Improved Forest Classification in the Northern Lake States Using Multi-Temporal Landsat Imagery

Peter T. Wolter, David J. Mladenoff, George E. Host, and Thomas R. Crow

Abstract
Forest classifications using single date Landsat TM data have been only moderately successful in separating forest cover types in the northern Lake States region. Few regional forest classifications have been presented that achieve genus or species level accuracy. We developed a more specific forest cover classification using TM data from early summer in conjunction with four MSS dates to capture phenological changes of different tree species. Among the 22 forest types classified, multi-temporal image analysis aided in separating 13 types. Of greatest significance, trembling aspen, sugar maple, northern red oak, northern pin oak, black ash, and tamarack were successfully classified. The overall classification accuracy was 83.2 percent and the forest classification accuracy was 80.1 percent. This approach may be useful for broad-scale forest cover monitoring in other areas, particularly where ancillary data layers are not available.

Introduction
Forest cover type mapping in the northern Lake States (Minnesota, Wisconsin, and Michigan) using spaceborne sensors has been a forest management goal since the launch of Landsat-1 on 23 July 1972. Forest classifications of large regions with Anderson Level III precision (Anderson *et al.*, 1976) are especially needed to assist landscape-scale analysis and management objectives (Mladenoff *et al.*, 1993; Mladenoff and Pastor, 1993). Unfortunately, detailed level III forest cover mapping efforts using a single date of Landsat Multispectral Scanner (MSS) data have been largely unsuccessful (Mead and Meyer, 1977; Roller and Visser, 1980; Downs, 1981). Moore and Bauer (1990) concluded that forest heterogeneity in northern Minnesota and the suboptimal spectral and radiometric resolution of the MSS sensor preclude detailed classification. The Thematic Mapper (TM) sensors aboard Landsats 4 and 5 (launched in 1982 and 1984, respectively) provide enhanced spatial, spectral, and radiometric resolution superior to the MSS sensor (Williams *et al.*, 1984; Toll, 1985). The addition of two middle infrared bands (band 5, 1.55 to 1.75μm, and band 7, 2.08 to 2.35μm), sensitive to moisture content of vegetation (Tucker, 1980; Ripple, 1986; Hunt *et al.*, 1987; Hunt and Rock, 1989; Wolter, 1990), has been shown to improve forest classification results (Toll, 1985; Benson and DeGloria, 1985; Stenback and Congalton, 1990; Moore and Bauer, 1990). However, the increased resolution of the TM sensor has not resulted in forest cover classifications of sufficient detail (i.e., Anderson Level III) to warrant practical use of this technology by forestland managers (Skidmore and Turner, 1988). Classifications using multi-temporal or multi-phenological imagery have potential for higher forest classification precision over single-date classifications (Schriever and Congalton, 1993). In this paper we develop an application of this multi-phenological approach to classify dominant forest species within northern Lake States conditions.

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Objectives
The objectives of this study include

- Developing a forest classification with dominant tree species level precision within northern Lake States conditions,
- Using MSS digital data to capture major phenological events of hardwood forest cover types,
- Reassessing the utility of MSS data for multi-temporal or multi-phenological forest classifications, and
- Determining the practicality of a layered classification approach utilizing image ratioing and ratio differencing techniques for multi-temporal image analysis.

Background
There are few accounts of research where TM data have been used to classify northern mesic and boreal Lake States forests. Studies that used TM or Thematic Mapper Simulator (TMS) data in this region have covered small areas (Shen *et al.*, 1985; Hopkins *et al.*, 1988; Moore and Bauer, 1990; Bolstad and Lillesand, 1992) relative to the 34,225-km² coverage of a full Landsat scene. Using airborne TMS in northern Minnesota, Shen *et al.* (1985) achieved 84.2 percent accuracy for five forest species: red pine (*Pinus resinosa*), jack pine (*P. banksiana*), black spruce (*Picea mariana*), paper birch (*Betula papyrifera*), and trembling aspen (*Populus tremuloides*). Their 23-km² study area was ideal as it contained mostly

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pure, spatially homogeneous cover types. Furthermore, because the TMS instrument was flown at an altitude of 7200 m, atmospheric affects may have been negligible. Buchheim *et al.* (1985), using simulated SPOT (Systeme Probatoire d'Observation de la Terre) data of a 60-km^2 study area in northwestern Wisconsin, were able to visually discriminate Anderson level III (species) forest types. However, while computer-aided classification (maximum likelihood) was excellent at level I (96 percent overall accuracy) and level II (91 percent overall accuracy), level III classification precision (90 percent overall accuracy) was limited to lowland types: white-cedar-balsam fir (*Thuja occidentalis-Abies balsamia*), tamarack (*Larix laricina*), and black spruce. Hopkins *et al.* (1988) used TM data of a 15-km^2 study area in northwestern Wisconsin and reported Anderson Level III accuracy for red pine and jack pine but only Level II accuracy for remaining forest classes. Hopkins *et al.*, (1988) and Shen *et al.* (1985) considered conditions in their respective study areas unrepresentative of typical northern Lake States forest cover.

In northern Wisconsin, Bolstad and Lillesand (1992) combined *a priori* information (soil and terrain position) and TM data in a maximum-likelihood classification of two study areas (each 300 km^2). Pooled classification accuracy for one of the areas reached 94 percent for northern hardwoods, red pine, jack pine, pine/hardwood, upland brush, lowland conifer, lowland brush, *Sphagnum*, lowland vegetation, crop/pasture, soil/urban, aquatic vegetation, and water, an increase of 24 percent compared to the same area classified without *a priori* knowledge. However, genus or species level discrimination was not obtained for most forest types. The ancillary data they used were manually digitized or scanned from 1: 24,000-scale U. S. Geological Survey maps (terrain position) and 1:20,000-scale U. S. Soil Conservation Service soil survey maps. Unfortunately, these types of ancillary data are not yet conveniently available in contiguous digital form for many areas (Mladenoff and Host, 1994). To manually digitize or scan these data layers for large regional classifications would be an enormous task. Multi-temporal image analysis provides additional forest cover information without reliance on human-derived ancillary data.

Changes in spectral reflectance caused by phenological differences among temperate forest tree species may allow for Anderson level III forest cover type classification on a regional scale. Large seasonal variations in forest species spectral response in the visible portion of the electromagnetic spectrum (Miller *et al.*, 1991; Eder, 1989; Schwaller and Tkach, 1985) and phenological differences in senescence among tree species (Ahlgren, 1957; Sayn-Wittgenstein, 1961; Eder, 1989) present unique forest classification opportunities. The accumulation or unmasking of pigments such as anthocyanins (responsible for scarlet to red leaf coloring), carotenoids (orange to yellow coloring), tannins (brown coloring), and xanthophylls (yellow coloring) following the denaturing of chlorophyll are responsible for spectral change (Goodwin, 1958; Moore, 1965; Sanger, 1971; Boyer *et al.*, 1988). Boyer *et al.* (1988) point out that tree species characterized by sequential chloroplast decline (such as *Quercus palustris*) may be significantly different spectrally from tree species exhibiting synchronous chloroplast decline.

