Mapping and Modelling Forest Change in a Boreal Landscape

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Introduction

Timber harvesting is one of the major factors altering the species composition, age class distribution, and carbon fluxes over much of forested North America. Timber harvesting in Minnesota, the nation's largest paper producer, is expected to increase by approximately 25% in the next several decades to supply increased fiber demand for paper mill expansions. Similar expansions are also expected in adjacent northwestern Ontario. In contrast to these managed forested lands, the 2.0 million ha of the Boundary Waters Canoe Area (BWCA) and Voyageurs National Park (VNP) in Minnesota and adjacent Quetico Provincial Park in Ontario is the largest contiguous, forested wilderness area in North America. This wilderness landscape has its own disturbance regime generated mainly by large fires (Heinselman 1973) which is distinctly different from the anthropogenic disturbance regime imposed by timber harvesting immediately outside the BWCA-VNP-Quetico wilderness (Hall et al. 1991). Much of the forest is old-growth conifer, but there are large patches of early-mid successional forest as well.

There is no other place in the 48 contiguous states where there are large, matched, forested landscapes with contrasting natural and anthropogenic disturbance regimes. Therefore, Minnesota and adjacent northwestern Ontario is a natural "landscape laboratory" for determining the impact of extensive timber harvesting on landscape structure in comparison with an equivalent large landscape of uncut forest subject only to a natural disturbance regime.

We are using multitemporal data from Landsat Thematic Mapper (TM) 5 or 7 to classify forest cover to near species level (Wolter et al. 1995), then map the changes in the forest mosaic through time on a biannual basis to determine successional pathways under natural and managed disturbance regimes. Markov transition matrices will be developed from these data and analyzed using Markov theory (Pastor et al. 1993) to assess current trends in forest cover and steady state land cover distributions in order to help shape management policy at federal, state, and local levels.

Hall, F.G. et al. 1991. Ecology 72: 628-640.

Heinselman, M.L. 1973. Quarternary Research 3: 329-382.

Pastor, J., et al. 1993. Lectures on Mathematics in the Life Sciences 23: 5-27.

Wolter, P.T., et al. 1995. Photogrammetric Engineering and Remote Sensing 61: 1129-1143.

Significance of Proposed Work

When completed, the proposed work will:

(1) provide a temporal sequence of classified images and error matrices for the boreal forests of the Western Great Lakes Region;
(2) provide algorithms for future classification of these forests;

