Evaluating Seasonal Variability as an Aid to Cover-Type Mapping from Landsat Thematic Mapper Data in the Northeast

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Abstract
Classification of forest cover types in the Northeast is a difficult task. The complexity and variability in species composition makes various cover types arduous to define and identify. This project employed recent advances in spatial and spectral properties of satellite data, and the speed and power of computers to evaluate seasonal variability as an aid to cover-type mapping from Landsat Thematic Mapper (TM) data in New Hampshire. Data from May (bud break), September (leaf on), and October (senescence) were used to explore whether different leaf phenology would improve our ability to generate forest-cover-type maps. The study area covers three counties in the southeastern corner of New Hampshire. A modified supervised/unsupervised approach was used to classify the cover types. A detailed accuracy assessment was performed to evaluate the classification. The results indicate that specific northeast hardwood species can be identified and that time of the year can significantly affect the cover-type classification accuracy.

Introduction
A relevant and accurate forest cover-type and/or land-classification system is essential to providing information for effective management of natural resources. Research aimed at developing methods for reliably classifying forest cover and/or habitat types dates back many decades and continues to this day (Heimburger, 1934; Westveld, 1952; Damman, 1964; Pfister *et al.*, 1977; Eyre, 1980; Leak, 1982; Smalley, 1986). Three approaches to the classification of habitat types have been outlined: biophysical, forest type, and forest type/forest soils classifications (Leak, 1982). The single factor important to all three approaches is the classification of forestland into specific cover types. Satellite imagery has been demonstrated to be a cost effective method for classifying forest cover types throughout the world (e.g., Joyce, 1978; Kushwaha, 1990; Green, 1990; Schardt *et al.*, 1990; Congalton *et al.*, 1993).

In the United States, remote sensing projects involving the classification of forest types have typically focused on forest types in the South or West. Recent advances in technology which have improved the spatial, spectral, and radiometric properties of Landsat Thematic Mapper (TM) satellite imagery have shown promise for increased success in accurate classifications for the Northeast (Nelson *et al.*, 1984; Hopkins *et al.*, 1988). However, despite these advances, specific hardwood forest types have not been reliably classified in the Northeast. Developments within the remote sensing community have shown promise for classification of forest cover types throughout the world. These developments indicate that, by combining supervised and unsupervised classification techniques, increases in the accuracy of forest classifications can be expected (Fleming, 1975; Lyon, 1978; Chuvieco and Congalton, 1988). By combining both the supervised and unsupervised processes, a set of spectrally and informationally unique training statistics can be generated. This approach results in improved classification accuracy due to the improved grouping of training statistics (Green and Teply, 1991). This study will utilize TM satellite data and a combined classification approach to help determine if it is possible to discriminate between specific northeastern hardwood forest types.

In addition, few studies to date have employed satellite imagery taken during autumnal senescence. Autumn data sets have been shown to increase accuracies in hardwood forest type delineations when applied to aerial photography (Eder, 1989). It is also possible that imagery acquired in the spring, at or shortly after bud break, may provide advantages for specific hardwood species delineation. Therefore, this study compared classification accuracies for three temporal data sets (autumn, spring, and summer) to determine if seasonal variability significantly affects classification accuracy.

Classification System
For information generated by satellite imagery to be useful, a classification system which utilizes this information must be developed. If the results of a classification are to be of value to potential users, it is also important that the classification scheme be well defined, relevant, understood, and accepted. To develop a relevant and useful classification, project objectives and data limitations must be determined.

One limitation of TM satellite imagery when compared to aerial photography is that spatial resolution cannot be controlled. To identify individual tree species using aerial photography, a scale of 1:8,000 or larger seems appropriate (Ciesla, 1989). The small scale associated with TM satellite

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imagery limits its usefulness to classification of forest stands with a minimum of several acres rather than individual trees. Therefore, forest cover type classification systems employed in studies utilizing satellite imagery must define cover types at the stand level.

An important consideration in choosing a forest-type classification system is if existing or potential (climax) vegetation types are to be described. Methods for gathering information to determine potential vegetation types typically involve examination of understory vegetation, regenerating tree species, and/or examination of soil conditions (Leak, 1982). Befort (1986) was able to utilize understory vegetation and regeneration for aerial identification of habitat types in northern Idaho and eastern Washington using very large scale photography. Dense canopy structure typical of the Northeast, and the small scale of satellite imagery, limits the usefulness of this technique for classification of northeastern cover types.

