Using satellite remote sensing to assess and monitor ecosystem integrity and climate change in Canada's National Parks

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Abstract- **Natural Resources Canada, Parks Canada Agency and the University of Ottawa are developing standardized approaches for monitoring landscape change within and surrounding Canada's National Parks using Earth observation. This paper focuses on remote sensing methodologies developed at the CCRS for three types of ecological indicators: Landscape Pattern, Succession & Retrogression, and Net Primary Productivity (NPP), using La Mauricie National Park to demonstrate the methods and results. Landscape pattern analyses are discussed in relation to landscape metric stability, scaling, and selection. Major vegetation disturbances through time were examined using a hybrid change detection technique combining vegetation index differencing and constrained signature extension. Ecosystem productivity measures were developed using a remote sensing-based modeling approach known as EALCO (Ecological Assimilation of Land and Climate Observations). It is anticipated that this pilot study will produce new automated EO processing methods that culminate in an operational remote sensing-based system for monitoring the ecological integrity of Canada's National Parks and their greater ecosystems.**

I. INTRODUCTION

Parks Canada Agency (PCA), under the Canada National Parks Act, is charged with the responsibility of managing Canada's National Parks through the maintenance or restoration of ecological integrity. One of the steps in the management process is the production of a *State of the Park Report* every 5 years for each park, which describes the state of health of the park in the context of the greater park ecosystem and the progress made toward achieving the goals of the previous park management plan. To improve monitoring efforts towards producing the *State of the Park Reports,* PCA has initiated collaboration with the Canada Centre for Remote Sensing (CCRS) and the University of Ottawa under the Canadian Space Agency's (CSA) Government Related Initiatives Program (GRIP) to use EO technology to monitor landscape change within and surrounding Canada's National Parks.

National Parks are well suited for detecting and monitoring impacts of climate change because of the relatively small effects of direct human disturbance within park boundaries.

Climate change is predicted to have a major impact on the biodiversity of many Canadian National Parks as a result of changes in species' ranges, altered disturbance regimes and successional trajectories, increased productivity, and vegetation shifts [1]. This paper focuses on the remote sensing technologies developed at CCRS for three classes of Parks indicator related to landscape pattern, succession and retrogression, and ecosystem vegetation productivity. La Mauricie National Park (LMNP), one of seven project pilot parks, will be used to illustrate the methods and results. General pre-processing steps are discussed first, followed by a discussion of methodologies and results specific to each of the remote sensing-based indicators. Fig. 1 provides a schematic overview of the processing methodology discussed in this paper.

II. STUDY AREA

Canada's La Mauricie National Park covers 536 km^2 and is located to the north of the St. Lawrence River near Shawinigan, Quebec, in the transition zone between boreal and northern hardwood/temperate forest. Dominated by forested uplands, LMNP includes over 150 lakes. The area outside the park within the Greater Park Ecosystem (GPE) experiences extensive forest harvesting, as well as intensive agricultural land use to the south.

III. DATA PREPARATION

A. Imagery and Vector Data

Landsat TM/ETM+ data for two scenes (14/27 and 14/28) covering the extent of LMNP GPE were acquired for each five-year interval circa 1985 to 2005 (Table 1). Ancillary vector data were provided by Parks Canada and included Park and GPE boundaries and an ecological forest inventory of the Park updated in 2001 providing detailed forest information such as stand height and age class.

Both Landsat scenes from each of the five dates were manually registered, mosaiced, and reprojected using an image-to-image warp. To obtain sub-pixel precision for change detection, an RMS error below 0.45 pixels was
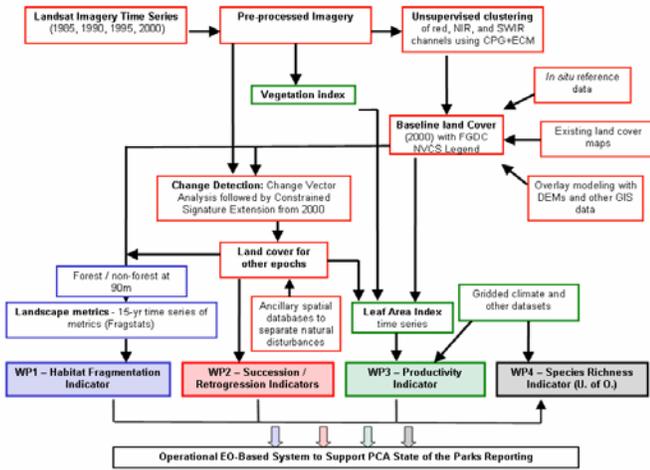
Figure 1. Overview of remote sensing processing methodology employed in GRIP Parks project.

maintained. The 1995 scene was atmospherically corrected using the Dense Dark Vegetation (DDV) approach [2] and other dates were normalized to the corrected 1995 imagery using Theil-Sen robust regression [3], first introduced to the remote sensing community by Fernandes and Leblanc [4], to account for differences in acquisition dates.

