

Discrimination of lianas and trees with leaf-level hyperspectral data

K.L. Castro-Esau^a, G.A. Sánchez-Azofeifa^{a,*}, T. Caelli^b

^aEarth Observation Systems Laboratory, Department of Earth and Atmospheric Sciences, University of Alberta, Edmonton, Alberta, Canada T6G 2E3

^bDepartment of Computing Science, University of Alberta, Edmonton, Alberta, Canada T6G 2E8

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Abstract

Lianas are an important component of the biological diversity in two tropical forests with contrasting moisture regimes in Panama. However, their presence in a tree crown may be a source of confusion in remotely sensed data collected for inventories or assessment of vegetation health. The structural growth form of lianas contrasts with trees in that their proportion of leafy biomass to woody biomass is much higher. In effect, they use trees for structural support and typically form a monolayer of leaves above the crown of the supporting tree. Here, we investigated possible differences between hyperspectral signatures of lianas and trees at the leaf level using pattern recognition techniques. Our method involves principal components analysis followed by training and classification using a selection of supervised parametric and nonparametric classifiers. At a tropical dry forest site (Parque Natural Metropolitano), lianas and trees are distinguishable as groups based on their leaf spectral reflectance characteristics in dry season conditions. Classification was improved using ancillary data on leaf chlorophyll content. Their distinction at this site may be related to drought stress and/or phenological differences between the two groups. At a tropical wet forest site (Fort Sherman), discrimination between the two groups was not as clear. Additional research is required to determine the physiological basis of possible differences as well as to determine if these differences are observable at the canopy level. © 2004 Elsevier Inc. All rights reserved.

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1. Introduction

There is mounting evidence towards the increasing dominance of lianas in tropical forests (Phillips et al., 2002). With little investment in woody biomass, these aggressive climbers take advantage of existing tree trunks and other lianas to make their way to the canopy where they are capable of rapidly forming a carpet of leafy vegetation, shading the tree beneath (Avalos et al., 1999). There are numerous implications of liana infestation to the supporting tree, including increased mechanical and wind damage, increased probability of falling, and decreased growth rates (Clark & Clark, 1990; Putz, 1984). Eventually, these deleterious effects can lead to increased tree mortality. Since lianas prefer disturbed habitats, promoting disturbances likewise promotes their own proliferation (Schnitzer et al., 2000). In the long run, these trends could lead to significant

alterations in forested ecosystems by affecting regeneration rates (Schnitzer et al., 2000) and tree species composition (Phillips et al., 2002).

Where lianas are abundant, their presence in the form of a monolayer on top of tree crowns has important implications for remote sensing studies. For instance, interpretation of vegetation indices relating to photosynthetic activity from hyperspectral data over such areas could be erroneous if lianas are interpreted as tree canopies. Similarly, little or no differences between spectral signatures of lianas vs. trees could also limit the potential for tree classification. From a different point of view, the ability to identify areas heavily infested with lianas would be beneficial to efforts at tracking the prevalence of lianas in tropical forests over time, a topic that demands serious attention in lieu of linkages between climate change and increased extent of liana coverage (Phillips et al., 2002).

The current status of hyperspectral research on tropical trees and/or lianas is highly preliminary. Very few datasets exist from airborne hyperspectral sensors in the Neotropics, and experimental satellite data is just now becoming available from the EO-1 Hyperion sensor, with a spatial resolu-

* Corresponding author. Tel.: +1-780-492-1822; fax: +1-780-492-2030.

E-mail address: arturo.sanchez@ualberta.ca (G.A. Sánchez-Azofeifa).

tion of 30 m. At the leaf level, studies by Fung et al. (1999) and Cochrane (2000) were aimed at determining if tree species recognition is possible with subtropical and tropical trees, respectively. Avalos et al. (1999) conducted a study to compare the optical properties of lianas and trees using absorptance, reflectance and transmittance over the photosynthetically active range rather than examining responses at individual wavebands. Their results indicated similar absorptance and reflectance between the two groups, but significantly lower transmittance of liana leaves as compared to tree leaves.

The specific objective of this paper is to determine if it is possible to distinguish between lianas and supporting trees, as groups, at the leaf level, using hyperspectral reflectance measurements taken from two communities of tropical liana/tree species in Panama, Republic of Panama: Parque Natural Metropolitano (tropical dry forest) and Fort Sherman (tropical wet forest). The approach involves principal components analysis (PCA) and pattern recognition techniques to differentiate between the two groups. The power of PCA for hyperspectral data analysis lies in the reduction of hundreds of highly correlated bands to a few highly discriminatory, uncorrelated eigenvectors, useful for isolating different groups (Chang et al., 2001; Lee et al., 1990). The study focuses on separation of the two structural groups, rather than individual species, since it would be impractical to separate individual liana species on a tree

crow where multiple liana species with different abundances from season to season are present. Although the current study does not extend to the canopy level, we believe that studying leaf reflectance is a critical step for a better understanding of spectral responses at the canopy level in tropical environments.

2. Methods

2.1. Study areas

2.1.1. Parque Natural Metropolitano

For this study, tree canopies were accessed using two canopy cranes installed by the Smithsonian Tropical Research Institute (STRI) in Panama. The first is located in a tropical dry forest at Parque Natural Metropolitano (PNM), just outside Panama City. The crane is 42 m high with a boom radius of 51 m. Annual rainfall at this site is approximately 1740 mm.

The dominant canopy species within reach of the crane is *Anacardium excelsum* (Anacardiaceae). Additional accessible tree species include *Luehea seemannii* (Tiliaceae), *Annona spraguei* (Annonaceae), *Cecropia longipes* (Cecropiaceae), *Enterolobium cyclocarpum* (Fabaceae-Mimosoideae), *Astronium graveolens* (Anacardiaceae), *Ficus insipida* (Moraceae), and *Cordia alliodora* (Boraginaceae).

Table 1
Liana and tree species sampled for this study

Parque Natural Metropolitano				Fort Sherman			
Lianas		Trees		Lianas		Trees	
Species	Family	Species	Family	Species	Family	Species	Family
<i>Aristolochia maxima</i>	Aristolochiaceae	<i>Anacardium excelsum</i>	Anacardiaceae	<i>Forsteronia myriantha</i>	Apocynaceae	<i>Aspidosperma cruenta</i>	Apocynaceae
<i>Mikania leiostachya</i>	Asteraceae	<i>Annona spraguei</i>	Annonaceae	<i>Odontadenia puncticulosa</i>	Apocynaceae	<i>Cordia bicolor</i>	Boraginaceae
<i>Arrabidaea candidans</i>	Bignoniaceae	<i>Cordia alliodora</i>	Boraginaceae	<i>Arrabidaea verrucosa</i>	Bignoniaceae	<i>Pourourma</i> sp. ^a	Cecropiaceae
<i>Stizophyllum riparium</i>	Bignoniaceae	<i>Ficus insipida</i>	Moraceae	<i>Phryganocydia corymbosa</i>	Bignoniaceae	<i>Marila laxiflora</i>	Clusiaceae
<i>Bonamia trichantha</i>	Convolvulaceae	<i>Luehea seemannii</i>	Tiliaceae	<i>Pleonotoma variabilis</i>	Bignoniaceae	<i>Terminalia amazonia</i>	Combretaceae
<i>Jacquemontia</i> sp. ^a	Convolvulaceae			<i>Maripa panamensis</i>	Convolvulaceae	<i>Tachigali versicolor</i>	Fabaceae-Caesalpinoideae
<i>Doliocarpus dentatus</i>	Dilleniaceae			<i>Doliocarpus multiflorus</i>	Dilleniaceae	<i>Lonchocarpus longifolium</i>	Fabaceae-Papilionoideae
<i>Stigmaphyllon hypargyreum</i>	Malpighiaceae			<i>Dioclea wilsonii</i>	Fabaceae-Papilionoideae	<i>Carapa guianensis</i>	Meliaceae
<i>Passiflora vitifolia</i>	Passifloraceae			<i>Tontelea ovalifolia</i>	Hippocrateaceae	<i>Brosimum utile</i>	Moraceae
<i>Gouania lupuloides</i>	Rhamnaceae			<i>Unknown sp. of liana</i>	Hippocrateaceae	<i>Ficus nymphaeifolia</i>	Moraceae
<i>Serjania</i> sp. ^a	Sapindaceae					<i>Virola surinamensis</i>	Myristicaceae
<i>Vitis tiliifolia</i>	Vitaceae					<i>Tocoyena pittieri</i>	Rubiaceae
						<i>Matayba apetala</i>	Sapindaceae
						<i>Manilkara bidentata</i>	Sapotaceae
						<i>Simarouba amara</i>	Simaroubaceae

^a In some cases it was possible to identify lianas to genus but not to species.

Lianas contribute significantly to the biodiversity of this area. There are numerous pockets within the jib radius where lianas have proliferated and, in some cases, cover portions of or entire tree crowns. Avalos and Mulkey (1999) sampled canopy transects from this location under dry and wet season conditions (1994–1995), and found 20 liana species. During the dry season, at which time only 13 of the liana species maintained foliage, they estimated that of the canopy surface beneath the crane, 14.0% was occupied by lianas and 50.7% was occupied by the supporting trees. During the wet season, however, these figures changed to 30.9% and 43.8%, respectively.

2.1.2. Fort Sherman

The second STRI canopy crane is located on the Caribbean coast near Colón, Panama, in a tropical wet forest that receives an annual precipitation of approximately 3300 mm. The crane at this site has a height of 56 m and a boom length of 54 m.

Species diversity at Fort Sherman (FTS) is greater than that at PNM. There are about 180 species of trees and lianas within the crane radius. Tree species include *Tapirira guianensis* (Anacardiaceae), *Aspidosperma cruenta* (Apocynaceae), *Cordia bicolor* (Boraginaceae), several *Inga* sp. (Fabaceae-Mimosoideae), *Carapa guianensis* (Meliaceae), *Brosimum utile* (Moraceae), several *Virola* sp. (Myristicaceae), *Manilkara bidentata* (Sapotaceae), *Simarouba amara* (Simaroubaceae), and *Vochysia ferruginea* (Vochysiaceae), among others.

Lianas appear to be an important component of the biodiversity at FTS as well, although not to as great an extent as at PNM. When sampling was undertaken (March 2003), numerous medium-sized and smaller trees were supporting lianas, whereas the tallest canopy trees were not. Lianas were particularly noticeable in the few cases where the supporting tree was in a partial to complete leaf-off condition.

