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Phenological differences in Tasseled Cap indices improve deciduous forest classification

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Abstract

Remote sensing needs to clarify the strengths of different methods so they can be consistently applied in forest management and ecology. Both the use of phenological information in satellite imagery and the use of vegetation indices have independently improved classifications of north temperate forests. Combining these sources of information in change detection has been effective for land cover classifications at the continental scale based on Advanced Very High Resolution Radiometer (AVHRR) imagery. Our objective is to test if using vegetation indices and change analysis of multiseasonal imagery can also improve the classification accuracy of deciduous forests at the landscape scale. We used Landsat Thematic Mapper (TM) scenes that corresponded to *Populus* spp. leaf-on and *Quercus* spp. leaf-off (May), peak summer (August), *Acer* spp. peak color (September), *Acer* spp. and *Populus* spp. leaf-off (October). Input data files derived from the imagery were: (1) TM Bands 3, 4, and 5 from all dates; (2) Normalized Difference Vegetation Index (NDVI) from all dates; (3) Tasseled Cap brightness, greenness, and wetness (BGW) from all dates; (4) difference in TM Bands 3, 4, and 5 from one date to the next; (5) difference in NDVI from one date to the next; and (6) difference in BGW from one date to the next. The overall kappa statistics (KHAT) for the aforementioned classifications of deciduous genera were 0.48, 0.36, 0.33, 0.38, 0.26, 0.43, respectively. The highest accuracies occurred from TM Bands 3, 4, and 5 (61.0% for deciduous genera, 67.8% for all classes) or from the difference in BGW (61.0% for deciduous genera, 67.8% for all classes). However, the difference in Tasseled Cap classification more accurately separated deciduous shrubs and harvested stands from closed canopy forest. Our results indicate that phenological change of forest is most accurately captured by combining image differencing and Tasseled Cap indices.

1. Introduction

For forestry applications, maps that distinguish tree species are highly desirable. Satellite imagery can be a relatively inexpensive way to produce these maps over large areas. However, while deciduous or coniferous forests can commonly be distinguished with ~90% accuracy (Horler & Ahern, 1986), classifications of deciduous species are not very accurate. Accuracy is limited for broad-leaved deciduous species because of their spectral similarity (Jensen, 2000; Schriever & Congalton, 1995). This technical limitation is one of the reasons why satellite data are rarely used in forest management. Developing new methods to improve satellite classification accuracy is necessary.

One approach to improve forest classifications is the use of multiseasonal data (Jensen, 2000). Leaf-flush or senescence is phenological change that can be captured by satellite images. Species can be distinguished when they are in different phenological stages in the same image, or when they change differently from one image to the next. Several studies utilized multiseasonal imagery for forest classifications. A classification of *Pinus*, *Tsuga*, *Quercus*, *Fagus*, and *Acer* forest types in the Northeastern US showed that the accuracy of different classes varied depending on the phenological period of the imagery (Schriever & Congalton, 1995). That study used a combination of raw Thematic Mapper (TM) bands and principal components analysis for the 10.5-km^2 area. A much larger area (28,000 km^2) in the northern hardwood forests of Northern Wisconsin, USA was classified into 23 forest types (Wolter, Mladenoff, Host, & Crow, 1995). That study used a combined raw Multispectral Scanner (MSS) and TM bands, plus the change in Normalized Difference Vegetation Index (NDVI) from four different

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phenological periods. A 24-km^2 forest area, including *Quercus*, *Acer*, *Fraxinus*, *Fagus*, *Pinus*, *Tsuga*, and *Picea* species, was accurately classified at the genus level using all nonthermal TM bands from three different seasons (Mickelson, Civco, & Silander, 1998). However, it is difficult to compare the accuracy of these different methods since the studies were completed in different areas and with different types of phenological data. Furthermore, these studies did not fully explore the potential advantages of vegetation indices.

The most common vegetation index in forest classification and land cover change studies is NDVI. It reportedly improves vegetation classifications by partially compensating for variation in illumination due to terrain (Lillesand & Kiefer, 1994), and is well correlated to vegetation biomass (Tucker, 1979). NDVI uses two bands of light, red and near-infrared. The Tasseled Cap transformation incorporates more information into vegetation indices by using six different bands of light (Crist & Cicone, 1984). The resulting brightness, greenness, and wetness (BGW) indices, so named for the features in the data that they emphasize, improve vegetation classifications because they are sensitive to phenological changes. Therefore, the indices can be used to distinguish green vegetation with soil from green vegetation with brown vegetation (Crist, Laurin, & Cicone, 1986). In addition, the wetness band correlates with shadows and forest stand density. These correlations improve the separation of fields from forest, and between forest classes (Crist et al., 1986).

The combination of vegetation indices with multiseasonal imagery that captures phenology has produced successful vegetation classifications of continents (at 1- to 25-km resolution) using Advanced Very High Resolution Radiometer (AVHRR) imagery (Sader, Stone, & Joyce, 1990). The differences between the vegetation types are usually emphasized by calculating NDVI. AVHRR studies take advantage of daily return intervals that permit acquiring cloud-free images of phenological change (Tucker, Towshend, & Goff, 1985). The frequent return intervals also allow studies to use statistical change analyses, such as a seasonality curve, which assume continuous data sets (Mora & Iverson, 1997; Stone, Schlesinger, Houghton, & Woodwell, 1994).

The success of combining phenological change analysis and vegetation indices at continental scales indicates this combination may also improve landscape-scale classifications. TM imagery, at 30-m resolution, has become the standard for landscape studies. This spatial resolution is necessary for forestry applications since the average size of forest management stands in temperate forests is 1–100 ha. In addition to this spatial information, TM also has spectral advantages over AVHRR data by capturing mid-infrared vegetation response (Jensen, 2000). The drawback to using TM data for a phenological study is that images of a point are only taken every 16 days. Since this makes it more difficult to find cloud-free images that correspond to phenological events, studies usually contain multiyear imagery and analyses that do not assume continuous change.

This paper compares the effectiveness of image differencing and vegetation indices to improve northern hardwood forest classifications. Specifically, we compared the classification accuracies from TM Bands 3, 4, and 5, NDVI, Tasseled Cap as multiseasonal composite images, and the difference in these values from one season to the next. These input data sets were derived from four phenologically significant TM scenes in Northern Wisconsin, USA.

