ISSN 1678-7226
Nero, M.; Oliveira, C.; Elmiro, M.; Tavares Junior, J.   (164 - 186)   Rev. Geogr. Acadêmica v.19, n.1 (2025)

LAND USE AND LAND COVER WITH AMAZONIA-1 IMAGERY BY MACHINE LEARNING IN THE CERRADO OF MINAS GERAIS-BRAZIL

USO E COBERTURA DA TERRA VIA IMAGENS AMAZÔNIA-1 POR MEIO DE MACHINE LEARNING NO CERRADO DE MINAS GERAIS-BRASIL

USO Y COBERTURA DE LA TIERRA DESDE IMÁGENES AMAZONIA-1 MDEDIANTE APRENDIZAJE DE MÁQUINA EN EL CERRADO DE MINAS GERAIS-BRASIL

Marcelo Antonio Nero
Professor Doutor, PPG ,Análise e Modelagem de Sistemas Ambientais-IGC-UFMG, marcelo-nero@ufmg.br, https://orcid.org/0000-0003-2124-5018

Cristiano Ferreira de Oliveira
Mestre em Ciências Ambientais, PPG ,Análise e Modelagem de Sistemas Ambientais-IGC-UFMG, cfo.1368836@gmail.com, https://orcid.org/0000-0001-5470-8352

Marcos Antônio Timbó Elmiro
Professor Doutor, PPG ,Análise e Modelagem de Sistemas Ambientais-IGC-UFMG, timboelmiro@gmail.com, https://orcid.org/0000-0001-7680-3131

João Rodrigues Tavares Júnior
Professor Doutor, PPG em Ciências Geodésicas e Tecnologias da Geoinformação-UFPE, joao.tavaresjr@ufpe.br, https://orcid.org/0000-0002-6583-962X

ABSTRACT: The Cerrado is the second largest biome in Brazil, with an area of over 200 million hectares and distributed across thirteen states of the Federation. It is a forested area of great importance for the biodiversity of Brazilian fauna and flora. However, the transformation of its vegetation has been accelerated in recent years, mainly due to the need for agricultural expansion and the search for pastures for cattle raising. In the specific case of the State of Minas Gerais, Brazil, the Cerrado Biome occupies over 54% of the territory and covers regions of great importance for agricultural productivity. In view of this, the research aims to perform a qualitative evaluation of thematic mapping based on the supervised classification of free orbital images (generated by the new Brazilian satellite Amazônia-1), which is considered a viable strategy for understanding the evolution of changes in land use and land cover. This research also analyzed the alerts for deforestation polygons generated by the Real-Time Deforestation Detection System (DETER) of the National Institute for Space Research (INPE), as well as the application of machine learning algorithms and techniques that can ensure the availability of this information with greater speed and reliability. The results achieved in terms of thematic quality, through the Kappa index, demonstrated great viability for the use of the methodologies used.
Keywords: Geoprocessing; Environmental monitoring; Free orbital images; Machine learning; thematic quality control.

RESUMO: O Cerrado é o segundo maior bioma do Brasil, com uma área de mais de 200 milhões de hectares e distribuído em treze estados da Federação. Trata-se de uma abrangência florestal de grande importância para a biodiversidade da fauna e da flora brasileiras. No entanto, a transformação da sua vegetação tem sido acelerada nos últimos anos, principalmente, em função da necessidade da expansão agrícola e da busca de pastagens para a criação de gado. No caso específico do Estado de Minas Gerais, Brasil, o Bioma Cerrado ocupa mais de 54% do território e cobre regiões de grande importância para a produtividade agrícola. Diante disso, a pesquisa tem por objetivo realizar uma avaliação qualitativa do mapeamento temático resultante da classificação supervisionada de imagens orbitais gratuitas (geradas pelo novo satélite brasileiro Amazônia-1), sendo esta considerada como uma estratégia viável para a compreensão quanto à evolução das mudanças do uso e cobertura da terra. Dentro desta pesquisa foram também analisados os alertas de polígonos de desmatamento gerados pelo Sistema de Detecção de Desmatamentos em Tempo Real (DETER) do Instituto Nacional de Pesquisas Espaciais (INPE), bem como a aplicação de algoritmos e técnicas de aprendizado de máquina (*Machine Learning*, em inglês) que podem garantir a disponibilização dessas informações com maior celeridade e confiabilidade. Os resultados alcançados em termos da qualidade temática, por meio do índice *Kappa*, demonstraram uma grande viabilidade para o emprego das metodologias utilizadas.
Palavras-chave: Geoprocessamento; fiscalização ambiental; imagens orbitais gratuitas; aprendizado de máquina; controle de qualidade temático.

RESUMEN: Cerrado es el segundo más grande bioma de Brasil, en donde el área llega a los 200 millones de hectáreas los cuales cobren trece estados de la federación. Se trata de una extensión forestal de gran importancia en términos de la biodiversidad de la flora y de la flora brasileñas. Sin embargo, la transformación de su vegetación ha sido acelerada en los últimos años, en especial, en función de la expansión agrícola y de la búsqueda de campos de creación de ganado. Especialmente, cuando se lleva en cuenta el Estado de Minas Gerais, Brasil, el Bioma Cerrado cubre más de los 54% del territorio y además cubre regiones de gran importancia desde la productividad agrícola. Por esto, esta investigación tiene como objeto realizar la evaluación cualitativa del mapeo temático en función de la clasificación supervisionada de imágenes orbitales sin costes (generadas desde el nuevo satélite brasileño Amazonia-1) en donde se considera esto como una estrategia viable en cuanto a la comprensión de la evolución de los cambios del uso y cobertura de la tierra. En esta investigación ha sido analizados también los avisos de los polígonos de deforestación generados desde el Sistema de Detección de los Deforestación en Tiempo Real (DETER) del Instituto Nacional de Investigaciones Espaciales (INPE), además de como la aplicación de las técnicas del aprendizaje de máquina (*Machine Learning*, en inglés) que pueden garantizar la disponibilidad de esas informaciones con más rapidez y fiabilidad. Los resultados obtenidos en términos de la calidad temática, por intermedio del índice Kappa, demuestran una gran viabilidad en cuanto al empleo de las metodologías utilizadas.
Palabras clave: Geoprocesamiento; fiscalización ambiental; imágenes orbitales libres; aprendizaje de máquina; control de calidad temático.

1. INTRODUCTION

The Cerrado biome is the second largest biome in Brazil, with a total area of 2,036,448 km² (IBF, 2024), corresponding to 22% of the entire territory. Its vegetation presents three main physiognomies, namely: forest formations, with the presence of tree species with or without continuous canopy; savannahs, in which trees and shrubs are spread over a grassy stratum (without continuous canopy); and grassland, where herbaceous and shrub species predominate, with an absence of trees (RIBEIRO and WALTER, 2008).

