LEAF-BASED SPECTROSCOPY AND SPECTRAL MODELS FOR AMAZONIAN TREE SPECIES DISTINCTION

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ABSTRACT

Sampling trees in a natural environment can be used in studies ranging from floristic composition and phytogeography to vegetation management and growth modeling. Relying on hyperspectral approach, this study aimed to differentiate spectral libraries of four Amazon tree species. Based on vegetation indices results to reduce data volume, the principal component and cluster analysis defined the best indices to differentiate spectrometry of leaves of Amazonian trees. These combined methods brought satisfactory results, with PC1 highly related to the variability of the vegetation indices results (99.37%). Adopting this approach in hyperspectral data at the leaf level and well-defined classes results in good responses. We emphasize the importance of using combined vegetation indices, with greater contributions by indices developed for quantization or absorption of electromagnetic radiation by chlorophyll, which are based in the visible region.

Key words — Amazonian trees, hyperspectral data, multivariate analysis, vegetation indices, forest management.

1. INTRODUCTION

Sampling trees in a natural environment can be used in studies ranging from floristic composition and phytogeography to vegetation management and growth modeling, and efficiently depends on knowledge of sampling procedures and statistical principles, which are the basis of plant sampling methods [1].

The floristic survey is one of the main types of diagnosis and classification of the plant communities in an environment, and from the survey, several aspects of the natural vegetation dynamics in forest environments can be understood [2]. Amazon biome lacks investigations regarding the identification [3], richness of species [4] and diversity patterns [5], even more so when considering the biome with the greatest biodiversity in the world [6].

Among the technologies to perform such a survey, spectroscopy is applied in studies of vegetation classification, in terms of species [7], varieties of the same species [8], water content [9], plant growth rate [10] and changes in chemical composition [11], [12].

In this regard, the floristic survey can be based on in-situ spectroscopy data, which for remote sensing science is the reference hyperspectral database for remote observations [13], and thus provide the database for agile and accurate observations [14]. Since hyperspectral sensors provide an enormity of data, the transformation is commonly accomplished through vegetation indices, where data is maximized to observe relative abundance, vegetation activity, or any biophysical parameters of interest [15].

In view of the above and of the difficulties in field identification, the objective of this study was to verify the ability to distinguish tree species in the Southern Brazilian Amazon using hyperspectral remote sensing in a native flora area, observing four species of economic interest for timber extraction and forest products for other purposes, as well as establishing a spectral library standard for each species.

2. MATERIAL AND METHODS

2.1. Climatic and geographical traits

The study area comprises the municipality of Alta Floresta (Latitude 09º52'32 "S and Longitude 56º05'10 "W), Mato Grosso, located in the Southern Amazon (Figure 1). With a tropical climate, two well-defined seasons occur, a wet and a dry period, i.e., according to the Köppen-Geiger classification, the region climate is Aw type, with average temperature ranging around 26.4°C, and average annual rainfall reaching 2,281 mm [16].

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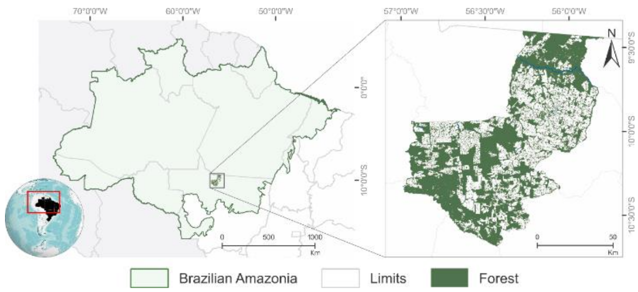

Figure 1. Forests areas over Alta Floresta – MT, at southern Amazonia.

2.2. Tree leaves spectroscopy

The definition of the tree species included in this analysis considered important species for logging and for bioprospecting activities over non-timber forest products (NTFP) tree species. From this, were deemed four species, namely (I) *Bertholletia Excelsa* Bonpl. – Lecythidaceae; (II) *Euterpe oleracea* Mart. – Arecaceae; (III) *Schizolobium parahyba* (Vell.) Blake – Fabaceae; and (IV) *Cedrela fissilis* Vell. – Meliaceae. Three of these species have timber economic value (I, III and IV), as two are important NTFPs source species (I and II).

