Serviço Público Federal
Ministério da Educação
Fundação Universidade Federal de Mato Grosso do Sul
Faculdade de Engenharias, Arquitetura e Urbanismo e Geografia - FAENG

PRISCILA LÔPO GUIMARÃES CANO

MAPPING OF PERMEABLE AREAS USING MACHINE LEARNING TECHNIQUES AND REMOTE SENSING DATA

PGRN

Campo Grande, MS.

2022

UNIVERSIDADE FEDERAL DE MATO GROSSO DO SUL
FACULDADE DE ENGENHARIAS E ARQUITETURA E URBANISMO E GEOGRAFIA
PROGRAMA DE PÓS-GRADUAÇÃO EM RECURSOS NATURAIS

PRISCILA LÔPO GUIMARÃES CANO

MAPPING OF PERMEABLE AREAS USING MACHINE LEARNING TECHNIQUES AND REMOTE SENSING DATA

Dissertação submetida ao Programa de Pós-graduação em Recursos Naturais da Universidade Federal do Mato Grosso do Sul como requisito parcial a obtenção do título de Mestre em Recursos Naturais. Geoprocessamento Aplicado.

Orientador: Prof. Dr. José Marcato Junior

Aprovada em: 09/02/2022

Banca Examinadora:

Prof. Dr. José Marcato Junior
Orientador PGRN- UFMS

Profª. Drª. Ana Paula Marques Ramos
Instituição: UNOESTE

Prof. Dr. Wesley Nunes Gonçalves
Instituição: UFMS

Prof. Dr. Jamil Alexandre Ayach Anache
Instituição: UFMS

Profª. Drª. Camila Aoki
Instituição: UFMS

Campo Grande, MS.
2022

AGRADECIMENTOS

A Deus, em primeiro lugar, pela minha vida e por me permitir conquistar mais um desígnio.

Aos meus pais, familiares e amigos pelo apoio incondicional, especialmente ao meu esposo Éric Vieira Cano pela paciência, dedicação, amor e parceria no decorrer desses últimos anos. Vocês foram essenciais para realização desta conquista.

Aos membros da Banca pelas valiosas contribuições, em especial ao meu orientador Prof. Dr. José Marcato Junior pela orientação, que mesmo nos vendo apenas por vídeo chamada conseguiu transmitir todo conhecimento e apoio para realização deste trabalho.

Agradeço a Coordenação de Aperfeiçoamento de Pessoal de Nível Superior – Brasil (Capes) pelo acesso ao Portal de Periódicos.

Agradeço aos professores e colaboradores do Programa de Pós-Graduação em Recursos Naturais (PPGRN), da Faculdade de Engenharias, Arquitetura e Urbanismo (FAENG) da Fundação Universidade Federal de Mato Grosso do Sul (UFMS), pela atenção, empenho e dedicação demonstrada no decorrer do curso.

O presente trabalho foi realizado com apoio da Fundação Universidade Federal de Mato Grosso do Sul - UFMS/MEC - Brasil.

SUMMARY

LIST OF FIGURES 01
LIST OF TABLES 02
ABSTRACT 03
RESUMO 03
GENERAL INTRODUCTION 05
STUDY AREA 08

FIRST CHAPTER: MAPPING URBAN FORESTS AND PERMEABLE AREAS COMBINING REMOTE SENSING AND MACHINE LEARNING 10
1.1. Introduction 11
1.2. Material and methods 12
1.3. Results and discussion 17
1.3.1. Permeable area mapping mapping 17
1.3.2. Urban Forests mapping 20
1.4. Conclusion 23
1.5. References 24

SECOND CHAPTER: SCIENTIOMETRIC ANALYSIS – DEEP LEARNING FOR REMOTE SENSING DATA 27
2.1. Introduction 28
2.2. Material and methods 29
2.3. Results and discussion 32
2.3.1. Annual Publication Analysis 32
2.3.2. Review of Magazines, Authors and Countries 33
2.3.3. Scientific Network Maps 36
2.4. Conclusion 39
2.5. References 39

THIRD CHAPTER: ANALYSIS OF DEEP LEARNING ALGORITHMS FOR MAPPING PERMEABLE AREAS IN HYDROGRAPHIC BASIN 41
3.1. Introduction 42

3.2. Material and methods 44
3.3. Results and discussion.. 46
3.3.1. Permeable area mapping.. 47
3.3.2. Urban Forests mapping.. 50
3.4. Conclusion.. 54
3.5. References 56

FINAL CONSIDERATIONS.. 59
BIBLIOGRAPHIC REFERENCES 60

LIST OF FIGURES

Figure 1. Study area location... 08
Figure 1.1. Work flowchart 13
Figure 1.2. Segmented image detail 14
Figure 1.3. Types of samples selected for permeable areas 15
Figure 1.4. Types of samples selected for urban forests 15
Figure 1.5. Supervised mapping details of permeable areas 18
Figure 1.6. Map of the permeable areas in the Prosa catchement 19
Figure 1.7. Supervised mapping of urban forests details 21
Figure 1.8. Map of the Urban Trees in the Prosa catchment 22
Figure 2.1 Keywords and search string 29
Figure 2.2. Data collect.. 30
Figure 2.3. Data Processing in Endnote 31
Figure 2.4. Publications per year 32
Figure 2.5. Number of Publications in Journal.. 33
Figure 2.6. Authors with the highest number of publications on the topic 34
Figure 2.7. Percentage of publications from countries.. 35
Figure 2.8. Co-occurrence of Keywords 36
Figure 2.9. Co-authorship of countries.. 37
Figure 2.8. Co-authorship of countries with Brazil 38
Figure 3.1. Work flowchart 44
Figure 3.2. Location of training and testing areas in the catchment............................ 45
Figure 3.3. Details of classifications of permeable areas in the test area 47
Figure 3.4. Map of the permeable areas in the Prosa catchment with DL model......... 49
Figure 3.5. Details of classifications of urban forests in the test area 51
Figure 3.6. Map of the urban forests in the Prosa catchment with DL model............. 52

LIST OF TABLES

Table 1.1. Classification Confusion Matrix for Permeable Areas................................ 17
Table 1.2. Classification Confusion Matrix for Urban Forests 20
Table 3.1. Permeable areas training metrics.. 47
Table 3.2. Metrics of classification of permeable areas in test area............................. 48
Table 3.3. Urban forest training metrics... 50
Table 3.4. Metrics of classification of urban forest in test area.................................... 51

GENERAL ABSTRACT

CANO, P. L. G. (2022). MAPPING OF PERMEABLE AREAS USING MACHINE LEARNING TECHNIQUES AND REMOTE SENSING DATA. 2022. 66 páginas. Dissertação - Programa de Pós Graduação em Recursos Naturais. Universidade Federal de Mato Grosso do Sul, Brasil.

This work proposes mapping permeable areas of an urban catchment in Campo Grande, Mato Grosso do Sul, Brazil, using machine learning techniques and remote sensing data. The dissertation is organized into three chapters. The first presents the mapping of urban forests and permeable areas, based on a supervised object-based method, the Random Forest machine learning algorithm using Google Earth (GE) Pro imagery. The second chapter presents a scientometric analysis of deep learning data for remote sensing, through 1.429 documents extracted from the Scopus and Web of Science databases, up to the year 2020. And the third chapter consists of the evaluation and validation of the performance of the deep learning algorithms like U-Net, PSPNet, and Deeplabv3, using Google Earth (GE) Pro imagery of the year 2020, allowing, after verification, the mapping of urban forests and permeable areas in the catchment of Prosa. The results obtained in chapters 1 and 3 indicated high accuracy, with F1-Score higher than 90% for mapping permeable areas using traditional machine learning and deep learning methods, indicating a excellent tool for mapping green areas in highly complex environments. It was possible to observe, with the case of the study, a considerable improvement in the mapping results of permeable areas using deep learning models. The contribution of this work is given by the development of automated approaches for mapping permeable areas, as they represent an important component of the urban ecosystem, serving as a tool for planning, monitoring and adequate urban management.

Keywords: deep learning, scientometric analysis, urban catchment, sustainable cities, environmental monitoring

RESUMO GERAL

Este trabalho propõe o mapeamento de áreas permeáveis de uma bacia hidrográfica em Campo Grande, Mato Grosso do Sul, Brasil, utilizando técnicas de aprendizado de máquina e dados de sensoriamento remoto. A dissertação está organizada em três capítulos. O primeiro apresenta o mapeamento de florestas urbanas e áreas permeáveis, através do método supervisionado baseado em objetos com o algoritmo de aprendizado de máquina Random Forest usando imagens do Google Earth (GE) Pro. O segundo capítulo apresenta uma análise cienciométrica de deep learning para dados de sensoriamento remoto, por meio de 1.429 documentos extraídos das bases de dados Scopus e Web of Science, até o ano de 2020. E o terceiro capítulo consiste na avaliação e validação do desempenho de algoritmos de deep learning U-Net, PSPNet e Deeplabv3, utilizando imagens do Google Earth (GE) Pro do ano de 2020, permitindo, após verificação, o mapeamento de florestas urbanas e áreas permeáveis na bacia do Prosa. Os resultados obtidos nos capítulos 1 e 3 indicaram alta precisão, com F1-Score superior a 90% para mapeamento de áreas permeáveis usando métodos tradicionais de aprendizado

de máquina e aprendizado profundo, indicando uma excelente ferramenta para mapeamento de áreas verdes em ambientes de alta complexidade. Foi possível perceber com o estudo uma melhora considerável no mapeamento de áreas permeáveis feito pelos modelos de deep learning. A contribuição deste trabalho se dá pelo desenvolvimento de abordagens automatizadas para mapeamento de áreas permeáveis, pois representam um importante componente do ecossistema urbano, servindo como ferramenta de planejamento, monitoramento e gestão urbana adequada.

Palavras-chave: aprendizado profundo, análise cienciométrica, bacia urbana, cidades sustentáveis, monitoramento ambiental

GENERAL INTRODUCTION

Urban environments are considered complex and heterogeneous systems, as they have ecological, physical, and socioeconomic components that interact and progress in multiple spatial and temporal scales (BLASCHKE *et al*., 2011). Therefore, the need for more information and understanding of how these systems work and progress are required for governments and decision-makers. This is especially due to they adopted the United Nations Sustainable Development Agenda for 2030, with the goal of making cities and human settlements inclusive, safe, resilient, and sustainable (ZHU *et al*., 2019).

Urbanization has a direct relation with the environment, where disorderly urban expansion generates, in a concentrated way, degrading impacts on the environment and society, affecting the ecosystem's biodiversity, altering the natural hydrological cycle of the basin and the biogeochemical cycle (CUI *et al*., 2019, ARABAMERI *et al*., 2019, LUO *et al*., 2020, LI *et al*., 2017, PAN *et al*., 2020). According to Jacobson (2011), among environmental problems, the main effect of urbanization on urban hydrology is the decrease in the permeability of soils in hydrographic basins. Seeking to control these degradation processes and preserve the environment, permeable areas play an important role both in the mitigation of urban rainwater runoff and in flood control, as they represent an important component of the urban ecosystem (REN *et al*., 2020).

Mapping and monitoring permeable areas are fundamental for the advancement and collection of information about the coverage and change of land use and control urbanization and support for the preservation of the environment (HUSSAIN *et al*., 2013). Studies related to remote sensing data used to detect, characterize and map urban land cover and changes have revolutionized the mapping task in recent decades. It consists of an effective tool for mapping vast geographic areas at various scales favoring the understanding of the spatiotemporal dynamics of the environment (SETO *et al*., 2011, ZHU *et al*., 2019). According to Maxwell *et al*. (2018), machine learning approaches have become widely accepted and effective for classifying remote sensing images, particularly evidenced for land-cover mapping.

Machine learning algorithms are capable of modeling complex class data to identify patterns and accept a variety of input datasets. Moreover, they have the advantage of being non-parametric and non-linear techniques, making decisions with little human intervention. Some examples of these algorithms are the support vector machine (SVM) and random forest (RF) (MAXWELL *et al*., 2018, LI; STEIN, 2020).

In the literature, there are many uses of remote sensing and machine learning applied for the urban areas mapping, such as automatic extraction of impermeable surfaces (MISRA *et al*., 2020), heat islands (YOO *et al*., 2019), classification of green infrastructure (KRANJČIĆ *et al*., 2019) susceptibility to urban flooding (ZHAO *et al*., 2019), and susceptibility of land subsidence (MOHAMMADY *et al*., 2019).

In recent years, deep learning methods have emerged in the area of machine learning to provide refined functionality for classifying remote sensing data (MAXWELL *et al*., 2018). These methods have been widely used in studies carried out in urban areas as well, such as classification tasks (XU *et al*., 2020), object detection and semantic segmentation (HUERTA *et al*., 2021), and instance segmentation (XI *et al*., 2021).

Therefore, our main purpose is to map permeable areas using machine learning techniques and remote sensing data. This work is divided into three chapters. In the first chapter, the mapping of permeable areas and urban forests of the Prosa catchment, located in Campo Grande, Mato Grosso do Sul, Brazil, is carried out based on remote sensing data and

Random Forest algorithm application. This chapter presents a product as input for decision-makers in terms of sustainable city planning and management, which can help and improve the ability to monitor and map urban land cover. Urban forests are a subclass of permeable areas, as they are composed of trees and blocks of trees. The choice to map urban forests separately from permeable areas is intended to fill a gap in studies and products related to their mapping around the city, since this information is important for biologists, architects and urban planners.

In chapter 2, a scientometric analysis of Deep Learning for Remote Sensing data is presented. As it is a relatively new topic and has expanded significantly in recent years, this chapter aims to show, through a scientometric analysis, the growing advance of research on the subject and the relevance of this method for this work. The chapter presents the number of articles published over the years, journal productions, authors and countries, co-authorship networks, and co-occurrence of keywords. Finally, chapter 3 consists of the evaluation and validation of the performance of the deep learning algorithms like U-Net, PSPNet, and Deeplabv3, using Google Earth (GE) Pro imagery of the year 2020, allowing, after verification, the mapping of urban forests and permeable areas in the catchment of Prosa.

Our main contribution is producing cartographic information that assists studies related to permeable areas, which are important for the planning and management of sustainable cities. This type of information is also important for monitoring and controlling the land occupation process, improving the environmental conditions of an urban catchment.

STUDY AREA

The study area is located in Campo Grande, Mato Grosso do Sul, Brazil (Figure 1), which has 96.3% of urban households on public roads with afforestation (IBGE, 2010). Campo Grande has the title "Tree Cities of the World", which recognizes the cities most committed to preserving urban forests and sustainable development by the Food and Agriculture Organization of the United Nations and Arbor Day Foundation.

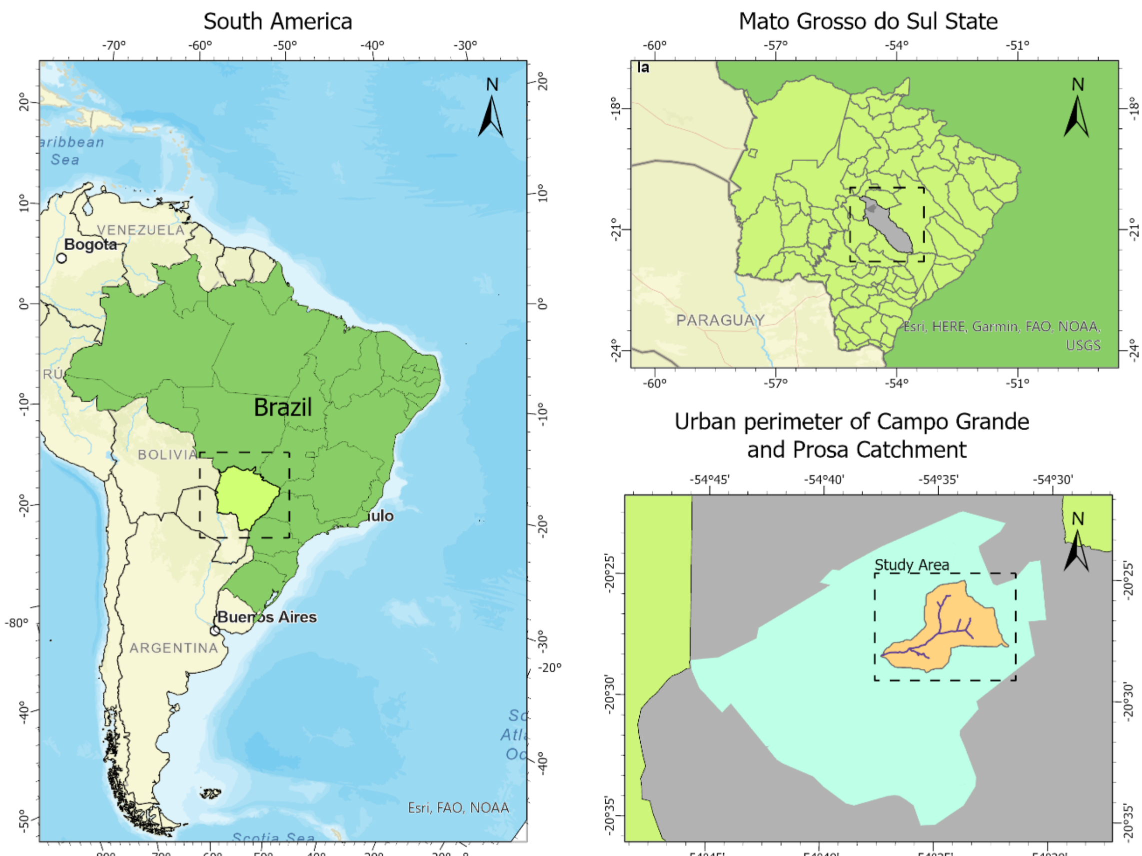


Figure 1: Study area location.
Source: Prepared by the Author

Specifically, the Prosa catchment was studied. It is located in the eastern portion of the urban area of the city. This catchment has a heterogeneity of land cover and usage, including commercial and residential buildings and vegetation reserves for preserving samples of the Cerrado ecosystem, such as the Parque das Nações Indigenas and the Parque Estadual do Prosa. The region where the catchment is located can also be characterized by an increase in the degree of impermeability of the soil due to the high urban development in recent years. Thus, contributing to intensifying surface runoff and, consequently, flooding and erosion processes (CAMPO GRANDE, 2015).