Two approaches that describe the existing vegetation are single-factor (Bailey *et al.*, 1978) or dominance type, and multi-factor classifications. The single-factor classification method is based on a single measure, for example, dominant vegetation. The multi-factor classification takes into account several distinguishing characteristics. Habitat types, for example, can be identified by soils, landforms, and chronosequences of vegetation (Leak, 1982).

Multi-factor classifications can result in the proliferation of categories. For example, five elevation classes, five soil-type classes, and five cover-types classes will result in 125 possible classifications. Congalton (1991) has stressed the importance of employing a mutually exclusive and totally exhaustive classification approach for determining the accuracy of remotely sensed classified data. For the multi-factor classification system to approach a mutually exclusive and totally exhaustive condition, it must be subjectively simplified into categories which have only a few distinguishing characteristics.

By way of contrast, a single-factor classification system is mutually exclusive, totally exhaustive, easy to define and apply, and is very objective. This approach can also be hierarchical in nature when more general categories are desired. In addition, a single-factor classification approach can be used to determine a variety of site characteristics because several resource values appear to be highly correlated (Bailey *et al.*, 1978; Leak, 1982).

Last, and perhaps most important, is that the classification chosen must be acceptable and relevant to potential users. The land classification scheme most popular within the remote sensing community is the one developed by Anderson *et al.* (1976). This system is described in detail in various manuals and texts (Jensen, 1983; Campbell, 1987; Lillesand and Kiefer, 1987) and is pertinent for a variety of project objectives. However, projects attempting to determine if TM satellite imagery can reliably classify specific forest cover types requires a classification scheme which describes forest cover types in greater detail than the one proposed by Anderson (1976).

The forest cover-type classification currently used in the State of New Hampshire is the Society of American Foresters (SAF) classification scheme (Eyre, 1980). In addition, Leak (1982) has identified seven forest types representing major stand conditions in New Hampshire. These approaches describe forest cover types in greater detail than the one developed by Anderson *et al.* (1976). However, neither approach can be termed a purely single- or multi-factor system. Although site factors are not considered in defining or identifying the types, the descriptions "give recognition to the ecological factors that helped to create the types and will continue to influence their development" (Eyre, 1980). Combining these classification schemes (see below) should facilitate applications which utilize satellite data for forest cover-type mapping in the forests common to the Northeast. In addition, forest-type recognition coupled with soil maps can provide information which indicates likely habitats, climax species, and management limitations and/or potential (Leak, 1982). This information will be valuable to foresters, wildlife ecologists, and other natural resource managers.

Forest-Cover Types

Coniferous

- **WP** - Eastern white pine comprises a majority of the stocking (>70 percent) and characteristically occurs in pure stands. On lighter textured soil its' associates include red pine, pitch pine, quaking and bigtooth aspen, red maple, pin cherry, and white oak. On heavier soils associates are birches(paper, sweet, and gray), black cherry, white ash, northern red oak, sugar maple, basswood, hemlock, red spruce, balsam fir, white spruce, and northern white cedar.
- **WH** - Eastern white pine and eastern hemlock, in combination, comprise the largest proportion of the stocking, but neither species alone represents more than half of the total. The combination rarely exists without associates and red maple is a very common one. Other common associates include paper birch, northern red oak, beech, sugar maple, yellow birch, gray birch, red spruce, white ash, and balsam fir.
- **HE** - Eastern hemlock is pure or provides a majority of the stocking (>70 percent). Common associates are eastern white pine, balsam fir, red spruce, sugar maple, beech, yellow birch, northern red oak, white oak, yellow poplar, basswood, black cherry, red maple, and white ash.
- **OC** - Other conifer species comprise a majority (>70 percent) of the stocking. In the study area the most common species is red pine. However, red spruce and any other conifer species in the study area which comprises a majority of the stocking may be included in this category.

Mixed

- **MX** - White Pine/Red Oak/Red Maple - Eastern white pine and northern red oak are the most important species in this forest cover type, although red maple is always present. White ash is often a major associate. Other trees commonly found are eastern hemlock, birches (paper, yellow, and sweet), black cherry, basswood, sugar maple, and beech.

