

# Hyperspectral discrimination of tropical dry forest lianas and trees: Comparative data reduction approaches at the leaf and canopy levels

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## Abstract

A dataset of spectral signatures (leaf level) of tropical dry forest trees and lianas and an airborne hyperspectral image (crown level) are used to test three hyperspectral data reduction techniques (principal component analysis, forward feature selection and wavelet energy feature vectors) along with pattern recognition classifiers to discriminate between the spectral signatures of lianas and trees. It was found at the leaf level the forward waveband selection method had the best results followed by the wavelet energy feature vector and a form of principal component analysis. For the same dataset our results indicate that none of the pattern recognition classifiers performed the best across all reduction techniques, and also that none of the parametric classifiers had the overall lowest training and testing errors. At the crown level, in addition to higher testing error rates (7%), it was found that there was no optimal data reduction technique. The significant wavebands were also found to be different between the leaf and crown levels. At the leaf level, the visible region of the spectrum was the most important for discriminating between lianas and trees whereas at the crown level the shortwave infrared was also important in addition to the visible and near infrared.  
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## 1. Introduction

Recently, the importance of lianas (non-self supporting parasitic climbers) has been recognized as an important contributor to tropical forest structure and biodiversity and the life histories of numerous tropical trees (Avalos & Mulkey, 1999; Gentry & Dobson, 1987; Perez-Salicrup, 2001). Lianas have been considered a significant fingerprint of the effects of global environmental change in tropical environments (Lewis et al., 2005). Field studies indicate liana coverage is increasing in neotropical forests (Phillips et al. 2002; Wright et al., 2004), which may be a biological signal of higher CO<sub>2</sub> concentration, increased disturbance or decreased precipitation (Schnitzer, 2005). Lianas have been shown to alter both old-growth and secondary forest structure (Laurance et al., 2001; Pérez-Salicrup, 2001; Pérez-Salicrup & de Meijere, 2005; Putz, 1984; Schnitzer & Bongers,

2002) and because lianas' impact on trees varies according to the tree's phylogeny and ecology, an increase in liana loading could alter tropical forest biodiversity (Phillips et al., 2002). Due to their different pollination and seed dispersal mechanisms (Gentry, 1992), their increase would also impact conservation of fauna and flora (Phillips et al., 2002). Moreover, lianas have been found to impact the carbon cycle with their high productivity, selective suppression of the growth and regeneration of non-pioneers and increased mortality risk for large trees (Hegarty & Caballé, 1992; Phillips et al., 2005; Schnitzer & Bongers, 2002).

In the years to come, remote sensing will be critical to quantifying the extent and dynamics of liana coverage at the landscape level. Currently large scale censuses of liana communities are carried out using stem diameter as indicator of canopy coverage (Makana et al., 2004; Chuyong et al., 2004), an approach that is a poor measure of the size and functional importance of lianas and with significant limitations regarding the percentage of the total crown area that they cover once they reach the top of the canopy. Satellite data can cover large areas with frequent temporal

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sampling and can potentially measure canopy coverage by lianas directly from above rather than using stem diameter as a proxy. In the context of current remote sensing technological developments, hyperspectral data has become a potentially feasible area of research for the quantification of the extent of liana coverage (Castro-Esau et al., 2004) because it offers a large number of bands; discrimination can potentially be facilitated because of subtle spectral features that are manifested in hyperspectral data as well as the inherent multiplicity of bands to choose from.

The majority of previous studies have focused on the separability among a limited number of species using leaf spectral properties (e.g. Cochrane, 2000; Castro et al., 2006; Lee & Graham, 1986; Lee et al., 1990) and from airborne imagery (Clark et al., 2005; Zhang et al., in press). The body of literature focusing on the spectral properties and separability of lianas from trees is scarce in comparison (Avalos et al., 1999; Castro-Esau et al., 2004). Castro-Esau et al. (2004), comparing spectral properties of liana and tree leaves from a tropical dry and tropical rainforest site have demonstrated that lianas and host tree spectra can be separated with greater accuracy at the tropical dry forest site. The transfer of the liana leaf spectral and biochemical traits to canopy scales have been demonstrated by Sánchez-Azofeifa and Castro-Esau (2005) for a site in Panama. They also showed that the reflectance of *Anacardium excelsum* canopies increases at 550 nm with an increase in liana loading, which correlates with a lower chlorophyll concentration in liana leaves in comparison to their host tree leaves. The separability of lianas and trees is also affected by the high density of species that can be present on a given crown. Castro-Esau et al. (2004) documented the presence of up to 27 species of lianas in one single crown, many of which covered small areas and displayed highly dynamic behavior throughout the year. The former observation tends to preclude the spectral identification of lianas at the species level on a tree crown basis from imagery (i.e. satellite or airborne). Furthermore, the former poses an additional challenge to the detection of lianas using remotely sensed data and suggests that most likely, the key to their detection is to focus on communities (groups of species) occupying a given canopy rather than the identification of individual species.

