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# Satellite Change Detection of Forest Harvest Patterns on an Industrial Forest Landscape

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**ABSTRACT.** Multiple dates of Landsat Thematic Mapper (TM) imagery were analyzed to compare a decade of forest harvest activity in northern Maine's industrial forest. Unsupervised clustering on three-date sequences of Normalized Difference Vegetation Index classified the harvest type and time period when change occurred. Problematic clusters were reclassified using the Normalized Difference Moisture Index, which improved the detection of light partial harvests. The procedure classified clearcuts and partial cuts in all time periods with at least 80% agreement with 250 reference sample points. Patch characteristics of the harvest areas revealed a shift from large clearcuts in the late 1980s and early 1990s to fewer and smaller clearcuts in the middle to late 1990s. By the late 1990s, large clearcuts (>40 ha) were eliminated, and partial cuts increased in size. Partial cuts affected more land area than did clearcuts in all time periods. Comparison of harvest patches between the two largest landowners in the study area revealed significant differences in the number and distance between clearcut harvest areas. The trends in decreasing clearcut harvesting practices over the past decade appear to have been influenced by forestry legislation, according to the results of this study and an independent report by the Maine Forest Service. The changing harvest patterns on the landscape were detectable on time-series satellite imagery. *FOR. SCI.* 49 (3):341–353.

**Key Words:** Satellite remote sensing, normalized difference vegetation index, harvest patch metrics, forest change detection.

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**T**HE MONITORING OF FOREST COVER is essential in providing forest managers with data they need to assess forest health and productivity, formulate policy decisions, and generate management plans. For decades, aerial photography has been an essential tool in facilitating forest mapping and inventory. More recently, the use of medium spatial-resolution (5–30 m) satellite images, as a forest cover mapping tool, has been growing steadily. Although the spatial resolution of multispectral satellite imagery is far less than that of traditional aerial photography, satellite-based remote sensing does offer some important advantages. Satellite multispectral scanners generally provide images with

greater spectral sensitivity; for example, the shortwave or midinfrared waveband on the Landsat thematic mapper and other sensor platforms is important for vegetation discrimination (Horler and Ahern 1986, Fiorella and Ripple 1993). The digital nature of satellite images allows for advanced computer-automated analysis, classification, and compatibility with geographic information systems (Wynne and Carter 1997).

On the national level, the Forest Inventory and Analysis (FIA) program, run by the USDA Forest Service, produces a baseline forest inventory to assess the extent and productivity of approximately 300 million ha in the United States. Until

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recently, the FIA has been completed under a 10–15 yr remeasurement cycle, and the last full FIA inventory for the state of Maine was completed in 1995. However, forest inventory data more than 5 yr old are considered unreliable, and currently over half of all FIA information is out of date (American Forest Council 1992). The Agricultural Research, Extension, and Education Reform Act of 1998 directs the Forest Service to produce more accurate FIA data through more frequent updates (annual surveys are now required) and better utilization of remotely sensed data obtained from aircraft and satellites. In Minnesota, Landsat TM imagery was utilized to detect major changes in forest inventory plot characteristics at 4 yr intervals (Bauer et al. 1994). The Georgia Department of Revenue initiated a project to detect forest change, for taxation purposes, using a combination of satellite imagery, aerial photography, and geographic information systems (GIS) data (Georgia Department of Revenue 2000).

Satellite images have great potential to monitor forest change in Maine and contribute to forest policy and management goals. The imagery covers large areas of land frequently and can be cost-effective for this application. Maine has the highest percentage of forested land (approximately 89%) of any state in the United States (Griffith and Alerich 1996). Maine's two major industries, forestry and tourism, depend heavily on a healthy, productive, and sustainable forest resource base.

### Harvesting Systems and Forest Practices

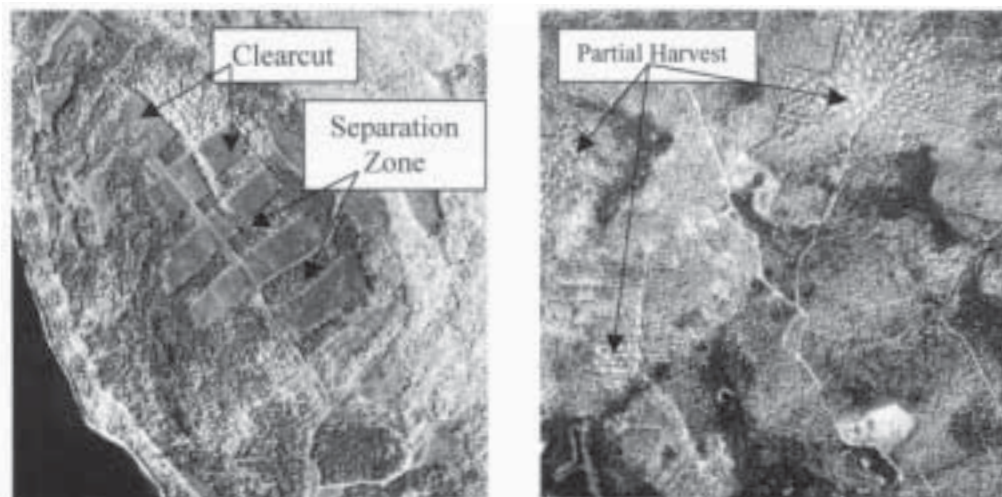
According to the Maine Forest Service (1999), landowners in Maine primarily use three silvicultural systems: selection, shelterwood, and clearcut harvesting. Selection harvest removes some trees in all size classes, either singly or in small groups, in order to regenerate and maintain a multi-aged stand structure. Various thinning operations, both commercial and precommercial, fall under this category. Usually at least one-third of the stand volume is removed. Depending on stand structure and species composition, trees can be re-

moved in strips by mechanical harvesting machines (leaving linear patterns on the landscape) or by manual cutting where the disturbance patterns appear more random and dispersed. Shelterwood harvest removes trees in two or more stages. The initial harvest removes most of the mature trees (usually more than one-half of the stand volume), leaving enough trees to serve as the seed source and to provide sufficient shade to produce a new crop. Both selection and shelterwood are partial harvesting systems. The third system is clearcut harvesting, where essentially all trees are removed in one operation, and regeneration will occur from natural seeding, planted seedlings, or advanced natural reproduction.

In response to public concern about some very large clearcuts (>1000 ha) that followed the spruce budworm outbreak in the 1980s, the Maine legislature passed the Forest Practices Act (FPA) (Hagan and Boone 1997). In addition, citizen referenda to ban clearcut harvest practices were introduced in 1994, 1996, and 2000; however, none of these initiatives were voted in by the electorate. Beginning in 1991, the Maine Forest Practices Act required that category I clearcuts (2–14 ha) have a 76 m separation zone between adjacent clearcuts (Figure 1). Category II clearcuts (14–50 ha) required a 76 m separation zone and a buffer zone equal to 1.5 times the area of the clearcut. Category III clearcuts (50–100 ha), approved only under exceptional conditions, required the separation zone and a buffer zone two times the area of the clearcut. The Maine FPA and its revisions did not regulate partial cuts, and because clearcuts were heavily regulated, partial harvesting on industrial forestland in northern Maine has been increasing since the early 1990s (Maine Forest Service 1999). For example, clearcut harvests made up only 3.5% of the total harvest area in 1999, the lowest level recorded statewide since data collection began in 1982.