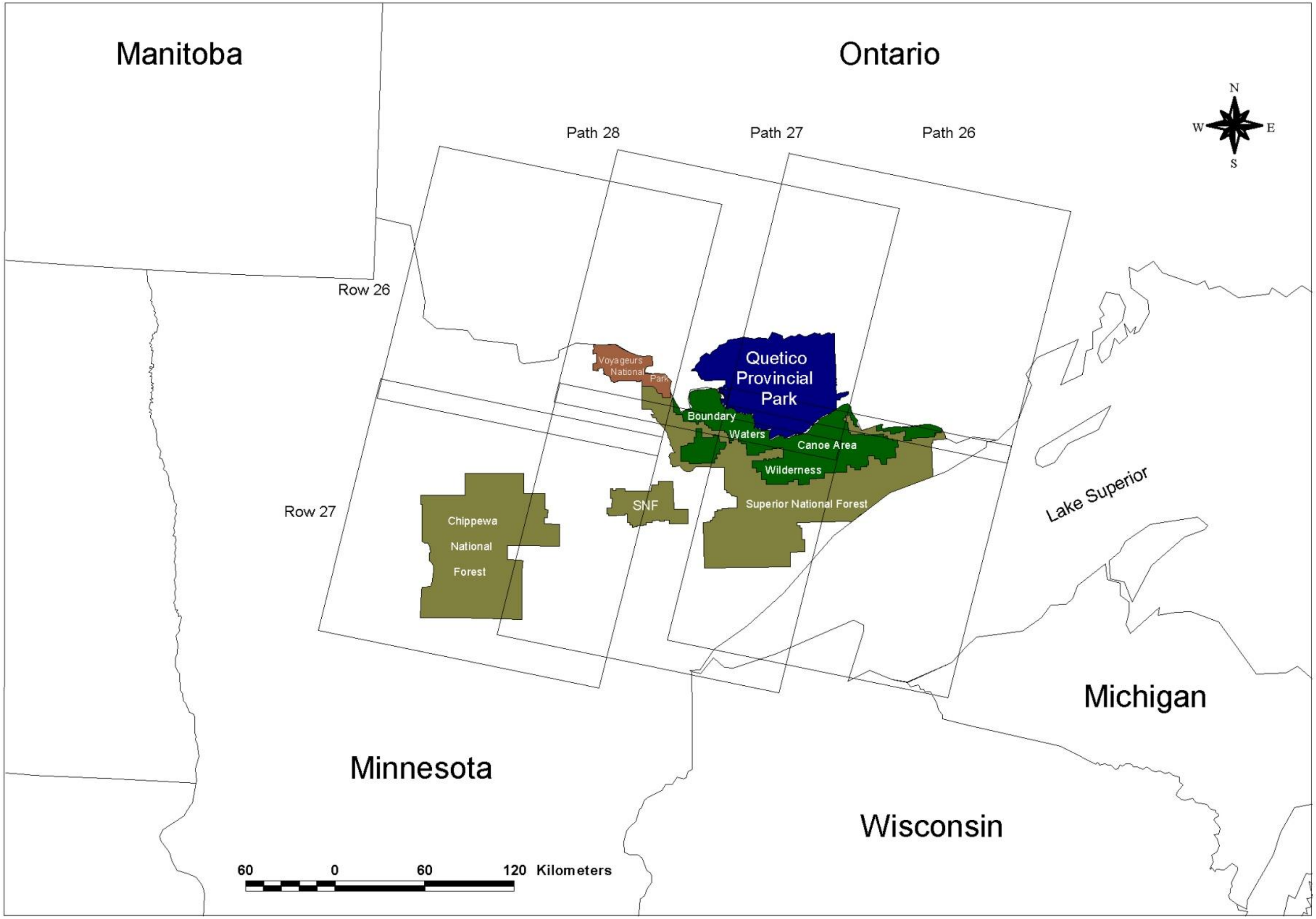
(3) demonstrate the use of Markov theory in analyzing these temporal sequences;

(4) compare dynamics of managed forests in the region with the dynamics of a large wilderness area subjected only to a natural disturbance regime.