2.2. Sample collection

From the gondola of each canopy crane, leaves of liana and tree species (Table 1) were collected March 5–14, 2003,

Table 3
Percentage of variance contained within first two eigenvectors/values in PCA1 and PCA2

	Dataset		
	Raw smoothed data	First derivative	Second derivative
<i>PCA1</i>			
PNM	97.61	94.08	95.40
FTS	98.89	97.25	96.80
<i>PCA2</i>			
PNM lianas	98.69	94.01	94.02
PNM trees	91.57	91.03	95.21
FTS lianas	99.79	99.33	99.16
FTS trees	97.78	94.34	93.63

near the end of the dry season. Ten leaves were collected per species. Leaves were immediately placed in sealable plastic bags containing moistened paper towels. These bags were placed in a cooler containing ice, brought promptly to ground level to extract samples for chlorophyll analyses, and taken to a makeshift laboratory for spectral reflectance measurements.

2.3. Measurements of chlorophyll content

For five of the ten leaves, samples were cored from one side of the leaf midrib and placed in small plastic vials that were covered in tinfoil and frozen (the remaining five leaves were retained for other analyses). The first three leaves were, in most cases, the same leaves used later for spectral reflectance measurements, which were taken on the remainder of the leaf. In the case of small leaves, different leaves were used for chlorophyll content and for spectral reflectance measurements. The corer had a diameter of 1.6 cm. Chlorophyll *a* and chlorophyll *b* content per core were determined using the dimethyl sulphoxide (DMSO) extraction technique described in Hiscox and Israelstam (1979). A standard two-sample *t*-test was used to determine if there were significant differences between the means of liana and tree chlorophyll contents at the two sites. Where the assumption of equal variances was not met, a Welch modified two-sample *t*-test was used instead (Ott, 1993).

Table 2
Supervised classifiers used in this study (source: Duin, 2000)

Code	Classifier	Description
loglc	Logistic linear classifier	Linear classifier computed by maximizing the likelihood criterion using the logistic (sigmoid) function.
qdc	Normal densities based quadratic classifier (Bayes' rule)	Quadratic classifier using the assumption of normal densities.
udc	Uncorrelated normal densities based quadratic classifier	Quadratic classifier using the assumption of normal densities with uncorrelated (independent) features.
lmnc	Train feed forward neural network by Levenberg–Marquardt rule	A neural network based on the backpropagation algorithm and Levenberg–Marquardt gradient descent.
treec	Binary decision tree classifier	Decision tree classifier using information gain as a binary splitting criterion.
knc	<i>k</i> -nearest neighbor classifier	Classifier for which the class labels of the <i>k</i> most similar neighbors are used to predict the class of the new object. The distance metric used in this case is the Euclidean distance.

2.4. Measurements of spectral reflectance

Spectral reflectance measurements were taken using a UniSpec Spectral Analysis System (PP Systems, Amesbury, MA, USA). The UniSpec VIS/NIR incorporates a 256-element photodiode array, which covers a spectral range of 306–1138 nm at a sampling interval of 3.3 nm. It has a built-in light source (7.0 W halogen lamp) and may be fitted with a leaf clip that holds the foreoptic at 60° and prevents entry of ambient light. The measuring diameter of the standard foreoptic used in this study is 2.3 mm.

The following sequence was used to perform spectral reflectance measurements of liana and tree leaves with the UniSpec spectrometer: (1) integration time was adjusted automatically with a white reference standard in the leaf clip, (2) number of scans per measurement was set to 10, (3) a dark scan was performed, (4) a reference scan was acquired, again with the white reference standard in the leaf clip, and (5) a sample was scanned.

Of the 10 leaves collected per species, spectral measurements were taken for the first three healthy, mature leaves also used for analyses of chlorophyll content, with the exception of small-leaved species, for which different leaves were used

Table 4
Training and testing error (in percentage) for dataset-classifier combinations used in this study

Parque Metropolitano						
Classifier	Raw smoothed data					
	PCA1		PCA2		PCA2 (+chl)	
	Training error	Testing error	Training error	Testing error	Training error	Testing error
loglc	19.23	20.00	3.85	20.00	0	16.00
qdc	15.38	20.00	7.69	4.00	100.00	100.00
udc	11.54	16.00	15.38	16.00	3.85	16.00
treec	0	20.00	0	24.00	0	12.00
lmnc (neurons=3)	3.85	16.00	3.85	16.00	0	8.00
knnc (k=2)	0	16.00	0	12.00	0	12.00
Classifier	First derivative					
	PCA1		PCA2		PCA2 (+ chl)	
	Training error	Testing error	Training error	Testing error	Training error	Testing error
loglc	11.54	16.00	11.54	16.00	0	12.00
qdc	7.69	16.00	7.69	4.00	0	8.00
udc	7.69	16.00	15.38	12.00	3.85	16.00
treec	0	20.00	0	24.00	0	8.00
lmnc (neurons=3)	0	12.00	0	16.00	0	4.00
knnc (k=2)	0	20.00	0	16.00	0	12.00
Fort Sherman						
Classifier	Raw smoothed data					
	PCA1		PCA2		PCA2 (+chl)	
	Training error	Testing error	Training error	Testing error	Training error	Testing error
loglc	26.32	35.14	23.68	32.43	33.33	36.67
qdc	23.68	40.54	13.16	29.73	50.00	50.00
udc	23.68	40.54	23.68	37.84	20.00	43.33
treec	0	21.62	0	21.62	0	43.33
lmnc (neurons=3)	15.79	27.03	0	24.32	6.67	36.67
knnc (k=2)	0	16.22	0	21.62	0	26.67
Classifier	First derivative					
	PCA1		PCA2		PCA2 (+chl)	
	Training error	Testing error	Training error	Testing error	Training error	Testing error
loglc	26.32	45.95	23.68	37.84	30.00	43.33
qdc	28.95	40.54	18.42	24.32	10.00	40.00
udc	23.68	37.84	26.32	45.95	20.00	40.00
treec	0	24.32	0	27.03	0	40.00
lmnc (neurons=3)	15.79	32.43	10.53	24.32	3.33	36.67
knnc (k=2)	0	24.32	0	27.03	0	46.67

Analyses based on first two spectral dimensions of the PCA only.

for the two types of measurements. Single-leaf reflectance spectra were obtained for only 3 of the total 10 leaves due to time constraints; however, the main purpose for collecting all

10 leaves was for leaf stack measurements, which are not analyzed in this paper. Six reflectance spectra were recorded per leaf, avoiding the midrib, and later averaged.

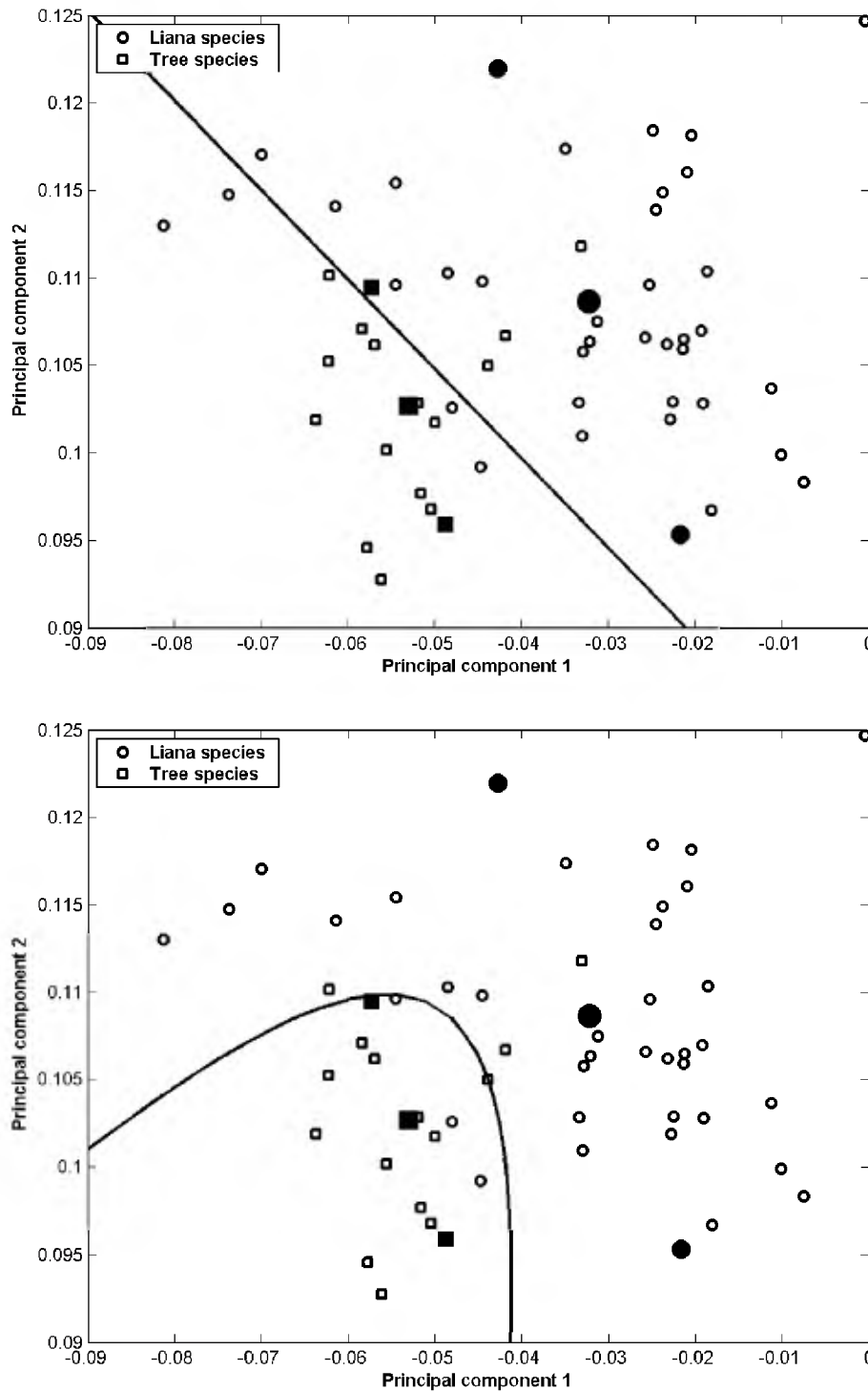


Fig. 1. Classification of PNM liana and tree first derivative spectra using PCA method 1 and six classifiers: logistic linear (loglc, top), quadratic (qdc, second from top), uncorrelated normal densities based quadratic (udc, third from top), decision tree (treec, fourth from top), neural network (lmnc, fifth from top), and k -nearest neighbor (knnc, bottom). Points correspond to individual leaves (three per species). The large filled circle represents the overall PNM liana mean; smaller filled circles are ± 1 standard deviation from the mean. The large filled square indicates the overall PNM tree mean; smaller filled squares are ± 1 standard deviation from the mean.