2. Methods

2.1. Study area

The study area in Northern Wisconsin includes two ecoregions: the outwash plain (632,384 ha) and the loess plain (881,245 ha) (Albert, 1995) (Fig. 1). These ecoregions have different surficial geology types and therefore different species compositions. We used the outwash plain to identify the optimal input data set. Then we used the loess plain to validate that the best method in one area could be consistently transferred to a different area.

The climate of Northern Wisconsin is continental with mean monthly temperatures ranging from -12.2 °C in January to 18.6 °C in July. Annual precipitation averages 850 mm with 60% falling between May and September

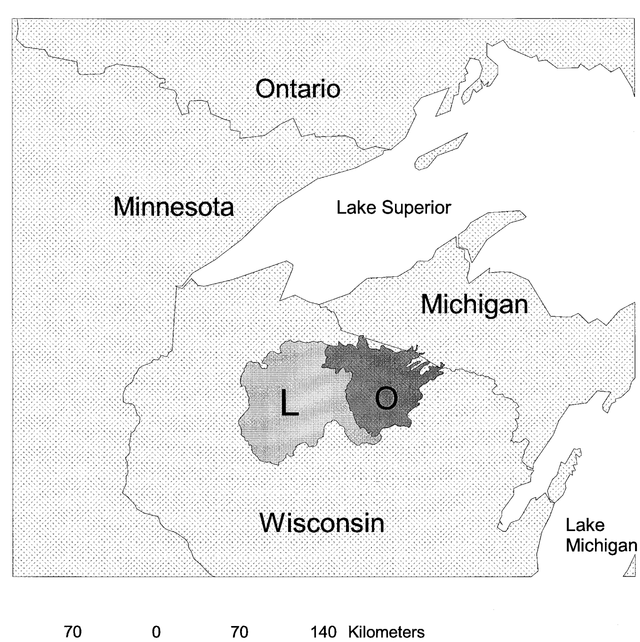

Fig. 1. Outwash plain (O) and loess plain (L) ecoregions in North Wisconsin, USA.

(Lac Vieux Desert Weather Station, National Climatic Data Center, Asheville, NC, 1993). There is north–south variation in temperature and precipitation due to latitude and the presence of Lake Superior, there is additional east–west variation due to Lake Michigan. This local climate variability creates differences in phenology that are visible within a single image, but are generally consistent within an ecoregion.

The glacial outwash plain topography has very little relief, with many kettle lakes, ponds, and peatlands (Albert, 1995). The upland soils are loamy sands, resulting in well-drained conditions. The loess plain also has very little relief, but lakes are less common. The soils are acidic silt loams that are often poorly drained.

The forests of Northern Wisconsin are dominated on uplands by sugar maple (*Acer saccharum* Marsh), aspen (*Populus tremuloides* Michaux or *Populus grandidentata* Michaux), yellow birch (*Betula alleghaniensis* Britton), and red pine (*Pinus resinosa* Aiton) (Curtis, 1959). Less common are oaks (*Quercus rubra* L., *Quercus macrocarpa* Michaux, *Quercus coccinea* Muenchh.), jack pine (*Pinus banksiana* Lamb.), hemlock [*Tsuga canadensis* L. (Carr.)], paper birch (*Betula papyrifera* Marsh.), and white spruce [*Picea glauca* (Moench) A. Voss]. The lowlands are dominated by tamarack (*Larix laricina* DuRoi), white cedar (*Thuja occidentalis* L.), red maple (*Acer rubrum* L.), black ash (*Fraxinus nigra* Marshall), and black spruce [*Picea mariana* (Miller) BSP.]. Mixed stands containing several of these species are common. The differences in species composition between the outwash plain and loess plain ecoregions are largely due to the soil drainage. There is a greater dominance of aspen in pure and mixed deciduous hardwood stands in the outwash plain. In the loess plain, sugar maple is the more dominant species. Furthermore, jack pine, which grows well on sandy outwash sites, is rarely found on the more clay-based loess soils.

All forests in this region are second or third growth after being clear-cut in the late 19th or early 20th century. Current forest management varies widely among landowners. Small private landowners often do not manage their holdings for timber harvest. Public forests (county, state, and federal) employ both clear-cutting (e.g., in aspen and pine stands) and selective cutting (e.g., in northern hardwood stands).

2.2. Class definitions

The classification scheme was a modification of a scheme previously developed for the Gap Analysis program in Wisconsin (WISCLAND; Lillesand et al., 1998). The forest classes are based on percent dominance of the canopy (Table 1). When species within a genus were indistinguishable with TM data, the genus applied (e.g., the aspen class has >80% canopy cover by *Populus* spp.).

2.3. Field observations

Ground truth data for the above classes were collected in the early to mid-1990s as part of the WISCLAND portion of the GAP Analysis program (Lillesand et al., 1998). Selection of ground truth sites was based on a random sample. Within the randomly selected areas, polygons representative of homogenous cover types were delineated on aerial photographs (National Air Photo Program at 1:40,000 scale) and satellite imagery. The polygons were required to be a minimum of 2 ha in size, along roads, and include a representative range of the spectral variability present in the area. For upland sites, the land cover was visually interpreted. This included identifying the percent composition of up to four canopy tree species, whether the forested stand was mature or not, and the presence or absence of understory shrubs and

Table 1
Class definitions based on percent canopy composition

Class (capitals are used to distinguish classes from species)	Definition
Jack pine	> 80% jack pine
Red pine	>80% red pine
Mixed Conifer upland or lowland	>66% conifers, < 80% jack pine or red pine
Oak	>80% oak species
Aspen	>80% aspen species
Sugar maple	>80% sugar maple
Mixed Deciduous upland or lowland	>66% deciduous, < 80% oak, aspen, or sugar maple
Deciduous–Coniferous upland or lowland	< 66% deciduous or coniferous, but still forest
Deciduous Shrubs	deciduous woody vegetation < 6.1 m tall, tree cover < 10%
Coniferous Shrubs	coniferous woody vegetation < 6.1 m tall, tree cover < 10%
Wet meadows	herbaceous plants standing above wet soil
Clearings	nonwoody vegetation, soil not saturated, includes agricultural fields, grassland, golf courses, landing strips, and small roads
Clearcuts (loess ecoregion only)	clearcut areas with regeneration generally less than 3 m tall and not a closed canopy
Urban	buildings and large roads
Water	lakes, ponds, and rivers