In order to quantify liana coverage on a landscape scale, it will be necessary to continue to develop new approaches to further the discrimination of lianas and trees at the crown scale. Such analyses could subsequently be used for the quantification of the changes of liana extent over time. A variety of data analysis techniques such as wavelet decomposition (Chan & Peng, 2003; Misiti et al., 1996), feature selection (De Backer et al., 2005; Duin, 2000) and pattern recognition (Bishop, 1995; Fukunaga, 1990; Ripley, 1996) have been developed that can take advantage of the large amount of data from hyperspectral sensors. Here we address which common and readily available techniques are most appropriate for the discrimination of the spectra of a community of lianas from canopy trees at the leaf and crown levels. The objective of this study is to evaluate which combination of data reduction technique and pattern recognition classifier best discriminates between the reflectance spectra of tropical dry forest trees and lianas at the leaf (spectrometer data) and canopy levels (airborne hyperspectral

imagery). We use some standard and readily accessible data reduction techniques to address this issue. Specifically we have compared Principal Component Analysis (PCA), Wavelet Energy Feature Vectors (WT) and Stepwise Feature Reduction (FFS) with some standard classifiers previously shown to be useful in separating the spectra of lianas and trees at the leaf level (Castro-Esau et al., 2004).

## 2. Methods

### 2.1. Study site

The study area for these analyses is the seasonally dry forest of Parque Natural Metropolitano (PNM) in Panama City, Republic of Panama. The forest at PNM receives approximately 1740 mm of precipitation per year. The canopy was accessed by a gondola attached to a 42 m construction crane (boom length 51 m) which allows for access to an area encompassing approximately 80 species of trees and lianas (Avalos & Mulkey, 1999; Kitajima et al., 2005; Phillips et al., 1999). Of the total number of tree species at the crane site, 15% are understory species and 85% are mid-canopy or canopy species (Table 1). The area accessible by the crane (8167 m<sup>2</sup>) is dominated by *A. excelsum* ((Bertero & Balb. ex Kunth) Skeels), with various levels of liana coverage (Sánchez-Azofeifa & Castro-Esau, 2005). We focused on collecting spectral data from canopy and exposed mid-canopy trees and the lianas present on those crowns because they are the most relevant for remote sensing studies making use of airborne or satellite imagery. Data was not collected from trees in the understory because they do not contribute to the question of detecting liana communities from airborne or satellite imagery. In addition, due to the large number of liana species on each host tree, this work focuses on exploring differences between crowns that are infested with lianas and those without lianas; we do not intend in this study to explore differences that may exist between species.

### 2.2. Collection of leaf level reflectance spectra

In December 2004, we collected reflectance spectra for 8 emergent tree species and 25 liana species (Fig. 1a, Table 1) with an ASD FieldspecFR spectrometer (Analytical Spectral Devices, Boulder CO) over the course of two days. The spectral range for this instrument is 350–2500 nm with a resolution of 3 nm in the 350–1000 nm range and 10 nm in the 1000–2500 nm range. A total of 10 mature sunlit leaves were collected for each species, which were identified in-situ and then transported within one hour to a laboratory where their spectral reflectance was measured. The time elapsed from collection to measurement is within the range recommended by Foley et al. (2006). The collection permit from the Panamanian Ministry of the Environment stipulated that a maximum of ten leaves per species could be collected. Because the goal of the study is to differentiate between life forms rather than species, we believe the sample size is adequate given the logistical constraints.

A total of three spectral reflectance measurements were taken of the leaf laminae (distal, middle and proximal) proximal to the