Deciduous

- **RM** - Red maple comprises a majority of the stocking. Most common associates include red spruce, balsam fir, white pine, sugar maple, beech, yellow birch, eastern hemlock, paper birch, aspen, black ash, pin cherry, northern red oak, and black cherry.
- **OAK** - White oak, black oak, or northern red oak comprise a majority of the stocking. One or more species of hickory are consistent components but seldom make up over 10 percent of the basal area. Other associates may include sugar and red maples, white and green ash, American and red elm, basswood, black cherry, American beech, and hemlock.
- **BH** - Beech must comprise at least 25 percent of the stocking and may be associated with any of the above listed hardwood species.

Study Area

The study area is located in southeastern New Hampshire and includes portions of Strafford, Merimack, and Rocking-

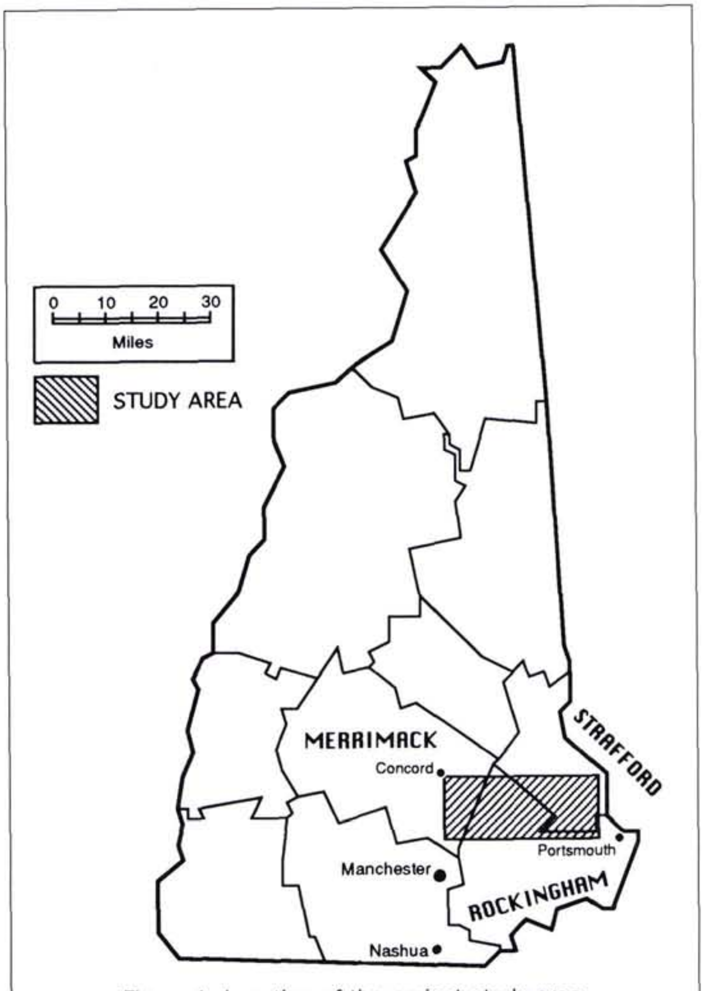

Figure 1. Location of the project study area.

ham counties and encompasses over 260,000 acres (Figure 1). Historically, much of the area was converted from forest land to agriculture during the eighteenth and nineteenth centuries (Irland, 1982). These farms have largely reverted to forest as agriculture moved west beginning in the late nineteenth century. Forest types in the area range from early successional stages to mature forests. Topography for the area is relatively flat with a range in elevation of sea level in the Great Bay area to 1,413 feet above sea level on Fort Mountain in the Nottingham Mountains.

The study area was chosen to help the University of New Hampshire (UNH) Woodlands Office in the development of a geographic information system (GIS) cover-type data layer. The Woodlands Office manages over 1,800 acres of University owned woodlands in the area. In addition, the area was chosen to maximize available state and university forest type existing reference data sets (over 17,000 acres), because of its close proximity to campus which eased the collection of field data, and to provide a variety of forest cover types.

Three Landsat TM satellite images were used in this study. Corresponding scene dates and ID numbers are 23 October 1989 (#5206214513), 8 September 1990 (#5238214466), and 13 May 1988 (#5153414570). All data were acquired from EOSAT Corporation.