FIRST CHAPTER: MAPPING URBAN FORESTS AND PERMEABLE AREAS COMBINING REMOTE SENSING AND MACHINE LEARNING

Abstract: Urban forests are one of the important indicators of a city's environmental quality, providing ecosystem services for human and ecological well-being. Permeable areas also play an important role in hydrological modeling. Mapping these urban features is necessary for supporting urban planning and management tasks. Therefore, our goal is to combine remote sensing data and machine learning algorithms to map the urban forests and permeable areas of the Prosa catchment, located in Campo Grande, Mato Grosso do Sul, Brazil. The study was carried out using high-resolution satellite imagery and an object-based classification supervised method with Random Forest machine learning algorithm. The experiments were conducted using Google Earth (GE) Pro imagery from May 14, 2020, and the ESRI ArcGIS Pro 2.9.0 software. We achieved an overall accuracy of 91.80% and an F1 Score of 91.88% for urban forests. Regarding permeable areas, an overall accuracy of 91.80% and an F1 score of 94.82% were obtained. The results indicate that the adopted strategy is satisfactory when used to map urban forests and permeable areas, showing the potential of using GE Pro data, which historical imageries are, in general, available for all the cities around the globe.

Keywords: urban vegetation, ArcGIS pro, supervised image classification, random forest.

Resumo: As florestas urbanas são um dos importantes indicadores da qualidade ambiental de uma cidade, fornecendo serviços ecossistêmicos para o bem-estar humano e ecológico. As áreas permeáveis também desempenham um papel importante na modelagem hidrológica. O mapeamento dessas características urbanas é necessário para apoiar as tarefas de planejamento e gestão urbana. Portanto, nosso objetivo foi combinar dados de sensoriamento remoto e algoritmo de aprendizado de máquina para mapear as florestas urbanas e áreas permeáveis da bacia do Prosa, localizada em Campo Grande, Mato Grosso do Sul, Brasil. O estudo foi realizado usando imagens de satélite de alta resolução e um método supervisionado de classificação baseada em objeto com algoritmo de aprendizado de máquina *Random Forest*. Os experimentos foram conduzidos usando imagens do Google Earth (GE) Pro de 14 de maio de 2020 e o software ESRI ArcGIS Pro 2.9.0. Alcançamos uma precisão geral de 91,80% e uma pontuação F1 de 91,88% para florestas urbanas. Em relação às áreas permeáveis, obteve-se uma acurácia geral de 91,80% e uma pontuação F1 de 94,82%. Os resultados indicam que a estratégia adotada é satisfatória quando utilizada para mapear florestas urbanas e áreas permeáveis, mostrando o potencial de utilização de dados do GE Pro, cujas imagens históricas estão, em geral, disponíveis para todas as cidades do globo.

Palavras-chave: vegetação urbana, arcgis pro, classificação de imagens supervisionadas, *random forest*.

1.1. INTRODUCTION

Urban forests, which are a subclass of permeable areas, have become essential areas for city sustainability, providing ecosystem services for human and ecological well-being. Many studies highlight the importance of these areas to the improvement of the health and leisure of the population, microclimate mitigation, air purification, protection of hydrographic basins, and better drainage (GÓMEZ-BAGGETHUN; BARTON, 2013, WEINBRENNER *et al*., 2021, NGHIEM *et al*., 2021, HIRABAYASHI, 2021). Urban forests are composed of scattered individual trees or blocks of trees located in parks, streets, lands, and gardens (JENSEN *et al*., 2009).

Permeable areas composed of grass, arboreal vegetation, and exposed soil, also play an important role in hydrological modeling (LI *et al.*, 2018). They are in highly altered and extremely complex ecosystems where humans are the main drivers of their types, amounts, and distribution (DOBBS *et al*., 2011). As it characterizes as important and potentially substantial areas, mapping and monitoring are necessary as an analysis tool aiming the adequate urban planning and management.

In recent years, image classification based on remote sensing data and machine learning algorithms has provided good results to urban forest mapping (CANETTI *et al.*, 2018, CHEŢAN *et al.*, 2017, NOVACK *et al.*, 2011) and permeable areas mapping (YANG *et al*., 2021, MAHATO *et al*., 2022). In the city of Campo Grande, some studies were carried out regarding urban vegetation. These studies used Deep learning segmentation-based methods for tree species identification (LOBO TORRES *et al*., 2020, ARCE *et al*., 2021), tree crown identification (MARTINS *et al*., 2020) and detection of individual trees (ZAMBONI *et al*., 2021); however, these methods require extensive labeling datasets, which, in general, are not available for cities around the globe.

Traditional machine learning methods, such as Random Forest, combined with image segmentation (PUISSANT *et al.*, 2014) emerge as an alternative in this scenario.

We intend to map urban forests and the permeable areas of the Prosa catchment in Campo Grande city (Mato Grosso do Sul - MS/Brazil), combining a supervised machine learning approach and high-resolution Google Earth (GE) Pro imageries. This information source can help and enhance the ability to monitor and map urban land cover around the globe due to their high availability. It is also essential to highlight the importance of our product as input for decision-makers in terms of sustainable city planning and management. Campo Grande has the title of “Tree Cities of the World", however, there is a gap of studies and products related to their mapping around the city, and the current work aims to fill this gap partially, as one of the hydrographic basins was totally mapped.

1.2. MATERIAL AND METHODS

The raster data used was a mosaic of satellite images from Google Earth Pro, from May 14, 2020, with a spatial resolution of 0.50 meters. The projection system adopted was the Universal Transverse Mercator (UTM), zone 21 South, Datum SIRGAS 2000. The vector data related to the boundaries of the city and the basin were acquired through the website of the Brazilian Institute of Geography and Statistics (IBGE) and the municipality of Campo Grande, respectively. We used Terra Incognita software to acquire georeferenced Google Earth Pro satellite images.

The study was divided into two parts, one for mapping the permeable areas and the second for urban forests. For that, a six-step workflow was defined, as shown in Figure 1.1, which was repeated for both tasks. All steps were performed in ArcGIS Pro.

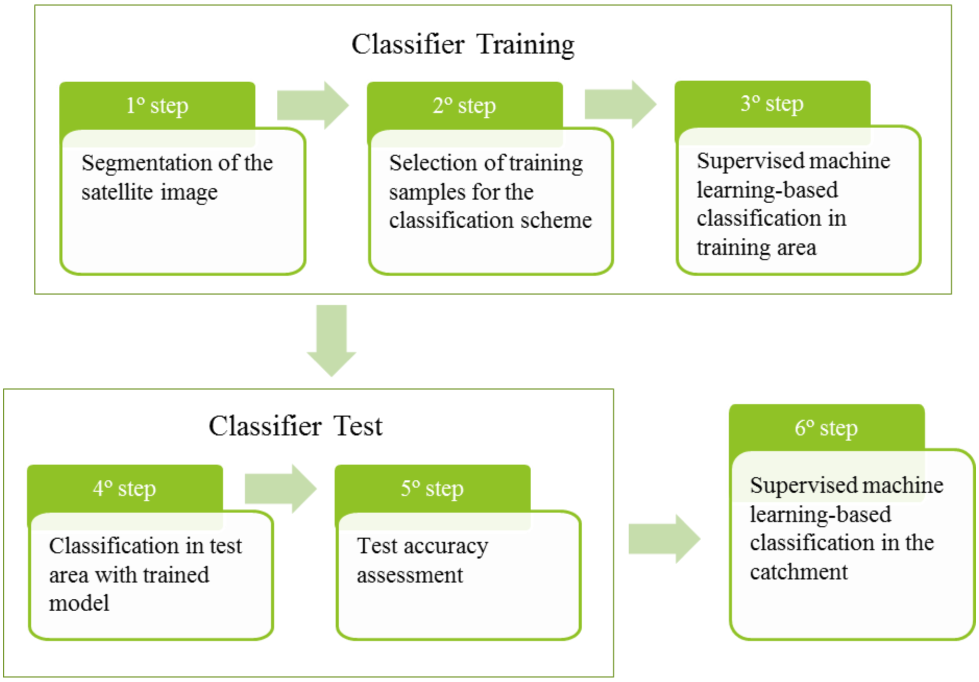


Figure 1.1: Work flowchart.

The steps 1, 2 and 3 consisted of training the classifier, steps 4 and 5 were defined to test the classifier, and the final step was carried out to map the total area of the catchment. It should be noted that the areas defined for training and testing are in different regions of the catchment, with 70% for training and 30% for testing.

In the first step, the image segmentation is performed through the Mean Shift approach. The segmentation grouping adjacent pixels with similar spectral characteristics and shapes into image objects. The processing units are converted from conventional pixels into image objects (HAN *et al*., 2015).

After tests, we considered the value of 18 (eighteen) for the spectral and spatial details to segment the image. The minimum size adopted for the segment was 700 pixels, with the purpose of easily mapping the samples. A patch from the original image and the corresponding segmented image can be seen in Figure 1.2.

Figure 1.2: Segmented image detail

We selected the training samples for the classification scheme in the second step. For the classification of permeable areas, two training samples were defined: permeable areas and impermeable. The permeable class contained 900 samples, and the impermeable class consisted of 900 samples. For urban forests, it was possible to vectorize two classes to compose the training samples called: trees and others (background). The trees class contained 800 samples with individual trees, blocks of trees, and forests of different shades of green, while the other class was composed of 800 samples that included buildings, exposed soil, grasses, lakes, swimming pools, and asphalts, that is, everything not characterized as a tree.

Classes were defined through visual interpretation to identify the main characteristics and targets mapped in the scene. Figures 1.3 and 1.4 show the types of samples selected from each class used for training.

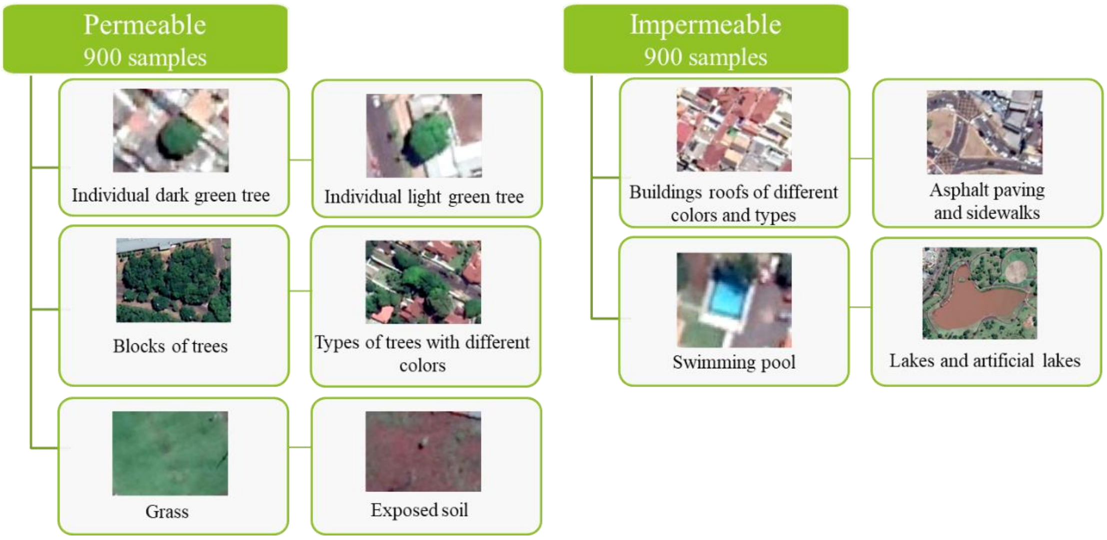


Figure 1.3: Types of samples selected for permeable areas.

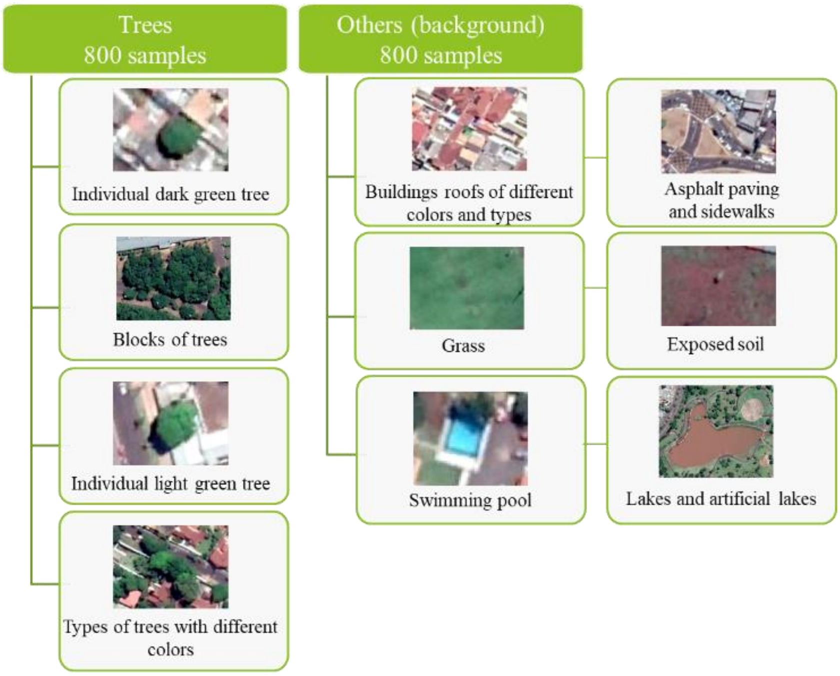


Figure 1.4: Types of samples selected for urban forests.

With the training samples defined, the classification scheme, and the segmented image, we proceed to the third step, which consists of the supervised machine learning-based classification in the training area. The chosen classifier was Random Forest. The Random Forest machine learning algorithm has become popular in the remote sensing community and appears in several studies proving to be an excellent classifier for urban areas (GUO *et al.*, 2011, PUISSANT *et al.*, 2014, JOMBO *et al.*, 2021). According to Puissant *et al*. (2014) the Random Forest does not require the adjustment of many parameters; therefore, it presents easier and more efficient ways to identify vegetation in the urban context. For the training of the classifier, the value of 50 was adopted for the maximum number of trees, for depth, the maximum value of 30 was adopted, and 1000 samples per class were selected.

After training, we proceeded to test the model. To do so, the classification in the test area was carried out with the trained algorithm and subsequently verified the accuracy of the classified image. We created automatically 500 points randomly distributed for the two classes. The input data was the classified image, and the chosen sampling scheme was the stratified random, where each class has a number of points proportional to its area. After manual verification, it was possible to generate a confusion matrix using the Compute Confusion Matrix tool.

The confusion matrix (SAMMUT; WEBB, 2011) contains information about the number of correctly and incorrectly sorted samples compared to the actual results. Through this matrix, we estimate some metrics: sensitivity, specificity, Precision, accuracy, and F1 Score. Sensitivity is a metric that indicates how well the model correctly ranked patterns that were positive, while specificity indicates correct ranking relative to negatives. Precision is about evaluating the number of true positives (TP) out of all positive values, accuracy indicates the accuracy of the model and how well it is detected correctly across all classifications, and the F1 Score is a harmonic average of Precision and sensitivity. Below are the equations for the reported metrics (LEVER *et al*., 2016):

$$\text{Sensitivity } = \frac{TP}{(TP + FN)} \qquad \text{Accuracy } = \frac{(TP + TN)}{(P + N)}$$

$$\text{Specificity } = \frac{TN}{(FP + TN)} \qquad \text{F1 Score} = \frac{(2\ x\ TP)}{[(2\ x\ TP) + FP + FN]}$$

$$\text{Precision} = \frac{TP}{(TP + FP)}$$

In which, TP (True Negative) is the correct prediction of a label; FP (False Positive) is the false prediction of a label; TN (True Negative) is the correct prediction of another label; and the FN (False Negative) refers to the label that was not predicted, but that exists.

