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COMPARING METHODOLOGIES FOR MAPPING THE AFFORESTATION OF PUBLIC STREETS IN CHAPADA NEIGHBOURHOOD, USING PLÉIADES IMAGES*

COMPARAÇÃO ENTRE METODOLOGÍAS PARA MAPEAMENTO DA ARBORIZAÇÃO DE VIAS PÚBLICAS DO BAIRRO CHAPADA, PONTA GROSSA-PR, COM USO DE IMAGENS PLÊIADES

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ABSTRACT

Knowing about the arboreal heritage present along the city's roads is a challenge. Acquiring this information requires personal experience, time, and investing financial resources in the field. It is not always possible to carry out counts in situ, so different techniques are implemented. Pixel-oriented methodologies (supervised, unsupervised classification) are used, along with NDVI segmented classification to gain prior knowledge of the roadside tree heritage, and to map and quantify them. The Chapada neighbourhood in the city of Ponta Grossa-PR (Brasil) has been previously mapped using the visual analysis methodology. The count of 3101 trees on 228 roads was used as a reference to compare with the three aforementioned methodologies. A soil classification was carried out using the three methodologies to find out about the presence of roadside vegetation. In the case of NDVI, it was possible to show 56.00 % similarity with the trees obtained in the visual analysis; the unsupervised classification obtained a map of 91.19 %, this being the largest number of trees counted, and the supervised classification figure was 82.68 %.

Keywords: Unsupervised classification, NDVI, supervised classification, urban forest.

RESUMO

O conhecimento do patrimônio arbóreo presente nos caminhos da cidade é um desafio. A aquisição dessas informações requer experiência pessoal, tempo e recursos econômicos colocados no campo. Em alguns casos não é possível realizar conta *in situ*, por esta razão são implementadas técnicas diferentes. as metodologias orientadas a pixels são utilizadas (classificação supervisionada, não supervisionada), junto com a classificação segmentada NDVI, para obter um conhecimento prévio do patrimônio das arvores, junto com o mapeio e quantificação delas. O bairro Chapada da cidade de Ponta Grossa-PR (Paraná, Brasil) conta com um mapeio prévio utilizando a metodologia de análise visual. Usou-se como referência o conteo de 3101 árvores em 228 vias para comparar com as três metodologias mencionadas anteriormente. Se realizou uma classificação de solos utilizando as três metodologias, para conhecer a presença de vegetação nas vias. No caso do NDVI se consegue-o mostrar um 56.00 % de similitude com as árvores obtidas na análise visual, a classificação não supervisionada obteve um mapa de 91.19 % obtendo a maior quantidade de árvores contadas, e a classificação supervisionada 82.68 %.

Palavras-chave: Classificação não supervisionada, NDVI, classificação supervisionada, floresta urbana.

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Introduction

The urban forest, an integral facet of urban spaces, plays a crucial role in mitigating the adverse impacts of global industrialization and residential expansion (Biondi, 2008). Its multifaceted functions, spanning ecological, aesthetic, and social dimensions, are consistently underscored (Biondi, 2008). Almeida (2009) further expounds on the advantageous outcomes of urban vegetation, elucidating its contributions to air purification, pollution reduction, and gas recycling through the process of photosynthesis.

A deeper exploration into the realm of urban vegetation emphasizes the imperative nature of tree planting, preservation efforts, and an intricate analysis of endemic, native, and exotic species, particularly along city streets. This emphasis is articulated by Biondi (2008), highlighting that the presence of vegetation along urban thoroughfares establishes crucial connections with the broader urban populace. Urban vegetation, by its very essence, nurtures a symbiotic relationship with open spaces, green areas, and forest reserves, thereby significantly contributing to biodiversity (Santos, Lisboa, and Carvalho, 2012).

Effective urban tree planting strategies require a profound understanding of the specific characteristics and environmental conditions prevalent in distinct zones within a city. To achieve this understanding, comprehensive tree inventories in each urban area become imperative. However, the execution of fieldwork, while invaluable, brings along inherent challenges, including additional costs in terms of time and the necessity for specialized personnel. In response to these constraints, an alternative approach involves the deployment of remote sensors for tree censuses, an emerging trend in the field (Ardila *et al.*, 2011). Nevertheless, as with any methodology, limitations arise, encompassing spatial resolution issues and the nuanced spectral differentiation between tree canopies and other vegetation surfaces within an image area (Pouliot *et al.*, 2002).

To overcome the challenges posed by remote sensors, Ardila (2012) advocates for the inclusion of image context – defined as any information characterizing the situation of an entity – as an indispensable element for feature recognition. This perspective aligns with the evolving landscape of technological solutions aimed at enhancing the precision and scope of urban tree mapping efforts.

In light of this context, the primary aim of this article was to embark on a multifaceted exploration, delving into a comprehensive comparative analysis aimed at meticulously mapping and quantitatively assessing the trees embellishing the sidewalks within the Chapada neighborhood in Ponta Grossa - PR. This ambitious undertaking unfolded through the adroit application of three distinct methodologies: NDVI segmentation, unsupervised classification, and supervised classification. By intricately weaving together these distinctive approaches, the research sought to unravel the intricacies of urban tree distribution, offering a nuanced perspective on the dynamic interplay between vegetation and the urban environment.

Delving into theoretical references unveils a rich tapestry of studies focused on mapping trees with the utilization of satellite images and digital processing techniques. These studies, as exemplified by LI *et al.* (2017), explore the nuances of supervised and unsupervised classification methodologies, coupled with the application of the Normalized Difference Vegetation Index (NDVI) for a nuanced understanding of vegetation dynamics.

A seminal study by Leckie *et al.* (1999) conducted in Vancouver, Canada, employed supervised classification alongside field inventory data and high-resolution satellite images. This comprehensive approach facilitated an understanding of tree planting patterns in urban areas, considering factors such as height, health, and tree species.

Further afield, studies conducted in Nanjing, China, and the Netherlands (Ardila *et al.*, 2011) harnessed remote sensing techniques, satellite images, and object-oriented classification methodologies to map and analyze trees. These endeavors encountered challenges related to shadows and the recognition of trees within groups, underscoring the complexity inherent in urban vegetation mapping.

A Shanghai-based study featuring the utilization of the LIDAR system (Light Detection and Ranging) demonstrated its efficacy in capturing objects in three dimensions. Despite its capabilities, challenges persist in accurately discerning trees based on their morphology, as articulated by Bin *et al.* (2013). The study showcased the utilization of Mobile Laser Scanning (MLS) and a voxel-based classification method, achieving remarkable precision in the recognition and classification of trees.

The continuous integration of remote sensing tools for urban tree planting, cartographic information preparation, and planning studies is acknowledged. These tools, as exemplified by the study cited by Xu *et al.* (2020), provide invaluable spatial data for the identification of urban vegetation with high accuracy, particularly in a rapidly evolving urban landscape.

In synthesizing these diverse studies and methodologies, it becomes apparent that the quest for effective urban tree mapping strategies involves a multifaceted approach, leveraging technological advancements, and addressing inherent challenges with ingenuity. As urban spaces continue to evolve, the amalgamation of theory and practical methodologies serves as a beacon guiding the way toward sustainable urban forestry practices and comprehensive tree inventories.