In studies of environments in the Cerrado Biome, Mota Júnior, Trentin and Silva (2023) used geotechnologies to analyze the historical process of occupation of traditional indigenous territories in southeastern Mato Grosso state and how such occupations transformed land use and land cover in neighboring areas between 1998 and 2018. To this end, they mapped land use and land cover using images from the Landsat 8/OLI and Landsat 5/TM satellites.

The analysis of land use and land cover showed that these areas have little vegetation cover and a large fragmentation of forest remnants, leaving indigenous lands isolated and surrounded by agricultural activities. Another study by Mendes et al. (2022) evaluated compliance with environmental legislation regarding Legal Reserve areas of rural properties in the Brazilian Cerrado, regarding compliance with the minimum percentage required by Law No. 12,651/2012 (BRASIL, 2012).

Other recent research in Cerrado environments is also worth highlighting, such as the following:

1) Oliveira and Körting (2025) developed a research to create a map burned areas in the Chapada dos Veadeiros National Park, in Goiás, Brazil, covering the years 2020 to 2022; this reasearch has based in multi-temporal tabular dataset derived from satellite images including data set dataset of blue, green, red, and near-infrared bands, as well as the BAI, EVI, GEMI, NDVI, and NDWI spectral indices from the WFI sensor on the CBERS-4A, CBERS-4, and AMAZONIA-1 satellites; in this process the authors applied the Random Forest classifier to develop and validate models based on samples labeled as totally burned, partially burned, and non-burnedthe;in addition the authors compared the annual results of this approach to the MCD64A1 product, where the errors of omission for the BA class results to 22% in 2020, 28% in 2021 and 59% in 2022, while the errors of commission were 46%, 43% and 46%, respectively; this study highlighted the utility of the WFI sensor for burned area mapping without intersatellite spectral calibration;

2) Boscolo et al. (2024) highlight the contributions of the National Institute for Space Research (INPE) to the emergency response in the International Space Charter and Major Disasters, so that this work used images from several satellites, including those from the Amazônia-1 satellite;

3) Messias et al. (2024) studied forest and non-forest phytophysiognomies of Roraima state, within the scope of the PRODES (Project for Monitoring Deforestation in the Legal Amazon by Satellite) and DETER (Real-Time Deforestation Detection System) projects, both managed by INPE (National Institute for Space Research), where several types of spatial images were used, such as those from the Amazônia-1 satellite, enabling the monitoring of deforestation in the study region;

4) Moura and Oliveira (2024) mapped water favorability in the Upper Meia Ponte River Basin, as a subsidy for water security policies in Goiânia city, state of Goiás, so that they constructed thematic maps using tools of the free software QGIS (Geographic Information Systems) and concluded that it is essential to carry out adequate soil management in all classes of water favorability, and that it is urgent to implement conservationist actions for water resources in areas identified as moderately favorable, slightly favorable, and unfavorable;

5) Silva Júnior et al. (2024) carried out a comparative analysis among remote sensing

products, including images from the Amazônia-1 satellite, for burned areas in Brazil, with a case study in an environmentally unstable river basin;

6) Ramos et al. (2023) analyzed the spatial dynamics of vegetation cover and land use and the deforestation rate in the Upper Paraguay River Basin, located in the Brazilian state of Mato Grosso, with the aim of developing territorial planning strategies for environmental conservation.

In terms of territorial extension, the Cerrado Biome comprises the Brazilian states of Goiás, Tocantins, Bahia, Ceará, Maranhão, Piauí, Mato Grosso, Mato Grosso do Sul, Minas Gerais, Paraná, Rondônia, São Paulo and the Federal District. In this research, a territorial region in the State of Minas Gerais corresponding to the municipality of João Pinheiro was studied, which will be described in more detail throughout this work.

It is important to highlight that Brazil is among the world's largest producers of agricultural commodities, which encourages the growing demand for new arable areas, especially those located in the Cerrado Biome (MUELLER and MARTHA JÚNIOR, 2008), favoring the occurrence of illegal deforestation. In view of the growing demands for monitoring environmental interventions, DETER was created in 2004 to support environmental monitoring by mapping forest suppression and degradation in the Amazon, as well as in the savannah and forest formations of the Cerrado biome.

The methodology used by DETER considers images from the WFI (Wide Field Imager) sensor on board the CBERS-4, 4A satellites and, from 2021, also with the Amazônia-1 satellite (MESSIAS et al., 2024). The spatial resolution of these satellites is 56 and 64 meters, which allows the detection of deforestation warnings in areas of up to 3 hectares. In this sense, recent research that uses DETER (INPE, 2023) and images from the Amazônia-1 satellite (INPE, 2021) can be highlighted, such as those carried out by Barbosa et al. (2023), Kiyohara and Sano (2023), Paz (2023), Messias et al. (2024), Oliveira and Körting (2025).

In the case of the State of Minas Gerais, between 2018 and 2022, monitoring of the evolution of deforestation in the Cerrado Biome based on alerts detected by DETER (INPE, 2023) identified approximately 6,100 deforestation polygons, corresponding to a total area of 1,607.02 hectares (ha), with an average of 0.26 ha per detection. During this period, among all the municipalities in Minas Gerais circumscribed in the Cerrado Biome, only in the territory of the municipality of João Pinheiro were 243 polygons counted, which is equivalent to a total area of 108.96 ha.

In turn, the use of digital processing techniques such as satellite image classification (grouping of pixels, according to specific characteristics, based on classes pre-defined or not by the user) allows a better understanding of land use and land cover mapping, as well as their trends (NASCIMENTO et al., 2013). Such information is important because it supports the analysis of degraded areas, such as those where deforestation or other types of environmental intervention occur, such as forest fires. In this sense, it is also worth highlighting the work carried out by Oliveira and Nero (2013), Oliveira et al. (2017), Fernandes et al. (2018, 2019, 2020), Nero et al. (2021), which deal with the prediction and prevention of forest fires using geoprocessing associated with multivariate analysis, fuzzy logic and artificial neural networks.

Image classification, therefore, aims to automatically categorize the pixels in an image to enable this evaluation. According to Lillesand, Kiefer and Chipman (2015), there are three general techniques for image classification: supervised (algorithm based on the analysis of representative samples of each class for training), unsupervised (algorithm identifies the classes, given the number of classes and the number of iterations) and hybrid (combination of the two methods for a more detailed thematic stratification).

These processes are built from mathematical models and machine learning (ML) or deep learning (DL) algorithms. The use of ML and DL has proven to be a very relevant option for the preparation, analysis and prediction of spatial data (BRAGAGNOLO, 2021; DOMINGUEZ et al., 2022; BARBOSA et al., 2023; GAO et al., 2024; GARCÍA PEDREROS et al., 2024; KOSTRZEWA et al., 2024; HAERY et al., 2024; LEMENKOVA, 2024a).