1.3. RESULTS AND DISCUSSION

1.3.1 Permeable area mapping

The classification was performed in the test areas with the model trained for mapping permeable areas and generated the evaluation metrics presented in Table 1.1 and the classification details presented in Figure 1.5.

CONFUSION MATRIX			
		TRUE VALUE	
		Positive	Negative
PREDICTED VALUE	Positive	**375 (TP)**	**24 (FP)**
	Negative	**17 (FN)**	**84 (TN)**
			VALUE OBTAINED (%)
MEASURE		Sensitivity	95.66
		Specificity	77.78
		Precision	93.98
		Accuracy	91.80
		F1 Score	94.82

Table 1.1: Classification Confusion Matrix for Permeable Areas

The number of permeable areas was correctly detected, indicating the sensitivity of the model was 95.66% (375 true positives of 399 points for permeable of the class). For the areas that the classifier detected as impermeable and correct, it obtained a percentage of 77.78%. From the confusion matrix, an overall accuracy of 91.80% and an F1 score of 94.82% were obtained.

1.5a

1.5b

1.5c

1.5d

Figure 1.5: Supervised mapping details of permeable areas

Figures 1.5a and 1.5b present a correct response for the classification, as it filled in all the areas that correspond to the permeable class. However, in Fig. 1.5c, it was verified that the algorithm did not obtain a satisfactory response, failing to classify the objects that characterize exposed soil. The spectral characteristic of the exposed soil is similar to that of roof surfaces, and it can be easily confused by the algorithm, thus defining false negatives. In Fig. 1.5d, there is a false positive. The lake has an excess of algae with spectral characteristics similar to the trees.

In the study by Feng *et al*. (2015), who used Random Forest for classification, the same confusion of features was obtained, and the authors reported that these errors occur mainly due to low spectral quality of images or the lack of a near-infrared band that reduces the separability of each type of ground cover.

The supervised classification of permeable areas in the Prosa catchment found an area of 13.9592 km² and resulted in a classification map shown in Figure 1.6. The permeable area occupies a total of 43.66% of the basin.

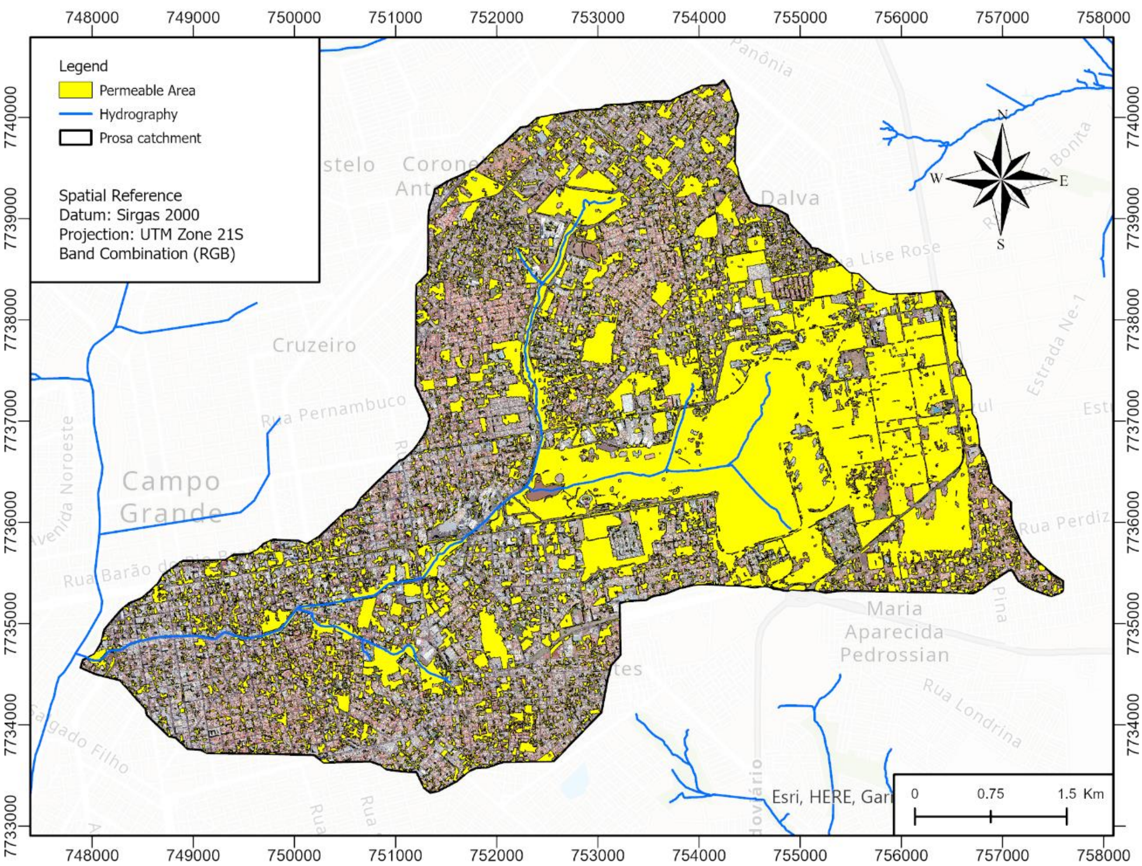


Figure 1.6: Map of the permeable areas in the Prosa catchment
Source: Prepared by the Author

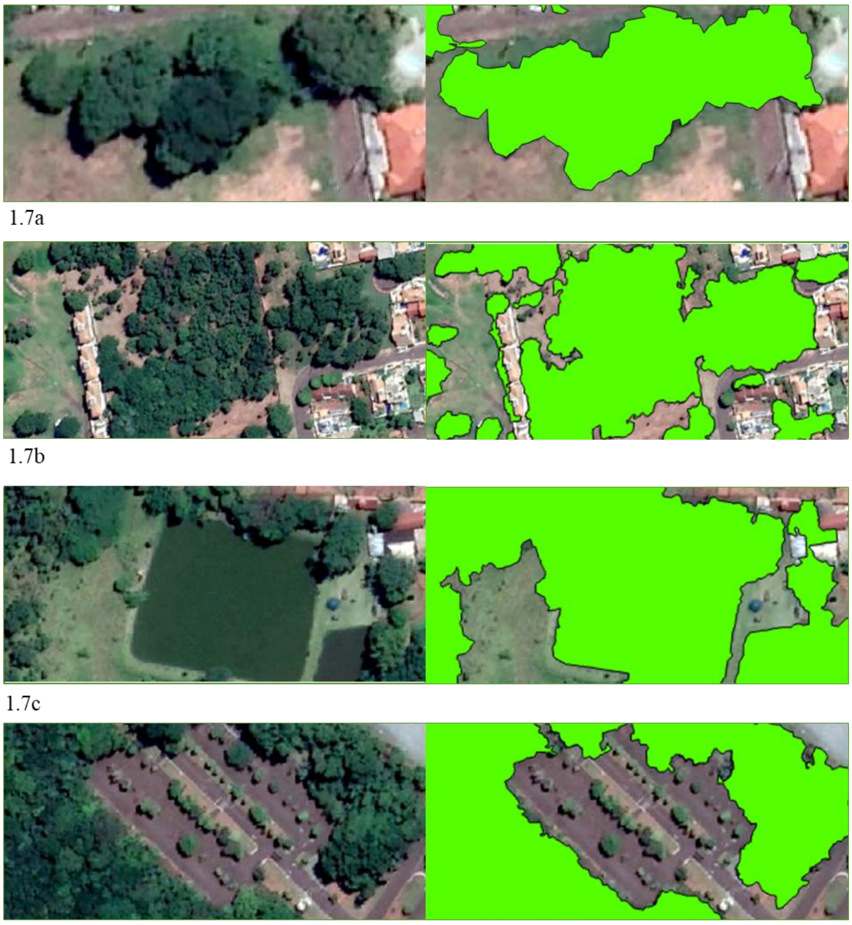
1.3.2 Urban Forests mapping

The validation of the classification of urban forests is reported in Table 1.2, where the number of trees correctly detected, indicating that the sensitivity of the model was 94.69% (232 true positives out of 260 points for class trees). For the areas that the classifier detected as not arboreal and got it right, it obtained a percentage of 89.02%. An overall accuracy of 91.80% and an F1 score of 91.88% were obtained from the confusion matrix. In Figure 1.7 presents a qualitative analysis for some test areas.

CONFUSION MATRIX			
		TRUE VALUE	
		Positive	Negative
PREDICTED VALUE	Positive	**232 (TP)**	**28 (FP)**
	Negative	**13 (FN)**	**227 (TN)**
			VALUE OBTAINED (%)
MEASURE		Sensitivity	94.69
		Specificity	89.02
		Precision	89.23
		Accuracy	91.80
		F1 Score	91.88

Table 1.2: Classification Confusion Matrix for Urban Forests.

The examples in Figures 1.7a and 1.7b present a correct classification, filling in all the areas that correspond to the tree class. However, in Fig. 1.7d, it was verified that the algorithm did not obtain a satisfactory response, failing to classify the objects with smaller-sized objects. These objects are small trees and with lighter colored foliage, easily confused with grass, characterizing false negatives. In Fig. 1.7c, the same occurs as in the classification of permeable areas presenting a false positive. The area of a tank with fish with excess algae was selected for having a similar spectral characteristic.



1.7a

1.7b

1.7c

1.7d

Figure 1.7: Supervised mapping of urban forests details.

The map resulting from the supervised classification of urban trees in the Prosa catchment can be seen in Figure 1.8. The Prosa catchment has an area of 31,9704 km², while the classified arboreal area corresponds to 7,8133 km². Therefore, urban afforestation occupies a total of 24.44% of the basin.

Compared to other Brazilian cities, for example, Mossoró-RN with 6.90% (EDUARDO *et al.*, 2013) and Rondonópolis-MT with 8% (PESSI *et al.*, 2019), the percentage found is higher and favorable to others, providing residents of the region with a better quality of life, serving as a barrier to pollutants and improving the thermal sensation of cities.

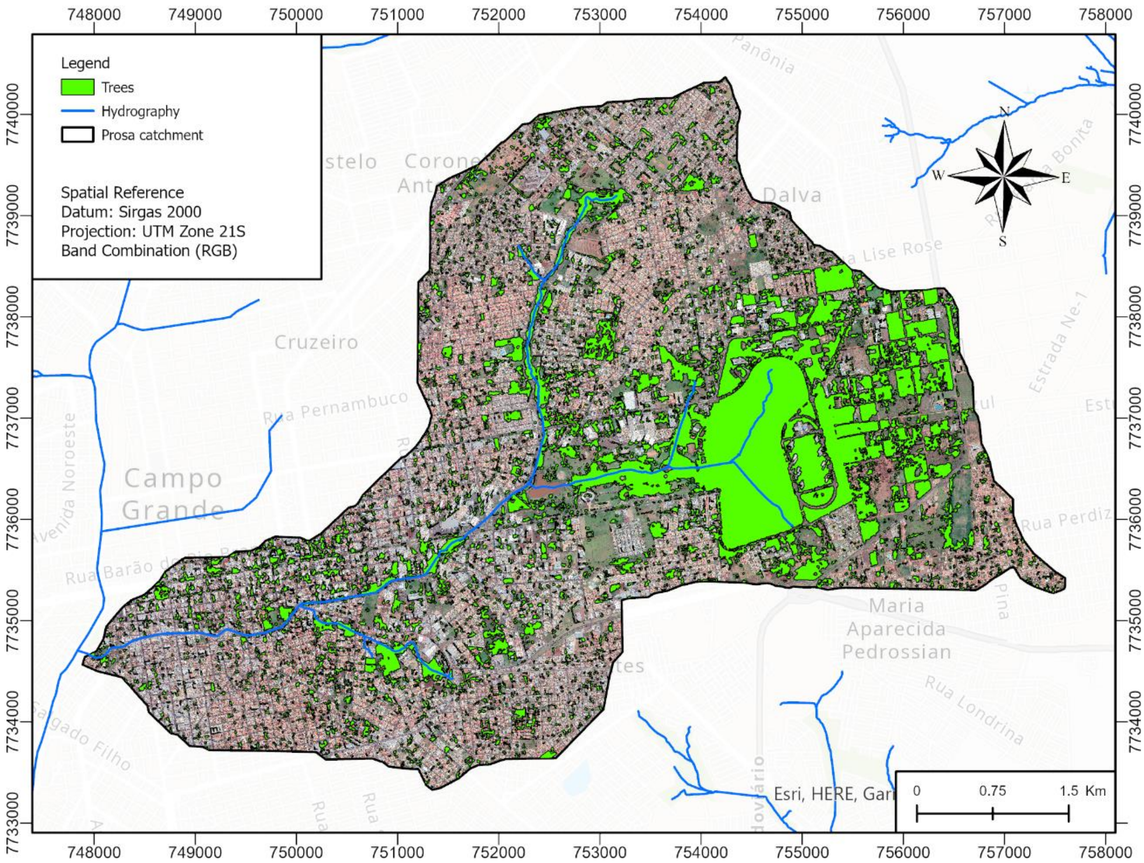


Figure 1.8: Map of the Urban Trees in the Prosa catchement.
Source: Prepared by the Author

The accuracy of supervised classification is related to the quality and quantitative balance of samples from different classes, where human misunderstandings can occur, as well as due to the complexity of land cover and variability between classes (EGOROV *et al*., 2015, PELLETIER *et al*., 2017).

Another issue that can interfere with the classification quality is the adopted image segmentation process, with a negative correlation between the ideal segmentation scale and the spatial resolution of the images. Since different types of land cover can be classified better on different scales, so if only one segmentation scale is used for classification, even if it is the optimal scale for the image as a whole, the coverage features are likely to be super or sub-segmented (MA *et al*., 2017, JOHNSON, 2013).

According to Ma *et al*. (2017), regarding the type of land cover of the areas in several studies, the object-based supervised classification proves to be more advantageous for mapping the land cover of the agricultural study areas. However, analyzing the two classifications carried out in urban areas, we noticed that both obtained satisfactory results.

The study carried out by Guan *et al*. (2013), who used the Random Forest algorithm in urban areas, obtained an overall accuracy of 86.01% for land cover, while Yang *et al*. (2021) who performed the classification of green spaces with Random Forest in an urban environment, obtained an accuracy of 87%. Regarding the mapping of large areas, the study carried out by Maxwell *et al*. (2019) obtained an overall accuracy of 96.7% using the Random Forest algorithm.

As a result of errors found, it is recommended: a) increase the amount of the number of samples for both classes; and b) for segmentation improvements, studies tend to adopt the multi-scale object-based approach segmentation technique (JOHNSON; XIE, 2013, MAXWELL *et al*., 2019).

1.4. CONCLUSION

The images available and used from Google Earth Pro, in addition to having a high spatial resolution, tend to be more advantageous as they allow for a large-scale application, involve an easy acquisition and zero investment and have updated images in the urban context, thus favoring the mapping and monitoring of urban forests across the globe.

The use of Google Earth Pro images submitted to classification with the Random Forest algorithm presents a good performance for mapping trees and permeable areas in an urban environment. Some errors occurred, which are related to the spectral similarity response of targets, but even with these confusions, an F1 score higher than 90% was achieved for both tasks.

Finally, this work indicated that the tool discussed helps in monitoring and sustainable planning, making it possible to classify, map and monitor urban forests and permeable areas simultaneously, and the data obtained can determine the carbon capture potential of these areas, as well as serve as information for other studies.

As a guide for future work, we anticipate applying the methodology to other areas, since the algorithm can be easily adapted for other studies using training data representing the study site under consideration. Besides, we also intend to use deep learning methods. However, it is important to highlight that these methods require large labeled datasets.

1.5. REFERENCES

ARCE, L. S. D. et al. Mapping Single Palm-Trees Species in Forest Environments with a Deep Convolutional Neural Network. 2021.

CANETTI, A. et al. Understanding multi-temporal urban forest cover using high resolution images. Urban Forestry & Urban Greening, v. 29, p. 106-112. 2018.

CHETAN, M. A.; DORNIK, A.; URDEA, P. Comparison of object and pixel-based land cover classification through three supervised methods. Journal of Geodasy, Geoinformation and Land Management. 2017.

DOBBS, C.; ESCOBEDO, F. J.; ZIPPERER, W. C. A framework for developing urban forest ecosystem services and goods indicators. Landscape and urban planning, v. 99, n. 3-4, p. 196-206, 2011.

EDUARDO, L. V. et al. Índice de área verde e de cobertura vegetal no perímetro urbano central do município de Mossoró-RN. Revista Verde de Agroecologia e Desenvolvimento Sustentável, v. 8, n. 2, 2013.

EGOROV, A. V. et al. Image interpretation-guided supervised classification using nested segmentation. Remote Sensing of Environment, v. 165, p. 135-147. 2015.

