IDENTIFYING LOBLOLLY PINE AND FOUR COMMON COMPETING HARDWOOD SPECIES USING MULTISPECTRAL REFLECTANCE ANALYSIS

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Abstract—Multispectral reflectance data were collected in midrotation loblolly pine plantations during spring, summer, and fall seasons with a hand-held spectroradiometer. All data were analyzed by discriminant analysis. Analyses resulted in species classifications with accuracies of 83 percent during the spring season, 54 percent during summer, and 82 percent during fall. Loblolly pine was correctly identified 100 percent of the time using the spring data. Multispectral remote sensing appears valuable in determining the level of hardwood competition within midrotation pine plantations and for separating pine from nonpine competitors.

INTRODUCTION

The art and science of forest management starts with field measurement. No forest, regardless of size or location, can be properly managed without a thorough knowledge of the forest conditions on site. Based on site assessment, silvicultural prescriptions can be formulated. Throughout the life or "rotation" of a forest stand, many problems may arise. Some result in detrimental effects on the growth and productivity of the stand. These include, but are not limited to, insect, fungal, bacterial, mammalian, and avian influences. The presence of other botanical species on the site can greatly influence pine growth as well. In most forest stands, noncrop species form a competitive relationship with the desired crop species; all compete for space, water, nutrients, and light.

BACKGROUND

The effects of competition on pine growth have been well researched. Control of hardwoods in young loblolly pine (*Pinus taeda* L.) stands is a management option that has resulted in good pine growth responses (Fortson and others 1996, Quicke and others 1996, Zutter and others 1988). Not only is the response to competition control at an early plantation age positive, but removal of competition at midrotation has proven to be beneficial as well. Investigators found that in treated plots within a 14-year-old pine plantation, basal area and volume of pine increased 11 percent and 20 percent, respectively, over all treatments compared to nontreated controls (Fortson and others 1996). Quicke (2001) also found that competition control in a 14-year-old pine plantation positively influenced pine growth. Six years after treatment, pine growth was 20 percent greater in treated plots than in control plots, yielding an additional ½ cord per acre per year.

Economic benefits of competition control—There are positive economic returns to midrotation hardwood control in pine plantations. Kline and Kidd (1986) estimated that under conservative economic assumptions, a 10-percent reduction in hardwood basal area yielded an average of $105 per acre increase in the net present value of a loblolly pine plantation. This estimate was based on a stand with a site index of 69 feet at base age 25 and grown through a 30-year rotation age. One study found that investment in midrotation hardwood control returned 8 percent to 14 percent annually over the remaining life of a rotation (Caulfield and others 1999). This study evaluated the returns to investment in herbicide application costs based on differing levels of control success and varying prices of pine products but did not include the costs of the competition control need assessment.

The competition assay—Assessment of competing vegetation within a pine plantation currently requires on-site measurement. As with most measurements conducted for silvicultural assessments, this often requires plots be established and physical measurements taken. Although per acre costs for such labor-intensive measurements decline as acreage increases, it remains a notable expense. Some classification systems have been outlined that require fewer measurements but include ocular estimates of competitive factors (Zutter and others 1984). The problem with these methods is the introduction of some degree of subjectivity because the systems are ocular rather than measured quantitative methods. However, the advantage of these methods is the ability to characterize species of competing woody vegetation.

Remote Sensing as a Means to Assess Competition

In order to reduce labor costs from on-site visits, other means to assess competitive conditions must be found. One promising way to make this determination with very limited *in situ* visitation is through the use of remote sensing and analysis. To effectively assess competition within a pine plantation, some means must be found to separate competitive species from the pine crop on the remotely acquired image.

Species' spectral responses—Separation of spectral responses has been a problem confronted by many investi-

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gators. From the beginning of multispectral remote sensing, scientists have investigated many variables that influence spectral signatures. These variables range from the chemical properties of the plant to environmental stresses experienced by the tree. Spectral signatures can vary simply based on the position individual leaves occupy on the tree. Atkinson and others (1997) found that leaf samples from two species of European birch taken from stump and basal sprouts were dissimilar in spectral response to samples taken from the lower crown. Other research found that concentrations of chlorophyll determine spectral response in the electromagnetic wavelengths between 400 and 700 nm (Gitelson and others 1996, Tucker and Garrett 1977). Stress factors (Westman and Price 1987), foliage age and position in the canopy (Atkinson and others 1997, Danson 1995, Gausman 1985), nitrogen and lignin concentrations (Martin and others 1998), and other variables can cause variation in reflectance.

