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Wetland Classification Using Machine Learning Models in the Brazilian Pantanal

Classificação de áreas úmidas usando modelos de Aprendizado de Máquina no Pantanal Brasileiro

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Abstract

The Pantanal is the largest tropical wetland in the world and covers the countries of Bolivia, Brazil, and Paraguay. Some regions within the Pantanal are part of the Convention on Wetlands or are recognized as Biosphere Reserves and World Heritage Sites by UNESCO. This work's objective is to classify surface water bodies into wetlands using machine learning techniques, through clustering techniques. Initially, the (Normalized Difference Vegetation Index) was used from a mosaic of images covering the study area from the Sentinel 2-A satellite processed on the Google Earth Engine platform. From this index, a threshold is established empirically, and the water bodies are segmented. The clustering technique is then applied to the morphological characteristics of each segmented object. The results obtained show that it is possible to categorize water bodies with unsupervised learning techniques.

Keywords:
Remote sensing, Artificial intelligence, Image processing, Water bodies.

Resumo

O Pantanal é a maior área úmida tropical do mundo e abrange os países da Bolívia, Brasil e Paraguai. Existem regiões dentro do Pantanal que estão aderidas ao tratado da Convenção de áreas úmidas ou que são reconhecidas como Reserva da Biosfera e Patrimônio da Humanidade pela UNESCO. O objetivo deste trabalho é a classificação de corpos d'água superficiais em áreas úmidas por meio do uso de técnicas de aprendizado de máquina, em particular técnicas de agrupamento. Inicialmente, utilizou-se o índice Índice de Vegetação por Diferença Normalizada a partir de um mosaico de imagens que cobre a área de estudo provenientes do satélite Sentinel 2-A processadas na plataforma Google Earth Engine. A partir deste índice, estabeleceu-se um limiar de maneira empírica para segmentar os corpos d'água. Em seguida, aplicou-se a técnica de agrupamento às

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características morfológicas de cada objeto segmentado. Os resultados obtidos mostram que é possível a categorização de corpos d'água com técnicas de aprendizado não supervisionado.
Palavras-chave:
Sensoriamento remoto, Inteligência artificial, Processamento de imagens, Corpos d'água.

I. INTRODUCTION

Wetlands constitute approximately 6% of our planet surface that are permanently or intermittently flooded. They are vital for the human survival and a source of water and primary productivity, the habitat of several plant and animal species. Despite its' global importance, half of the Earth's wetlands have disappeared. Currently, there is a Wetlands Convention Treaty for the conservation and rational use of these areas and its' resources. This treaty covers 2,513 areas of international importance, covering an area of 257,254,185 ha (Ramsar, 2024). The Pantanal is the world's largest tropical wetland region, and encompasses parts of Bolivia, Brazil and Paraguay. Some sections within the Pantanal joined the Wetlands Convention Treaty or are considered as a Biosphere Reserve and World Heritage Site by UNESCO. Although its global environmental importance is recognized, more than 90% of its' area is under private ownership and used mostly for extensively for cattle ranching.

Recently, with the availability of satellite images and platforms for accessing and processing a large datasets, information of wetlands increased significantly. It has driven research and the application of spatial technologies to a variety of fields, from environmental monitoring to natural resource management and urban planning.

Within Artificial Intelligence (AI), Machine Learning (ML) is a powerful tool for environmental monitoring (Avci, 2023; Costa et al., 2016; Immitzer et al., 2012; Hino et al., 2018; Milutinovic, 2024; Wurm, 2019; Zhang et al., 2021). ML offers tools which contribute to the conservation of natural resources and the mitigation of climate change, among other global environmental challenges. As for the satellite images, ML allows the efficient and automated exploration of spatial patterns, image segmentation, anomaly detection and data compression. It provides geospatial information for a wide range of applications, including environmental management, agriculture, and natural resource monitoring, among others.

There are situations when the analysis covers large areas and the a priori manual labeling by experts is impossible. In such cases, the use of unsupervised machine learning (ML) models or algorithms is a fundamental tool to explain and understand the geospatial information analyzed.

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This is an essential approach for the study of water bodies in the Pantanal wetlands, where there is a large amount of geospatial data and the diversity of features is very complex. Using particularly clustering it is possible to identify spatial patterns and distributions of features in satellite images, without labeling (Subbiah; Christopher, 2012; Usman, 2013; Abburo; Golla, 2015; Bezerra et al., 2022).

The objective of this study is to classify surface water bodies within wetlands using ML techniques, especially clustering. This work is a contribution to the achievement of the Sustainable Development Goal 6 "Clean water and sanitation" (SDG 6), providing relevant information and analysis on wetlands, specifically focused on the Brazilian Pantanal. With the provision of relevant information on environmental changes and its impacts on water resources, this approach can support policies and practices related to water management and sanitation, promoting the sustainability of these vital resources.

