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Detection of forest harvest type using multiple dates of Landsat TM imagery

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Abstract

A simple and relatively accurate technique for classifying time-series Landsat Thematic Mapper (TM) imagery to detect levels of forest harvest is the topic of this research. The accuracy of multidate classification of the normalized difference vegetation index (NDVI) and the normalized difference moisture index (NDMI) were compared and the effect of the number of years (1–3, 3–4, 5–6 years) between image acquisition on forest change accuracy was evaluated. When Landsat image acquisitions were only 1–3 years apart, forest clearcuts were detected with producer's accuracy ranging from 79% to 96% using the RGB-NDMI classification method. Partial harvests were detected with lower producer's accuracy (55–80%) accuracy. The accuracy of both clearcut and partial harvests decreased as time between image acquisition increased. In all classification trials, the RGB-NDMI method produced significantly higher accuracies, compared to the RGB-NDVI. These results are interesting because the less common NDMI (using the reflected middle infrared band) outperformed the more popular NDVI. In northern Maine, industrial forest landowners have shifted from clearcutting to partial harvest systems in recent years. The RGB-NDMI change detection classification applied to Landsat TM imagery collected every 2–3 years appears to be a promising technique for monitoring forest harvesting and other disturbances that do not remove the entire overstory canopy.

1. Introduction

Forests encompass 89% of Maine's land area (Griffith & Alerich, 1996), which distinguishes Maine as the most forested state in the United States (Maine Forest Service, 1999). Of the 17.1 million hectares of forestland, approximately 95% is classified as commercial timberland (Maine Forest Service, 1995, 2000). Currently, most forest disturbance is a result of timber harvesting. Landowners in Maine use three harvesting systems: selection, shelterwood, and clearcut harvesting (Maine Forest Service, 1999). In the past, industrial forest landowners primarily used clearcut methods for timber harvesting. However, since the implementation of the Maine Forest Practices Act (MFPA) in 1991, clearcuts have been heavily regulated, and the use of partial harvest methods has increased. A partial harvest is defined as all harvest systems except clearcut harvest (Maine Forest Service, 1995). Partial harvests are more difficult to detect on satellite imagery than clearcuts, although previous studies have reported good relationships using Landsat TM imagery (Franklin, Moskal, Lavigne, & Pugh, 2000; Hame, 1991; Olsson, 1994).

Satellite images covering large areas of land have potential to monitor forest change in Maine and contribute to forest inventory and management goals in a cost effective manner. Bertrand, Sader, and Hayes (2000) used Landsat change detection over an 11-year (1988–1999) time period to explore the effect of the MFPA on clearcut and partial cut harvesting patterns in 29 towns in northwestern Maine. Change maps had overall accuracies between 90.0% and 94.0% and distinguished between clearcut and partial cuts over four time periods. During the 11 years, they found the number of clearcuts as well as the mean size decreased. The percentage of area that experienced partial cutting remained constant, with a decrease in the number of partial cuts and an increase in size (Bertrand et al., 2000).

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Partial harvests on satellite imagery look distinctly different from the relatively homogeneous appearance of undisturbed forest or clearcut harvests. Partial harvests appear textured with distinct boundaries and adjacent road features. The textured appearance is likely due to the heterogeneous canopy with tall trees and canopy gaps causing mixed pixels with varying digital numbers. When attempting to distinguish western US old growth forest stands from mature forests, Fiorella and Ripple (1993) state that the two most distinguishing features observed at the forest canopy level were differences in the number and size of gaps and heterogeneity of tree sizes. They found good correlation between several Thematic Mapper (TM) bands and forest structure.

New methods that utilize time series satellite imagery to detect levels of harvest disturbance in forest stands are the topic of this research. The objective is to compare the success of different satellite remote sensing techniques to detect forest harvest intensity over time in a northern Maine industrial forest setting. The first study compares two vegetation indices, the normalized difference vegetation index (NDVI) and the normalized difference moisture index (NDMI), for detecting forest change. The second study compares the accuracy of forest change detection maps when images are 1–3, 3–4, and 5–6 years apart.

1.1. Comparative studies

Successful results from previous research guided the selection of the change detection method evaluated in this study. Muchoney and Haack (1994) compared four change detection techniques to identify changes in hardwood forest defoliation caused by gypsy moth. The four change detection techniques were merged principal components analysis, image differencing, spectral–temporal (layered temporal) change classification, and postclassification change differencing (delta classification). These authors reported that detection of forest change due to gypsy moth defoliation was most accurate using the image differencing and principal components analysis methods. Coppin and Bauer (1996) reviewed more than 75 change detection studies and concluded that image differencing and linear transformations appeared to perform better than other change detection methods.

Hayes and Sader (2001) compared image differencing, principal component analysis, and RGB-NDVI methods for a tropical forest study site. They found the RGB-NDVI change detection method to be the most accurate and efficient to analyze several dates of Landsat TM imagery. When determining change, RGB-NDVI incorporated three dates at one time as opposed to two-date sequences used with other methods such as image differencing, delta classification, and multitemporal linear data transformations. The RGB-NDVI unsupervised classification avoided subjective decisions in setting histogram thresholds (which would have been necessary for several two-date image differencing sequences) and was more straightforward and time efficient. Finally, the analysis of cluster statistics (e.g., mean NDVI value over time) and visual interpretation of RGB-NDVI composites aided by additive color theory logic (Sader & Winne, 1992), facilitated identification of classified clusters representing forest clearing classes, a no change class, and regrowth classes in a time-series (Hayes & Sader, 2001). For these reasons, the RGB-NDVI classification (Sader, Hayes, Coan, Hepinstall, & Soza, 2001) was selected as the change detection method suitable for analyzing multiple dates (seven) of satellite imagery in this study.

