


FINAL REPORT

Spatio-Temporal Dynamic Modelling of Mixed-Severity Fire Regimes in the SW Foothills of Alberta

Final Report
fRI Research Landscapes in Motion,
part of Healthy Landscapes Program

June 1st, 2020

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Disclaimer

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ACKNOWLEDGEMENTS

We acknowledge funding from a Mitacs Accelerate Award no. IT10289 and Mitacs Elevate Fellowship no. IT12391, in partnership with the Foothills Research Institute (fRI), both awarded to Ceres Barros. We would also like to thank the Forest Resource Improvement Association of Alberta for funding support.

INDIGENOUS PEOPLES ACKNOWLEDGEMENTS

We respectfully acknowledge that the land on which we have conducted our research is the traditional territory of the *Piikáni* Nation, the *Siksika* Nation, the *Kainai* Tribe, the *Tsuut'ina* Nation, and the *Iyarhe Nakoda* First Nation of the Treaty 7 region in southern Alberta[1].

[1] Spelling follows the websites of each Nation and Tribe.

https://www.stoneynation.com/
http://siksikanation.com/wp/
https://bloodtribe.org/
https://tsuutinanation.com/
http://piikanination.wixsite.com/piikanination

REPORT SUMMARY

The long-standing assumption that boreal and mountain forests are driven by stand-replacing fires in which mortality approaches 100% resulting in patches of even-aged forests across the landscape has been questioned by recent research. Partial mortality creates multiple cohorts of trees with high structural and compositional complexity that may be critical for habitat, successional recovery trajectories, "old growth" definitions, carbon sequestration, and landscape-scale biodiversity. Unfortunately, many of the available landscape dynamics models that simulate and project changes in landscape conditions do not represent partial mortality, assuming stand-replacing fire events instead. Others that represent partial mortality are either mostly focused on simulating detailed fire behaviour, ignoring post-fire vegetation dynamics and feedbacks, or have a number of simplifying assumptions, or have a limited data-parametrization-simulation integration which prevents transferability.

Given the potentially critical role of partial mortality, this is a critical gap. The modelling component of the LIM Project, was then to create a partial mortality module that could be integrated with an existing fire spread model and an existing landscape dynamic vegetation model, as well as on-the-fly data sourcing/treatment and parametrization, to explore the potential feedbacks between fire and vegetation within the SW Alberta Foothills.

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1. INTRODUCTION

1.1 BACKGROUND

The forests of southwestern Alberta are valued in many ways. They are the headwaters of our rivers; providing opportunities for recreation; diverse habitats for wildlife and fish; and jobs in forestry, ranching, tourism and oil and gas. Like all forest types in Canada, these forests are "disturbance dependent". They constantly change as natural disturbances such as fire and insect outbreaks reshape the landscape, resulting in a shifting pattern of old and younger forests, habitat types, nutrient availability, and even water flow and sedimentation. In Alberta, our approach to caring for our forests is to learn from these natural patterns and to try to maintain them with the idea that the forest ecosystem will continue to provide the range of services and habitats we value. To do so, we need to understand not only how, where, when, and in what form disturbances occur (i.e. a "disturbance regime"), but how disturbances influence other landscape values over time and space.

Appling this concept to southwestern Alberta has proven to be a challenge for several reasons. First, we are discovering that the pattern of fires is more complex in this area than we previously assumed. Rather than seeing only intense forest fires that kill all the trees, which are then replaced by a completely new, young forest, it appears that lower intensity fires also occur that kill only a portion of the trees. Therefore, rather than having even-aged forests covering the landscape, historic landscapes may have had a mixture of even and multi-aged stands resulting from a "mixed severity fire regime" (MSRF). A second challenge is that many human disturbance activities in our forests are very different from natural disturbances. For example long linear features like trails and roads through the forests are not seen in the patterns created by fires and insects. These human disturbances can create unforeseen, and often negative impacts on forest ecosystems, including altering predator-prey interactions, and increasing sedimentation in streams and rivers. Both challenges have potential implications for forest managers who are trying to be informed by natural patterns in how they can better manage the forests.

Towards addressing this knowledge gap, a larger project proposal for Alberta Innovates called *"Science-based management tools to support Ecosystem-Based Management of forests in Southwestern Alberta"* was developed and approved in 2016 that included four elements with four goals:

1) Provide the details of what the historic fire regime in southwestern Alberta was through dendrochronological field sampling, lab processing, cross-dating, and spatial analyses.
2) Understand better what the historic landscape condition was, and how they have changed over the last century through the use of historical oblique aerial photos, and
3) Create computer models that will integrate knowledge gained from the first two elements to simulate these patterns over time and space.
4) Understand the differences between the sedimentation caused by both natural and human caused disturbances.

This report describes the findings and outcomes from the third element from above on spatial modelling.

1.2 Landscapes in Motion

The intimate and logical relationship between the first three of these elements from the original SW Alberta AI proposal quickly teamed up under the lead of Dr. Andison to enable a) greater integration, communications, and efficiencies, and b) apply for additional funding (as per the AI proposal). This team became known as ***Landscapes in Motion***, or LIM.

The subsequent funding application to the Forest Resource Improvement Association of Alberta (FRIAA) not only allowed for the completion of the original objectives from the Alberta Innovates proposal, but expanded on it. The following is a list from the FRIAA proposal. Items 1-4 were the promised deliverables to Alberta Innovates (conditional on finding supporting funding). Items 5-7 (in italics) were the additional items as part of the FRIAA proposal.

1) Develop and refine two interrelated analytic tools for assessing vegetation pattern changes in historical and repeat oblique photographs. The first tool extends from an adaptation of a mono-plotting tool that transforms digital oblique images to an overhead projection suitable for spatial analysis. The second tool uses web-based visualization tools to segment, classify and calculate statistical changes in images over time.
2) Develop a first approximation landscape-scale 'model' of mixed-severity fire regime dynamics in southwestern Alberta using available related studies, knowledge of mixed-severity fire regimes in related ecosystems, and knowledge gained from objective #1.
3) Document the patterns of historical fire severity (including the incidence of partial severity burning), frequency, and size in the SW Alberta foothills.
4) Develop a first approximation of a fire spread module capable of dealing with partial mortality.
5) *Evaluate the external drivers (i.e. topography, climate) and key self-regulating fire feedbacks (fire severity-frequency interactions) of the historical fire regimes in the SW Alberta foothills.*
6) *Integrate the new knowledge from objectives #1, #2, #3, and #5, and the new module from #4, into an existing modular spatial simulation modelling framework called SpaDES. Included in this objective will be the calibration of all modules, and other fire regime parameters (as available) to the SW Alberta study area.*
7) *Share the process of the exploration of historical landscape dynamics and model development with stakeholders and the public via a dedicated outreach program.*

This report describes the findings and outcomes from the original third Alberta Innovates LIM element on computer modelling, and item #4 above. Work on item #6 above continues under the FRIAA funding.

1.3 Study Area

The study area for the larger SW Rockies project covers about 950,000 ha bordered by the US border to the south, Bow Valley to the north, the treeline to the west, and a mix of parkland and fescue to the east. It is a long, narrow zone in which elevation, physiography, soils, and climate change over very short distances from east to west. It includes parts of the Montane (55%) and Subalpine (45%) natural subregions. The climate ranges from mild summers and warm winters at lower elevations to cool wet summers and long cold winters at higher elevations, and conditions can change dramatically over very short distances in response to topography. Tree species range from Douglas fir, aspen, lodgepole pine and white spruce to englemann spruce and subalpine fir at higher elevations to the west. Soils are similarly variable, from chernozems to the east to luvisols and brunisols to the west.

1.4 Indigenous Peoples

The Landscapes in Motion study area is strongly associated with the traditional territory of the *Piikáni* Nation (Reeves and Peacock 2001, McMillan and Yellowhorn 2004) and is encompassed by *Kitaowahsinnoon*, the broader territory of the Blackfoot Confederacy (Blackfoot Confederacy 2020). As well, the traditional territory of the *K'tunaxa* Nation, who live west of the Rocky Mountains, overlapped the southern Alberta Foothills where they travelled annually to hunt (Brink 1986, Reeves and Peacock 1995, 2001, McMillan and Yellowhorn 2004, ?*aq'am* 2020).

Since time immemorial, the southern Alberta Foothills have been home to the *Piikáni* (Peigan), *Iyarhe Nakoda* (Stoney Nakoda), and *Tsuut'ina* (Sarcee) Nations, as well as the *Siksika* (Blackfoot) and *Kainai* (Blood) Nations who live on the Great Plains to the east (McMillan and Yellowhorn 2004). Today, the *Siksika*, *Kainai* and *Piikáni* (*Apatohsipiikani* in Alberta and *Amsskaapipiikani* in Montana) are collectively known as *Siksikaitsitapi* or the Blackfoot Confederacy (Yellowhorn and Plain Eagle undated, McMillan and Yellowhorn 2004, Oetelaar and Oetelaar 2006).

The member Nations of the Blackfoot Confederacy travelled seasonally within their territories to hunt game and collect plants, moving onto the grasslands in summer and returning to the valleys of the foothills during winter (Reeves and Peacock 2001, McMillan and Yellowhorn 2004, Oetelaar and Oetelaar 2006). The foothills environments also provided year-round habitat for bison (*iini*), a coveted resource that provided food, clothing, shelter, and was the foundation of many cultural and spiritual customs (Yellowhorn and Plain Eagle undated, McMillan and Yellowhorn 2004). A rich archaeological record within our study area (Brink 1986, Reeves and Peacock 1995, 2001, Hannis 2012, Zedeño et al 2014), including important sites such as Heads-Smashed-In Buffalo Jump (Reeves 1978, Brink 2008) and Napi's Playground (Yanicki 2014), attest to the enduring and intimate use of this landscape by the *Siksikaitsitapi* and other First Nations.

The name "Blackfoot" comes from a legend of walking across burned prairie (McMillan and Yellowhorn 2004). Oral histories and physical evidence indicate controlled burning was practiced to cultivate plants for harvesting and maintain productive meadows for bison and horses, especially near seasonal encampments and bison jumps (MacMillan and Yellowhorn 2004, Brink 2008, Oetelaar and Oetelaar 2008, Zedeño et al. 2014, Roos et al. 2018). As well, burning the perimeter of camps, especially near tree groves near springs and river crossings along travel corridors, reduced surface fuels and the chance of crown fire ignited by uncontrolled grassfires (Oetelaar and Oetelaar 2008). Journal entries by Peter Fidler of the Hudson Bay Company, who lived with the *Piikáni* in 1792-3, documented these practices (Fidler 1991). He recorded numerous controlled burns over large areas in the grasslands along the Foothills between November and March and noted they were ignited by people (Fidler 1991), rather than lightning (Oetelaar and Oetelaar 2008). Although Fidler did not report burning in mountain valleys, others have attributed the establishment and persistence of grasslands in river valleys of the Foothills, including the Old Man River, to Indigenous fire management (Pickard 1981; Stockdale et al. 2019).

The arrival of Europeans disrupted the Blackfoot way of live, with direct and indirect impacts on cultural fire practices (Stockdale et al. 2019). Epidemics of smallpox and other diseases were introduced by Europeans in 1730s, 1830s and 1860s (Reeves and Peacock 1995, 2001, McMillan and Yellowhorn 2004, Hannis 2012). The rapid destruction of bison herds to near-extinction during the 1860-80s undermined the lifeblood of the Blackfoot traditional land and cultural practices (McMillan and Yellowhorn 2004, Brink 2008, Oetelaar and Oetelaar 2006). In 1877, the Blackfoot Treaty (Treaty #7) was signed by the five Indigenous Nations of southern Alberta, yielding 129,500 square kilometers of land in return for reserves, the promise of livestock, farming implements and other considerations (Government of Canada 2009). Ultimately, the Treaties and Indian Act largely removed the Blackfoot from their traditional territories and cultural practices by confining people to reserves where farming and ranching were controlled by federal Indian Agents and by requiring children to attend residential schools (McMillan and Yellowhorn 2004, Appendix 1 in Yanicki 2014). Nevertheless, many Blackfoot traditions remain strong and Elders hold knowledge of their traditions associated with the land, plants, and animals (Reeves and Peacock 1995, McMillan and Yellowhorn 2004), which is critical for understanding, managing and restoring the Foothills landscape (Oetelaar and Oetelaar 2006, 2008).

1.5 Partners

The Southern Rockies project began as an Alberta Innovates project on behalf of the Government of Alberta. The delivery of the four project elements was the responsibility of fRI Research, who managed that administration and budget. The fRI Programs involved includes the Healthy Landscapes Programs (elements 1-3, or LIM) and the Water Program (element 4). The LIM component was further supported by a FRIAA application, as well as two successful Mitacs Accelerates, and two more Mitacs Elevates.

2. The LIM Modelling Element

2.1 Background

Ecosystem-Based Management (EBM) embraces the idea of managing forests as whole systems and with greater humility. The EBM premise suggests that if we shift away from trying to manage individual values (e.g. timber or single species) to focusing on overall ecosystem function, we are more likely to be ecologically, socially, and economically sustainable. This idea has been increasingly embraced by industry, governments, and international certification agencies across western Canada for the last 10 years or so (McAfee & Malouin, 2008), and most recently and notably by the Canadian Boreal Forest Agreement (CBFA) (CBFA 2015). Successfully implementing this approach requires understanding the natural dynamics of ecosystems, including how they respond to disturbances (Pickell *et al.*, 2013).

Wildfires are amongst the most common disturbances across the Boreal and Montane Forest Regions (see Rowe, 1972) in Canada (McGee *et al.*, 2015). While it has been known that fires occurring in the Montane Forests can be a mix of infrequent large and high intensity fires and more frequent low-to-moderate intensity fires (McGee *et al.*, 2015), in the Canadian Boreal Forest, fires have been characterised and assumed to be infrequent, large (>200 ha) and high intensity crown fires (De Groot *et al.*, 2013) that cause the total removal of forest cover (100% mortality) and reset forest successional dynamics. However, mounting evidence shows that mixed severity fire (MSF) regimes may be more common than previously thought, even in boreal forests across North America (Burton *et al.*, 2008; Perry *et al.*, 2011). Dendroecological studies have shown that high severity, stand-replacing fires (i.e. fires that kill 100% of the vegetation originating even-aged forests) are historically interspersed with fires of lower severity in montane forests of British Columbia (Chavardès & Daniels, 2016; Greene & Daniels, 2017), and interpretation of historical aerial photographs has revealed that individual fires can produce complex spatial patterns of mixed severity levels within fire perimeters in boreal forests of Western Canada (Andison, 2012; Andison & McCleary, 2014; Krawchuk *et al.*, 2016), and montane forests in Washington state (Hessburg *et al.*, 2007), Idaho and Montana (Birch *et al.*, 2015).

However, efforts to simulate MSF regimes in Canadian landscapes have are still uncommon (but see Sirois *et al.*, 1994; De Groot *et al.*, 2003; Sturtevant *et al.*, 2009; Miquelajauregui *et al.*, 2019; Marchal *et al.*, 2020). This is partly due to data and knowledge limitations and poor data integration (Marcoux *et al.*, 2013; Williams *et al.*, 2016), which introduce bias when investigating severity-vegetation-climate relationships, and partly due to model simplifications of fire-vegetation feedbacks (e.g. assuming stand-replacing fires). MSF regimes result from the interplay of topographic, vegetation and climate conditions acting at different spatio-temporal scales. While large-scale topography and climate act as top-down drivers that largely determine fire size and frequency at large spatio-temporal scales (in the order of 10^2 Km and 10^2 years), vegetation, weather and topographic conditions act as bottom-up drivers that create heterogeneous fire severity patterns at smaller spatio-temporal scales (Cumming, 2001; Lentile *et al.*, 2006; Madoui *et al.*, 2010; Falk *et al.*, 2011; Perry *et al.*, 2011; Ferster *et al.*, 2016). Notably, evidence suggests that even a single fire can produce heterogeneous severity patterns in relatively homogeneous forest stands (Keyser *et al.*, 2006). This heterogeneous fire severity impacts vegetation succession and resulting forest composition and structure, which in turn can affect future fires and fire regimes (Girardin *et al.*, 2013; Terrier *et al.*, 2013; Marchal *et al.*, 2020). Furthermore, pockets of surviving vegetation that can sustain ecosystem functioning and promote recovery (Halofsky *et al.*, 2011), thus influencing ecosystem service provisioning and landscape-wide fire resilience.

Hence, understanding MSF regimes, their dynamics and drivers is crucial for an adequate landscape management in line with the EBM approach. This requires a combination of empirical research – to capture individual elements such as fire spread and frequency, vegetation mortality and succession – and modelling – to connect these various elements across time and space, test hypotheses and project changes into the future. As part of the Landscapes In Motion (LIM) project our objective was to capture the modelling component of this research gap.

Spatial modelling of boreal and montane forest dynamics is not new, but most models focus on a small number of elements (or 'modules') such as fire behaviour and spread (Parisien *et al.*, 2005), vegetation succession (Pennanen *et al.*, 2004), habitat (Bayne et al., 2005), or carbon (Boisvenue & Running, 2010). More holistic and complex landscape models (Cumming & Armstrong, 2001; Fall & Fall, 2001; Scheller & Mladenoff, 2004) connect our understanding of individual ecosystem elements such as disturbance, climate, succession, and habitat over time and space. These integrated models are important tools for EBM because they help us understand and predict how ecosystems respond to changing natural and human-induced input conditions.

The way landscape models simulate disturbances varies greatly from model to model, from simple and random distribution of "disturbance boxes" of different sizes (Schneider et al. 2003), to complex spread algorithms calibrated to create disturbances of different sizes, shapes, and levels of retention in the landscape (Andison, 1998). It is common, however, that individual disturbances are presumed to cause 100% vegetation mortality (but again, see Sturtevant *et al.*, 2009). In fire models, assuming complete mortality was driven by the long-held assumptions about stand-replacing boreal wildfires (as discussed above) and by model simplicity. Erasing all vegetation in a pixel/polygon and (re-)starting a successional sequence from stage zero (e.g. no stand biomass or no tree cover) is simple to code and explain. However, predicting and managing forest changes (and of the ecosystem services they provide) in line with the EBM approach requires the recognition that climate, fire and vegetation interactions create spatio-temporally heterogeneous patterns of mortality, which ultimately influence future wildfire and vegetation dynamics.

Our team aimed to create an integrated landscape dynamic vegetation model, capable of simulating fire disturbances while taking into account partial tree mortality and survival, as well as forest succession and the effects of climate on fire spread. It was also our objective that this model be developed within a reusable, flexible, interoperable and continuous workflow, in order to ensure full transparency but also that the model can be updated, further expanded and improved as new data and knowledge become available.

2.2 Goals and Objectives

Within the two main goals mentioned above (creating an integrated landscape dynamic vegetation model within a reusable, flexible, interoperable and continuous workflow), the modelling component of LIM had the following objectives:

<u>Goal 1: Creating integrated landscape dynamic vegetation model, capable of simulating fire spread, partial tree mortality and survival, as well as forest succession</u>

Objective 1a: develop a partial severity module

Objective 1b: integrate a partial severity module with a fire spread module and a landscape vegetation dynamics module.

Objective 1c: parameterise and test the integrated module in the LIM study area, in the SW Alberta Foothills

Objective 1d: compare landscape dynamics and patterns obtained when assuming a partial severity fire regime *versus* a stand-replacing fire regime.

<u>Goal 2: Guarantee model development within a reusable, flexible, interoperable and continuous workflow</u>

Objective 2a: develop the above-mentioned components using the *SpaDES* modelling framework

Objective 2b: host *SpaDES* modules in a transparent and collaborative platform for future users and developers.

3. METHODOLOGY

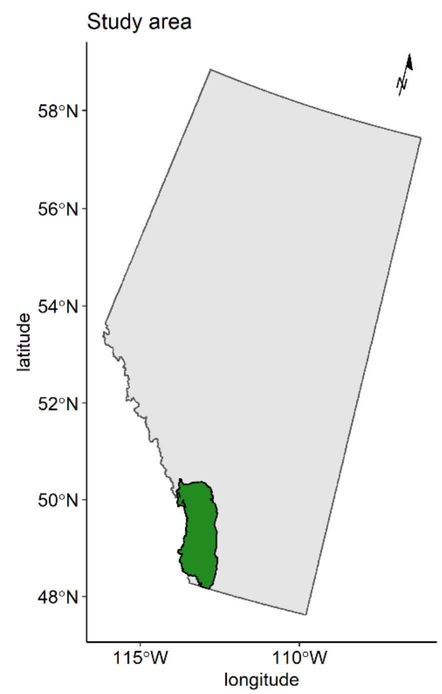

FIGURE 1. STUDY AREA WITHIN THE PROVINCE OF ALBERTA.

We tested the effects of two alternate assumptions of post-fire vegetation mortality (stand-replacement *vs.* partial mortality) using the landscape dynamic vegetation model LandR Biomass. The model was parametrized for an area of ca. 2 000 000 ha in the foothills of the Rocky Mountains in SW Alberta, Canada (Fig. 1), which includes the Boreal Plain, Montane Cordillera and Prairie Canadian Ecozones (NRCan, 2013). The area is characterised by strong elevational gradients and ecosystem transitions between grasslands, mixed aspen woodlands (*Populus sp.* and minor components of *Betula sp.*) and pure coniferous forests. Coniferous forests are dominated by Douglas-fir (*Pseudotsuga menziesii*) and Lodgepole pine (*Pinus contorta*) at lower elevations, and spruce-fir forests (*Picea sp.* and *Abies sp.*) at higher elevations (REF).

LandR Biomass is a group of SpaDES modules (Chubaty & McIntire, 2019) that simulates the population dynamics, competition, dispersal and responses to disturbances of different forest species (trees only) in terms of cohort biomass changes, with cohorts being unique combinations of species and age (Barros et al., *in prep.*). Only a few modules are implicated in the actual simulation of forest succession, with many being dedicated to data preparation and parameter fitting for the core simulation modules, or the conversion of cohort biomass into other properties (e.g. fire fuels). This means that LandR Biomass can self-parametrize on-the-fly provided that it has access to the study area and the repositories where the raw data is kept. This is one of the major benefits of using LandR over other landscape dynamic simulation models, which often require an impressive amount of work to estimate and compile necessary parameters and inputs in a new study area, or as more or better data become available. Publicly available data were used as much as possible to derive model parameters and inputs, however in some cases privately owned data was used. The second great benefit is that LandR Biomass modules can be plugged to other SpaDES modules to simulate different dynamics or estimate parameters. In this case, we plugged it to modules that parametrized fire ignitions as functions of weather, topography and vegetation composition (i.e. fire fuels; see Fig. 2 and Table A1 Appendix A for module list and description). Finally, being open-source and coded in R opens LandR Biomass to the scrutiny of other experts, makes its development by ecologists easier and allows for greater reusability (Barros et al., *in prep.*).