Acquisition of Reference Data

The forest cover-type reference data utilized in this study were acquired from three different sources: the State of New Hampshire, UNH Woodlands Office, and additional field work conducted as part of this project. Guidelines for defining cover types are outlined in the SAF publication (Eyre, 1980), and were the standard utilized by all three sources. Specific cover types utilized for this project are defined above. Part of the reference data was utilized to help develop training areas and the remainder was used to perform an accuracy assessment for resulting classifications. Reference data provided by the State included two wildlife management units and three State parks and totaled 15,775 acres. The University data provided an additional 1,800 acres.

Due to the lack of certain cover types, it was necessary to supplement the existing reference database through personal field work. The assistance of University of New Hampshire Cooperative Educators in forestry for Strafford and Rockingham Counties was essential to the completion of this study. To identify, delineate, and locate these areas in the field, National High Altitude Photography (NHAP) color-infrared (CIR) photos, topographic maps, orthophotos, and tree farm management maps were utilized. Once the areas were located, a ten basal area factor (BAF) point cruise of the area was performed. Resulting inventory data provided the means for cover typing specific forest stands in accordance with the previously defined cover types.

Analysis

Analysis of the three TM satellite data sets was divided into five major steps: (1) deriving new bands, (2) delineating training areas, (3) generating statistics and spectral pattern analysis, (4) classifying the images, and (5) assessing the accuracy. All image processing for this study was performed using ERDAS Version 7.5 software on a 486 personal computer (ERDAS, 1991).

In addition to the original raw bands 1 to 5 and 7, two types of derivative bands were utilized in the analysis. The first was a principle component analysis of the three visible bands. Because of the strong correlation between the three visible bands, the first principal component of these bands explains a large portion of the visible band variability (85 to 95 percent). Therefore, the first principal component of the visible bands (PC1) can potentially be used as a substitute for these bands and can be thought of as similar to a panchromatic rendition of a combination of the three bands. The second method was band ratio analysis. Band ratios 4/3 (R4/3) and 5/4 (R5/4) have been shown to be sensitive to changes in vegetation characteristics (Peterson *et al.*, 1986). Therefore, this study employed the above mentioned ratios and also included a 7/5 (R7/5) ratio band. This resulted in a final image containing ten bands: raw bands 1 to 5 and 7; the first principle component for the visible bands (PC1); and ratios R4/3, R5/4, and R7/5.

The training area delineation technique utilized in this study was a traditional approach whereby training area polygons are digitized on the image display device. Criteria important to the selection of training areas include representation or distribution of the areas for each class throughout the image, the ability to locate training areas on the image dis-

play device (this generally required stand size to be a minimum of ten acres), and areas must represent normal conditions for the class which they represent.

Generation of statistics and spectral pattern analysis was performed to meet two specific objectives: (1) to determine if training areas were acceptable for the final classification process, and (2) to reduce the data to only those bands necessary for the final classification. A statistical analysis of each potential training area was performed. The statistics file produced in the training area selection provides a covariance matrix and standard deviations for each band, as well as a histogram for each band. It is important that training areas used in the final classification display unimodal histograms and have relatively low standard deviations and low values in either major diagonal of their covariance matrices.

To help speed up computer processing time and reduce data redundancy, it is valuable to reduce the data to only those bands which maximize class separability. The graphical and statistical spectral pattern analysis techniques employed include spectral pattern plots (Stenback and Congalton, 1990), divergence analysis, and ellipse plots as a final diagnostic. It should be noted that only the statistics generated from the training areas during the supervised approach were utilized for the spectral pattern analysis. This was essential for determining which bands best discriminated between forested classes.

Spectral pattern plots are a simple graphical technique in which the average value for each band for each category in the classification is plotted. The graphs can then be studied to see which bands provide the best visual separation between categories. Divergence analysis is a mathematical technique which computes a statistical distance between categories in a classification based on variances and covariances as well as average values. The divergence analysis provides a more robust analysis than the spectral pattern plots. Finally, ellipse plots can be used to further verify the spectral pattern analysis by plotting, in two bands, the signatures of the categories in the classification and looking for signature overlap. Ellipse is best performed after the number of bands has been limited because the plots are performed on two bands at a time. Once the appropriate bands are selected, the classification of the data may proceed.