Table 1  
List of tree and liana species examined at the leaf and canopy levels

Family	Species	Life form	Position	Accessible by crane	Leaf level	Canopy level
Anacardiaceae	<i>Anacardium excelsum</i>	Tree	Canopy	Yes	X	X
Anacardiaceae	<i>Astronium graveolens</i>	Tree	Canopy	Yes	X	X
Anacardiaceae	<i>Mangifera indica</i>	Tree	Mid-canopy	No	–	X
Anacardiaceae	<i>Spondias mombin</i> **	Tree	Canopy	No	–	X
Annonaceae	<i>Annona spraguei</i> **	Tree	Mid-canopy	Yes	X	X
Apocynaceae	<i>Forsteronia spicata</i>	Liana	–	Yes	X	† † †
Araliaceae	<i>Schefflera morototni</i>	Tree	Mid-canopy	No	–	X
Arecaceae	<i>Palm -</i>	Tree	Mid-canopy	No	–	X
Aristolochiaceae	<i>Aristolochia maxima</i>	Liana	–	Yes	X	† † †
Asteraceae	<i>Mikania leiostachya</i>	Liana	–	Yes	X	† † †
Bignoniaceae	<i>Amphilophium paniculatum</i>	Liana	–	Yes	X	† † †
Bignoniaceae	<i>Arrabidaea candicans</i>	Liana	–	Yes	X	† † †
Bignoniaceae	<i>Phryganocydia corymbosa</i>	Liana	–	Yes	X	† † †
Bignoniaceae	<i>Stizophyllum corymbosa</i>	Liana	–	Yes	X	† † †
Bignoniaceae	<i>Tabebuia rosea</i> **	Tree	Canopy	No	–	X
Bombacaceae	<i>Cavanillesia plantanifolia</i> **	Tree	Canopy	No	–	X
Bombacaceae	<i>Pseudobombax septenatum</i> **	Tree	Canopy	Yes	X	X
Boraginaceae	<i>Cordia alliodora</i>	Tree	Canopy	Yes	X	X
Burseraceae	<i>Bursera simaruba</i> **	Tree	Canopy	No	–	X
Cecropiaceae	<i>Cecropia obtusifolia</i>	Tree	Canopy	No	–	X
Cecropiaceae	<i>Cecropia peltata</i> **	Tree	Mid-canopy	No	–	X
Cecropiaceae	<i>Cecropia longipes</i>	Tree	Canopy	No	–	X
Combretaceae	<i>Terminalia amazonia</i>	Tree	Canopy	No	–	X
Convolvulaceae	<i>Bonamia trichantha</i>	Liana	–	Yes	X	† † †
Convolvulaceae	<i>Jacquemontia perryana</i>	Liana	–	Yes	X	† † †
Dilleniaceae	<i>Dolioscarpus dentatus</i>	Liana	–	Yes	X	† † †
Dilleniaceae	<i>Dolioscarpus major</i>	Liana	–	Yes	X	† † †
Dilleniaceae	<i>Tetracera portobellensis</i>	Liana	–	Yes	X	† † †
Fabaceae/Caes.	<i>Hymenaea courbaril</i>	Tree	Canopy	No	–	X
Fabaceae/Mim.	<i>Albizia adinocephala</i>	Tree	Canopy	No	–	X
Fabaceae/Mim.	<i>Enterolobium cyclocarpum</i> † †	Tree	Canopy	No	–	X
Fabaceae/Mim.	<i>Machareium milleflorum</i>	Liana	–	Yes	X	† † †
Fabaceae/Mim.	<i>Pithecoctenium crucigerum</i>	Liana	–	Yes	X	† † †
Fabaceae/Pap.	<i>Andira inermis</i>	Tree	Mid-canopy	No	–	X
Flacourtiaceae	<i>Zuelania Guidonia</i> **	Tree	Mid-canopy	No	–	X
Hippocrateaceae	<i>Hippocratea volubilis</i>	Liana	–	Yes	X	† † †
Hippocrateaceae	<i>Prionostemma aspera</i>	Liana	–	Yes	X	† † †
Lauraceae	<i>Phoebe cinnamomifolia</i>	Tree	Mid-canopy	No	–	X
Malpighiaceae	<i>Hiraea reclinata</i>	Liana	–	Yes	X	† † †
Malpighiaceae	<i>Stigmaphyllon hypargyreum</i>	Liana	–	Yes	X	† † †
Moraceae	<i>Castilla elastica</i> **	Tree	Mid-canopy	Yes	X	X
Moraceae	<i>Ficus insipida</i>	Tree	Canopy	Yes	X	X
Moraceae	<i>Maclura tinctora</i>	Tree	Mid-canopy	No	–	X
Passifloraceae	<i>Passiflora vitifolia</i>	Liana	–	Yes	X	† † †
Phytocalaceae	<i>Trichostigma octandrum</i>	Liana	–	Yes	X	† † †
Rhamnaceae	<i>Gouania lupuloides</i>	Liana	–	Yes	X	† † †
Rubiaceae	<i>Antirhea tricantha</i>	Tree	Canopy	No	–	X
Rubiaceae	<i>Calycophyllum candidissimum</i> **	Tree	Canopy	No	–	X
Sapindaceae	<i>Serjania atrolineata</i>	Liana	–	Yes	X	† † †
Sapindaceae	<i>Serjania mexicana</i>	Liana	–	Yes	X	† † †
Sapotaceae	<i>Chrysophyllum cainito</i>	Tree	Canopy	Yes	X	X
Sterculiaceae	<i>Guazuma ulmifolia</i> **	Tree	Mid-canopy	No	–	X
Tiliaceae	<i>Luehea seemannii</i>	Tree	Canopy	No	–	X
Urticaceae	<i>Myriocarpa longipes</i>	Tree	Mid-canopy	No	–	X
Verbenaceae	<i>Tectona grandis</i> **	Tree	Canopy	No	–	X
Vitaceae	<i>Vitis tiliifolia</i>	Liana	–	Yes	X	† † †

X indicates the sampling level (i.e. leaf and/or canopy), \*\* indicates the most distinct deciduous tree species. † † † the species of lianas at the crown level could not be distinguished because lianas occur in multiple species, occur on most host trees and could not be identified from the ground. It is also not possible to state which species of lianas occur in what quantity on which specific host tree. † † *Enterolobium cyclocarpum* was the only species with a crown of entirely newly flushed leaves.

leaf acumen (where present) using a leaf probe (12° illumination angle and 32° viewing angle) and clip developed specifically for the ASD. The final reflectance for each measurement spot was

determined from the average of 20 scans (reduces noise in the spectra). The final average for each sample was the mean of the 3 samples. Due to the commingled nature of lianas in their