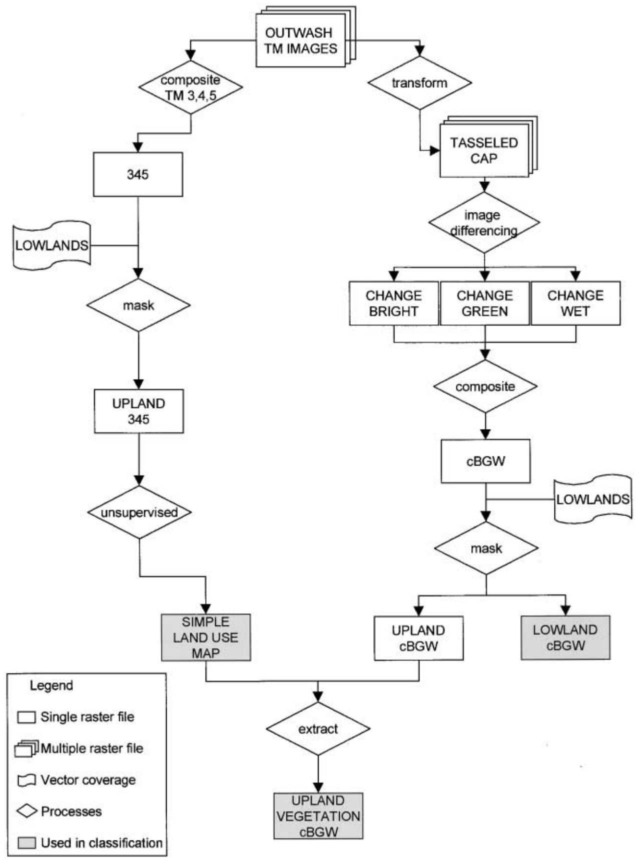

Fig. 2. Index calculation, image differencing, and upland–lowland stratification using cBGW for the outwash plain as an example.

trees. For shrublands, this interpretation distinguished deciduous from coniferous or ericaceous species.

Field work verified the cover types in each polygon. For lowland sites, ground truth polygons were assigned to classes using the Wisconsin Wetland Inventory. This inventory relied on visual interpretation of air photos. The 1055 ground truth sites for the outwash plain, and 1664 for the loess plain were assigned to classes based on their vegetation, then equally divided into training and testing data sets. For more information on ground truth collection, see Lillesand et al. (1998).

The ground truth polygons identified from air photos often included mixed pixels or edge pixels. Some of the mixed pixels may have been a consequence of rectification errors. Spectrally similar pixels within each ground truth polygon were identified using a region-growing algorithm and the TM Bands 3, 4, and 5 from all dates (ERDAS, 1997; Mickelson et al., 1998). In this procedure, a seed pixel near the center of the polygon was selected. The algorithm included neighboring pixels in the region when they fell within an operator-specified range of digital numbers (DN). In this study, the range was 15–20 DN for most classes and 20–25 DN for mixed classes. The area overlapping the region and the original polygon was used for signature generation.

2.4. Image acquisition and preprocessing

Four TM scenes, with less than 5% cloud cover and average wind speeds less than 16 km/h at the time of data capture, were acquired to correspond with phenological events as described previously for Northern Wisconsin (Wolter et al., 1995). May 19, 1992-captured aspen leaf-flush before most other trees. In general, aspens leaf-flush 1 week before other associated hardwoods. In the August 10, 1993 image, all species were in peak summer leaf-out. September 24, 1992 was selected to capture maple trees in peak color, which usually happens in this area around September 21. Oaks reach peak color about 2 weeks later. Aspen and maple trees had lost their leaves by the time the October 8, 1991 image was taken. Oaks lose their leaves later in the season; therefore, they were in leaf-off condition only in the May image.

The August image was geometrically corrected to a UTM grid using the TIGER road and stream line files from the 1990 Census. The other images were registered to the August image. All RMS errors were below half a pixel. Atmospheric correction was not applied because the classification relies on the relative change, not the absolute change. Atmospheric correction performs a linear transformation of the image feature space (Mather, 1987; Schowengerdt, 1983). However, a linear transformation does not affect the relative change of DN, and therefore the subsequent classification.

2.5. Image processing for each ecoregion

To test the effectiveness of vegetation indices to improve forest classifications, we computed NDVI and Tasseled Cap BGW using the TM image for each phenological period (Jensen, 2000) (Fig. 2). NDVI combines the red and near-infrared bands, whereas Tasseled Cap combines the six nonthermal TM bands. The Tasseled Cap coefficients were the default values for Landsat 5 as set in

Table 2
Description of input data files to compare the effectiveness of vegetation indices and image differencing change detection at classifying northern hardwood forests

Name of input	Description of input to classifications
345	12 TM bands from four dates
NDVI	4 NDVI layers, one from each date
BGW	12 Tasseled Cap layers from four dates
c345[a]	12 difference layers, where each TM 3, 4, or 5 band for a date was subtracted from the seasonally previous date
cNDVI	4 difference layers, where each NDVI layer for a date was subtracted from the seasonally previous date
cBGW	12 difference layers, where each Tasseled Cap index layer for a date was subtracted from the seasonally previous date

[a] The letter "c" denotes a change detection algorithm used in image processing.

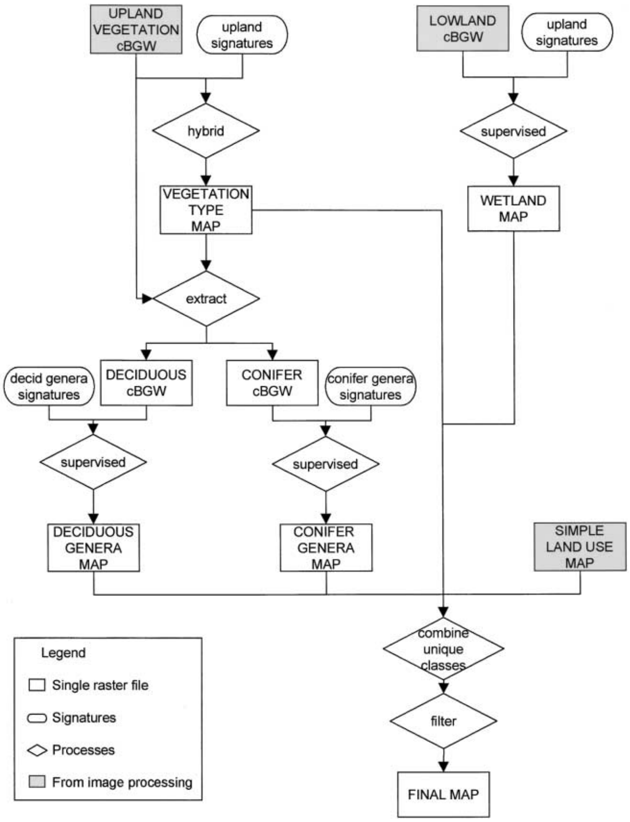

Fig. 3. Hierarchical classification steps using cBGW for the outwash plain as an example.