The best means to differentiate species may not be through pure spectral signature; it may be best to identify spectral regions occupied by the spectral radiance of species relative to neighboring species. Regardless of environmental or biotic influences, it might be assumed that all individuals of a species occupying a particular site will exhibit similar reactions to those influences and, hence, similar changes in spectral reflectance characteristics. The use of statistical analysis may define this region relative to other species growing under the same conditions (Curran and Atkinson 1998). Extensive use could be made of a method to simply identify pine and nonpine located within a pine plantation, but a means to identify the particular species growing in competition with the loblolly pine would be more valuable. Because species separation is desirable for competitive assessment, a need has been identified to assess means to spectrally differentiate loblolly pine and competing hardwood trees in pine plantations.

Spectral separation of pine from competition—The basis of this study relies heavily on the fact that the number of hardwood species in direct competition with loblolly pine in plantation environments is finite. The most important competing species can be grouped to include gums, oaks, hickories, and elms. Theoretically, since species found within an individual pine plantation are subjected to the same influences, it may be possible to assume these species occupy a spectral position relative to each other, which changes in only minor ways with changes in soil moisture, fertility, and other abiotic factors. Based on this assumption, first advanced by Cochrane (2000), it is believed that most of the important competitive woody species will occupy a fairly constant spectral region relative to the region occupied by loblolly pine. Although the spectral relationship between species may change from season to season, it should prove fairly constant during the same season from year to year. This study was undertaken to determine a methodology to separate species based on spectral response.

MATERIAL AND METHODS

Loblolly pine plantations in Attala County, MS, were selected for this study. The site was chosen based on pine plantation ages and site characteristics. The area consists of 1,100 acres of pine plantations, natural pine-hardwood stands, and agricultural fields. Within this study area, three plantations were chosen, and study sites of 1 acre each were selected within each plantation. These sites had been used for cotton production for many years and were planted with loblolly pine the year following the last cotton crop. Site and stand conditions ranged from a low alluvial site with a plantation age of 15 years to an upland site with a plantation age of 18 years. The sites occur in the sand-clay hills physiographic region of Mississippi. The soil was originally overlain by a thin layer of loessial brown loam which has, in most instances, been lost to erosion.

Data Collection

Site locations were accurately defined using a Global Positioning System (GPS). During this phase, site boundaries were established for eventual airborne data collection. Handheld spectroradiometer (HHSR) measurements were taken within each plantation on representatives of major woody species selected for this study. Species were selected based on their position within the canopy of the plantations. Species common to each site and with crowns positioned in the upper canopy with the loblolly pine crop were chosen for this study; they included sweetgum (*Liquidambar styraciflua* L.), winged elm (*Ulmus alata* Michx.), water oak (*Quercus nigra* L.), and white oak (*Quercus alba* L.) and the crop species, loblolly pine.

GPS data collection—A Landmark GPS (Landmark Systems Inc., Tallahassee, FL, U.S.A.) connected to a Juniper Pro4000 (Juniper Systems Inc., Logan, UT, U.S.A.) field computer was used for this study. The system incorporated a Trimble AG132 (Trimble Navigation Ltd., Sunnyvale, CA, U.S.A.) receiver and large dome antenna using an Omni Star Geostationary Satellite (Omnistar Inc., Houston, TX, U.S.A.) for differential correction. Global positioning was used to determine area boundaries of the study sites by latitude and longitude.

HHSR data collection—On-site spectral data were collected using a Field Spec Pro FR portable spectroradiometer (Analytical Spectral Devices, Inc., Boulder, CO, U.S.A.). The HHSR measures spectral responses of reflecting objects in the electromagnetic spectrum range of 350 to 2,500 nm. The device has a spectral resolution of 3 nm from 350 to 700 nm and 30 nm at 1,400 nm and higher. Although the device is capable of providing reflectance data in each of 2,151 individual spectral bands from visible to far infrared, only four multispectral bands were used in this study (green, red, red-edge, and near infrared) as they coincided with available airborne instrument capability used in a companion study. The bands were centered on 550, 675, 700 and 840 nm, respectively, with a bandwidth of ± 5 nm. Extracted multispectral data included each of these bands. A fiber-optic strand is used to transmit electromagnetic energy from the “pistol grip” head to the recording unit; in this study, the bare fiber was used in order to get a wide field of view of foliage. The field of view was approximately 230 at the fiber-optic tip. The tip was held 1.5 feet from the sample to collect spectral radiance information from the entire branch rather than individual leaves. The samples were placed on a 3 by 4 foot black foam-core board for data collection to reduce spectral noise. The device was calibrated using a white reference tile every 2 to 5 minutes. The calibration was performed to assure changing atmospheric conditions, and battery power did not bias the reflectance values.