ESRI - Environmental Systems Research Institute. 2021. Software ArcGIS Pro. Available in:< https://www.esri.com.>

FENG, Q.; LIU, J.; GONG, J. UAV remote sensing for urban vegetation mapping using random forest and texture analysis. Remote sensing, v. 7, n. 1, p. 1074-1094. 2015.

GÓMEZ-BAGGETHUN, E.; BARTON, D. N. Classifying and valuing ecosystem services for urban planning. Ecological economics, v. 86, p. 235-245. 2013.

GUAN, Haiyan et al. Integration of orthoimagery and lidar data for object-based urban thematic mapping using random forests. International journal of remote sensing, v. 34, n. 14, p. 5166-5186, 2013.

GUO, Li et al. Relevance of airborne lidar and multispectral image data for urban scene classification using Random Forests. ISPRS Journal of Photogrammetry and Remote Sensing, v. 66, n. 1, p. 56-66, 2011.

HAN, N. et al. Exploring the synergistic use of multi-scale image object metrics for land-use/land-cover mapping using an object-based approach. International Journal of Remote Sensing, v. 36, n. 13, p. 3544-3562. 2015.

HIRABAYASHI, S. Technical specifications of urban forests for air purification: A case study in Tokyo, Japan. Trees, Forests and People, v. 4, p. 100078. 2021.

IBGE – Instituto Brasileiro de Geografia e Estatística. Brasil. 2010. Censo Demográfico. Available in:< https://cidades.ibge.gov.br/brasil/ms/campo-grande/panorama> Access in 20 jul. 2021.

JENSEN, R. R. et al. Modeling urban leaf area index with AISA+ hyperspectral data. Applied Geography, v. 29, n. 3, p. 320-332. 2009.

JOHNSON, Brian A. High-resolution urban land-cover classification using a competitive multi-scale object-based approach. Remote Sensing Letters, v. 4, n. 2, p. 131-140, 2013.

JOHNSON, Brian; XIE, Zhixiao. Classifying a high resolution image of an urban area using super-object information. ISPRS journal of photogrammetry and remote sensing, v. 83, p. 40-49, 2013.

JOMBO, Simbarashe; ADAM, Elhadi; ODINDI, John. Classification of tree species in a heterogeneous urban environment using object-based ensemble analysis and World View-2 satellite imagery. Applied Geomatics, p. 1-15, 2021.

LEVER, Jake; KRZYWINSKI, Martin; ALTMAN, Naomi. Classification evaluation. Nature Methods, v. 13, n. 8, p. 603-604, 2016.

LI, X. et al. Estimating time of concentration for overland flow on pervious surfaces by particle tracking method. Water, v. 10, n. 4, p. 379, 2018.

LOBO TORRES, D. et al. Applying fully convolutional architectures for semantic segmentation of a single tree species in urban environment on high resolution UAV optical imagery. Sensors, v. 20, n. 2, p. 563. 2020.

MA, Lei et al. A review of supervised object-based land-cover image classification. ISPRS Journal of Photogrammetry and Remote Sensing, v. 130, p. 277-293, 2017.

MAHATO, A. et al. Detection of Green Belt Area Using Machine Learning Algorithms. In: International Conference on Innovative Computing and Communications. Springer, Singapore, 2022. p. 403-413.

MARTINS, J. et al. Aerial Image Segmentation In Urban Environment For Vegetation Monitoring. IEEE Latin American GRSS & ISPRS Remote Sensing Conference (LAGIRS). p. 375-379. 2020.

MAXWELL, Aaron E. et al. Large-Area, High Spatial Resolution Land Cover Mapping Using Random Forests, GEOBIA, and NAIP Orthophotography: Findings and Recommendations. Remote Sensing, v. 11, n. 12, p. 1409, 2019.

NGHIEM, T. P. L. et al. Biodiverse urban forests, happy people: Experimental evidence linking perceived biodiversity, restoration, and emotional well-being. Urban Forestry & Urban Greening, v. 59, p. 127030. 2021.

NOVACK, T. et al. Machine learning comparison between WorldView-2 and QuickBird-2-simulated imagery regarding object-based urban land cover classification. remote sensing, v. 3, n. 10, p. 2263-2282. 2011.

PELLETIER, C. et al. Effect of training class label noise on classification performances for land cover mapping with satellite image time series. Remote Sensing, v. 9, n. 2, p. 173. 2017.

PESSI, D. D. et al. Vegetation cover in urban microbasins: temporal analysis of the arboreal cover and temperature of Rondonópolis, Mato Grosso. Revista Brasileira de Geografia Física, v. 12, n. 1, p. 299-309, 2019.

PUISSANT, A. et al. Object-oriented mapping of urban trees using Random Forest classifiers. International Journal of Applied Earth Observation and Geoinformation, v. 26, p. 235-245, 2014.

SAMMUT, Claude; WEBB, Geoffrey I. (Ed.). Encyclopedia of machine learning. Springer Science & Business Media, 2011.

WEINBRENNER, H. et al. "The Forest Has Become Our New Living Room"–The Critical Importance of Urban Forests During the COVID-19 Pandemic. Frontiers in Forests and Global Change, v. 4, p. 68. 2021.

YANG, Zhiqi et al. Integrating multiple semantics data to assess the dynamic change of urban green space in Beijing, China. International Journal of Applied Earth Observation and Geoinformation, v. 103, p. 102479, 2021.

ZAMBONI, P. et al. Benchmarking Anchor-Based and Anchor-Free State-of-the-Art Deep Learning Methods for Individual Tree Detection in RGB High-Resolution Images. Remote Sensing, v. 13, n. 13, p. 2482, 2021.

SECOND CHAPTER: SCIENTIOMETRIC ANALYSIS – DEEP LEARNING FOR REMOTE SENSING DATA

Abstract: This study intends to carry out a scientometric analysis on Deep Learning for Remote Sensing data. We chose only articles and review articles that contained the terms "deep learning" and "remote sensing" in the title, abstract or keywords between 2010 and 2020, resulting in a total of 2,248, extracted from the Scopus and Web of Science, a previous analysis was performed by excluding duplicate documents and aligning titles and abstracts, generating a final study sample with 1,429 documents. Through scientometric analysis, it was possible to find the number of articles published over the years, journal productions, authors and countries, co-authorship networks and co-occurrence of keywords. The results indicated that (a) publications on the topic had a significant increase over the years, indicating a greater interest in researchers; (b) the most productive authors are linked to Chinese research institutions, and most of the journals are the Remote Sensing; (c) China is the country with the largest participation in productions and presents 63% of publications worldwide. Finally, it is expected that the study presents the current research access points on the subject and can guide other researchers in their work, contributing to the advancement of scientific knowledge.

Keywords: Quantitative Analysis. Endnote. Research Progress. Network Analysis. VOSviewer.

Resumo: Este estudo pretendeu realizar uma análise cienciométrica de dados de Aprendizagem Profunda para dados de Sensoriamento Remoto. Escolhemos apenas artigos e artigos de revisão que continham os termos "deep learning" e "remote sensing" no título, resumo ou palavras-chave entre 2010 e 2020, resultando em um total de 2.248, extraídos da Scopus e Web of Science, foi realizada uma análise prévia, através da exclusão de documentos duplicados e alinhamento dos títulos e resumos, gerando uma amostra final do estudo com 1.429 documentos. Por meio da análise cienciométrica, foi possível encontrar o número de artigos publicados ao longo dos anos, produções de periódicos, autores e países, redes de coautoria e coocorrência de palavras-chave. Os resultados indicaram que (a) as publicações sobre o tema tiveram um aumento significativo ao longo dos anos, indicando maior interesse dos pesquisadores; (b) os autores mais produtivos estão vinculados a instituições de pesquisa chinesas, sendo a maioria dos periódicos de Sensoriamento Remoto; (c) A China é o país com maior participação nas produções e apresenta 63% das publicações mundiais. Por fim, espera-se que o estudo apresente os atuais pontos de acesso à pesquisa sobre o tema e possa orientar outros pesquisadores em seus trabalhos, contribuindo para o avanço do conhecimento científico.

Palavras-chave: Análise Quantitativa. Endnote. Progresso da Pesquisa. Análise de Rede. VOSviewer.

2.1. INTRODUCTION

The remote sensing scientific community is always committed to develop methods to improve performance aspects such as pre-processing, segmentation, and classification images. Over the past few years, there has been increased interest from researchers in deep learning methods in remote sensing community due to their ability to automatically: (a) extract feature information from the image dataset; (b) conduct high-level semantic segmentation; (c) perform nonlinear problem modeling, and; (d) map complex environments, such as urban environments (MA *et al.*, 2019, ZHANG *et al.*, 2016). Therefore, as it is a relatively new subject, starting the application in remote sensing in 2014, and with growing use, it is necessary to analyze the progress and behavior of the productions through the scientometrics approach.

Scientometrics is related to bibliometrics and infometry, where over the years, they presented different definitions, thus occurring a mixture of meanings, but they may not be considered synonyms. Therefore, Scientometrics can be defined as the study of the quantification of the analysis of scientific and technological performance through the application of mathematical and statistical methods to assess scientific productivity, which through its techniques helps researchers to find various studies related to the literature, which could be overlooked in manual searches (HOOD; WILSON, 2021, MADDISETTY; BABU, 2020, SU; LEE, 2010).

In the literature, scientific studies were found on deep learning (GUPTA; DHAWAN, 2019, TOLCHEEV, 2019) and remote sensing (MURUGAN; SARAVANAN, 2017, MADDISETTY; BABU, 2020). These articles provide a quantitative and qualitative description of research on a global scale, using scientometric methods, visualizing trends in existing literature as well as helping in future research.

Recently, the study developed by Bai *et al.* (2021) carried out a bibliometric and visualized analysis of deep learning in remote sensing, with the documents extracted from the Web of Science database, it used a method called Visualized Analysis (BVA) through the CitySpace software and later used a traditional method combing the literature (TLC), resulting in a systematic review of the subject.

Although the field of remote sensing and deep learning have been approached separately in scientometric or bibliometric studies, and even if together in a bibliometric study, it is important to emphasize the different ways of extracting data and performing quantitative and quantitative analyses.

Therefore, the goal of this work is to carry out a Scientometric Analysis of Deep Learning for Remote Sensing data, using the Scopus and Web of Science databases, between 2010 and 2020.

2.2. MATERIAL AND METHODS

To carry out the scientometric analysis, we sought to acquire the data through the Scopus and Web of Science databases, which are considered relevant knowledge bases and present a significant number of publications with works and scientific journals of impact. After choosing the databases, the study keywords are defined to build a search string, shown in Figure 2.1.

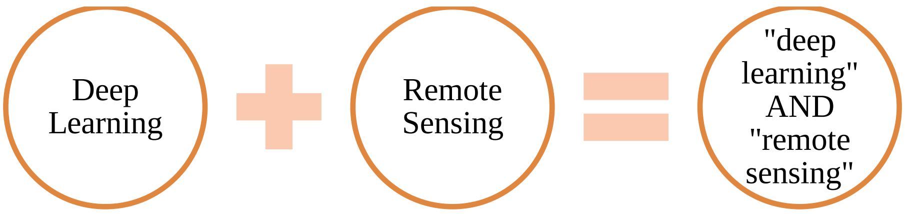


Figure 2.1 – Keywords and search string

The search performed in the databases used the same string, filtering the type of document and year of publication, so we chose only articles and review articles that contained the terms "deep learning" and "remote sensing" in the title, abstract or keywords between 2010 and 2020, resulting in a total of 2,248 documents (Figure 2.2).

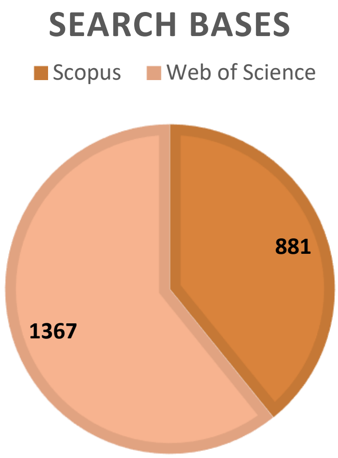


Figure 2.2 – Data collect

As they are two distinct databases, it was necessary to process the data, enabling the alignment of titles and abstracts of documents, and exclusion of those documents that are part of the research topic (Figure 2.3), resulting in the final sample of 1,429 documents related to the use of Deep Learning for Remote Sensing data during the period 2010-2020.

This method involving EndNote© software (BRAMER *et al*., 2016) is very efficient for studies that have documents from several databases and needed to merge and delete documents in duplicate, thus creating a single database (MAYRHUBER *et al*., 2018, BOSSHARD *et al*., 2018)

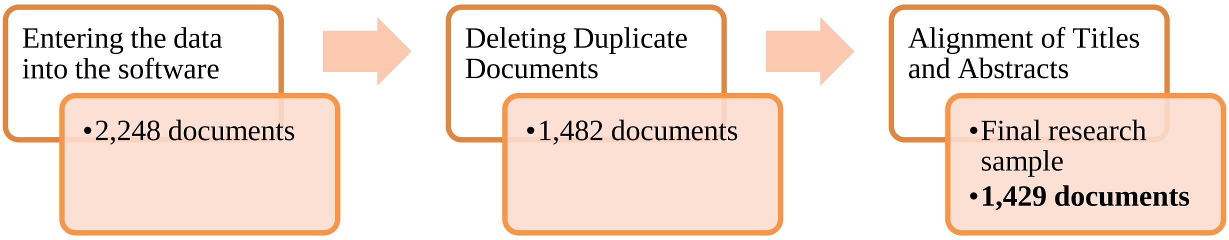


Figure 2.3 - Data Processing in Endnote

From the final sample of 1.429 documents, trends in the number of academic publications per year were evaluated; the periodicals, authors and countries with the largest publications on the subject, as well as the works with the greatest impact. To carry out this first step, we collected the information and quantitative data through the EndNote© software, confirming the information in the databases, later graphs were developed.

The second step was the creation of scientific maps of networks through the VOSviewer software (VAN ECK; WALTMAN, 2013), enabling the visualization of the co-occurrence of keywords and co-authorship of countries. In this step, only the data from the Scopus database were selected, as it has complete information in its extension file (.csv).

In the network map of keywords, the type of analysis "co-occurrence" was used, the unit of analysis was "all keywords" and the method of counting was "fractional count" and performed a filter of "minimum number of occurrences of the keyword" where it was set to 200. For the analysis of countries, "co-authorship" was used, the unit of analysis was "countries" and the method of counting was "fractional counting", in filtering the "minimum number of documents of a country" was defined as 15.

2.3. RESULTS AND DISCUSSION

2.3.1. Annual Publication Analysis

In total, 1,429 articles were obtained on the use of Deep Learning for Remote Sensing data between the years 2010 and 2020. Figure 4 below shows the relation between the number of articles published over the years.

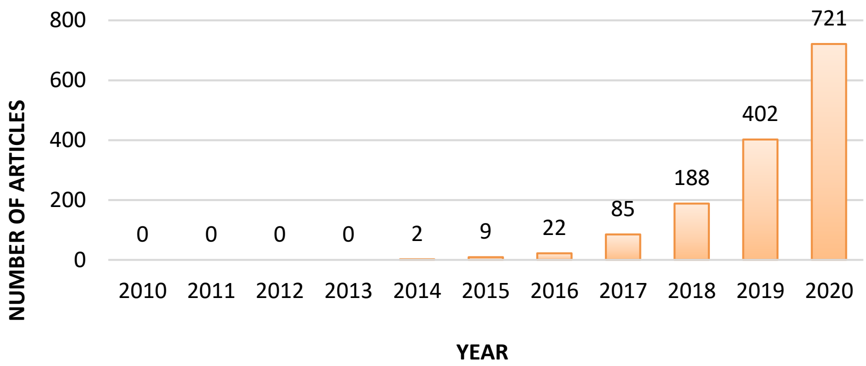


Figure 2.4 – Publications per year

The publications on the subject started in 2014 with two documents, and over the years there has been a significant increase in scientific publications, reaching a milestone of 721 publications in 2020. Of the first documents published, the paper by Chen *et al*. (2014) stands out, which had the highest citation rate until the year 2020 with 1,300 citations “Deep learning-based classification of hyperspectral data”, published pela IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing (vol. 7, no. 6, pp. 2094-2107). The work of Chen *et al*. (2014) discusses, for the first time, hyperspectral data classification methods using Deep Learning resources and manages to demonstrate the enormous potential of these resources for image classification, opening a new perspective for future research.

Analyzing the numbers found in the annual publications, the general trend towards the development of publications related to the topic is shown, where there has been a growing interest in the last three years due to the immense availability of data and advances in image processing.

2.3.2. Review of Journal, Authors and Countries

The production of Deep Learning research for Remote Sensing data is disseminated through several journals. Figure 5 shows the performance of the five most relevant journals in the analyzed period. The first article on the subject was published in 2014 by the IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, while the Remote Sensing Journal presented the highest number of articles published, with 333 articles, in the period from 2014 to 2020.