One of these most used algorithms is Random Forest (RF), proposed by Breiman (2001) and recently applied in studies such as Albertini et al. (2024), Fernando and Senanayake (2024), Lemenkova (2024b). It is a machine learning model used for image classification (OLIVEIRA, MORAIS and NERO, 2022), whose method is composed of a set of decision trees, built from a random sample of training data that allows determining the assignment of a final class (SILVA JUNIOR, SILVA JUNIOR and PACHECO, 2021).

Although there are different algorithms for image classification to achieve reliability regarding the data generated, it is important to carry out procedures to evaluate the performance and thematic quality of the mapping. Some of these evaluation parameters to be observed are the confusion matrix, global accuracy and the Kappa index, according to Fleiss, Cohen and Everitt (1969), Congalton and Green (2019) (based on LANDIS and KOCH, 1977) and Monserud and Leemans, (1992), and demonstrated by Foody (2020) and presented in Table 1.

Table 1 - Accuracy levels of classification, according to the Kappa index.

<table>
<tr><th colspan="2"></th><th>Congalton and Green (2019)</th><th>Fleiss, Cohen and Everit (1969)</th><th>Monserud and Leemans (1992)</th></tr>
<tr><td rowspan="9">Kappa</td><td>> 0.8 a1.0</td><td>Almost Perfect</td><td rowspan="2">Excellent</td><td>Excellent</td></tr>
<tr><td rowspan="3">> 0.6 a 0.8</td><td rowspan="3">Substantial</td><td rowspan="2">Good Enough</td></tr>
<tr><td rowspan="4">Good Enough</td></tr>
<tr><td rowspan="2">Good</td></tr>
<tr><td rowspan="2">> 0.4 a 0.8</td><td rowspan="2">Moderate</td></tr>
<tr><td>Enough</td></tr>
<tr><td>0.2 – 0.4</td><td>Enough</td><td rowspan="3">Poor</td><td>Poor</td></tr>
<tr><td>> 0.0 a 0.2</td><td>Smooth</td><td>Very Poor</td></tr>
<tr><td>0.0</td><td>Poor</td><td>None</td></tr>
</table>

Source: Adapted (FOODY, 2020)

2. MATERIAL AND METHODS

2.1. Study area

To analyze the evolution of deforestation in the Cerrado Biome in the State of Minas Gerais, the territorial cutout corresponding to the municipality of João Pinheiro was delimited as the object of study, as shown in (Figure 1). It is the largest municipality in the State of Minas Gerais, with a territorial area of 10,727.097 km2 and entirely inserted in the Cerrado Biome (BRASIL, 2023).

Additionally, IMAGENS DO BRASIL (2024) and ALMEIDA et al. (2011) relate the main characteristics, such as: 1) the terrain is diverse, comprising about 20% flat, 40% undulating, and 40% mountainous areas, with elevations ranging from 535 m to over 900 m; 2) the municipality lies within the São Francisco River Basin, and its geology is dominated by formations of the Bambuí Group, consisting of limestones, shales, and marls; 3) the landforms reflect an interplanaltic depression structure with pediplains, erosion surfaces, and floodplains along major rivers; 4) the soils are mainly latosols (low fertility but good physical properties), quartz sands, litholic soils (in rocky, eroded areas), and alluvial soils along the river valleys; 5) the hydrography features several important rivers, such as the Verde, Santo Antônio, and Caatinga Rivers, which are tributaries of the Paracatu River; 6) the climate is classified as tropical savanna, with annual rainfall around 1,360 mm, concentrated between December and February. Temperatures range from 18 °C to 30 °C, with an annual average of 24 °C; 7) the natural vegetation is primarily cerrado (Brazilian savanna), with patches of veredas (palm wetlands) and some caatinga-like areas, depending on the soil and moisture conditions.

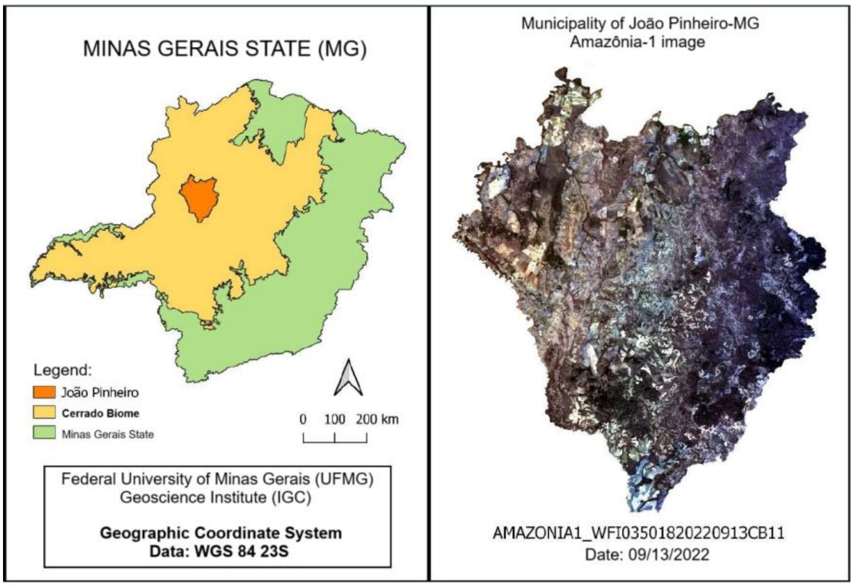


Figure 1 - Municipality of João Pinheiro (Minas Gerais).Source: Prepared by the authors (2025).

2.2. Orbital images

The orbital images used (made available free of charge) were captured by the Amazônia-1 satellite, obtained from the image catalog on the website of the National Institute for Space Research (INPE). It was decided to use Level 4 (L4) images because they were already orthorectified and had the system's radiometric and geometric corrections, with the use of terrain control points and a digital elevation model (INPE, 2021). These images are available in 4 spectral bands (Table 2), the spatial resolution is 64 meters, the swath width is 850 km and the temporal resolution is 5 days.

Table 2 - Technical specifications of the images from the Amazônia-1 satellite.

Imaging Sensor	Band	Spectral range	Quantization	Pixel size
WFI (Wide Field Imager)	1	Blue (0.45-0.52 μm)	16 bit	64 m
	2	Green (0.52-0.59 μm)		
	3	Red (0.63-0.69 μm)		
	4	NIR (0.77-0.89 μm)		

Source: SANTOS (2022).
Adapted by the authors (2025).

The scene captured on September 13, 2022 (named “AMAZONIA1_WFI03501820220913CB11”) free of cloud cover was selected to give better results in supervised classification.

2.3. Image analysis and processing

The vector and raster files were processed in the QGIS program version "3.16.5 Hannover" and the "GRASS 7.8.5" plugin (QGIS, 2023). The supervised classification was performed with the Semi-automatic Classification Plugin (SCP) (CONGEDO, 2023) for QGIS (QGIS, 2023).