II. Materials and Methods

The Pantanal is a vast floodplain located in south-central Brazil and extending to NE Paraguay and SE Bolivia (Brazil, 2022) (Figure 1). The vegetation of the Pantanal is heterogeneous and influenced mainly by the Cerrado ecosystem, presenting also elements of the Amazon rainforest, the Chaco and the Atlantic forest. These characteristics, together with the different soil types and flooding regimes, is responsible for the great variety of plant formations and the heterogeneity of the landscape, which is home to a rich aquatic and terrestrial biota (Adámoli; Pott, 1999). The main ecological factor which determines the patterns and processes in the Pantanal are the flood pulses (Alho, 2008; Junk et al., 2013; Milien et al., 2023), with large amplitudes and a duration of three to six months.

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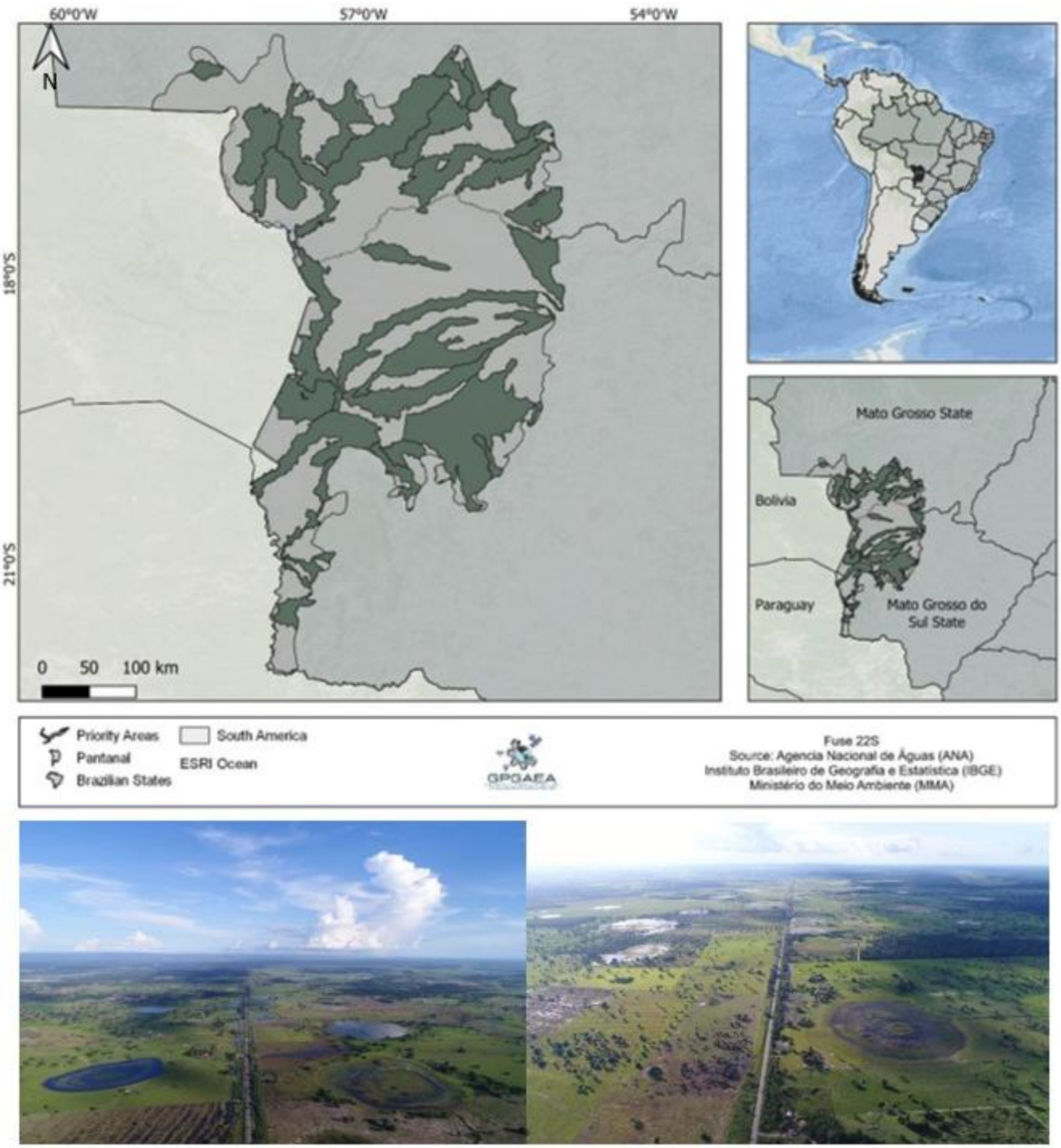

Figure 1 – Location of the Pantanal within Brazil. Source: Authors.
Brazilian Pantanal areas obtained by drone (below), Source: LABGEO (2024).