3.1 SIMULATING VEGETATION DYNAMICS AND RESPONSES TO FIRE

LandR Biomass_core (hereafter Biomass_core) is the core forest succession simulation module and simulates cohort aging, growth, mortality and competition for light resources, as well as seed dispersal (Fig. 3). It was initially a ported version of the LANDIS-II Biomass Succession Extension v.3.2.1 model (LANDIS-II BSE; Scheller & Miranda, 2015), and a few minor model components have since changed: namely, the initialisation of the landscape no longer follows a

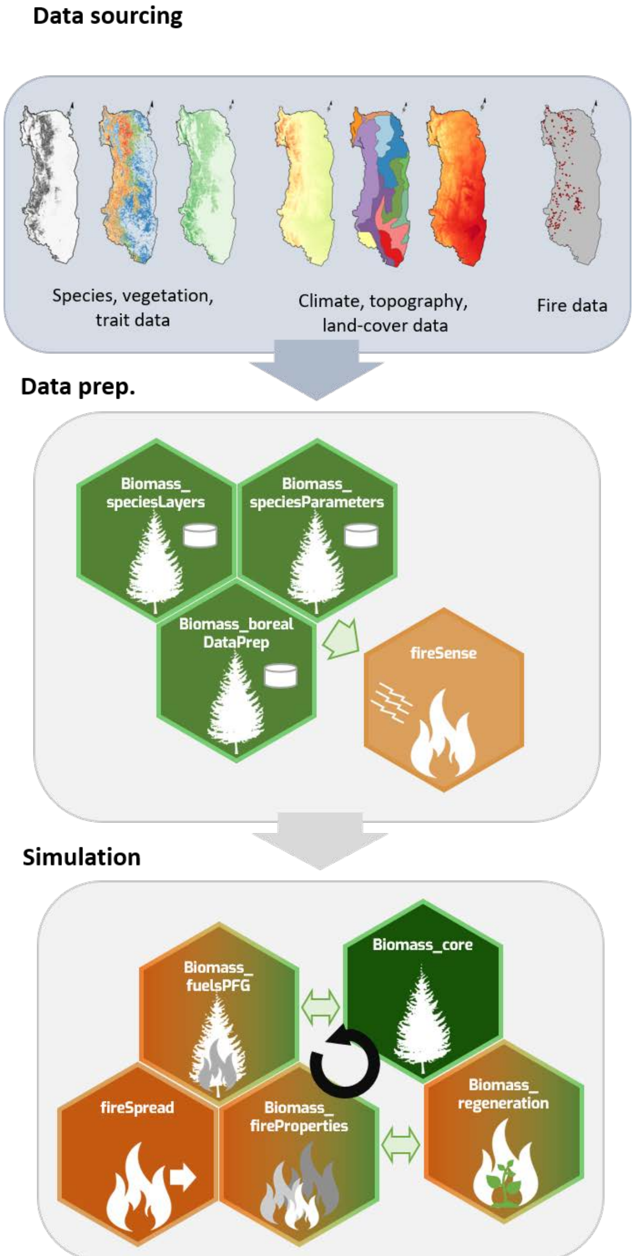

FIGURE 2. LANDR BIOMASS AND OTHER SPADES MODULES USED IN THE SIMULATIONS, AND THEIR GENERAL DATA DEPENDENCIES SHOWN IN THE LIM STUDY AREA.

spin-up phase, but comes fully from data, and some algorithmic changes were made to correct for model bugs and improve speed and efficiency. These changes are presented in detail in Barros et al. (*in prep.*). Nonetheless, the essential functioning of the succession model still largely follows its LANDIS-II counterpart, and we refer the reader to the corresponding LANDIS-II BSE manual (Scheller & Miranda, 2015) for a detailed reading of the mechanisms implemented in the model. LandR Biomass_regeneration (hereafter Biomass_regeneration) is the second module affecting forest succession directly by simulating cohort responses to fire. It also follows the post-fire regeneration mechanisms in LANDIS-II BSE, whereby burnt pixels lose all their cohorts and biomass, and serotiny and resprouting are activated depending on which species (and their ages) were present in the pixel before the fire (Scheller & Miranda, 2015; Fig. 3). An essential difference from LANDIS-II BSE, however, is that we allow serotiny and resprouting to occur in the same pixel (although not for the same species) should they both be activated following a given fire event (in LANDIS-II BSE, resprouting cannot occur in a pixel if serotiny has been activated for any species). We felt that this makes more sense ecologically, as serotinous species like Lodgepole pine can suffer competition from fast-growing resprouters like Trembling aspen (*Populus tremuloides*) following a fire (Johnstone, 2005; Landhäusser *et al.*, 2010). LandR Biomass_regenerationPM (for Partial Mortality; hereafter Biomass_regenerationPM) replaces Biomass_regeneration when simulating mixed-severity fire regimes. It follows the LANDIS-II Dynamic Fire System v3.0 equations to calculate severity (i.e. the level of stand mortality; Sturtevant *et al.*, 2018) and 'kills' cohorts according to the calculated severity level. Briefly, severity is calculated for each burnt pixel in function of three fire behaviour properties: crown fraction burnt (CFB), equilibrium head fire rate of spread (HFI) and critical rate of spread for crowning (RSO) which determine the general 'fire damage'. These properties were calculated by the LandR Biomass_fireProperties module using the Canadian Forest Fire Danger Rating System, *cffdrs*, R package (Wang *et al.*, 2017), in a spatio-temporally varying manner in function of topography, weather and fuel conditions. We varied weather conditions every timestep for every pixel, by randomly sampling a 'typical' fire day (fire weather index, FWI, ≥ 19; Podur and Wotton 2011) from the daily weather data generated for the baseline climate period. Fuel conditions were also updated every time step by the LandR Biomass_fuelsPFG module, which translated pixel species composition into fuel types necessary to estimate fire behaviour properties. Fire damage is then compared against the fire tolerances of the species present in the pixel to determine which of their cohorts (i.e. ages) will be killed, with more tolerant species being more resistant to fire damage at younger ages. Hence, across all species, younger ages are always more susceptible to fire-driven mortality. Besides simulating partial stand mortality, Biomass_regenerationPM also activates serotiny and resprouting mechanisms in the same way as the Biomass_regeneration module. Please see Appendix B for further detail on the assignment of fire fuel types to pixels, the calculation of fire behaviour properties and the calculation of fire damage and fire severity (also in the LANDIS-II Dynamic Fire System manual; Sturtevant *et al.*, 2018).

3.2 Simulating fire

Fire dynamics were simulated as a two-stage process, fire ignition and fire spread. Fire ignition in each pixel depended on the estimated pixel's average number of fires, with reference to fires that occurred in the LIM study area between 1961-1990 (see below on *Parametrizing fire dynamics*). Each year, every pixel was assessed for ignition success by drawing a random number of fires events from a Poisson distribution, using the estimated average number of fires as λ – ignition being a success if the drawn value was ≥ 1.

Once a fire started in a pixel, spread was simulated based on the fire percolation model by Favier (2004), which simulates fire spread between pixels as a function of the probability of spread, p, and the probability of persistence, q. We made both p and q conditional on fire behaviour properties, which varied every time step per pixel (see above). This meant p and q, were both conditional on spatio-temporally varying weather, fuel and topography conditions. Given the limited data on perimeters of naturally caused fires in the LIM study area, an estimation of average fire size was not possible. Hence, ranges of p and q probabilities were calibrated to produce sensible fire sizes and fires spread until they exhausted themselves - this rarely resulted in extremely large fires. Once all fires were spread in any given simulation year, either Biomass_regeneration or Biomass_regenerationPM calculated severity (always equal to 100% mortality with Biomass_regeneration), and activated mortality, serotiny and resprouting in each pixel. See Appendix B for further detail on the calculation of fire ignitions and probabilities p and q, and Appendix C for details on fire weather data.3.3 Parametrizing vegetation dynamics

Inputs for the simulation of vegetation dynamics (happening in Biomass_Core and Biomass_regeneration(PM)) were prepared by a series of modules, involved in retrieving data from public and private repositories, cleaning and reformatting this data and estimating parameters – LandR Biomass_speciesData, Biomass_borealDataPrep and Biomass_speciesParameters. The different data preparation and parametrization steps and modules involved are explained in greater detail in Appendices 2 and 3, but also each module's documentation available online (see Table A1 Appendix A for online module repository URLs). Here, we provide only a brief overview of the steps involved in this parametrization.

Vegetation dynamics were only simulated in pixels with forested land-cover classes, according to the Land Cover Map of Canada 2005 (v1) (Fig. A3, Table A2 Appendix A; see Appendix C for further detail). Other non-forested but vegetated pixels (e.g. shrublands and open grasslands; Table A8 Appendix A; Appendix C) were not included for vegetation dynamics but were included for fire ignition and spread. LandR Biomass requires a number of input parameters to run vegetation dynamics. We divide these into three main categories: i) invariant species traits, ii) spatially varying species traits, and iii) ecolocation-specific parameters. Invariant species traits are spatio-temporally constant for any given species and mostly influence growth, mortality and dispersal dynamics, as well as responses to disturbances (i.e. fire). They were obtained from a combination of published literature, default species trait tables used in LANDIS-II and from our own statistical fitting using LandR Biomass_speciesParameters. LandR Biomass_speciesParameters estimates species-specific growth and mortality curve parameters using permanent sample plot data (see Appendices 2 and 3). Only a few invariant species traits needed to be adjusted "manually" to obtain more realistic successional dynamics in the LIM study area (see Table A3 Appendix A and Appendix C). Spatially varying species traits varied by 'ecolocation', but not through time. Here we define ecolocation as a combination of ecological zone and land-cover class (with ecological zones following the Natural Regions and Subregions of Alberta and land cover following the Land Cover of Canada 2005 v1); Table A2, Fig. A3) that reflects a particular combination of biophysical characteristics and similar growth conditions for a species. Spatially varying species traits were maximum biomass (maxB), maximum aboveground net primary productivity (maxANPP), species establishment probability (SEP) and the probabilities of germination for a given species tolerance and site shade combination. maxB, maxANPP and SEP were estimated from available data on species cover, biomass and age (Table A4 Appendix A and Appendix B). As for the probabilities of germination, these were directly obtained from LANDIS-II parameter values (Table A6 Appendix A). Finally, minimum relative biomass (minRelativeB) is the only ecolocation-specific parameter, meaning that it can only vary across ecolocations. It determines the shade thresholds that result in successful germination of a species given its shade tolerance. In this case, we took the minRelativeB values used in LANDIS-II and lowered them for the higher shade classes (Table A7 Appendix A and Appendix C). This reflects lower shade levels observed in Western Canadian forests with respect to their Eastern counterparts at similar density levels (Messier *et al.*, 1998), likely driven by higher resource (i.e. moisture) limitation in the west (Hogg *et al.*, 2008; Peng *et al.*, 2011). As in the LANDIS-II default input tables, all ecolocations shared the same minRelativeB values. Before estimating any traits/parameters and initialising the landscape (see *Initial conditions* section), we assessed data quality and

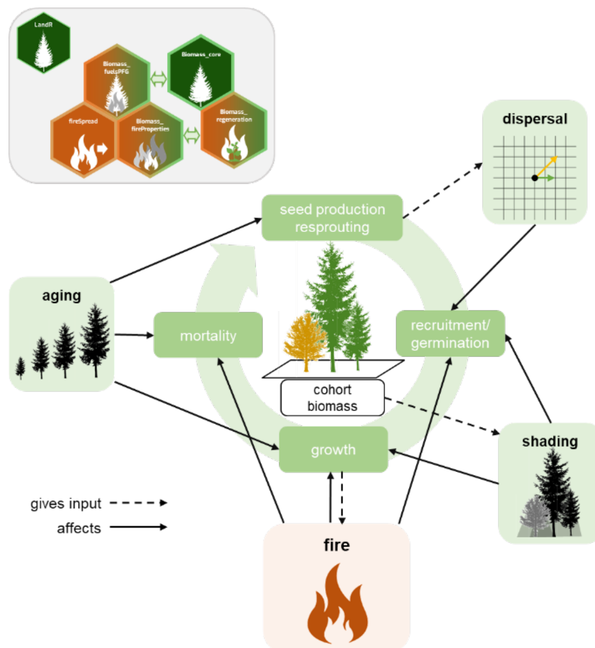

Figure 3. Model scheme of how different components of vegetation and fire dynamics interact with each other in LandR Biomass modules (modules involved shown in the upper left corner).

corrected for any issues. This mostly consisted in finding mismatches between the various datasets and imputing missing data (see Appendix C).

3.4 Parametrizing fire dynamics

Fire ignitions depended on the estimated average number of fires per pixel, which were calculated based on observed data from the climate baseline (i.e. pre-climate change) period between 1961-1990. We followed the approach described in Marchal *et al.* (2017) (implemented in the fireSense_IgnitionFit and fireSense_IgnitionPredict SpaDES modules), and modelled fire occurrences (i.e. presences and absences) as a function of the interaction between weather (July average monthly drought code) and fuel conditions (percent cover of each fire fuel type) during the reference period, using a generalised linear model. This model was then used by fireSense_IgnitionPredict to predict the average number of fires for each pixel across the LIM study area, used throughout the simulation to calculate fire ignitions (see *Simulating fire*; Fig. A6b Appendix A*).*

Fire spread, on the other hand, depended on the probabilities *p* and *q*. To account for the effect of the spatio-temporal variability of fuel and weather on the spread of fire, we made *p* and *q* conditional on pixel-level fire behaviour properties, an approach has also been applied in cellular automata models (Yassemi *et al.*, 2008). We chose three fire behaviour properties: critical spread rate for crowning (RSO), head fire intensity (HFI), and total fuel consumption (TFC), calculated using Biomass_fireProperties in a spatio-temporally varying manner. Although non-forested pixels were not simulated in LandR Biomass, they were considered able to sustain and spread fire between them and to forested pixels. To calculate spread probabilities, *p*, we multiplied ROS and HFI per pixel and rescaled all values above 0 to range between 0.20 and 0.25, in order to obtain sensible fire sizes and perimeters. Persistence probabilities, *q*, were also calculated per pixel by multiplying TFC and HFI and rescaled to values between 0 and 1. The choice of fire behaviour properties and how they translate into percolation probabilities followed our best judgement, due to the lack of fire perimeter data that could be used for a pattern-oriented modelling approach to parametrization. We assumed that 1) higher rates of spread and higher fire intensities will lead to higher probability of passing to a neighbour cell, 2) that the more fuel a fire consumes and the more intensity it has and the longer it burns at a given location, and 3) that these variables affect the probabilities of spread and persistence synergistically, rather than additively. Please see Appendix B for further detail on the estimation of average number of fires, the calculation of fire behaviour properties and of *p* and *q* values. See Appendix C for further detail on topography, fire and weather data.

3.5 Model runs

Initial conditions and simulations

The model was initialised entirely from available data, which was obtained, cleaned and formatted by the Biomass_speciesData and Biomass_borealDataPrep modules (Appendix C). Species cohorts were “seeded” in forested pixels across the landscape by multiplying the observed species % cover in a pixel by the observed stand biomass and assigning the observed stand age. Since we used satellite-derived data on species cover and stand biomass, the allocation of biomass to deciduous species cohorts was adjusted to reflect the fact that broadleaf canopies will typically have higher cover values for the same amount of biomass as coniferous species (see Appendix C for further detail). Each pixel was then initialised with one cohort per species and all cohorts had equal ages.

Simulations were run for 100 years, under two scenarios of post-fire vegetation mortality: stand-replacement (no partial mortality, hereafter 'noPM') *vs.* partial mortality (hereafter 'PM'), both starting under the same initial conditions. Each scenario was run 5 times, which was sufficient to capture the variability of the model coming from stochastic events, such as dispersal, germination, fire ignitions and spread.

3.6 Analysis of results

We analysed the effects of incorporating partial mortality in our model in terms of the vegetation temporal dynamics and spatial patterns, and in terms of the overall responses of particular stand characteristics (namely, age and alpha-diversity – diversity of species in a stand) and landscape characteristics (namely, beta-diversity – heterogeneity of species composition across the landscape). We also assessed which scenario of post-fire mortality, noPM or PM, produced the closest stand age patterns to those observed in the field. Since age field data was collected only in the Montane subregion (Fig. A3a Appendix A) and plots were classified into cover types based on the abundance of species and functional groups of species (hereafter, 'functional cover types'), we subset our simulation outputs to pixels within the Montane subregion and classified them into cover types using the same approach (Appendix D). This subsetting was only applied when comparing the simulated and observed data.

For age analyses we calculated average biomass-weighted ages per species in each pixel (i.e. stand), per type of stand in terms of dominant species (species with the most biomass across cohorts; hereafter 'dominant species cover type'), or per functional cover type. Total biomass was calculated as the sum of cohort biomass per species, or per dominant species cover type. The abundance of different cover types was calculated for both cover type definitions (dominant species cover types and functional cover types) by counting the number of pixels of each cover type across the landscape. Alpha-diversity (α) was calculated using the inverse Simpson concentration metric of species diversity (Whittaker, 1972; Eq. 1), and beta-diversity (β) was calculated using a multiplicative decomposition of gamma- and alpha-diversity, where gamma-diversity (γ) was also calculated as the inverse Simpson concentration (Eq. 2):

$$\gamma/\alpha = \frac{1}{\sum p_{(i)}^2} \qquad \text{[Eq. 1]}$$

$$\beta = \gamma \times \sum\left(\frac{1}{n} \times \frac{1}{\alpha_i}\right) \qquad \text{[Eq. 2]}$$

where *p* is the relative abundance of each species across pixels (for gamma-diversity), or in each pixel *i* (for alpha-diversity), and *n* is the total number of pixels. The inverse Simpson concentration index measures the effective number of species after considering their relative abundance. Alpha and gamma-diversity are then bounded between unity and the maximum number of species; beta-diversity is bounded between unity and the maximum number of pixels (Tuomisto, 2010). Calculations of average age, total biomass, abundance of cover types and diversity metrics were done either across the whole landscape to analyse landscape-level responses, or per pixel to analyse pixel-level (i.e. stand level) responses. In either case, pixels were grouped per scenario, repetition, year, cover type or species, by the presence/absence of fire across the simulation period or by number of fires across the simulation period (both assessed on a pixel basis).

Temporal dynamics and spatial patterns were averaged across repetitions and analysed visually. Spatial patterns were only analysed for the last year of the simulation.

To test the overall responses of particular stand and landscape characteristics to the two scenarios of post-fire mortality, we ran linear mixed effects models (LMEMs) that related average pixel age, pixel alpha-diversity and landscape beta-diversity with scenario at the end of the simulation. The average age ($\overline{age}$) and alpha-diversity models included a random effect of ecolocation on the slopes and intercepts of scenario (Eq. 3); the beta-diversity model accounted for the random effect of ecolocation on the intercepts (Eq. 4).

$$\overline{age}/\alpha \sim scenario + (scenario|ecolocation) \quad \text{[Eq. 3]}$$

$$\beta \sim scenario + (1|ecolocation) \quad \text{[Eq. 4]}$$

All models were run using outputs from the last year of the simulations, with repetitions treated as repeated measures. Models of average age and alpha-diversity were run separately for pixels that did not experience any fire during the simulation and for pixels that experienced at least one fire. The beta-diversity model was run for all pixels together, as we were interested in the effect of scenario on species diversity across the entire study area.

Finally, we compared simulated and observed stand ages for each scenario by visually inspecting mean absolute deviations from average observed ages, and by modelling the effect of scenario on the absolute deviations between simulated and observed ages. In both cases, we subset simulation outputs to the last year of the simulation. The mean absolute deviation (*MAD*) of simulated average age ($\overline{age}_{sim}$) was calculated per cover type (using functional cover types) on a pixel-basis *i*, with respect to the average observed age ($\overline{age}_{obs}$) of each cover type *j* as:

$$\mathrm{MAD_j} = \frac{1}{\mathrm{n}} \times \sum_{\mathrm{i}}^{\mathrm{n}} \left| \overline{age}_{\mathrm{sim_{ij}}} - \overline{age}_{\mathrm{obs_j}} \right| \quad \text{[Eq. 4]}$$

with *n* being the total number of pixels. Calculations were done per combination of scenario, repetition, functional cover type and presence/absence of fire. Absolute deviations between simulated and observed ages (absDev) were also calculated by cover type *j* on a pixel basis (for each combination of scenario, repetition, functional cover type and presence/absence of fire):

$$\mathrm{absDev_{ij}} = \left| \overline{age}_{\mathrm{sim_{ij}}} - \overline{age}_{\mathrm{obs_j}} \right| \quad \text{[Eq. 5]}$$

We evaluated their response to scenario using a LMEM, with functional cover type (coverType) included as a random effect on the intercepts and slopes:

$$absDev \sim scenario + (scenario|coverType) \quad \text{[Eq. 6]}$$

As with the average age and alpha-diversity models, the model was run separately for pixels that experienced no fires during the simulations and for those that had at least one fire.

All LMEMs were fit using the *lmer* function of the *lme4* R package (v1.1.21; Bates *et al.*, 2015) and explained variance was computed using the *r.squaredGLMM* function of the *MuMIn* R package (v1.43.15; Bartoń, 2019) .

4. Results

4.1 Development of an integrated landscape dynamic vegetation model capable of simulating mixed-severity fire regimes

We successfully met the first two objectives of this project concerning the development of an integrated landscape dynamic vegetation model capable of simulating mixed-severity fire regimes (objectives 1a and 1b). Our model explicitly simulates vegetation and fire dynamics, together with variable fire severity (i.e. post-fire mortality), both in space and time. The third objective, concerning model parametrisation, was almost met in full (objective 1c). Initial landscape conditions were based in observed data from the LIM study area, as were the majority of parameters used in the model to simulate vegetation and fire dynamics. In addition, fire ignitions and spread were simulated taking into account baseline fire weather variability (i.e. pre-climate change) in the LIM study area. Unfortunately, due to the limited amount of data on fire perimeters in the LIM study area, we were not able to parameterize or calibrate fire sizes: we used reasonable values derived from our knowledge of similar systems. Visual inspection of the simulated fire perimeters showed that these were of reasonable size and results showed that very few pixels burned more than 4 times during the simulation (roughly corresponding to a pixel-level fire interval of 25 years). Spatially explicit fire severity information was also not sufficiently available in the LIM study area to parameterize or calibrate calculations of fire severity after spreading fires in the model. Hence, we adopted the LANDIS-II Dynamic Fire System v3.0 approach to calculate severity and post-fire biomass removal.

Finally, we compared our simulation outputs with dendroecological data obtained within the LIM Project to assess whether the inclusion of post-fire partial mortality resulted in more realistic outputs. This is discussed below in *Comparisons with observed data* in section 4.2.

4.2 Landscape dynamics with and without partial severity

The last objective of Goal 1 (objective 1d) focused on comparing landscape dynamics and patterns under two scenarios of post-fire mortality: no partial mortality (i.e. stand replacing regime; 'noPM') and partial mortality ('PM'). We have analysed the effects of two scenarios on i) the temporal dynamics across the landscape, ii) the spatial patterns at the end of the simulation and iii) the proximity of simulated ages to observed ages from field dendroecological data. In general, we found no major differences between the noPM and PM scenarios in pixels that suffered no fires throughout the simulation. This indicated that the influence of the degree of post-fire mortality was mostly at the local level (i.e. pixel), with limited influence on surrounding unburnt areas.

4.2.1 Temporal dynamics across the landscape

Our results show that trends in species biomass and average age across the landscape were considerably different between the noPM and PM scenarios, when considering pixels that burned at least once during the simulation. Douglas-fir and fir species saw their total biomass decrease under the noPM scenario, while pine, deciduous species and spruces (White and Engelmann's) either increased or maintained their total biomass across the landscape. This trend was in general reversed under the PM scenario, with the most obvious exception being deciduous species, whose biomass also increased with PM (Fig. 4a). Grouping pixels by the number of fires they suffered during the simulation showed some trend differences. For instance, with noPM, decreases in Douglas-fir biomass were more pronounced and fir species disappeared earlier as fire frequency increased. Also with noPM, pine species shifted from increasing biomass under low fire frequencies to decreasing biomass under very frequent fires. On the other hand, trends with PM were more stable across different fire frequencies, except when they were highest (four fires in 100 years; Fig. 4b). Trends were similar when biomass and average age were calculated across pixels with the same dominant species cover type (Fig. E1 Appendix E). With respect to age, most species saw their average ages decrease under both scenarios and these decreases were steeper across pixels that burned more often (Fig. 5). A clear exception was Douglas-fir, which showed a relatively steady increase in average age with PM across all fire frequencies, albeit less pronounced for the highest number of fires (Fig. 5b). As with biomass, these trends were generally similar to the average stand ages of different dominant species cover types, with the exception of stands dominated by Engelmann's spruce, which did not show a continuous decrease in average age with PM, even under more frequent fires (Fig. E2 Appendix E).

