Spectral Separability among Six Southern Tree Species

Jan A.N. van Aardt

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Randolph H. Wynne, Chair
Richard G. Oderwald
James B. Campbell

Virginia Polytechnic Institute and State University
Blacksburg, VA, 24061

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(ABSTRACT)

Spectroradiometer data (350 – 2500 nm) were acquired in late summer 1999 over various forest sites in Appomattox Buckingham State Forest, Virginia, to assess the spectral differentiability among six major forestry tree species, loblolly pine (Pinus taeda), Virginia pine (Pinus virginiana), shortleaf pine (Pinus echinata), scarlet oak (Quercus coccinea), white oak (Quercus alba), and yellow poplar (Liriodendron tulipifera). Data were smoothed using both moving (9-point) and static (10 nm average) filters and curve shape was determined using first and second differences of resultant data sets. Stepwise discriminant analysis decreased the number of independent variables to those significant for spectral discrimination at α-level of 0.0025. Canonical discriminant analysis and a normal discriminant analysis were performed on the data sets to test separability between and within taxonomic groups. The hardwood and pine groups were shown to be highly differentiable with a 100% cross-validation accuracy. The three pines were less differentiable, with cross-validation results varying from 61.64% to 84.25%, while spectral separability among the three hardwood species showed more promise, with classification accuracies ranging from 78.36% to 92.54%. The second difference of the 9-point weighted average filter was the most effective data set, with accuracies ranging from 84.25% to 100.00% for the separability tests. Overall, variables needed for spectral discrimination were well distributed across the 350 nm to 2500 nm spectral range, indicating the usefulness of the whole wavelength range for discriminating between taxonomic groups and among species. Derivative analysis was shown to be effective for between and within group spectral discrimination, given that the data were smoothed first. Given the caveat of the limited species diversity examined, results of this study indicate that leaf-on hyperspectral remotely sensed data will likely afford spectral discrimination between hardwoods and softwoods, while discrimination within taxonomic groups might be more problematic.

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S.D.G.

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Chapter 1
INTRODUCTION AND OBJECTIVES

An accurate classification of any given forested area is important to commercial and environmental forest management, aiding in forest inventory (yield per species or group), pest and environmental stress management (dying/decaying/drought-stressed trees), and assessing habitat ranges or managing human impacts on a forest environment. To be able to effectively manage forests and assess forest conditions, it is therefore imperative not only to locate forest species (or forest taxonomic groups such as hardwoods and softwoods), but also to assess various biophysical parameters subsequent to identifying the species/group location. One of the most important techniques for forest assessment and inventory is remote sensing. Air- and spaceborne sensors are now available in a wide variety of spatial, spectral and temporal resolutions. Forest classification has evolved through time as new sensors have become available.

Hyperspectral sensors, collecting hyperspectral data (data covering a broad range of wavelengths with high spectral resolution), are a relatively new development. Sensors defined as being hyperspectral split the at-sensor reflected light energy into many separate, narrow channels on a pixel-by-pixel basis. This makes discernment of an area's composition through spectral response discrimination more effective than is possible with the broader band multispectral sensors (Birk and McCord, 1994). Hyperspectral data also have a very distinct advantage over those derived from traditional sensors in that they are often spectrally contiguous (Niemann, 1995). Sensors such as the Airborne Visible and Infrared Imaging Spectrometer (AVIRIS) (range: 400 nm – 2500 nm; resolution: 10 nm), Hymap (range: 400 nm – 2500 nm; resolution: 16 nm) and Hydice (range: 400 nm – 2500 nm; resolution: 10.2 nm) have prepared the way for a new set of applications to be explored by providing data in high enough quantity and high spectral resolution to resolve the natural variability in features such as minerals, vegetation and atmospheric gases (Birk and McCord, 1994).

The first forestry studies using hyperspectral data included the monitoring of vegetation water content and estimation of foliar chemistry utilizing absorption features caused by chemicals

present in vegetation matter. These uses of remotely sensed data for the estimation of foliar chemistry have come a long way, with very promising results obtained by Wessman *et al.* (1989) and Curran (1989). Both these authors identified radiometric regions correlated with nitrogen and lignin contents, as well as chlorophyll and O-H bonds, but concluded that much more work needs to be done in the area. The absorption features at 0.4-0.7 μm, due to chlorophyll, and at 0.97, 1.2, 1.4 and 1.94 μm due to the stretching of the O-H bond in water and other chemicals proved especially significant (Curran, 1989; Yoder and Pettigrew-Cosby, 1995). Another study successfully associated water content and foliar biomass with spectral brightnesses (Peterson *et al.*, 1988). Kokaly and Clark (1999) introduced a new method, normalized band depths calculated from continuum-removed reflectance spectra, to estimate nitrogen, lignin and cellulose concenbtrations in dried and ground leaves. It was concluded that leaf water is a significant barrier to accurate assessment of nitrogen in particular.

The identification of bands correlated with leaf chemical compounds opened new possibilities for forest classification, as leaf chemistry characteristics might vary between forest taxonomic groups or even species. The broad "Forest" category could now be subdivided into its constituents, i.e., all the species contributing to the forest's composition, thus enabling the analyst to make a more detailed classification available to the user. Therefore, a more comprehensive approach that involves the use of hyperspectral data and its analysis has been taken of late (Lawrence *et al.*,1993; Gong *et al.*, 1997; Martin *et al.*, 1998; Fung *et al.*, 1999) rather than the traditional "broader wave range and fewer classes" approach (Nelson *et al.*, 1984; Shen *et al.*, 1985; White *et al.*, 1995; Franklin, 1994) that has been utilized for so long in natural resources research. The use of hyperspectral data collected with a spectroradiometer for tree species recognition has been explored to a certain extent, by among others, Gong *et al.* (1997) and Fung *et al.* (1999). Although the results were very promising with accuracies of up to 91% obtained for sunlit samples, Martin *et al.* (1998) found the classification of tree species, red maple (Acer rubrum), red oak (Quercus rubra), white pine (Pinus strobus), red pine (Pinus resinosa), Norway spruce (Picea abies) and pure hemlock (Tsuga canadensis), as well as mixtures thereof, using AVIRIS data to be no higher than 75%. A decisive study is needed to determine whether or not commercially and ecologically important tree species are spectrally

separable at canopy level, not only using very high spectral resolution spectroradiometer data, but also commercially available hyperspectral sensors.

This study explores the possibility of distinguishing (at canopy level) between six important forestry species in the southern Appalachian region of Virginia, USA, on a spectral basis. The spectral data was collected using a spectroradiometer with a wavelength range of 350 nm to 2500 nm, and spectral resolutions of 3 nm (350 nm – 1050 nm range) and 10 nm – 12 nm (900 nm – 2500 nm range). The spectral data are, however, resampled to 1 nm intervals during operation to facilitate analysis (Beal, 1998). The field data collection was controlled carefully so as to collect data that will stand up to rigorous statistical testing and will simulate hyperspectral data collected using conventional airborne sensors. A robust statistical approach will be presented for the analysis of the hyperspectral data, as well as the results concerning the spectral separability among these six important species.

This study assesses the inherent separability of overstory field spectra in the 350 nm – 2500 nm range (3nm – 12 nm spectral resolution). The specific objectives are as follows:

(1) Assess taxonomic group and species level separability of field canopy spectra derived from the following groups and species:
Pines - Loblolly (Pinus taeda), Virginia (Pinus virginiana), and shortleaf (Pinus echinata) pine
Hardwoods - Scarlet oak (Quercus coccinea), white oak (Quercus alba), and yellow poplar (Liriodendron tulipifera)

(2) Identify the wavelength regions that define the inherent spectral separability between taxonomic groups and species

(3) Identify the data pre-processing techniques most suited as preparation for species separability tests

Chapter 2
LITERATURE REVIEW

The use of remotely sensed data in cover type discrimination has evolved forest/non-forest delineation and relatively successful within group classification using Landsat-type sensors to an attempt to accurately classify forest types using higher spectral resolution sensors. Spectral resolution is perhaps the most important property of sensors used for this application, as they have to be able to resolve the natural variability in the system being studied. The Landsat sensors cannot resolve fine diagnostic spectral features, as their spectral bandwidths are 100-200 nm and are not contiguous (Vane and Goetz, 1988). Hyperspectral data was thus thought to be well suited for this application, as it is by definition oversampled, consists of a set of contiguous bands and usually stretches across a relatively wide wavelength range (Rinker, 1990). The difference between spectral resolution for the AVIRIS hyperspectral sensor and the well-known Landsat TM sensor is very evident in Figure 1.

For use in vegetation separability, a hyperspectral spectrometer would have to record a spectrum from 350 nm – 2400 nm, with a resolution of 10 nm or less and have a signal-to-noise ratio smaller than the depth of the absorption feature of interest (Curran, 1989). Two types of hyperspectral sensors, airborne imaging spectrometers and ground-based spectroradiometers, will be discussed first. This will be followed by a discussion of the applications of hyperspectral data in the vegetation arena and its use for determining species separability.

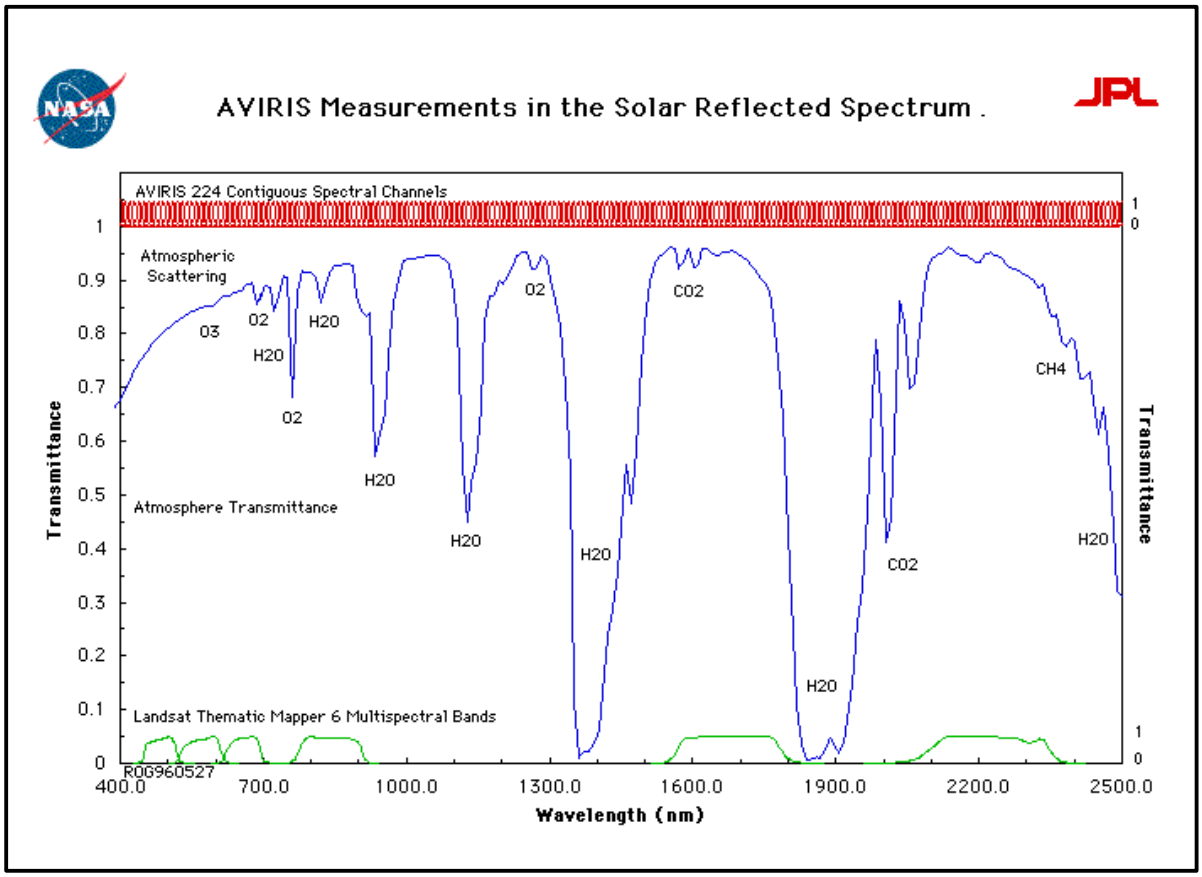

Figure 1. Comparison between AVIRIS contiguous hyperspectral data and Landsat TM multi-spectral data (Chovit, 1999, http://makalu.jpl.nasa.gov/html/img_spectroscopy.html)

2.1 Hyperspectral Sensors

The first type of sensors to be discussed are the airborne imaging spectrometers. These sensors provide a radiance (digital number) reading for each picture element (varying in size) for a set of contiguous wavebands at a high (±10 nm bandwidths) spectral resolution. An example of this sensor application can be seen in Figure 2. As of yet, there is not a spaceborne hyperspectral sensor available, so only airborne sensors are of interest in this discussion. The second type of sensors are the spectroradiometers, which are usually ground-based. Data are also collected in a contiguous fashion, using a foreoptic with a specified viewing angle.

Thus, reflectance values for the target for all the bands of interest are gathered and stored as numerical values, which can be represented as a reflectance graph.

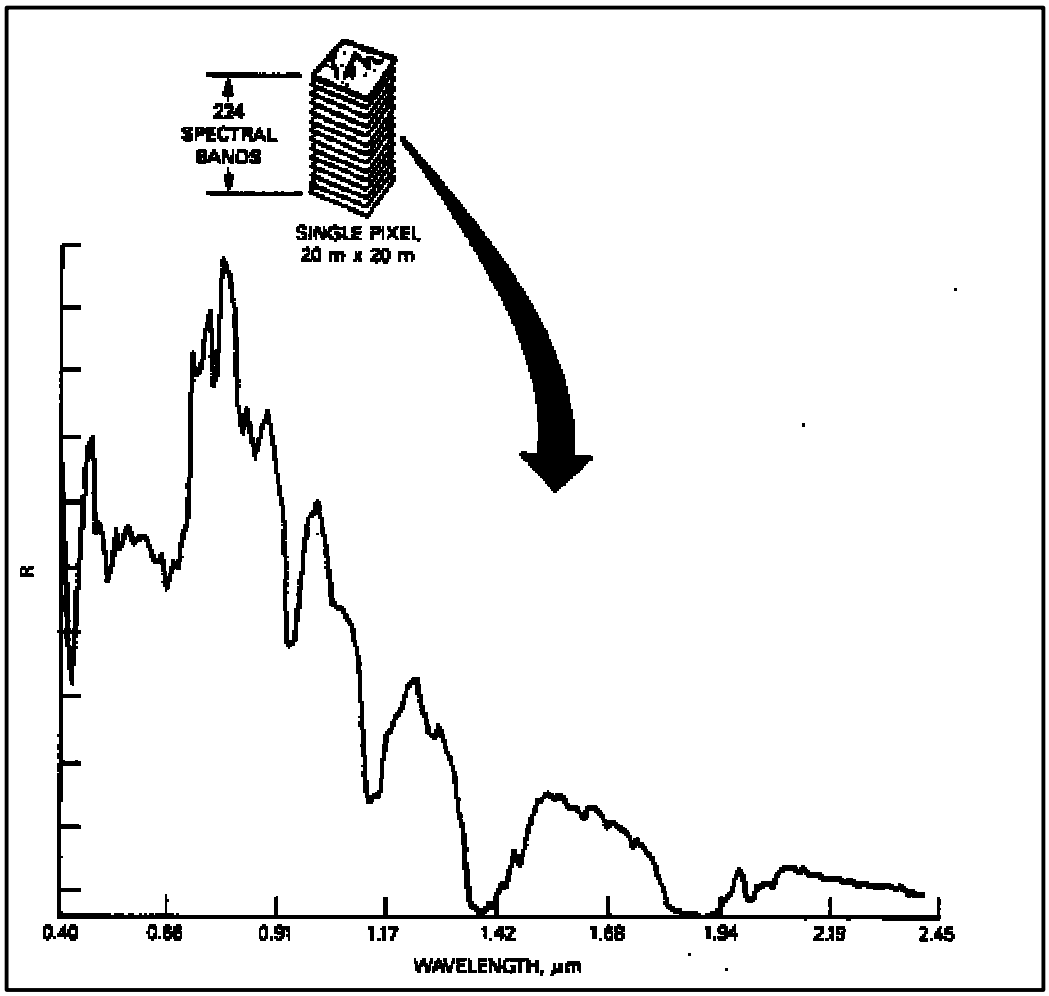

Figure 2. An example of AVIRIS hyperspectral data collected in 224 bands for each 20 m pixel data (Barr, 1994; Chovit, 1999, http://makalu.jpl.nasa.gov/html/spectrum.html)

2.1.1 Airborne Imaging Spectrometers

The first imaging spectrometer to measure the solar reflected spectrum from 400 nm to 2500 nm at 10 nm intervals was the AVIRIS sensor from NASA's Jet Propulsion Laboratories, which became operational in 1987. Radiance spectra are collected as images of 11 km width and up to 800 km in length. AVIRIS acquires its data from a NASA ER-2 aircraft at an altitude of

20000 m (Green *et al.*, 1998). The preceding sensor was called AIS (Airborne Imaging Spectrometer), and the last version had a spectral coverage ranging from 800-2400 nm. The AIS sensor had a fairly low signal-to-noise ratio (40:1 up to 110:1) as well as other problems such as vertical striping after radiometric calibration (Vane and Goetz, 1988). AVIRIS, on the other hand, boasts a very high signal-to-noise ratio (exceeding 100:1 requirement), especially after improvements were made to the sensor in 1995 (Green *et al.*, 1998). Hyperspectral sensors that have followed include HYDICE, CASI, DAIS (2815 and 7915), MIVIS, TRWSIII and HyMap/Probe 1 (Birk and McCord, 1994). Nineteen different airborne hyperspectral systems and 14 agencies with data acquisition aircraft were in existence in 1994 (Birk and McCord., 1994). The sensor characteristics vary from sensor to sensor, but the set of properties that define hyperspectral sensors, namely a broad spectral range, contiguous bands and high spectral resolution, remain the same. HYDICE, for instance, has a spatial resolution of 3 m, a swath of 936 m and spectral resolution of 10.2 nm ranging from 400-2500 nm (Lewotsky, 1994). Table 10 in Appendix A gives a brief overview of the airborne hyperspectral sensors that operated in 1994 (Birk and McCord, 1994).

2.1.2 Forthcoming Spaceborne Hyperspectral Sensors

Only airborne hyperspectral sensors are currently available for both commercial and government use. The trend of remote sensing platforms moving away from large, complex civil governmental and military systems to an increasing number of purely commercial, hybrid government/commercial and commercial/university collaboration systems, is changing the face of the remote sensing industry. As the applications and implications of remote sensing data for commercial ventures become more evident, the sensors are evolving to meet new needs and better address old ones. Just as spatial resolution has dropped to 1 meter and below for commercially available imagery, spectral resolution's importance and application are also coming to the fore (Glackin, 1998).

Glackin (1998) predicts that the number of spectral bands in space-based electro-optical systems will increase dramatically between 1998-2007. Multispectral imagery will most probably have as many as 36 bands (Earth Observing System's MODIS instrument), while hyperspectral

spaceborne sensors like these to be aboard OrbView-4 and the Naval EarthMap Observer (NEMO) are to be launched within this time frame. The OrbView-4 Hyperspectral Imager (HSI), for example, will have 200 hyperspectral channels (450 – 2500 nm) at 8 m spatial resolution and a swath width of 5 km. The same instrument will also have multispectral (4 m, 4 channels) and panchromatic (1 m, 1 channel) capabilities, making it extremely versatile by extending its application milieu tremendously (Glackin, 1998).

With commercial hyperspectral sensors such as these becoming available in the near future, the necessity for research to establish hyperspectral data's niche is even more important. Old problems can be addressed using new technology and algorithms, and the user's ability to solve new problems that arise becomes that much better.

2.1.3 Spectroradiometers

Spectroradiometers have been used with varying success for different applications. These instruments are usually ground-based and can be used in laboratory or in-field conditions, depending on the make and model. The spectroradiometer used in this study is the FR (full range) model from Analytical Spectral Devices Incorporated, which covers the range from 350 nm – 2500 nm and utilizes three detectors. The Visible/Near Infrared (VNIR) portion of the spectrum (350-1050 nm) has a spectral resolution of approximately 3 nm at 700 nm wavelength. The short-wave infrared (SWIR) region is measured by two detectors, SWIR1 (900-185 nm) and SWIR2 (1700-2500 nm). The spectral resolution varies between 10-12 nm and the sampling interval is about 2 nm (Beal, 1998).

At this time it is probably necessary to define a couple of terms to avoid confusion. *Spectral resolution* can be defined as the measure of the narrowest spectral feature that can be resolved by the spectrometer and can be characterized by the full width at half maximum (FWHM) of an instrument's response to a signal. *Spectral sampling interval* is the interval between data points in wavelength units. The *spectral sampling interval* is generally smaller than the spectral resolution. *Spectral bandwidth* is synonymous with spectral sampling interval (Analytical Spectral Devices Inc., 1999; Curtiss and Goetz, 1994). Figure 3 describes these definitions

graphically. A spectral sampling interval of about 2-3 nm provides 3-4 data points in field spectral data that have 10 nm spectral resolution. This oversampling results in less degradation when a spectrum is resampled to match wavelengths of other hyperspectral sensor channels. It also greatly benefits analysis methods that utilize derivative techniques (Tsai and Philpot, 1998).

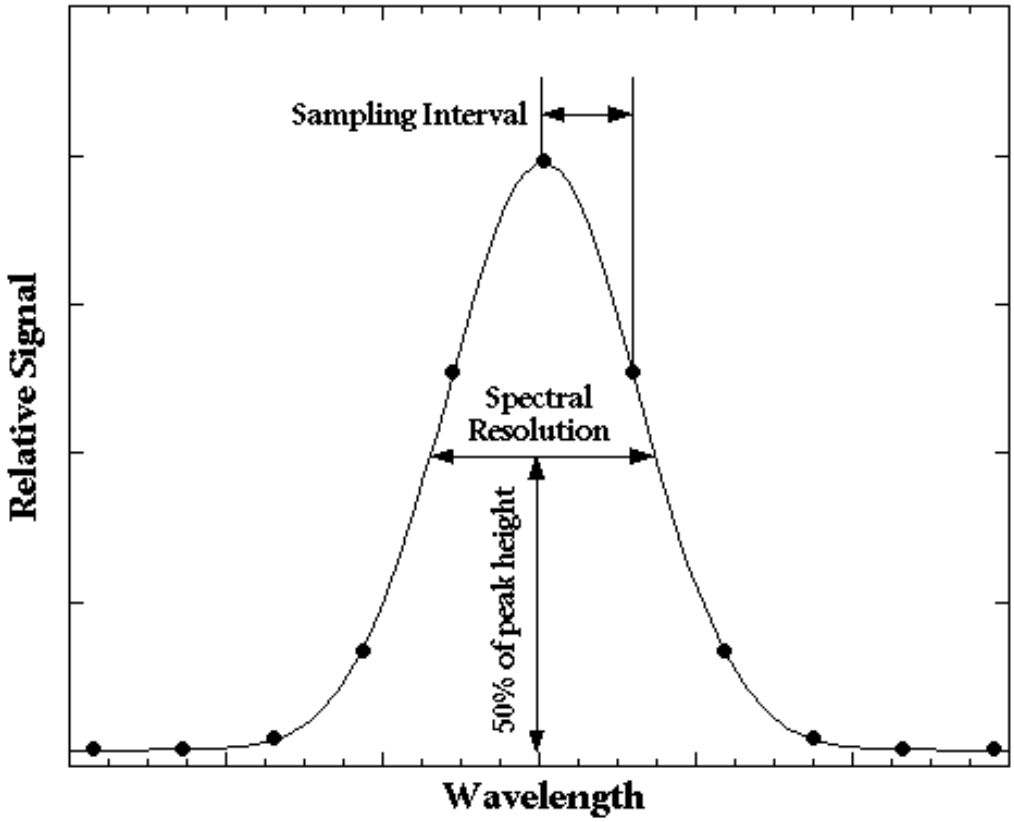

Figure 3. An illustration of the terms *Sampling Interval*, *Spectral Resolution* and *Full Width Half Maximum* (Analytical Spectral Devices Inc., 1999, http://www.asdi.com/apps/inst_sr.html)

2.2 Hyperspectral Remote Sensing Applications

Many features on the earth's surface can be identified by unique absorption features in their reflectance spectra. This knowledge has been used extensively in attempts to identify features (or feature groups) from remote platforms and in doing subsequent classification of imagery.

The process of species classification was preceded by studies that attempted to identify the regions of dissimilarity in vegetation spectra. For this study's purpose, the studies concerning leaf chemical content and characteristics are of particular interest. Not only do these studies provide the base from which spectral separability between species can be tested, they also identify the regions which might be most important in distinguishing one species from another.

2.2.1 Remote Sensing of Forest Foliar Chemistry

Most studies utilized spectroradiometers, although a few also investigated foliar chemistry determination by using sensors from remote platforms. Card *et al.* (1988) used a spectroradiometer with a wavelength range from 400-2446 nm to analyze dried and ground leaf samples. The natural logarithm of 1/reflectance was regressed against nitrogen content and R^2 = 0.93 was obtained. The R^2 values for other chemicals were lower, although protein, with R^2= 0.77, and lignin, with R^2 = 0.70, also yielded good results. Stepwise regression was used and this might be problematic, as the analysis methods are not independent of the samples chosen for calibration and the mathematical transformations used (Card *et al.*, 1988).

This was followed by incorporating AIS airborne data in a similar study (Peterson *et al.*, 1988), as well as using laboratory readings from both fresh and dried samples. Although a significant correlation between leaf area index and AIS spectral data was expected, none was found. A strong inverse relationship between canopy water content and AIS data was found and this resulted in great variations between the field data and the laboratory data. An important feature was also identified between 1500-1750 nm and linked to lignin and starch content. Due to sensor noise, the region from 2036-2400 nm was not used, although it was recognized that this area in the spectrum might contain predictive information for nitrogen (Peterson *et al.*, 1988). Wessman *et al.* (1989) also used AIS data in a study to estimate forest canopy chemistry. A mixture of band differencing techniques (first and second order differences) and principal components analysis were used. Band differencing reduces baseline shifts and decreases the effects of slowly varying absorption features in the spectra. Nitrogen had a strong relationship with first-order bands 1265 nm and 1555 nm, but in the second-order bands, only lignin proved significant. In the principal component analysis, 91% of the variance in the first-order difference

was explained by the first seven principal components. Again a warning is issued to the use of stepwise procedures, as the authors felt more evidence to its validity was needed (Wessman *et al.*, 1989).

Chlorophyll concentration in slash pine (Pinus elliottii) was shown to be highly correlated (correlation coefficient = 0.85) with the first derivative of wavelength 723 nm in an AVIRIS data set (Kupiec and Curran, 1993). The stepwise regression analysis (dependent variable was chlorophyll concentration; independent variables were AVIRIS wavebands) was highly significant with R^2 = 0.96 when using bands 723 nm, 2371 nm and 1552 nm, with band 723 accounting for 73% of the variation in chlorophyll concentration. The absorption features at 0.4-0.7 μm, due to chlorophyll, and at 0.97, 1.2, 1.4 and 1.94 μm due to the stretching of the O-H bond in water and other chemicals proved especially significant in other studies (Curran, 1989; Yoder and Pettigrew-Cosby, 1995). Curran (1989) warns of the dangers of overfitting when the number of samples is smaller than the number of wavebands used in the analysis.

Ground breaking work in the leaf biochemistry arena was done by both Martin and Aber (1997) and Kokaly and Clark (1999). Martin and Aber (1997) attempted to characterize forest canopy chemistry using AVIRIS data at a spatial resolution of 20 m. The forest stands studied were composed of either mixed broad-leaved species of primarily oak (Quercus rubra) and maple (Acer rubrum) or needle-leaved species consisting of red pine (Pinus resinosa), white pine (Pinus strobus), Norway spruce (Abies balsamea), larch (Larix laricina), and Eastern hemlock (Tsuga canadensis). Leaf samples were analyzed for nitrogen and lignin concentration. Multiple linear regression was used to investigate the relationship between the AVIRIS imagery (pre-processed to obtain the first-difference transformation) and the field-measured foliar chemical concentration. The two bands that were selected for input in the nitrogen prediction equation were centered at 750 nm and 2140 nm (Harvard Forest) and 950 nm and 2290 nm (Blackhawk Island). Absorption in the 700 nm region is related to foliar chlorophyll concentration, which is in turn highly correlated with protein content, and hence nitrogen content. Lignin content was in turn related to the AVIRIS imagery using four bands in the range 1660 – 2280 nm (Harvard Forest) and 790 nm and 1700 nm (Blackhawk Island). For combined site calibration the 783 nm and 1640 nm bands were used for nitrogen concentration prediction and 1660 nm for lignin

concentration. For nitrogen prediction at Harvard Forest and Blackhawk Island, $R^2 = 0.87$ and $R^2 = 0.85$ were obtained respectively, while $R^2 = 0.70$ and $R^2 = 0.78$ were obtained for the lignin concentration at the same sites. Combined-site predictions were also very promising with $R^2 = 0.87$ for nitrogen and $R^2 = 0.77$ for lignin. Cross-site predictions were slightly lower, especially for lignin with $R^2 = 0.01$ for Blackhawk Island using the lignin equation calibrated at the Harvard Forest site (Martin and Aber, 1997).

The latest approach taken by Kokaly and Clark (1999) utilizes normalized band depths which are calculated from continuum-removed reflectance spectra of dried, ground leaves for estimation of nitrogen, lignin and cellulose concentrations. The steps in this process include (i) the continuum removal from reflectance spectra after selection of broad absorption features at 1730 nm, 2100 nm and 2300 nm for continuum analysis, (ii) band-depth normalization through division of channel band depth by band center band-depth and (iii) analysis of normalized band-depth values for all the wavelengths in the three continuum-removed absorption features using stepwise multiple linear regression to determine wavelengths correlated with leaf chemistry. The analysis was done using single channel values which had a 10 nm bandpass in order to develop a method applicable to remote sensing data and not only to spectroradiometer data. Five wavelengths were selected for nitrogen prediction, all of which fell in the 2100 nm absorption feature; six wavelengths were selected for the lignin prediction, two in in the 1730 nm and four in the 2300 nm absorption features; eight wavelengths were selected for the cellulose regression, with a few in each of the absorption features. Wavelength correlations with chemistry at other eastern United States sites were also tested and correlations as high as $R^2 = 0.75$ to 0.94 were found in the case of nitrogen. The R^2 for lignin and cellulose were as high as 0.65 and 0.78, respectively. This marks the way for the establishment of a single equation used to estimate chemical concentrations in dried leaves from reflectance spectra. It was found leaf water content is the greatest impediment to extending this method to complete vegetation canopies and fresh leaves. It was concluded that the influence of leaf water content on reflectance spectra must be removed to within 10% for effective utilization of this technique. Other effects, such as signal-to-noise ratio, atmospheric effects and background noise, were reduced by continuum removal and normalization of band depths (Kokaly and Clark, 1999).

Studies such as the ones discussed here indicate that there might be reason to expect spectral differences among species due to different chemical make-up. Whether differences in vegetative chemical constituents truly exist for different species, or whether foliar chemical analysis can in any way only be done on a per species basis, are questions that the locations of wavebands significant for species separation might shed some light on.

2.2.2 Spectral Separability among Species using Hyperspectral Sensors

2.2.2.1 Related Studies

It was recognized from an early stage on that the spectral separation between forest species might not be as easy as it is between soils (or other more specific mineralogical types) and other vegetation types. A study of a classification of soil spectra (Palacios-Orueta and Austin, 1996) proved successful and many of the techniques used by this type of study might be useful in later vegetation related studies. Methods such as the use of principal components analysis for the reduction of data dimensionality and stepwise discriminant analysis again proved to be successful in the identification of those variables important for discrimination (Palacios-Orueta and Austin, 1996). Two noxious woody pest plants in Texas, Chinese tallow (Sapium sebiferum) and Macartney rose (Rosa bracteata), could be spectrally distinguished from surrounding vegetation using only multispectral imagery (multispectral radiometer, color and near-infrared aerial photographs) (Everitt *et al.*, 2000). When compared to the surrounding vegetation, which included hackberry (Celtis laevigata), dryland willow (Baccharis neglecta), dewberry (Rubus trivalis) and mixed herbaceous species, Chinese tallow had a higher reflectance in the visible red region (630-690 nm) during fall, while Macartney rose showed higher reflectance in the near-infrared region (760-900 nm) during winter (Everitt *et al.*, 2000).

Separation of three types of mosses (*Spaghnum* spp., feather and brown mosses) has been successfully attempted using the Visible/Infrared Imaging Spectrometer (VIRIS; range: 400 nm – 2500 nm; spectral resolution: 2 nm – 4 nm) under laboratory conditions, but mosses do exhibit different reflectance characteristics than do vascular plants for the visible, NIR and SWIR regions (Bubier *et al.*, 1997). Four species of mosses in the genus *Spaghnum* were further shown

to be spectrally separable using the VIRIS instrument, concentrating on the visible (450 nm – 700 nm) and near infrared (700 nm – 1300 nm) regions (Vogelmann and Moss, 1993).

The TWRIS III sensor (range: 400 nm – 2450 nm, spectral resolution: 5 – 6 nm) was used for spectral vegetation separation of agricultural crops ranging from row vegetable crops to fruit orchards. A comparison between the results obtained after an orthogonal subspace projection across the whole spectral range (PCA technique used) and that of a spectral ratio approach (bandwidths ranging from 682 nm to 776 nm), showed the spectral ratio approach to be more successful. However, when the PCA was applied to the same twenty red and near-infrared bands used in the ratio approach, the results were similar (Winter, 1998). This again highlights the necessity for data reduction, either by identifying bands inherently important in discriminating between the species being studied, or by data compression (averaging or sampling). AVIRIS data have been used to map chaparral successfully (over 80% of the image modeled) by using multiple endmember spectral mixture models. Although the study image could be modeled to over 80% completeness using only two endmembers in a linear mixture model, a total of 24 endmembers were mapped across the image (Roberts *et al.*, 1998). AVIRIS imagery (SWIR only region: 2 – 2.5 μm) was used in a similar study by (Drake *et al.*, 1999) for mapping vegetation, soils and geology in semi-arid shrublands. Spectral matching of pure library spectra were more successful for geological mapping, as opposed to mixture modeling being more successful for rangeland vegetation studies. The SWIR data's low signal-to-noise ratio introduced some problems related to random and systematic noise, but the image was smoothed by performing a PCA analysis and inverting the transform using just the components that contained genuine information (Drake *et al.*, 1999). Much more research in this arena is required, but these results may indicate the possibility of mapping large forested areas using forest species spectral endmembers (pure species spectra/signatures) as input to such a classification scheme, given that the applicable species are spectrally separable.

2.2.2.2 ***Forestry Specific Studies***

Hyperspectral approaches have also been applied to various forestry related research questions, but to a far lesser degree than was done in agriculture and mining (mineralogical) applications.

The CASI sensor range: 430 nm – 950 nm; spectral resolution: 1.8 nm) was used in a relatively successful study to separate different forest stand ages for Douglas fir (Pseudotsuga menziesii). Linear discriminant analysis was used on the green-red ratios and the NDVI and accuracies ranged from 54% (class 1: 0 –20 years) to 84% (class 2: 21 – 40 years). No separation was possible between stands older than 40 years (Niemann, 1995).

Considering this, it might be a fruitful exercise to compare spectra collected for which all the sampled trees are older than approximately forty years. This could reduce within species variation and highlight genuine or absolute spectral differences that exist between different species. This would unfortunately not be applicable to operational data, in which case one usually deals with imagery which covers a broad range for a larger number of species.

Another aspect to consider is that of spectral reflectance properties and different scales within a single tree. Williams (1991) has shown that spectral reflectance properties differ at the needle, branch and canopy scales for three conifer (Norway spruce, red pine, and white pine) and one deciduous species, sugar maple (Acer saccharum), when measured using a spectrometer. In general it was found that reflectance magnitude decreased throughout the visible and near-infrared wavelengths for the conifer species as the scene complexity increased from needle to the coarser canopy level. Hardwoods were also shown to be less absorptive than conifers and it was concluded that canopy constituents play a big part in changing reflectance characteristics of the overall scene (Williams, 1991). This indicates the necessity of a vegetative reflectance study to be carried out at a specified scale throughout sample collection.

Although reflectance magnitude may differ between the needle and branch levels for a single age-class, Rock *et al.* (1994) mention that the shape of the reflectance curves (400 nm – 2500 nm) remains the same for red spruce (Picea rubens) and eastern hemlock (Tsuga canadensis). The study also showed that spectral differences between spruce and hemlock first– and second-year needles included differences in the peak green reflectance, red-edge characteristics and amplitude characteristics of the near-infrared plateau (Rock *et al.*, 1994). The use of such specific spectral features for spectral curve comparison might thus be precluded because of the high variation in these features between different ages and growth conditions. This is confirmed

by Ferns *et al.* (1984) in a study that stresses the effect chlorophyll concentration, not only within the leaves themselves, but also between plants, has on the red-edge position.

In another study focusing on forest vigor characterization through hyperspectral data, reflectance characteristics of balsam fir (Abies balsamea) were shown to differ between different levels of forest vigor (defined by length of first-order terminal shoots, chlorophyll *a* and *b*, nitrogen concentrations, and percent moisture) (Luther and Carroll, 1999). One-way analysis of variance at each 1 nm waveband (350 nm – 2500 nm) was used to determine where treatment vigor (which included root pruning, thinning, thinning with fertilization and control) had the greatest influence in reflectance. The control plots did not receive any of the treatments. Reflectance was generally found to decrease with vigor, with the most significant wavebands showing the effects of the treatments situated in the chlorophyll absorption range (500 nm – 740 nm), while foliage age class and sample date also influenced reflectance. The ratio and normalized difference between the most significant (711 nm) and least significant (913 nm) wavebands were affected by treatments and the normalized difference index correlated with chlorophyll content ($R^2 \geq 0.75$ for chlorophyll a). The authors concluded that the normalized difference index could thus be seen as a spectral index of tree vigor, integrating several aspects of forest condition (Luther and Carroll, 1999). In another treatment vs. spectral reflectance study, needle and canopy treatments' spectral characteristics were shown to be significantly different between treatments (low, medium and high fertilization) in the visible region (Dungan *et al.*, 1996). Some significant differences were also found between the two higher fertilization application treatments in the near-infrared region. Most of these differences were ascribed to the large variation in chlorophyll content due to the different fertilization regimes (Dungan *et al.*, 1996). Studies such as the latter two accentuate the point that any given spectral analysis and its results are very reliant on the physiological conditions of the vegetation being studied.

Shaw *et al.* (1998) found a correlation between Scots pine (Pinus sylvestris) sapling cover and waveband-ratios from a hyperspectral dataset. Changes in sapling cover were most highly correlated with the ratio of reflectance at 757 nm and 722 nm (R_{757}/R_{722}). Using first derivative data as a curve shape descriptor, the highest correlations between sapling cover and first derivative spectra were found at the ratios of the wavebands at 719 nm and 703 nm (D_{719}/D_{703}),

which characterized the red-edge inflection point, and 730 nm and 700 nm (D_{730}/D_{700}). Neither seasonal color changes in canopy appearance nor the seasonal greening of background vegetation had any effect on the correlation between reflectance indices and pine cover (Shaw *et al.*, 1998).

2.2.2.3 Spectral Separability among Forestry Species using Hyperspectral Data

The importance of the visible and near-infrared wavelength regions, as well as derivative spectral analysis, were stressed in almost all of the vegetation studies utilizing hyperspectral data. Hyperspectral technology, with its inherent resolving properties, does appear to be ideally suited to a task as difficult as species separation on a spectral basis. The use of hyperspectral data collected with a spectroradiometer for conifer species recognition has been explored to a certain extent, although not extensively. The results obtained by Gong *et al.* (1997) were very promising and showed very good spectral differentiation for the six coniferous species, sugar pine (Pinus lambertiana), ponderosa pine (Pinus ponderosa), white fir (Abies concolor), Douglas fir (Pseudotsuga menziesii), incense cedar (Calocedrus decurrens), giant sequoia (Sequoiadendron giganteum), and one hardwood species, California black oak (Quercus keloggii), tested. The data were collected using a ground-based spectroradiometer with a wave range of 250-1050 nm and spectral resolution of 2.6 nm. The analysis methods consisted of two approaches, namely an artificial neural network algorithm and a discriminant analysis, after initial pre-processing (smoothing and derivative analysis) was done on the data. In some cases, an accuracy of greater than 91% was obtained using sunlit samples alone. The effects of site background and illumination changes on species' spectra were found to be large (influenced by conditions as well as leaf properties). Their study also found that the visible bands had higher discriminating power than near-infrared bands (blue-green the best followed by the red-edge), although this is in contrast with other findings (Gong *et al.*, 1997).