The primary aim of this article was to elucidate a comprehensive comparative analysis for the meticulous mapping and quantitative assessment of trees adorning the sidewalks within the Chapada neighborhood in Ponta Grossa - PR. This endeavor was achieved through the adept implementation of three distinctive methodologies, namely, classification via NDVI segmentation, unsupervised classification, and supervised classification.

Material and methods

The Chapada Neighborhood is located in the northwest part of Ponta Grossa, with an approximate area of 17 km^2. It was chosen because it has a large percentage of vegetation, which contributed to the use of methodologies for the elaboration of the objective of this work (fig. 1). Tadenuma (2019) mapped the trees in the Chapada neighborhood, using the visual analysis methodology, with 3101 trees being mapped on 208 roads, with greater concentration in the north and east of the neighborhood, which correspond to the most urbanized areas.

The available database was composed of: digital files of the street city and perimeter of the neighborhood, vector information of the mapping of trees from visual analysis (Tadenuma, 2019), satellite image of the commercial sensor Pléiades (geometric correction included). The images have a spatial resolution of 50 cm in the panchromatic band and 2 m in the multispectral bands.

Three methodologies were used for mapping street trees: classification by NDVI segmentation, supervised classification and unsupervised classification, Procedures by ArcGIS 10.5 software. Under licensing provided by the Laboratory of Environmental and Social Studies (LAESA)

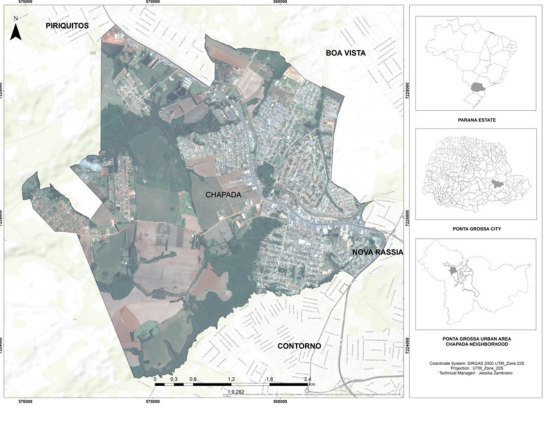

Fig. 1 - Location of Chapada Neighbourhood. (Source: Tadenuma, 2019).

Fig. 1 *- Localização Bairro Chapada (Fonte: Tadenuma, 2019).*

at the State University of Ponta Grossa. The procedure was performed with the PCI Geomatic 2018 software. (University of Coimbra), it was based on the union of the spectral bands of the Pléiades image by performing a UNB-Pansharp transformation generating a better spatial resolution and spectral resolution.

Normalized Difference Vegetation Index From the Chapada neighborhood

The calculation of the NDVI was carried out for the entire neighborhood, with the purpose of differentiating between vegetation and non-vegetation. The formula used for the index calculation is (Campbell and Wynne, 2002):

$$NDVI=((NIR-RED))/((NIR+RED))$$

WHERE NIR= Near Infrared

RED: Visible Red

Six land-use classes were selected (IBGE, 2006), with the following intervals: urbanized area (-0.57 to 0.13), uncovered area (0.14 to 0.25), grasslands (0.26 to 0.36), crops (0.37 to 0.49), field (0.5 to 0.61), and forest area (0.62 to 0.96).

Only the vegetation layer was subsequently used, to later establish, through a reclassification of values, within this vegetation that was afforestation.

An influence buffer of 10 m was established from the center of the urban street, in order to select this area, since the trees are planted linearly along the sidewalks. The classes of use, with the presence of vegetation, were redefined as follows: Uncovered area, grasses, forestry, trees, forest area. Among these classes, the classes of pasture, trees and forest areas were effectively used, since they were the classes that contained the possibility of the presence of trees. Subsequently, the information obtained as a raster was converted to a vector format of the polygon type, in order to map and quantify the trees.

Behavior of spectral bands for classifications.

To conduct both unsupervised and supervised classifications, a mask outlining the Chapada neighborhood perimeter was extracted from the Pléiades image. Implementing the filter to identify elements present in the image, this method is known as Red, Green, and Blue (RGB) (Audebert *et al.*, 2018). A false color composition (with band 1 in the red channel, band 4 in the green channel, and band 3 in the blue channel) was generated to accentuate vegetation features.

Understanding pixel behavior within each class was crucial for contextualizing the objects to be identified. The process involved the selection of 50 training area polygons for each of the six classes utilized in the NDVI calculation.

During the buffer analysis, a noticeable lack of separability among classes was observed, posing challenges in classification. Notably, the buildings class exhibited clear separability in all four bands. Regarding the trees and grass classes pertinent to this study, separability between the two was discernible across all bands. However, pixel mixing with other classes posed challenges in accurate classification. Scatter diagrams, particularly with band 4 (infrared), were instrumental in highlighting the separability of these classes.

Unsupervised classification

The method allows to carry out internal iterations of image characteristics automatically, without the need to establish training areas, therefore it does not require decision criteria by the professional. Basically, it acts in areas where there is no prior knowledge, generating a number of categories that will be determined by the interpreter (Chuvieco, 2000).

The unsupervised classification was carried out in the entire area of the Chapada neighborhood, with the objective of knowing how the classes behaved. The results to be considered were those, from the classification performed for a 10m buffer on the roads. The algorithm used was ISODATA and the values provided for the software were, the number of classes (= 6), the number of iterations (= 5). This last value was chosen after a test in which the number of interactions where the value was increased than those provided default by the ARCGIS 10.5 software.

The unsupervised classification is a process used to preliminarily know the behavior of the classes, this methodology does not work with satisfaction in large areas and requires a visual review to corroborate the information and detect the pixels that were classified within a class without belonging to that. In the same way, it is possible to extract the trees located on the roads. In the same way, it is possible to extract the trees located on the roads.

To gain a preemptive understanding of the optimal distribution of classes within the neighborhood, the initial step involves implementing a 10 m buffer using the NDVI methodology and unsupervised classification. Subsequently, this process allows for the extraction of a mask applied to the multispectral image, enabling a targeted classification exclusively for the roads within the Chapada neighborhood.

In the same way that it was carried out in the procedure of the two methodologies, the raster information obtained through the classification of the roads, became vector information generating polygon entities. This obtained layer had to be purified by removing the polygons with areas smaller than (1 m^2) The way in which this range was determined was through the visualization of the observer, because using a greater range of (1 m^2) valuable information was being withdrawn. In this way the centroids of the resulting polygons will be calculated and compared with the work of (Tadenuma, 2019).

Classification supervised

It is used to perform a quantitative analysis of the data provided by the image, based on a series of suitable algorithms to recognize the pixels that represent the types of land cover (Richards, 2013; Centeno, 2009).

The supervised classification began with image segmentation, to observe the clustering of pixels with the same spectral behavior and to obtain true object recognition, with a RGB 1 4 3 (G, NIR, R) composition. The supervised classification was performed using the maximum likelihood method by (ARCGIS, 10.5). Later, using the 10 m buffer already made in the NDVI methodology and unsupervised classification, this mask was extracted for the multispectral image, to carry out the classification only for roads in the Chapada district.

Accuracy Assessment

With the results obtained through the use of the three methodologies, an evaluation of the classifications is necessary. Each classification must be evaluated by its accuracy. Congalton (2004) recommends measures of reliability and suggests three ways to obtain the accuracy of the classification process:

- Comparison of the classification with other sources;
- Study the reliability of the classification of training areas;
- Select some verification areas with true ground cover.

