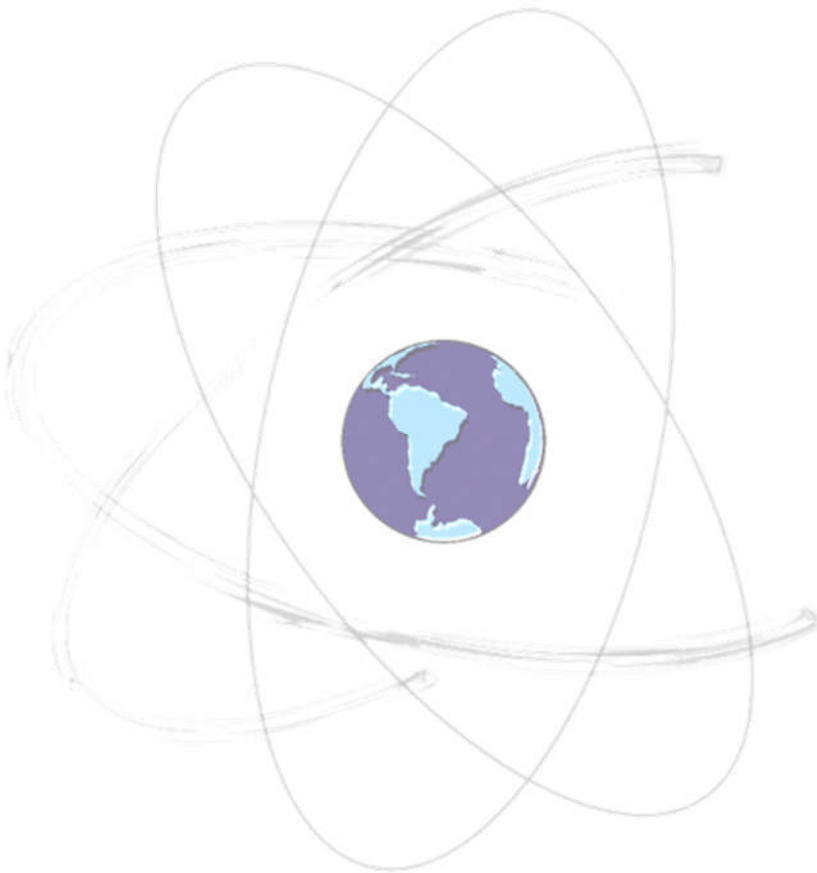


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GABRIELA TAKAHASHI MIYOSHI

**EMERGENT TREE SPECIES IDENTIFICATION IN HIGHLY
DIVERSE BRAZILIAN ATLANTIC FOREST USING
HYPERSPETRAL IMAGES ACQUIRED WITH UAV**





UNIVERSIDADE ESTADUAL PAULISTA
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Câmpus de Presidente Prudente

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Doctoral dissertation presented to the Graduate Program in Cartographic Sciences (PPGCC) at São Paulo State University (UNESP), School of Technology and Sciences, campus Presidente Prudente, SP, Brazil, for the partial fulfillment of the requirements for the grade of Doctor in Cartographic Sciences.

Advisors: Dr. Nilton Nobuhiro Imai
Dr. Antonio Maria Garcia Tommaselli
Dr. Eija Honkavaara

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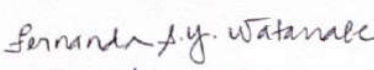
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Prof. Dr. NILTON NOBUHIRO IMAI 

Profa. Dra. FERNANDA SAYURI YOSHINO WATANABE 

Profa. Dra. MARIA DE LOURDES BUENO TRINDADE GALO 

Prof. Dr. VERALDO LIESENBERG 

Dra. YUNSHENG WANG

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To my beloved ones. We did it.