B. Classification and Land Cover Time Series Generation

The 1995 imagery was classified using a combination of Enhancement Classification Method (ECM) and Classification by Progressive Generalization (CPG) [5] to create a land cover product consistent with the Federal Geographic Data Committee (FGDC) legend modified for Canadian vegetation. Essentially, this involved image enhancement, unsupervised generation of 150 initial clusters, and progressive merging and labeling to land cover without significant loss of information from the original image. Signatures were extracted from the 1995 master classification and extended to the other time periods while constraining land cover transitions to their most likely outcome based on expert knowledge. This constrained signature extension approach [6] was employed to generate a multitemporal land cover time series, which was used as primary input to the landscape pattern analyses, post-classification change detection, and productivity modeling.

IV. REMOTE SENSING-BASED INDICATORS

A. Landscape Patterns

This work examines the potential for fragmentation metrics to quantify changes in landscape pattern over time. A suite of metrics commonly applied for landscape pattern assessment was evaluated including percent forest, core area percent forest, patch density, edge density, mean patch size, mean perimeter to area ratio, mean perimeter to area fractal dimension, mean shape index, mean Euclidean nearest neighbor distance, mean proximity index, percentage of like adjacencies, adjacency index, clumpy, division, and split. Metrics were calculated using the software Fragstats [7] at

image resolutions of 30, 90, 150 and 210 m, using simple forest\non-forest landscape models derived from the land cover time series. At 30 m resolution, most of the metric temporal trends followed the expected trends based on visual image interpretation, field data, and other historical sources of change information for the park (Table 1). The shape and proximity metrics did not appear to provide meaningful temporal trends. This is likely the result of the majority of the forest area consisting of one patch with few other patches occurring in the defined landscapes.

As errors in land cover classification are inevitable, the sensitivity of metrics to noise in the data needed to be evaluated. Thus, a signal-to-noise index (SNI) was developed. Three sets of overlapping image scenes with near coincident dates were used. Differences in metric values between image data within the overlap areas were therefore due to undesirable variation (i.e. noise) resulting from atmosphere, sun-sensor viewing geometry, phenology, and sensor errors. Sub-areas within the image scenes were selected representing fragmented forest landscapes and non-fragmented forest landscapes, and used in the SNI equation (1).

TABLE 1
SUMMARY RESULTS FOR LANDSCAPE PATTERN ANALYSIS FOR LMNP

Metric	Conceptual Group[a]	S/N Index Rank[b]	Followed Exp. Temporal Trajectory?[c]
Percent forest	Area	$5_F, 1_A$	Yes
Core Area Percent Forest	Area	$25_F, 4_A$	Yes
Patch Density	Density	$8_F, 2_A$	Yes
Edge Density	Edge	$27_F, 12_A$	Yes
Mean Patch Size	Area	$40_F, 35_A$	Yes, but error for park landscape
Mean Perimeter to Area Ratio	Shape	$72_F, 64_A$	?
Mean Perimeter to Area Fractal Dimension	Shape	$35_F, 51_A$	?
Mean Shape Index	Shape	$67_F, 78_A$	?
Mean Nearest Neighbor Distance	Isolation/ Proximity	$80_F, 80_A$	?
Mean Proximity Index	Isolation/ Proximity	$65_F, 68_A$	?
Percentage of Like Adjacencies	Contagion	$21_F, 3_A$	Yes
Clumpy	Contagion	$2_F, 17_A$	Yes, but error for park landscape
Adjacency Index	Contagion	$30_F, 7_A$	Yes
Division	Contagion	$6_F, 5_A$	Yes
Split	Contagion	$22_F, 32_A$	Yes