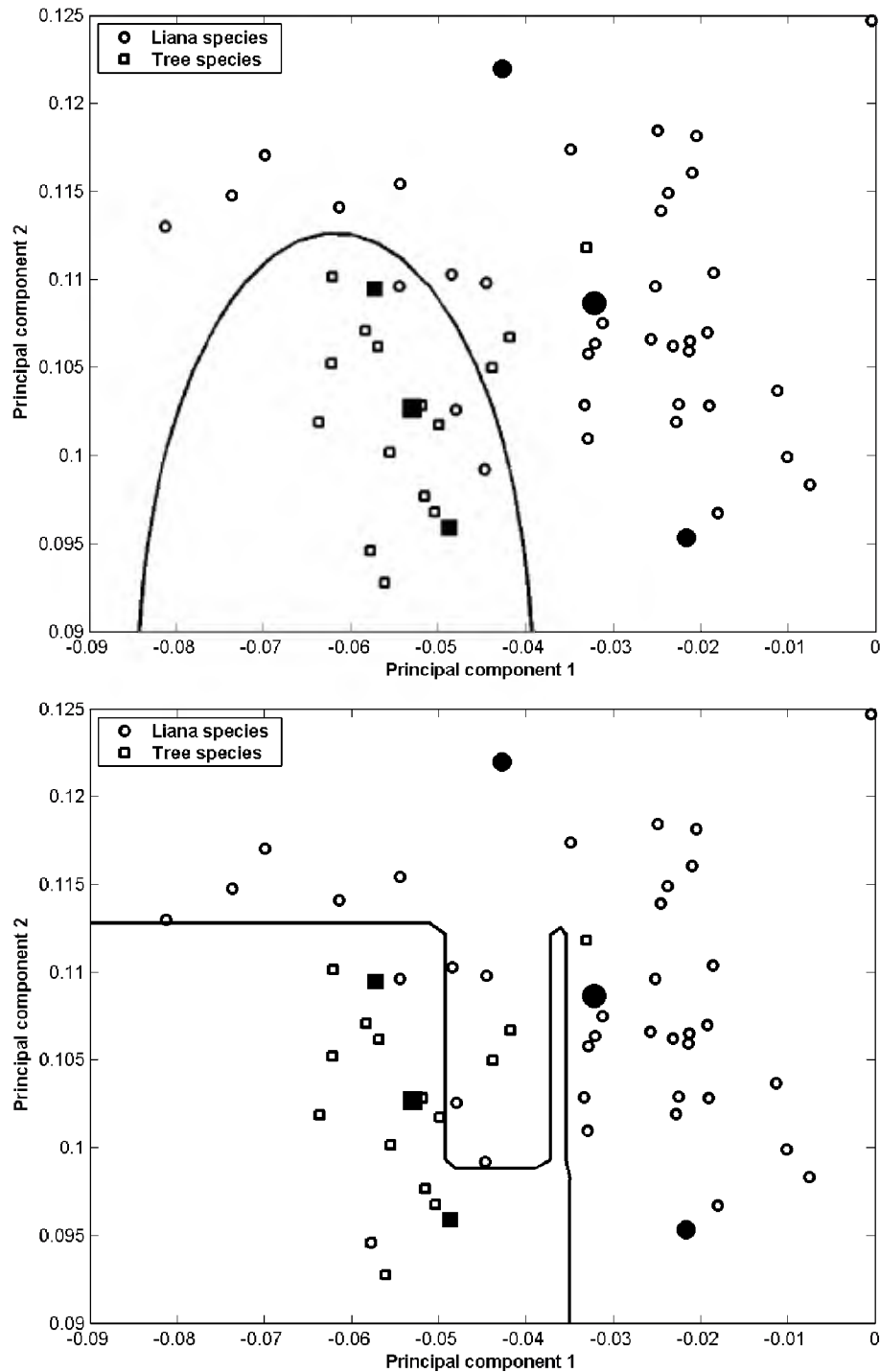


Fig. 1 (continued).

2.5. Spectral analysis

2.5.1. Spectral smoothing and differentiation

Raw spectral reflectance data were smoothed with the Savitsky–Golay least squares filter using a quadratic polynomial and a 25-point window. This filter was chosen because it smoothed the spectral data well with minimal effect on the position, shape and depth of spectral features

(Press et al., 1996). First and second derivatives of the raw smoothed data were also computed using finite central differences from adjacent wavebands. Resulting datasets, therefore, were (1) raw smoothed data, (2) first derivative of raw smoothed data, and (3) second derivative of raw smoothed data. The wavelength range retained for analysis was 450–950 nm in the case of datasets (1) and (2) and 500–800 nm in the case of dataset (3). These

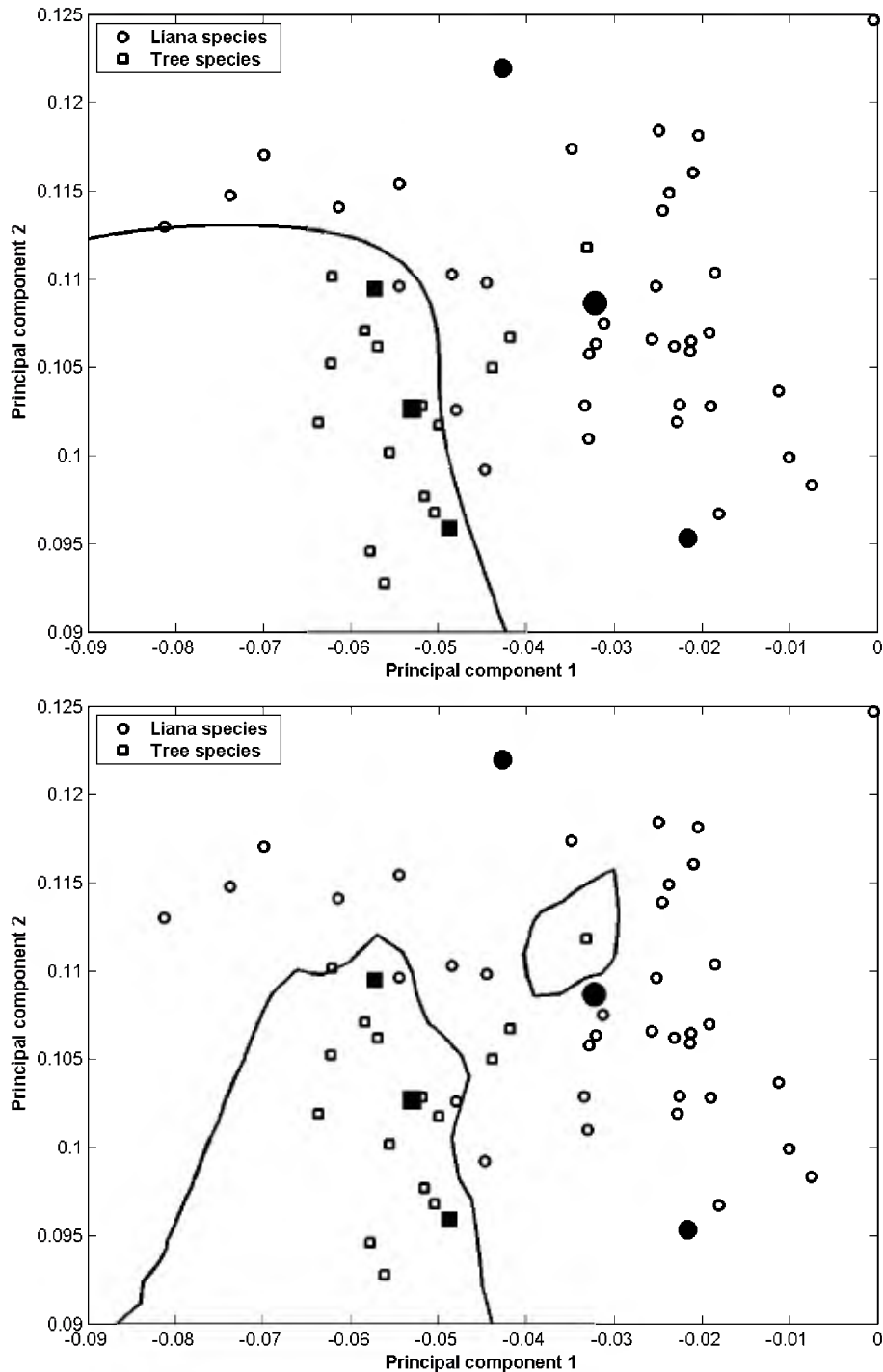


Fig. 1 (continued).

regions were shortened as such due to noise on either end of the spectrum.

2.5.2. Principal components analysis

Principal components analysis (PCA) was used to reduce data dimensionality by isolating a small number of orthogonal (uncorrelated) spectral attributes that constitute the maximum variations in the dataset (Fernández-Cáceres et

al., 2001). This approach involved computing the eigenvectors and eigenvalues of covariance matrices computed using two different sampling schemes.

In PCA method 1 (PCA1), the smoothed data array containing all liana and tree spectra for the particular site was split in half, by taking every other spectrum, into training and testing sets. The PCA was then performed on the training data, after which all sample spectra (training and

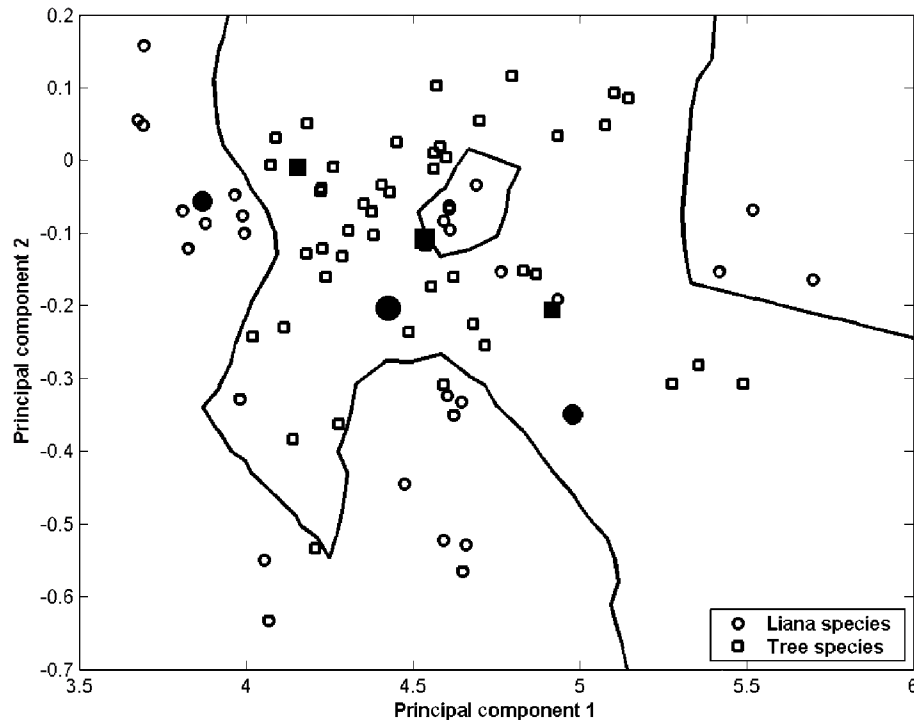


Fig. 2. Classification of FTS liana and tree raw smoothed spectra by a k -nearest neighbor (knnc, $k=2$) classifier using PCA method 1. Points correspond to individual leaves (3 per species). The large filled circle indicates the overall FTS liana mean; smaller filled circles are ± 1 standard deviation from the mean. The large filled square indicates the overall FTS tree mean; smaller filled squares are ± 1 standard deviation from the mean.

testing data) were projected into the eigenspace formed by the first two to four eigenvectors.