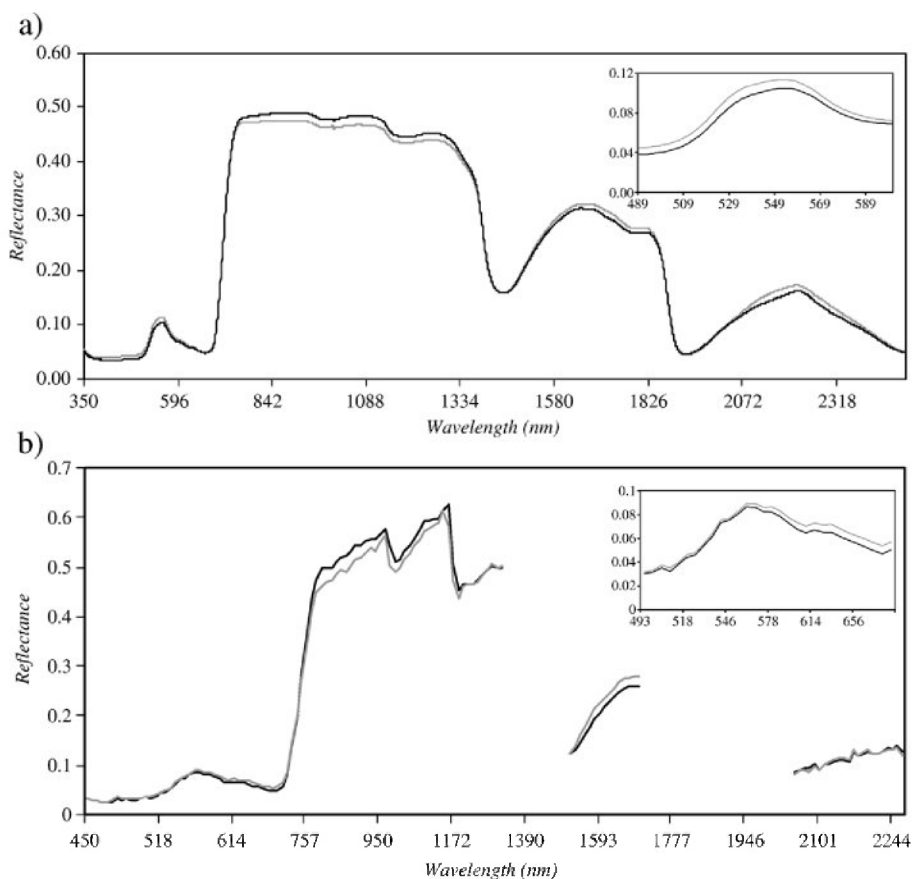


Fig. 1. a) Mean leaf level spectra for lianas (grey) and trees (black). b) Mean canopy level spectra extracted from the HYDICE image for crowns with over 40% liana coverage (grey) and crowns with less than 40% liana coverage (black). Insets are a close-up of the green peak of the spectra.

growth pattern it is uncertain how many individuals the leaves came from. For the tree species, data collection was limited to the crowns that are accessible by the crane, resulting in one to two trees being sampled per species.

### 2.3. Hyperspectral image (HYDICE) processing

For the crown-level analyses, we used an airborne hyperspectral image collected by the Hyperspectral Digital Imagery Collection Experiment (HYDICE) sensor in March 1998 for Parque Metropolitan. The image has a spatial resolution of 1 m and has 210 bands with a range of 400–2500 nm. Eight  $5 \times 5$  m plywood calibration panels painted with matte paint (white, black and two shades of grey) were used at the time of the image collection in order to apply an ‘Empirical Line Method’ calibration to the data (Bohman & Lashlee, 2004). The average radiance values of each of the panels (from the image) were used for regression equations relating image radiance and reflectance measured in the field with a handheld spectrometer (ASD FieldSpec from Analytical Spectral Devices, Boulder CO, USA) which were subsequently applied to each pixel in the image (Bohman & Lashlee, 2004). Tree crowns in the image were identified in the field to species and characterized by percentage liana coverage. The percentage of the crowns covered by lianas was estimated visually from the ground during the dry season.

For this study we group the crowns into two classes:  $\geq 40\%$  liana coverage (44 crowns) and  $<40\%$  liana coverage (244 crowns) (Table 1). While arbitrary, this threshold was used to maximize the contribution of the lianas to the spectral reflectance of the crowns, while still maintaining a dataset large enough to conduct the analysis. For example, with a cutoff of 80 or 90% liana coverage there would not have been enough tree crowns in that class to conduct the analysis. In addition, Meyer et al. (1996) found favourable results with a threshold of 35%. The purpose of this analysis is to determine whether crowns with relatively high coverage can be identified spectrally from trees with minimal to no liana coverage, regardless of species. The pixels representing the crowns of each individual were extracted and averaged. The wavebands representing atmospheric water absorption were subsequently removed as well as those below 450 nm and above 2270 nm. The average spectra of the individuals were then subjected to a wavelet energy feature vector transformation (Bruce et al., 1999; Li et al., 2001) and forward feature selection data reduction techniques (van der Heijden et al., 2004) prior to being analyzed with the parametric and non-parametric classifiers (see below).

### 2.4. Processing of the spectra

Principal component analysis (PCA) is a common technique for reducing the data dimensionality and highlighting variation

(Schowengerdt, 1996). The effects of PCA are the orthogonalization of the components of the input data (i.e. outputs from PCA will be uncorrelated with each other), the ordering of the components from those with the greatest variation to those with the least and the elimination of the components that have the least contribution to the variation in the dataset. In this analysis, we conducted two types of PCA analysis as per Castro-Esau et al. (2004) for the leaf level data. The first PCA approach (PCA1) uses an array of the full spectra of lianas and trees which is split in half using every other spectrum for training and testing datasets. The first four weighted eigenvectors are then used as inputs for the classifiers. The second PCA approach (PCA2) splits the array of liana and tree spectra twice, once into the respective life forms (i.e. lianas and trees) and secondly into training and testing datasets (i.e. separate training and testing datasets for lianas and trees). For this PCA2 analysis, PCA is carried out separately for the liana and tree datasets. The first four weighted eigenvectors are then used as inputs for the classifiers.

