

## Spectral discrimination of Brazilian Atlantic Forest tree species

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**Abstract.** Management and conservation efforts of tropical forests frequently require detailed assessments of species numbers and distributions. High costs of such information restrict their collection for large areas. In this context, remotely sensed data obtained by airborne and spaceborne sensors have been widely used. Recently, airborne hyperspectral sensors have been used to map floristic composition in tropical forest sites. Techniques and methodologies to explore hyperspectral data in this kind of application are in the early stages of development. Therefore, it is still necessary to conduct further research in recognizing and mapping tree species using remote sensing, including spectroscopy measurements. In this study, spectroscopy measurements were used to discriminate eight Brazilian Atlantic Forest tree species. Statistical analysis, based on hemispherical reflectance and transmittance measurements, were performed to select the most relevant wavebands to discriminate the species studied. Reflectance measurements showed low variability among species once a small number of wavebands reached high separability values. These wavebands were located near the water absorption feature at 1.200 nm and some of them around 1.300 nm. In the transmittance measurements, a higher number of wavebands proved to be valuable to species discrimination. For instance, those located in the liquid water absorption feature at 1.400 nm, evidencing that leaf water content is an important parameter to species discrimination. It is still difficult to discriminate species based solely on their leaf reflectance or transmittance. However, spectroscopy measurements are performed in thousands of spectral bands, allowing the detection of suitable variations on the spectral response of plants.

**Keywords:** Leaf spectroscopy, Jeffries-Matusita distance, Tropical forest.

### 1. Introduction

The Brazilian Atlantic Forest (BAF) originally covered an area of 1.3 million km<sup>2</sup>, of which less than 8% remains today due to the expansion of the agricultural frontier (Dean, 1996; Morellato e Haddad, 2000). Management and conservation efforts of tropical forests, such as BAF, frequently require detailed assessments of species numbers and distributions (Tuner et al., 2003). However, high costs of such information restrict their collection for large areas. In this context, remotely sensed data obtained by airborne and spaceborne sensors have been used.

Tree species mapping of tropical forests are usually based on visual interpretation of aerial photographs (e.g. Trichon, 2001) and on classification of moderate spatial resolution satellite imagery (e.g. Johansen e Phinn, 2006). The visual interpretation technique depends on various subjective criteria (e.g. Herwitz et al., 1998) and can vary according to the analyst. The use of satellite images acquired, for example, by *Satellite Pour l'Observation de la Terre 5* (SPOT 5) e *Landsat 5* does not have the required spectral and spatial resolution.

Recently, airborne hyperspectral sensors have been used to map floristic composition in tropical forest sites (Funga et al., 2003; Clark et al., 2005; Zhang et al., 2006; Lucas et al., 2008; Asner e Martin, 2009). These sensors are capable to slice the electromagnetic spectrum into hundreds of narrow spectral bands. Moreover, its spatial resolution is fine enough to resolve individual tree crowns, enabling the detection of peculiar spectral signatures of tree species (Clark et al., 2005). Techniques and methodologies to explore hyperspectral data in this kind of application are in the early stages of development (Asner e Martin, 2009). Therefore, it is still necessary to conduct further research in recognizing and mapping tree

species using remote sensing, including spectroscopy measurements (e.g. Sánchez-Azofeifa et al., 2009; Pu, 2009). Spectroscopy measurements contribute to characterize leaf spectral responses, identifying reflective and absorption features and guide the recognition of tree species in hyperspectral imagery. Such data have been successfully used on the recognition of tree species (e.g. Cochrane, 2000; Pu, 2009; Ullah et al., 2012), evidencing its potential for floristic studies.

In this work, spectroscopy measurements were used to discriminate eight BAF tree species. Statistical analysis, based on hemispherical reflectance and transmittance measurements, were performed to select the most relevant wavebands to discriminate the species studied.

## 2. Methods

### 2.1 Leaf Spectroscopy

An integrating sphere (ASD/RTS-3ZC), coupled in a high resolution spectroradiometer ASD/FieldSpec®3, was used to measure spectral reflectance and transmittance from eight BAF tree species (Figure 1). The ASD/FieldSpec®3 instrument consists of three spectrometers. The first one covers the visible (VIS) and near infrared (NIR) regions of the electromagnetic spectrum (350-1.000 nm) and has a spectral resolution of 3 nm. The second and third spectrometers have a spectral resolution of 10 nm and cover the short wave infrared (SWIR) region (1.001-2.500 nm).

