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Forest Change Detection and Landscape Structure Mapping in Canada's Model Forests: the Role of Satellite Remote Sensing

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Abstract

Satellite remote sensing has long held promise as a powerful method of detecting forest canopy changes and mapping landscape structure over vast, often multijurisdictional forest areas. Landsat Thematic Mapper (TM) spectral response, for example, can be related accurately to changes in physiology and cover at a range of small to intermediate mapping scales. These data have been available continuously for almost 20 years; many areas have earlier satellite image archives stretching back to the early 1970s. When considering spatially-explicit changes to landscapes – caused by natural and human disturbances – over this time period, digital, synoptic, and repeatable satellite remotely-sensed data are emerging as the observational media of choice that forest managers must possess and use wisely. In this paper, successful use of satellite remote sensing in two of Canada's Model Forests is described. First, in the Fundy Model Forest in southeastern New Brunswick, a 15-year TM image sequence was used to detect area changes associated with different harvesting and silvicultural practices. Second, in the Foothills Model Forest in west-central Alberta, grizzly bear habitat maps have been created from multi-scene TM landcover mosaics. These map products constitute critical information on landscape change and configuration required to answer key management questions. The paper concludes with a prognosis for the future role of satellite remote sensing in sustainable forest management as data quality continues to improve (i.e., increasing spatial, spectral, temporal, and radiometric resolutions), and methods are brought into the purview of forest managers and practitioners.

Key words: remote sensing, landscape change, forest fragmentation, human disturbance, management information needs, habitat.

INTRODUCTION

Forest management must increasingly address a myriad of issues associated with measuring ecological processes and change over large areas and at many different spatial scales. A greater appreciation of the appropriate role of satellite remote sensing technology in monitoring forests in a wide range of ecological settings is emerging as the defining characteristics of remotely-sensed data become more widely well-known and the methods of handling those data become increasingly available (Franklin, 2001). Resource management applications of remote sensing can be understood by considering scale and four types of image resolution. *Spatial resolution* is the minimum resolvable unit of measurement and is typically expressed as a pixel or raster size (e.g., Landsat-7 Enhanced Thematic Mapper (ETM+) multispectral data are 30 m resolution). *Spectral resolution* is the number and quality of bands in the electromagnetic spectrum in which the sensor was designed to measure response. *Radiometric resolution* is a measure of the systems' signal-to-noise ratio; higher radiometric sensitivity, for example, suggests a greater likelihood of measuring a small radiant flux. *Temporal resolution* refers to the image frequency of a particular area.

Each of these resolutions imposes limits on the ways in which remotely-sensed data can be used at particular scales; for example, as large-area coverage increases, spatial resolution typically decreases. In other words, less detail is mapped over larger and larger areas. Much of the impetus to develop satellite remote sensing technology has been aimed at producing higher and higher amounts of detail at what are traditionally considered small-or-intermediate-area mapping scales (e.g., 1:100 000 or 1:50 000). The trade-offs between the image characteristics, image extent, and related costs are summarized in a relative fashion for various sensor options in Figure 1. The interconnectedness of the factors requires users to determine in advance what the goals of the analysis are to enable the selection of the most appropriate data source (Woodcock and Strahler, 1987; Wulder, 1998).

Typical analysis goals include the production of land cover classification maps, estimations of continuous variables such as leaf area index (LAI) or crown closure, and change detection map products. Multispectral Landsat data, with 30 m spatial resolution over an image extent of 185 x 185 km, are an ideal data source in these applications at the small-to-intermediate mapping scales. Landsat data provide reasonably high spatial detail at a low cost, and are also well established with a rich research history resulting in a wide range of processing options, predictable geometric properties, and robust radiometric processing techniques. Landsat-7 data are not subject to copyright once purchased, which facilitated the development of a freely available Landsat-7 orthoimage coverage of Canada representing year 2000 conditions (Wulder *et al.,* 2002).