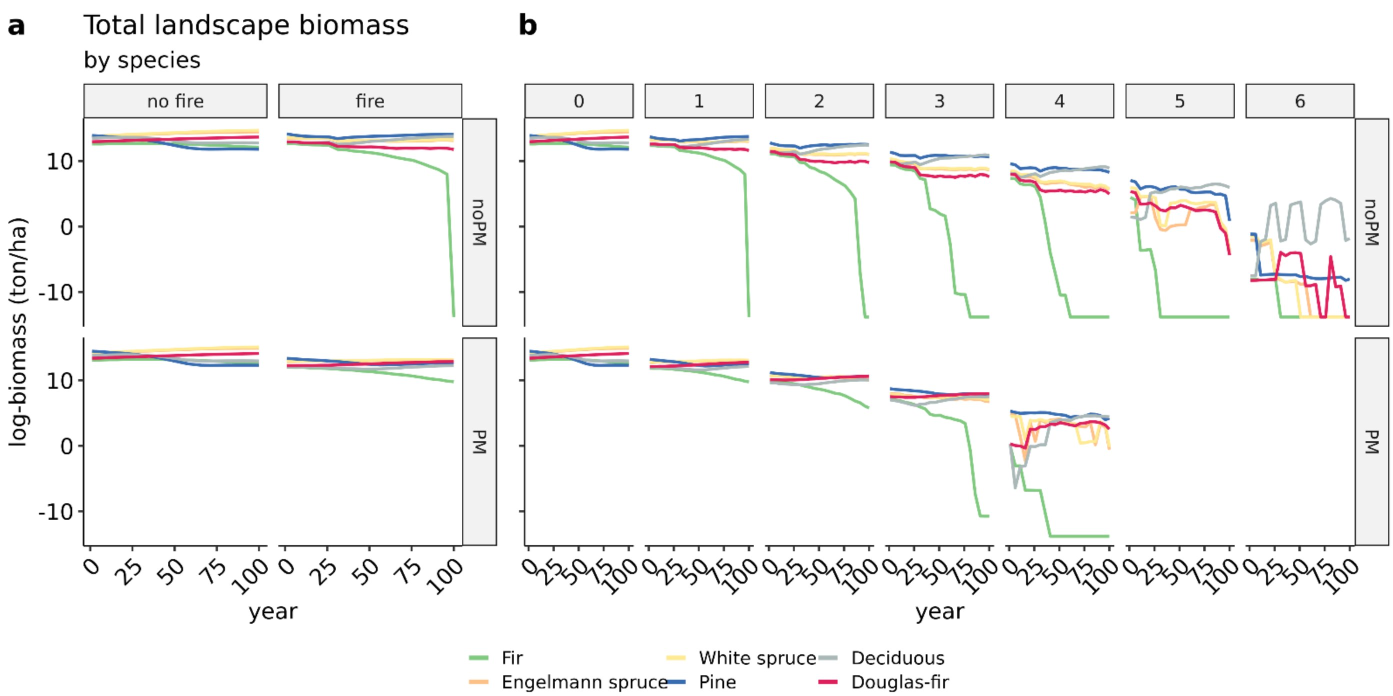

Figure 4. Total species biomass across the landscape. Species biomass was summed across pixels, which were grouped according to a) whether they suffered fires during the simulation or not and b) the number of fires they suffered.

These trends resulted in different degrees of forest heterogeneity across the landscape. Although average pixel-level species diversity (alpha-diversity) was similar for both scenarios and showed a general decrease even when pixels did not burn (Fig. 6a), landscape species diversity (beta-diversity) increased more with PM than with noPM, particularly in pixels that burned (Fig. 6b). This increased landscape heterogeneity was also visible in the relative abundance of pixels with a particular cover type defined by species dominance (dominant species cover type). Under a scenario of PM, different cover types maintained a more even representation across the landscape (Fig. 7). Cover types that quickly became dominant with noPM fires, such as pine-dominated stands, required higher fire frequencies under PM to become as widespread across the landscape. On the other hand, cover types that were lost or almost lost under noPM, such as Engelmann spruce-, fir- and Douglas-fir- dominated stands, were able to persist in the landscape for longer or even increase their abundance, as was the case of Douglas-fir-dominated stands (Fig. 7b). Similar trends were observed for functional cover types (Fig. E3 Appendix E).

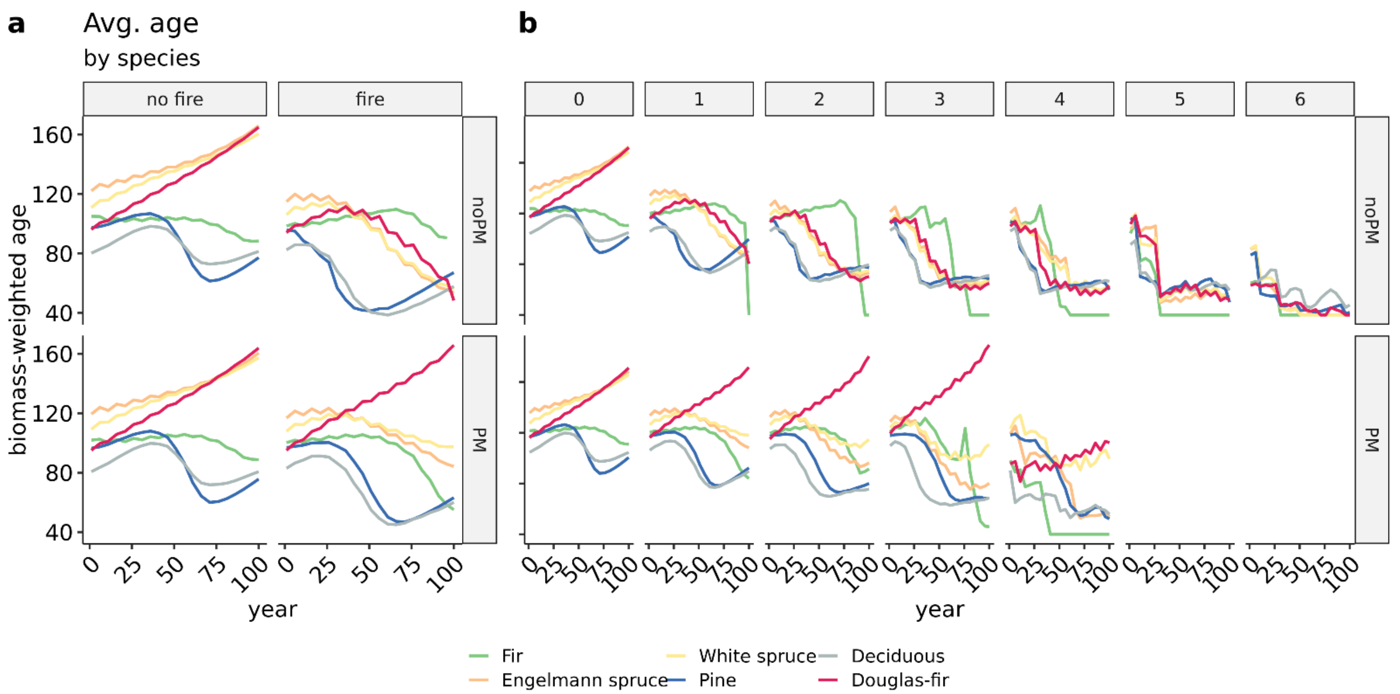

Figure 5. Average species age across the landscape. Age was weighted by cohort biomass and averaged across all cohorts in a pixel, then averaged across pixels grouped according to a) whether they suffered fires during the simulation or not and b) the number of fires they suffered.

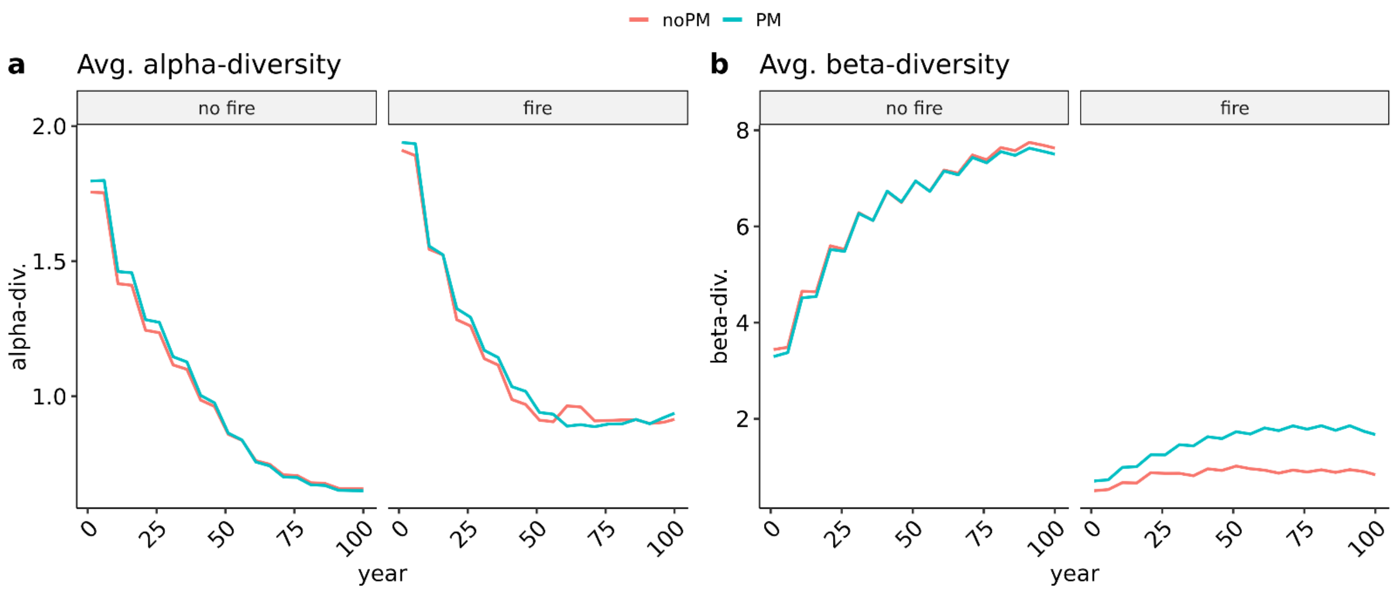

FIGURE 6. STAND AND LANDSCAPE-LEVEL BIODIVERSITY. A) STAND-LEVEL SPECIES DIVERSITY (ALPHA-DIVERSITY) WAS CALCULATED PER PIXEL AS THE INVERSE SIMPSON CONCENTRATION. B) LANDSCAPE-LEVEL SPECIES DIVERSITY (BETA-DIVERSITY) WAS CALCULATED AS THE MULTIPLICATIVE DECOMPOSITION OF ALPHA- AND GAMMA-DIVERSITY, BOTH OF WHICH WERE ALSO CALCULATED AS THE INVERSE SIMPSON CONCENTRATION.

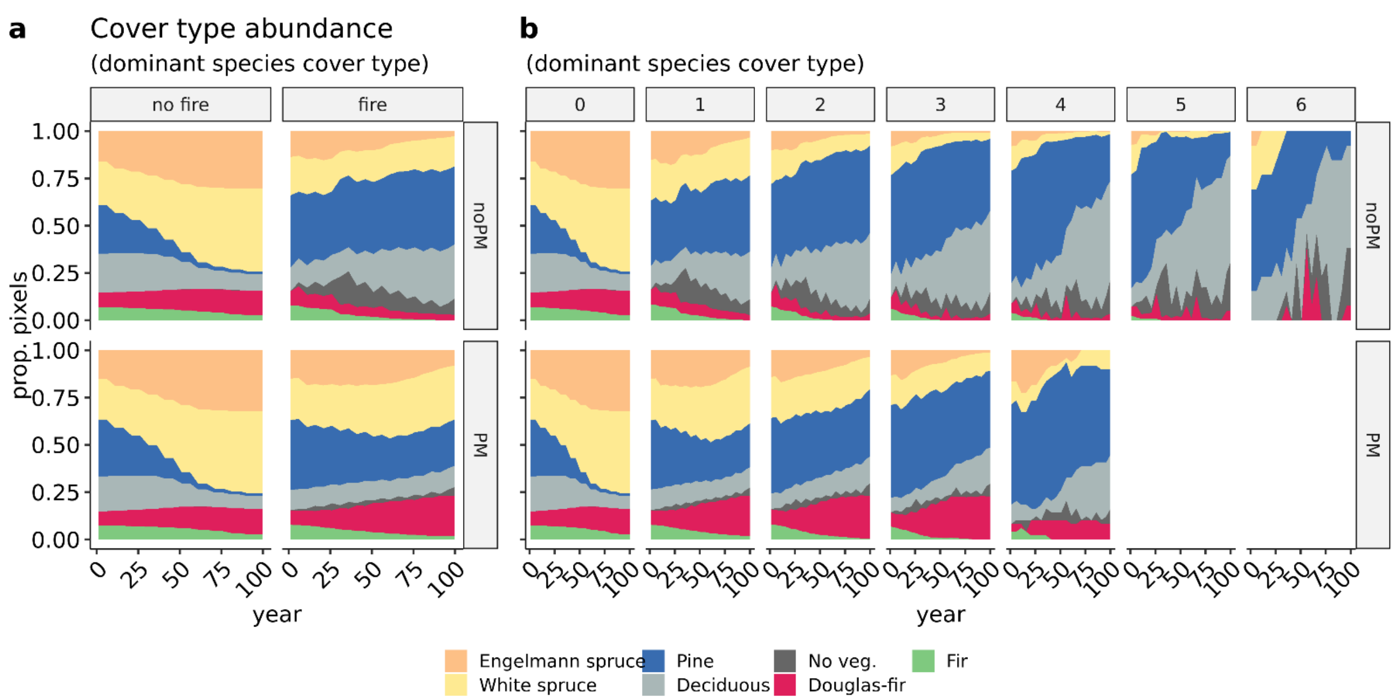

FIGURE 7. RELATIVE ABUNDANCE OF DIFFERENT STAND COVER TYPES ACROSS THE LANDSCAPE. HERE, COVER TYPE IS DEFINED AS THE SPECIES WITH THE HIGHEST BIOMASS IN THE PIXEL (I.E. STAND) – DOMINANT SPECIES COVER TYPE. ABUNDANCES WERE CALCULATED AS NUMBER OF PIXELS OF EACH COVER TYPE, GROUPED BY PIXELS THAT A) SUFFERED FIRES DURING THE SIMULATION OR NOT AND BY B) THE NUMBER OF FIRES THEY SUFFERED.

4.2.2 Landscape spatial patterns

Differences in average spatial patterns were particularly noticeable in the spatial distribution of species dominance (i.e. dominant species cover types). At the end of the simulation with a noPM scenario, the study area was mostly dominated by pine species, followed by White spruce towards higher elevations and more northern areas (Fig. 8a). Under the PM scenario, many of these pine-dominated stands (i.e. pixels) were instead dominated by White spruce and Douglas-fir. As was observed in the temporal trends, cover types that had lower abundance across the landscape with noPM (fir-, Engelmann spruce and Douglas-fir-dominated stands), showed higher abundances with PM (Fig. 8a). Average stand age patterns also changed spatially, with older stands becoming significantly more widespread under the PM scenario, when considering pixels that burned at least once (Figs. 8b and 10a; Table E1 Appendix E).

Conversely, stand species diversity (alpha-diversity) did not show clear spatial differences between the two scenarios at the end of the simulation, despite a general shift towards lower species diversity with PM (Fig. 9), which was driven by unburnt pixels (Fig. 10b; Table E1 Appendix E). In burnt pixels, PM seems to have had a small positive effect on alpha-diversity (Table E1 Appendix E). In contrast, species diversity at the landscape level (i.e. beta-diversity) was higher under the PM scenario across the entire landscape, despite the large variability attributed to different ecolocations (Fig. 10c; Table E1 Appendix E). Although the effects were small across the entire landscape, Figure 6b supports that they are more salient across pixels that were burnt at least once.

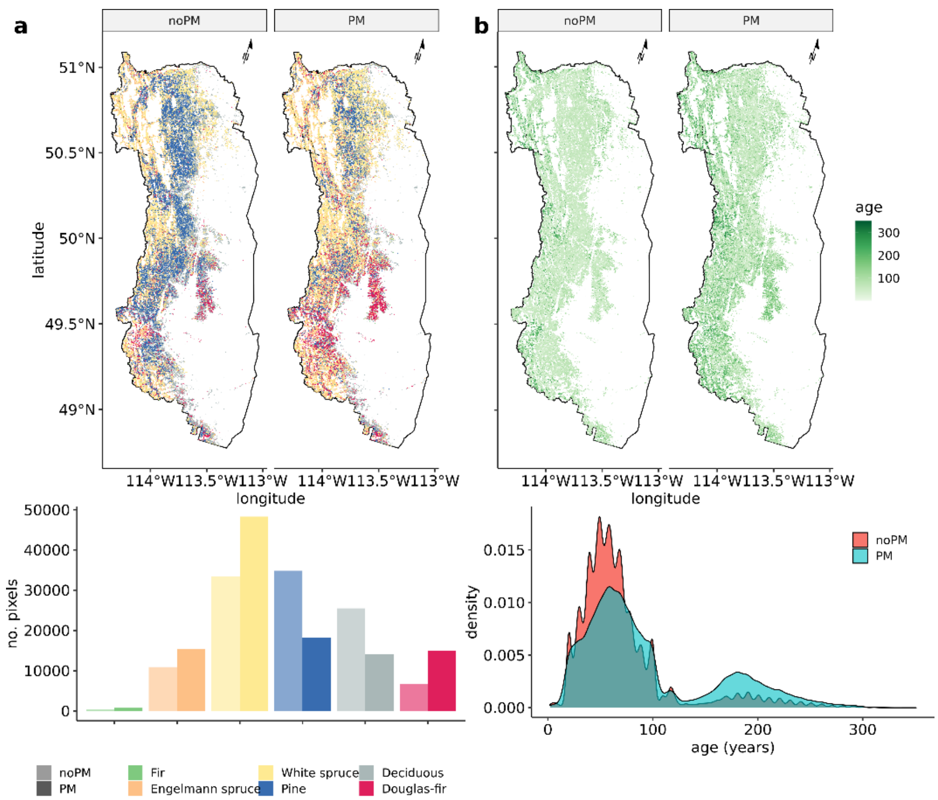

Figure 8. Spatial distribution of a) cover types and b) average age at the end of the simulation under the noPM and PM scenarios. Here, cover type is defined as the species with the highest biomass in the pixel (i.e. stand) – dominant species cover type. Maps show averages across repetitions. For cover types, this meant reclassifying pixels after calculating repetition-wise biomass averages per species.

4.2.3 Comparisons with observed data

The effect of scenario on the differences between simulated and observed average stand (i.e. pixel) ages depended on stand functional cover type (defined in terms of the representation of different species and functional groups of species). A visual analysis of absolute differences between simulated and observed ages showed that the PM scenario led to dramatically smaller mean absolute deviations in Douglas-fir, spruce, with marginally smaller deviations in mixed and dry conifer/Douglas-fir stands in the Montane subregion; in pine stands, moist conifer and deciduous stands it led to marginally larger differences in average (Fig. 11a). Thus, the largest changes were *improvements* in the fit to observed data. These differences amongst stand cover type were also apparent in the ca. 52% explained variability attributed to the random effect of cover type in the LMEM run for pixels with fires (Table E1 Appendix E). Furthermore, model results showed that despite the low explained variance attributed to scenario alone, the PM scenario led to smaller differences between simulated and observed ages across cover types (Fig. 11b; Table E1 Appendix E).

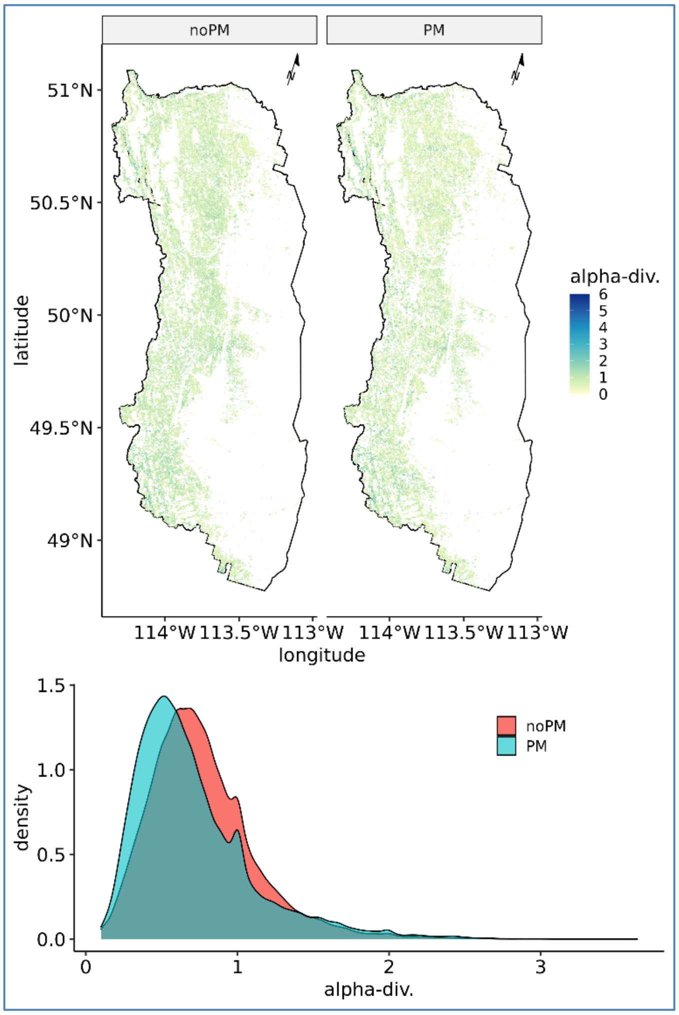

FIGURE 9. SPATIAL DISTRIBUTION OF STAND SPECIES DIVERSITY (ALPHA-DIVERSITY) AT THE END OF THE SIMULATION UNDER THE NOPM AND PM SCENARIOS. MAP SHOWS AVERAGES ACROSS REPETITIONS.

4.3 Model development in a reusable, interoperable and continuous workflow

The second main goal of this project was to develop our model within a reusable, flexible, interoperable and continuous workflow using *SpaDES* (objective 2a). In addition, *SpaDES* modules had to be hosted in a transparent and collaborative platform (objective 2b). Both of these objectives were fully met. Our model is entirely composed of *SpaDES* modules, which automatically download, treat and prepare data available from public or private sources, prepare parameters on-the-fly using these data for statistically-derived parameterization (otherwise parameters are mostly created by the modules and/or have default values available), run simulations, and output results for posterior analyses. All modules are hosted on the GitHub platform (an online collaborative and transparent platform) in publicly available repositories, with the exception of fireSense_dataPrep and fireWeather that have private repositories. The model used in this work (i.e. the combination of modules and scripts to prepare and run simulations), together with scripts containing analyses of results and visual outputs, is also hosted on a dedicated GitHub repository (https://github.com/CeresBarros/LandscapesInMotion). This repository will be kept private until the submission and publication of manuscripts and of this report. However, any parties involved in the Landscapes In Motion Project who wish to access the repository will be granted permission to do so, together with the access to any data that we privately host (e.g. daily weather data, shapefiles of the study area, etc.).