1.2. Length of time between satellite acquisition dates

When classifying an agricultural region of Egypt, Pax-Lenney and Woodcock (1997) reported that the number and timing of images are of primary importance, and that the optimum number of images needed can be difficult to determine. Coppin and Bauer (1996) found, after reviewing the literature, that the availability of satellite data often determined the intervals between data acquisition. Pax-Lenney amd Woodcock listed two factors that contributed to the difficulty of conducting temporal resolution studies. First, the compilation of comprehensive data sets is limited by weather conditions, cost, computing resources, and sensor capabilities. Second, landscapes are dynamic and the ideal number and timing of image acquisition for monitoring varies with location, time, and measure of interest. Therefore, although research addressing the question of temporal resolution is location and application specific, and whether multitemporal images are used for change detection or classification, the amount of time between satellite acquisition needs to be determined. Without compromising accuracy, fewer images would result in savings in terms of imagery costs as well as time for processing (Pax-Lenney & Woodcock, 1997). In a tropical forest study site, Kimes, Nelson, Skole, and Salas (1998) reviewed the potential error from "temporal gaps" involved in sequential satellite image analyses, as well as ways to measure it.

1.3. Vegetation indices

The NDVI separates green vegetation from other surfaces because the chlorophyll of green vegetation absorbs red light for photosynthesis and reflects the near-infrared (NIR) wavelengths due to scattering caused by internal leaf structure (Tucker, 1979). Thus, high NDVI values indicate high leaf biomass, canopy closure, or leaf area (Jasinski, 1990; Sader & Winne, 1992; Sellers, 1985). The ease of calculating NDVI from various types of satellite data, the success of the NDVI in detecting vegetation, and its ease in calculation and interpretation has made it a popular spectral vegetation index (Cohen, 1994; Gao, 1996; Myneni & Asrar, 1994), as well as a widely used data product for studying vegetation with remotely sensed images (Chavez & MacKinnon, 1994). The NDVI is calculated using the formula in Eq. (1).

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

The method of change detection used in this study, RGB-NDVI, incorporates multiple NDVIs for detecting and quantifying major decreases or increases in green biomass associated with forest harvest or regeneration (Hayes & Sader, 2001; Sader et al., 2001).

NDMI is the second index and is calculated by Eq. (2) where the NIR is Landsat TM Band 4 and the mid-infrared (MIR) is Landsat TM Band 5.

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

This index is referred to as the NDMI, however, the term *moisture* is conventional and retained for lack of a better term. One reason a universally accepted term is lacking is because the biophysical interpretation of indices that use the MIR bands is more problematic than indices that use only red and NIR bands. Other factors such as emissivity, energy balance, forest structure, and forest cover must be considered (McDonald, Gemmell, & Lewis, 1998).

The difference between the NIR and the MIR appears to be the ability of the MIR wavelengths to absorb water. From a green leaf, the NIR band has the maximum reflectance of the six shortwave TM bands, and the reduction of reflectance of the MIR as compared to the NIR is due to the absorption of water (Cibula, Zetka, & Rickman, 1992; Hunt, Rock, & Nobel, 1987). Hunt et al. found that reflectance of TM5 for dry leaves was almost exactly equal to reflectance of TM4, so that the difference between TM4 and TM5 for a fresh leaf should equal the water absorbance in that leaf. The NDMI is formulated using a contrast between the NIR band and MIR band. The tasseled cap transformation of Landsat TM has a "wetness" feature that contrasts the visible and NIR bands (TM1–4) with the MIR bands (TM5 and 7) (Crist & Cicone, 1984). Because this feature is theoretically similar to the NDMI, it is discussed in some detail.

The "tasseled cap" transformation is a method of rotating satellite data such that the majority of the information is contained in components or features that relate directly to physical scene characteristics (Kauth & Thomas, 1976; Lillesand & Kiefer, 1994). The first and second features of TM are brightness and greenness, respectively. The third feature is termed "wetness" because it is sensitive to soil and plant moisture (Crist & Cicone, 1984). Cohen (1994) reported that the "scant literature on the subject" revealed that the wetness feature responds to both water and shadows in a ground scene. Other researchers have found the "wetness" feature to be sensitive to shadowing, leaf water content, and possibly other effects not yet discovered (Horler & Ahern, 1986) or to reflect a combination of structure and water content (Cohen, Spies, & Fiorella, 1995).

Although there is debate surrounding a suitable term for "wetness," it is nevertheless useful for forest applications. Fiorella and Ripple (1993) attempted to separate old growth and mature forests in the Pacific Northwest using Landsat TM imagery. They found that the tasseled cap features of brightness and greenness did not separate old growth and mature forests. However, wetness was highly significant and better than all other single TM bands and most band ratios. Landsat TM4/5 ratio and tasseled cap wetness had similar significance levels and were highly correlated. They suggest using the TM4/5 ratio rather than tasseled cap wetness because the former is simpler to calculate and interpret. Collins and Woodcock (1996) utilized the multitemporal Kauth-Thomas method of change detection and found change in wetness is a good indicator of conifer mortality, and the most consistent single indicator of forest change due to its capture of MIR changes. Franklin et al. (2000) found the wetness component to be an important feature in detecting changes due to partial harvesting in eastern Canada. Because wetness is a good indicator of forest change, the NDMI is thought to be also.

1.4. Study area and imagery

Seven dates (1988, 1991, 1993, 1995, 1997, 1998, and 1999) (Fig. 1) of satellite imagery were acquired in the summer months representing hardwood "leaf on" conditions. All satellite data were recorded by the Landsat TM sensor except the 1997 image, which was recorded by the Indian Remote Sensing Satellite (IRS-1C). The Landsat scene locations were based on the Landsat worldwide reference system, and were either Path 12 Row 28 or Path 11 Row 28. The IRS scene was recorded on Path 293 Row 37.