Innovative methods are required to assist in converting Landsat data into the desired information products required for decision-making. This situation has helped create opportunities for scientists to demonstrate forest management applications for which large-area mapping data and methods are particularly well-designed. While many potential applications exist, what is needed now are concrete examples of how remotely-sensed data have been converted to information products that have led to improved management in forests. Canada's Model Forest Network has been on the forefront of this task of meeting critical forest management information needs at the large-area scale with medium spatial resolution mapping systems, such as Landsat. Two examples are described in this paper that address the immediate need for high-quality, detailed information over large areas on horizontal and vertical forest changes caused by human disturbances to determine the sustainability of economic use of forest resources and to identify critical areas where resource conflicts may occur and wildlife may be threatened. Managers need to know: *What is the sensitivity of Landsat data to forest changes such as clearcuts, partial harvesting, precommercial thinning, and regeneration? What is the best way to extract landcover information from Landsat TM imagery for input to large-area wildlife habitat mapping applications?*

To address these questions, Landsat TM imagery were used in detecting forest changes and mapping land cover in two of Canada's Model Forests: the Fundy Model Forest and the Foothills Model Forest. These are two large-area, multi-jurisdictional forest management units in southeastern New Brunswick and north-central Alberta, respectively (Figure 2). In the Fundy Model Forest, the objective was to report the area of *change in forest structure* in each year for which suitable Landsat image data were available over a 15 year time period (1984-1999) (Franklin *et al.,* 2001a). In the Foothills Model Forest, validated grizzly bear (*Ursus arctos horribilis*) habitat maps were required (Franklin *et al.,* 2001b). The objective was to generate a Landsat TM land cover map that could provide a suitable input layer for models of bear habitat use and population dynamics.

DATA COLLECTION AND PROCESSING

Landsat Image Processing Tasks

Landsat imagery were acquired of the Fundy Model Forest on September 18, 1984, September 21, 1985, August 23, 1986, August 10, 1988, August 7, 1992, September 6, 1997, and September 12, 1999. Landsat imagery were acquired of the Foothills Model

Forest on August 8, 1999 and September 20, 1999. These images represent the best imagery in the archives for the months of August and September in which most of the areas of interest were relatively cloud free; a few very small areas of cloud and cloud shadow were identified by thresholding bright areas and shadows supplemented with manual digitizing on-screen. Those areas were removed from the analysis with no effect on the image processing results.

Each image was solar-zenith angle (illumination) and atmospherically-corrected using a standard-atmosphere, model-based correction routine (Richter 1990), then geometrically registered to the UTM projection with more than 20 ground control points at key road intersections dispersed throughout the scene. Typically, the resulting transformations were accomplished with less than 0.5 pixel RMSE. Cubic convolution resampling was used to create a 25 m output grid; in the Foothills Model Forest, an additional step was to mosaic the Landsat images together and normalize the result such that the seam between them – principally due to phenonological differences – was not visible. The Tasseled Cap Transformation (Crist 1985) was used to derive the brightness/greenness/wetness spectral indices for input to the mapping procedures for each Model Forest.

Mapping Change in the Fundy Model Forest

The TM wetness index was subtracted from each preceding image date and linearly-enhanced to emphasize the forest differences of interest. Thresholds were applied based on field knowledge of areas disturbed by clearcutting, partial harvesting or silvicultural treatments; for example, the largest difference in wetness was found in the clearcut areas, followed by shelterwood and seed tree cuts, partial harvesting with legacy patches, and precommercial thinning. The available New Brunswick forest inventory GIS data were used to 'mask' all non-forest areas from the change detection procedure; obviously, since the GIS forest cover data were a static layer (compiled in 1997 from 1993 photography) some minor error may have been introduced in this masking process (i.e. some areas that changed in the 1984-1985 scene were not changes to forest cover, but occurred in agricultural or wetland areas for example, and may have 'escaped' the mask). The thresholds of wetness differences were used to develop a map. This process is illustrated graphically for the 1984-1985 image pair in Figure 3. The final results of the image thresholding process for the Model Forest – the accumulated changes – are shown for the available image sequence in Figure 4.