With wavelet transforms for spectral analysis, signals (spectra) are decomposed into a hierarchical set of approximations and details (Bruce et al., 2002). For each level of the decomposition ( $j$ ), approximation  $A_j$  and detail  $D_j$  coefficients are calculated. The original spectrum is similar to the approximation at level 0 ( $A_0$ ) (Bruce et al., 2001; Mallat, 1989; Misiti et al., 1996). At level 1, the approximation coefficient ( $A_1$ ) is an approximation of the low frequencies of  $A_0$  and the detail coefficient ( $D_1$ ) is the high frequency correction for  $A_0$  (Bruce et al., 2002), and so on for each subsequent level. One dimensional wavelet analysis (such as for signals or spectra) is based on a mother wavelet (of various forms) and an associated scaling function as opposed to two dimensional wavelet analysis (such as for image processing) which is based on an associated scaling function and three wavelets (Mallat, 1989; Misiti et al., 1996). We conducted a discrete wavelet transform of the leaf and canopy level spectra using a third order mother wavelet from the Daubechies family (db3) (Daubechies, 1992). This multilevel decomposition (11 levels for the leaf level and 7 levels for HYDICE pixel values) was implemented in Matlab v.6.5 resulting in 11 and 7 detail coefficients ( $cD_j$ ) and the largest approximation coefficient ( $cA_j$ ). Subsequently, scalar energy feature vectors of the wavelet coefficients were calculated (Bruce et al., 1999; Li et al., 2001; Pu & Gong, 2004):

$$F_j = \sqrt{\frac{1}{K} \sum_{k=1}^K W_{jk}^2} \quad (1)$$

where  $K$  is the number of coefficients at level  $j$ ,  $W_{jk}$  is the  $k^{\text{th}}$  coefficient at level  $j$ . The length of the vector is  $(p+1)$  (i.e. the detail coefficients and the approximation coefficient) where  $p$  is the maximum number of decomposition levels. For the leaf level spectra there were 2101 bands available (following preprocessing) from the ASD Fieldspec Pro spectrometer, therefore,  $p$  is equal to 11 ( $p = \log_2 N$ , where  $N = \text{length of original signal: 2101}$ ) and the energy feature vector to 12. With

this method, the original 2101 dimensions of the data have been reduced to 12. For the crown-level spectra from the HYDICE image, there were 124 bands available (following preprocessing), therefore,  $p$  is equal to 7 and the energy feature vector to 8.

Stepwise feature selection is another alternative for dimensionality reduction of hyperspectral data. Forward stepwise selection is initiated by finding the best single waveband (referred to as “feature” from this point forward) for predicting group membership. Subsequent features are added according to which improves performance the most. The selection is guided by a criterion such as  $F$  value or by effect on classification accuracy (Duin, 2000; van der Heijden et al., 2004). The result of both types of stepwise feature selection is a smaller set of highly effective features for discriminating between groups. The maximum number of features (wavebands in this case) that can be used without overfitting is  $F = (n-g)/3$  where  $n$  is the number of spectra and  $g$  is the number of classes (Defernez & Kemsley, 1997). For both the leaf level and crown-level data we used forward feature selection to reduce the 2101 bands from the leaf level analysis to sets of 10–100 features in increments of 10 and the 124 wavebands from the HYDICE data to sets of 10–80 features (wavebands) in increments of 10. For the crown data, the water absorption bands had been previously removed.

The reduced data from each of the four aforementioned techniques were subsequently used as inputs for nine parametric and non-parametric pattern recognition classifiers using PRTools (Castro-Esau et al., 2004; Duin, 2000). The classifiers included were the log linear classifier (loglc), quadratic classifier (qdc), decision tree classifier (treec), neural network classifier (lmnc) with 2–5 layers and the k-nearest neighbour classifier with 2 and 3 nearest neighbours (Castro-Esau et al., 2004; Duin, 2000; van der Heijden et al., 2004).

The loglc classifier is a linear classifier with a logistic function to separate classes; qdc is a quadratic classifier which assumes normal densities for the classes; treec is a decision tree classifier the fundamental goal of which is to continually split the data into subsets that are subsequently purer classes; lmnc is a feed forward neural network using the Levenberg Marquardt optimization with two to five layers [lmnc2–5] (Hagan & Menhaj, 1994). Finally, the knnc classifier examines the closest 2 or 3 neighbours to determine the class of each new object (i.e. spectrum) [knnc2, knnc3]. The data were divided equally into training (165 for leaf level and 144 for canopy level) and testing datasets (165 for leaf level and 144 for canopy level). The training datasets were used to train the classifiers as well as to provide an error estimate. The testing datasets provided an indication of how well each classifier discriminated between the two classes and provided error estimation for each classifier. For the feature selection process specifically, in order to determine the ideal number of features to use with each classifier, training and testing errors were plotted on a dual y-axis plot against number of features (10–100 for the leaf level data and 10–80 for the crown-level data). The ideal number of features was selected to be the number where the two measurements of error reached global minima (Fielding, 1999).

### 3. Results

#### 3.1. Leaf level

At the leaf level for the feature selection analysis, the optimal number of features ranged from 10 to 100 features. The lowest overall error was achieved with the *lmnc5* classifier with fifty features (0.4% overall error; 0% training error, 0.86% testing error). The *knnc2* (ten and twenty features) and *qdc* (forty features) classifiers achieved the next lowest overall error rates of 0.6% and 0.75% respectively (0% training error and 1.2% testing error for both). All other classifiers also achieved good discrimination between the spectra of tree and liana leaves with overall error rates below 4% with a range of optimal number of features from ten to one hundred. Due to the computational intensity however, when examining more than forty features, the *knnc2* classifier with only ten features is preferred at the leaf level.