### Research Approach

In Maine, recent forestry legislation (e.g., FPA) and public opinion may have influenced forest harvesting practices (Maine Forest Service 1995), and we hypothesized that the



**Figure 1.** The appearance of Maine Forest Practices Act, category 1 clearcuts (<14 ha with minimum 76 m separation zone) and partial harvests in northern Maine. National Aerial Photography collected in spring 1996. Original scale approximately 1:40000 scanned at 1x.

changing cutting patterns would be detectable across Maine's industrial forest landscape. For example, if industrial forest landowners were shifting from fewer, larger clearcuts (before FPA) to more category 1 clearcuts and partial harvesting (no regulation) after FPA implementation in 1991, then the analysis of harvest patch characteristics should reveal some patterns and trends on the landscape over time. Forest fragmentation and patch analysis studies have been conducted using data derived from the interpretation of aerial photographs (LaGro 1991) and digital analysis of satellite imagery (Ripple et al. 1991, Vogelmann, 1995). Once the remotely sensed imagery is classified into discrete land cover classes, a suite of spatial indices can be computed to analyze the landscape spatial characteristics and patterns (Franklin and Forman 1987). Some common spatial metrics include: size, shape, perimeter, and connectivity (O'Neill et al. 1988).

We attempted to assess the extent to which Landsat TM satellite imagery could facilitate forest harvest monitoring in northwestern Maine. There were two major objectives of this study: (1) Determine the capabilities of multitemporal, medium resolution satellite imagery to detect two levels of harvest (clearcuts and partial cuts), and (2) Examine the temporal patterns of harvesting activity from 1988 to 1999 by comparing harvest patch characteristics over all land ownerships and between two major landowners.

Although the Maine FPA has specific rules and definitions for clearcut and partial cutting, for the purposes of this study, a clearcut is one that removes essentially all trees in one operation and a partial cut includes all harvest systems except clearcuts. We adopt these working definitions used by the Maine Forest Service in their 1995 report to the 116th legislature (Maine Forest Service 1995). Our study period corresponds to the original FPA clearcut size regulations and not to the revisions of October 1999.

## Forest Change Detection

Forest and land cover change detection is one of the major applications of satellite-based remote sensing. Satellite images from different dates for a particular geographic area are analyzed for changes in spectral patterns, and these changes are classified into appropriate forest change or land cover categories. It is accepted that remotely sensed imagery can be used to monitor forest changes (Hame 1991, Olsson 1994, Coppin and Bauer 1996, Collins and Woodcock 1996, Hame et al. 1998, Franklin et al. 2000). Initiatives to monitor forest disturbances, either human-caused or natural, are increasingly reliant on information from remotely sensed data.

Franklin et al. (2000) used two dates of Landsat TM to analyze partial harvesting of forests in New Brunswick, Canada. They reported an overall 71% accuracy in detecting different levels of partial harvesting. In general, they documented increased visual reflectance, decreased near-infrared and increased shortwave (TM 5) reflectance in partially harvested stands. These results agree with reflectance changes following harvest reported by others in European forests (Hame 1991, Olsson 1994). Increased reflectance in the red spectrum is expected following a partial harvest, but the original stand density and time since disturbance will be

contributing factors in the magnitude of reflectance change (Franklin et al. 2000). According to spectroradiometer measurements in Finnish forests and the spectral value analysis of Landsat TM images, the best individual bands to separate thinning cuts and light removals in the canopy were red light (TM 3), middle-infrared (TM5), and near-infrared (TM 4) in that order (Hame 1991). Landsat TM channels were almost optimally located for damage detection according to the spectroradiometer results. The MIR band (TM 5) was the best channel to separate the obvious damage classes using unsupervised clustering methods.

Satellite methods have been reviewed by Milne (1988) and Coppin and Bauer (1996), among others. Milne (1988) grouped the methods into four broad categories: (1) linear procedures (difference images, ratioed images); (2) classification routines (postclassification change, spectral pattern change); (3) transformed data sets (vegetation indices, principal components analysis), and (4) other (regression analysis, knowledge-based expert systems, neural networks). Coppin and Bauer (1996) conducted a comprehensive review of methods used in forest surveys and grouped the methods into 11 distinct categories. These authors concluded that image differencing and linear transformations generally performed better than other methods.

Muchoney and Haack (1994) compared four change-detection techniques (including principal components, image differencing, spectral-temporal change, and postclassification) for identifying hardwood defoliation levels caused by gypsy moth. They concluded that detection of gypsy moth's defoliation (light, medium, and heavy damage) was most accurate and simple to perform using image differencing or principal component analysis techniques. Hame (1991), however, suggested that a weakness of principal components analysis is that changes of interest covered only a minor part of all intensity value variation and the changes occurred in the minor components, together with the noise in the data.

One of the most common methods of change detection using satellite imagery is image differencing. Image differencing usually involves cell-by-cell subtraction of the digital numbers of one coregistered image from another (Lillesand and Kiefer 1994, p. 621). The resulting map shows increased and decreased reflectance values of surface features (Muchoney and Haack 1994), which can be interpreted into forest change classes. A variant of this method is ratio image differencing, where band ratios or a vegetation index such as the normalized difference vegetation index (NDVI) is used for image differencing.

The NDVI separates green vegetation from other surfaces because the chlorophyll of green vegetation absorbs red light for photosynthesis (Tucker 1979) and reflects the near-infrared wavelengths due to scattering caused by internal leaf structure (Crist and Ciccone 1984). Thus, high NDVI values indicate high leaf biomass, canopy closure, or leaf area (Sellers 1985, Running et al. 1986, Jasinski 1990, Sader and Winne 1992). The ease in calculating NDVI from a variety of satellite data types and the success of the NDVI in detecting vegetation and vegetation change has made it a popular

spectral vegetation index (Myneni and Asrar 1994), as well as the most widely used data product for studying vegetation with remotely sensed images (Chavez and MacKinnon 1994). Lyon et al. (1998) found NDVI differencing to be the most successful change-detection method of several indices tested in a southern Mexico study site and the only histograms displaying a normal distribution.