Mapping Land Cover in the Foothills Model Forest

The approach to producing a land cover map of the Foothills Model Forest was based on a decision-tree classifier, a unique combination of unsupervised and supervised classification techniques that rely on spectral, digital elevation model, and polygonal GIS data to extract the maximum information content from the assembled mapping database (Franklin *et al.,* 2001b). First, an interdisciplinary team of remote sensing scientists, foresters, wildlife biologists, and botanists measured conditions at 320 field data locations, each approximately 0.1 ha in area. These locations were used as maximum likelihood training areas (to separate forest and vegetated classes) after comparison with Alberta Vegetation Inventory (AVI) data and digital orthophotography to determine the confidence that the training area pixels belonged to the identified field class. Second, the following sequence of processing steps was implemented: K-means unsupervised classification was used to separate forest and non-forested areas; an empirical slope decision rule separated lakes and shadows; an empirical elevation decision rule separates shadows and closed conifer stands at lower elevations; empirical slope decision rules separated different shrub and wetland classes based on distances to roads and streams; and empirical GIS overlay decision rules were used to embed cultural features, forest harvest polygons, and to merge classes which were considered spectrally indistinguishable based on Bhattacharryya Distance measures.

The final land cover classification map is shown in Figure 5. Accuracy assessment of this map product was based on the available digital orthophotography and a random sample of 494 locations.

RESULTS AND ANALYSIS

Fundy Model Forest Change Detection Application

The final map of forest structural changes detected in forest areas of the Fundy Model Forest is contained in Figure 4. The average annual change on the landscape was approximately 3068 ha over the 15 year interval, with apparently declining mean annual change from the mid-1980s to the late 1990s. The maximum annual change was more than 7000 ha in 1985-1986; the minimum annual change was less than 2500 ha in each of the years from 1986 to 1992. This estimate of change is almost certainly low; an artifact of the six year time interval between the 1986 and 1992 TM images in which changes of lesser severity (e.g., some partial cutting, thinning) could not be distinguished. In the late 1990s, the annual change was approximately 3500 ha. These estimates of total change (almost 50 000 ha) as a percentage of the total Fundy Model Forest land base (more than 400 000 ha) suggest that approximately 12% of the total land area has experienced a change in forest structure; annually, this is equivalent to a rate of change of 0.81%. Since the available productive forest land (approximately 240 000 ha) represents approximately 60% of the total land base, the true estimate of forest structure change is probably closer to 20% in the time interval studied, which translates into a rate of change of approximately 1.3% annually.

Great care must be taken in comparing rates of change in forests from different areas of the world and using different methods of analysis. Typically, *rates of forest loss* are reported rather than changes in forest structure; and, typically, only two image dates some years or decades apart are compared, rather than the detailed year-by-year or multiple comparisons as reported in this study. For example, in a large forested area on the border of China and North Korea, 1972 and 1988 Landsat imagery were classified into forest and non-forest classes and difference image maps created (Zheng *et al.* 1997). Much of the change detected was a result of clearcutting; partial harvesting had increased in this area after 1980 as a result of government policies encouraging selective harvest over clearcutting, but the classification scheme did not show many of those areas as changes. Their method was unable to distinguish natural and human disturbances because not enough training data were available for use in the classification procedure. The annual rate of forest cover loss was –0.73% over the 16 year period for the study area, a comparable rate to that reported by Spies *et al.* (1994) in the US Pacific Northwest for a similar period using two Landsat images. Outside the Changbai Biosphere Reserve, the annual rate of forest disturbance increased to 1.12% (Zheng *et al.*, 1997).

In British Columbia, Sachs *et al.* (1998) reported a large region of the interior forests to be in the early stages of fragmentation. Their analysis was based on the classification of Landsat imagery acquired in 1975 and 1992. Human disturbance was shown to have affected 8.4% of the forest structure in a large study area outside protected areas between 1975 and 1992. Mature and older conifer forest area decreased more than 10%, accompanied by decreases in mean conifer patch size and the percentage of interior forest area. The annual rate of change was estimated to be 0.49% per year. This was thought to be at the low end of the range of disturbance rates for managed, temperate forests (Sachs *et al.* 1998). For example, in Minnesota, Hall *et al.* (1991) reported Landsat-derived annual conifer forest disturbance rates of 1.8% over a 10-year period; in New Jersey, Luque *et al.* (1994) classified two Landsat images and found pine-oak forest stands over a wide area to be subject to an annual forest disturbance rate of 2.2%. Influences on forest fragmentation in different watersheds can be strikingly different (Tinker *et al.*, 1998), and order-of-magnitude changes in rates of forest disturbances can occur on public, private and wilderness (protected) lands.