Fung *et al.* (1999) used a spectroradiometer with range 210-1050 nm, but only used the portion of the spectrum between 400-900 nm. A hyperspectral database was constructed for the species being studied by collecting spectral samples from each species during all four seasons. These species included slash pine (Pinus elliottii), baldcypress (Taxodium distichum), tallowtree (Sapium sebiferum), punktree (Melaleuca quinquenervia) and bottletree (Firmiana simplex). The

first and second derivatives of the spectra were used in a linear discriminant analysis and the accuracies varied from 56-91%. The original spectra tended to produce better results than the first and second differences. Summer and spring accuracies were found to be significantly lower than those obtained for winter and autumn, which can be attributed to leaf color changes and hence lower reflectance in the green and near-infrared reflectance for the latter two seasons. The lower leaf water content during the two drier seasons (winter and autumn) could also have made a difference as this reduced the effect of water content on spectral readings. A principal components analysis also showed the first four components to be of value, while in the case of broadband imagery, most of the information is usually contained in the first two components (Fung *et al.*, 1999).

A classification of AVIRIS data into 11 different forest cover types, including red maple (Acer rubrum), red oak (Quercus rubra), white pine (Pinus strobus), red pine (Pinus resinosa), Norway spruce (Picea abies), and pure hemlock (Tsuga canadensis), as well as mixtures thereof, has been attempted and also yielded very promising results (Martin *et al.* 1998). This approach implemented a maximum likelihood classifier and was based on 11 AVIRIS bands previously used to derive relationships between foliar chemistry (nitrogen and lignin concentration) and hyperspectral data. It was shown that both nitrogen and lignin information were important for species discrimination. The bands corresponding to these chemicals are 620 - 820 nm, 1640 - 1740 nm, and 2140 - 2280 nm. The overall classification accuracy was 75% (Martin *et al.*, 1998). Lawrence *et al.* (1993) found distinct visual differences between coniferous and deciduous vegetation using AVIRIS imagery acquired over hemlock-spruce-fir (*Tsuga* spp., *Picea* spp. and *Abies* spp.) hemlock-hardwood (*Tsuga* spp. and hardwoods) and aspen-birch (*Populus.* spp and *Betula* spp.) mixed stands. Although no quantitative result is given, the possibilities of linear mixture modeling and distinct spectral differences (especially in the near-infrared region of the spectrum) are mentioned. The intrinsic problems that arise when in-field or airborne spectra are analyzed are also mentioned. These problems include noise due to atmospheric absorption regions, spectral curves that differ from laboratory derived curves due to this “rougher” (noisier) appearance, and mixed pixels (Lawrence *et al.*, 1993).

An attempt at classifying forests (containing oak, beech and pine trees) using a combination of airborne spectrometer and SAR data yielded classification accuracies ranging from 82.1% to 97.6% (Volden *et al.*, 1998). The spectrometer used was the Reflective Optics Spectrometric Imaging System (ROSIS), with 81 spectral bands (4 nm – 12 nm sampling) and 16 m spatial resolution. The auxiliary data consisted of 10 SAR images, covering the X, P and C bands. Classification accuracies for six classes, namely three oak (*Quercus* spp.) height classes (0 - 13 m, 13 – 30 m, > 30 m), two beech (*Fagus* spp.) classes (13 – 30 m, > 30 m), and a pine (*Pinus* spp.) class were determined. Accuracies varied between 80.8% and 96.5% when using only the hyperspectral data, and increased to 86.4% - 97.5% using the 81 hyperspectral bands in conjunction with the 10 SAR images. For the 10 SAR images alone, the highest accuracy for the four-class classification was 67.5% (Volden *et al.*, 1998). Although the classification accuracy of the ROSIS data alone was not lower than 80.8%, the use of the SAR images as auxiliary data shows the usefulness of such auxiliary data in deriving a more accurate classification. The results for studies looking at spectral discrimination of species using hyperspectral data are summarized in Table 1.

Table 1. A summary of studies determining spectral discrimination of species using hyperspectral data

Study	**Sensor**	**Wavelength range (nm)**	**Bandwidths (nm)**	**Species**	**Discriminating regions (nm)**
Lawrence *et al.* (1993)	AVIRIS	400 - 2500	10	Hemlock-spruce-fir (*Tsuga* spp., *Picea* spp. and *Abies* spp.), hemlock-hardwood (*Tsuga* spp. and hardwoods), aspen-birch mixtures (*Populus* spp and *Betula* spp.)	Used 150 of the 224 bands (bands that were discarded were located in the atmospheric absortion regions)
Gong *et al.* (1997)	High spectral resolution dual spectro-meter PSD 1000	210 - 1050	0.5	Sugar pine (Pinus lambertiana), ponderosa pine (Pinus ponderosa), white fir (Abies concolor), Douglas fir (Pseudotsuga menziesii), incense cedar (Calocedrus decurrens) and giant sequoia (Sequoiadendron giganteum) and California black oak (Quercus keloggii)	Visible bands (333 nm – 700 nm) better than near-infrared (700 nm – 923 nm) bands; blue-green (462 nm – 505 nm) best, with red-edge (700 nm – 744 nm) second best. The yellow-edge (590 nm – 641 nm) was the worst

Table 1. A summary of studies determining spectral discrimination of species using hyperspectral data (continued)

Study	Sensor	Wavelength range (nm)	Bandwidths (nm)	Species	Discriminating regions (nm)
Martin *et al.* (1998)	AVIRIS	400 - 2500	10	Red maple (Acer rubrum), red oak (Quercus rubra), white pine (Pinus strobus), red pine (Pinus resinosa), Norway spruce (Picea abies) and pure hemlock (Tsuga canadensis), and mixtures thereof	627, 750, 783, 822, 1641, 1660, 2140, 2280, 2290
Volden *et al.* (1998)	Reflective Optics Spectrometric Imaging System (ROSIS) and the Synthetic Aperture Radar (SAR) sensor	Spectrometer 350–850 nm (visible and near-infrared spectrum), SAR: X (3 cm), P (65 cm), C (6 cm) and L (24 cm) bands	Spectrometer 12 (visible portion of spectrum) and 4 (near-infrared portion of spectrum)	Oak (*Quercus* spp.), beech (*Fagus* spp.) and pine (*Pinus* spp.)	Used all 81 bands and combinations thereof to simulate Landsat TM and SPOT data
Fung *et al.* (1999)	PSD 2000 high spectral resolution spectrometer	210 – 1050	0.5	Slash pine (Pinus elliottii), baldcypress (Taxodium distichum), tallowtree (Sapium sebiferum), punktree (Melaleuca quinquenervia) and bottletree (Firmiana simplex)	Used all the bands between 400 nm – 900 nm (689 in all) and 138 systematically selected bands

2.3 Analysis of Hyperspectral Data

Almost all studies utilizing hyperspectral data require some form of data pre-processing. The most important steps in such pre-processing stages are the reduction of data dimensionality and the smoothing (or averaging) of spectral curves through some method or another. According to Hsieh and Landgrebe (1998) the performance of any classification is dependent on four factors:

- Class separability
- Size of the training sample
- Data dimensionality
- Type of classifier (or discriminant function)

The reduction of data dimensionality makes valid statistical inferences possible, as the ratio of variables and sample size is usually very large in the case of hyperspectral data and has to be reduced (Hoffbeck and Landgrebe, 1996). Dimensionality reduction techniques are plentiful and broad categories include spatial autocorrelation-based band selection strategies, as well as spectral autocorrelation-based approaches, which in turn includes optimization of distance matrices (e.g., divergence) and basis function optimization (*n* basis functions that represent the original data set) (Petrie and Heasler, 1998). Warner and Shank (1997) investigated the use of spatial autocorrelation techniques (narrow band feature selection, broad band feature selection and nonadjacent multiple band feature selection) for data reduction when using AVIRIS imagery. It was shown, for example, that the visible and near-infrared portion of the spectral data (less than 1250 nm) were the most important regions for the imagery used in the study (AVIRIS data of a shrub-steppe environment in southcentral Washington). The nonadjacent multiple band feature selection algorithm tended to group adjacent bands in the visible and near-infrared spectral regions, thereby showing that unique absorption features that are broader than the spectral resolution of the AVIRIS sensor exist in the image (Warner and Shank, 1997). The strong spectral wavelength correlation that exists for reflectance data has been used in another band selection study to discriminate five surface types (water, snow, fire, vegetation and a residual class, which is mainly soil). Five spectral bands (460-540 nm, 610-690 nm, 990-1090, 1520-1610 nm and 2080- 2170 nm) were shown to contain 98% of the mean square spectral

signal and were adequate to distinguish between the five surface types. Twenty bands were necessary to describe spectral behavior with a mean square error of less than 0.1%, except for the water class which was at the noise level of the AVIRIS sensor. Interestingly, the spectral band that was statistically the most significant, 990–1090 nm, is not present in many Earth-observing instruments (Price, 1998).

Principal component analysis can be very successful in reducing data dimensionality to the components containing inherent image (reflectance) information (Fung *et al.*, 1999). Stepwise discriminant analysis, a procedure that reduces the data set to those variables that maximize between statistical group variability while minimizing within group variability, has also been used successfully to reduce the number of wavelength variables (data dimensionality). Principal component analysis differs from discriminant analysis in that new vector variables that define the axes of greatest variability in the data are created in the first case, while the original variables that best decribe differences between given groups are identified in the second case. Stepwise discriminant analysis was done specifically as a precursor to other statistical techniques (such as canonical discriminant analysis) for group separation based on spectral characteristic analysis by Palacios-Orueta and Ustin (1996).

Smoothing or averaging of hyperspectral curves, on the other hand, plays a very important role, especially in studies where the first and second differences of spectral data are analyzed. Since these differences are taken across each spectrum at relatively small intervals, very small local peaks or valleys in the spectrum can affect them (i.e., spectrum derivatives are very sensitive to random noise). This is especially true in the case of the second difference, and very powerful smoothing algorithms are sometimes needed in spectral analysis (Jain *et al.*, 1995; Tsai and Philpot, 1998).

Smoothing algorithms can take many shapes and forms. Calculating a mean across a number of values, or spectrum averaging, is a very common way of attempting to decrease noise present in samples collected with a hyperspectral scanner (Williams, 1991; Bubier *et al.*, 1997; Gong *et al.*, 1997; Shaw *et al.*, 1998; Luther and Carroll, 1999). Rock *et al.* (1994) and Vogelmann and Moss (1993) used a simple nine-point weighted averaging function which assigned a greater

weight to the central spectrum value and smaller weights towards the periphery of the filter. This can be a very handy tool, as critical features in a spectrum are not averaged out but maintained while smoothing of the curve takes place. Drake *et al.* (1999) smoothed spectral curves collected by the AVIRIS system by calculating the principal components of the curves and just using those components containing any valuable information.

This might be a dangerous route to follow, since principal component analysis separates the data along its axes of major variation, and these axes might not lay along breaks between two or more species spectra, but within a species or taxonomic group itself. The use of the frequency domain (Fourier transform) in identifying and removing spectrum components of high frequency (i.e., noise-components) has also been implemented successfully in species discrimination studies (Fung *et al.*, 1999).

Other well-known smoothing algorithms include the Savitzky-Golay smoothing and derivative algorithm (simplified least-square-fit) (Savitzky and Golay, 1964; Tsai and Philpot, 1998) and Kawata and Minami linear least mean-square smoothing (Kawata and Minami, 1984; Tsai and Philpot, 1998), which uses a least mean square process, adapted to take noise that varies with wavelength into account. These two filters and a mean (moving window) filter were compared in a study by Tsai and Philpot (1998). The mean filter achieved the greatest smoothing effect, but might also have suppressed more details than the two more advanced filters. The Savitzky-Golay or Kawata-Minami filters will perform better than a mean filter when spectral features are smaller than or on the same order as the filter size. When the spectral features are broad and the noise is of high frequency compared to actual features, there is however little difference between the three smoothing methods. The mean filter is preferred because of its simplicity and high computation speed (Tsai and Philpot, 1998).

Introducing a low pass (or smoothing filter) in a classification algorithm can actually increase class separability. The lowpass filter can actually reduce the variation of samples within each class, thereby widening the gap between classes in the feature space and reducing the constraint on the precision of decision boundary. These two attributes can thus increase classification accuracy and the ease of implementing a low pass filter is an added benefit. The crucial

requirement for such an approach is that the data set has solid information about class-dependent spatial correlation. In an attempt to alleviate the peaking phenomenon that appears in the relation of classification accuracy versus data dimensionality (called the Hughes phenomenon), it was shown that a low pass filter was one of the components that contributed to the reduction of this peaking effect in classification. The filter consisted of a moving window, with each sample being replaced by the weighted average of its neighboring samples (equal weighting was used for simplicity and efficiency). The data set did, however, consist of multipixel homogeneous objects (Hsieh and Landgrebe, 1998). Classification of a homogeneous data set would more accurate when compared to that for a mixed-pixel data set, but the usefulness of the smoothing filter was proven.

The first and second difference of reflectance spectra also features in many studies across the range of hyperspectral vegetation analysis (Niemann, 1995; Bubier *et al.*, 1997; Gong *et al.*, 1997; Martin and Aber, 1997; Martin *et al.*, 1998; Shaw *et al.*, 1998; Fung *et al.*, 1999). The use of spectral derivatives (after mean filter smoothing) to classify seven wetland plant associations (*Carex*, *Zizania*, *Artemisia*, *Cardamine* species and mixtures thereof) yielded an average classification accuracy of 84% (Wang *et al.*, 1998). The main reason for this is that derivatives of spectral data should be relatively insensitive to variations in illumination intensity caused by sun angle, cloud cover and topography (Tsai and Philpot, 1998). This makes the comparison of hyperspectral data collected at different times of day and at different sensor angles more attainable, since curve shape now becomes inherently important, as opposed to curve magnitude. The effect of band separation on second order derivatives has also been studied (Tsai and Philpot, 1998) and it was concluded that derivatives extract different information from spectra at different wavelength scales. Another way of matching curve shape and not differences in reflectance magnitude is by normalizing spectra. One example of such a normalization procedure (Drake *et al.*, 1999) converted reflectance spectra to variations about the mean of each spectrum.

Many studies utilize ratios between known key-feature points in vegetation spectra, such as the red-edge inflection point, the chlorophyll absorption well, the green reflectance peak, or vegetation indices such as the normalized difference vegetation index or NDVI (Rock *et al.*,

1994; Bubier *et al.*, 1997; Shaw *et al.*, 1998; Winter, 1998; Luther and Carroll, 1999). Some of these curve features (e.g., the red-edge position) show variations with different vegetation ages and are thus unstable indices when attempting to separate species (Niemann, 1995). Some of the key features in vegetation spectra are shown in Figure 4.

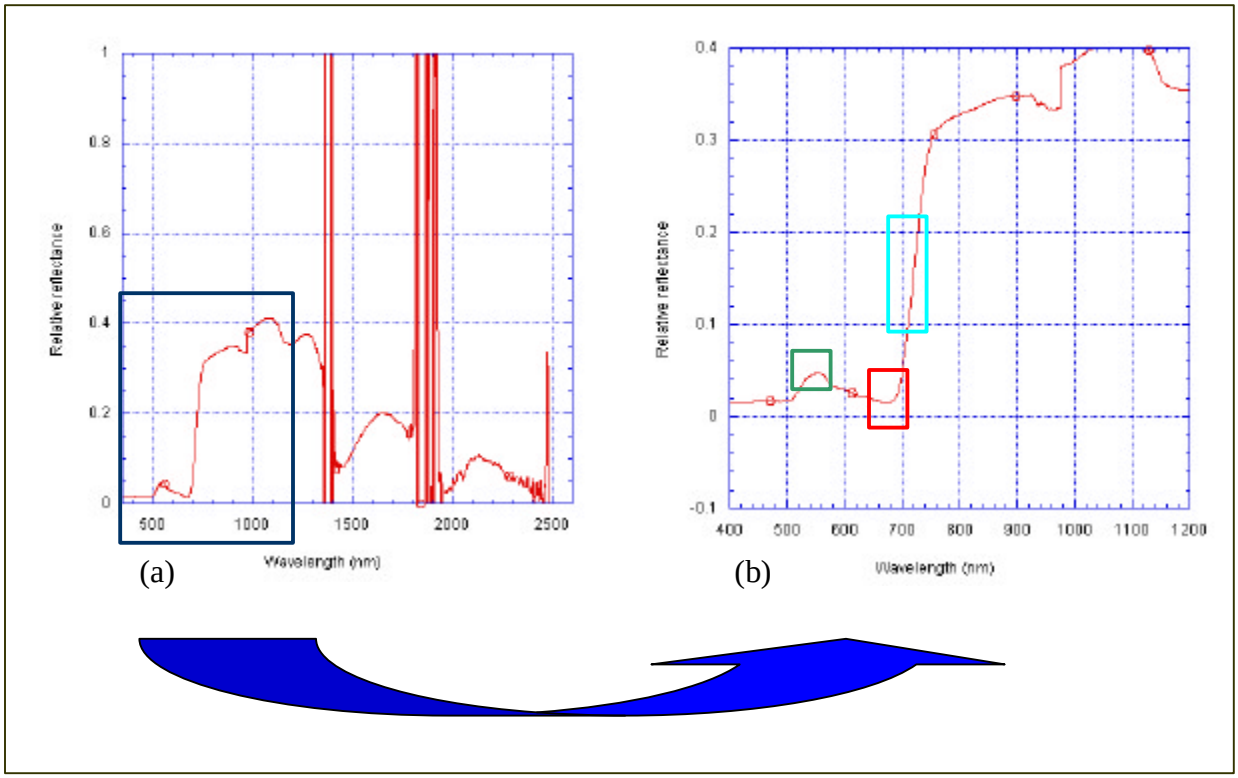

Figure 4. An illustration of some key features in a typical vegetation spectrum (a). The green reflectance peak (green), chlorophyll absorption well (red), and red-edge inflection point (cyan) are shown in (b)

The method used to detect significant differences among groups is also of critical importance. Every method has its particular prerequisites, strengths, and weaknesses. Statistical approaches include one-way analyses of variance (Luther and Carroll, 1999), correlation analyses (Shaw *et al.*, 1998), linear discriminant analysis (Niemann, 1995; Gong *et al.*, 1997; Fung *et al.*, 1999) and canonical discriminant analysis (Palacios-Orueta and Ustin, 1996). Gong *et al.* (1997) found that a neural network approach was more accurate than the discriminant analysis used, but their results varied depending on the number of samples and site chosen and might thus be considered

to be inconclusive. Other ways of matching different spectra include distance functions, which calculate the relative fit of one spectrum vs. a reference spectrum (Drake *et al.*, 1999), K-means clustering (unsupervised classification), and maximum likelihood classifiers (Hoffbeck and Landgrebe, 1996; Martin *et al.*, 1998; Volden *et al.*, 1998). Hoffbeck and Landgrebe (1996) (AVIRIS data used for soil mineral classification) warn that discriminant analysis only delivers reliable features for class separation up to the number of classes minus one. The benefits are the identification of features that maximize the separation of classes and the ability to handle high-dimensional data effectively. The Gaussian maximum likelihood classifier was shown to be relatively insensitive to noise, yielding the same results with or without the inclusion of the water absorption bands in the study (Hoffbeck and Landgrebe, 1996). The fact that the study was done on soil minerals, whose reflectance spectra have been proven to be more separable than those for vegetation, is something that has to be kept in mind. Landgrebe (1999) recognized Discriminate Analysis Feature Extraction (DAFE) as being very suitable for feature extraction when analyzing many spectral dimensions. The basic concept is for DAFE to form a linear combination of the features to maximize the ratio of between class and within class variance and it is most effective when there are relatively big differences in class mean vectors (Landgrebe, 1999).

As a final consideration, Curtis and Goetz (1994) stresses the complex mixture of transmitted and/or reflected components when measuring the light returned from a vegetation canopy. Since the canopy level light energy signal is dependent on illumination, viewing geometry, canopy structure, leaf optical properties and the optical properties of other vegetative and non-vegetative components in or below the canopy, careful consideration needs to be given to the sampling method. Only by controlling the viewing and illumination geometry can changes in canopy reflectance attributable to the canopy itself be detected. Time of day/year of data collection and viewing angles are very important considerations, especially when a comparison between in-field data and remotely sensed reflectance data needs to be done (Curtis and Goetz, 1994). The choice of sampling time and viewing angle range, as well as the randomization of canopies sampled and sampling position above canopies, are therefore all factors that are important when measuring in-field solar reflectance at a canopy level.

Chapter 3
MATERIALS AND METHODS

3.1 Sampling Methods

Spectral data were collected in the Appomattox Buckingham State Forest in Appomattox County, Virginia, USA, on August 16–18, August 28 and September 8, 1999. The data were collected using a Dodge bucket truck with a fifty-foot boom length. As canopy spectral data were used for this study, the spectral samples were taken from either above tree canopies or at least in the top third of the crown of larger (taller than 50 feet) trees. Care was also taken to only sample sunlit portions of the crown so as to avoid the inclusion of too much shadow in the samples. The data were only collected between 10h00 – 15h00 (Eastern daylight time) each day to ensure high enough sun angles resulting in adequate lighting of each sample (reduction of shadow effects). More details about the sampling method will follow later.

291 samples were collected during the five sampling days, this total being limited by accessibility and weather conditions. An effort was made to only collect a spectral sample when the sun was obscured by neither clouds nor excessive haziness. An attempt was made to randomize the collection of samples from the six species of interest: loblolly pine (Pinus taeda), Virginia pine (Pinus virginiana), shortleaf pine (Pinus echinata), scarlet oak (Quercus coccinea), white oak (Quercus alba), and yellow poplar (Liriodendron tulipifera). The first three species can be classified into the broader pine/coniferous group, while the latter three species are classified as belonging to the hardwoods/deciduous group. 280 samples were eventually used in the statistical analysis, with eleven samples eliminated due to abnormal leaf-discoloration or suspicious reflectance values. The leaf-discoloration was especially evident in some yellow poplar samples, with seasonal changes (yellowing) and brown leaf spots occuring. The samples that were identified as having suspicious reflectance values might have been over-saturated at sampling time and had zero values for most of the visible portion (350 nm – 700 nm) of the spectrum. The division of the samples per taxonomic group and species are given in Table 2. The sequence and time of day of collection, as well as the foreoptic angle, were varied. Spatial randomization was sometimes difficult, as access with the truck proved to be limiting, as well as

the heights of the trees that could be reached using a 50 foot boom. All these attempts at randomization, as well as controlling the viewing and illumination geometry, are crucial because they allow for changes in canopy reflectance attributable to the canopy itself to be detected (Curtiss and Goetz, 1994).

Table 2. Number of samples per taxonomic group/species used for statistical analysis

Taxonomic group	**Species**	**Samples**	**Total**
Hardwoods/deciduous	Scarlet oak	43	134
	White oak	47	
	Yellow poplar	44	
Softwoods/coniferous (Pines)	Loblolly pine	50	146
	Shortleaf pine	42	
	Virginia pine	54	

3.2 Equipment Used

A fifty foot boom bucket truck was used to take measurements from above tree canopies, or very high in the crowns. The spectroradiometer, a digital camera and a compass were used in the bucket for taking the spectral reflectance reading, and associated measurements. The measurement procedure and a digital photograph of a tree crown sample are shown in Figure 5, with the bucket truck that was used shown in Figure 6.

The spectroradiometer used for field data collection in this study, is the FR (Full Range) FieldSpec spectroradiometer manufactured by Analytical Spectral Devices, Incorporated. It uses a fiber optic bundle for light collection and covers the range from 350 nm – 2500 nm. The light is then projected from the fiber optics onto a holographic diffraction grating where the different wavelength components are separated and reflected for collection by the three different detectors. The Visible/Near Infrared (VNIR) portion of the spectrum (350-1050 nm) is measured by a 512-channel silicon photodiode array and has a spectral resolution of approximately 3 nm at

700 nm wavelength. The short-wave infrared (SWIR) region is measured by two detectors, SWIR1 (900-1850 nm) and SWIR2 (1700-2500 nm). The spectral resolution varies between 10-12 nm and the sampling interval is approximately 2 nm. The detectors convert the incoming photons into electrons that are stored or integrated until the detector reading is finished. This photoelectric current for each detector is then converted to a voltage, which is in turn digitized by a 16-bit analog to digital converter. The digital data are then transferred to the controlling computer resting on top of the actual radiometer (Beal, 1998).

For this study an 8° foreoptic was attached to the bare fiber bundle, enabling the user to point the instrument more accurately. This allows for a field-of-view of approximately 1.4 units diameter at a reading distance of 10 units. Each reading consisted of a 10-sample average for that particular field-of-view.

The instrument had to be "optimized" a couple of times each day. This procedure can be compared to the adaptation of a human's pupil to varying light conditions. The dark current, or the influence of the machine and environment on the readings, is measured during this operation and the gains and biases of the instrument are set. The integration time for the Visible Near-Infrared (VNIR) detector and the gain factors for each of the two Short Wave Infrared (SWIR) detectors are set when optimization takes place. Another optimization parameter, the SWIR-offset, an artificially induced dark current in the SWIR regions of the spectrum, keeps the collected spectrum situated squarely in the middle of the dynamic range of the instrument during and after optimization.

As the instrument measures the intensity of the light source through given point in space, reflectance and transmittance are calculated using measurements from both the unknown material (target) and a reference material with known spectral (reflectance/transmittance) properties.

(a) (b)

Figure 5. (a) The field measurement procedure using a bucket truck and the FieldSpec FR spectroradiometer. An example of a digital photograph of a tree crown is also shown. (b) The spectroradiometer set-up (the white reference can be seen in the top right)

A white reference material must have approximately 100% reflectance across the entire spectrum. Therefore the characteristics (change) of the light source are taken into account by taking a "white reference" and using this reading as the denominator in the ratio (relative reflectance). This is especially crucial if light conditions vary even slightly in the field. It also

Figure 6. The bucket truck used for this study and the measurement position

makes the comparison of samples taken on different times of day and between days possible (Beal, 1998). A Spectralon surface of approximately 2x2 inches was used to collect the white reference data before each sample reading. Relative reflectance or transmittance are calculated with the formula:

R (or T) = Light emitted from sample / Light emitted from white reference ….(1)

Absolute reflectance can also obtained by multiplying the relative spectra with the callibration "spectrum" (specific to the white reference used) during postprocessing (Beal, 1998).

The spectroradiometer had to be cooled down by using a battery operated fan and by keeping the instrument in the shade (umbrellas) the whole day. This was done because of temperatures reaching 100° F on some days. If the instrument overheats, the SWIR2 detector becomes especially problematic, as the dark current values used to set the gains and biases of the instrument become too large and results in zero values after subtraction for the SWIR2 region of the spectrum.

A crude device was attached to the pistol grip for measuring the angle of the reading. It was set up in such a way so that the needle was pointing at 0° when the grip (and foreoptic) were pointing straight down. A Kodak DC260 Zoom digital camera was used to collect a digital picture of each tree sampled.

Ground readings for each tree were taken using a measurement tape to record diameter at breast height and a differential PC5-L GPS unit (MS-DOS™ 5.0) from Corvallis Microtechnologies, Inc., was used to record the position of each tree from which a spectral sample was taken. The GPS data were differentially corrected using the Richmond, Virginia base station (UTM coordinates, NAD 83 datum: X = 1102094.556 m, Y = -4942504.491 m, Z = 3864934.747 m, latitude = 037° 32' 16.42942" N, longitude = 077° 25' 46.77618" W, ellipsoid height = 56.746 m) from the National Geodetic Survey's continually operating reference stations (CORS, 2000). Corvallis Microtechnologies, Inc., PC-GPS software (Version 2.5, 1993-1996) was used for the differential correction.

3.3 Field Procedure

For each tree the following data were recorded:

1. A relative reflectance reading (10-sample average) using the FR spectroradiometer, after taking a white reference reading.
2. The angle at which the reading was taken, read from the angle gauge attached to the pistol grip.
3. A digital photo of the tree crown that was sampled, pointing the camera at the same spot at which the foreoptic of the spectroradiometer was pointed.
4. Wind speed and direction, using a qualitative scale (None/Light/Moderate/Strong/Very Strong) and a compass (0.5° increments; distinction made between the eight principal wind directions).
5. Diameter at breast height of the stem of the tree that was sampled.
6. A GPS location at the stem of the tree that was sampled.
7. Notes were made to record anything of interest (weather conditions, tree appearance and condition, etc.).

A sample data sheet is contained in Appendix B. Daily weather data was obtained from the Appomattox Buckingham State Forest headquarters. The weather data are fire weather forecasts, provided by the National Weather Service (from Baltimore, Washington D.C. and Charleston, West Virginia). This included relative humidity, high and low temperatures, dew point temperature, expected cloud cover and wind speed and direction. A summary of the weather conditions for each day during the data collection is given in Table 3.

Figure 7 shows sample spectra for the three deciduous and pine species.

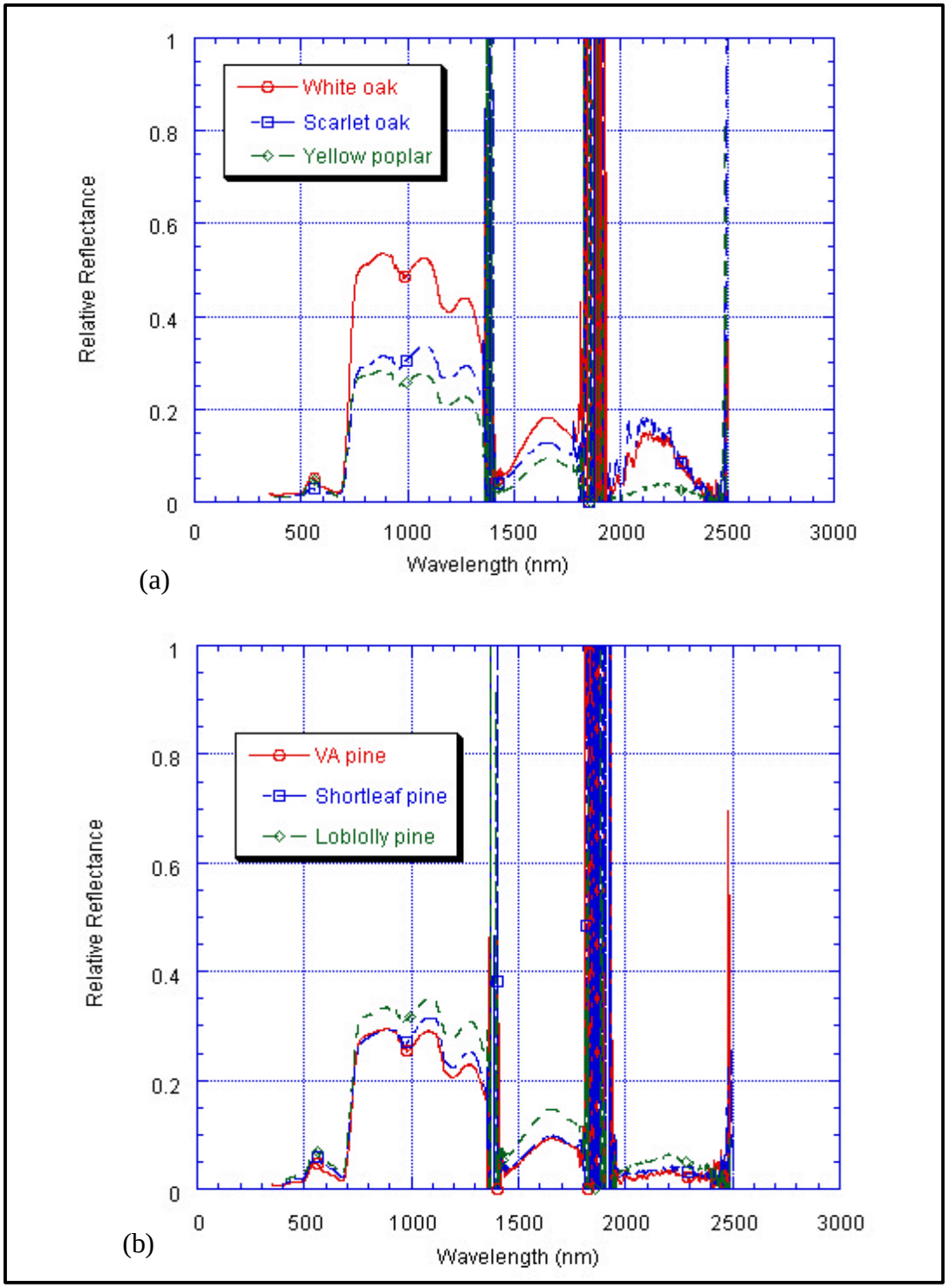

Figure 7. Sample raw relative reflectance curves for (a) decidous species and (b) pine species, collected at Appomattox Buckingham State Forest, Virginia

Table 3. Summary of the weather conditions during the data collection period

Day	Minimum humidity	Low temperature	High temperature	Wind	
				Direction	Speed
8/16/1999	45%	± 65-69° F	± 90-94° F	Variable	5 mph
8/17/1999	40%	± 65-69° F	± 90-95° F	W	5-15 mph
8/18/1999	35%	± 65° F	± 90° F	NW	5-15 mph
8/28/1999**	50%	± 65-69° F	± 90° F	W	5-10 mph
9/8/1999	40%	± 60-65° F	± 90-95° F	W	5 mph

**Extended weather forecast from 8/27/1999 used

3.4 Analysis

SAS Version 7.00 TS Level 00P1 software was used for the statistical analysis of the spectral data. The data sets used for statistical analysis varied by the type of smoothing and the derivative function applied. A total of twelve data sets were evaluated:

- The raw relative reflectance data and its first and second derivatives
- A nine-point weighted moving average filter and its first and second derivatives
- A nine-point moving median filter and its first and second derivatives
- A ten-point static average filter and its first and second derivatives (simulation of general AVIRIS spectral resolution)

In all of these data sets the water absorption regions, identified through literature (Palacios-Orueta and Ustin, 1996; Price, 1998) and visual inspection, were removed. Any range in averaged spectra that was in any way influenced by these water absorption regions was also removed. The removed water absorption regions included the following spectral ranges:

- 1350 - 1416 nm
- 1796 – 1970 nm
- 2470 – 2500 nm

The water absorption ranges that were removed are shown in Figure 8, which includes some relative reflectance curves for the three pine species studied.

The nine-point weighted averaged data sets had the following weights:

$$Y_n = 0.04R_{(n-4)} + 0.08R_{(n-3)} + 0.12R_{(n-2)} + 0.16R_{(n-1)} + 0.20R_{(n)} + 0.16R_{(n+1)} + 0.12R_{(n+2)} + 0.08R_{(n+3)} + 0.04R_{(n+4)} \quad \ldots(2)$$

where Y_n is the weighted reflectance of the target for a particular channel, R is the reflectance measured by the instrument for a particular channel and n is the channel number (Rock *et al.*, 1994).

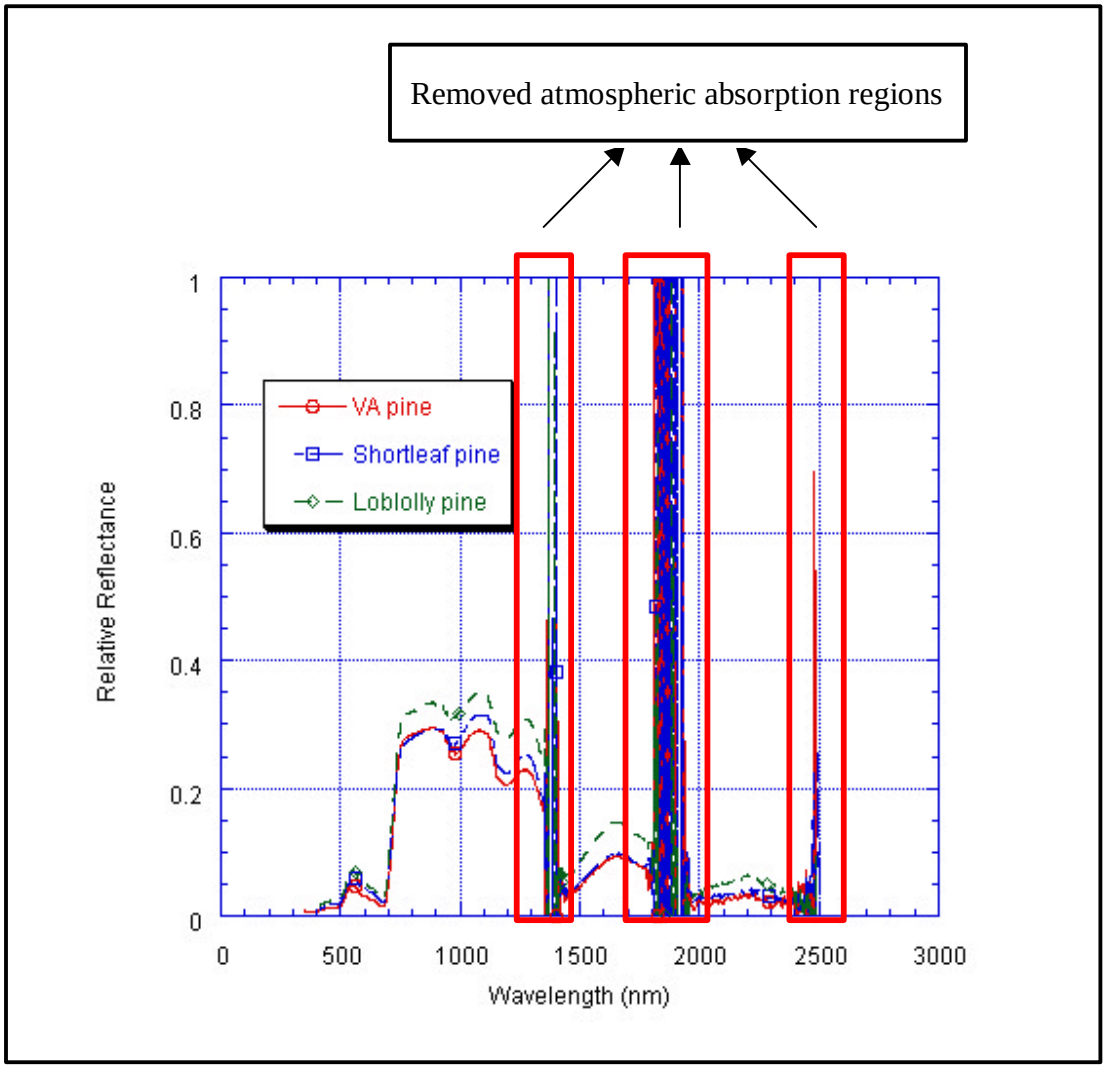

Figure 8. Relative reflectance plots for the three pine species studied, with water absorption regions that were removed as part of the data pre-processing

The calculation of the first difference of reflectance data was done by using the convolution filter:

-1	1

(Jain *et al.*, 1995)

This derivative filter approximates the first derivative of a function *f (x)* as follows:

$$\frac{df}{dx} = \lim_{\delta x \to 0} \frac{f(x + \delta x) - f(x)}{\delta x} \qquad \ldots(3)$$

This is a zero-sum filter, with the left-most value being the origin for the filter and the denominator (δx) being equal to 1. Applying the same template on the first derivative values results in the second difference of the function *f(x)*.

The ten-point static average filter was used to calculate an average value at each ten nanometer interval, derived the average of the values in the range 6-15 nm for the subsequent 10 nm averaged value. This data set was assumed to approximate operational 10 nm spectral resolution data, although specific sensor sensitivity to different radiometric regions was not taken into account.

To address the problem of the availability of a limited number of samples versus the large number of variables present in the hyperspectral data set, the reduction of data dimensionality is of utmost importance. This is also necessary in order to address the problem of correlation between adjacent wavelengths in a sample (Hoffbeck and Landgrebe, 1996). This reduction of data dimensionality was done by using a stepwise discriminant procedure (PROC STEPDISC in SAS), which selects the variables that minimize within statistical group variance while maximizing the between group variance for a given α-level. Some experimentation was needed to find the best α-level resulting in an acceptable number of variables to use in the next statistical analysis step. An α-level = 0.0025 was finally decided on, as this resulted in 5 – 20 variables, varying among data sets, being selected from the 2150 original wavelengths. These selected variables were then used in subsequent analysis. The variables chosen by the stepwise discriminant procedure were used as input to discriminant and canonical discriminant procedures (PROC DISCRIM and CANDISC in SAS) to test between and within taxonomic group species separability. The results were verified by running a cross-validation routine within the discriminant procedure, which substitutes samples in the procedure one-by-one in an iterative manner, thereby validating the results for the particular data set with the data set's own

observations. It was felt that this added to the robustness of the statistical approach discussed thus far. Plots of the canonical variables resulting from the canonical discriminant procedure were used to view and validate results visually, as well as the inspection of observations that were misclassified, or boundary cases. A data analysis flow chart is shown in Figure 9. The SAS-code for the various procedures is given in Appendix C. The variance of the canonical variables for each taxonomic group or species was also evaluated as a measure of the spectral tightness (similarity) for that group.