To use the SCP, it was also necessary to install and configure the ESA SNAP GPT executable plugin (ESA, 2023). Thematic accuracy assessments were performed with the AcATaMa plugin (LLANO, 2024). The comparative supervised classification was performed with the R Language algorithm (as well as the respective thematic accuracy, in addition to data and map plotting) using the RStudio program (2023.06.1) (AHMAD et al., 2023; R CORE TEAM, 2021). The RandomForest (RF) classifier was used in all processing. The graphs and statistical analyses were constructed using the Microsoft Excel 365 program (MICROSOFT, 2021). The classification results were interpreted and the metrics obtained were analyzed as illustrated in (Figure 2).

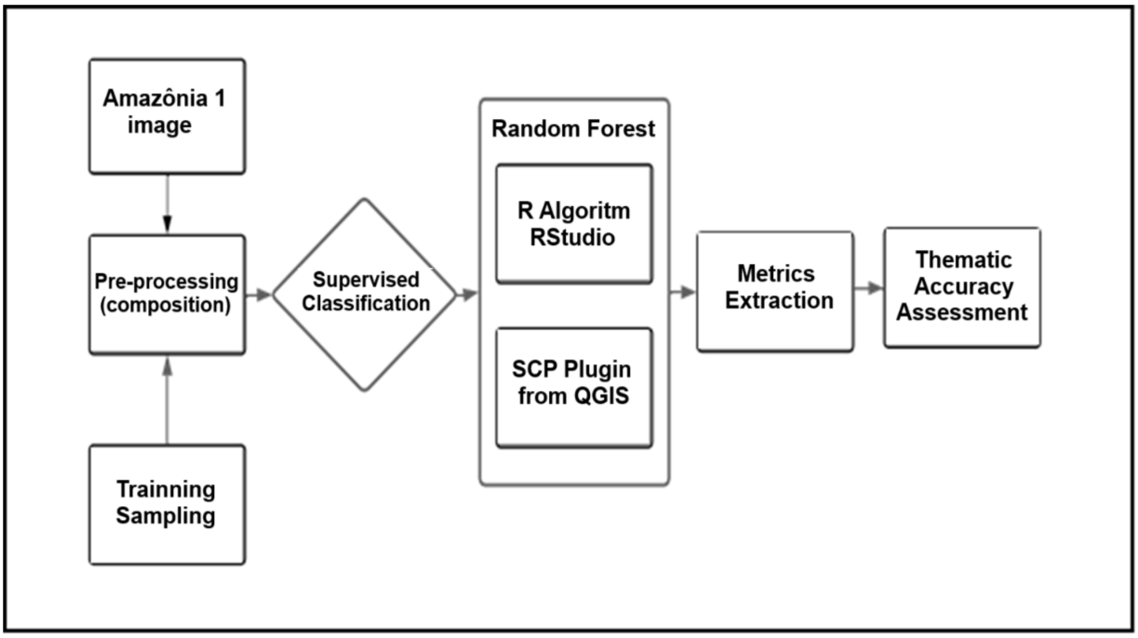


Figure 2 - Image analysis and processing.
Source: Prepared by the authors (2025).

2.4. Supervised classification

To perform the supervised classification, a vector file (shapefile) was created containing training samples for the 10 different classes related to the various land uses and covers, namely: Agriculture1, Agriculture2, Agriculture3, Water, Cerrado1, Cerrado2, Fallow, Exposed soil, Urban and Tree vegetation. For each of these classes, 5 polygons representative of the class were collected for training, except for the “water” class with only 4 polygons), accounting for a total of 49 samples based in four spectral bands (Figure 3).

To inspect and validate the training sample polygons comparatively, an image from the Planet Scope constellation (PLANET TEAM, 2023) with better spatial resolution was used, made freely available by the Norwegian International Climate and Forest Initiative (NICFI, 2023). Table 3 presents the established classes and comparative image clippings for visual interpretation of the samples.

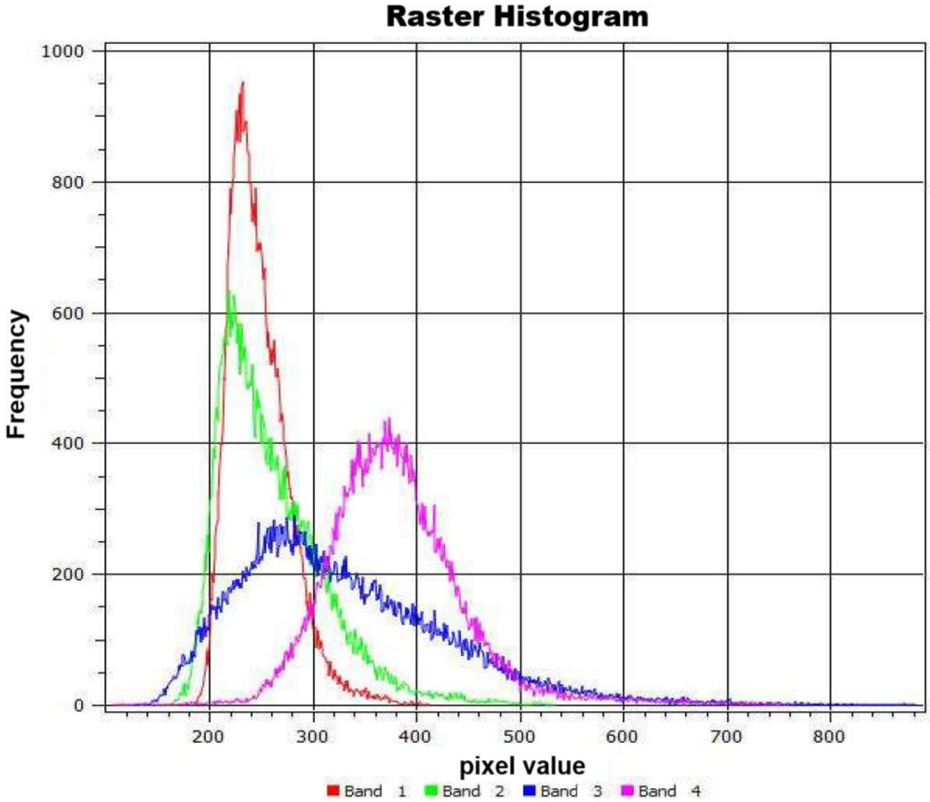
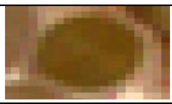
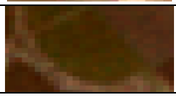
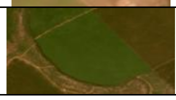


Figure 3 - Histogram of spectral bands. Source: Prepared by the authors (2025).

Table 3 - Examples of two training samples selected for supervised classification.