Such trends are apparent in the Fundy Model Forest change detection map, which has been used in a forest fragmentation analysis leading to insight into sustainability of economic use of the forest resource (Betts and Taylor, 2002). The large, intact 'white' area in the bottom right (southeast corner) of the map comprises Fundy National Park; only a few small changes occurred inside the park boundary compared to the areas adjacent to the park but within the Model Forest. These small areas of change inside the park represent a number of small human disturbances (e.g., road widening) and natural disturbances – such as beaver pond flooding, tree blowdown, and insect defoliation – that are likely also present but undistinguished from other changes in the larger mapping product.

Foothills Model Forest Grizzly Bear Habitat Application

The overall classification accuracy of the final map generated by the decision tree classification procedure was approximately 83% (Figure 5). In the forest and vegetation plots only, 75% accuracy was achieved; collectively, these were the lowest accuracies, compared with higher classification accuracy in the non-vegetated classes (e.g., snow, rock, shadow were all above 90%). First, the mixed deciduous and mixed conifer classes resembled each other as well as resembling the closed or open deciduous and conifer classes. In the mixed classes, the actual amount of mixing of the two plant lifeforms and the appearance of the crowns on the image did not provide a spectral difference that could be consistently identified.

The map has been used in several ways to support bear management in the greater Yellowhead Ecosystem. The primary use is in the creation of a grizzly bear *habitat map*; land cover maps are needed to provide interpretations of habitat classes, which often rely on predictive or assumed characteristics that accompany the various cover types, such as understory conditions and presence/absence of certain food plants. One procedure is to assign classes a habitat quality ranking (e.g., Kansas, 2001). Another approach is to develop resource selection functions (RSFs), which are models that enable prediction of *habitat use* by grizzly bears, or the 'probability of occurrence' of bears on the landscape (Manly *et al.,* 1993, Boyce and McDonald, 1999). For example, Nielsen *et al.* (2002a, 2002b) suggested the Landsat land cover map produced for the Foothills Model Forest area explained approximately 6% of the variance in bear habitat use/availability data, depending on season.

The Foothills land cover map was also used to generate landscape metrics at different spatial scales; for example, at the watershed scale (approximately 300 km^2) areas of low and high disturbance were related to bear distribution data obtained from DNA-samples at bait stations (Popplewell *et al.,* 2002). Areas with low mean patch size, high edge density, and a large number of patches were associated with low bear density estimates.

CONCLUSION

Satellite remote sensing imagery acquired by the Landsat Thematic Mapper and similar sensors can be used to generate information products of high interest and value to forest managers concerned with large-area, multijurisdictional forest management questions. Forest cover change maps and landscape structure maps are two such information products available with reasonably modest investments in understanding image resolution, mapping scale, and processing methods. Two examples are used here to emphasize this key point:

1) Mapping differences in Landsat TM wetness indices acquired in 1984, 1985, 1986, 1992, 1997, and 1999 in the Fundy Model Forest of New Brunswick showed distinctive patterns associated with forest structure changes known to have occurred as a result of silvicultural and harvesting operations. The rate of change in forest structure was quantified over the 15 year time period and the spatial arrangement of the changes detected used as input to a forest fragmentation analysis.
2) A 'decision-tree' classification of a Landsat TM image mosaic in the Foothills Model Forest of Alberta was determined to be approximately 83% accurate in separating open and closed conifer and deciduous forests, wetlands, shrub and grass areas, which are of interest in identifying bear habitat and relating structural features to bear behaviour over time. This land cover map was used in two

principal ways: a) to develop a grizzly bear habitat map in conjunction with resource selection functions, which predict bear habitat use, and b) to provide a consistent and quantitative data layer for derivation of forest fragmentation landscape metrics, which were related to bear density estimates.

Future Directions

Many new options will be available in the near future for the remote detection, mapping, and monitoring of forest cover and change largely based upon research efforts with current and newly available data types and national mapping programs. For example, the existence of comprehensive large area sampling campaigns, such as the National Forest Inventory, that regularly capture broad-scale forest characteristics provide for a training data source for remotely-sensed data allowing for forest monitoring over a range of ecosystems and jurisdictions.