As a last verification of the results, the Pearson correlations among the variables selected by the stepwise discriminant procedure were calculated. If these correlations were deemed as being too high (≥ 0.90), variable sub-selection was performed and the discriminant tests were re-run to examine the influence of the elimination of these high correlations from the data sets. A method of adjusting the variables about their group means in order to address high correlations was also performed, and the actual positions of these highly correlated variables were evaluated in spectral space (relative to their respective group means). These methods helped to explain the necessity of all the variables selected by the stepwise discriminant procedure for group/species discrimination, even though some of the variables showed high linear correlations.

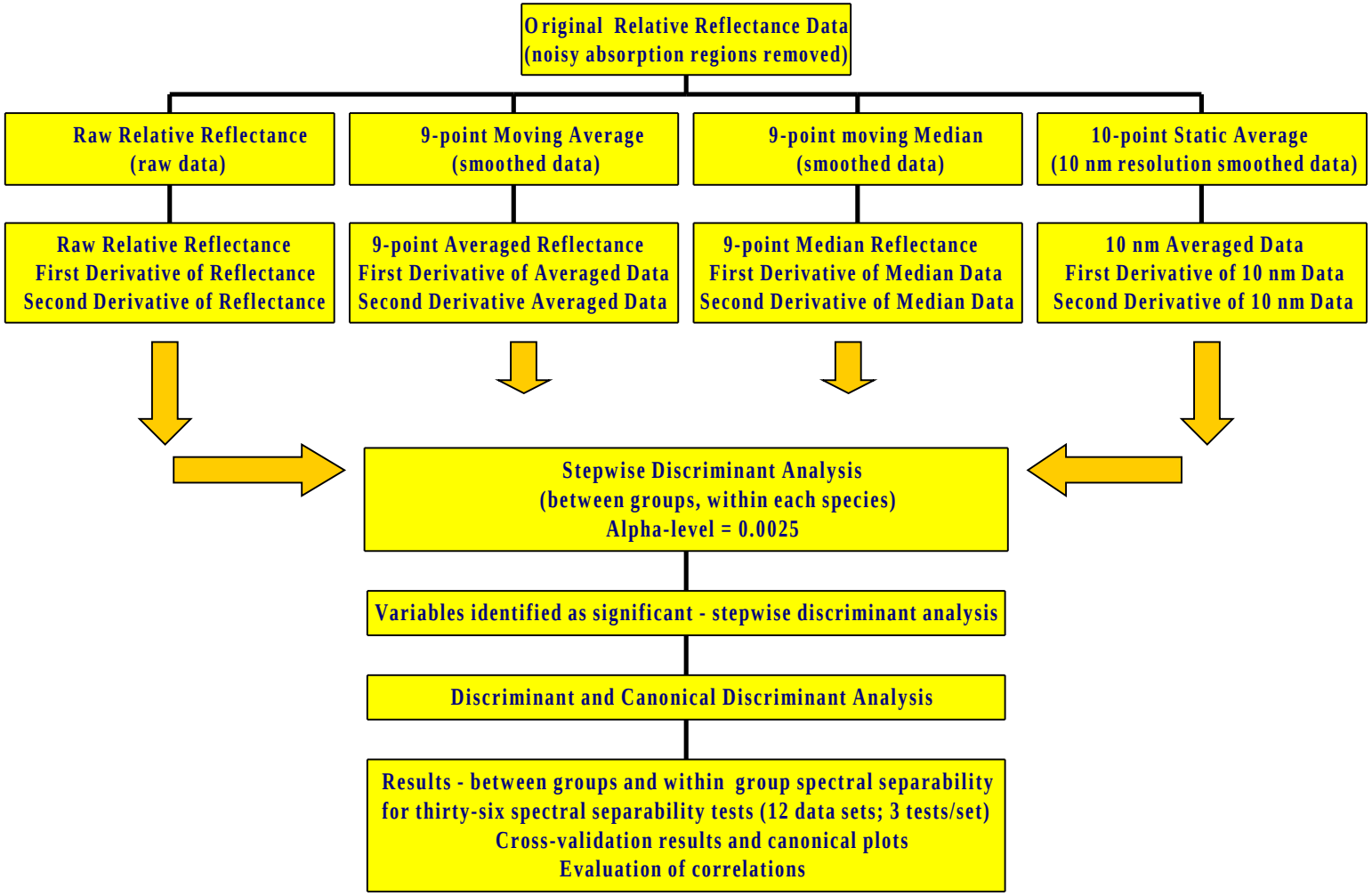

Figure 9. Data analysis flow-chart

Chapter 4
RESULTS AND DISCUSSION

4.1 Introduction

Relative reflectance data were collected for six forestry species, loblolly pine (Pinus taeda), Virginia pine (Pinus virginiana), shortleaf pine (Pinus echinata), scarlet oak (Quercus coccinea), white oak (Quercus alba), and yellow poplar (Liriodendron tulipifera). This was done using a FR Fieldspec^{TM} spectroradiometer with a spectral range of 350 nm – 2500 nm and a resampled spectral output of 1 nm bandwidths. The main objectives were as follows:

(i) assess taxonomic group and species level separability of field canopy spectra for the six species,

(ii) identify the radiometric wavelength regions that define the inherent spectral separability between taxonomic groups and species, and

(iii) identify the data pre-processing techniques most suited as preparation for species separability tests.

The data sets used for this study included the raw relative reflectance data, a 9-point weighted average data set (moving filter, 1 nm bandwidth data set), a 9-point median data set (moving filter, 1 nm bandwidth data set) and a 10-point average data set (static filter, 10 nm bandwidth data set). The variable ("noisy") water absorption regions were removed from the raw relative reflectance data set before any analysis or derivation of other data sets. The first and second differences of each data set were also derived, resulting in a total of twelve data sets for analysis. Each of these data sets were then used to assess spectral separability between coniferous and deciduous species, spectral separability among pine species and the separability among hardwood species, resulting in a total of thirty-six tests.

A stepwise discriminant analysis was performed on the data sets to identify the variables that would maximize differences between statistical groups (between species or taxonomic groups), while minimizing within group differences at the same time. After experimentation with

different α-levels (0.001 – 0.0001), a α-level of 0.0025 was chosen as the significant level for variable entry into the model during each run, because the number of significant variables was lower than twenty (to avoid overfitting), but still high enough to allow for adequate discrimination. The Pearson correlations among the variables identified were calculated to assess each variable's unique contribution as an information component before the next step in the analysis.

A discriminant procedure was performed for each data set using the variables shown by the stepwise discriminant procedure to be significant for distinguishing between statistical groups. Cross-validation was done for each model and data set in order to show the separation accuracy. A canonical discriminant procedure was also performed for each data set yielding new canonical variables. These canonical variables were plotted for each spectral separability test to show the amount of separability between different groups visually. The variance for each canonical variable was calculated on a per species basis to quantify the variation inherent in each taxonomic group or species.

The results for each of these steps will be shown in chronological order to show the logical evolution of the analysis process, which supports the conclusions drawn.

4.2 Spectral Data Smoothing

The shorter wavelengths, especially those in the visible range (higher energy, lower absorption wavelengths), are less susceptible to environmental influences and therefore the raw relative reflectance curves have smooth response curves in these ranges, as can be seen in Figure 10. The effect of the three smoothing filters (moving 9-point weighted average , moving 9-point median, static 10-point average) for two different regions are shown in Figure 11. The smoothing showed significant visual improvement only at wavelengths longer than 1400 nm. This can probably be ascribed to these wavelengths being of low energy content and susceptible to environmental influences such as atmospheric moisture and gases, high temperatures, and general instrument influences. The smoothing of raw reflectance curves plays an important role in further derivative analysis, especially since derivative techniques are very sensitive to noise.

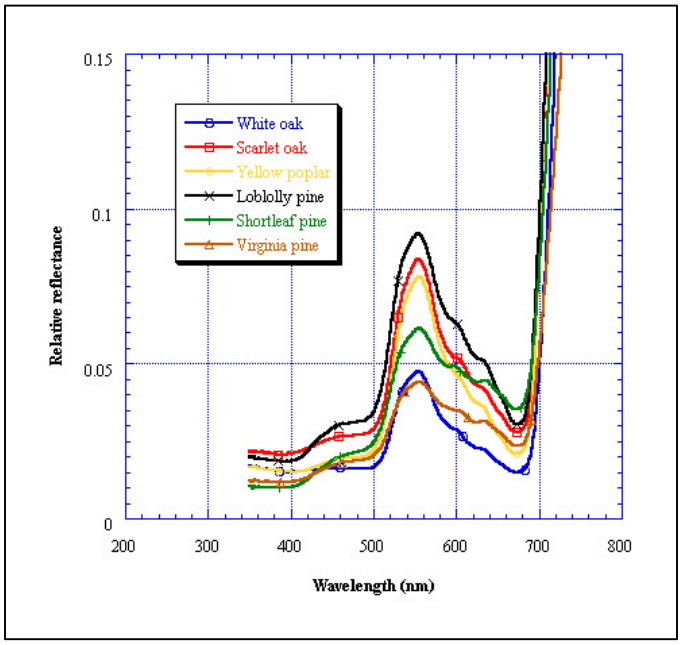

Figure 10. Raw relative reflectance for the visible wavelengths

The effect of the smoothing algorithms on the statistical analysis (discriminant analysis) will be discussed in a later section. It must be noted that other smoothing algorithms, such as smoothing in the frequency domain (Fourier space) also exist, but because of their simplicity, time/space filters were chosen for this study. A general smoothing filter (moving or static) is also easy to interpret.

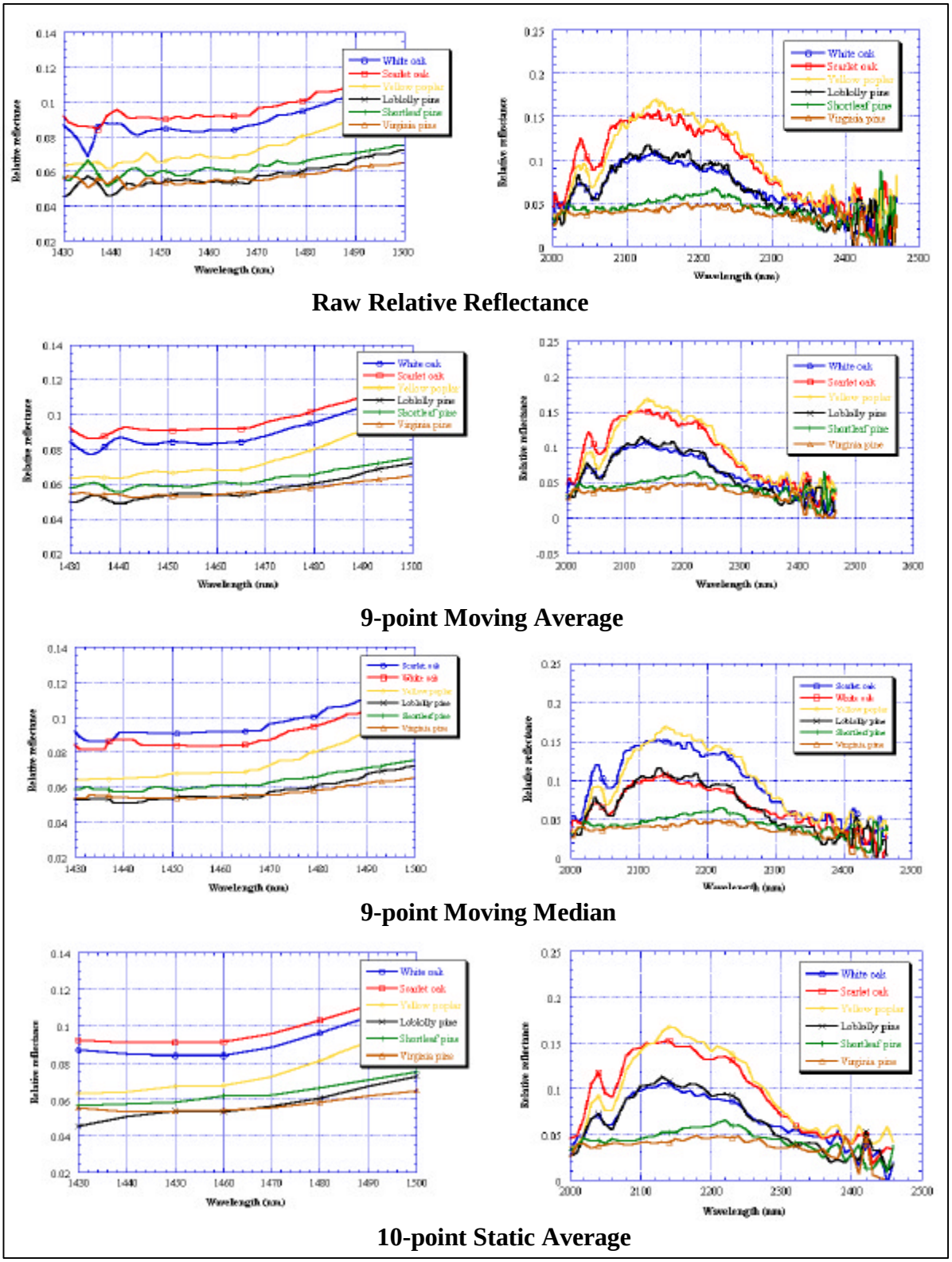

Figure 11. Smoothing of spectral data – comparison of the three methods used

4.3 Stepwise Discriminant Analysis

The wavelength variables (nm) indicated by the stepwise discriminant procedure to be significant at $\alpha = 0.0025$ for between group and among species discrimination are shown in Table 4.

Table 4. Variables shown to be significant by Stepwise Discriminant Procedure at $\alpha = 0.0025$ for all thirty-six separability tests (twelve data sets and three tests per data set)

Data set	Variables (nm)			Significance level
	Between groups	Within hardwoods	Within pines	
Raw relative reflectance (reduced set)	731; 963; 1169; 1193; 1274; 1540; 1548; 1579; 1659	350; 643; 694; 764; 1122; 1340; 1639; 1662; 1730; 1747	354; 404; 421; 435; 490; 712; 1463; 1771; 2460	0.0025
First difference of raw relative reflectance (reduced set)	402; 417; 425; 634; 711; 752; 1136; 1212; 1246; 1250; 1502; 1510; 1514; 2009; 2420	398; 411; 425; 438; 448; 547; 614; 637; 1304; 1568; 1694; 2188	408; 433; 503; 533; 587; 776; 950; 1109; 1161	0.0025
Second difference of raw relative reflectance (reduced set)	429; 474; 522; 524; 688; 690; 696; 698; 703; 705; 718; 732; 748; 750; 1066; 1103; 1264; 1279; 1633; 2038	644; 646; 648; 694; 722; 735; 737; 1072; 1171; 1310; 2019; 2373	495; 512; 523; 529; 727; 1063; 1653	0.0025
9–point averaged relative reflectance	520; 872; 1100; 1170; 1198; 1213; 1340	418; 691; 1590; 1631; 1655; 1691; 1700; 1725; 1746	355; 515; 713; 1463; 1772	0.0025
First difference of 9-point averaged relative reflectance	363; 414; 489; 750; 949; 1211; 1247; 1561; 1646;	399; 467; 487; 620; 759; 794; 1023; 1645; 1664; 1695; 1711	401; 416; 440; 502; 526; 587; 994; 1110; 1460	0.0025

Table 4 (continued). Variables shown to be significant by Stepwise Discriminant Procedure at $\alpha = 0.0025$ for all thirty-six separability tests (twelve data sets and three tests per data set)

Second difference of 9-point averaged relative reflectance	417; 426; 431; 523; 542; 546; 662; 722; 964; 970; 1244; 1285; 1479; 1564; 1991; 2055; 2215	518; 547; 559; 645; 661; 693; 717; 735; 1521; 1610; 1715; 1753; 2111; 2186; 2326	417; 422; 427; 523; 563; 591; 691; 1255; 2065; 2411	0.0025
9–point median relative reflectance	731; 958; 1170; 1188; 1273; 1453; 1547	354; 561; 1001; 1008; 1121; 1340; 1724; 1747; 2465	354; 515; 712; 1465; 1755	0.0025
First difference of 9-point median relative reflectance	414; 425; 430; 752; 1000; 1135; 1212; 1246; 1250; 1502; 1510; 1514	396; 404; 457; 497; 547; 637; 648; 1027; 1650; 1670; 2017; 2418	380; 419; 420; 429; 441; 499; 587; 667; 672; 920; 1256; 1632; 2450	0.0025
Second difference of 9-point median relative reflectance	364; 430; 523; 524; 525; 688; 690; 696; 698; 703; 705; 723; 730; 748; 749; 2103; 2239; 2296	419; 553; 644; 646; 648; 649; 651; 694; 703; 710; 1499; 2327	422; 423; 529; 676; 886; 1063; 1108; 1567; 1745; 2354	0.0025
Simulated AVIRIS 10 nm data	520; 730; 970; 1160; 1190; 1270; 1310; 1340	380; 420; 680; 690; 970; 1200; 1530; 1590; 1630; 1660; 1700	360; 410; 420; 440; 490; 650; 1340	0.0025
First difference of simulated AVIRIS 10 nm data	360; 390; 410; 480; 750; 930; 1160; 1240; 1500	400; 480; 750; 770; 940; 1640; 1670; 1690; 1730	390; 410; 420; 490; 540; 1050	0.0025
Second difference of simulated AVIRIS 10 nm data	430; 440; 480; 520; 660; 720; 1070; 1590; 1660	380; 390; 480; 590; 660; 1650; 1660; 1700	420; 430; 520; 590; 670; 800; 1150	0.0025

4.4 Discriminant Analysis and Cross-Validation

The discriminant cross-validation results are shown in Appendix D. All thirty-six spectral separability tests (twelve data sets, three tests per set) were shown to be significant at an α-level = 0.05 with P-values of 0.0001, using Wilks' Lambda test. The constants and coefficients for the discriminant functions of all the discriminant tests are given in Appendix E. By substituting the wavelength values for an unknown sample in each of the functions for a given test and data set, the function having the highest score represents the species or taxonomic group to which the sample will be assigned.

There are again a few trends that can be identified when the results are considered on a per separability test (between taxonomic groups, within hardwoods, within pines) basis. The discussion can be divided into the between groups (deciduous vs. coniferous), and the within groups spectral separability tests.

4.4.1 Spectral Separability between Deciduous and Coniferous Trees

Spectral discrimination between the deciduous and coniferous groups is a very successful endeavor when variable reduction through stepwise discriminant analysis is followed by the discriminant procedure. This is not surprising, especially when considering the distinct difference between these two groups in the near-infrared reflectance region. The lowest cross-validation result is 97.76% (hardwoods, 9-point average), with four of the data sets having accuracies of 100% (raw relative reflectance, second difference of raw relative reflectance, second difference of 9-point averaged data, second difference of 9-point median data). Hardwood discriminant accuracy ranged from 97.76% to 100.00%. Pines were never misclassified, with at most only two hardwood samples being misclassified as belonging to the pine group. This is probably due to the distinct spectral characteristics of coniferous trees as a group, while, at least in this case, there is more spectral variability in the deciduous group. This is due in part to visible phenological changes, particularly in yellow poplar (slight yellowing had occurred in some leaves). Even the "coarser" AVIRIS simulation data with a 10 nm resolution never had accuracies lower than 98.51% for hardwoods and 100% for pines. These results

indicate the existence of inherent spectral differences between the deciduous and coniferous species studied, and it seems highly likely that these two groups will be spectrally separable at an operational level.

4.4.2 Spectral Separability among the Three Deciduous Species

Spectral discrimination among the three hardwood species proved less accurate, but is still higher than 80% for most of the thirty-six tests that were done, with the discriminant classification accuracy for hardwood species ranging between 78.36% and 92.54%. The discrimination function's cross validation results underline this, with the best results being those for the second difference of the 10 nm AVIRIS simulation data, the second difference of the 9-point average data, and the first difference of the 9-point median data (92.54%). In the case of the second difference of the 10 nm AVIRIS simulation data, scarlet oak, white oak, and yellow poplar showed accuracies of 90.70%, 89.36% and 97.73%, respectively (the first difference of the 9-point median relative reflectance had a lower percentage only for white oak at 87.23%). The second difference of the 9-point average data set showed accuracies of 88.37%, 91.49%, and 97.73%, for scarlet oak, white oak, and yellow poplar, respectively. These results are very encouraging, especially in the case of the 10 nm resolution AVIRIS simulation data, which mimics the resolution available in most airborne sensors that are operational today.

The importance of the difference operators is also underlined, as these "curve shape descriptors" seem to be amenable to within species spectral discrimination. Even the first difference of the raw relative reflectance data set had high cross-validation results, with scarlet oak, white oak and yellow poplar's results being 86.05%, 89.36% and 95.45%, respectively. The non-differenced data sets also show a lot of promise, which come as a surprise, since one would not generally expect significant differences in spectral magnitude among deciduous species. This is corroborated by the fact that both the oak species had lower discriminant accuracies than yellow poplar, which might be indicative of the confusion existing between scarlet oak and white oak at the non-derivative data set level. Yellow poplar's high discriminant accuracy can in turn probably be attributed to its higher reflectance (lighter colored leaves).

The worst performer was the second difference of the raw relative reflectance (scarlet oak: 65.12%, white oak: 74.47%, yellow poplar: 95.45%), with a discriminant accuracy of 78.36%, followed by the second difference of the 9-point median data (79.10%). This can perhaps be attributed to the sensitivity of the difference operator to noise. It can thus be concluded that although the difference operators are useful for spectral discrimination among these species, their sensitivity to noise is something that should be taken into account.

On a per-species basis, yellow poplar had the highest cross-validation results, ranging between 93.18% (first difference of the 9-point averaged data and second difference of the 9-point median data) and 100% (9-point median data). The relatively high reflectance of the brighter yellow poplar leaves, when compared to those of scarlet and white oak, might explain this phenomenon. There were a lot of confusion between scarlet and white oak, which might be expected given that they belong to the same genus. The discrimination accuracy for white oak ranged between 74.47% (second difference of raw relative reflectance, 9-point median data, second difference of the 9-point median data) to 91.49% (second difference of the 9-point averaged data). For scarlet oak the range was 65.12% (second difference of raw relative reflectance) to 90.70% (first difference of 9-point median data, second difference of AVIRIS simulation data).

Spectral discrimination among these three deciduous species at an operational level is not unlikely, but one has to consider (i) the unavailability of high spectral resolution airborne and spaceborne sensors such as the one used in this study and (ii) that the AVIRIS simulation data give only a rough indication of spectral data with a 10 nm resolution and are not true to AVIRIS operational conditions (e.g., differences in wavelength sensitivities and probable atmospheric effects were not taken into account). Given these caveats, the very promising cross-validation result from the second difference of the AVIRIS simulation data is an indicator of possible operational implementation.

4.4.3 Spectral Separability among the Three Coniferous Species

The cross-validation accuracy percentages for the three pine species were lower than those for hardwoods in general. This can probably be attributed to the *Pinus*–genus having less spectral

variation among species, thus rendering pine species spectrally less separable. The results for the three pine species ranged between 61.64% (second difference of raw relative reflectance) and 84.25% (second difference of the 9-point averaged). The second difference of the 9-point averaged data set showed discrimination accuracies of 90%, 83.33% and 79.63% for loblolly, shortleaf and Virginia pine, respectively. There does not seem to be one pine species in particular that is more separable than any other one. The second difference of the raw relative reflectance, as the worst data set, again illustrates the second difference's sensitivity to noisy data. The first and second differences of the smoothed data sets were better for spectral separation among the species than the differenced data sets of the raw relative reflectance. Except for the raw AVIRIS simulation and raw relative reflectance data, the raw data sets had worse cross-validation results than the differenced data sets.

The cross-validation accuracies for the three pine species were in the low to mid 80% range, with the most confusion existing between Virginia pine and the other two species, followed by shortleaf pine and lastly loblolly pine. Loblolly pine's cross-validation results ranged between 54.00% (second difference of the raw relative reflectance) and 90.00% (second difference of the 9-point averaged data). The cross-validation ranges for shortleaf and Virginia pine ranged from 61.90% (9-point median data) to 88.10% (first difference of the 9-point averaged data) and 55.56% (second difference of the raw relative reflectance) to 87.04% (first difference of the 9-point median data), respectively. Loblolly pine tends to have a denser canopy leaf structure compared to either Virginia or shortleaf pine, with this perhaps being the reason for the lowest confusion and generally better cross-validation results.

4.5 Variables Significant for Spectral Discrimination

When considering the variables that were shown to be significant for each data set and separability test, there are a couple of trends that are worth mentioning:

(i) The short-wave infrared II (SWIR2) region (wavelengths > 1800 nm) are poorly represented for almost all the separability tests. This is especially true when relative reflectance data, and not the difference data, are considered. The SWIR2 region is better

represented in the difference data. This phenomenon might be due to spectral differences that exist in curve shape, and not curve magnitude, between and within taxonomic groups. The differencing operators might thus extract information useful for species and group discrimination which are hidden at a non-derivative level. Derivative noise, where it occurs in abundance, might also be significant because of chance contribution alone.

(ii) The strong presence of the visible wavelengths in all the separability test cases is striking. This highlights the usefulness of the visible spectrum for species and taxonomic group discrimination, utilizing the subtle differences not detectable by the human eye. This result corresponds to the results found by Gong *et al.* (1997), who concluded that the visible bands are essential for species discrimination. This is accentuated by the strong presence of bands in the blue-green portion of the spectrum, as found by Gong *et al.* (1997).

(iii) The near-infrared and short-wave infrared region I (SWIR1) are also very well represented in all the test cases. This is not an unexpected occurrence, since the near-infrared region is well known for its information content in vegetation studies. The SWIR1 region is especially important for between group (coniferous vs. deciduous) discrimination. The inherently higher spectral reflectance of hardwoods as opposed to conifers in the near-infrared bands explains this result. Even though AVIRIS data were used, Martin *et al.* (1998) also found these regions of importance in species discrimination, but a strong presence of bands greater than 2000 nm was also found. The presence of wavelengths in the 700 nm – 750 nm is also encouraging, as Luther and Carroll (1999) found high correlations ($R^2 \geq 0.75$) between the 711 nm band and chlorophyll a. This is confirmed through findings by Kupiec and Curran (1993), who found an $R^2 = 0.96$ when regressing bands 723 nm, 1552 nm and 2371 nm with chlorophyll concentration in slash pine (Pinus elliottii).

(iv) The wavelengths that are useful for between taxonomic group discrimination at $\alpha = 0.0025$ are limited to between five (within pines , 9-point average relative reflectance) and twenty (between groups, second difference of raw relative reflectance). This reduction in the variables from the initial 2150 variables to as few as five, makes the statistical approach taken in this study robust. The danger of overfitting, so easily encountered when analyzing hyperspectral data, is thus avoided.

(v) The longer wavelengths (SWIR2) only became more important contributors to defining type differences when the first and second differences of most of the data sets were analyzed. This might be due to the curve shape information contained in these longer wavelengths, rather than unique magnitude differences being present. This is substantiated by Martin *et al.*'s (1997) work in which AVIRIS data (coarser 10 nm resolution) were used and longer wavelengths also proved useful.

(vi) The higher order second difference is not useful when the data have been smoothed by a relatively large (10-point), static filter. This can be attributed to the suppression of local curve shape information by the smoothing algorithm, i.e., the shape is generalized instead of well defined.

Although specific wavelengths associated with stretching in O-H bonds (970 nm, 1200 nm, 1400 nm and 1940 nm) do not seem to stand out from the data as a whole, these wavelenghts are represented in some of the data sets and tests, but not to such an extent that it might be deemed significant. Overall, the variables are fairly well distributed across the instrument's spectral range, indicating the usefulness of the whole wavelength range for discriminating between taxonomic groups and among species. This underlines the useful application hyperspectral data have to problems such as the ones addressed in this study.

4.6 Canonical Discriminant Analysis

The results of the canonical discrimination plots for the spectral separability among species and the variances of the canonical variables for all the tests are given in Appendix F. The plots shown merely serve as visual indicators of spectral separability among species and the spectral similarity (tightness) within each species. The canonical variables' variances further supplement the visual interpretations with quantitative measures of the within taxonomic group and species spectral similarities.

When considering the between taxonomic group tests, the canonical variance for the only canonical variable present is much higher for the hardwood than the pine group in each case. In fact, the canonical variable's variance of the hardwood group is very often more than double that

of the pine group, with examples being the first difference of the raw relative reflectance (pines: 0.606, hardwoods: 1.429), the raw 9-point averaged data (pines: 0.593, hardwoods: 1.443), the first difference of the 9-point averaged data (pines: 0.569 , hardwoods: 1.47), the raw 9-point median data (pines: 0.589 , hardwoods: 1.448) and the raw AVIRIS simulation data (pines: 0.543 , hardwoods: 1.50). This is very indicative of the much higher spectral variation present in the deciduous or hardwood group as opposed to the coniferous or pine group.

For the within hardwood separability tests, yellow poplar seems to form a very distinct grouping compared to the two oak species (scarlet and white oak). Yellow poplar has, however, the highest pooled variance for the two canonical variables in most of the tests' cases, for example the second difference of the 9-point averaged data (yellow poplar: 1.313, white oak: 0.82, scarlet oak: 0.877). Only scarlet oak has a higher pooled variance for the second difference of the 9-point median (yellow poplar: 1.036 , white oak: 0.926, scarlet oak: 1.044) and the raw AVIRIS simulation data (yellow poplar: 1.066 , white oak: 0.853, scarlet oak: 1.093). The two oak species, scarlet and white oak, generally have much lower variances than yellow poplar, but there is clearly a higher degree of confusion between the oaks.

As far as the pine species are concerned, Virginia pine has the highest pooled variance in most cases with loblolly (second difference of the raw relative reflectance) and shortleaf pine (first difference of the 9-point median data) having a higher pooled variance in only one test case each. Examples are the first difference of the 9-point averaged data (loblolly pine: 0.877 , shortleaf pine: 0.584, Virginia pine: 1.435) and the first difference of the AVIRIS simulation data (loblolly pine: 0.899, shortleaf pine: 0.588, Virginia pine: 1.412). There seems to be a generally higher degree of confusion among the pine species than for the hardwood species, with many "confused/misclassified" samples present on the periphery of each of the pine groups.

The canonical plot for the data set that yielded the best discriminant accuracy for the within deciduous species separabilty, namely the second difference of the simulated 10 nm AVIRIS data set, is shown in Figure 12. The plot for the data set that yielded the best discriminant accuracy for the within coniferous species separabilty, namely the second difference of the 9-point averaged data set, is shown in Figure 13. The plots for the data sets that performed the

worst in each case are given in Figure 14 (within deciduous test - second difference of the raw relative reflectance) and Figure 15 (within coniferous test - second difference of the raw relative reflectance), respectively. The increase in variation within each species and taxonomic group is evident when evaluating Figure 12 vs. Figure 14 (deciduous species) and Figure 13 vs. Figure 15 (coniferous species).

These canonical variable plots and variances are very useful for visualizing and interpreting the spectral characteristics of each species or taxonomic group. One should, however, realize that canonical variables are transformed or re-projected variables and do not represent the physical reflectance quantities found in real world measurements.

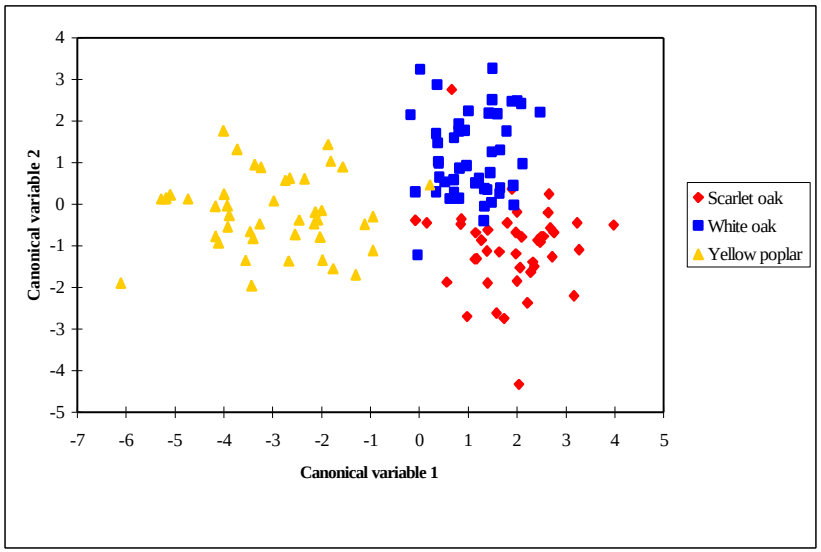

Figure 12. Canonical variable plot: Second difference of AVIRIS simulation 10 nm data for hardwood spectral separability (best performing data set – within deciduous species)

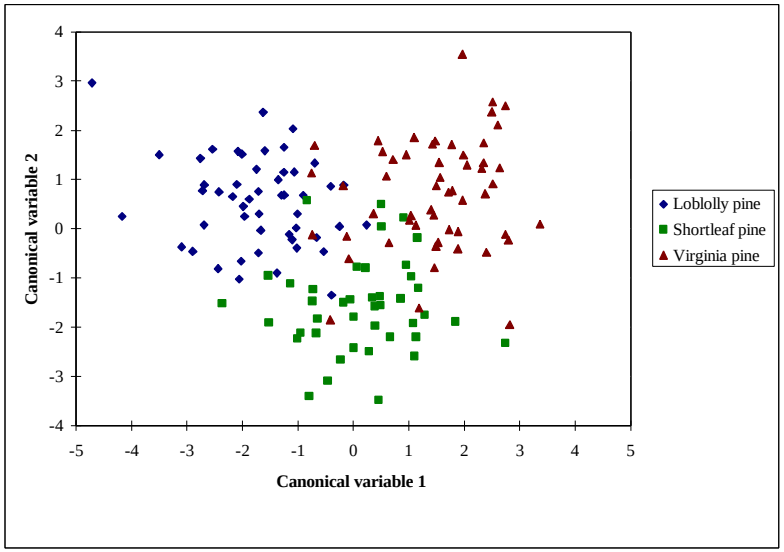

Figure 13. Canonical variable plot: Second difference of 9-point averaged data for pine spectral separability (best performing data set – within coniferous species)

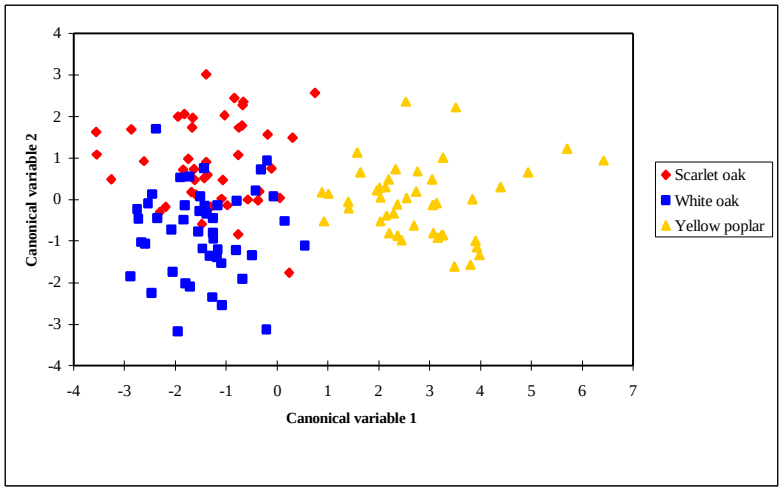

Figure 14. Canonical variable plot: Second difference of raw relative reflectance data for hardwood spectral separability (worst performing data set – within deciduous species)

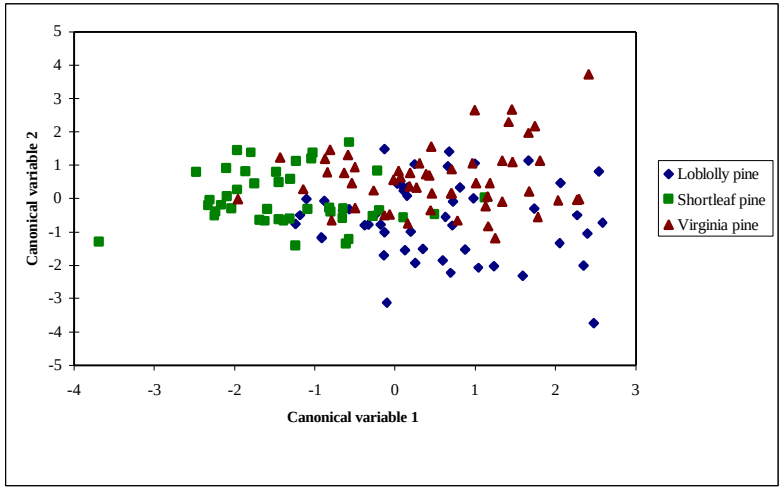

Figure 15. Canonical variable plot: Second difference of raw relative reflectance data for pine spectral separability (worst performing data set – within coniferous species)

4.7 Pearson's Correlation Analysis and Discriminant Results after Variable Sub-Selection

The Pearson correlation results for the wavelength variables used in each spectral separability test are given in Appendix G. There are high correlations among the variables for most of the raw reflectance data sets. Correlations of up to 0.99 (1193 nm vs. 1274 nm, raw relative reflectance for between taxonomic group separability) were found in some cases. Correlations as high as this are, of course, expected for variables that are proximate wavelengths, with trends in one variable being mirrored in a closely nearby/related variable. This is especially true for wavelength variables in the visible and near-infrared ranges. Variables for both of these regions have similar trends or values when closely spaced wavelengths and different samples are compared. Data sets such as the ones used in this study, are also very conducive to high correlations, especially considering the low α-level (0.0025) used by the stepwise discriminant procedure to identify significant variables. The spectral data sets not only have very high spectral resolutions (1 nm – 10 nm), but the low α-level ensures the selection of only the most significant variables, even though some of these variables might be in close proximity to each other in spectral space. Some of these high correlations might also be an artifact of the resampling that is done during actual data collection. The spectroradiometer has spectral resolutions of 3 nm (350 nm – 1050 nm range) and 10 nm – 12 nm (900 nm – 2500 nm range), depending on which of the three detectors are considered. Although the resampling of values to 1 nm increments facilitates comparisons between data collected at different times (instrument gains and biases differ depending on conditions), the resampling has the disadvantage of variables being derived from the same measurements in many cases, thus increasing spectral correlation.

The high correlations are mostly limited to the raw reflectance data sets, with the differenced data sets having substantially lower correlations. This is probably due to the differenced variables being transformed variables (less inherent correlation) of the original relative reflectance, resulting in the subsequent selection not only being broader, but also less correlated even if variables are spectrally proximate. The discriminant analysis and its cross-validation results, as well as the canonical discriminant analysis results for the variables initially selected

were discussed in spite of the high correlations that exist among variables. This was mainly done because it was felt that such an approach would not detract from the robustness of this study, given that the main purpose is not to present a predictive, but rather a descriptive model. In order to advance to a stage at which inherent spectral separability among species are not being determined, but the selection of variables for use in an operational predictive classification scheme is necessary, high correlations need to be addressed.

If the correlations for the best performing data sets were deemed too high (greater than 0.90), sub-selection from the already selected variables was performed based on wavelengths shown to be significant by previous studies. This was done to minimize or reduce correlations among variables. The results for the subsequent discriminant analysis are also given for these data sets and the influence of further variable reduction will now be discussed.

Variable reduction or sub-selection will only be done for data sets that (i) performed the best when considering cross-validation results and (ii) had high correlations (higher than ±0.90). The data sets that will be considered are as follows:

- **Between deciduous and coniferous species**: Raw relative reflectance , second difference of the raw relative reflectance, second difference of the 9-point averaged data and second difference of the 9-point median data (100.00% cross-validation result)
- **Among deciduous species**: Second difference of the 9-point averaged data (92.54% cross-validation result)
- **Among coniferous species**: Second difference of the 9-point averaged data (84.25% cross-validation result)

The variables of the raw relative reflectance data set (between taxonomic group separability) with correlations higher than ±0.90 are shown in Table 5. It is clear from Table 5 that a large portion of the correlations are very high, with as many as nine showing correlations of up to 0.99. Except for the second difference of the 9-point averaged data (among deciduous species separability), with correlations shown in Table 6, all of the other second difference data sets had correlations lower than ±0.90.