Traditional approaches to classification include supervised and unsupervised techniques. Because both techniques have inherent advantages as well as disadvantages, many combined approaches aimed at maximizing the advantages while minimizing the disadvantages have been developed. The combined approach utilized for this study was developed by Chuvieco and Congalton (1988). This approach utilizes the mean data values (training area means or cluster means) generated from both the supervised and unsupervised classification approaches. Mean values for each band are input into another clustering routine which begins merging statistics which are similar. The final output is a dendrogram indicating the numeric distance between statistics which were merged or grouped together.

The information from the dendrogram is used in labeling the unknown clusters as well as in reducing the number of training areas. When training areas of known classes (supervised areas) were grouped with training areas of unknown classes (unsupervised areas), it was possible to label the unknown spectrally unique classes. In addition, some training areas displaying spectrally similar characteristics could be merged into one class, thereby reducing the total number of training areas. This process was repeated until results produced classes which did not meet a pre-determined minimum criteria for similarity. If classes with unknown labels were still present, visual inspection, analyst expertise, and/or personal field work were used for final labeling. After all statistics were labeled and similar statistics were merged, the final classification was performed.

The classification algorithm utilized was a maximum-likelihood classifier with a first-pass parallelepiped optimization set at two standard deviations. Initial classifications were run without the first-pass parallelepiped optimization. A comparison of runs with and without the optimization showed virtually no difference. Because the parallelepiped optimization cuts computer processing time and does not assume a normal data distribution, it was utilized. The main advantage of the maximum-likelihood classifier is that it takes the variability of classes into account by using the covariance matrices of classes.

Accuracy assessment is an essential component of the classification process. Therefore, a complete accuracy assessment was performed on all three classifications generated during this project. Over 335 polygons or forest stands were utilized as reference data for testing the accuracy of all ten classes in each classification. None of the training data polygons utilized in the classification was used in performance of the accuracy assessment. To determine which class reference data polygon was assigned in the final classification, an ERDAS program called SUMMARY was run on the reference polygons and the final classified images. This program provides a cross tabulation between the reference data polygon and the classified image. Analyst judgment (in accordance with the guidelines outlined in the classification system) was then used to determine which class was assigned to specific polygons.

Descriptive statistics calculated from the error matrices include user's error (error of commission), producer's error (errors of omission), overall accuracy (total percent correct), and normalized accuracy. Analytical techniques utilized discrete multivariate techniques and include normalization or standardizing the matrices and performance of a KAPPA analysis. Normalization allows for an effective comparison between error matrices because the normalized value takes into account both user's and producer's error, allowing for direct comparisons within individual cells. The KAPPA analysis utilized in this study provides information about a single matrix and facilitates a statistical comparison of several matrices. For a complete description of these accuracy assessment techniques, see Congalton (1991).

Results

Three spectral pattern analysis techniques were employed in this study. The first technique utilized was spectral pattern plots. The statistics for all training areas in each class were merged, and the mean digital number (DN) values for each class were graphed and visually inspected to determine which bands maximized separability (Figure 2). This step serves as an excellent preliminary check as to which classes can be discriminated. However, because there is little indication as to the loss or gain of separability by the addition or subtraction of bands and the standard deviation and covariance statistics are not considered, it is difficult to assess which bands maximize separability from this technique alone.

A more robust method for determining which bands maximize separability is through signature divergence. The DIVERGE command in ERDAS offers both transformed diver-