The area of overlap of all seven dates of imagery determined the final study site (Fig. 1). It was necessary to select an area covered by all seven images to allow the testing and evaluation of methods including the effect of time interval between image acquisition dates on change detection accuracy. The study site is approximately 499,176 ha and includes part or all of 84 townships in northern Maine, USA. Its approximate latitude and longitude are N45°44′00″, N46°35′00″, W69°35′00″, and W68°30′00″. The area is almost entirely industrial forestland with extensive forest harvest activity and minimal urban development.

2. Methods

2.1. Preprocessing

After data acquisition, all scenes were georeferenced to the previously rectified 1991 Landsat TM scene corres-

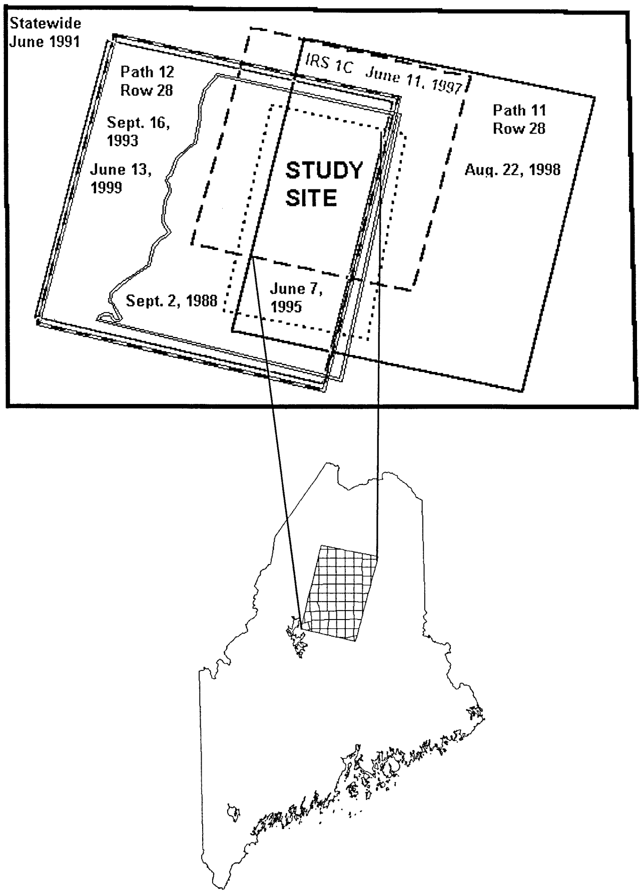

Fig. 1. The northern Maine study site (determined by overlap of all seven dates of satellite imagery). The grids correspond to the location of the townships within the study area.

ponding to the Clark 1866 spheroid, NAD27 datum, and UTM projection at 30-m pixel resolution with less than half a pixel error (Hepinstall, Sader, Krohn, Boone, & Bartlett, 1999). Each of the other scenes was georeferenced to the 1991 image using well-distributed ground control points. All images were referenced so that the root mean square error was below half a pixel or 15 m. Image processing was performed using ERDAS Imagine versions 8.3 and 8.4 on the UNIX operating system on Silicon Graphics O_2 workstations.

Without radiometric calibration of multitemporal images, nonsurface factors can make it difficult to quantify and interpret change (Chavez & MacKinnon, 1994). An absolute correction algorithm can be used to correct images to absolute surface reflectance only if atmospheric depth and sensor calibration data are available for all dates of imagery (Hall, Strebel, Nickeson, & Goetz, 1991). No such data were available for the seven images used in this study. Hall et al. found that image to image relative radiometric correction, called radiometric rectification, is a useful alternative when data for absolute atmospheric corrections are not available. Radiometric rectification corrects images of a common scene relative to a reference image using dark and bright pixel control sets. It was performed on each of the red, NIR, and MIR bands of the images with the reference being the 1991 Landsat TM scene. Following radiometric rectification, Bands 3, 4, and 5 of each date (IRS Bands 2, 3, and 4 for 1997) were concatenated to combine the bands into one file for further processing.

Several binary masks were applied to the TM (and IRS) images to eliminate contaminated areas (clouds and their shadows) and irrelevant areas (water, areas with extreme slopes) (Coppin & Bauer, 1996). A cloud mask was created by screen digitizing clouds and their shadows. A water mask was created from several Maine land cover map classes (Hepinstall et al., 1999). Because water level fluctuates over time, obvious areas missed by the water mask were added by screen digitizing.

Topographic effects have been identified as a major problem in image processing without an adequate solution (Cohen, 1994; Cohen & Spies, 1992). Sader, Waide, Lawrence, and Joyce (1989) found local topographic effects to influence NDVI in tropical forest regions with mountainous terrain. Before masking, the mountains primarily in Baxter State Park consistently appeared wrongly as "change" due to variations in sun illumination angle and shadows relating to the time of day and year each image was captured. The extremely steep slopes of Mt. Katahdin and neighboring mountains shaded large areas including upper canopy layers making it difficult or impossible to detect change. To eliminate false change, a mountain mask was produced from screen digitizing and several Maine land cover map classes.

Two vegetation indices (NDVI and NDMI) were computed for each date of imagery. All NDVI and NDMI were histogram matched to the 1991 NDVI and NDMI, respectively. The authors do not advocate the histogram match as an essential step and no comparative testing was performed to determine its effect on results. However, in this study, the histogram match visually enhanced subtle changes in both the NDVI and NDMI images (e.g., partial cuts), and therefore was employed prior to unsupervised clustering.