There are simple methods to calculate the differences between the data that are considered reliable or the ones that were taken with a process in the field and the results obtained through the classifications. The processes can be statistical, obtaining a numerical error, however this cannot be observed on the map, although the result is a first approximation to the imprecision.

Similarly, you can find the method to classify training areas, in order to verify if they fit in the defined classes, creating the error matrix. To know the accuracy of the map, test areas must be established, that is, areas on the real terrain and then made the comparison.

These areas must be independent of the map, the ideal is to carry out a classification in the field and carry out a study of the information before making the classification (Agyemang, *et al*., 2011). However, the calculation of the error matrix of the present study was carried out, taking as real areas, the training areas taken directly from the image, since a fieldwork was not possible.

The error matrix must have a size of n * n, in which its columns and lines correspond to an equal size: the lines are the reference class and the columns are the categories obtained through the classification (Congalton, 2004; Moreira, 2007).

The following flowchart will summarize the methodology used, as depicted in fig. 2.

Results

It was determined that the processes of converting pixels to polygons should be replicated in any methodology, as the omission of this step could introduce biases into the results. Similarly, the need to eliminate additional information during this transformation to prevent the introduction of biases in the obtained results was emphasized. Through this transformation, additional information was acquired—data not pertinent to the study—necessitating a subsequent refinement process (fig. 3). Following this, the centers of each polygon were calculated and compared to the results obtained through visual analysis, with the goal of identifying potential disparities in capture.

NDVI mapping

The main objective of the NDVI generation is to obtain discrimination based on values, and to closely observe what vegetation is and what is not. NDVI was calculated for the entire Chapada perimeter (fig. 4), with the objective of differentiating the vegetation and non-vegetation classes present in the neighborhood Between the values -0.51 and 0.13 no vegetation was observed, even with the latter being positive values. The standard deviation was 0.21 and the average was 0.4, which indicates that data has significant variability, so it is not easy to identify pixel homogeneity.

The next step was to apply the 10 m buffer from the center of the lanes (fig. 5), the distance was selected by means of tests, the first probe was 5 m, from which it was observed that the majority of trees obtained by means of analysis visual are not located inside the buffer.

The second test was with an 8m buffer, from which it was observed that it included the majority of trees also in the log including them all. So, the conclusion was

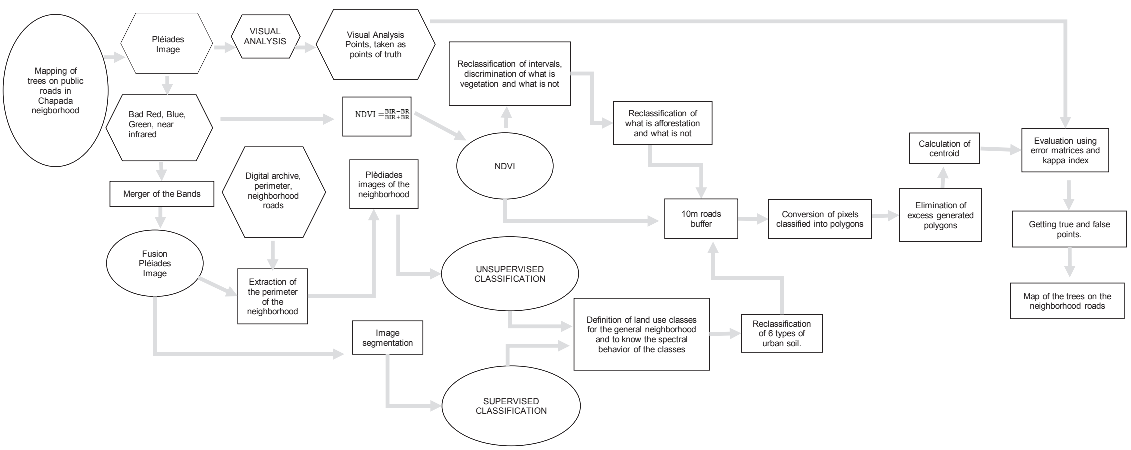

Fig. 2 - Methodological flowchart.

***Fig. 2 -** Fluxograma Metodológico.*

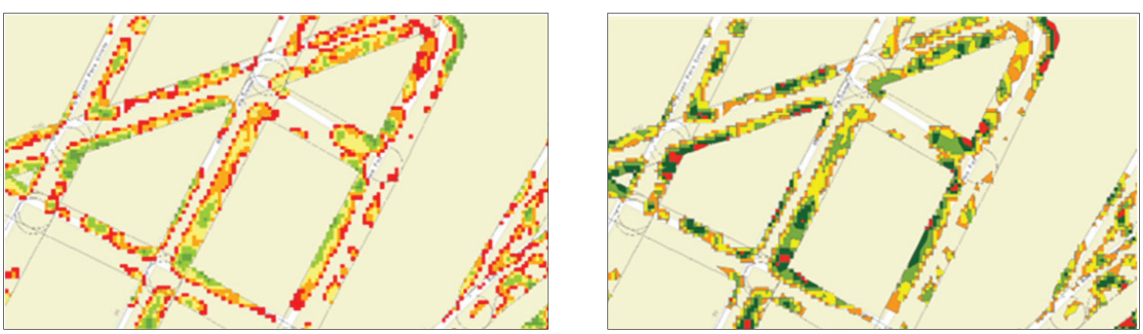

Fig. 3 - Conversion of pixels to polygons.

***Fig. 3 -** Conversão de pixels em polígonos.*

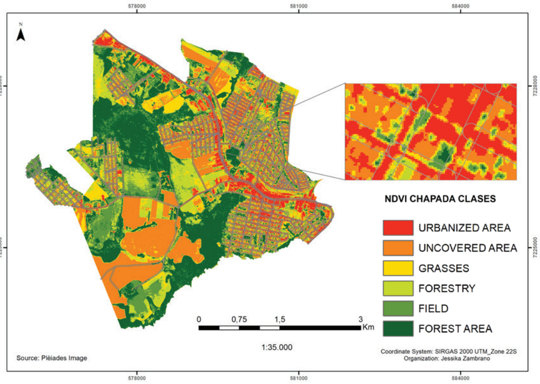

Fig. 4 - NDVI of Chapada neighbourhood - Ponta Grossa - PR.

***Fig. 4** - NDVI bairro Chapada Ponta Grossa - PR.*

reached that the 10 m buffer would be a convenient distance, even if it contained the trees in their entirety, but the majority of them were inside, and increasing the distance would include extra information that could hinder the mapping process.

To obtain only the intervals that contained the classes where there was possibly the presence of trees, only the following classes were selected: Forestry, Field and Forest Area. The NDVI contains raster type information and to perform the counting of the trees the information must be vector type, the software allows that conversion, by means of the tools, converter raster polygon. Consequently, when obtaining the results, extra information was also obtained being necessary that the information be the debugged.

The way to clarify the information, was through the calculation of areas, removing the less than 1 m^2 performing a check to the image using visual analysis again (fig. 6), to finally apply the with calculation of the centroids of each polygon and obtain the trees.