[a]**Conceptual Group:** As per Fragstats software.
[b]**S/N Index Rank:** Signal-to-noise index rank out of 90 metrics evaluated: subscript F indicates results for forest landscapes and subscript A indicates results for agricultural landscapes.
[c]**Followed Exp. Temporal Trajectory:** Answers the question "Did the metric appear to respond to the trajectory of change based on visual image interpretation, field data, and other auxiliary information through time?".

$$S/N\ Index = \frac{|\mu f - \mu nf|}{\sqrt{\frac{1}{n}\sum_{i=1}^{n}(f_{i_t} - f_{i_{t-1}})^2} + \sqrt{\frac{1}{n}\sum_{i=1}^{n}(nf_{i_t} - nf_{i_{t-1}})^2}} \quad (1)$$

where :
μf = mean for fragmented landscape samples
μnf = mean for non –fragmented landscape samples
f_{i_t}, nf_{i_t} = metric value for fragmented/non - fragmented sample i at time t
$f_{i_{t-1}}, nf_{i_{t-1}}$ = metric value for fragmented/non - fragemented sample i at time t + 1
n = number of paired samples

Overall, the shape and proximity metrics had low SNI values indicating that they were the most sensitive to noise. The area, edge, and density metrics had the highest SNI values, indicating that this group was the most robust and had the greatest potential to separate fragmented and non-fragmented forest. Further research is required to determine if more stable results can be achieved over a larger range of landscapes.

B. Succession & Retrogression

To identify areas of change in and around LMNP, a hybrid change detection method was employed that combines two separate techniques: simple ratio (SR=TM5/TM4) vegetation index differencing for identifying changed areas, and constrained signature extension for labelling of those changes. Change masks were created to include disturbed areas from the preceding time period, and subtle change areas identified using a vegetation index difference between the previous and current time period. Areas beneath the change mask were updated using a subset of spectral signatures from the baseline classification, and all other areas identified as having remained unchanged were classified using spectral signatures applied to mean clear sky Landsat data from all dates. The subset of spectral signatures used in the updating procedure includes only those signatures that represent regeneration classes to avoid known confusion between young and mature forest classes. Fig. 2 provides an example of the classification updating process.

The majority of changes detected were due to human land use that occurred outside the Park boundary within the GPE, and were mainly attributable to extensive forest harvesting and regeneration of previously harvested forest. The bulk of such changes occurred between 1995 and 2005, with extensive disturbances due to forest harvesting appearing to the northwest of the park. Within the park boundary, there were relatively few changes identified, except for several small-scale prescribed burns, a blow down, and an insect defoliation (and subsequent tree-removal) event within a campground area.

C. Primary Productivity

Vegetation productivity is another key indicator of ecosystem function. Primary productivity, a measure of the amount of energy available in a system, is thought to be one of the major determinants of species diversity, especially species richness [8]. Net Primary Productivity (NPP) is the net amount of primary production after the costs of plant respiration are included. To better evaluate the ecosystem

vulnerabilities to climate change at the national scale and provide improved scientific support for policy making, it is imperative that ecosystem models have the capability of assimilating the large scale geospatial information including satellite observation, GIS datasets, and climate model output or reanalysis. The EALCO model (Ecological Assimilation of Land and Climate Observations) was developed for such purposes and includes the comprehensive interactions among ecosystem processes and incorporates a variety of remote sensing products and GIS data [9]. Model inputs include meteorological observation as well as soil, land cover and leaf area index maps. Carbon simulations in EALCO provide outputs of ecosystem gross primary productivity (GPP), net primary productivity (NPP), net ecosystem production (NEP) and other measures of the ecosystem carbon sequestration and greenhouse gas (CO_2) exchange with the atmosphere. This work package focuses on developing ecosystem productivity measures and indicators using a remote sensing-based modeling approach. These indicators will track past and future changes in ecosystem vegetation productivity, and will be updated every five years for each park.

The EALCO model simulates annual Gross Primary Productivity, NPP and NEP, the difference between NPP and soil CO_2 release due to soil organic matter decomposition. NPP is usually the dominant component of NEP. The annual modelled NPP for LMNP for 2000 is shown in Fig. 3. While the long-term trends in NPP over LMNP showed that there may be some evidence of an impact of climate change and variations on ecosystem productivity, the influence of stand age must be separated first in order to accurately assess the climate signal. Fig. 4 shows the ecosystem productivity changes over the 41-year period (1960-2000) for a deciduous forest in LMNP, illustrating the significant impact of age and its role in climate change impact assessment.