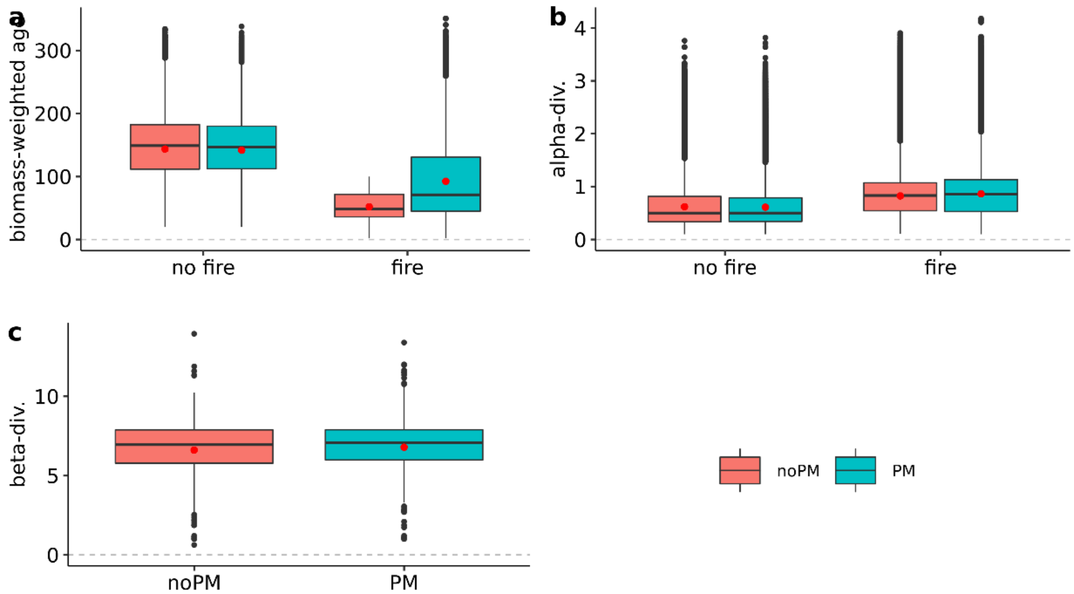

Figure 10. Effect of scenario on a) average stand age, b) stand species diversity (alpha-diversity) and c) landscape diversity (beta-diversity). Boxplots show the distribution of the data used to fit LMEMs models, while red dots are the average values predicted by the models accounting for random effects (see Table E1 Appendix E for model results).

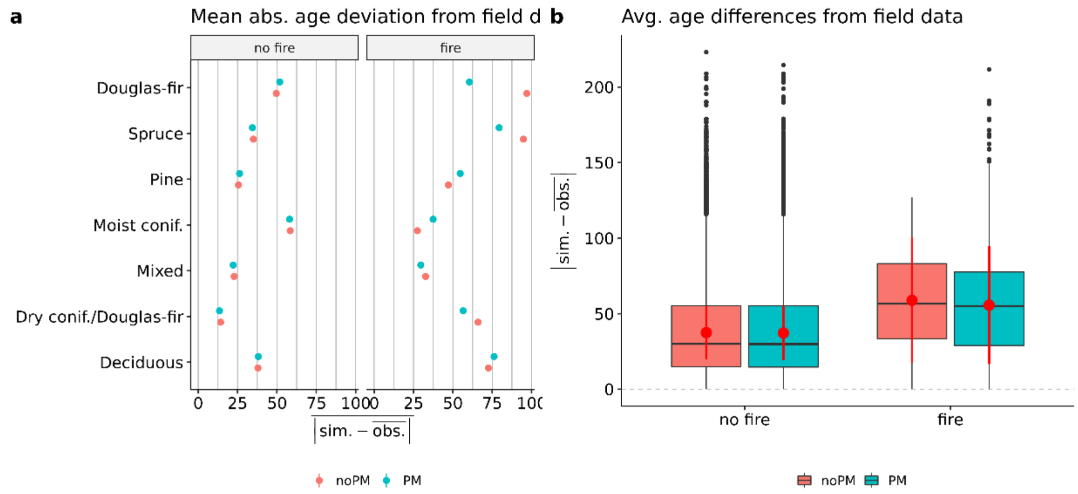

Figure 11. Comparisons between simulated and observed ages in the Montane subregion. Plot a) shows mean absolute age deviations between simulated stand (i.e. pixel) average age and the average observed age across stands, per cover type. Boxplots in b) show the distributions of absolute differences used to fit LMEMs models, with red dots showing the average values predicted by the models accounting for random effects (see Table E1 Appendix E for model results). Here, cover type is defined as the as a combination of species and functional groups of species in the pixel (i.e. stand) – functional species cover type (Appendix D).

5. Implications

With stand-replacing fires regimes having been widely assumed to be the norm across Canadian forests, the incorporation of mixed-severity fire regimes to model Canadian landscape vegetation dynamics is still not widespread (but see Sirois *et al.*, 1994; De Groot *et al.*, 2003; Sturtevant *et al.*, 2009; Miquelajauregui *et al.*, 2019; Marchal *et al.*, 2020). Instead, several models have assumed stand replacing fires and/or no feedbacks between vegetation and fire (Flannigan *et al.*, 2001; Hély *et al.*, 2001; e.g. Bond-Lamberty *et al.*, 2007; Krawchuk *et al.*, 2009; Hessl, 2011; Wang *et al.*, 2016; Stralberg *et al.*, 2018). Yet, the importance of fire-vegetation feedbacks for forest succession, fire regimes and, ultimately, forest resilience has been recognised by many (Halofsky *et al.*, 2011; Girardin *et al.*, 2013; Terrier *et al.*, 2013; Marchal *et al.*, 2020). Here, we present a first attempt at parameterizing and running a landscape dynamic vegetation model in the SW Foothills of Alberta while taking into account mixed-severity fire regimes, via the incorporation of climate-fire-vegetation feedbacks in a spatio-temporal dynamic way. *We do not intend to make predictions about future landscape dynamics in the SW Foothills of Alberta, nor to reconstruct past fire regimes in this area.* Yet, as highlighted in sections 4.1 and 4.3, we were largely successful in achieving our goals and believe that the model presented here can be used in for future predictions and/or the reconstruction of past fire regimes, provided that additional data is available to fill in the parameterization gaps we encountered (see section 6.).

Even if our goal was not centred around prediction, the results we presented here can have important implications for our understanding of how mixed-severity fire regimes may impact biodiversity and forest structure at the landscape and local (i.e. stand) levels. Like Miller & Urban (1999), our results also showed higher levels of stand stand-level diversity (measured as alpha-diversity) in pixels that burned vs. pixels that did not burn (Fig. 10c).

However, stand-level diversity did not appear to change significantly between the two scenarios of post-fire mortality. Conversely, simulations with post-fire partial mortality led to an overall higher tree species diversity across the landscape in the form of higher heterogeneity between patches (measured by beta-diversity; Fig. 6), to higher diversity of different stand cover types across the landscape (Fig. 8a), and to older stand ages being more widespread (Fig. 8b). Increases in landscape heterogeneity with mixed-severity fire regimes have been also observed across forested landscapes in Canada (Burton *et al.*, 2008) and the US (Halofsky *et al.*, 2011), and can have important consequences for biodiversity and landscape resilience to other disturbances such as pest outbreaks (Hood *et al.*, 2016). On the other hand, spatially heterogeneous severity can foster higher biodiversity not only in terms of forest structure and composition, but also for animal communities (Kelly & Brotons, 2017), by creating a wider variety of habitats (Tingley *et al.*, 2016; DellaSala *et al.*, 2017). Additionally, our simulations with post-fire partial mortality resulted in a higher number of Douglas-fir- and spruce-dominated stands, the latter of which has been shown to be important habitat for Grizzly bear (*Ursus arctos*; Ciarniello *et al.*, 2007). The landscape-wide increase in forest age can also have consequences for biodiversity by itself, as old-growth forests are known to provide habitat and resources for several plant (Dittrich *et al.*, 2014) and animal species, such as caribou (Dalerum *et al.*, 2007; Hins *et al.*, 2009) and several species of birds (Schieck *et al.*, 2000). Comparing our model with dendroecological data sampled in the Montane subregion of the LIM study area showed that accounting for post-fire partial mortality led to stand ages that were closer to what is observed in the field. This was especially true in Douglas-fir-dominated stands, but also spruce-dominated stands. This is an important finding, as it suggests that the assumption of stand-replacing fires in these forests is not adequate, and accounting for post-fire partial mortality when modelling forest dynamics in the region produces realistic more consistent with observations.

Accounting for partial survival also changes how patch dynamics are simulated and arise in the landscape. If only stand-replacing fires are assumed, spatially heterogenous fire severity can only arise under relatively fine spatial scales. From a modelling perspective, this leads to computationally heavy simulations that are hard to run at large spatial scales. If post-fire partial mortality is allowed, then patch survival can be simulated at coarser scales and across larger areas, as we have done here. Patch survival is also extremely important when considering both post-fire vegetation dynamics and how fauna recolonizes the landscape after a fire. Fires with higher levels of surviving patches are revegetated faster and recolonized faster by fauna. Low to medium severity patches (i.e. with surviving vegetation) can sometimes have higher conifer seedling densities than high severity patches (i.e. almost no survivors; Crotteau *et al.*, 2013), dependent on surrounding forests. In addition, low to medium severity patches can provide habitat for recolonizing fauna after fire, such as the Canada lynx (*Lynx canadensis*; Vanbianchi *et al.*, 2017) and the fisher (*Pekania pennant*; Blomdahl *et al.*, 2019). Surviving patches could also influence vegetation dynamics at larger scales by providing seed sources to high severity patches that lost their seed bank (Turner *et al.*, 1994; Halofsky *et al.*, 2011).

In our simulations, we saw virtually no effect of post-fire mortality scenario on the dynamics and properties of non-burnt pixels, indicating that the influence of post-fire survival was either mostly at the local level (i.e. burnt pixel), or amongst burnt neighbours. This is in part due to the relationship between the spatial scale of the simulation and the average dispersal distances of the simulated species. All species' average dispersal distances were shorter than pixel size (250 x 250m) and only *Populus* species had a maximum dispersal distance that was large enough for seeds to significantly travel across pixels. Being seed dispersal the only interaction between pixels in terms of vegetation dynamics, this meant that accounting for surviving vegetation at this spatial scale has a small effect on neighbouring pixels. It will be interesting to evaluate how this may change at smaller pixel resolutions. This pattern is also affected by the fact that the spreading of fires in our project was not dependent on vegetation, as we were unable to estimate these parameters (though see Marchal et al 2020 for a possible approach). In addition, most species were relatively shade intolerant, which meant that dispersing seeds would have low probability of germination in unburnt pixels that have an intact canopy. Another reason why unburnt pixels may not have shown differences between scenarios comes from the relative small proportion of burnt pixels in the landscape. In this case, the two scenarios were affecting only a small proportion of the landscape, meaning that spill-over effects are hard to detect (Fig. E4 Appendix E).

Finally, our work and findings can not only impact future model predictions for this landscape, but also landscape planning and management. Considering post-fire partial mortality raises new challenges when it comes to the complexity of post-fire dynamics (Burton *et al.*, 2008; Miquelajauregui *et al.*, 2016), the role of scale and edge effects (Burton *et al.*, 2008) and our expectation of with regards to the prevalence of old-growth forests across the landscape. If, as the LIM project suggests, natural disturbance regimes in this region are composed of a mixed-severity fire regime and landscape management in the area attempts to follow Ecosystem Based Management principles, there may need to be changes to how these landscapes are managed and perceived.

6. Next steps

6.1 Statistically-driven fire severity estimates

We did not attempt to estimate spatially-explicit fire severity parameters nor did we calibrate fire severity after spreading fires in the model. Although a statistically driven fire severity model would have been ideal, we believe that using the Fire Behaviour Prediction (FBP) system to calculate fire properties and translating these into fire severity categories as in the LANDIS-II Dynamic Fire System v3.0 extension was an adequate approach. The FBP system is widely used for operational purposes and rests on solid evidence and expertise of fire behaviour and physics, while the LANDIS-II Dynamic Fire System extension has been thoroughly tested and used by others to simulate interactions between weather, fuels and fire severity (Flatley & Fulé, 2016; Cassell *et al.*, 2019). Nonetheless, our goal is to be able to derive parameters from observed data as much as possible. Hence, our team is currently developing a statistical model of fire severity using available severity data from outside the LIM study area. This model will allow predicting fire severity (i.e. stand level post-fire mortality) directly from stand structure and composition, weather and topography without the need to pass by the FBP system. The FBP system has been designed for particular forest types in Canada, many of which already did not have a direct correspondence to forest types in the LIM study area. The advantage in predicting severity directly from landscape covariates is then to enhance the scalability and transferability of the model. Provided that there is sufficient data to re-fit the model at a different scale or in another location, and that the covariates are the same (or a new model structure is fit), severity can be predicted and we can attribute a degree of confidence to those predictions.

Alternatively, fire severity could be estimated from statistical models built using dendroecological records collected for the dendroecological fire regime analysis component of the LIM Project (Naficy and Daniels 2020). The severity of a given fire is expected to be related with time since the last fire and the severity of the previous fire (Collins *et al.*, 2007; Parks *et al.*, 2014), and this relationship can be used in a simulation context to estimate the severity of a given fire. We are currently participating in a project led by Dr C. Naficy that will attempt to develop a statistical model relating fire severity with time since fire, severity of the previous fire and, potentially, other covariates such as drought index. This project is still in its infancy, but paves the avenue for another statistically-driven approach to estimate severity in our simulation model.

6.2 Historical fire ignitions and frequency

We parameterized pixel-level frequency of fire ignitions using fire point data spanning the baseline climate period (1961-1990). We are aware that pre-industrial (pre-1940s) fire ignition patterns in the region may have been different. To use our model to reconstruct historical fire patterns, pre-industrial fire records would probably be more appropriate for parameterization. Hence, a next step would be to incorporate fire occurrence data collected for the dendroecological fire regime analysis component of the LIM Project. Nonetheless, the pixel-level fire frequencies generated by our model were in-line with evidence coming from the existing dendroecological analyses of fire regime in the LIM study area (Naficy and Daniels 2020). Our simulations generated a maximum of 6 fires per pixel ($\approx$16 years fire interval) under the noPM scenario and a maximum of 4 fires per pixel (25 years fire interval) under the PM scenario. These estimates are well within the distribution of observed fire intervals, whose medians vary between $\approx$20 and $\approx$40 years, depending on the cover type (Naficy and Daniels 2020) REF CAMERON'S REPORT).

6.3 Fire spread calibration and parameterization

The percolation model we used to spread fires across the landscape depends on the probabilities of spread, p, and persistence, q (Favier, 2004). We made these probabilities conditional on fire behaviour properties, but the relationship between p/q and fire behaviour properties was not statistically estimated from data. Instead we used a visual evaluation of generated fire sizes to scale p/q. A more adequate approach would be to use pattern-oriented modelling (POM) to calibrate the effects of fire behaviour properties on p/q. This could be achieved by comparing fire perimeters simulated under different effects of fire behaviour properties on p/q with observed fire perimeters. At each iteration (i.e. comparison) the POM algorithm would adjust the effects of fire behaviour properties to obtain a closer match between simulated and observed perimeters. Unfortunately, as already mentioned, there is limited data on fire perimeters in the study area and it is likely that this approach would require pulling in data from other locations. Alternatively, the FireSense model has components of fire ignitions, escapes, and percolation (fireSense_IgnitionFit, fireSense_IgnitionPredict, fireSense_EscapeFit, fireSense_EscapePredict, fireSense_SpreadFit, fireSense_SpreadPredict) that could be used to estimate and simulate fire spread and replace Favier's fire percolation model. Like the POM approach, FireSense requires more data on fire perimeters than what is currently available for the LIM study area, so data from other areas would need to be included.

6.4 Future projections

Finally, we believe that an obvious next step to this work will be to project landscape vegetation (and fire) dynamics under different scenarios of climate change. The different modelling pieces necessary to do so are already in place. The SpaDES module LandR.CS (not used here) simulates climate effects on vegetation growth and mortality, and the fire components used in this project are all climate sensitive. Hence, simulating future climate change effects would mostly require gathering the appropriate climate projections data.

Appendix A: Supplementary tables and figures

Table A1. LandR Biomass modules and other SpaDES modules used in the simulations and their corresponding repositories.

	Module name	Description	Repository URL
Data prep. and parametrization modules	LandR Biomass_borealDataPrep	Prepares multiple inputs and parameters used by Biomass_core; customized for Western Canadian boreal and montane forests.	https://github.com/PredictiveEcology/Biomass_borealDataPrep
	LandR Biomass_speciesParameters	Estimates invariant species traits (growth and mortality-related life-history traits) and adjusts spatially varying species traits (*maxB* and *maxANPP)* used by Biomass_core from permanent sample plot data	https://github.com/PredictiveEcology/Biomass_speciesParameters.git
	LandR fireWeather	Prepares and summarizes weather data into raster layers used by LandR Biomass_fireProperties and by	https://github.com/CeresBarros/fireWeather

		fireSense_DataPrep.	
	fireSense_DataPrep	An accessory module to FireSense that prepares fire, weather and fuel data for the statistical fire models	https://github.com/CeresBarros/fireSense_dataPrep
	FireSense (fireSense_IgnitionFit and fireSense_IgnitionPredict)	Fits a fire frequency model (i.e. fire ignition probability) which is then used to predict fire frequencies across the landscape under changing conditions of covariates.	https://github.com/PredictiveEcology/fireSense_IgnitionFit https://github.com/PredictiveEcology/fireSense_IgnitionPredict
Vegetation and fire simulation modules	LandR Biomass_speciesData	Prepares species input layers from multiple data sources.	https://github.com/PredictiveEcology/Biomass_speciesData
	LandR Biomass_core	Simulates vegetation growth, mortality, aging, and dispersal. Updates biomass following other modules' events, and produces summary figures and tables.	https://github.com/PredictiveEcology/Biomass_core

LandR Biomass_regeneration	Simulates post-disturbance (fire) biomass regeneration assuming 100% post-disturbance mortality	https://github.com/PredictiveEcology/Biomass_regeneration
LandR Biomass_regenerationPM	Simulates post-disturbance (fire) biomass regeneration assuming partial mortality (PM) following a disturbance	https://github.com/PredictiveEcology/Biomass_regenerationPM
LandR Biomass_fuelsPFG	Converts cohort biomasses generated by LandR Biomass_core into fire fuels, using fuel type classification from Canadian Forest Fire Behaviour Prediction System, adapted to the study area forest systems.	https://github.com/PredictiveEcology/ Biomass_fuelsPFG
LandR Biomass_fireProperties	Calculates fire (behaviour) properties in function of vegetation (fuels), climate and topography conditions, using the Canadian Forest	https://github.com/PredictiveEcology/Biomass_fireProperties

	Fire Behaviour Prediction System.	
LandR fireSpread	Ignites and spreads fire in function of fire behaviour properties calculated by Biomass_fireProperties. Spreading follows the fire percolation model by Favier (2004)	https://github.com/CeresBarros/LandscapesInMotion/tree/master/R/SpaDES/m/fireSpread

Table A2. Data used to parametrize vegetation and fire dynamics.

	Data used for	Data type	Data source(s)
Species % cover	– initialising species in the landscape (location and biomass) – estimating spatially varying species traits	Spatial raster layers	In increasing order of data quality: National Forest Inventory, Natural Resources Canada, Canadian Forest Service (Beaudoin et al. 2017); https://open.canada.ca/data/en/dataset/ec9e2659-1c29-4ddb-87a2-6aced147a990) CASFRI v4 (2016; Cosco 2011) Pickell Forest Resource Inventory (LandWeb project partners, prepared by Silvacom)
Stand age, stand biomass	– initialising species in the landscape (age and biomass) – estimating spatially varying species traits	Spatial raster layers	National Forest Inventory, Natural Resources Canada, Canadian Forest Service (Beaudoin et al. 2017); https://open.canada.ca/data/en/dataset/ec9e2659-1c29-4ddb-87a2-6aced147a990)
Ecological zonation	– defining ecolocations (by combining with land cover) – estimating spatially varying species traits	Spatial polygons layer	Natural Regions and Subregion of Alberta (https://www.albertaparks.ca/media/429607/natural_regions_subregions_of_alberta.zip)
Land cover	– defining ecolocations (combined with ecological zonation) – estimating spatially varying species traits	Spatial raster layers	Land Cover of Canada 2005 (v1), Canada Centre for Remote Sensing (CCRS), Earth Sciences Sector, NRCan (ftp://ftp.ccrs.nrcan.gc.ca/ad/NLCCLandCover/LandcoverCanada2005_250m/LandCoverOfCanada2005_V1_4.zip)

Elevation, aspect, slope	– calculation of fire behaviour properties	Spatial raster layers	Derived from a digital elevation model (DEM) raster layer covering the study area (https://open.canada.ca/data/en/dataset/7f245e4d-76c2-4caa-951a-45d1d2051333)
Permanent sample plot data	– estimating/adjusting invariant species traits	Tables	Proprietary provincial data.
Simulated species growth curves	– estimating invariant species traits (growth and mortality curve parameters) – adjusting and estimating spatially varying species traits (adjusting maxB and estimating maxANPP)	Tables	NA
Invariant species traits, ecolocation-specific parameters		Tables	Dominic Cyr's LANDIS-II traits (https://raw.githubusercontent.com/dcyr/LANDIS-II_IA_generalUseFiles/master/speciesTraits.csv) LANDIS-II default inputs (https://raw.githubusercontent.com/LANDIS-II-Foundation/Extensions-Succession/master/biomass-succession-archive/trunk/tests/v6.0-2.0/biomass-succession-dynamic-inputs_test.txt and https://github.com/LANDIS-II-Foundation/Extensions-Succession-Archive/blob/master/biomass-succession-archive/trunk/tests/v6.0-2.0/biomass-succession_test.txt)
Weather data	– estimating average number of fires per pixel – calculating fire behaviour properties during the simulation	Table	BioSIM-generated daily weather (Jan. 1st 1961 to Dec. 31st 1990), using Canada-US climate normals 1961-1990 (ftp://ftp.cfl.scf.rncan.gc.ca/regniere/Data11/Weather/Normals/past/Canada-USA_1961-1990.zip)

Fire locations	– estimating average number of fires per pixel	Spatial points layer	Canadian Wildland Fire Information System database, National Fire Database fire point data (Canadian Forest Service) (https://cwfis.cfs.nrcan.gc.ca/datamart/datarequest/nfdbpnt)

Table A3. Invariant species traits. List of species trait values that are spatio-temporally constant. Most trait values were obtained from Dominic Cyr's publicly available LANDIS-II species trait tables (Table A2). Longevity values were adjusted following Burton and Cumming (Burton & Cumming, 1995) **and shade tolerance (shadetolerance) values were lowered to obtain a more realistic recruitment pattern. Mortality (mortalityshape) and growth curve parameters (growthcurve), and the adjustment factor for maxANPP (mANPPproportion) were estimated from data where possible using LandR Biomass_speciesParameters, otherwise the default LANDIS-II values were kept. In this case, *P. engelmannii*, *P. glauca* and *Pseudotsuga menziesii* had enough data for the estimation of these parameters. maxB (an asymptotic parameter) was rescaled so that species could achieve the maximum biomass observed in the field during the simulation. See Appendix B and 3 for further detail on parameter estimation.**

species	longevity	sexual mature	shade tolerance	fire tolerance	post-fire regen.	resprout prob.	resprout age min.	resprout age max.	seed distance eff.	seed distance max.	mortality shape	growth curve	mANPP proportion
Abie_sp	200	20	2.3	1	none	0.0	0.0	0	25	100	15	0.0	3.33
Pice_eng	460	30	2.1	2	none	0.0	0.0	0	30	250	15	0.5	3.00
Pice_gla	400	30	1.6	2	none	0.0	0.0	0	100	303	15	0.5	3.25
Pinu_sp	150	15	1.0	2	serotiny	0.0	0.0	0	30	100	15	0.0	3.33
Popu_sp	140	20	1.0	1	resprout	0.5	10	70	200	5000	25	0.0	3.33
Pseu_men	525	25	2.0	3	none	0.0	0.0	0	100	500	15	0.5	0.75