A similar vegetation index, but one that uses a mid-infrared (MIR) waveband, is the Normalized Difference Moisture Index (NDMI). The term "moisture" is conventional and is retained for lack of a better term (Cohen et al. 1995, Hoffhine-Wilson and Sader 2002). A universally accepted term seems to be lacking because the biophysical interpretation of indices that use the MIR bands is more problematic than those that use near-infrared (NIR) and red bands (Cohen et al. 1995). The MIR wavelengths are highly absorbed by leaf and soil water (Hunt et al. 1987, Hunt and Rock 1989). Hunt et al. (1987) found that reflectance of TM band 5 (MIR) for dry leaves was almost equal to reflectance of TM band 4 (NIR), suggesting the difference between TM band 4 and 5 should equal the water absorbance for a fresh leaf. The Landsat TM 4/5 ratio was a good predictor of conifer stand age and structure in the northwestern United States (Fiorella and Ripple 1993, Cohen et al. 1995). This index was shown to be highly correlated with the tasseled cap wetness component but easier to calculate and interpret (Fiorella and Ripple 1993). The wetness component was reported by Franklin et al. (2000) to be an important variable in detecting changes due to partial harvesting in eastern Canada. The use of the 4/5 ratio or NDMI for change detection appears to show promise; however, its use in forest change-detection studies is nearly absent from the published literature (Hoffhine-Wilson and Sader 2002).

### **RGB-NDVI Unsupervised Classification Method**

In practice, digital change detection is commonly performed stepwise using only two dates of satellite imagery at each step; however, the analysis of three or more dates of imagery allows trends to be examined at more than one interval of time. The visual RGB-NDVI method (Sader and Winne 1992) involves creation of color composite images and utilization of additive color theory, where each NDVI from three dates is combined with the red, green, and blue color write functions of the computer monitor. Any combination of primary colors of similar brightness produces a complementary color (Lillesand and Kiefer 1994, p. 80). By knowing the date of NDVI coupled with each color write function, the colors can be interpreted to identify change or no-change events in a forested landscape (Sader and Winne 1992). To automate the change detection and turn the three-layer NDVI stack into a thematic map, an unsupervised classification (ISODATA clustering) is performed on each NDVI stack (Sader et al. 2001). Unsupervised classification is a multivariate method where a classifier identifies distinct spectral groupings among unknown pixels in an image and aggregates them into a specified number of cluster classes (Lillesand and Kiefer 1994, p. 604). Water, wetlands, and

clouds are routinely masked out prior to clustering. Hame (1991) reported that unsupervised change-detection methods are appropriate in cases where the information on forest changes is lacking, and where one is interested in changes over large areas.

Hayes and Sader (2001) compared image differencing, principal component analysis, and RGB-NDVI methods for a tropical forest study site. The goal of the study was to determine which technique was most accurate and efficient for multirate forest change detection. In previous studies and reviews of change-detection methods, image differencing and principal components methods were indicated as among the most successful and simple to apply (Muchoney and Haack 1994, Coppin and Bauer 1996). Hayes and Sader (2001) found the RGB-NDVI change-detection method to be the most accurate and efficient of the three methods for several reasons. When determining change, RGB-NDVI incorporated three dates at one time as opposed to two-date stepwise sequences using image differencing methods. This is particularly advantageous when several image dates (e.g., five) are analyzed in a sequence to detect change. The RGB-NDVI unsupervised classification (Sader et al. 2001) avoided analyst subjectivity in selecting appropriate histogram thresholds for several stepwise sequences and was more straightforward and time efficient. Interpretation of change over time was intuitive and logical using additive color theory. Finally, the interpretation of the clusters and their multivariate statistics facilitated identification of forest clearing, no change, and regrowth classes in a time-series. Based on these results, the RGB-NDVI method was selected as the change-detection method suitable for analyzing and interpreting five dates of satellite imagery in the Maine study area.

### **Study Area**

The study was conducted in the subboreal Acadian forest in northwestern Maine, an area covering all or part of 29 townships (approximately 2,700 km<sup>2</sup>) in Piscataquis county, north of Moosehead Lake (Figure 2). The terrain is variable with flat expanses and scattered small mountains on a glaciated landscape, with thin and relatively nutrient-poor soils. The elevation ranges from approximately 325 to 655 above sea level. The area is located within the Saint John Uplands biophysical region (McMahon 1990), with forest vegetation dominated by deciduous species (*Quercus* sp., *Acer* sp., *Betula* sp., *Fagus* sp.) on the ridges and spruce-fir (*Picea* sp., *Abies* sp.) in the valleys and lowlands. Mixed stands are often transitional between the ridge and valley but found in lowlands depending on prior harvesting history and successional status. Most of the land is exclusively owned by private forest products companies and is managed primarily for timber and pulp production. The study area contains numerous wetlands, lakes, and riparian systems. There are no urban or residential areas other than scattered sporting camps and inholdings.

### **Methods**

#### ***Satellite Image Acquisition and Preprocessing***

Five satellite images collected during the summer months were acquired for the study area: four Landsat Thematic



**Figure 2. Location of the 29 township study area, north of Moosehead Lake, in Northwestern Maine, USA.**

Mapper (TM) scenes from 1988, 1991, 1993, and 1999, and one Indian Resource Satellite, Linear Imaging Self-scanning Sensor (LISS-3) scene from 1997 (Bertrand and Sader 2000). A suitable TM scene was not available for 1995 through 1997, therefore the 1997 LISS-3 data were used as a replacement. The LISS-3 visible red and near-infrared bands were recorded at 23.5 m pixel resolution. The MIR band has a 70 m resolution on the ground resolution cell size. Each scene was georeferenced, spatially subset to the extent of the study area, and spectrally subset to three bands: visible red (TM band 3, LISS band 2), near-infrared (TM band 4, LISS band 3), and mid-infrared (TM band 5, LISS band 4). The red, near-infrared and mid-infrared bands are often cited as the most important in forest mapping and change-detection studies (Horler and Ahern 1986, Hame 1991, Coppin and Bauer 1996), and these bands were needed to compute the NDVI and NDMI values at each image date. The LISS data were resampled (nearest neighbor) to 30 m to match the TM pixel size. All scenes were radiometrically normalized using the 1999 TM image as a reference (Hall et al. 1991). Water, wetlands, and clouds were masked out of all scenes to reduce nontarget cover types and spectral confusion in subsequent classification steps.

The normalized difference vegetation index (NDVI) and mid-infrared normalized difference moisture index (NDMI) were calculated for each date, based on the following equations:

$$NDVI = \frac{\text{near IR band} - \text{red band}}{\text{near IR band} + \text{red band}} \quad (1)$$

$$NDMI = \frac{\text{near IR band} - \text{mid-IR band}}{\text{near IR band} + \text{mid-IR band}} \quad (2)$$

The NDVI and NDMI features were concatenated to produce two images, each containing values for three dates of satellite imagery: 1988–1991–1993, and 1993–1997–1999.