HHSR data were collected to document two transition seasons (fall and spring) and midgrowing season (summer) conditions. Data collection was attempted on numerous occasions, but most failed due to inclement weather. Successful data collection was made in November 2001, April 2002, and August 2002 to represent fall, spring, and summer samples, respectively. HHSR measurements were taken between 10:00 a.m. and 2:00 p.m. on cloudless days to insure consistent sun angle and radiance magnitude. The spectral-reflectance data were collected for both loblolly pine and four woody competitors located within the pine plantation study site. On each day that data were collected, representative samples of each species were collected from each study area and immediately measured with the HHSR against a flat black panel. A full branch from the species being collected was cut and oriented upright against the panel in a manner similar to that which would be measured by an airborne sensor. Samples were measured within 3 to 5 minutes of harvest to avoid changes in chemistry and physiology of the plant material. Samples were measured in full sunlight at any convenient open central location adjacent to or within the study area. To reduce noise, all profile measurements were calculated as averages of 20 sampling points. Each sample was taken from a different individual within the study area. Care was taken to collect samples growing in full sun to mimic those clearly visible on aerially collected images. The multispectral data were converted to text format by software provided by the manufacturer of the HHSR. The converted data included the wavelengths, spectral response values, and sample numbers. The converted data were loaded into Microsoft Excel spreadsheet software (Microsoft Corporation, Redmond, WA, U.S.A.). In this format, each sample was labeled for name of the appropriate species recorded for that repetition. The data were arranged by band and grouped by species.

DATA ANALYSIS

Indices, including the normalized vegetation index (NDVI), the normalized vegetation index with green band (NDVIg), red vegetation index (RVI), and the density vegetation index (DVI) were added to the data set and treated as spectral bands (table 1). The indices provided additional “bands” of data previously proven useful in separating vegetation characteristics. These additional bands were added to increase the power of statistical analyses and the chances of accurate classification. The results were eight “bands” for analysis: green, red, RE, NIR, NDVI, NDVIg, DVI, and RVI. All statistical analysis was accomplished using Minitab 13.32 statistical analysis software (Minitab Inc., State College, PA 16801, U.S.A.). The eight bands were then subjected to correlation tests. Statistical analysis was completed by discriminant analysis using each of the band combinations derived from the above steps. The purpose of this analysis was to find a minimal set of bands that, when used in combination, held the best promise for discriminating between species.

Table 1—Vegetation indices used as additional bands in multispectral data analysis

Index name	Index formula
NDVI	NIR-Red/NIR+Red
NDVIg	NIR-Green/NIR+Green
RVI	NIR/Red
DVI	NIR-Red

NDVI = normalized vegetation index; NDVIg = normalized vegetation index with green band; RVI = red vegetation index; DVI = density vegetation index.

Correlation analysis—Huberty and Wisenbaker (1992) reported that using correlated bands in combination will result in discriminant analysis functions with false positive classification accuracy results. To eliminate variables (bands), which would tend to skew discriminant power, a correlation analysis was performed for all bands and indices in combination. Bands found to be correlated with other bands were removed from the final analysis.

Discriminant analysis—Discriminant analysis was conducted to test the performance of those bands in separating spectra into species classes. The species groups and band data were used as the response and predictor variables in the discriminant analysis, respectively. After analysis, species were cross-validated in a user accuracy test to determine the power of the resultant discriminant functions. Discriminant analysis is an unambiguous mathematical method to determine the identity of an unknown sample. A good discriminant function can recognize the spectral reflectance of a species by use of a training set of known spectral signatures of that species. Samples in the training set are assumed to represent the variance of the reflectance for a particular species. Discriminant analysis allows the construction of models for each known species that can be compared to samples of unknown species in an attempt to classify it. The reflectance of the unknown sample is compared to multiple models of different species. The models can then predict the likelihood that the sample matches the training spectral responses by returning a “yes” or “no” answer (Thermo Galactic 2002).