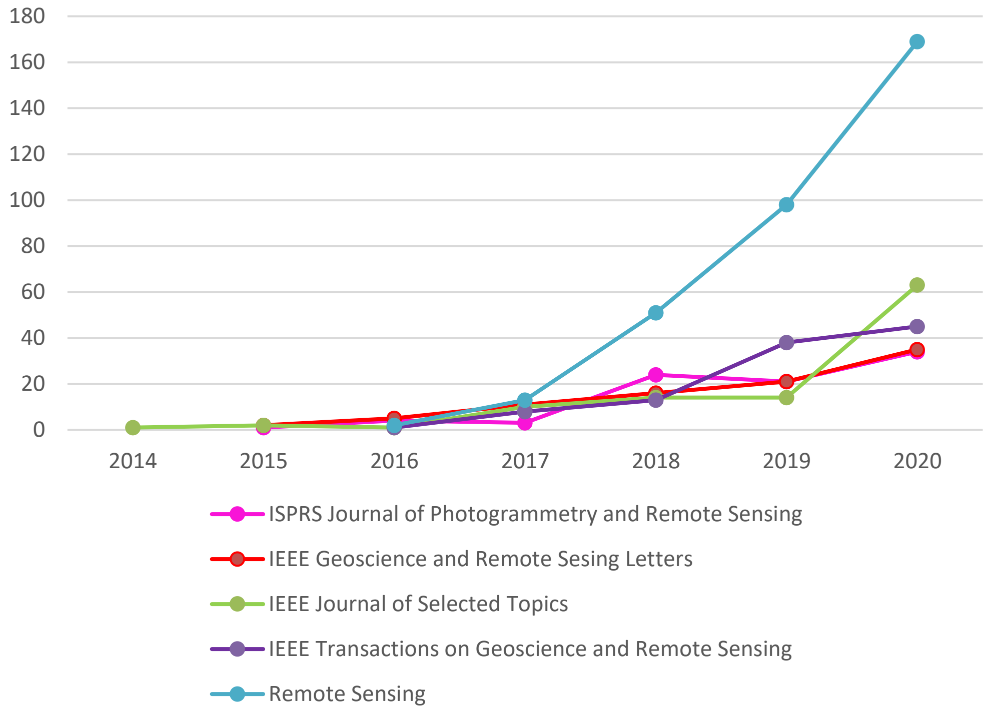


Figure 2.5 – Number of Publications in Journal

The author with the highest number of publications was Zhang, L., a professor at the University of Wuhan in China, with 28 articles published on the topic (Figure 6).

Followed by Jiao, L., professor at Xidian University and China's Minister of Education, with 21 articles; Ghamisi, P., a researcher at HZDR – Dresden in Germany, with 19 articles; Zhu, X.X., professor at the Technical University of Munich; and Sun, X., a professor at the Institute of Electronics of the Chinese Academy of Sciences in China, with 13 articles published on the topic.

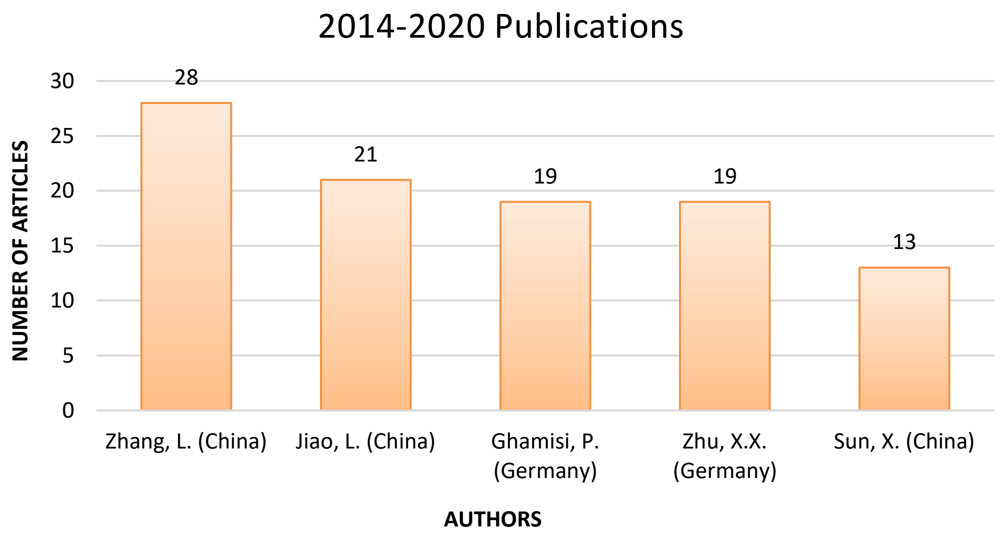


Figure 2.6 - Authors with the highest number of publications on the topic

It is noteworthy that the search for publications by authors in the Scopus and Web of Science databases was performed using a search string, refining the data to only the words that make up the string. The results found in this session are for the search string "deep learning" and "remote sensing". Among these, Zhang, L. stands out, who developed, together with Lefei Zhang and Bo Du, the second most cited article until the year 2020 with 1,293 citations: Deep learning for remote sensing data: A technical tutorial on state-of-the-art, published in 2016 by the journal IEEE Geoscience and Remote Sensing (vol. 4, n. 2, pp. 22-40). The article presents the first technical tutorial in the study of the art. It provides a general structure of Deep Learning data for Remote Sensing, as well as methods that can guide future research on the use of Deep Learning for Remote Sensing data.

At the institutional level, it is noted that the three authors are from Chinese institutions, while the others are from Germany. This is confirmed in Figure 7, where China has a total of 63% of world publications, followed by the United States of America and Germany.

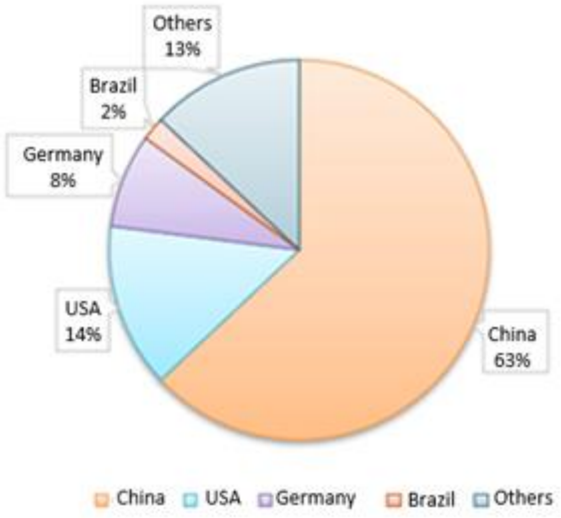


Figure 2.7 – Percentage of publications from countries

Brazil makes up 2% of publications worldwide, and the first Brazilian article on Deep Learning for Remote Sensing data was published in 2017 by the authors Nogueira, K.; Penatti, O.; Dos Santos, J., with title: Towards better exploiting convolutional neural networks for remote sensing scene classification, by Pattern Recognition magazine (v. 61, p. 539-556, 2017).

Regarding the journals with the highest production, Remote Sensing magazine stands out, with 333 publications, that is, it is the magazine with the largest volume of productions with an impact on the subject. As for the authors with the highest number of publications, Zhang, L., a professor at the University of Wuhan in China, stands out, with 28 articles published on the subject, therefore, China leads the productions with 63% of the world publication. This type of analysis informs which places and means are being used to advance the studies.

2.3.3. Scientific Network Maps

Discovering the collaboration network of keywords, co-authored by authors and countries is extremely important, as it identifies the growth trend of a given topic, in addition to helping new scientific research. For the keywords network, of the 8,727 found, 19 reached the minimum limits of 200 occurrences and were included in the map, according to Figure 8.

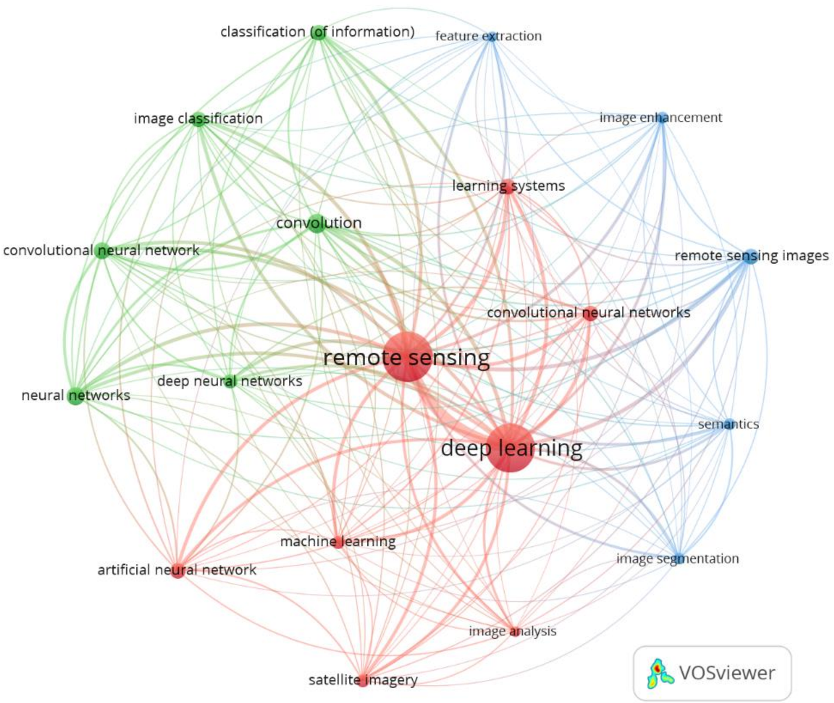


Figure 2.8 - Co-occurrence of Keywords

The size of the nodes represents the frequency of co-occurrence of the keywords and the connecting lines between the nodes demonstrate the degree of interaction between the keywords. The colors of nodes and lines are defined by "clusters", it is understood that they are sets of keywords that have relation in publications.

The keyword network reveals the main results: a) “remote sensing” was the largest node with a record of 1,440 occurrences, followed by “deep learning” with 1,401. These are the two most popular keywords and consequently have the highest degree of interaction; b) “convolution” (465) and “neural network” (397 occurrences) that are inserted in the green cluster, indicate that part of the articles is bringing information and development of types of networks for the processing and analysis of digital images.

As for the network of countries, after filtering, 17 countries reached the minimum limits of 15 published documents, according to Figure 9. The size of the nodes and the font are proportional to the volume of publication, the colors of the nodes are equivalent to the "clusters" created by the publication relationship between the countries and the thickness of the connection lines between the countries demonstrate the intensity of the cooperation.

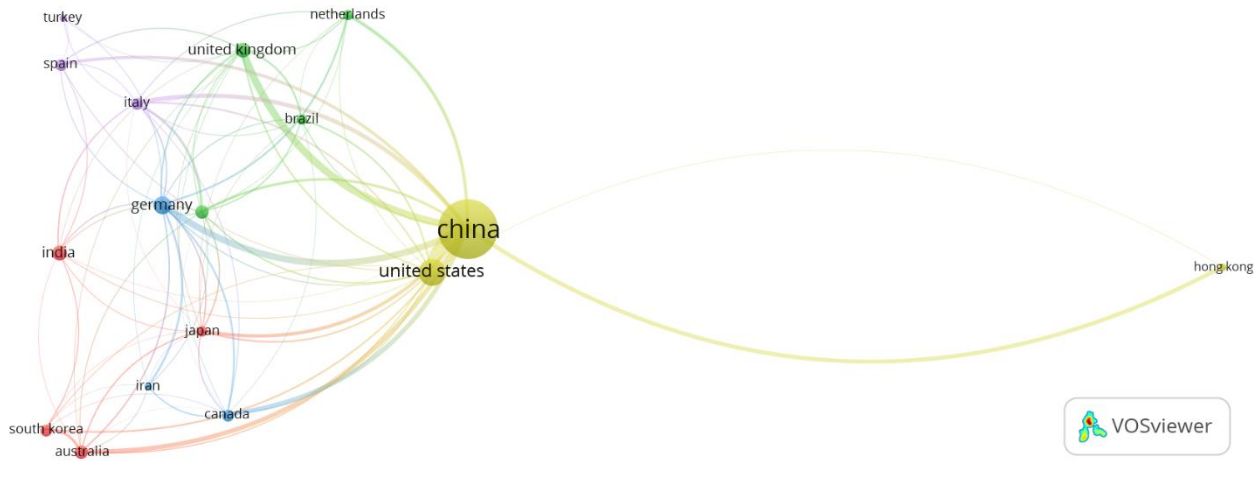


Figure 2.9 - Co-authorship of countries

The network of countries presents the following results: a) China is the most influential country with the highest production in the sample period. It plays an important role in the cooperation network, as it is interconnected with practically all countries, but demonstrates a greater intensity of cooperation in documents with the United States, United Kingdom and Germany; b) On the map we find countries in Europe, Asia, Oceania, North and South America. Highlighting Brazil, the only represented country in South America that has collaboration with China, United States, United Kingdom, Germany, Canada, France, Japan, Italy and the Netherlands (Figure 10); c) Hong Kong has interaction only with China, so its location on the map is isolated from other countries, being inserted in the same yellow "cluster".

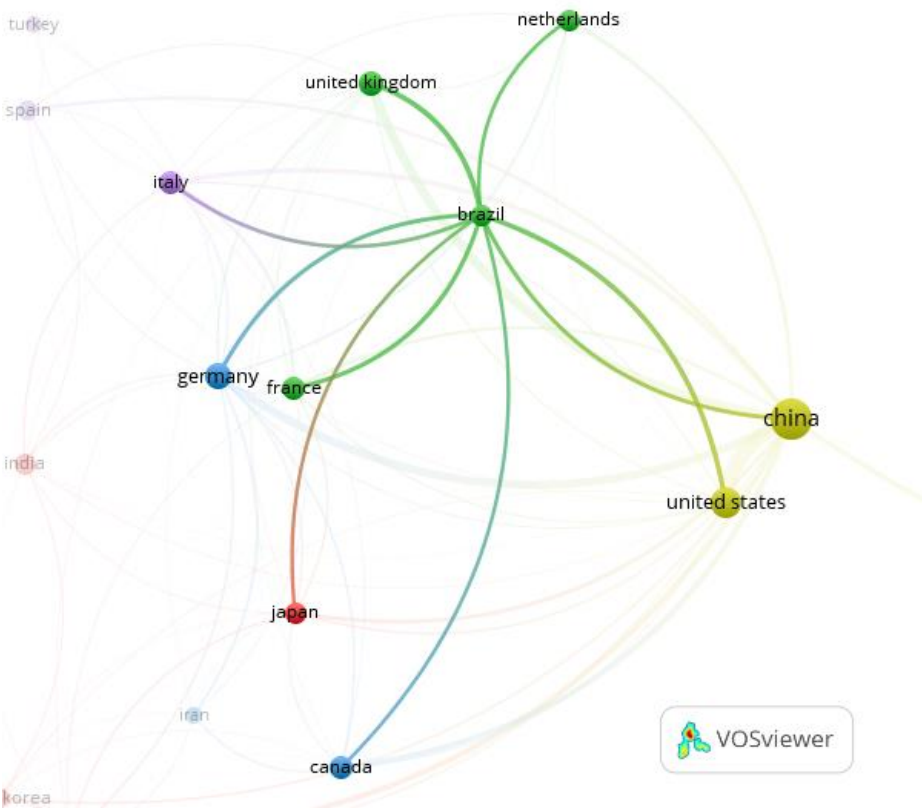


Figure 2.10 - Co-authorship of countries with Brazil

The network maps illustrate keyword collaborations and country co-authorship. The keywords with the highest occurrences are "Deep Learning" and "Remote Sensing", as they are words chosen in the string search, and are inserted in all selected articles. This type of analysis is important to select which keywords have the highest occurrences over the years. On the map of the network of countries, he identified China as the most influential country, which leads research on the subject, presenting, consequently, a larger network of document cooperation with the United States, the United Kingdom and Germany.

2.4. CONCLUSION

This study sought to present a scientometric analysis on Deep Learning for Remote Sensing, through research and data collection in the Scopus and Web of Science databases, between 2010 and 2020. The results showed the advancement of publications over the years and the growing interest of the scientific community through the development of studies for the use of Deep Learning.

With the results released, the production on the subject will continue to grow as it is a relatively new subject with great evolution. The adopted methodology can be used in the coming years to monitor new publications, carrying out continuous analysis in addition to serving for research on any other topic.

2.5. REFERENCES

BAI, Yang et al. Bibliometric and visualized analysis of deep learning in remote sensing. International Journal of Remote Sensing, p. 1-38, 2021.

BOSSHARD, Rachel et al. Systematic reviews of economic burden and health-related quality of life in patients with acute myeloid leukemia. Cancer treatment reviews, v. 69, p. 224-232, 2018.

BRAMER, Wichor M. et al. De-duplication of database search results for systematic reviews in EndNote. Journal of the Medical Library Association: JMLA, v. 104, n. 3, p. 240, 2016.