In PCA method 2 (PCA2), the smoothed data array containing all liana and tree spectra for a particular site was split twice, first into separate liana and tree arrays, and then, within each, into training and testing sets corresponding to even and odd samples, respectively. PCA was performed twice, first for the liana training data, and then for the tree training data. The first two to four eigenvectors from each, weighted by their eigenvalues, were used to form a multi-dimensional subspace in which both the liana and tree spectra were projected for later training and classification.

The methods described above were applied to the raw smoothed, first derivative, and second derivative datasets for the two locations.

2.5.3. Pattern recognition techniques

To test the hypothesis that tree and liana leaf spectra are separable, classification of spectra was attempted using a selection of supervised parametric (logistic linear classifier (loglc), normal densities based quadratic classifier (qdc), and uncorrelated normal densities based quadratic classifier (udc)) and nonparametric (neural network (lmnc), decision tree (treec), and k -nearest neighbor (knnc)) classifiers (Table 2). The parametric classifiers incorporate assumptions about population distributions, i.e. that classes are normally distributed, whereas the nonparametric classifiers are relatively free of assumptions about population parameters. The six classifiers included in this study are representative of currently used classifiers and were used to avoid possible biases due to the nature of the classifier, per se. The classifiers are

Table 5
Results of chlorophyll analyses for liana and tree leaves at PNM and FTS

	PNM						p -value	FTS						p -value
	Lianas			Trees				Lianas			Trees			
	Min	Max	Mean	Min	Max	Mean		Min	Max	Mean	Min	Max	Mean	
Chl <i>a</i>	0.0150	0.1694	0.0748	0.0885	0.1451	0.1113	<0.001	0.0148	0.1802	0.0846	0.0184	0.1518	0.0867	0.734 ^a
Chl <i>b</i>	0.0035	0.0523	0.0219	0.0178	0.0761	0.0356	<0.001	0.0036	0.0443	0.0242	0.0040	0.0719	0.0289	0.095
Total chl	0.0184	0.2217	0.0967	0.1128	0.1828	0.1468	<0.001	0.0184	0.2233	0.1088	0.0224	0.2236	0.1158	0.458 ^a

All minimum, maximum, and mean values expressed in units of mg/sample.

Chl=chlorophyll. All others tested with a Welch modified two-sample t -test due to unequal variances.

^a Tested using a standard two-sample t -test. All others tested with a Welch modified two-sample t -test due to unequal variances.

described in PRTools (Duin, 2000) and have the following characteristics when trained using supervised learning:

- 1) Linear classifiers generate linear decision boundaries; they use estimates of the probability density functions to minimize the expected classification error.
- 2) Quadratic classifiers fit gaussian models to data clusters that maximally discriminate between training samples.
- 3) Uncorrelated normal densities quadratic classifiers are quadratic classifiers that make the assumption of independent features (a valid assumption when using PCA).
- 4) Decision trees generate classification rules based on the selection of greatest to least important attributes and their ranges.
- 5) Neural networks generate classification rules in terms of linear discriminate functions, over the attributes space, determined by non-linear perceptrons.
- 6) *k*-nearest neighbor classifiers classify unlabeled samples based on their similarity with *k* samples in the training set, where similarity is determined using a distance metric.

Classification involved training and testing stages, which were identical regardless of the classifier used. In the first stage, the scalar products of the training data generated from the PCA were labeled 1 or 2, where 1=liana and 2=tree, and used to train the various classifiers. Error estimation was generated for the training data. In the second stage, the projections of the testing data were classified based on the trained classifiers, and error estimation was performed again, this time for the testing set. In the case of PCA1, figures were plotted to show the projections of the liana and tree spectra in the eigenspace formed by the first two eigenvectors as well as the decision functions generated by each classifier. Figures were not plotted for PCA2 due to higher dimensionality. The above steps were repeated for each PCA output and each of the classifiers described in Table 2.

In addition to these analyses, a variation of PCA2 was included in which four additional features (chlorophyll *a*, chlorophyll *b*, total chlorophyll, chlorophyll *a/b* ratio) were used as ancillary data in the classification. In this case, a total of eight features were used in both training and classification, four from PCA2 (the first two eigenvectors each from the liana and tree PCA) and the additional four based on chlorophyll analyses. Although this study is primarily aimed at remote sensing applications, the chlorophyll data was used to explore the nature of possible differences in tree and liana leaves, since chlorophyll content is the dominant factor influencing reflectance in the visible region.

2.5.4. Evaluation

Evaluation was made at three levels in this study. The first was to determine the effectiveness of PCA1 versus PCA2 for the separation of liana and tree spectra. The second was to assess the usefulness of the raw versus the first or second derivative data in the classification. The last

was to compare the performance of the six classifiers used to distinguish between lianas and trees.

At all three levels, performance was evaluated in terms of classification errors for both training and testing datasets.

2.5.5. Software

All calculations were performed using MATLAB Version No. 12 (The Mathworks). Classification of spectra was performed using the pattern recognition toolbox, PRTOOLS Version 3.0 (Duin, 2000), developed for use within Matlab.

3. Results

3.1. PCA approach

The use of eigenvectors beyond the first and second was ineffective or detrimental to classification accuracy in many,

Table 6
Influence of number of spectral dimensions on classification accuracy (in percentage) using parametric classifiers

PCA1	Classifier					
	loglc		qdc		udc	
	Training error	Testing error	Training error	Testing error	Training error	Testing error
<i>PNM raw smoothed</i>						
2 eig	19.23	20.00	15.38	20.00	11.54	16.00
4 eig	7.69	20.00	7.69	16.00	7.69	8.00
<i>PNM first derivative</i>						
2 eig	11.54	16.00	7.69	16.00	7.69	16.00
4 eig	11.54	16.00	11.54	8.00	7.69	12.00
<i>FTS raw smoothed</i>						
2 eig	26.32	35.14	23.68	40.54	23.68	40.54
4 eig	23.68	37.84	21.05	27.03	15.79	24.32
<i>FTS first derivative</i>						
2 eig	26.32	45.95	28.95	40.54	23.68	37.84
4 eig	23.68	35.14	21.05	29.73	21.05	32.43
PCA2						
<i>PNM raw smoothed</i>						
2 eig	3.85	20.00	7.69	4.00	15.38	16.00
4 eig	0.00	24.00	0.00	16.00	11.54	16.00
<i>PNM first derivative</i>						
2 eig	11.54	16.00	7.69	4.00	15.38	12.00
4 eig	0.00	20.00	3.85	16.00	15.38	8.00
<i>FTS raw smoothed</i>						
2 eig	23.68	32.43	13.16	29.73	23.68	37.84
4 eig	18.42	40.54	2.63	18.92	18.42	24.32
<i>FTS first derivative</i>						
2 eig	23.68	37.84	18.42	24.32	26.32	45.95
4 eig	15.79	40.54	2.63	21.62	18.42	29.73

eig=eigenvectors.

but not all cases (exceptions are noted below). As a result, the majority of the results shown are based on analyses involving the first two eigenvectors, which contained more than 90% of the data variance (Table 3).

Over both sites, neither PCA1 nor PCA2 provided consistently better separation of lianas and trees although PCA2 resulted in better classification accuracy than PCA1 with over half of the classifiers used (Table 4). Classification accuracy of the PNM data was improved with the addition of chlorophyll ancillary data (PCA2+chl), for which the lowest error estimation was obtained using the first derivative and neural network classifier in combination (lmnc, 0% training error, 4% testing error). Under similar conditions, but using the raw smoothed data, the quadratic classifier (qdc) broke down likely due to overfitting (Table 4). Fig. 1 presents the PNM tree and liana first derivative

spectra projected into the eigenspace generated by PCA1 along with decision functions generated by the six classifiers (due to higher dimensionality it was not possible to plot the results of PCA2). Whereas most of the highest classification accuracies were obtained using PCA2 with chlorophyll ancillary data for PNM, the opposite occurred for the FTS data, for which the worst classification accuracies resulted from the PCA2 variation using chlorophyll data, although the two groups were not very distinct overall at this site. For the FTS data, the best classification resulted from the combination of the raw smoothed data and the *k*-nearest neighbor classifier (knn), analyzed using PCA1 (0% training error and 16.22% testing error) (Fig. 2).