CLASS	NAME	AMAZONIA-1 IMAGE	PLANETSCOPE IMAGE
1	Agriculture1		
2	Agriculture2		

Source: prepared by the authors (2025).

2.5. Assessment of thematic accuracy of the map resulting from supervised classification

To assess the thematic accuracy of the classification maps, the sample size was calculated according to each class stratum (FINEGOLD *et al.*, 2016) according to Equation 1. The size of the areas corresponding to the classes and the respective percentage proportion were obtained with the R.report function of the QGIS GRASS plugin.

Equation (1) - sample size:

$$n = \frac{\left(\sum W_i S_i\right)^2}{\left[S(\hat{O})\right]^2 + (1/N)\sum W_i S_i^2} \approx \left(\frac{\sum W_i S_i}{S(\hat{O})}\right)^2$$

Where: Wi = proportion of the mapped area of class i; Si = standard deviation of stratum i; So = expected standard deviation of the overall accuracy (the value of So = 0.01 was assumed);

The standard deviation of the stratum (Si) of each class was calculated according to the user accuracy values (Ui), as described in Equation 2. For this purpose, the following references were used: 0.50 for the crop classes (Agriculture1, Agriculture2 and Agriculture3); 0.60 for Water; 0.95 for Cerrado1, Cerrado2 and Arboreal Vegetation; 0.90 for Fallow; 0.70 for Exposed Soil and 0.90 for Urban (based on OLOFSSON *et al.*, 2014).

Equation (2) – strata standard deviations: $S_i = \sqrt{U_i(1 - U_i)}$

The stratified number of samples, Ni (see Equation 3), to be collected in each class was defined considering the average value between the normal distribution and the weighted distribution of these samples (CONGEDO, 2023).

Equation (3) – stratified number of samples: $Ni = \left(\frac{N}{c} + N * Wi\right)/2$

Where: N = total number of samples; c = total number of classes; Wi = proportion of the mapped area of class i;

Thus, using the equations shown, the total number of samples required to assess the thematic accuracy of each classified image was calculated. The values and parameters used to define the stratified samples are shown in Tables 4 and 5.

Table 4 - Samples for analysis of thematic accuracy of classification with Random Forest from the SCP plugin.

Class	Description	Area (Km2)	Wi	Ui	Si	Wi*Si	N*Wi	N/c	Ni
1	Agriculture1	27.44	0.0026	0.50	0.5	0.0013	2	89	46
2	Agriculture2	286.15	0.0267	0.50	0.5	0.0133	24	89	56
3	Agriculture3	1,592.74	0.1486	0.50	0.5	0.0743	132	89	111
4	Water	66.43	0.0062	0.60	0.5	0.0030	6	89	47
5	Cerrado1	2,491.07	0.2323	0.95	0.2	0.0506	207	89	148
6	Cerrado2	2,643.39	0.2466	0.95	0.2	0.0537	220	89	154
7	Fallow	2,694.44	0.2513	0.90	0.3	0.0754	224	89	156
8	Exposed_soil	293.47	0.0274	0.70	0.5	0.0125	24	89	57
9	Urban	189.99	0.0177	0.90	0.3	0.0053	16	89	52
10	Tree vegetation	436.34	0.0407	0.95	0.2	0.0089	36	89	63
	Total	10,721.46	-	-	-	0.2984	-	-	891

Source: prepared by the authors (2025).

Table 5 - Samples for analysis of thematic accuracy of Random Forest classification with the R Language algorithm.

Class	Description	Area (Km2)	Wi	Ui	Si	Wi*Si	N*Wi	N/c	Ni
1	Agriculture1	30.12	0.0028	0.50	0.5	0.0014	2	78	40
2	Agriculture2	209.77	0.0196	0.50	0.5	0.0098	15	78	47
3	Agriculture3	917.00	0.0855	0.50	0.5	0.0428	67	78	73
4	Water	22.43	0.0021	0.60	0.5	0.0010	2	78	40
5	Cerrado1	2,695.82	0.2514	0.95	0.2	0.0548	197	78	138
6	Cerrado2	3,222.67	0.3006	0.95	0.2	0.0655	235	78	157
7	Fallow	2,959.04	0.2760	0.90	0.3	0.0828	216	78	147
8	Exposed_soil	356.24	0.0332	0.70	0.5	0.0152	26	78	52
9	Urban	28.15	0.0026	0.90	0.3	0.0008	2	78	40
10	Tree vegetation	280.23	0.0261	0.95	0.2	0.0057	20	78	49
	Total	10,721.46	-	-		0.2798	-	-	783

Source: prepared by the authors (2025).

After defining the total number of samples and their distribution by class, the Kappa statistic was applied, a method that allows comparative analysis of maps obtained through remote sensing data, within a certain limit (LANDIS and KOCH, 1977).

The error matrix used to measure thematic accuracy was constructed according to the model presented in Table 6, through which the following statistical information was obtained: Kappa index (Equation 4), overall accuracy (Equation 5), producer accuracy (Equation 6) and user accuracy (Equation 7).

Table 6 - Error matrix model (4 x 4) for thematic accuracy.

Classes	A	B	C	D	Sum of Rows
A	n11	n12	n13	n1k	n1+
B	n21	n22	n23	n2k	n2+
C	n31	n32	n33	n3k	n3+
D	n41	n42	n43	n4k	nK+
Sum of Columns	n+1	n+2	n+3	n+K	N

Source: Adapted from Santos, Peluzio and Saito (2010) and Congalton and Green (2019).

Equation (4) – index *Kappa*: $$\frac{\sum_{i=1}^{k} n_{ii} - \sum_{i=1}^{K} n_{i+} + n_{+i}}{n^2 - \sum_{1=1}^{K} n_i + n_{+1}}$$

Equation (5) – Overall Accuracy: $$\frac{\sum_{i=1}^{k} n_{ij}}{n}$$

Equation (6) – Producer Accuracy: $$\frac{n_{ij}}{n_{+j}}$$

Equation (7) – User Accuracy: $$\frac{n_{ii}}{n_{i+}}$$

The calculated data was used to evaluate the performance of each of the methods employed. For this purpose, the validation procedures of the stratified samples were performed with the AcATaMa plugin (LLANNO, 2019) of QGIS. The results obtained allowed the construction of the respective confusion matrices, as well as the Global Accuracy and Kappa indexes.

2.6. Thematic Accuracy Assessment with R Language

The R Language (see RSTUDIO TEAM, 2020 and R CORE TEAM, 2021) is an open-source tool that aims to express ideas and statistical operations in an environment for interactive data analysis. RStudio, in turn, is an Integrated Development Environment (IDE) used for this type of programming in R Language (FARIA, 2020).

The algorithm developed in this work for supervised classification used the same image from the Amazonia-1 Satellite and the same previous training samples. To assist in the classification process, the colored representation of each image band spectral response was generated using the plot function (Figure 4).