CHEN, Y. et al. Deep learning-based classification of hyperspectral data. IEEE Journal of Selected topics in applied earth observations and remote sensing, v. 7, n. 6, p. 2094-2107, 2014.

GUPTA, B. M.; DHAWAN, S. M. Deep learning research: Scientometric assessment of global publications output during 2004-17. Emerging Science Journal, v. 3, n. 1, p. 23-32, 2019.

HOOD, W. W.; WILSON, C. S. The literature of bibliometrics, scientometrics, and informetrics. Scientometrics, v. 52, n. 2, p. 291-314, 2001.

MA, L. et al. Deep learning in remote sensing applications: A meta-analysis and review. Isprs Journal of Photogrammetry and Remote Sensing, v. 152, p. 166-177, Jun 2019.

MADDISETTY, B.; BABU, K.S. Scientometric Study of Publications of 'Journal of Indian Society of Remote Sensing'. Library Philosophy and Practice, Lincoln, p. 1-9, 04 2020.

MAYRHUBER, Elisabeth Anne-Sophie et al. Vulnerability to heatwaves and implications for public health interventions–A scoping review. Environmental research, v. 166, p. 42-54, 2018.

MURUGAN, K.; SARAVANAN, G. A Scientometric Study on International Journal of Remote Sensing: 2006-2015. Journal of Advances in Library and Information Science, v. 6, n. 2, p. 139-145, 2017.

NOGUEIRA, K.; PENATTI, O.; DOS SANTOS, J. Towards better exploiting convolutional neural networks for remote sensing scene classification. Pattern Recognition, v. 61, p. 539-556, 2017.

O'NEIL, G. L. et al. Deep learning Using Physically-Informed Input Data for Wetland Identification. Environmental Modelling and Software, v. 126, 2020.

SU, H. N.; LEE, P. C. Mapping knowledge structure by keyword co-occurrence: a first look at journal papers in Technology Foresight. Scientometrics, v. 85, n. 1, p. 65-79, 2010.

VAN ECK, Nees Jan; WALTMAN, Ludo. VOSviewer manual. Leiden: Univeristeit Leiden, v. 1, n. 1, p. 1-53, 2013.

TOLCHEEV, V. O. Research and Analysis of the Subject Area of Deep Learning. Automatic Documentation and Mathematical Linguistics, v. 53, n. 3, p. 103-113, 2019.

YUAN, Q. et al. Deep learning in environmental remote sensing: Achievements and challenges. Remote Sensing of Environment, v. 241, 2020.

ZHANG, L.; ZHANG, L.; DU, B. Deep learning for remote sensing data: A technical tutorial on the state of the art. IEEE Geoscience and Remote Sensing Magazine, v. 4, n. 2, p. 22-40, 2016.

THIRD CHAPTER: ANALYSIS OF DEEP LEARNING MODELS FOR MAPPING PERMEABLE AREAS IN HYDROGRAPHIC BASIN

Abstract: Permeable areas are important components for the urban ecosystem, serving as a solution in the mitigation of rainwater runoff and in flood control, being indispensable for the planning of sustainable cities. Therefore, our objective was to assess the performance of deep learning models for the classification of permeable areas and urban forests. The study was conducted using Google Earth (GE) Pro imagery from May 14, 2020 and the deep learning algorithms U-Net, PSPNet and DeepLabV3, available in ArcGIS Pro. We achieved an F1-score of 92.56% in the U-net model, which was chosen to perform the classification of urban forests. The PSPNet model with F1-score 94.69% was selected for mapping permeable areas. The results indicate that the selected models are efficient for the mapping of urban forests and permeable areas, presenting a good behavior to classify environments of high heterogeneity and complexity, and serving as an aid tool for the monitoring of urban changes and sustainable planning of cities.

Keywords: green spaces, arboreal vegetation, sustainable cities, environmental monitoring.

Resumo: As áreas permeáveis são componentes importantes para o ecossistema urbano, servindo como solução na mitigação do escoamento de águas pluviais e no controle de enchentes, sendo indispensáveis para o planejamento de cidades sustentáveis. Portanto, nosso objetivo foi avaliar o desempenho de modelos de aprendizado profundo para a classificação de áreas permeáveis e florestas urbanas. O estudo foi realizado usando imagens do Google Earth (GE) Pro de 14 de maio de 2020 e os algoritmos de aprendizado profundo U-Net, PSPNet e DeepLabV3, disponíveis no ArcGIS Pro. Atingimos um F1-score de 92,56% no modelo U-net, o qual foi escolhido para realizar a classificação das florestas urbanas. O modelo PSPNet com F1-score de 94,69% foi selecionado para mapeamento de áreas permeáveis. Os resultados indicam que os modelos selecionados são eficientes para o mapeamento de florestas urbanas e áreas permeáveis, apresentando um bom comportamento para classificar ambientes de alta heterogeneidade e complexidade, e servindo como ferramenta de auxílio para o monitoramento das mudanças urbanas e planejamento sustentável das cidades.

Palavras-chave: espaços verdes, vegetação arbórea, cidades sustentáveis, monitoramento ambiental

3.1. INTRODUCTION

Urban catchments are heterogeneous in terms of land use and feature natural and artificial drainage systems (BOUIZROU, 2021). The effects of rain in urban basins and the response of the runoff in these areas are sensitive (SEGOND *et al*., 2007), once impermeable surfaces such as buildings, roads, and other paved areas reduce the infiltration, increasing rainwater runoff (JACOBSON, 2011). The permeable areas play an important role both in mitigating the flow of urban stormwater runoff and flood control, and are indispensable components of the urban ecosystem (REN *et al*. 2020).

According to De Araújo *et al*. (2000), there is a trend in the urban drainage area, which is the search for the maintenance of pre-development conditions of runoff in urban basins, acting as the source of its generation. Green areas and green infrastructures, which are strategies to increase permeable surfaces, serve as a solution to these problems, for example, the green roof (CIPOLLA *et al*., 2016), and green concrete (SUHENDRO, 2014). Permeable areas are fundamental for the project and planning of sustainable cities, and vegetation cover is necessary to avoid supersaturation in the processes of runoff, infiltration, and evapotranspiration that occur within a hydrological system (BAUTISTA; PEÑA-GUZMÁN, 2019).

The combination of remote sensing and machine learning techniques proved its efficiency in many mapping studies, including the mapping of permeable and impermeable areas (MISRA *et al*., 2020, OKUJENI *et al*., 2015, WELLMANN *et al*., 2020, FENG *et al*., 2015). However, the remote sensing community is always committed to developing methods to improve the performance of aspects such as pre-processing, segmentation, and classification (MA *et al*, 2019). Deep learning studies in remote sensing started to grow in 2014. The attention is increasing from remote sensing researchers because of its ability to automatically extract resources from the image dataset, high semantic segmentation level, non-linear problem modeling, and mapping in complex environments (ZHANG *et al*, 2016).

Deep learning is a subfield of machine learning that can extract features from images using convolutional neural networks (CNN), deep neural networks, among others. These features refer, for example, to spectral, texture, semantic and potential feature information. Using deep learning networks for classification can help to obtain tools and produce more accurate classification results (MOHSEN *et al*., 2018, CHEN *et al*., 2021). Thus, it has been applied in many studies, including automatic extraction of impervious surfaces (HUANG *et al*., 2019), mapping of impermeable areas (FU, *et al*., 2019), analysis and mapping of green spaces (MORENO-ARMENDÁRIZ *et al*., 2019) and automatic extraction of urban green space (LIU *et al*., 2019).

It is notable in the literature a greater concentration of research related to impermeable areas and that studies with specific mapping and classification of permeable areas are still little addressed. It also has a confusion of termologies for the definition of permeable areas, but checking the termology used in recent studies we highlight the term "urban green space" (UGS) (XU *et al*., 2020; CHEN *et al*., 2021; HUERTA *et al*., 2021) that are being used more for specific researches using deep learning, while the terminology "pervious surfaces" it is directly associated with research on impervious areas.

In this chapter, we intend to analyze and evaluate deep learning models, and define the best model for performing the classification of permeable areas and urban forests. Deep learning algorithms work like human neurons, which through their classifications and automatic extractions, are very useful for mapping complex environments, facilitating the monitoring and control of these areas, as well as helping in decision making using other geotechnologies.

3.2. MATERIAL AND METHODS

The raster data used was a mosaic of satellite images from Google Earth Pro, from May 14, 2020, with a spatial resolution of 0.50 meters. The projection system adopted was the Universal Transverse Mercator (UTM), zone 21 South, Datum SIRGAS 2000. The vector data related to the boundaries of the city and the catchment were acquired through the website of the Brazilian Institute of Geography and Statistics (IBGE) and the municipality of Campo Grande, respectively.

We used a notebook with a CPU Intel Core i5-10210 of 2.11GHz, 8GB of main memory and an GPU NVIDIA® GeForce MX250 with 2GB of dedicated memory. All procedures were performed using ArcGIS Pro version 2.9.0 software.

The workflow was defined in six steps, as shown in Figure 3.1, which was repeated for mapping permeable areas and urban forests.

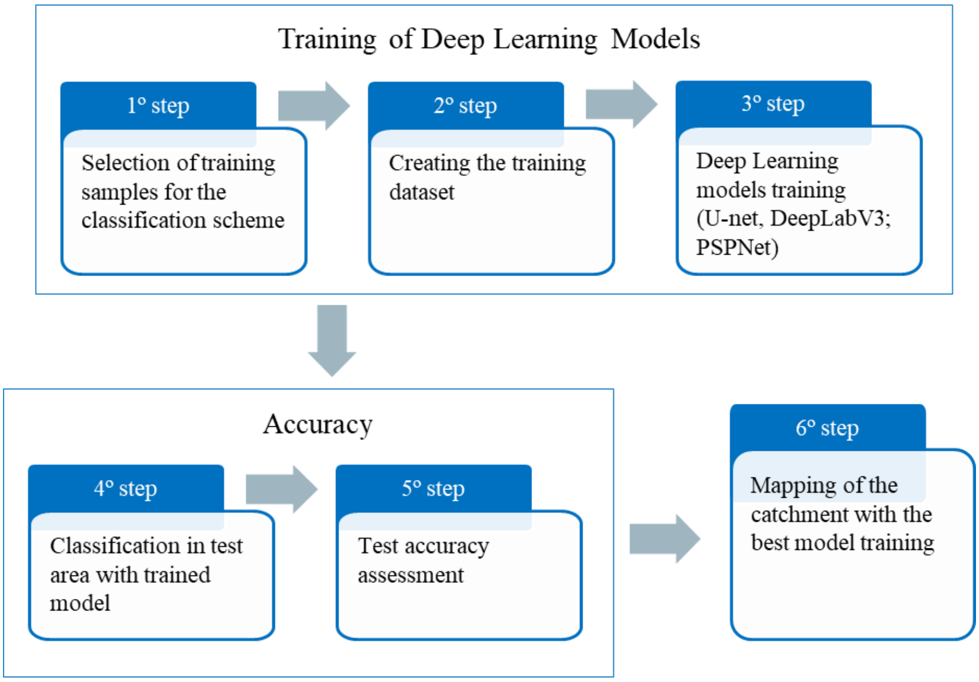


Figure 3.1: Work flowchart.

For the study in question, training areas and test areas were defined without data overlap (Figure 3.2).

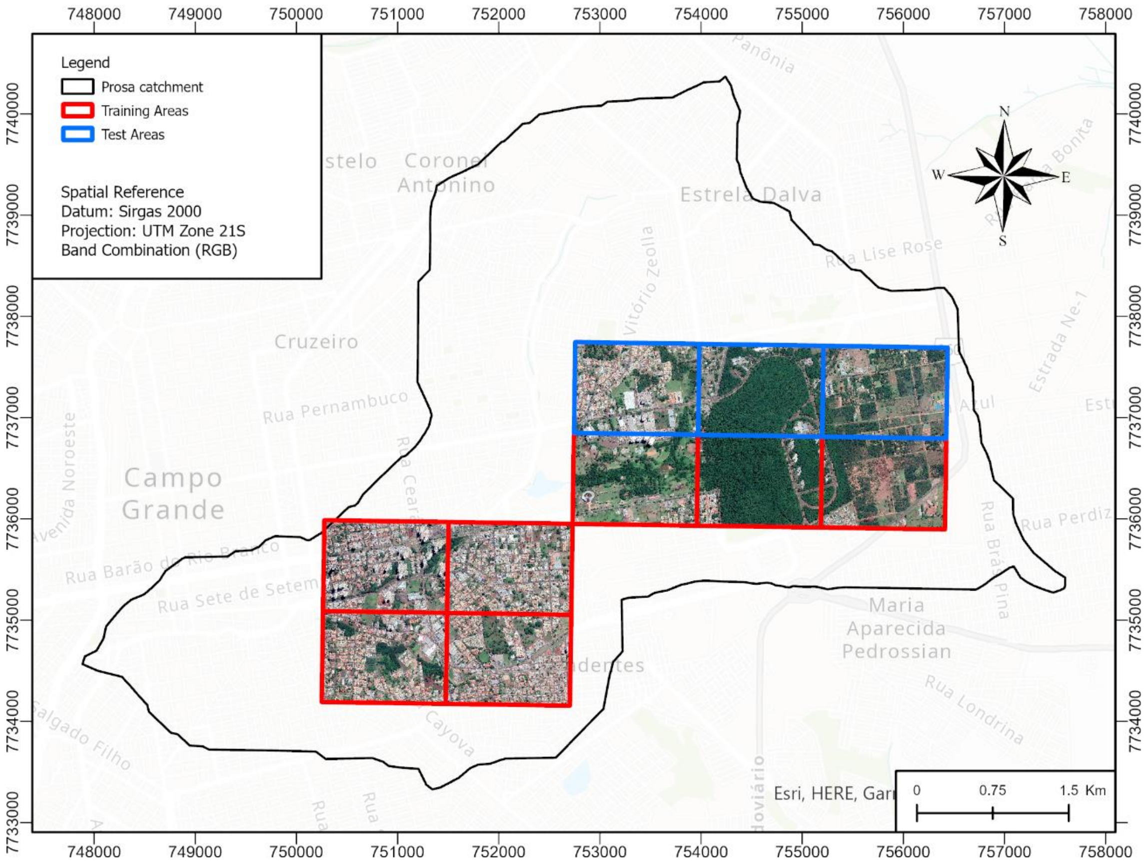


Figure 3.2: Location of training and testing areas in the catchment

In the first and second steps, we selected the training samples for the classification scheme and created the training dataset, where the samples were defined using visual interpretation with identification of the main features and targets mapped in the scene. For urban forests, 4,687 samples were selected composed of individual trees, blocks of trees, and forests of different shades of green. The training dataset was created with 2,048 TIFF images, which were exported with dimensions of 256x256 pixels, with a pixel size of 0.50 m. For the permeable areas, the class contained 3,301 samples composed of trees, grasses, and exposed soil. The training dataset has 2,060 TIFF images, were exported with dimensions of 256x256 pixels, with a pixel size of 0.50m.

The third step consisted of training the deep learning models using the Train Deep Learning Model tool in ArcGIS Pro. U-net, PSPNet, and DeepLabV3 were selected as they compose the state-of-the-art for semantic segmentation of remote sensing imagery. For all training, the Backbone ResNet-34 model was selected, the models were trained in 20 epochs, and validations were carried out from 10% of the total. These configurations were defined due to computational performance.

After completing the model training part, we moved on to the fourth and fifth stages, where it was possible to verify the accuracy of the models through assessment metrics. In these stages, the classification was performed using each model trained in the test areas and subsequently generating the confusion matrix for each classification. Based on the confusion matrix, we estimated the metrics: sensitivity, specificity, accuracy, and F1 Score, so an analysis was performed to choose the best model.

The last step was to map the urban forests and permeable areas through the model with the best performance found in the previous step, where each valid pixel has a class label assigned. This mapping was performed by the Classify Pixels using Deep Learning tool in ArcGIS Pro.

3.3. RESULTS AND DISCUSSION

3.3.1 Permeable areas mapping

The trained models, through the dataset of permeable areas, obtained the following metrics (Table 3.1). These metrics showed that the U-net model with batchsize 8 presented the best Precision with 95.29%, and there were similar F1 Scores were obtained by the U-net (batchsize 8) model and the model PSPNet, with 92.71% and

92.72%, respectively. The model with the worst Precision was U-net (batchsize 2) with 65.26% and DeepLabV3 had the best Recall 97.10%.

MODELS	MEASURE		
	Precision	Recall	F1 Score
U-net (batchsize 2)	65.26	74.79	69.70
U-net (batchsize 4)	79.64	89.05	84.08
U-net (batchsize 8)	95.29	90.26	92.71
PSPNet	92.21	93.24	92.72
DeepLabV3	80.88	97.10	88.26

Table 3.1: Permeable areas training metrics

After classifying the permeable areas in the test areas, we obtained the following details in Figure 3.3. The classification performed by the U-net model (batchsize 2) presents many omissions of permeable areas. In Quadrant B3 and C3, it is shown that the U-net (batchsize 4) and U-net (batchsize 8) models omit areas with exposed soil. The classification performed by the DeepLabV3 model includes impermeable areas that can be visualized in all details. In Quadrant A2, B2, C2, D2, and E2 there is an error of classification in relation to the tank with algae.