Table 5. Correlations for raw relative reflectance data: Between group separability

Variable pairs (nm)	**Correlation**	**Variable pairs**	**Correlation**
731/963	0.960	1193/1540	0.918
731/1169	0.919	1193/1548	0.923
731/1193	0.916	1193/1579	0.940
731/1274	0.918	1193/1659	0.956
963/1169	0.973	1274/1540	0.912
963/1193	0.970	1274/1548	0.917
963/1274	0.970	1274/1579	0.934
1169/1193	0.999	1274/1659	0.951
1169/1274	0.999	1540/1548	0.999
1169/1540	0.912	1540/1579	0.997
1169/1548	0.917	1540/1659	0.990
1169/1579	0.934	1548/1579	0.998
1169/1659	0.951	1548/1659	0.992
1193/1274	0.999	1579/1659	0.997

The cut-off value of ±0.90 for the correlation value is considered to be adequate, since high correlations among proximate wavelengths are suspected with hyperspectral data. Two criteria were used to decide which variables should be kept in the model for further statistical analysis, namely (i) correlation magnitude and (ii) those wavelengths previously shown to be important for species discrimination and for assessing canopy chemistry.

Table 6. Correlations - second difference of the 9-point averaged data: Deciduous species separability

Variable pairs (nm)	Correlation
518/559	-0.91
518/693	0.948
547/559	0.945
547/693	-0.914
559/693	-0.9595

Gong *et al.* (1997) favoured wavelengths in the visible region, followed by the near-infrared region of the spectrum. The blue-green portion was considered best for species (coniferous) discrimination, followed by the red-edge. Martin *et al.* (1998) used the bands centered at the following AVIRIS channels: 627 nm, 750 nm, 783 nm, 822 nm, 1641 nm, 1660 nm, 2140 nm, 2280 nm and 2290 nm. Wessman *et al.*'s (1989) forest canopy chemistry study identified the first-order difference bands 1265 nm and 1555 nm as having strong relationships with canopy nitrogen concentration. Martin and Aber (1997) used the first difference of the bands centered at 750 nm and 2140 nm for nitrogen and 700 nm for cholorphyll content prediction. Absorption in the 2110 nm – 2200 nm region has also been attributed to N-H bonds in amino acids and proteins (Martin and Aber, 1997). None of the variables with high correlations are in the range beyond 1659 nm , therefore some of the longer wavelengths' importance can be disregarded for the purpose of variable sub-selection.

In the case of the raw relative reflectance (between taxonomic group discrimination), the following variables were kept for further analysis based on the criteria mentioned: 731 nm, 1274 nm and 1659 nm. For the second difference of the 9-point averaged data (deciduous species discrimination), the following variables were used as a non-correlated subset: 518 nm, 559 nm, 645 nm, 661 nm, 717 nm, 735 nm, 1521 nm, 1610 nm, 1715 nm, 1753 nm, 2111 nm. The cross-validation results for these two tests, using the sub-selected variables, are given in Table 7 (raw relative reflectance, between taxonomic group discrimination) and Table 8 (second difference of the 9-point averaged data, deciduous species discrimination).

Table 7. Between group separability - Reduced relative reflectance data using sub-selected variables

Species	**Hardwoods**	**Pines**	**Total**	**Discrimination%**
Hardwoods	107 79.85%	27 20.15%	134 100.00%	86.79% (Previous test using all the selected correlated variables = 100.00%)
Pines	10 6.85%	136 93.15%	146 100.00%	
Total	117 41.79%	163 58.21%	280 100.00%	

Table 8. Within hardwoods separability - Second difference 9-point averaged data using sub-selected variables

Species	**Scarlet oak**	**White oak**	**Yellow poplar**	**Total**	**Discrimination%**
Scarlet oak	36 83.72%	7 16.28%	0 0.00%	43 100.00%	85.07% (Previous test using all the selected correlated variables = 92.54%)
White oak	7 14.89%	38 80.85%	2 4.26%	47 100.00%	
Yellow poplar	0 0.00%	4 9.09%	40 90.91%	44 100.00%	
Total	43 32.09%	49 36.57%	42 31.34%	134 100.00%	

It is clear from both Table 7 and Table 8, that the overall discrimination is less accurate compared to the original cases where all the variables after stepwise discriminant selection were used in the discriminant analysis. The discriminant cross-validation accuracy dropped from 100.00% to 86.79% in the case of the between taxonomic group test using the raw relative reflectance data and from 92.54% to 85.07% for the among deciduous species test using the

second difference of the 9-point averaged data. These two sets of results show that although high correlations might be present in the original data, even the highly correlated variables contribute to the explanation of the variability present in each data set. All the variables that were removed from the sub-selected sets had correlations of 0.90 or higher, with some as high as 0.99, yet their correlated counterparts failed to provide as good cross-validation accuracies or explain as much of the variability as the initial variables. This might be attributed to the fact that many highly correlated variables are correlated when projected onto the x – and y-axis, but in re-projected space, as would be the case with discriminant analysis, the correlated variables add to the discrimination between two or more groups. This concept is illustrated in Figure 16. Although variables 1169 nm and 1659 nm have a correlation of 0.951, they are both informative as far as describing differences between the hardwoods and pines are concerned. An example of the re-projected axes in Figure 16 shows the discriminative power of these two variables in re-projected space.

Another approach is to adjust correlated variables about the group mean of each set of variables. This would reduce the inflated correlation present in linear space due to the influence of the other set's variables. Each variable's contribution to the correlation coefficient is now corrected about the specific group mean for that same variable and not for the whole data set (all the groups as a whole). This can be done by taking the mean of each variable for each group and subtracting the value of each sample for the variable in question from the group mean. It can be described mathematically as:

$x_{adjusted} = x_{mean} - x_i$, where i ranges from 1.. n ….(4)

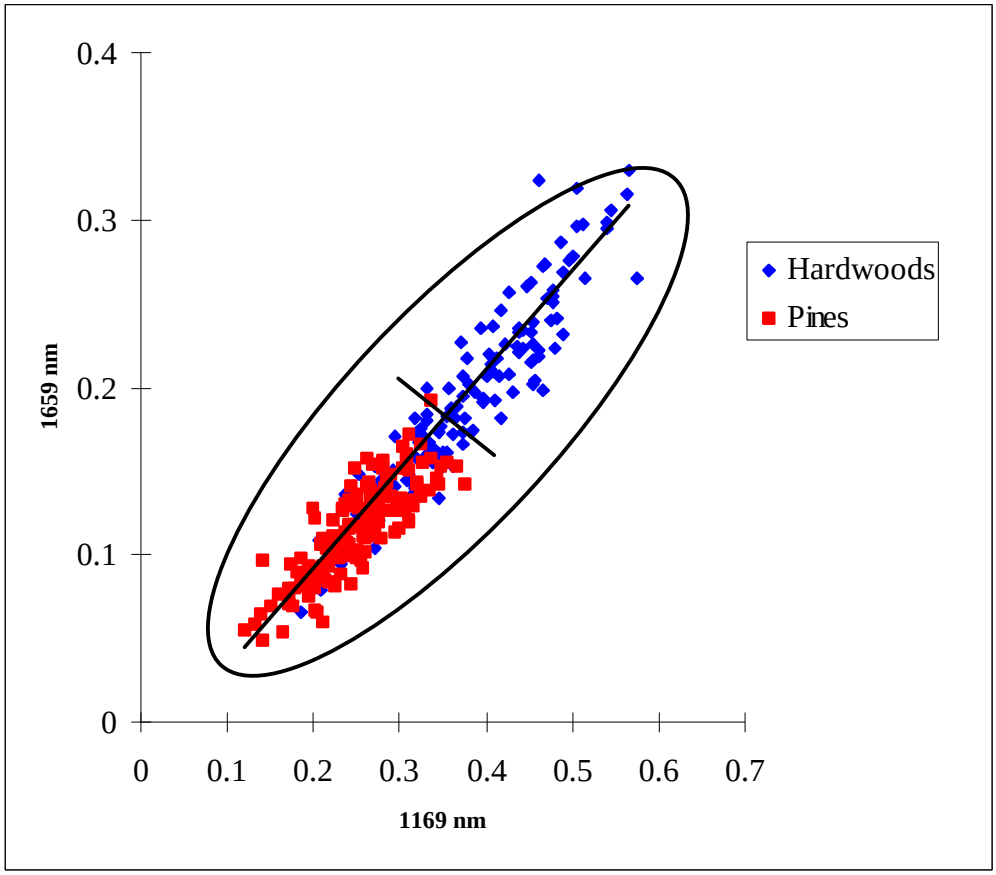

Figure 16. Correlation between 1169 nm and 1659 nm: Hardwood vs. pine spectral discrimination

The Pearson correlation for the adjusted variables 1169 nm $_{adjusted}$ and 1659 nm $_{adjusted}$ are shown in Table 9. The adjusted correlation has dropped from 0.951 to 0.908 and although this does not seem significant, it serves to illustrate the principle. The usefulness of correlated variables for discriminant analysis is therefore not precluded, but the correlation that exists might be reduced when considering the re-projection of variables in feature space as is done by a discriminant analysis. Even though variables might be highly correlated, is logical that the variables selected by the stepwise discriminant procedure will be useful in the subsequent discriminant procedure.

Table 9. Pearson correlation for the adjusted 1169 nm and 1659 nm variables

Statistic	**Variable**	**1169 $nm_{adjusted}$**	**1659 $nm_{adjusted}$**
Correlation	**1169 $nm_{adjusted}$**	1.000	0.908
	1659 $nm_{adjusted}$	0.908	1.000

Chapter 5

CONCLUSIONS

The use of hyperspectral data for between and within forest taxonomic groups (deciduous vs. coniferous) classification has great potential, but is not without pitfalls. From an analytical perspective the greatest challenges are data smoothing and reduction to those variables that truly delineate taxonomic group or species differences. From an operational perspective, the inherent spectral separability of some forest groups and species is just non-conclusive, with a lot of confusion found among especially the coniferous (pine) species.

Variables shown by the stepwise discriminant procedure to be significant for discriminating between taxonomic groups and among species were well distributed across the entire 350 nm – 2500 nm range. Variables for the different data sets were mostly limited to the visible and near-infrared regions, with very few variables in the short-wave infrared region at wavelengths greater than 2000 nm. This confirms the findings by Gong *et al.* (1997), who identified the visible portion of the spectrum as being important for species discrimination, and Martin *et al.* (1998), who identified wavelengths in the near-infrared regions as being important for spectral separation between species. The differenced data sets did have more of the "greater than 2000 nm region" represented, but this increase did not seem substantial. For between taxonomic group tests using raw reflectance, the use of near-infrared variables was especially striking, with the significantly higher reflectance of deciduous species relative to coniferous species again being confirmed. Specific wavelengths shown to be significant by literature for characterizing nitrogen and chlorophyll content were among the variables chosen for their discriminative power (Kupiec and Curran, 1993; Luther and Carroll, 1999). This was mostly true for regions of importance, while the actual wavelengths were few and scattered, e.g., the 700 nm – 750 nm range (chlorophyll content) compared to the 1660 nm as an example of a wavelength correlated with canopy nitrogen content. Variables greater than 1800 nm were better represented in the second difference data sets than in the raw data, which might indicate that this spectral region has greater value for separation studies when the shape (slope of the slope, curvature), and not the magnitude of the curves, is considered.

The between group separation (deciduous vs. coniferous species) had very high cross-validation accuracies, with the lowest result being that for hardwoods using 9-point averaged data (97.76%). The raw relative reflectance, second difference of the raw relative reflectance, second difference of the 9-point averaged data, and the second difference of the 9-point median data had overall cross-validation accuracies of 100%. None of the pine samples were ever misclassified. This not only confirms the usefulness of even raw reflectance data for discriminating between these groups, but the usefulness of the differenced data (second differences), especially when the differenced data were derived from smooth data sets, was also shown. The fact that the second difference of the raw relative reflectance also had an accuracy of 100%, even though difference operators are very sensitive to noise, indicates that the operational discrimination between deciduous and coniferous species is very likely. Spectral unmixing techniques might defuse problems with mixed pixels in operational data, especially given that deciduous and coniferous groups will not always be represented in distinct pixels.

Cross-validation results for the within deciduous species discrimination ranged from 78.36% to 92.54%. The best results were for the second differences of the 10 nm AVRIS simulation data and the 9-point median data. Yellow poplar had the highest cross-validation results, with some confusion existing between scarlet and white oak. This can be attributed to yellow poplar having a different visual and structural appearance (reflected in its distinct genus assignment). The highest accuracies for the three hardwood species were 90.70%, 89.36%, and 97.73% for scarlet oak, white oak, and yellow poplar, respectively. Although spectral discrimination among the three hardwood species seems likely on an operational basis, especially considering the good performance by the 10 nm AVIRIS simulation data set, the results should not be oversold. This study dealt with almost pure spectra, while satellite imagery has as a confounding factor the problem of mixed pixels. Given that an endmember might be present for each species of interest, accuracies in the higher 80% - range can perhaps be attained using linear spectral unmixing.

The three coniferous species studied had lower cross-validation results than the deciduous species for within species discrimination. The results ranged from 61.64% to 84.25%, with the second difference of the 9-point averaged data resulting in the highest cross-validation results. Although the second difference of a smoothed data set performed the best, the second difference

of the raw relative reflectance showed the worst results, underlining the difference operator's sensitivity to noisy data. Virginia pine had the highest confusion with the other species, followed by shortleaf and lastly loblolly pine. This might be due to loblolly pine having a generally dense leaf structure, while the other two species' spectral responses were more contaminated by background noise (bark, stem, etc.). Given the other factors related to remotely sensed imagery (spatial resolution, mixed pixels, atmospheric effects, etc.), the operational discrimination of the three pine species is unlikely in the near future.

High correlations between variables were found for especially the raw data sets. The differenced data sets had much lower correlations since these data sets are transformed and vary over a shorter distance within the data itself. The correlations, although high in linear terms, were shown to still have high discriminative power, especially when considering a transformation of data axes, as is done in discriminant analysis. By adjusting correlated variables by their respective group means, correlations were also lowered. Correlations could now be evaluated on a per group basis and not across the whole data set.

The canonical discriminant plots were very useful for showing visual separation of the species studied. The variances and pooled variances of the canonical variables also aided in defining the taxonomic group and species that were spectrally less variable ("tighter"). The hardwoods as a group often exhibited canonical variances of more than double that of the variances for the pines, which is most probably due to greater physiological variation within these hardwoods as a group when compared to the coniferous species studied. This confirms the difficulty of trying to discriminate among pines on a spectral basis. Although yellow poplar formed a distinct grouping when considering the canonical plots, this species also had the highest pooled canonical variance. The higher cross-validation results for yellow poplar could thus be confirmed by the clear canonical separation between yellow poplar and the oaks as two separate groupings. Virginia pine had the highest pooled canonical variance among the pine species, which can perhaps be attributed to its generally sparser needle cover, thus allowing background influences to pollute the spectral response.

The use of derivative techniques to enhance spectral differences between and within taxonomic groups proved to be very effective, contrary to findings by Fung *et al.* (1999). Given derivative operators' sensitivity to noisy data, spectral data smoothing does appear to be a prerequisite for the use of derivatives. The second difference of the 9-point averaged data, for example, was one of the data sets with the highest cross-validation accuracies (84.25 – 100.00%) for all three separability tests. The 10-point static average used to derive the simulated 10 nm AVIRIS data set was also very successful, with a high accuracy (92.54%) shown for the second difference of the 10 nm AVIRIS data set for the within deciduous species separability test.

Among the preprocessing techniques found to be most successful, the weighted 9-point average of the relative reflectance data deserves to be mentioned (cross-validation accuracies of 84.25 – 100.00% for all three separability tests). Given the effectiveness of the difference operators in general for spectral discrimination among species, it can be concluded that spectral smoothing can be considered a prerequisite for this type of spectral analysis. A moving weighted average or median filter does seem preferable over a static filter, since the latter may suppress localized curve shape (difference operators) because of its more general smoothing effect.

Among the greatest limitations or caveats of this study were the following:

- Randomization of sampling points was difficult due to limited access with the bucket truck.
- The angle variation (0° - 15°) of the spectroradiometer's foreoptic still allowed for relatively large variations in reflectance magnitude in particular. (I compensated for this using the first and second differences of each data set.)
- The issue of sample size remains a serious problem, with even approximately 50 samples per species possibly being too few. More samples are needed for validation as well as model prediction, given the large number of independent wavelength variables.
- The reduction of data dimensionality from 2150 wavelength variables to as few as 5 variables remained a challenge, although the statistical technique used in this study can be regarded as being both objective and repeatable.

- The short-wave infrared regions were very variable (noisy), making it difficult to extract useful information. (This was alleviated using data averaging or smoothing techniques, but quantification of noise reduction is difficult to do.)
- There exist some caveats as far as the applicability to AVIRIS (or similar hyperspectral) data is concerned. Firstly, the AVIRIS sensor's spectral sensitivity to different wavelengths was not addressed in the static average. Secondly, the AVIRIS sensor has a lower signal-to-noise ratio in the visible portion of the spectrum when compared to the Fieldspec FR spectroradiometer used in this study. Lastly, the requisite smoothing (for difference operators) may additionally reduce the effective AVIRIS spectral resolution, given that the AVIRIS sensor's signal-to-noise ratio is comparable to the spectroradiometer's signal-to-noise ratio in the short-wave infrared region and lower in the visible spectrum.

It is recommended that further research should focus on identifying and testing the spectral differentiation among different tree types (e.g., white oaks vs. red oaks) within a genus of interest. This might be a very enlightening research avenue, as the natural variation present in many species might not allow for accurate species differentiation from a spaceborne platform. As was seen in the case of the distinct yellow poplar and oak groupings, spectral separation at the genus-level will probably have to be ascertained first, before attempts are made to separate species within a genus. The use of other techniques (such as continuum removal, cross-entropy as a spectral dissimilarity measure, and the use of vegetation spectral features such as the red-edge inflection point or chlorophyll absorption well) can also be evaluated. The effect of seasonal variation on spectral differentiation of taxonomic groups and species and its quantification also deserves attention, as accurate spectral separability among any given set of species might be limited to certain times of year. The effects of varying soil and growing conditions, crown closure, and tree age are also closely related to the issue of seasonal variation. The success of spectral unmixing techniques given these variable factors also needs to be established.

In conclusion it can be said that spectral discrimination between deciduous and coniferous species is very likely in an operational context, especially since it does not require smoothed data. The discrimination among hardwood species is encouraging, but unless advanced spectral

unmixing algorithms can be developed, there may be too many external influences diluting classification accuracy. The pine species studied might only be discriminated among at a much lower accuracy level (probably lower than 80%) in an operational context, but the accuracies of as high as 84% obtained in this study are still encouraging. When the cross-validation and canonical results are considered, it appears that three distinct groupings, namely conifers, oaks and yellow poplar, can be discerned. This indicates that these levels of separation might be the highest obtainable with the data set given, and also that the limited species selection of this study should be kept in mind. Given a sample taken across a broader species diversity, more conclusive decisions can probably be made on whether or not within hardwood and softwood species spectral discrimination is possible. Although the number of species is limited in this study, it does shed some light on the possibilities for not only hardwood vs. softwood separation, but also the spectral separability of species within these two groups. The reduction of data dimensionality (to avoid statistical overfitting) and the use of the cross-validation method (to verify the discriminant procedure's results) make the approach taken in this study robust, especially considering that other hyperspectral species separability studies have not followed this route.

Following the determination of spectral separability of different genera, the identification of distinct types within each genus of interest (e.g., the white oaks vs. the red oaks) might be the next step toward discrimination among species on a spectral basis. The accurate, categorically-specific type maps thus produced would be beneficial to both forest monitoring and management.

Chapter 6
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Appendix A

Table 10. Airborne hyperspectral sensors that operated in 1994 (Birk and McCord, 1994)

System		Range (nm)	Bandwidth (nm)	Quantization (bits)
AAHIS-1		440 – 835	11	12
AHS	#1	430 – 830	20	12
	#2	1605 – 2405	50	
	#3	3000 – 5400	300	
	#4	8200 – 12700	400 - 1500	
AIS	#1	400 – 1050	25.4	16
	#2	1080 – 1800	102	
	#3	2000 – 2500	15.6	
AMSS	#1	400 – 1050	20	8
	#2	2050 – 2400	44	
	#3	8500 – 12000	530	
ASAS		420 – 1037	11	12
AVIRIS		400 – 2500	10	12
CASI		430 – 870	3	12
CHRISS		425 – 850	3.4	
DAIS-2815	#1	700 – 1000	300	15
	#2	3000 – 5000	600	
	#3	8000 – 12000	200	

Table 10. Airborne hyperspectral sensors that operated in 1994 (continued) (Birk and McCord, 1994)

System		Range (nm)	Bandwidth (nm)	Quantization (bits)
DAIS-7915	#1	400 – 1000	16	16
	#2	1000 – 1800	100	
	#3	1970 – 2450	16	
	#4	3000 – 5000	2000	
	#5	8000 – 12300	600	
HYDICE		400 – 2500	3.1 (min.); 14.9 (max.); 10.2 (avg.)	12
MIVIS	#1	430 – 830	20	12
	#2	1150 – 1550	50	
	#3	2000 – 2500	8	
	#4	8200 – 12700	400 - 500	
MUSIC	#1	2500 – 7000	25 – 70	80 frames/s digital PCM
	#2	6000 – 14500	60 – 1400	
ROSIS		430 – 880	5	12
SMIFTS		1000 – 5200		12
TRWIS-B		460 – 880	4.8	8
TRWIS-SC		460 – 880	4.8	8
TRWIS-II		1500 – 2500	12	8
WIS (anticipated in 1994)		400 – 600	12.5	12
		600 – 1000	6	
		1000 – 1800	30	
		1800 – 2500	12.5	

Appendix B

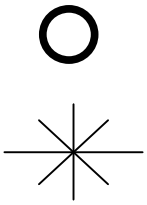
Data Sheet

Number: _____ Spectrum number:_____ Species: L / S / V / C / W / Y
Nadir : On / Off ____ Photo number: _____ GPS number: _____
Dbh: _____ Wind direction: _____ and speed: None / Light/ Moderate / Strong / Very strong

Description:
_____
_____
_____

Comments:
_____
_____
_____

Relative reading position:

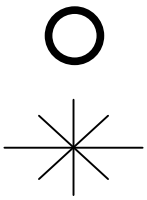


Number: _____ Spectrum number:_____ Species: L / S / V / C / W / Y
Nadir : On / Off ____ Photo number: _____ GPS number: _____
Dbh: _____ Wind direction: _____ and speed: None / Light/ Moderate / Strong / Very strong

Description:
_____
_____
_____

Comments:
_____
_____
_____

Relative reading position:



Appendix C

SAS-code for data transposition, PROC STEPDISC, DISCRIM and CANDISC

1. Data transposition and species/group labeling

```
*INITIAL SAS PROGRAM FOR DATA TRANSPOSITION;

title1 'Jan vanAardt - 1999 - Hyperspectral reflectance data for species identification';

*Transpose the data sets to place wavelengths as variables in top row ;
proc transpose data= <SAS data set name> out=transout(rename=(col1=y)) name=sample;
  by wavelen;
  var  <variable range>;
run;

*Rename wavelenghts by compressing to _Number ;
data transout;
  set transout;
  wave = wavelen;
* wave='W'||compress(wavelen);
  sample=substr(sample,3,3);
run;

*Sort the data set;
proc sort data=transout out=sout;
  by sample wave;

*Transpose data to have samples in first column; wavelenghts in first row;
proc transpose data=sout out=newout;
  by sample;
  var y;
  id wave ;
run;

*Delete junk samples and label species and groups ;
data  <Data set name> (drop=_name_);

       set newout;

*Delete all junk files ;

       if sample=<'Number1' or sample= <'Number2'> then delete;

*Name all Loblolly pine ;
  if sample = <'Number1'> or sample = <'Number2'> then species ='Loblolly';

*Name all Shortleaf pine ;
 if sample = <'Number1'> or sample = <'Number2'> then species='Shortlf';
```

```
*Name all Virginia Pine  ;
 if sample = <'Number1'> or sample = <'Number2'> then species='Vapine';

*Name all Yellow poplar ;
 if sample = <'Number1'> or sample = <'Number2'> then species ='Yellow';



*Name all Scarlet oak ;
 if sample = <'Number1'> or sample = <'Number2'>  then species ='Scarlet';

*Name all White oak ;
 if sample = <'Number1'> or sample = <'Number2'> then species ='White';

*Name all Pines ;
if sample = <'Number1'> or sample = <'Number2'> then group='Pines';

*Name all Hardwoods;
if sample = <'Number1'> or sample = <'Number2' then group = 'Hardwds';

run;

quit;

*End of program;
```

2. PROC STEPDISC: The discriminant stepwise selection of significnant variables

```
*Discriminant stepwise selection of significnant variables;

title1 'Jan vanAardt - 1999 - hyperspectral reflectance data for species identification';

*If among species separability needs to be analyzed, only the species of interest are used;
*This section creates the sub-set needed;

*data one;
*   set <SAS data set name>;
*   if GROUP='<Pines / Hardwoods>' then output;
*run;

*Proc Stepdisc uses either the sub-set from above (one) or the whole data set;
*This is dependent on whether or not the analysis is performed for species or group, respectively ;

proc stepdisc short slstay=0.0025 data= <SAS data set name / one>;

title2 'Data set = <SAS data set name>';
title3 'This is to discriminate between species / groups';

*Variables not specified through ‘var’ option, since all of the wavelength variables will be used  ;

*Select group / species depending on whether the analysis is for group or species;

class <group / species>;


run;

quit;

*End of program;
```

3. PROC DISCRIM and CANDISC: Discriminant (with cross-validation) and canonical discriminant (with canonical plots) analysis

```
*Proc Discrim is performd first, followed by Proc Candisc ;

*If among species separability needs to be analyzed, only the species of interest are used;
*This section creates the sub-set needed;

data one;
   set <SAS data set name>;
   if GROUP='Pines / Hardwoods' then output;
  run;

*Proc Discrim uses either the sub-set from above (one) or the whole data set;
*This is dependent on whether or not the analysis is performed for species or group, respectively ;

proc discrim pool=yes listerr crosslisterr data = <SAS data set name / one>;

*The class has to be defined based on whether the analysis is for group or species ;
class <group / species>;

title2 'Discriminant Analysis - Data set = <SAS data set name>';
title3 'Analysis for <specify>';

*variables associated with <SAS data set name>;
          var  <specify all the variables or ranges);

run;

*Proc Candisc uses either the sub-set from above (one) or the whole data set;
*This is dependent on whether or not the analysis is performed for species or group, respectively ;

proc candisc data= <SAS data set name / one> out=outcan;

*variables associated with <SAS data set name>;
          var  <specify all the variables or ranges);

*The class has to be defined based on whether the analysis is for group or species ;
class <group / species>;
run;

*Plot the canonical variables for visual inspection ;
proc plot;
plot can2*can1=species;
run;

quit;
*End of program;
```

Appendix D

Cross-tabulation results for all thirty-six separability tests

(twelve data sets, and three separability tests per set)

1. Reduced Raw Data

Table 11. Cross-tabulation results for between group separability - Reduced relative reflectance data

Table	**Hardwoods**	**Pines**	**Total**	**Discrimination %**
Hardwoods	134 100.00%	0 0.0%	134 100.00%	
Pines	0 0.0%	146 100.00%	146 100.00%	
Total	134 47.86%	146 52.14%	280 100.00%	100.00%

Table 12. Cross-tabulation results for within hardwoods separability - Reduced relative reflectance data

Table	**Scarlet oak**	**White oak**	**Yellow poplar**	**Total**	**Discrimination %**
Scarlet oak	37 86.05%	6 13.95%	0 0.0%	43 100.00%	
White oak	5 10.64%	42 89.36%	0 0.0%	47 100.00%	
Yellow poplar	0 0.0	1 2.27	43 97.73%	44 100.00%	
Total	42 31.34%	49 36.57%	43 32.09%	134 100.00%	91.05%

Table 13 Cross-tabulation results for within pines separability - Reduced relative reflectance data

Table	**Loblolly pine**	**Shortleaf pine**	**Virginia pine**	**Total**	**Discrimination %**
Loblolly pine	43 86.00%	5 10.00%	2 4.00%	50 100.00%	
Shortleaf pine	2 4.76%	36 85.71%	4 9.52%	42 100.00%	
Virginia pine	3 5.56%	8 14.81%	43 79.36%	54 100.00%	
Total	48 32.88%	49 33.56%	49 33.56%	146 100.00%	83.56%

Table 14. Cross-tabulation results for between group separability – First difference of reduced relative reflectance data

Table	**Hardwoods**	**Pines**	**Total**	**Discrimination %**
Hardwoods	133 99.25%	1 0.75%	134 100.00%	
Pines	0 0.0%	146 100.00%	146 100.00%	
Total	133 47.50%	147 52.50%	280 100.00%	99.64%

Table 15. Cross-tabulation results for within hardwoods separability – First difference of reduced relative reflectance data

Table	**Scarlet oak**	**White oak**	**Yellow poplar**	**Total**	**Discrimination %**
Scarlet oak	37 86.05%	6 13.95%	0 0.0%	43 100.00%	
White oak	5 10.64%	42 89.36%	0 0.0%	47 100.00%	
Yellow poplar	1 2.27%	1 2.27%	42 95.45%	44 100.00%	
Total	43 32.09%	49 36.57%	42 31.34%	134 100.00%	90.30%

Table 16. Cross-tabulation results for within pines separability – First difference of reduced relative reflectance data

Table	**Loblolly pine**	**Shortleaf pine**	**Virginia pine**	**Total**	**Discrimination %**
Loblolly pine	42 84.00%	5 10.00%	3 6.00%	50 100.00%	
Shortleaf pine	6 14.29%	32 76.19%	4 9.52%	42 100.00%	
Virginia pine	4 7.41%	9 16.67%	41 75.93%	54 100.00%	
Total	52 35.62%	46 31.51%	48 32.88%	146 100.00%	78.77%

Table 17. Cross-tabulation results for between group separability – Second difference of reduced relative reflectance data

Table	**Hardwoods**	**Pines**	**Total**	**Discrimination %**
Hardwoods	134 100.00%	0 0.0%	134 100.00%	
Pines	0 0.0%	146 100.00%	146 100.00%	
Total	134 47.86%	146 52.14%	280 100.00%	100.00%

Table 18. Cross-tabulation results for within hardwoods separability – Second difference of reduced relative reflectance data

Table	Scarlet oak	White oak	Yellow poplar	Total	Discrimination%
Scarlet oak	28 65.12%	14 32.56%	1 2.33%	43 100.00%	
White oak	11 23.40%	35 74.47%	1 2.13%	47 100.00%	
Yellow poplar	1 2.27%	1 2.27%	42 95.45%	44 100.00%	
Total	40 29.85%	50 37.31%	44 32.84%	134 100.00%	78.36%

Table 19. Cross-tabulation results for within pines separability – Second difference of reduced relative reflectance data

Table	Loblolly pine	Shortleaf pine	Virginia pine	Total	Discrimination %
Loblolly pine	27 54.00%	8 16.00%	15 30.00%	50 100.00%	
Shortleaf pine	6 14.29%	33 78.57%	3 7.14%	42 100.00%	
Virginia pine	13 24.07%	11 20.37%	30 55.56%	54 100.00%	
Total	46 31.51%	52 35.62%	48 32.88%	146 100.00%	61.64%

2. 9-point Moving Average Data

Table 20. Cross-tabulation results for between group separability - 9-point averaged data

Table	**Hardwoods**	**Pines**	**Total**	**Discrimination %**
Hardwoods	131 97.76%	3 2.24%	134 100.00%	
Pines	0 0.0%	146 100.00%	146 100.00%	
Total	131 46.79%	149 53.21%	280 100.00%	98.93%

Table 21. Cross-tabulation results for within hardwoods separability - 9-point averaged data

Table	**Scarlet oak**	**White oak**	**Yellow poplar**	**Total**	**Discrimination%**
Scarlet oak	35 81.4%	8 18.6%	0 0.0%	43 100.00%	
White oak	6 12.77%	41 87.23%	0 0.0%	47 100.00%	
Yellow poplar	0 0.0%	1 2.27%	43 97.73%	44 100.00%	
Total	41 30.6%	50 37.31%	43 32.09%	134 100.00%	88.81%

Table 22. Cross-tabulation results for within pines separability - 9-point averaged data

Table	**Loblolly pine**	**Shortleaf pine**	**Virginia pine**	**Total**	**Discrimination %**
Loblolly pine	38 76.00%	4 8.00%	8 16.00%	50 100.00%	
Shortleaf pine	3 7.14%	30 71.43%	9 21.43%	42 100.00%	
Virginia pine	8 14.81%	11 20.37%	35 64.81%	54 100.00%	
Total	49 33.56%	45 30.82%	52 35.62%	146 100.00%	70.55%

Table 23. Cross-tabulation results for between group separability - First difference 9-point averaged data

Table	Hardwoods	Pines	Total	**Discrimination %**
Hardwoods	132 98.51%	2 1.49%	134 100.00%	
Pines	0 0.0%	146 100.00%	146 100.00%	
Total	132 47.14%	148 52.86%	280 100.00%	99.29%

Table 24. Cross-tabulation results for within hardwoods separability - First difference 9-point averaged data

Table	**Scarlet oak**	**White oak**	**Yellow poplar**	**Total**	**Discrimination %**
Scarlet oak	37 86.05%	5 11.63%	1 2.33%	43 100.00%	
White oak	4 8.51%	42 89.36%	1 2.13%	47 100.00%	
Yellow poplar	1 2.27%	2 4.55%	41 93.18%	44 100.00%	
Total	42 31.34%	49 36.57%	43 32.09%	134 100.00%	89.55%

Table 25. Cross-tabulation results for within pines separability - First difference 9-point averaged data

Table	**Loblolly pine**	**Shortleaf pine**	**Virginia pine**	**Total**	**Discrimination %**
Loblolly pine	40 80.00%	6 12.00%	4 8.00%	50 100.00%	
Shortleaf pine	3 7.14%	37 88.1%	2 4.76%	42 100.00%	
Virginia pine	4 7.41%	7 12.96%	43 79.63%	54 100.00%	
Total	47 32.19%	50 34.25%	49 33.56%	146 100.00%	82.19%

Table 26. Cross-tabulation results for between group separability - Second difference 9-point averaged data

Table	**Hardwoods**	**Pines**	**Total**	**Discrimination %**
Hardwoods	134 100.00%	0 0.0%	134 100.00%	
Pines	0 0.0%	146 100.00%	146 100.00%	
Total	134 47.86%	146 52.14%	280 100.00%	100.00%

Table 27. Cross-tabulation results for within hardwoods separability - Second difference 9-point averaged data

Table	**Scarlet oak**	**White oak**	**Yellow poplar**	**Total**	**Discrimination %**
Scarlet oak	38 88.37%	5 11.63%	0 0.0%	43 100.00%	
White oak	4 8.51%	43 91.49%	0 0.0%	47 100.00%	
Yellow poplar	0 0.0%	1 2.27%	43 97.73%	44 100.00%	
Total	42 31.34%	49 36.57%	43 32.09%	134 100.00%	92.54%

Table 28. Cross-tabulation results for within pines separability - Second difference 9-point averaged data

Table	**Loblolly pine**	**Shortleaf pine**	**Virginia pine**	**Total**	**Discrimination %**
Loblolly pine	45 90.00%	3 6.00%	2 4.00%	50 100.00%	
Shortleaf pine	3 7.14%	35 83.33%	4 9.52%	42 100.00%	
Virginia pine	7 7.41%	7 12.96%	43 79.63%	54 100.00%	
Total	52 35.62%	45 30.82%	49 33.56%	146 100.00%	84.25%

3. 9-point Moving Median Data

Table 29. Cross-tabulation results for between group separability - 9-point median data

Table	**Hardwoods**	**Pines**	**Total**	**Discrimination %**
Hardwoods	133 99.25%	1 0.75%	134 100.00%	
Pines	0 0.0%	146 100.00%	146 100.00%	
Total	133 47.50%	147 52.50%	280 100.00%	99.64%

Table 30. Cross-tabulation results for within hardwoods separability - 9-point median data

Table	**Scarlet oak**	**White oak**	**Yellow poplar**	**Total**	**Discrimination %**
Scarlet oak	36 83.72%	6 13.95%	1 2.33%	43 100.00%	
White oak	12 25.53%	35 74.47%	0 0.0%	47 100.00%	
Yellow poplar	0 0.0%	0 0.0%	44 100.00%	44 100.00%	
Total	48 35.82%	41 30.60%	45 33.58%	134 100.00%	85.82%

Table 31. Cross-tabulation results for within pines separability - 9-point median data

Table	**Loblolly pine**	**Shortleaf pine**	**Virginia pine**	**Total**	**Discrimination %**
Loblolly pine	39 78.00%	4 8.00%	7 14.00%	50 100.00%	
Shortleaf pine	3 7.14%	26 61.90%	13 30.95%	42 100.00%	
Virginia pine	8 14.81%	11 20.37%	35 64.81%	54 100.00%	
Total	50 34.25%	41 28.08%	55 37.67%	146 100.00%	68.49%

Table 32. Cross-tabulation results for between group separability – First difference 9-point median data

Table	**Hardwoods**	**Pines**	**Total**	**Discrimination %**
Hardwoods	133 99.25%	1 0.75%	134 100.00%	
Pines	0 0.0%	146 100.00%	146 100.00%	
Total	133 47.50%	147 52.50%	280 100.00%	99.64%

Table 33. Cross-tabulation results for within hardwoods separability – First difference 9-point median data

Table	**Scarlet oak**	**White oak**	**Yellow poplar**	**Total**	**Discrimination %**
Scarlet oak	39 90.70%	4 9.30%	0 0.0%	43 100.00%	
White oak	5 10.64%	41 87.23%	1 2.13%	47 100.00%	
Yellow poplar	0 0.0%	1 2.27%	43 97.73%	44 100.00%	
Total	44 32.84%	46 34.33%	44 32.84%	134 100.00%	91.79%

Table 34. Cross-tabulation results for within pines separability – First difference 9-point median data

Table	**Loblolly pine**	**Shortleaf pine**	**Virginia pine**	**Total**	**Discrimination %**
Loblolly pine	41 82.00%	6 12.00%	3 6.00%	50 100.00%	
Shortleaf pine	4 9.52%	34 80.95%	4 9.52%	42 100.00%	
Virginia pine	4 7.41%	3 5.56%	47 87.04%	54 100.00%	
Total	49 33.56%	43 29.45%	54 36.99%	146 100.00%	83.56%

Table 35. Cross-tabulation results for between group separability – Second difference 9-point median data

Table	**Hardwoods**	**Pines**	**Total**	**Discrimination%**
Hardwoods	134 100.00%	0 0.0%	134 100.00%	
Pines	0 0.0%	146 100.00%	146 100.00%	
Total	134 47.86%	146 52.14%	280 100.00%	100.00%

Table 36. Cross-tabulation results for within hardwoods separability – Second difference 9-point median data

Table	**Scarlet oak**	**White oak**	**Yellow poplar**	**Total**	**Discrimination %**
Scarlet oak	30 69.77%	12 27.91%	1 2.33%	43 100.00%	
White oak	11 23.40%	35 74.47%	1 2.13%	47 100.00%	
Yellow poplar	2 4.55%	1 2.27%	41 93.18%	44 100.00%	
Total	43 32.09%	48 35.82%	43 32.09%	134 100.00%	79.10%

Table 37. Cross-tabulation results for within pines separability – Second difference 9-point median data

Table	**Loblolly pine**	**Shortleaf pine**	**Virginia pine**	**Total**	**Discrimination %**
Loblolly pine	35 70.00%	11 22.00%	4 8.00%	50 100.00%	
Shortleaf pine	6 14.29%	28 66.67%	8 19.05%	42 100.00%	
Virginia pine	9 16.67%	7 12.96%	38 70.37%	54 100.00%	
Total	50 34.25%	46 31.51%	50 34.25%	146 100.00%	69.18%

4. AVIRIS Simulation Data (10 nm bandwidths)

Table 38. Cross-tabulation results for between group separability – 10 nm resolution AVIRIS simulation data

Table	**Hardwoods**	**Pines**	**Total**	**Discrimination %**
Hardwoods	132 98.51%	2 1.49%	134 100.00%	
Pines	0 0.0%	146 100.00%	146 100.00%	
Total	132 47.14%	148 52.86%	280 100.00%	99.29%

Table 39. Cross-tabulation results for within hardwoods separability – 10 nm resolution AVIRIS simulation data

Table	**Scarlet oak**	**White oak**	**Yellow poplar**	**Total**	**Discrimination %**
Scarlet oak	36 83.72%	7 16.28%	0 0.0%	43 100.00%	
White oak	5 10.64%	42 89.36%	0 0.0%	47 100.00%	
Yellow poplar	0 0.0%	1 2.27%	43 97.73%	44 100.00%	
Total	41 30.60%	50 37.31%	43 32.09%	134 100.00%	90.30%

Table 40. Cross-tabulation results for within pines separability – 10 nm resolution AVIRIS simulation data

Table	**Loblolly pine**	**Shortleaf pine**	**Virginia pine**	**Total**	**Discrimination %**
Loblolly pine	41 82.00%	8 16.00%	1 2.00%	50 100.00%	
Shortleaf pine	4 9.52%	37 88.10%	1 2.38%	42 100.00%	
Virginia pine	1 1.85%	10 18.52%	43 79.63%	54 100.00%	
Total	46 31.51%	55 37.67%	45 30.82%	146 100.00%	82.88%