The Brazilian Biome Monitoring Program (PMDBBS) indicated that the Pantanal wetland is undergoing a drying process due to soil degradation, with the loss of 17% native vegetation cover in the last decades. Furthermore, the political pressure for the installation of infrastructure projects increased, causing significant environmental damage.

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In this context, the Priority Areas for Conservation, Sustainable Use and Sharing of Biodiversity Benefits are essential for the Pantanal. These areas are of fundamental importance for the maintenance of the biome's unique and threatened ecosystems, and its conservation is crucial to guarantee the regional biodiversity and ecosystem services.

The proposed methodology intends to integrate with these priority areas, using remote sensing technologies to monitor and classify water bodies. This will assist in decision-making for the management and conservation of the critical environments, thus contributing to the environmental and socioeconomic sustainability of the Pantanal.

Processing of Geoespatial information

The Region of Interest (ROI) is delimited by a combination of Geospatial Information (GI) in vector format from the Brazilian Pantanal and GI in raster format from the Sentinel 2-A satellite. Sentinel-2 is a high-resolution, wide-scan multispectral imaging system for monitoring vegetation, soil and water, as well as inland waterways and coastal areas. The images were obtained from the Google Earth Engine (GEE) platform.

These images were ortho-rectified and the surface reflectance values atmospherically corrected. They were filtered for cloudiness below 5%. The ROI is represented by a mosaic that merges multiple individual images with an average image that represents the rainy season in the Pantanal during the months of October to May. From this average image, the Normalized Difference Water Index (NDWI) (Avezov et al., 2024; Gao, 1995; Li et al., 2022; McFeeters, 1996) was obtained, which is widely used to detect and map water bodies from satellite images. To evaluate this index, a combination of green wavelengths in the visible and near infrared was used. The former maximizes the usual reflectance of the water surface.

The latter increases the high reflectance of terrestrial vegetation and soil zones, while minimizing the low reflectance of water masses. NDWI values are positive for water elements and negative (or nil) for soil and terrestrial vegetation (Equation 1).

$$NDWI = \frac{GREEN-NIR}{GREEN+NIR} \quad (1)$$

where: GREEN and NIR are the reflectance values in the green band and the reflectance in the near infrared band, respectively.

Additionally, three ROIs were selected within the "Priority Areas for the Conservation, Sustainable Use and Benefit Sharing of Brazilian Biodiversity". These areas were established as a public policy instrument, guiding the development for research actions, biodiversity inventory, recovery of degraded areas and overexploited or

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endangered species, environmental licensing, inspection, identification of areas with potential for the creation of conservation units, ecological corridors, actions to promote sustainable use and environmental regularization actions (Brazil, 2022).

These are geographically defined areas based on spatial information considering the occurrence of conservation objects (endangered, rare or endemic species, terrestrial and aquatic ecosystems and ecosystem services relevant to the conservation of the biodiversity existing in them), specialized information on anthropogenic activities (dams, roads, areas without vegetation cover, mining, etc.), as well as activities that favor the conservation and sustainable use of biodiversity (environmental projects, ecotourism, among others). The sections considered to evaluate water bodies are extremely high, very high and high zones.

For each zone, the NDWI image is segmented to discriminate the water bodies. The segmentation is performed using an empirically established threshold based on visual evaluations by experts. This threshold allows the classification of water and other types of land cover, resulting in a binary representation of the image. After the identification of the water bodies, they are converted to polygons in vector format.

Machine Learning in Supervised GI Classification

In this step, the morphological descriptors of each segmented object are calculated. There is a variety of descriptors based on contours or on the total set of pixels that make up the segmented object (Bober et al., 2002; Zhang; Lu, 2004; Heilbronner, 2014; Neal; Russ, 2012) which are frequently used for object recognition and identification. So it is possible to characterize water bodies using a vector of shape features (Table 1).

For the object classification process, the Principal Component Analysis (PCA) technique was applied, followed by the Clustering algorithm. The PCA technique is used to reduce the dimensionality of the data set, through which a new set of variables is obtained at a 95% confidence level. In unsupervised algorithms, it is essential to determine the optimum number of clusters into which the data can be grouped. To perform this task, the elbow method was used, which calculates the value of an evaluation metric known as inertia. The inertia values are obtained using Equation 2, applying the cluster algorithm to different numbers of clusters (k), and a graph of these values is generated. Finally, those points where the curve begins to smooth out are checked.

Table 1 – Morphologic Descriptors.