2.2. Change detection

2.2.1. RGB-NDVI method

The visual RGB-NDVI method (Sader & Winne, 1992) involves creation of color composites and utilization of additive color theory where three NDVI are each combined with either the red, green, or blue color write functions of the computer monitor. Any combination of primary colors of similar brightness produces a complementary color (Lillesand & Kiefer, 1994; Sader & Winne, 1992). This is similar to the multidimensional temporal feature space analysis method (Coppin & Bauer, 1996), except RGB-NDVI uses three NDVI as opposed to three TM bands. By knowing the date of each NDVI coupled with each color write function, the colors are used to identify change

Table 1
The RGB-NDVI additive color theory interpretation of associated forest change detection classes (Sader & Winne, 1992)

Additive color	Date 1 (R)	Date 2 (G)	Date 3 (B)	Interpretation
Red	H	L	L	Harvest between dates 1 and 2
Green	L	H	L	Harvest before date 1, regrowth, harvest between dates 2 and 3
Blue	L	L	H	Harvest before date 1, regrowth by date 3
Yellow	H	H	L	Harvest between dates 2 and 3
Magenta	H	L	H	Harvest between dates 1 and 2, regrowth
Cyan	L	H	H	Harvest before date 1, regrowth by date 2
Black	L	L	L	Low biomass — no change
Gray/white	H	H	H	Medium to high biomass — no change

The "H" and "L" indicate relatively high and low mean NDVI (or NDMI) values in a classification cluster. The colors occur when three NDVI or NDMI are concatenated and displayed using the RGB functions of the color monitor and represent the changes listed under "interpretation."

(Table 1). To automate the change detection and turn the three-NDVI composite into a thematic map, an unsupervised classification (ISODATA clustering) is performed on each NDVI composite (Sader et al., 2001). This part of the RGB-NDVI method is similar to composite analysis (Coppin & Bauer, 1996). Clusters are interpreted visually and guided by evaluation of major shifts in cluster statistics (NDVI or NDMI means) then assigned to specific change or no change classes (Table 1). The method is particularly efficient when several image dates (e.g., seven in this study) are analyzed in a sequence to detect harvest and regrowth patterns (Hayes & Sader, 2001). Separate composite classifications can be concatenated and the change events interpreted for more than three dates.

2.2.2. Change detection maps

The purpose of the mapping sequences was to evaluate the effect of time between satellite acquisition dates on change detection mapping accuracy. To create the change maps, three-date composites (Table 2) were combined. A total of six change maps were created: six-interval NDVI, six-interval NDMI, three-interval NDVI, three-interval NDMI, two-interval NDVI, two-interval NDMI. The 1988 was the first image for all of the change maps and the 1999 image was the last. The sequences vary by the number of images between 1988 and 1999, or the number of intervals between acquisition dates (Table 2).

An unsupervised classification was performed on each composite. Clusters were interpreted and named as change or no change by observing major changes (increases or decreases) in mean NDVI value (or NDMI value) between acquisition dates. The "change" pixels were reclassified and each cluster was assigned to one of the following categories: clearcut dates 1 to 2, partial cut dates 1 to 2, clearcut dates 2 to 3, partial cut dates 2 to 3, or no change. This process was repeated for all composites.

For the six-interval maps, three composite classifications needed to be merged to create one change map. Two problems arose in this step. First, because a change could occur in more than one composite, there was the large number of possible classes. To remedy this problem, clearcut and partial cut distinctions were dropped when a change occurred in more than one time period to the same area. Although this could result in a loss of information, the large number of classes was far too cumbersome, especially for accuracy assessment. Although some cases where change occurred more than once are unlikely, especially two clearcuts within an 11-year period, some cases such as a thinning followed by a complete overstory removal (as in a shelterwood system) or two thinnings are possible. The authors felt that it was necessary to maintain these classes indicating more than one change and assess their accuracy appropriately. The second problem with merging composites occurred when a class had very few pixels indicating that a "false" change had been detected. Classes with 45 or fewer pixels (4.5 ha) were determined to be insignificant from a forest management perspective. Pixels occurring in these classes were scattered, hence, never covered a single 4.5-ha stand. The pixels were located on the images and reassigned to classes based on spatial context and initial cluster mean NDVI value (Table 1).

The two composites associated with the three-interval change maps were also merged. The two-interval change map included only one composite and therefore no merge was necessary. A 3×3 majority filter was applied to each of the final change maps to remove "salt and pepper" artifacts (Bauer et al., 1994). The filter improves the visual appearance of the change map with insignificant loss of information from a forest management perspective (Sader & Winne, 1992).

Table 2
The RGB-NDVI change method incorporates three dates in one step (each composite)

Change maps	Composite	Composite	Composite	Details
Six-interval change maps	1988, 1991, 1993	1993, 1995, 1997	1997, 1998, 1999	Seven dates of imagery, 2–3 years apart
Three-interval change maps	1988, 1991, 1995	1991, 1995, 1999		Four dates of imagery, 3–4 years apart
Two-interval change maps	1988, 1993, 1999			Three dates of imagery, 5–6 years apart

To create the change maps, three-date composites (listed above) were combined. A total of six change maps were created (six-interval NDVI, six-interval NDMI, three-interval NDVI, three-interval NDMI, two-interval NDVI, two-interval NDMI). All change maps begin with the 1988 image and end with the 1999 image, varying by the number of images and thus intervals between 1988 and 1999.