Table 41. Cross-tabulation results for between group separability - First difference 10 nm resolution AVIRIS simulation data

Table	**Hardwoods**	**Pines**	**Total**	**Discrimination %**
Hardwoods	132 98.51%	2 1.49%	134 100.00%	
Pines	0 0.0%	146 100.00%	146 100.00%	
Total	132 47.14%	148 52.86%	280 100.00%	99.29%

Table 42. Cross-tabulation results for within hardwoods separability - First difference 10 nm resolution AVIRIS simulation data

Table	**Scarlet oak**	**White oak**	**Yellow poplar**	**Total**	**Discrimination %**
Scarlet oak	34 79.07%	9 20.93%	0 0.0%	43 100.00%	
White oak	5 10.64%	42 89.36%	0 0.0%	47 100.00%	
Yellow poplar	0 0.0%	1 2.27%	43 97.73%	44 100.00%	
Total	39 29.10%	52 38.81%	43 32.09%	134 100.00%	88.81%

Table 43. Cross-tabulation results for within pines separability – First difference 10 nm resolution AVIRIS simulation data

Table	**Loblolly pine**	**Shortleaf pine**	**Virginia pine**	**Total**	**Discrimination %**
Loblolly pine	42 84.00%	7 14.00%	1 2.00%	50 100.00%	
Shortleaf pine	6 14.29%	35 83.33%	1 2.38%	42 100.00%	
Virginia pine	2 3.70%	9 16.67%	43 79.63%	54 100.00%	
Total	50 34.25%	51 34.93%	45 30.82%	146 100.00%	82.19%

Table 44. Cross-tabulation results for between group separability – Second difference 10 nm resolution AVIRIS simulation data

Table	**Hardwoods**	**Pines**	**Total**	**Discrimination %**
Hardwoods	132 98.51%	2 1.49%	134 100.00%	
Pines	0 0.0%	146 100%	146 100.00%	
Total	132 47.14%	148 52.86%	280 100.00%	99.29%

Table 45. Cross-tabulation results for within hardwoods separability – Second difference 10 nm resolution AVIRIS simulation data

Table	**Scarlet oak**	**White oak**	**Yellow poplar**	**Total**	**Discrimination %**
Scarlet oak	39 90.70%	4 9.30%	0 0.0%	43 100.00%	
White oak	5 10.64%	42 89.36%	0 0.0%	47 100.00%	
Yellow poplar	0 0.0%	1 2.27%	43 97.73%	44 100.00%	
Total	44 32.84%	47 35.07%	43 32.09%	134 100.00%	92.54%

Table 46. Cross-tabulation results for within pines separability – Second difference 10 nm resolution AVIRIS simulation data

Table	**Loblolly pine**	**Shortleaf pine**	**Virginia pine**	**Total**	**Discrimination %**
Loblolly pine	42 84.00%	6 12.00%	2 40.00%	50 100.00%	
Shortleaf pine	5 11.90%	35 83.33%	2 4.76%	42 100.00%	
Virginia pine	5 9.26%	6 11.11%	43 79.63%	54 100.00%	
Total	52 35.62%	47 32.19%	47 32.19%	146 100.00%	82.19%

Appendix E

Linear Discriminant Functions (constants and coefficients) for each Data Set

1. Reduced Raw Data

Table 47. Discriminant function for between group separability - Reduced relative reflectance data

Variable	Hardwoods	Pines	Variable	Hardwoods	Pines
Constant	-26.542	-27.268			
731 nm	-130.840	158.785	**1540 nm**	-545.642	7378.192
963 nm	177.834	-115.759	**1548 nm**	-2095.667	-7603.136
1169 nm	-1979.562	96.954	**1579 nm**	3920.958	-65.470
1193 nm	1240.224	-1859.574	**1659 nm**	-1448.177	354.852
1274 nm	774.322	1782.063			

Table 48. Discriminant function for within hardwoods separability - Reduced relative reflectance data

Variable	Scarlet oak	White oak	Yellow poplar	Variable	Scarlet oak	White oak	Yellow poplar
Constant	-17.637	-21.669	-27.578	**Constant**	-17.637	-21.669	-27.578
350 nm	294.679	1039.428	1078.299	**1340 nm**	25.013	99.017	-364.612
643 nm	460.715	257.180	-1265.351	**1639 nm**	3801.426	2261.988	-297.720
694 nm	-445.099	-402.335	998.384	**1662 nm**	-3230.577	-1030.864	1952.704
764 nm	5.238	-53.424	-107.814	**1730 nm**	-549.404	-164.198	2320.475
1122 nm	78.637	89.209	300.200	**1747 nm**	-153.545	-1360.883	-4057.767

Table 49. Discriminant function for within pines separability - Reduced relative reflectance data

Variable	Loblolly pine	Shortleaf pine	Virginia pine	Variable	Loblolly pine	Shortleaf pine	Virginia pine
Constant	-19.915	-10.477	-11.393	**Constant**	-19.915	-10.477	-11.393
354 nm	6413.289	4048.241	1698.921	**712 nm**	-118.766	16.866	59.416
404 nm	-12988.169	-8386.700	3063.972	**1463 nm**	-846.769	-269.756	-282.505
421 nm	15003.898	9543.306	-7454.116	**1771 nm**	620.463	271.162	340.523
435 nm	-8107.760	-5494.042	5335.135	**2460 nm**	-62.426	-8.526	-37.156
490 nm	1341.962	737.881	-2035.965				

Table 50. Discriminant function for between group separability – First difference of reduced relative reflectance data

Variable	Hardwoods	Pines	Variable	Hardwoods	Pines
Constant	-23.242	-13.148	**Constant**	-23.242	-13.148
402 nm	15990.424	-8586.299	**1246 nm**	4403.795	15901.157
417 nm	-31197.451	9157.074	**1250 nm**	-7778.961	9247.595
425 nm	-12806.286	23337.200	**1502 nm**	10599.259	422.725
634 nm	-51127.311	8475.971	**1510 nm**	13898.318	-2652.924
711 nm	-3157.034	829.420	**1514 nm**	9502.034	-4285.594
752 nm	12767.411	-57.599	**2009 nm**	971.756	233.811
1136 nm	1311.790	-123.076	**2420 nm**	-207.541	59.274
1212 nm	7088.202	19224.817			

Table 51. Discriminant function for within hardwoods separability – First difference of reduced relative reflectance data

Variable	Scarlet oak	White oak	Yellow poplar	Variable	Scarlet oak	White oak	Yellow poplar
Constant	-9.858	-13.059	-28.488	**Constant**	-9.858	-13.059	-28.488
398 nm	-13816.522	-16394.250	-53167.322	**614 nm**	9266.609	-14460.920	-3417.102
411 nm	17269.673	53644.099	-35742.463	**637 nm**	2426.119	-7367.035	-105434.588
425 nm	-18142.012	18051.254	56082.136	**1304 nm**	-10930.432	-13118.554	-18790.055
438 nm	-7382.186	-63470.554	-108439.096	**1568 nm**	5080.313	4372.358	14323.757
448 nm	33603.960	-28489.057	25238.765	**1694 nm**	-2658.460	-5125.827	8904.590
547 nm	13966.534	-4142.907	-58712.537	**2188 nm**	-279.241	1154.099	1069.446

Table 52. Discriminant function for within pines separability – First difference of reduced relative reflectance data

Variable	Loblolly pine	Shortleaf pine	Virginia pine	Variable	Loblolly pine	Shortleaf pine	Virginia pine
Constant	-13.817	-16.149	-15.046	**Constant**	-13.817	-16.149	-15.046
408 nm	7330.186	2090.025	-32357.559	**776 nm**	44172.872	63721.158	77483.515
433 nm	1837.119	7250.088	28451.488	**950 nm**	192.041	-784.300	960.351
503 nm	18436.361	62080.425	24354.569	**1109 nm**	-2559.571	-3360.489	1422.323
533 nm	-4039.471	-26545.326	-4821.262	**1161 nm**	974.473	4196.988	4205.936
587 nm	-14540.520	15728.876	15047.779				

Table 53. Discriminant function for between group separability – Second difference of reduced relative reflectance data

Variable	Hardwoods	Pines	Variable	Hardwoods	Pines
Constant	-16.283	-10.884	**Constant**	-16.283	-10.884
429 nm	-29542.210	14622.061	**718 nm**	12722.940	-26.259
474 nm	-16184.848	31693.460	**732 nm**	9575.692	-11224.710
522 nm	88520.053	-167505.827	**748 nm**	-23007.632	-792.910
524 nm	21854.995	-54947.428	**750 nm**	-78850.117	-11750.696
688 nm	-15641.070	33246.868	**1066 nm**	-5152.808	8220.702
690 nm	-25997.899	65114.174	**1103 nm**	-2140.129	895.887
696 nm	88077.392	-57168.964	**1264 nm**	6668.863	409332.199
698 nm	17187.561	-24945.572	**1279 nm**	-10039.216	3794.871
703 nm	-88587.940	79345.219	**1633 nm**	-3260.366	2868.115
705 nm	-24756.292	30077.495	**2038 nm**	450.648	-761.559

Table 54. Discriminant function for within hardwoods separability – Second difference of reduced relative reflectance data

Variable	Scarlet oak	White oak	Yellow poplar	Variable	Scarlet oak	White oak	Yellow poplar
Constant	-8.414	-10.543	-22.272	**Constant**	-8.414	-10.543	-22.272
644 nm	7957.429	332.677	80330.396	**737 nm**	15502.071	10950.994	-36002.425
646 nm	50214.803	-51146.415	405521.731	**1072 nm**	-238.522	-3908.339	-139.377
648 nm	29129.294	651.171	70126.980	**1171 nm**	-2582.329	-1636.362	-12526.754
694 nm	15265.687	26654.168	-36000.295	**1310 nm**	-149162.924	-171990.610	-388520.862
722 nm	12543.197	4506.954	-9085.076	**2019 nm**	-139.147	521.156	2201.389
735 nm	1324.366	2862.067	-38943.070	**2373 nm**	306.288	445.514	1081.219

Table 55. Discriminant function for within pines separability – Second difference of reduced relative reflectance data

Variable	Loblolly pine	Shortleaf pine	Virginia pine	Variable	Loblolly pine	Shortleaf pine	Virginia pine
Constant	-7.126	-4.289	-4.461	**Constant**	-7.126	-4.289	-4.461
495 nm	-19161.924	44789.208	-37191.305	**727 nm**	13662.190	-6933.545	4085.612
512 nm	144873.318	35327.200	158400.494	**1063 nm**	-3793.773	-495.160	-3307.651
523 nm	-159.545	-41308.241	9496.421	**1653 nm**	1367.576	-1673.674	2236.018
529 nm	-85213.905	-58727.337	-38597.968				

2. 9-point Moving Average Data

Table 56. Discriminant function for between group separability - 9-point averaged data

Variable	Hardwoods	Pines	Variable	Hardwoods	Pines
Constant	-19.308	-20.579	**Constant**	-19.308	-20.579
520 nm	-199.089	310.705	**1198 nm**	-1632.557	-6822.441
872 nm	39.876	-33.721	**1213 nm**	2426.180	5812.871
1100 nm	-36.549	267.695	**1340 nm**	-21.066	436.488
1170 nm	-682.161	311.288			

Table 57. Discriminant function for within hardwoods separability - 9-point averaged data

Variable	Scarlet oak	White oak	Yellow poplar	Variable	Scarlet oak	White oak	Yellow poplar
Constant	-17.862	-19.002	-22.765	**Constant**	-17.862	-19.002	-22.765
418 nm	226.495	988.436	257.324	**1691 nm**	-64.628	987.809	-4756.625
691 nm	-71.209	-337.312	115.513	**1700 nm**	4828.087	912.227	6211.486
1590 nm	-2398.641	-2384.689	-207.730	**1725 nm**	-4959.268	-2724.625	843.070
1631 nm	6991.912	5575.812	-997.287	**1746 nm**	1319.034	720.166	-3958.735
1655 nm	-5858.673	-3249.823	2619.724				

Table 58. Discriminant function for within pines separability - 9-point averaged data

Variable	Loblolly pine	Shortleaf pine	Virginia pine	Variable	Loblolly pine	Shortleaf pine	Virginia pine
Constant	-15.681	-9.011	-11.005	**Constant**	-15.681	-9.011	-11.005
355 nm	1903.362	891.134	1661.982	**1463 nm**	-628.890	-180.164	-190.811
713 nm	55.219	115.076	181.482	**1772 nm**	422.934	171.618	234.135
515 nm	-403.250	-382.033	-1028.336				

Table 59. Discriminant function for between group separability - First difference 9-point averaged data

Variable	Hardwoods	Pines	Variable	Hardwoods	Pines
Constant	-25.534	-21.253	**Constant**	-25.534	-21.253
363 nm	-99798.497	-57320.692	**1211 nm**	18259.278	50709.629
414 nm	-64434.279	41161.975	**1247 nm**	14541.081	49244.008
489 nm	64413.982	-33258.795	**1561 nm**	32988.127	-4927.076
750 nm	6968.782	-3855.363	**1646 nm**	-33876.921	-11924.074
949 nm	7674.978	349.666			

Table 60. Discriminant function for within hardwoods separability - First difference 9-point averaged data

Variable	Scarlet oak	White oak	Yellow poplar	Variable	Scarlet oak	White oak	Yellow poplar
Constant	-18.385	-21.411	-34.128	**Constant**	-18.385	-21.411	-34.128
399 nm	-70642.006	-25616.214	-162555.119	**1023 nm**	30590.818	27387.618	53219.384
467 nm	-107897.627	-238011.838	-355374.814	**1645 nm**	-31660.617	-13389.652	6202.791
487 nm	69889.018	59965.372	231980.903	**1664 nm**	3586.772	-14875.635	-20206.070
620 nm	-7276.566	-28725.238	-32110.790	**1695 nm**	-87.360	-18483.960	20790.894
759 nm	-494.426	-3703.334	-6154.077	**1711 nm**	-35527.826	-14800.707	-27005.300
794 nm	7837.068	31938.748	24396.254				

Table 61. Discriminant function for within pines separability - First difference 9-point averaged data

Variable	Loblolly pine	Shortleaf pine	Virginia pine	Variable	Loblolly pine	Shortleaf pine	Virginia pine
Constant	-13.322	-15.911	-11.812	**Constant**	-13.322	-15.911	-11.812
401 nm	-58078.744	-8342.722	49893.664	**587 nm**	-14929.522	22263.756	11801.476
416 nm	91194.584	25269.173	-85692.926	**994 nm**	13872.151	27756.235	25356.553
440 nm	-39227.376	-19821.986	95994.973	**1110 nm**	-6308.128	-7316.834	-2775.369
502 nm	32345.278	88118.205	31798.001	**1460 nm**	954.803	5465.244	5932.865
526 nm	-13185.394	-23831.023	-3829.771				

Table 62. Discriminant function for between group separability - Second difference 9-point averaged data

Variable	Hardwoods	Pines	Variable	Hardwoods	Pines
Constant	-16.495	-7.325	**Constant**	-16.495	-7.325
417 nm	-244437.482	140008.057	**970 nm**	-31296.015	2814.391
426 nm	316190.663	-234754.631	**1244 nm**	-81066.462	1103.133
431 nm	562857.481	-215725.010	**1285 nm**	11756.125	-71346.583
523 nm	208089.206	-300003.629	**1479 nm**	17098.543	-2676.745
542 nm	-695979.657	-23867.196	**1564 nm**	-91609.286	21216.924
546 nm	-1368251.660	294482.592	**1991 nm**	-4772.528	1626.614
662 nm	-111090.393	323511.243	**2055 nm**	4695.467	-2564.532
722 nm	89935.541	-1008.475	**2215 nm**	-4668.381	978.458
964 nm	-11941.667	9976.061			

Table 63. Discriminant function for within hardwoods separability - Second difference 9-point averaged data

Variable	Scarlet oak	White oak	Yellow poplar	Variable	Scarlet oak	White oak	Yellow poplar
Constant	-10.356	-12.073	-24.662	**Constant**	-10.356	-12.073	-24.662
518 nm	-196797.306	-127543.460	-517402.662	**1521 nm**	17578.207	-58301.962	-49350.906
547 nm	237886.229	-407433.122	-1300801.561	**1610 nm**	6230.562	-71388.904	-84326.720
559 nm	-391544.042	226370.141	5609.851	**1715 nm**	38221.164	1731.605	-16019.339
645 nm	-299452.886	-53225.113	842011.022	**1753 nm**	-6414.173	-36911.287	-19370.026
661 nm	-264319.435	129777.662	556880.187	**2111 nm**	3432.570	1275.958	14607.146
693 nm	40946.386	58096.501	-84975.173	**2186 nm**	-2985.895	3608.512	-221.681
717 nm	44530.713	25439.939	13395.916	**2326 nm**	824.485	-4572.331	-6643.027
735 nm	53716.310	-36908.470	-194641.965				

Table 64. Discriminant function for within pines separability - Second difference 9-point averaged data

Variable	Loblolly pine	Shortleaf pine	Virginia pine	Variable	Loblolly pine	Shortleaf pine	Virginia pine
Constant	-11.636	-7.587	-6.886	**Constant**	-11.636	-7.587	-6.886
417 nm	-37255.938	-129550.801	211088.056	**591 nm**	126770.298	4587.663	6363.139
422 nm	-260028.164	-22147.974	388643.558	**691 nm**	-31348.712	22605.676	48357.858
427 nm	-227915.675	-136477.537	173439.999	**1255 nm**	-53851.090	-59224.812	-10169.221
523 nm	216180.497	-265979.585	100423.886	**2065 nm**	3468.038	-305.980	-811.548
563 nm	-589200.538	-57541.400	-63896.790	**2411 nm**	1059.043	-477.482	489.442

3. 9-point Moving Median Data

Table 65. Discriminant function for between group separability - 9-point median data

Variable	Hardwoods	Pines	Variable	Hardwoods	Pines
Constant	-24.558	-25.492	**Constant**	-24.558	-25.492
731 nm	-119.993	146.772	**1273 nm**	712.744	1548.551
958 nm	140.381	-106.427	**1453 nm**	-169.451	635.516
1170 nm	-2627.917	-412.853	**1547 nm**	-11.653	-555.624
1188 nm	1992.183	-1061.297			

Table 66. Discriminant function for within hardwoods separability - 9-point median data

Variable	Scarlet oak	White oak	Yellow poplar	Variable	Scarlet oak	White oak	Yellow poplar
Constant	-13.957	-19.073	-21.427	**Constant**	-13.957	-19.073	-21.427
354 nm	271.259	928.751	468.727	**1340 nm**	324.172	419.417	-141.745
561 nm	0.543	-140.601	3.203	**1724 nm**	-1574.309	-796.054	3367.817
1001 nm	-3429.375	-4154.640	-1097.436	**1747 nm**	1331.475	463.661	-3422.169
1008 nm	3576.974	4280.235	1059.960	**2465 nm**	-20.013	-50.998	27.643
1121 nm	-239.240	-265.176	137.810				

Table 67. Discriminant function for within pines separability - 9-point median data

Variable	Loblolly pine	Shortleaf pine	Virginia pine
Constant	-16.098	-9.181	-11.239
354 nm	1874.471	867.255	1629.368
515 nm	-277.766	-279.567	-908.867
712 nm	-3.498	71.296	129.971
1465 nm	-733.395	-292.187	-326.493
1755 nm	504.923	254.593	334.849

Table 68. Discriminant function for between group separability - First difference 9-point median data

Variable	Hardwoods	Pines	Variable	Hardwoods	Pines
Constant	-19.492	-13.595	**Constant**	-19.492	-13.595
414 nm	-19255.290	24018.838	**1212 nm**	5873.287	19034.607
425 nm	-27698.892	20149.201	**1246 nm**	3811.039	14575.889
430 nm	21783.040	-3039.293	**1250 nm**	-8582.944	8701.227
752 nm	7973.193	-231.859	**1502 nm**	8820.720	-720.716
1000 nm	-1174.361	3403.741	**1510 nm**	9433.636	-1187.612
1135 nm	836.985	-712.687	**1514 nm**	6672.678	-3181.506

Table 69. Discriminant function for within hardwoods separability - First difference 9-point median data

Variable	Scarlet oak	White oak	Yellow poplar	Variable	Scarlet oak	White oak	Yellow poplar
Constant	-5.960	-6.572	-24.308	**Constant**	-5.960	-6.572	-24.308
396 nm	4071.118	-2776.877	-55250.190	**648 nm**	38682.465	-20787.203	-12946.394
404 nm	-11153.482	17340.005	-50131.796	**1027 nm**	4858.637	7098.874	12003.550
457 nm	2376.237	-96670.250	-183523.463	**1650 nm**	-7758.546	-2645.014	17337.223
497 nm	50827.857	13586.274	71401.375	**1670 nm**	-2277.480	-6147.289	-32643.743
547 nm	38483.527	9210.575	-52945.324	**2017 nm**	142.669	-805.768	-1842.117
637 nm	20688.310	4366.881	-95617.760	**2418 nm**	-97.623	250.492	693.735

Table 70. Discriminant function for within pines separability - First difference 9-point median data

Variable	Loblolly pine	Shortleaf pine	Virginia pine	Variable	Loblolly pine	Shortleaf pine	Virginia pine
Constant	-13.658	-8.238	-7.451	**Constant**	-13.658	-8.238	-7.451
380 nm	-90360.123	-33530.640	-52719.737	**667 nm**	30916.485	20233.935	-2633.632
419 nm	24658.694	10935.593	-6598.527	**672 nm**	-53059.964	11891.412	5248.489
420 nm	27943.694	12977.015	-8957.007	**920 nm**	-6735.821	-3150.127	1808.033
429 nm	16983.849	-6444.601	23069.649	**1256 nm**	8136.753	1096.929	14723.906
441 nm	-41564.859	-1120.503	50445.235	**1632 nm**	8384.978	-583.034	3213.973
499 nm	8610.199	48358.343	-15543.472	**2450 nm**	-76.304	-258.183	10.008
587 nm	-41982.813	-10478.126	-22167.124				

Table 71. Discriminant function for between group separability - Second difference 9-point median data

Variable	Hardwoods	Pines	Variable	Hardwoods	Pines
Constant	-16.686	-9.260	**Constant**	-16.686	-9.260
364 nm	-20741.169	4246.522	**703 nm**	-59981.306	62685.904
430 nm	18148.196	-846.633	**705 nm**	-11990.188	26890.655
523 nm	30197.707	-75382.504	**723 nm**	43203.547	13492.393
524 nm	25161.162	-71602.545	**730 nm**	50437.149	9485.752
525 nm	20459.349	-68458.989	**748 nm**	-19219.429	1739.467
688 nm	-2605.945	27842.608	**749 nm**	-29709.326	2407.580
690 nm	-6006.475	50217.774	**2103 nm**	1902.794	-1021.257
696 nm	97957.715	-35123.526	**2239 nm**	-1300.546	770.470
698 nm	14407.676	-13419.823	**2296 nm**	-966.712	412.047

Table 72. Discriminant function for within hardwoods separability - Second difference 9-point median data

Variable	Scarlet oak	White oak	Yellow poplar	Variable	Scarlet oak	White oak	Yellow poplar
Constant	-8.305	-9.298	-20.596	**Constant**	-8.305	-9.298	-20.596
419 nm	16497.054	-7873.884	-34757.061	**651 nm**	-6860.867	3297.454	46600.624
553 nm	-18935.062	-1104.895	-8692.765	**694 nm**	8401.279	23383.679	-12673.664
644 nm	15915.384	9191.029	65993.309	**703 nm**	6461.551	33561.451	66146.525
646 nm	174678.480	67941.305	504265.269	**710 nm**	74539.337	35271.045	83861.388
648 nm	54235.119	22253.864	108633.104	**1499 nm**	1184.566	4881.455	10244.420
649 nm	-756.162	53754.119	217087.950	**2327 nm**	8.683	-773.647	-1782.777

Table 73. Discriminant function for within pines separability - Second difference 9-point median data

Variable	Loblolly pine	Shortleaf pine	Virginia pine	Variable	Loblolly pine	Shortleaf pine	Virginia pine
Constant	-6.559	-3.795	-3.893	**Constant**	-6.559	-3.795	-3.893
422 nm	-10183.291	8722.914	40334.617	**1063 nm**	-4008.189	-515.392	-5034.009
423 nm	3269.310	-748.936	20154.831	**1108 nm**	44.866	-1915.940	1231.587
529 nm	-126366.945	-78018.363	-80999.018	**1567 nm**	284.372	1298.653	-3345.673
676 nm	-11100.377	16616.702	27535.536	**1745 nm**	-2429.387	2748.676	-2316.352
886 nm	15059.361	5323.226	2068.514	**2354 nm**	-287.714	477.659	-349.882

4. AVIRIS Simulation Data 10 nm bandwidths

Table 74. Discriminant function for between group separability – 10 nm resolution AVIRIS simulation data

Variable	Hardwoods	Pines	Variable	Hardwoods	Pines
Constant	-25.379	-26.490	**Constant**	-25.379	-26.490
520 nm	91.407	414.854	**1190 nm**	1066.661	-1706.180
730 nm	-146.067	-24.511	**1270 nm**	-913.219	1245.375
970 nm	136.650	-5.119	**1310 nm**	2043.827	592.282
1160 nm	-1098.543	136.936	**1340 nm**	-1103.567	-328.338

Table 75. Discriminant function for within hardwoods separability – 10 nm resolution AVIRIS simulation data

Variable	Scarlet oak	White oak	Yellow poplar	Variable	Scarlet oak	White oak	Yellow poplar
Constant	-20.653	-23.475	-20.668	**Constant**	-20.653	-23.475	-20.668
380 nm	823.705	-423.200	2193.698	**1530 nm**	1489.498	1738.461	-1373.846
420 nm	-785.361	1940.753	-2013.370	**1590 nm**	-5337.113	-5665.208	1525.179
680 nm	848.991	-766.470	-298.269	**1630 nm**	8697.439	7259.246	-1317.521
690 nm	-668.546	-88.037	585.813	**1660 nm**	-5033.633	-2156.572	2185.972
970 nm	48.372	-35.681	-44.915	**1700 nm**	154.640	-1340.285	-1377.264
1200 nm	77.491	207.991	86.092				

Table 76. Discriminant function for within pines separability – 10 nm resolution AVIRIS simulation data

Variable	Loblolly pine	Shortleaf pine	Virginia pine
Constant	-22.963	-13.682	-16.040
360 nm	7757.073	4777.103	2792.763
410 nm	-24065.535	-14021.940	5808.215
420 nm	26432.635	15710.561	-9927.922
440 nm	-10097.868	-6610.524	3883.946
490 nm	2474.580	1314.525	-1376.351
650 nm	-1175.352	-529.572	-455.289
1340 nm	148.443	139.383	190.901

Table 77. Discriminant function for between group separability - First difference 10 nm resolution AVIRIS simulation data

Variable	Hardwoods	Pines	Variable	Hardwoods	Pines
Constant	-26.211	-23.256	**Constant**	-26.211	-23.256
360 nm	-22952.735	-6862.982	**930 nm**	307.313	-32.385
390 nm	4279.377	-4135.464	**1160 nm**	1893.436	502.942
410 nm	-6405.356	4514.856	**1240 nm**	6243.621	11778.144
480 nm	6005.499	-7961.978	**1500 nm**	1960.618	284.757
750 nm	645.374	-856.717			

Table 78. Discriminant function for within hardwoods separability - First difference 10 nm resolution AVIRIS simulation data

Variable	Scarlet oak	White oak	Yellow poplar	Variable	Scarlet oak	White oak	Yellow poplar
Constant	-16.033	-17.009	-21.275	**Constant**	-16.033	-17.009	-21.275
400 nm	-165.413	4431.185	-6730.463	**1640 nm**	-5133.050	-1174.777	3129.798
480 nm	2306.422	-7616.869	6515.001	**1670 nm**	3306.954	2117.108	-2528.120
750 nm	541.976	102.591	-627.915	**1690 nm**	-4683.947	-5431.198	393.236
770 nm	898.047	1960.583	2787.811	**1730 nm**	-88.437	107.787	-3119.871
940 nm	-440.661	-356.985	-1576.181				

Table 79. Discriminant function for within pines separability – First difference 10 nm resolution AVIRIS simulation data

Variable	Loblolly pine	Shortleaf pine	Virginia pine
Constant	-13.694	-12.613	-12.521
390 nm	-22871.190	-11503.374	-5305.955
410 nm	17022.297	3728.199	-14625.133
420 nm	-6746.741	617.740	13787.376
490 nm	-1676.011	5188.921	2696.793
540 nm	1401.925	-2304.976	-423.196
1050 nm	3288.121	4388.292	5109.980

Table 80. Discriminant function for between group separability – Second difference 10 nm resolution AVIRIS simulation data

Variable	Hardwoods	Pines	Variable	Hardwoods	Pines
Constant	-13.793	-6.780	**Constant**	-13.793	-6.780
430 nm	1423.424	-9068.744	**720 nm**	519.917	83.659
440 nm	8752.474	-2170.789	**1070 nm**	280.154	-2953.913
480 nm	36879.071	5288.688	**1590 nm**	-1385.051	1247.044
520 nm	7516.487	-1874.769	**1660 nm**	2632.326	985.490
660 nm	-3298.359	8832.153			

Table 81. Discriminant function for within hardwoods separability – Second difference 10 nm resolution AVIRIS simulation data

Variable	Scarlet oak	White oak	Yellow poplar	Variable	Scarlet oak	White oak	Yellow poplar
Constant	-5.489	-6.819	-14.522	**Constant**	-5.489	-6.819	-14.522
380 nm	1094.162	3881.035	-7856.927	**660 nm**	-1540.564	7380.737	2829.294
390 nm	7082.703	14199.635	-7818.411	**1650 nm**	-788.318	-3310.380	-5489.344
480 nm	-5593.685	-3254.819	37447.601	**1660 nm**	2601.457	-140.057	-4169.390
590 nm	2777.111	-17.201	23.543	**1700 nm**	-1423.253	817.906	-1776.343

Table 82. Discriminant function for within pines separability – Second difference 10 nm resolution AVIRIS simulation data

Variable	Loblolly pine	Shortleaf pine	Virginia pine
Constant	-11.467	-12.396	-9.503
420 nm	1807.342	1334.906	10935.723
430 nm	-13503.829	-3030.878	4833.673
520 nm	-2777.329	-7724.021	-2595.332
590 nm	1190.877	-2604.956	-1227.438
670 nm	824.772	2506.108	1667.460
800 nm	-1785.881	-2136.865	-694.571
1150 nm	462.782	968.888	911.843

Appendix F

Canonical Variable Plots and Statistics

1. Relative Reflectance Data

1.1 Raw Relative Reflectance

Table 83. Canonical variances (between group) – Raw relative reflectance data

Group	N	Canonical 1 variance
Hardwoods	134	1.332
Pines	146	0.696

Table 84. Canonical variances (within hardwoods) - Raw relative reflectance data

Species (hardwoods)	N	Canonical 1 variance	Canonical 2 variance	Pooled variance
Scarlet oak	43	0.868	1.191	1.030
White oak	47	0.813	0.893	0.853
Yellow poplar	44	1.329	0.927	1.128

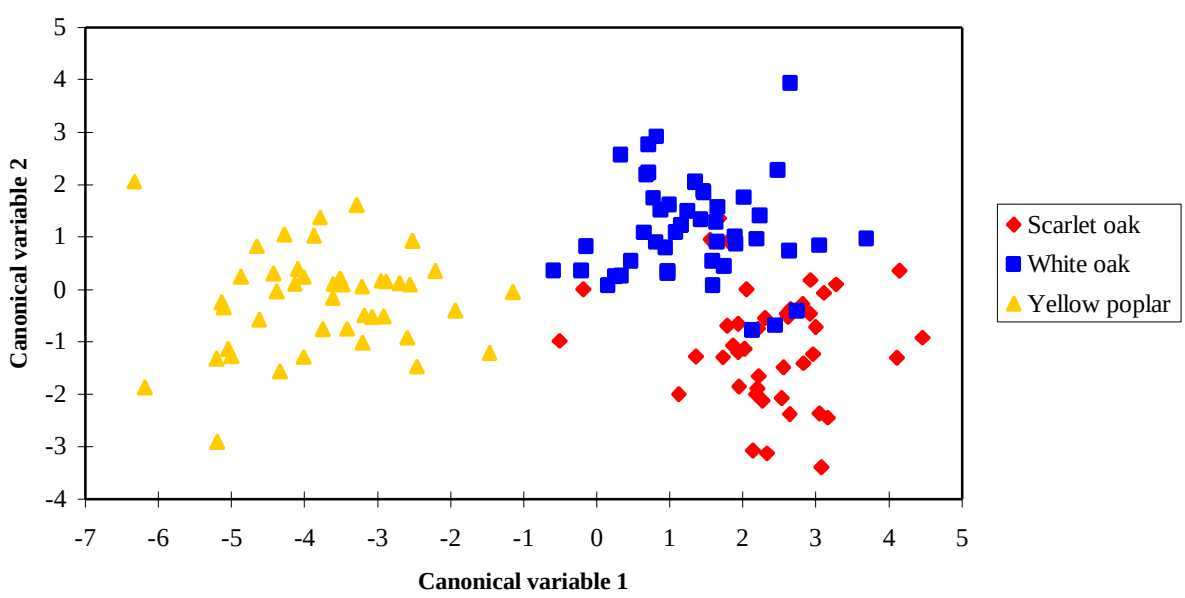


Figure 17. Canonical variable plot: Raw relative reflectance data for hardwood spectral separability

Table 85. Canonical variances (within pines) - Raw relative reflectance data

Species (pines)	N	Canonical 1 variance	Canonical 2 variance	Pooled variance
Loblolly	50	0.903	0.625	0.764
Shortleaf	42	0.892	0.587	0.739
Virginia	54	1.174	1.666	1.420

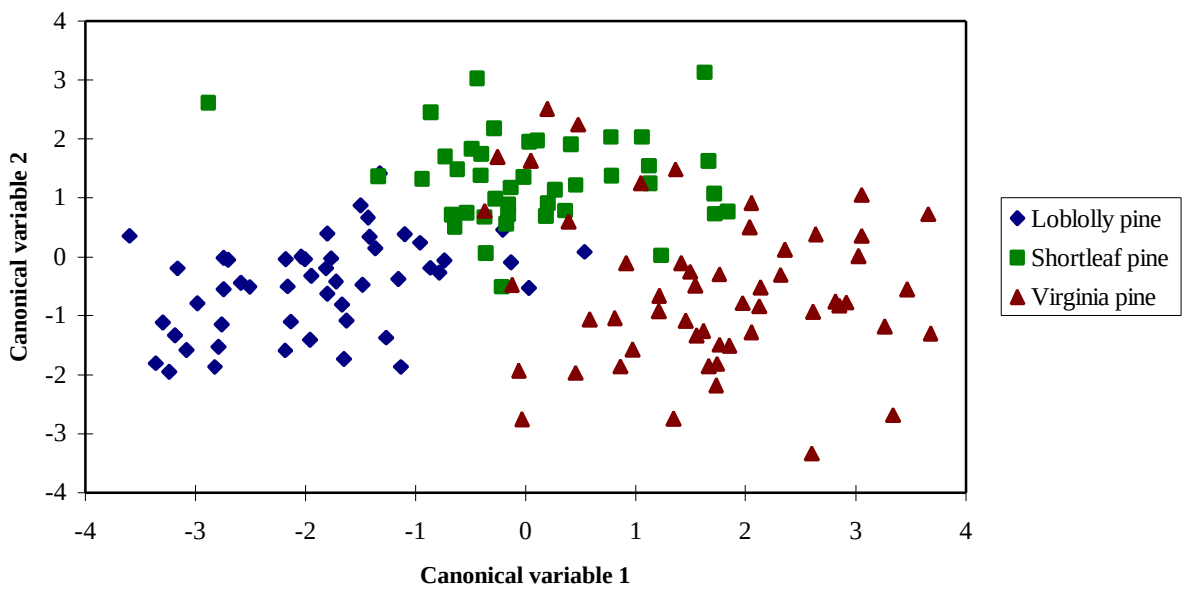


Figure 18. Canonical variable plot: Raw relative reflectance data for pine spectral separability

1.2 First Difference of Raw Relative Reflectance

Table 86. Canonical variances (between group) – First difference of r aw relative reflectance data

Group	N	Canonical 1 variance
Hardwoods	134	1.429
Pines	146	0.606

Table 87. Canonical variances (within hardwoods) - First difference of r aw relative reflectance data

Species (hardwoods)	N	Canonical 1 variance	Canonical 2 variance	Pooled variance
Scarlet oak	43	0.682	1.397	1.039
White oak	47	0.828	0.816	0.822
Yellow poplar	44	1.494	0.810	1.152

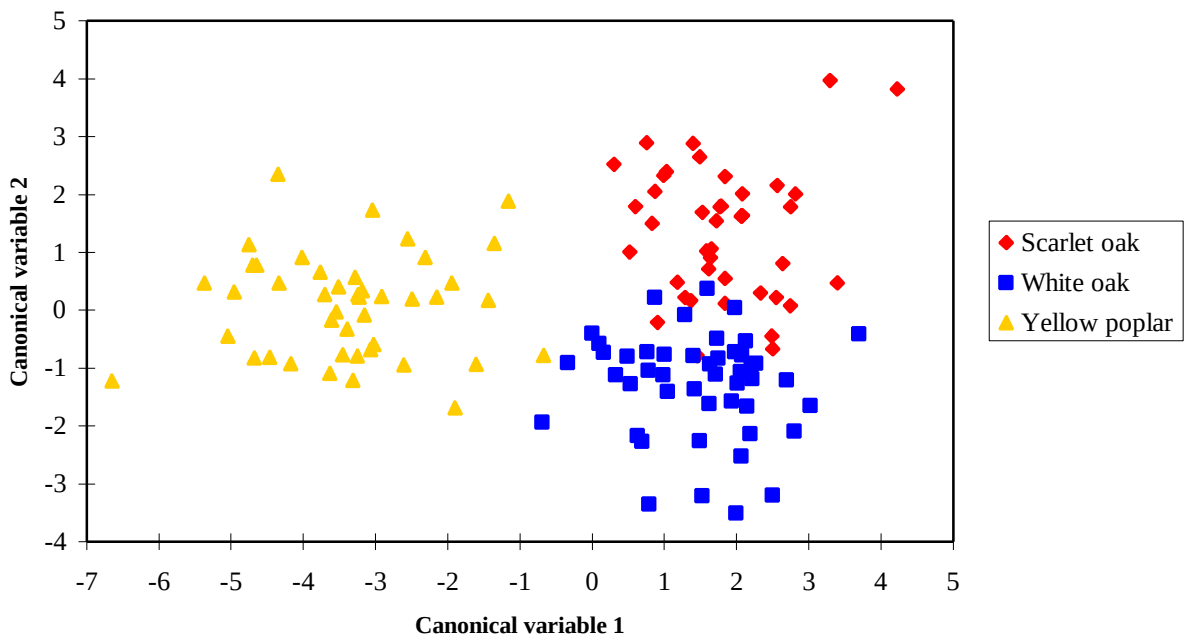


Figure 19. Canonical variable plot: First difference of raw relative reflectance data for hardwood spectral separability

Table 88. Canonical variances (within pines) - First difference of raw relative reflectance data

Species (pines)	N	Canonical 1 variance	Canonical 2 variance	Pooled variance
Loblolly	50	0.919	0.620	0.770
Shortleaf	42	1.373	0.801	1.087
Virginia	54	0.786	1.505	1.145

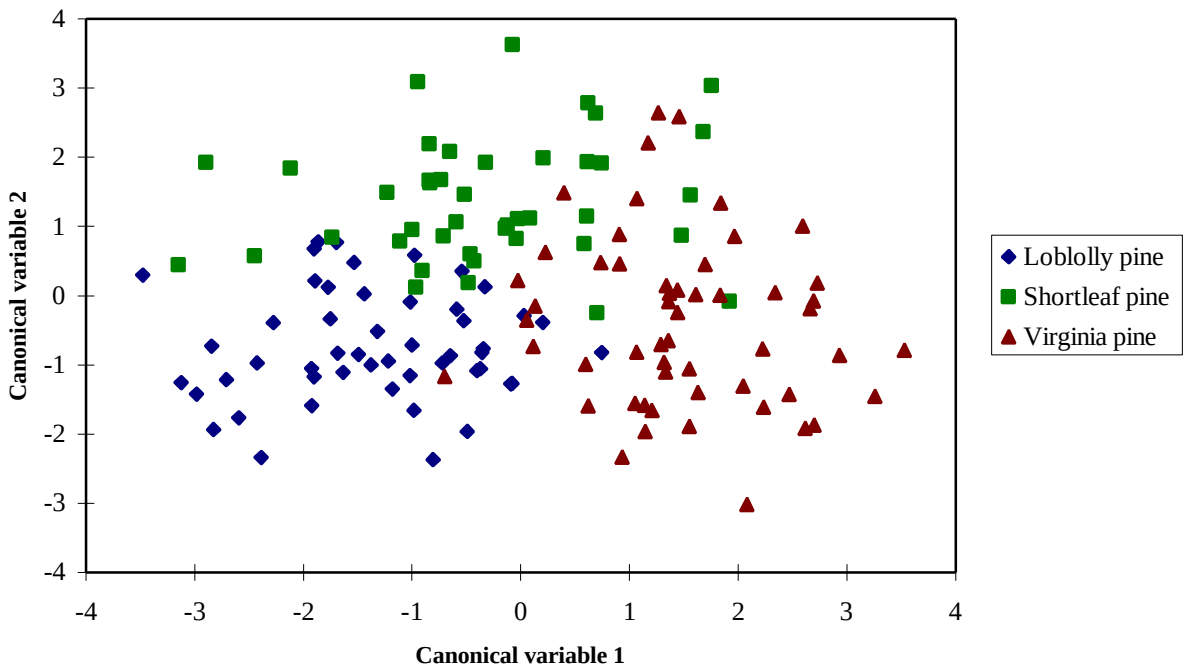


Figure 20. Canonical variable plot: First difference of raw relative reflectance data for pine spectral separability