Shape Descriptor	Description	Equation
Area	Surface of water body	A
Perimeter	Longitude of water body perimeter	P

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Compactness	How a water body resembles to a compact figure	$C = \frac{A}{p^2}$
Aspect ratio	Relationship between the width and length of a water body	$RA = \frac{width}{Máximum}$
Circularity	Extent to which a body of water resembles a circle	$\circ = \frac{4\pi A}{P^2}$
Form fator	Measure of the ratio between the area of the object and the area of the smallest circle that contains it	$FF = \frac{A}{A_c}$
Maximum longitude	The maximum length measured in any direction within the water body	ML
Maximum width	The maximum width measured in any direction within the water body	MA
Amplitude	Measurement that indicates how stretched or elongated the water body is compared to its width	$E = \frac{Longitude\ of object}{width\ of\ object}$
Complex envelope	Smallest convex polygon that contains all the points of the water body	EC

Own authorship.

$$Inercia\ (k) = \sum_{i=1}^{k} \left|\left|x - \mu_i\right|\right|^2 \quad (2)$$

where:
k is the cluster number,
μ_i is the centroid of the ithcluster,
$\left|\left|x - \mu_i\right|\right|^2$ is the squared distance between a point x and the centroid μ_i of the cluster to which it belongs.

At the classification of water bodies, the K-Means technique (MacKay, 2003) is used for the morphological descriptors of each generated polygon. This technique partitions the set of n observations into k clusters based on an average Euclidean distance. It has the advantage of being simple and fast to process, although it has the limitation that the number of classes $(x_1, x_2, \ldots.., x_n)$ where each x_i is a real vector of d dimensions, from which a partition of observations into k sets $(k \leq n)$ is constructed in order to minimize the sum of squares within each group.

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$$arg\ min\ S\ \sum_{x_j \epsilon S_i}^{k} \left|\left| x_j - \mu_i \right|\right|^2 \tag{3}$$

where μ_i is the average of points S_i.

Validation

The object segmentation validation is performed using the Dice Similarity Coefficient (DSC) (Dice, 1945) Equation 4. This is a metric commonly used in medical images, although its application has been expanded to other areas. To do this, objects segmented with the proposed methodology are randomly selected in a vector information layer. These objects, from satellite images, are then manually digitized by experts using the QGIS platform (QGIS.org, 2024). In this way, two data sets are obtained to apply the DSC.

$$DSC = \frac{2 \times |A \cap B|}{|A| + |B|} \tag{4}$$

where $|A \cap B|$ represents the size of the intersection area between sets A and B, $|A|$ and $|B|$ represents the size of these sets A and B.

Categorization of Water Bodies

Once the objects have been grouped into classes, a descriptive categorization of each classified water body is carried out. This categorization is made by experts working in the area, to identify groups of objects with similar shapes or morphological structures. For this purpose, the selected vector format files are visually evaluated and categories are defined, adding additionally a descriptive field within the alphanumeric information associated to each water body. The flowchart of the proposed methodology is presented in **Figure 2**.

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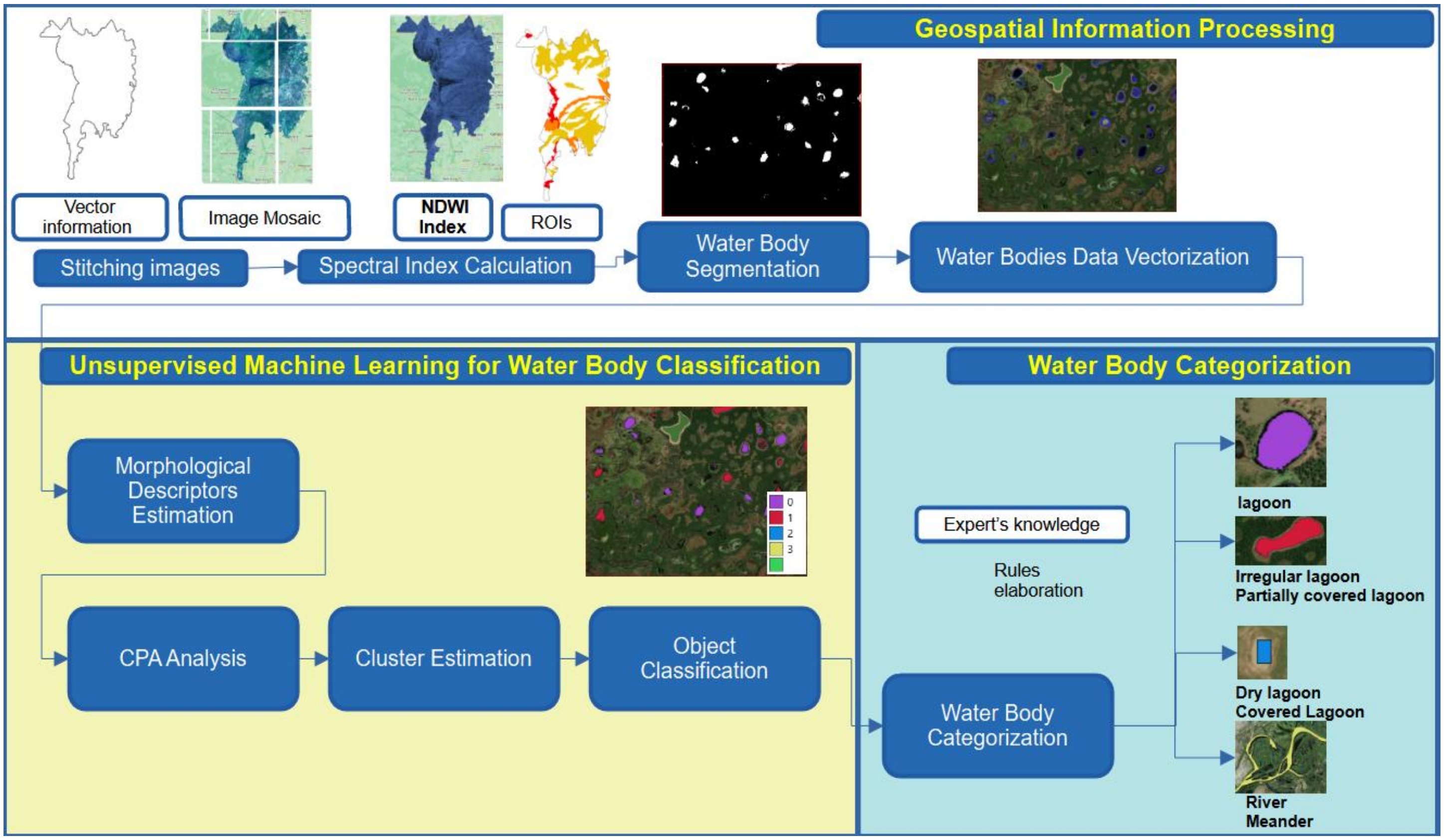