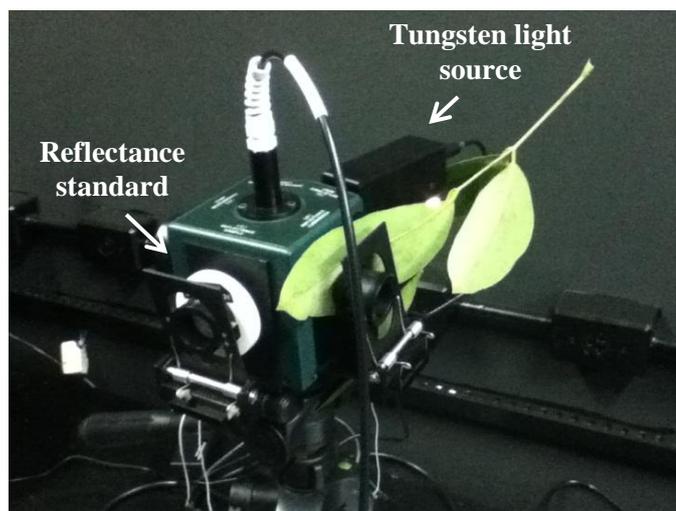


Figure 1. Calibration to leaf reflectance measurement using the ASD/RTS-3ZC integrating sphere.

The ASD/RTS-3ZC integrating sphere was designed to collect all the radiation produced by a collimated tungsten light source, reflected from, or transmitted through a leaf sample over a full hemisphere. Its internal diffuse (Lambertian) surface, i.e. constant radiance independent of the viewing angle, avoids bidirectional reflectance features coming from the sample. Therefore, an averaged response to the reflectance of the sample placed in the beam at the sphere port is given (ASD, 2008).

Leaves were detached from trees from a forest fragment located on the surroundings of Porto Alegre city, Rio Grande do Sul State, south of Brazil. The eight species included *Schinus terebinthifolius* (ST), *Ceiba speciosa* (CS), *Eugenia uniflora* (EU), *Calophyllum brasiliensis* (CB), *Vochysia bifalcata* (VB), *Bauhinia forficata* (BF), *Cedrela fissilis* (CF) and *Ocotea spixiana* (OS). Immediately after being detached from each tree branch, leaves were

taken to the laboratory of spectroradiometry of the Federal University of Rio Grande do Sul (UFRGS), where the measurements were performed. Four leaves of each species were measured to account for spectral variation. Leaf spectra were then averaged, in order to obtain a single spectrum per species. Each measurement was repeated 20 times, calibrated for dark current and stray light, and referenced to a reflectance standard (SphereOptics GmbH, Uhldingen, Germany). Finally, five reflectance spectra per species were retained for further use.

## 2.2 Data processing and analysis

Species were identified by a band selection procedure, in which the most relevant wavebands to separate the species were selected. First, was conducted a one-way analysis of variance (ANOVA) followed by a post-hoc Tukey honestly significance (Tukey HSD) test. Second, spectral separability between species was estimated in each waveband by the Jeffries-Matusita (JM) distance. These methods proven to be universally superior for the optimal feature selection (Yang et al., 2005) and have been successfully used to spectral discrimination of plant species (Ullah et al., 2012; Adam e Mutanga, 2009; Vaiphasa et al., 2007). Prior to performing the statistical tests, it was verified normality and homoscedasticity (homogeneity of variances) of the reflectance and transmittance values across each waveband. All processing procedures were performed in MatLab® environment.

In this study, spectral regions were determined according to Asner (1998) and included the visible (VIS=400-700 nm), near-infrared (NIR=700-1.300 nm) and shortwave infrared (SWIR=1.500-1.900 nm) regions. Although the ASD/FieldSpec®3 spectroradiometer engine with a spectral range from 350 nm to 2.500 nm, the tungsten light source does not radiate strong energy bellow 400 nm and above 1.900 nm. Therefore, the measurements are extremely noisy in these regions and should be discarded.

## 2.3 Statistical tests

One-way ANOVA coupled with a post-hoc Tukey HSD test was used to verify the statistical difference between species in each waveband. The ANOVA tested the following hypothesis:

$$H_0 = \mu_1 = \mu_2 = \dots = \mu_n \quad (1)$$

$$H_1 = \text{Not all } \mu_n (i) \text{ are equal} \quad (2)$$

Where  $\mu_n$  represents the reflectance or transmittance of the  $n^{\text{th}}$  species ( $n=1, 2\dots 8$ ) and  $i$  denotes the waveband. Rejection of the null hypothesis ( $H_0$ ) indicated the wavebands, at a 99% ( $p<0.01$ ) confidence level, in which the species differ statistically.  $H_0$  rejection was followed by pairwise multiple comparisons with the post-hoc Tukey HSD test. The total number of pair combinations was calculated as  $n((n-1)/2)$  and equaled 28, note that  $n$  are the number of species. By counting the number of pairs that are statistically significantly different on each waveband, it was possible to identify the spectral regions where the species differ most. Only the wavebands with 28 statistically significantly different pairs, i.e. all possible combination between species, were retained for further use.