1.3 Second Difference of Raw Relative Reflectance

Table 89. Canonical variances (between group) - Second difference of r aw relative reflectance data

Group	N	Canonical 1 variance
Hardwoods	134	1.324
Pines	146	0.702

Table 90. Canonical variances (within hardwoods) - Second difference of r aw relative reflectance data

Species (hardwoods)	N	Canonical 1 variance	Canonical 2 variance	Pooled variance
Scarlet oak	43	0.961	1.084	1.022
White oak	47	0.690	1.130	0.910
Yellow poplar	44	1.370	0.779	1.075

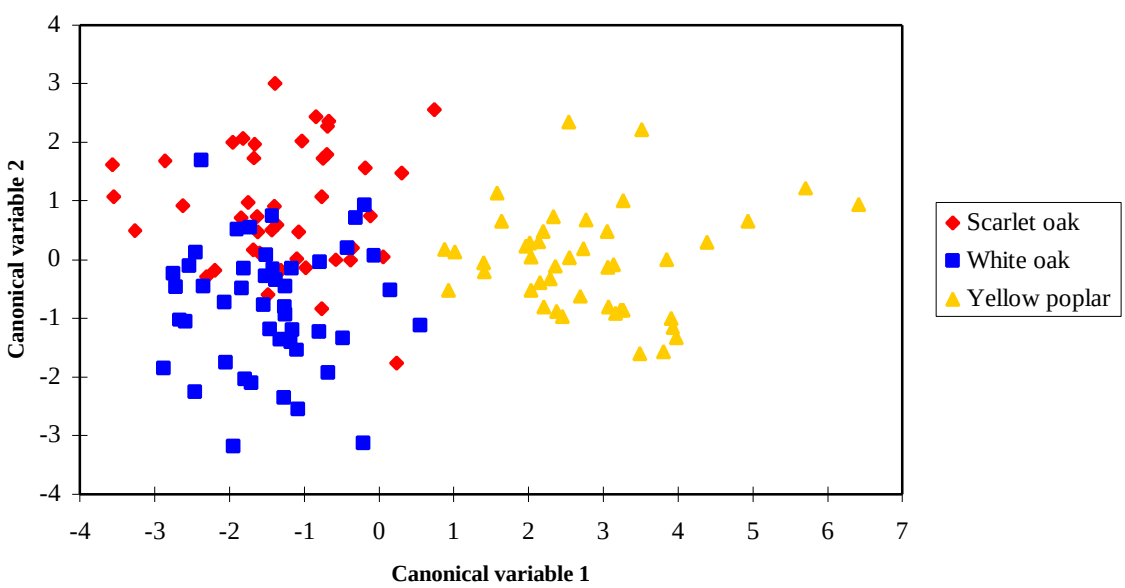


Figure 21. Canonical variable plot: Second difference of raw relative reflectance data for hardwood spectral separability

Table 91. Canonical variances (within pines) - Second difference of raw relative reflectance data

Species (pines)	N	Canonical 1 variance	Canonical 2 variance	Pooled variance
Loblolly	50	1.126	1.345	1.235
Shortleaf	42	0.808	0.665	0.737
Virginia	54	1.031	0.940	0.986

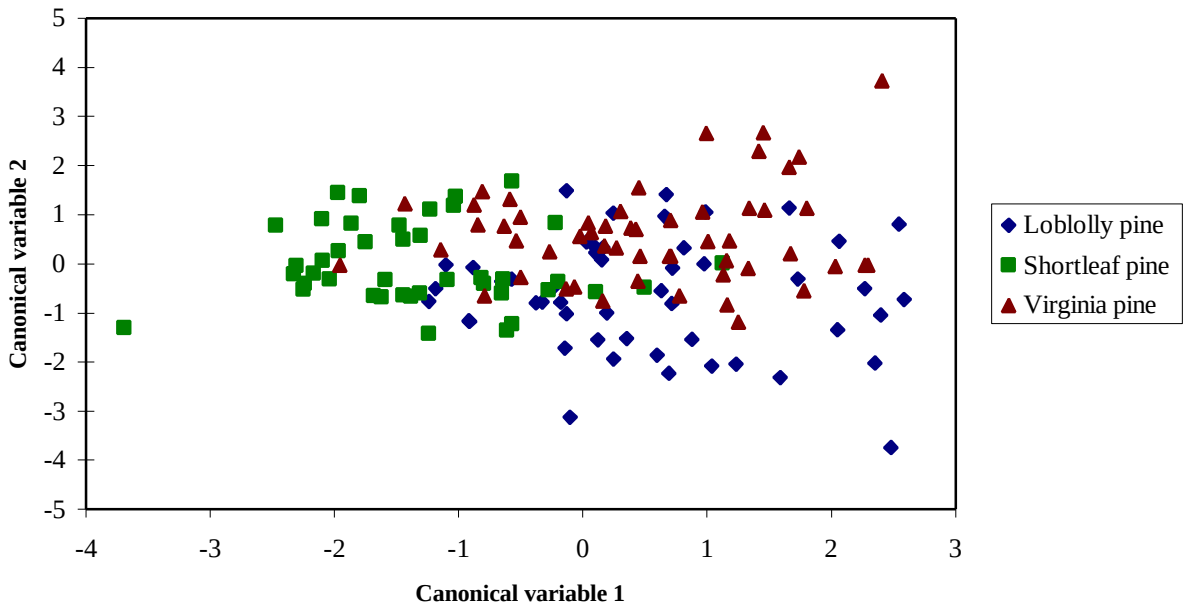


Figure 22. Canonical variable plot: Second difference of raw relative reflectance data for pine spectral separability

2. 9-point Averaged Relative Reflectance Data

2.1 9-point Averaged Raw Relative Reflectance

Table 92. Canonical variances (between group) - 9-point averaged data

Group	N	Canonical 1 variance
Hardwoods	134	1.443
Pines	146	0.593

Table 93. Canonical variances (within hardwoods) - 9-point averaged data

Species (hardwoods)	N	Canonical 1 variance	Canonical 2 variance	Pooled variance
Scarlet oak	43	0.718	1.464	1.091
White oak	47	0.632	0.929	0.781
Yellow poplar	44	1.669	0.622	1.146

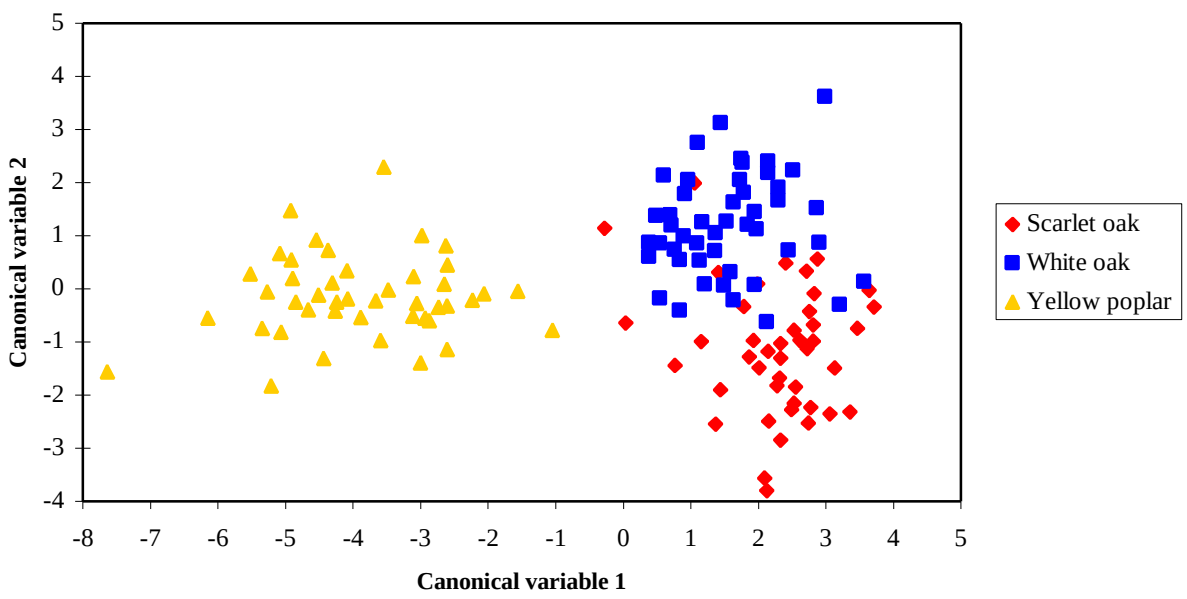


Figure 23. Canonical variable plot: 9-point averaged data for hardwood spectral separability

Table 94. Canonical variances (within pines) - 9-point averaged data

Species (pines)	N	Canonical 1 variance	Canonical 2 variance	Pooled variance
Loblolly	50	1.107	0.802	0.955
Shortleaf	42	0.716	0.739	0.727
Virginia	54	1.121	1.385	1.253

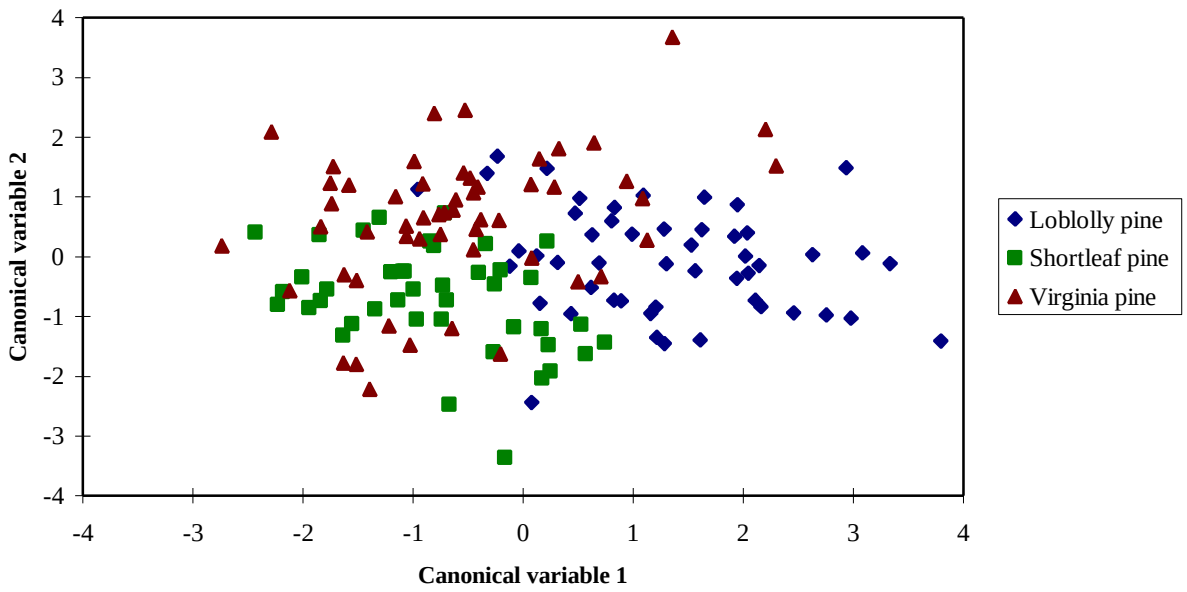


Figure 24. Canonical variable plot: 9-point averaged data for pine spectral separability

2.2 First Difference of 9-point Averaged Relative Reflectance

Table 95. Canonical variances (between group) – First difference of the 9-point averaged data

Group	N	Canonical 1 variance
Hardwoods	134	1.470
Pines	146	0.569

Table 96. Canonical variances (within hardwoods) - First difference of the 9-point averaged data

Species (hardwoods)	N	Canonical 1 variance	Canonical 2 variance	Pooled variance
Scarlet oak	43	0.766	1.013	0.890
White oak	47	0.662	0.851	0.757
Yellow poplar	44	1.590	1.146	1.368

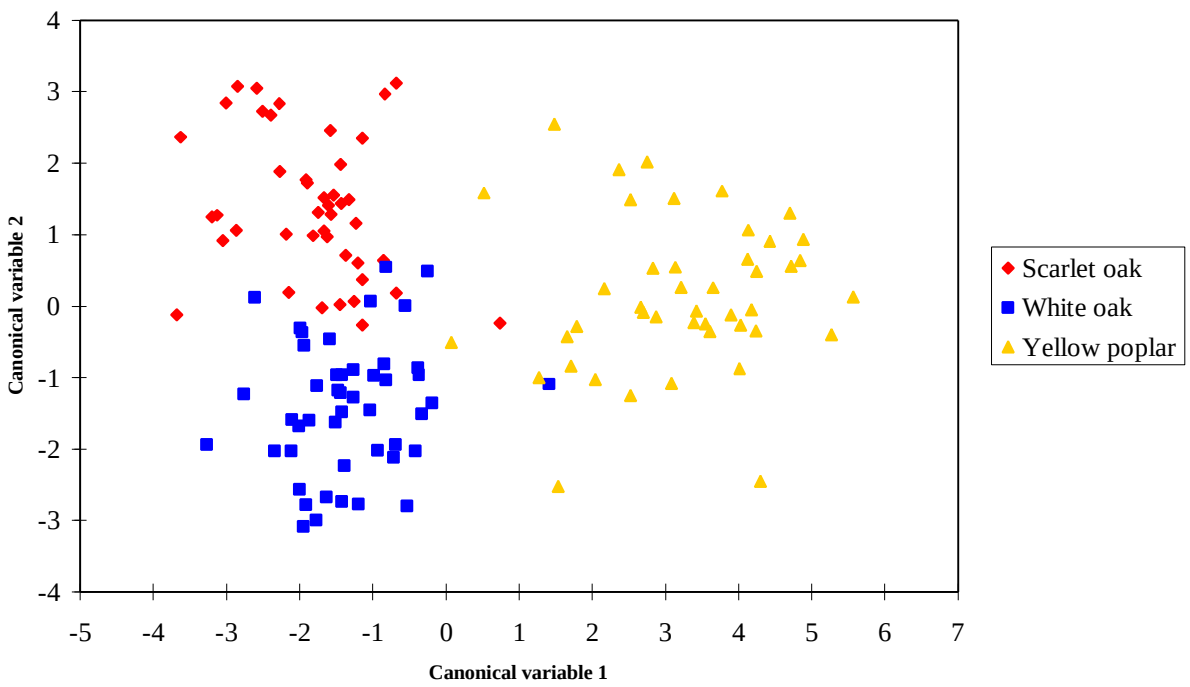


Figure 25. Canonical variable plot: First difference of 9-point averaged data for hardwood spectral separability

Table 97. Canonical variances (within pines) - First difference of the 9-point averaged data

Species (pine)	N	Canonical 1 variance	Canonical 2 variance	Pooled variance
Loblolly	50	1.002	0.752	0.877
Shortleaf	42	0.653	0.516	0.584
Virginia	54	1.267	1.603	1.435

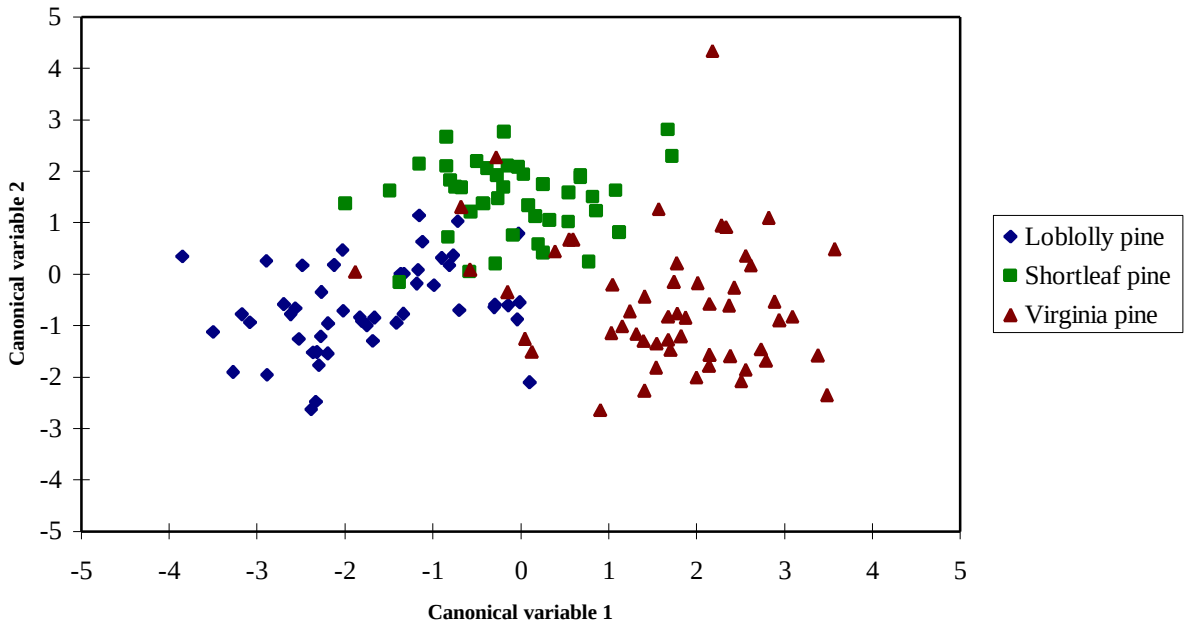


Figure 26. Canonical variable plot: First difference 9-point averaged data for pine spectral separability

2.3 Second Difference of 9-point Averaged Relative Reflectance

Table 98. Canonical variances (between group) - Second difference of the 9-point averaged data

Group	N	Canonical 1 variance
Hardwoods	134	1.146
Pines	146	0.866

Table 99. Canonical variances (within hardwoods) - Second difference of the 9-point averaged data

Species (hardwoods)	N	Canonical 1 variance	Canonical 2 variance	Pooled variance
Scarlet oak	43	0.781	0.972	0.877
White oak	47	0.796	0.844	0.820
Yellow poplar	44	1.432	1.194	1.313

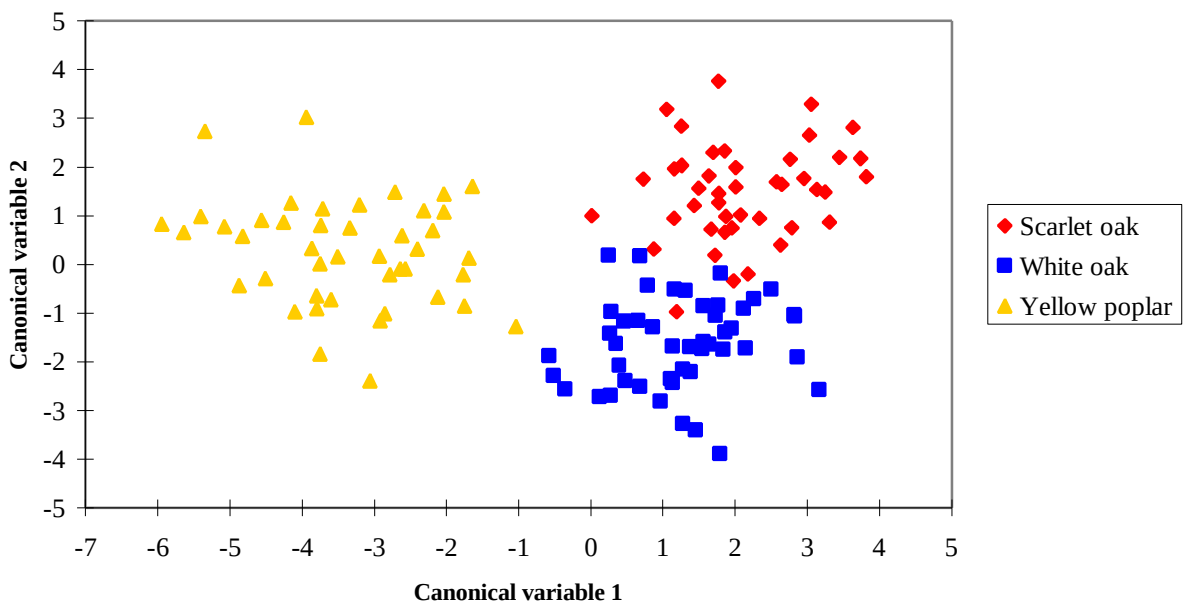


Figure 27. Canonical variable plot: Second difference of 9-point averaged data for hardwood spectral separability

Table 100. Canonical variances (within pines) - Second difference of the 9-point averaged data

Species (pines)	N	Canonical 2 variance	Canonical 2 variance	Pooled variance
Loblolly	50	0.983	0.828	0.905
Shortleaf	42	0.995	0.878	0.937
Virginia	54	1.019	1.254	1.136

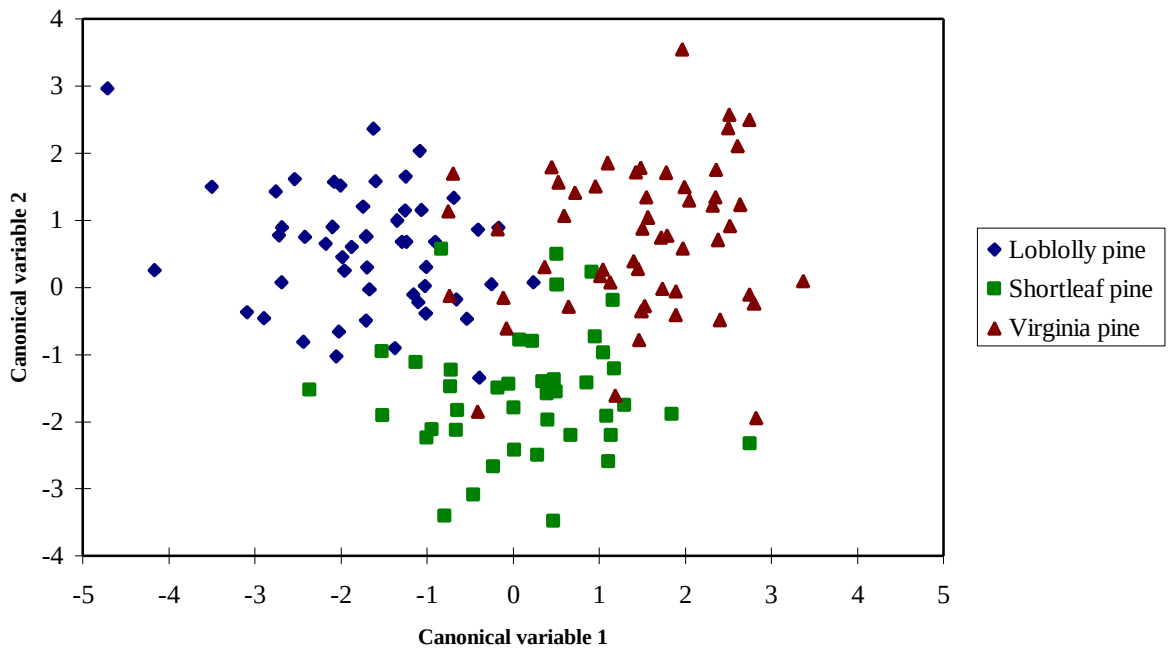


Figure 28. Canonical variable plot: Second difference of 9-point averaged data for pine spectral separability

3. 9-point Median Relative Reflectance Data

3.1 9-point Median Raw Relative Reflectance

Table 101. Canonical variances (between group) - 9-point median data

Group	N	Canonical 1 variance
Hardwoods	134	1.448
Pines	146	0.589

Table 102. Canonical variances (within hardwoods) - 9-point median data

Species (hardwoods)	N	Canonical 1 variance	Canonical 2 variance	Pooled variance
Scarlet oak	43	1.068	0.814	0.941
White oak	47	0.795	1.164	0.979
Yellow poplar	44	1.153	1.006	1.080

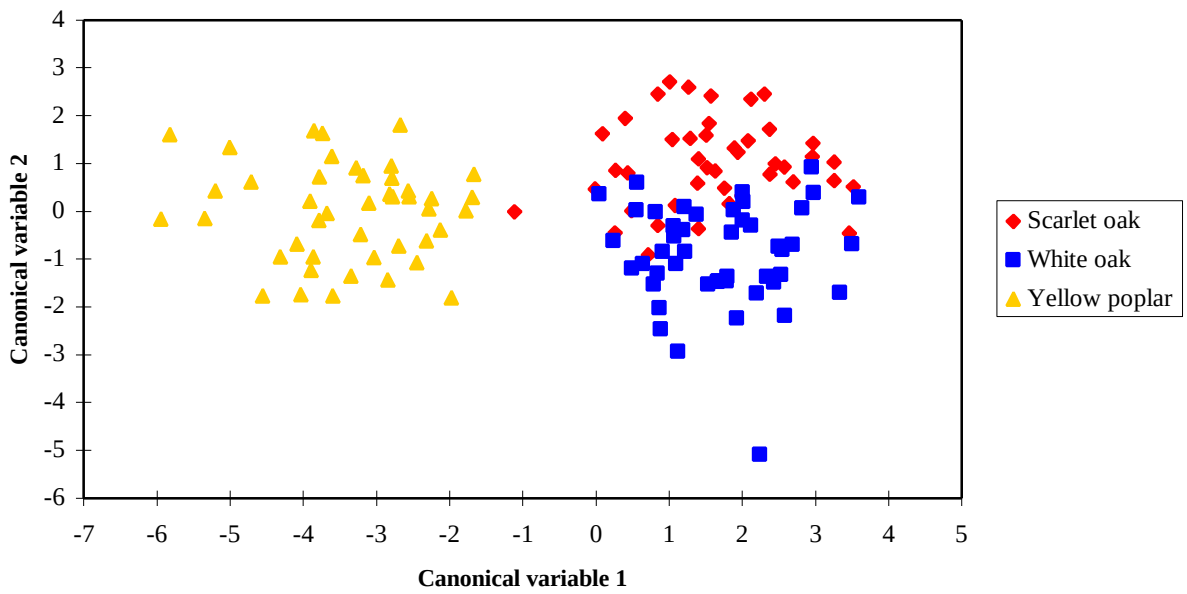


Figure 29. Canonical variable plot: 9-point median data for hardwood spectral separability

Table 103. Canonical variances (within pines) - 9-point median data

Species (pines)	N	Canonical 1 variance	Canonical 2 variance	Pooled variance
Loblolly	50	0.977	0.787	0.882
Shortleaf	42	0.762	0.755	0.759
Virginia	54	1.205	1.386	1.296

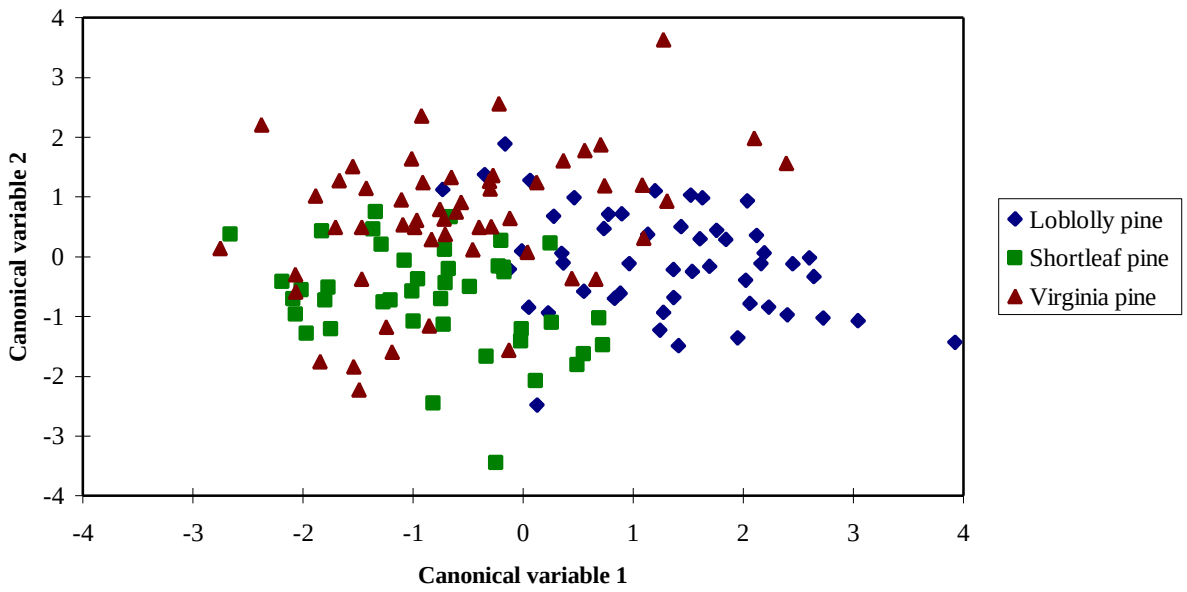


Figure 30. Canonical variable plot: 9-point median data for pine spectral separability

3.2 First Difference of 9-point Median Relative Reflectance

Table 104. Canonical variances (between group) – First difference of the 9-point median data

Group	N	Canonical 1 variance
Hardwoods	134	1.535
Pines	146	0.509

Table 105. Canonical variances (within hardwoods) - First difference of the 9-point median data

Species (hardwoods)	N	Canonical 1 variance	Canonical 2 variance	Pooled variance
Scarlet oak	43	0.719	0.834	0.777
White oak	47	0.978	0.610	0.794
Yellow poplar	44	1.298	1.579	1.439

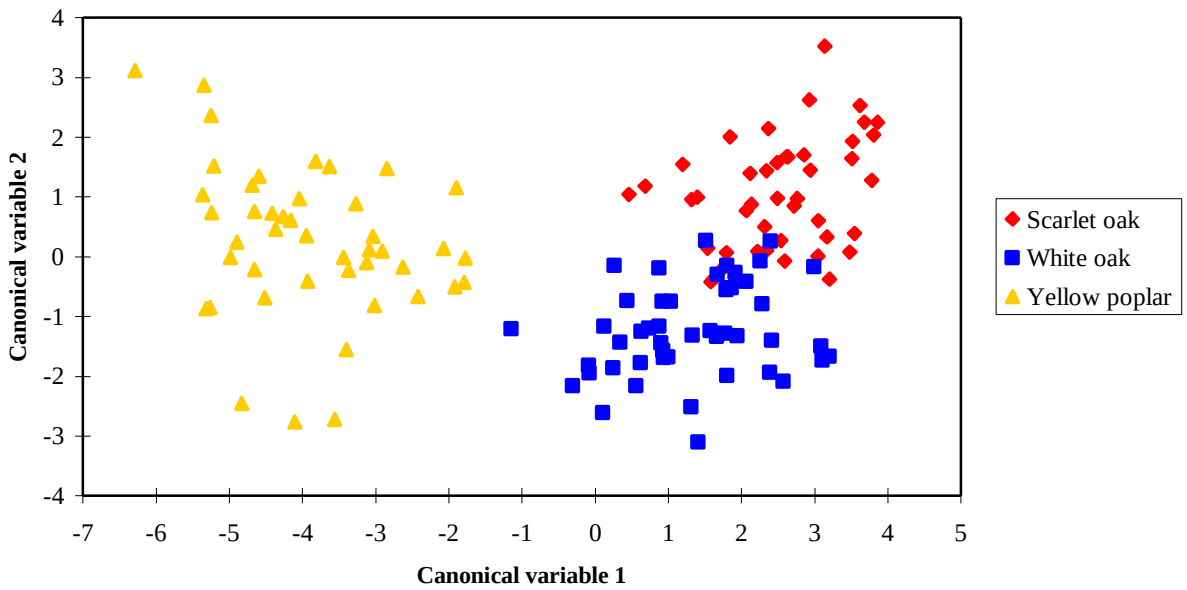


Figure 31. Canonical variable plot: First difference of 9-point median data for hardwood spectral separability

Table 106. Canonical variances (within pines) - First difference of the 9-point median data

Species (pines)	N	Canonical 1 variance	Canonical 2 variance	Pooled variance
Loblolly	50	0.884	1.068	0.976
Shortleaf	42	1.120	0.992	1.056
Virginia	54	1.014	0.943	0.979

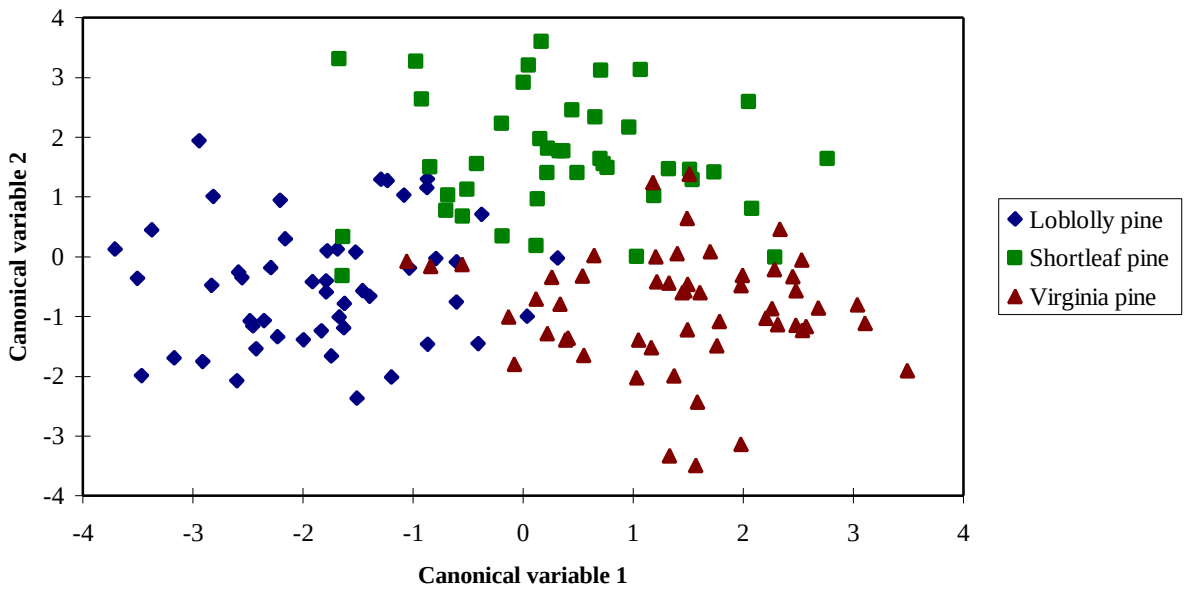


Figure 32. Canonical variable plot: First difference of 9-point median data for pine spectral separability

3.3 Second Difference of 9-point Median Relative Reflectance

Table 107. Canonical variances (between group) - Second difference of the 9-point median data

Group	N	Canonical 1 variance
Hardwoods	134	1.269
Pines	146	0.753

Table 108. Canonical variances (within hardwoods) - Second difference of the 9-point median data

Species (hardwoods)	N	Canonical 1 variance	Canonical 2 variance	Pooled variance
Scarlet oak	43	0.986	1.102	1.044
White oak	47	0.700	1.152	0.926
Yellow poplar	44	1.334	0.738	1.036

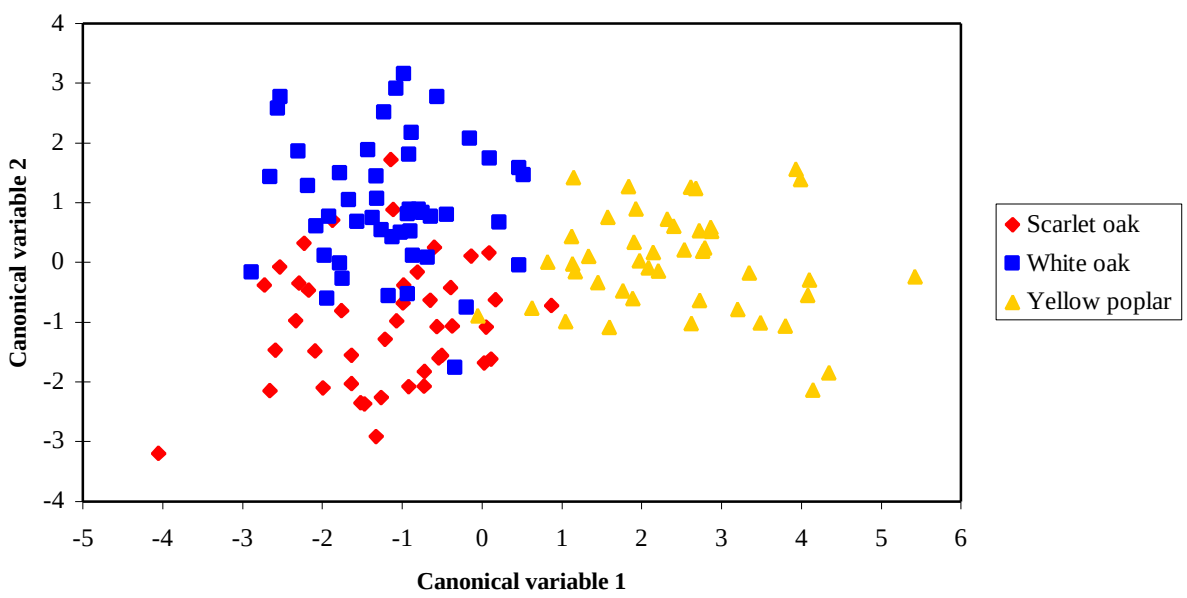


Figure 33. Canonical variable plot: Second difference of 9-point median data for hardwood spectral

Table 109. Canonical variances (within pines) - Second difference of the 9-point median data

Species (pines)	N	Canonical 1 variance	Canonical 2 variance	Pooled variance
Loblolly	50	0.953	0.766	0.859
Shortleaf	42	0.797	1.201	0.999
Virginia	54	1.201	1.061	1.131

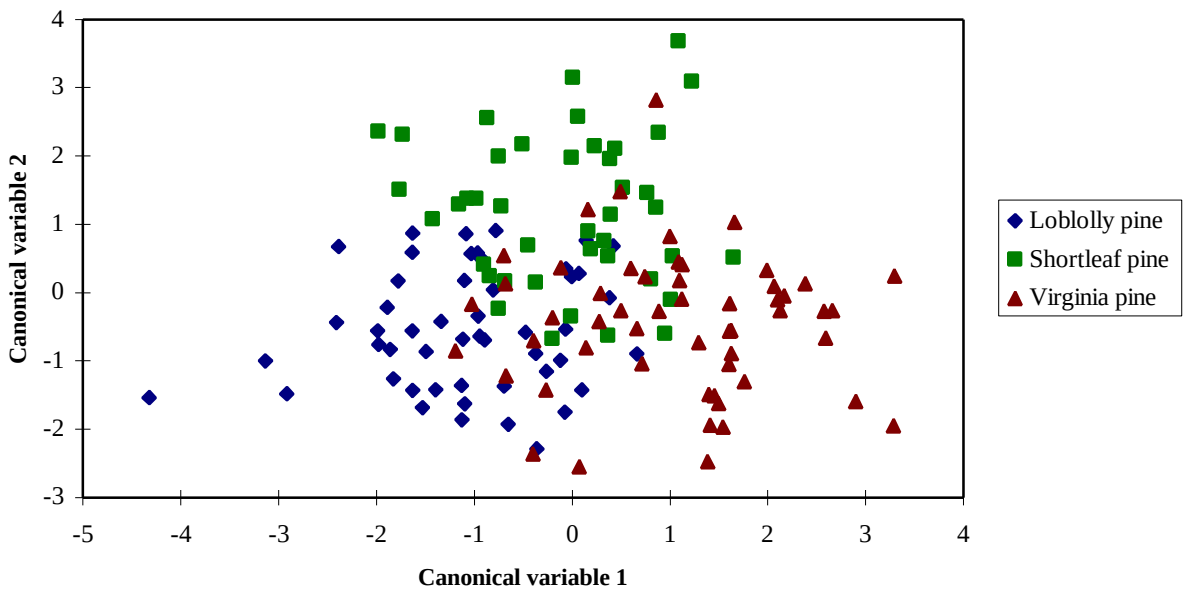


Figure 34. Canonical variable plot: Second difference of 9-point median data for pine spectral separability