The addition of chlorophyll ancillary data was clearly useful for discrimination between liana and tree leaf spectra at PNM, but not so for FTS. Indeed, analysis of

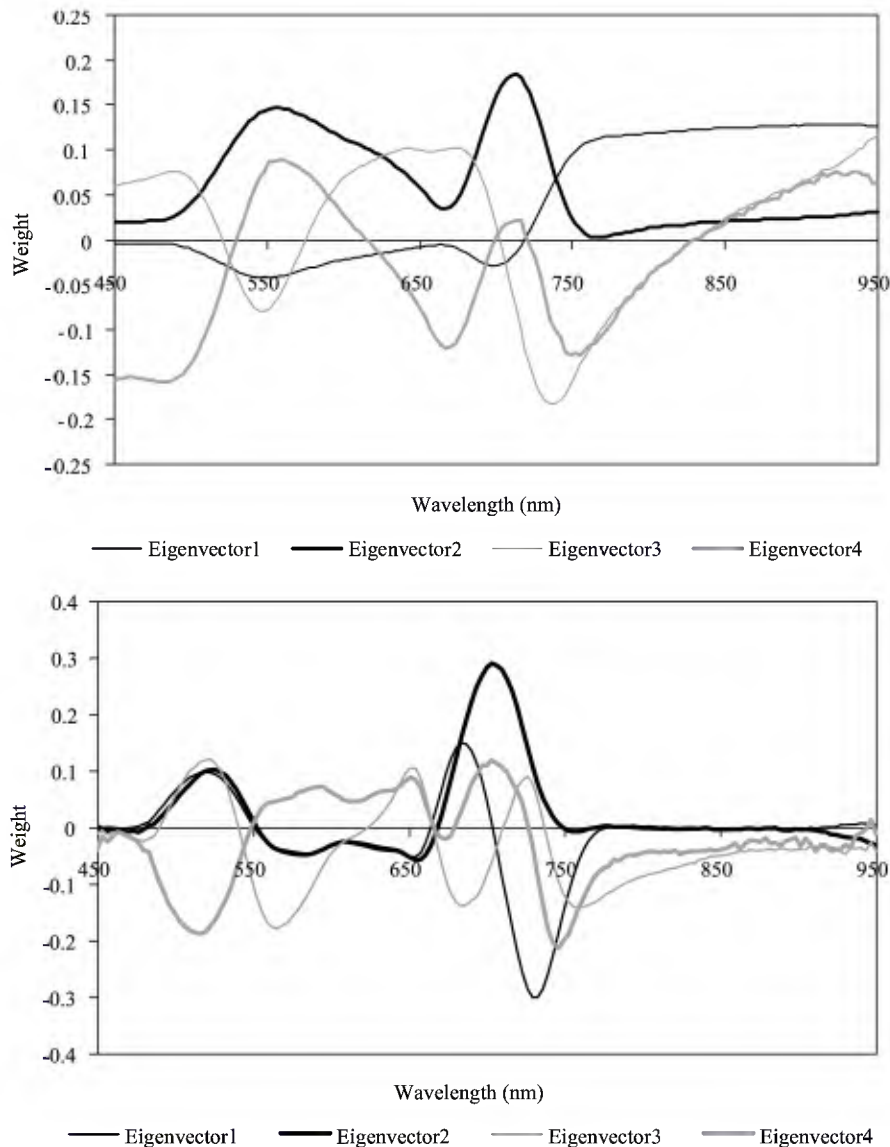


Fig. 3. Principal component loadings in the spectral bands for PNM PCA1 raw smoothed data (top), PNM PCA1 first derivative data (second from top), FTS PCA1 raw smoothed data (3rd from top), and FTS PCA1 first derivative data (bottom).

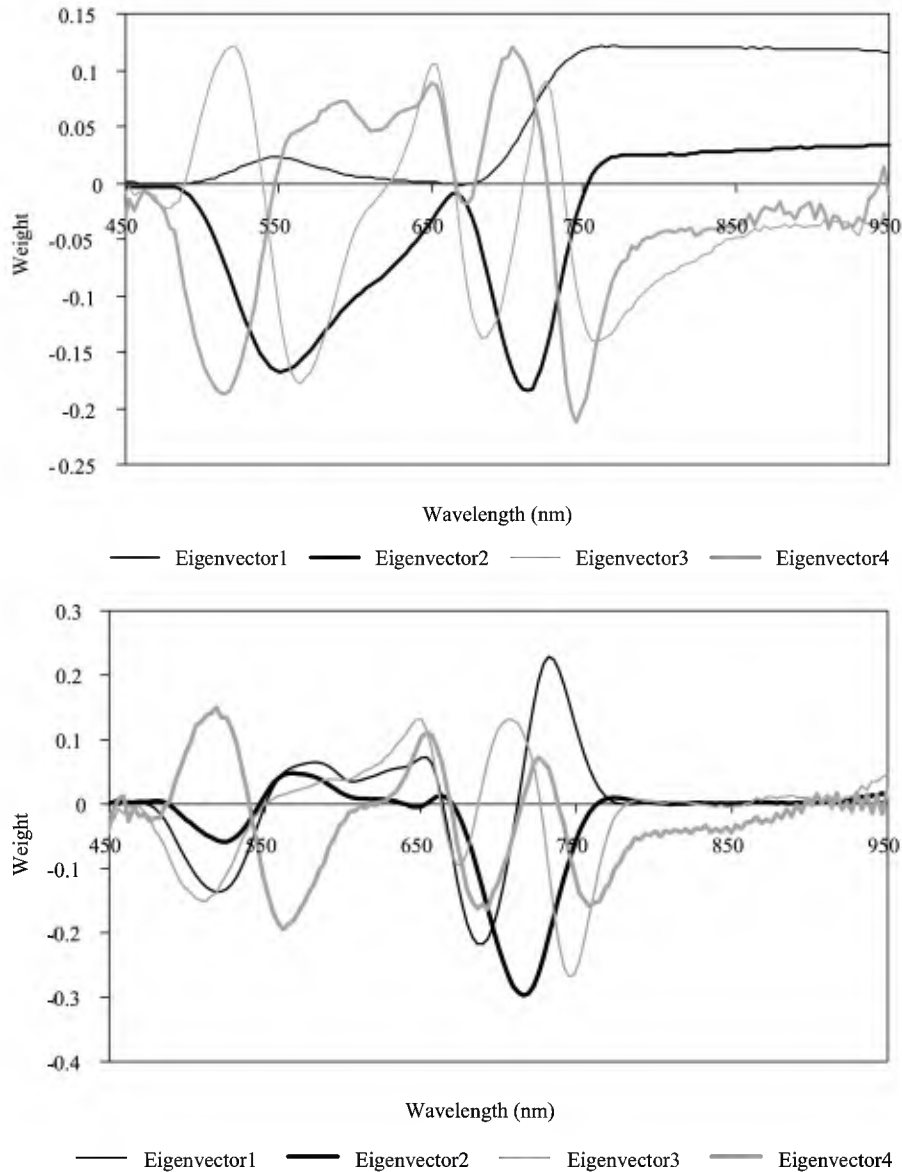


Fig. 3 (continued).

chlorophyll content showed highly significant differences in chlorophyll *a*, chlorophyll *b*, and total chlorophyll content between lianas and trees at the PNM site, whereas there were no significant differences at the FTS site (Table 5).

Although not beneficial for nonparametric classifiers, the use of principal component dimensions beyond the second led to significant improvements in classification by the parametric classifiers, particularly qdc and udc (Table 6). Training errors were reduced in the majority of instances. Testing error was also reduced in many cases, and most notably by over 10% for a number of the FTS data classifications.

Regardless of PCA method or site, the first principal component extracted from the raw smoothed data generally followed the shape of the leaf reflectance spectrum (Fig.

3). In other words, since reflectance was highest in the near-infrared, the highest loadings were also in this region. The second principal component stressed the green peak region (550 nm) as well as the red edge (~710 nm). The PNM and FTS sites have similar principal component loadings; they are simply mirror images of each other. In the first principal component of the first derivative data, the areas just beyond (~730 nm) and before the red edge (the chlorophyll absorption well, ~685 nm) are stressed, followed in importance by the slopes before and after the green peak. The second principal component of the first derivative data has the greatest weightings in the red edge region (~710 nm) as well as the slope leading up to the green peak (~525 nm). These findings were fairly consistent for the PNM and FTS data as well as for the two PCA methods.

3.2. Dataset evaluation

When comparing average raw smoothed spectra of the liana group vs. the tree group at the two sites (Figs. 4 and 5), the average tree leaf reflectance is lower than the average liana leaf reflectance in the visible region, and the opposite occurs in the near-infrared. The trend in the visible region is more evident for the PNM site than the FTS site. For both sites, although similar phenomena occur in the near-infrared when averaged over all spectra (higher reflectance for trees than for lianas), near-infrared reflectance was extremely variable between species of the same structural group. Despite this, it was noted above that in the PCA, the near-infrared bands were consistently highly weighted in the first principle component of the raw smoothed data.

Besides amplitude differences in the reflectance spectra of lianas and trees, shape differences are also confirmed by the first derivative spectra, such as in the immediate vicinity of the red edge at approximately 715 nm (Fig. 4). As well, the slope is greater for lianas in the region approaching the green peak.

For the PNM dataset, there appears to be an advantage to using the first derivative of the dataset instead of the raw smoothed dataset in many cases, particularly when combined with PCA1 or the PCA2 variation involving chlorophyll data (Table 4). For example, there is a consistent improvement in the error of estimation for the training data when comparing, within the PNM data and PCA1, the raw and first derivative datasets. The opposite was true for the FTS dataset, for which classification was superior using the raw smoothed data rather than the first derivative. Classification results using the second derivatives were inferior to those involving either the raw or first derivative data, and were excluded from Table 4. This may have been related to noisiness as well as the fact that a reduced range of spectral reflectance data was used for the analysis (500–800 nm only).

3.3. Classifier evaluation

Evidently, classifier performance is highly dependent on the PCA method (PCA1, PCA2) as well as whether the data were in the raw or 1st derivative form (Table 4).

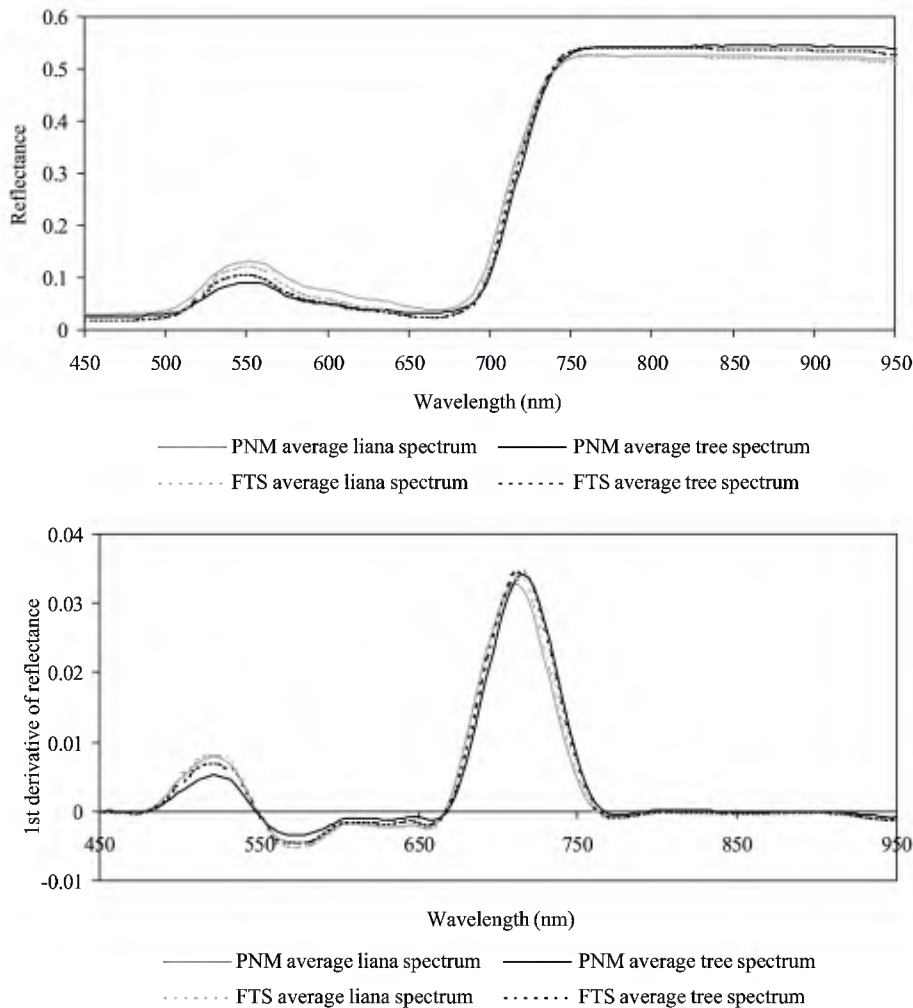


Fig. 4. Comparison of PNM and FTS average liana and tree spectra (top) and first derivative spectra (bottom) over the range 450–950 nm.