Figure 2 – Proposed methodology for the classification of water bodies in wetlands. (Source: Authors).

III. Results and discussion

A pseudo color RGB mosaic of images from Sentinel-2 satellite was obtained with the red, blue, green and near-infrared spectral bands, with a size of 12,143 GB. An ROI of this mosaic is presented in **Figure 3a**. It is located in the high, very high and extremely high zones defined as Priority Areas for Brazilian Biodiversity, with a total area of 100,000 km². The NDWI index was calculated from the spectral bands, where it is possible to visualize the water bodies (**Figure 3b**).

Based on an empirical threshold established in consensus with three experts who studied this type of wetland, the groups of pixels whose NDWI value exceeds this threshold are selected, obtaining the segmented image (**Figure 3c**). It is noteworthy that there are bodies of water not detected by the proposed method or that are detected as several objects. This in some cases is due to the fact that they are dry or partially/totally covered by some type of vegetation. There are also cases where rivers or streams present discontinuities due to the appearance of vegetation or the lack of water. Therefore, for each segmented object, the contours were calculated in a vector format, obtaining polygons for the sets of pixels detected as water (**Figure 3d**).

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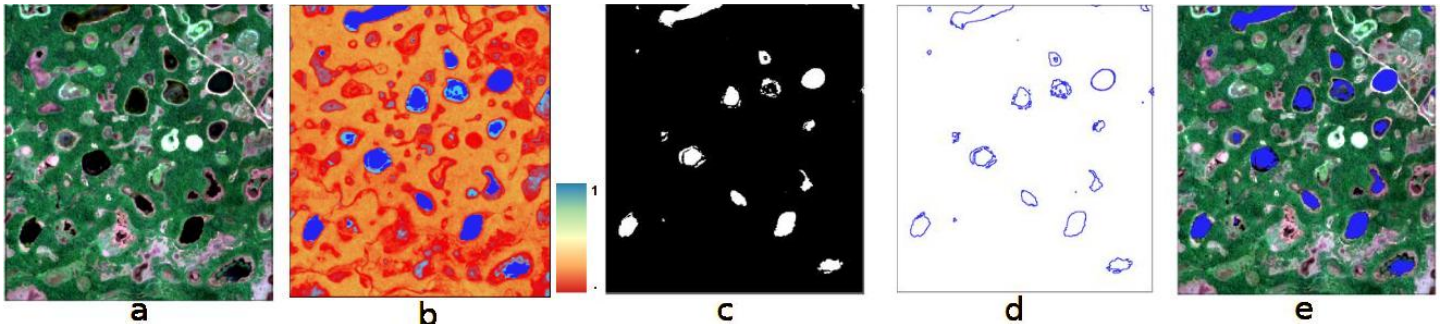

Figure 3 – Results of the segmentation algorithm applying an empirical threshold determined subjectively by an expert from an NDWI image. a) Pseudo color image in natural color. b) Pseudo color NDWI image. c) Segmented image. d) Contour image in vector format. e) Superposition of detected water bodies over the natural color image. (Source: Authors).

The advantage of the vector format is the possibility of a faster access to information, as it takes up less computational capacity than the raster format. It is possible to incorporate descriptive alphanumeric information into each detected object and also to join objects that are detected separately through geospatial operations. The combination of the natural color image and the contours in vector format allows a visual interpretation of the results (**Figure 3e**).