Improvements in spatial, spectral, radiometric, and temporal resolution are expected in forthcoming satellite sensors. Panchromatic image spatial resolution is currently approximately 1m over image swath-widths up to 11 km (IKONOS), and 15 m over image swath-widths of 185 km (Landsat-7 ETM+), but data fusion and large-area mosaicking protocols are vastly improved (Solberg, 1999). Future sensors will combine high spatial resolution with increased spectral resolution – commonly known as *hyperspectral* imagery. The radiometric resolution of several recently-launched and proposed sensors is also higher; for example, IKONOS imagery are collected at 11 bits per pixel, compared to the more familiar Landsat 8-bit data. Temporal resolution may be more difficult to increase for higher spatial sensors, but directable sensor heads, and using multiple sensors with compatible data provide for additional data acquisition flexibility.

Data acquisition and processing costs are often an inhibiting factor in satellite remotely sensed data use, but both continue to decrease significantly as new sensors are deployed and computer hardware/software costs decline relative to performance. An example of a new sensor configuration with great promise in forestry applications is light detection and ranging (lidar). Lidar data are well suited to measurements of the vertical distribution of forest structure (Lefsky *et al.,* 2001). Multiple dates of processed lidar imagery enable the detection of subtle changes at very high spatial resolution. For example, with lidar it is possible to consider monitoring forests, or individual trees, for height increment over time. The increasingly refined nature of data products available ready to use directly from the data vendors allows analysts to spend less time processing imagery and more time analyzing imagery. In turn, this will enable a larger user group for imagery to emerge, with the user group largely composed of individuals who are experts in domain areas of interest, such as forest pathology and inventory, rather than image processing.

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List of Figures

Figure 1.

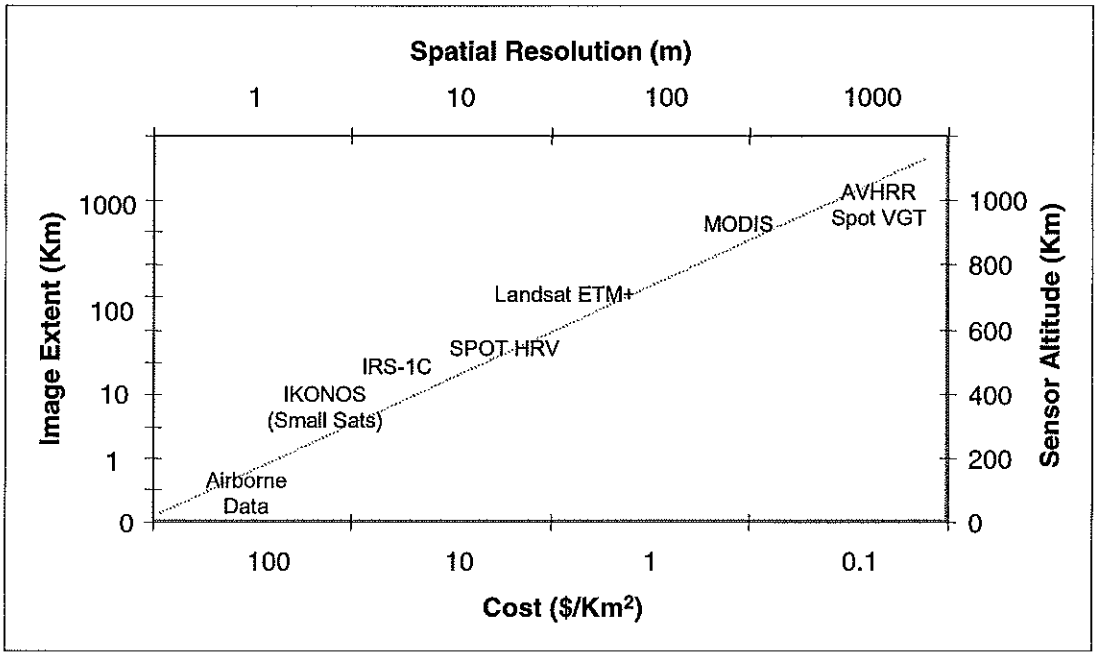
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Image Extent (Km)
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AVHRR
Spot VGT
MODIS
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SPOT HRV
IRS-1C
IKONOS
(Small Sats)
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Data
Sensor Altitude (Km)
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1
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Cost ($/Km²)