### 2.3.1 Spectral separability

Aiming to estimate the spectral separability of species at the wavebands identified on the previous subsection, it was calculated the Jeffries-Matusita (JM) distance. According to Richards and Jia (2006) JM distance is calculated using Equation 3:

$$JM_{ij} = 2 (1 - e^{-B}) \tag{3}$$

in which

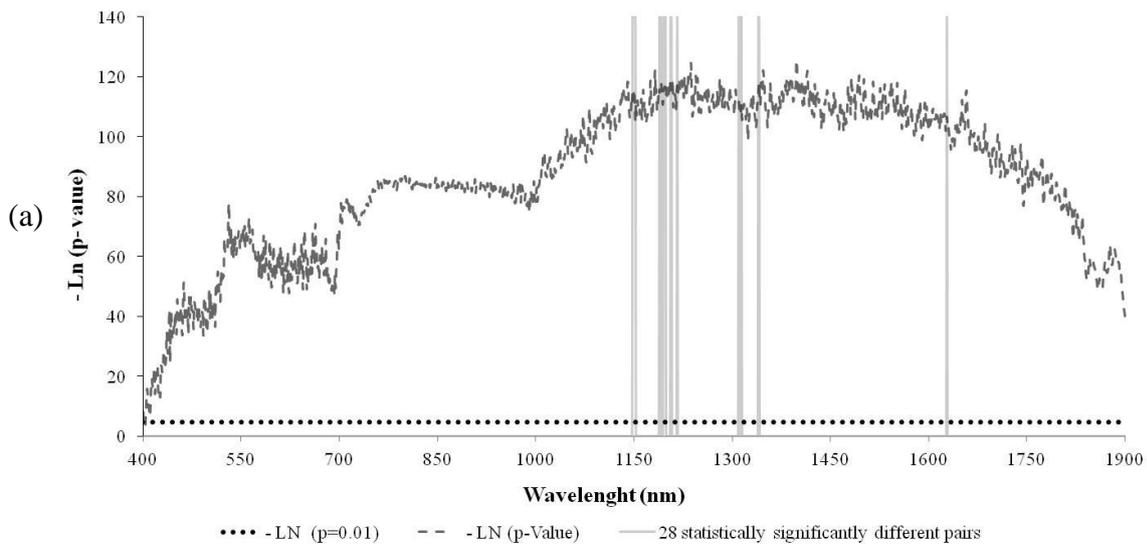
$$B = \frac{1}{8} (m_i - m_j)^T \left\{ \frac{\sum_i + \sum_j}{2} \right\}^{-1} (m_i - m_j) + \frac{1}{2} \ln \left\{ \frac{|\left(\sum_i + \sum_j\right)/2|}{|\sum_i|^{1/2} |\sum_j|^{1/2}} \right\} \tag{4}$$

which is known as Bhattacharyya distance (Kailath, 1967), where  $i$  and  $j$  are the two species being compared;  $\sum_i$  = covariance matrix of  $i$  species;  $\sum_j$  = covariance matrix of  $j$  species;  $m_i$  = mean vector of  $i$ ;  $m_j$  = mean vector of  $j$ ;  $T$  = transposition function;  $\ln$  = natural logarithm;  $|\sum_i|$  = determinant of  $\sum_i$ ;  $|\sum_j|$  = determinant of  $\sum_j$ . The calculation of  $\sum_i$ ,  $\sum_j$  as well as  $m_i$ ,  $m_j$  was possible for each selected waveband because five spectra per species were obtained. JM distance values vary between 0 and 2, with higher values indicating total separability of the species pairs in the wavebands being used (Richards, 1996). A JM distance threshold of  $\geq 1.90$ , a value commonly adopted in the remote sensing practice (Thomas et al. 2003; ENVI, 2004.), were used to indicate whether any two species were spectrally separable.

### 3. Results and Discussion

#### 3.1 Statistical tests

One-way ANOVA results indicated that the reflectance and transmittance of at least one pair of species was statistically different at each waveband. The p-values, along the entire wavelength region, assumed numbers far below the 99% confidence level (i.e.  $p < 0.01$ ) and should be plotted on a logarithm scale to be visualized, as shows Figure 2. The post-hoc Tukey HSD test identified 23 wavebands on the reflectance spectra (Figure 2a) and 281 wavebands on the transmittance spectra (Figure 2b) with 28 statistically significantly different pairs (i.e. the maximum possible number of pairs).