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“Those who have a 'why' to live, can bear with almost any 'how'”
Viktor E. Frankl

ABSTRACT

The objective of this doctoral dissertation is to propose a new methodology to identify eight emergent tree species (i.e., that stood out from the canopy) belonging to highly diverse Brazilian Atlantic forest and with different ages and development stages. To achieve the objective, hyperspectral images were acquired in July/2017, June/2018, and July/2019 in a transect area located in the western part of São Paulo State. The area is in Ponte Branca ecological station, where the forest is classified as submontane semideciduous seasonal with different stages of succession. Images with a spatial resolution of 10 cm were acquired with a hyperspectral camera (500–900 nm) onboard unmanned aerial vehicle (UAV) and geometrically and radiometrically post-processed. In sequence, the individual tree crowns (ITCs) were manually delineated in each dataset to be used as reference in the experiments. From the performed experiments, it is highlighted the use of mean normalized spectra to reduce the within-species spectral variability, the use of region-based classification with the Random Forest algorithm, and the use of superpixels to automatically delineate the ITCs in each dataset. Additionally, the multitemporal superpixels with different multitemporal features (normalized spectra, texture and vegetation indexes) and structural features derived from the canopy height model, combined or not, were assessed to the tree species classification. The best result was achieved merging normalized spectra and vegetation indexes, where the value of area under the receiver operating characteristics curve (AUCROC) achieved values up to 0.964. From the obtained results it is pointed out the challenge when working with this type of forest due to the lack of emergent trees, which restrict the number of samples recognized in the field, and the existence of different ages and stages of development to the same tree species. Besides, the use of structural and textural features did not improve the tree species identification. Besides, the high spatial resolution of the images showed the slight differences in the spatial position of the tree crowns between the datasets. Finally, despite the challenges the results are promising and showed the feasibility to identify the tree species using multitemporal information.

Keywords: Tree species identification; Atlantic forest; multitemporal spectral information; superpixels, UAV.

RESUMO

O objetivo desse doutorado é propor uma nova metodologia para identificar oito espécies arbóreas emergentes (i.e., que se sobressaem do dossel florestal), em diferentes idades e estágios de desenvolvimento e pertencentes à Mata Atlântica brasileira. Para tal, imagens hiperespectrais foram adquiridas em Julho/2017, em Junho/2018, e em Julho/2019 em um transecto localizado no fragmento florestal Ponte Branca, localizado a Oeste do Estado de São Paulo, onde a floresta é considerada estacional semidecidual e submontana. As imagens com resolução espacial de 10 cm foram adquiridas com câmara hiperespectral (500–900 nm) acoplada em veículo aéreo não tripulado (VANT ou UAV, do inglês *Unmanned aerial vehicle*) e, posteriormente corrigidas geometricamente e radiometricamente. Em seguida, as copas arbóreas individuais (ITCs, do inglês *Individual tree crowns*) foram delineadas manualmente em cada conjunto de dados para serem utilizadas como referência para os experimentos. Dentre os experimentos realizados, destaca-se o uso do espectro normalizado para redução da variabilidade espectral intra-espécies, o uso da classificação baseada em regiões utilizando o algoritmo *Random Forest* e o uso de *superpixels* para delineamento automático das ITCs em cada conjunto de imagens. Além disso, avaliou-se o uso dos *superpixels* multitemporais com diferentes atributos multitemporais (espectro normalizado, textura e índices de vegetação) e estruturais (derivados do modelo de altura das copas), sozinhos ou combinados, para identificação das espécies arbóreas. O melhor resultado foi obtido a partir do uso combinado do espectro normalizado com os índices de vegetação, onde o valor da área sobre a curva característica de operação do receptor (AUCROC, do inglês *Area under the receiver operating characteristics curve*) atingiu valores de até 0.964. A partir dos resultados obtidos destaca-se o desafio ao trabalhar com esse tipo de floresta, devido à falta de árvores emergentes (que se sobressaem do dossel florestal), e a existência de árvores com diferentes idades e estágios de desenvolvimento, resultando em alta variabilidade espectral e estrutural para uma mesma espécie. Adicionalmente, foi verificado que o uso dos atributos estruturais e texturais não auxiliaram a tarefa de identificação de espécies e, que a alta resolução espacial das imagens mostrou as sutis diferenças de posição espacial das copas nas imagens dos diferentes anos. Por fim, apesar dos desafios, tem-se que os resultados são promissores e mostraram ser possível identificar espécies de árvores utilizando a informação multitemporal.