The U-net (batchsize 8) and PSPNet models have only a few differences in classifications that can be observed in quadrants C1, D1, C3, and D3. The U-net (batchsize 8) omitted areas with exposed soil, while the PSPnet omitted areas with grass. Regarding small trees, all models omitted them equal to urban forest classification.

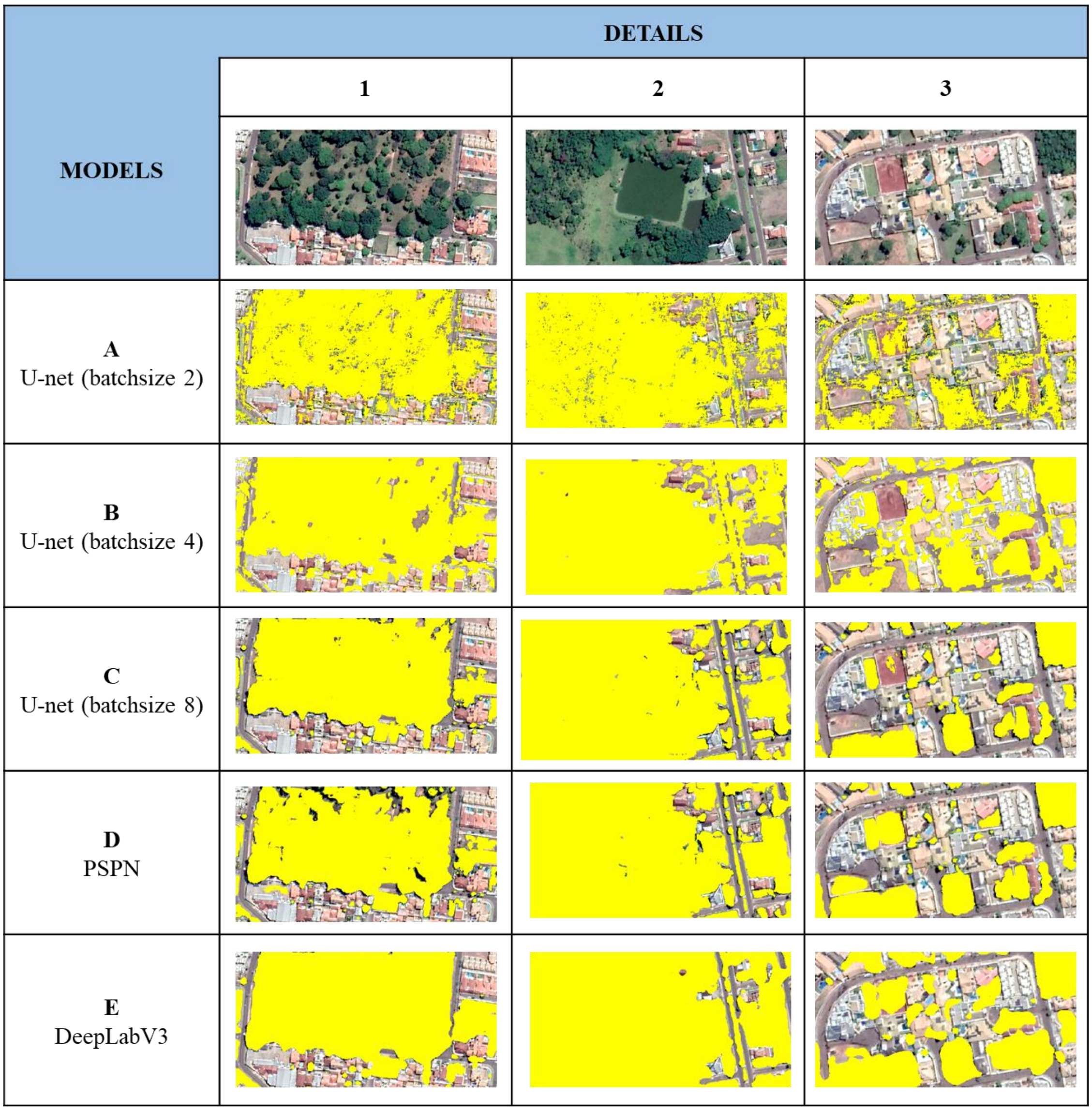


Figure 3.3: Details of classifications of permeable areas in the test area.

The classification details serve as a basis for the confirmation presented in Table 3.2, where the confusion matrix metrics generated through the classifications of each model are presented.

MODELS	MEASURE			
	Sensitivity	Specificity	Accuracy	F1 Score
U-net (batchsize 2)	88.52	80.56	86.80	91.32
U-net (batchsize 4)	88.78	75.00	85.80	90.74
U-net (batchsize 8)	90.82	99.07	92.60	95.06
PSPNet	91.07	95.37	92.00	94.69
DeepLabV3	97.19	87.04	95.00	96.82

Table 3.2: Metrics of classification of permeable areas in the test area

Analyzing the generated metrics, the model that presented the best F1 Score was DeepLabV3; however, its specificity was much lower, indicating that the model did not correctly classify the negatives. We proceed to the U-net model (batchsize 8) that obtained the second best metric with an F1Score of 95.06%, followed by the PSPNet model with 94.69%, analyzing the classification and metrics of these two models, it is remarkable that the classification generated by the PSPNet model obtained better identification of areas with exposed soil.

Therefore, the PSPNet model obtained the best performance in the classification and better extraction of information about permeable areas, which was selected to carry out the mapping of permeable areas. The mapping found an area of 13.4104 km², which occupies a total of 41.95% of the catchment (Figure 3.4).

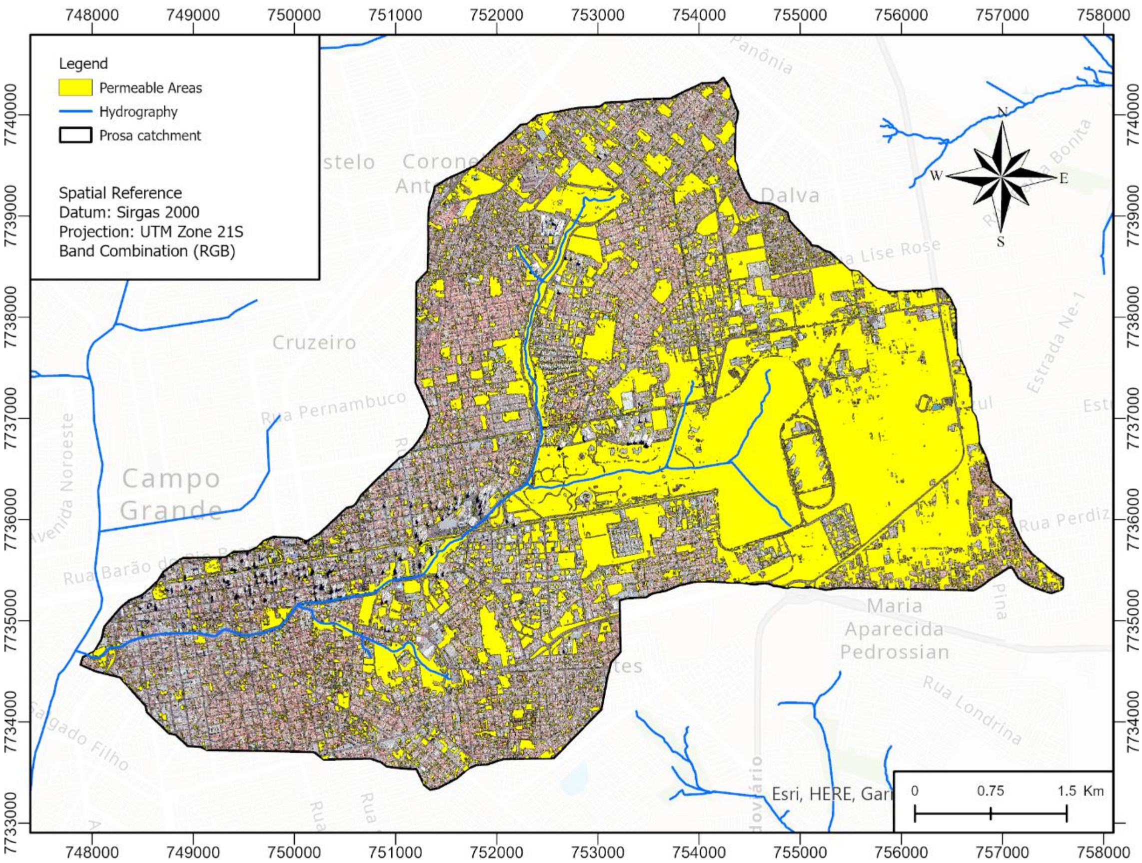


Figure 3.4: Map of the permeable areas in the Prosa catchement with Deep Learning model
Source: Prepared by the Author

3.3.2 Urban Forests mapping

Through the training metrics (Table 3.3), it is possible to verify that the PSPNet model obtained the best Precision with 95.47%, but presented the worst Recall and F1 Score. Then, we have the U-net model with batchsize 8, which has the second-best Precision and the best F1Score with 87.87%.

MODELS	MEASURE		
	Precision	Recall	F1 Score
U-net (batchsize 2)	88.67	84.22	86.39
U-net (batchsize 4)	87.16	86.47	86.82
U-net (batchsize 8)	89.70	86.10	87.87
PSPNet	95.47	49.37	65.09
DeepLabV3	94.29	72.32	81.77

Table 3.3: Urban forest training metrics

After classifying the urban forests in the test areas, we obtained the following details in Figure 3.5. Quadrants D1 and D3 show that the PSPNet model omitted the classification of pixels that characterize the tree class, and the same occurs in the classification performed by the DeepLabV3 model in quadrants E1, E2 and E3. In quadrant D2, there is an error similar to what occurred in the classification permeable areas in relation to the tank with algae. These observations characterize that these models did not present the expected performance for tree classification. However, the classifications performed by the U-net model with batchsize 2, 4 and 8 showed the best behavior with only a few differences that can be observed in quadrants A2, B2 and C2. The U-net (batchsize 2) showed misclassification in the area of a tank with algae and the U-net (batchsize 4) classified some areas of grass as trees. Another omission found in all models was in relation to smaller trees; however, the U-net (batchsize 4) model was able to identify some smaller trees.

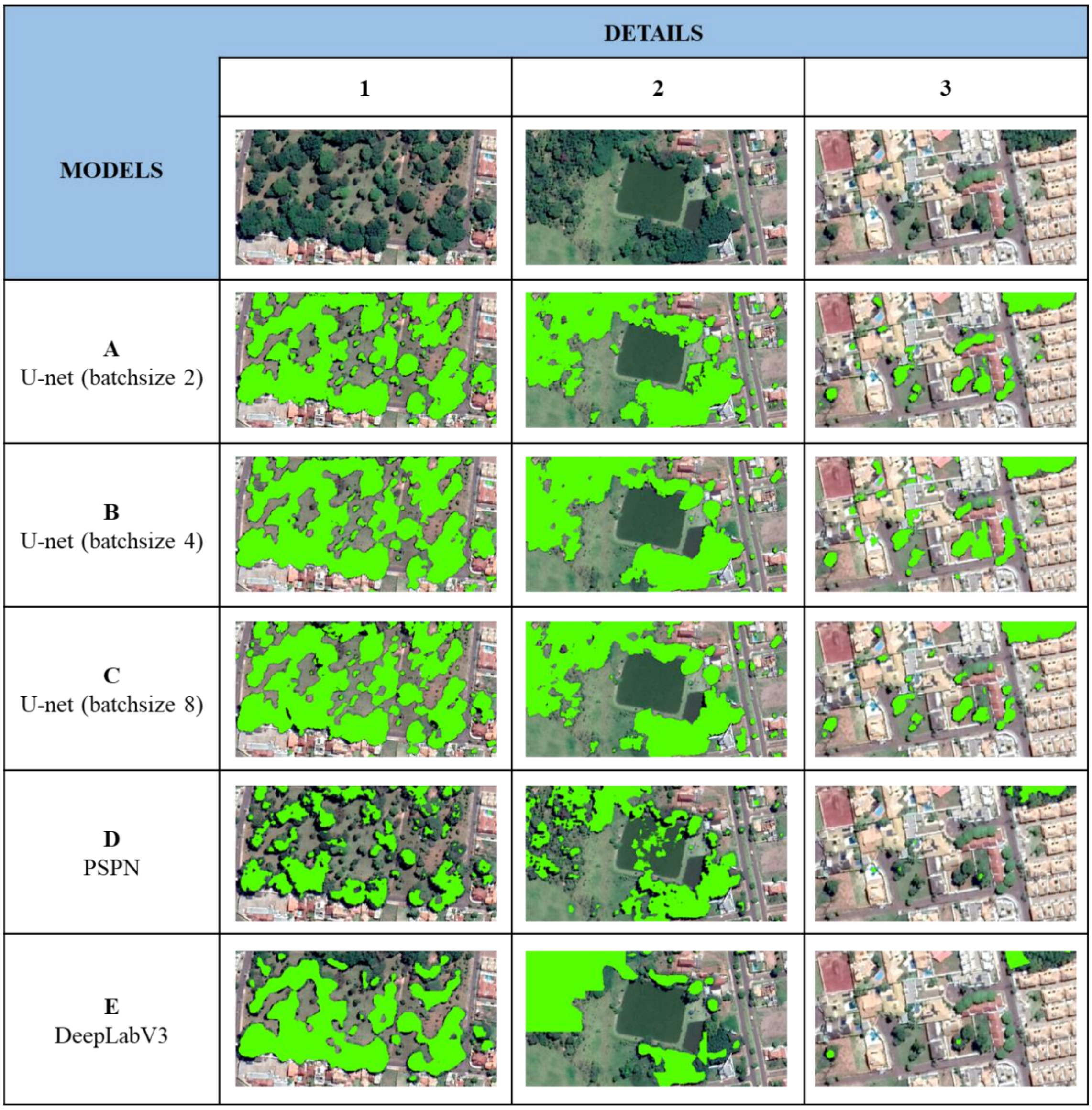


Figure 3.5: Details of classifications of urban forests in the test area

Table 3.4 presents the metrics generated through the confusion matrix referring to the classifications performed in the test areas.

MODELS	**MEASURE**			
	Sensitivity	Specificity	Accuracy	F1 Score
U-net (batchsize 2)	89.80	94.90	92.40	92.05
U-net (batchsize 4)	91.43	94.12	92.80	92.56
U-net (batchsize 8)	88.57	94.51	91.60	91.18
PSPNet	62.04	98.04	80.40	75.62
DeepLabV3	78.78	97.25	88.20	86.74

Table 3.4: Metrics of classification of the urban forest in the test area

The model that obtained the worst metrics was the PSPN that presented an F1 Score of 75.62%, while the U-net with batchsize 4 obtained the best F1 Score with 92.56%. U-net with batchsize 8 obtained a similar classification in the details to batchsize 4, but with lower accuracy and F1 Score. Therefore, the model that obtained the best behavior in all metrics was the U-net with batchsize 4, so this model was selected for the classification of the urban forest in the catchment (Figure 3.6).