Kalensky (1974) states that significant improvements in multi-date image classification could be made if the images used were selected on the basis of spectral patterns rather than on the basis of image availability alone. Kalensky and Scherk (1975) analyzed single-stage classification accuracies for various combinations of spring to autumn MSS data for a forested area near Ottawa, Canada. For discrimination of coniferous forest, deciduous forest, and agricultural land using a maximum-likelihood decision rule, they found that three dates of MSS imagery from June, September, and October provided the best results (84 percent overall classification accuracy) over all other single- or multiple-date classifications tested. The October MSS scene captured peak senescence for most hardwoods while the June MSS scene captured hardwood leaf flush. Kalensky and Scherk (1975) concluded that, although the October, June, and September MSS scenes individually produced low overall classification accuracies (67 percent, 69 percent, and 81 percent, respectively), their collective use mitigated the effects of individual image noise. Beaubien (1979) concluded that comparing or superimposing MSS images taken at different seasons provides better contrast among certain types of vegetation in eastern Quebec. Using MSS data for a classification of the Crater Lake National Park region, Walsh (1980) found that September imagery provided more information than summer MSS data due to the phenological condition of vegetation and the lower sun angle.

Conversely, Kan and Weber (1978) determined that there was no clear benefit of multiple-date classifications over single-date classifications using MSS data for nine broad vegetation communities across the United States (including central hardwoods, northern hardwoods, northern conifers, and boreal). Nelson *et al.* (1984) stated that senescent imagery should be avoided for forest classifications in New England. Their imagery recorded the later stages of senescence where many forest stands were leafless. Similarly, Toll (1985) in a Maryland study used both November (MSS and TM) and July (MSS and TM) data in a comparison between classification potentials of the two sensors. Toll (1985) concluded that the November TM classification accuracy was not significantly better than MSS accuracy. This result was attributed to fall color variability and foliar loss in the November imagery. Their November results also suggest that MSS data may be superior to TM data when analyzing senescent imagery. That is, the greater pixel size of MSS data (79 by 56 m) could alleviate some of the spatial/spectral heterogeneity caused by autumn senescence.

The identification of tree species on aerial photographs using phenological aids has been studied in great detail (Sayn-Wittgenstein, 1961). Eder (1989) used true color aerial photography of autumn senescence to map hardwood forest species in the Medford Ranger District of the Chequamegon National Forest in northern Wisconsin. He found best separation between sugar maples (*Acer saccharum*) and mixed aspen/paper birch stands was achieved by acquiring photography during the peak of sugar maple senescence. Eder (personal comm., 1992) notes that paper birch, trembling aspen, and bigtooth aspen (*P. grandidentata*) will remain green for approximately one week after peak sugar maple senescence. Thereafter, paper birch tended to color a few days prior to trembling aspen and bigtooth aspen (Ahlgren, 1957; J.J. Eder, personal comm., 1992). Conversely, black ash (*Fraxinus nigra*) trees lose their leaves prior to peak sugar maple senescence (Eder, 1989), providing a window that can last as long as two weeks (personal observations).

Schriever and Congalton (1993) used TM imagery covering three key dates to determine if phenological differences could improve forest classification accuracy of a 1052-km^2 region in southern New Hampshire. They performed separate forest classifications on imagery from May (bud break), September (stable growing season), and October (senescence),

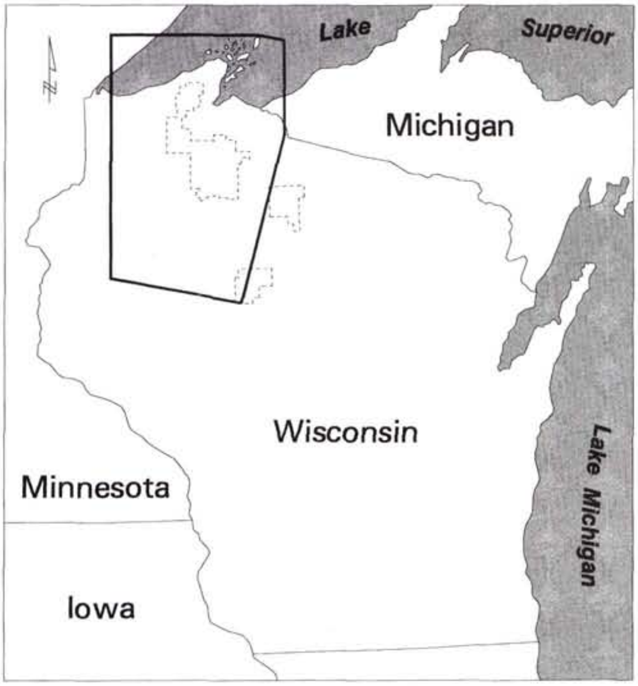

Figure 1. Location of study area in northwestern Wisconsin. Chequamegon National Forest (- - -).

and found that the October scene provided the best discrimination among the hardwood species American beech (*Fagus grandifolia*), northern red oak (*Q. rubra*), and red maple (*A. rubrum*). May imagery was second best with an overall accuracy of 69 percent compared to 62 percent for September and 74 percent for October classifications. Schriever and Congalton (1993) suggest that the success of the October and May classification over the September classification is a function of differential chlorophyll absorption, foliar moisture, and forest canopy characteristics.

Schriever and Congalton (1993) compared the results of three separate forest classifications with no attempt to combine raw data from different dates in either a layered classification (Weismiller *et al.*, 1977; Hixson *et al.*, 1980; Lozano-Garcia and Hoffer, 1985) or a single-stage classification. Lozano-Garcia and Hoffer (1985) state that layered classifications applied to multi-temporal satellite data are more efficient and accurate than single-stage classifications. The stepwise nature of layered classifications allows the analyst (1) to optimize the use of specific spectral bands and (2) to choose the best season for the identification and classification of individual cover types (Lozano-Garcia and Hoffer, 1985).

Previous work demonstrates that temporal image differencing techniques are powerful tools for characterizing changes in forest canopy characteristics (Vogelmann, 1988; Vogelmann and Rock, 1989). Vegetation indices such as the normalized difference vegetation index (NDVI) derived from remotely sensed data collected throughout a growing season can enhance differences in vegetation phenology (Tucker *et al.*, 1985; Goward *et al.*, 1985; Loveland *et al.*, 1991; Samson, 1993). MSS data have been used to discriminate major changes in green leaf biomass by combining NDVI layers from different dates (Sader and Winne, 1992). Some investigators consider image differencing and image ratio differencing techniques for change detection relatively uncomplicated and somewhat more accurate than comparing multiple classifications (Woodwell *et al.*, 1983; Singh, 1986). Furthermore, Sader and Winne (1992) suggest that image ratioing and image ratio differencing techniques are preferred over principal components analysis (PCA) because the transformed results of PCA are often difficult to interpret.

Materials and Methods

Study Region

The study region encompasses an area of 28,000 km^2 or roughly 83 percent of a full Landsat TM scene in northwestern Wisconsin (Figure 1). The Chequamegon National Forest is located approximately in the north-central portion of this region. This glaciated landscape is characterized by gentle topographic relief with boreal forests in the north along Lake Superior where clay soils are often quite wet, northern mesic forests on loamy moraines which make up the majority of the central region, northern xeric forests or pine barrens on sandy soils, and some areas of oak savanna to the south (Curtis, 1959; Pastor and Mladenoff, 1992). This region is a complex mosaic of successional forest types due to widespread and destructive logging practices that took place in the late nineteenth and early twentieth centuries (Mladenoff and Pastor, 1993; Mladenoff and Stearns, 1993).

TM Image Acquisition Constraints

All Landsat data used correspond to Worldwide Reference System coordinates path 26 row 28 which are centered at approximately 46°N, 91°26'W. TM image selection was based on several constraints:

- imagery at least 90 percent cloud free
- relative humidity less than 60 percent
- wind speed less than 30 km/h
- date within 6 June - 21 June

Satellite image data acquired for this study are summarized in Table 1. The TM image selected was ID 5120016163 acquired on 14 June 1987. According to data gathered from three weather stations within the region, mean relative humidity between 900 and 1000 hours on this date was approximately 48 percent and average wind speed was 24 km/h. Relative humidity was considered because incident and reflected visible radiation scattered by water vapor in the atmosphere could adversely affect classification precision (Potter and Shelton, 1974). Wind speed was considered because excessive winds would expose abaxial surfaces of forest leaves. The axial and abaxial leaf surfaces of many plant species have very different albedo values which may introduce problematic spectral variability (Kharuk, 1992). Finally, date was important because forest tree species are best separated using remote sensing techniques with imagery gathered

Table 1. Summary of Imagery Used in the Classification.