4. AVIRIS Simulation 10 nm Relative Reflectance Data

4.1 AVIRIS Simulation 10 nm Raw Relative Reflectance Data

Table 110. Canonical variances (between group) – 10 nm simulated AVIRIS data

Group	N	Canonical 1 variance
Hardwoods	134	1.499
Pines	146	0.543

Table 111. Canonical variances (within hardwoods) - 10 nm simulated AVIRIS data

Species (hardwoods)	N	Canonical 1 variance	Canonical 2 variance	Pooled variance
Scarlet oak	43	0.674	1.513	1.093
White oak	47	0.745	0.960	0.853
Yellow poplar	44	1.591	0.542	1.066

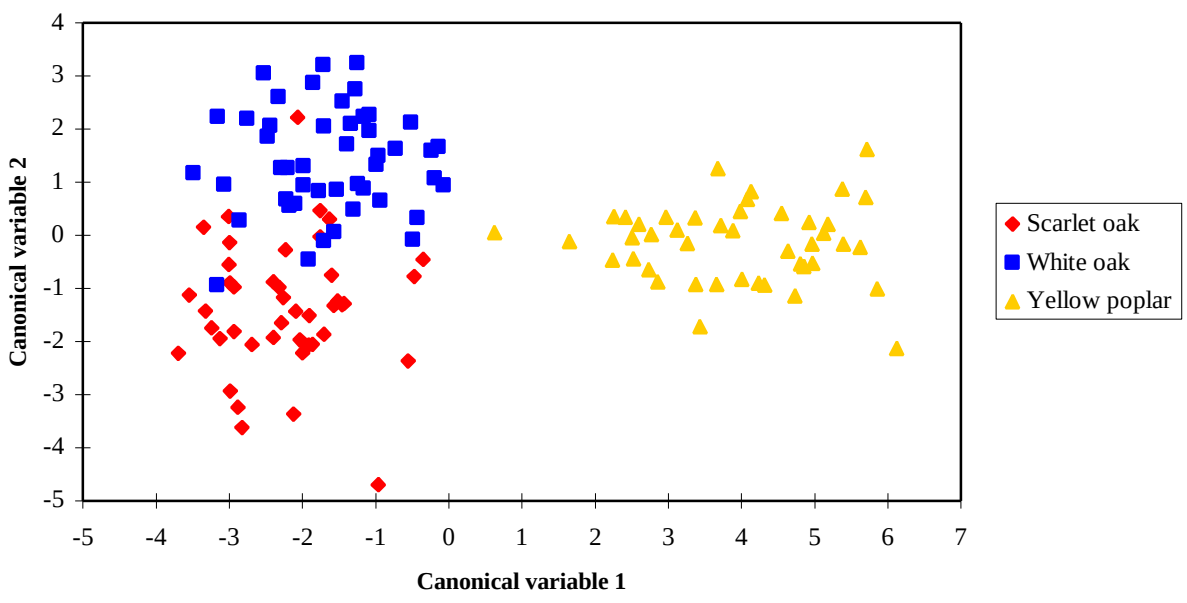


Figure 35. Canonical variable plot: Simulated AVIRIS 10 nm data for hardwood spectral separability

Table 112. Canonical variances (within pines) - 10 nm simulated AVIRIS data

Species (pines)	N	Canonical 1 variance	Canonical 2 variance	Pooled variance
Loblolly	50	0.910	0.815	0.863
Shortleaf	42	0.596	0.486	0.541
Virginia	54	1.396	1.568	1.482

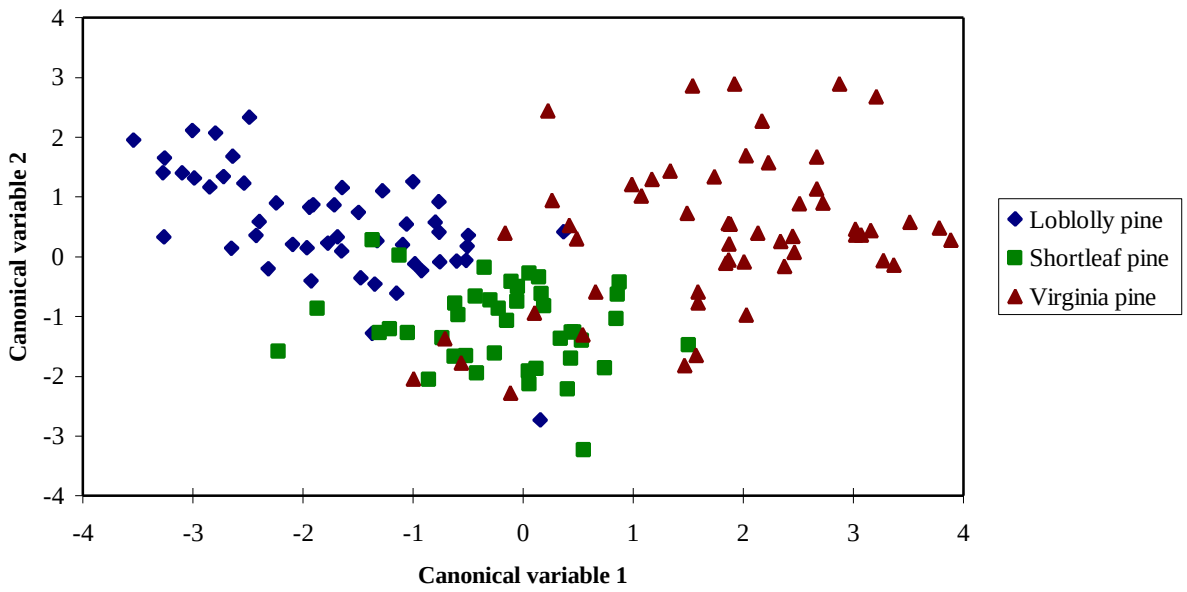


Figure 36. Canonical variable plot: Simulated AVIRIS 10 nm data for pine spectral separability

4.2 First Difference of AVIRIS Simulation 10 nm Data

Table 113. Canonical variances (between group) – First difference of the 10 nm simulated AVIRIS data

Group	N	Canonical 1 variance
Hardwoods	134	1.486
Pines	146	0.554

Table 114. Canonical variances (within hardwoods) - First difference of the 10 nm simulated AVIRIS data

Species (hardwoods)	N	Canonical 1 variance	Canonical 2 variance	Pooled variance
Scarlet oak	43	0.831	1.359	1.095
White oak	47	0.707	0.815	0.761
Yellow poplar	44	1.479	0.848	1.163

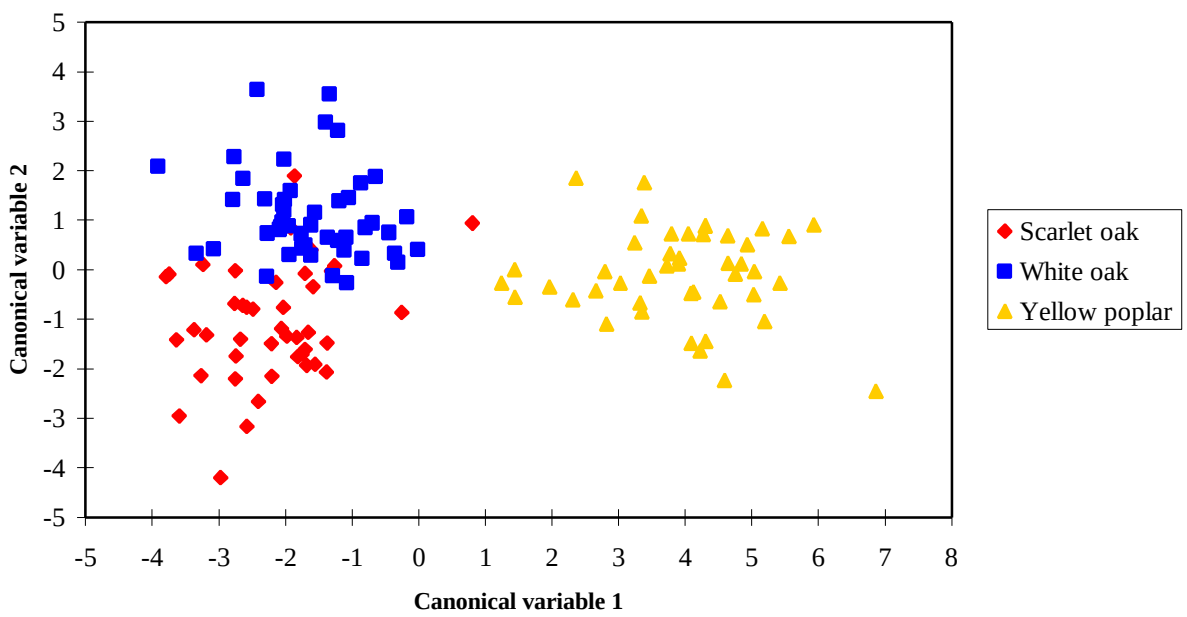


Figure 37. Canonical variable plot: First difference of AVIRIS simulation 10 nm data for hardwood spectral separability

Table 115. Canonical variances (within pines) - First difference of the 10 nm simulated AVIRIS data

Species (pines)	N	Canonical 1 variance	Canonical 2 variance	Pooled variance
Loblolly	50	0.823	0.975	0.899
Shortleaf	42	0.693	0.484	0.588
Virginia	54	1.401	1.422	1.412

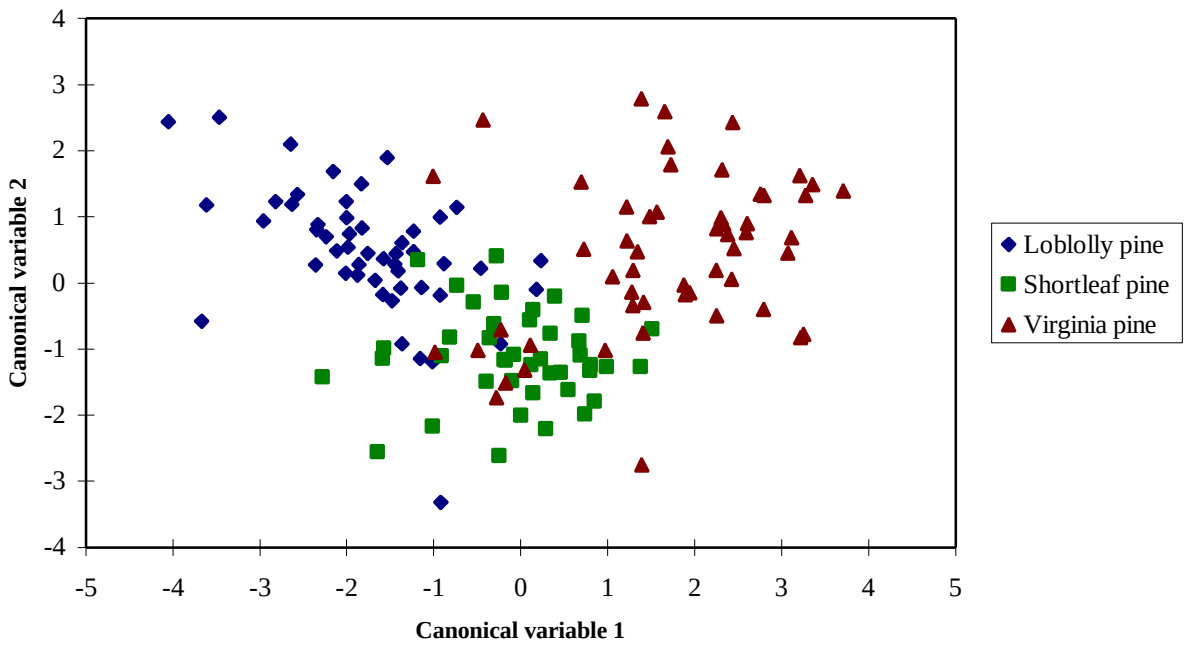


Figure 38. Canonical variable plot: First difference of AVIRIS simulation 10 nm data for pine spectral separability

4.3 Second Difference of AVIRIS Simulation 10 nm Data

Table 116. Canonical variances (between group) - Second difference of the 10 nm simulated AVIRIS data

Group	N	Canonical 1 variance
Hardwoods	134	1.403
Pines	146	0.631

Table 117. Canonical variances (within hardwoods) - Second difference of the 10 nm simulated AVIRIS data

Species (hardwoods)	N	Canonical 1 variance	Canonical 2 variance	Pooled variance
Scarlet oak	43	0.742	1.152	0.947
White oak	47	0.434	1.041	0.737
Yellow poplar	44	1.858	0.808	1.333

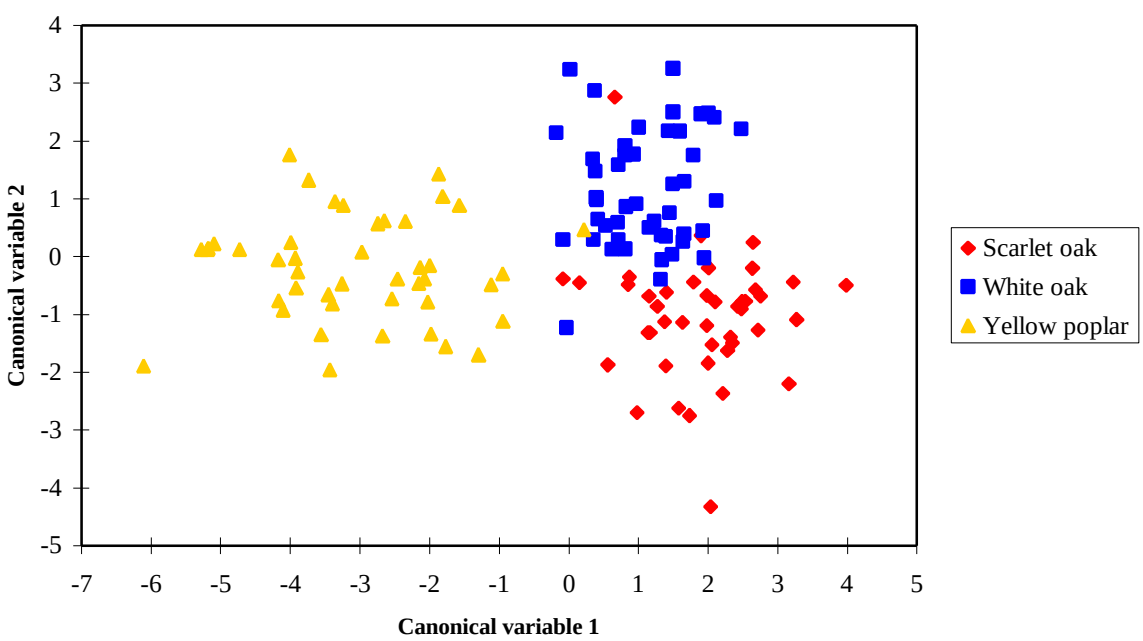


Figure 39. Canonical variable plot: Second difference of AVIRIS simulation 10 nm data for hardwood spectral separability

Table 118. Canonical variances (within pines) - Second difference of the 10 nm simulated AVIRIS data

Species (pines)	N	Canonical 1 variance	Canonical 2 variance	Pooled variance
Loblolly	50	0.790	0.645	0.717
Shortleaf	42	0.831	1.017	0.924
Virginia	54	1.325	1.315	1.320

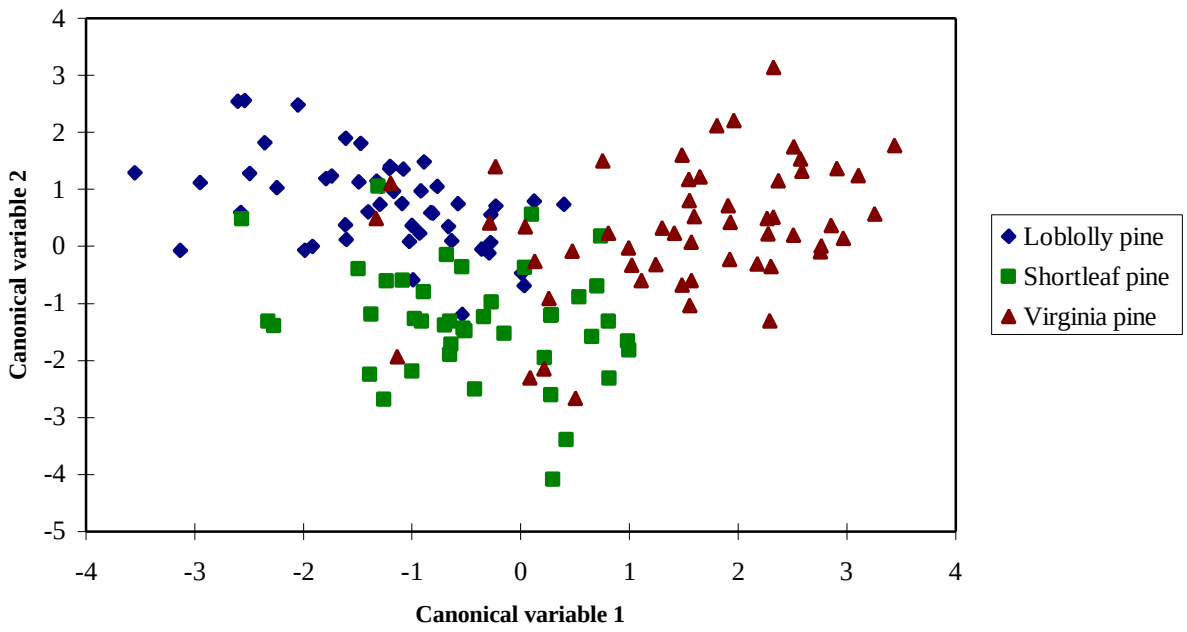


Figure 40. Canonical variable plot: Second difference of AVIRIS simulation 10 nm data for pine spectral separability

Appendix G

Correlation Tables for all Data Sets

1. Relative Reflectance Data

1.1 Raw Relative Reflectance

Table 119. Correlations for between group separability test using raw relative reflectance data

Statistic	Variable	731 nm	963 nm	1169 nm	1193 nm	1274 nm	1540 nm	1548 nm	1579 nm	1659 nm
Correlation	**731 nm**	1.000	0.960	0.919	0.916	0.918	0.772	0.780	0.803	0.834
	963 nm	0.960	1.000	0.973	0.970	0.970	0.821	0.829	0.852	0.878
	1169 nm	0.919	0.973	1.000	1.000	0.999	0.911	0.917	0.934	0.951
	1193 nm	0.916	0.970	1.000	1.000	0.999	0.918	0.923	0.940	0.956
	1274 nm	0.918	0.970	0.999	0.999	1.000	0.912	0.917	0.934	0.951
	1540 nm	0.772	0.821	0.911	0.918	0.912	1.000	1.000	0.997	0.989
	1548 nm	0.780	0.829	0.917	0.923	0.917	1.000	1.000	0.998	0.992
	1579 nm	0.803	0.852	0.934	0.940	0.934	0.997	0.998	1.000	0.997
	1659 nm	0.834	0.878	0.951	0.956	0.951	0.989	0.992	0.997	1.000

Table 120. Correlations for within hardwoods separability test using raw relative reflectance data

Statistic	Variable	350 nm	643 nm	694 nm	764 nm	1122 nm	1340 nm	1639 nm	1662 nm	1730 nm	1747 nm
Correlation	**350 nm**	1.000	0.794	0.785	0.584	0.569	0.652	0.695	0.696	0.700	0.702
	643 nm	0.794	1.000	0.987	0.575	0.563	0.644	0.708	0.707	0.712	0.711
	694 nm	0.785	0.987	1.000	0.643	0.627	0.690	0.747	0.748	0.753	0.749
	764 nm	0.584	0.575	0.643	1.000	0.945	0.849	0.766	0.777	0.771	0.758
	1122 nm	0.569	0.563	0.627	0.945	1.000	0.948	0.870	0.877	0.873	0.864
	1340 nm	0.652	0.644	0.690	0.849	0.948	1.000	0.966	0.967	0.964	0.964
	1639 nm	0.695	0.708	0.747	0.766	0.870	0.966	1.000	1.000	0.999	0.999
	1662 nm	0.696	0.707	0.748	0.777	0.877	0.967	1.000	1.000	0.999	0.998
	1730 nm	0.700	0.712	0.753	0.771	0.873	0.964	0.999	0.999	1.000	0.999
	1747 nm	0.702	0.711	0.749	0.758	0.864	0.964	0.999	0.998	0.999	1.000

Table 121. Correlations for within pines separability test using raw relative reflectance data

Statistic	Variable	354 nm	404 nm	421 nm	435 nm	490 nm	712 nm	1463 nm	1771 nm	2460 nm
Correlation	**354 nm**	1.000	0.981	0.964	0.942	0.878	0.577	0.571	0.600	0.258
	404 nm	0.981	1.000	0.987	0.970	0.926	0.620	0.675	0.696	0.289
	421 nm	0.964	0.987	1.000	0.994	0.963	0.711	0.682	0.730	0.273
	435 nm	0.942	0.970	0.994	1.000	0.983	0.765	0.694	0.759	0.261
	490 nm	0.878	0.926	0.963	0.983	1.000	0.820	0.760	0.828	0.256
	712 nm	0.577	0.620	0.711	0.765	0.820	1.000	0.544	0.736	0.165
	1463 nm	0.571	0.675	0.682	0.694	0.760	0.544	1.000	0.949	0.289
	1771 nm	0.600	0.696	0.730	0.759	0.828	0.736	0.949	1.000	0.269
	2460 nm	0.258	0.289	0.273	0.261	0.256	0.165	0.289	0.269	1.000

1.2 First Difference of Raw Relative Reflectance

Table 122. Correlations for between group separability test using the first difference of the raw relative reflectance data

Statistic	Variable	402 nm	417 nm	425 nm	634 nm	711 nm	752 nm	1136 nm	1212 nm	1246 nm	1250 nm
Correlation	**402 nm**	1.000	0.118	0.182	0.163	-0.006	-0.017	0.034	0.087	0.110	0.011
	417 nm	0.118	1.000	0.856	-0.162	0.028	-0.282	-0.167	0.299	0.169	0.297
	425 nm	0.182	0.856	1.000	-0.142	0.014	-0.324	-0.146	0.292	0.162	0.254
	634 nm	0.163	-0.162	-0.142	1.000	-0.747	-0.252	0.082	-0.055	-0.002	0.030
	711 nm	-0.006	0.028	0.014	-0.747	1.000	0.679	-0.229	0.197	0.142	0.092
	752 nm	-0.017	-0.282	-0.324	-0.252	0.679	1.000	-0.230	0.136	0.163	0.052
	1136 nm	0.034	-0.167	-0.146	0.082	-0.229	-0.230	1.000	-0.288	-0.220	-0.166
	1212 nm	0.087	0.299	0.292	-0.055	0.197	0.136	-0.288	1.000	0.114	0.380
	1246 nm	0.110	0.169	0.162	-0.002	0.142	0.163	-0.220	0.114	1.000	0.200
	1250 nm	0.011	0.297	0.254	0.030	0.092	0.052	-0.166	0.380	0.200	1.000
	1502 nm	0.031	-0.192	-0.204	-0.540	0.787	0.636	-0.058	0.027	-0.017	-0.068
	1510 nm	-0.001	-0.199	-0.215	-0.574	0.807	0.614	-0.060	0.084	-0.013	0.011
	1514 nm	0.006	-0.164	-0.179	-0.584	0.828	0.671	-0.067	0.031	0.012	-0.041
	2009 nm	0.035	0.095	0.091	0.035	-0.067	-0.088	-0.037	-0.026	-0.187	0.048
	2420 nm	0.063	0.006	0.002	-0.077	0.039	0.033	-0.034	-0.015	-0.035	0.011

Table 122. Correlations for between group separability test using the first difference of the raw relative reflectance data (continued)

Statistic	Variable	1502 nm	1510 nm	1514 nm	2009 nm	2420 nm
Correlation	**402 nm**	0.031	-0.001	0.006	0.035	0.063
	417 nm	-0.192	-0.199	-0.164	0.095	0.006
	425 nm	-0.204	-0.215	-0.179	0.091	0.002
	634 nm	-0.540	-0.574	-0.584	0.035	-0.077
	711 nm	0.787	0.807	0.828	-0.067	0.039
	752 nm	0.636	0.614	0.671	-0.088	0.033
	1136 nm	-0.058	-0.060	-0.067	-0.037	-0.034
	1212 nm	0.027	0.084	0.031	-0.026	-0.015
	1246 nm	-0.017	-0.013	0.012	-0.187	-0.035
	1250 nm	-0.068	0.011	-0.041	0.048	0.011
	1502 nm	1.000	0.853	0.855	-0.050	0.017
	1510 nm	0.853	1.000	0.800	-0.010	0.093
	1514 nm	0.855	0.800	1.000	-0.044	0.071
	2009 nm	-0.050	-0.010	-0.044	1.000	0.058
	2420 nm	0.017	0.093	0.071	0.058	1.000

Table 123. Correlations for within hardwoods separability test using the first difference of the raw relative reflectance data

Statistic	Variable	398 nm	411 nm	425 nm	438 nm	448 nm	547 nm	614 nm	637 nm	1304 nm
Correlation	**398 nm**	1.000	0.460	0.211	0.193	0.225	0.083	-0.055	-0.037	0.026
	411 nm	0.460	1.000	0.729	0.645	0.637	0.337	-0.336	-0.345	-0.078
	425 nm	0.211	0.729	1.000	0.878	0.870	0.421	-0.479	-0.554	-0.308
	438 nm	0.193	0.645	0.878	1.000	0.900	0.405	-0.474	-0.517	-0.340
	448 nm	0.225	0.637	0.870	0.900	1.000	0.537	-0.601	-0.657	-0.370
	547 nm	0.083	0.337	0.421	0.405	0.537	1.000	-0.891	-0.857	-0.241
	614 nm	-0.055	-0.336	-0.479	-0.474	-0.601	-0.891	1.000	0.870	0.370
	637 nm	-0.037	-0.345	-0.554	-0.517	-0.657	-0.857	0.870	1.000	0.385
	1304 nm	0.026	-0.078	-0.308	-0.340	-0.370	-0.241	0.370	0.385	1.000
	1568 nm	0.060	0.079	0.104	0.109	0.197	0.397	-0.420	-0.401	-0.360
	1694 nm	-0.083	-0.018	-0.017	0.040	0.008	-0.167	0.173	0.027	0.029
	2188 nm	-0.127	-0.057	0.114	0.073	0.040	0.024	-0.073	-0.037	-0.082

Statistic	Variable	1568 nm	1694 nm	2188 nm
Correlation	**398 nm**	0.060	-0.083	-0.127
	411 nm	0.079	-0.018	-0.057
	425 nm	0.104	-0.017	0.114
	438 nm	0.109	0.040	0.073
	448 nm	0.197	0.008	0.040
	547 nm	0.397	-0.167	0.024
	614 nm	-0.420	0.173	-0.073
	637 nm	-0.401	0.027	-0.037
	1304 nm	-0.360	0.029	-0.082
	1568 nm	1.000	-0.214	-0.116
	1694 nm	-0.214	1.000	-0.010
	2188 nm	-0.116	-0.010	1.000

Table 124. Correlations for within pines separability test using the first difference of the raw relative reflectance data

Statistic	Variable	408 nm	433 nm	503 nm	533 nm	587 nm	776 nm	950 nm	1109 nm	1161nm
Correlation	**408 nm**	1.000	0.236	0.559	0.547	-0.488	0.264	-0.217	-0.096	-0.198
	433 nm	0.236	1.000	0.431	0.498	-0.337	0.290	-0.103	0.062	-0.195
	503 nm	0.559	0.431	1.000	0.913	-0.775	0.238	-0.200	0.018	-0.266
	533 nm	0.547	0.498	0.913	1.000	-0.852	0.330	-0.266	-0.064	-0.222
	587 nm	-0.488	-0.337	-0.775	-0.852	1.000	-0.255	0.272	0.173	0.089
	776 nm	0.264	0.290	0.238	0.330	-0.255	1.000	-0.296	-0.229	-0.264
	950 nm	-0.217	-0.103	-0.200	-0.266	0.272	-0.296	1.000	-0.028	0.174
	1109 nm	-0.096	0.062	0.018	-0.064	0.173	-0.229	-0.028	1.000	-0.133
	1161nm	-0.198	-0.195	-0.266	-0.222	0.089	-0.264	0.174	-0.133	1.000

1.3 Second Difference of Raw Relative Reflectance

Table 125. Correlations for between group separability test using the second difference of the raw relative reflectance data

Statistic	Variable	429 nm	474 nm	522 nm	524 nm	688 nm	690 nm	696 nm	698 nm	703 nm
Correlation	**429 nm**	1.000	0.039	0.207	-0.038	0.069	0.152	0.150	0.180	-0.023
	474 nm	0.039	1.000	0.114	-0.088	-0.004	-0.023	-0.019	-0.069	-0.057
	522 nm	0.207	0.114	1.000	-0.145	0.046	0.277	0.564	0.492	0.220
	524 nm	-0.038	-0.088	-0.145	1.000	-0.073	0.129	0.334	0.259	0.198
	688 nm	0.069	-0.004	0.046	-0.073	1.000	0.621	0.435	0.434	-0.350
	690 nm	0.152	-0.023	0.277	0.129	0.621	1.000	0.747	0.760	-0.177
	696 nm	0.150	-0.019	0.564	0.334	0.435	0.747	1.000	0.871	0.222
	698 nm	0.180	-0.069	0.492	0.259	0.434	0.760	0.871	1.000	0.228
	703 nm	-0.023	-0.057	0.220	0.198	-0.350	-0.177	0.222	0.228	1.000
	705 nm	0.008	-0.073	0.221	0.130	-0.079	0.037	0.318	0.379	0.526
	718 nm	-0.014	-0.045	-0.197	0.079	-0.331	-0.378	-0.191	-0.220	0.327
	732 nm	-0.145	0.130	-0.100	-0.134	-0.385	-0.494	-0.563	-0.615	-0.191
	748 nm	-0.136	0.064	-0.436	-0.129	-0.167	-0.407	-0.609	-0.650	-0.452
	750 nm	-0.066	0.067	-0.376	-0.251	-0.093	-0.359	-0.632	-0.665	-0.565
	1066 nm	-0.017	-0.056	0.046	0.091	0.039	0.044	0.048	0.057	-0.109
	1103 nm	0.023	0.041	0.063	0.043	-0.045	0.084	0.147	0.097	0.084
	1264 nm	-0.204	0.048	-0.092	-0.030	0.013	-0.054	-0.131	-0.135	-0.095
	1279 nm	-0.008	-0.043	0.038	-0.008	0.076	0.006	-0.001	0.059	-0.053
	1633 nm	-0.080	0.017	-0.098	0.015	-0.091	-0.073	-0.058	-0.077	0.070
	2038 nm	-0.056	-0.004	-0.089	0.067	0.046	-0.010	-0.027	-0.046	-0.004

Table 125. Correlations for between group separability test using the second difference of the raw relative reflectance data (continued)

Statistic	Variable	705 nm	718 nm	732 nm	748 nm	750 nm	1066 nm	1103 nm	1264 nm	1279 nm
Correlation	**429 nm**	0.008	-0.014	-0.145	-0.136	-0.066	-0.017	0.023	-0.204	-0.008
	474 nm	-0.073	-0.045	0.130	0.064	0.067	-0.056	0.041	0.048	-0.043
	522 nm	0.221	-0.197	-0.100	-0.436	-0.376	0.046	0.063	-0.092	0.038
	524 nm	0.130	0.079	-0.134	-0.129	-0.251	0.091	0.043	-0.030	-0.008
	688 nm	-0.079	-0.331	-0.385	-0.167	-0.093	0.039	-0.045	0.013	0.076
	690 nm	0.037	-0.378	-0.494	-0.407	-0.359	0.044	0.084	-0.054	0.006
	696 nm	0.318	-0.191	-0.563	-0.609	-0.632	0.048	0.147	-0.131	-0.001
	698 nm	0.379	-0.220	-0.615	-0.650	-0.665	0.057	0.097	-0.135	0.059
	703 nm	0.526	0.327	-0.191	-0.452	-0.565	-0.109	0.084	-0.095	-0.053
	705 nm	1.000	0.181	-0.354	-0.514	-0.641	-0.058	0.119	-0.091	-0.029
	718 nm	0.181	1.000	-0.236	-0.035	-0.085	-0.103	-0.053	-0.247	-0.112
	732 nm	-0.354	-0.236	1.000	0.448	0.478	0.090	-0.114	0.234	0.081
	748 nm	-0.514	-0.035	0.448	1.000	0.628	0.008	-0.080	0.144	0.033
	750 nm	-0.641	-0.085	0.478	0.628	1.000	0.053	-0.103	0.110	-0.015
	1066 nm	-0.058	-0.103	0.090	0.008	0.053	1.000	-0.035	0.145	-0.010
	1103 nm	0.119	-0.053	-0.114	-0.080	-0.103	-0.035	1.000	-0.062	0.016
	1264 nm	-0.091	-0.247	0.234	0.144	0.110	0.145	-0.062	1.000	0.050
	1279 nm	-0.029	-0.112	0.081	0.033	-0.015	-0.010	0.016	0.050	1.000
	1633 nm	-0.020	0.076	-0.012	0.022	0.030	-0.137	0.007	0.063	-0.013
	2038 nm	0.013	0.099	0.028	-0.013	-0.011	0.046	-0.067	0.058	-0.081

Table 125. Correlations for between group separability test using the second difference of the raw relative reflectance data (continued)

Statistic	Variable	1633 nm	2038 nm
Correlation	**429 nm**	-0.080	-0.056
	474 nm	0.017	-0.004
	522 nm	-0.098	-0.089
	524 nm	0.015	0.067
	688 nm	-0.091	0.046
	690 nm	-0.073	-0.010
	696 nm	-0.058	-0.027
	698 nm	-0.077	-0.046
	703 nm	0.070	-0.004
	705 nm	-0.020	0.013
	718 nm	0.076	0.099
	732 nm	-0.012	0.028
	748 nm	0.022	-0.013
	750 nm	0.030	-0.011
	1066 nm	-0.137	0.046
	1103 nm	0.007	-0.067
	1264 nm	0.063	0.058
	1279 nm	-0.013	-0.081
	1633 nm	1.000	0.049
	2038 nm	0.049	1.000

Table 126. Correlations for within hardwoods separability test using the second difference of the raw relative reflectance data

Statistic	Variable	644 nm	646 nm	648 nm	694 nm	722 nm	735 nm	737 nm	1072 nm	1171 nm
Correlation	**644 nm**	1.000	-0.346	0.106	0.008	0.003	0.095	-0.043	0.153	0.041
	646 nm	-0.346	1.000	0.081	0.487	-0.279	-0.334	-0.087	0.007	-0.184
	648 nm	0.106	0.081	1.000	0.460	-0.385	-0.355	-0.203	0.098	0.035
	694 nm	0.008	0.487	0.460	1.000	-0.166	-0.594	-0.514	0.036	-0.042
	722 nm	0.003	-0.279	-0.385	-0.166	1.000	0.180	-0.333	-0.019	0.004
	735 nm	0.095	-0.334	-0.355	-0.594	0.180	1.000	0.257	0.170	0.053
	737 nm	-0.043	-0.087	-0.203	-0.514	-0.333	0.257	1.000	-0.006	-0.011
	1072 nm	0.153	0.007	0.098	0.036	-0.019	0.170	-0.006	1.000	0.010
	1171 nm	0.041	-0.184	0.035	-0.042	0.004	0.053	-0.011	0.010	1.000
	1310 nm	-0.070	-0.265	-0.120	-0.369	-0.285	0.240	0.387	-0.129	-0.063
	2019 nm	-0.037	0.007	-0.006	0.025	0.107	0.034	-0.157	0.012	-0.011
	2373 nm	-0.028	-0.079	-0.045	-0.039	-0.038	-0.002	-0.080	-0.198	0.070

Statistic	Variable	1310 nm	2019 nm	2373 nm
Correlation	**644 nm**	-0.070	-0.037	-0.028
	646 nm	-0.265	0.007	-0.079
	648 nm	-0.120	-0.006	-0.045
	694 nm	-0.369	0.025	-0.039
	722 nm	-0.285	0.107	-0.038
	735 nm	0.240	0.034	-0.002
	737 nm	0.387	-0.157	-0.080
	1072 nm	-0.129	0.012	-0.198
	1171 nm	-0.063	-0.011	0.070
	1310 nm	1.000	-0.030	0.160
	2019 nm	-0.030	1.000	0.069
	2373 nm	0.160	0.069	1.000

Table 127. Correlations for within pines separability test using the second difference of the raw relative reflectance data

Statistic	Variable	495 nm	512 nm	523 nm	529 nm	727 nm	1063 nm	1653 nm
Correlation	**495 nm**	1.000	0.385	0.088	-0.273	-0.233	0.122	-0.021
	512 nm	0.385	1.000	-0.039	-0.619	-0.551	0.180	-0.135
	523 nm	0.088	-0.039	1.000	-0.007	0.052	-0.023	-0.031
	529 nm	-0.273	-0.619	-0.007	1.000	0.458	-0.219	0.017
	727 nm	-0.233	-0.551	0.052	0.458	1.000	-0.109	0.034
	1063 nm	0.122	0.180	-0.023	-0.219	-0.109	1.000	-0.086
	1653 nm	-0.021	-0.135	-0.031	0.017	0.034	-0.086	1.000

2. 9-point Averaged Relative Reflectance Data

2.1 9-point Averaged Raw Relative Reflectance

Table 128. Correlations for between group separability test using the 9-point averaged relative reflectance data

Statistic	Variable	520 nm	872 nm	1100 nm	1170 nm	1198 nm	1213 nm	1340 nm
Correlation	**520 nm**	1.000	0.510	0.499	0.485	0.482	0.485	0.479
	872 nm	0.510	1.000	0.978	0.945	0.940	0.941	0.895
	1100 nm	0.499	0.978	1.000	0.979	0.975	0.976	0.943
	1170 nm	0.485	0.945	0.979	1.000	1.000	1.000	0.989
	1198 nm	0.482	0.940	0.975	1.000	1.000	1.000	0.991
	1213 nm	0.485	0.941	0.976	1.000	1.000	1.000	0.991
	1340 nm	0.479	0.895	0.943	0.989	0.991	0.991	1.000

Table 129. Correlations for within hardwoods separability test using the 9-point averaged relative reflectance data

Statistic	Variable	418 nm	691 nm	1590 nm	1631 nm	1655 nm	1691 nm	1700 nm	1725 nm	1746 nm
Correlation	**418 nm**	1.000	0.850	0.756	0.748	0.745	0.746	0.746	0.748	0.754
	691 nm	0.850	1.000	0.738	0.736	0.735	0.737	0.738	0.740	0.738
	1590 nm	0.756	0.738	1.000	0.999	0.997	0.997	0.996	0.996	0.998
	1631 nm	0.748	0.736	0.999	1.000	0.999	0.999	0.999	0.998	0.999
	1655 nm	0.745	0.735	0.997	0.999	1.000	1.000	1.000	0.999	0.998
	1691 nm	0.746	0.737	0.997	0.999	1.000	1.000	1.000	1.000	0.999
	1700 nm	0.746	0.738	0.996	0.999	1.000	1.000	1.000	1.000	0.999
	1725 nm	0.748	0.740	0.996	0.998	0.999	1.000	1.000	1.000	0.999
	1746 nm	0.754	0.738	0.998	0.999	0.998	0.999	0.999	0.999	1.000

Table 130. Correlations for within pines separability test using the 9-point averaged relative reflectance data

Statistic	Variable	355 nm	713 nm	515 nm	1463 nm	1772 nm
Correlation	**355 nm**	1.000	0.574	0.789	0.577	0.610
	713 nm	0.574	1.000	0.914	0.536	0.726
	515 nm	0.789	0.914	1.000	0.693	0.807
	1463 nm	0.577	0.536	0.693	1.000	0.946
	1772 nm	0.610	0.726	0.807	0.946	1.000

2.2 First Difference of 9-point Averaged Relative Reflectance

Table 131. Correlations for between group separability test using the first difference of the 9-point averaged relative reflectance data

Statistic	Variable	363 nm	414 nm	489 nm	750 nm	949 nm	1211 nm	1247 nm	1561 nm	1646 nm
Correlation	**363 nm**	1.000	0.173	0.122	-0.248	0.161	0.158	0.319	-0.201	-0.174
	414 nm	0.173	1.000	0.709	-0.304	-0.270	0.434	0.410	-0.188	0.178
	489 nm	0.122	0.709	1.000	-0.152	-0.198	0.362	0.278	0.191	0.264
	750 nm	-0.248	-0.304	-0.152	1.000	-0.378	0.185	0.137	0.696	0.206
	949 nm	0.161	-0.270	-0.198	-0.378	1.000	-0.410	-0.471	-0.214	-0.512
	1211 nm	0.158	0.434	0.362	0.185	-0.410	1.000	0.515	0.111	0.261
	1247 nm	0.319	0.410	0.278	0.137	-0.471	0.515	1.000	0.045	0.259
	1561 nm	-0.201	-0.188	0.191	0.696	-0.214	0.111	0.045	1.000	0.362
	1646 nm	-0.174	0.178	0.264	0.206	-0.512	0.261	0.259	0.362	1.000