In Predictive Discriminant Analysis (PDA) in this study, the multiple response variables play the role of predictor variables, much like a regression equation. Analysis of the variables will predict the proper classification of unknown species reflectance values into the known species group. Accuracy of these predictions is a direct result of the accuracy of the data set used to “train” the discriminant function. These training sets are made more accurate by tests for linear relationships to eliminate problems with error capitalization due to correlation between variables (Huberty and Wisenbaker 1992). Although step-wise discriminant analysis is successfully used for a variety of data analyses, it was not used with these data because of the inherent problems this method presents. Step-wise analysis tends to calculate incorrect degrees of freedom, capitalizes on relatively small sampling error (Whitaker 1997), and does not necessarily identify the best predictors of a given data-set size (Thompson 1995). Since the probability of any sample falling within any given species classification is not known, the statistical method assumed prior probabilities were even; that is, the probability of a sample being classified into any species class is assumed to be equal throughout the data set.

When discriminant analysis was performed using the data collected for this comparison, squared distances between spectral signatures of the species groups were calculated. The clearest advantage of using squared distances is that the distances are calculated in units of standard deviation from the group mean. This allows an assignment of a statistical probability to the measured distance from one species mean to the other. Squared distances are reported here and used in this study to determine if spectral response of each species occupies a specific spectral region in relation to the spectral response of the other species. In theory, sample spectra with a squared distance of 3 nm or greater from a known species spectra have a probability of 0.01 or less of belonging to that species. Samples with a distance of less than 3 nm are then classified as members of the species. However, in practice, using aerial or satellite images, researchers have found that a distance of 10-15 nm works best as a maximum variance for classification of data (Thermo Galactic 2002).

The drawbacks to using squared distances include the fact that discriminant analysis relies on selecting a subset of bands to represent the entire spectrum for a species. More bands can not be added to increase accuracy, however, because the method tends to “over fit” very quickly. Using a combination of more than 10 to 15 bands can lead to Type I errors: failing to classify species into a group in which they belong (Thermo Galactic 2002). Although the squared distances reported for this study are two dimensional and can relate only to the distances between two species spectral regions, it is still useful in comparing those two species. The comparison of the spectral distance between loblolly pine and its competitors will prove useful in determining if the spectral regions are far enough apart to allow separation of the two species. With a maximum of four bands of spectral data used in these analyses, using a two-dimensional approach should not result in Type I errors.

RESULTS AND DISCUSSION

The multispectral data were analyzed by season of acquisition with all measurements for each collection date grouped by species. For each season, correlation tests, PCA, and discriminant analysis were performed to identify the bands suitable for correctly classifying the species of interest.

Table 2—Pearson correlation coefficients of spectral values for loblolly pine and four woody competing species from HHSR samples taken in pine plantations in Attala County, MS

	Green	Red	Red edge	NIR	NDVI	NDVIg	RVI
			Spring (April 2002)				
Red	0.43						
Red edge	0.90	0.62					
NIR	0.63	-0.15	0.53				
NDVI	0.32	-0.64	0.16	0.77			
NDVIg	0.14	-0.50	0.13	0.80	0.87		
RVI	0.28	-0.60	0.11	0.87	0.89	0.87	
DVI	0.55	-0.28	0.43	0.99	0.84	0.85	0.93
			Summer (August 2002)				
Red	0.76						
Red edge	0.92	0.71					
NIR	0.34	0.20	0.33				
NDVI	-0.35	-0.61	-0.27	0.62			
NDVIg	-0.34	-0.28	-0.24	0.75	0.86		
RVI	-0.45	-0.70	-0.40	0.46	0.89	0.73	
DVI	0.27	0.11	0.27	1.00	0.69	0.79	0.54
			Fall (November 2001)				
Red	0.23						
Red edge	0.49	0.82					
NIR	0.33	-0.09	0.30				
NDVI	-0.14	-0.91	-0.62	0.48			
NDVIg	-0.75	0.26	-0.26	0.35	0.45		
RVI	-0.33	-0.79	-0.71	0.39	0.87	0.58	
DVI	0.22	-0.43	-0.01	0.94	0.74	0.41	0.63

HHSR = handheld spectroradiometer; NDVI = normalized vegetation index; NDVIg = normalized vegetation index with green band; RVI = red vegetation index; DVI = density vegetation index.

Correlations—Each band and all indices were tested for correlation. In both the fall and spring data, the RVI, NDVI, and DVI were correlated with most other bands (table 2). The correlation of the indices with one or more of their component bands was expected. Unexpectedly, green was found to be highly correlated with red (Pearson correlation coefficient of 0.76) in the August data and with NIR in the April data. This was an interesting phenomenon in that combinations including green, red, and NIR see widespread use for classification purposes. Although the NDVIg index is a function of both the green and NIR bands, it was found to be correlated with only one or the other of its components in any single data set. The significance of this relationship is not known.