Imagine 8.2 (ERDAS, 1997). To test the effectiveness of image differencing change detection, we computed the change in TM Bands 3, 4, and 5 and each of the four indices by subtracting the values from one phenological period to the next. For example, May brightness was subtracted from August brightness, August brightness was subtracted from September brightness, September brightness was subtracted from October brightness, and October brightness was subtracted from May brightness. This image differencing technique is simple and effective, plus has been shown to be the most effective method in extracting variability due to defoliation (Muchoney & Haack, 1994). The difference layers were rescaled from floating point to 8-bit using a two standard deviation stretch, and combined into a single file with many data layers. The result of this image processing was six data files (Table 2).

The ecoregions were subdivided into lowlands and uplands using the Wisconsin Wetland Inventory, as processed by Lillesand et al. (1998). This step reduced the number of categories in each classification, and reduced variation within each class (e.g., upland and lowland deciduous species were separated into different classes). This reduction of variation also reduces opportunities for error (Stewart, 1994).

An unsupervised classification of the upland 345 input data produced simple land use classes. Ground data and visual inspection helped identify these classes. Areas classed as shrubs, clearings, grassland, grain, corn, clearcuts, urban areas, roads, and edges where images did not fully overlap were eliminated from any further classification because the goal of this project was separation of forest classes.

2.6. Signature generation for each input data set and each ecoregion

A number of unsupervised classifications (ISODATA algorithm; ERDAS, 1997) were run on the pixels corresponding to the training sites for each class. The resulting signatures were examined, similar signatures were merged, and extremely different signatures or those with few contributing pixels (<15) were eliminated. Each class had a number of signatures, but each signature had low variance. This helped reduce signature overlap between classes. All of

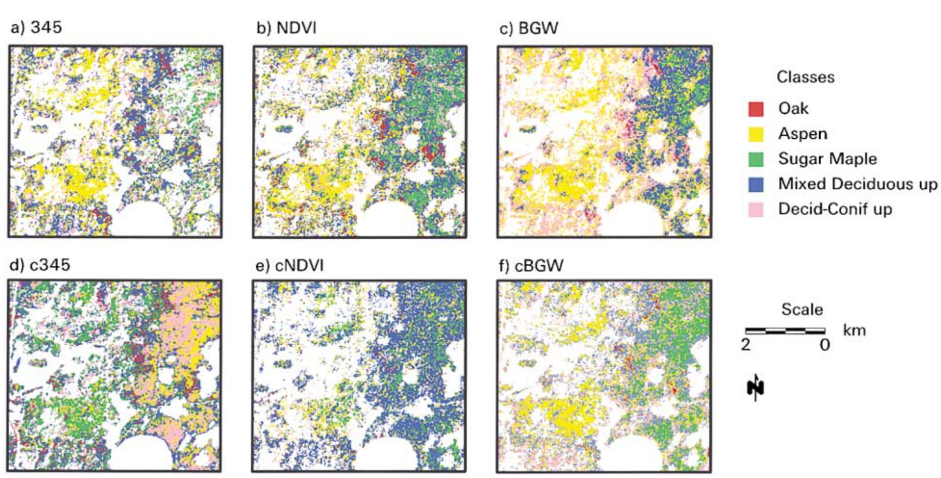

Fig. 4. A small section of the Deciduous genera maps using (a) 345, (b) NDVI, (c) BGW, (d) c345, (e) cNDVI, and (f) cBGW.

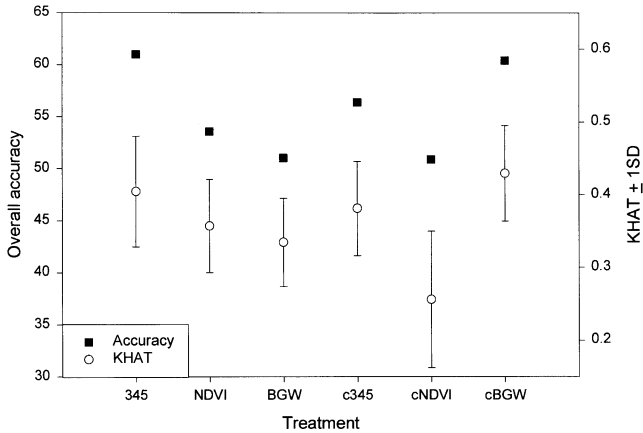

Fig. 5. The accuracy assessments for the deciduous genera classifications for the outwash plain.

the appropriate signatures were used in the classification process, the result was then recoded into fewer classes before completing postclassification processing.

2.7. Hierarchical classifications

2.7.1. Uplands

The most general level for the uplands was a vegetation-type classification (Fig. 3). The upland signatures were used as seeds to generate clusters in an unsupervised classification. The result of this hybrid classification (ERDAS, 1997), was recoded using the original signature classes, into deciduous, deciduous–coniferous, and either grain or corn depending on the ecoregion. This procedure was repeated for each of the six input data files (Table 2). The hybrid classification method is reported here because the accuracies were higher than using a maximum likelihood supervised classifier.

For the genera level classification, the area corresponding to a vegetation type classified in the previous step was extracted from the input data file. These extracted data were input to a maximum likelihood supervised classification with only the signatures of the general that composed the vegetation type. For example, in the outwash ecoregion, we classified the deciduous and deciduous–coniferous area into aspen class, sugar maple class, oak class, mixed deciduous, and deciduous–coniferous. This procedure was repeated for deciduous, deciduous–coniferous, and coniferous areas in each of the six input data files (Table 2).

2.7.2. Lowlands

The outwash plain contained many lowland areas that were delineated by the wetland inventory. This allowed us to derive an accurate classification using wetland-type signatures. The loess plain had enough upland forest and clearings in the wetland inventory to generate signatures, so the classification required three steps, similar to the upland areas. The first step was a general vegetation type, then the upland forested areas were classed to genera, and the wetlands and lowland forests were classed into more detailed categories.