Palavras-chave: Identificação de espécies arbóreas; Mata Atlântica, informação espectral multitemporal, superpixels, VANT.

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LIST OF ABBREVIATIONS AND ACRONYMS

AG	- <i>Astronium graveolens</i>
AL	- <i>Apuleia leiocarpa</i>
ALS	- Aerial laser scanning
AP	- <i>Aspidosperma polyneuron</i>
AS	- <i>Aspidosperma subincanum</i>
ASM	- Angular second moment
ATM	- Airborne Thematic Mapper
AUC	- Area under curve
AUCROC	- Area under the receiver operating characteristics curve
BBA	- Bundle block adjustment
BRDF	- Bidirectional reflectance distribution function
CHM	- Canopy height model
CHMm	- Mean value of the canopy height model
CHMstd	- Standard deviation of the canopy height model
CL	- <i>Copaifera langsdorffii</i>
CON	- Contrast
COR	- Correlation
D	- Spectral distance
DBH	- Diameter at breast height
DIS	- Dissimilarity
DN	- Digital number
DSM	- Digital surface model
DTM	- Digital terrain model
EOP	- Exterior orientation parameter
EP	- <i>Endlicheria paniculata</i>
FGI	- Finnish Geospatial Research Institute
FPI	- Fabry–Pérot Interferometer
FPR	- False positive rate
FWHM	- Full width at half maximum
GCP	- Ground control point
GNSS	- Global navigation satellite system
GPS	- Global positioning system
GSD	- Ground sample distances
HA	- <i>Helietta apiculata</i>
HC	- <i>Hymenaea courbaril</i>
HOM	- Homogeneity
ID	- Identification abbreviation
IOP	- Interior orientation parameter
ITC	- Individual tree crown
IV	- <i>Inga vera</i>
KUR	- Kurtosis of the canopy height model
LOOCV	- Leave-one-out cross validation
Mean	- Mean reflectance factor spectra
MeanNorm	- Mean normalized reflectance factor spectra
NDVI	- Normalized difference vegetation index
NIR	- near-infrared part of the electromagnetic spectrum
OA	- Overall accuracy
p25	- 25th percentile of the height

p50	- 50th percentile of the height
p75	- 75th percentile of the height
p90	- 90th percentile of the height
PP	- <i>Pterodon pubescens</i>
PRI	- Photochemical reflectance index
PSRI	- Plant senescence reflectance index
REP	- Red-edge position
RF	- Random forest
ROC	- Receiver operating characteristics
SIPI	- Structure insensitive pigment reflectance index
SKE	- Skewness of the canopy height model
SLIC	- Simple linear iterative clustering
SR	- <i>Syagrus romanzoffiana</i>
SVM	- Support vector machine
SWIR	- Short-wave infrared
TPR	- True positive rate
UAV	- Unmanned aerial vehicle
VIS	- Visible part of the electromagnetic spectrum

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1 INTRODUCTION

Forests play an important role in biodiversity, carbon stocks, the water cycle, and feedstock, but they are rapidly being deforested. In Brazil, they are targets of illegal loggers or even converted to crops, pasture, and urbanization. Knowledge about the tree species of a forest is a fundamental information. Tree species recognition can be performed through fieldwork campaigns, but generally, this practice has limitations, since it is expensive and laborious because of the forest density and forest access, which can be far from roads and thus, it is a time-consuming task. Remote sensing, together with automatic analysis techniques, has become a prominent tool for tree species mapping. Since the '80s, research papers related to “forest” and “Remote Sensing” exponentially increased (WEB-OF-SCIENCE, [s.d.]) showing that forest researches are a trending topic.