The collected samples were healthy leaves from the top of mature trees, which were removed with a tree pruner. Three leaves at the top of the tree were chosen since these data most closely resemble those generated remotely (orbital or airborne), and seeking data closer to natural occurrence, each leaf was removed from random mature individuals in a forest in the study area, and immediately submitted to the spectroradiometer.

Concerning spectrometry, radiometric readings were performed using the FieldSpec® 4 Hi-Res, a high spectral resolution spectroradiometer designed for accurate spectral data measurements for a wide range of remote sensing applications. With spectral resolution varying from 3 (VIS-NIR) to 8 nm (SWIR), ranging from 0.35 to 2.5 μm. The leaf-based assessment with this spectrometer requires ASD *Plant Probe* equipment, which provide non-destructive sampling and no interference and variance from external electromagnetic radiation.

2.3. Spectral models

Spectral curves obtained through FieldSpec® 4 Hi-Res are huge, taking into account its spectral resolution and range. In view of data volume reduction, we applied several spectral indices, which could reliably express this data enormity and, in turn, express vegetation traits related to its spectral curve. Here, a reduced dataset relying on each species was based on EVI (Enhanced Vegetation Index), NDVI (Normalized Difference Vegetation Index), GNDVI (Green NDVI), SAVI (Soil Adjusted Vegetation Index), TVI (Transformed Vegetation Index), OSAVI (Optimized Soil Adjusted Vegetation Index), NPCI (Normalized Pigment Chlorophyll Index), CARI2 (Chlorophyll Absorption Ratio Index 2), LCI (Leaf Chlorophyll Index), LWCI (Leaf Water Content Index), and GLI (Green Leaf Index) indices.

2.4. Statistical approach

The indices dataset was submitted to Principal Component (PC) analysis. Based on 'ggfortify' library at R software [17]. Further, the assessment involved cluster analysis and contribution to differentiation by using Singh's Criterion (S_j).

3. RESULTS

From FieldSpec® 4 Hi-Res data, the spectral curves of the evaluated plant species were created (Figure 2), and the vegetation indices were calculated for discriminatory analysis.

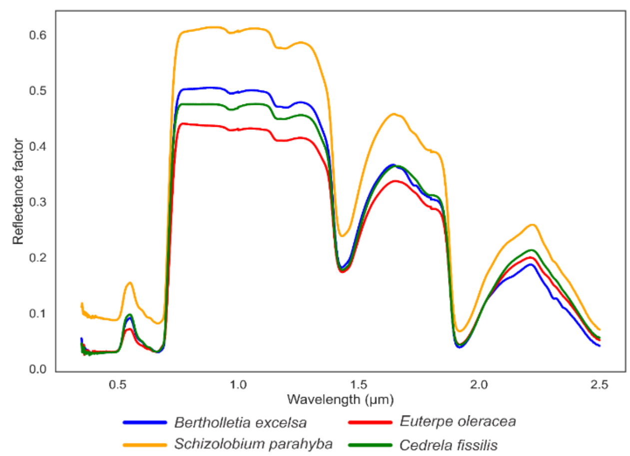

Figure 2. Spectral curves based on the evaluated species. Horizontal axis means wavelength (μm), and vertical axis mean reflectance factor.

By visual analysis, some regions of the electromagnetic spectrum with higher differentiation in reflectance responses can be seen, in portions of the visible spectrum (0.5 - 0.65 μm), near-infrared (0.913 – 1.25 μm) and SWIR 2 (2.1 – 2.5 μm).

For the PC analysis, it was possible to observe that the NPCI, TVI, and CARI2 indices contained in cluster 1 were those closest to the species vectors (Figure 3A). Among them, Singh's criterion (1981) reveals that the CARI2 and NPCI indices accounted for 70.45% and 16.73% of the differentiation of the evaluated species, respectively (Table 1). From a graphical representation perspective, the heatmap (Figure 3B) was elaborated to visualize the vegetation indices in relation to the analyzed species. In this figure, higher values are represented by pink and lower values are represented by blue color.