Bands were chosen for inclusion in further analysis by direct observation of the correlation matrices and manually selecting combinations of bands not correlated with any other bands in the proposed combination. Bands were assumed to be correlated if the Pearson correlation coefficients were between 0.60 and 1.00 (positive correlation) and -1.00 and -0.60 (negative correlation). Possible variable combinations remaining after correlation tests are shown in table 3. It is interesting to note that only the August and November data have a combination in common (combination two - green, NIR, and RVI).

Discriminant analysis—Discriminant analysis revealed that there was no real difference between classification accuracy of the April and November data sets. The discriminant function classified species with 82-and 83-percent accuracy using the November and April HHSR data, respectively (table 4). The August data performed much less effectively. The best classification accuracy was 51 percent and used the combination of red, NIR, and NDVI. The highest classification accuracy obtained with the spring data was the combination of the green, red, and DVI bands. For the November data, the combination of green, NIR, and RVI was most effective.

Species classification accuracy—A band combination common to both the November and August data sets (Combination 2, table 3) was the most effective band combination for predicting species classification in the November data and the least effective when used for the August data. The green, NIR, and RVI combination in the August data correctly classified species to class with only 41 percent accuracy but with 82 percent accuracy using the November data (table 4). This indicates that the widespread use of standard band combinations (i.e., green, red, NIR) or indices may not return the highest and most accurate classification for any two data sets. Because loblolly pine is the crop species and most important in classification accuracy, observations on classification of this species are of particular importance. With the April data set, loblolly pine was 100 percent correctly classified (table 5). However, in the November data set, classification accuracy was only 80 percent, with loblolly erroneously classified as winged elm. Although overall classification accuracy (table 4) was statistically the same for both the April and November samples, the fact that the crop species was always correctly classified in the April data makes this season more attractive for separating this species from its main competitors. Winged elm was incorrectly classified 40

Table 3—Usable band and indices combinations derived from statistical tests of seasonal HHSR data

	Combination 1	Combination 2	Combination 3
April	Green, Red, NDVIg	Green, Red, RVI	Green, Red, DVI
August	Green, Red, NDVIg	Green, NIR, RVI	Red, NIR, NDVI
November	Green, Red, NIR	Green, NIR, RVI	NIR, NDVIg, RVI

HHSR = handheld spectroradiometer; NDVI = normalized vegetation index; NDVIg = normalized vegetation index with green band; RVI = red vegetation index; DVI = density vegetation index.

Table 4—Overall classification accuracy of band combinations using discriminant analysis of multispectral bands and indices

Data set	Most effective band combination	Classification accuracy
		percent
April	green, red, DVI	83
August	green, NIR, NDVI	54
November	green, NIR, RVI	82

DVI = density vegetation index; NDVI = normalized vegetation index; RVI = red vegetation index.

Table 5—Percentage of loblolly pine and four competing woody species' samples correctly classified to species group using discriminant analysis functions

	Species groups				
Data set	LOB	SWG	WAO	WHO	WIE
	- - - - - - - - - - *percent* - - - - - - - - - -				
April	100	83	100	75	60
August	50	56	19	75	56
November	80	100	75	67	100

LOB = loblolly pine; SWG = sweet gum; WAO = water oak; WHO = white oak; WIE = winged elm.

percent of the time in the April dataset but was correctly classified 100 percent of the time in the November data set. Forty percent of winged elm was classified as white oak using the April data. Thirty-three percent of white oak was classified as water oak using the November data, and 25 percent was classified this way in the April data. This may indicate that the oaks are somewhat similar in reflectance during most of the year. However, control prescriptions may not need to be altered by any misclassification of these species since current control methods are similar for most oak species.

Squared distances and misclassification—One of the hypotheses of this study is that species reflectance values may occupy spectral regions that stay constant in relation to their distances from the spectral regions of other species. If this theory were correct, then species separation using spectral reflectance would prove successful regardless of biotic and abiotic influences on the species because all species on a particular site would be subject to the same influences. An observation of the squared distances between loblolly pine and four competitive hardwood species examined in this study proves this theory is not upheld from season to season. The squared distances between the spectral range of loblolly pine and its competitors vary by season (table 6); the average squared distances become much less during the August period. Although the table indicates the average squared distances for all samples, reflectance values of individual trees may be much closer, thus indicating the standard deviations of spectral values change dramatically due to seasonal influences. In the November data set, loblolly pine was misclassified as winged elm. The average squared distance between the misclassified loblolly pine and winged elm samples was 1.598 nm. The probability of loblolly being classified as winged elm was 52.8 percent due to close spectral proximity of the two species. In this particular study, overall seasons and all data, misclassifications occurred when the squared distances were less than or equal to 8.6991 nm. The mean squared distances between species misclassified was 2.507, and the median squared distance was 2.151 with a standard deviation of 1.75505. Standard error of squared distances between misclassified species was 0.2676. It is assumed that the threshold misclassification level of mean squared distances given are unique to this study and can not be assumed for all spectral response studies.