Sensor	Date	Season	Phenology
MSS	10 May 1992	spring	aspen leaf flush
TM	14 Jun 1987	early summer	all leaves flushed
MSS	13 Sep 1985	early autumn	black ash leaf-off
MSS	08 Oct 1980	autumn	oak senescence
MSS	25 Feb 1988	winter	tamarack leaf-off

TABLE 2. CLASSIFIED COVER TYPES AND VALIDATION METHOD USED. FOREST CLASSES INCLUDE SAF FOREST CLASSES[1], USFS CLASSES[2], AND CLASSES DERIVED USING USFS SPECIES CODES AND DNR FOREST STAND INFORMATION[3]. COVER TYPES CLASSIFIED USING MULTI-TEMPORAL IMAGE ANALYSIS (■) AND COVER TYPES INDIRECTLY IMPROVED AS A RESULT OF MULTI-TEMPORAL IMAGE ANALYSIS (□).

Forest types validated using USFS and DNR forest stand information			
Pr	- red pine[1]	Pt	- trembling aspen[3]
Pb	- jack pine[1]	P	- mixed aspen□[1]
Pm	- black spruce□[1]	Abp	- balsam fir-aspen[1]
Pg	- white spruce[1]	Psh	- E. white pine-hardwood[1]
msc	- mixed swamp conifer□[1]	Bpc	- paper birch-conifer□[1]
LI	- tamarack■[1]	Toh	- Northern white-cedar[1]
Fn	- black ash■[1]	Tch	- E. hemlock-yellow birch[1]
Qr	- Northern red oak■[1]	Fnc	- black ash-lowland conifer■[3]
Qe	- Northern pin oak■[1]	Qep	- Northern pin oak-pine■[3]
As	- sugar maple□[1]	Pbo	- jack pine-oak■[2]
Cover types validated by photo-interpretation and field verification			
ss	- sparsely stocked forest	sh	- shrub and herb.□
up	- urban or pavement	ff	- flooded forest
gf	- grass-forb	ow	- open water
cf	- cleared forest■	S	- *Sphagnum sp.*

early in the growing season (Kan and Weber, 1978; Shen *et. al.*, 1985).

MSS data selection was based upon availability of cloud free dates that corresponded with the unique phenological windows of the target forest species (Table 1). The number of suitable dates was few due to the 16-day repeat cycle of Landsat and to frequent cloud coverage. MSS digital data were chosen over TM data primarily because MSS data are more affordable. In addition, MSS data are of sufficient resolution to detect coarse forest canopy differences such as leaf-on versus leaf-off (Williams, 1975) associated with the phenology windows exploited in this study.

Forest Phenology and MSS Image Acquisition

Peak fall color for sugar maple at Park Falls, Wisconsin, roughly the center of our TM scene, is approximately 21 September with an annual variance of ± 4 days (J.J. Eder, personal comm., 1992). One scene in the MSS archive came near this phenological constraint (ID 85056016214, 12 September 1985). Based on personal observations, peak fall color for red oak tended to be about two weeks later than sugar maple for our region. There were no cloud-free MSS scenes similar in age to our TM scene for this oak phenology window. Therefore, an older MSS scene was selected (ID 2208616141, 8 October 1980) (Table 1). Conversely, the best phenologic state for the classification of trembling aspen is between trembling aspen leaf flush (first hardwood tree species to leaf out in spring) and leaf flush of other associated hardwood species such as sugar maple which leafs-out about one week later (Sayn-Wittgenstein, 1961). This condition was best met with scene ID 5299216161 acquired on 10 May 1992 (Table 1). Field verification in the north-central portion of the study area on this date (approx. 48 km south of the northern edge of the study region) revealed that trembling aspen leaf flush had begun while sugar maple had not. Although aspen and maple phenology were not observed in the southern portion of the study area on this date, reflectance values (10 May 1992 MSS) of known sugar maple dominated stands in the southern region led us to believe sugar maple leaf flush had begun. Finally, a winter scene (ID 5145616221, 25 February 1988) was chosen to classify the leaf-off phenology of tamarack (Table 1).

Spectral Calibration and Geometric Registration

All digital MSS and TM data were calibrated to reflectance according to Price (1987) before geometric corrections were made. We geometrically registered the TM imagery to UTM zone 15 coordinates with a pixel size of 28.5 metres using nearest-neighbor resampling with second-order polynomial transformation equations. We achieved a root-mean-squared error (RMSE) of unit weight of approximately 0.35 pixels for the fit between the digital TM data and the 1:24,000-scale USGS topographic maps using 26 evenly distributed ground control points gathered from the USGS topographic maps.

All MSS scenes were initially transformed (first order) from 57-metre pixels to 28.5-metre pixels using nearest-neighbor resampling (RMSE = 0.0 pixels). Each MSS scene was then coregistered to the TM digital data (bilinear interpolation resampling) using 26 image-to-image control points per MSS scene with a second-order geometric model. All RMS errors were less than 0.5 pixels for the fit between 28.5-metre MSS digital data and TM digital data. An independent assessment of the MSS coregistration to the TM digital data was performed by looking at 18 check points throughout the study area. All RMS errors were within 0.7 pixels (first order) for the fit between 28.5-metre MSS and TM data.

Forest Classification System

We chose to follow the Society of American Foresters (SAF) classification system (Eyre, 1980) to define most of the forest types (Table 2). The SAF forest types used in this classification are the same or similar to the types used by the United States Forest Service (USFS) except for the jack pine-oak. We included a trembling aspen type to subdivide the SAF description of mixed aspen. Wisconsin Department of Natural Resources (DNR) forest stand information (Locey, 1990) and USFS species codes were used for forest types that did not fit either the SAF or USFS type descriptions (Table 2). We used DNR and USFS forest stand maps as well as 6 June 1988 National High Altitude Aerial Photography (NHAP) as reference information in training and assessment of the classification. Stand maps are extremely useful as ground truth information (Kalensky and Scherk, 1975) because they provided stand location and an indication of stand composition (Shen *et. al.*, 1985).

Preliminary Classification and Validation

We used TM bands 3 (0.63 to 0.69μm), 4 (0.76 to 0.90μm), and 5 (1.55 to 1.75μm) to separate forest from nonforest as well as to stratify forested regions into conifer, hardwood, and mixed conifer-hardwood classes (Figure 2). For northern temperate forests, these spectral regions possess practically all the information contained in TM data, and afford the best symmetry between classification accuracy and processing efficiency (Nelson *et al.*, 1984; Horler and Ahern, 1986; Moore and Bauer, 1990; Bolstad and Lillesand, 1992). While TM bands 4 and 5 provide for the best discrimination among forest types, a visible band is also necessary for discriminating forested from nonforested types (Hopkins *et al.*, 1988).