2.8. Postclassification processing

The classifications were combined into a single ecoregion map, while retaining as much detail as possible. Therefore, all of the areas classified at the genera level were

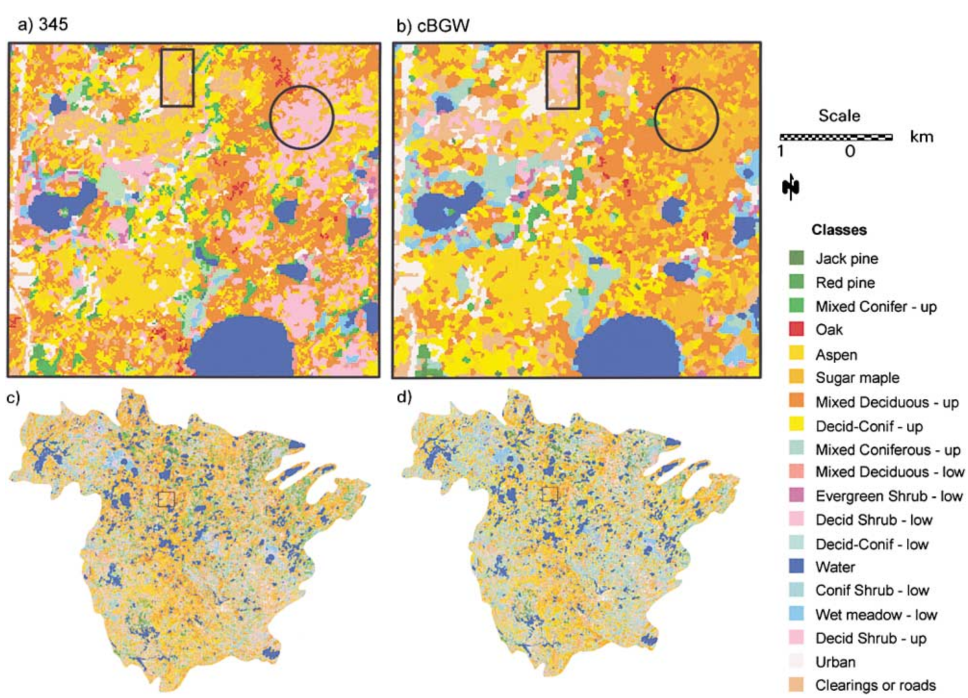

Fig. 6. The completed outwash plain classification using 345 where (a) is a small section of (c) or using cBGW where (b) is a small section of (d).

included, plus all of the areas in the wetland classification. Only areas, such as clearings or urban, which were not classified in detail were included from the general vegetation map, and the land cover map. The classifications were filtered to remove patches smaller than 4 pixels (3600 m^2) and replace them with the surrounding land type to eliminate patches smaller than the resolution of the ground truth sites. The complete outwash and loess classifications were also combined into a regional map.

Accuracy assessments were conducted for each classification step, and for the combined map after the filter was applied. Assessments compared the known class of a test site with the majority class of a 3×3-pixel neighborhood around the center point of that test polygon. Only the center points of each polygon were used to reduce errors due to the spatial autocorrelation inherent in raster land cover data (Cliff & Ord, 1975). Assessments were calculated as percent accuracies and compared using estimates of the kappa statistic (KHAT) (Congalton & Green, 1999). KHAT uses the entire error matrix to produce a measure of accuracy that takes into account agreements expected by chance. This statistic, and its variance, can be used in a standard statistical Z test to compare the accuracies of different classifications (Congalton & Green, 1999).

2.9. Comparisons with other Wisconsin data

Additional data were used to assess how harvested stands were being classified. These data came from a forest management map of the American Legion and Northern Highlands State Forest. Stands that were clearcut between 1981 and 1992 were rasterized. We then calculated the percent area assigned into each class from the different input data sets.

Comparisons were also made with two other multiseasonal classifications completed in Wisconsin. WISCLAND classified the principal components of TM Bands 3, 4, and 5 from two image dates (Lillesand et al., 1998). The outwash ecoregion was extracted from the WISCLAND classification

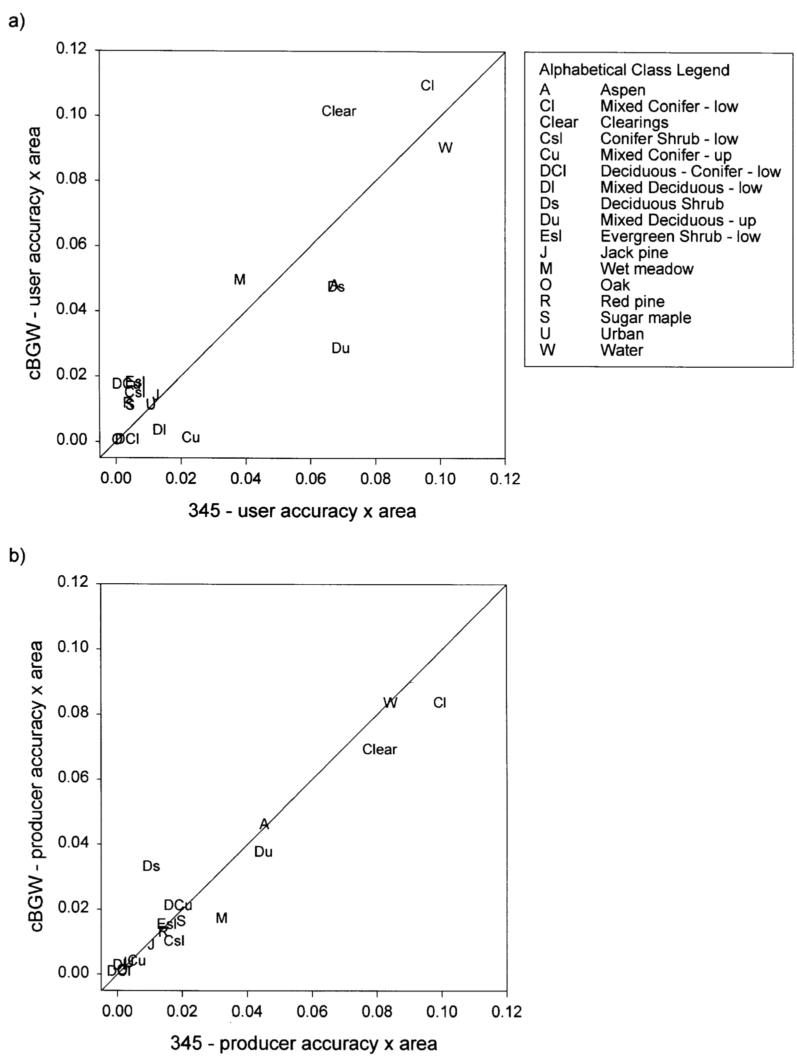

Fig. 7. A comparison of the 345 and cBGW complete classifications. (a) The user's percent accuracy multiplied by the percent area for each class. (b) The producer's percent accuracy multiplied by the percent area for each class. The diagonal is a 1:1 relationship.

