the grizzly landcover. Percent conifer and crown closure is assigned to each block in relation to stand age. This was based on a regression analysis of the Phase 6 Remote Sensing representation of these attributes relative to cutblocks within the model boundary (McDermid, 2005); harvest age ranged from 0 to 55 years old.

Road Reclamation Tool for Grizzly Bear

Data Layers & Models - A road within grizzly bear habitat can turn an area of secure, high-quality habitat into an attractive sink (Nielsen et al., 2004b), where bears are attracted to habitats near roads, presumably because of available food resources (Roever et al., 2008), but are at risk of human caused mortality. The road reclamation tool defines the area of habitat associated with a given set of roads, and evaluates current and future habitat security risks.

For a user-specified Area of Interest, the script will summarize the current state of grizzly bear habitat represented by models of RSF, risk, and Habitat States (Nielsen et al., 2006), and by other measures of habitat security such as length of road within the AOI and the mean distance to road.

Optionally, the user may also enter a set of roads selected for reclamation. The script will recalculate the mortality risk for the AOI and combine it with the RSF to create new Habitat State values. Other measures of habitat security are also summarized by the application including: 1) current and projected road density; 2) mean distance to road within the AOI; 3) and area of safe harbor.

User Interface – The user inputs are (Figure 5.3):

1) **Area of interest** (Required): This is a polygon shapefile or feature class representing an analysis area, such as a watershed unit or operating compartment. The grizzly bear Habitat States model will be generated for this area along with summary statistics.

2) **Road Removals** (Optional): This is a line shapefile or feature class representing roads selected for reclamation.

3) **Output filename** (Required): This is a string that names the habitat state model to be generated. Raster name must not exceed 13 characters.

Process Description - The script accepts a polygon layer as the first parameter and converts it to a raster with a 30m cell size. This is used to clip out the current grizzly bear RSF and risk models for the area, and combine them into a Habitat State model (named in the third parameter), representing current habitat conditions. Mean values for these three models across the AOI are written to a dbf file. A fourth habitat security metric written to an output file is the mean cost distance to roads over the AOI. This statistic is more indicative of road impact than length of road per unit area since it reflects how widely dispersed roads are distributed across the AOI. The cost surface used was a Terrain Ruggedness Index, which is a predictor variable for mortality risk and is perhaps more biologically meaningful than Euclidean distance.

Optionally, if a set of roads selected for reclamation is entered as the second parameter, the application will erase the selected roads from the clipped road layer, and regenerate the mortality risk model. This modified risk surface will be used in recalculating the Habitat State values for the unit. Another cost distance to road surface is generated from the modified road layer, and the mean written to a dbf file.

As an example (Figure 5.4), the removal of a selected road (dashed) from the watershed (highlighted) has caused the mean Habitat State value for the watershed to increase from 0.8177 to 0.8291, and the mean cost distance to roads has increased from 4107m to 4344m. Such statistics are useful to compare the costs and benefits of various road reclamation options.

Visibility Tool for Grizzly Bear

User interface - The viewshed tool (Figure 5.5) uses Lidar surfaces to evaluate cutblock design by calculating the area within a block that will be visible from an observer position along the roadside. The tool will also simulate forest regeneration within the block according to a user-specified density and height.

Inputs -

Note: all inputs to this tool are supplied by the user, including the Lidar surfaces; therefore, it may be applied anywhere that Lidar coverage is available, and is not limited to the extent outlined in the Appendix Figure C3.

1) **Observer position** (Required): This a line feature layer representing a roadside vantage point.

2) **Full Feature Lidar surface** (Required): Raster layer representing Full Feature Lidar. The surface must fully cover the analysis area (buffered road).

3) **Resampling size** (Required): This is an integer between 1 and 20 that determines the pixel size of the output. The larger the resampling size, the shorter the processing time. This may be appropriate as a basic measure of habitat security within a watershed. For detailed block design, and particularly for design scenarios incorporating regeneration, a better result is obtained using the highest-resolution surface available.

4) **Output filename** (Required): A string is entered as the name of the viewshed raster in /GBtools/OP/. Filenames must not exceed 13 characters and should not contain special characters.

5) **Planned openings** (Optional): This is a polygon feature layer representing planned harvest blocks. If a parameter is entered here, the script will update the Full feature Lidar surface with the block, by substituting Bare Earth elevation values within the block.

Note: retention shapes, whether roadside, edge or interior, are not entered explicitly as a tool parameter; rather, they are incorporated into any planned opening by erasing the retention feature from the opening shape.

6) **Bare Earth Lidar surface** (Optional): A Bare Earth raster surface must be entered as a parameter if planned openings are entered. The grid must fully encompass the planned openings.

7) **Regeneration density** (optional): A user may enter an integer between 100 and 10,000, which represents a target regeneration density (stems per ha). This parameter may be left empty to model conditions immediately post-harvest. If a number is entered here, random points will be generated within the planned cutblock at the specified density.

8) **Regeneration height** (Optional): User may enter an integer between 0 and 20, which represents regeneration height (m). This parameter may be left empty if regeneration density is also left empty. If a number is entered, the random points are assigned this value, and converted to grid. The pixels are added in MapAlgebra to the updated Full Feature Lidar surface.

Process Description - The road feature entered as an observer position is buffered by 1000m, based on the assumption that if a bear was situated > 1 km from a road side, even if visible, is not likely at imminent risk of poaching. This imposes a biologically meaningful limit on the line-of-sight analysis, which is very computationally time-consuming. The buffered polygon is converted to raster (using the cell size entered as the 3rd parameter) and multiplied by the Full Feature Lidar surface (entered as the second parameter) in a MapAlgebra expression. This process "clips" the Full feature surface to within 1 km of the roadside.

If no optional inputs are entered, the application will generate an integer raster (named as the fourth required parameter) that represents areas visible from the roadside. Pixel values are the number of observer points from which the pixel can be seen. This layer shows conditions current at the time the Lidar was flown. A hillshade layer of the clipped Full Feature surface is also generated for map display.

Optionally, the user may enter a polygon shapefile or feature class representing planned cutblocks to be evaluated. The planned cutblocks are first clipped by the 1-km road buffer and joined. The resulting shape is converted to raster and reclassified into a position raster. This is used by Spatial Analyst Pick tool to substitute Bare Earth elevation values (using the Bare Earth Lidar surface entered as the 6th parameter) for Full Feature elevation values within the planned blocks.

If no values are entered for the 7th and 8th parameters, the script will recalculate sightlines from the road using this modified Full Feature surface. The resulting viewshed surface can be overlaid with the original surface to determine the increase in sightlines resulting from the opening.

If the user enters a value for regeneration density as stems per ha (sph) as the 7th parameter, the script will generate random points within the cutblocks to represent regenerating trees and model their effect on sightlines. The script first dissolves the layer of planned cutblocks into a single multipart feature, and stores the feature's area (ha) from the Shape_Area field. The total number of trees to be regenerated is the density (sph) times the number of hectares. The Minimum Inter-Tree Distance (MITD) is calculated as the inverse of the density (1.0m for a density of 1000 sph), to ensure that random points are as evenly spaced as possible. The height of the regenerating trees is entered as the 8th and final parameter. The random points are attributed with this height and converted to raster at 1m pixel size. Null values are converted to zeroes, and this raster is added to the elevation values of the clipped Full Feature raster using MapAlgebra. Sightlines are then recalculated (Figure 5.6).

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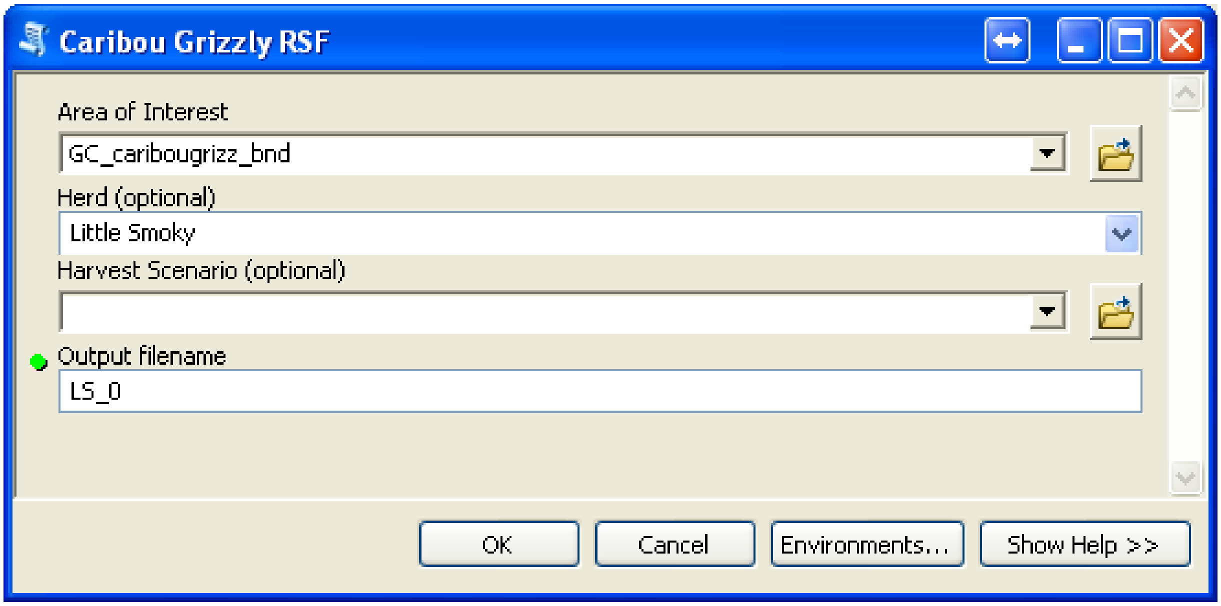
Table 1. Matrix of grizzly bear and caribou RSF model values.

	Grizzly: LO (5)	**Grizzly: MED (6)**	**Grizzly: HIGH (7)**
Caribou: LO (1)	5	6	7
Caribou: MED (2)	10	12	14
Caribou: HIGH (3)	15	18	21



Area of Interest: GC_caribougrizz_bnd

Herd (optional): Little Smoky

Harvest Scenario (optional):

Output filename: LS_0

Figure 1. Caribou Grizzly RSF tool User interface.

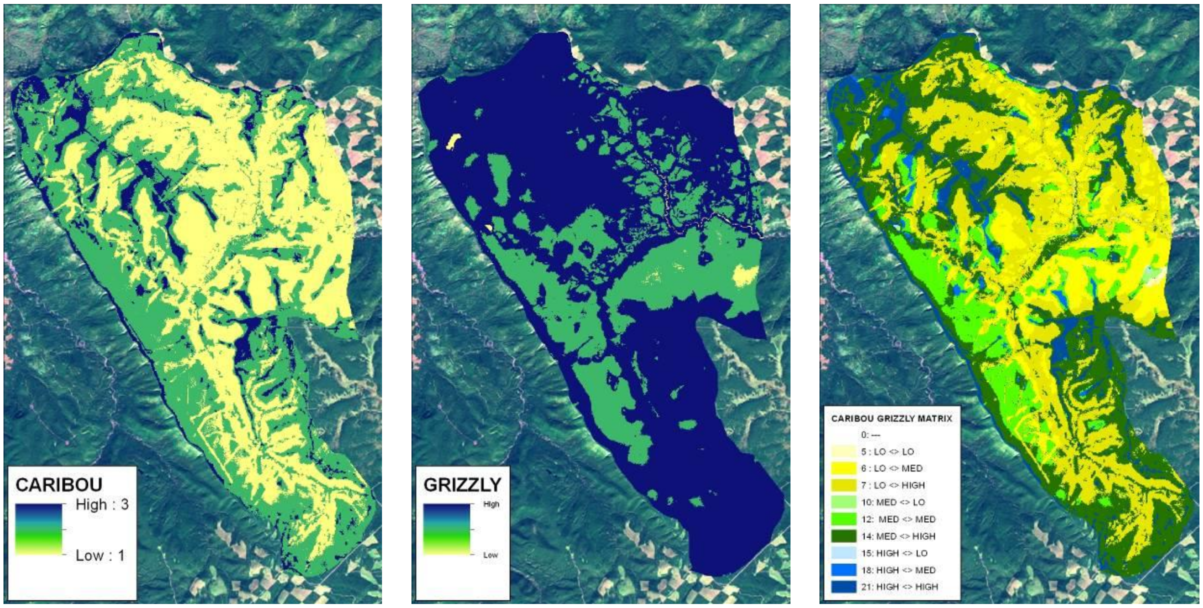
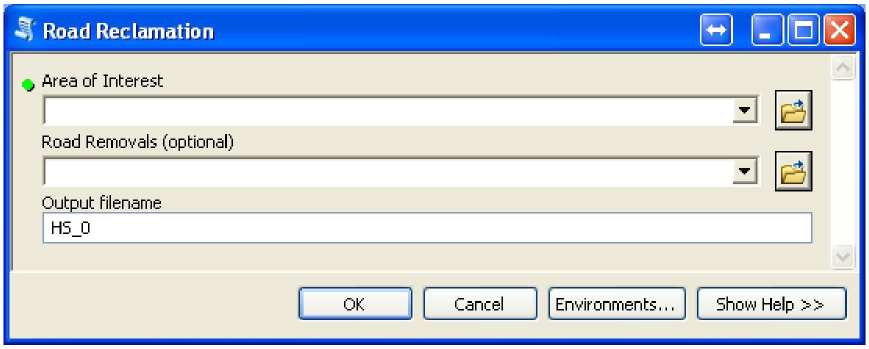


Figure 2. Caribou RSF (left), grizzly bear RSF (center), and the interaction matrix (right).



Area of Interest

Road Removals (optional)

Output filename

HS_0

Figure 3. Road Reclamation tool: user interface.

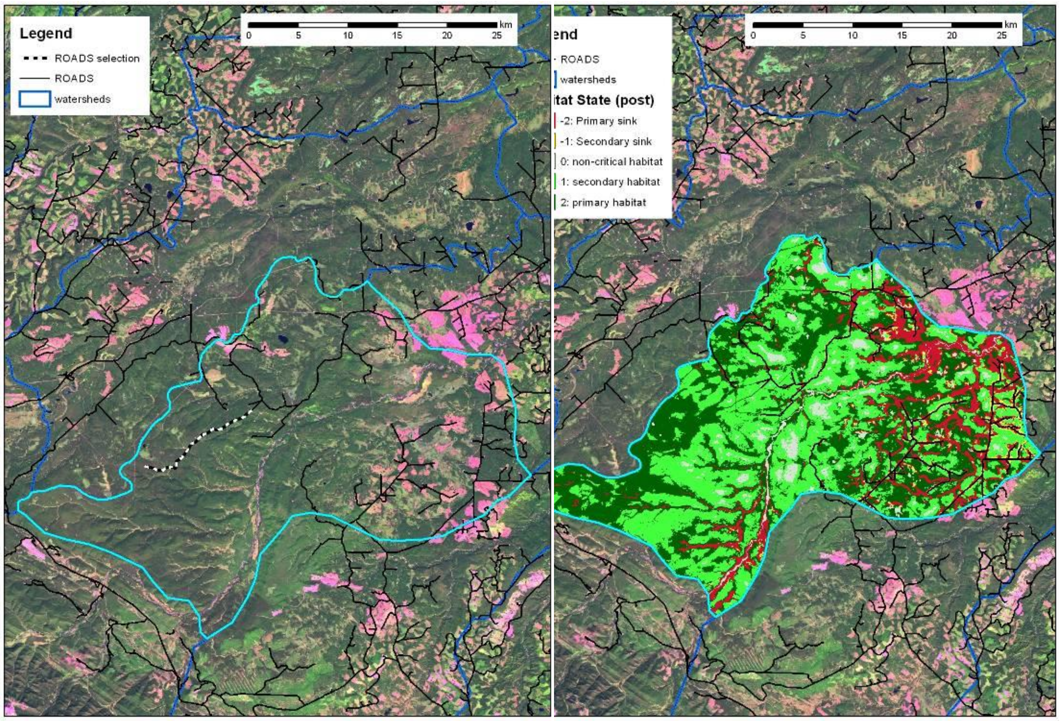
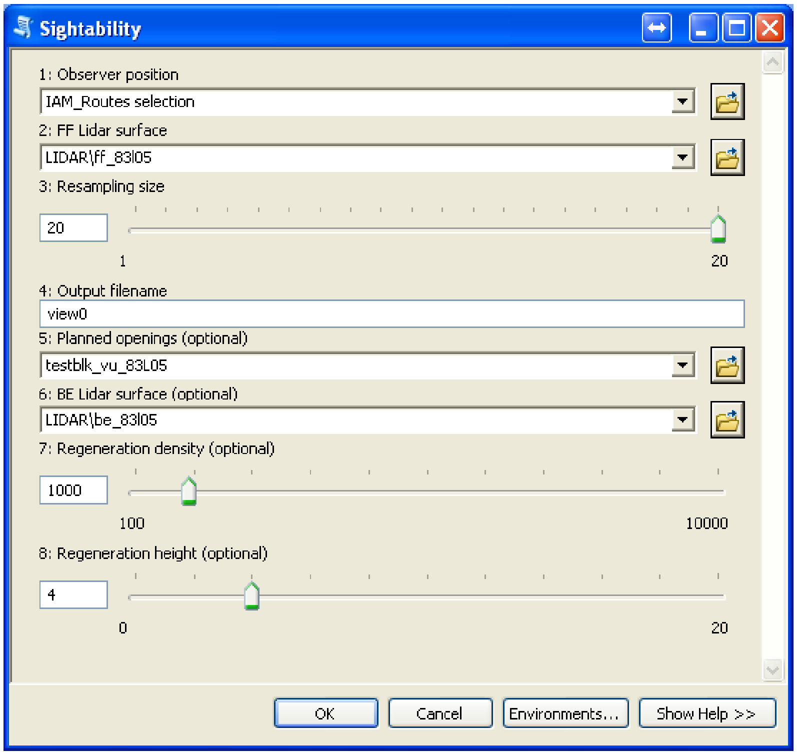


Figure 4. Watershed (highlighted) and road selected for reclamation (dashed), and the regenerated Habitat State model (left) with road removed (right).