Table 3
The error matrix, user's, producer's, and overall accuracy for the six-interval NDMI change map

Classified data		Reference data															
Class		1	2	3	4	5	6	7	8	9	10	11	12	13	14–32	Total	User's (%)
C 1988–1991	1	31	0	0	0	0	0	0	0	0	0	0	0	0	1	32	96.9
PC 1988–1991	2	4	16	0	0	0	0	0	0	0	0	0	0	0	1	21	76.2
C 1991–1993	3	1	0	22	4	0	0	0	0	0	0	0	0	0	8	35	62.9
PC 1991–1993	4	0	0	1	21	0	0	0	0	0	0	0	0	2	1	25	84.0
C 1993–1995	5	0	0	0	0	20	5	0	0	0	0	0	0	0	0	25	80.0
PC 1993–1995	6	1	0	0	0	1	18	0	0	0	0	0	0	0	0	20	90.0
C 1995–1997	7	0	0	0	0	0	0	15	4	0	0	0	0	0	2	21	71.4
PC 1995–1997	8	0	0	0	0	0	0	1	13	0	0	0	0	1	0	15	86.7
C 1997–1998	9	0	0	0	0	0	0	0	0	15	1	0	0	0	0	16	93.8
PC 1997–1998	10	0	0	0	0	0	0	0	0	2	21	0	0	0	0	23	91.3
C 1998–1999	11	0	0	0	0	0	0	0	0	0	0	19	6	0	0	25	76.0
PC 1998–1999	12	0	0	0	0	0	0	0	0	0	0	0	16	0	0	16	100.0
No change	13	1	1	0	0	0	0	0	1	0	1	0	5	70	1	80	87.5
Change in two or three comp.	14–32	1	3	0	2	1	6	0	2	2	6	4	2	18	106	153	69.3
	Total	39	20	23	27	22	29	16	20	19	29	23	29	91	120	507	
Producer's (%)		79.5	80.0	95.7	77.8	90.9	62.1	93.8	65.0	78.9	72.4	82.6	55.2	76.9	88.3		
Overall accuracy (%)		77.7															
κ		0.76															

Because the original 32-class error matrix was too large to include in this manuscript, all classes representing change in more than one composite are grouped together under "change in two or three comp." C indicates clearcut and PC indicates partial cut.

2.3. Accuracy assessment

Accuracy assessment evaluates the quality of information derived from remote sensing data (Congalton & Green, 1999) and was an essential part of the study to determine how methods and image acquisition date affect change results (NDVI vs. NDMI and six- vs. three- vs. two-interval). Accuracy assessment also indicates the types and sources of error for future study. An independent interpreter (forestry student) performed the accuracy assessment in this study without reference to the change maps. The interpreter viewed examples of both clearcut and partial cut changes to establish confidence and proficiency in interpretation, prior to the accuracy assessment phase.

The reference source for the change detection classification was visual interpretation of TM color composites as described by Cohen, Fiorella, Gray, Helmer, and Anderson (1998). However, Cohen et al. only tested this

Table 4
The error matrix, user's, producer's, and overall accuracy for the six-interval NDVI change map

Classified data		Reference data															
Class		1	2	3	4	5	6	7	8	9	10	11	12	13	14–32	Total	User's (%)
C 1988–1991	1	17	3	0	0	0	0	0	0	0	0	0	0	0	3	23	73.9
PC 1988–1991	2	0	2	0	13	0	0	0	0	0	0	0	0	4	2	21	9.5
C 1991–1993	3	1	0	9	8	0	0	0	0	0	0	0	0	1	1	20	45.0
PC 1991–1993	4	0	0	8	3	0	0	0	0	0	0	0	0	5	4	20	15.0
C 1993–1995	5	0	0	0	0	18	2	0	0	0	0	0	0	0	1	21	85.7
PC 1993–1995	6	0	0	0	0	3	20	0	0	0	0	0	0	0	1	24	83.3
C 1995–1997	7	0	0	0	0	1	0	9	2	0	0	0	0	0	4	16	56.3
PC 1995–1997	8	0	0	0	0	0	0	5	14	0	0	0	0	0	0	19	73.7
C 1997–1998	9	0	0	0	0	0	0	0	0	15	10	0	0	0	1	26	57.7
PC 1997–1998	10	0	0	0	0	0	0	0	0	2	15	0	0	2	4	23	65.2
C 1998–1999	11	0	0	0	0	0	0	0	0	0	0	21	1	0	6	28	75.0
PC 1998–1999	12	0	0	0	0	0	0	0	0	0	0	2	25	0	11	38	65.8
No change	13	2	14	0	2	0	6	0	3	0	1	0	1	77	5	111	69.4
Change in two or three comp.	14–32	21	0	10	1	2	1	2	1	1	1	0	1	1	78	120	65.0
	Total	41	19	27	27	24	29	16	20	18	27	23	28	90	121	510	
Producer's (%)		41.5	10.5	33.3	11.1	75.0	69.0	56.3	70.0	83.3	55.6	91.3	89.3	85.6	64.5		
Overall accuracy (%)		60.8															
κ		0.58															

Because the original 32-class error matrix was too large to include in this manuscript, all classes representing change in more than one composite are grouped together under "change in two or three comp." C indicates clearcut and PC indicates partial cut.