Table A4. Spatially varying species traits. Species establishment probability (SEP), maximum biomass (maxB) and maximum aboveground net primary productivity (maxANPP) varied across species and by ecolocation. Ecolocations were defined as the combination of ecological zone (digits before "_") and land-cover (the digits after "_"), where the Natural Regions and Subregions of Alberta were used as ecological zones and land-cover followed the Land Cover Map of Canada 2005 (Fig. A3). For *Picea engelmannii*, *P. glauca* and *Pseudotsuga* menziesii, maxB and maxANPP were adjusted using the adjustment factors estimated by LandR Biomass_speciesParameters (see Table A3 and Appendix B). Species' mean trait values and 95% confidence intervals across ecolocations are shown in Table A##.

ecolocation	speciesCode	SEP	maxB	maxANPP
1_03	Abie_sp	1.000	8567	285
1_09	Abie_sp	0.112	1499	50
1_10	Abie_sp	0.955	10835	361
1_11	Abie_sp	0.504	8075	269
1_12	Abie_sp	0.202	3806	127
1_13	Abie_sp	0.498	6984	233
1_14	Abie_sp	0.725	6873	229
1_15	Abie_sp	0.361	9963	332
2_09	Abie_sp	0.737	3637	121
2_36	Abie_sp	0.183	2689	90
3_03	Abie_sp	0.194	11244	374
3_04	Abie_sp	0.476	10225	340
3_10	Abie_sp	0.072	8533	284
3_11	Abie_sp	0.032	7745	258
3_12	Abie_sp	0.007	7069	235
3_13	Abie_sp	0.098	7962	265
3_15	Abie_sp	0.096	8438	281
4_01	Abie_sp	1.000	7840	261
4_02	Abie_sp	1.000	7035	234
4_03	Abie_sp	1.000	9283	309
4_04	Abie_sp	1.000	7460	248
4_05	Abie_sp	1.000	7959	265
4_06	Abie_sp	1.000	6544	218
4_07	Abie_sp	0.999	4492	150
4_08	Abie_sp	0.981	3176	106
4_09	Abie_sp	0.895	2566	85
4_10	Abie_sp	0.982	4683	156
4_11	Abie_sp	0.983	4744	158
4_12	Abie_sp	0.982	3706	123
4_13	Abie_sp	0.998	2858	95
4_14	Abie_sp	0.995	5161	172
4_15	Abie_sp	0.987	4009	133
5_01	Abie_sp	0.949	11658	388

5_02	Abie_sp	0.932	9130	304
5_03	Abie_sp	0.945	9252	308
5_04	Abie_sp	0.921	8303	276
5_05	Abie_sp	0.921	10316	344
5_06	Abie_sp	0.925	10316	344
5_07	Abie_sp	0.896	9057	302
5_08	Abie_sp	0.654	6544	218
5_09	Abie_sp	0.887	8138	271
5_10	Abie_sp	0.799	7895	263
5_11	Abie_sp	0.711	7180	239
5_12	Abie_sp	0.746	5564	185
5_13	Abie_sp	0.762	7984	266
5_14	Abie_sp	0.960	7792	259
5_15	Abie_sp	0.988	7144	238
6_01	Abie_sp	0.986	10272	342
6_02	Abie_sp	0.992	9125	304
6_03	Abie_sp	0.988	8756	292
6_04	Abie_sp	0.994	7286	243
6_05	Abie_sp	0.966	9767	325
6_06	Abie_sp	0.963	9011	300
6_07	Abie_sp	0.994	6980	232
6_08	Abie_sp	0.981	5958	198
6_09	Abie_sp	0.967	5799	193
6_10	Abie_sp	0.983	6348	211
6_11	Abie_sp	0.985	5078	169
6_12	Abie_sp	0.974	6005	200
6_13	Abie_sp	0.993	6527	217
6_14	Abie_sp	0.990	6967	232
6_15	Abie_sp	0.959	6693	223
1_01	Popu_sp	0.589	3344	111
1_02	Popu_sp	0.396	5880	196
1_03	Popu_sp	0.737	8794	293
1_07	Popu_sp	0.749	3717	124
1_09	Popu_sp	0.607	3292	110
1_10	Popu_sp	0.737	10436	348
1_11	Popu_sp	0.736	8629	287
1_12	Popu_sp	0.691	5377	179
1_13	Popu_sp	0.571	7419	247
1_14	Popu_sp	0.349	7451	248
1_15	Popu_sp	0.663	9734	324
2_11	Popu_sp	0.669	9134	304

2_12	Popu_sp	0.723	10043	334
2_36	Popu_sp	0.094	4220	141
3_01	Popu_sp	0.708	6350	211
3_02	Popu_sp	0.742	8625	287
3_03	Popu_sp	0.750	10684	356
3_04	Popu_sp	0.748	10048	335
3_05	Popu_sp	0.746	9733	324
3_06	Popu_sp	0.750	8532	284
3_07	Popu_sp	0.747	7967	265
3_08	Popu_sp	0.750	7326	244
3_09	Popu_sp	0.640	5929	197
3_10	Popu_sp	0.750	8930	297
3_11	Popu_sp	0.749	8386	279
3_12	Popu_sp	0.744	7905	263
3_13	Popu_sp	0.750	8277	276
3_14	Popu_sp	0.750	9945	331
3_15	Popu_sp	0.749	8863	295
4_01	Popu_sp	0.066	8582	286
4_03	Popu_sp	0.361	9529	317
4_05	Popu_sp	0.073	8626	287
4_06	Popu_sp	0.013	7278	242
5_01	Popu_sp	0.684	11166	372
5_02	Popu_sp	0.743	8832	294
5_03	Popu_sp	0.749	9212	307
5_04	Popu_sp	0.750	8665	289
5_05	Popu_sp	0.745	9935	331
5_06	Popu_sp	0.718	10027	334
5_07	Popu_sp	0.670	8910	297
5_08	Popu_sp	0.681	7073	236
5_09	Popu_sp	0.736	8327	277
5_10	Popu_sp	0.750	8358	278
5_11	Popu_sp	0.749	7956	265
5_12	Popu_sp	0.739	6683	223
5_13	Popu_sp	0.749	8324	277
5_14	Popu_sp	0.746	8153	271
5_15	Popu_sp	0.739	7589	253
6_01	Popu_sp	0.190	10623	354
6_02	Popu_sp	0.556	9068	302
6_03	Popu_sp	0.592	8884	296
6_04	Popu_sp	0.596	7816	260
6_05	Popu_sp	0.281	10098	336

6_06	Popu_sp	0.238	9496	316
6_07	Popu_sp	0.080	7544	251
6_08	Popu_sp	0.119	6608	220
6_09	Popu_sp	0.212	6505	217
6_10	Popu_sp	0.490	7185	239
6_11	Popu_sp	0.687	6240	208
6_12	Popu_sp	0.320	6938	231
6_13	Popu_sp	0.223	7111	237
6_14	Popu_sp	0.472	7556	252
6_15	Popu_sp	0.413	7667	255
1_03	Pice_eng	0.983	10156	305
1_12	Pice_eng	0.079	4761	143
2_11	Pice_eng	0.893	10594	318
2_12	Pice_eng	0.773	12145	364
3_03	Pice_eng	0.539	13570	407
3_04	Pice_eng	0.737	12017	361
3_05	Pice_eng	0.511	12070	362
3_06	Pice_eng	0.812	10088	303
3_07	Pice_eng	0.707	9160	275
3_09	Pice_eng	0.651	6178	185
3_10	Pice_eng	0.049	10101	303
3_11	Pice_eng	0.189	9158	275
3_12	Pice_eng	0.227	8646	259
3_13	Pice_eng	0.098	9635	289
3_14	Pice_eng	0.616	12866	386
3_15	Pice_eng	0.506	9929	298
4_01	Pice_eng	1.000	8979	269
4_02	Pice_eng	1.000	8842	265
4_03	Pice_eng	1.000	10620	319
4_04	Pice_eng	1.000	8884	267
4_05	Pice_eng	1.000	8797	264
4_06	Pice_eng	1.000	7821	235
4_07	Pice_eng	1.000	6045	181
4_08	Pice_eng	1.000	4149	124
4_09	Pice_eng	1.000	3571	107
4_10	Pice_eng	1.000	6157	185
4_11	Pice_eng	1.000	6423	193
4_12	Pice_eng	1.000	5114	153
4_13	Pice_eng	1.000	3996	120
4_14	Pice_eng	1.000	6883	206
4_15	Pice_eng	1.000	5262	158

5_01	Pice_eng	0.997	13887	417
5_02	Pice_eng	0.988	10433	313
5_03	Pice_eng	0.995	10614	318
5_04	Pice_eng	0.997	9523	286
5_05	Pice_eng	0.991	11928	358
5_06	Pice_eng	0.998	11336	340
5_07	Pice_eng	1.000	10860	326
5_08	Pice_eng	1.000	7873	236
5_09	Pice_eng	0.999	9716	291
5_10	Pice_eng	0.880	9202	276
5_11	Pice_eng	0.589	8650	260
5_12	Pice_eng	0.562	6879	206
5_13	Pice_eng	0.831	9519	286
5_14	Pice_eng	0.961	9107	273
5_15	Pice_eng	0.969	8547	256
6_01	Pice_eng	1.000	11354	341
6_02	Pice_eng	1.000	11048	331
6_03	Pice_eng	1.000	10662	320
6_04	Pice_eng	1.000	8897	267
6_05	Pice_eng	1.000	11226	337
6_06	Pice_eng	1.000	10351	311
6_07	Pice_eng	1.000	8273	248
6_08	Pice_eng	1.000	7471	224
6_09	Pice_eng	1.000	7466	224
6_10	Pice_eng	1.000	7884	237
6_11	Pice_eng	1.000	6326	190
6_12	Pice_eng	1.000	7493	225
6_13	Pice_eng	1.000	8124	244
6_14	Pice_eng	1.000	8713	261
6_15	Pice_eng	1.000	8477	254
1_01	Pice_gla	0.386	3031	98
1_02	Pice_gla	0.106	6738	219
1_09	Pice_gla	0.302	3143	102
1_10	Pice_gla	0.955	13610	442
1_11	Pice_gla	0.745	10349	336
1_12	Pice_gla	0.171	5467	178
1_13	Pice_gla	0.498	9378	305
1_15	Pice_gla	0.361	12481	406
2_36	Pice_gla	0.237	4523	147
3_01	Pice_gla	0.737	7228	235
3_02	Pice_gla	0.838	10805	351

3_03	Pice_gla	0.999	14282	464
3_04	Pice_gla	0.875	12796	416
3_05	Pice_gla	0.995	12793	416
3_06	Pice_gla	1.000	10833	352
3_07	Pice_gla	0.992	9892	321
3_08	Pice_gla	0.996	8915	290
3_09	Pice_gla	0.987	6899	224
3_10	Pice_gla	0.895	10828	352
3_11	Pice_gla	0.765	9928	323
3_12	Pice_gla	0.814	9311	303
3_13	Pice_gla	0.924	10364	337
3_14	Pice_gla	0.993	13515	439
3_15	Pice_gla	0.994	10757	350
4_01	Pice_gla	1.000	9699	315
4_02	Pice_gla	1.000	9533	310
4_03	Pice_gla	1.000	11357	369
4_04	Pice_gla	0.838	9614	312
4_05	Pice_gla	1.000	9595	312
4_06	Pice_gla	1.000	8549	278
4_07	Pice_gla	0.999	6663	217
4_08	Pice_gla	0.991	4912	160
4_09	Pice_gla	0.898	4265	139
4_10	Pice_gla	0.984	6838	222
4_11	Pice_gla	0.983	7075	230
4_12	Pice_gla	0.995	5766	187
4_13	Pice_gla	0.999	4664	152
4_14	Pice_gla	1.000	7545	245
4_15	Pice_gla	0.994	5964	194
5_01	Pice_gla	1.000	14559	473
5_02	Pice_gla	0.999	11258	366
5_03	Pice_gla	1.000	11391	370
5_04	Pice_gla	1.000	10318	335
5_05	Pice_gla	1.000	12709	413
5_06	Pice_gla	0.999	12256	398
5_07	Pice_gla	0.998	11644	378
5_08	Pice_gla	0.998	8710	283
5_09	Pice_gla	0.998	10445	339
5_10	Pice_gla	0.995	10000	325
5_11	Pice_gla	0.956	9359	304
5_12	Pice_gla	0.783	7590	247
5_13	Pice_gla	0.962	10334	336

5_14	Pice_gla	0.994	9915	322
5_15	Pice_gla	0.971	9316	303
6_01	Pice_gla	1.000	12156	395
6_02	Pice_gla	1.000	11667	379
6_03	Pice_gla	1.000	11247	366
6_04	Pice_gla	1.000	9456	307
6_05	Pice_gla	1.000	11942	388
6_06	Pice_gla	1.000	11087	360
6_07	Pice_gla	1.000	9096	296
6_08	Pice_gla	0.999	8179	266
6_09	Pice_gla	0.992	7990	260
6_10	Pice_gla	0.999	8492	276
6_11	Pice_gla	0.997	6931	225
6_12	Pice_gla	0.997	8075	262
6_13	Pice_gla	0.994	8694	283
6_14	Pice_gla	1.000	9288	302
6_15	Pice_gla	0.995	8903	289
1_01	Pinu_sp	0.632	2591	86
1_07	Pinu_sp	0.893	3067	102
1_09	Pinu_sp	0.714	2569	86
1_10	Pinu_sp	0.955	11190	373
1_11	Pinu_sp	0.263	8438	281
1_12	Pinu_sp	0.208	4786	159
1_13	Pinu_sp	0.761	7460	248
1_14	Pinu_sp	0.265	7460	248
1_15	Pinu_sp	0.224	10355	345
2_12	Pinu_sp	0.070	10865	362
3_02	Pinu_sp	0.142	8898	296
3_03	Pinu_sp	0.774	11268	375
3_04	Pinu_sp	0.476	10617	354
3_05	Pinu_sp	0.296	10252	341
3_07	Pinu_sp	0.324	8033	267
3_09	Pinu_sp	0.224	5750	191
3_10	Pinu_sp	0.299	8878	296
3_11	Pinu_sp	0.156	8136	271
3_12	Pinu_sp	0.129	7476	249
3_13	Pinu_sp	0.577	8453	281
3_14	Pinu_sp	0.412	10418	347
3_15	Pinu_sp	0.478	8849	295
4_01	Pinu_sp	0.996	8742	291
4_03	Pinu_sp	0.879	10304	343

4_05	Pinu_sp	0.994	8979	299
4_06	Pinu_sp	0.987	7290	243
4_07	Pinu_sp	0.867	5177	172
4_08	Pinu_sp	0.830	3991	133
4_09	Pinu_sp	0.543	3552	118
4_10	Pinu_sp	0.622	5498	183
4_11	Pinu_sp	0.386	5304	177
4_12	Pinu_sp	0.819	4592	153
4_13	Pinu_sp	0.791	3872	129
4_14	Pinu_sp	0.881	5770	192
4_15	Pinu_sp	0.810	4838	161
5_01	Pinu_sp	1.000	12369	412
5_02	Pinu_sp	0.999	9833	327
5_03	Pinu_sp	0.999	9776	326
5_04	Pinu_sp	0.993	8974	299
5_05	Pinu_sp	1.000	11078	369
5_06	Pinu_sp	1.000	10809	360
5_07	Pinu_sp	1.000	9566	319
5_08	Pinu_sp	0.999	7443	248
5_09	Pinu_sp	0.999	8940	298
5_10	Pinu_sp	0.939	8475	282
5_11	Pinu_sp	0.721	8064	269
5_12	Pinu_sp	0.628	6816	227
5_13	Pinu_sp	0.736	8595	286
5_14	Pinu_sp	0.990	8532	284
5_15	Pinu_sp	0.960	7938	264
6_01	Pinu_sp	1.000	11278	376
6_02	Pinu_sp	1.000	9892	329
6_03	Pinu_sp	1.000	9357	312
6_04	Pinu_sp	1.000	7863	262
6_05	Pinu_sp	1.000	10661	355
6_06	Pinu_sp	1.000	10099	336
6_07	Pinu_sp	0.999	8178	272
6_08	Pinu_sp	0.997	7048	235
6_09	Pinu_sp	0.982	7059	235
6_10	Pinu_sp	0.999	7143	238
6_11	Pinu_sp	0.972	5770	192
6_12	Pinu_sp	0.995	6947	231
6_13	Pinu_sp	0.985	7398	246
6_14	Pinu_sp	1.000	7740	258
6_15	Pinu_sp	0.994	7514	250

1_01	Pseu_men	0.879	5888	44
1_03	Pseu_men	1.000	17534	132
1_07	Pseu_men	1.000	7152	54
1_08	Pseu_men	1.000	9563	72
1_09	Pseu_men	0.997	6020	45
1_10	Pseu_men	0.893	21584	162
1_11	Pseu_men	0.836	15724	118
1_12	Pseu_men	0.484	8937	67
1_13	Pseu_men	0.893	14832	111
1_14	Pseu_men	0.807	14469	109
1_15	Pseu_men	0.541	19282	145
2_01	Pseu_men	0.999	9561	72
2_09	Pseu_men	0.997	9518	71
2_11	Pseu_men	0.893	18179	136
2_12	Pseu_men	0.773	20888	157
2_36	Pseu_men	0.498	7813	59
3_02	Pseu_men	0.545	17289	130
3_03	Pseu_men	0.966	21833	164
3_04	Pseu_men	0.875	19850	149
3_05	Pseu_men	0.960	19736	148
3_06	Pseu_men	0.998	16997	127
3_07	Pseu_men	0.986	15405	116
3_08	Pseu_men	0.965	14238	107
3_09	Pseu_men	0.541	11619	87
3_10	Pseu_men	0.933	16400	123
3_11	Pseu_men	0.929	14686	110
3_12	Pseu_men	0.812	13998	105
3_13	Pseu_men	0.814	16154	121
3_14	Pseu_men	0.972	20973	157
3_15	Pseu_men	0.933	16249	122
4_01	Pseu_men	0.461	16505	124
4_02	Pseu_men	0.737	15187	114
4_03	Pseu_men	0.692	19245	144
4_05	Pseu_men	0.678	16305	122
4_06	Pseu_men	0.516	14600	109
4_07	Pseu_men	0.255	11785	88
4_08	Pseu_men	0.123	8597	64
4_09	Pseu_men	0.141	7878	59
4_10	Pseu_men	0.344	12140	91
4_12	Pseu_men	0.086	10550	79
4_13	Pseu_men	0.124	8492	64

4_14	Pseu_men	0.318	12700	95
5_01	Pseu_men	0.989	23424	176
5_02	Pseu_men	0.996	18298	137
5_03	Pseu_men	0.996	18465	138
5_04	Pseu_men	0.984	16507	124
5_05	Pseu_men	0.985	20547	154
5_06	Pseu_men	0.989	19786	148
5_07	Pseu_men	0.990	18789	141
5_08	Pseu_men	0.970	14078	106
5_09	Pseu_men	0.997	17014	128
5_10	Pseu_men	0.954	15694	118
5_11	Pseu_men	0.948	14500	109
5_12	Pseu_men	0.988	11894	89
5_13	Pseu_men	0.925	15906	119
5_14	Pseu_men	0.999	15765	118
5_15	Pseu_men	1.000	14918	112
6_01	Pseu_men	0.869	19880	149
6_02	Pseu_men	0.993	19512	146
6_03	Pseu_men	0.981	18860	141
6_04	Pseu_men	0.983	16204	122
6_05	Pseu_men	0.943	19595	147
6_06	Pseu_men	0.897	18450	138
6_07	Pseu_men	0.705	15314	115
6_08	Pseu_men	0.597	14266	107
6_09	Pseu_men	0.685	15211	114
6_10	Pseu_men	0.922	14383	108
6_11	Pseu_men	0.994	11948	90
6_12	Pseu_men	0.911	14309	107
6_13	Pseu_men	0.812	15829	119
6_14	Pseu_men	0.956	15974	120
6_15	Pseu_men	0.981	15958	120

Table A5. Spatially varying species traits averaged across ecolocations. Mean and 95 % confidence intervals (*lower CI 95%* and *upper CI 95%*) of species establishment probability (SEP), maximum biomass (maxB) and maximum aboveground net primary productivity (maxANPP) for each species were calculated across all ecolocations (see Table A4 for ecolocation-specific values), assuming a normal distribution.

speciesCode	SEP			maxB			maxANPP		
	mean	lower CI 95%	upper CI 95%	mean	lower CI 95%	upper CI 95%	mean	lower CI 95%	upper CI 95%
Abie_sp	0.79	0.87	0.71	7137.18	7730.11	6544.25	237.67	257.41	217.92
Popu_sp	0.58	0.63	0.52	8056.10	8492.02	7620.17	268.27	282.78	253.75
Pice_eng	0.85	0.92	0.79	8925.51	9522.72	8328.30	267.77	285.68	249.85
Pice_gla	0.90	0.95	0.84	9317.57	9944.76	8690.38	302.82	323.20	282.44
Pinu_sp	0.75	0.82	0.67	7921.12	8499.87	7342.38	263.77	283.05	244.50
Pseu_men	0.81	0.87	0.75	15244.90	16192.93	14296.87	114.34	121.45	107.23

Table A6. Probability of germination for species shade tolerance and shade level combinations. Species shade tolerances can take any value between 1-5 and pixel shade levels can vary between X0 (no shade) and X5 (maximum shade). If a species' shade tolerance is a non-integer, the resulting probability of germination in a given pixel (with a given shade level) is interpolated between the corresponding lower and upper shade tolerance values. Table values correspond exactly to the publicly available LANDIS-II default input data (see Table A2 for source URL).

shade tolerance	X0	X1	X2	X3	X4	X5
1	1	0	0	0	0	0
2	1	1	0	0	0	0
3	1	1	1	0	0	0
4	1	1	1	1	0	0
5	0	0	1	1	1	1

Table A7. Minimum relative biomass values used to determine the shade level in each pixel. All ecolocations shared the same values. Shade levels of X0 had 0 biomass. Values taken from publicly available LANDIS-II default input data. Initial runs revealed excessive recruitment of moderately shade intolerant species even as stand biomass increased, so we adjusted values for shade levels X4 and X5 downwards (X4: 0.8 to 0.75; X5: 0.90 to 0.85) to reflect higher competition for resources in Western Canadian forests with regards to Eastern Canadian forests.

ecolocation	X1	X2	X3	X4	X5
all	0.15	0.25	0.5	0.75	0.85

Table A8. Non-forest fuels. Pixels with non-forested, but vegetated land-cover classes were assigned fire fuel types (FTs) following the Canadian Forest Fire Behaviour Prediction System (Taylor & Alexander, 2016), to allow fire dynamics (ignition and spread) to occur in these pixels. For land-cover classes with a varying curing level (fixedCuring set to FALSE), the curing level was drawn each year from a skewed normal distribution, with the mean set to curingMean, and variance and slant set to 10, and constrained between curingMin and curingMax levels. All values were obtained from expert knowledge of common curing values observed in Albertan non-forested habitats (D. Perrakis pers. comm.).

landCover	FT	Name	fixedCuring	curingMean	curingMin	curingMax
16	O1b	Grass - Standing	FALSE	60	50	80
17	O1b	Grass - Standing	FALSE	60	50	80
21	O1b	Grass - Standing	FALSE	60	50	80
22	O1b	Grass - Standing	FALSE	60	50	80
23	O1b	Grass - Standing	FALSE	35	0	60
24	O1b	Grass - Standing	TRUE	30	30	30
25	NF	Non-fuel	NA	NA	NA	NA

TABLE A9. FIRE PLANT FUNCTIONAL GROUPS (PFGS), USED TO ATTRIBUTE A FIRE FUEL TYPE TO PIXELS, BASED ON SPECIES AGES AND BIOMASS. IN EACH PIXEL, THE TOTAL BIOMASS OF EACH PFG IS CALCULATED BY SUMMING THE COHORTS THAT CONSTITUTE IT. A FIRE FUEL TYPE IS LATER ASSIGNED TO THE PIXEL DEPENDING ON THE RELATIVE BIOMASS OF ITS PFGS (SEE TABLE A10).