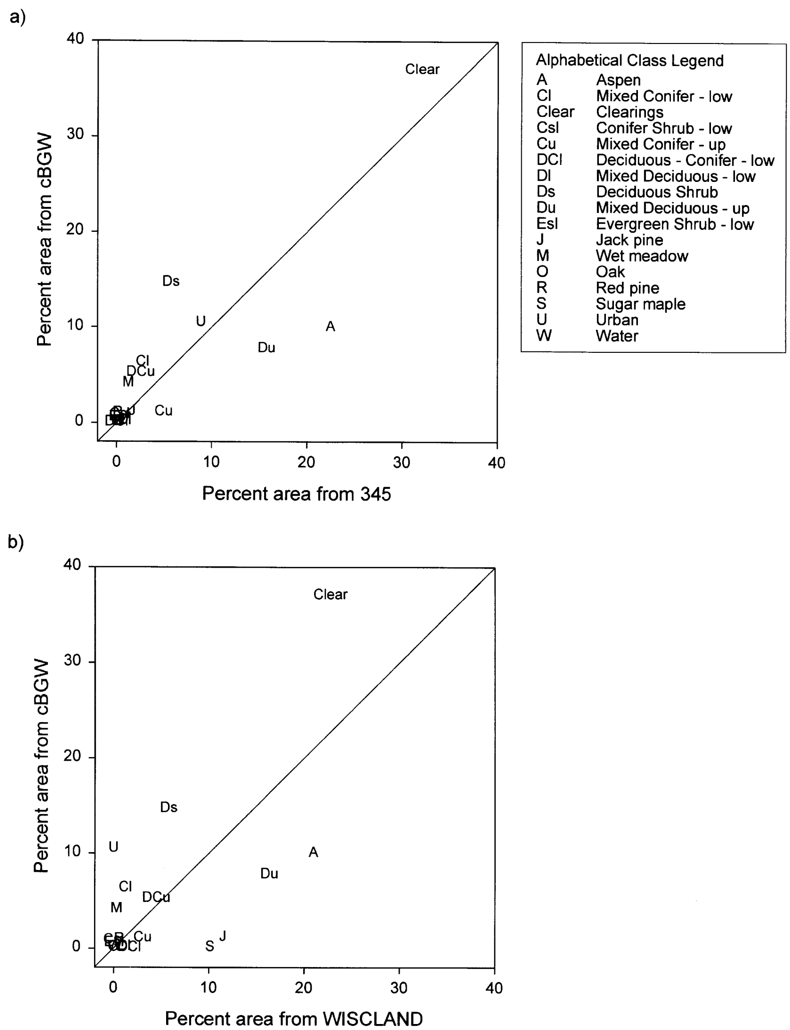

Fig. 8. A comparison of raw spectral and cBGW classification of < 10-year-old harvested stands. (a) Percent of harvested stand area in 345 or cBGW. (b) Percent of harvested stand area in WISCLAND or cBGW. Diagonal is a 1:1 relationship.

and we calculated the overall accuracy and the assignment of harvested stands to compare how the addition of two more dates and the calculation of the change in Tasseled Cap affected the classification. Since the same ground truth data were used in WISCLAND as in this study, only input data files should affect the results. Wolter et al. (1995) classified TM Bands 3, 4, and 5 and the change in MSS NDVI from five image dates creating forest species map with 30-m resolution. This classification overlapped with 67.8% of the loess plain ecoregion. This overlapping area was extracted from the Wolter classification and the categories simplified to match our ground truth data. An accuracy assessment of this area was used to compare how the higher spatial resolution and the calculation of cBGW affected the results.

3. Results

The deciduous genera classification varied considerably depending on the input data (Fig. 4). A small cutout from the outwash ecoregion illustrates the variability in classifications. The overall accuracy was highest for the 345 input data (60.9%) and the cBGW input data (60.4%) (Fig. 5). The lowest accuracy classification used cNDVI (50.9%). The cBGW was statistically more accurate than cNDVI ($Z_{\mathrm{cBGW,cNDVI}} = 1.88$, $\alpha = .05$). Examination of the classifications and the accuracies made it clear that 345 and cBGW were the most viable methods. The following results focus on comparing these two methods.

The complete classifications with 19 classes were similar whether 345 or cBGW was the input data (Fig. 6). The

Table 3
Three different classification results for areas harvested within 10 years of the imagery dates

Classes assigned to harvested areas	345	cBGW	WISCLAND
Closed canopy forest classes	51.5	32.5	71.0
Open classes	48.5	67.5	28.9
Water	0.03	0.06	0.1

Values are percent area for the population.

Table 4
Confusion matrix for the cBGW classification of the outwash plain ecoregion