### **Image Classification**

An unsupervised classification using the ISODATA clustering algorithm (ERDAS 1997) was performed on each three-date NDVI data set, resulting in two classified images with 45 multitemporal cluster classes. The color table option was selected so the classified images would retain a similar color pattern as the visual RGB-NDVI color composite. For each classification, all classes were assigned to one of ten change, no-change categories (Table 1). The cluster class assignment was aided by additive color theory based on comparison of the classified image (with color table) to the visual RGB-NDVI composite. The visual observations were used in combination with the analysis of the cluster means at each date and standard deviations. Clusters indicating substantial shifts in NDVI values, between dates, were apparent by observing the cluster means. Sometimes a more subtle change could be detected for certain pixel locations in the visual color composite but would be less apparent in the classified image and in the cluster class statistics representing those pixels. Observation of the RGB-NDMI visual composites appeared to highlight the subtle or lighter disturbance features better than the RGB-NDVI composites. Therefore, pixel positions belonging to a few cluster classes exhibiting confusion between categories (usually between light partial

**Table 1. Harvest and land cover classes\* derived from unsupervised classification and GIS coverages for the northern Maine study area.**

Code	1988–1993	1993–1999
Unsupervised classification		
1	Clearcut 1988–1991	Clearcut 1993–1997
2	Heavy partial cut 1991–1993	Heavy partial cut 1993–1997
3	Light partial cut 1991–1993	Light partial cut 1993–1997
4	Clearcut 1991–1993	Clearcut 1997–1999
5	Heavy partial cut 1991–1993	Heavy partial cut 1997–1999
6	Light partial cut 1991–1993	Light partial cut 1997–1999
7	Prior Cut (before 1988)	Prior Cut (before 1993)
8	No change, coniferous forest	No change, coniferous forest
9	No change, mixed forest	No change, mixed forest
10	No change, deciduous forest	No change, deciduous forest
Other		
11	Old roads (before 1988)	Old roads (before 1993)
12	New roads	New roads
13	Water	Water
14	Wetlands	Wetlands

\* Light partial = <30% crown closure removal; heavy partial = 30 to 90% crown closure removal; coniferous = >75% conifer species; deciduous = >75% deciduous species; mixed = 25–75% conifer or deciduous.

cut and no-change, coniferous forest) were subset from the NDMI 3-date images, run through a 20-class unsupervised classification and assigned to the appropriate change, no-change category. This method has been referred to as “cluster busting,” and is a commonly used procedure to improve unsupervised classification results (Jensen 1996, p. 238). The NDMI cluster values contained spectral information, not present in the NDVI data, that minimized the confusion between the light partial cuts and no-change, coniferous forest (Bertrand and Sader 2000). The NDMI clustering conceivably could have been performed in one classification run; however, cluster busting may still have been necessary. The major changes were easily detected using NDVI during the first clustering sequence.

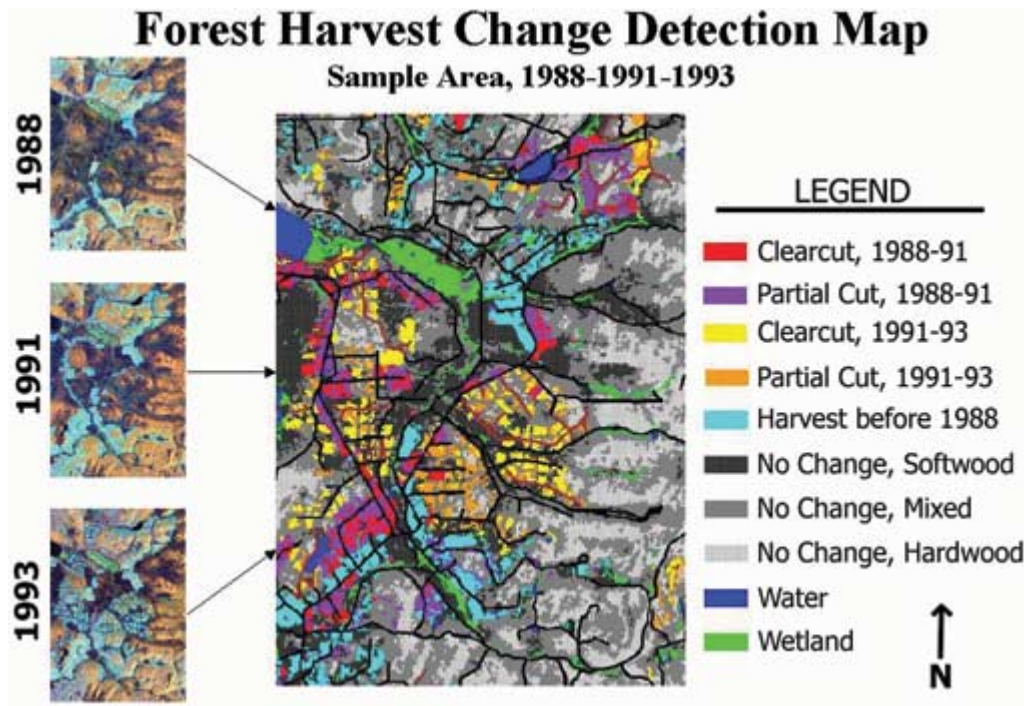
Each cluster was assigned to one of the change or no-change categories to produce a 10-class change-detection map for each time sequence (1988–1991–1993 and 1993–1997–1999). Water and wetlands were overlaid back onto each change-detection map as separate classes. All areas classified as a cut between 1988–1991–1993 were overlaid on the 1993–1997–1999 change-detection map and assigned to the “prior cut” category (Table 1). A vector coverage of roads was buffered to a width of 90 m (3 pixels) to minimize misclassifications due to edge effects. The road categories were overlaid on each change-detection map. An intelligent filtering software program, MegaMerge (Glacier Software Engineering 1999), was used to reduce isolated pixels or “speckling” in the classifications while minimizing degradation of the original spatial data (Hepinstall et al. 1999). The MegaMerge program uses a class similarity matrix to merge pixels into appropriate classes. This is dissimilar from filtering in that contiguous pixels of the same class are merged with neighboring areas and not neighboring pixels. MegaMerge allows for a user specified minimum output area, where areas smaller than this value are merged based on the similarity matrix, as well as a list of “always merge” and “never merge” classes (Hepinstall et al. 1999). An example of the 1988–1991–1993 forest harvest change-detection map is provided as Figure 3.

### *Comparison of Harvest Sites on Forest Type Maps, Aerial Photography and Satellite Images*

Aerial photo interpretation has been the standard method for forest stand type mapping used in Maine for decades. Even light partial harvests (thinning) have a characteristic texture resulting from tree removals and soil disturbance (e.g., skid trails and landings) that can be easily detected on medium scale aerial photography (Figure 1). Clearcuts are even more obvious by the stark contrast in image tone, texture, and pattern compared to the surrounding forest. Forest industry type maps in the form of geographic information system (GIS) polygons were acquired for a few of the townships, from one of the landowners. However, we found that some harvest sites that were clearly visible on the images were either not updated on the maps, or not coincident with the image dates in our analysis. In the first case, the satellite would detect a harvest but the type map excluded it due to an updating error. In the latter case, a harvest occurred in the same year, but a few months after the satellite image was recorded. The satellite would not detect the change and the reference map would indicate an omission error in the satellite change detection. Using the type map as the reference source would not be a fair assessment of the satellite harvest detection accuracy, given these discrepancies. This situation is not uncommon, and other researchers have documented the problems that can occur when using existing type maps (GIS digital maps) as reference or surrogate “ground truth” for satellite change-detection accuracy assessments (Congalton and Green 1993). For this reason, the type maps were used only to select a few training examples of partial harvests and clearcuts as a means for the photo interpreter to examine their tones, textures, and patterns on the 1997 and/or 1999 aerial photography. These sites were also located on the satellite images to cross-reference their appearance with the aerial photographs and to improve the interpreter’s confidence in identifying the partial harvests from satellite images.