Most of the previous studies related to tree species identification using Remote Sensing have been performed in forests in the North hemisphere (FASSNACHT et al., 2016). There is a lack of studies in forests such as the Brazilian Atlantic forest, which encompasses different ecosystems, such as mixed ombrophilous, dense ombrophilous, open ombrophilous, semideciduous seasonal, and deciduous seasonal forests (BRASIL, 2006). Sothe et al. (2019) studied a mixed ombrophilous forest whose floristic compositions and forest structure characteristics differ from those of other types of Brazilian Atlantic forest, especially the semideciduous and deciduous seasonal forests (BRASIL, 2006), which highlights the importance of studying them separately.

In addition, most studies have investigated well-developed forests or forests in which trees with different heights are spatially distinguished such as coniferous forests. Plots containing tree species in different successional stages and ages can present similar heights, and thereby, cause spectral mixing due to leaf mixture and the effect of neighborhood spectra because the number of emergent trees, i.e., trees that stood out from the canopy, is lower than the number of smaller trees. Notwithstanding the importance of monitoring mature forests, monitoring fragments that are in the initial or intermediary regeneration process is considered a key element in the connection of forest patches, and contributes to the maintenance of biodiversity (LIRA et al., 2012; RIBEIRO et al., 2009). Emergent trees are equally important when it comes to tropical forests. From its importance it is highlighted their use for the movement of primates, who also use the emergent trees to sleep (ALEXANDER et al., 2018) and because of its transpiration rate when considering the water cycle (KUNERT et al., 2017).

Bearing the Remote Sensing concept, Jensen (2007) defines Remote Sensing as the art and science of acquiring information without the physical contact with the objects. The information is extracted by the acquisition and interpretation of the reflected energy from the objects (JENSEN, 2007). Considering the vegetation as a target, the amount of reflected light depends on the leaves' content, such as pigments and structure (PONZONI; KUPLICH; SHIMABUKURO, 2012). The reflected light can be registered by different sensors, which can be classified according to its platform as orbital, aerial or terrestrial sensors. Satellite sensors and airborne passive and/or active sensors, combined with the use of field spectroscopy, provide valuable information for the identification of tree species (COLGAN et al., 2012; HEINZEL; KOCH, 2012; IMMITZER; ATZBERGER; KOUKAL, 2012; WAGNER et al., 2018; ZHANG et al., 2012). Besides, the use of unmanned aerial vehicles (UAVs) has become a powerful tool to acquire forest information (NEVALAINEN et al., 2017; OTERO et al., 2018; SOTHE et al., 2020).

UAVs enable fast information acquisition, and despite their constraints regarding the trade-off between resolution and coverage, they are low-cost alternatives for capturing information in areas that are endangered or need constant monitoring, such as mines or crops (COLOMINA; MOLINA, 2014; KANG et al., 2019; POPESCU et al., 2020; SHAKHATREH et al., 2019). UAVs can fly over many areas that are challenging for field data acquisition, such as water surfaces or dense forest areas. UAV missions can be quickly configured according to the user's needs. Furthermore, in the past few years, UAVs have been rapidly developed to fly for several hours; an example of such a platform is the fixed-wing Batmap II UAV, which can fly for more than 2 hours (NUVEM UAV, [s.d.]). UAVs can capture very high or ultrahigh spatial resolution data with ground sampling distances (GSD) ranging from centimeters to decimeters (AASEN et al., 2018; COLOMINA; MOLINA, 2014; PANEQUE-GÁLVEZ et al., 2014; SANCHEZ-AZOFEIFA et al., 2017) using small-format multispectral or hyperspectral cameras, such as MicaSense RedEdge-MX (MICASENSE, [s.d.]), Rikola hyperspectral imager (SENOP, [s.d.]), and Cubert FirefLEYE (CUBERT, [s.d.]). Beyond that, UAVs can acquire information of surface targets, such as trees, with high temporal frequency, which is a promising option in forest monitoring, since it can measure dynamic phenological behavior according to seasons and tree characteristics.