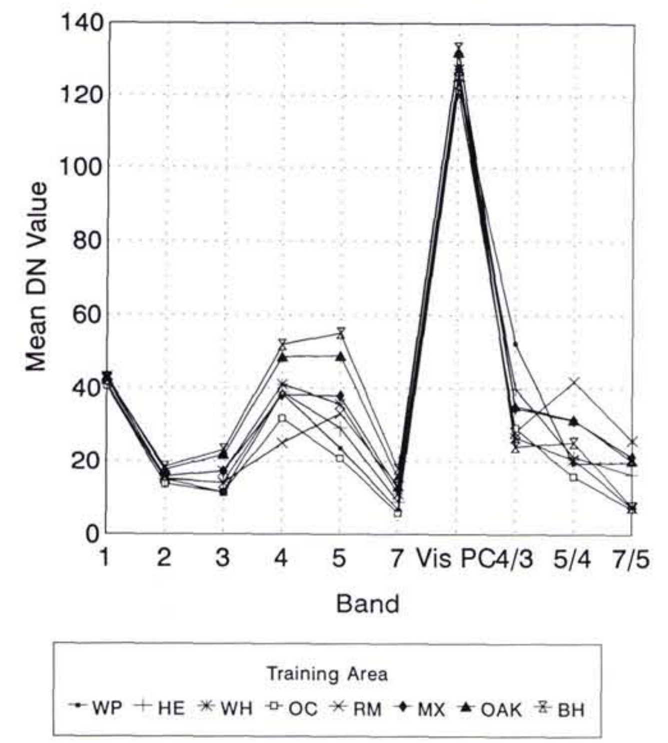

Figure 2. Spectral pattern plot of the mean digital number (DN) values for the forest classes in the October data set.

gence and Jefferies-Matusita distance formulas for calculating spectral distances between classes. Both formulas produced identical results; that is, only four bands of imagery were needed for the final classification. The addition of a fifth band did not increase forest class separability for any of the imagery, while utilizing only three bands would have resulted in a loss of forest class separability. The ellipse program, which graphs any user specified combination of training area statistics two bands at a time, was utilized as a final check to verify the final band combinations.

Results of the spectral pattern analysis indicate that TM raw bands 3, 4, and 5 are valuable for forest cover-type classifications in the Northeast. In addition, the value of deriving new bands (in this case, principle component analysis of the visible bands and band ratio techniques) was demonstrated. Each of the images used in the final classification contained at least one derived band. For the September, October, and May data, the bands utilized were [PC1, 4, 5, and R5/4]; [3, 4, 5, and R4/3]; and [PC1, 4, 5, and R4/3], respectively. In this study, bands 1, 2, and R7/5 were not utilized. The fact that the R7/5 band was not utilized agrees with results from Gallup (1991) who found that, in the Northwest, band ratio 7/5 did not aid in maximizing separability of forest cover types.

All images were classified in ERDAS 7.5 using the MAXCLAS program (maximum-likelihood classifier) with a two-standard-deviation parallelepiped optimization option. To produce the final classified image, two iterations of the combined classification approach (Chuvieco and Congalton, 1988) were run on the data. In two iterations, it appears this classification approach can begin to distinguish between specific hardwood species. For the October image the hardwood species American beech, northern red oak, and red maple had user's and producer's accuracies of 69 percent and 73 percent, 83 percent and 91 percent, and 85 percent and 94 percent, respectively (Table 1).

Table 2 presents the results of the accuracy assessment for each date of imagery using all three measures of accuracy: overall accuracy, KHAT accuracy, and normalized accuracy. These three measures produce identical results in that they all rank October with the highest accuracy level and September as the lowest. Table 3 shows the results of the KAPPA analysis. Both the October and May classification were significantly better than the September classification at the 99 percent and 95 percent level, respectively. However, although the October classification has slightly higher accuracies, it is not significantly different from the May classification.

These findings seem to indicate that successes similar to

Table 1. Error Matrix for the Classification of the October Image.

Reference Data
October

Classification	WP	WH	HE	OC	RM	NF	MX	OAK	BH	ROW TOTAL
WP	43	7	3	5			1			59
WH	7	14	9	9						39
HE			4							4
OC			2	5	1	2				10
RM		1		1	34					36
NF						53		1		54
MX		8	12		5	1	48	4	2	80
OAK							1	43	3	47
BH								4	11	15
COL TOTAL	50	30	30	20	40	56	50	52	16	255

OVERALL ACCURACY = 255/344 = 74%

PRODUCER'S ACCURACY	USER'S ACCURACY	VEGETATION TYPES
WP = 43/50 = 86 %	WP = 43/59 = 73 %	WP = white pine
WH = 14/30 = 47 %	WH = 14/39 = 36 %	WH = white pine, hemlock
HE = 4/30 = 13 %	HE = 4/ 4 = 100 %	HE = hemlock
OC = 5/20 = 25 %	OC = 5/10 = 50 %	OC = other conifer
RM = 34/40 = 85 %	RM = 34/36 = 94 %	RM = red maple
NF = 53/56 = 95 %	NF = 53/54 = 98 %	NF = non - forested
MX = 48/50 = 96 %	MX = 48/80 = 60 %	MX = white pine, red oak, red maple
OAK = 43/52 = 83 %	OAK = 43/47 = 91 %	OAK = oak(black, red, white)
BH = 11/16 = 69 %	BH = 11/15 = 73 %	BH = beech, hardwood

Table 2. Comparison of All Three Accuracy Measures for the Classifications.