Table 5
The error matrix, user's, producer's, and overall accuracy for the three-interval NDMI change map

Classified data		Reference data												
Class		1	2	3	4	5	6	7	8	9	10	11	Total	User's (%)
C 1988–1991	1	35	1	0	0	0	0	0	7	24	0	1	68	51.5
PC 1988–1991	2	2	13	0	0	0	0	1	0	1	2	0	19	68.4
C 1991–1995	3	0	0	41	3	0	0	3	0	0	17	0	64	64.1
PC 1991–1995	4	0	0	6	52	1	1	3	0	0	9	0	72	72.2
C 1995–1999	5	0	0	0	0	43	10	0	0	0	0	0	53	81.1
PC 1995–1999	6	0	0	0	0	16	52	1	0	1	3	0	73	71.2
No change	7	1	5	2	7	3	14	82	0	0	1	2	117	70.1
1988–1991, 1991–1995	8	0	0	0	0	0	0	0	3	0	0	0	3	100.0
1988–1991, 1995–1999	9	0	0	0	0	0	0	0	0	10	0	0	10	100.0
1991–1995, 1995–1999	10	0	0	0	0	0	0	0	0	0	17	0	17	100.0
1988–1991, 1991–1995, 1995–1999	11	0	0	0	0	0	0	0	0	0	0	0	0	0.0
	Total	38	19	49	62	63	77	90	11	36	49	3	497	
Producer's (%)		92.1	68.4	83.7	83.9	68.3	67.5	91.1	27.3	27.8	34.7	0.0		
Overall accuracy (%)		70.0												
κ		0.66												

C indicates clearcut and PC indicates partial cut.

method for clearcuts in the Pacific Northwest. Because of this, it was necessary to compare the TM interpretation with large-scale aerial photography and forest industry GIS data to determine the accuracy of visual interpretation of TM color composites for identifying partial cuts. Fifty-five accuracy assessment plots were checked against Industry stand history/stand exam data, aerial photography (scale 1:15,840), or Digital Orthophoto Quadrangles (DOQs) where the historical data and industry aerial photos were not available. More than 75% of the 55 plots represented partial harvests with a few representing clear-cuts or no change. Most of the harvesting occurred between 1993 and 1999.

Based on this comparison, 50 of the 55 plots were correctly identified (using TM visual interpretation) by harvest type (clearcut or partial harvest) and date of harvest for an overall accuracy of 91%. The errors break down as follows: two plots interpreted as clearcut were heavy partial cuts; two plots interpreted as partial cuts were no change; and one plot interpreted as partial cut was a clearcut.

Having established our confidence in the TM visual interpretation method for detecting clearcuts, partial cuts, no change, and the date of change, we recommend visual interpretation of TM color composites as a valid alternative for change detection accuracy assessment. When adequate historical ground data, GIS data or multidate aerial photography is not available, visual TM interpretation by a trained interpreter familiar with forest cover type and harvest practices on the ground may be the only reasonable choice to conduct the necessary accuracy assessment.

Stratified random sample points were generated and interpreted for each class of the six-interval change maps. The points were then applied to the three- and two-interval change maps. Additional points were generated and interpreted to satisfy minimum numbers per class. In total, a minimum of 495 points were interpreted and applied to each

Table 6
The error matrix, user's, producer's, and overall accuracy for the three-interval NDVI change map

Classified data		Reference data												
Class		1	2	3	4	5	6	7	8	9	10	11	Total	User's (%)
C 1988–1991	1	33	6	0	0	0	0	0	0	20	0	0	59	55.9
PC 1988–1991	2	2	6	0	1	0	0	8	1	0	0	0	18	33.3
C 1991–1995	3	0	0	37	2	0	1	2	2	0	9	1	54	68.5
PC 1991–1995	4	0	0	3	33	1	0	1	1	0	4	0	43	76.7
C 1995–1999	5	0	0	0	0	34	14	0	0	1	8	0	57	59.7
PC 1995–1999	6	0	0	0	0	17	33	0	0	1	14	0	65	50.8
No change	7	1	6	8	25	9	27	79	0	0	4	2	161	49.1
1988–1991, 1991–1995	8	0	0	0	0	0	0	0	4	0	0	0	4	100.0
1988–1991, 1995–1999	9	2	1	0	0	0	0	0	0	14	0	0	17	82.4
1991–1995, 1995–1999	10	0	0	1	1	2	2	0	0	0	10	0	16	62.5
1988–1991, 1991–1995, 1995–1999	11	0	0	0	0	0	0	0	0	0	0	0	0	0.0
	Total	38	19	49	62	63	77	90	8	36	49	3	494	
Producer's (%)		86.8	31.6	75.5	53.2	54.0	42.9	87.8	50.0	38.9	20.4	0.0		
Overall accuracy (%)		57.3												
κ		0.51												

C indicates clearcut and PC indicates partial cut.

Table 7
The error matrix, user's, producer's, and overall accuracy for the two-interval NDMI change map

Classified data		Reference data							
Class		1	2	3	4	5	6	Total	User's (%)
C 1988–1993	1	32	0	0	0	0	20	52	61.5
PC 1988–1993	2	21	27	0	0	0	21	69	39.1
C 1993–1999	3	0	0	53	26	0	13	92	57.6
PC 1993–1999	4	0	0	20	30	3	7	60	50.0
No change	5	8	19	13	60	86	9	195	44.1
1988–1993, 1993–1999	6	0	0	4	0	0	20	24	83.3
	Total	61	46	90	116	89	90	492	
Producer's (%)		52.5	58.7	58.9	25.9	96.6	22.2		
Overall accuracy (%)		50.4							
κ		0.40							

C indicates clearcut and PC indicates partial cut.

change detection map. Once a complete set of sample reference points had been developed for each change map, error matrices were created and overall accuracy, user's accuracy, and producer's accuracy were calculated. κ analysis uses the KHAT statistic, which is a measure of accuracy or agreement based on the difference between the actual agreement in the error matrix and chance agreement (Congalton & Green, 1999). KHAT values and variance for each matrix were used to calculate Z statistics to determine if an error matrix is significantly different from random and if two error matrices are significantly different from each other.

3. Results and discussion

3.1. Change detection maps

Z statistics revealed that all change maps were significantly different from random and significantly different from each other.