1: Observer position
IAM_Routes selection

2: FF Lidar surface
LIDAR\ff_83l05

3: Resampling size
20 (1 – 20)

4: Output filename
view0

5: Planned openings (optional)
testblk_vu_83L05

6: BE Lidar surface (optional)
LIDAR\be_83l05

7: Regeneration density (optional)
1000 (100 – 10000)

8: Regeneration height (optional)
4 (0 – 20)

Figure 5. Viewshed calculator: user interface.

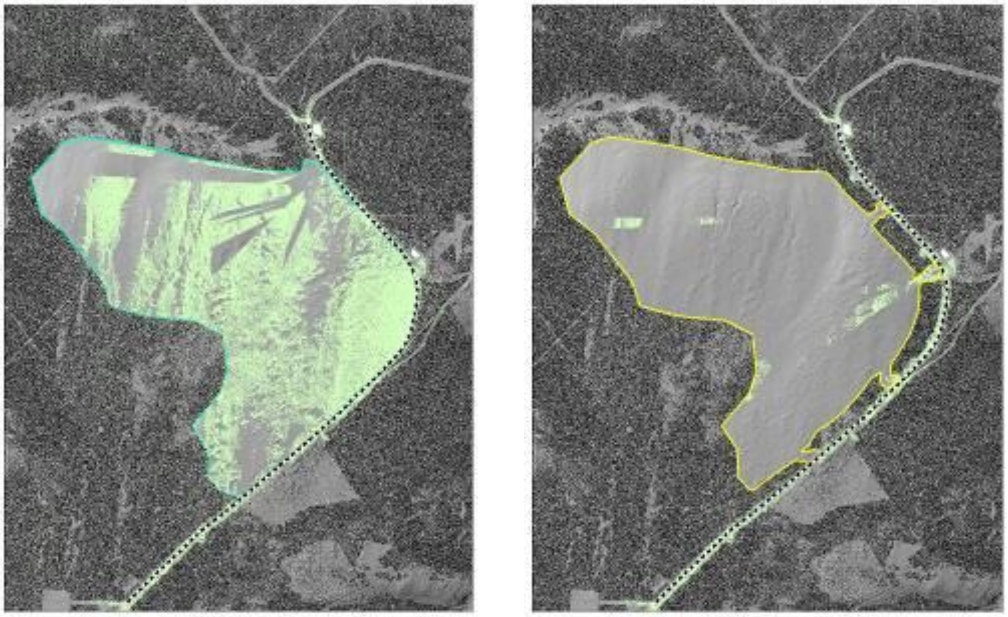


Figure 6. Sightlines (green) from roadside (dashed) with timber visual buffers (right) and without (left).

Appendix D.1.: Grizzly Bear Activity

Data Collection - Grizzly bear activity (foraging, resting) data was collected from field use-site (GPS locations) investigations (n=270) carried out between June and September, 2006 and 2007. Sampling consisted of randomly selecting one GPS location for each bear day from a sample of collared grizzly bears (5 females and 1 male). GPS locations were visited on average 22 days (SD=8, Min=1, Max=47) after the bear left the location. At each location (<10m GPS error) a 20x20m area was searched to find bear sign (activity). Activity consisted of the following: 1) torn open or rolled coarse woody debris such as logs or stumps, 2) ant mound or sweet-vetch root digging; 3) ungulate remains and burial site; 4) clipped forbs; 5) fruiting shrubs with broken branches and missing leaves; 6) or bed sites as a shallow depression or dig confirmed by grizzly bear hair (Munro *et al.*, 2006). Identifying foraging events with certain forbs (e.g. horsetail) and fruit (*Vaccinium* spp.) is most likely difficult to detect with any certainty, therefore, observer's judgment regarding this form of foraging was not as stringent as it was with other activities (Mattson, 1997).

Statistical Analysis - We created binary variables for bear activities including: no activity, bed, carcass, herbaceous and berry feeding, and digging for roots and ants (coarse woody debris, anthills). To quantify the influence of edge distance in relation to bear activities, we used summary statistics (mean, standard deviation, max, and median). For activities excluding root digging (few observations), we used logistic regression to determine the probability of a grizzly bear activity as a function of model covariates. A binary variable (Ed90) was used to identify activities near (1) or far (0) from edges using a 90m cutoff. In addition, a binary variable (Block) was generated to identify activities in cutblocks vs uncut forest, and an additional categorical variable (Agec) was used to represent forest age as two stages of cutblock regeneration (1-20 and 11-20 years) including uncut stands (Chapter 1). An AIC_i approach was used to assess whether or not edge proximity and/or forest age best explained bear activity. A cluster variable (bear) was used to estimate robust standard errors of regression coefficients. Stata 12.1 was used for statistical analyses (StataCorp., 2011).

Summary Statistics - Grizzly bear activities in relation to edge distance appeared to be influenced by forest age. Resting (bed) occurred more frequently and was further from the edge of cutblocks as forest age increased (Table 1); 80m in younger cutblocks versus 120m in those older than 20 years. Distance of foraging activities also appeared to increase with cutblock age based on average and maximum distances, yet no clear patterns could be elucidated for each specific activity type (Table 1). In cutblocks, carcass sites and herbaceous feeding were closer (mean=47, max=99) to the edge whereas foraging for berries and ants tended to be further away (mean=106, max=262). In uncut forest, edge distance for activities ranged from relatively close to relatively far away, the exception being that herbaceous feeding was substantially closer on average (Table 1). Overall, foraging activities were about 88m from the edge in cutblocks and 258m in uncut forest.

Logistic Regression - We found little support for models containing the edge proximity variable with the exception of herbaceous feeding. The best herbaceous feeding model included edge proximity (Ed90) and an additional term for forest age (Agec). However, there was also support for a model with edge proximity and where forest age was defined by the variable Block because the ΔAIC_i value for this model was within two units of the best model. Regardless, the effect of Ed90 on the probability of herbaceous feeding was significant (Ed90: coef=1.38, se=0.20, z=6.75, p<0.01). Holding all variables at their mean value using the margins command in Stata 12.1 (StataCorp., 2011), the probability of herbaceous feeding in the interior was significantly (α=0.05) lower (0.04; CI=0.004-0.083) compared to the edge (0.15; CI=0.031-0.277), however, 95% confidence intervals overlapped. The probability of a bed site was best explained by a model with a variable for forest age (Agec) while the best model for kill sites and berry feeding was the intercept only model.

Table 1. Summary statistics (edge distance) of grizzly bear (n=6) activities by forest age (years) class.

Activity Type	Age	n	Mean	Min	Max	SD	Median
No Sign	**1-10**	17	84.4	12.6	196.2	59.7	71.7
Bed		13	76.8	1.3	224.0	72.7	57.0
Carcass		0					
Herb		4	44.2	3.6	77.9	35.2	47.7
Berry		7	83.1	7.1	186.6	63.0	66.1
Root		3	125.6	104.1	142.3	19.5	130.5
Ant		10	107.6	3.3	197.3	69.9	116.2
No Sign	**11-20**	4	46.5	7.9	66.5	27.6	55.7
Bed		5	83.7	24.1	200.7	71.2	66.9
Carcass		1	24.1	24.1	24.1	.	24.1
Herb		2	80.7	66.9	94.6	19.6	80.7
Berry		3	158.5	88.1	195.9	61.1	191.6
Root		0					
Ant		13	117.8	24.1	231.4	73.1	94.6
No Sign	**>20**	12	97.2	26.5	237.4	71.5	74.7
Bed		39	126.1	5.5	574.0	108.0	93.6
Carcass		5	68.1	18.1	111.4	44.0	73.2
Herb		12	73.8	18.2	195.5	45.5	66.0
Berry		4	59.9	32.2	120.2	41.3	43.6
Root		0					
Ant		23	106.1	8.7	574.0	116.6	78.5
No Sign	**Uncut**	35	268.3	5.2	1018.9	263.6	218.2
Bed		61	243.9	5.9	855.3	229.8	184.7
Carcass		10	308.2	2.2	813.2	311.8	152.8
Herb		8	138.9	28.7	435.1	141.2	95.1
Berry		6	337.1	81.2	911.7	302.1	280.2
Root		11	196.5	10.1	435.1	139.8	235.7
Ant		6	307.8	13.9	516.2	193.1	316.1

Table 2. AIC$_i$ table of competing logistic regression models explaining variation in the probability of a grizzly bear bed site.

Model	n	log(L_i)	k	AIC$_i$	Δ_i (AIC)	W_i	% Dev
Null	315	-216.2	1	434.3	28.2	0.00	-
Block	315	-210.6	2	425.2	19.1	0.00	0.03
Ed90	315	-216.1	2	436.3	30.2	0.00	0.00
Block + Ed90	315	-210.3	3	426.5	20.4	0.00	0.03
Agec	315	-199.1	4	406.1	0.0	0.73	0.08
Agec + Ed90	315	-199.0	5	408.1	2.0	0.27	0.09
EdInt	315	-210.2	4	428.5	22.4	0.00	0.03

Table 3. AIC$_i$ table of competing logistic regression models explaining variation in the probability of a grizzly bear kill site.

Model	n	log(L_i)	k	AIC$_i$	Δ_i (AIC)	W_i	% Dev
Null	315	-82.3	1	166.7	0.0	0.27	-
Block	315	-81.5	2	167.0	0.3	0.23	0.01
Ed90	315	-82.3	2	168.6	2.0	0.10	0.00
Block + Ed90	315	-79.6	4	167.1	0.5	0.21	0.03
Agec	315	-79.5	5	169.0	2.4	0.08	0.04
Agec + Ed90	315	-79.5	5	169.0	2.4	0.08	0.04
EdInt	315	-81.4	4	170.8	4.1	0.03	0.01

Table 4. AIC$_i$ table of competing logistic regression models explaining variation in the probability of a grizzly bear herbaceous feeding site.

Model	n	log(L_i)	k	AIC$_i$	Δ_i (AIC)	W_i	% Dev
Null	315	-109.9	1	221.8	9.5	0.00	-
Block	315	-106.2	2	216.5	4.2	0.06	0.03
Ed90	315	-106.5	2	217.0	4.8	0.05	0.03
Block + Ed90	315	-103.9	3	213.8	1.5	0.24	0.06
Agec	315	-104.8	4	217.6	5.3	0.04	0.05
Agec + Ed90	315	-101.1	5	212.3	0.0	0.52	0.08
EdInt	315	-103.8	4	215.6	3.4	0.10	0.06

Table 5. AIC$_i$ table of competing logistic regression models explaining variation in the probability of a grizzly bear berry foraging site.

Model	n	log(L_i)	k	AIC$_i$	Δ_i (AIC)	W_i	% Dev
Null	315	-87.3	1	176.6	0.0	0.28	-
Block	315	-87.0	2	178.0	1.4	0.14	0.00
Ed90	315	-87.3	2	178.6	2.0	0.10	0.00
Block + Ed90	315	-87.0	3	180.0	3.3	0.05	0.00
Agec	315	-84.4	4	176.8	0.1	0.26	0.03
Agec + Ed90	315	-84.2	5	178.4	1.8	0.12	0.04
EdInt	315	-86.2	4	180.3	3.7	0.04	0.01

Appendix D.2.: Outline of the GBtools folder

Table 1. Dataset name, description, and folder path within GBtools.

Folder Path	Dataset Name	Description
/GBtools/BaseIP/		
/Access/	access.mdb/GC_caribougrizz_bnd	boundary of habitat models
	access.mdb/ROADS	Roads (driveable by on-highway vehicles)
	access.mdb/TRAILS	Trails (potentially driveable by off-highway vehicles)
	access.mdb/watersheds	watershed units
	ned_rd	cost distance to road
	ned_tr	cost distance to trail
/Canopy/	cc	crown closure
	p_uptree	proportion of upland tree within 17km radius
	pctcon0	percent conifer
/Distance/	ddtree_01k	decay distance to treeline, 1km search radius
	ddtree_05k	decay distance to treeline, 5km search radius
	ddtree_12k	decay distance to treeline, 12km search radius
	ddwater_01k	decay distance to water, 1km search radius
	ddwater_05k	decay distance to water, 5km search radius
/Habitat/	risk	grizzly bear mortality risk model
	rsf_max	grizzly bear RSF model (seasonal maximum)
/Landcover/	landcover	landcover 10-class
	mask	Nonhabitat mask (water, snow/ice, rock)
	regen	regenerating forest
	regenage	age of regenerating forest
/NDVI/	ndvi	Normalized Difference Vegetation Index
/Regional/	femalerngpct	female range scalar (occupancy surrogate)
	protd6mi_pct	proportion of protected area within 10km radius
/snow/	snow_s	Proportion of days pixel is under snow (summer)
	snow_w	Proportion of days pixel is under snow (winter)
/Terrain/	asp_ew	East-west aspect
	asp_ns	Morth-south aspect
	cti150m	Compound Topographic Index
	d100_strm	Proximity to streams
	d500_strm	Distance to streams
	dem_km	elevation
	p6tri	Terrain Ruggedness Index
	slope	Slope
	tpi_01k	Topographic Position Index (1 km scale)
	tpi_05k	Topographic Position Index (5 km scale)
	tri_cost	reclassified TRI

Appendix D.3. GBTools User Interface

The three GIS planning tools are accessed through an ESRI ArcGIS Desktop (v10) toolset that consists of:

- Base GIS layers representing model predictor variables
- Geoprocessing scripts, written in Python 2.6.5
- An ArcGIS Toolbox (*.tbx), containing the user interface to the scripts

The toolset is contained in the folder *GBtools*. The Python scripts reference subfolders by their relative path within the *GBtools* folde*r*, therefore, subfolders must not be renamed. This folder structure is consistent with other versions of *GBtools* produced by the FRIGBP, which are distributed annually to program partners.

Take the following steps to use the tools:

1) Copy the folder *GBtools* to a location on your PC or server.

2) In an ArcMap or ArcCatalog session, add the *GBtools_FRIAA.tbx* toolbox to ArcToolbox (Figure C1).

The scripts were written for ArcGIS 9.3 but have been tested on version 10.0. *ArcInfo functionality and Spatial Analyst extension are required*.