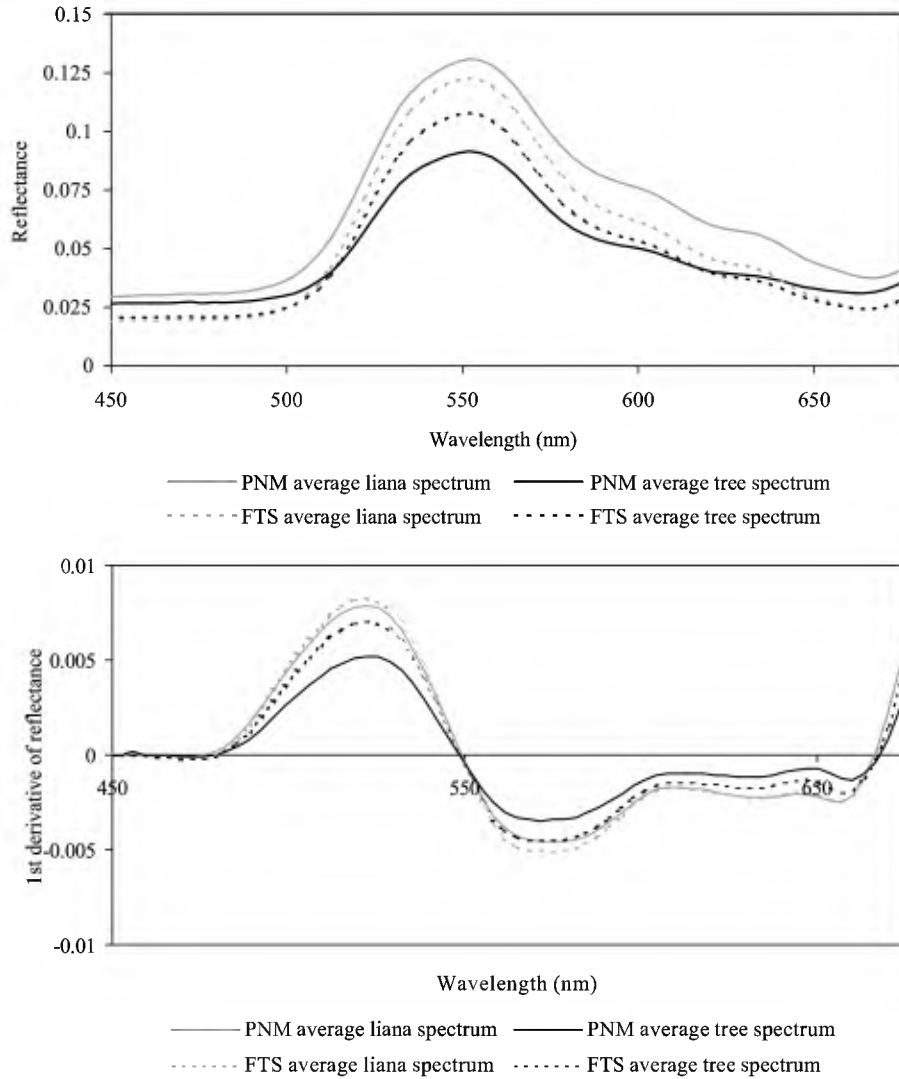


Fig. 5. Comparison of PNM and FTS average liana and tree spectra (top) and first derivative spectra (bottom) over the visible region (450–675 nm) of the electromagnetic spectrum.

The parametric classifiers (loglc, qdc, udc) provided a consistent classification in most instances; however, their performance was generally surpassed by the nonparametric classifiers (treec, lmnnc, knnc), predominantly with regard to training accuracy. One noteworthy exception was the combination of PCA2 with either the raw or first derivative PNM data, and the qdc classifier for which training error was 7.69% and testing error was 4.00%. With respect to each other, the three parametric classifiers gave fairly similar classification results within a particular PCA method and dataset (raw or first derivative) combination. Uncorrelated normal densities (udc) was an appropriate assumption for PCA1 since the two eigenvectors retained from the PCA are by definition independent; however, that was not the case when the chlorophyll ancillary data was included (chlorophyll *a*, chlorophyll *b*, total chlorophyll, and chlorophyll *a/b* ratio).

The three nonparametric classifiers (treec, lmnnc, knnc) produced higher overall classification accuracy than the

parametric classifiers; however, no one was consistently superior to the other two. For instance, for the PNM data (PCA1), the neural network classifier (lmnc) had the lowest training and testing errors (Table 4). For the FTS data (PCA2), the lowest training and testing errors were obtained using the *k*-nearest neighbor classifier (knnc) (Table 4). It is important to remember that each classifier has its own advantages and disadvantages, however. For instance, each time the neural network was used to classify the same dataset, the output was slightly different. This lack of reproducibility, which was a problem for this dataset, may become negligible for a larger dataset, however. Decision trees perform best when each attribute takes on a small number of disjoint possible values (Mitchell, 1997), which is not the case for this dataset. Performance on training data is excellent for decision trees while performance on testing data may be mediocre to poor. *k*-nearest neighbor classifiers have the disadvantage of long search times for classification

of the test data. For neural networks, choice of number of neurons, and for k -nearest neighbor classifiers, choice of k , also have an important influence on classification results and must be chosen carefully after initial experimentation. For decision trees, optimal pruning also requires additional tuning. Overall, it appears useful to test several classifiers for any classification, since their output is related to a number of factors, including the manner in which PCA is executed, the dataset used (raw, first or second derivative), as well as the amount of training and testing data available. The use of ancillary data, such as chlorophyll content in this case, was valuable for improving the classification of the PNM leaf spectra. A summary of results is presented in Table 7, which ranks each combination used in the analysis.

3.4. Within-leaf and within-species variability

Thus far, results have been shown for lianas and trees as two separate structural groups. Initially, this was

Table 7
Ranking of methods used in this study for the two sites, PNM and FTS, based on overall percent classification error calculated from Table 4 (1=lowest percentage error)

PCA method	Dataset	Classifier	PNM	FTS
PCA2 (chl)	first derivative	lmnc	1	7
PCA2 (chl)	raw	lmnc	2	11
PCA2 (chl)	first derivative	qdc	2	14
PCA2 (chl)	first derivative	treec	2	7
PCA2	raw	qdc	3	10
PCA2	first derivative	qdc	3	8
PCA2	raw	knnc	4	2
PCA2 (chl)	raw	treec	4	11
PCA2 (chl)	raw	knnc	4	4
PCA1	first derivative	lmnc	4	13
PCA2 (chl)	first derivative	loglc	4	24
PCA2 (chl)	first derivative	knnc	4	12
PCA1	raw	knnc	5	1
PCA2 (chl)	raw	loglc	5	22
PCA2	first derivative	lmnc	5	6
PCA2	first derivative	knnc	5	5
PCA1	raw	lmnc	6	9
PCA2	raw	lmnc	6	3
PCA2 (chl)	raw	udc	6	19
PCA2 (chl)	first derivative	udc	6	16
PCA1	raw	treec	7	2
PCA1	first derivative	treec	7	3
PCA1	first derivative	knnc	7	3
PCA1	first derivative	qdc	8	21
PCA1	first derivative	udc	8	18
PCA2	raw	loglc	9	15
PCA2	raw	treec	10	2
PCA2	first derivative	treec	10	5
PCA2	first derivative	udc	11	23
PCA1	raw	udc	12	20
PCA1	first derivative	loglc	12	23
PCA2	first derivative	loglc	12	18
PCA2	raw	udc	13	18
PCA1	raw	qdc	14	20
PCA1	raw	loglc	15	17
PCA2 (chl)	raw	qdc	16	25

justified using the argument that species-level analyses would be impractical at the remote sensing level, since multiple liana species were found on single tree crowns at both sites, and their percentage abundances on the crowns are unknown and changing. This approach leaves a number of unanswered questions regarding the variability present within the species studied, as well as within and between the two groups. In addition, which liana species are most indistinguishable from the tree species, and vice versa? If the hard-to-distinguish species are the most abundant at the site, potential classification could become even more difficult.

Answering these questions requires a comprehensive discussion, which we aim to cover thoroughly in a future article, along with data to be acquired at PNM during the wet season. At this time, however, a number of preliminary observations may be made. First of all, within-leaf variability (based on six measurements per leaf) appears to be fairly low, as does between-leaf variability (based on three leaf samples per species) for a particular species (an example is given in Fig. 6). However, this depends highly on the condition of the leaves collected; in this case, uniform, healthy, mature leaves were collected. Leaves of the same species, but of different ages or health, will vary widely in their spectral reflectance properties. Within the PCA eigenspace, leaf samples from the same species in many cases clustered more tightly than with samples from other species within the same group, but there were exceptions. There were, therefore, species that exhibited greater within-leaf and within-species variability than others. Furthermore, three leaves per species is not a large enough sample size to make conclusive arguments on within-species variability in spectral reflectance. Within each group (lianas and trees), a large degree of variability was observed in the spectra, especially in the near-infrared region. Between the two groups, evidently some species are situated closer to decision boundaries than others, and are thus more easily confused (Fig. 1). Within the lianas group, the main species that were confused with trees were: *Arrabidaea candicans*, *Dolioscarpus dentatus*, and *Mikania leiostachya*. The tree species that was most often confused with the lianas was *A. excelsum*, the dominant canopy tree species within the reach of the crane. Although the difficulty rendered by this species appears to preclude classification of lianas and trees at PNM, it should be mentioned that the dominance of *A. excelsum* is particularly evident within the small PNM crane radius; beyond this radius, greater heterogeneity in the tree species composition is observed.