### *Comparative Assessment of Classification Results*

Accuracy assessments of change-detection maps involving multiple landowners and multiple dates of historical events are more complicated than accuracy assessments of



**Figure 3.** An example of the 10 class forest harvest change detection map (1988–1991–1993) including roads and nonforest cover types. Harvest areas on Landsat-TM color composite images (TM bands 4,5,3) of each date are provided for visual comparison (left side).

single date land cover maps. Due to the absence of aerial photography and lack of suitable industry harvest maps that coincided with each date of the satellite images, the agreement of the change-detection maps was assessed through a comparison to visual interpretation of the original TM color composite images (Cohen et al. 1998). A stratified random sample of 250 points (25 in each of the original 10 change classes) was generated for each change-detection map. The points were overlaid concurrently on the original satellite images representing each of the three dates with the near-infrared, mid-infrared, and red bands displayed on the computer monitor in red, green, and blue, respectively. Each point was then visually interpreted to one of the change/no-change classes without knowledge of the classified change class represented. Although such an assessment lacks complete independence from the data used in the classification process, it has been shown to be a credible method that provides results similar to an interpretation based on independent data (Cohen et al. 1998).

The agreement of the ten-class error matrices with the random sample points was not as high as desired for separating heavy and light partial cuts (Bertrand and Sader 2000). To improve the reliability of the harvest classes prior to calculating harvest patch statistics, the ten classes were collapsed into five forest harvest classes by combining the reference and classified counts for heavy and light partial cuts into a generic partial cut category. The prior cut, hardwood, softwood and mixed classes were combined into a “no-change forest” class. The five-class error matrix for each of the two maps were compiled to conduct the comparative assessment of the change-detection classification results.

As an independent check on the visual TM interpretation method, another assessment based on interpretation of aerial photography was performed on a two-township subset of the 1993–1997–1999 change-detection map, using black and white photography from 1997 and color infrared photography from 1999. A stratified random sample of 170 points was generated with 20 points selected for each of the original ten classes (1993–1999), with the exceptions of prior cuts and 1997–1999 clearcuts. All ten original classes were sampled to cover the entire range of change categories and time sequences. Only ten points were generated for the 1997–1999 clearcuts because there were few available pixels of this class in the subset area. No points were generated for the prior cut class, due to the lack of available photography for 1993. A collapsed five-class matrix was developed as described above. Overall accuracy, producer’s, and user’s accuracy (related to omission and commission errors, respectively), Kappa values, and Z-statistics were calculated for each error matrix (Congalton and Green 1993).

#### **Patch Statistics**

The two classification sequences (1988–1991–1993) and (1993–1997–1999) produce clusters that identify each change category by time period. The change/no-change classes were coded and labeled for extraction and analysis of the harvest patch statistics. Harvest patch characteristics, derived from the change-detection maps, were compared across all ownerships in the study area. The area of each clearcut and partial cut “patch” was calculated using Fragstats (McGarigal and Marks 1995). Analysis of variance (ANOVA) was used to determine if significant differences in patch size existed between time intervals (1988–1991, 1991–1993, 1993–1997,

and 1997–1999). Separate ANOVAs were run for clearcuts and partial cuts, with patch size as the dependent variable and time interval as the single categorical variable.

Within each time interval, the annual number of clearcut and partial cut patches per township was derived from the Fragstats results. Within each township, the total number of patches was calculated for each time interval, then divided by the number of years within that time interval (i.e., divided by two for 1991–1993, four for 1993–1997, etc.). Separate ANOVAs were performed on clearcut and partial cut patches to analyze the effect of time interval on annual patch count. Similarly, the annual percentage of land harvested within each township was calculated for each period, and ANOVAs were performed on clearcuts and partial cuts separately to detect temporal trends. The percentage of land harvested was selected as a metric for comparison, rather than total hectares harvested, because the forest available for harvest can vary substantially among townships, depending on the area of surface water and amount of previous harvesting (prior cuts).

Harvest patch characteristics were also compared between the two largest forest landowners in the study area. Collectively, 72% of the study area was managed by the two companies during the study period. We selected five townships per company (approximately 466 km<sup>2</sup> each) that exhibited some harvesting activity. Company 1 was an industrial forest products corporation with pulp mills in northern Maine. The forest managed by Company 1 had changed ownership four times within the study period. Company 2 managed the forest for a family-based corporation, and the land has been under the same ownership for over 100 yr.

## Results

### Comparative Assessment of Classification Results

In describing these results, we use the traditional term “accuracy”; however, the reference for the assessment of classification results was the TM composite visual inter-

pretation method (Cohen et al. 1998), as discussed previously. Overall classification accuracy (agreement with visual TM reference points) for the five-class 1988–1993 and 1993–1999 change-detection map was 94.0% ( $KHAT = 0.92$ ,  $Z_{stat} = 45.8$ ) and 90.4% ( $KHAT = 0.87$ ,  $Z_{stat} = 34.8$ ), respectively (Table 2). Both provided results that were significantly better than random ( $Z_{stat} > 1.96$ ). The user’s and producer’s accuracies ranged from 80 to 99% for all time intervals. There was some confusion between clearcuts and partial cuts, particularly from 1993–1997, resulting in slightly lower agreement (80–87%) for user’s and producer’s accuracy. The agreement of partial cuts with the reference sample points was roughly equivalent to clearcuts across all time intervals. The agreement of the “no-change” class was consistently high (equal or better than 93%) for both map assessments.

### Comparative Assessment with Photo Interpretation

Based on the aerial photo interpretation for 2 of the 29 townships, the five-class comparative assessments (Table 3) produced an overall agreement of 90% ( $KHAT = 0.87$ ,  $Z_{stat} = 28.2$ ). Producer’s and user’s accuracies were higher than 82% for all classes. There was no significant difference between the five-class aerial photo interpretation (a traditional reference source) and the results produced through visual interpretation of satellite imagery for the 1993–1999 time period (comparative Z statistic = 0.9).