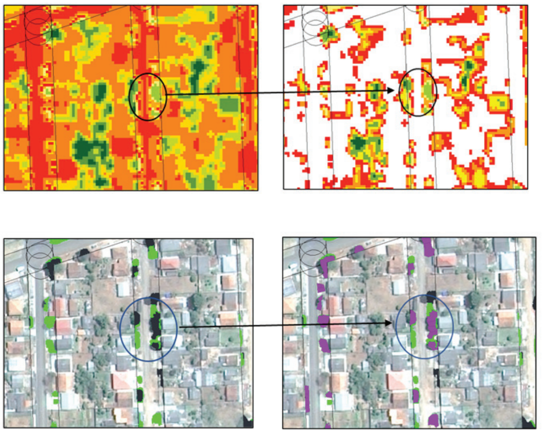

Fig. 6 - Expansion of the region showing the removal o extra polygons.

Fig. 6 - Expansão da região mostrando a remoção de polígonos extras.

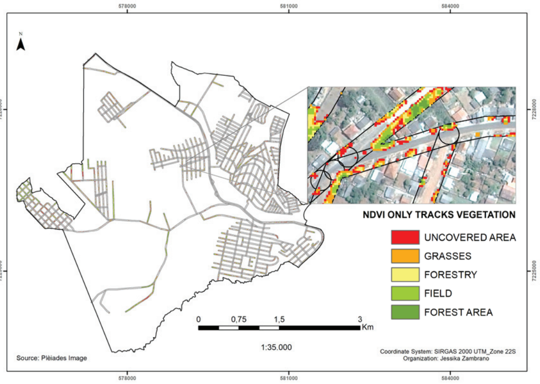

Fig. 5 - Vegetation included in the urban streets - Chapada neighbourhood.

***Fig. 5** - Vegetação incluída nas vias urbanas - Bairro Chapada.*

The number of trees extracted for the neighborhood with the NDVI was 1680 trees, well below the values indicated by Tadenuma (2019). These results can be given because the spatial resolution was not the same as the panchromatic image, because the NDVI was calculated with multispectral bands individually, which have a spatial resolution of 2 m (fig. 7).

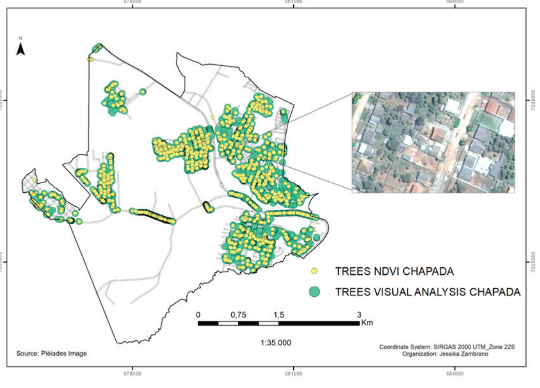

Fig. 7 - Mapping of trees by visual analysis and NDVI of the Chapada neighbourhood.

Fig. 7 - Mapeamento de árvores por analise visual e NDVI do Bairro Chapada.

The mapping with the application of the NDVI calculation corresponded to 56.00%, that is, half of the trees obtained by visual analysis, which were 3101 trees.

Image segmentation

Segmentation of a satellite image before classification is employed to enhance the accuracy and efficiency of the classification process. Segmentation divides the image into homogeneous regions based on features such as texture, color, and shape. This approach enables the grouping of pixels with similar characteristics into larger, more coherent areas, creating meaningful and distinct regions. By applying segmentation prior to classification, the identification of patterns and discrimination between different objects or terrains are facilitated. This optimization improves the accuracy of classification, as the segmented regions represent more coherent units for analysis, allowing for a more precise interpretation of satellite imagery. (Malik *et al.*, 2023)

Selected, six classes were defined for the buffer established from the streets as follows: roads, trees, grass, uncovered areas, and buildings. In addition to the training areas, dispersion diagrams of histograms were generated, providing an approximation of the separability of the classes (fig. 8).

In the case of the trees and grass classes relevant to this study, in all the bands it was possible to observe a separability between the two, however the mixture of pixels with the other classes made it difficult to assign pixels in the classification. Another way to highlight the separability of the classes was through the scatter diagrams, in which the band 4, being the infrared band, highlighted the two classes in question more easily (fig. 8).

In order to know the behavior of the classes in the spectrum, another image was made (fig. 9) and based on their statistics. With the information obtained, the behavior of the pixels in each of the bands can be observed.

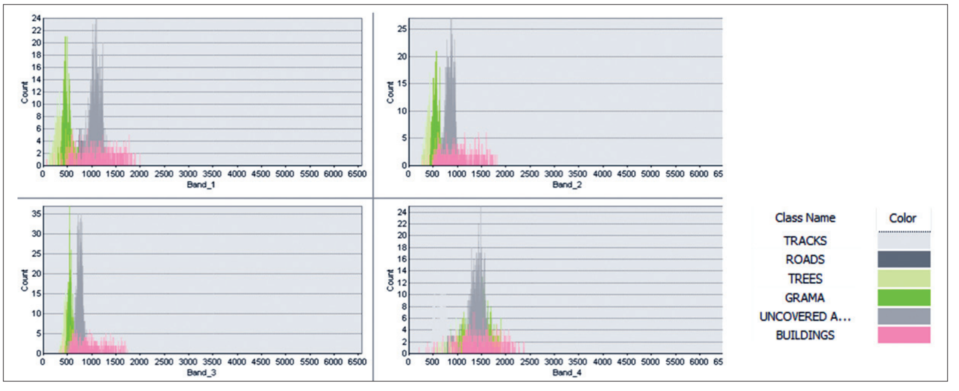

Fig. 8 - Histogram and diagrams of the road classes.

Fig. 8 - *Histograma e diagramas das classes de vias.*

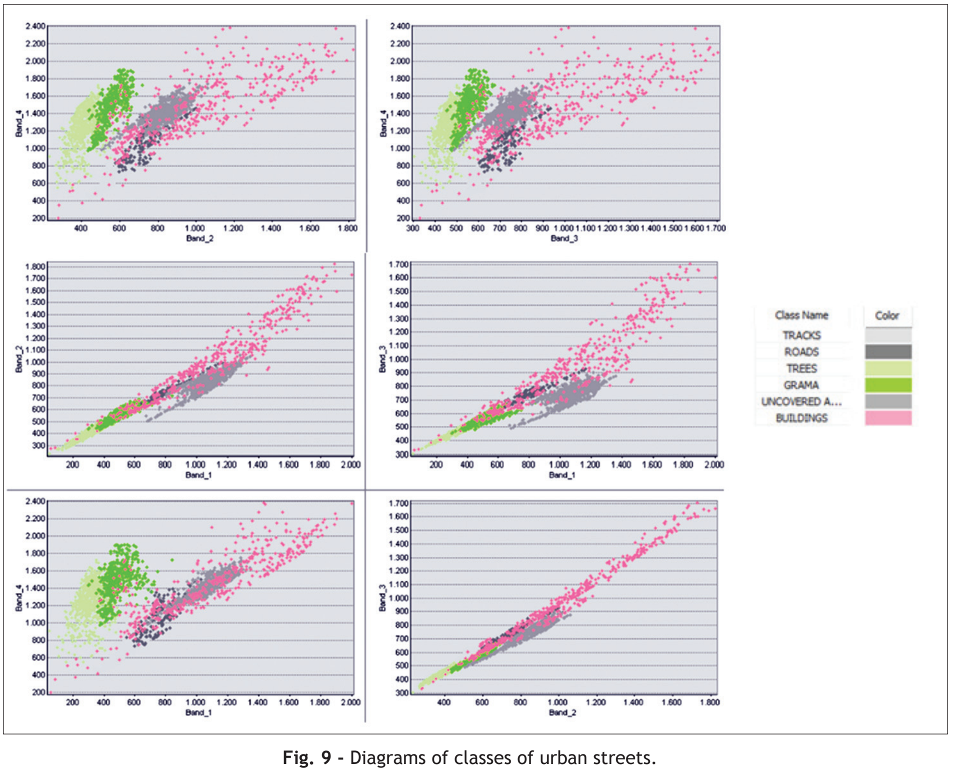

Fig. 9 - Diagrams of classes of urban streets.