At the leaf level as well, the neural network and k-nearest neighbour classifiers discriminated between the liana and leaf spectra consistently across all data reduction techniques with the lowest error. However, there was very little difference between the classification accuracy of all classifiers with the feature selection method of data reduction when the optimal number of features are considered (i.e. less than 4% overall error). For the wavelet energy feature reduction method, *lmnc4* had the best discrimination with 1.7% training error and 5.4% testing error. The same classifier also had the best discrimination with the two PCA techniques; 2.9% training error and 8.1% testing error for PCA1 and 2.6% training error and 4.6% testing error for PCA2. The better performance of PCA 2 over PCA 1 is attributed to its inherent technique which is similar to the Karhunen–Love Transformation Method described in (Cheriyadat & Bruce, 2003) where class specific matrices are used rather than an overall matrix.

The top ten wavebands for separating the liana and tree leaf spectra include the visible (405 nm, 535 nm, 688 nm), near infrared (987 nm), and shortwave infrared regions (2252 nm, 1389 nm, 1376 nm, 1661 nm, 1350 nm, 1888 nm). When the top one hundred bands are considered (i.e. maximum without overfitting at the leaf level — if a model with too many parameters is used the model's performance may be artificially

Table 2  
Percentage of bands from the different spectral regions chosen by the five classifiers with the lowest overall error at the leaf level

Classifier	Optimal number of features	Overall error (%)	Visible (%)	Near infrared (%)	Shortwave infrared 1 (%)	Shortwave infrared 2 (%)
Max <sup>a</sup>	100	–	62	4	24	10
<i>lmnc5</i>	60	0.43	57	7	20	17
<i>knnc2</i>	10	0.60	30	10	40	20
<i>knnc2</i>	20	0.60	35	10	40	20
<i>lmnc4</i>	50	0.72	54	8	18	20
<i>Qdc</i>	40	0.75	48	8	20	25

<sup>a</sup> Max indicates the maximum number of bands for the dataset without overfitting.

Table 3

Percentage of bands from the different spectral regions chosen by the five classifiers with the lowest overall error at the crown level

Classifier	Optimal number of features	Overall error (%)	Visible (%)	Near infrared (%)	Shortwave infrared 1 (%)	Shortwave infrared 2 (%)
Max <sup>a</sup>	80	–	50	12	10	28
<i>knnc2</i>	80	7.0	50	12	10	28
<i>knnc2</i>	30	7.1	33	0	3	64
<i>lmnc5</i>	40	8.1	40	3	3	54
<i>lmnc2</i>	40	8.4	40	3	3	54
<i>lmnc4</i>	40	8.7	40	3	3	54

<sup>a</sup> Max indicates the maximum number of bands for the dataset without overfitting.

inflated), 62% are in the visible, 4% are in the near infrared and 34% are in the shortwave infrared areas of the spectrum (Table 2). If the top fifty wavebands are considered (i.e. ones used by the *lmnc5* classifier for the optimal classification results), 54% are from the visible, 8% are from the near infrared and 38% from the shortwave infrared regions. Table 2 presents a summary of the more relevant wavelength regions as function of the number of bands used in the analysis.

Because of the stronger performance of the wavelet energy feature and the forward feature selection techniques at the leaf level, we subsequently restricted the analysis of the airborne data to those two techniques.

#### 3.2. Canopy level

At the canopy level using spectra extracted from the HYDICE image, the optimal number of features for the feature selection method ranged from 20 (*treec*) to 80 (*knnc2*). The lowest overall error rate was achieved by the *knnc2* classifier with 80 features (7% overall; 0% training, 14.1% testing errors) and with 30 features (7.1% overall; 0% training, 14.1 testing errors) followed by the *lmnc5* classifier with 40 features (8.1% overall; 1.3% training, 14.8% testing errors). All non-parametric classifiers performed better than the parametric classifiers with overall error rates below 10% with the exception of *knnc3* (12.4%). With the wavelet energy features technique, the best results were obtained with the *treec* classifier (7.7% overall; 0% training, 15.4% testing errors) following by the *lmnc2* classifier (9.7% overall; 2.6% training, 16.8% testing errors).

The difference in season when the leaf level data and the HYDICE image were collected may contribute to the higher error rate at the crown level. The HYDICE image was taken at the peak of the dry season, when most species that are deciduous in the dry season have shed their leaves. The leaf spectra were taken at the very beginning of the dry season, when many dry season deciduous species have not yet dropped their leaves. Three of the five crowns (from two species *Pseudobombax septenatum* and *Cecropia peltata*) with less than 40% liana coverage that were misclassified (feature selection technique) were deciduous when HYDICE image was taken. Of the crowns with greater than 40% lianas that were misclassified, only two of twelve crowns (from the species *Bursera simaruba* and *Calyculphyllum candidissimum*) were deciduous.

The top ten wavebands with the greatest discriminatory power at the crown-level were all above 2000 nm. However, when the distribution of the top 80 wavebands are considered (i.e. maximum without overfitting, and ones used by the knnc2 classifier), 50% are from the visible, 12% from the near infrared and 38% from the shortwave infrared regions (Table 3). If the top 30 wavebands are considered (i.e. ones used by the knnc2 classifier), 33% are from the visible and 67% from the shortwave infrared regions. Table 3 presents a summary of the most relevant bands as function of wavelength region and classification technique.