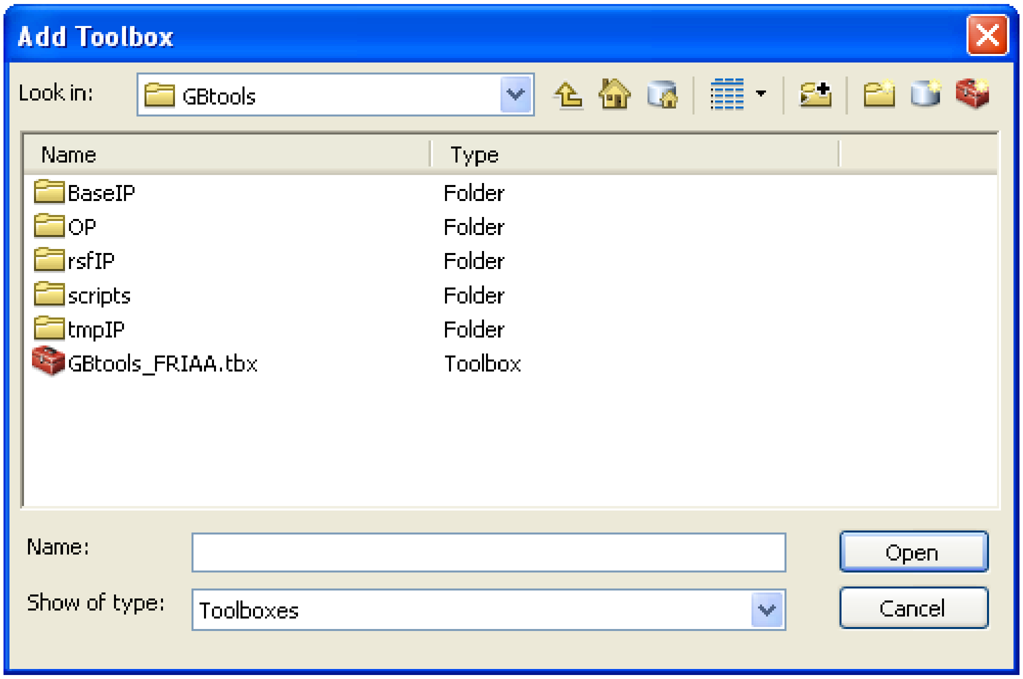
3) Examine the layers in ArcCatalog to ensure they have copied correctly (Figure C2). The folder *GBtools* contains the following subfolders:

- */BaseIP/* - This folder contains GIS base layers containing inputs to the various models.
- */OP/* - This folder (initially empty) is used to store tool outputs.
- */rsfIP/* - This folder (initially empty) is used to store temporary datasets created during tool processing.
- */scripts/* - This folder contains the Python geoprocessing scripts.
- */tmpIP/* - This folder (initially empty) is used to store temporary datasets created during tool processing. Also it contains *temp.mdb*, a personal geodatabase used to store temporary datasets.

The folder *GBtools* also contains the file *GBtools_FRIAA.tbx*, which stores the user interface to the scripts.

Model extents - The caribou/grizzly RSF tool and the road reclamation tool can be applied anywhere within the extent of the base layers, which is defined as follows:

- The portion of the core and secondary grizzly bear conservation areas within the Grande Cache grizzly bear population unit that are covered by the caribou RSF models (15,585 km^2) (Yellow, Figure C3).



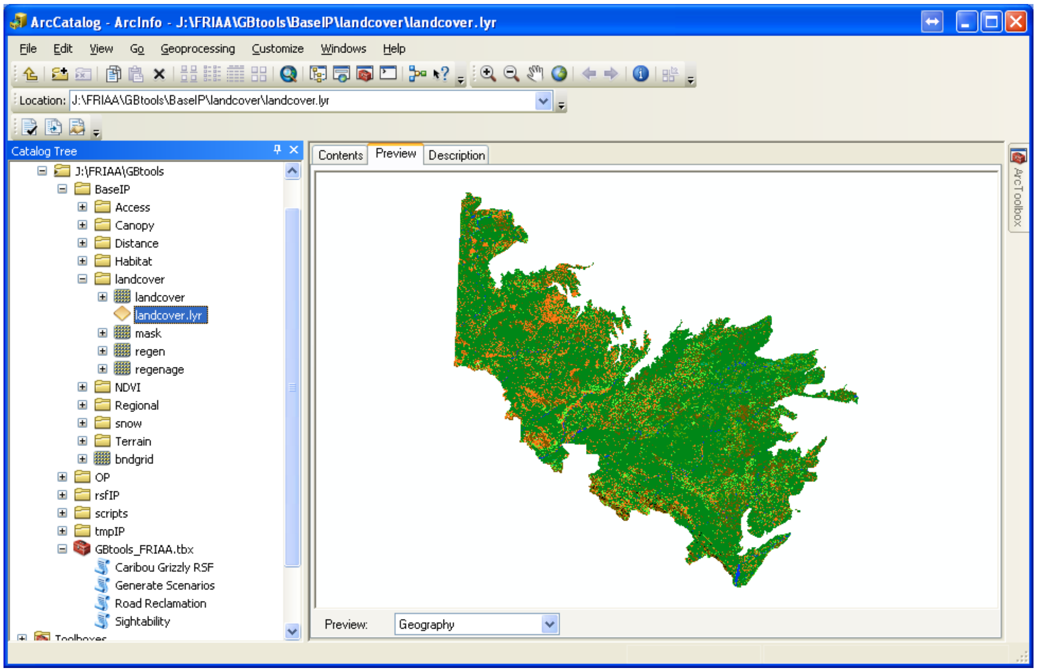
Look in: GBtools

Name	Type
BaseIP	Folder
OP	Folder
rsfIP	Folder
scripts	Folder
tmpIP	Folder
GBtools_FRIAA.tbx	Toolbox

Name:

Show of type: Toolboxes

Figure 1. GIS tools in ArcToolbox.



Location: J:\FRIAA\GBtools\BaseIP\landcover\landcover.lyr

Preview: Geography

Figure 2. ArcCatalog layers.

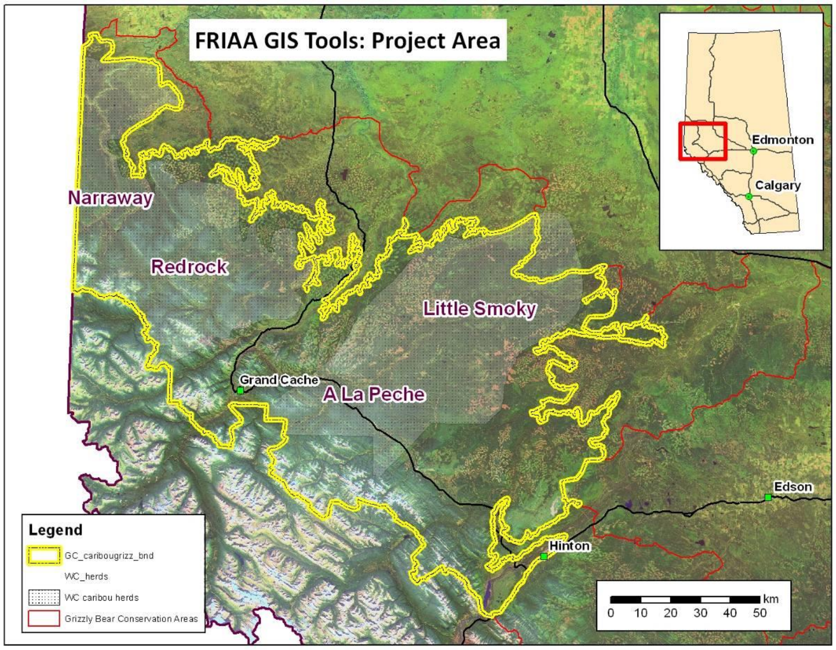


Figure 3. Model extent.

REPORT E: A SUMMARY OF EIGHT YEARS OF ANTHROPOGENIC DISTURBANCE IN THE YELLOWHEAD POPULATION UNIT 2004-2012

Prepared by

Jerome Cranston

Introduction

Grizzly bear habitat in Alberta is undergoing rapid and extensive change due to anthropogenic disturbance from logging, mining, and oil and gas development. This section summarizes eight years of habitat change in the Yellowhead population unit, from 2004 to 2012. (Figure 1)

The FRIGBP has undertaken to update habitat maps to be as current as possible using a variety of Remote Sensing-based methods. Base maps have been created for all of grizzly bear habitat in Alberta using Landsat imagery, at 30m resolution, representing categorical land cover (vegetation) classes, canopy closure, and coniferous/deciduous mix. These layers have been updated annually with anthropogenic disturbance features such as roads, well sites, pipeline rights-of-way, open-pit mines, and cut blocks, along with natural features (streams, ponds) too narrow to be captured by the sensors.

Study Area

The Yellowhead population is one of seven distinct grizzly bear populations in Alberta (Proctor et al. 2012) which are divided by major east-west highway corridors (the Albert North population is separated from other populations by the Peace River and surrounding agricultural lands). The Yellowhead population unit (19,845 sq km) is bounded by the Alberta/BC border on the west, Highway 16 (Yellowhead) on the north, Highway 11 on the south, and on the east, by the eastern limit of grizzly bear range, which has been delineated based on watershed units. For this study, two additional watersheds in the southeast that were subject to a DNA-based population inventory survey in 2013 were also included, for a total area of 21,331 sq km (yellow boundary, Figure 1).

The Core and Secondary grizzly bear conservation areas defined by ESRD (green lines) exclude Jasper National Park (cross-hatched) and comprise 11,956 sq km.

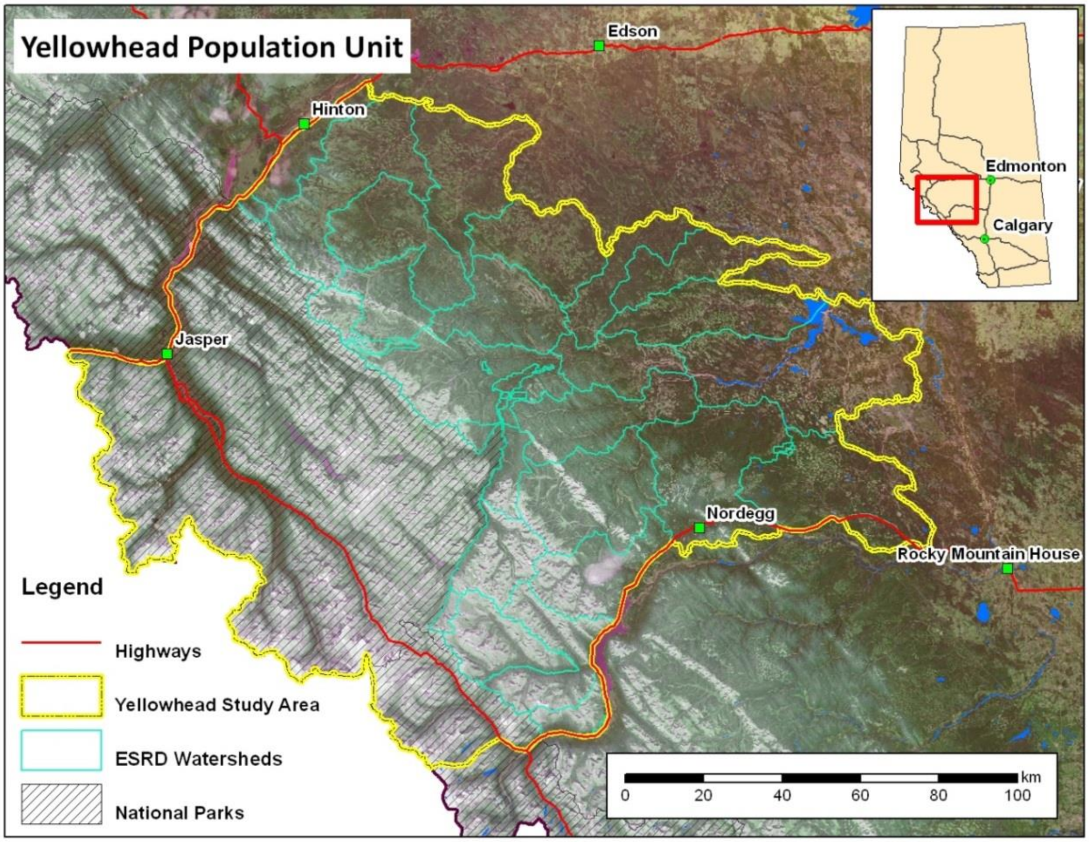


Figure 1: Study area

Methods

Disturbance features representing various types of anthropogenic disturbance were compiled from various sources to match 2.5m SPOT imagery acquired in 2012. Features were then classified as existing or not in 2004 by comparison with a 2004 Landsat image. Features not existing in 2004 were then classified by the year in which they first appeared on a Landsat or other image. Reference images used are listed in Table 1:

Table 1: Reference images

YEAR	IMAGE	RESOLUTION	DATE
2004	Landsat	30m	Aug. 13 2004
2005	Landsat	30m	Sep. 17 2005
2006	Landsat	30m	27 Aug. 2006
2007	Color orthophotos	1m	Summer 2007
2008	SPOT	2.5m	var 2008
2009	Landsat	30m	Sep. 12 2009
2010	Landsat/SPOT	30m/2.5m	Sep. 30 2010
2011	Landsat/SPOT	30m/2.5m	Sep. 10 2011
2012	SPOT	2.5m	Var 2012

Disturbance types

Seven types of anthropogenic disturbance features were compiled and backdated.

1. Roads: Roads features were based on ESRD's Open Routes layer (June 29 2011) and supplemented with features manually digitized from 2.5m SPOT (Systeme Pour l'Observation de la Terre) imagery. Roads were either paved or all-weather gravel roads. Truck trails or winter roads were not included. Note that while construction of new roads or widening of seismic lines to road standard is readily apparent on a Landsat image, reclamation of roads or access restriction is not; therefore, roads cannot be assumed to be drivable or open to public use.

2. Pipeline corridors: these are linear features cleared for gas pipelines. Base layer was ESRD Base Features, supplemented with manually digitized features. Pipelines in the base layer were either adjacent to roads or occupied their own corridor, but new pipelines were only added if they had their own right-of-way, distinct from existing road corridors.

3. Railways: No new railways were constructed in the YH during the term of the study.

4. Powerlines: These are corridors cleared for power transmission lines, and are typically 50m wide. Although tree growth is deliberately suppressed within the right-of-way, either manually or chemically, the ground is usually seeded with grasses or other herbaceous vegetation. No new transmission lines were constructed within the study area during the term of the study.

5. Oil and gas well sites: These are cleared areas, typically square and 1.0 to 1.5 ha in size. They may be active or abandoned. Due to soil compaction and loss of organic layers, older well sites are often still deforested decades after abandonment.

6. Forestry cutblocks: Cutblock shapes were compiled from harvest block boundaries supplied by various FMA-holders, from planned blocks in a Spatial Harvest Sequence, or were manually digitized from 2.5m SPOT imagery.

7. Coal mines: There are three coal mines in the Yellowhead: Luscar/Gregg (reclaimed), Cheviot (active), and Mercoal (active). The disturbed area includes both active and reclaimed land.

One common type of anthropogenic disturbance that was not tracked was the seismic cutline. These are straight, narrow (~6m width) linear trails constructed for oil and gas exploration, mostly during the 1970s and 1980s before the advent of low-impact seismic trails. These features are significant to grizzly bears as they enable humans to access grizzly habitat through the use of small motorized off-highway vehicles (OHVs). Seismic lines were not included in this summary as it is difficult to determine date of construction from Landsat imagery due to their narrow footprint, and it is unlikely that new seismic lines were constructed during the term of the study.

Results

The changes in footprint of the seven types of disturbance are summarized in Table 2:

Table 2: Annual change by disturbance type

	2004	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**Total**	% increase
wells (n)	1770	107	85	236	25	107	23	29	114	2496	41.0
mines (ha)	37	4	2	3	0	2	3	1	4	56	51.4
roads (km)	5188	156	71	194	10	88	15	18	77	5817	12.1
pipelines (km)	1979	21	12	100	7	31	9	4	47	2210	11.7
railway (km)	173	0	0	0	0	0	0	0	0	173	0.0
powerline (km)	323	0	0	0	0	0	0	0	0	323	0.0
cutblock (sq km)	1276	88	43	55	30	63	33	62	56	1706	33.7

Figure 2 shows the annual change in four of the seven types of disturbance features.