Fig. 9 - *Diagramas de classes de vias urbanas.*

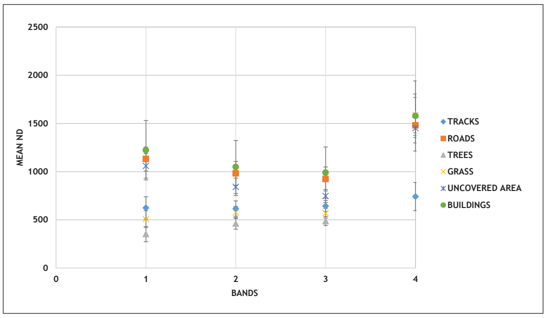

Fig. 10 - Behaviour of digital levels in spectral bands.

Fig. 10 *- Comportamentos dos níveis digitais nas bandas espectrais.*

The tracks class, in band 1, has a low separability, presenting a mixture with the gram class, in the same way, in band 2 and 3, already in band 4 a separability can be observed. The roadway class had a separability in band 1, 2, 4, however in band 3 it had a mix with the uncovered area class. Unlike the class trees which had a high separability in band 4, which facilitated the classification. In the case of the gram class, it had a low separability in the 4 bands, resulting in a difficulty to perform the classification, having a mixture of pixels with the class roads. The discovered area class presented a separability in band 3, but in the other bands it had a mixture with the building and roadway classes. Already for the class buildings had a high separability in bands 2 and 3, presenting a mixture with the class area discovered and grass.

Unsupervised Classification Mapping

The unsupervised classification for the Chapada neighborhood was carried out with the purpose of observing the behavior of the classes, but the results considered were those based on the classifications made for the 10m buffer area applied to the tracks.

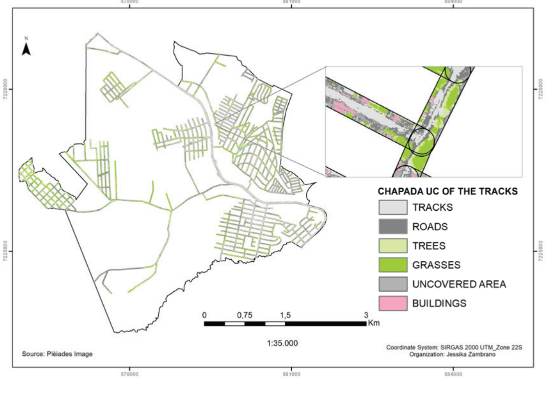

Fig. 11 - Unsupervised classification of roads in the Chapada neighbourhood.

Fig. 11 *- Classificação não supervisionada das vias do bairro Chapada.*

This classification was used to assess the results of the tree mapping. This method when used over large areas requires a visual review to corroborate the identified information, which can inappropriately group pixels into classes. For the case under study, it was possible to extract the trees located on the roads (fig. 11). The mapping with the unsupervised classification application corresponded 2828, that is, 91.19% of trees obtained by visual analysis.

Supervised Classification

It consists of making a classification by pixel, delimiting the pixels with the same spectral behavior, but it is possible that a decrease in precision may be presented when pixels of heterogeneous digital levels are found, which occurs in most studies.

One of its main drawbacks is the failure to consider mixed pixels representing two or more layers, simultaneously, and the pixel size exceeding that of the object, this limitation can be addressed by utilizing high-resolution images. Hao, *et al*. (2021).

For the classification of the Chapada neighborhood, it was decided to perform the supervised classification of the coverage in the whole neighborhood, in order to have a prior knowledge of the distribution of said coverage. To perform this classification, the segmented image was used, in order to group the pixels with the same spectral behavior and obtain a successful recognition of the objects in the image.

The supervised classification of the neighborhood was carried out using the maximum likelihood method; the visual analysis of the tests was carried out with tools belonging by ArcGis 10.5 software. This allowed us to observe if the algorithm had an adequate behavior to perform the classification. It was made a comparison with the main component method and a low grouping of pixels was observed leaving a classification similar to the image display.

For the realization of the supervised classification, the same classes as the previous methods were chosen, with the difference that the training areas were performed with the segmented image, but using the same methodology used in the methodology of the unsupervised classification (fig. 12).

Applying again the 10 m buffer to the segmented image, which corresponded only to the area of influence, training areas were extracted and then a classification was carried out only for this range. In addition, it is possible to observe the behavior of the pixels through the histograms and scatter diagrams, in which it was feasible to verify the separability in bands 1 and 2 and in band 3 the spectral behavior of the pixels was similar.

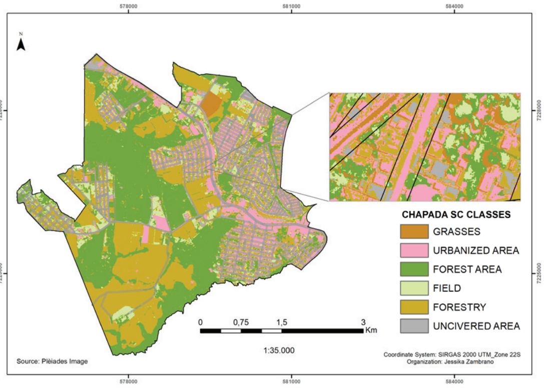

Fig. 12 - Supervised classification of the Chapada neighbourhood.

Fig. 12 - *Classificação supervisionada do bairro Chapada.*

Evidently, the separability was greater than in the non-segmented image (fig. 13). The classes, grass and trees, had a separability in bands 1 and 2, helping in the classification. With respect to the scatter diagrams, there was a greater difficulty in recognizing the behavior, however, it can be inferred that in bands 1 and 2, the classes of grass and trees had a different spectral behavior so that the classification can have a concordance regarding reality.

Using statistics, other images was constructed (fig. 14), where it is possible to visualize the digital levels of each class and the behavior of the classes in the three spectral bands of the image.

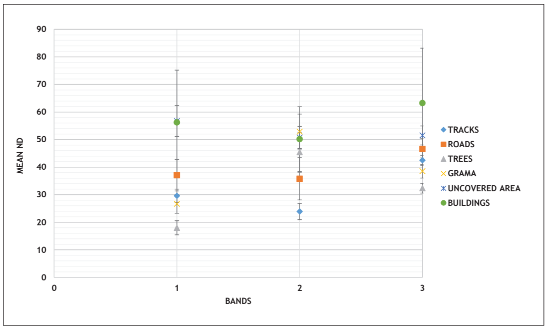

Fig. 14 - Behaviour of digital levels in the spectral bands, segmented image.