4. Discussion and conclusion

We have shown that lianas and trees at the tropical dry forest site of Parque Natural Metropolitan are separable based on their spectral reflectance at the leaf level and the use of pattern recognition techniques. Classification errors

on the PNM test data were low (4–16% in most cases) regardless of the PCA method, use of raw or 1st derivative, or classifier, indicating that the two structural groups were clearly separable at that site (Fig. 1). The chlorophyll ancillary data, therefore, led to improvements on what

was already a reasonably accurate classification. This distinction, however, is much less clear at the tropical wet forest site of Fort Sherman, where the lowest classification error on the test data was 16% (Table 4), but in most cases varied between 20% and 40%.

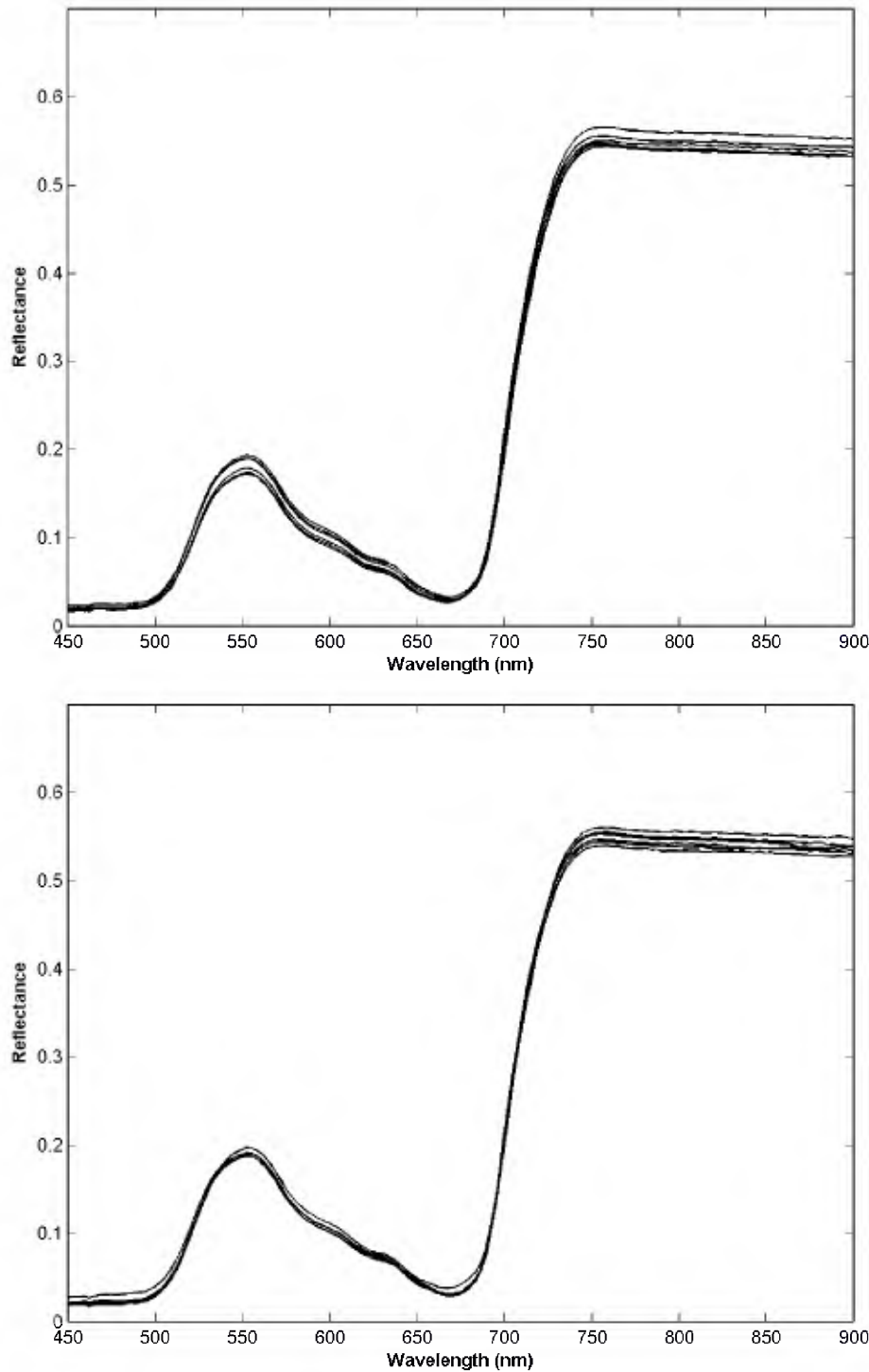


Fig. 6. An illustration of within-leaf and within-species variability for two species. The three top graphs show reflectance spectra (six/leaf) measured for each of three leaves of the liana species *Tontolea ovalifolia*. The fourth through sixth graphs (from the top) show reflectance spectra (six/leaf) gathered for each of three leaves of the tree species *Simarouba amara*. In the bottom graph, average leaf spectra (three/species) are plotted for both species.

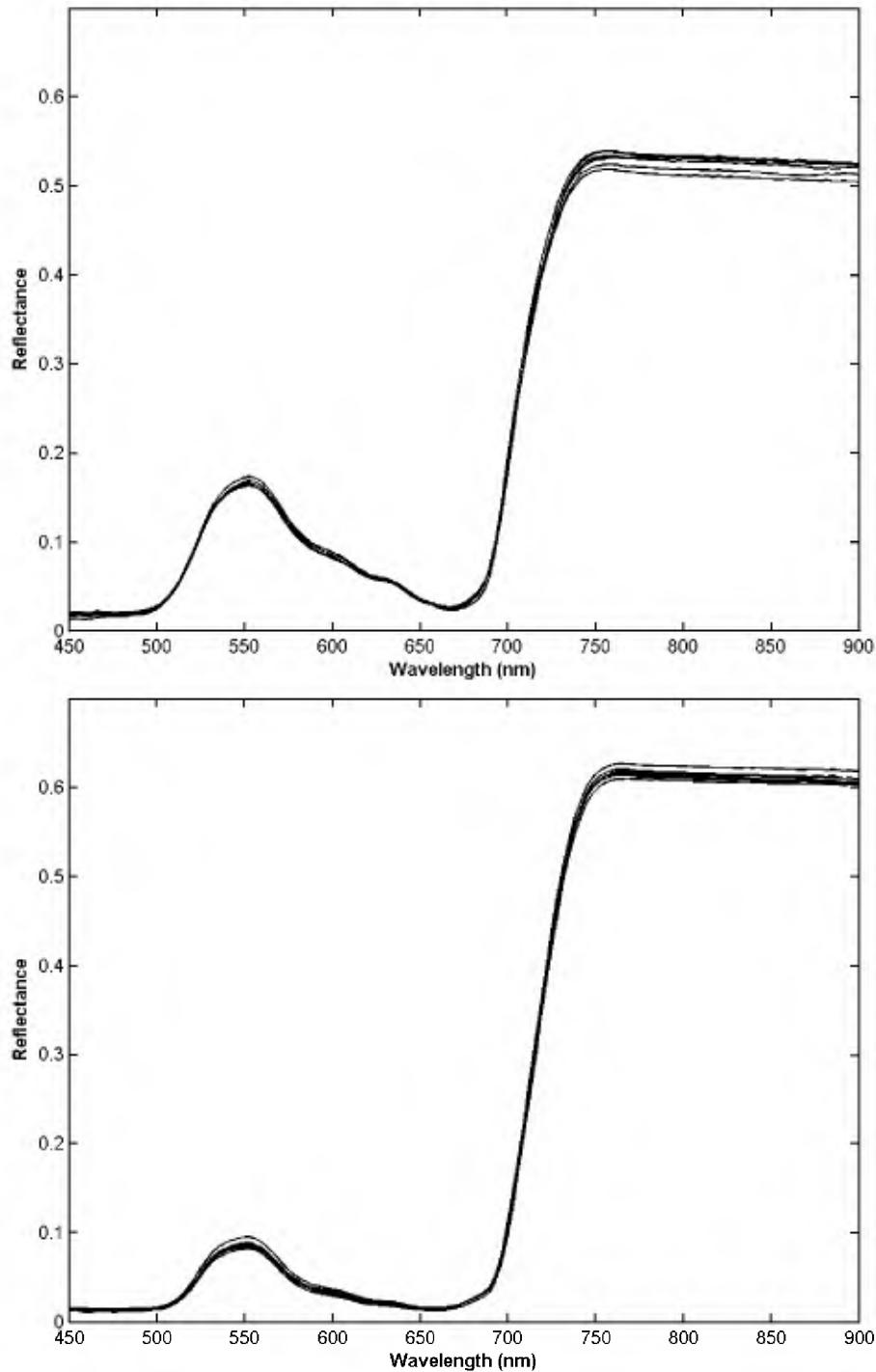


Fig. 6 (continued).

PCA2 may have been advantageous over PCA1 in the case of the PNM data because it projected the test data into both liana and tree eigensubspaces and then combined the two subspaces to form a 4-D feature space for classification (in contrast to a simpler 2-D feature space for PCA1). In this 4-D space, liana test spectra, if they are distinct from tree spectra, would be expected to cluster closer to the liana training spectra than the tree training spectra. As mentioned

previously, this was not the case for the FTS data, for which distinctions were not clear regardless of the combination of method and classifier used.