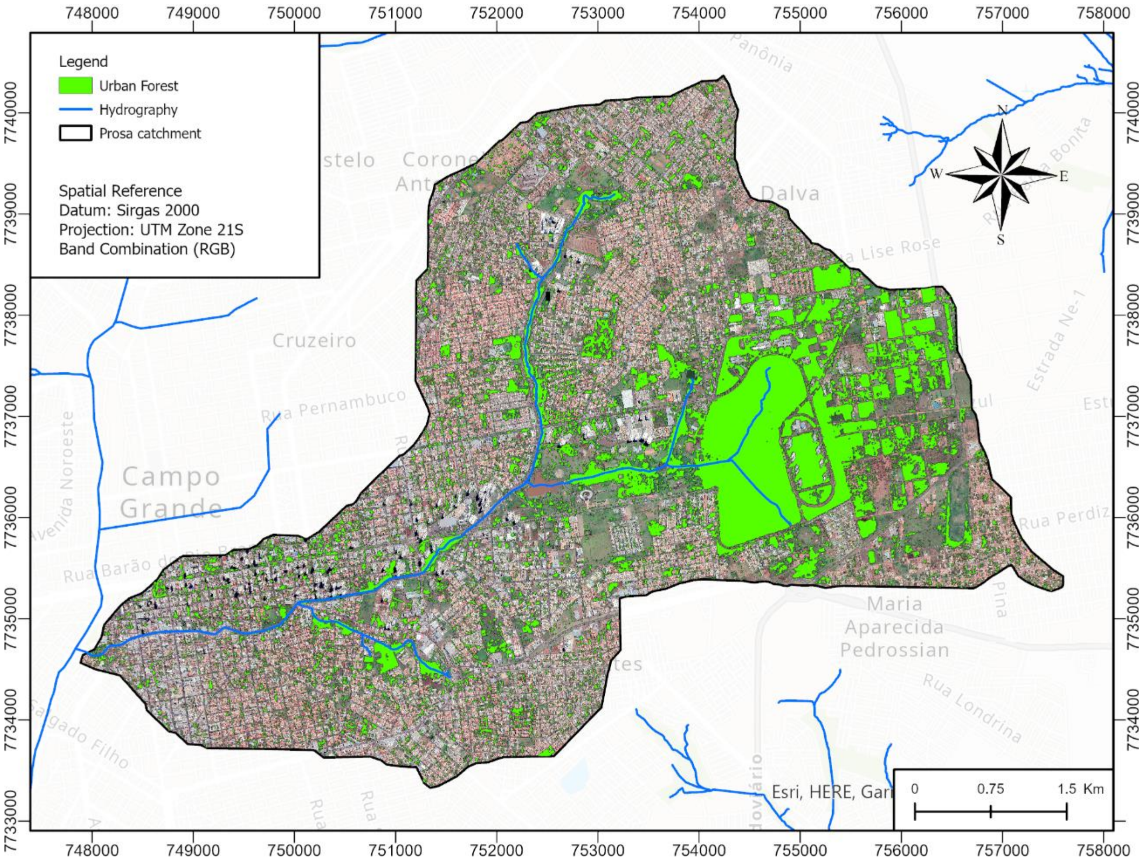


Figure 3.6: Map of the urban forests in the Prosa catchment with Deep Learning model.
Source: Prepared by the Author

The mapping found an area of 7.0572 km², which occupies a total of 22.07% of the catchment. According to the Campo Grande Urban Drainage Master Plan (CAMPO GRANDE, 2008) the Prosa catchment has 21% of vegetation cover, while in this study, it was found, for May 2020, a percentage of 22.07% of arboreal vegetation.

The two models selected for mapping urban forests and permeable areas were effective and provided good results. In the article by Martins *et al*. (2021), the authors compared several models for segmenting trees in the urban context in images with a pixel size of 10 centimeters and similar results were obtained with the FCN, SegNet, U-net and DeepLabv3+ models. In our work, when considering images with a 50 cm pixel, U-net proved to be more consistent in arboreal mapping.

U-net and its variants have been shown to be quite accurate in remote sensing applications (WANG *et al*., 2022, TORRES *et al*., 2021, MCGLINCHY *et al*., 2019). And in the present work it was also more consistent when compared to the other networks to perform the two tasks (tree segmentation and permeable areas).

In the study carried out by Martins *et al*. (2021), where five CNNs were evaluated for the semantic segmentation of urban forests using airborne high spatial resolution RGB images, similar errors to this study occurred. Most of the problems faced by deep networks were related to shadow areas, small trees and isolated, and areas of grass and shrubs within the images. Regarding the small isolated trees, all the CNNs tended to classify them wrongly and even ignore them, this is because they are in the same patch as large groups of trees. Concerning the grasses, the CNNs can interpret them as a continuation of the patches of trees and classify them as trees. This also happens for the tank with algae, creating false positives.

However, to achieve better accuracy in any deep learning model, a large number of true, high-quality terrain samples are required for training data, and this generation is extremely labor-intensive for urban environments. As a solution, some studies included traditional methods to support DL methods, using it before training, as pre-processing or as a post-processing method (NEUPANE *et al*., 2021). In the study developed by Mutreja *et al*. (2020) a supervised classification is performed with the

Support Vector Machine (SVM), and the generated dataset, after manual cleaning, is used for training the model in Deep Learning. This process aimed to increase training and precision data.

Another way to improve the samples is in relation to the images used for the classification of urban areas. The spatial resolution is considered more important than the spectral resolution because, with the increase of the spatial resolution, more urban objects are clearly visible. Another option is to use higher resolution RGB image datasets and use different types of datasets together, such as RGB and LiDAR (NEUPANE *et al*., 2021, MARTINS *et al*., 2021). These are solutions designed to eliminate omissions from mapping small and isolated trees and errors with grasses, exposed soil, and the tank with algaes.

3.4. CONCLUSION

In this work, we evaluated the deep learning algorithms U-net, PSPNet and DeepLabV3 for mapping urban forests and permeable areas. The U-net model with batchsize 4 presented the best F1 Score with 92.56% and, therefore, was selected to perform the classification of urban forests. Meanwhile, the PSPNet model with F1 Score 94.69% was selected for mapping permeable areas.

The classification performed with the U-net model obtained a good result. Areas that characterized trees were correctly classified, except for small and isolated trees, which were omitted. However, there was no confusion of similar textures and colors between tree and grass or tree and tank with alges, as well as very few concreted areas were identified.

For the classification of permeable areas, the PSPNet model also performed well. It correctly classified the trees, grasses and exposed soil, and there was very little confusion between roofs and exposed soil. It obtained some wrong classifications in relation to tank areas that present texture and coloration similar to vegetation, as well as omitted small and isolated trees.

The deep learning tools available in ArcGIS Pro software provide an enriching experience for users who do not master programming environments. However, like any system that generates Deep Learning models, it needs GPU-based computing and a large volume of storage. In this work, the training of the models took an average of 15 hours, but the time to perform the tests was relatively faster.

It is suggested for future works: a) to increase the efficiency in the creation of the training dataset, using in other ways not only manually; b) improve training parameters, with an increase in the number of epochs, test other backbones and models; c) evaluate the capacity of models trained in different regions, combining multitemporal and spatial training.

The results indicate that the selected models are efficient for the mapping of urban forests and permeable areas, presenting a good performance to classify environments of high heterogeneity and complexity. Once trained and with satisfactory results, the models can be applied in mapping tasks in other urban areas using similar high-resolution data sets, facilitating the monitoring of urban changes and favoring sustainable planning.

3.5. REFERENCES

BAUTISTA, D.; PEÑA-GUZMÁN, C. Simulating the hydrological impact of Green roof use and an increase in Green areas in an urban catchment with i-tree: a case study with the town of Fontibón in Bogotá, Colombia. Resources, v. 8, n. 2, p. 68, 2019.

BOUIZROU, I. et al. Network representation in hydrological modelling on urban catchments in data-scarce contexts: A case study on the Oued Fez catchment (Morocco). Journal of Hydrology: Regional Studies, v. 34, p. 100800, 2021.

CIPOLLA, S. et al. A long-term hydrological modelling of an extensive green roof by means of SWMM. Ecological Engineering, v. 95, p. 876-887, 2016.

DE ARAÚJO, P. R.; TUCCI, C. EM; GOLDENFUM, J. A. Avaliação da eficiência dos pavimentos permeáveis na redução de escoamento superficial. Braz. J. Water Resour, v. 5, n. 3, p. 21-29, 2000.

CHEN, Caiyan et al. A New Individual Tree Species Classification Method Based on the ResU-Net Model. Forests, v. 12, n. 9, p. 1202, 2021.

CHEN, Y. et al. Automatic mapping of urban green spaces using a geospatial neural network. GIScience & Remote Sensing, p. 1-19, 2021.

FENG, Q. et al. UAV remote sensing for urban vegetation mapping using random forest and texture analysis. Remote sensing, v. 7, n. 1, p. 1074-1094, 2015.

FU, Y. et al. Mapping impervious surfaces in town–rural transition belts using China's GF-2 imagery and object-based deep CNNs. Remote Sensing, v. 11, n. 3, p. 280, 2019.

HUERTA, E. et al. Mapping Urban Green Spaces at the Metropolitan Level Using Very High Resolution Satellite Imagery and Deep Learning Techniques for Semantic Segmentation. Remote Sensing, v. 13, n. 11, p. 2031, 2021.

HUANG, F. et al. Automatic extraction of impervious surfaces from high resolution remote sensing images based on deep learning. Journal of Visual Communication and Image Representation, v. 58, p. 453-461, 2019.

JACOBSON, C. R. Identification and quantification of the hydrological impacts of imperviousness in urban catchments: A review. Journal of environmental management, v. 92, n. 6, p. 1438-1448, 2011.

LIU, W. et al. An Automatic Extraction Architecture of Urban Green Space Based on DeepLabv3plus Semantic Segmentation Model. In: 2019 IEEE 4th International Conference on Image, Vision and Computing (ICIVC). IEEE, 2019. p. 311-315.

MA, L. et al. Deep learning in remote sensing applications: A meta-analysis and review. Isprs Journal of Photogrammetry and Remote Sensing, v. 152, p. 166-177, Jun 2019.

MCGLINCHY, Joe et al. Application of UNet fully convolutional neural network to impervious surface segmentation in urban environment from high resolution satellite imagery. In: IGARSS 2019-2019 IEEE International Geoscience and Remote Sensing Symposium. IEEE, 2019. p. 3915-3918.

MARTINS, José Augusto Correa et al. Semantic segmentation of tree-canopy in urban environment with pixel-wise deep learning. Remote Sensing, v. 13, n. 16, p. 3054, 2021.

MISRA, M. et al. Assessing machine learning based supervised classifiers for built-up impervious surface area extraction from sentinel-2 images. Urban Forestry & Urban Greening, v. 53, p. 126714, 2020.

MOHSEN, Heba et al. Classification using deep learning neural networks for brain tumors. Future Computing and Informatics Journal, v. 3, n. 1, p. 68-71, 2018.

MORENO-ARMENDÁRIZ, M. A. et al. Deep green diagnostics: Urban green space analysis using deep learning and drone images. Sensors, v. 19, n. 23, p. 5287, 2019.

MUTREJA, Guneet et al. Identifying Settlements Using SVM and U-Net. In: IGARSS 2020-2020 IEEE International Geoscience and Remote Sensing Symposium. IEEE, 2020. p. 1217-1220.

NEUPANE, Bipul; HORANONT, Teerayut; ARYAL, Jagannath. Deep Learning-Based Semantic Segmentation of Urban Features in Satellite Images: A Review and Meta-Analysis. Remote Sensing, v. 13, n. 4, p. 808, 2021.

OKUJENI, A. et al. Extending the vegetation–impervious–soil model using simulated EnMAP data and machine learning. Remote Sensing of Environment, v. 158, p. 69-80, 2015.

REN, X. et al. Effect of infiltration rate changes in urban soils on stormwater runoff process. Geoderma, v. 363, p. 114-158, 2020

SEGOND, M. et al. The significance of spatial rainfall representation for flood runoff estimation: A numerical evaluation based on the Lee catchment, UK. Journal of Hydrology, v. 347, n. 1-2, p. 116-131, 2007.

SUHENDRO, B. Toward green concrete for better sustainable environment. Procedia Engineering, v. 95, p. 305-320, 2014.

TORRES, Daliana Lobo et al. Deforestation Detection with Fully Convolutional Networks in the Amazon Forest from Landsat-8 and Sentinel-2 Images. Remote Sensing, v. 13, n. 24, p. 5084, 2021.

WANG, Zewei et al. Semantic Segmentation and Analysis on Sensitive Parameters of Forest Fire Smoke Using Smoke-Unet and Landsat-8 Imagery. Remote Sensing, v. 14, n. 1, p. 45, 2022.

WELLMANN, T. et al. Green growth? On the relation between population density, land use and vegetation cover fractions in a city using a 30-years Landsat time series. Landscape and Urban Planning, v. 202, p. 103857, 2020.

XU, Z. et al. A novel intelligent classification method for urban green space based on high-resolution remote sensing images. Remote Sensing, v. 12, n. 22, p. 3845, 2020.

ZHANG, L. et al. Deep learning for remote sensing data: A technical tutorial on the state of the art. IEEE Geoscience and Remote Sensing Magazine, v. 4, n. 2, p. 22-40, 2016.

FINAL CONSIDERATIONS

The study carried out is valid, not only for meeting all the objectives initially proposed for each chapter, but also for opening several possibilities for new studies involving the mapping of permeable areas, generating important information for the planning and management of sustainable cities.

The satellite images used, Google Earth Pro, favored this work, as they allow a large-scale application, involve easy acquisition and zero investment and have updated images in the urban context.

The use of Google Earth Pro images submitted to classifications with the Random Forest algorithm and with the deep learning methods U-net and PSPNet obtained a high precision, with an F1-score greater than 90% for the mapping of permeable areas, indicating a excellent tool for mapping green areas in highly complex environments, which can be applied on a large scale and monitoring urban changes.

The machine learning and deep learning tools available in ArcGIS Pro software provided an enriching experience for this work, as it does not require a high level of user knowledge in programming and presents a didactic and easy-to-use tool. However, as with any system that generates Deep Learning models, it needs GPU-based computing and a large amount of storage.

This study confirms that deep learning models for remote sensing data will continue to grow, given that the results can always be improved, as well as the methodology can be applied to different regions.

BIBLIOGRAPHIC REFERENCES

ARABAMERI, A. et al. A comparison of statistical methods and multi-criteria decision making to map flood hazard susceptibility in Northern Iran. Science of the Total Environment, v. 660, p. 443-458, 2019.

BLASCHKE, T. et al. Collective sensing: Integrating geospatial technologies to understand urban systems—An overview. Remote Sensing, v. 3, n. 8, p. 1743-1776, 2011.

CUI, X. et al. Assessing sustainability of urbanization by a coordinated development index for an Urbanization-Resources-Environment complex system: A case study of Jing-Jin-Ji region, China. Ecological Indicators, v. 96, p. 383-391, 2019.

HUERTA, Roberto E. et al. Mapping Urban Green Spaces at the Metropolitan Level Using Very High Resolution Satellite Imagery and Deep Learning Techniques for Semantic Segmentation. Remote Sensing, v. 13, n. 11, p. 2031, 2021.

HUSSAIN, M. et al. Change detection from remotely sensed images: From pixel-based to object-based approaches. ISPRS Journal of photogrammetry and remote sensing, v. 80, p. 91-106, 2013.

IBGE – Instituto Brasileiro de Geografia e Estatística. Brasil. 2010. Censo Demográfico. Available in:< https://cidades.ibge.gov.br/brasil/ms/campo-grande/panorama> Access in 20 jul. 2021.

JACOBSON, C. R. Identification and quantification of the hydrological impacts of imperviousness in urban catchments: A review. Journal of environmental management, v. 92, n. 6, p. 1438-1448, 2011.

KRANJČIĆ, N. et al. Machine learning methods for classification of the green infrastructure in city areas. ISPRS International Journal of Geo-Information, v. 8, n. 10, p. 463, 2019.

LI, M.; STEIN, A. Mapping land use from high resolution satellite images by exploiting the spatial arrangement of land cover objects. Remote sensing, v. 12, n. 24, p. 4158, 2020.

LI, X. et al. The surface urban heat island response to urban expansion: A panel analysis for the conterminous United States. Science of the Total Environment, v. 605, p. 426-435, 2017.

LUO, Z. et al. Impact of land use and urbanization on river water quality and ecology in a dam dominated basin. Journal of Hydrology, v. 584, p. 124655, 2020.

MAXWELL, A. et al. Implementation of machine-learning classification in remote sensing: An applied review. International Journal of Remote Sensing, v. 39, n. 9, p. 2784-2817, 2018.

MISRA, M. et al. Assessing machine learning based supervised classifiers for built-up impervious surface area extraction from sentinel-2 images. Urban Forestry & Urban Greening, v. 53, p. 126714, 2020.

MOHAMMADY, M. et al. Land subsidence susceptibility assessment using random forest machine learning algorithm. Environmental Earth Sciences, v. 78, n. 16, p. 1-12, 2019

PAN, H. et al. Understanding interactions between urban development policies and GHG emissions: A case study in Stockholm Region. Ambio, v. 49, n. 7, p. 1313-1327, 2020.

REN, X. et al. Effect of infiltration rate changes in urban soils on stormwater runoff process. Geoderma, v. 363, p. 114-158, 2020

SETO, Karen C. et al. A meta-analysis of global urban land expansion. PloS one, v. 6, n. 8, p. e23777, 2011.

XI, Xiangshu et al. Evaluation of dimensionality reduction methods for individual tree crown delineation using instance segmentation network and UAV multispectral imagery in urban forest. Computers and Electronics in Agriculture, v. 191, p. 106506, 2021.

XU, Zhiyu et al. A novel intelligent classification method for urban green space based on high-resolution remote sensing images. Remote Sensing, v. 12, n. 22, p. 3845, 2020.

YOO, C. et al. Comparison between convolutional neural networks and random forest for local climate zone classification in mega urban areas using Landsat images. ISPRS Journal of Photogrammetry and Remote Sensing, v. 157, p. 155-170, 2019

ZHAO, G. et al. Assessment of urban flood susceptibility using semi-supervised machine learning model. Science of The Total Environment, v. 659, p. 940-949, 2019.

ZHU, Z. et al. Understanding an urbanizing planet: Strategic directions for remote sensing. Remote Sensing of Environment, v. 228, p. 164-182, 2019