3.1.1. Six-interval change maps

The overall classification accuracy of the six-interval NDMI change map was 77.7% with a κ of 0.76. This was the highest accuracy of all change maps produced. There was minimal confusion between clearcuts and partial cuts (Table 3). Where confusion did exist, often the point was a partial cut while the change map indicated a clearcut of the same period. A number of misclassified points were those that had experienced only one change but were classified as having experienced more than one change. Except for the partial cut 1988–1991 class, partial harvest had a substantially higher user's accuracy than producer's accuracy indicating higher omission error than commission error in partial cut classes (Table 3). Surprisingly, little commission error existed in the no change class, which had a user's accuracy of 87.5%. The lower producer's accuracy for the no change class occurred because 18 points were identified as no change but classified as change.

The overall classification accuracy of the six-interval NDVI change map was 60.8% with a κ of 0.58. There was error between partial cut and clearcut classes as well as between partial cut classes and the no change class (Table 4). For example, 14 points were partial cut 1988–1991, but classified as no change. Substantial confusion occurred between the partial cut 1988–1991 and the partial cut 1991–1993 classes with 13 misclassified points.

3.1.2. Three-interval change maps

The overall classification accuracy of the three-interval NDMI change map was 70.0% and the κ was 0.66. The

Table 8
The error matrix, user's, producer's, and overall accuracy for the two-interval NDVI change map

Classified data		Reference data							
Class		1	2	3	4	5	6	Total	User's (%)
C 1988–1993	1	40	1	0	0	4	22	67	59.7
PC 1988–1993	2	8	14	0	1	1	9	33	42.4
C 1993–1999	3	1	0	48	13	0	14	76	63.2
PC 1993–1999	4	0	1	16	30	3	17	67	44.8
No change	5	12	30	26	72	81	29	250	32.4
1988–1993, 1993–1999	6	0	0	0	0	0	0	0	0.0
	Total	61	46	90	116	89	91	493	
Producer's (%)		65.6	30.4	53.3	25.9	91.0	0.0		
Overall accuracy (%)		43.2							
κ		0.31							

C indicates clearcut and PC indicates partial cut.

Table 9
The overall accuracy of each change map and user's accuracy for the no change classes

	Six-interval NDMI	Six-interval NDVI	Three-interval NDMI	Three-interval NDVI	Two-interval NDMI	Two-interval NDVI
Overall accuracy	77.7%	60.8%	70.0%	57.3%	50.4%	43.2%
No change user's accuracy	87.5%	69.4%	70.1%	49.1%	44.1%	32.4%
Partial cut points	8	27	26	58	79	102
Clearcut points	1	2	6	18	21	38
Change in more than one composite	1	5	3	6	9	29

The no change user's accuracy is an indicator of change missed on the change maps. The points are those contributing to the no change user's accuracy measurements.

most serious error occurred when a reference point represented change in more than one composite and the change map placed it in a one time change category (Table 5). For example, 24 points changed between 1988–1991 and 1995–1999, but were mapped as clearcut 1988–1991 on the change map resulting in a producer's accuracy of 27.8%. There was also confusion between the clearcut 1995–1999 and partial cut 1995–1999 classes.

The overall accuracy of the three-interval NDVI change map was 57.3% with a κ of 0.51. Similar to the three-interval NDMI, many points that changed in both composites were misclassified as change in only one composite (Table 6). For example, 20 points fell in areas that changed between 1988–1991 and 1995–1999, but were shown as clearcut 1988–1991 on the change map. Confusion occurred between the clearcut and partial cut 1995–1999 classes. Error was also apparent when a partial cut points were classified as no change.

3.1.3. Two-interval change maps

The overall accuracy for the two-interval NDMI change map was 50.4% with a κ of 0.40. There were three major sources of error in the two-interval NDMI change map (Table 7). The first was the low user's accuracy for the no change class at 44.1%. Points representing change classes were classified as no change. The most obvious case was with the partial cut 1993–1999 class, where 60 points were partial cut 1993–1999 but classified as no change. A second source of error was the confusion between partial cut and clearcut classes. Twenty-one points were partial cut 1988–1993, but were classified as clearcut 1988–1993. Also, 46 points were confused between the clearcut 1993–1999 and partial cut 1993–1999 classes.

The overall accuracy of the two-interval NDVI change map was 43.2% with a κ of 0.31. The most serious problem with the two-interval NDVI change map was that no areas experiencing change in both time periods were detected (Table 8). Therefore, the 91 points that changed in both composites were classified as a one-time change or no change, resulting in a producer's accuracy of 0%. A second problem was the low user's accuracy for the no change class (32.4%). This is similar to the two-interval NDMI change map where the reference indicated a change but the change map showed no change. Finally, there was confusion between clearcut and partial cut for the 1988–1993 changes as well as the 1993–1999 changes.

3.2. Evaluation of classification trials

3.2.1. NDVI vs. NDMI

The first experiment was to compare the use of the NDVI and NDMI in the context of the RGB-NDVI change detection method. All Z statistic comparisons indicated that all NDMI-derived change maps were significantly different from all NDVI-derived change maps.