The segmentation validation was performed calculating the Dice Similarity Coefficient (DSC), using manual segmentations of water bodies in QGIS for comparison with the results of the automatic segmentation (**Figure 4**). The DSC value obtained was 0.91, indicating a high overlap and agreement between the two segmentations, with approximately 90% of the segmented objects coinciding with each other.

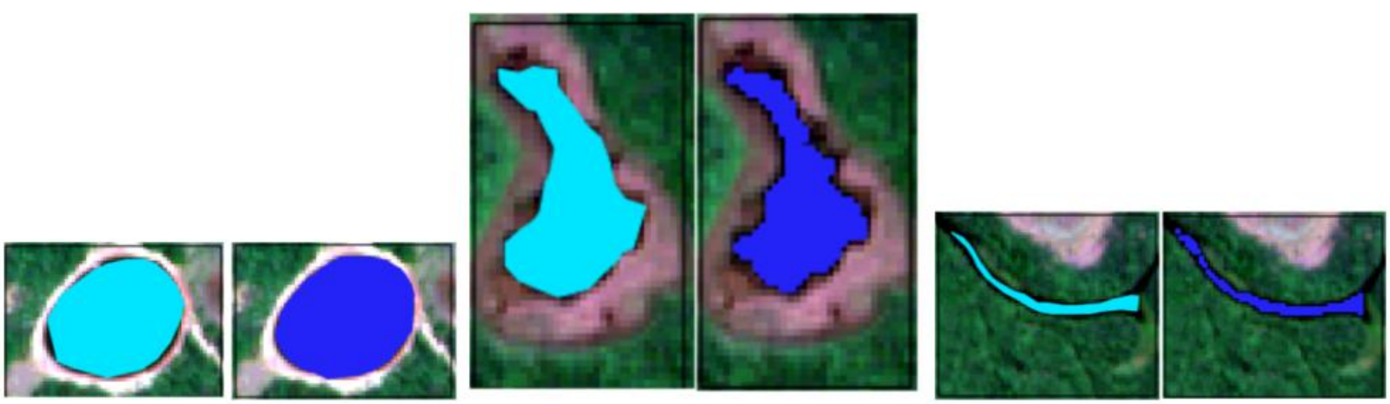

Figure 4 – Comparison between manual segmentation (cyan) and segmentation applying the methodology (blue). (Source: Authors).

Using geographic information representing the water body layer, ten morphological descriptors were estimated for each geographic object. So a feature vector was obtained for each object. The PCA technique was then applied to determine the number of variables representing 95% of the variance, which was achieved with two components. Initially, to apply the k-means clustering method, the optimal number of clusters was

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estimated using the elbow method, resulting in a value of k = 4 groups. Therefore, the results obtained classify the geographic objects into four classes. From this image, each group was manually categorized with visual interpretation according to the experts' feedback.

After grouping the geographic objects in 4 classes, the following classes were defined: class 1: Regular lagoon, class 2: Irregular lagoon or irregular lagoon partially covered by vegetation or other, class 3: Dry lagoon, covered lagoon, dam or water reservoir, and class 4: River or meander. **Figure 5a** shows an irregular lake covered by vegetation in its surroundings. **Figure 5b** presents a lake with more regular edges.

Objects categorized as streams, rivers, or meanders can be separated after applying the clustering algorithm (**Figure 5c**). Finally, **Figure 5d** shows an example of a water reservoir. Since k-means is an unsupervised algorithm, the validation of the categories proposed by the model was performed with experts in water bodies. This process was carried out qualitatively, observing whether the resulting clusters were consistent with the known classes of water bodies. Although the sample was small and random, the validation allowed the verification of correspondence between the groupings generated by k-means and the categories reported by the experts.