V. CONCLUSIONS

With support from the Canadian Space Agency, Natural Resources Canada is continuing collaborative efforts with Parks Canada Agency and university partners to advance and improve ecosystem monitoring in Canada's National Parks using EO and space technology. These methods will provide key indicators of ecosystem function involving succession and retrogression, and measures of productivity. The project will also deliver indicators on landscape pattern based on an optimal set of metrics that remain stable over time and are most sensitive to stressors such as habitat fragmentation. It is anticipated that the EO-based methods developed at CCRS for this pilot project will result in a new framework for operational remote sensing-based monitoring of ecological integrity in Canada's National Parks.
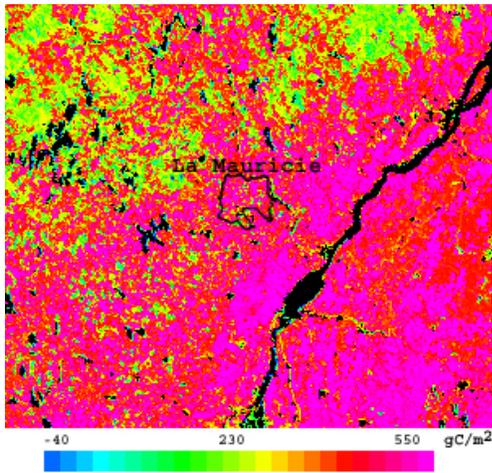
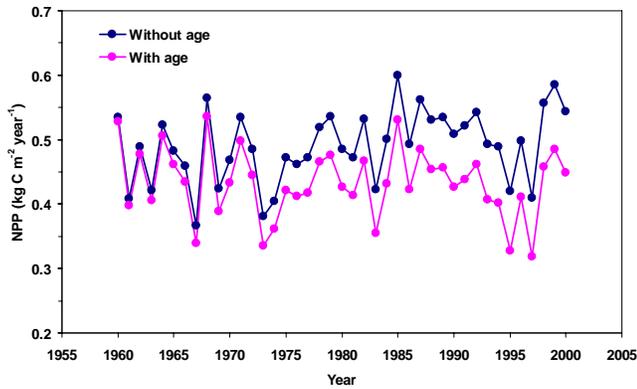Figure 3. Modelled annual net primary productivity [gC/m²] for LMNP and GPE, 2000.

Figure 4. Ecosystem productivity changes over the 41-year period (1960-2000) for a deciduous forest in LMNP, illustrating the influence of stand age on signal.

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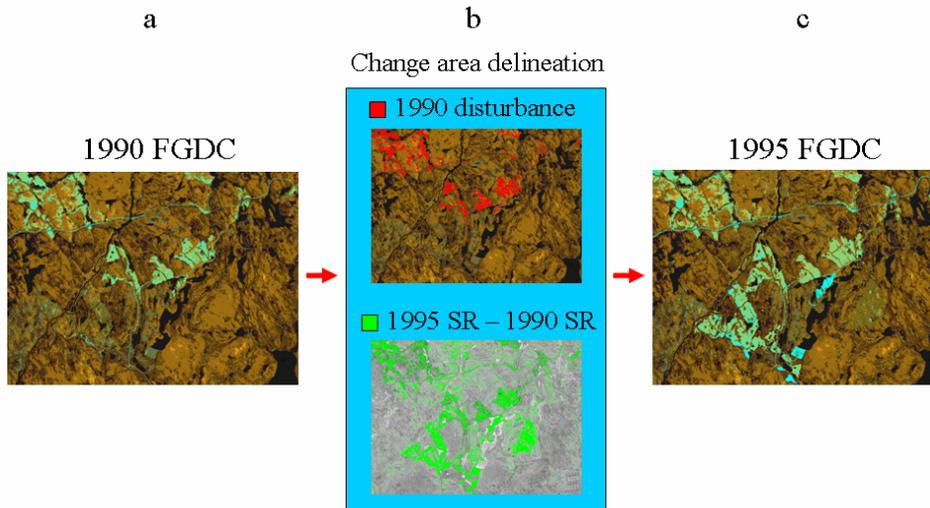
Figure 2. Classification updating procedure: a) 1990 FGDC classification of an area west of LMNP within its GPE, b) change area delineation of areas for updating that include 1990 disturbances and a Simple Ratio (SR) vegetation index difference threshold, and c) updated 1995 FGDC classification with change areas labelled using constrained signature extension.