Fig. 14 - *Comportamento dos níveis digitais nas bandas espectrais, imagem segmentada.*

In each of the bands it was possible to observe a separability that helped in tCnted only in the band 2 a mixture of pixels with a similar spectral behavior, in the remaining bands was it is possible to perceive a separability, which indicates that it was possible to

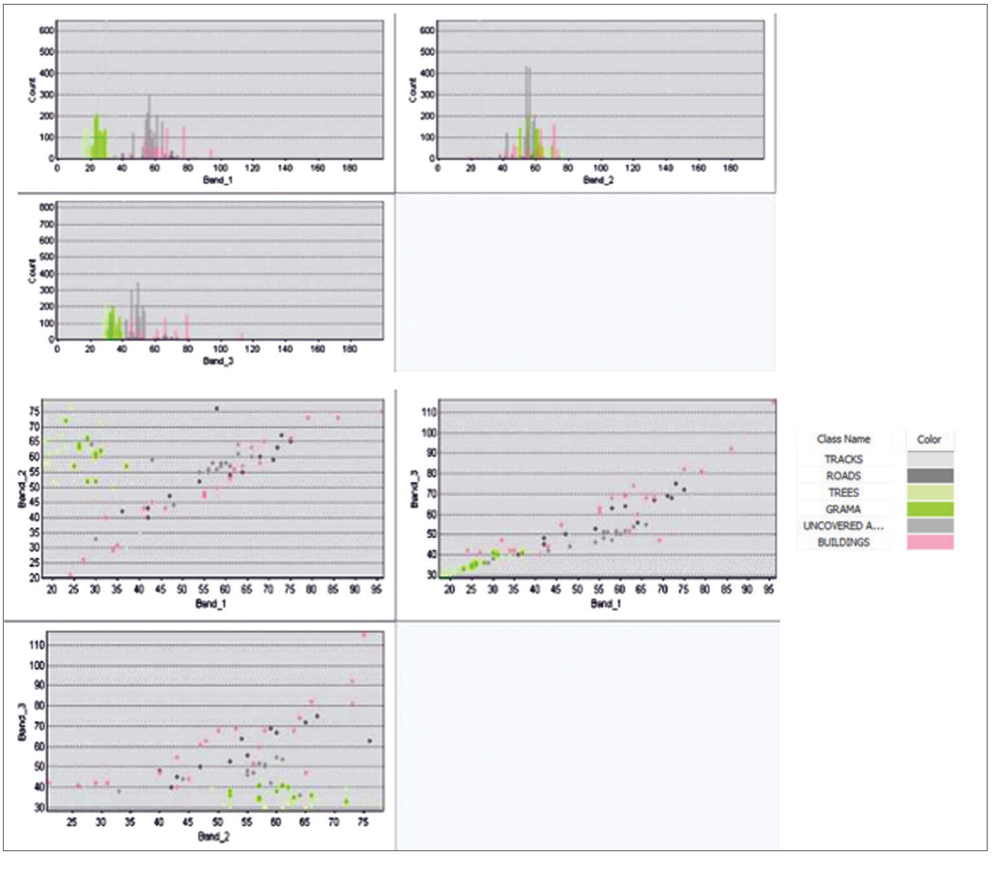

Fig. 13 - Histogram and diagram of road classes with segmented image.

Fig. 13 - *Histograma e diagramas das classes nas vias com imagem segmentada.*

assign the pixels correctly. The classes of tracks and grass presented a similar spectral behavior, which indicates that a mixture of pixels would probably be present in the classes. As with the general supervised classification, the classification of the pathways was performed using the maximum likelihood algorithm (fig. 15).

To obtain the additional information that generated the

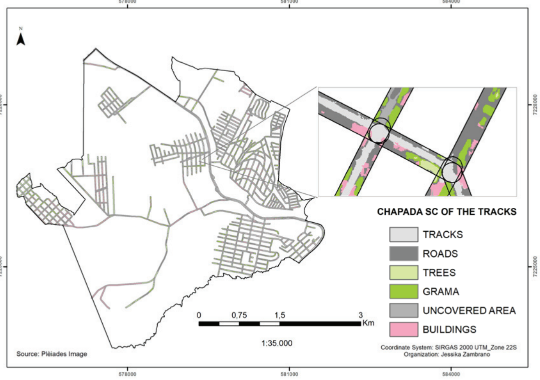

Fig. 15 - Supervised classification of the roads in the Chapada neighbourhood.

***Fig. 15** - Classificação supervisionada das vias do bairro Chapada.*

conversion from raster to vector (fig. 16), it was decided to eliminate the additional polygons generated, making an area calculation and choosing areas smaller than 1 m^2, excluding these polygons.

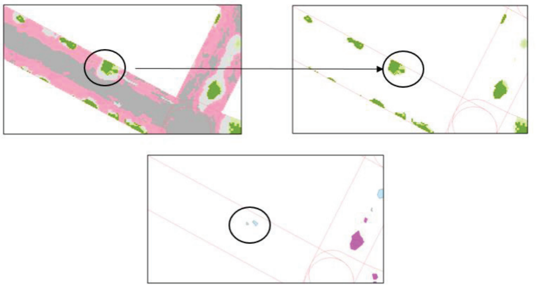

Fig. 16 - Enlarging the display from pixel to polygon and debugging polygons.

***Fig. 16** - Conversão pixel para polígono e depuração de polígonos.*

Subsequently, as in the unsupervised classification process, the centroids were calculated to obtain the number of mapped trees, 2564 trees were identified, that is, 82.62% compared to data from Tadenuma (2019).

It is important to know how the software is mapping trees, since the information may not be accurate compared to the methodology of visual analysis (Table III). Observing the behavior and the difference in mapping between the methodologies, it was decided to calculate the true positives, false positives and false negatives, (Table IV), which helped to identify possible errors in relation to obtaining trees, in addition to the identification of trees initially mapped by visual analysis and those that were omitted by it.

For this, the theory of true positives is used, which refers to the data that the data process declared as true trees and turned out to be true, then there are false positives, which refer to the number of trees that the classifier declared true, which really are not, in turn you get the false negatives that is the number of trees that the classifier identified as negative and that they are actually true (Burgos e Manterola, 2010).

Emphasizing Table IV, where the true positives, the false positives, and the false negatives can be observed, it should be taken into account that by means of the 10m buffer of tracks that were made; 27 trees of the visual analysis were out of range, however the analysis was carried out including them, since they were at minimum distances from the buffer and could mark a bias in the evaluation of false and true positives.

The results shown in Table III correspond to points established at a distance of 5 m in relation to the trees identified through the visual analysis methodology. These points represent the trees obtained in the visual analysis methodology, which were positioned in the center of the tree canopy. In contrast, the points obtained through supervised, unsupervised classification, and NDVI reveal lateral displacement and even positioning outside the tree canopies, although still in close proximity. The generation of the tree map through the application of these methodologies demonstrated optimal results Table V).

The matrices demonstrated the errors of the methods, but did not prevent their use. The mappings obtained an accuracy greater than 50.00% and the kappa index greater than 0.4, which means that the concordance was always of good quality or even better. In addition to these errors, the context of the tree in the image should be considered, since the biggest problem is the mixing of pixels in the classes.

Regarding the best results, according to the percentages obtained (Table IV), it can be observed that the best tree registration was the one with the unsupervised classification, however it is convenient to consider proposing the supervised classification, since the Research and classification of the land in the neighborhood required prior knowledge of the classes to reduce errors.