We stratified nonforested areas from forested cover types by applying a threshold classification algorithm on TM bands 3, 4, and 5 (Figure 2). This method of classification is similar to a knowledge-based classification technique using TM physical principles described by Civco (1989). Forested cover

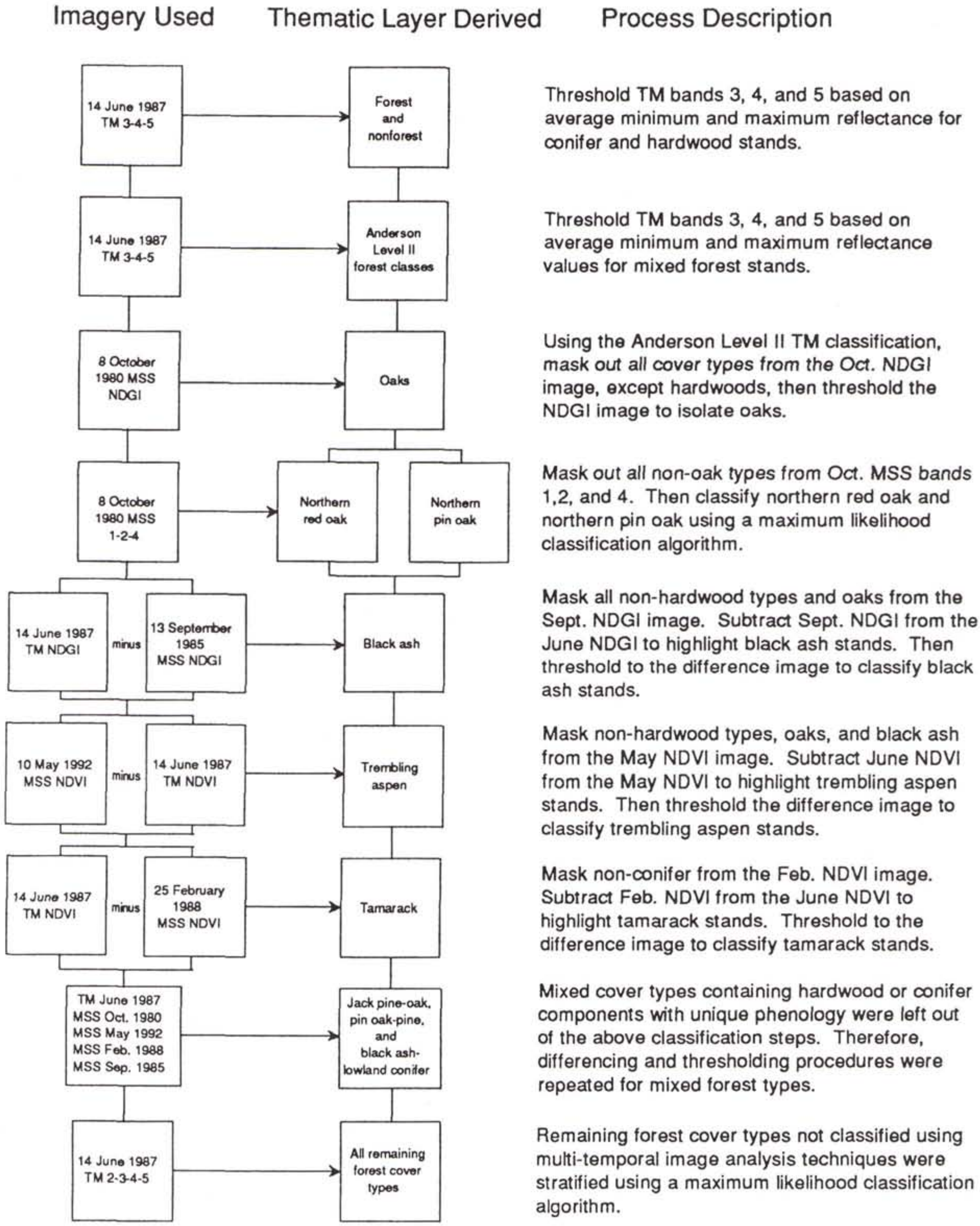

Figure 2. Diagram describing each step of the forest classification, imagery used, and intermediate layers generated.

types have relatively high reflectance values in the near infrared, moderate reflectance in the middle infrared, and low reflectance in the red spectral regions compared with most nonforested areas. However, some nonforest vegetation (e.g., *Sphagnum*) has reflectance values in the near infrared spectral region similar to some forest species (Vogelmann and Moss, 1993). In contrast, middle infrared and visible reflectance tend to be lower for *Sphagnum* than for forested cover types.

Spectral differences among these major classes (forest and nonforest) permitted the use of a general rule:

> IF pixel reflectance in TM band 3 is low (between lower and upper thresholds), very high in TM band 4 (between lower and upper thresholds), and moderate in TM band 5 (between lower and upper thresholds), THEN the pixel most likely represents forest cover.

Bands 3, 4, and 5 average minimum and maximum reflectance values for 30 forested training areas containing known conifer and hardwood stands were used to determine threshold values for the forest-nonforest classification. Once classified, a qualitative visual assessment of the classification was performed using 6 June 1988 color-infrared NHAP. The distinction between forested and nonforested cover types was good. Confused cover types included sparsely wooded areas such as shelterwood clearcuts, apple orchards, and forested areas flooded by beaver activity, all of which were classified into nonforest.

We stratified forested land into conifer, hardwood, and mixed cover types (Anderson Level II) by again applying the threshold classification algorithm on TM bands 3, 4, and 5 (Figure 2). Hardwood tree species have greater reflectance than conifer species in each of these spectral regions (Vogelmann and Rock, 1988) with near infrared providing the best separability (Benson and DeGloria, 1985; Shen *et al.*, 1985). Shen *et al.* (1985) suggested that a threshold performed on TMS near infrared reflectance would discriminate between hardwoods and conifers. However, mixed conifer-hardwood stands have intermediate reflectance in TM bands 3, 4, and 5 relative to pure stands. Therefore, we selected 30 mixed conifer-hardwood forest stands to determine thresholds for the Anderson Level II forest classification. Only those stand maps which corresponded to the same year as our TM data were used. Assessment of the hardwood, conifer, and mixed forest classification precision was performed qualitatively by visually comparing the classified data with independent stands identified on both NHAP and forest stand maps. Correspondence between ground truth information and the three coarse forest classes was very good.

We then classified nonforested areas using the unsupervised classification algorithm ISODATA (ERDAS, 1991). The resulting 50 classes were visually interpreted using 6 June 1988 NHAP and recoded into eight classes (urban-pavement, cleared forest, sparsely stocked forest, flooded forest, shrub-herbaceous, grass-forb, *Sphagnum spp.*, and open water) (Table 2). No further division of the nonforested classes was pursued.

Multi-Temporal Image Classification Overview

The remainder of the forest classification relies predominantly on layered image classification techniques (Figure 2). The 14 June 1987 TM image is the base image for this classification. The greatest difference in image date relative to the base date is roughly 6.6 years (8 October 1980 to 14 June 1987) (Table 1). The greatest absolute difference in image date is approximately 11.6 years (Table 1). The layered classification techniques described in this paper, at most, compare only small portions of data from one MSS date at each decision step to the base TM image (Figure 2). Therefore, no comparisons between dates of greater temporal difference than 6.6 years are made (Figure 2).

Vegetation indices derived from the MSS data and the June TM data are systematically combined utilizing subtraction to highlight and classify specific forest cover types. For example, during early September black ash is the first hardwood type to lose its leaves. The NDVI derived from satellite data gathered shortly after black ash leaf drop exhibits lower index values for black ash than other forest types. Classification of black ash using one date of imagery would be difficult because (1) defoliated black ash stands and nonforested wetlands are spectrally similar and (2) summer black ash stands and other hardwood cover types are spectrally similar. To enhance black ash stands, then, we subtract autumn NDVI image (leaf-off black ash) from a summer NDVI image (leaf-on black ash). High index values (summer leaf-on maple or aspen) minus other high index values (autumn leaf-on maple or aspen) results in a very low to negative difference. On the other hand, a high index value (summer leaf-on black ash) minus a low index value (autumn leaf-off black ash) results in a medium difference. A threshold applied to this difference image classifies black ash.