Besides the different platforms to acquire remotely sensed data, it is important to consider the need to interpret and label the registered information. This process is called as classification (RICHARDS; JIA, 2006). There are many methods to classify the data, where it

is highlighted the machine learning algorithms, which is a potential alternative to the traditional classification approaches (LARY et al., 2016). Santos et al. (2010) showed that genetic programming, a subset of the machine learning, presented better results to recognize coffee crops than using the maximum likelihood approach. Support vector machine (SVM) (MELGANI; BRUZZONE, 2004) and random forest (RF) (BREIMAN, 2001) are examples of machine learning algorithms that have been successfully applied to identify tree species in urban environments (LI et al., 2015), savannas (COLGAN et al., 2012), and different types of forests, including northern, boreal, temperate, and tropical forests (FERET; ASNER, 2013; FERREIRA et al., 2016; IMMITZER; ATZBERGER; KOUKAL, 2012; MASCHLER; ATZBERGER; IMMITZER, 2018; MATSUKI; YOKOYA; IWASAKI, 2015; WAGNER et al., 2018).

Moreover, efforts concerning the best features extracted to tree species classification is also highlighted. Spectral features comprised from the visible (VIS) to short-wave infrared (SWIR) region, texture, vegetation indexes, and structural features are among the most useful features to the tree species classification (BALDECK et al., 2015; DALPONTE et al., 2014; HEINZEL; KOCH, 2012; TUOMINEN et al., 2018). Textural and vegetation indexes can be extracted from the imagery information whereas structural features can be calculated from point clouds derived from aerial laser scanning (ALS), which can be used to obtain the canopy height model (CHM) of a forest (NEVALAINEN et al., 2017; SILVA et al., 2016). Besides, considering the vegetation context, relevant parameters can be extracted from multitemporal information. The differences in trees blossoming and defoliation depend on the season, weather conditions, and soil moisture. Consequently, the spectral response of crowns belonging to different tree species changes with the time. Although most of the previous studies conducted with seasonal/temporal information have not employed UAVs, they have shown spectral differences within tree species and reported whether the tree species classification was improved (CASTRO-ESAU et al., 2006; DEVENTER; CHO; MUTANGA, 2017; FERREIRA et al., 2019; HILL et al., 2010; IMMITZER et al., 2019; KARASIAK et al., 2019; KEY et al., 2001; LI et al., 2015; SOMERS; ASNER, 2014).

In this regard, considering that UAVs can fly over many areas acquiring fast information with high spatial resolution and temporally, the joint use of this information could be helpful to identify the tree species. However, at the same time, it would be challenging because all the variations within a tree crown would be recorded in the high spatial resolution of images. Differences in tree growth from one year/season to the next one can appear even

coregistering the images. Thus, methods to handle with such small variations would be needed, not to mention the bidirectional reflectance distribution function (BRDF) effects because of the sunlit variations and different crown geometries.

1.1 HYPOTHESIS AND OBJECTIVE

The hypothesis of this doctoral dissertation is based on the knowledge that tree species have different characteristics depending on the weather conditions, and the recent availability of UAVs, which can quickly acquire information and has been successfully applied in Northern forests to identify tree species. In this sense, the hypothesis is that tree species identification of a fragment from the Brazilian Atlantic forest can be improved by using temporal information acquired with sensors onboard UAV, integrated with structural data derived from ALS. Bearing the hypothesis, this doctoral dissertation aims to propose a new methodology to identify selected tree species belonging to the Brazilian Atlantic forest using temporal information acquired with sensor onboard UAV. Further objectives are to:

- Evaluate the spectral differences among the tree species;
- Evaluate the pixel-based and region-based classification approaches;
- Delineate the individual tree crowns (ITCs); and
- Identify the tree species.