PFG	Name	species	ageMin	ageMax
1	Mature Flammable Pines	Pinu_sp	60	1000
2	Non-Flammable Conifer	Pseu_men	40	1000
3	Immature Flammable Pines	Pinu_sp	15	60
4	All conifers, all ages	Abie_sp	15	1000
		Pice_eng	15	1000
		Pice_gla	15	1000
		Pinu_sp	15	1000
		Pseu_men	15	1000
5	All deciduous, all ages	Popu_sp	15	1000
6	Open, all species	Abie_sp	0	15
		Pice_eng	0	15
		Pice_gla	0	15
		Pinu_sp	0	15
		Popu_sp	0	15
		Pseu_men	0	15

TABLE A10. CORRESPONDENCE TABLE BETWEEN PLANT FUNCTIONAL GROUPS (PFGS) AND FIRE FUEL TYPES (FTS). THE DOMINANT FT OF EACH PIXEL IS DETERMINED BASED ON THE RELATIVE BIOMASS OF THE PIXEL'S PFGS. PFGS MUST MEET THE MINIMUM THRESHOLD OF RELATIVE ABUNDANCE IN ORDER TO APPLY A PARTICULAR FUEL TYPE TO A STAND. SEE TABLE A9 FOR PFG DEFINITIONS AND THEIR SPECIES. FTS WERE ADAPTED (IN TERMS OF SPECIES COMPOSITION) FROM THE CANADIAN FOREST FIRE BEHAVIOUR PREDICTION SYSTEM FUEL TYPE CLASSIFICATION (Taylor & Alexander, 2016). THE M2 FUEL TYPE WAS CONVERTED TO M1 (BOREAL MIXEDWOOD - LEAFLESS) WHEN CALCULATING FIRE PROPERTIES, SINCE THE *CFFDRS* R PACKAGE FUNCTIONS DO NOT RECOGNISE M2.

FT	Name	PFG	Threshold
C2	Boreal spruce	4	0.76
C3	Mature Jack or Lodgepole pine	1	0.8
C4	Immature Jack or Lodgepole pine	3	0.8
C7	Ponderosa pine/Douglas-fir	4	0.75
		2	0.5
M2	Boreal mixedwood – green	4	0.25
		5	0.26
D2	Green Aspen	5	0.76
O1b	Grass - standing	6	0.8

Table A11. Fire damage table. The difference between fire 'severity' (sensu Sturtevant *et al.*, 2018) **and species fire tolerances (see Table A3), 'severity tolerance dif.', determines which cohorts of a species will be removed ('ages killed'). The more tolerant a species or the lower the severity of the fire, the younger the cohorts that survive, with 'ages killed' representing the minimum age of survival as a proportion of species longevity.**

ages killed	severity tolerance dif.
0.20	-2
0.50	-1
0.85	0
1.00	1

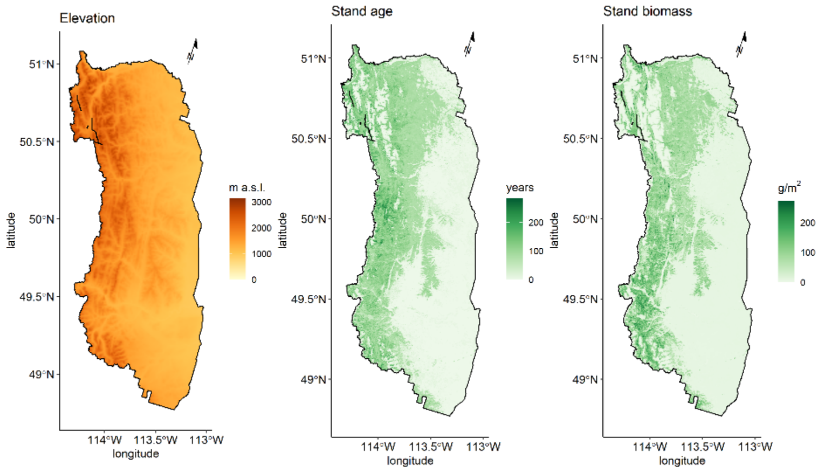

Figure A1. Elevation, stand age and stand aboveground biomass in the LIM study area. Please see Table 2 for data sources.

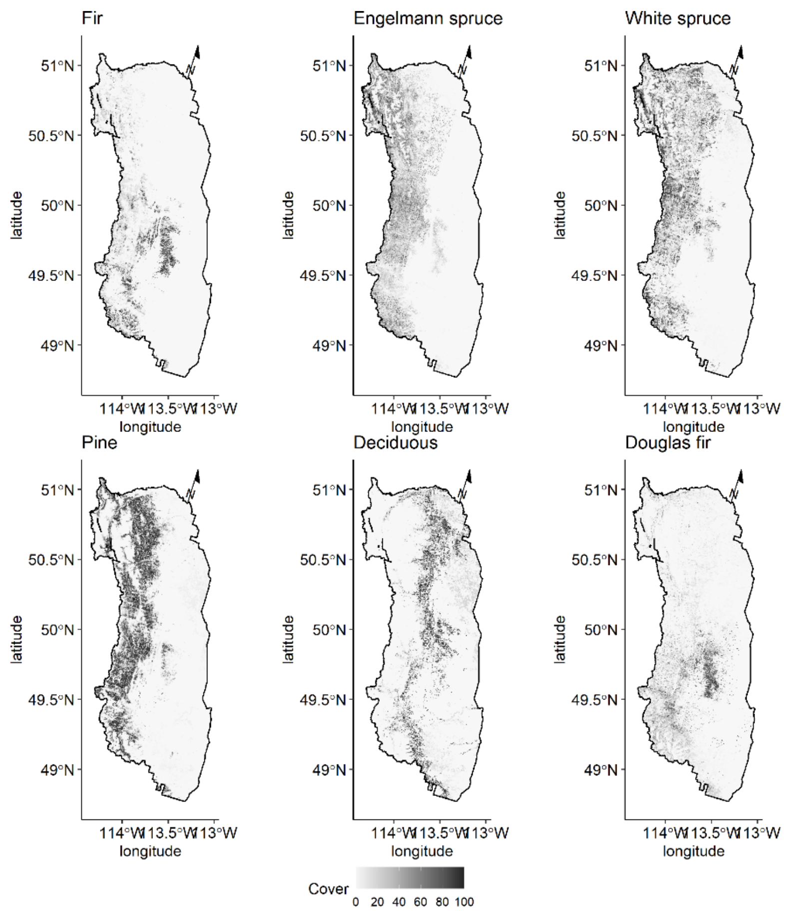

Figure A2. Percent cover of species entering the simulation model, in the LIM study area. Fir comprises all *Abies* species found in the study area, Pine comprises all *Pinus* species in the area (mostly *Pinus contorta*), Deciduous comprises *Populus tremuloides*, *P. balsamifera* and *Betula papyrifera*. Please see Table 2 for data sources.

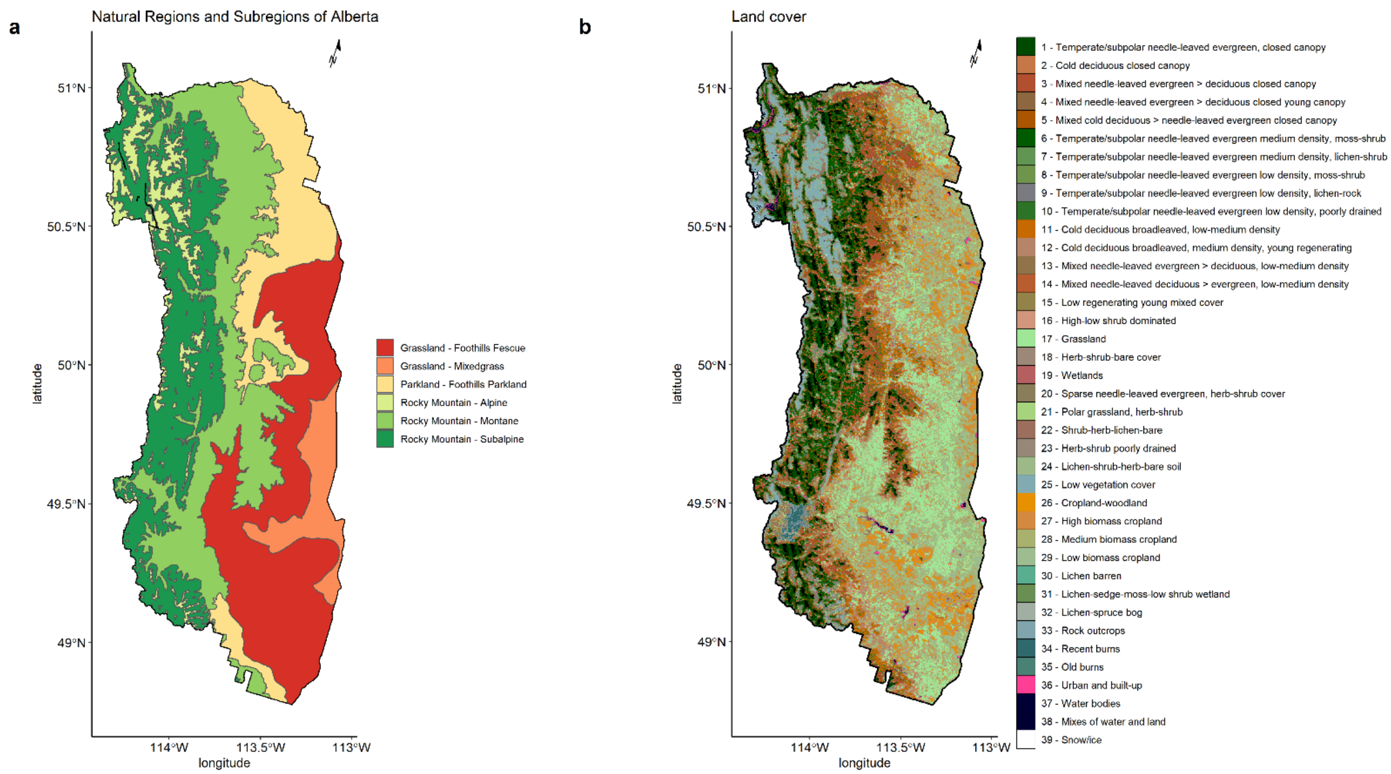

Figure A3. Ecological zones and land-cover used to define ecolocations. Ecological zones were defined using the a) Natural Regions and Subregions of Alberta (Alberta Sustainable Resource Development, 2005) **and land cover was defined using the b) Land Cover Map of Canada 2005 (v1)** (Canada Centre for Remote Sensing, 2008)**. See Appendix 3 for the land-cover classes considered for the simulation.**

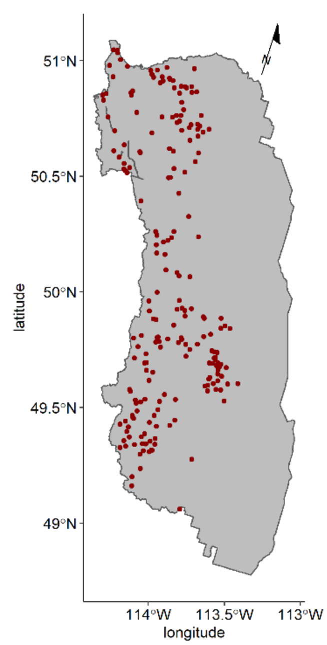

Figure A4. Fire point data. Locations of lightening-caused fires between 1961-1990 in the LIM study area. Source: Canadian Wildland Fire Information System database, National Fire Database fire point data (Canadian Forest Service; see also Table A2).

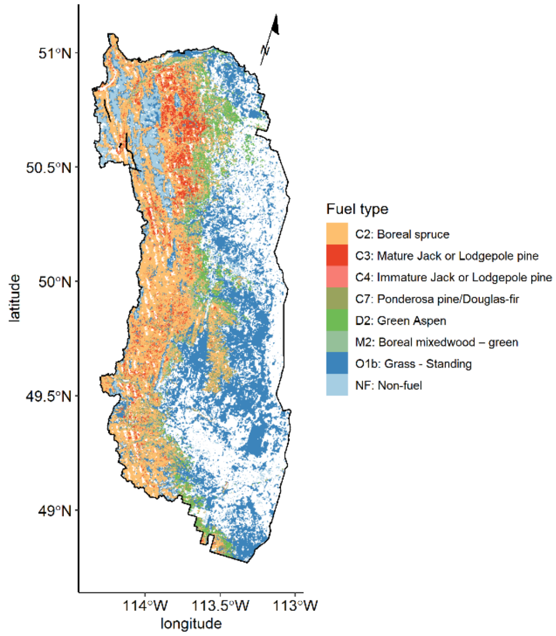

Figure A5. Map of dominant fuel type per pixel. Fuel types follow the Canadian Forest Fire Behaviour Prediction System, adapted to the LIM study area. Only pixels entering the simulation (either as forested or non-forested pixels) are shown.

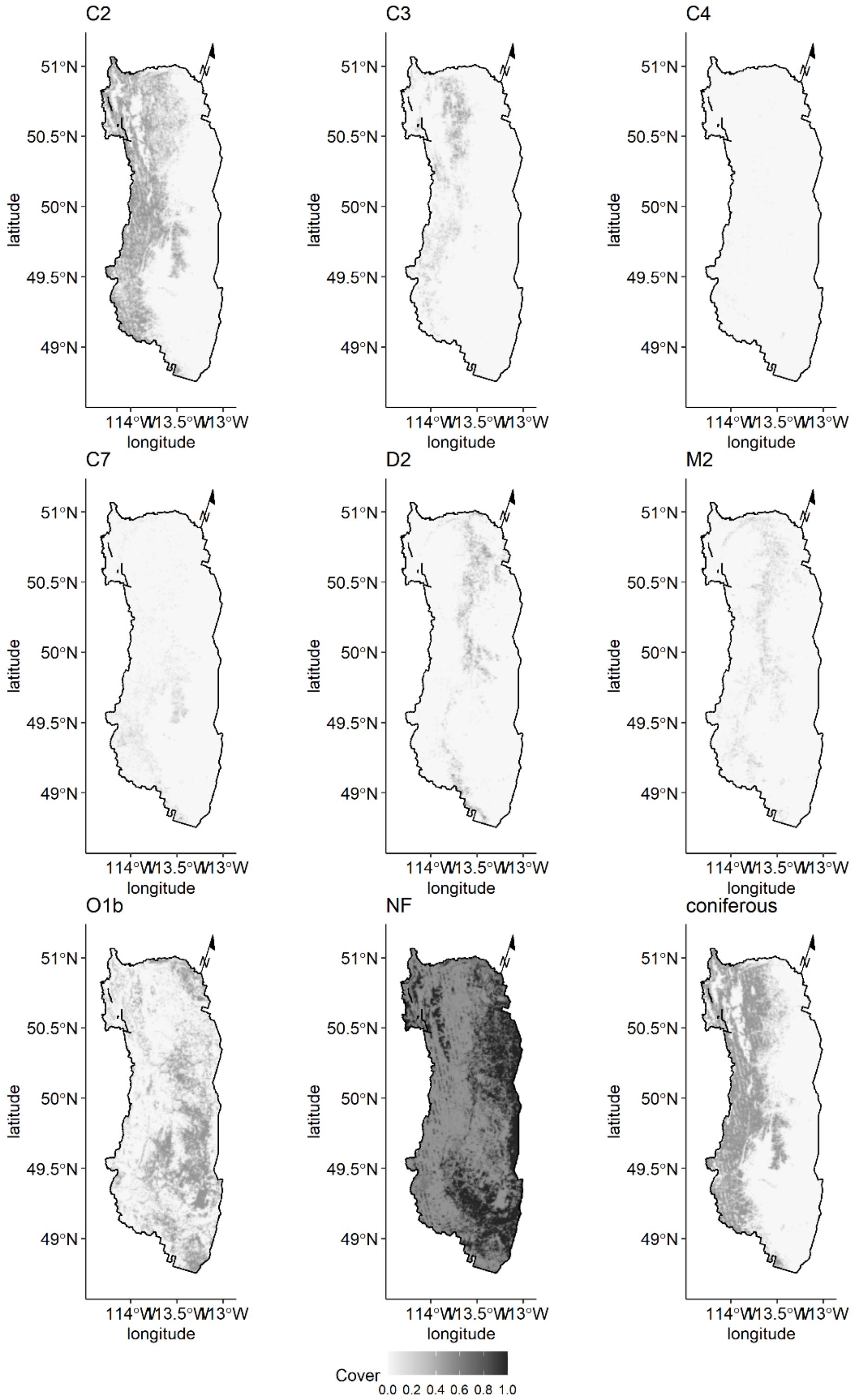

Figure A6. Map of fuel type cover per pixel. Cover was calculated as the proportion of 250 m^2 pixels inside each larger 1 Km^2 pixel. Fuel types follow the Canadian Forest Fire Behaviour Prediction System, adapted to the LIM study area. Additionally, the cover of

CONIFEROUS FUEL TYPES (C2, C3, C4 AND C7) WAS SUMMED INTO A GENERAL "CONIFEROUS" FUEL TYPE, USED TO FIT FIRE OCCURRENCE MODELS. SEE FIG. A5 FOR FUEL TYPE NAMES.

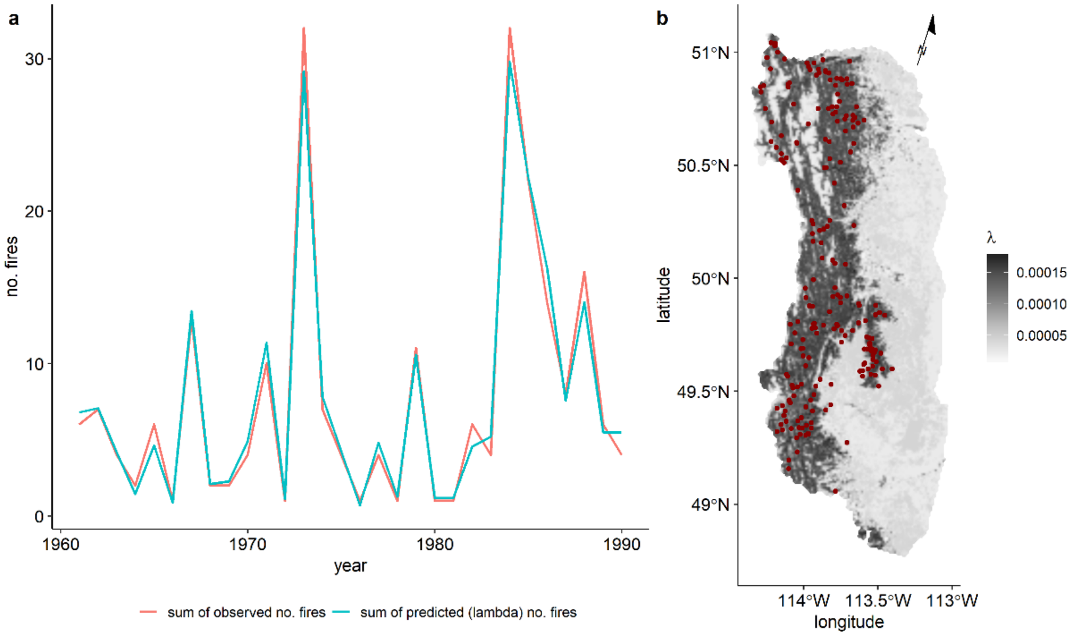

FIGURE A7. DIAGNOSTIC PLOTS OF FIRE OCCURRENCES MODEL. THE MODEL WAS FITTED FOR FIRE OCCURRENCE AND CLIMATE DATA FROM 1961-1990 AND FUEL COVER CONDITIONS IN 2001, SHOWING HIGH CONGRUENCE WITH OBSERVED DATA IN TERMS OF A) THE TOTAL NUMBER OF FIRES PER YEAR AND B) WHERE FIRES ARE MORE LIKELY TO OCCUR SPATIALLY.

Appendix B: Data-driven parameter estimation and simulation of fire and regeneration

Estimation of vegetation parameters

After sourcing and preparing data (see Appendix C) the modules Biomass_borealDataPrep and Biomass_speciesParameters prepare invariant and spatially varying species traits tables (Tables A3 and A4 Appendix A, respectively) by compiling existing trait data and estimating trait values statistically. Below we detail the statistical estimation of some of these traits. For information on sources for other traits see their respective table captions in Appendix A.

Growth- and mortality curve parameters, maximum biomass and maximum aboveground net primary productivity adjustment factors (Biomass_speciesParameters module)

Cohort growth and mortality in LandR Biomass is essentially determined by four parameters: ‘growth curve’, ‘mortality shape’, maximum biomass (maxB) and maximum aboveground net primary productivity (maxANPP). The ‘growth curve’ and ‘mortality shape’ parameters (so called in LANDIS-II Biomass Succession Extension v3.2) modulate the shape of species growth curves and were estimated using Biomass_speciesParameters. Biomass_speciesParameters attempts to match the theoretical species curves obtained by varying parameter values (namely, ‘growth curve’, ‘mortality shape’, ‘longevity’ and ‘mANPPproportion’) against observed species growth curves from permanent sample plot (PSP) data (see Appendix C for details on simulated and observed data, as well as the ranges of parameter values used). The parameter mANPPproportion reflects the relationship between maxB and maxANPP and was later used to adjust the values of maxANPP estimated by Biomass_borealDataPrep.

Before calculating the observed species growth curves, the PSP data was subset to stand ages below the 95th percent quantile (for each species), as records for larger age classes were limited and constituted statistical outliers. In addition, 50 points were added at the origin (age = 0 and biomass = 0), since very young trees (diameters < 10 cm) were not measured in the original data. This forced the intercept to be essentially 0 age and 0 biomass. Growth curves for each species were then modelled using a generalised additive mixed effects model (GAMM) that related species biomass (B) with stand age (standAge), accounting for the random effects of the measurement year (measureYear) and plot (plotID) on the intercept:

$$B \sim f_1(standAge) + (\sim 1\ |measureYear + plotID) \quad \text{[Eq. B1]}$$

where f_1 denotes the smoother function. To avoid overfitting, we constrained the smoother on stand age to a maximum smoothing degree of 3 (i.e. 3 knots and a polynomial degree of 2) and a point constraint at 0 that attempted to force the intercept to 0. In addition, B was weighted with respect to species dominance. This consisted in 1) calculating the average biomass of each dominant species, *i* (i.e. relative biomass in a plot > 0.5; $domSpeciesB_i$), in each plot and measurement year, and 2) dividing the species average biomass by the average biomass across all *n* dominant species (allDomSpecies):

$$\frac{\overline{\mathrm{domSpeciesB}_i}}{\overline{\mathrm{allDomSpeciesB}}} \quad \text{[Eq. B2]}$$

For the added 0 age and 0 biomass data we used weights equal to 1. Some species did not have enough data to allow for model convergence, thus their growth and mortality curve parameters, together with mANPPpropotion, were assigned LANDIS-II default values (see Table A3). Biomass_speciesParameters generated a large number of curves (the "theoretical" curves) in a factorial simulation experiment with many growth curve and mortality shape values that span all reasonable values. Longevity is assumed to be an input by user as it was not possible to estimate using PSP data. After fitting the GAM curves to PSP data, Biomass_speciesParameters compared these to the theoretical curves and picked the best one for each species, using maximum likelihood. The user had the option to constrain the values of the growth and mortality curve parameters. We noted that the theoretical curves never achieved the biomass indicated by maxB (set to 5000 for all simulations of theoretical species curves). This is because maxB is an asymptotic parameter that reflects the potential maximum biomass for a species in an ecolocation. Hence, we used the relationship between the achieved and potential maximum biomass in the theoretical species curves, to rescale the maxB parameter estimated from data (by Biomass_borealDataPrep; see bellow) so that species could achieve maximum observed biomasses during the simulations. Not all species had enough data to build an observed growth curve and find the best matching growth and mortality curve parameters. In this study, observed curves were successfully built for *Picea engelmannii*, *P. glauca* and *Pseudotsuga menziesii*. For the remaining species growth and mortality curve trait values were not changed, maxB was not rescaled and maxANPPproportion kept its default value (see below).