Forest Classification

DNR and USFS stand maps were used in combination with field observations to verify that senescent forest types observed in the October MSS imagery were indeed northern red oak and northern pin oak (*Q. ellipsoidalis*) (Plates 1a and 1b). Based upon comparisons made with September MSS imagery, the October MSS imagery, and forest stand maps, we determined that the oaks were the only hardwoods still holding their leaves. Because leaf-on and leaf-off stands of trees have very different reflectance values in the near infrared and visible portions of the electromagnetic spectrum (Williams, 1975, Vogelmann and Rock, 1989), a vegetation index was chosen to discriminate oaks from defoliated hardwoods (e.g., sugar maple, aspen, birch, and black ash).

We separated both oak species (red and pin) from other hardwood cover types by first masking all but pure hardwood forest types from the October MSS data using the June TM hardwood, conifer, and mixed forest classification (Figure 2). This method of masking the October MSS data (approx. 6.6 years older than the TM data) assured that most hardwood forest types between the two dates were unchanged in terms of dominant forest species. For example, what were mature oak dominated stands in 1987 most likely were mature oak dominated stands in 1980. Furthermore, clearcut oak stands identified in 1980 would not have regenerated back to oak sufficiently enough to be classified as mature hardwood forest in 1987. Once masking was completed, we applied a threshold to the normalized difference greenness index (NDGI) image derived from the October MSS data to classify oak stands (Figure 2). Here the term "greenness" refers to the use of visible green instead of visible red reflectance: i.e.,

$$\text{NDGI} = [(\text{MSS4} - \text{MSS1}) / (\text{MSS4} + \text{MSS1}) + 1] \times 100 \quad (1)$$

We chose the MSS green band (0.50 to 0.60μm) over the MSS red band (0.60 to 0.70μm) for this vegetation index because the red band of the October MSS data was corrupted by a striping pattern that was not entirely regular. Upon visual inspection, the MSS green band from this date had noticeably fewer problems of this nature. Because green reflectance is strongly correlated to red reflectance (Badhwar and Henderson, 1982; Badhwar *et al.*, 1984; Hall *et al.*, 1991), the infor-

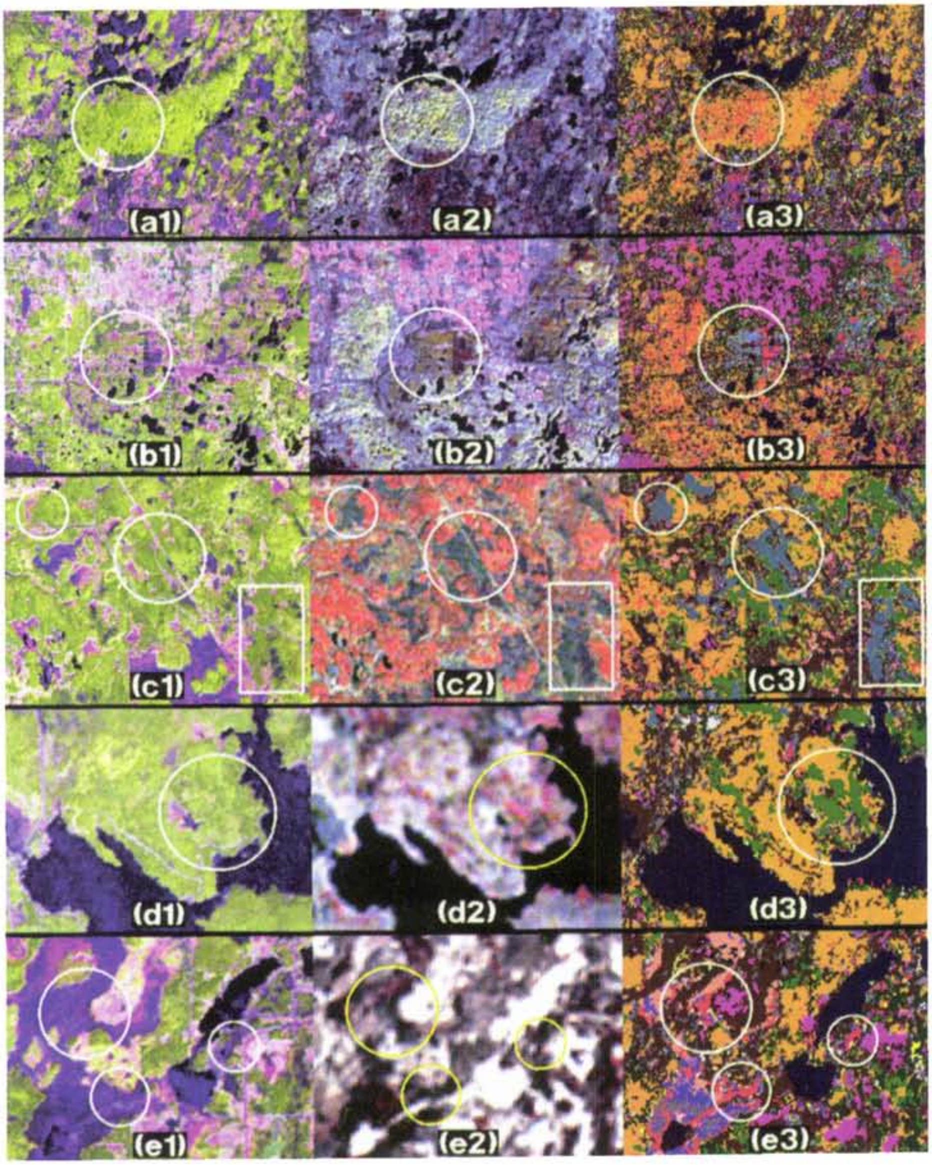

Plate 1. Column (1) are 14 June 1987 TM data (bands 5-4-3), column (2) are MSS data (bands 4-2-1), and column (3) are classified data. Row (a) shows mid-fall (8 October 1980) northern red oak senescence as yellow (a2) and classified N. red oak as dark orange. Red oak stands are visually indistinguishable from surrounding sugar maple dominated northern hardwood stands in the TM data (a1). (Row (b) shows senescent N. pin oak as brownish-yellow (b2) and classified N. pin oak as cyan (b3). Row (c) shows the locations of three black ash stands highlighted by white lines representing summer leaf on black ash (c1), early fall (13 September 1985) leaf-off black ash stands as black (c2), and classified black ash stands colored dark blue (c3). Row (d) shows trembling aspen and sugar maple-dominated northern hardwood stands in summer (d1), mid-spring trembling aspen leaf-flush (10 May 1992) as red (d2), and classified trembling aspen stands in green and northern hardwood stands in yellow (d3). Row (e) shows summer leaf-on tamarack as maroon (e1), winter (2 February 1988) leaf-off tamarack as black (e2), and classified tamarack as dark red (e3).

mation derived from the NDGI was expected to be comparable to the information provided by the NDVI (Equation 3). This intermediate classification was then qualitatively checked against forest stand information which revealed good discrimination between the oak dominated stands and other hardwood stands.

Senescent northern red oak stands (yellow when bands 4, 2, and 1 are displayed in RGB) were clearly distinguishable from northern pin oak stands (brownish yellow) in the October MSS imagery (Plates 1a2 and 1b2, respectively). Separation of the two oak species from each other was accomplished by performing a supervised maximum-likelihood classification on the October MSS data (bands 1, 2, and 4) with 15 training samples for each species (Figure 2). The red oak and pin oak types were then overlaid onto the hardwoods class of the TM classification.