1.2 INTERNATIONAL COOPERATION

This doctoral dissertation was developed under the framework of the international joint project called “*Unmanned Airborne Vehicle - Based 4D Remote Sensing for Mapping Rain Forest Biodiversity and its Change in Brazil (UAV_4D_Bio)*”. This Project is a partnership between researchers from São Paulo State University (UNESP), and Finnish Geospatial Research, part of the National Land Survey of Finland. UAV_4D_Bio project was supported in part by The São Paulo Research Foundation (FAPESP) (grant number 2013/50426-4) and in part by the Academy of Finland (AKA) (grant number 273806). The project aimed to develop technologies to map and detect biodiversity changes in Brazilian Atlantic forests.

1.3 CONTENT

Section 1 introduced the objectives of the doctoral dissertation. Section 2 shows the study area, which is used in all experiments. Section 3 presents the Remote Sensing data used, i.e., the ALS and the hyperspectral imagery data, how they were acquired and processed. In Section 4 the developed methodology is described. Section 5 shows the results and discussion from the performed experiments. The first experiment (Section 5.1) is based on the papers of Miyoshi et al. ([s.d.], 2020) which show and evaluate the spectral differences between and within-species of trees belonging to the Brazilian Atlantic forest. The second experiment (Section 5.2) is an improvement of the work from Miyoshi et al. (2019), where the comparison of the pixel-based and region-based classification approaches when using the mean spectra and the mean normalized spectra as features are performed. Section 5.3 shows the third experiment, which is based on Miyoshi et al. (2020). This experiment evaluates the usefulness of multitemporal spectral information to identify tree species. Section 5.4 compares the superpixels and watershed methods to automatically delineate the ITCs in each imagery data. The last result is presented and discussed in Section 5.5. In this section, tree species identification using the findings from previous sections (5.1 to 5.4) and using additional set of features (vegetation indexes, texture, and structural features) is carried out. Finally, Section 6 shows the conclusion, contribution and recommendations of this doctoral dissertation.

6 CONCLUSION

The objective of this doctoral dissertation was to develop a methodology to improve the tree species identification and to evaluate whether the multitemporal information could improve the tree species identification. Hyperspectral images were acquired by Rikola camera onboard an unmanned aerial vehicle (UAV) over an area of the Brazilian Atlantic forest having great species diversity and different successional stages. Further objectives were the evaluation of spectral differences, the automatic ITC delineation and the combination of different temporal features to the classification task.

The use of mean normalized spectral features showed a better performance than the non-normalized features in classifying tree species. Even applying the radiometric block adjustment, the pixel normalization indeed reduced the differences in shadowed and sunlit pixels and thus, increasing the tree species separability. Radiometric block adjustment was equally important and highlighted. Different cloud covering density affects the spectral response of samples from the same tree species because the incident light is different and the method to acquire the spectral response of the images is the empirical line method. The importance of the radiometric block adjustment should be emphasized because the high spatial resolution images show detailed information of the tree crown and are subject to the anisotropy effects when not properly corrected.

Furthermore, the region-based approach presented the best results when compared with the pixel-based approach. Temporal spectral information improved the performance of the random forest classifier for three of the eight tree species analyzed, indicating that better accuracy could be obtained when using temporal spectral information. Separated analysis of single-date datasets showed that the weather pattern directly influenced the classification performance of some of the tree species. The analysis of datasets from several years of the same season showed that differences in weather conditions in different years resulted in some changes in the species spectra and these changes were useful for differentiating some of the selected tree species.

Automatic ITC delineation was shown to be a highly complex task. The lack of a standard tree shape, the high forest density, its different development stages, and the similarity of heights directly affected the automatic ITC delineation, are weakness in all techniques for tree species identification. Considering the *Syagrus romanzoffiana*, this task is even more challenging. Its regular shape requires smaller superpixels, but it may cause the over-segmentation of wider crowns. Both assessed methods did not achieve an F-Score value

higher than 70%. However, the superpixels application provided similar AUCROC values when compared with the use of manually delineated polygons.

The knowledge of the different tree heights was essential as well as the use of the spectral information. The use of spectral differences was crucial to deal with the different spatial positions of the ITC over the years. Concerning the spatial position of the trees, the initial EOP information from the camera GPS was important to geometrically produce the mosaic of hyperspectral images. There is a challenge to introduce GCPs inside of the forest because of its high density. Furthermore, even though the georeferencing of the three datasets was carried out in a single process there appeared small geometric differences as expected.