### Harvest Area, Patch Size and Number—All Landowners

The five-class comparative assessment results were considered to be of sufficient reliability to support the harvest patch comparisons, across time intervals. Analysis of harvest patch sizes (Figure 4) indicated that significant differences existed between time intervals for both clearcuts ( $F = 11.48$ ,  $df = 3$ , 2247,  $P < 0.0001$ ) and partial cuts ( $F = 20.68$ ,  $df = 3$ , 6547,  $P < 0.0001$ ). Post hoc Tukey comparisons indicated that clearcuts were significantly larger in

**Table 2. Five-class comparative assessment results (with randomly sampled reference points) for Landsat classified 1988–1993 and 1993–1999 clearcut (c), partial cut (pc), and no change forest classes.**

Class name	Reference totals	Classified totals	No. correct	Producer’s accuracy		User’s accuracy	
				..... (%) .....		..... (%) .....	
CC 88-91	25	25	22	88.0	88.0	88.0	88.0
PC 88-91	50	50	47	94.0	94.0	94.0	94.0
CC 91-93	24	25	22	91.7	88.0	88.0	88.0
PC 91-93	53	50	47	88.7	94.0	94.0	94.0
No change	98	100	97	99.0	97.0	97.0	97.0
Total	250	250	235				
CC 93-97	23	25	20	87.0	80.0	80.0	80.0
PC 93-97	53	50	43	81.1	86.0	86.0	86.0
CC 97-99	25	25	23	92.0	92.0	92.0	92.0
PC 97-99	51	50	47	92.2	94.0	94.0	94.0
No change	98	100	93	94.9	93.0	93.0	93.0
Total	250	250	226				
				1988–1991–1993		1993–1997–1999	
				Producer's accuracy	User's accuracy	Producer's accuracy	User's accuracy
				..... (%) .....		..... (%) .....	
Overall classification agreement	94.0	94.0		90.4	90.4	90.4	90.4
Harvest agreement	90.8	92.0		87.5	88.7	88.7	88.7
CC agreement	89.8	88.0		89.6	86.0	86.0	86.0
PC agreement	91.3	94.0		86.5	90.0	90.0	90.0

**Table 3. Five-class accuracy assessment results for aerial photo interpreted 1993–1999 clearcut (c), partial cut (pc), and no change forest classes.**

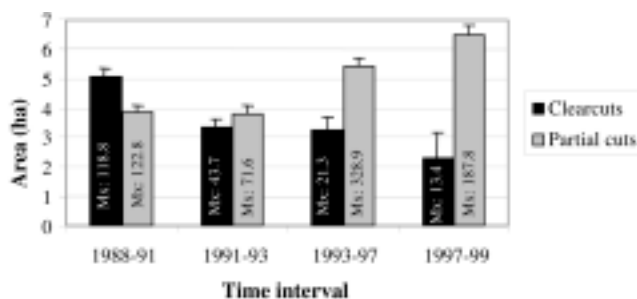
Class name	Reference totals	Classified totals	No. correct	1993–1997–1999	
				Producer's accuracy (%)	User's accuracy
CC 93-97	23	20	19	82.6	95.0
PC93-97	37	40	36	97.3	90.0
CC 97-99	11	10	10	90.9	100.0
PC97-99	40	40	34	85.0	85.0
No change	59	60	54	91.5	90.0
Total	170	170	153		

	1993–1997–1999	
	Producer's accuracy (%)	User's accuracy
Overall classification agreement	90	90
Harvest Agreement	89.2	90
CC Agreement	85.3	96.7
PC Agreement	90.9	87.5

1988–1991 than all subsequent time intervals ( $P \leq 0.006$ ). Partial cuts in 1993–1997 were significantly larger than those in 1988–1993 ( $P < 0.001$ ), and there was also a marginally significant increase in partial cut patch size from 1993–1997 to 1997–1999 ( $P = 0.061$ ). The maximum size of clearcut patches was highest from 1988–1991 and decreased steadily thereafter, but the maximum size of partial cuts did not exhibit any obvious pattern over time (Figure 4).

The mean annual number of harvest patches also differed significantly between time intervals, among both clearcuts ( $F = 17.44$ ,  $df = 3, 112$ ,  $P < 0.001$ ) and partial cuts ( $F = 3.32$ ,  $df = -3, 112$ ,  $P = 0.023$ ). Post hoc Tukey comparisons indicated that the mean annual number of clearcuts from 1993–1999 was significantly lower than from 1988–1993 ( $P < 0.001$ ). The mean annual number of partial cuts in 1997–1999 was significantly lower than in 1991–1993 ( $P = 0.038$ ). Both clearcuts and partial cuts exhibited the same overall trend: a slight increase in number from 1988–1991 to 1991–1993, then a large decrease from 1991–1993 to 1993–1997, followed by a smaller decrease from 1993–1997 to 1997–1999 (Figure 5). The annual percentage of land area subjected to clearcuts differed significantly between time intervals ( $F = 16.16$ ,  $df = 3, 112$ ,  $P < 0.001$ ). Clearcut area percentages were significantly higher in 1988–1991 and 1991–1993 than the subsequent two intervals ( $P < 0.001$ ) (Figure 6). The annual percentage of each town subject to partial cuts did not differ significantly between time intervals ( $F = 0.057$ ,  $df = 3, 112$ ,  $P = 0.982$ ).



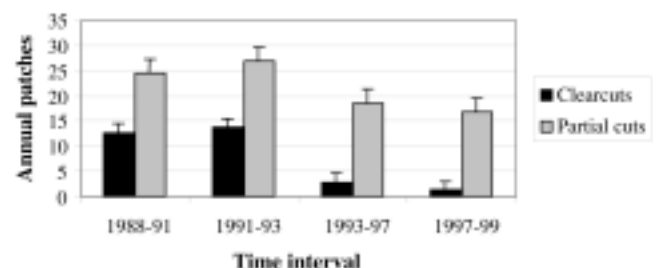
**Figure 4. Mean patch size of clearcuts and partial cuts per time interval for all landowners. Maximum patch sizes are indicated inside bars.**

### Harvest Patch Characteristics—Differences Between Landowners

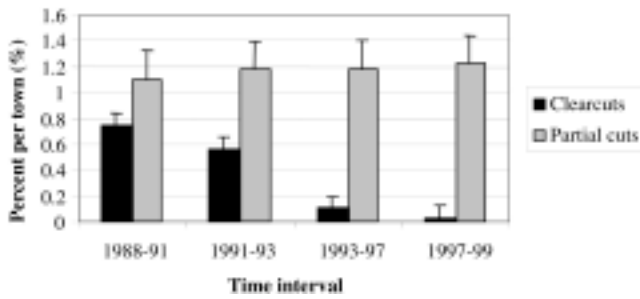
The size of clearcut patches per time period was not significantly different between the two major landowners in the study area. Only two clearcuts were detected for Company 2 between 1997 and 1999, leading to a large standard error in patch size and no nearest neighbor distance for that year. There was no significant difference in partial cut patch size between companies. The size of partial cut patches increased over time for both companies. This was the same trend previously observed for all ownerships within the study area (Figure 4).