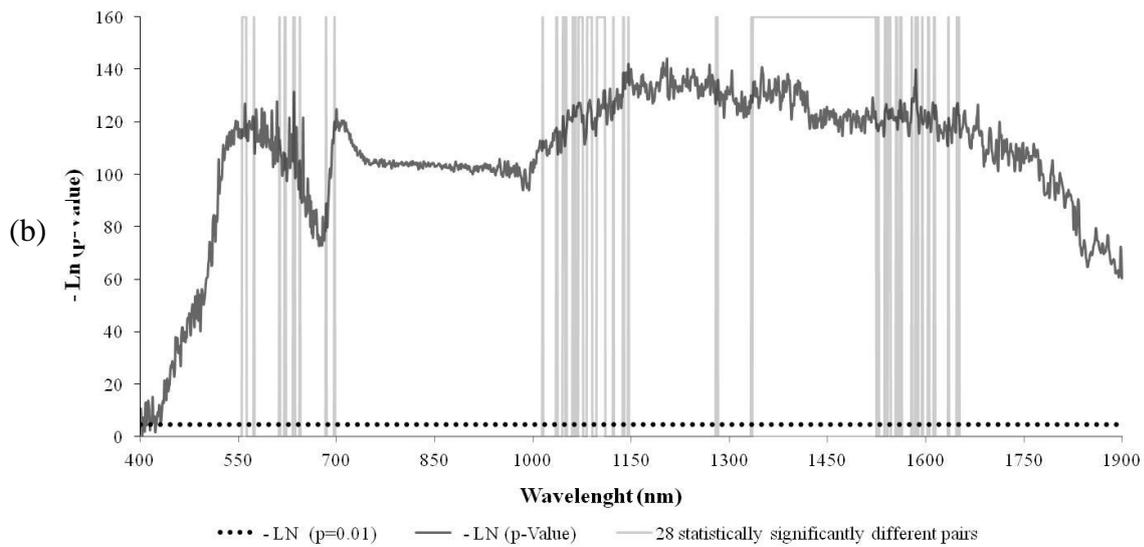


Figure 2. P-value plots for reflectance (a) and transmittance spectra (b). The gray areas represent the wavebands with 28 statistically significantly different pairs of species identified by the post-hoc Tukey HSD test. These were regions where the species most differ.

### 3.2 Spectral separability

Results of the Tukey HSD test showed that some wavebands have higher counts of vegetation pairs with statistically significant differences and that those wavebands concentrate the spectral diversity of species. JM distance values for the 28 pairs of each waveband were calculated in order to measure the spectral separability of species. The wavebands with more than one pair combination with JM distance below 1.90 were considered ambiguous for species discrimination and were excluded from the analysis. This procedure selected six and 121 wavebands on the reflectance and transmittance spectra, respectively.

### 3.3 Reflectance spectra

Typical patterns of green vegetation were observed in the leaf spectra of the eight tree species (Figure 3): low VIS reflectance because of light absorption by chlorophylls and carotenoids, high NIR reflectance due to multiple-scattering at the air-cell interfaces in the leaf internal tissue (Gates et al., 1965), weak NIR water absorption features at 980 and 1.200 nm, and moderate reflectance in SWIR with a peak at 1.650 nm caused by dominant water absorption features at 1.400 and 1.900 nm (Roberts et al., 2004, Clark et al., 2005).

The spectral responses of species in the visible region (400-700 nm) followed similar patterns (Figure 3). Although the one-way ANOVA results showed significantly difference among species in this region (Figure 2a), there were not a single waveband in which all species statistically differ among themselves. This demonstrates how difficult would it be to differentiate the tree species solely based on their VIS reflectance spectra.

On the contrary, along the NIR region (700-1.300 nm) was observed high variability among species. Differences in leaf thickness and density number of empty spaces in the mesophyll may have significant effects on the overall NIR reflectance from the leaves (Gates et al., 1965). The wavebands with major variability were those located around the water absorption feature at 1.200 nm (gray areas in Figure 3). Furthermore, another two wavebands centered at 1.340 and 1.341 nm were selected by the methodology.