#### 4. Discussion

The different wavelength regions between the leaf and crown levels with the greatest discriminatory power indicate that some of the pigment and structural differences between dry forest liana and tree leaves (i.e. lower chlorophyll concentration, lower carotenoid concentration, 50% more inter-cellular space, higher water content, and thinner leaves for lianas, Sánchez-Azofeifa et al., unpublished data) that account for their different spectral signatures may not be as important at the canopy level. For separating liana from tree leaves, the top ten bands for discrimination were dominated by the visible (3 bands) and the shortwave infrared (6 wavebands), with the near infrared region being less important (1 band) in contrast to the canopy level for which the top ten wavebands were from the shortwave infrared (Table 2). Our results contrast with those presented by Clark et al. (2005) when comparing wavelengths, which in the case of Clark et al. (2005) was aimed to separate among leaves of different tropical wet forest species. Clark et al. (2005) found that nine of the top ten significant wavebands were in the near infrared and mid-infrared regions; areas where they found large variations in the absolute reflectance values. A possible explanation for these differences is that chlorophyll and other pigments vary more than photon scattering in the internal cellular structures between tree and liana leaves, whereas the opposite may be true for discriminating leaves of different tree species. In terms of separating lianas from trees, Sánchez-Azofeifa et al. (unpublished data) document that differences in inter-cellular space between lianas and trees for over 60 species are not significant in either the dry or wet forest tree or liana species.

At the crown level, the most important bands for discriminating lianas versus trees were overwhelmingly in the short infrared with contribution from the visible range as well. Similarly, Sánchez-Azofeifa and Castro-Esau (2005) found the 550 nm waveband to be important in discriminating liana loads in one species (*A. excelsum*) at the same study location. In a separability analysis between trees species examined at the crown level from HYDICE data, Clark et al. (2005) found that the most significant bands were spread out over the entire spectral range from the visible to the shortwave infrared. This is contrary to our findings for differentiating lianas from trees (regardless of species), where at the crown level the most significant wavebands are clustered in both the visible and shortwave infrared (Table 3). However, because a different methodology was used to analyze the spectra,

it not possible to say conclusively whether actual different wavelength regions are important for differentiating between species and life forms, or whether that difference is an artifact of the differences in sampling and analysis methodologies (Castro et al., 2006). Again, Clark et al. (2005) were discriminating crowns of different tree species, whereas here we are discriminating crowns with high and low liana loads. We expect liana loads to lead to the orientation of elements (leaves, branches) within a tree crown to be different than variations among tree species (discussed below).

It is also important to consider that the leaf level data is of higher 'spectral purity' than the data from the HYDICE image, which at 1 m spatial resolution is an average not only of leaves, but also exposed branches, tree trunks and, in some cases where the canopy is sparse or has openings, the ground or other vegetation below (Asner, 1998). The reflectance is also affected by crown architecture, leaf orientation, leaf area index, etc., whereas the leaf level data is free from such complicating factors (Asner, 1998). Gamon et al. (2005), discussing the role of photosynthesis and leaf angle distribution at the same crane site, demonstrate the significant impact of those variables on spectral reflectance. In addition, we considered the entire spectra at the leaf level while for the HYDICE image, the bands corresponding to the atmospheric absorption were removed and the average for each crown was used. These differences partly account for the higher error rates seen in the classification of the spectra from the image. Other forthcoming band selection techniques such as those presented by De Backer et al. (2005) and Huang and He (2005) or the selection of the most significant wavelet approximation and detail coefficients (rather than the energy feature vector) may also improve classification accuracy at the crown level. The effects of scale are an important determinant of the information that can be derived from the spectra. In the process of scaling up from the leaf to the crown level, such differences in the main components of reflectance must be taken into consideration. Asner (1998) demonstrates at the canopy level that the nonphotosynthetic elements of the canopy can significantly alter reflectance spectra. Contrarily, lianas in full foliage may obscure the contribution of these elements.

We attribute the overall success of these classification techniques not only to the intrinsic differences in leaf spectra between lianas and trees but also to architectural changes imposed by lianas at the canopy level (Fig. 2). Lianas tend to form a continuous mat of leaves over a single tree crown with leaf angles close to horizontal. Tree leaves, especially at the top of the crown, tend to be at angles off horizontal and even changing during the day for certain species (Gamon et al., 2005). The steeper angles cause more within-crown shadowing. Thus, the surface of trees with high liana loads may be viewed by the airborne sensors as smoother than liana-free crowns and more closely resembling a large mat of green vegetation (with an increased green leaf area visible) (Fig. 3). The large contribution of the shortwave infrared (an area sensitive to water content) to the separability of the canopy level spectra also tends to indicate that differences in water content between crown with and without liana loading is an important factor for



Fig. 2. Photographs of the lianas at a) ground level, b) covering crowns and reducing the branch and crown architecture of the tree crowns and c) tree crowns with minimal to no liana coverage d) subset of the HYDICE Image (909 nm: 615 nm: 529 nm) with  $\Psi$  indicating examples of crowns with >40% lianas and  $\S$  indicating examples of crowns with <40% liana coverage.

mapping liana coverage. Sánchez-Azofeifa et al. (unpublished data) have shown that at the leaf level, lianas have significantly higher water content than tree leaves. And based on the importance of the shortwave infrared this difference may translate to the canopy level as well. A combination of spectral and texture analysis of satellite or airborne imagery may aid in future investigations of liana coverage at the canopy level to