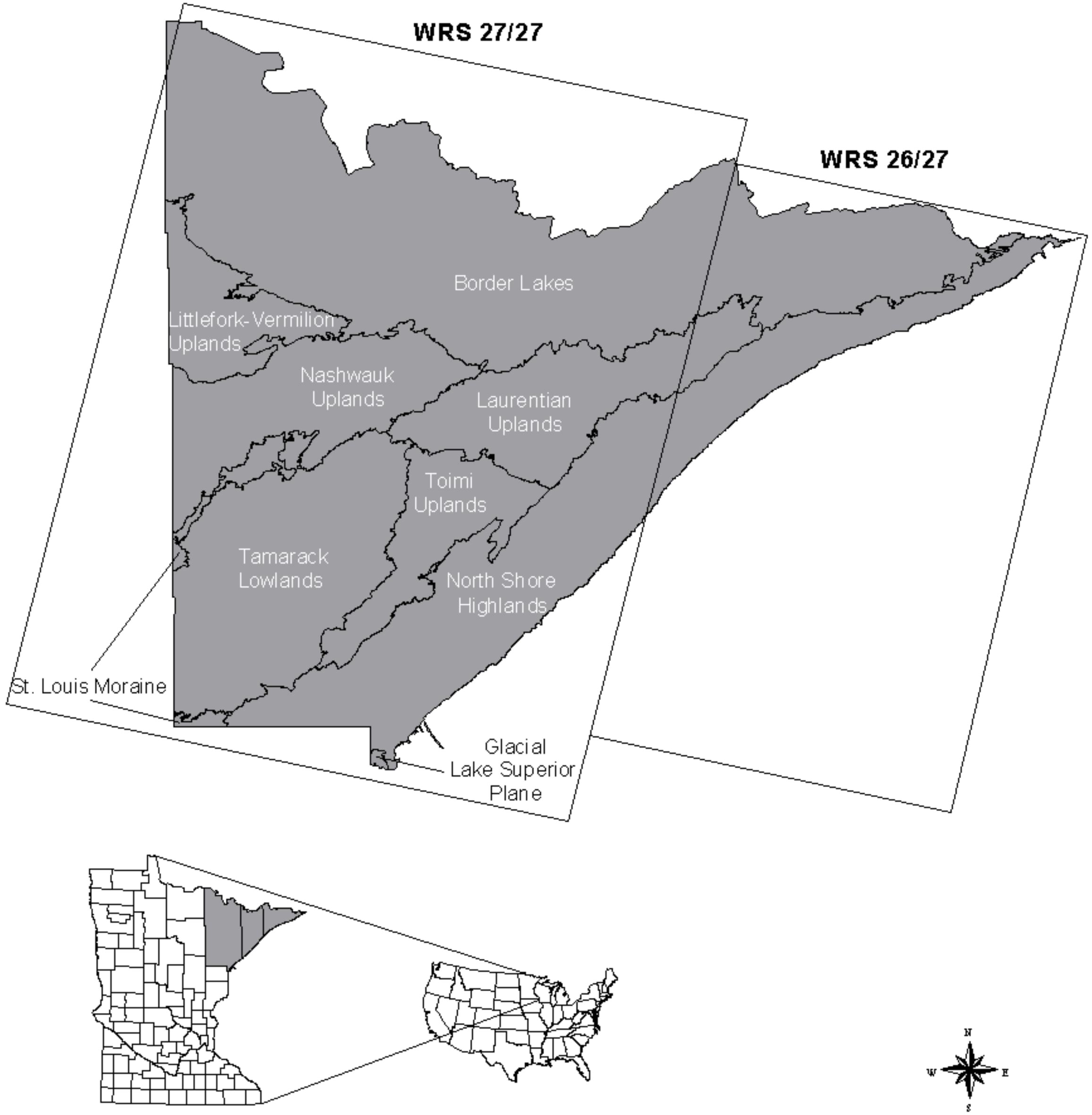
These milestones are in accordance with various NASA goals, especially those of the CEOS Global Observation of Forest Cover (GOFC) Project.

Study Region

The study region encompasses approximately 137,000 km^2 or six Landsat Thematic Mapper (TM) footprints in northeast Minnesota and southern Ontario. The Boundary Waters Canoe Area, Voyageurs National Park, Quetico Provincial Park, Superior National Forest, and the Chippewa National Forest are all located within the boundary of this study. The remaining area is largely managed state, county, or industrial forest.



Study region defined by Landsat TM data frames.



Example study area in northeast Minnesota, two Landsat TM footprints that cover the area and Ecological Subsection boundaries.

Forest Classification

The classification techniques employed in this example study are essentially those used by Wolter et al. (1995) in northern Wisconsin, USA.

Base TM images from each footprint were classified into conifer, hardwood, mixed conifer-hardwood, and non-forest using Minnesota Department of Natural Resources (MnDNR) Phase II forest inventory data (MnDNR, 1995) and 1:40,000 color infrared (CIR) aerial photographs as ground truth. The hardwoods class was used to clip the September and May Landsat data for each footprint to classify black ash (*Fraxinus nigra*), maple-dominated (*Acer saccharum* and *A. rubra*) northern hardwoods and aspen-birch (*Populus tremuloides-Betula papyrifera*) cover types. The conifers class was used to clip the winter TM data for classifying tamarack (*Larix laracina*), a deciduous conifer. Winter TM data were also used to detect the presence of understory conifer components among types classified as hardwood using summer TM data.

Peak maple senescence in this region typically occurs near the autumnal equinox (Eder 1989) while black ash trees are completely defoliated by this time (Wolter et al 1995). Conversely, aspen-birch is the first hardwood cover type to flush leaves in the spring -- usually by mid-May (Ahlgren 1957). Senescent, maple-dominated, northern hardwood cover types were classified using a combination of July (bands 1-5) and September (bands 1-5) TM data. Black ash, aspen-birch and tamarack were classified by applying thresholds to NDVI difference images: September-July, May-July and winter-July respectively. Forest inventory data and CIR aerial photos were used to guide threshold selection for the difference images. Remaining cover types were classified using traditional iterative classification techniques using forest inventory data, CIR aerial photos and field visits for validation.