Maximum biomass and maximum aboveground net primary productivity (Biomass_borealDataPrep and Biomass_speciesParameters modules)

Biomass_borealDataPrep statistically estimates maximum biomass (maxB), maximum aboveground net primary productivity (maxANPP) using observed data. maxB was estimated from a linear mixed effects model reflecting the response of species-specific biomass (B) to the interaction between age (on the log scale, logAge) and species, and the interaction between % cover and species, while accounting for the random effect of ecolocation (here, the combination of ecological zone and land-cover) on the calculated slopes (per species) and intercepts:

$$B \sim logAge * species + \text{cover} * \text{species} + (\text{logAge} + \text{cover} + \text{species} \mid \text{ecolocation}) \quad \text{[Eq. B3]}$$

Where '*' denotes the inclusion of separate fixed effects and the interaction between them. Coefficients were estimated by maximum likelihood and model fit was calculated as the proportion of explained variance explained by fixed effects only (marginal r^2) and by the entire model (conditional r^2), which was 0.45 and 0.62 respectively. We then estimated maxB by species and ecolocation combination, by setting cover to 100% and log age to log longevity and predicting biomass at that point value(i.e. log-longevity; Table A4 Appendix A). As mentioned above, maxB was rescaled so that species could achieve maximum observed biomasses during the simulation. maxANPP was calculated as maxB * mANPPproportion/100, where mANPPproportion came from the Biomass_speciesParameters module above. It defaults to 3.33, which is the same as the LANDIS-II default (Table A3 Appendix A). Only the species that had enough data to estimate growth and mortality curve parameters and maxANPPproportion were adjusted for maxB – in this case, *P. engelmannii*, *P. glauca* and *Pseudotsuga menziesii*. Others kept defaults from LANDIS-II and a non-rescaled maxB.

Species establishment probability (Biomass_borealDataPrep module)

Species establishment probability (SEP) was estimated by modelling the probability of observing a given species in each ecolocation (again, combination of Alberta Natural Regions and Land Cover Classification). For this, we used a generalised linear mixed model, whereby the probability of occurrence of a species (π) – calculated as the number of pixels with % cover > 0 divided by the total number of pixels, by ecolocation and species identity following a binomial distribution (with a logit link), while accounting for the random effect of ecolocation on the intercepts.

$$\text{logit}(\pi) \sim \text{species} + (1 \mid \text{ecolocation}) \quad \text{[Eq. B4]}$$

where π is the probability of finding a species in an ecolocation. Model fit resulted in 0.99 for both the marginal r^2 and the conditional r^2. The fitted values were used as the spatially varying SEP trait values for each species and ecolocation combination (Table A4 Appendix A)

Fire parameters and fire dynamics

Converting simulated biomass to fire fuels (Biomass_fuelsPFG module)

Each pixel was assigned a dominant fire fuel type based on simulated species composition and age structure in forested pixels and land-cover class in non-forested pixels. Fuel types followed the Canadian Forest Fire Behaviour Prediction System (hereafter 'FBP System') fuel classification and the conversion between simulated pixel composition and fuels was adapted to our study area. In forested pixels, species were initially assigned to a fire plant functional group (PFG) according to their identity and age (Table A9 Appendix A). Species biomasses were summed for each PFG and divided by the total stand biomass to obtain relative PFG abundance per pixel. The dominant PFG determined the final fuel type based on a minimum threshold of relative abundance (Table A10 Appendix A). Fuel types that were characterised by more than one PFG needed to meet the minimum relative abundance thresholds of all PFGs. For instance, the mixed stand fuel type M2 required a minimum of 25% conifer species abundance and 26% deciduous species abundance (PFGs 4 and 5, respectively), and the Douglas-fir dominated fuel type 'C7' required a minimum 50% abundance of Douglas-fir (*Pseudotsuga menziesii*) and at least 75% of conifer species abundance (PFGs 2 and 4, respectively; Table A9). In cases where several fuel types filled the minimum requirements, the final fuel type was the one that had the most PFGs meeting the requirements or the highest thresholds of minimum relative biomass. In 'mixed' fuel types, we also calculated the relative abundance of conifers used to calculate fire behaviour properties in *Biomass_fireProperties module*.

Fuel types in non-forested pixels were based on pixel land-cover class (see Appendix C for non-forested pixel land-cover classes and Table A8 Appendix A for conversion table). 'Open' fuel types can be associated with a degree of curing, important for the calculation of fire behaviour properties. For land-cover classes with a varying curing level (fixedCuring set to FALSE), the curing level was drawn for each pixel and each year from a skewed normal distribution, with a mean set to curingMean, variance and slant set to 10, and constrained between curingMin and curingMax levels (Table A8). Values for curingMean, curingMin and curingMax were obtained from expert knowledge of common curing values and intervals observed in non-forested habitats of Alberta (D. Perrakis pers. comm.).

Fire behaviour properties (Biomass_fireProperties module)

We calculated five fire behaviour properties using the Canadian Forest Fire Danger Rating System, *cffdrs*, R package (Wang *et al.*, 2017): crown fraction burned, CFB, equilibrium head fire rate of spread, ROS, critical spread rate for crowning, RSO, head fire intensity, HFI, and total fuel consumption, TFC. This consists in first calculating Fire Weather Index (FWI) System components (fine fuel moisture code, FFMC and buildup index, BUI) from weather and geographical data (latitude, longitude, day, month, temperature, relative humidity, wind speed at 10m, precipitation). Together with topography (slope and aspect) and fuel conditions (fuel type, conifer cover for mixed fuel types and degree of curing for open fuel types), FWI components are then used as inputs to the Fire Behaviour Prediction (FBP) System, which calculates the above-mentioned fire behaviour properties. Both FWI and FBP outputs were calculated in a spatio-temporally varying manner, whereby both weather and fuel conditions varied at each time step per pixel. To vary fire weather, we randomly sampled a 'typical' fire day (fire weather index, FWI $\geq$ 19) from the daily weather data generated for the baseline climate period (Appendix C); similarly, fuel conditions were updated every time step at the pixel level by converting simulated cohort biomass into fire fuel types (see above). Finally, slope and aspect were calculated from a Digital Elevation Model subset to the study area (Table A2 Appendix A) using the *gdalUtils* R package (Greenberg & Mattiuzzi, 2020). Given that the *fbp* function of the *cffdrs* package does not accept the deciduous 'D2 - Green Aspen' fuel type, we converted all pixels with this fuel type to the allowed 'D1 - Leafless Aspen'. The two differ in their ability to reach higher fire intensity classes, with D1 being able to reach the two highest classes under extremely dry and windy conditions, but not D2.

Probability of ignition (FireSense and fireSpread modules)

Fire ignitions depended on the estimated average number of fires per pixel, which were calculated from observed data referring to a climate baseline period between 1961-1990 (i.e. pre-climate change). We followed the approach described in Marchal, et al. (2017) (implemented in the fireSense_IgnitionFit and fireSense_IgnitionPredict SpaDES modules) and modelled fire occurrences (i.e. presences and absences) as a function of weather and fuel conditions during the reference period (see Appendix C for fire and weather data details). This model was then used to estimate pixel-level average number of fires, which were later used to estimate the probability of a fire ignition. Hence, we used a temporally static map of average number of fires per pixel throughout the simulation.

Fuel conditions used to fit the model were obtained by converting the species composition per pixel at the beginning of the simulation into a dominant fuel type, following the FBP System fuel classification (see above; Fig. A5 Appendix A). We then calculated the cover of each fuel type at 1Km2, by calculating the proportion of 250m2 pixels of each fuel type inside each 1Km2 pixel (Fig. A4 Appendix A). We crossed each fire occurrence (usually just one 1 per 1Km2 pixel) with the July average monthly drought code (MDC) of the fire year and with fuel composition. To balance the design, we added a number of fire absences equal to twice the number of fire occurrences for each fire year. Fire absences were randomly placed in pixels with no fire records and assigned their respective pixels' and years' July MDC and fuel composition. The module fireSense_IgnitionFit then fit a generalised linear model of fire average expected number fires (Y_i) per pixel across years, as a function of the interaction between July MDC (julMDC) and each fuel type's cover, removing the intercept and following a Poisson distribution (with an identity link):

$$Y_i \sim \text{Poisson}(\lambda)$$
$$\lambda \sim \text{coniferous} * \text{julMDC} + \text{D2} * \text{julMDC} + \text{M2} * \text{julMDC} + \text{O1b} * \text{julMDC} + \text{NF} * \text{julMDC} - 1 \qquad \text{[Eq. B5]}$$

where 'coniferous' is the sum of all coniferous fuel types in a pixel, and remaining fuel types are deciduous, 'D2, mixed, 'M2', open habitat, 'O1b', and non-fuel, 'NF', and '*' denotes the inclusion of separate fixed effects and the interaction between them. Model coefficients were estimated by direct minimization of the negative log-likelihood function, on a constrained optimization procedure ensuring that all coefficients were non-negative, so that the $\lambda \geq 0$ (see Marchal *et al.*, 2017). The model was then used by fireSense_IgnitionPredict to spatially predict the average number of fires per pixel. Model performance was high. The fitted values matched the observed data well (Fig. A6a Appendix A) and larger average number of fires spatially coincided with actual fire locations (Fig. A6b).

Finally, annual fire ignitions were generated by the *fireSpread* module using the map of estimated average number of fires. Each year, every pixel was assessed for ignition success by drawing a random number of fire events from a Poisson distribution, using the estimated average number of fires as the λ parameter of the Poisson. We considered a successful ignition if the drawn value was ≥ 1.

Fire spread and persistence probabilities (fireSpread module)

Fire spread was modelled using a percolation model by Favier (2004), which simulates fire spread between pixels as a function of the probability of spread, *p*, and the probability of persistence, *q*. Values of *p* and *q* were recalculated every year, on a pixel basis, in function of fire behaviour properties:

$$\begin{cases} p_i = ROS_i \times HFI_i \\ q_i = TFC_i \times HFI_i \end{cases} \qquad \text{[Eq. B6]}$$

where *i* denotes a pixel, ROS is the equilibrium head fire rate of spread, HFI is the head fire intensity and TFC the total fuel consumption (see *Fire behaviour properties* above for details on the calculation of fire behaviour properties). This is based on the assumption that 1) higher rates of spread and higher fire intensities will cause fires to spread faster in the landscape, 2) that the more fuel a fire consumes and the more intensity it has the longer it burns at a given location, and 3) that these variables have a synergistic relationship rather than an additive one. To convert *p* and *q* to actual probability values bounded to [0,1], we rescaled all *p* > 0 to values ranging 0.20-0.25 and all *q* to values ranging 0-1. Bounding *p* between 0.20 and 0.25 ensured sensible fire sizes and perimeters.

Post-fire vegetation responses - partial mortality (Biomass_regenerationPM module)

The simulation of partial mortality after a fire followed the approach used in LANDIS-II Dynamic Fire System v3.0 (Sturtevant *et al.*, 2018). For every burn pixel (pixels where fire spread to in the fireSpread module) Biomass_regenerationPM module calculates the fire 'severity' class (sensu Sturtevant *et al.*, 2018) in each pixel in function of fire behaviour properties (crown fraction burnt, CFB, equilibrium head fire rate of spread, ROS, and critical rate of spread for crowning, RSO; see *Fire behaviour properties* above):

$$\begin{cases} severity_i = 1,\ CFB_i < 0.1 \wedge ROS_i < \frac{(ROS_i + 0.458)}{2} \\ severity_i = 2,\ CFB_i < 0.1 \wedge ROS_i \geq \frac{(ROS_i + 0.458)}{2} \\ severity_i = 3,\ 0.1 \leq CFB_i < 0.495 \\ severity_i = 4,\ 0.495 \leq CFB_i < 0.9 \\ severity_i = 5,\ CFB_i \geq 0.9 \end{cases} \quad \text{[Eq. B7]}$$

A severity of class 5 constitutes a stand-replacing fire, killing all cohorts in that pixel. The remaining classes are compared against species fire tolerances, by subtracting fire tolerance from fire severity (severityToleranceDif), to determine the fire 'damage' (i.e. which cohorts are killed; Table A11 Appendix A). Each value of severityToleranceDif corresponds to a minimum age of survival with respect to species longevity. Hence, a value of 0.5 means that all cohorts aged 0.5 x species longevity are removed from the pixel. From Table A11 we see that the more tolerant a species or the lower the severity of the fire (i.e. lower value of severityToleranceDif), the younger the cohorts that survive.

APPENDIX C: DATA TREATMENT

The LandR Biomass metamodel differs from LANDIS-II in that its workflow consists of semi-automated, on-the-fly parametrization. The only object that the user *must* supply is a shapefile or raster that defines the study area. If this study area is within Canada, the model is able to parametrize itself, provided that it finds enough data. In this work we also used proprietary datasets to complement the freely available, but often poorer quality, ones that are used by default by the modules.

Our study area in the SW Alberta Foothills of the Rocky Mountains range was rasterized using a 250 m^2 grid. Hence, after sourcing the data, most spatial objects were subset and reprojected to match the study area perimeter, geographical coordinate system and resolution.

LAND COVER DATA (BIOMASS_BOREALDATAPREP MODULE)

Land cover data was used to define the pixels where vegetation and fire dynamics would be simulated (forested pixels), pixels where only fire dynamics were simulated (non-forested, but vegetated pixels - 'non-forested pixels' hereafter) and pixels that were excluded entirely from the simulation. We used land-cover classes from the Land Cover Map of Canada 2005 (v1; Table A1, Fig. A3 Appendix A) product. Pixels with classes 1 to 15 were included as 'forested pixels' and classes 16, 17, 21-25 were included as 'non-forested pixels'. Recent burns (class 34), old burns (35) and urban and built-up pixels (36) were reclassified into forest pixels, by searching the focal neighbourhood using adjacent forested cover classes (up to a radius of 1250 m from the focal cell). When no forested class was found within this perimeter, the pixel was excluded entirely. Reclassified pixels were omitted from the fitting of statistical models used for parameter estimation but were assigned predicted values from these models.

VEGETATION DATA (BIOMASS_BOREALDATAPREP, BIOMASS_SPECIESDATA AND BIOMASS_SPECIESPARAMETERS MODULES)

Species cover (Biomass_speciesData module)

Species percent cover (% cover) data were obtained from open and proprietary sources (Table A2) and pre-processed by the Biomass_speciesData module. This module ensures 1) all data use the same geospatial geometries and 2) that these match the study area, and 3) attempts fills-in and replaces the lowest data with higher quality data, sequentially. For this work, we used the freely available species % cover rasters derived from MODIS satellite imagery from 2001, prepared by the National Forest Inventory, Natural Resources Canada Canadian Forest Service (NRCan), (hereafter 'NFI species data'; Beaudoin *et al.*, 2017), as the lowest quality dataset and filled it with better quality proprietary data (in order of lower to higher quality): vegetation inventory data from the Common Attribute Schema for Forest Inventories, spanning years 1990 to 2016 (CASFRI v4, 2016; Cosco, 2011), LandSat-derived data from (Pickell & Coops, 2016) using satellite images from 1990, and species % cover rasters derived from forest inventories by SilvaCom in 2018. After overlaying these four datasets, we selected the species that would be included in the simulation based on a minimum threshold of cover in the study area. The species need to be present in at least 5% of the study area and have at least one pixel with ≥ 10% cover). This resulted in a total of six species or genera: *Abies sp* (also referred to as 'Fir'), *Picea engelmannii* (Engelmann's spruce), *Picea glauca* (White spruce), *Pinus sp* ('Pine'), *Populus sp* ('Deciduous', comprising *P. tremuloides*, *P. balsamifera* and *Betula papyrifera*) and *Pseudotsuga menziesii* (Douglas-fir).

Stand age and aboveground biomass (Biomass_borealDataPrep module)

Stand age and stand aboveground biomass (hereafter 'biomass') were obtained and prepared by the Biomass_borealDataPrep module. Like the NFI species data, both stand age and biomass were rasters derived from MODIS satellite imagery from 2001 prepared by the National Forest Inventory, NRCan (Beaudoin *et al.*, 2017). Biomass_borealDataPrep directly downloads this data and performs a number of data cleaning operations to treat pixels with data inconsistencies. For instance, we detected pixels where species cover was > 0 but biomass was 0, or, inversely, where stand biomass was > 0 but cover was 0. Both age and biomass required fidelity to species % cover, as cover is presumed to be the most accurately estimated variable (especially after the afore-mentioned overlays). We considered age to be the least accurate. In cases with data mismatches, e.g. biomass = 0, cover = 0 and stand age > 0, or where age was missing, we imputed species ages using a linear mixed effects model relating age with the interaction between the log of stand biomass (standB), species % cover (cover) and species identity (species), while accounting for the random effect of ecolocation (ecological zone and land cover combination) on intercepts and the slope of the interaction between log standB and species.

$$\mathrm{age} \sim \log \mathrm{standB} * \mathrm{cover} * \mathrm{species} + (\log \mathrm{standB} * \mathrm{species} \mid \mathrm{ecolocation}) \qquad \text{[Eq. C1]}$$

where '*' denotes the inclusion of separate fixed effects and the interaction between them. Predicted ages were subsequently bounded to 0 on the lower limit.

Species-specific biomass (B) was estimated for each species present in a given pixel by multiplying its relative cover by stand biomass. Since we used satellite-derived species cover data, the allocation of biomass to deciduous species cohorts was adjusted to reflect the fact that broadleaf canopies will typically have higher cover values for the same amount of biomass as coniferous species. Deciduous species cover was then multiplied by ≈ 0.84 before being multiplied by stand biomass to obtain the species biomass in the pixel. This value comes from a Gaussian generalised linear model (GLM) relating deciduous species biomass (B) with an interaction term between the log of stand age (logAge), standB, *species* and land cover (LC):

$$\log\left(\frac{\mathrm{B}}{100}\right) \sim \log Age * \log\frac{standB}{100} * species * LC \qquad \text{[Eq. C2]}$$

where '*' denotes the inclusion of separate fixed effects and the interaction between them. The model was parameterized using similar data covering the entire Northwest Territories Province, Canada, and an optimization routine that searched the best conversion factor between deciduous cover and B, by minimizing AIC. The best conversion factor was found by refitting the model on different sets of B values (the response), recalculated by changing deciduous relative cover values between 0.1 and 1.

Permanent sample plot data and simulated species data (Biomass_speciesParameters module)

The Biomass_speciesParameters module used permanent sample plot (PSP) and simulated data to estimate species traits associated with growth and mortality. The PSP were obtained from the Canadian provinces of British Columbia, Alberta and Saskatchewan, treated for errors and standardized into a single dataset. The data include individual species and diameter at breast height (DBH) measurements for each tree in a plot, as well as stand age. As part of the standardization process, dead trees were removed from the dataset, and a minimum DBH of 10 cm was applied to ensure a consistent measurement cut-off. Tree biomass was then derived from DBH using the model by Lambert and colleagues (2005) and summed by plot. Lastly, the proportional biomass of each species was calculated for every individual measurement of each plot. General additive mixed effect models (GAMMs) were then used to model the annual biomass of the real species in the PSP dataset. For a given species, observations were excluded from the data if the corresponding species proportional biomass did not exceed 50% (e.g. for *P. tremuloides,* plots were only included if 50% of the biomass was composed of *P. tremuloides)*. Measurement year and plot ID were random variables, and the proportional biomass was used to weight observations.

The simulated data came from runs of LandR Biomass used to create over 200,000 growth curves of theoretical species that differed in terms of growth and mortality traits (growth curve and mortality shape), longevity, and maximum aboveground net primary productivity (maxANPP). The annual biomass of each theoretical species (i.e. growth curves) was simulated using LandR Biomass with no reproduction, competition, disturbance, or dispersal, and only one cohort. These theoretical species growth curves were later used to find the most likely combination of species traits by comparing the simulated growth curves and the PSP-derived GAMMs (see Appendix B).

Invariant species traits

Most species traits that did not vary spatio-temporally were obtained from available species trait tables used in LANDIS-II (Table A2 Appendix A). Some were then adapted to our study using published literature and statistical models using LandR Biomass_speciesParameters (see Appendix B). Only a few invariant species traits needed to be adjusted "manually" to obtain more realistic successional dynamics in the study area.

The LANDIS-II species trait table contains species trait values for each Canadian Ecozone (NRCan, 2013), which we filtered to the Boreal Shield West (BSW), Boreal Plains (BP) and Montane Cordillera (MC) Canadian Ecozones. Most trait values did not vary across these ecozones, but when they did, we took the minimum value. Longevity values were adjusted to match the values in Burton & Cumming (Burton & Cumming, 1995), where the region considered in Table 2 matched the BSP and BP, and Tables 1 and 2 both corresponded to MC depending on the species considered. These adjustments resulted in higher longevity for most species. As first runs revealed an excessive recruitment of young cohorts even after several decades of biomass accumulation, we lowered shade tolerance values (shade tolerance in Table A3 Appendix A) to decrease cohort recruitment as stand biomass increased. We maintained the relative ranking of species shade tolerances (*Abies sp.* from 4 to 2.3, *Picea engelmannii* from 4 to 2.1, *P. glauca* from 3 to 1.6, *Pseudotsuga menziesii* from 3 to 2), except for *Picea glauca* and *Pseudotsuga menziesii*, the first becoming slightly less shade tolerant than the second. This aims at reflecting *P. glauca*'s ability to recolonize disturbed sites alongside *Pinus contorta*, while *P. menziesii* is successional to *P. contorta* (Steinberg, 2002; Abrahamson, 2015). *Pinus sp* and *Populus sp* already had the lowest value of shade tolerance possible, 1.0.

Fire data (fireSense_dataPrep module)

We used fire point data to estimate the average number of fires across the landscape during a reference period. Fire point data were directly downloaded by the fireSense_dataPrep module from the National Fire Database available at Canadian Wildland Fire Information System database (Canadian Forest Service; see also Table A2 Appendix A). The module then filtered the fire occurrences to lightning-caused fires that occurred between 1961-1990, resulting in a total of 213 fire locations in the study area (Fig. A7b Appendix A). Although this period does not reflect 'pre-industrial' conditions (i.e. pre-1940's), it provides good-confidence data on both fire occurrences and climate, while still being commonly accepted as a baseline with regards to climate change.

WEATHER DATA (FIREWEATHER MODULE)

Weather data used to determine fire ignitions across the landscape, fire spread and fire severity, came from simulations of 'historic' daily weather using the software BioSIM v11 (Régnière *et al.*, 2017). To generate these simulations, we provided BioSIM with a digital elevation model raster layer of the LIM study area at 1 Km^2 resolution and Canada-US climate normals between 1961-1990 to generate daily values of average air temperature, total precipitation, relative humidity and wind speed at 10m high, for each pixel (see Table A2 Appendix A for data sources). The generated daily weather data are kept in a private online storage (GoogleDrive) and imported automatically by the fireWeather module if the user has permission to access it. The module then summarises the data in two ways. Into a table of July's average monthly drought code (MDC) for each year and each pixel, used by FireSense modules to estimate the average number of fires in the landscape; and into a table of daily weather values per pixel subset for 'fire days' only. We considered a day to be a 'fire day', if the fire weather index (FWI) was ≥ 19, a value considered to define a potential fire spread day (Podur & Wotton, 2011). Both July's MDC and FWI were calculated using the *cffdrs* R package (Wang *et al.*, 2017), using default initial values for fine fuel moisture code, duff moisture code and drought code: 85, 6 and 15, respectively.