Table 6—Average squared distances between loblolly pine spectra and the spectral regions of selected hardwood species based on band combinations[a] with highest overall classification accuracy

Species	April	August	November
Water oak	6.7792	5.3399	5.9066
Sweetgum	13.0503	9.8167	16.0741
White oak	15.3399	4.7059	15.5052
Winged elm	11.0394	3.8657	9.4649

[a]April = green and red bands and density vegetation index, August = red and NIR bands and normalized vegetation index, and November = green and NIR bands and red vegetation index.

Many classification tasks undertaken in standard “off the shelf” remote sensing software require the user to input a maximum squared distance between spectral responses required in order to place a spectral response in a particular class. As discussed earlier, current theory indicates that samples with a squared distance of 3 nm or greater have a probability of 0.01 or less of belonging to that species, and that in actual practice users will use a distance of 10 to 15 nm (Thermo Galactic 2002). If this study is an indicator of actual results, a user-defined squared distance of 9 to 10 nm will return more accurate results and may reduce “unclassified” spectral responses. However, it cannot be stated for certain that the results of this study are globally useful.

Seasonal influences on classification accuracy—When comparing the seasons in which data were collected, the spring transitional season had the best overall accuracy for species separation and was best for separation of loblolly pine from the competitive species. During this season, the competitive and largely deciduous species are in the “green up” process. That is, these species have new growth and young foliage. Loblolly pine still retains its old needle foliage from the preceding year and does not replace 2-year-old needles with new foliage until later in the season. Concentrations of chlorophyll will differ greatly during this period. Chlorophyll concentrations have more influence on spectral responses in the 400-to 700-nm range of electromagnetic wavelengths (Tucker and Garrett 1977). Although the competitive species are in varied stages of transition during this time period, most of the foliage on the species is new growth (water oak individuals were observed to have some retained foliage from the preceding year). This similarity in foliage growth stage may explain the variability in classification accuracy between the competitive species (60 to 100 percent). Gausman (1985) and Atkinson and others (1997) found that foliage age causes variation in reflectance response.

The summer season is least useful; the spectral response of the older foliage of all species becomes less well-defined. The classification accuracy between deciduous species ranges from 67 to 100 percent using the fall data, but spectral confusion is introduced when comparing these species with loblolly pine. The greater classification accuracy from fall data may be a function of the chemical changes taking place in leaves in the fall in preparation for winter dormancy. Chlorophyll begins breaking down, which “unmasks” other pigments. However, confusion in the identification of pine with the competitor winged elm is an undesirable effect.

SUMMARY AND CONCLUSIONS

Based on this study, the spring transition period appears most valuable in determining the level of competition within loblolly pine plantations using remote sensing reflectance data. The overall accuracy of 83 percent is similar to the 82-percent accuracy obtained using fall transition data, but loblolly pine can be completely separated from the competitive species in April. Using remote sensing reflectance data, a forest manager may make decisions on competition control based solely upon the proportion of nonpine species observed in the upper canopy. If this controlled study can be carried over into an operational environment, it may prove particularly beneficial. However, making these discoveries operationally useful will require further study. The methods and findings of this study will need to be applied to data collected by remote sensors in an operational setting to determine if the results are similar.

Remote sensing methods used in this study are not without problems. Weather plays a major role in the collection of remotely acquired data. The spring transition period normally has many cloudy and stormy days; however, sunny days of pristine atmospheric conditions also occur. Flexibility in scheduling is the key to data acquisition. Even with extensive funding from NASA's Stennis Space Center, problems occurred with data storage, data loss, and scheduling. This reinforces observations that these problems will likely occur with any system of data collection until routines and methods are established that safeguard against mishaps.

Remote sensing holds great promise in reducing *in situ* visits for forest competition assessment. It is anticipated that future access to hyperspectral remote sensors (more bands for greater discrimination) with finer spatial resolution than what is currently commercially available will open the way to widespread use of remote sensing to identify competitive species in tree plantations.

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