Rating evaluation

The calculation of the error matrix was carried out for the classifications of the entire neighborhood and subsequently for the classifications made to the track

Table I - Identification of trees according to different methodologies..

***Tabela I** - Identificação das arvores a partir de diferentes metodologias.*

TREE IDENTIFICATION		
METHODOLOGY	**IMAGE**	**DESCRIPTION**
VISUAL ANALYSIS		In the case of the classification of visual analysis, it is observed that 3 trees were identified in an area.
NDVI		In the case of the NDVI index, it recognizes only 2 trees as opposed to the methodology of visual analysis.
UNSUPERVISED CLASSIFICATION		In the case of the unsupervised classification, a mapping of 4 trees was presented where 3 were recognized through visual analysis, that is, a non-existent tree was mapped.
SUPERVISED CLASSIFICATION		For the methodology of the supervised classification, the same three trees were identified as the methodology of the visual analysis recorded.

Table II - Identification of false positives, false negatives, and true positives..

***Tabela II** - Identificação de falsos positivos, falsos negativos e verdadeiros positivos.*

NEIGHBORHOOD	METHOD	FALSE POSITIVE	FALSE NEGATIVO	TRUE POSITIVE	OUT OF 10M BUFFER	INSIDE THE 10M BUFFER	TREES OBTAINED BY THE CLASSIFIER
CHAPADA	**VISUAL ANALYSIS**	0	0	3101	27	3074	3101
	NDVI	171	1335	174	27	3074	1680
	UNSUPERVISED CLASSIFICTION	122	292	2414	27	3074	2828
	SUPERVISED CLASSIFICATION	134	531	1899	27	3074	2564

Table III - Summary of error matrices by neighbourhood and method used.

***Tabela III** - Resumo das matrizes de erro por bairro e método utilizado.*

NEIGHBORHOOD	VIAL ERROR MATRIX	METHOD USED	INDEX KAPPA	AGREEMENT
CHAPADA	61,60%	NDVI	0,43	GOOD
	70,33%	SUPERVISED CLASSIFICATION	0,64	VERY GOOD
	83,00%	UNSUPERVISED CLASSIFICATION	0,79	VERY GOOD

Table IV - Percentages of mapped trees and the method used.

Tabela IV - Porcentagens de árvores mapeadas por método utilizado.

NEIGHBORHOOD	METHOD	MAPPING PERCENTAGE
CHAPADA	NDVI	56,00%
	SUPERVISED CLASSIFICATION	82,68%
	UNSUPERVISED CLASSIFICATION	91,19%

buffer. In addition, the error matrix allows determining the Kappa index, (Foody, 2020), which is based on the diagonal data of the matrix and includes the general accuracy and the classes that agreed.

The NDVI carried out for the Chapada neighborhood was taken as a segmentation to later carry out the classification, this because the NDVI is a mathematical operation but not a classification, by means of which the trees present on the tracks of the neighborhood were easily recognized.

The calculation of the error matrices was carried out for each methodology used. Calculations were made for the entire neighborhood and the previously named road buffer, the behavior of each class was similar in the three methodologies, the percentages obtained for the class Trees and grass classes the classes that refer to the presence of vegetation in the study area were highlighted, for which an average accuracy percentage of 64.00% was obtained for the tree class, 88.00% was registered in the lawn class.

The NDVI, in comparison with the other methodologies, records results with percentages below 50.00%, this was due to the spatial resolution of 2.m of the image with which the mapping was performed, as it is a comparison among the methodologies used, it was analyzed as a methodology with the same characteristics in terms of inputs.

The unsupervised classification was the methodology that registered the highest percentage of veracity, however, the registration of the two previously mentioned classes of grass and tree registered low veracities, which indicates that it is not correct to infer that it is the most convenient methodology for the tree mapping.

Discussion

The study endeavored to identify and quantify urban tree heritage in the Chapada neighborhood of Ponta Grossa, PR (Brazil), focusing on the meticulous selection and evaluation of methodologies for mapping and quantifying trees along urban thoroughfares. The outcomes underscored the efficacy of unsupervised classification in achieving a mapping accuracy of 91.19%, distinguishing itself by capturing the highest number of trees. In contrast, supervised classification attained an accuracy of 82.68%, while NDVI exhibited a congruence of 56.00% with visually identified trees. These findings accentuate the nuanced efficacy across methodologies for mapping and quantifying trees along roadways, underscoring the paramount importance of methodological selection tailored to specific contexts.

The ensuing discussion underscores the need to regard these methodologies as complementary adjuncts. While unsupervised classification may be optimal for intricate urban landscapes, supervised classification and segmented NDVI also furnish invaluable insights into urban vegetation distribution and health.

Furthermore, it is imperative to acknowledge the significance of employing high-fidelity data and conducting preliminary mapping utilizing visual methodologies as benchmarks to augment the precision of automated classifications. These findings hold significant ramifications for urban tree management and strategic urban planning, facilitating a comprehensive understanding of urban vegetation distribution and health that can inform policies and practices conducive to sustainable urban conservation and management.

Additionally, the integration of high-resolution imagery, such as that from the Pleiades sensor, presents an opportunity to refine mapping accuracy. Employing an enhanced segmentation methodology, inclusive of preliminary cloud and shadow extraction, could streamline tree counting and identification in urban landscapes.

Finally, the prospect of iterative segmentation in conjunction with pass filters holds promise for precise spectral separation. This iterative approach, coupled with pass filter application, could heighten the accuracy of object identification, including urban trees, warranting consideration in future research endeavors within this domain.

Conclusions

The identification of trees exhibiting false positives and false negatives revealed concerning discrepancies, particularly evident in the case of NDVI analysis. However, these outcomes are subject to variation contingent upon the distance range utilized, suggesting the potential for alternative findings through exploration with a radius of influence exceeding 5 meters. It’s crucial to acknowledge that adjusting the distance parameter may inadvertently introduce additional, irrelevant data due to inherent spatial resolution constraints of the imagery. Furthermore, considering NDVI as an auxiliary spectral band in classification analyses is advised, albeit with careful interpretation of its spectral resolution to mitigate outlier effects.

Mitigation of errors associated with automated classifications can be achieved through experimentation with adjustments to interaction counts or alterations to statistical distribution methodologies, alongside exploration of diverse RGB combinations. Fieldwork remains indispensable for attaining heightened result accuracy and ensuring data fidelity. The overarching objective of such research endeavors is to furnish insights facilitating effective urban tree management encompassing planting, pruning, and maintenance, necessitating a comprehensive qualitative and quantitative inventory.

Effective shade management emerges as a critical imperative, given its potential to distort precise tree identification, particularly within densely populated urban landscapes. Image segmentation emerges as a potent tool for enhancing the accuracy of supervised classification, albeit necessitating exploration of iterative approaches integrating low- or high-pass filters to refine this process and mitigate potential classification anomalies.

The paramount importance of field validation in affirming data accuracy and reliability is underscored, alongside the ongoing imperative to explore novel techniques and harness multitemporal imagery to enhance mapping efficacy within dynamic urban contexts.

Strong advocacy is put forth for integrating unsupervised classification as a foundational step in the supervised classification workflow, given its capacity to furnish invaluable ground-truth data complementing insights derived from satellite imagery. This integrative framework fosters a comprehensive understanding of the environment, thereby maximizing the accuracy of urban tree mapping—a critical component for effective management of urban green spaces and sustainable urban planning.