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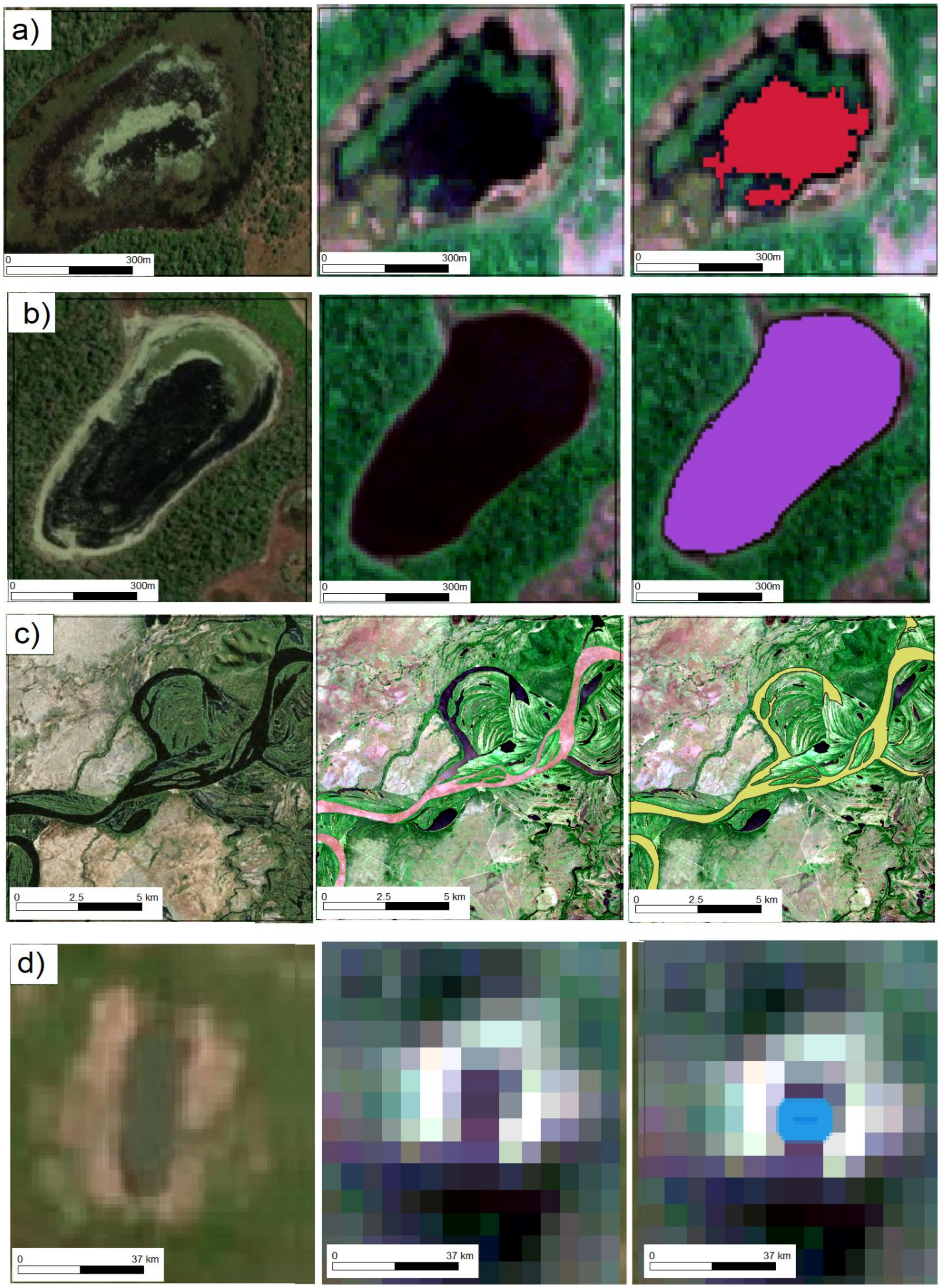

Figure 5 – Classification results: high-resolution image (first column), Sentinel 2-A image (second column) and superimposed classification (third column). a) Irregular water body, b) Regular water body, c) Meander and d) artificial water reservoir. (Source: Authors).

The proposed model allowed the segmentation of more than 100,000 objects in the priority areas of the Brazilian Pantanal. Figure 6, on the right, shows the results of the classification and categorization for the priority areas. In the selected region of interest (ROI), it is possible to notice that there are watercourses belonging to

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rivers that the model classifies as irregular water bodies. This is because they are discontinuous due to riparian zones. However, it is possible to notice that the continuity of a watercourse is categorized in yellow. Each categorized object is validated by three experts who, according to their criteria, can accept, reject or modify the category indicated by the model.