Significant differences between the two companies occurred in the annual number of clearcuts (Figure 7) and partial cuts (Figure 8). Company 1 had more clearcuts and partial cuts than Company 2. The number of clearcuts decreased over time for both companies, which was the same trend observed over all ownerships in the study area (Figure 5). For Company 1, there was a steady decline in the mean annual number of partial cuts from 1988 to 1997. Company 2 had a slight but gradual increase in the number of partial cuts from 1988 to 1999 (Figure 8). There was no significant difference in the percentage of forest area harvested. For example, from 1993 to 1999, Company 1 harvested 7.1% and Company 2 harvested 7.5% of their forests, in each of the five townships that we analyzed.

For comparing the harvest patches between the two companies, we added the nearest neighbor distance as an additional spatial metric. This measures the closest linear distance between harvest patches. When clearcuts were combined into two time intervals (1988–1993 and 1993–1999), the



**Figure 5. Mean annual number of harvest patches per time interval for all landowners.**



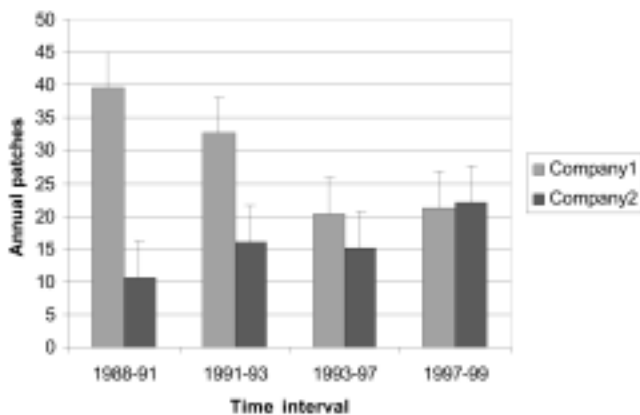
**Figure 6.** Mean annual percentages of forest harvested per time interval for all landowners.

mean nearest neighbor distance between clearcuts was significantly smaller for Company 1 as compared to Company 2 (Figure 9). Company 1 had significantly smaller nearest neighbor distance when partial cuts were examined for the 1988–1993 interval (Figure 10); however, the distance was nearly equal (not significant) for 1993–1999.

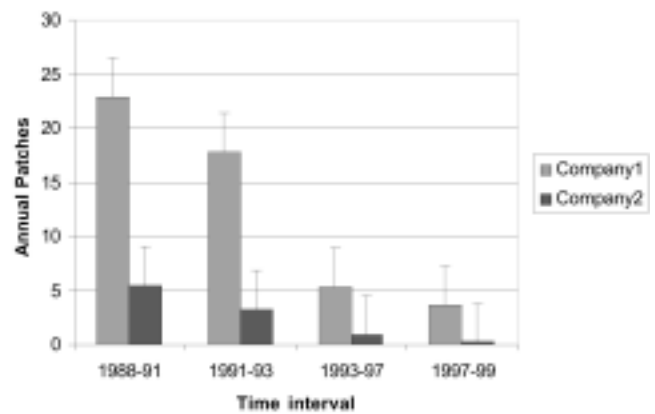
## Discussion

Analysis of temporal trends in harvest patch characteristics suggest that industrial forest products companies substantially reduced clearcutting activities within the study area after 1991. The mean size of clearcuts decreased significantly after 1991 (Figure 4), while the annual number of clearcuts (Figure 5) and the percentage of area clearcut per township (Figure 6) decreased after 1993. The maximum size of clearcut patches dropped from 118 ha in 1988–1991 to 43 ha (just below the legal limit) in 1991–1993. By 1997–1999, the maximum clearcut size was 13 ha, indicating that there were no longer any Category II FPA clearcuts within the study area (Figure 4).

These results agree with the Maine Forest Service (1995) report of a decrease in clearcut area statewide between 1991 and 1995 and to the lowest levels recorded in 1999 (Maine Forest Service 1999). The agency acknowledged that the enactment of the Maine Forest Practices Act was the single most important factor in the reduction of clearcut harvest area statewide (Maine Forest Service 1995). They also reported an increase in partial cut area based on a sample survey of harvest sites. Our study found only a slight increase in the percentage of each township subject to partial cuts from the 1988–1991 to 1991–1993 time intervals (Figure 6). Overall



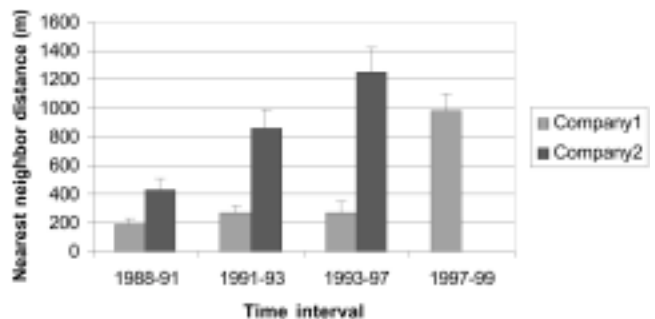
**Figure 8.** Mean annual number of partial cuts per time interval for two forest management companies.



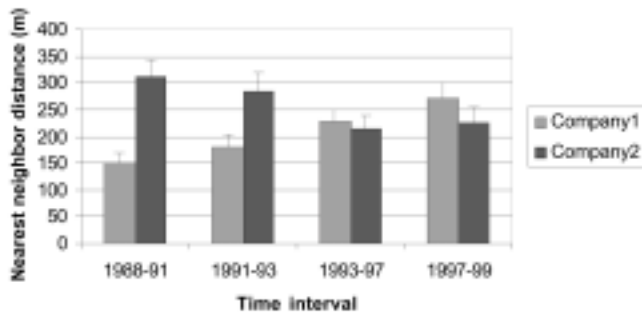
**Figure 7.** Mean annual number of clearcuts per time interval for two forest management companies.

the percentage of land subject to partial cuts in our study did not change significantly over time, but this may not be indicative of statewide trends, as not all of the forest management companies were represented within our study area. There are more than ten companies that manage over 40,000 ha of forest in Maine.

The two major companies in our study area had different ownership histories. Corporate ownership for Company 1 forests changed hands four times between 1988 and 1999, while Company 2 ownership was stable throughout the study period and decades before. These two companies also had significant differences in some of the harvest patch metrics that were detectable from time-series, medium spatial resolution satellite imagery. Company 1 had significantly more clearcuts (Figure 7) and smaller nearest neighbor distance between clearcuts than Company 2. These results suggest that Company 1 was applying more FPA category 1 clearcuts (2–14 ha). Category 1 clearcuts during the early 1990s were often clustered (see Figures 1 and 3) on the landscape. The Maine Forest Service acknowledged the post-FPA phenomena of clustered, category 1 clearcuts in their 1995 report to the 116th legislature (Maine Forest Service 1995). Clustered, category 1 clearcuts were not observed anywhere within the entire study area on the 1988 satellite images and maps, prior to the implementation of the Maine FPA. Also, many fewer category 1 clearcuts were observed on the maps after 1997 compared to the years between 1991 and 1997. This may help to explain the increase in nearest neighbor distance between clearcuts that we observed for Company 1 from 1997 to 1999



**Figure 9.** Mean nearest neighbor distance between clearcuts per time interval for two forest management companies.



**Figure 10. Mean nearest neighbor distance between partial cuts per time interval for two forest management companies.**

(Figure 9). There were too few clearcuts to compute nearest neighbor distance from 1997–1999 for Company 2.