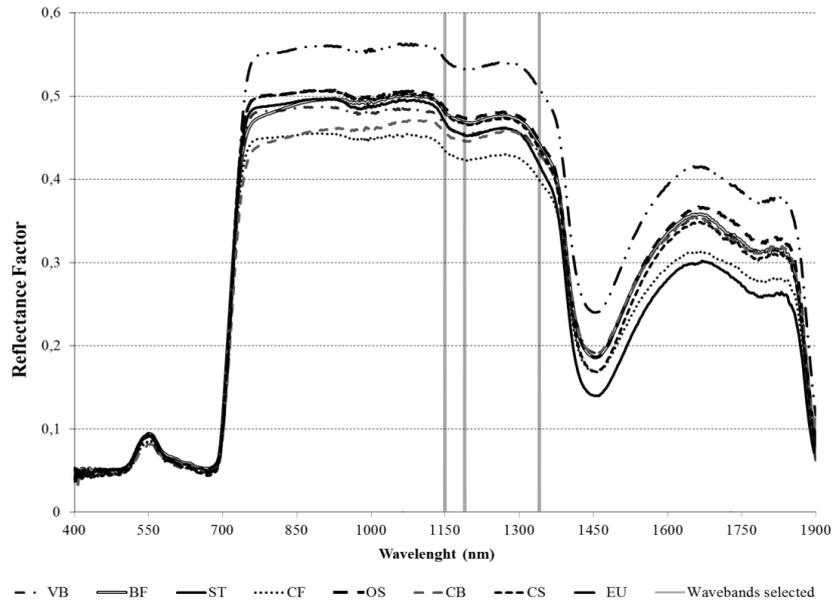


Figure 3. Reflectance spectra of eight Brazilian Atlantic Forest tree species. The gray areas depicted the wavebands selected by the methodology.

### 3.4 Transmittance spectra

Spectral variability of species was observed in several regions along the transmittance spectra, depicted by the gray areas in Figure 4. It is of value to note the differences on the transmittance spectra of species in the VIS region (400-700 nm). As observed in the reflectance spectra, the wavebands around the weak NIR water absorption features at 980 and 1.200 nm showed high separability values (Fig. 4). Moreover, around the water absorption feature at 1.400 nm the species demonstrated high spectral variability, caused by different leaf water content of species.

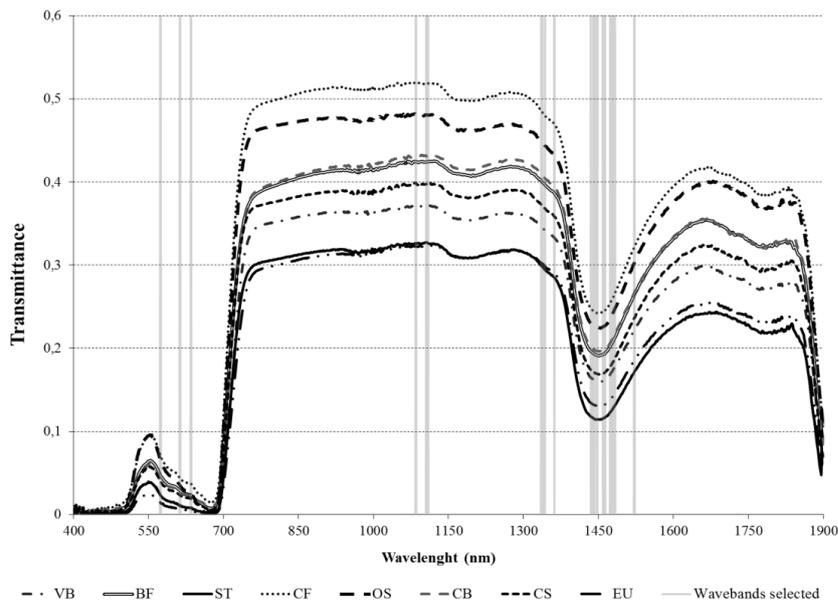


Figure 4. Transmittance spectra of eight Brazilian Atlantic Forest tree species. The gray areas depicted the wavebands selected by the methodology.

#### 4. Conclusions

In this experiment, spectroscopy data were used to discriminate eight Brazilian Atlantic Forest tree species. Reflectance measurements showed low variability among species once a small number of wavebands reached high separability values. These wavebands were located near the water absorption feature at 1.200 nm and some of them around 1.300 nm. In the transmittance measurements, a higher number of wavebands proved to be valuable to species discrimination. For instance, those located in the liquid water absorption feature at 1.400 nm, evidencing that leaf water content is an important parameter to species discrimination. Furthermore, the concentration of chlorophylls and carotenoids, which have absorption peaks in the VIS region, showed more influence in the transmittance than in the reflectance spectra.

Particularly for plants, which spectral responses are controlled for small number of factors, it is still difficult to identify species based solely on their leaf reflectance. However, spectroscopy measurements are performed in thousands of spectral bands, allowing the detection of suitable variations that can discriminate species.

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