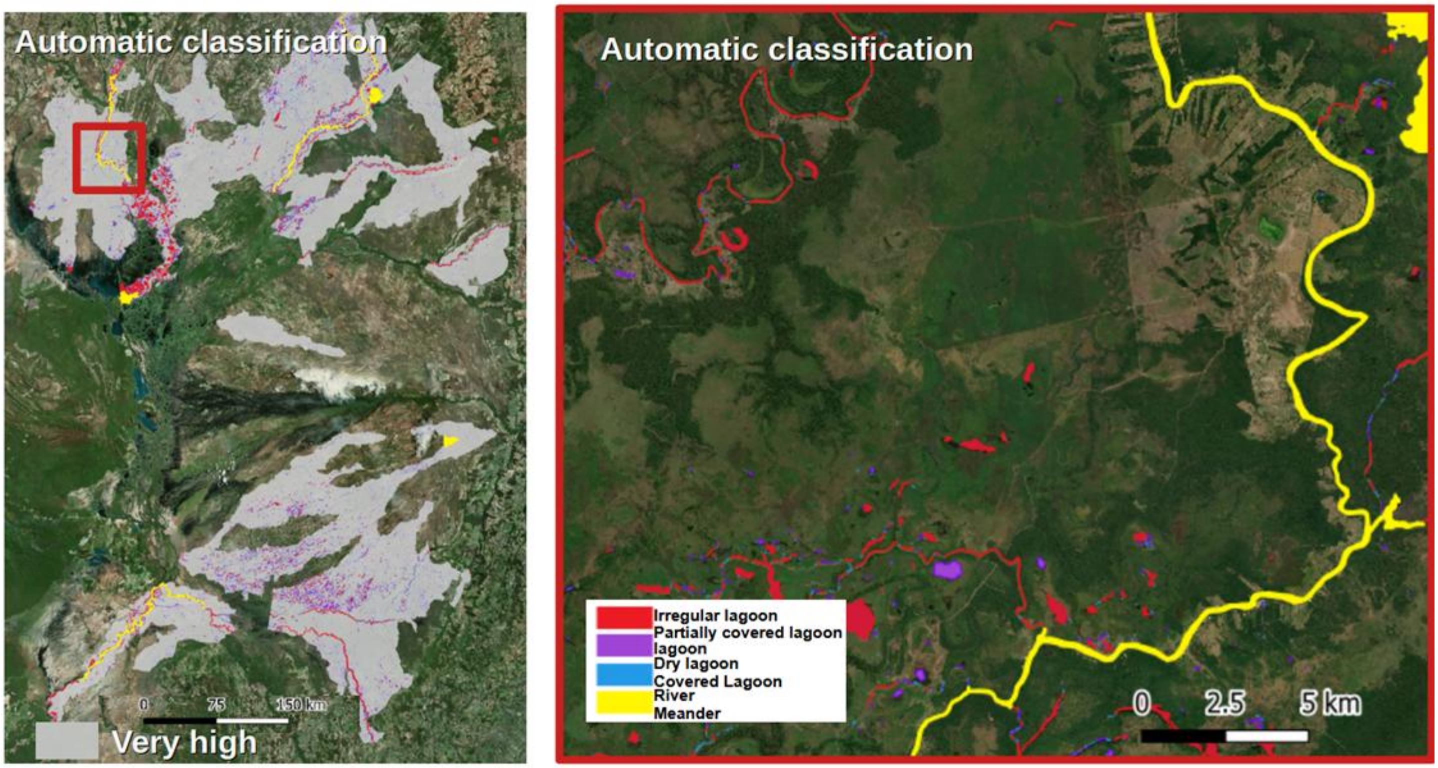

Figure 6 – Classification results for Very High priority areas corresponding to a Sentinel-2 image for the rainy season of 2018 and 2019. (Source: Authors).

Studies on the Pantanal highlight the importance of balancing economic development with environmental conservation. The literature suggests that cultural and environmental sustainability are crucial to maintain the balance of the natural landscape (Rossetto; Brasil Junior, 2003). The segmentation model can be a useful tool to identify priority areas for conservation, aligning with these sustainability goals.

Rural tourism and ecotourism are mentioned as ways to promote sustainable development, valuing local culture (Almeida, 2003). The segmentation and classification of objects can help to identify areas suitable for these activities, promoting biodiversity conservation.

The segmentation and classification model of objects in the Pantanal can be an important tool for the conservation and sustainable development of the region, especially when integrated with other technologies and considering the local culture and socioeconomics.

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IV. Conclusions

The proposed methodology allows the segmentation, classification and, subsequently, categorization of each water body within Brazilian Pantanal. The use of unsupervised k-means machine learning made it possible to categorize the geographic objects in four groups. This algorithm is a valuable tool for the analysis and understanding of the morphological characteristics from the terrain. The use of spectral bands, such as near infrared, in combination with bands in the visible spectrum, is a simple method for the segmentation of water bodies.

With the segmentation of data into clusters by k-means, it is possible to identify patterns that highlight the different regions according to its morphology. Unlike supervised techniques, where information labeling is necessary to classify objects, this methodology does not require previously labeled data. As for the Pantanal, given the large number of geographic objects within it, this would result in a task consuming a long processing and many human resources.

The results not only provide a deeper understanding of the Pantanal water bodies, but provide also environmental, social or economic information for decision-making. The amount of data evaluated was obtained by both the Google Earth Engine platform and the Sentinel-2 mission. They provide researchers and professionals with information and tools to study the Earth's characteristics.

Due to its ability to efficiently process and analyze huge amounts of data, these platforms are revolutionizing the way to study and understand our planet, enabling large-scale investigations and informing decision-makers in areas ranging from environmental management to precision agriculture.

As a future work, we propose the development of a catalog from water body types within the Pantanal that can be used for the spatial-temporal study of wetlands. Additionally, we suggest the analysis of the landscape connectivity, integrating data obtained with ecological connectivity models. This would allow us to identify key areas for the conservation and connectivity restoration, thus contributing to the environmental and socioeconomic sustainability of the Pantanal. Furthermore, considering the recent wildfires in the Pantanal, it is important to investigate which lakes have disappeared, whether new lakes have formed, as well as other relevant questions related to the presence or absence of water.

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