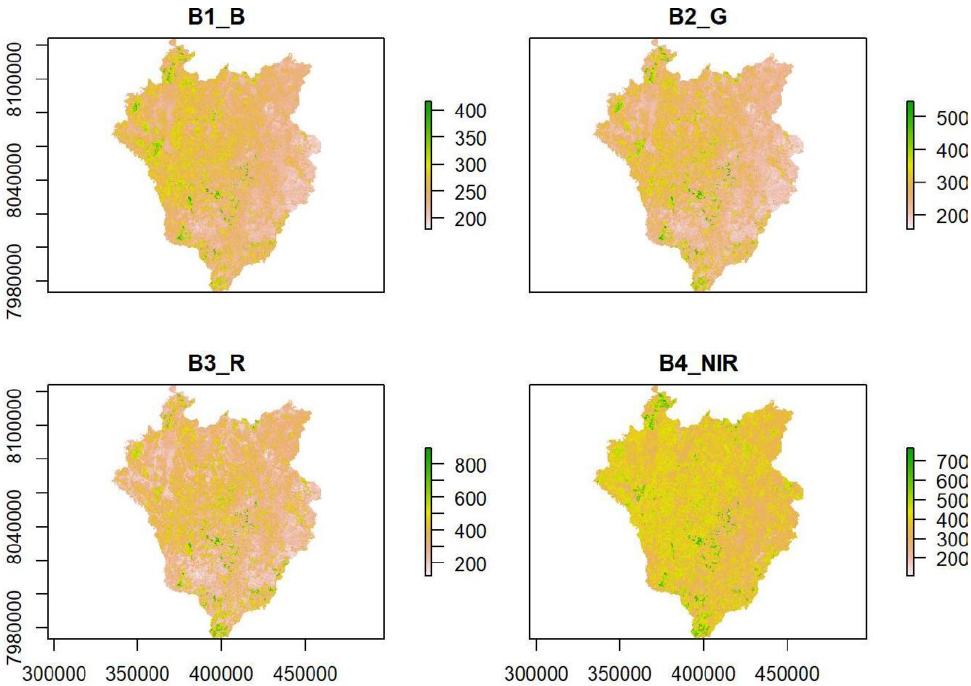


Figure 4 – Colored representation according to each image band from the Amazônia-1 satellite. Source: prepared by the authors (2025).

Using the melt() function from the reshape2 package, a graph of the average reflectance spectrum was constructed for each of the classes as a function of the image bands (Figure 5).

To train and test the algorithm (ML), random training and testing samples were selected in a ratio of 70%/30% for the supervised classification process with the RandomForest function. The RF classifier is based on the random tree model for decision making and the greater the number of trees, the more calculations and processing in the model, but resulting in greater accuracy. To choose the best classification, values of 5 and 1000 trees (ntree) were tested and the second was chosen due to its better performance.

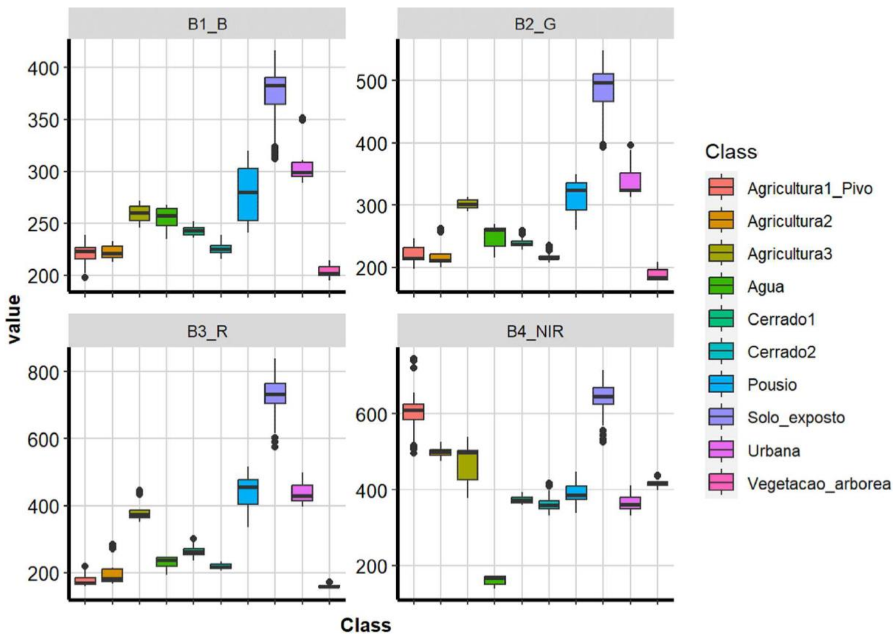


Figure 5 - Spectral response of the samples of each class as a function of the bands of the analyzed image. Source: prepared by the authors (2025).

3. RESULTS AND DISCUSSION

Figure 6 illustrates the thematic maps that were generated with the Random Forest classification method, using the QGIS SCP plugin, as well as using the algorithm developed in R Language (built in RStudio). As described in Table 3, the ten representative classes of land use and land cover were established based on the interpretation of the specific characteristics present in the Cerrado Biome.

As can be seen in the thematic maps generated, some classes presented very divergent areas in the two classifications, with the classes of arboreal vegetation, urban vegetation and water standing out, as represented in the graph in Figure 7. This divergence is possibly related to the classification process of the two methods, which indicated the need for an assessment of thematic quality.

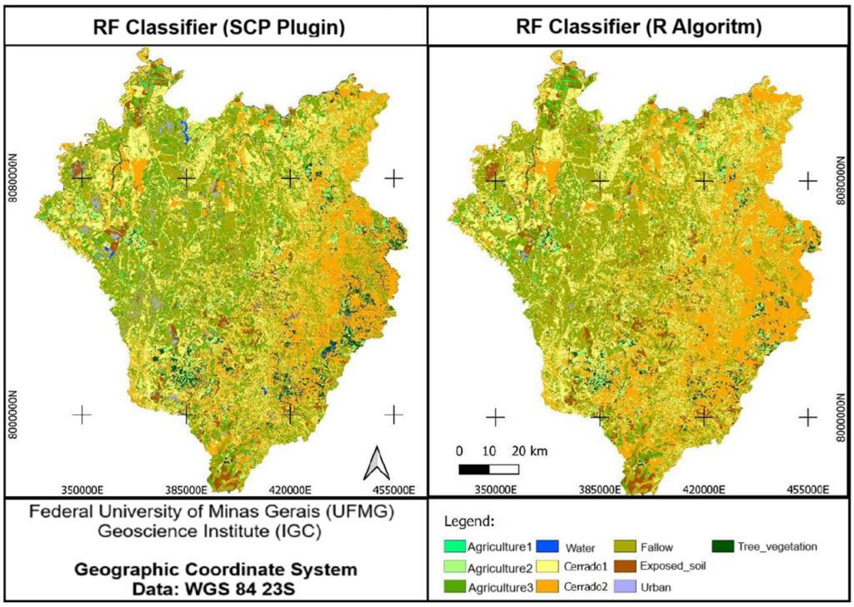


Figure 6 - Supervised classification of the Amazônia-1 Satellite image.
Source: prepared by the authors (2025).