Although there was no significant difference in the percentage of forest harvested between the two companies during the study period, we found that this was not the case prior to 1988. Results of the Maine Gap Analysis project (Hepinstall et al. 1999), based on Landsat-TM land cover classification, indicated that the five townships under Company 1 ownership were harvested much heavier than Company 2 townships, prior to 1988. Approximately 30% of Company 1 townships were in early to late regeneration classes (<10 yr old) compared to less than 15% for Company 2. This was a period when many companies in Maine were conducting salvage logging in the wake of the spruce budworm outbreak of the late 1970s.

The assessment of classification results based on visual interpretation of color composite satellite images for 170 sample points did not produce significantly different results from an independent assessment based on aerial photography for the 1993–1999 time period (Table 3). As photo interpretation is the traditional reference source for industry forest type maps in Maine and other states, the agreement between the satellite and photo interpretation methods lends some confidence for the use of satellite interpretation as reference data for the time-series forest harvest classification assessment, as originally demonstrated by Cohen et al. (1998) in an Oregon study. Ideally, multirate aerial photo interpretation or industry GIS and field data would be the desired source of reference data to support the historical satellite change-detection accuracy assessment; however, this was not feasible for the reasons we mentioned previously.

The unsupervised classification technique applied in this study produced good results for detection of clearcuts, partial cuts, and no-change forest classes. Overall agreement was at least 90%. All producer's and user's accuracies were at least 80%, and for most change categories were better than 88%, with the exception of the 1993–1997 time interval (Table 2). The longer duration of the time between satellite data acquisition (4 yr) may be at least partly responsible for the confusion. Clearcuts that occurred in late 1993 or 1994 were more difficult to distinguish spectrally from heavy partial cuts given the green biomass increases that can occur in each harvest site by the time the 1997 images were recorded. It should be noted that the 1997 Indian satellite, LISS-3, had a 70 m mid-IR waveband that is coarser than the Landsat 30 m mid-IR

band used for all other dates. The coarser spatial resolution of the 1997 LISS data, in addition to the longer image acquisition gap, is a confounding variable that could have contributed to the lower accuracy in the 1993–1997 time period.

When acquiring imagery for forest change detection, it may be prudent to minimize the amount of time between consecutive image dates. This is supported by a concurrent study in northern Maine where Hoffhine-Wilson and Sader (2002) compared the RGB-NDVI and RGB-NDMI methods and the effect of the number of years (1–3, 3–4 and 5–6) between image acquisitions, on forest change-detection accuracy. When Landsat-TM image acquisitions were only 1–3 yr apart, forest clearcuts were detected with high accuracy (>90%) using either the RGB-NDVI or RGB-NDMI classification method. However, heavy and light partial cuts were detected with lower accuracy, using both methods when time between image acquisition increased. In all classification trials, the RGB-NDMI produced significantly higher accuracies compared to RGB-NDVI. The RGB-NDMI was more successful in detecting the difference between light partial cuts and no forest change, thus improving the overall change-detection accuracy, which was highest when image acquisition dates were less than 3 yr apart (Hoffhine-Wilson and Sader 2002).

## Conclusions

This research indicates that satellite-based change-detection methods can provide reliable information about forest disturbance for assessing temporal trends in harvesting patterns over large areas. Forest changes due to clearcut and partial harvesting practices in a section of northwestern Maine were classified with good agreement with randomly sampled reference points over an 11 yr period. The Maine Forest Service (1995 and 1999) reported a decrease in the size and area of clearcuts statewide. Our study in northern Maine also documents a trend in decreasing clearcut size and area, particularly after 1991, when the Maine Forest Practices Act went into effect. These landscape-level harvest trends over time were measurable on multirate Landsat-TM imagery.

The unsupervised RGB-NDVI classification method is very efficient for analyzing several dates of satellite imagery for forest change. The use of NDMI (RGB-NDMI) in cluster busting or as a replacement for NDVI in the original clustering shows good promise in detecting partial cuts (Hoffhine-Wilson and Sader 2002). In this study, five dates were analyzed in two classification sequences. If we had used image differencing methods, four image differencing sequences (two dates each) would have been required to process these data, adding more time and complication in merging the data sets for change type and patch analysis. Most simultaneous multirate classification methods and transforms create classes that can be more difficult to interpret (when three or more image dates are involved) and less intuitive than the time series RGB-NDVI classification, which is facilitated by additive color theory to assist in multi-date interpretation and cluster assignment.

The presence of roads created some problems in computation of harvest patch statistics that represented the contiguous harvest sites, as defined on the ground. Roads are not considered part of the area calculation for a clearcut or partial cut by FPA definition. We digitized and removed roads so that they would not confuse with detection of harvest pixels on the satellite images. However, roads bisected some harvest areas and created two harvest patches where only one would be defined on the ground. Therefore, the harvest patch sizes were lower than expected and the number of patches was likely higher. The calculation of the road buffers may have slightly reduced our estimates of the percentage of forest area harvested per time period. Nevertheless, our major objective here was to examine the temporal trends in harvest patterns, and we submit that the significance tests indicating differences in patch size, number, and area are valid for the time period comparisons. We base this conclusion on the fact that the roads were consistent features in each time period as was the methodology used to calculate the harvest patch metrics, therefore the trend in harvest patch and area changes should be comparable in the relative sense.

Future research is needed to improve the spatial representation of harvest patches detected on satellite images to match the FPA defined criteria. Experimentation with intelligent filtering operators and conditional statements, to fill in harvest patches bisected by road features, are being considered as possible methods to improve the representation of harvest configurations and size. In Maine, partial harvest accounted for 96.5% of the total harvest area in 1999 (Maine Forest Service 1999). It is essential that research continues to improve the detection and mapping of partial harvests if significant progress is to be made in integrating satellite remote sensing methods in forest inventory and monitoring.

It is important that decision-makers have access to updated information on current harvest activity, timing of harvest, and its effect on the landscape in order to design and implement science-based policy. Analysis of time-series satellite images will likely become an important data source to address these information needs. With the recent decrease in Landsat-TM image acquisition costs from approximately \$4000 to \$600, and improvement in methods, the use of multirate satellite imagery for change detection in operational forest inventory and monitoring programs (e.g., USDA Forest Service's FIA and Forest Health Monitoring) may become more cost-effective than in the past.

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