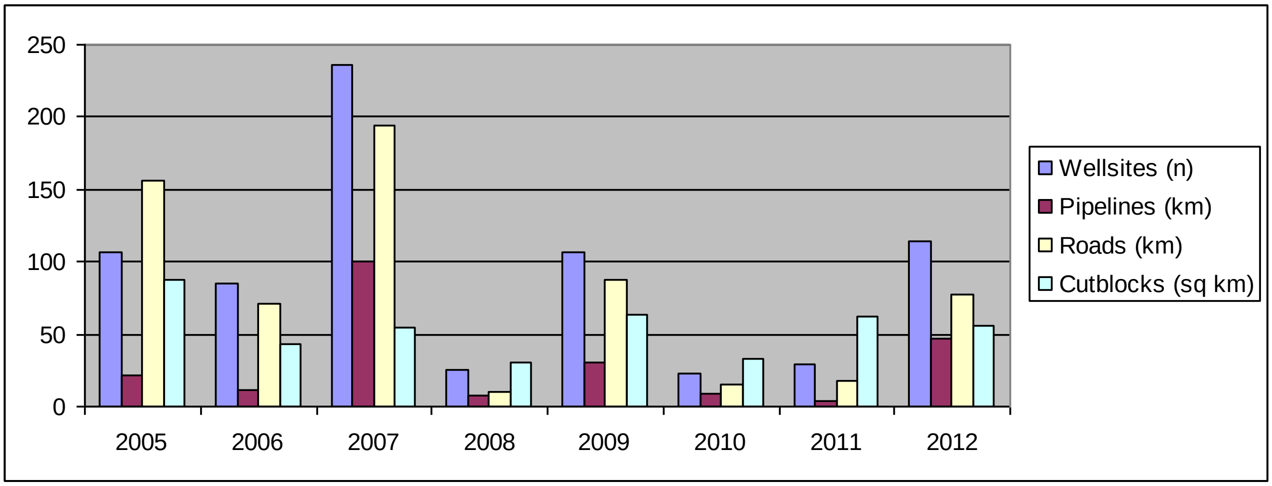


Figure 2: Annual change by disturbance type

Discussion

While there was considerable variation in the amount of disturbance from year to year for all disturbance types, the annual change in the footprint of oil and gas exploration and production (wellsites and pipelines) showed greater variation than for cutblocks. This may reflect the greater volatility of gas prices as compared to prices for wood products.

The expansion of the industrial footprint should not necessarily be regarded as an indicator of habitat degradation. Logging, for example, typically replaces close-canopy mature forest with younger seral stages, and increases the amount of edge habitat, both of which may be beneficial to grizzly bears. Furthermore, logging has replaced fire as the dominant mechanism of stand-replacing disturbance. In the study area, only 537 sq km of forest was burned since 1941, an extent only slightly greater than the area logged during the study period; almost half of this (248 sq km) was burned in the Syncline Ridge fire in Jasper National Park in 2003.

Nor should the growth of industry's footprint be considered entirely cumulative in nature. By law in Alberta, cutblocks are quickly reforested and other denudations, such as well pads and pipelines, are eventually reclaimed once they are decommissioned, although there may be a considerable time lag between construction and restoration.

What is most significant about the increase in anthropogenic disturbance is the construction of new access features associated with forestry or energy development. New research (Boulanger and Stenhouse, In Review) suggests that increases in road density directly affects population persistence. Figure 3 below shows the increase in new roads (red) constructed during the term of the study.

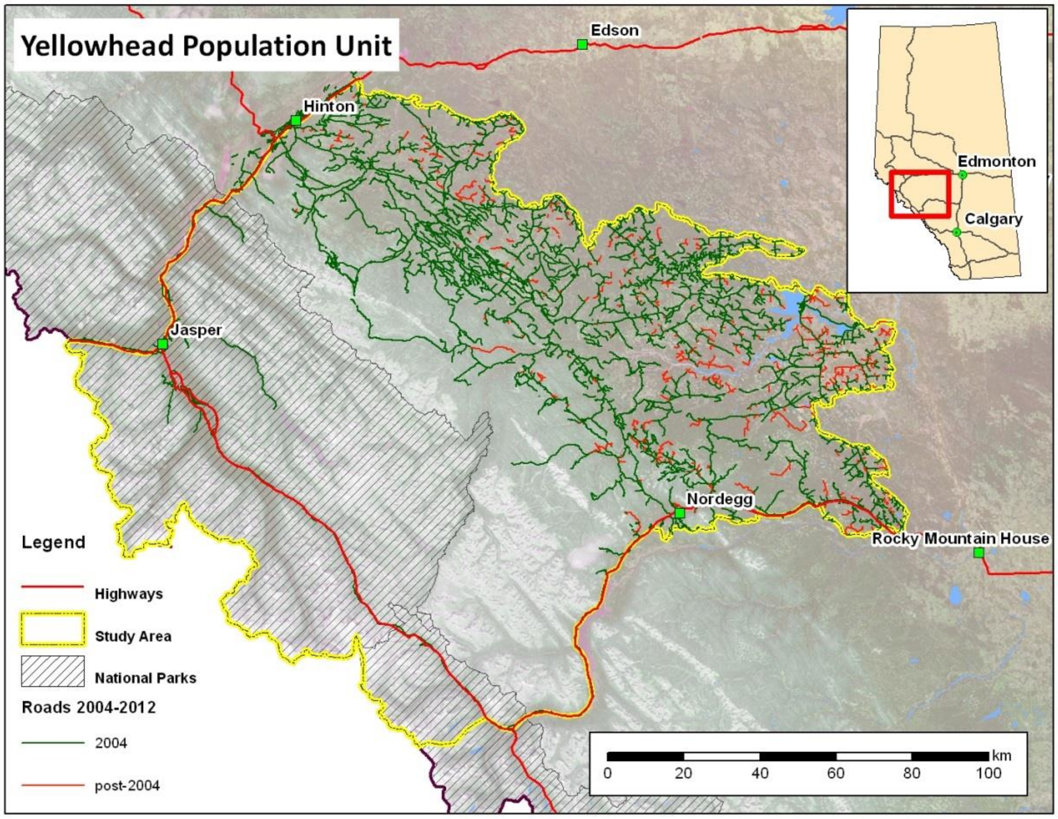


Figure 3: New roads constructed in study area after 2004

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Proctor, M. F., D. Paetkau, B. N. McLellan , G. B. Stenhouse, K. C. Kendall, R. D. Mace, W. F. Kasworm, C. Servheen, C. L. Lausen, M. L. Gibeau, W. L. Wakkinen, M. A. Haroldson, G. Mowat, C. D. Apps, L. M. Ciarniello, R. M. R. Barclay, M. S. Boyce, C. C. Schwartz, and C. Strobeck. 2012. Population fragmentation and inter-ecosystem movements of grizzly bears in western Canada and the northern United States. Wildlife Monographs 180:1-46.

Boulanger, J. and G.B. Stenhouse. (In Review). The demography of grizzly bears in Alberta: the effect of roads on population viability.

REPORT F: NEW GIS TOOLS FOR LIDAR-BASED MAPPING AND ANALYSIS OF SEISMIC CUTLINES IN NORTHERN ALBERTA

Prepared by

Jerome Cranston

Executive summary

Seismic cutlines are long, narrow clearings in the boreal forest constructed during oil and gas exploration in the 1970s and 1980s. They form an extensive network of access routes into grizzly bear habitat for motorized off-highway vehicles (OHVs), at densities often far above the thresholds for Open Route densities recommended in the Grizzly Bear Recovery Plan. However, their reclamation status with respect to revegetation and OHV trafficability is mostly unknown. Seismic cutline features were manually digitized from air photo interpretation and are represented in the Provincial GIS Base Features dataset, but with limited accuracy and no attribute information. Lidar data acquired by GoA has an advantage over traditional optical remote sensing platforms in acquiring attribute information for seismic cutlines, in that it has the high horizontal (1m) and vertical (0.3m) resolution to accurately measure vegetation height with within their narrow right-of-way. This paper describes a GIS process developed by the Foothills Research Institute Grizzly Bear Program (FRIGBP) to delineate and derive topographic and vegetation attributes of seismic cutlines using Lidar-based surfaces, in order to predict their potential for off-highway vehicle (OHV) use and to inform the planning of reclamation treatments.

Introduction

Seismic cutlines are long, narrow clearings in the boreal forest constructed during oil and gas exploration in the 1970s and 1980s, before the advent of low-impact seismic methods. Today there are over half a million km of abandoned seismic cutlines in western Alberta, 120,000 km in grizzly bear range south of the Peace River alone, and their effect on predator/prey dynamics has important implications for species at risk such as caribou and grizzly bear, an impact often far out of proportion to their limited physical footprint.

Figure 1: Seismic cutline.

To grizzly bears (*Ursus arctos*) , seismic lines enable human motorized ingress into otherwise inaccessible habitat, increasing their risk of encounter with people. Grizzly bears were listed as Threatened in Alberta in 2010 (Alberta Sustainable Resource Development, 2010a), with excessive rates of human-caused mortality considered the primary risk factor in population decline (Jalkotzy et al. 1997, Benn 1998, Nielsen et al. 2004, Boulanger et al. 2013). The more people travel in grizzly bear habitat, the greater the chance of problem encounters that may result in bear mortalities or relocations.

Mountain caribou (*Rangifer tarandus*), whose survival strategy is to disperse into vast tracts of old, dense coniferous forest (Apps and McLellan 2006), tend to avoid linear features (James & Stuart-Smith 2000, Dyer et al. 2001), as seismic lines provide predators such as wolves, cougars, and coyotes with an easy travel path into these stands, where their straightness allows them to see for long distances (Figure 1) (Thurber et al. 1994, Musiani et al. 1998, James & Stuart-Smith 2000, Whittington et al. 2005, McKenzie et al. 2012). The lines may also become revegetated with forage species such as willow, attracting other ungulates - deer, moose, and elk - which in turn attracts more predators (Simkin 1965, Siep 1992). Caribou are listed as Threatened in Alberta (Alberta Sustainable Resource Development, 2010b).

Compounding these effects on wildlife is the fact that most cutlines are slow to reforest, due to cold soils, shading from adjacent stands, and soil compaction resulting from the original construction (usually done with bulldozers), or from subsequent use by off-highway vehicles (OHVs) and wildlife (Revel et al. 1984).

Seismic cutlines have recently been the focus of reclamation efforts by companies looking to offset new road construction within grizzly bear and caribou habitat. Reclamation treatments for cutlines can include reforestation, either by spreading cones, planting nursery seedlings, or transplanting bigger trees form nearby stands; and line-blocking, in which mature trees are felled across the openings to discourage travel by OHVs and predators, and to obstruct sightlines.

However, the vast number of cutlines on the landscape means that reclamation efforts must be carefully targeted. Although the lines have been digitally mapped by photo-interpreters, and are part of Government of Alberta's Base Features dataset, for the most part, very little is known about their current status: whether they can be driven on, whether they are revegetated or reforested, regeneration growth rates, etc.

Traditional optical remote sensing platforms, such as Landsat, do not have high enough spatial resolution to collect information from within their narrow footprint, typically 5 to 8m (Linke, 2003).

Until recently, the only way of determining the revegetation status of seismic cutlines, other than expensive ground or aerial surveys, was to examine them using stereo pairs of digital air photos loaded into a Softcopy system. Air photos have the high resolution required (less than 1m horizontal resolution) to capture vegetation within the narrow footprint of seismic lines. However, this type of visual interpretation is labor-intensive, expensive, and subject to human error.

The advent of Lidar mapping provided an opportunity to automate the collection of information about seismic lines. Lidar surfaces have sufficiently high resolution (1m horizontal resolution) to accurately measure vegetation height within cutline corridors (Wulder et al., 2008), with vertical and horizontal accuracies of about 40 cm (Davenport et al., 2004).

Between 2003 and 2008, the Albert government acquired Lidar data over 28 million sq km of grizzly bear habitat for research and management purposes. The raw Lidar signal returns (the Point Cloud) was resolved into 2 sets of points (Bare Earth, representing ground signals) and Full feature (representing returns from the forest canopy) and converted to ASCII text files of x, y, and z coordinates. These were converted to Bare Earth (Digital Elevation model, or DEM) and Full Feature (Digital Surface Model, or DSM) ESRI grid surfaces at 1m horizontal resolution. A Canopy Height surface was derived by subtracting the DEM from the DSM. Seismic line features (polyline) were obtained from ESRD Base features.

Here we describe an automated GIS process to derive topographic and vegetation metrics for seismic lines from Lidar-based surfaces, to predict the potential for human (OHV) and animal use, and to inform reclamation treatments that can offset the impact of new construction within caribou and grizzly bear range. Because the process is automated it is far less expensive than Softcopy interpretation, thereby freeing up more resources to be directed to actual on-the-ground reclamation treatments. The process consists of five components:

1) updating the Lidar canopy height surface with post-Lidar stand-removing disturbance, to match current forest conditions;

2) redrawing seismic line features to follow a least-cost path within the disturbance corridor along the canopy height surface (yellow line, Figure 2);

3) delineating the edges of the disturbance corridor, to distinguish adjacent mature timber (circled red, Figure 2) from young regeneration growing on the right-of-way (circled in yellow, Figure 2);

4) Extracting topographic and vegetation metrics of the path (circled in blue, Figure 2);

5) Measuring tree heights adjacent to the corridor, to identify trees suitable for creating barriers to OHV use.

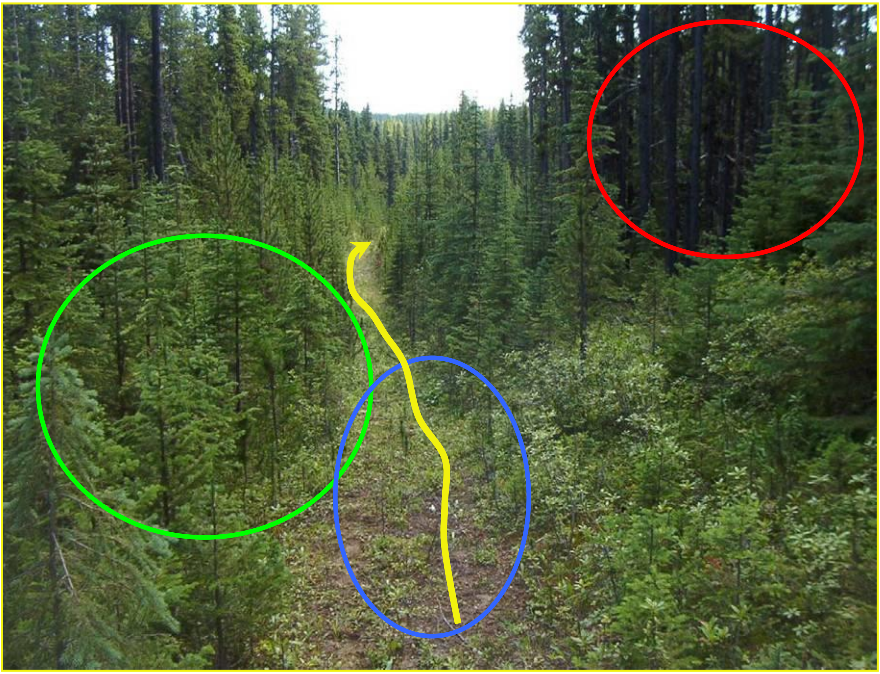

Figure 2: OHV trail (yellow) and regenerating trees (green) within cutline corridor.

METHODS

Study area

The study area where these methods have been applied is in the eastern slopes of the Rocky Mountains, in four distinct areas totalling over 14,000 sq km (Figure 3): in the range of the Redrock Prairie Creek and Narraway caribou herds, north of Grande Cache (outlined in yellow); in the range of the A La Peche and Little Smoky caribou herds to the east of Grande Cache (outlined in red); south of Hinton, in the Yellowhead grizzly bear population unit (outlined in green); and overlapping Highway 11 between Rocky Mountain House and Nordegg, which forms the boundary between the Yellowhead and Clearwater population units (outlined in blue). Within these four areas, a total of 22,683 km of seismic lines has been delineated using Lidar surfaces.

