

# Comparative Analysis of the Quality of the Riparian Gallery of the Sabor River in Montesinho Natural Park

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## Summary

This study focuses on the analysis of the quality of the riparian gallery of the Sabor River along three distinct stretches within the Montesinho Natural Park, using Remote Sensing techniques and using images from Sentinel-2 L2A. The Normalized Difference Vegetation Index (NDVI) was evaluated using the summer images of 2023 and 2017. The Land Use Intensification Index (LUI) was calculated using the 2017 and 2023 land use classifications. The methodology included image classification, post-processing, and calculation of index variations. The NDVI results showed a significant degradation of the riparian gallery, with a total reduction of 26.6% in quality, while 70.9% remained stable and only 2.6% showed improvement. The sectional analysis revealed that the greatest degradation occurred in the third section, highlighting an increasing gradient of deterioration along the river from the headwaters to the boundaries of the Park. The LUI indicated that 44% of the studied area suffered some type of intensification, with a greater impact also in Section 3. This study shows that the riparian gallery is going through a period of degradation and that measures should be put in place to study and mitigate the pressures on this class of soil, which is so important for the functioning of ecosystems.

**Keywords:** Sabor River; Riparian gallery; Sentinel-2 L2A; Supervised Classification; NDVI; LUI.

## 1 Introduction

The conservation of riparian ecosystems is vital for biodiversity and environmental sustainability. The riparian gallery of the Sabor River was a biotope of enormous relevance for the Montesinho Natural Park, and it is essential to ensure its safeguarding, within the framework of modern management (Arizpe et al., 2009).

Alluvial forests (habitat 91E0 under the Natura 2000 sectoral plan) are among the most biodiverse and threatened habitats in Europe. Despite the dominance of alders (*Alnus glutinosa*) is the diagnostic factor of this habitat, other species of arboreal size, such as the ash tree (*Fraxinus angustifolia*) or the willow (*Salix atrocinera*) (91E0 - *Alluvial forests of Alnus glutinosa and Fraxinus excelsior* (Alno-Padion, Alnion incanae, Salicion albae., 2004).

The riparian gallery, which these forests form, is not only home to a large number of species of flora, but also provides refuge for highly endangered animal species, such as the water mole (*Galemys pyrenaicus*) (Mathias et al., 2023), or the black stork (*Ciconia nigra*) (Almeida et al., 2022). The continuity of this habitat in the Northeast of Trás-os-Montes is equally important for species such as the Iberian wolf (*Canis lupus signatus*) by providing large ecological corridors for the dispersal of juveniles (Pimenta et al., 2005).

In addition to its importance for biodiversity, this priority habitat, recognised by the Habitats Directive and included in Annex I, provides key ecosystem services for rural communities, including: water filtration and cleaning; aquifer supply; soil retention and erosion protection; CO<sub>2</sub> sequestration; flood prevention; wood production; regulation of nutrient cycling; increase in the value of the landscape.

These services are equally or more relevant in the current scenario of biodiversity crisis and climate change, in which water appears to be an increasingly scarce commodity. This study aims to carry out a comparative analysis of the quality of the riparian gallery of the Sabor River, focusing on the changes observed between 2017 and 2023. This need for study arises from the importance of understanding the dynamics that affect the conservation of this crucial habitat, conditioned by anthropogenic actions, such as the unregulated cleaning of the banks of watercourses, the clear-cutting of healthy trees and the construction of hydraulic works, as well as by natural elements, including the presence of the fungus *Phytophthora sp.*, responsible for significant damage to flood forests across Europe (Jung et al., 2016). In 2023, a study was published in Portugal that warned of the presence of the fungus in five populations of alders, with high incidence rates of the disease, and with an average lethality that exceeded a quarter of the affected trees (Kanoun-Boulé et al., 2016).

The disappearance or drastic reduction of this habitat has considerable impacts on the dynamics of rivers. In fact, energy transfers and the composition of riparian trophic networks are directly related to the deposition of senescent leaves in the beds of watercourses. These leaves are an indispensable trophic resource for several species of invertebrates, which will later become a resource for fish, birds and amphibians. In this sense, the safeguarding of this habitat is essential for maintaining the health of rivers.

## **2 Methods**

### **2.1 Location of the Study Area**

The source of the Sabor River is located in Spain, and runs for about 131 km to its mouth in the Douro River (Silva, 2010), passing through the Montesinho Natural Park (PNM). This park, located in the district of Bragança, is a protected area of significant biodiversity, serving as a habitat for endemic and protected species in an ecosystem that ranges from vast forest areas to agricultural areas punctuated by traditional villages (Rodrigues, 2008). It is in the context of the Sabor River in the PNM that this work focused (Figure 1).

The Sabor watershed is characterized by a diversity of habitats that are essential for the sustainability of local aquatic and terrestrial communities. The river and its banks are crucial for maintaining water quality and ecosystem stability, supporting a rich riparian flora and diverse species of fauna (Silva, 2010).

However, the region faces environmental challenges, due to human interventions, such as intensive agriculture, aggregate extraction, and pollution, which negatively impact the integrity of the river and associated ecosystems. These anthropogenic activities have caused significant changes in the ecological quality of the Sabor River, affecting the morphology of the river and its aquatic and riparian biodiversity (Silva, 2010).