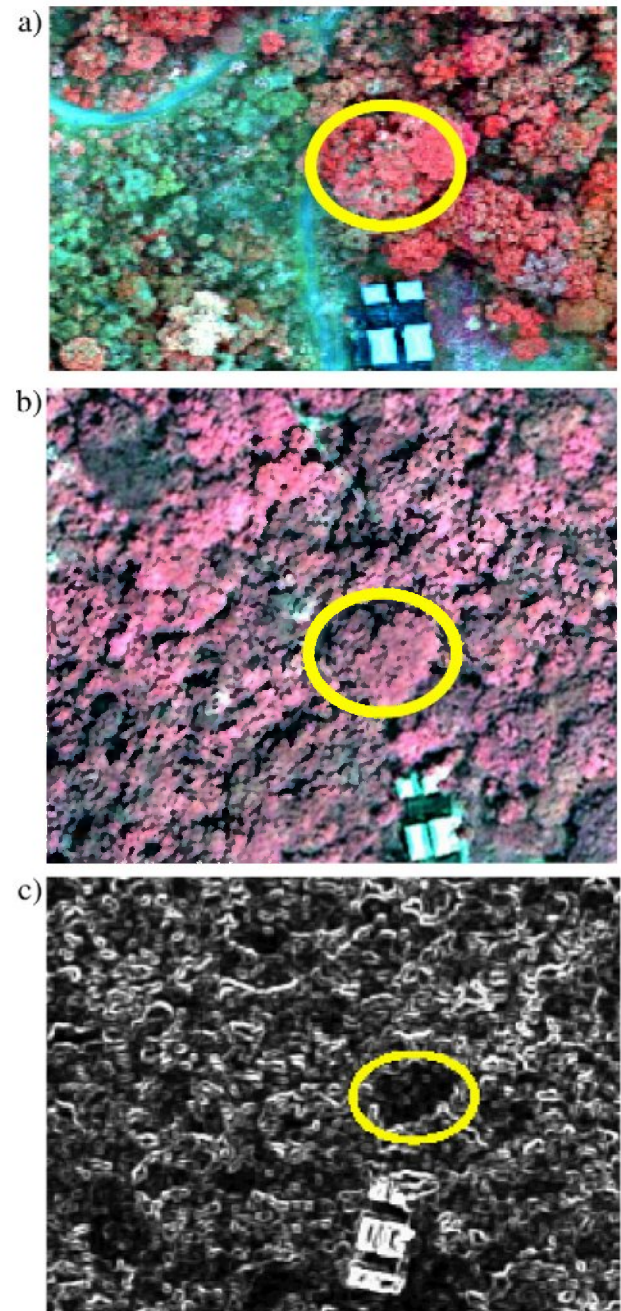


Fig. 3. a) HYDICE image from 1998 (909 nm: 615 nm: 529 nm) b) Quickbird image from 2000 c) results from a  $5 \times 5$  variance filter on the panchromatic band of the Quickbird image from 2000. Yellow oval highlights a set of crowns that are individually distinguishable in 1998 but appear to be a single crown from the 2000 image because of becoming completely covered by lianas. As illustrated in Fig. 2d, two of the crowns highlighted by the yellow oval in (a) have a 40% or greater coverage of lianas in 1998. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)



locate crowns with broad liana coverage. The separation of lianas from trees at the canopy scale is also important for canopy metrics. As illustrated in Fig. 3, when lianas cover several canopies as a continuous mat, the estimation of crown area may become inflated. Rather than measuring the area of the three separate crowns infested by lianas (Fig. 3a), one would assume that there is only one crown (Fig. 3b) which is much larger.

The deciduous nature of the canopy in this dry forest site also complicates the separability of the tree crowns with and without liana loading. The deciduous trees have a higher risk of being misclassified because the leaves of the lianas are the only leaves being seen (i.e. the classifier is not separating tree and liana leaves as at the leaf level) since in many cases lianas lose their leaves after the host trees (Kalacska et al., 2005) or may maintain leaves through the dry season (Schnitzer, 2005). A possibility (though not investigated in this study) is that because of intra-species spectral variability, the aggregated spectra from those canopies resembled that of the trees with less than 40% liana coverage (Zhang et al., in press).

## 5. Conclusions

Despite greater error than at the leaf level discrimination, lianas were separable with a relatively high degree of accuracy at the crown level (7.1% overall error) when a threshold of 40% liana coverage was considered. We have illustrated four data reduction techniques for discriminating between leaf level vegetation spectra (lianas and trees) as well as two techniques with crown-level airborne hyperspectral data (trees with and without significant liana coverage). Our results have shown that at the leaf level there is little difference (less than five percentage points) in the best results that may be achieved by using different reduction techniques and classifiers; results which are superior to what can be achieved from the airborne data. Nevertheless, if the feature selection technique is chosen with the optimal number of features, the difference in classifier performance is even less (three percentage points). We have also shown that when considering the airborne data, there is no “optimal” data reduction technique, but that the same result in terms of classifying trees with and/or without significant liana loading can be achieved with both feature selection and wavelet energy features. The waveband regions important for separating lianas from trees at the leaf level are different than at the canopy level implying that pigment and leaf structural differences between the two life forms are not the only important factors at the canopy level, where the overall architecture and water content also become factors affecting separability.

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