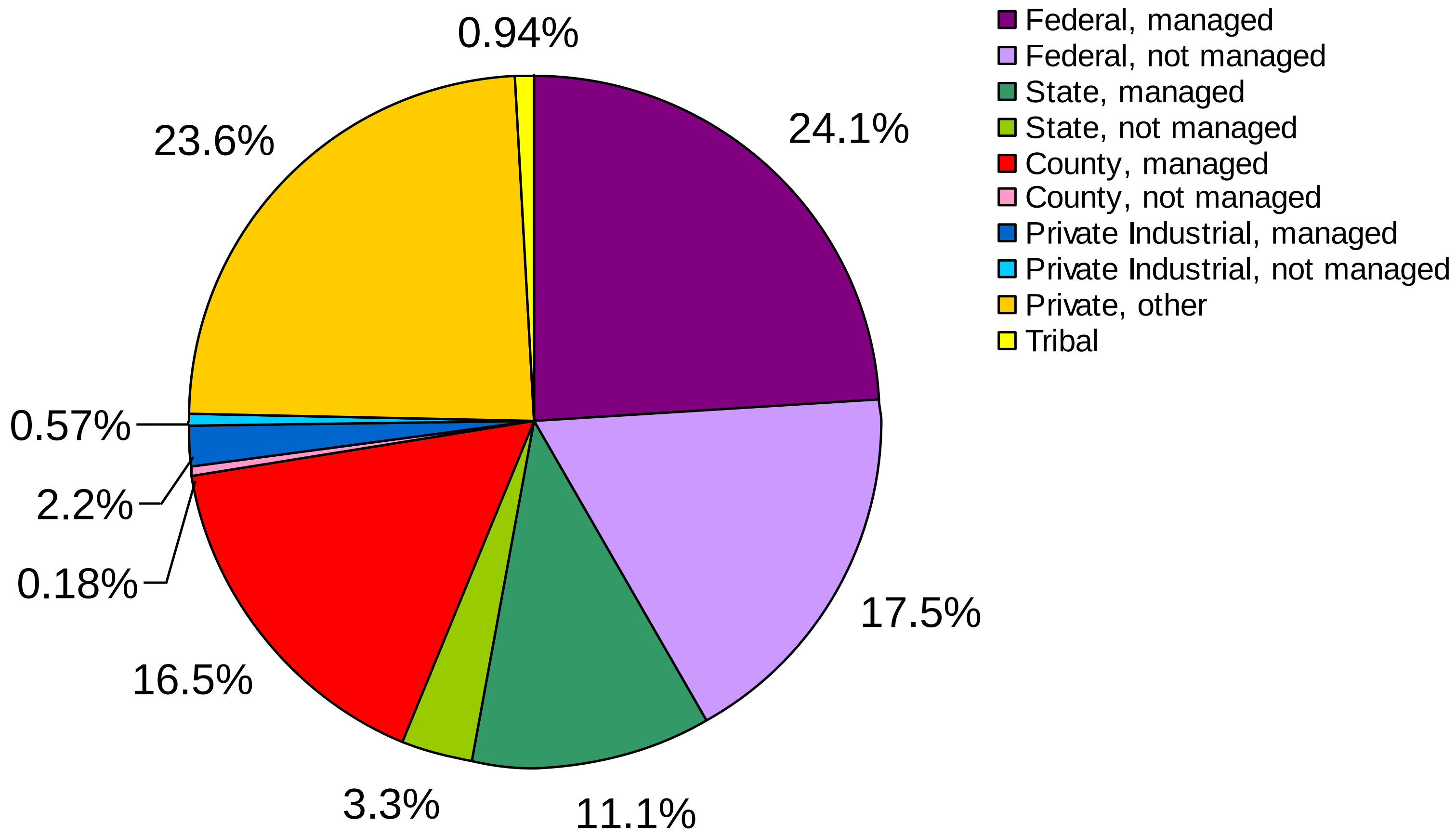
Change Detection

TM scenes 7/29/1995 and 6/1/1994 represented the second time-step for footprints WRS 27/27 and 26/27 respectively. To detect land-cover changes in time-2, we first identified pixels that exhibited a difference, either positive or negative, in reflectance between time-1 and -2. To accomplish this, we utilized a normalized version of the short-wave infrared/near infrared ratio (SWIR/NIR) using TM bands centered at 1.65 um (TM Band 5; 1.55-1.75 μm) and 0.83 μm (TM Band 4; 0.76-0.90 μm) respectively. The normalized difference SWIR/NIR ratio (NDSN) is defined as:

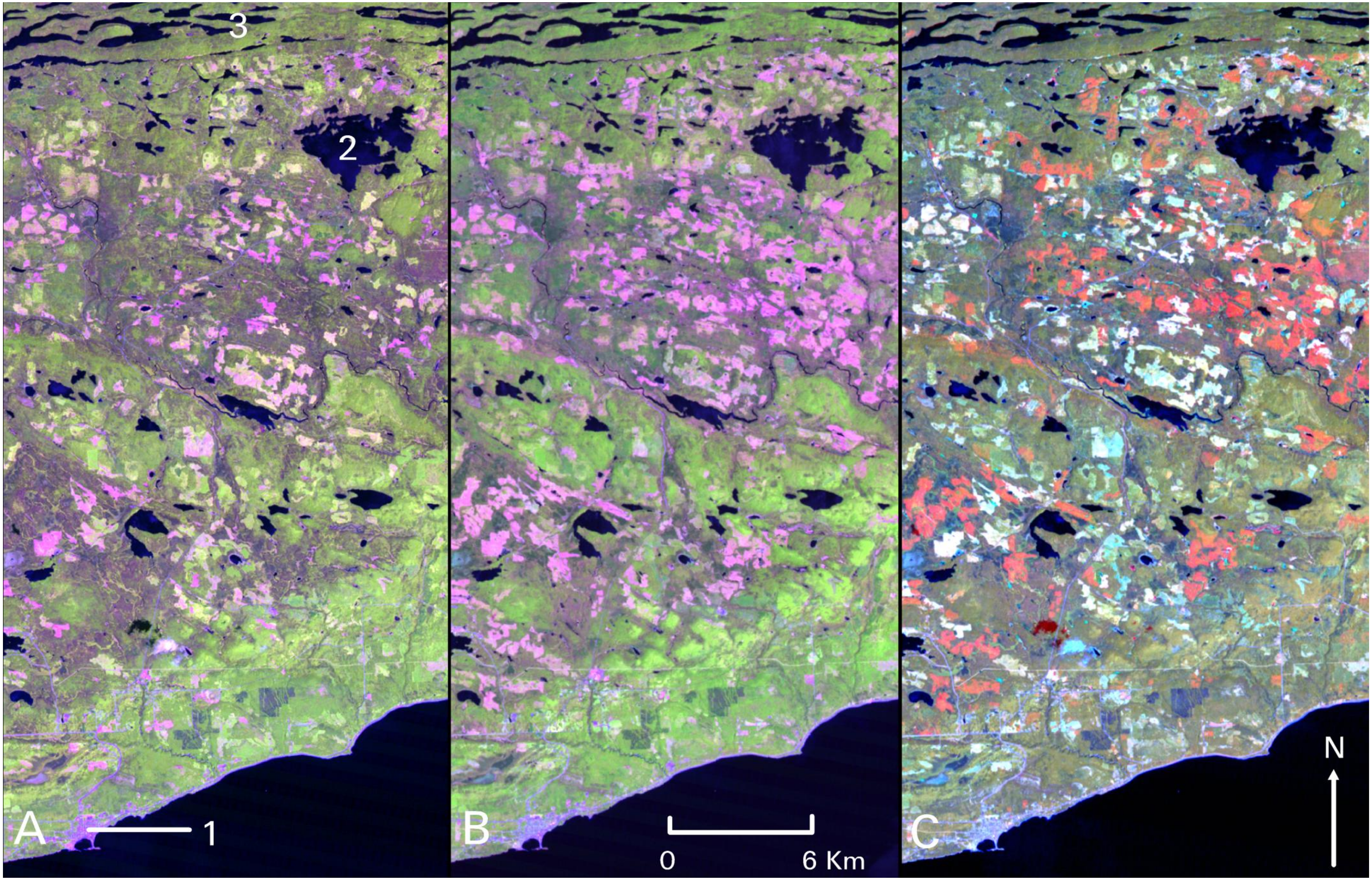
$$\{[(TM5 - TM4)/(TM5 + TM4)] + 1\} * 100$$

This basic ratio has been used extensively in the eastern United States to detect changes in forest cover due to insect outbreaks (Vogelmann and Rock 1989) and forest decline (Vogelmann and Rock 1988). Vogelmann (1990) showed that the SWIR/NIR ratio is far more sensitive to forest canopy disturbance than the widely used NDVI. Interpreted CIR aerial photographs (May 1991 and September 1997) were use to determine appropriate discriminant values for change in the NDSN difference image.