Attempts to classify sugar maple dominated northern hardwoods using autumn leaf color were not successful. Senescence in sugar maple had not progressed sufficiently to be distinguished from other hardwood species in the 12 September 1985 MSS imagery. However, field checking revealed that defoliated regions in the September MSS imagery were black ash stands that had dropped their leaves prior to Landsat overpass (Plate 1c). To separate black ash from remaining hardwood cover types, all non-hardwood types and oaks were masked from the September MSS data (Figure 2). The black ash type was then classified as described above by applying a threshold to a difference image (June TM NDGI minus September MSS NDGI): i.e.,

$$\text{TM NDGI} = [(\text{TM4} - \text{TM2}) / (\text{TM4} + \text{TM2}) + 1] \times 100 \quad (2)$$

Like the October MSS data, the September MSS red band had more sensor noise than did the green band; therefore, the green band was used for the vegetation index. Classified black ash was then overlaid onto the hardwoods class derived from the TM data. The remaining hardwood stands to be classified were sugar maple dominated northern hardwoods, trembling aspen, and mixed aspen.

Observations made in the field at the time of Landsat overpass confirmed that the 10 May 1992 MSS image was highlighting trembling aspen leaf flush (Plate 1d). To separate trembling aspen from other hardwood cover types, all non-hardwood forest types, oaks, and black ash were masked from the May MSS data. Trembling aspen was separated from sugar maple and other hardwood species by applying a threshold to a difference image (May MSS NDVI minus June TM NDVI) (Figure 2). NDVI rather than NDGI was used for the difference image because the red band from the May MSS image did not exhibit serious sensor noise (striping): i.e.,

$$\text{MSS NDVI} = [(\text{MSS4} - \text{MSS2}) / (\text{MSS4} + \text{MSS2}) + 1] \times 100 \quad (3)$$

$$\text{TM NDVI} = [(\text{TM4} - \text{TM3}) / (\text{TM4} + \text{TM3}) + 1] \times 100 \quad (4)$$

The trembling aspen type was then overlaid onto the hardwoods class of the TM classification.

Sugar maple dominated hardwoods and mixed aspen were the only hardwood types left to classify. Thirty training polygons per type were used to train a maximum-likelihood classification of TM bands 2, 3, 4, and 5 (Figure 2). Sugar maple and mixed aspen were then overlaid onto the TM hardwoods class, thus completing the classification of hardwood forest cover types.

Because tamarack is a deciduous conifer, winter NDVI values were expected to be lower than other conifer types. Stand information and field observations confirmed that leaf-off tamarack stands were visible in the February MSS imagery (Plate 1e). Therefore, all but pure conifer stands were masked from the June TM and February MSS data using the TM conifers class as a template. Tamarack was separated from black spruce and other coniferous types by applying a threshold to a difference image (June TM NDVI minus February MSS NDVI) (Figure 2). The tamarack class was then overlaid onto the conifers class of the master TM classification.

By applying image differencing techniques to only pure hardwood and pure conifer stands, remaining mixed conifer-hardwood cover types which contained oaks, black ash, and tamarack in combination with other species were missed. Therefore, image differencing procedures were repeated separately for the mixed hardwood-conifer types (Figure 2). The resulting classified data (jack pine-oak, pin oak-pine, and black ash-lowland conifer) were then overlaid onto the mixed conifer-hardwood class of the master TM classification.

Remaining forest cover types (red pine, jack pine, black spruce, white spruce (*P. glauca*), mixed swamp conifers, white pine (*P. strobus*)-hardwood, balsam fir-aspen, hemlock-yellow birch (*Tsuga canadensis-B. alleghaniensis*), white-cedar-hardwood, and paper birch-conifer) were separated using bands 2, 3, 4, and 5 of the June TM image employing traditional iterative supervised training and classification techniques (Figure 2). Training information was gathered by ground-based sampling and from DNR and USFS stand maps. Fifteen training polygons per remaining class were used in this classification.

Accuracy Assessment

Accuracy assessment of the final classification (Tables 3 and 4) was performed using USFS and DNR stand information. The stand information was preferred as reference information for classification validation because it contains no bias that the investigators might introduce if conducting their own reconnaissance (Bryant *et al.*, 1980). DNR and USFS tabular forest stand information (1985-1988), independent of data used for training, was randomly sampled to decide which forest stands would be used as reference data for the classification accuracy assessment. Queries of the tabular data were made for each forest cover type based on primary type, secondary type, height, basal area, and harvest year. For example, five queries were used to select suitable mixed white pine-hardwood stands. The first query selected all white pine stands with oak as a secondary forest type. Query two added to the first query all white pine stands whose secondary types were either aspen, paper birch, or sugar maple dominated northern hardwoods. Query three selected from the result of queries one and two all stands with basal areas ≥ 16.09 m²/ha. Query four chose from the result of queries one through three stands that were at least 9.15 m in height. Query five ensured that the resulting stands from queries one through four were uncut at the time of sensor overpass (14 June 1987).

Once all potential reference stands were tagged, a random numbers generator was used to select those stands that would be used as reference data. When the use of USFS and DNR forest stand information was inappropriate (e.g., flooded forest, urban or pavement, *Sphagnum*, etc.), sites were randomly selected from interpreted aerial photography (6 June 1988 NHAP) or field checked (Table 2). A minimum of 30 reference sample sites (greater than 2 ha per site) for each classified cover type was selected with the exception of jack pine-oak (26 sites) and paper birch-conifer (26 sites). Individual sites consisted of several pixels of classified data rather than single-pixel samples as recommended by Roller and Visser (1980).

Results and Discussion

The overall classification accuracy was 83.2 percent (KHAT = 82.5) (Table 3) while the accuracy for the forest classes was

TABLE 3. ERROR MATRIX FOR THE OVERALL CLASSIFICATION (ABBREVIATIONS DEFINED IN TABLE 2).

CLASSIFIED DATA	REFERENCE DATA Pr	Pb	Pm	Pg	msc	LI	Fn	Qr	Qe	As	P	Pt	Abp	ss	Psh	Pbo	Qep	Tch	Toh	Fnc	Bpc	up	gf	cf	sh	ff	S	ow	Row Total	User's Accuracy
Pr	64		2	8																									74	86.49
Pb	1	31	3			1										3													39	79.49
Pm	1	2	39	5	9	1												2	5										64	60.94
Pg	2			21																									23	91.30
msc			7		22	2																							31	70.97
LI			2			37																							39	94.87
Fn							43			2		1	2							3									51	84.31
Qr								39	2	2	1	2																	46	84.78
Qe									31																				31	100.00
As								5	1	52	3	2																	63	82.54
P								1			35	1									2								39	89.74
Pt										2		31	3																36	86.11
Abp				4	7				1	1	2	1	41		19		1	4			1								82	50.00
ss						3	1							49						1									54	90.74
Psh															23			2											25	92.00
Pbo		1		1	1								6		2	23	2		1										37	62.16
Qep						1			3				1	4			36												45	80.00
Tch																		33	5										38	86.84
Toh																			22										22	100.00
Fnc					3															33									36	91.67
Bpc										3	2	4								1	31								41	75.61
up																						29	3	1					33	87.88
gf																							80		4				84	95.24
cf																						1	8	34					43	79.07
sh																						1	3		38				42	90.48
ff																						1			1	31			33	93.94
S																											30		30	100.00
ow																												30	30	100.00
Column Total	68	34	53	39	42	45	44	45	38	62	43	42	53	53	44	26	39	41	33	38	34	32	94	35	43	31	30	30	1211	
Producer's Accuracy	94.12	91.18	73.58	53.85	52.38	82.22	97.73	86.67	81.58	83.87	81.40	73.81	77.36	92.45	52.27	88.46	92.31	80.49	66.67	86.84	91.18	90.63	85.11	97.14	88.37	100.00	100.00	100.00		

Overall Accuracy = 83.24 KHAT = 82.55 Diagonal Total = 1008

TABLE 4. ERROR MATRIX FOR FORESTED COVER TYPES (ABBREVIATIONS DEFINED IN TABLE 2).