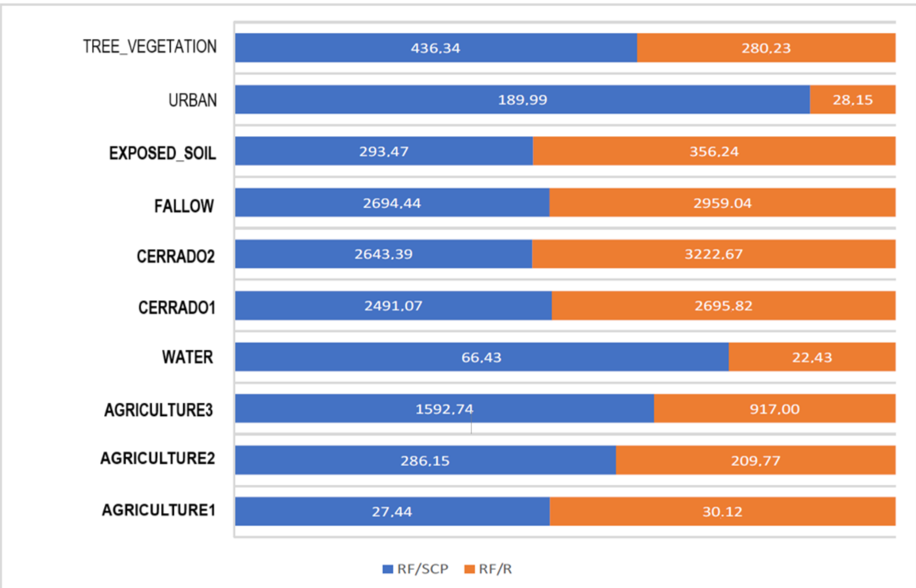


Figure 7 - Metrics of the classified areas in the Amazônia-1 Satellite image.
Source: prepared by the authors (2025).

Considering the data presented in Tables 4 and 5 (see item 2.5), confusion matrices were constructed to assess the thematic quality of the classifications performed. For the image classified with RF in the SCP add-on, 891 samples were inspected with the AcATaMA add-on (LLANO, 2024), obtaining the values described in Table 7. The overall accuracy achieved was 0.7838 (σ = 0.0129) and the Kappa Index obtained was 0.6966.

Table 7 - Confusion matrix – Supervised Classification (SCP).

Classe		1	2	3	4	5	6	7	8	9	10	Total
Agriculture1	1	44	2	0	0	0	0	0	0	0	0	46
Agriculture2	2	2	41	1	0	10	1	0	0	0	1	56
Agriculture3	3	0	0	38	0	9	7	54	1	1	1	111
Water	4	0	0	0	21	8	17	1	0	0	0	47
Cerrado1	5	0	0	0	0	124	24	0	0	0	0	148
Cerrado2	6	0	0	0	0	9	145	0	0	0	0	154
Fallow	7	0	0	2	0	14	1	138	0	1	0	156
Exposed_soil	8	0	0	1	0	0	0	0	56	0	0	57
Urban	9	0	1	1	0	0	0	46	3	1	0	52
Tree vegetation	10	0	3	0	0	1	10	0	0	0	50	64
	Total	46	47	43	21	175	205	239	60	3	52	891

Source: prepared by the authors (2025).

In the supervised classification of the image performed with the Random Forest algorithm programmed in R Language, the same procedure was carried out, with 783 samples being analyzed, resulting in the values described in Table 8. The overall accuracy achieved was 0.9473 (σ = 0.0078) and the Kappa Index was 0.9474.

Table 8 - Confusion matrix – Supervised Classification (R Language).

Class		1	2	3	4	5	6	7	8	9	10	Total
Agriculture1	1	37	1	0	0	1	0	0	0	0	1	40
Agriculture2	2	0	47	0	0	0	0	0	0	0	0	47
Agriculture3	3	0	0	49	1	11	2	10	0	0	0	73
Water	4	0	0	0	34	2	3	1	0	0	0	40
Cerrado1	5	0	0	0	0	134	2	1	0	0	1	138
Cerrado2	6	0	0	0	0	0	154	2	0	0	1	157
Fallow	7	0	0	2	0	1	1	143	0	0	0	147
Exposed_soil	8	0	0	0	0	0	0	0	52	0	0	52
Urban	9	0	0	0	0	1	0	35	0	4	0	40
Tree vegetation	10	0	1	0	0	0	1	0	0	0	47	49
	Total	37	49	51	35	150	163	192	52	4	50	783

Source: prepared by the authors (2025).

The values referring to user accuracy (Equation 7) and producer accuracy (Equation 6) of the two classifications were also calculated by AcATaMa (LLANO, 2024) and are described in Table 9.

Table 9 - User accuracy and producer accuracy of the two classification methodologies.

Class	SCP Classification		R Language Classification	
	User	Producer	User	Producer
Agriculture1	0.9565	0.7197	0.0304	0.1409
Agriculture2	0.7321	0.8923	0.0597	0.0467
Agriculture3	0.3423	0.9184	0.0452	0.0403
Water	0.4468	1.0000	0.0733	0.0000
Cerrado1	0.8378	0.7783	0.0304	0.0275
Cerrado2	0.9416	0.8008	0.0190	0.0236
Fallow	0.8846	0.7162	0.0257	0.0215
Exposed_soil	0.9825	0.9193	0.0175	0.0457
Urban	0.0192	0.1036	0.0192	0.1074
Tree vegetation	0.7813	0.9460	0.0521	0.0400

Source: prepared by the authors (2025).

3.1. Comparative analysis of the quality by SCP and by in R Language algorithm

Using specific ML functions, specifically the Random Forest algorithm - programming in R language, the values referring to the supervised classification were also calculated. The confusion matrix was generated with the confusionMatrix function, with 435 samples randomly selected as shown in Table 10. It can be observed that the overall accuracy achieved was even higher, at 0.9793 ($\sigma = 0.0112$) and the Kappa Index was 0.9708.

Table 10 - Confusion matrix – Supervised Classification (Algorithm in R Language).