Table 132. Correlations for within hardwoods separability test using the first difference of the 9-point averaged relative reflectance data

Statistic	Variable	399 nm	467 nm	487 nm	620 nm	759 nm	794 nm	1023 nm	1645 nm	1664 nm
Correlation	**399 nm**	1.000	0.336	0.185	-0.053	0.250	0.296	-0.072	-0.329	0.183
	467 nm	0.336	1.000	0.838	-0.393	-0.065	0.014	0.014	-0.070	0.017
	487 nm	0.185	0.838	1.000	-0.568	-0.028	-0.058	0.169	0.228	-0.109
	620 nm	-0.053	-0.393	-0.568	1.000	0.028	0.043	-0.208	-0.415	0.130
	759 nm	0.250	-0.065	-0.028	0.028	1.000	0.662	0.288	0.036	-0.001
	794 nm	0.296	0.014	-0.058	0.043	0.662	1.000	0.408	0.029	0.043
	1023 nm	-0.072	0.014	0.169	-0.208	0.288	0.408	1.000	0.496	-0.112
	1645 nm	-0.329	-0.070	0.228	-0.415	0.036	0.029	0.496	1.000	-0.297
	1664 nm	0.183	0.017	-0.109	0.130	-0.001	0.043	-0.112	-0.297	1.000
	1695 nm	-0.446	-0.239	-0.125	0.225	-0.223	-0.263	-0.096	0.178	-0.089
	1711 nm	-0.285	-0.294	-0.292	0.458	-0.155	-0.218	-0.197	-0.152	0.056

Statistic	Variable	1695 nm	1711 nm
Correlation	**399 nm**	-0.446	-0.285
	467 nm	-0.239	-0.294
	487 nm	-0.125	-0.292
	620 nm	0.225	0.458
	759 nm	-0.223	-0.155
	794 nm	-0.263	-0.218
	1023 nm	-0.096	-0.197
	1645 nm	0.178	-0.152
	1664 nm	-0.089	0.056
	1695 nm	1.000	0.562
	1711 nm	0.562	1.000

Table 133. Correlations for within pines separability test using the first difference of the 9-point averaged relative reflectance data

Statistic	Variable	401 nm	416 nm	440 nm	502 nm	526 nm	587 nm	994 nm	1110 nm	1460 nm
Correlation	**401 nm**	1.000	0.556	0.394	0.467	0.428	-0.268	0.226	-0.086	-0.040
	416 nm	0.556	1.000	0.794	0.887	0.888	-0.804	0.356	-0.098	-0.109
	440 nm	0.394	0.794	1.000	0.759	0.736	-0.596	0.296	0.085	-0.029
	502 nm	0.467	0.887	0.759	1.000	0.929	-0.819	0.312	-0.003	-0.145
	526 nm	0.428	0.888	0.736	0.929	1.000	-0.911	0.444	-0.115	-0.181
	587 nm	-0.268	-0.804	-0.596	-0.819	-0.911	1.000	-0.392	0.231	0.218
	994 nm	0.226	0.356	0.296	0.312	0.444	-0.392	1.000	-0.377	-0.107
	1110 nm	-0.086	-0.098	0.085	-0.003	-0.115	0.231	-0.377	1.000	0.132
	1460 nm	-0.040	-0.109	-0.029	-0.145	-0.181	0.218	-0.107	0.132	1.000

2.3 Second Difference of 9-point Averaged Relative Reflectance

Table 134. Correlations for between group separability test using the second difference of the 9-point averaged relative reflectance data

Statistic	Variable	417 nm	426 nm	431 nm	523 nm	542 nm	546 nm	662 nm	722 nm	964 nm	970 nm
Correlation	**417 nm**	1.000	0.100	-0.442	-0.405	-0.160	-0.160	0.132	-0.368	0.156	-0.038
	426 nm	0.100	1.000	-0.190	0.363	-0.215	-0.161	-0.089	0.027	0.007	-0.122
	431 nm	-0.442	-0.190	1.000	0.498	0.030	-0.055	-0.181	0.161	-0.086	-0.103
	523 nm	-0.405	0.363	0.498	1.000	-0.432	-0.385	0.016	0.203	-0.007	-0.090
	542 nm	-0.160	-0.215	0.030	-0.432	1.000	0.862	-0.581	0.445	-0.116	0.068
	546 nm	-0.160	-0.161	-0.055	-0.385	0.862	1.000	-0.525	0.587	-0.092	0.129
	662 nm	0.132	-0.089	-0.181	0.016	-0.581	-0.525	1.000	-0.447	0.065	0.064
	722 nm	-0.368	0.027	0.161	0.203	0.445	0.587	-0.447	1.000	0.039	0.044
	964 nm	0.156	0.007	-0.086	-0.007	-0.116	-0.092	0.065	0.039	1.000	-0.508
	970 nm	-0.038	-0.122	-0.103	-0.090	0.068	0.129	0.064	0.044	-0.508	1.000
	1244 nm	-0.069	-0.015	0.008	0.020	-0.023	-0.028	0.032	-0.019	-0.220	0.232
	1285 nm	0.011	-0.083	0.089	-0.047	0.164	0.135	-0.089	0.060	-0.216	0.203
	1479 nm	0.053	0.039	-0.028	0.024	-0.060	-0.072	0.127	-0.040	-0.041	0.037
	1564 nm	0.045	0.085	-0.034	0.052	-0.097	-0.034	0.007	0.050	-0.103	0.046
	1991 nm	-0.052	0.067	0.007	0.097	-0.048	-0.061	0.056	-0.022	-0.040	0.014
	2055 nm	-0.035	-0.029	0.020	-0.003	-0.052	-0.098	0.026	-0.077	-0.002	0.089
	2215 nm	-0.055	-0.059	0.093	0.034	0.014	-0.022	-0.053	0.015	0.065	-0.099

Table 134. Correlations for between group separability test using the second difference of the 9-point averaged relative reflectance data (continued)

Statistic	Variable	1244 nm	1285 nm	1479 nm	1564 nm	1991 nm	2055 nm	2215 nm
Correlation	**417 nm**	-0.069	0.011	0.053	0.045	-0.052	-0.035	-0.055
	426 nm	-0.015	-0.083	0.039	0.085	0.067	-0.029	-0.059
	431 nm	0.008	0.089	-0.028	-0.034	0.007	0.020	0.093
	523 nm	0.020	-0.047	0.024	0.052	0.097	-0.003	0.034
	542 nm	-0.023	0.164	-0.060	-0.097	-0.048	-0.052	0.014
	546 nm	-0.028	0.135	-0.072	-0.034	-0.061	-0.098	-0.022
	662 nm	0.032	-0.089	0.127	0.007	0.056	0.026	-0.053
	722 nm	-0.019	0.060	-0.040	0.050	-0.022	-0.077	0.015
	964 nm	-0.220	-0.216	-0.041	-0.103	-0.040	-0.002	0.065
	970 nm	0.232	0.203	0.037	0.046	0.014	0.089	-0.099
	1244 nm	1.000	0.055	-0.001	-0.114	0.012	0.073	-0.056
	1285 nm	0.055	1.000	0.079	0.049	0.079	-0.036	-0.105
	1479 nm	-0.001	0.079	1.000	0.028	0.131	0.047	-0.069
	1564 nm	-0.114	0.049	0.028	1.000	0.001	-0.058	0.021
	1991 nm	0.012	0.079	0.131	0.001	1.000	0.024	0.072
	2055 nm	0.073	-0.036	0.047	-0.058	0.024	1.000	-0.006
	2215 nm	-0.056	-0.105	-0.069	0.021	0.072	-0.006	1.000

Table 135. Correlations for within hardwoods separability test using the second difference of the 9-point averaged relative reflectance data

Statistic	Variable	518 nm	547 nm	559 nm	645 nm	661 nm	693 nm	717 nm	735 nm	1521 nm	1610 nm
Correlation	**518 nm**	1.000	-0.852	-0.910	0.552	0.517	0.948	0.035	-0.803	-0.028	0.120
	547 nm	-0.852	1.000	0.945	-0.726	-0.313	-0.914	0.123	0.768	-0.050	-0.154
	559 nm	-0.910	0.945	1.000	-0.744	-0.340	-0.960	0.086	0.809	-0.007	-0.120
	645 nm	0.552	-0.726	-0.744	1.000	-0.064	0.667	-0.057	-0.598	0.058	-0.002
	661 nm	0.517	-0.313	-0.340	-0.064	1.000	0.461	-0.085	-0.317	-0.012	0.134
	693 nm	0.948	-0.914	-0.960	0.667	0.461	1.000	-0.062	-0.798	-0.027	0.122
	717 nm	0.035	0.123	0.086	-0.057	-0.085	-0.062	1.000	-0.374	0.148	-0.126
	735 nm	-0.803	0.768	0.809	-0.598	-0.317	-0.798	-0.374	1.000	-0.094	-0.053
	1521 nm	-0.028	-0.050	-0.007	0.058	-0.012	-0.027	0.148	-0.094	1.000	-0.126
	1610 nm	0.120	-0.154	-0.120	-0.002	0.134	0.122	-0.126	-0.053	-0.126	1.000
	1715 nm	-0.118	0.127	0.117	-0.048	0.012	-0.114	-0.169	0.150	0.077	0.052
	1753 nm	0.008	0.028	0.018	0.024	-0.050	-0.013	0.343	-0.164	0.119	-0.151
	2111 nm	-0.053	0.121	0.071	-0.049	0.046	-0.082	-0.026	0.039	-0.145	0.030
	2186 nm	0.009	-0.055	-0.038	0.028	0.013	0.027	-0.015	-0.047	0.036	-0.007
	2326 nm	0.047	-0.091	-0.037	0.133	-0.082	0.030	0.132	-0.087	0.068	0.090

Table 135. Correlations for within hardwoods separability test using the second difference of the 9-point averaged relative reflectance data (continued)

Statistic	Variable	1715 nm	1753 nm	2111 nm	2186 nm	2326 nm
Correlation	**518 nm**	-0.118	0.008	-0.053	0.009	0.047
	547 nm	0.127	0.028	0.121	-0.055	-0.091
	559 nm	0.117	0.018	0.071	-0.038	-0.037
	645 nm	-0.048	0.024	-0.049	0.028	0.133
	661 nm	0.012	-0.050	0.046	0.013	-0.082
	693 nm	-0.114	-0.013	-0.082	0.027	0.030
	717 nm	-0.169	0.343	-0.026	-0.015	0.132
	735 nm	0.150	-0.164	0.039	-0.047	-0.087
	1521 nm	0.077	0.119	-0.145	0.036	0.068
	1610 nm	0.052	-0.151	0.030	-0.007	0.090
	1715 nm	1.000	-0.059	0.198	-0.012	0.083
	1753 nm	-0.059	1.000	0.011	0.079	0.067
	2111 nm	0.198	0.011	1.000	0.163	0.065
	2186 nm	-0.012	0.079	0.163	1.000	0.139
	2326 nm	0.083	0.067	0.065	0.139	1.000

Table 136. Correlations for within pines separability test using the second difference of the 9-point averaged relative reflectance data

Statistic	Variable	417 nm	422 nm	427 nm	523 nm	563 nm	591 nm	691 nm	1255 nm	2065 nm	2411 nm
Correlation	**417 nm**	1.000	-0.409	0.087	-0.309	-0.444	0.256	0.411	-0.090	0.029	-0.011
	422 nm	-0.409	1.000	-0.201	0.348	0.322	-0.274	-0.196	0.041	-0.021	0.118
	427 nm	0.087	-0.201	1.000	0.155	0.155	-0.025	-0.208	-0.013	0.057	0.051
	523 nm	-0.309	0.348	0.155	1.000	0.747	-0.503	-0.718	0.068	-0.111	-0.001
	563 nm	-0.444	0.322	0.155	0.747	1.000	-0.701	-0.934	0.068	-0.042	0.061
	591 nm	0.256	-0.274	-0.025	-0.503	-0.701	1.000	0.628	-0.052	0.056	-0.119
	691 nm	0.411	-0.196	-0.208	-0.718	-0.934	0.628	1.000	-0.079	0.052	-0.090
	1255 nm	-0.090	0.041	-0.013	0.068	0.068	-0.052	-0.079	1.000	-0.091	0.009
	2065 nm	0.029	-0.021	0.057	-0.111	-0.042	0.056	0.052	-0.091	1.000	-0.008
	2411 nm	-0.011	0.118	0.051	-0.001	0.061	-0.119	-0.090	0.009	-0.008	1.000

3. 9-point Median Relative Reflectance Data

3.1 9-point Median Raw Relative Reflectance

Table 137. Correlations for between group separability test using the 9-point median relative reflectance data

Statistic	Variable	731 nm	958 nm	1170 nm	1188 nm	1273 nm	1453 nm	1547 nm
Correlation	**731 nm**	1.000	0.961	0.919	0.916	0.918	0.653	0.779
	958 nm	0.961	1.000	0.971	0.968	0.969	0.692	0.823
	1170 nm	0.919	0.971	1.000	1.000	0.999	0.805	0.916
	1188 nm	0.916	0.968	1.000	1.000	0.999	0.811	0.922
	1273 nm	0.918	0.969	0.999	0.999	1.000	0.809	0.916
	1453 nm	0.653	0.692	0.805	0.811	0.809	1.000	0.961
	1547 nm	0.779	0.823	0.916	0.922	0.916	0.961	1.000

Table 138. Correlations for within hardwoods separability test using the 9-point median relative reflectance data

Statistic	Variable	354 nm	561 nm	1001 nm	1008 nm	1121 nm	1340 nm	1724 nm	1747 nm	2465 nm
Correlation	**354 nm**	1.000	0.808	0.581	0.578	0.573	0.660	0.710	0.712	0.199
	561 nm	0.808	1.000	0.702	0.699	0.681	0.708	0.771	0.761	0.148
	1001 nm	0.581	0.702	1.000	1.000	0.993	0.935	0.865	0.854	0.143
	1008 nm	0.578	0.699	1.000	1.000	0.993	0.933	0.863	0.851	0.142
	1121 nm	0.573	0.681	0.993	0.993	1.000	0.947	0.873	0.863	0.159
	1340 nm	0.660	0.708	0.935	0.933	0.947	1.000	0.964	0.963	0.192
	1724 nm	0.710	0.771	0.865	0.863	0.873	0.964	1.000	0.999	0.184
	1747 nm	0.712	0.761	0.854	0.851	0.863	0.963	0.999	1.000	0.190
	2465 nm	0.199	0.148	0.143	0.142	0.159	0.192	0.184	0.190	1.000

Table 139. Correlations for within pines separability test using the 9-point median relative reflectance data

Statistic	Variable	354 nm	515 nm	712 nm	1465 nm	1755 nm
Correlation	**354 nm**	1.000	0.790	0.584	0.575	0.606
	515 nm	0.790	1.000	0.920	0.694	0.816
	712 nm	0.584	0.920	1.000	0.546	0.749
	1465 nm	0.575	0.694	0.546	1.000	0.941
	1755 nm	0.606	0.816	0.749	0.941	1.000

3.2 First Difference of 9-point Median Relative Reflectance

Table 140. Correlations for between group separability test using the first difference of the 9-point median relative reflectance data

Statistic	Variable	414 nm	425 nm	430 nm	752 nm	1000 nm	1135 nm	1212 nm	1246 nm	1250 nm	1502 nm
Correlation	**414 nm**	1.000	0.860	0.747	-0.311	0.033	-0.153	0.254	0.196	0.248	-0.243
	425 nm	0.860	1.000	0.809	-0.327	0.040	-0.138	0.285	0.162	0.247	-0.208
	430 nm	0.747	0.809	1.000	-0.278	0.090	-0.118	0.235	0.086	0.222	-0.207
	752 nm	-0.311	-0.327	-0.278	1.000	0.226	-0.192	0.131	0.164	0.058	0.635
	1000 nm	0.033	0.040	0.090	0.226	1.000	-0.218	0.233	0.149	0.272	0.038
	1135 nm	-0.153	-0.138	-0.118	-0.192	-0.218	1.000	-0.192	-0.207	-0.197	-0.014
	1212 nm	0.254	0.285	0.235	0.131	0.233	-0.192	1.000	0.115	0.359	0.028
	1246 nm	0.196	0.162	0.086	0.164	0.149	-0.207	0.115	1.000	0.210	-0.013
	1250 nm	0.248	0.247	0.222	0.058	0.272	-0.197	0.359	0.210	1.000	-0.058
	1502 nm	-0.243	-0.208	-0.207	0.635	0.038	-0.014	0.028	-0.013	-0.058	1.000
	1510 nm	-0.264	-0.218	-0.186	0.614	0.073	-0.009	0.082	-0.008	0.005	0.847
	1514 nm	-0.218	-0.182	-0.182	0.673	0.074	-0.011	0.027	0.017	-0.038	0.852

Table 140. Correlations for between group separability test using the first difference of the 9-point median relative reflectance data (continued)

Statistic	Variable	1510 nm	1514 nm
Correlation	**414 nm**	-0.264	-0.218
	425 nm	-0.218	-0.182
	430 nm	-0.186	-0.182
	752 nm	0.614	0.673
	1000 nm	0.073	0.074
	1135 nm	-0.009	-0.011
	1212 nm	0.082	0.027
	1246 nm	-0.008	0.017
	1250 nm	0.005	-0.038
	1502 nm	0.847	0.852
	1510 nm	1.000	0.796
	1514 nm	0.796	1.000

Table 141. Correlations for within hardwoods separability test using the first difference of the 9-point median relative reflectance data

Statistic	Variable	396 nm	404 nm	457 nm	497 nm	547 nm	637 nm	648 nm	1027 nm	1650 nm	1670 nm
Correlation	**396 nm**	1.000	0.314	0.088	0.005	0.044	0.005	0.044	-0.026	-0.172	0.174
	404 nm	0.314	1.000	0.381	0.294	0.145	-0.105	-0.242	0.079	-0.145	0.050
	457 nm	0.088	0.381	1.000	0.751	0.496	-0.534	-0.627	0.077	0.047	0.150
	497 nm	0.005	0.294	0.751	1.000	0.728	-0.857	-0.889	0.128	0.253	-0.075
	547 nm	0.044	0.145	0.496	0.728	1.000	-0.857	-0.899	-0.031	0.224	0.027
	637 nm	0.005	-0.105	-0.534	-0.857	-0.857	1.000	0.916	-0.084	-0.375	0.168
	648 nm	0.044	-0.242	-0.627	-0.889	-0.899	0.916	1.000	-0.070	-0.277	0.042
	1027 nm	-0.026	0.079	0.077	0.128	-0.031	-0.084	-0.070	1.000	0.129	-0.096
	1650 nm	-0.172	-0.145	0.047	0.253	0.224	-0.375	-0.277	0.129	1.000	-0.216
	1670 nm	0.174	0.050	0.150	-0.075	0.027	0.168	0.042	-0.096	-0.216	1.000
	2017 nm	0.214	0.165	0.037	0.100	0.133	-0.044	-0.063	0.006	-0.155	-0.016
	2418 nm	0.139	-0.053	-0.068	-0.036	-0.009	-0.003	0.066	-0.093	0.083	-0.021

Table 141. Correlations for within hardwoods separability test using the first difference of the 9-point median relative reflectance data (continued)

Statistic	Variable	2017 nm	2418 nm
Correlation	**396 nm**	0.214	0.139
	404 nm	0.165	-0.053
	457 nm	0.037	-0.068
	497 nm	0.100	-0.036
	547 nm	0.133	-0.009
	637 nm	-0.044	-0.003
	648 nm	-0.063	0.066
	1027 nm	0.006	-0.093
	1650 nm	-0.155	0.083
	1670 nm	-0.016	-0.021
	2017 nm	1.000	0.039
	2418 nm	0.039	1.000

Table 142. Correlations for within pines separability test using the first difference of the 9-point median relative reflectance data

Statistic	Variable	380 nm	419 nm	420 nm	429 nm	441 nm	499 nm	587 nm	667 nm	672 nm	920 nm
Correlation	**380 nm**	1.000	0.156	0.001	0.105	0.164	0.077	-0.026	-0.067	0.058	-0.181
	419 nm	0.156	1.000	0.587	0.531	0.629	0.634	-0.629	-0.622	-0.269	0.041
	420 nm	0.001	0.587	1.000	0.599	0.629	0.687	-0.647	-0.650	-0.256	0.071
	429 nm	0.105	0.531	0.599	1.000	0.620	0.522	-0.524	-0.526	-0.173	0.082
	441 nm	0.164	0.629	0.629	0.620	1.000	0.716	-0.534	-0.718	-0.290	0.054
	499 nm	0.077	0.634	0.687	0.522	0.716	1.000	-0.722	-0.856	-0.411	0.183
	587 nm	-0.026	-0.629	-0.647	-0.524	-0.534	-0.722	1.000	0.675	0.369	0.008
	667 nm	-0.067	-0.622	-0.650	-0.526	-0.718	-0.856	0.675	1.000	0.578	-0.145
	672 nm	0.058	-0.269	-0.256	-0.173	-0.290	-0.411	0.369	0.578	1.000	-0.102
	920 nm	-0.181	0.041	0.071	0.082	0.054	0.183	0.008	-0.145	-0.102	1.000
	1256 nm	0.234	0.120	0.067	0.078	0.172	0.167	0.079	-0.034	0.221	-0.124
	1632 nm	0.023	0.204	0.253	0.317	0.269	0.308	-0.235	-0.295	-0.183	0.143
	2450 nm	0.036	0.110	0.174	0.134	0.056	0.040	-0.173	-0.074	0.041	0.020

Table 142. Correlations for within pines separability test using the first difference of the 9-point median relative reflectance data (continued)

Statistic	Variable	1256 nm	1632 nm	2450 nm
Correlation	**380 nm**	0.234	0.023	0.036
	419 nm	0.120	0.204	0.110
	420 nm	0.067	0.253	0.174
	429 nm	0.078	0.317	0.134
	441 nm	0.172	0.269	0.056
	499 nm	0.167	0.308	0.040
	587 nm	0.079	-0.235	-0.173
	667 nm	-0.034	-0.295	-0.074
	672 nm	0.221	-0.183	0.041
	920 nm	-0.124	0.143	0.020
	1256 nm	1.000	0.027	0.079
	1632 nm	0.027	1.000	-0.097
	2450 nm	0.079	-0.097	1.000

3.3 Second Difference of 9-point Median Relative Reflectance

Table 143. Correlations for between group separability test using the second difference of the 9-point median relative reflectance data

Statistic	Variable	364 nm	430 nm	523 nm	524 nm	525 nm	688 nm	690 nm	696 nm	698 nm	703 nm
Correlation	**364 nm**	1.000	0.008	-0.031	-0.090	-0.021	-0.009	-0.019	-0.089	-0.119	-0.060
	430 nm	0.008	1.000	-0.112	0.009	-0.161	-0.032	-0.119	-0.156	-0.147	-0.098
	523 nm	-0.031	-0.112	1.000	-0.288	0.240	0.055	0.177	0.409	0.365	0.161
	524 nm	-0.090	0.009	-0.288	1.000	-0.316	-0.073	0.129	0.334	0.259	0.198
	525 nm	-0.021	-0.161	0.240	-0.316	1.000	-0.288	-0.198	0.016	0.019	0.101
	688 nm	-0.009	-0.032	0.055	-0.073	-0.288	1.000	0.621	0.435	0.434	-0.350
	690 nm	-0.019	-0.119	0.177	0.129	-0.198	0.621	1.000	0.747	0.760	-0.177
	696 nm	-0.089	-0.156	0.409	0.334	0.016	0.435	0.747	1.000	0.871	0.222
	698 nm	-0.119	-0.147	0.365	0.259	0.019	0.434	0.760	0.871	1.000	0.228
	703 nm	-0.060	-0.098	0.161	0.198	0.101	-0.350	-0.177	0.222	0.228	1.000
	705 nm	-0.016	-0.094	0.183	0.130	0.049	-0.079	0.037	0.318	0.379	0.526
	723 nm	-0.068	-0.138	0.321	0.199	0.144	-0.061	0.216	0.517	0.583	0.531
	730 nm	0.050	0.123	-0.320	-0.120	0.085	-0.454	-0.671	-0.730	-0.799	-0.174
	748 nm	0.040	0.164	-0.320	-0.129	-0.071	-0.167	-0.407	-0.609	-0.650	-0.452
	749 nm	0.083	0.099	-0.166	-0.199	-0.001	-0.075	-0.305	-0.507	-0.538	-0.458
	2103 nm	-0.043	-0.024	0.039	0.002	0.002	-0.049	0.010	0.051	0.022	0.077
	2239 nm	-0.013	0.045	-0.016	0.048	-0.023	-0.029	-0.035	0.035	-0.003	0.041
	2296 nm	0.037	-0.031	0.038	0.049	-0.095	0.042	0.033	0.079	0.065	0.024

Table 143. Correlations for between group separability test using the second difference of the 9-point median relative reflectance data (continued)

Statistic	Variable	705 nm	723 nm	730 nm	748 nm	749 nm	2103 nm	2239 nm	2296 nm
Correlation	**364 nm**	-0.016	-0.068	0.050	0.040	0.083	-0.043	-0.013	0.037
	430 nm	-0.094	-0.138	0.123	0.164	0.099	-0.024	0.045	-0.031
	523 nm	0.183	0.321	-0.320	-0.320	-0.166	0.039	-0.016	0.038
	524 nm	0.130	0.199	-0.120	-0.129	-0.199	0.002	0.048	0.049
	525 nm	0.049	0.144	0.085	-0.071	-0.001	0.002	-0.023	-0.095
	688 nm	-0.079	-0.061	-0.454	-0.167	-0.075	-0.049	-0.029	0.042
	690 nm	0.037	0.216	-0.671	-0.407	-0.305	0.010	-0.035	0.033
	696 nm	0.318	0.517	-0.730	-0.609	-0.507	0.051	0.035	0.079
	698 nm	0.379	0.583	-0.799	-0.650	-0.538	0.022	-0.003	0.065
	703 nm	0.526	0.531	-0.174	-0.452	-0.458	0.077	0.041	0.024
	705 nm	1.000	0.658	-0.443	-0.514	-0.525	0.011	-0.021	0.010
	723 nm	0.658	1.000	-0.691	-0.709	-0.684	0.070	0.015	0.050
	730 nm	-0.443	-0.691	1.000	0.590	0.539	-0.043	0.014	-0.117
	748 nm	-0.514	-0.709	0.590	1.000	0.421	-0.079	0.095	-0.048
	749 nm	-0.525	-0.684	0.539	0.421	1.000	-0.050	-0.012	-0.014
	2103 nm	0.011	0.070	-0.043	-0.079	-0.050	1.000	0.024	0.363
	2239 nm	-0.021	0.015	0.014	0.095	-0.012	0.024	1.000	-0.049
	2296 nm	0.010	0.050	-0.117	-0.048	-0.014	0.363	-0.049	1.000

Table 144. Correlations for within hardwoods separability test using the second difference of the 9-point median relative reflectance data

Statistic	Variable	419 nm	553 nm	644 nm	646 nm	648 nm	649 nm	651 nm	694 nm	703 nm	710 nm
Correlation	**419 nm**	1.000	0.160	-0.068	-0.040	-0.223	0.068	-0.069	-0.106	0.072	0.041
	553 nm	0.160	1.000	-0.006	-0.268	-0.285	-0.229	-0.299	-0.386	0.480	0.598
	644 nm	-0.068	-0.006	1.000	-0.346	0.106	0.018	0.050	0.008	0.087	0.097
	646 nm	-0.040	-0.268	-0.346	1.000	0.081	0.358	0.114	0.487	-0.319	-0.303
	648 nm	-0.223	-0.285	0.106	0.081	1.000	0.179	0.387	0.460	-0.345	-0.355
	649 nm	0.068	-0.229	0.018	0.358	0.179	1.000	-0.201	0.476	-0.183	-0.145
	651 nm	-0.069	-0.299	0.050	0.114	0.387	-0.201	1.000	0.332	-0.136	-0.204
	694 nm	-0.106	-0.386	0.008	0.487	0.460	0.476	0.332	1.000	-0.245	-0.217
	703 nm	0.072	0.480	0.087	-0.319	-0.345	-0.183	-0.136	-0.245	1.000	0.787
	710 nm	0.041	0.598	0.097	-0.303	-0.355	-0.145	-0.204	-0.217	0.787	1.000
	1499 nm	0.149	0.056	-0.023	-0.041	-0.055	-0.150	0.006	-0.148	0.140	0.024
	2327 nm	0.006	0.102	0.155	-0.149	-0.044	-0.118	0.018	-0.080	0.147	0.113

Statistic	Variable	1499 nm	2327 nm
Correlation	**419 nm**	0.149	0.006
	553 nm	0.056	0.102
	644 nm	-0.023	0.155
	646 nm	-0.041	-0.149
	648 nm	-0.055	-0.044
	649 nm	-0.150	-0.118
	651 nm	0.006	0.018
	694 nm	-0.148	-0.080
	703 nm	0.140	0.147
	710 nm	0.024	0.113
	1499 nm	1.000	-0.014
	2327 nm	-0.014	1.000

Table 145. Correlations for within pines separability test using the second difference of the 9-point median relative reflectance data

Statistic	Variable	422 nm	423 nm	529 nm	676 nm	886 nm	1063 nm	1108 nm	1567 nm	1745 nm	2354 nm
Correlation	**422 nm**	1.000	-0.384	0.170	0.008	0.012	0.061	0.141	-0.030	-0.056	0.110
	423 nm	-0.384	1.000	0.079	-0.149	-0.111	0.078	-0.080	0.018	-0.044	0.044
	529 nm	0.170	0.079	1.000	-0.119	0.065	-0.210	0.031	-0.036	-0.081	0.009
	676 nm	0.008	-0.149	-0.119	1.000	0.005	0.133	-0.164	0.069	-0.020	-0.099
	886 nm	0.012	-0.111	0.065	0.005	1.000	0.137	0.066	0.046	0.054	-0.012
	1063 nm	0.061	0.078	-0.210	0.133	0.137	1.000	-0.040	-0.028	0.037	0.008
	1108 nm	0.141	-0.080	0.031	-0.164	0.066	-0.040	1.000	0.035	0.150	-0.010
	1567 nm	-0.030	0.018	-0.036	0.069	0.046	-0.028	0.035	1.000	-0.043	-0.001
	1745 nm	-0.056	-0.044	-0.081	-0.020	0.054	0.037	0.150	-0.043	1.000	-0.106
	2354 nm	0.110	0.044	0.009	-0.099	-0.012	0.008	-0.010	-0.001	-0.106	1.000

4. AVIRIS Simulation 10 nm Relative Reflectance Data

4.1 AVIRIS Simulation 10 nm Raw Relative Reflectance Data

Table 146. Correlations for between group separability test using the simulated AVIRIS 10 nm relative reflectance data

Statistic	Variable	520 nm	730 nm	970 nm	1160 nm	1190 nm	1270 nm	1310 nm	1340 nm
Correlation	**520 nm**	1.000	0.685	0.512	0.492	0.490	0.500	0.495	0.486
	730 nm	0.685	1.000	0.958	0.919	0.915	0.917	0.902	0.876
	970 nm	0.512	0.958	1.000	0.973	0.970	0.971	0.960	0.939
	1160 nm	0.492	0.919	0.973	1.000	0.999	0.999	0.997	0.988
	1190 nm	0.490	0.915	0.970	0.999	1.000	0.999	0.998	0.991
	1270 nm	0.500	0.917	0.971	0.999	0.999	1.000	0.998	0.988
	1310 nm	0.495	0.902	0.960	0.997	0.998	0.998	1.000	0.996
	1340 nm	0.486	0.876	0.939	0.988	0.991	0.988	0.996	1.000

Table 147. Correlations for within hardwoods separability test using the simulated AVIRIS 10 nm relative reflectance data

Statistic	Variable	380 nm	420 nm	680 nm	690 nm	970 nm	1200 nm	1530 nm	1590 nm	1630 nm	1660 nm	1700 nm
Correlation	**380 nm**	1.000	0.986	0.838	0.811	0.614	0.650	0.742	0.736	0.730	0.729	0.730
	420 nm	0.986	1.000	0.897	0.862	0.617	0.658	0.766	0.755	0.748	0.745	0.746
	680 nm	0.838	0.897	1.000	0.977	0.587	0.629	0.747	0.731	0.723	0.718	0.720
	690 nm	0.811	0.862	0.977	1.000	0.640	0.666	0.737	0.741	0.738	0.738	0.741
	970 nm	0.614	0.617	0.587	0.640	1.000	0.952	0.740	0.802	0.822	0.834	0.833
	1200 nm	0.650	0.658	0.629	0.666	0.952	1.000	0.879	0.923	0.936	0.942	0.941
	1530 nm	0.742	0.766	0.747	0.737	0.740	0.879	1.000	0.991	0.984	0.977	0.977
	1590 nm	0.736	0.755	0.731	0.741	0.802	0.923	0.991	1.000	0.999	0.997	0.996
	1630 nm	0.730	0.748	0.723	0.738	0.822	0.936	0.984	0.999	1.000	0.999	0.999
	1660 nm	0.729	0.745	0.718	0.738	0.834	0.942	0.977	0.997	0.999	1.000	1.000
	1700 nm	0.730	0.746	0.720	0.741	0.833	0.941	0.977	0.996	0.999	1.000	1.000

Table 148. Correlations for within pines separability test using the simulated AVIRIS 10 nm relative reflectance data

Statistic	Variable	360 nm	410 nm	420 nm	440 nm	490 nm	650 nm	1340 nm
Correlation	**360 nm**	1.000	0.984	0.972	0.943	0.889	0.773	0.499
	410 nm	0.984	1.000	0.995	0.975	0.938	0.847	0.587
	420 nm	0.972	0.995	1.000	0.990	0.962	0.877	0.637
	440 nm	0.943	0.975	0.990	1.000	0.986	0.911	0.701
	490 nm	0.889	0.938	0.962	0.986	1.000	0.956	0.767
	650 nm	0.773	0.847	0.877	0.911	0.956	1.000	0.809
	1340 nm	0.499	0.587	0.637	0.701	0.767	0.809	1.000

4.2 First Difference of AVIRIS Simulation 10 nm Data

Table 149. Correlations for between group separability test using the first difference of the simulated AVIRIS 10 nm relative reflectance data

Statistic	Variable	360 nm	390 nm	410 nm	480 nm	750 nm	930 nm	1160 nm	1240 nm	1500 nm
Correlation	**360 nm**	1.000	0.562	0.202	0.269	-0.329	0.215	0.087	0.335	-0.365
	390 nm	0.562	1.000	0.445	0.373	-0.024	0.228	-0.086	0.356	-0.063
	410 nm	0.202	0.445	1.000	0.678	-0.307	-0.109	-0.186	0.470	-0.249
	480 nm	0.269	0.373	0.678	1.000	-0.183	-0.117	0.002	0.340	0.123
	750 nm	-0.329	-0.024	-0.307	-0.183	1.000	-0.272	-0.436	0.212	0.680
	930 nm	0.215	0.228	-0.109	-0.117	-0.272	1.000	-0.024	-0.223	-0.142
	1160 nm	0.087	-0.086	-0.186	0.002	-0.436	-0.024	1.000	-0.432	-0.050
	1240 nm	0.335	0.356	0.470	0.340	0.212	-0.223	-0.432	1.000	-0.084
	1500 nm	-0.365	-0.063	-0.249	0.123	0.680	-0.142	-0.050	-0.084	1.000

Table 150. Correlations for within hardwoods separability test using the first difference of the simulated AVIRIS 10 nm relative reflectance data

Statistic	Variable	400 nm	480 nm	750 nm	770 nm	940 nm	1640 nm	1670 nm	1690 nm	1730 nm
Correlation	**400 nm**	1.000	0.506	0.062	0.074	0.137	-0.149	-0.070	-0.438	0.030
	480 nm	0.506	1.000	-0.194	-0.053	-0.193	0.286	-0.227	-0.182	-0.455
	750 nm	0.062	-0.194	1.000	0.582	-0.437	0.224	-0.230	-0.320	-0.160
	770 nm	0.074	-0.053	0.582	1.000	-0.174	0.090	-0.137	-0.396	-0.182
	940 nm	0.137	-0.193	-0.437	-0.174	1.000	-0.730	0.369	-0.139	0.661
	1640 nm	-0.149	0.286	0.224	0.090	-0.730	1.000	-0.494	0.197	-0.804
	1670 nm	-0.070	-0.227	-0.230	-0.137	0.369	-0.494	1.000	0.338	0.471
	1690 nm	-0.438	-0.182	-0.320	-0.396	-0.139	0.197	0.338	1.000	0.036
	1730 nm	0.030	-0.455	-0.160	-0.182	0.661	-0.804	0.471	0.036	1.000

Table 151. Correlations for within pines separability test using the first difference of the simulated AVIRIS 10 nm relative reflectance data

Statistic	Variable	390 nm	410 nm	420 nm	490 nm	540 nm	1050 nm
Correlation	**390 nm**	1.000	0.404	0.308	0.346	0.233	0.466
	410 nm	0.404	1.000	0.927	0.837	0.856	0.317
	420 nm	0.308	0.927	1.000	0.792	0.876	0.296
	490 nm	0.346	0.837	0.792	1.000	0.860	0.293
	540 nm	0.233	0.856	0.876	0.860	1.000	0.232
	1050 nm	0.466	0.317	0.296	0.293	0.232	1.000

4.3 Second Difference of AVIRIS Simulation 10 nm Data

Table 152. Correlations for between group separability test using the second difference of the simulated AVIRIS 10 nm relative reflectance data

Statistic	Variable	430 nm	440 nm	480 nm	520 nm	660 nm	720 nm	1070 nm	1590 nm	1660 nm
Correlation	**430 nm**	1.000	0.295	-0.370	0.542	-0.108	0.261	0.136	-0.216	0.280
	440 nm	0.295	1.000	-0.162	0.243	0.246	-0.056	0.181	-0.204	0.136
	480 nm	-0.370	-0.162	1.000	0.010	0.175	-0.283	-0.205	-0.130	-0.302
	520 nm	0.542	0.243	0.010	1.000	0.559	0.058	0.000	-0.457	0.058
	660 nm	-0.108	0.246	0.175	0.559	1.000	-0.302	-0.063	-0.289	-0.046
	720 nm	0.261	-0.056	-0.283	0.058	-0.302	1.000	-0.332	-0.018	0.054
	1070 nm	0.136	0.181	-0.205	0.000	-0.063	-0.332	1.000	0.071	0.245
	1590 nm	-0.216	-0.204	-0.130	-0.457	-0.289	-0.018	0.071	1.000	0.052
	1660 nm	0.280	0.136	-0.302	0.058	-0.046	0.054	0.245	0.052	1.000

Table 153. Correlations for within hardwoods separability test using the second difference of the simulated AVIRIS 10 nm relative reflectance data

Statistic	Variable	380 nm	390 nm	480 nm	590 nm	660 nm	1650 nm	1660 nm	1700 nm
Correlation	**380 nm**	1.000	0.269	0.250	0.195	-0.153	-0.019	0.055	-0.060
	390 nm	0.269	1.000	0.300	0.251	0.076	-0.128	0.170	-0.083
	480 nm	0.250	0.300	1.000	0.568	0.074	-0.398	-0.400	-0.363
	590 nm	0.195	0.251	0.568	1.000	0.595	-0.414	-0.238	-0.473
	660 nm	-0.153	0.076	0.074	0.595	1.000	-0.338	-0.074	-0.324
	1650 nm	-0.019	-0.128	-0.398	-0.414	-0.338	1.000	0.266	0.341
	1660 nm	0.055	0.170	-0.400	-0.238	-0.074	0.266	1.000	0.499
	1700 nm	-0.060	-0.083	-0.363	-0.473	-0.324	0.341	0.499	1.000

Table 154. Correlations for within pines separability test using the second difference of the simulated AVIRIS 10 nm relative reflectance data

Statistic	**Variable**	**420 nm**	**430 nm**	**520 nm**	**590 nm**	**670 nm**	**800 nm**	**1150 nm**
Correlation	**420 nm**	1.000	0.252	0.312	0.041	0.165	0.076	-0.040
	430 nm	0.252	1.000	-0.056	-0.669	-0.671	0.114	-0.489
	520 nm	0.312	-0.056	1.000	0.217	0.031	-0.307	0.302
	590 nm	0.041	-0.669	0.217	1.000	0.715	-0.298	0.521
	670 nm	0.165	-0.671	0.031	0.715	1.000	0.023	0.407
	800 nm	0.076	0.114	-0.307	-0.298	0.023	1.000	-0.350
	1150 nm	-0.040	-0.489	0.302	0.521	0.407	-0.350	1.000