CLASSIFIED DATA	REFERENCE DATA Pr	Pb	Pm	Pg	msc	LI	Fn	Qr	Qe	As	P	Pt	Abp	Psh	Pbo	Qep	Tch	Toh	Fnc	Bpc	Row Total	User's Accuracy
Pr	64		2	8																	74	86.49
Pb	1	31	3			1									3						39	79.49
Pm	1	2	39	5	9	1											2	5			64	60.94
Pg	2			21																	23	91.30
msc			7		22	2															31	70.97
LI			2			37															39	94.87
Fn							43			2		1	2						3		51	84.31
Qr								39	2	2	1	2									46	84.78
Qe									31												31	100.00
As								5	1	52	3	2									63	82.54
P								1			35	1								2	39	89.74
Pt										2		31	3								36	86.11
Abp				4	7				1	1	2	1	41	19		1	4			1	82	50.00
Psh														23			2				25	92.00
Pbo		1		1	1								6	2	23	2		1			37	62.16
Qep						1			3				1			36					41	80.00
Tch																	33	5			38	86.84
Toh																		22			22	100.00
Fnc					3														33		36	91.67
Bpc										3	2	4							1	31	41	75.61
Column Total	68	34	53	39	42	42	43	45	38	62	43	42	53	44	26	39	41	33	37	34	858	
Producer's Accuracy	94.12	91.18	73.58	53.85	52.38	88.00	100.0	86.67	81.58	83.87	81.40	73.81	77.36	52.27	88.46	92.31	80.49	66.67	86.84	91.18		

Overall Accuracy = 80.1   KHAT = 76.0   Diagonal Total = 687

TABLE 5. ERROR MATRIX FOR ANDERSON LEVEL II FOREST CLASSES.

Classified Data	Reference Data Conifer	Hardwood	Mixed	Row Total	User's accuracy
Conifer	260		10	270	96.3%
Hardwood		256	10	266	96.2%
Mixed	18	17	287	322	89.1%
Col. Total	278	273	307	858	
Producer's Accuracy	93.5%	93.8%	93.5%	Diagonal total = 803	
	Overall accuracy 93.6%		KHAT = 90.4		

80.1 percent (KHAT = 76.0) (Table 4) and, for Anderson Level II forest classes, 93.6 percent (KHAT = 90.4) (Table 5).

The greatest amount of confusion occurred between forest types where only TM data were used for classification (e.g., black spruce, white spruce, mixed swamp conifers, white-cedar-hardwood, balsam fir-aspen, and white pine-hardwood) (Tables 3 and 4). The poor discrimination between the black spruce type (user's accuracy 61 percent and producer's accuracy 74 percent) and the mixed swamp conifer type (user's accuracy 71 percent and producer's accuracy 52 percent) may be because mixed swamp conifer types within this region are made up of predominantly black spruce and balsam fir with associates of white-cedar and tamarack. Beaubien (1979) found black spruce and balsam fir were very similar in terms of MSS spectral reflectance, except when balsam fir grew in older, pure stands. When black spruce and mixed swamp conifer types are combined, the aggregated accuracy becomes 81 percent for both user's and producer's while overall forest cover accuracy increases from 80.1 percent to 83.2 percent (Table 4). Error associated with confusion between lowland conifer classes (i.e., black spruce, tamarack, mixed swamp conifers) and upland conifer classes (i.e., red pine, jack pine, etc.) could be resolved with the incorporation of digital wetlands data (Polzer, 1992) or digital soil information (Bolstad and Lillesand, 1992).

Substantial errors also occurred between the white pine-hardwood type and balsam fir-aspen type (Table 4). Some of the error is due to the fact that image differencing procedures used to classify balsam fir-aspen types were abandoned. This procedure was unsuccessful because the May trembling aspen leaf flush signature was eclipsed by the more dominant balsam fir signature. Therefore, classification of this type was performed using the June TM data alone. Of the 44 sites which indicated white pine-hardwood in the reference data, 21 were misclassified. Nineteen of the 21 omitted sites went to balsam fir-aspen (Table 4). But, of the 53 balsam fir-aspen reference sites, 12 were incorrectly classified though none were omitted as white pine-hardwood mix. Six were omitted as jack pine-oak, one as pin oak-pine, three as trembling aspen, and two as black ash. The misclassification of two black ash stands and three trembling aspen stands into mixed forest categories indicates error with the initial Anderson level II forest classification (Table 5).

Accuracies for forest cover types classified using multitemporal image analysis are highest for non-aspen forest types (Table 4). Trembling aspen stands (36) were classified with 86 percent accuracy (Table 4). But, of the 42 trembling aspen stands selected from the reference information, only 74 percent were correctly classified. Upon checking DNR and USFS tabular stand information, we learned that over 900 aspen stands in the study region were scheduled for harvest between 1987 and 1992 on public lands alone. Initially, we thought the NDGI difference image (May MSS NDGI minus June TM NDGI) used to stratify trembling aspen stands from the remaining hardwood cover types (mixed aspen and sugar maple dominated northern hardwoods) had missed trembling aspen stands harvested after 14 June 1987. Closer inspection of the NDGI difference image and the raw 1992 May MSS imagery revealed that trembling aspen stands harvested between 1987 and 1989 had apparently regenerated sufficiently enough to be classified as trembling aspen by the difference image technique. It was not possible to determine from the May MSS data where trembling aspen harvesting operations within this time period had occurred. Trembling aspen stands cut later (between 1990 and 1992) were progressively more distinguishable in the May 1992 MSS imagery. Obviously, most of the problems associated with harvesting operations would have been avoided if the MSS and TM data were all from the same year. Imagery acquired within a single year would also eliminate any forest successional effects. Hall (1991) found that forest succession within time spans as little as 10 years can be significant from a remote sensing perspective.

In addition to problems associated with harvesting operations, trembling aspen leaf flush apparently had not progressed far enough in the extreme northern portion of the study region to be detected by the MSS sensor and was also missed using the NDGI difference image technique. Ultimately, trembling aspen stands missed using the NDGI difference image approach, because of harvesting operations between 1987 and 1992 or because of delayed phenology, were classified (maximum likelihood) using the 14 June 1987 TM image (bands 2, 3, 4, and 5) into either sugar maple dominated northern hardwoods or mixed aspen stands. This was a relatively safe assumption because oak stands and black ash stands had been stratified prior to the trembling aspen step of the classification (Figure 2).

Using the TM data alone to classify the remaining hardwood stands as well as the problems associated with using the 10 May 1992 MSS data most likely contributed to some of the error reported for trembling aspen, mixed aspen, and sugar maple because these types are notoriously similar in terms of TM spectral and radiometric resolution. Other cover types in which trembling aspen stands were confused (paper birch-conifer, balsam fir-aspen, and one black ash stand) did have a fair amount of trembling aspen within them except for the black ash stand. When the two aspen classes (trembling aspen and mixed aspen) are combined, the aggregated user's and producer's accuracies become 89 percent and 79 percent, respectively.