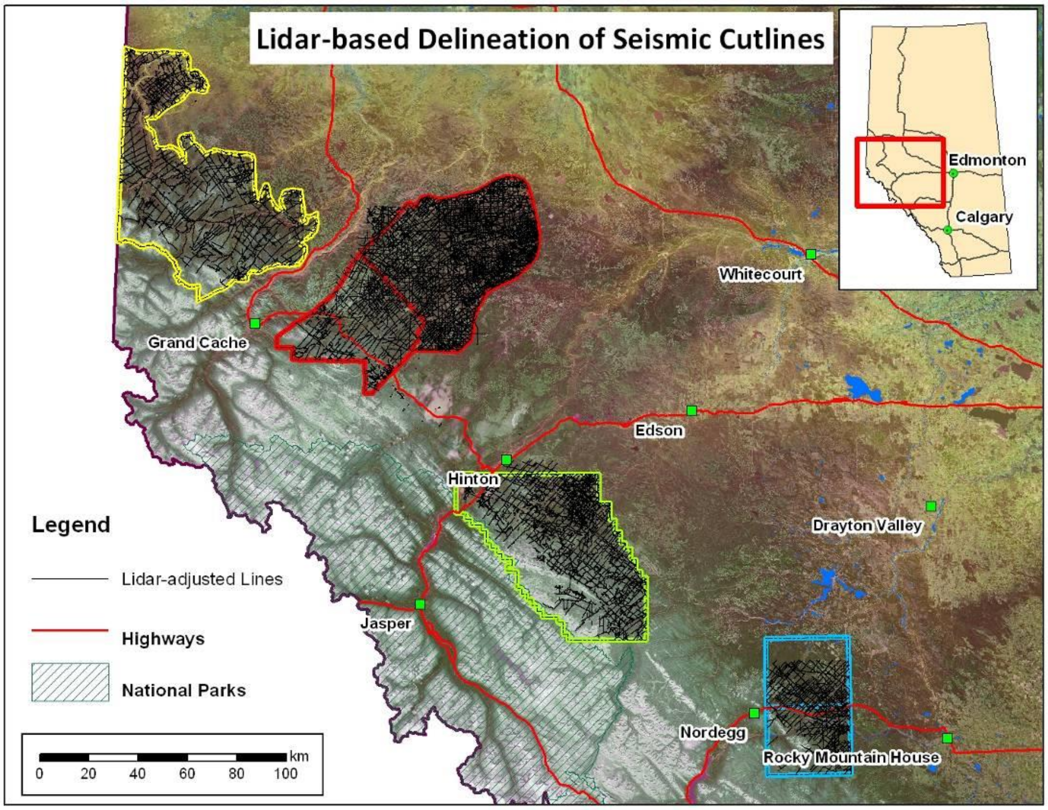

Figure 3: Areas where seismic lines have been delineated using Lidar surfaces.

Process

Update of Lidar canopy surface

The landscape of western Alberta is subject to frequent disturbances, both natural, such as fire, MPB infestation, and windthrow events, and anthropogenic, such as timber harvesting and oil and gas development (Nielsen et al. 2004). Lidar was flown over western Alberta between 2003 and 2008. While many of the changes to seismic lines since then have been incremental, such as regeneration growth along the right-of-way, the most significant changes have involved stand-removing disturbances such as clear-cutting, road-building, and wellsite and pipeline construction. The Lidar Full Feature surface has been updated to reflect those changes by substituting Full Feature elevation values with Bare Earth elevation values within the disturbance extent (Figure 4).

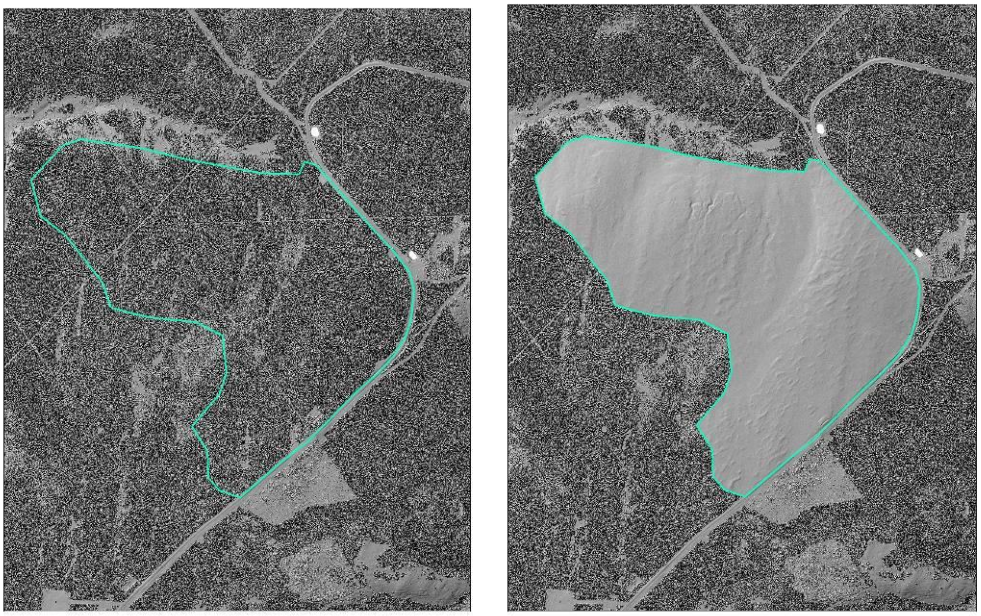

Figure 4: Original (left) and updated (right) Full Feature Lidar surface.

Spatial adjustment of digitized line features to follow the disturbance corridor

GIS tools can extract underlying raster attributes from digitized lines, such as mean, minimum, and maximum values for slope and elevation, and surface length (the length of line draped over a surface). However, seismic line features digitized by photo-interpreters usually are not accurate enough to yield reliable information on vegetation along the line. Cutline rights-of-way are typically so narrow (3 to 6m) that small errors in digitizing or georefencing will cause the digitized line to lie outside the corridor in the adjacent stand (Figure 5, red). To get correct canopy height values along the line, the line must precisely follow the cutline corridor. The GIS process clips the canopy height surface to within 20m of the original line feature, and a least-cost path raster is generated between the start point (source) and endpoint (destination) of the line feature. This raster is then converted into a new vector line feature (Figure 5, yellow).

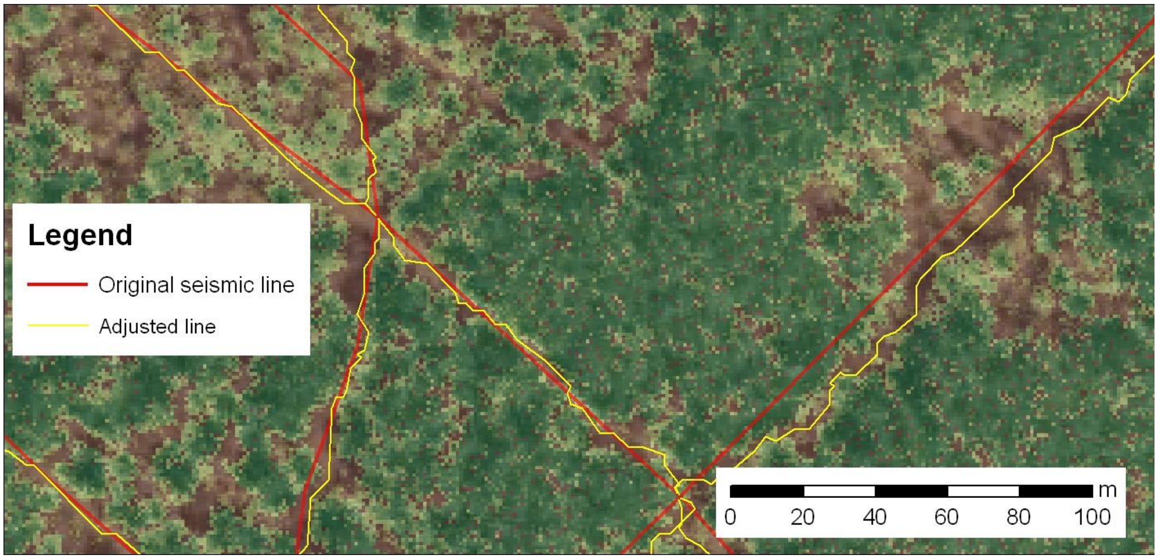

Figure 5: Manually digitized (red) and adjusted seismic line (yellow).

Delineation of disturbance corridor

Defining the edges of the disturbance corridor helps to distinguish new regenerating trees on the right-of-way from mature trees outside the corridor. If the age of the cutline is known, growth rates can be inferred from the height of the regenerating trees. Corridors are considered to be restored as functional habitat if both height and percent cover of regeneration has met certain criteria. Defining the corridor also serves to define the adjacent timber, which can be used to identify trees tall enough to block OHV access (see step 5).

To define the edges, the adjusted lines are buffered by 20m each side, and the canopy height surface is clipped to this buffer. The clipped height surface is smoothed by assigning each pixel the mean value of the pixels within a 3m-radius circular search window. This eliminates noise due to gaps in the canopy. A contour is placed on the smoothed height surface, and appended to the lines representing the boundary of the buffer. The set of lines is converted to polygons, and sliver polygons are eliminated if less than 10 pixels in area. The mean height of each polygon is then calculated and polygons less than 2m mean height are considered part of the right-of-way (yellow lines, Figure 6).

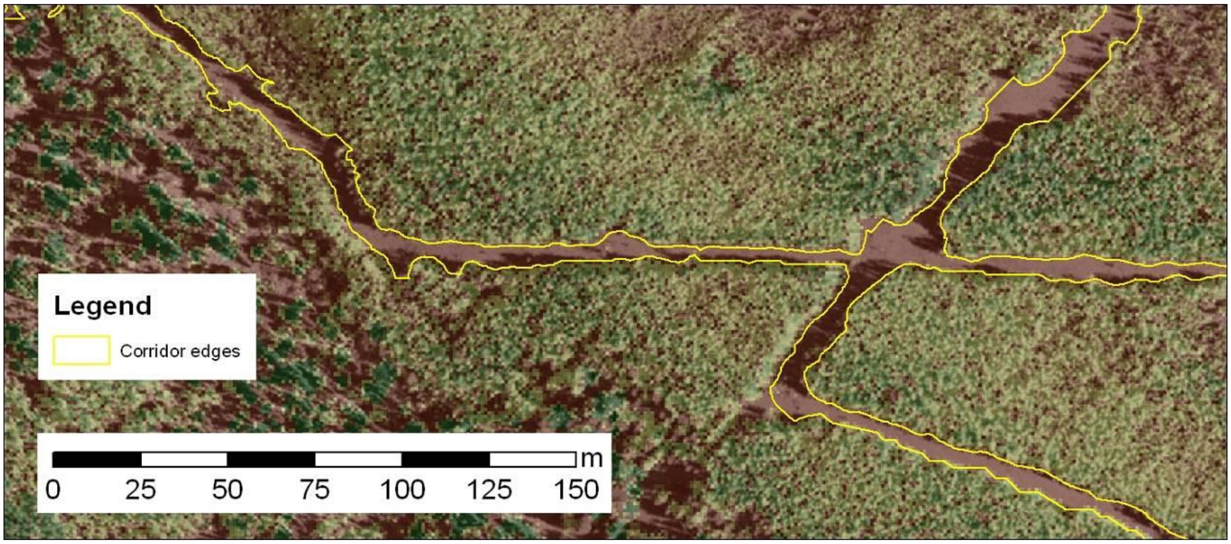

Figure 6: Disturbance corridor.

Extraction of topographic and vegetation metrics along the trail

Attributes for the adjusted lines can be extracted and compared with measured levels of OHV use to model the potential for OHV use as a function of trail characteristics. Actual levels of OHV use will likely depend on external, regional factors such as proximity to campgrounds, towns, and industrial sites, and whether OHV use is permitted, such as within mine leases or Forest Land-Use Zones (FLUZ). However, the *potential* for OHV use will depend on physical thresholds of drivability: that is, whether a trail is too steep, too wet, or too overgrown to navigate with an OHV.

The factors that are considered to determine potential OHV trafficability are:

1) **Vegetation**: the height, density, and variability of vegetation on the right-of-way. Vegetation height along the least-cost path can be derived by intersecting the adjusted line feature with the canopy height surface to derive mean and maximum canopy height for each segment, and the ratio of surface length to planimetric length. Figure 7 shows two seismic line features symbolized by mean canopy height over 100m segments. The red line is an unadjusted line; most of the line passes through treetops on the height surface, close to the actual corridor, and therefore has mean height values between 5 and 15m. The green line has been adjusted to a least-cost path on the height surface; mean height values for each 100m segment range from 0 to 5m, with an average of less

than 2m. Even if most of the corridor is overgrown with trees, OHV use is still possible as long as there is minimal vegetation along the least-cost path (see Figure 2).

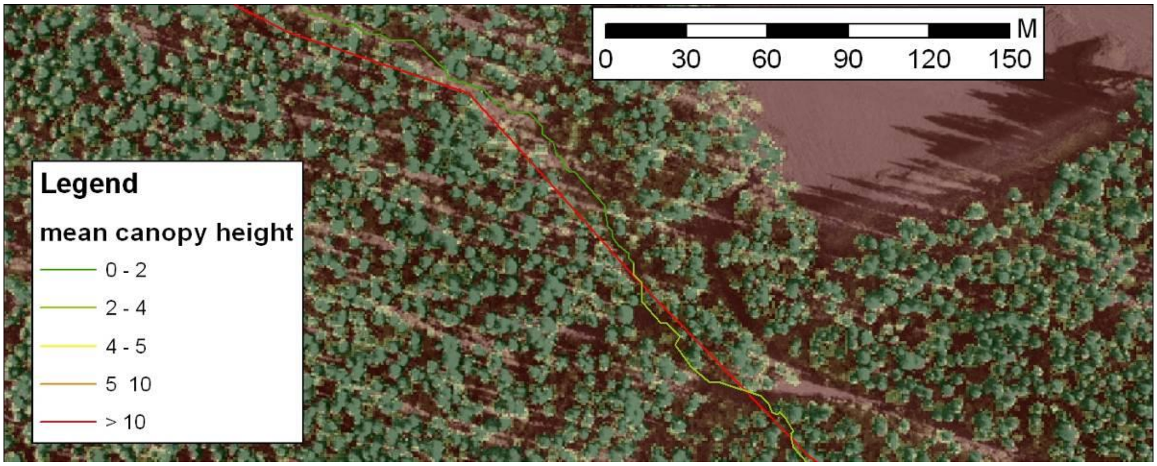

Figure 7: Vegetation height along Least-cost path.

2) **Terrain**: steep slopes are a limiting factor for OHV use, as slopes greater than 65% are too dangerous for OHVs. The maximum slope along a segment is derived from the Bare Earth surface. Thresholds for maximum drivable slope can be inferred from detours, which are short sections of trail that have been constructed to circumvent impassable sections. Figure 8 shows a detour constructed to avoid a steep grade into a gully; the original seismic trail (red) has a maximum slope of 80%, while the detour (green) has a maximum slope of less than 50%.

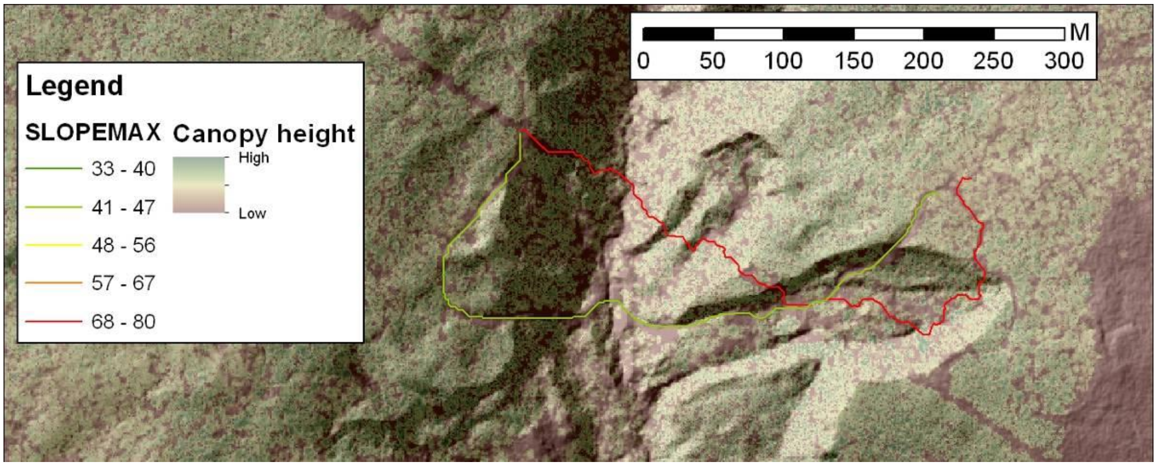

Figure 8: Steep trail bypassed by detour.