Data	J pine	R pine	Mix Conif up	Oak	Aspen	Sugar maple	Mix Decid up	Dec–Con up	Mix Conif low	Mix Decid low	Everg shb	Dec–Con low	Water	Con shb low	Wet mead	Dec shrub	Urban	Clearings	Total	User's accuracy
Jack pine	**10**	**3**	2	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	16	62.5%
Red pine	**1**	**35**	3	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	40	87.5%
Mix Conif up	0	2	1	0	1	0	0	1	0	0	0	0	0	0	0	1	0	0	6	16.7%
Oak	0	0	0	1	1	0	1	0	0	0	0	0	0	0	0	0	0	0	3	33.3%
Aspen	0	0	2	1	**39**	**0**	**14**	1	0	0	0	0	0	0	0	2	1	0	60	65%
Sugar maple	0	0	0	0	**1**	**19**	5	0	0	0	0	0	0	0	0	0	0	0	25	76%
Mix Decid up	0	0	0	2	**12**	6	**24**	2	0	0	0	0	0	0	0	0	1	1	48	50%
Dec–Con up	0	0	1	2	**4**	0	7	3	0	2	0	1	0	0	0	0	0	0	20	15%
Mix Conif low	2	3	5	0	0	0	0	2	70	0	4	1	1	2	1	2	1	0	94	74.5%
Mix Decid low	0	0	0	0	0	0	1	0	0	1	0	0	0	0	0	0	0	0	2	50%
Everg shrub low	0	0	0	0	0	0	0	0	0	0	10	2	0	0	0	0	0	0	12	83.3%
Dec–Con low	0	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	3	100%
Water	0	0	0	0	0	0	0	0	0	0	0	0	23	0	0	0	0	0	23	100%
Con shrub low	0	0	0	0	0	0	0	0	1	0	0	0	0	4	1	1	0	0	7	57.1%
Wet meadow	0	0	0	0	0	0	0	0	3	0	0	0	0	0	14	1	0	1	19	73.7%
Dec shrub	0	0	0	0	1	0	0	0	3	0	1	0	0	0	2	23	0	2	32	71.9%
Urban	0	0	0	0	3	0	0	0	0	0	0	0	0	0	0	0	4	13	20	20%
Clearings	1	1	0	0	3	1	2	1	0	0	0	0	0	0	1	5	2	81	98	82.6%
Total	14	44	14	6	65	26	55	10	77	3	15	8	24	6	19	35	9	98	528	
Producer's accuracy	71.4%	79.5%	7.14%	17%	60%	73.1%	43.6%	30%	90.1%	33.3%	66.7%	37.5%	95.8%	66.7%	73.7%	65.7%	44.4%	82.7%		

Numbers in bold are discussed in the Results.

overall accuracies were 67.8% and 69.13%, respectively, and were not statistically different (KHAT for 345 was 0.643, for cBGW was 0.656). However, the user's accuracy multiplied by percent area showed higher accuracy for cBGW clearings (Fig. 7a). This difference occurred because the cBGW clearing had less confusion with the urban areas than the 345 clearings. The higher accuracy of 345 mixed deciduous upland occurred because mixed deciduous was confused with mixed deciduous–coniferous in the cBGW (Fig. 7a). The mixed deciduous was confused with the aspen class using either cBGW or 345.

One of the biologically important differences between the maps was the overclassification of deciduous shrub from 345. In the circled areas, it is apparent that the purple deciduous shrub in the 345 classification was mixed deciduous in the cBGW classification (Fig. 6a and b). The producer's accuracy multiplied by the percent area showed the deciduous shrub class in 345 was less accurate than in cBGW (Fig. 7b). We also found overclassification of deciduous shrubs in the Wolter et al. (1995) classification where the user's accuracy was 18.8%. Areas originally classified as alder, willow, ericaceous, or miscellaneous brush were identified in the reference data as conifer (20%), aspen (12%), sugar maple (6%), mixed deciduous (12%), wet meadow (5%), clearings (11%), and clearcuts (8%), as well as deciduous shrubs (19%).

Using vegetation indices and four phenologically significant dates improved the classification of recently harvested forest (Fig. 8). When cBGW was classified, harvested stands were more likely to be assigned to deciduous shrub or urban, two mixed classes that more appropriately reflected the mixed vegetation and soil of the stand. The 345 classification confused some harvested stands with the forests in the aspen class or the mixed deciduous upland class (Fig. 8a). This difference was illustrated in the rectangular stand that was harvested in 1987, 5 years before the satellite image dates (Fig. 6a and b). The WISCLAND classification, which relied on principal components analysis of TM bands from two dates, showed similar inaccuracy (Fig. 8b). The overall accuracy of that classification was 60.5%, compared to 69.13% using cBGW. The WISCLAND classification had lower percent harvested area in clearings, and higher percent area as aspen class, mixed deciduous upland, jack pine class, and sugar maple class compared to using cBGW. In comparing the percent areas assigned to open classes, using cBGW improved the classification 19% over 345, and 38.6% over WISCLAND (Table 3). However, we cannot presuppose that the cBGW classification was wrong in assigning 32.5% of the harvested area to closed canopy classes, as some forest types can reach a closed canopy state within 10 years.

The cBGW classification produced a map useful for managers and modelers working over large areas (Table 4). There was a more consistent separation of the aspen class from the sugar maple class, which are the two main silviculture species. This separation was an improvement over the Wolter et al. (1995) classification, where only 18.5% of the aspen class test sites were correctly classified and 39% of the aspen sites were classed as northern hardwoods (sugar maple class and mixed deciduous). Furthermore, Wolter et al. (1995) did not distinguish sugar maple stands from the rest of the mixed deciduous forest. The cBGW also separated the jack pine class from the red pine class, the two dominant conifer species. In contrast, there was confusion of the aspen class with mixed deciduous upland. This confusion was inevitable since aspen dominates the mixed stands. Similar results were found in the loess plain between the sugar maple class and

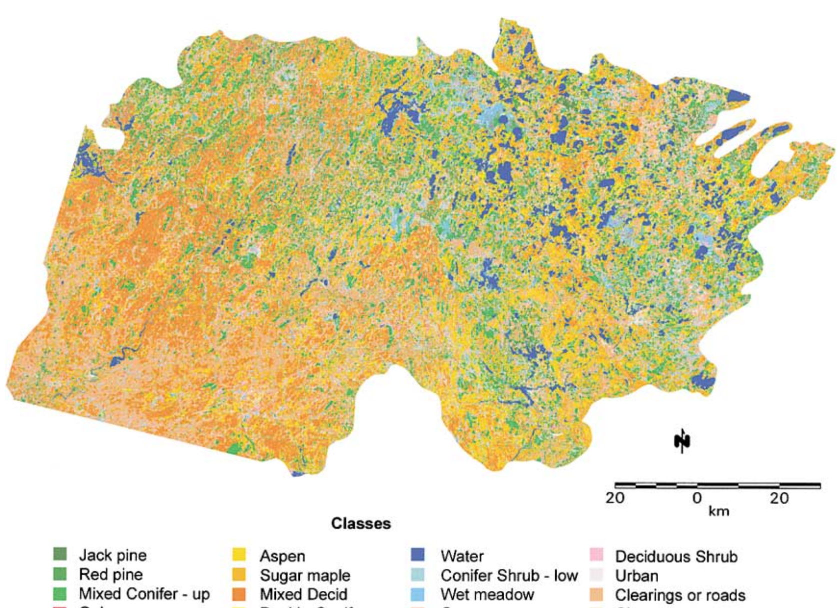

Fig. 9. Combination of complete outwash plain and loess plain classifications. Overall accuracy is 65.44%.

mixed deciduous upland, because in that ecoregion, the mixed stands are often dominated by sugar maple (data not shown).