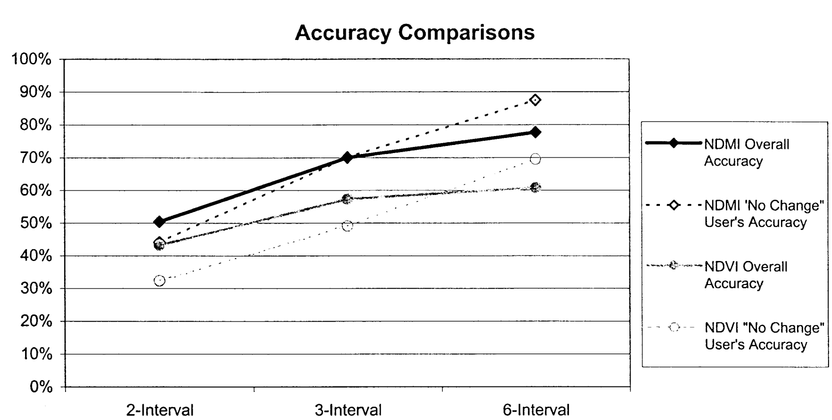

Fig. 2. The overall accuracy and the no change user's accuracy for the two-, three-, and six-interval NDMI and NDVI forest change maps.

Table 10
The number of points wrongly included in the no change class for the three- and two-interval change maps

	Three-interval					Two-interval				
Six-interval class	Class	NDMI		NDVI		Class	NDMI		NDVI	
PC 1988–1991	–	–	–	–	–	PC 1988–1993	14	74%	16	53%
PC 1991–1993	PC 1991–1995	6	86%	20	71%		5	26%	14	47%
PC 1993–1995		0	0%	6	21%	PC 1993–1999	26	22%	28	42%
PC 1995–1997	PC 1995–1999	8	57%	15	55%		13	11%	13	19%
PC 1997–1998		3	21%	6	30%		5	4%	13	19%
PC 1998–1999		3	21%	4	15%		7	6%	10	15%

These are the same points shown in Table 9 "partial cut," however, here they are further separated by corresponding six-interval class. The count represents the actual number of partial cut accuracy points classified as no change. The percent is the count divided by the total number of points wrongly included in the no change class. Because not all six-interval classes are present here, the total percent per three- and two-interval class does not necessarily equal 100.

In all cases, the NDMI change maps had a higher overall accuracy than the NDVI change maps. It is likely that the higher accuracy of the NDMI change maps was due to an increased ability to detect partial cuts. A good indicator is the user's accuracy of the no change class. The user's accuracy for the no change class is a measure of commission error where a low accuracy percentage indicates points wrongly included in the "no change" class or, in other words, real change missed by the change detection method. In all cases, the user's accuracy for the no change class was lower for the NDVI classifications than the NDMI classifications (Table 9, Fig. 2). The misclassified points contributing to low no change user's accuracy are shown in Table 9. These points indicate what kind of change (clearcut or partial cut) was missed on the change maps. In all cases, far more partial cut points were missed and contributed to error than clearcut points or points representing change in more than one composite. Also, more points, especially those representing partial cuts, were missed on the NDVI change maps than the NDMI change maps. It can be concluded that change maps created using NDMI were more successful at detecting partial harvests than change maps created using NDVI.

3.2.2. Six- vs. three- vs. two-interval

The second objective compared the time intervals between satellite data acquisition for detecting change. All Z statistics comparing the six-, three-, and two-interval NDVI and NDMI were significant demonstrating that time between acquisition affects the accuracy of the results. For both the NDMI and NDVI, the six-interval change maps had a higher overall accuracy than the three-interval change maps, which was higher than the two-interval change maps (Fig. 2).

The results indicated that the overall accuracy decreased as the number of years between image acquisition increased. Again, the no change user's accuracy is a good indicator because it is a measure of missed change. As the number of years between images increased, the no change user's accuracy decreased indicating that points were wrongly included in the no change class (Table 9, Fig. 2) and change was not detected. Points wrongly included were mainly partial cut points indicating that subtle forest disturbances such as partial harvests were missed in the change detection process as the interval between image acquisition increased.

3.2.3. Effect of number of years between acquisition dates on detection of partial cuts

As stated earlier, the overall accuracy of change maps decreased as the interval between acquisition dates increased due primarily to the lack of detection of partial cuts. A partial cut was more likely to be missed if it occurred early in the time period. For example, in a two-interval change class of partial cut 1993–1999, a partial cut occurring in 1994 was more likely to be missed and classified as no change than a partial cut that occurred in 1998.

This is demonstrated in Table 10. This table shows the number of points wrongly included in the no change class (causing a decrease in no change user's accuracy) for the three- and two-interval change maps. These are the same points as Table 9 under the "partial cut" class, however, Table 10 further separates them according to the corresponding six-interval class. The actual count of partial cut accuracy points classified as no change are presented as well as a percent of the total number of points wrongly included in the no change class.

The result of this comparison is that partial cuts and possibly other subtle forest disturbances in a forest are more likely to be missed if there is a longer time period between image acquisition and if the change occurred shortly after the acquisition of the earlier date.

4. Conclusions

When image acquisitions were only 1–3 years apart, clearcuts were detected with better accuracy using either NDMI or NDVI; however, partial harvests were detected with lower accuracy (especially using NDVI) as time interval between image acquisition dates increased. The NDVI technique for monitoring vegetation greenness and biomass is a well known and commonly used method in forest change detection, yet this study confirmed that the less common NDMI method (utilizing the middle infrared band instead of the visible red) produced significantly higher accuracies for detecting forest harvest in all classification trials. The RGB-NDMI unsupervised classification was efficient for detecting changes over multiple dates (seven) in this study.

In northern Maine forests, where the industrial landowners have shifted from clearcutting to partial harvest silvicultural systems, the RGB-NDMI method applied to Landsat TM imagery collected every 2–3 years appears to be a promising technique for monitoring forest harvesting and other disturbances that do not remove the entire overstory canopy. The methods reported here have applicability to other forest regions; for example, related studies have resulted in high change detection and regrowth accuracies (>85%) in tropical forests (Hayes & Sader, 2001).

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