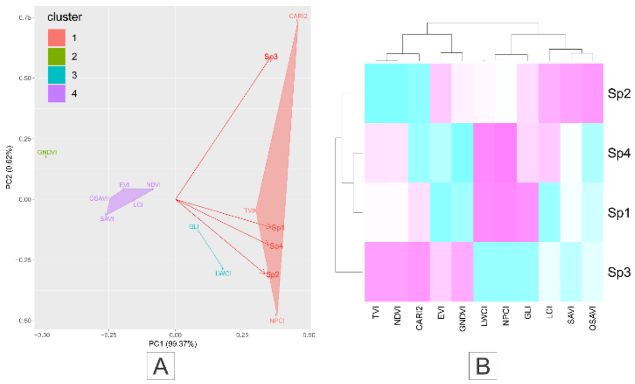

Figure 3. Graphical representation of PC analysis with sample and vegetation index datasets (A) and heatmap with sample and vegetation index datasets (B), where: *B. excelsa* (Sp1), *E. oleracea* (Sp2), *S. parahyba* (Sp3), and *C. fissilis* (Sp4).

Vegetation index	S_j	S_j %
EVI	0.000593	0.17
NDVI	0.000393	0.11
GNDVI	0.006261	1.76
SAVI	0.007144	2.01
TVI	0.000207	0.06
OSAVI	0.002625	0.74
NPCI	0.059369	16.73
CARI2	0.250080	70.45
LCI	0.001586	0.45
LWCI	0.022424	6.32
GLI	0.004288	1.21

Table 1. Singh criterion over vegetation indices applied to the spectral responses.

4. DISCUSSION

Based on the spectral curves obtained, the reflectance characteristics between species occurring in a native environment can be compared, where trees with a sunlit canopy show a higher difference between NIR and SWIR reflectance factors than species with a shade canopy), followed by species with medium height [19]. This response is evident when comparing the curves of *C. fissilis* and *B. excelsa*, with shade [20] and sunlit canopy [21], respectively, as seen in Figure 2. It is noteworthy that leaf morphology has no significant impact on the leaf-based spectrum, where the spectral behavior suggests a substantial similarity between *E. oleracea* and *C. fissilis*, in which the first is a palm tree with long and narrow folioles, and the second is a woody tree with short and wide folioles [22].

The application of vegetation indices was intended to summarize the spectral curve response to a mathematical value and become a tool for discriminant analysis. It is notable that vegetation indices have become effective in applications with hyperspectral data [23] compared to notable research from decades past [24]. The PC analysis applied to the vegetation indices brought satisfactory results, with PC1 highly related to the variability of the vegetation indices results (99.37%). Adopting this approach in hyperspectral data at the leaf level and well-defined classes results in good responses [23]. We emphasize the importance of using combined vegetation indices, with greater contributions by indices developed for quantization (NPCI) or absorption of electromagnetic radiation by chlorophyll (CARI2), which are based in the visible region.

Concerning forestry research, implementing vegetation indices as reduction method, combined to spectrometer instruments data are potential single-method in forestry research. We hypothesize that computational-based approach using spectrometric data as input can support especially in situ sampling and assessment, where further research to contribute and improve our results, as well as to patent a system to manage spectral libraries of trees and relate to data entry.

5. CONCLUSIONS

The analysis of spectral curves of plant species allows their characterization based on several key reflectance points. The vegetation indices results subjected to principal component analysis show significant contribution in the distinction, mainly with vegetation indices related to the interaction of chlorophyll with radiation in the visible region. The methodology applied based on the spectral libraries generated for each plant was effective, proving to be a successful model in distinguishing plant species through spectroradiometry combined to vegetation indices. Based on the depicted spectral curves, future research using hyperspectral remote sensing in floristics and species conservation will be feasible.

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