Higher classification accuracy results were obtained for pin oak (100 percent user's and 82 percent producer's), black ash (84 percent user's and 98 percent producer's), tamarack (95 percent user's and 82 percent producer's), black ash-lowland conifer mix (92 percent user's and 86 percent producer's), red oak (85 percent user's and 87 percent producer's), and pin oak-pine mix (80 percent user's and 92 percent producer's) (Tables 3 and 4). Overall, the results for red oak classification are good, although some problem areas were noticed. Red oak classification precision was lower along the northern tier of the study area due to delayed senescence caused by the temperature buffering effects of Lake Superior. For example, when sugar maple, aspen, and paper birch leaves have fallen farther to the south, as was the case with the October MSS data, oak stands adjacent to Lake Superior remain fully green. At the same time sugar maples, aspens, and paper birch trees adjacent to Lake Superior are just beginning to show signs of fall color. The temperature buffering effects of Lake Superior extend inland roughly 5 to 10 kilometres, forming a gradient of senescence. Within this buffer zone, discrimination between red oak, sugar maple, and aspen types was poorer than the overall classification precision suggests. Although no attempts were made to isolate and quantify these effects on the classification within this buffer zone, theoretically, digital climate date could have been used to address this problem (Host *et al.*, submitted ms., 1994.).

Forest cover types classified using only TM data exhibited mixed precision results (Tables 3 and 4). The user's and producer's accuracy for red pine reached 86 percent and 94 percent, respectively. Some errors of commission occurred between red pine plantations with high basal area (≥ 62 m²/ha) and white spruce plantations of similar density. Both of these forest types are characterized as having very dark understories devoid of ground vegetation. On the other hand, jack pine, sugar maple, hemlock-yellow birch, and paper birch-conifer exhibited only moderate precision with user's and producer's accuracies of 79 percent and 91 percent, 83 percent and 84 percent, 87 percent and 80 percent, and 76 percent and 91 percent, respectively. Furthermore, white spruce (user's accuracy 91 percent and producer's accuracy 54 percent) and white-cedar (user's accuracy 100 percent and producer's accuracy 67 percent) exhibited poor agreement with reference data. Oddly enough, white-cedar did not have any errors of commission with lowland conifer types, although several errors of omission with black spruce and hemlock-yellow birch did occur. The lack of commission errors with lowland conifer types is puzzling because the black spruce and hemlock-yellow birch types within this region often have associates of white-cedar within them and vice versa.

Some of the forest cover types not directly classified using ancillary MSS data most likely improved in classification precision because they were adjacent to forest cover types that were classified using multi-temporal image data. For example, classification of the sugar maple dominated northern hardwood type was simplified because adjacent stands of red oak, pin oak, and trembling aspen were subtracted from the greater hardwoods type, leaving fewer hardwood types with which sugar maple could be confused. Table 2 lists the five forest cover types that benefitted from this indirect multi-temporal image classification method.

It is likely that some of the within-class heterogeneity problems, which have been the bane of many forest classifications in this region using TM data, were reduced by utilizing the spatial resolution of MSS data. The 79-m² radiative input of an MSS pixel sufficiently generalizes spatial and spectral cover type characteristics similar to the way in which a photo-interpreter allows for some degree of within-class heterogeneity when delineating cover-type boundaries. Toll (1985) alluded to the spatial and spectral generalization properties of MSS data when studying sensor parameters responsible for differences in TM and MSS classification accuracies.

Furthermore, other studies suggest that classification accuracies are likely to degrade as a result of improved spatial resolution while other sensor parameters are kept constant (Townsend and Justice, 1981; Toll, 1984; Latty *et al.*, 1985; Martin *et al.*, 1988; Moore and Bauer, 1990). Because it was only necessary in most instances to detect leaf-on versus leaf-off vegetation status using the MSS data, it is doubtful that the added spectral and radiometric resolution of TM data would have improved precision of multi-temporal image classifications. One obvious advantage of using multi-temporal TM over MSS data would be the potential for more accurate image coregistration. However, we question whether repeating the procedures using exclusively TM data would have increased classification precision enough to justify the greater cost over MSS data. Unfortunately, the MSS sensor was turned off on 19 October 1992, ending its life as both an effective and affordable resource assessment tool.

Conclusions and Suggestions for Future Research

Distinguishing among deciduous forest types in the Great Lakes region, especially the so-called sugar maple dominated northern hardwoods, has been very difficult using single-date image classifications. Using a layered, multi-temporal image classification approach, we were able to separate two oak species — black ash and tamarack — and, most importantly, separate aspen types from sugar maple-dominated northern hardwoods. It is apparent that a layered multi-temporal approach to the classification of Landsat data, combined with a specific knowledge of cover-type phenology, is not only possible but is preferable to single-date classifications or to multi-date classifications where only a broad knowledge of forest phenology is incorporated into image acquisition. Using a layered multi-temporal image classification approach, a species level forest classification was achieved with an accuracy of 80.1 percent (KHAT = 76.0). Accuracy for forest classes aggregated to Anderson Level II (hardwood, conifer, and mixed) was 93.6 percent (KHAT = 90.4). Overall classification accuracy was 83.2 percent (KHAT = 82.5).

By incorporating specific knowledge of forest species phenology, it is possible to

- Develop a forest classification with dominant tree species level precision within northern Lake States conditions,
- Use MSS digital data to capture specific phenology of forest cover types,
- Successfully incorporate multi-temporal MSS and TM data for detailed forest classifications, and
- Use a layered classification approach exploiting image ratioing and ratio differencing techniques for multi-temporal image analysis.

There clearly are advantages to this layered, multi-temporal classification method where phenological changes occur across large regions. In many instances, spectral variability within a single forest type over large regions is great due to the effects of atmosphere, soil, climate, and aspect. To gather enough training statistics to adequately account for these types of variability is a difficult task. By using multi-temporal image ratioing and ratio differencing techniques, many of these effects are normalized, and comparatively few training statistics are necessary.

Although the classification techniques presented in this paper generally worked well, there is potential for improvement and refinement. First, images from the same year or a short span of years will work better when using the forest phenology approach for forest cover-type classification. Contemporaneous imagery will minimize or eliminate problems associated with forest harvesting operations and errors associated with forest succession. Second, incorporation of digital National Wetlands Inventory information or digital soils information (soil series) would help resolve errors between upland and lowland forest classes. These types of ancillary data, though not available to date, will be available for this region in the near future. Third, variations in forest phenology within large regions remain somewhat problematic. Theoretically, large scale (full TM scene) forest classifications employing digital climate data could be used to stratify these effects. Finally, the use of the more expensive TM data in place of MSS data could provide some improvement in classification results due to the potential for refinements in image coregistration accuracy. However, besides registration improvements, previous studies show that the 30-m spatial resolution of TM data is responsible for only slight increases in classification accuracy between MSS and TM data. Therefore, from an economic standpoint, using multi-temporal TM data rather than MSS data (using the same methods) may not produce results that justify the added cost.

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SAGEEP '96 Call for Papers

Keystone Resort, Colorado
April 28 - May 1, 1996

The ninth Annual Symposium on the Application of Geophysics to Engineering and Environmental Problems (SAGEEP), sponsored by the Environmental and Engineering Geophysical Society (EEGS), will be held at Keystone Resort, Colorado, 28 April - 1 May, 1996. SAGEEP is dedicated to sharing new applications of geophysics with those working in the geotechical, hydrogeological, environmental, and regulatory as well as the geophysical professions.

Leading off on Sunday, 28 April, will be a short course on Environmental Geophysics and Groundwater Modeling. Planned sessions on Monday-Wednesday, 29 April -1 May include:

Applications:

Evaluation of Exhisting Structures
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Location of Buried Objects
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Contaminant Detection

Technology Advancements:

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Legal/Professional Issues:

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Abstracts should be directed to Program Chairman: Linda Hadley, SAGEEP '96, Geophysical 2221 East Street, Golden CO 80401; phone/fax: 303-278-1488.