3) **Soil wetness**: soil wetness may impede use during periods of non-frozen ground. Flat, boggy sections of line may be impassable to OHVs, particularly following wet weather. Mean depth to water table, and minimum depth to water table, can be derived for a line segment from Wet Areas Mapping, a raster surface generated from hydrological modeling of the Bare Earth surface, in which pixel values represent predicted depth to water table (Murphy et al, 2008).

4) **Isolation** (connectivity with other trafficable cutlines): a cutline can only be used by OHVs if it can be accessed along other cutlines or trails (including pipeline or powerline rights-of-way), across openings (whether natural, such as meadows, or anthropogenic, such as clearcuts), or from roads. The connectivity of any line feature with all other features can easily be determined using network analysis in a GIS.

Measurement of tree heights adjacent to the corridor

Although artificial reforestation is often necessary to restore seismic openings to functional habitat, this may take decades, and even then will not be successful as long as OHV use continues to maintain a cleared path within the regeneration. One inexpensive and effective way to discourage travel by OHVs is by blocking the line with felled trees (Fig. 9, left).

Line-blocking requires trees with sufficient height, crown width, and proximity to the right-of-way to form an effective barrier when felled. Once the edges of the corridor have been defined, attributes of trees adjacent to the corridor can be identified. The corridor is buffered by 5m each side and the corridor is erased from the buffer. The canopy height surface is clipped to this buffer and converted to point features, where each pixel is represented by a point feature with pixel value (height) as an attribute. Cluster analysis is used to identify groups of points, weighted by canopy height, that represent tree crowns. These points are buffered by 3m and dissolved into single-part features, and the maximum height value within each crown, or group of crowns, is extracted (Figure 9, right).

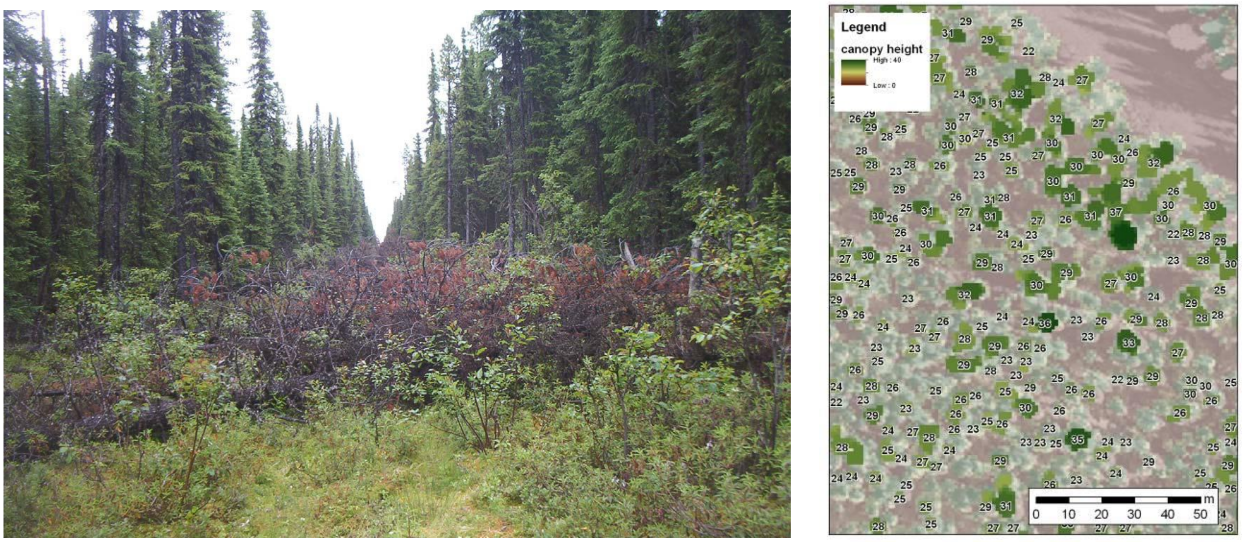

Figure 9: Line-blocking, left; trees heights derived from cluster analysis, right

Discussion

The broad extent and high spatial resolution of Lidar mapping has created an opportunity to address the significant information gap surrounding seismic cutlines in Alberta. The automated GIS process described here for extracting cutline attributes from Lidar can serve to guide reclamation efforts by ensuring that resources are allocated most effectively to achieve habitat restoration targets for at-risk wildlife species. Figure 10 illustrates the completed map product: input seismic line features (black) redrawn to follow a least-cost path (blue-green) on an updated Lidar canopy height surface; line segments attributed with slope, vegetation heights, and depth to water table; corridor edges delineated (yellow); and adjacent trees suitable for line-blocking identified. The process is currently being applied in a study of caribou habitat in the west-central mountain caribou ranges (*Analysis and Restoration of Seismic Cutlines in Southern Mountain and Boreal Caribou Range in West-Central Alberta; Habitat Stewardship Program 2013HSP-6617*), and in a doctoral study of grizzly bear response to human use of trails and cutlines south of Hinton.

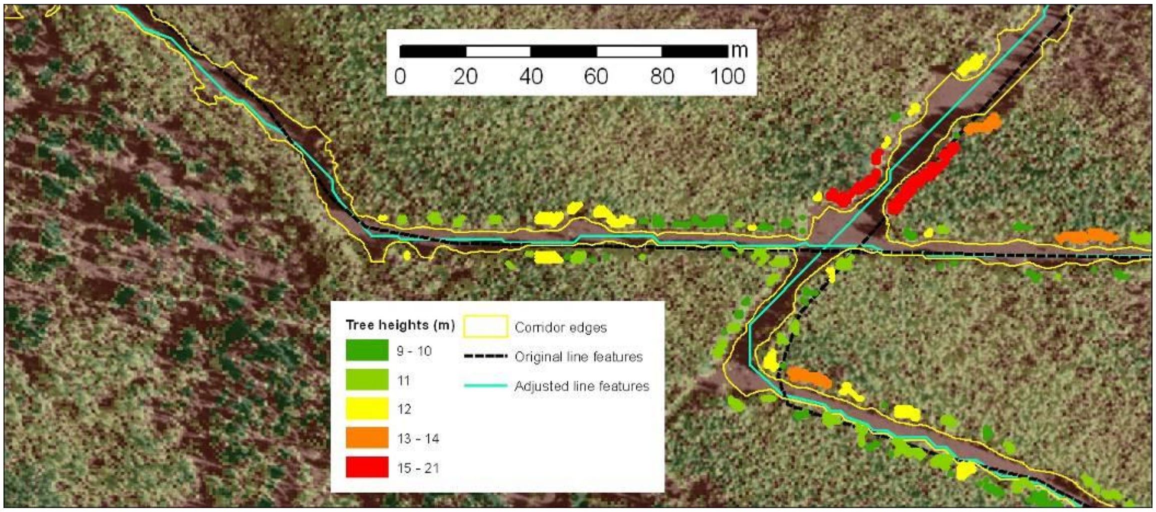

Figure 10: Seismic cutlines: original line feature (dotted black); adjusted line (blue-green); corridor edge (yellow); heights of adjacent trees color-coded green to red

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REPORT G: MODELING THE SEQUENCE AND INTERANNUAL TEMPORAL VARIATION OF CANADIAN BUFFALOBERRY (*SHEPHERDIA CANADENSIS*) USING BROAD-SCALE CLIMATE PROXIES.

D.N. Laskin, S.E. Nielsen, K. Graham, T. McKay, G. McDermid, G.B. Stenhouse

Prepared by D.N. Laskin

Introduction

Phenology examines the annual timing of plant and animal life-cycles such as the blooming of flowers in spring, or the departure of migratory birds in autumn (Post and Inouye 2008). For vegetation, the timing of these events is highly influenced by seasonal and interannual variations in climate and temperature (Vitasse *et al.* 2011; Schwartz *et al.* 2006; Parmesan and Yohe 2003; Inouye *et al.* 2000). Modeling this variability is particularly important, as plants are integral bottom-up drivers of ecosystem processes (Kerby *et al.* 2012). With northern latitudes experiencing increasingly fluctuating weather under climate change (Tingley and Huybers 2013), the ability to model and predict shifts in vegetation phenology is becoming more and more crucial (Paremesan 2006).

Currently, most studies examine only a single life-cycle event, such as spring budburst, to monitor these temporal changes (Linkosalo *et al.* 2008; Hänninien 1995). This paper looks to model the complete phenological progression from budburst to senescence, as it is currently not well known how to model nominal specific phenophase events over time. The timing of phenological sequences in vegetation provides insight into the potential impacts of climate variability on ecosystem function. Phenophases beyond budburst, such as *fruiting*, represent the timing of available nutrition and are therefore fundamental controllers of higher trophic levels (Power 1992). The focus-species of this study is Canadian buffaloberry (*Shepherdia canadensis*), a widespread and critical food-source for many species living in the Rocky Mountains of Canada. Of which, grizzly bears (*Ursus arctos*) are a generalist omnivore represented by a diverse diet and temporally variable habitat use (Jacoby *et al.* 1999). Understanding the phenology of food resources is important in interpreting grizzly bear habitat needs (Nielsen *et al*. 2010) and annual variations in the pattern of reproduction and health (Nielsen *et al*. 2013).

Variability in temperature over western Canada is mainly attributed to broad-scale climate anomalies originating over the Pacific Ocean, chiefly the Pacific Decadal Oscillation (PDO) and the El Niño-Southern Oscillation (ENSO) (Shabar and Khandekar 1996; Redmond and Koch 1991). These anomalies are initiated by changing patterns of ocean circulation, sea surface temperatures, and air surface pressures that are capable of modifying weather around the globe. The amplitude of these climate phenomena vary irregularly at interannual-to-inderdecadal time scales, either increasing or decreasing temperatures over Canada depending on the phase of the oscillation (Mantua 1997). Deviations from average seasonal temperatures result in an advance or delay in the normal phenological development of vegetation in western Canada (Beaubien and Freeland 2000). A change in annual average temperature of 1°C can shift the timing of phenophases by up to one week (Busetto *et al.* 2010). The temperature response in western Canada during a significant ENSO anomaly can be considerably large (~5°C) (Shabbar and Khandekar 1996). There have been a number of studies on coupled ocean-atmosphere indices altering the timing of phenological events (Li *et al.* 2012; McCabe 2012; Ault *et al.* 2011; Cook *et al.* 2005; Beaubien and Freeland 2000). These large-scale climate indices have been found to be useful predictors of ecological processes, even more so than local climate (Hallet *et al.* 2004). This is attributable to the persistence of anomalies and their atmospheric teleconnection lags that provide ample time to forecast phenological events elsewhere (McCabe 2012).

In seasonal latitudes, ecosystem function is synchronized by the timing of annual events such as pollination, spawning, and blooming (Dube 1984). There are numerous studies on the impact of climate change on phenophase timing and the potential for cascading ecosystem repercussions (Buermann *et al.* 2013; Naef-Daenzer *et al.* 2012; Post *et al.* 2008; Cleland *et al.* 2007; Williams *et al.* 2007; Paremesan 2006; Walther *et al.* 2002). Recent investigations in wildlife ecology have used shifting phenology as a proxy to interpret biological aberrations, such as changes in species range and distribution (Middleton *et al.* 2013; Mysterud 2013); climate-forced mismatch of producer-consumer trophic relationships (Kerby *et al.* 2012); and changes in population dynamics as a result of large-scale climate oscillations specifically (Hegel *et al.* 2010; Hebblewhite 2005; Mantua *et al.* 1997). Analysis of phenological variability can be applied to grizzly bear ecology, where nutritional intake by this *threatened species* is maximized through exploiting the differential timing of plant phenology (Coogan *et al.* 2014; Nielsen *et al.* 2010; Munro *et al.* 2006).

This study has two objectives: First, to model the complete phenological sequence of *S. canadensis* along the Central Rocky Mountains of Alberta, using large-scale climate indices as proxies for temperature. Second, to model the interannual variation of this sequence using these same climate proxies to predict the temporal lag (or advance) of phenological timing in *S. canadensis* year-to-year. By using climate indices as proxies for at-site temperature significantly reduces data collection effort as these data are easily acquired online. This study found that the Multivariate El Niño-Southern Oscillation Index (MEI) has a substantial influence on the phenology of *S. canadensis*, but is limited in its predictive capacity.

Methods

Study Area

The study area is located in west-central Alberta, Canada along the eastern slopes of the Rocky Mountain cordillera (Figure. 1). The region is characteristic of mixed montane forests, wetlands, and complex foothill topography with *S. canadensis* regularly distributed and abundant throughout. 12 observation sites were selected at various elevations (900-1700m) across the study area to incorporate a range of temperature regimes.

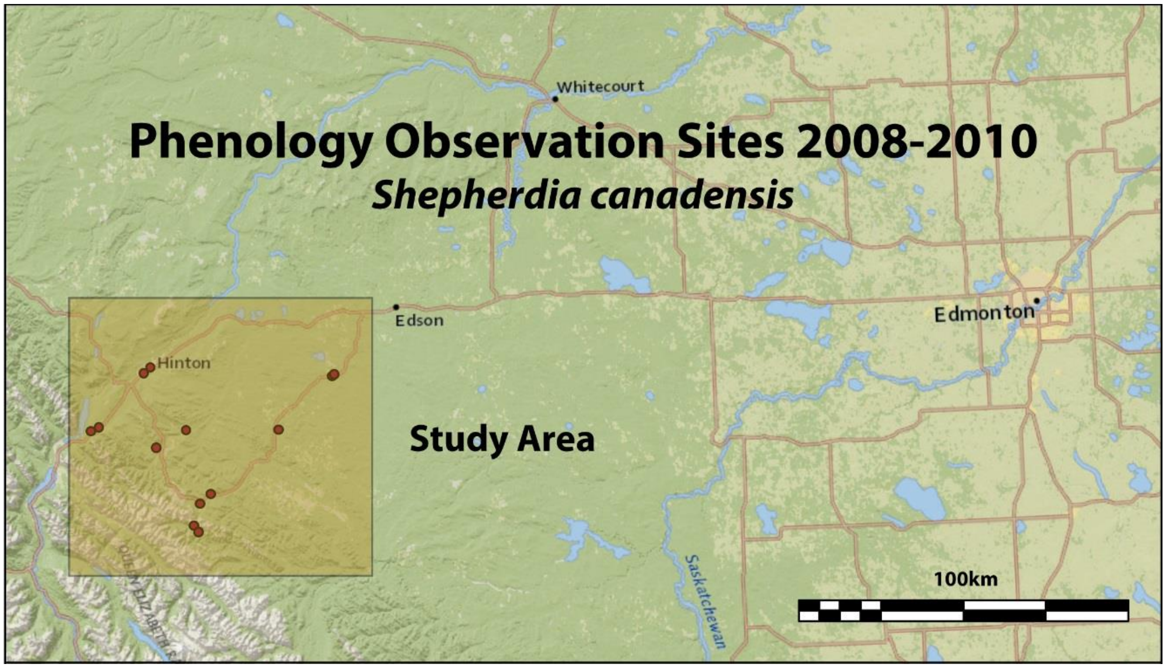

Figure 1. Study Area and observation sites 2008-2010.

Phenological Data

S. canadensis is a deciduous shrub that is approximately 1.5m tall, with oval 3-5cm long dark green leaves (Figure. 2). Fruit are 4-6mm across and ill-tasting (also known as soapberry), but are a significant source of nutrition for grizzly bears and the many other species in the study area (Hamer and Herrero 1987). *S. canadensis* has distinct, easily observable phenophases with budburst occurring in mid-May, flowering in late-May/early-June, and ripe fruit appearing in the latter part of July. Phenological observations were made weekly from May until October over three seasons (2008-2010). *S. canadensis* is a dioecious plant, therefore only females were selected for observation to maximize the number of reproductive phenophases observed. Nominal phenophase designations were assigned during each site visit based on those developed by Dierschke (1972) for both the vegetative (green leaf) and reproductive (flower and berry) progression (Table 1.).