After change pixels between time-1 and time-2 were identified, they were used as a template to clip the classification from time-1. The clipped time-1 classification was then used as a template to stratify and classify raw TM data from time-2 on a class-by-class basis. For example, change pixels originating from the time-1 aspen-birch class were used to focus the classification of raw TM data for time-2. In doing this, potential illogical transition classes for this time span may be ruled out in favor of more logical aspen-birch transition endpoints (e.g., upland grass/brush, regeneration, burned or flooded) when time-2 spectra are confused with illogical transition types. For example, an aspen-birch stand that was harvested between time-1 and time-2 should not be classified as ericacious brush, sphagnum moss or acid-bog conifers in time-2. This would be a highly unlikely transition of cover types. Conversely, if some of the change identified by the difference image classifies out to be mature hardwood it is most likely aspen-birch and can be treated as no change. This scenario occurs when discriminants chosen to quantify change using the NDSN difference image are not precise. Classification of the raw TM data from time-2 was accomplished using ISODATA (ERDAS 1997). Once all cover type transitions were identified, they were merged with the time-1 classification to produce a complete classification layer for time-2.



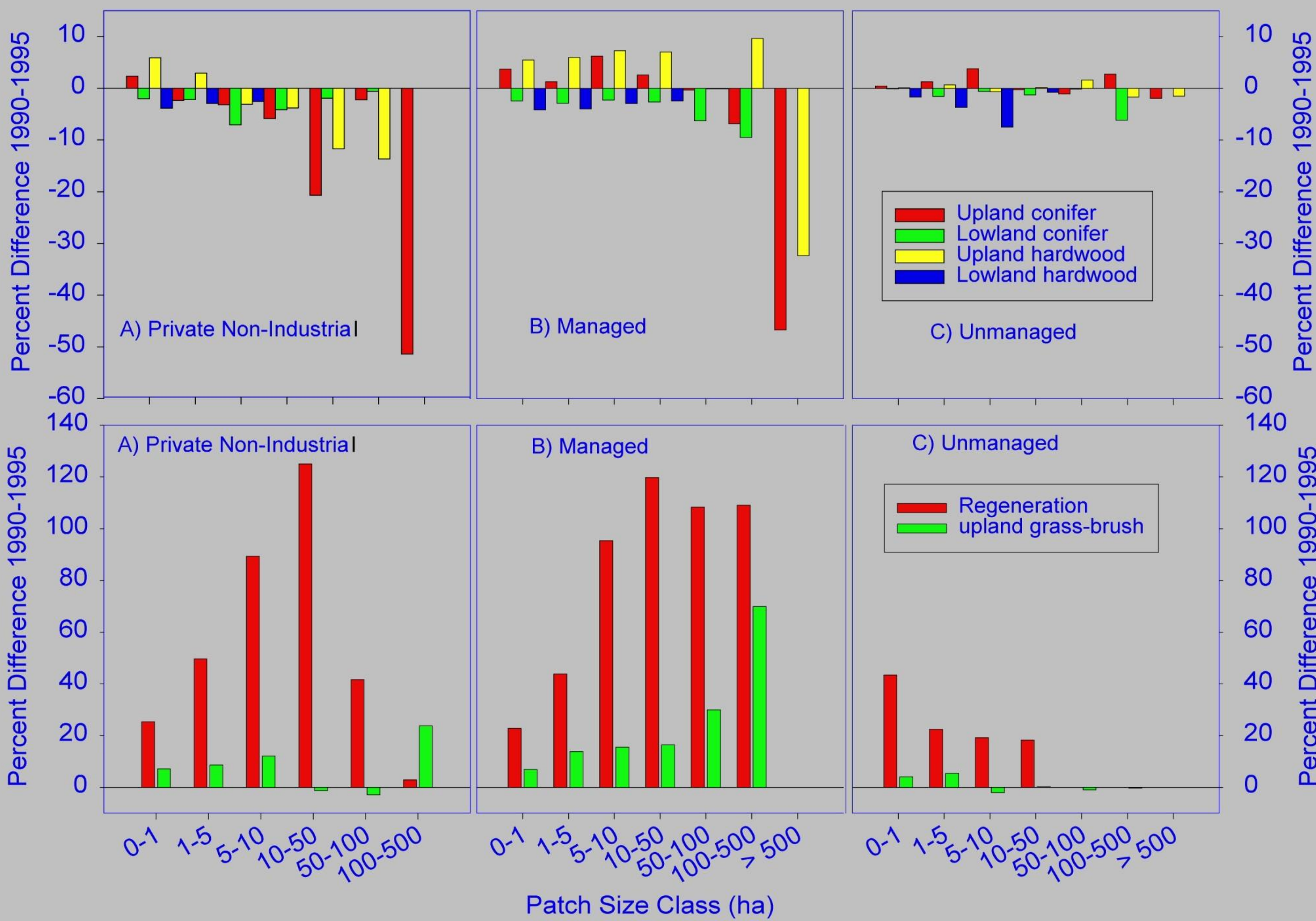
Breakdown of mature forest area (1,755,367 ha) by ownership and management status.