Weather conditions directly affect the tree species bloom or defoliation because some species were better identified when using all temporal data, such as *Hymenaea Courbaril* and *Inga vera*. Further, the use of vegetation indexes is of fundamental importance. They were shown to provide similar results as the use of normalized features. The use of textural features was shown not to be relevant in our study area due to the high spatial resolution of the images, which might result in the textural features to be noisy and thus, not producing the best results. A similar analysis is applied to the use of structural features because the similar tree heights did not improve the tree species identification. Finally, despite the RF appeared to be insensitive to the number of attributes, the results showed its sensitivity to noisy features, as pointed out by other researches also. When using all textural, spectral, vegetation indexes and structural features, the results were worse than when using only the spectral features or the vegetation indexes.

To the best of our knowledge, this is the first work to use hyperspectral UAV images acquired over several years to classify the highly diverse Atlantic Forest. Improvements should be applied regarding the number of samples per class and the seasonality for data acquisition. For some species, finding a higher number of tree samples is quite challenging, such as for *Aspidosperma polyneuron* which only had three individual samples identified in the field and was removed from the classification experiments.

6.1 CONTRIBUTIONS AND FUTURE WORKS RECOMMENDATION

As final remarks of this doctoral dissertation, it is highlighted the use of temporal information for tree species identification. Despite the images were not acquired in different seasons, it was possible to improve the identification of at least three tree species. The use of

an innovative lightweight hyperspectral sensor acquiring information from the VIS to the NIR over a small fragment of the Brazilian Atlantic forest in one of the novelties of this research. The multitemporal data analysis was a very challenging task because it involved not only the data acquisition, but the understanding of how to process and analyze all data together as well as the comprehension of forest components and behavior over the years. Another point to be reminded is the use of an area still not well-developed with similar tree heights surrounded by crops. Moreover, it was a protected area inside an ecological station, being required authorization from the environmental agencies to collect the data. It is worthy of mention the need for suitable forest management even when protected by laws. Therefore, the reported results are of great importance to decision-makers and can be used as key information to monitor this fragment.

Bearing the recommendations, there is the use of a higher number of samples and tree species. Despite being a small fragment, a higher number of samples per tree species and the use of a higher number of classes can improve the monitoring task of this forest. The lack of samples could affect the classification results because of the unbalanced number of samples. Image acquisition in different seasons is another recommendation. Images acquired during Spring, Summer or Autumn can show higher discrepancies in the ITCs because of the different aspects of the soil moisture, weather and pigment content in each ITC. The use of a higher number of tree characteristics in different seasons could improve not only the tree species identification but also follow its evolution, consequently providing information to monitor the degree of forest restoration and conservation.

The employment of recent deep learning approaches is encouraged. They are an emergent approach from the machine learning field being the state of the art of the classification methods in Remote Sensing. When using deep learning approaches, increasing the number of samples will be of higher importance, since the application of these algorithms requires a larger number of samples to properly model the classifiers. In the case of our study area it is possible to identify the *Syagrus romanzoffiana* because, during fieldworks and image interpretation, hundreds of samples were recognized. Nevertheless, the use of different machine learning algorithms is also suggested such as the SVM and the Multilayer perceptron.

Considering the assessed features, there is the recommendation to apply different criteria to calculate the features importance and their application in classification experiments. Regarding the textural features, there is the use of different window sizes, the use of non-

normalized pixel values, the use of different spatial resolution imagery and the use of other textural features not used in this doctoral dissertation. Regarding the vegetation indexes, different vegetation indexes assessment is encouraged. Hence, there is a recommendation to evaluate multispectral images in the multitemporal form.

Finally, as a final recommendation, there is the application of the developed methodology in well-developed areas or even in different forest areas, such as the remaining types of Atlantic Forest, the Amazon forest or the Northern forests.

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