Figure 2. *Shepherdia canadensis* bearing ripe fruit. (Photo credit: David Laskin)

Table 1. Phenophase codes for *Shepherdia canadensis* and other deciduous shrubs. Dierschke 1972).

Vegetative Phenophases	Reproductive Phenophases
0. Closed leaf bud	0. Without blossom buds
1. Green leaf out but not unfolded	1. Blossom buds recognizable
2. Green leaf out, start of unfolding	2. Blossom buds strongly swollen
3. Leaf unfolding up to 25%	3. Shortly before flowering
4. Leaf unfolding up to 50%	4. Beginning to flower
5. Leaf unfolding up to 75%	5. In bloom up to 25%
6. Leaf fully unfolded	6. In bloom up to 50%
7. First leaves fading	7. Full bloom
8. Yellowing up to 50%	8. Flowers fading
9. Yellowing over 50%	9. Flowers completely faded
10. Dead	10. Bearing green fruit
	11. Bearing ripe Fruit
	12. Bearing overripe fruit
	13. Fruit dispersal/drop

Climate Data

Monthly MEI and PDO index values were acquired from NOAA and the University of Washington's Joint Institute for the Study of Atmosphere and Oceans (JISAO). These indices are used to synthesize complex sea-surface and atmospheric variables into a single summarized value (McCabe 2012). Both the MEI and PDO index are derived by extracting the leading, unrotated principle component of observed meteorological phenomena over the North Pacific poleward of 20°N (Mantua *et al.* 1997; Wolter and Timlin 1993). The PDO index is calculated monthly, while the MEI is computed separately for each of twelve sliding bi-monthly seasons (i.e. Dec/Jan, Jan/Feb...). Warm North American climate anomalies associated with the PDO are similar to those connected with El Niño (MEI) and La Niña, though generally not as extreme (Latif and Barnett 1994). Both the PDO index and the MEI have two phases: warm and cool, where index values are positive for warm phase conditions and negative for cool phase conditions. Currently the PDO and El Nino Southern Oscillation are both in a cool phase which tends to exacerbate precipitation and temperature patterns over western Canada; potentially resulting in the study area having a greater snowpack during this period. While these oscillations affect broad-scale trends over the study area, higher frequency temperature-shifts are a result of the local micro climate typical of mountainous topography. It's for this reason medium-scale mean annual temperature (MAT) from 30-year climate normals (1960-1999) was collected to account for local spatial variation primarily due to elevation differences.

Shepherdia canadensis Phenology Models

Using STATA version 12.0 (StataCorp 2013) a logit transformation was applied to proportionally scale the nominal phenophase values to between 0 and 1, this way a Generalized Liner Model (GLM) could be used [1]. This particular model was chosen by virtue of the logistic curve's shape best representing the sigmoid growth curve typical to plant development (Fisher *et al*. 2007). The vegetative (green leaf) developmental sequence is in fact a double sigmoid, whereby the growth curve in early spring is flat and static until budburst, and then rapidly progresses through phenophases as leaves unfold and fully develop in only a matter of weeks. The sequence plateaus again mid-summer as there is no change in mature leaves until senescence. At this point leaves begin to yellow, followed by a rapid transition through the final phenophases until leaf abscission. Because no single model is capable of fitting a double sigmoid dataset, the vegetative sequence was split in two, modeled separately, and then stacked to represent the entire season. The first model encompassing early-season developmental phenophases (0-6) and the second including the late-season senescence phenophases (6-10) hereafter referred to as the *green-up* and *senescence* models respectively. Reproductive phenology transitions consistently across the growing season and was modeled as a single dataset. All model datasets were declared as panel data because of repeated observations at each site, and *random effects* were employed to offset this bias.

$$y = a + b_1x_1 + b_2x_2 \ldots + b_nx_n \qquad [1]$$

A series of candidate models were assembled and ranked to estimate the complete phenological sequence of *S. canadensis* as a function of time (Julian day), and various combinations of average monthly PDO/MEI index values, mean annual temperature (MAT), non-linear factors, and interaction terms (Table 2). *Akaike's Information Criterion* (AIC) was used to determine the best model. AIC ranks the top model as the one with the lowest *AIC score*, calculated as a compromise between reducing deviance in model fit (log likelihood) and reducing the total number of parameters (Burnham and Anderson 2002; Hosmer and Lemeshow 2000). Models with fewer explanatory variables tend to be more robust as they approach parsimony. The explanation of any phenomenon should hold as few assumptions as possible, and eliminate those that make no difference in observable predictions (Young *et al*. 1996). Therefore, penalties are added to the AIC scores of models having more parameters than necessary (MacKenzie 2006).

$$AIC = -2\{\log_e(L_M)\} + 2n \qquad [2]$$

Where L_M is the maximized likelihood for the fitted model, and n is the number of unknown parameters in the model that must be estimated (Manly *et al*. 2002). A *Spearman's Rank* correlation was used to limit collinearity between explanatory variables (Hosmer and Lemeshow 2000). A predetermined threshold of R^2= 0.7 was used to exclude excessively-related variables from the candidate models.

In addition to using *a priori* knowledge to reduce the permutations of explanatory variables in the candidate models, an initial series of iterative AIC rankings were performed to isolate the most significant monthly index between December and August. It was found that the two-month average index values during March and April consistently dominated the top-ranked models. A final series of candidate models were developed isolating these early-season values, with the *standard null* model simply being Julian date where phenological sequences should be explained by the day of the year without regard to site differences (MAT) or inter-annual variability due to climate proxies (Table 2). This includes interactions between Julian day and climate proxies to acknowledge that the Julian date at which phenophases are observed among years would be potentially dependent on the climate proxy used (advancing or retracting phenophase Julian dates).

Table 2. Explanatory variables used for modeling the phenological sequence of *S. canadensis.*

Variable Code	**Variable Name**
jday	Julian day
$jday^2$	quadratic of Julian day
mat	mean annual temperature
mei_mar_apr	averaged MEI index for March and April
pdo_mar_apr	averaged PDO index for March and April
jday*mei_mar_apr	interaction of Julian day and March/April MEI
jday*pdo_mar_apr	interaction of Julian day and March/April PDO

Interannual Phenological Variability

The annual timing of the phenological sequence in vegetation is highly influenced by the predominant seasonal climate (Parmesan and Yohe 2003). Therefore, given the range of climate index values experienced during the study period, we aimed to predict the resulting variability in phenological timing of *S. canadensis*. Discrete daily probabilities of phenological timing were modeled given a particular early-spring index value [3]. Variability of the models to changes in the PDO index, MEI or MAT could be observed as a lag or advancement in the developmental sequence. Throughout the 3 year study period, MEI index values in March/April varied from -1.3 to 1.13 and PDO varied from -1.62 to 0.61; MAT (30-year normal) across sites of -1.9°C to 2.63°C. Model sensitivity was estimated by inserting these minimum-maximum and neutral index values.

$$\rho = 1/(1 + e^{-(b_i \cdot x_i)}) \qquad [3]$$

Validation

Model validation was performed using phenological data from 2011 collected at different observation sites within the same study area as the 2008-10 model data. Validation observations were made at 10 sites using daily repeat time-lapse cameras and visits by field personnel. Model accuracy was tested by comparing model predictions of 2011 phenological timing using MEI values for that year, and then comparing this prediction with the actual 2011 observations (RMSE).

Results

Phenology Models

The phenological timing of *S. canadensis* is largely explained by climate index values occurring in early spring, at the beginning of the growing season. Preliminary AIC iterations of candidate model-sets identified the two-month average index value March and April for each MEI and PDO as having the most influence on phenological timing. There was no significant explanatory improvement between these two months when modeled individually. The quadratic term of Julian day was included in the vegetative models as it was found to alter the logistic growth curve to significantly improve model fit. However, there was not a similar effect for the reproductive models and this non-linear term was excluded.

Interaction terms dominate the vegetation models near the top of the AIC ranking list. The interactions between variables suggest that the effect of early-spring MEI index values on phenophase timing is different for different values of Julian day. Without an interaction term we are simply trying to predict a phenophase as a unique effect of early-spring MEI values. To test how these terms affect phenophase timing is through sensitivity analysis, by adding different MEI index values to see how the response variable (phenophase timing) changes; which was the second objective of this study, modeling interannual variability.

The most supported green-up model was explained by the interaction term of March/April MEI with Julian day (Table 3). The same model was also ranked highest for senescence (Table 4). The continuity between model variables indicates that early-spring MEI index values are linked to the green-leaf phenological progression of *S. canadensis* across the growing season. Assessment of the vegetative models using AIC weights (w_i) show that the PDO index has a similar relative likelihood as the AIC selected top model containing MEI. However, MEI distinctly influences the highest weighted senescence models.

Table 3. Model performance for AIC-selected generalized linear models for the prediction of vegetative green-up timing in *S. canadensis* (Phenophases 0-6). Model rank was assessed through AIC values (Δ_i) and weights (w_i) which describe model likelihood. Model complexity, the number of parameters, is symbolized by K_i.

Vegetative Green-up Phenophase AIC Models	K_i	AICc	Δ_i	w_i
jday+ jday^2+mei_mar_apr+jday*mei_mar_apr	5	544.9	0.0	0.38
jday+ jday^2+pdo_mar_apr+jday*pdo_mar_apr	5	545.1	0.2	0.35
jday+ jday^2+mat+mei_mar_apr+jday*mei_mar_apr	6	546.8	1.8	0.15
jday+ jday^2+mat+pdo_mar_apr+jday*pdo_mar_apr	6	547.3	2.3	0.12
jday+ jday^2+pdo_mar_apr	4	583.7	38.7	0.0
jday+ jday^2+mat+pdo_mar_apr	5	585.7	40.7	0.0
jday+ jday^2+mei_mar_apr	4	586.1	41.1	0.0
jday+ jday^2+mat+mei_mar_apr	5	588.2	43.2	0.0
jday+jday^2	3	591.3	46.4	0.0
jday+jday^2+mat	4	593.3	48.3	0.0
jday	2	671.4	126	0.0

Table 4. Model performance for AIC-selected generalized linear models for the prediction of late-season vegetative senescence timing in *S. canadensis* (Phenophases 6-10).

Vegetative Senescence Phenophase AIC Models	K_i	AICc	Δ_i	w_i
jday+jday^2+mei_mar_apr+jday*mei_mar_apr	5	472.9	0.0	0.74
jday+jday^2+mat+mei_mar_apr+jday*mei_mar_apr	6	475.0	2.1	0.25
jday+jday^2+pdo_mar_apr+jday*pdo_mar_apr	5	481.6	8.8	0.01
jday+jday^2+mat+pdo_mar_apr+jday*pdo_mar_apr	6	483.5	10.6	0.0
jday+jday^2+mei_mar_apr	4	497.3	24.4	0.0
jday+jday^2+mat+mei_mar_apr	5	499.4	26.5	0.0
jday+jday^2+pdo_mar_apr	4	501.4	28.5	0.0
jday+jday^2+mat+pdo_mar_apr	5	503.2	30.3	0.0
jday+jday^2+mat	4	509.5	36.6	0.0
jday+jday^2	3	509.8	36.9	0.0
jday	2	642.3	169	0.0

The top reproductive models all include MAT, models that do not include temperature had a significant drop in AIC weight (Table 5). The influence of climate indices was not as strong in predicting reproductive phenology as they were with the green-leaf vegetation. However, the interaction between Julian day and March/April PDO had a significant, inverse relationship on reproductive phenology – outperforming the null model which was exclusively Julian day (Table 6). The quadratic term of Julian day had a much higher influence on the vegetative models than reproductive, suggesting very little non-linear effect on reproduction and more gradual development.

Table 5. Model performance for AIC-selected generalized linear models for the prediction of reproductive phenophase timing in *S. canadensis.*

Reproductive Phenophase AIC Models	K_i	AICc	Δ_i	w_i
jday+jday^2+mat	4	656.2	0.0	0.30
jday+jday^2+mat+pdo_mar_apr	5	656.4	0.2	0.26
jday+jday^2+mat+pdo_mar_apr+jday*pdo_mar_apr	6	657.5	1.3	0.16
jday+jday^2+mat+mei_mar_apr	5	657.6	1.4	0.15
jday+jday^2+mat+mei_mar_apr+jday*mei_mar_apr	6	659.8	3.6	0.05
jday+jday^2	3	660.7	4.5	0.03
jday+jday^2+pdo_mar_apr	4	662.3	6.1	0.01
jday	2	662.4	6.2	0.01
jday+jday^2+mei_mar_apr	4	662.7	6.5	0.01
jday+jday^2+pdo_mar_apr+jday*pdo_mar_apr	5	663.3	7.1	0.01
jday+jday^2+mei_mar_apr+jday*mei_mar_apr	5	664.8	8.6	0.0

The estimated model parameters in Table 6 are coefficients expressed in the units of each explanatory variable. For green-leaf development in *S. canadensis*, both the green-up and senescence models are significantly explained by March/April MEI, and further supported by a weak interaction of Julian day with March/April MEI.

Table 6. Estimated model parameters for top-ranked AIC models of *S. canadensis* phenological timing. Raw coefficients and Standard errors (in parentheses) are presented by model.

Phenology model	jday	jday^2	mat	mei_mar_ apr	jday*mei_mar_ apr
Vegetative Green-up	0.694 (0.043)	-0.002 (0.000)		6.916 (0.886)	-0.033 (0.005)
Vegetative Senescence	-0.505 (0.034)	0.001 (0.000)		-3.332 (0.740)	0.018 (0.003)
Reproductive	0.027 (0.015)	0.00007 (.00003)	0.891 (0.296)		

Interannual Phenological Variability

Models were re-scaled from the logit proportion to their original nominal phenophase sequences. The value of the MEI was modified to determine the sensitivity of developmental timing to this climate proxy, and the resulting phenological advance or delay. For the vegetative models, there was an advance in green-leaf development across the entire season when MEI is high (warm phase). Alternatively, phenological development was delayed when this value dropped (Figure 3). Compared to an average year (MEI=0), using the maximum index value advanced the model by approximately 12 days, while using the minimum index value slowed development by 10 days. The maximum absolute difference in timing for *leaf out*, and *full leaf* was therefore 22 days, and for *beginning to yellow* was nearly two weeks. For reproductive phenology, the model predicted up to a 39 day delay in timing between average MAT and the coldest site (highest elevation). There was also nearly a two week difference between average MAT and the site with the warmest MAT (low elevation) (Figure 4). The maximum absolute variation between max and min at-site MAT values was therefore 52 days for the timing of the *beginning to flower* phenophase.

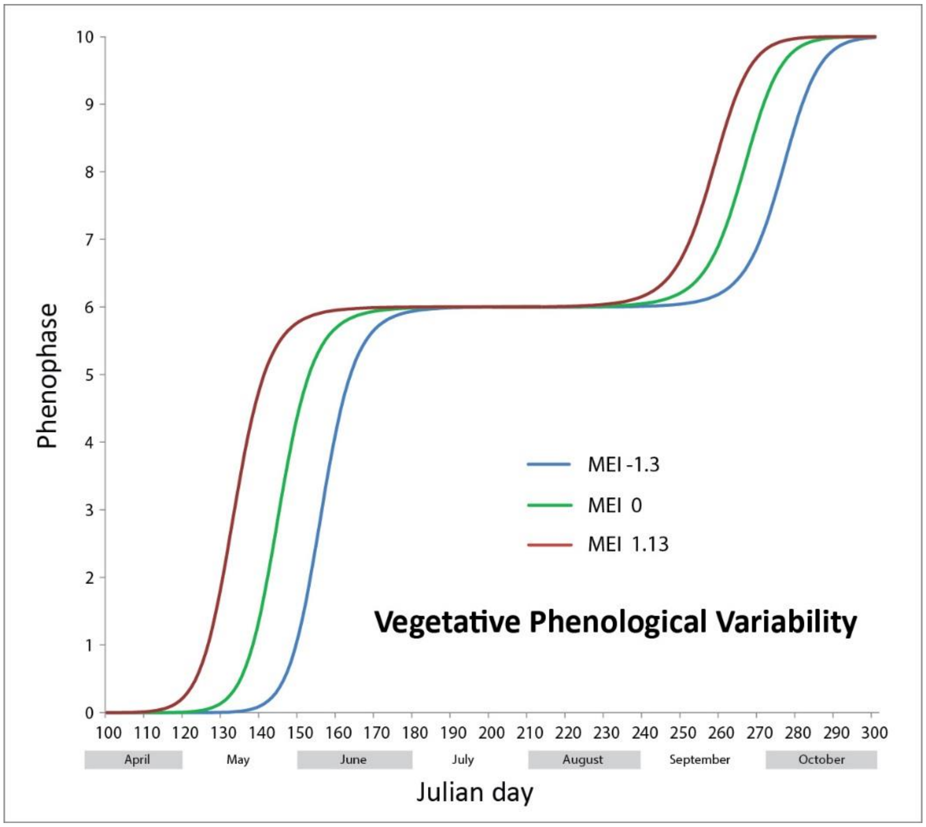

Figure 3. Stacked green-up and senescence S. canadensis vegetative models predicting interannual phenological variability based on the minimum, maximum, and neutral MEI values occurring during the study period.