The general effectiveness of both raw and first derivative datasets in these analyses indicates that both amplitude and shape differences between liana and tree spectra played a role in the classifications, although poor classifications resulted from the use of the second derivative. Particularly

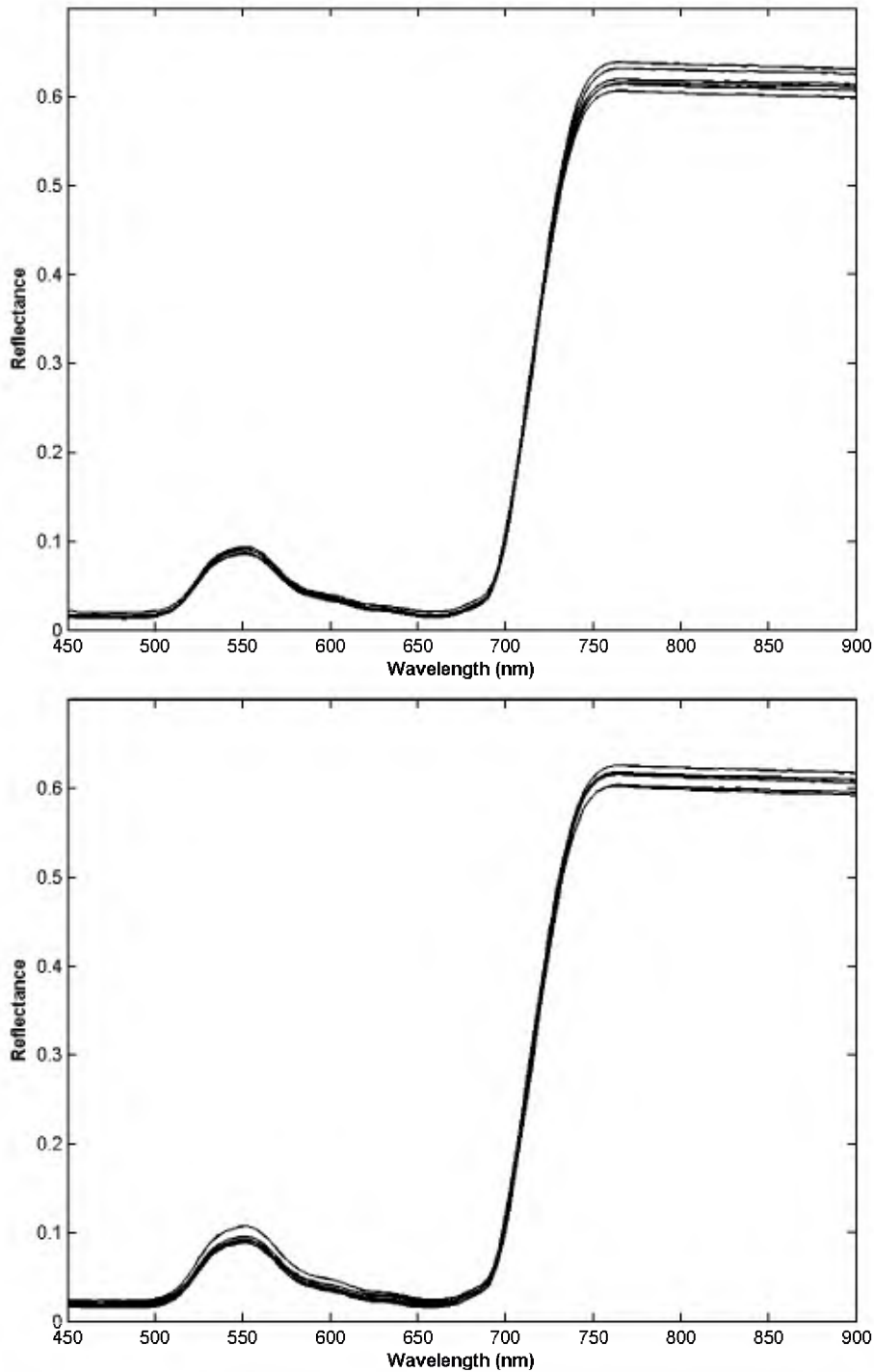


Fig. 6 (continued).

notable, more so at the tropical dry forest site but also for the wet forest site, is a higher reflectance of liana leaves in the visible region as compared to trees, which was consistent with chlorophyll analyses that indicated lower chlorophyll *a*, chlorophyll *b*, and total chlorophyll content in lianas than in trees at PNM (not significant at FTS).

Overall, nonparametric classifiers (lmnc, knnc, treec) performed better than parametric classifiers in the analyses

(Tables 4 and 7). This is most probably due to the fact that parametric classifiers, besides assumptions about population normality, need a significant amount of training data to fit the decision functions. In particular, training error estimations tended to be lower for the nonparametric classifiers than for the parametric classifiers.

Why do liana and tree leaf spectra differ at PNM? Differences in chlorophyll content between the two struc-

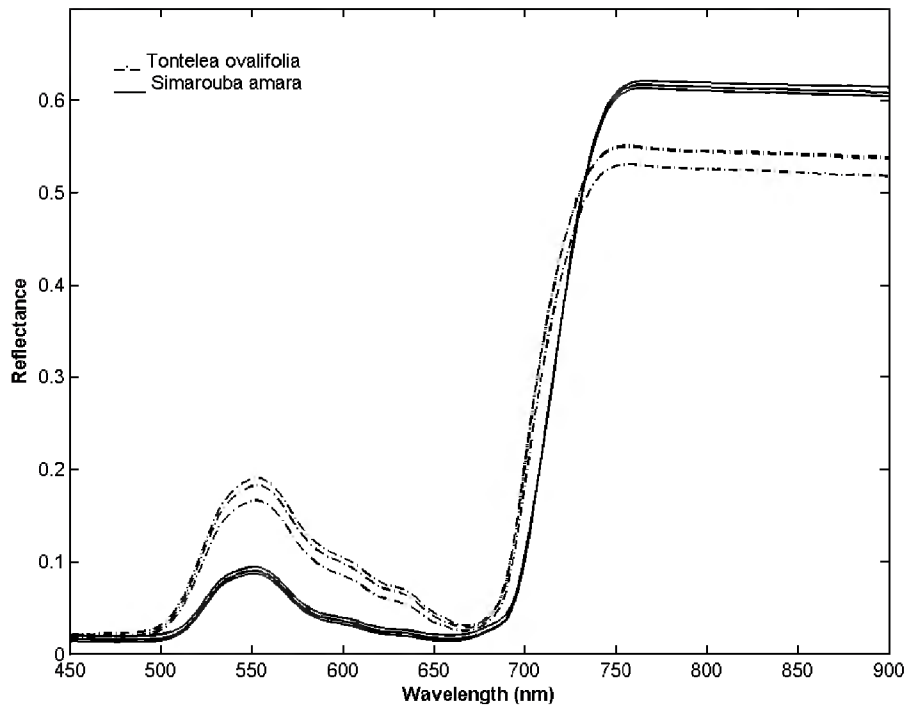


Fig. 6 (continued).

tural groups may provide only part of the answer. Additional differences may come to light with examination of accessory pigments (e.g. carotenoids) as well as internal leaf structural characteristics such as the degree of compactness of the mesophyll layer. Internal leaf structure is known to influence leaf reflectance in the near-infrared region such that higher reflectance occurs the greater the number of air-cell wall interfaces (Danson, 1995). Water content is another important factor determining leaf reflectance in the near-infrared (Grant, 1987). The greater the water content, the lower the reflectance in the near-infrared, especially around water absorption bands at 1.4 and 1.9 μm . Another closely related question that arises is what sort of strategies have these two structural groups adopted that lead to differences in chlorophyll content and leaf reflectance? The most obvious possibility is phenological differences in the two groups. It has already been noted that, at PNM, there seems to be a greater tendency towards deciduousness in lianas than in trees (Avalos & Mulkey, 1999), and although the attempt was made to collect mature, healthy leaves, it is possible that, given the dry season conditions, some of the liana leaves were already progressing toward senescence, more so than for the tree leaves sampled, resulting in lower chlorophyll contents. A study of chlorophyll and leaf reflectance of lianas and trees at regular time intervals over the period of a year would elucidate these types of issues. Differing levels of water stress, or other stresses, such as nutrient stress (e.g. nitrogen), between the two groups, could also have induced the differences we observed in leaf reflectance between lianas and trees, and/or possibly differ-

ences in photosynthetic capacity between the two structural groups. Avalos et al. (1999) formerly detected higher transmittance in tree leaves as compared to liana leaves, which was deemed a product of the distinctive crown architecture of each group. Lianas, which typically form monolayers above tree crowns, favor high light interception and low light transmission. Trees, in contrast, which typically have many leaf layers, favor greater light transmission in order that inferior leaf layers also receive light.

Drought stress and varying phenologies under the dry season conditions at PNM may have played a role in the fact that lianas and trees could be distinguished at PNM more readily than at FTS, a tropical wet forest. The difference in chlorophyll content between lianas and trees was greater at PNM than at FTS, which was mirrored in the leaf reflectance spectra. In addition, there was a notably higher chlorophyll *a* content of tree leaves at PNM as compared to tree leaves at FTS. This finding may be linked to the suggestion that deciduous dry forest tree leaves have higher photosynthetic capacities and nitrogen content than evergreen tree leaves (Medina & Klinge, 1983; Murphy & Lugo, 1986). Alternatively, disparate results between PNM and FTS may be due to non-stress related factors, but rather to dissimilarities in the spectral characteristics of species adapted to two different environments. That the differences observed are related to species selection is another possibility, especially at FTS where only a few of the total number of species of lianas and trees were sampled.

The utility of finding spectral differences between liana and tree leaves will be apparent if these differences translate

to the canopy level, and are detectable by airborne or satellite-borne hyperspectral sensors. If that is the case, it would be possible to map the current extent of liana communities and track their changes over time. In particular, mapping liana communities could have significance for biodiversity assessments and carbon budgets, the latter due to the fact that carbon sequestration is impeded in areas where liana proliferation hinders tree regeneration (Schnitzer & Bongers, 2002). On the other hand, where a tree species classification is the desired result, liana abundance could be a significant source of confusion.

Detecting lianas at the canopy scale will not be as straightforward as detecting differences in spectral reflectance between lianas and trees at the leaf level. Parque Natural Metropolitan, for example, is considered tropical dry forest, and both liana and tree species have varying degrees of leaf longevity and deciduousness. Thus, for any liana-supporting tree, the proportion of liana leaves to tree leaves in the exposed upper crown area will vary throughout the year. Staggered leaf flush and leaf senescence between tree and liana species could also exaggerate or minimize spectral differences between the two groups at different times, since leaf age also is known to affect leaf spectral reflectance (Carter, 1993; Gausman, 1985). Diurnal changes in leaf angle will also affect spectral reflectance, especially if those changes are inconsistent between species, which appears to be the case. Lastly, helpful ancillary data, such as leaf chlorophyll content, may be difficult and expensive to acquire.

We therefore conclude that, at the leaf level, we have identified a highly useful combination of principal components analysis and pattern recognition techniques to distinguish between liana and tree species at a tropical dry forest site; however, we recognize that further study is required to clarify what physiological mechanisms are behind the differences between the two groups and if these differences are maintained throughout the year. As well, we recognize that additional research will be required, from both the ecological and remote sensing perspectives, to determine whether or not our results are transferable to the canopy level. At present it seems that the distinctions observed may be restricted to lianas and trees under dry season conditions.

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