Lastly, the methodologies employed underscore the criticality of continual tree heritage inventorying across global urban landscapes. These findings serve as an initial foray for broader initiatives, such as Light Detection and Ranging (LiDAR) methodologies or acquisition of high spatial resolution imagery from unmanned aerial devices, showcasing commendable efficiency and efficacy while maintaining resource economy.

Reference

Agyemang, T., Heblinski, J., Schmieder, K., Sajadyan, H., Vardanyan, L. (2011). Accuracy Assessment of Supervised Classification of Submersed Macrophytes Using GIS and Error Matrices: The Case of Lake Sevan, Armenia. *Hidrobiology,* n. 661, 85-96.

Almeida, D. (2009). *Análise da arborização urbana de cinco cidades da região norte do estado de Mato Grosso (Dissertação de Mestrado em Ciências Florestais e Ambientais).* Faculdade De Engenharia Florestal, Universidade Federal de Mato Grosso, Cuiabá, 62f. Disponível em https://www.ufmt.br/fenf/arquivos/0a241f85423324b3077c8ee2dc7b6748.pdf. Acceso em 8 jul. 2018.

Ardila, J., Bijker, W., Topelkin, V., & Stein, A. (2011). Context-sensitive extraction of tree crown objects in urban areas using VHR satellite images, *International Journal of Applied Earth Observation and Geoinformation*, Netherland, V. 15, jun, 57-69.

Ardila, J. P. (2012). *Object-based methods for mapping and monitoring of urban trees with multitemporal image analysis (Tese de Doutorado em Geoformação).* Faculty of Geo-Information Science and Earth Observation, University Of Twente, Netherlands, 176 f.

Audebert, N., Bertrand, S., Lefévre, S. (2018). Beyond RGB: Very high resolution urban remote sensing with multimodal deep networks. *ISPRS Journal of Photogrammetry and Remote Sensing,* v. 140, p. 20-32

Batista dos Santos, C. e Carvalho, F. G. (2012). Análise da arborização viária do bairro de Petrópolis, natal, rn: uma abordagem para diagnóstico e planejamento da flora urbana. *REVSBAU,* Piracicaba – SP, v.7, n.4, 90-106.

Biondi, D. (2008). *Arborização Urbana Aplicada à educação Ambiental nas escolas*. Curitiba: [s.n.]. 120 p.

Burgos, M., Manterola, C. (2010). Cómo interpretar un artículo sobre pruebas diagnósticas. *Revista Chilena de Cirugía,* n. 3, v. 62, 301-308.

Campbell, J., Wynne, R. (2022). Introduction to remote sensing. 2 ed. London: Taylor and Francis, 667 p.

Centeno, J. (2009). *Sensoriamento Remoto e Processamento de Imagens Digitais*. Curitiba: Universidade Federal de Paraná (UFPR).

Congalton, R. (2004). *Putting the Map Back in Map Accuracy Assessment*. *In:* Lunetta, R., Lyon, J. *Geoespatial Data Accuracy Assessment*. Environmental Agency: United States, 1-13.

Chuvieco, E. (2000). *Fundamentos de Teledetección Espacial*. 2 ed. Rialp, Madrid, 449 p.

Foody, G. (2020). Explaining the unsuitability of the kappa coefficient in the assessment and comparison of the accuracy of thematic maps obtained by image. *Remote Sensing of Environment,* Nottingham, UK.

Hao, S., Cui, Y., Wang, J. (2021). Segmentation Scale Effect Analysis in the Object-Oriented Method of High-Spatial-Resolution Image Classification. *Sensors, China,* v.21.2-17.

Hong, Z., Xu, S., Wang, J., Xiao, P. (2009). Extraction of Urban Street Trees from High Resolution Remote Sensing Image. *Urban Remote Sensing Joint Event*, Shanghai, China.

IBGE - INSTITUTO BRASILEIRO DE GEOGRAFIA A ESTATISTICA. Disponivel em: https://cidades.ibge.gov.br/brasil/pr/ponta-grossa/panorama. Acesso em: 12 out. 2018.

IBGE - INSTITUTO BRASILEIRO DE GEOGRAFIA A ESTATISTICA (2006). *Manual Técnico de Uso da Terra*. 2. ed. Rio de Janeiro: Instituto Brasileiro de Geografia e Estatística.

Leckie, D., Burnett, C., Nelson, T., Jay, C., Walsworth, N., Gougeon, F., Cloney, E. (1999). Forest Parameter Extraction through Computer-Based Analysis of High Resolution Imagery. In: *21st Canadian Symposium on Remote Sensing*, 21, Ottawa, 1-9.

LI, F., Song, G., Liujun, Z., Yanan, Z., Di, L. (2017). *Urban vegetation phenology analysis using high spatio-temporal NDVI time series*. Urban Forestry & Urban Greening, Nanjing, China

Malik, P., Chourasiya, A., Pandit, R., Bharaskar, K. (2023). Satellite Image Segmentation Using Neural Networks: A Comprehensive Review. International *Journal of Enhanced Research in Educational Development (IJERED)*.

Moreira, M. (2007). *Fundamento do Sensoriamento Remoto e Metodologias de Aplicação*. Viçosa: UFV.

PCI GEOMATICS. (2018). Geosoluciones: Geomatica OrthoEngine Ortorectificando datos Pleiades 1ª, 1-12.

Pouliot, D., King, D., Bell, F., Pitt, D. (2002). Automated tree crown detection and delineation in high-resolution digital camera imagery of coniferous forest regeneration, *Remote Sensing of Environment*, Ontario, v. 82, mar, 322-334.

Recio, J. A. (2009). *Técnicas De Extracción De Características Y Clasificación De Imágenes Orientada A Objetos Aplicadas A La Actualización De Bases De Datos De Ocupación Del Suelo (Tesis Doctoral en Ingeniería Cartográfica, Geodesia Y Fotogrametría)*. Universidad de Valencia, Valencia, 310 f.

Richards, J. (2013). *Supervised Classification Techniques in: Remote Sensing Digital Image Analysis*. 5 th. Ed. Australia: Springer, 173-184.

Santos, T., Lisboa, C., Carvalho, F. (2012). Análise da arborização viária do bairro de Petrópolis, Natal, RN: uma abordagem para diagnóstico e planejamento da flora urbana. *Revista da Sociedade Brasileira de Arborização Urbana*, Piracicaba, v.7, n.4, 90-106.

Tadenuma, S. (2019). *Espacialização Da Arborização De Vias Públicas Por Densidade E Níveis De Atenção Na Na Área Urbana De Ponta Grossa (Pr) (Dissertação de Mestrado em Gestão do Território)*. Sector De Ciências Exatas E Naturais, Universidade Estadual De Ponta Grossa, Ponta Grossa.

Wu, B., Yu, B., Yue, W., Shu, S., Tan, W., Hu, C., ... & Liu, H. (2013). A voxel-based method for automated identification and morphological parameters estimation of individual street trees from mobile laser scanning data. *Remote Sensing,* 5(2), 584-611.

Xu, Z., Zhou, Y., Wang, S., Li, F., Wang, S., Wang, Z. (2022). A Novel Intelligent Classification Method for Urban Green Space Based on High-Resolution Remote Sensing Images. *Remote Sensing*, 2-18.