Class		1	2	3	4	5	6	7	8	9	10	Total
Agriculture1	1	31	1	0	0	0	0	0	0	0	0	32
Agriculture2	2	0	22	0	0	0	0	0	0	0	0	22
Agriculture3	3	0	0	16	0	0	0	1	0	0	0	17
Water	4	0	0	0	8	0	0	0	0	0	0	8
Cerrado1	5	0	0	0	0	36	4	0	0	0	0	40
Cerrado2	6	0	0	0	0	0	35	0	0	0	0	35
Fallow	7	0	0	0	0	0	0	45	0	3	0	48
Exposed_soil	8	0	0	0	0	0	0	0	220	0	0	220
Urban	9	0	0	0	0	0	0	0	0	5	0	5
Tree vegetation	10	0	0	0	0	0	0	0	0	0	8	8
	Total	31	23	16	8	36	39	46	220	8	8	**435**

Source: prepared by the authors (2025).

The values referring to user accuracy (Pos Pred Value variable) and producer accuracy (Sensitivity variable) obtained by processing the algorithm were also calculated and transcribed in Table 11.

The thematic quality parameters, mainly the global accuracy and the Kappa index (considering the thematic quality scale proposed by CONGALTON and GREEN, 2019) for the two supervised classification processes are presented in Table 12.

Table 11 - User accuracy and producer accuracy.

	Algorithm (R Language)	
	User	Producer
Agriculture1	0.9688	1.0000
Agriculture2	1.0000	0.9565
Agriculture3	0.9412	1.0000
Water	1.0000	1.0000
Cerrado1	0.9000	1.0000
Cerrado2	1.0000	0.8974
Fallow	0.9375	0.9783
Exposed_soil	1.0000	1.0000
Urban	1.0000	0.6250
Tree vegetation	1.0000	1.0000

Source: prepared by the authors (2025).

Table 12 - Assessment of thematic and performance accuracy parameters.

	Parameter	SCP Plugin	R Language
1	Classification Type	Supervised	Supervised
2	Number of classes	10	10
3	Total samples (N)	891	783
4	Classifier	RF	RF
5	Global Acuracy	0.7838 (σ = 0.0129)	0.9474 (σ = 0.0078)
5	*Kappa*	0.6966	0.9474
6	Assessment (Table 1)	Substantial	Almost perfect

Source: prepared by the authors (2025).

Despite using the same supervised classification methods with the RF classifier, the SCP plugin presented a lower value for global accuracy and the Kappa Index.

The image classified with the RF algorithm coded in R Language presented a higher value for the Kappa index, considered as “almost perfect” according to Table 1 (see 1. INTRODUCTION).

Even with this superior result, the number of samples used to assess thematic quality was significantly lower than the first. This analysis is corroborated by the results of the global accuracy and Kappa Index, obtained by the comparative classification of the RF algorithm coded in R Language.

To better understand the probable reasons for the divergence of the metrics calculated in the classification procedures, a visual analytical interpretation was performed based on the sampling points generated by the AcATaMa program (LLANO, 2024).

To this end, the images from the raster file generated by the Amazônia-1 Satellite and the image with the best spatial resolution (from the Planet constellation), corresponding to the same period, were also simultaneously considered.

The images were analyzed and organized by classes, using the comparative layout to analyze the samples in Table 13.

Table 13 - Method of analysis and interpretation of samples.

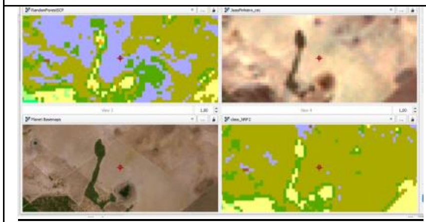
Sample RF classification with the SCP plugin / R Algorithm	Image from the Amazon-1 satellite
Planet Scope Scene Assessment	Sample RF classification with the R Algorithm / SCP plugin

Source: prepared by the authors (2025).

Some examples of inconsistencies that are frequently observed include: the mistaken identification of areas of the Water class in areas of Cerrado Biome vegetation and the presence of areas classified as urbanized areas (Urban class) in places that correspond to fallow areas. Some of these observations are illustrated and analyzed in Table 14.

Therefore, considering the findings of the supervised classification, as well as those of the assessment of the situation at the actual site, it is observed that despite the high assertiveness, relevant errors still occur that require visual interpretation procedures by human analysts.

Table 14 - Examples of observations analyzed through visual interpretation of samples.

Comparison (AcATaMa)	Classification	Situation at the actual site
	The area classified by the SCP suggests the presence of urban buildings.	This is a fallow area, that is, a place where crops have been interrupted to improve soil fertility.
	The pixel classified by SCP as blue suggests the presence of water.	According to the images, this is an area with vegetation typical of the Cerrado Biome.

Source: prepared by the authors (2025).

4. FINAL CONSIDERATIONS

The use of orbital remote sensing images for different analyses and modeling of spatial and environmental data has become essential for understanding interventions that are harmful to the environment, such as deforestation and forest fires.

In this sense, the images from the Amazônia-1 satellite (made available free of charge by INPE) have demonstrated great potential for use in land use and land cover mapping applications. However, due to their spatial resolution limited to 64 meters, it is essential that the products generated are analyzed quantitatively before any more detailed qualitative assessment.

The images with the best spatial resolution (Planet) used, despite operational restrictions in their free version, have an excellent application for the validation process of samples analyzed with the AcATaMa plugin.

In turn, procedures for remote inspection of areas have been increasingly used in environmental analyses, mainly due to the variety of orbital image sources available, enabling a reduction in the costs associated with field visits. Images from the Planet constellation, for example, have a daily revisit rate, which increases the effectiveness of strategies to combat illegal and harmful environmental interventions.

The supervised classification (with Random Forest classifier) analyzed in this work was demonstrated as an effective method for mapping land cover and different land uses and land covers. However, the procedure performed with an algorithm programmed in R language (using ML techniques) achieved superior thematic quality to the results obtained with the SCP plugin. Considering the literature criteria presented in Table 1, the Kappa Index obtained from R programming reached the level of near perfection.

The great success of the results achieved by the RF algorithm programmed in R language is possibly due to the processing methodology used for decision making based on the greater the number of decision trees defined for validation of the training and test samples, the greater the assertiveness of the mapping and the better the indicators related to thematic quality.

The method employed in this study enabled an innovative comparative analysis compared to conventional tools presented in the literature, as it performed a qualitative assessment of the thematic mapping resulting from classification of images from the Brazilian Amazonia-1 satellite in the context of Brazilian Cerrado biome, allowing a clear understanding of the evolution of land use and land cover changes. Also noteworthy in the research methodology is the integration with deforestation polygon alerts from the Real-Time Deforestation Detection System of the National Institute for Space Research, as well as the application of machine learning techniques that can ensure speed and reliability. Also noteworthy is the thematic quality, assessed by the Kappa index, in determining the innovative value of the research methodology.

As a suggestion for the development of new research work, it would be of great scientific interest to develop and analyze classification procedures based on deep learning techniques (DL) and convolutional neural networks (CNN), with the aim of evaluating the results regarding thematic quality.

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