A. 1988 TM false color composite of a portion of the Superior National Forest and the Pat Bayle State Forest in northern Minnesota.
1 = Grand Marais, MN, 2 = Greenwood Lake and 3 = a portion of the Boundary Waters Canoe Area Wilderness.

B. 1994 TM false color composite of the same area – pink areas are forest cuts.

C. 1988 to 1994 change image. White areas are forest cuts from 1988 and earlier. Red areas are cuts from 1988 through 1994.



Percent Difference 1990-1995
10
0
-10
-20
-30
-40
-50
-60
A) Private Non-Industrial
B) Managed
C) Unmanaged
Upland conifer
Lowland conifer
Upland hardwood
Lowland hardwood
140
120
100
80
60
40
20
0
Regeneration
upland grass-brush
0-1
1-5
5-10
10-50
50-100
100-500
> 500
Patch Size Class (ha)

Analysis of Changes Using Markovian Theory

The theory of Markov chains provides a tool for analyzing the dynamics of landscapes.

A Markov chain consist of a vector ***x*** of the distribution of land-covers at time *t* and a matrix ***A***(τ) of transition probabilities of changes from each land-cover class to the others during a time period τ:

$$\mathbf{x}_{t+\tau} = \mathbf{A}(\tau)\,\mathbf{x}_t$$

The matrix of transition probabilities ***A***(τ) can be analyzed for a number of useful features, including the steady state distribution of land-cover classes under a particular disturbance regime, and the rate of approach to steady state.

Calculation of Transition Probabilities

Assuming no error in the classification, the maximum likelihood estimates of probabilities of change from one land-cover to another during time interval τ are:

$$p_{a,b,\tau} = \frac{n_{a,b,\tau}}{\sum_{b=1}^{m} n_{a,b,\tau}}$$

where $p_{a,b,\tau}$ are the transition probabilities from land-cover *a* to land-cover *b* in time interval τ, and $n_{a,b}$ are the number of such transitions across all pixels of the landscape of *m* land-cover classes.

Accounting for Producer and User Errors in Classification

However, the classification of land-covers and the transitions between them includes producer and user errors, which will be enumerated in the error classification matrix described above. The "true" transition probabilities will then be determined from the observed transition probabilities and the error classification matrix using the method of Hall et al. (1991): Let *a* and *b* be the "true" ecological land-covers between which transitions take place and let α and β be the corresponding classified (observed) land-covers. Let $p_{a,b}$ be the joint probability of a pixel having "true" land-cover *a* at time *t* and "true" land-cover *b* at time $t + \tau$ and $p_{\alpha,\beta}$ be the joint probability of an observed pixel being in land cover α at time *t* and land-cover β at time $t + \tau$. Let $C(i|j)$ be the collection of conditional error probabilities between "true" and observed land-covers. For example, $C(a|\beta)$ is the conditional probability that a pixel mistakenly classified as in being in land-cover β is in fact "truly" in land-cover *a*. Let the use of a prime superscript indicate "not ~" – for example, α' is taken to mean "not α". Then the "true" transition probabilities can be calculated from the observed probabilities and the error classification matrix as:

$$p_{a,b} = p_{\alpha,\beta} C(a|\alpha) C(b|\beta) - C(a|\alpha) \sum_{\beta' \neq \beta} p_{\alpha,\beta'} C(b|\beta')$$
$$- C(b|\beta) \sum_{\alpha' \neq \alpha} p_{\alpha',\beta} C(a|\alpha') + \sum_{\alpha' \neq \alpha} \sum_{\beta' \neq \beta} p_{\alpha',\beta'} C(a|\alpha') C(b|\beta')$$

The first term on the r.h.s of this equation represents the observed transitions from α to β which were true transitions from *a* to *b*; the second term represents observed transitions from α to β which were not true transitions from *a* to *b*; the third term represents observed transitions from not α to β which were true transitions from *a* to *b*; and the fourth term represents observed transitions from not α to not β which were true transitions from *a* to *b*. The conditional classification probabilities *C* represent the collection of user and producer errors in the classification error matrix, whose construction has been described above.

Normalizing the Transition Probabilities for Standard Time Intervals

When the time interval of the two successive maps is something other than the desired time interval of a model, then the probabilities of change can be normalized to the desired time step (Pastor et al. 1993) as follows:

$$
\begin{cases}
p_{a,b} = 1 - e^{\left(\ln\left(1 - p_{a,b,\tau}\right)/\tau\right)} & \textit{when} \quad a \neq b \\
p_{a,a} = 1 - \sum_{b=1}^{m} p_{a,b;b\neq a}
\end{cases}
$$

where τ is expressed as some fraction of the desired time scale.

Analyzing Transition Matrices

The matrices of transition probabilities can answer the following questions:

What will eventually be the steady state distribution of land-cover classes?

How long will it take to get there?

Two properties of the matrix, known as the eigenvalues and eigenvectors, are useful for answering these questions. These satisfy the equation:

$$\mathbf{A}\mu = \lambda\mu$$

where **A** is the final matrix of transition probabilities, μ is an eigenvector and λ is an eigenvalue (a scalar). Non-trivial eigenvalues satisfy the Hamilton-Cayley Theorem:

$$|\mathbf{A} - \lambda\mathbf{I}| = 0$$

where **I** is the identity matrix. Eigenvalues and associated eigenvectors will be calculated with either Mathematica or MatLab.

What will eventually be the steady state distribution of land-cover classes?

The dominant eigenvector is therefore where the landscape will end up if the disturbance regime remains constant. It is the steady state endpoint of land-cover classes and therefore constitutes an attractor of the landscape under a given disturbance regime.

We hypothesize that managed and wilderness areas will have different steady state endpoints because of the differences in their disturbance regimes.

How long will it take the landscape get there?

To determine this, one must calculate the ratio of the dominant eigenvalue to the absolute value of the second largest eigenvalue. This ratio is known as the damping; the greater this ratio, the faster the approach to steady state.

The approach to steady state, *r*, is exponentially asymptotic and is given by:

$$r = ke^{-t\ln\rho}$$

where ρ is the damping ratio and *k* is a constant (Caswell 1989). Because the approach to steady state is asymptotic, it is more convenient to calculate the time for some proportion of convergence to steady state, say 95% convergence. This time, t_x, is given by

$$t_x = \ln(x)/\ln(\rho)$$

The percentage of convergence to steady state equals 100 - (100/*x*). For example, the time required for 95% convergence to steady state is equivalent to the solution of the above equation for *x* = 20 (i.e., 100-(100/20) = 95).

Applications of Markov Theory to Policy Questions

Once the steady state endpoints and rates of convergence are calculated for managed and wilderness areas, the following policy questions can be addressed:

Is the current policy moving the landscape towards a desired future condition?

Is the policy moving it at an acceptable rate?

Is the managed landscape moving toward its steady state endpoint faster or slower than the wilderness area?

Various alternatives to move the managed landscape faster (or slower) to its steady state can be determined by "experimentally" changing certain transition probabilities to correspond to alternative policies, such as longer or shorter rotation times.