LOCALLY OBSERVED AGE DATA

We compared our simulated results with a dendroecological dataset of species age collected in a smaller region within the LIM study area. The data was collected and analysed as part of the "Fire dynamics of the southern Alberta foothills" element of the Landscapes in Motion Project, during three summer field campaigns in 2017, 2018 and 2019 (Naficy and Daniels 2020). The age data was built from crossdated increment cores collected from trees in plots distributed in the Montane subregion (Fig. A3a Appendix A). Plot distribution followed a stratified sampling approach that aimed at maximizing the range of forest types sampled within the Montane subregion. Small trees (< 10 cm of diameter at breast height) were not sampled. In total, the age data came from 51 distinct plots where the number of cores sampled varied between 26 and 90. The reconstructed ages varied between 27 and 449 years.

APPENDIX D: FUNCTIONAL COVER TYPE CLASSIFICATION

The age data obtained from field campaigns in the LIM study area was organised into sampling plots that were classified in terms of cover type. This cover type classification was based on a series of rules evaluating the basal area densities of different species and functional groups in the plot. In order to compare our simulated ages with those observed in the field, we classified our pixels using a similar approach based on relative biomass (relB) of different species grouped into the same functional types. Here, we detail rule set behind this classification. Several of the species considered in this classification are not present or relevant in the LIM study area, and others were not explicitly simulated in our model but could be seen as part of a simulated group of species (e.g. *Pinus* species were collapsed to genus level). In the later case, we considered that the simulated "species" represented either of the corresponding species in the field.

Species codes and names, with correspondences to simulated species in brackets:

- PIP: *Pinus ponderosa* (not simulated)
- QUGA: *Quercus garryana* (not simulated)
- PIED: *Pinus edulis* (not simulated)
- PIMO2: *Pinus monophyla* (not simulated)
- PIMO: *Pinus monticola* (not simulated)
- PIFL: *Pinus flexilis* (Pinu_sp)
- PICO: *Pinus contorta* (Pinu_sp)
- PIEN: *Picea engelmannii* (Pice_eng)
- PIGL: *Picea glauca* (Pice_gla)
- ABLA: *Abies lasiocarpa* (Abie_sp)
- JUSC, JUOC and JUOS: *Juniperus scopulorum*, *J. occidentalis*, *J. osteosperma* (not simulated)
- POTR5: *Populus trichocarpa* (not simulated)
- POTR: *Populus tremuloides* (Popu_sp)
- POBA: *Populus balsamifera* (Popu_sp)
- BEPA: *Betula papyrifera* (Popu_sp)
- PSME: *Pseudotsuga menziensii* (Pseu_men)
- THPL: *Thuja plicata* (not simulated)

Cover type codes and names:

- Oak: Garry oak woodland
- PJ: Pynion juniper woodland
- purePIPO: relatively pure Ponderosa pine
- DMCPIPO: Dry mixed conifer (DMC) with Ponderosa pine
- dryPSME: Dry Douglas-fir-dominated

- PSME: Douglas-fir dominated (dry species absent)
- DMCPSME: Dry mixed conifer
- PICO: relatively pure Lodgepole pine
- PIEN: Spruce-dominated
- Broadleaf: relatively pure broadleaf
- Mixedwood: relatively even broadleaf and conifer mix.
- MMC: Moist mixed conifer

Parameters used in classification:

- pure.cutoff: threshold of relative biomass defining a relatively pure composition. Set to 0.8.
- drySpp: a vector of species considered to be indicators of dry site conditions. Set to {PSME, PIPO, PIFL, JUSC, QUGA}.
- moistSpp: a vector species considered to be indicators of moist site conditions. Set to {ABLA, BEPA, PIEN, PIGL, PIMO, POBA, THPL}.

Ruleset:

Relative biomass (relB) was calculated per simulated species in a pixel, by dividing the sum of cohort biomasses by the total stand biomass. When a simulated species corresponded to several species codes the relative biomass was only counted once for summing purposes (e.g. "$\Sigma(relB_{POTR}, relB_{BEPA})$" was actually just "$\Sigma(relB_{POTR})$", as these species were not simulated independently). The rules are a series of hierarchical decisions (which we numbered here), whereby if the first condition applies the pixel/stand is classified as that cover type (and following conditions are not evaluated).

Table D1. List of hierarchical conditions constituting the rules used to classify pixels according to functional cover types used in the age dataset collected in the field.

	Conditions	Cover type
1	$relB_{QUGA} \geq$ pure.cutoff AND $\Sigma(relB_{PIPO}, relB_{PSME}, relB_{PIED}, relB_{PIMO2}, relB_{JUSC}, relB_{JUOC}, relB_{JUOS}) < 0.05$	Oak
2	$\Sigma(relB_{PIED}, relB_{PIMO2}, relB_{JUSC}, relB_{JUOC}, relB_{JUOS}, relB_{QUGA}) \geq$ pure.cutoff AND $\Sigma(relB_{PIPO}, relB_{PSME}) < 0.05$	PJ
3	$\Sigma(relB_{PIPO}) \geq$ pure.cutoff AND $\Sigma(relB_{PSME}, relB_{PIFL}, relB_{PIED}, relB_{PIMO2}, relB_{JUSC}, relB_{JUOC}, relB_{JUOS}, relB_{QUGA}) < 0.30$	purePIPO
4	$relB_{PIPO} \geq 0.10$ AND $relB_{PIPO} <$ pure.cutoff AND $\Sigma(relB_{PSME}, relB_{PIPO}, relB_{PIFL}, relB_{PIED}, relB_{PIMO2}, relB_{JUSC}, relB_{JUOC}, relB_{JUOS}, relB_{QUGA}) \geq 0.50$	DMCPIPO

5	$relB_{PSME} \geq$ pure.cutoff AND Σ(moistSpp) $<$ 0.10 AND $\Sigma(relB_{JUSC}, relB_{JUOC}, relB_{JUOS}, relB_{PIFL}, relB_{PIED}, relB_{PIMO2}, relB_{QUGA}) > 0.05$	dryPSME
6	$relB_{PSME} \geq$ pure.cutoff AND Σ(moistSpp) $<$ 0.10 AND $\Sigma(relB_{JUSC}, relB_{JUOC}, relB_{JUOS}, relB_{PIFL}, relB_{PIED}, relB_{PIMO2}, relB_{QUGA}) \leq 0.05$	PSME
7	Σ (drySpp) $\geq$ 0.50 AND Σ(moistSpp) $<$ 0.10	DMCPSME
8	$relB_{PICO} \geq 0.50$	PICO
9	$\Sigma(relB_{PIEN}, relB_{PIGL}, relB_{ABLA}) > 0.50$	PIEN
10	$\Sigma(relB_{POTR}, relB_{POTR5}, relB_{POBA}, relB_{BEPA}) \geq$ pure.cutoff	Broadleaf
11	$\Sigma(relB_{POTR}, relB_{POTR5}, relB_{POBA}, relB_{BEPA}) \geq 0.25$ AND $\Sigma(relB_{POTR}, relB_{POTR5}, relB_{POBA}, relB_{BEPA}) <$ pure.cutoff	Mixedwood
12	If none of the above conditions apply	MMC

APPENDIX E: SUPPLEMENTARY RESULTS

TEMPORAL DYNAMICS OF BIOMASS AND AGE PER 'DOMINANT SPECIES COVER TYPE'

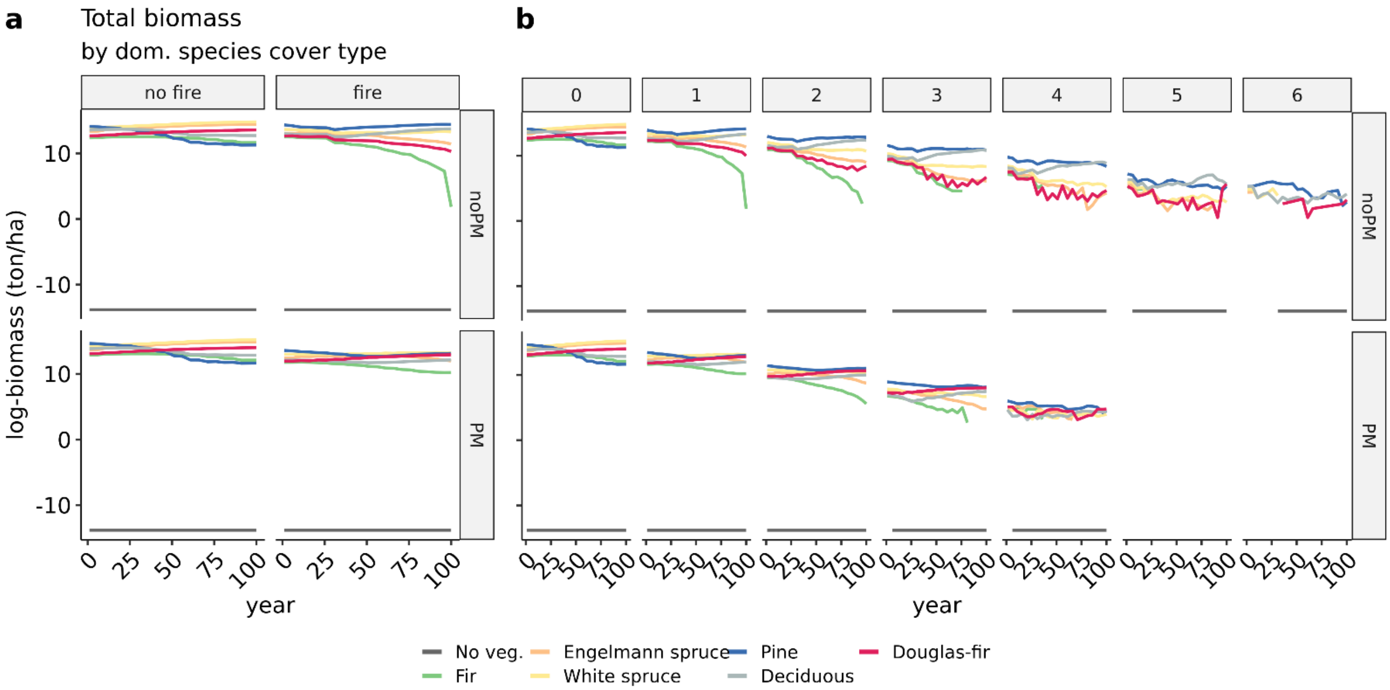

FIGURE E1. TOTAL BIOMASS ACROSS THE LANDSCAPE PER STAND COVER TYPE. HERE, COVER TYPE IS DEFINED AS THE SPECIES WITH THE HIGHEST BIOMASS IN THE PIXEL (I.E. STAND) – DOMINANT SPECIES COVER TYPE. BIOMASS WAS SUMMED ACROSS PIXELS, WHICH WERE GROUPED ACCORDING TO A) WHETHER THEY SUFFERED FIRES DURING THE SIMULATION OR NOT AND B) THE NUMBER OF FIRES THEY SUFFERED.

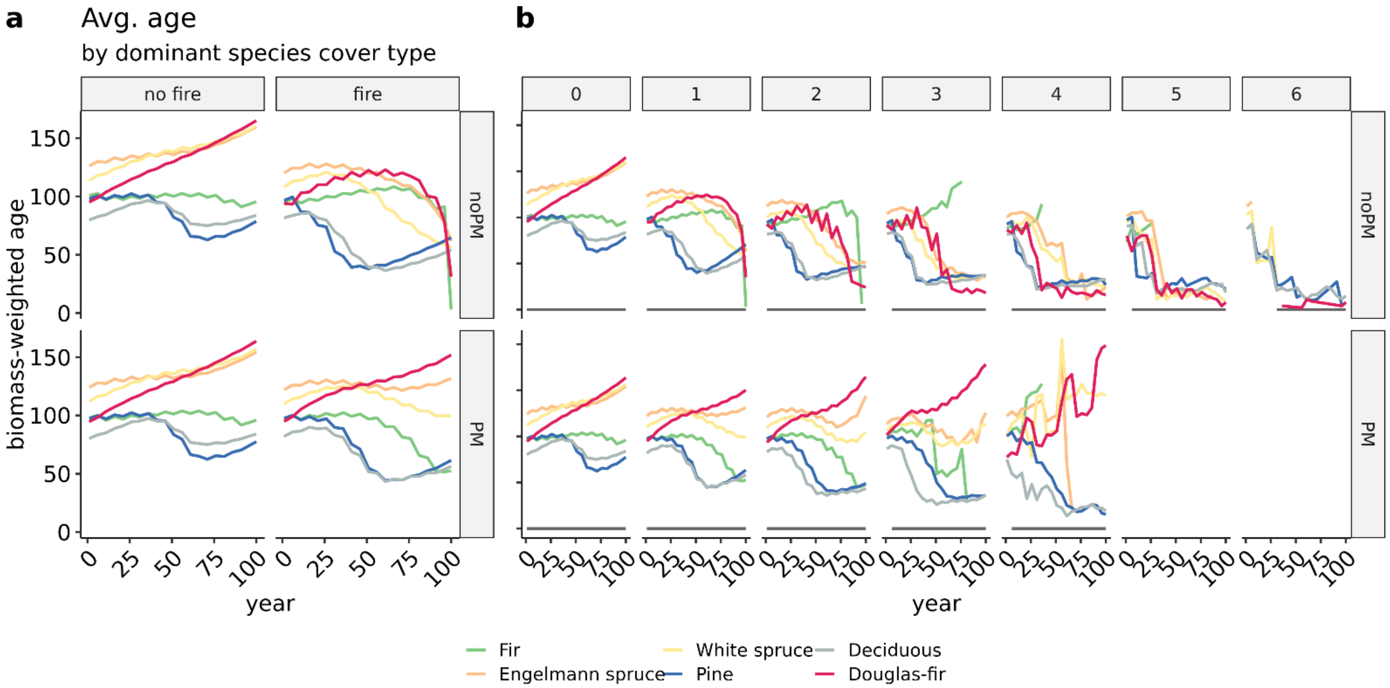

Figure E2. Average stand age across the landscape per cover type. Here, cover type is defined as the species with the highest biomass in the pixel (i.e. stand) – dominant species cover type. Age was weighted by cohort biomass and averaged across all cohorts in a pixel, then averaged across pixels grouped according to a) whether they suffered fires during the simulation or not and b) the number of fires they suffered.

TEMPORAL DYNAMICS OF NO. OF PIXELS PER FUNCTIONAL COVER TYPE

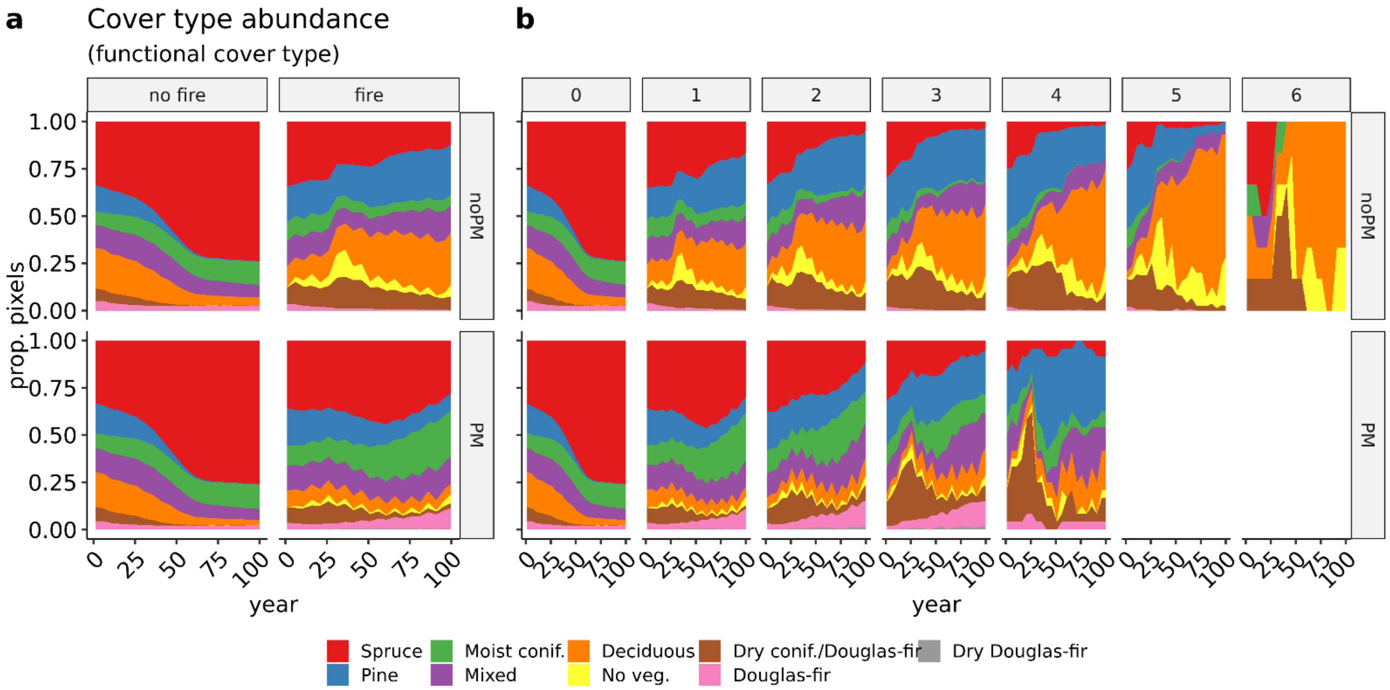

FIGURE E3. RELATIVE ABUNDANCE OF DIFFERENT STAND COVER TYPES ACROSS THE LANDSCAPE. HERE, COVER TYPE IS DEFINED AS THE AS A COMBINATION OF SPECIES AND FUNCTIONAL GROUPS OF SPECIES IN THE PIXEL (I.E. STAND) – FUNCTIONAL SPECIES COVER TYPE (APPENDIX D). ABUNDANCES WERE CALCULATED AS NUMBER OF PIXELS OF EACH COVER TYPE, GROUPED BY PIXELS THAT A) SUFFERED FIRES DURING THE SIMULATION OR NOT AND BY B) THE NUMBER OF FIRES THEY SUFFERED.

Number of pixels per 'fire frequency' level

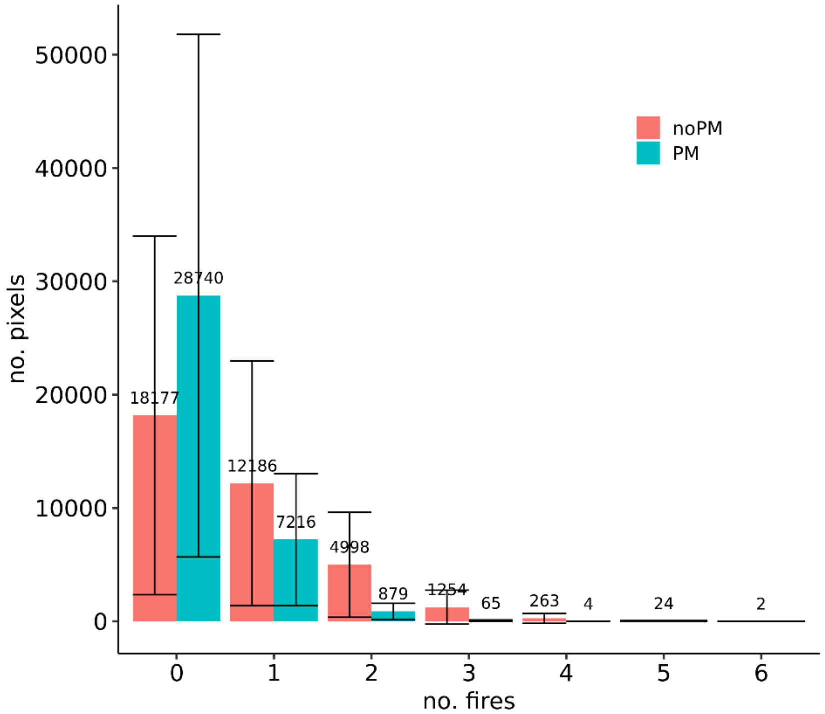

Figure E4. Number of pixels per level of fire frequency, in terms of number of fires in 100 years of simulation. Bars and number annotations show the average number of pixels across repetitions, per scenario, with error bars showing the standard deviation across repetitions.

STATISTICAL MODELS

TABLE E1. RESULTS OF LINEAR MIXED EFFECTS MODELS (LMEMS) USED TO ANALYSE THE EFFECT OF SCENARIO ON AVERAGE STAND (I.E. PIXEL) AGE ($\overline{age}$), STAND ALPHA-DIVERSITY (α), BETA-DIVERSITY (β) ACROSS THE LANDSCAPE AND ABSOLUTE DIFFERENCES BETWEEN SIMULATED AVERAGE STAND AGE AND OBSERVED AVERAGE AGE (ABSDEV). ALL MODELS WERE RUN SEPARATELY FOR PIXELS THAT SUFFERED NO FIRES DURING THE SIMULATION AND PIXELS THAT SUFFERED AT LEAST ONE FIRE. 'VAR.' STANDS FOR VARIANCE, 'SD'FOR STANDARD DEVIATION, 'CORR.'THE CORRELATION BETWEEN INTERCEPTS AND SLOPES AND 'SE' FOR STANDARD ERROR. THE MODELS' EXPLAINED VARIANCE WAS PARTITIONED INTO THE VARIANCE EXPLAINED BY THE FIXED EFFECTS ONLY (I.E. MARGINAL R^2, R^2_M) AND THE VARIANCE EXPLAINED BY THE RANDOM EFFECTS (I.E. CONDITIONAL R^2, R^2_c).

Model	Random effects					Fixed effects				r^2_m	r^2_c
	Groups	Name	Var.	SD	Corr.		Estimate	SE	t-value		
$\overline{age}$~scenario+(scenario|ecolocation)											
No fire	ecolocation	(Intercept)	821.99	28.67		(Intercept)	143.72	3.30	43.57	0.0003	0.2870
		scenarioPM	3.27	1.81	-0.49	scenarioPM	-1.94	0.30	-6.45		
	Residual		1975.16	44.44							
Fire	ecolocation	(Intercept)	2.71	1.65		(Intercept)	52.00	0.28	186.82	0.1608	0.2440
		scenarioPM	618.18	24.86	-0.71	scenarioPM	40.46	3.17	12.77		
	Residual		1696.43	41.19							
α ~scenario+(scenario|ecolocation)											
No fire	ecolocation	(Intercept)	0.03	0.18		(Intercept)	0.62	0.02	29.75	0.0001	0.1183
		scenarioPM	0.00	0.02	-0.68	scenarioPM	-0.01	0.00	-2.81		
Fire	Residual		0.22	0.47							
	ecolocation	(Intercept)	0.01	0.10		(Intercept)	0.82	0.01	59.90	0.0012	0.0409
		scenarioPM	0.00	0.04	-0.17	scenarioPM	0.04	0.01	5.79		
	Residual		0.25	0.50							
β ~scenario+(1|ecolocation)											
All pixels	ecolocation	(Intercept)	3.92	1.98		(Intercept)	6.61	0.23	28.87	0.0018	0.8707
	Residual		0.58	0.76		scenarioPM	0.18	0.06	3.31		
absDev ~ scenario+(scenario|coverType)											
No fire	vegTypeCN	(Intercept)	239.13	15.46		(Intercept)	34.95	5.85	5.97	0.0000	0.2557

Model	Random effects					Fixed effects				r^2_m	r^2_c
	Groups	Name	Var.	SD	Corr.		Estimate	SE	t-value		
		scenarioPM	0.94	0.97	0.44	scenarioPM	-0.08	0.44	-0.17		
Fire	Residual		721.04	26.85							
	vegTypeCN	(Intercept)	782.10	27.97		(Intercept)	62.49	10.57	5.91	0.0065	0.5281
		scenarioPM	259.90	16.12	-0.78	scenarioPM	-6.16	6.10	-1.01		
	Residual		583.60	24.16							

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