Image	Overall Accuracy	KHAT Accuracy	Normalized Accuracy
September	62%	56%	54%
October	74%	70%	64%
May	69%	64%	60%

TABLE 3. RESULTS OF THE KAPPA ANALYSIS FOR COMPARISON OF TM CLASSIFICATIONS.

Comparison	Z Statistic
October versus September	3.665**
October versus May	1.568
May versus September	−2.097*

* significant at 95% level
** significant at 99% level

those found in classification of hardwood species using aerial photography acquired during autumnal senescence (Eder, 1989) may also be expected from classifications which utilize satellite data. It also appears that satellite data acquired at or shortly after bud break may provide advantages over summer data sets for classification of hardwood species found in New Hampshire.

Summary and Discussion

This study had two primary objectives. The first was to determine if seasonal variablitity makes a significant difference in accuracy of TM cover-type classifications in New Hampshire. The second was to determine if advanced techniques and methodologies for classification of remotely sensed satellite data would enable the classification of specific hardwood species found in the Northeast.

To meet the first objective, TM satellite data sets from various times during the year were acquired. The fact that October classification accuracy was the highest did not come as a surprise. It was hypothesized that the difference in hardwood foliage reflectance characteristics (e.g., leaf biomass, water moisture, and chlorophyll absorption) between species would be at a maximum during autumnal senescence. However, the fact that the May classification was also shown to be significantly better than September was interesting. Because some species break bud sooner than others, chlorophyll absorption rates, water moisture levels, and leaf biomass levels should be distinctly different between species in May. It is also likely that understory reflectance characteristics associated with species such as red maple that typically lose there leaves before 23 October or species that break bud at or after 13 May aided in the discrimination of specific species.

This project also seems to indicate that specific hardwood species can be discriminated by classification of TM imagery. It also clearly demonstrates the value of an iterative, hierarchical classification scheme combined with a complete accuracy assessment. Many resource managers may question the value of data found to have an overall accuracy of 74 percent. However, when project objectives are defined, classes may be aggregated, thereby improving expected accuracy dramatically. For example, a wildlife project interested in mapping hardwood mast production may aggregate both the American beech and red oak classes. This aggregation will result in a producer's and user's accuracy of 90 percent and 98 percent, respectively.

This study utilized a fairly extensive reference data set. However, even with the extensive reference data available, projects involving a larger database and a wider variety of cover types should be employed. It would be beneficial to have a study area that encompassed a wider variety of cover types with at least 50 accuracy assessment reference stands each. It is also important that the species present are available as pure stands in the reference data in order to avoid problems associated with mixed cover types.

The problem which still remains for classification of Northeastern cover types which utilize satellite imagery appears to be associated with the complex mixed forest types. The eastern white pine/eastern hemlock, and eastern white pine/northern red oak/red maple mixed types accounted for most of the off-diagonal errors. This makes sense because there are so many factors which can affect the spectral reflectance of mixed types. These types can be hard to distinguish in the field, and subjective techniques are often used in creating the final delineation of stand cover-type maps. Questions regarding the legitimacy of the mixed types and how to compensate for these problems are difficult to answer, but certainly relate back to how we define and establish the criteria for mixed stand designations.

The only criterion utilized for designation of individual stands in this study was species type. While employing the combined classification approach, it became very clear that additional criteria were needed to maximize the data potential of satellite imagery as well as the diagnostic value of the combined classification approach. The combined approach showed that statistics generated through the unsupervised approach were measuring more variables than were being explained by the supervised cover-type data. Therefore, future studies should strive for reference data that contain more information regarding specific forest types. Some of the data that would be useful include stand age, size class, structure, overall stocking levels, and a specific breakdown of species percentages within the mixed forest types.

Finally, it should be noted that methods aimed at combining imagery and utilizing additional data enhancement techniques should help increase classification accuracy. Additional techniques include principal component analysis utilizing a wide variety of combined data, spatial filtering of the final classified image, use of combined and individual multitemporal data sets for generating additional vegetation indices and band ratios, utilization of ancillary data, and edge analysis investigations. Also, because it appears that certain image dates may map specific species more effectively, a combining of the classified images may also improve classification accuracies.

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