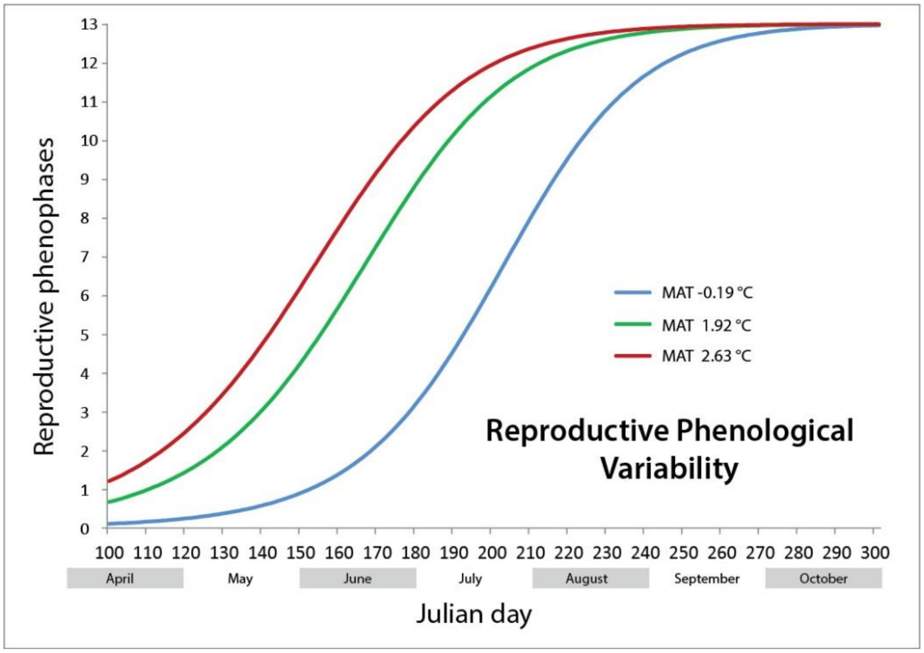

Figure 4. *S. canadensis* reproductive model predicting interannual phenological variability based on the minimum, maximum and average MAT values occurring during the study period.

Validation results

The green-up model had excellent predictive accuracy with an RMSE of only 3 days (Table 7). The senescence model, however, performed unsatisfactorily with an average error of 3 weeks, consistently predicting phenophases to occur much later in the season than observed. The reproductive model contained no climate proxies, so predictions of 2011 phenological timing were made by using the average at-site MAT from the 2011 validation sites. The model was an average of two weeks off in its predictions, mostly later than the observed timing.

Table 7. Green-up, senescence, and reproductive model prediction RMSE validation.

Model	*RMSE*	Best Prediction	Worst Prediction
Green-up	3 days	Leaves fully unfolded (0)	Leaves 25% unfolded (-6)
Senescence	21 days	Over 50% yellow (+18)	Leaves beginning to fade (+28)
Reproduction	14 days	Bearing green fruit (-4)	Bearing overripe fruit (+38)

Discussion

The phenology of *S. canadensis* was found to be controlled, to some extent, by the MEI. However the correlation with this climate proxy is solely with *Shepherdia's* green-leaf development, while neither proxy appears to have any influence over its reproductive phenology. Julian day anchors all the models by dictating the rate of progress through the growing season, with variation in timing arising from changes in MEI or MAT. The green-up and senescence models are both improved with the presence of this particular climate proxy, substantially more than predicting phenology by date or MAT alone. Index values throughout the entire growing season were modeled, but it was those from early spring (March/April) that had the predominant influence in predicting both green-up and senescence. This makes sense as the timing of spring onset is contingent on these early season conditions which trigger the phenological schedule for the remainder of the growing season. Conversely, this could be a spurious correlation between the March/April MEI value and normal spring temperature phenomena too diluted in the MAT data. The PDO index had no influence in the top models; this could simply be because it is uncorrelated, but more likely its effects are too weak or confounded by the more prominent MEI or local climate factors. The PDO was identified relatively recently in 1996, and there is still a lack of understanding of how it operates or works to impact climate (Wolter and Timlin 1998). It is known that the cool phase of PDO will moderate El Nino events, which could very well indicate its effects are somewhat unified with the MEI (Figure 5).

Modeling the complete nominal phenology of *S. canadensis* was successful using the *double-sigmoid* (stacked logistic) model. The first portion of the progression, the green-up model, performed very well in predicting the timing phenophases until mid-august to within 3 days. This period includes budburst, which is a critical event commonly used for monitoring spring onset and trends in climate change. *S. canadensis* is widely distributed throughout the study area and throughout Alberta, and could potentially be used as a long-term gauge of variability in the timing of spring. As for predicting seasonal nutrition for bears however, the green-leaf phenology is inconsequential, but has the capacity to be linked to other long-term ecosystem processes that impact grizzly ecology. The senescence model had the identical explanatory variables as the green-up model, including the MEI, but made poor predictions of late season events. This could be partially due to these particular phenophases having long durations and gradual transitions, making them more difficult to pinpoint. Also, spring phenophases (budburst) have been found to be more responsive to temperature change than those occurring later in summer/autumn (Pudas *et* al. 2008; Chuine and Beaubien 2001). Photoperiod may also play a larger role in leaf-yellowing and senescence than temperature (Partanen 2004).

Where green-leaf models incorporated the MEI climate proxy, variability of reproductive phenology was chiefly controlled by MAT. Although statistically significant, model predictions were poor, with calculations of ripe berries occurring two weeks too late. Temperature is a major driver of plant development, and therefore included in the candidate models. However, unlike climate indices, a 30-year normal MAT is constant at each site, varying only across elevation making it a relatively poor predictor of inter-annual variability. Contrarily, it appears that there actually may be too much intra-annual variability within climate indices to produce a consistent proxy on which to base predictive models. On average these indices have broad-scale trends of 5-10 years for MEI, and upwards of 20-30 for PDO. Over the course of the three year study period, the overarching trends are likely obscured by short-term noise (Figure 5). A longer study period would have certainly strengthened these models.

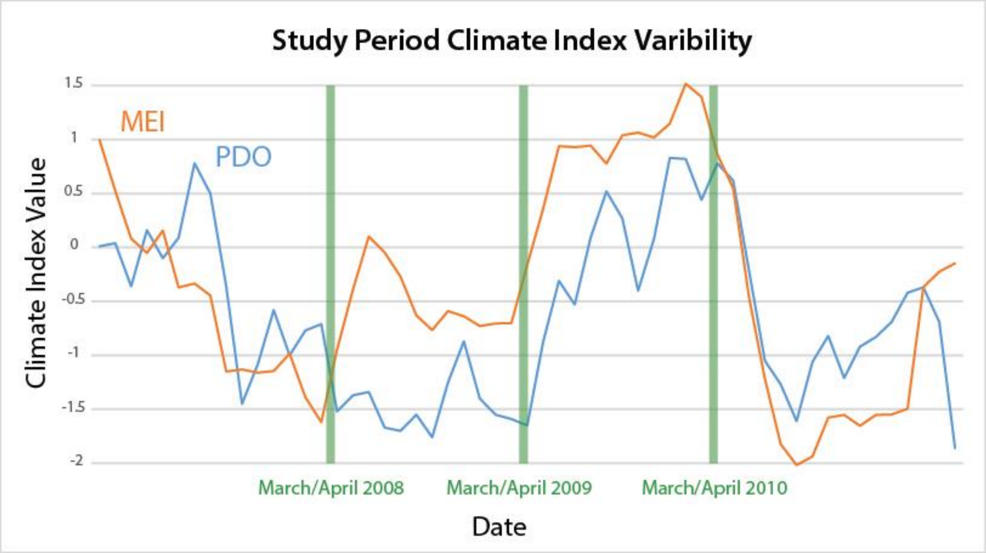

Figure 5. Variability of MEI and PDO index values throughout the study period with the most phenologically influential periods highlighted.

Modeling the complete nominal progression of *S. canadensis* had a reasonable outcome which paves the way for more rigorous explorations of grizzly bear habitat phenology. The next step in this research, and a recommendation to the FRI Grizzly Bear Program, is that future investigations use at-site local temperature in the form of Growing Degree Days (GDD's). Hourly temperature accumulations would capture all of the variability in phenological timing at most scales (Haggerty and Mazer 2008; Schwartz 2003). It is believed that the models also suffered from temporal holes in the phenophase observation data. Increasing plant observation frequencies to sub-weekly (or even daily with phenology cameras) would significantly improve model results (Nijland *et al.* 2013; Bater *et al.* 2011).

This inquiry into using easily-obtained climate proxies provided an understanding of the climatic scales at which this mountain environment operates. How these proxies from the distant Pacific will be compounded with trending climate change is difficult to predict. However continued phenological studies in relation to grizzly bear habitat will surely reveal patterns of critical ecosystem dynamics. Within this particular region, an increased frequency of extreme climatic events, such as an unseasonable cold-snap or sudden winter warming, can lead to near-complete elimination of fruit production the following summer (Eccel *et al.* 2009). Woody plants such as *S. canadensis* are especially at risk of climate change because of their limited rates of dispersal and growth (Thomas *et al.* 2004).

Conclusion

Broad-scale climate proxies have the potential to rapidly model and predict variability in phenological timing. However, for *S. canadensis*, they proved too coarse to produce accurate predictions for all phenophase conditions within the study area. These models do hold potential as excellent tools for managing habitat quality and forecasting bear-food availability year-to-year. There was success in modeling the complete nominal phenological progression of *S. canadensis* with predictions of early season, green-leaf phenology being remarkably accurate. However late season predictions were unsatisfactory, as were forecasts of flowering and the ripening of berries.

This study provided insight into the mechanisms that drive the timing of ecosystem processes along the Eastern Slopes of the Rockies. Given the occurrence of increasing incidences of climate anomalies, it is vital to consider their potential impact on temporal variations in the availability and quality of food resources for grizzly bears. Vegetation phenology is becoming increasingly important in wildlife ecology, as it adds a dynamic, essential, temporal aspect to ecosystem function.

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APPENDIX E: LIST OF PROGRAM PARTNERS (1999 – 2013)

- Ainsworth Lumber Co. Ltd.
- Alberta Advanced Education and Technology - (formerly Innovation and Science)
- Alberta Conservation Association
- Alberta Environment and Sustainable Resource Development
- Alberta Fish & Game Association
- AB Innovates Biosolutions
- Alberta Newsprint Company
- Alberta Summer Temporary Employment Program
- Alberta Tourism, Parks and Recreation
- Anadarko Canada Corporation
- Anderson Exploration Ltd.
- AVID Canada
- B P Canada Energy Company
- BC Oil and Gas Commission
- Buchanan Lumber – Tolko OSB
- Canada Centre for Remote Sensing
- Canadian Association of Petroleum Producers (CAPP)
  - Petroleum Technology AllianceCanada (PTAC)
  - Environmental Research Advisory Council (ERAC) Fund
  - Alberta Upstream Petroleum Research Fund
- Canadian Cooperative Wildlife Health Centre
- Canadian Natural Resources Ltd.
- Canfor Corporation
- Center for Wildlife Conservation
- ConocoPhillips Canada
  - (formerly Burlington Resources Canada Ltd.)
  - (formerly Canadian Hunter Exploration Ltd.)
- Conservation Biology Institute
- Daishowa Marubeni International Ltd.
- Devon Canada Corp
- Enbridge Inc.
- Encana Corporation
- ENFORM
- Foothills Research Institute
  - (formerly FoothillsModelForest)
- Forest Resources Improvement Association of Alberta (FRIAA)
- G&A Petroleum Services
- GeoAnalytic Inc.
- Government of Canada
  - CanadianForest Service, Natural Resources Canada
  - Canadian Wildlife Service
  - Environment Canada – HSP
  - Human Resources and Skills Development Canada (CSJ)
  - Natural Sciences and Engineering Research Council of Canada (NSERC)
  - Parks Canada
    - BanffNational Park
    - JasperNational Park
- Grande Cache Coal Corporation
- Hinton Fish and Game Association
- Hinton Training Centre
- Husky Energy Inc.
- Komex International Ltd.
- Lehigh Inland Cement Limited
- Luscar Ltd.
- Gregg River Resources Ltd.
- Manning Diversified Forest Products Ltd.
- Manning Forestry Research Fund
- Millar Western Forest Products Ltd.
- Millennium – EMS Solutions Ltd.
- Mountain Equipment Co-op
- Nature Conservancy
- Natural Resources Canada
- NatureServe Canada
- Nexen Inc.
- Northrock Resources Ltd.
- Pembina Pipelines
- Peregrine Helicopters
- Persta
- Petro Canada Ltd.
- Peyto Energy Trust
- Precision Drilling Corporation
- Progress Energy Resources Corp
- Rocky Mountain Elk Foundation - Canada
- Shell Canada Limited
- Sherritt International – Coal Valley Resources
- Slave LakeDivision – Alberta Plywood
- SprayLake Sawmills Ltd.
- Suncor Energy Inc.
- Sundance Forest Industries Ltd.
- Sustainable Forest Initiative
- Talisman Energy Inc.
- TECH – CardinalRiver Operations
  - (formerly Elk Valley Coal)
- Telemetry Solutions
- TransCanada Pipelines Ltd.
- University of Alberta
- University of Calgary
- University of Lethbridge
- University of Saskatchewan
  - WesternCollege of Veterinary Medicine
- University of Victoria
- University of Washington
- University of Waterloo
- Veritas DGC Inc.
- West Fraser Mills Ltd.
  - Alberta Plywood
  - Blue Ridge Lumber Inc.
  - Hinton Wood Products
  - SlaveLake Pulp
  - SundreForest Products
- Weyerhaeuser Company Limited
- WilfredLaurierUniversity
- World Wildlife Fund Canada
- Yellowstone to Yukon

APPENDIX F: LIST OF PROGRAM PARTNERS (2014)

Alberta Innovates Biosolutions
Alberta Environment and Sustainable Resource Development
Alberta Tourism, Parks and Recreation
Alberta Newsprint Company
Alberta Upstream Petroleum Research Fund
Canadian Cooperative Wildlife Health Centre
Canadian Natural Resources Limited
Canfor Forest Products
Conoco-Phillips
Devon Canada
Encana
Foothills Research Institute
Forest Resources Improvement Association of Alberta
Grande Cache Coal Corp
Human Resources and Skills Development Canada – Canada Summer Jobs
Husky Oil
Millar Western
Natural Resources Canada
Parks Canada
Pembina Pipelines
Progress Energy Resources Corp.
Shell Canada
Sherritt International. – Coal Valley Resources Inc
Spray Lakes Sawmills
Suncor Energy
Sundance Forest Industries Ltd.
Sustainable Forestry Initiative
Talisman Energy
Teck Coal
TransCanada Pipelines
University of Alberta
University of British Columbia
University of Calgary
University of Victoria
West Fraser Ltd.
Weyerhaeuser Ltd
Yellowstone to Yukon

APPENDIX G: LIST OF REPORTS, THESES AND PUBLISHED PAPERS.

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