The cBGW method developed here can be applied to different areas. The same methods applied to the loess plain resulted in 62.7% overall accuracy. Due to inconsistencies in the wetland classification, mixed forest stands could not be distinguished into upland or lowland classes. The combination of the outwash plain with the loess plain had 65.4% accuracy overall (Fig. 9).

4. Discussion

Phenological change captured by Landsat TM satellite data in the northern hardwoods region can improve forest classifications significantly. Overall accuracy for raw TM bands (345) was similar to using cBGW, (67.8% vs. 69.13%), however the change in Tasseled Cap more accurately classified deciduous shrubs sites and had a lower tendency to class harvested stands with unharvested stands. Achieving accuracy in these two areas is especially important for forest management applications. Furthermore, models that derive primary productivity estimate from satellite imagery (Bonan, 1993; Fassnacht & Gower, 1997) require accurate identification of harvested areas.

The image differencing of Tasseled Cap bands (cBGW) may have produced the best classification because the transformation ion emphasized the shadows of the vegetation structure and the phenological differences. Tasseled Cap improves the separation of agricultural fields from forest because the forest stands contain more deep shadow, and this is captured in wetness (Crist et al., 1986). Within agricultural fields, Tasseled Cap improves the separation of developing green vegetation from fully green vegetation and from senescing vegetation (Crist et al., 1986). Our results showed that this ability also extends to forest systems. Explicit modeling using image differencing emphasized the phenological change in the data and produced the highest classification accuracy. Change analysis of Tasseled Cap is also effective in detecting deforestation (Cohen, Fiorella, Gray, Helmer, & Anderson, 1998; Collins & Woodcock, 1994; Fung, 1990).

The success of cBGW in distinguishing the aspen class from the sugar maple class is important for management applications since these silviculturally important species have different ecological characteristics and silvicultural treatments. These classes were separated because the sugar maple class had a greater change in brightness and greenness from August to September as the maple leaves change color. The sugar maple class also had a greater change in brightness from September to October as the leaves fall, revealing the dark brown bark of the maple, and the light, photosynthesizing bark of the aspen. Furthermore, there is a greater increase in brightness of the sugar maple class compared to the aspen class from May and August. This occurred because aspen have most of their leaves by May, but maples develop most of their leaves later in the spring. These differences reflect the appropriateness of the image dates. The separation of the aspen class from mixed deciduous possibly could be improved with a spring date that captures aspen flowering, because this occurs very early in the spring before other species are leafing up or flowering. The confusion of mixed deciduous with deciduous–coniferous in cBGW was not found in 345. Therefore, this confusion may be due to Tasseled Cap sensitivity to shadows (Crist et al., 1986) and the algorithm interpreting forest gaps as conifers. Accuracy may be increased further by using change algorithms designed specifically for Tasseled Cap data (Collins & Woodcock, 1994, 1996).

NDVI and cNDVI possibly produced poor results because only using two spectral bands makes NDVI more affected by many nonvegetation conditions including soil color, soil moisture, and the presence of dead material in the canopy (Jensen, 2000; Qi, Cabot, Moran, & Dedieu, 1995). This creates up to 50% errors in classifications (Goward, Markham, Dye, Dulaney, & Yang, 1991). The poorer separation of senescent, brown, and green vegetation created signature overlap between the different classes compared to using Tasseled Cap data. This error, combined with lower spatial resolution, may also explain the relatively poor separation of aspen and maple by Wolter et al. (1995) compared to the results from cBGW in this study. Incorporating the additional spectral information available from the TM sensor, either as raw data or Tasseled Cap, should produce the more detailed landscape-scale models and classifications.

The incorporation of four images and the use of cBGW improved the classification compared to using principal components from two images by WISCLAND (Lillesand et al., 1998). The overall accuracy was increased by 9% and the detection of harvested stands was also improved. Further improvement in the classification may come from the incorporation of additional remote sensing data. TM data are limited in spatial resolution (30 m), so the addition of higher resolution imagery may better isolate different land cover types into different pixels (Coppin & Bauer, 1996; Franklin, Hall, Moskal, Maudie, & Lavigne, 2000; Franklin & Peddle, 1990).

The incorporation of additional spectral bands by Tasseled Cap compared to NDVI, or the empirical relationships between indices and land cover characteristics, do not always result in increased accuracy. The application of Tasseled Cap transformations has expanded beyond its initial development to distinguish agricultural crops (Crist & Cicone, 1984; Kauth & Thomas, 1976). For instance, it has been applied to mapping forest composition (Bauer et al., 1994; Woodcock et al., 1994), estimating forest mortality (Collins & Woodcock, 1996), stand age, and structure (Cohen, Spies, & Fiorella, 1995). However, our results showed that Tasseled Cap indices without image differencing (BGW) produced one of the lowest accuracy deciduous genera classifications (Fig. 5). These results are consistent with the similarity of classifications using raw TM bands or Tasseled Cap indices for wetlands (Sader, Ahl, & Liou, 1995), and forest successional stage (Fiorella & Ripple, 1993). Further comparisons on the effectiveness of different input data sets for both phenology and land cover change would ensure the most appropriate methods are being employed.

Combining image differencing and vegetation indices may improve classification accuracy on a variety of landscapes. For example, wet–dry deciduous forests have leaf-flush and leaf-senesce events that occur over weeks (Daubenmire, 1971), although some species may remain bare for only a few days (Ewusie, 1992). Tall-grass prairie guilds may also be able to be distinguished by variation in leaf-flush, shoot elongation, and senescence (Leopold & Jones, 1947). Tropical evergreen forest guilds might be separable using flowering phenology. Some tropical species mass produce flowers over a short season, whereas others produce flowers throughout the year, but in general, flowering events are spread out between species (Frankie, Baker, & Opler, 1974; Stiles, 1977). Another application would be to help locate and monitor exotic species that have a different phenological response from indigenous vegetation (Holmes & Rice, 1996; Marigo & Pautou, 1998), although these differences do not always occur (Harrington, Brown, Reich, & Fownes, 1989).

Our results showed that satellite classifications of broad-leaved deciduous forests can be improved by using the differences in Tasseled Cap indices from phenological change. These greatest improvements were in separating the classes with similar species, but different structural features. Our results support the research showing that good results can be achieved using Tasseled Cap indices to detect a variety of forest change events.

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