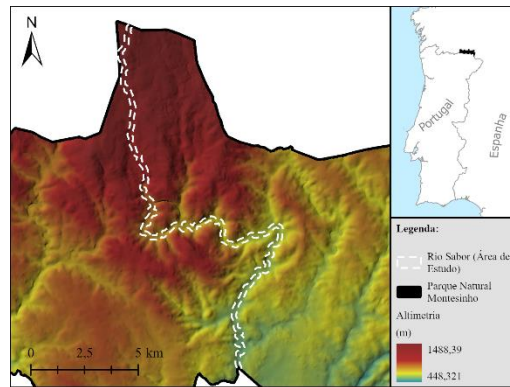


Figure 1 - Location of the Study Area

## 2.2 Data

### 2.2.1 Data Sources

In order to carry out this Remote Sensing project, several data sources were integrated, essential for the analysis and interpretation of the results obtained for the study area, and these were selected based on their relevance, accuracy and accessibility.

The core data of this study is based on satellite imagery obtained through the *Copernicus Browser* (About Copernicus / Copernicus, 2024). In this portal, satellite images from Sentinel-2 L2A were extracted, where the days with less than 50% cloud cover were filtered, within the limits of the study area. These were obtained in the JPEG2000 format, with optical bands of 10 m of spatial resolution, using Bands 02, 03, 04 and 08, corresponding to blue, green, red and near infrared, respectively.

Thus, the following dates were selected: Spring period, April 19, 2023 (*Copernicus Browser*, 2024a) and April 5, 2017 (*Copernicus Browser*, 2024b); Summer Period, July 18, 2023 (*Copernicus Browser*, 2024c) and July 29, 2017 (*Copernicus Browser*, 2024d).

It is important to note that the images were extracted for the years 2017 and 2023, as only from 2017 onwards were images obtained for the intended months (ESA - *About the launch*, 2024), where spring and summer images are crucial to analyse the development of deciduous vegetation, also serving as a basis for assessing the health status of vegetation, through indices such as NDVI. This seasonal change coincides with the beginning of leaf development, around April, and its optimal period, in July.

Regarding the boundaries of the study area, they were delimited by a *buffer* of 100 m to each side of the axis defined by the Sabor River, identified through the digitization of images of the service *World Imagery*, made available by ArcGIS Online. Data from the same services were also obtained from the 30 m Digital Terrain Model (DTM). In the project, the Land Use and Occupation Chart of 2018 (COS2018v2.0) was used to help and clarify certain visualizations of results (*Land Use and Occupation Charter - 2018. Directorate-General for the Territory.*, 2022).

### 2.2.2 Data Integration Methodology

As for the methodology used throughout the project, it was adapted from the practical e-book of the discipline, made available by the faculty, which was carried out in the ArcGIS Pro software,

version 3.2.2, where, first, the images of the respective bands and creation of the RGB composites were imported, as well as the definition of the study area (Caetano & Costa, 2023). Then, artificial bands were created, in addition to principal component analysis (PCA) and map algebra for the production of NDVI indexes.

The pre-processing of the bands has not been carried out, as the Sentinel-2 L2A images have already undergone a series of in-house corrections, namely atmospheric, geometric and radiometric correction (ESA, 2024). On the other hand, care was taken to select images with a low percentage of clouds within the limits of the study area.

Subsequently, the supervised classification was carried out, where several training polygons were created for the application of the maximum likelihood classifier. In the next step, landscape changes were analysed based on NDVI. A post-processing stage was also carried out, through the generalization of the maps and respective conversions from *raster* to vector format and generalization of the same to a Minimum Cartographic Unit (UMC) as well as the extraction of the parameters for the analysis of the Land Use Intensification Index (LUI). Finally, the thematic accuracy of the classification stage was evaluated and the maps were compared to characterize the landscape dynamics between 2017 and 2023.

In Annex 1 it presents the Summary of the Stages and Data of the Remote Sensing Project, concluding, among others, the definition of the technical specifications of the maps to be produced, and the different stages of the entire process from the acquisition of the images to the final outputs. It should also be noted that all the information was compiled in a *file geodatabase*. The reference system used was PT-TM06/ETRS89.

## 2.3 Land Use Classification

### 2.3.1 Supervised Classification

The nomenclature of the map was defined according to the respective classes of land use and occupation existing within the limits of the study area, which is indicated in the Table 1.

Table 1 - Land Use and Occupation Classes for the Study Area.

Code	Name	Description
1	Riparian Gallery	Areas with dense and varied vegetation, adjacent to watercourses, essential for the protection and biodiversity of riverine rivers.
2	Agriculture	Cultivated land where food, fiber, and other agricultural products are produced, representing an extension of the modified human landscape.
3	Pastures	Areas of herbaceous vegetation used primarily for cattle grazing, reflecting an interaction between agricultural practices and natural ecosystems.
4	Bush	Land covered by shrubby and herbaceous vegetation, often used as transition areas between human and natural habitats.
5	Water	Bodies of water, such as rivers, lakes, and reservoirs.

6	Artificial Territory	Urbanized or industrialized areas that represent the transformation of the natural environment to meet human needs.
7	Forest	Large tracts of land densely covered with trees, which are vital for biodiversity.
8	Bare Rock	Exposed surfaces of solid rock or deposits, with little or no vegetation cover.

Regarding the training polygons, they were defined by visualizing the spectral bands (Sentinel-2 L2A images) together with *World Imagery*, provided by the ArcGIS Online imagery service. Of the 194 polygons defined, they were distributed among the 8 classes of the nomenclature, in order to provide the model with the largest amount of information for the various pixels. Next, the spectral signatures for the three projects were constructed, through the bands of the principal components with the highest percentage of eigenvalues, followed by a brief analysis of the training sample by dendrograms, which allowed to visualize the differences and similarities between the different classes.

### 2.3.2 Postprocessing

After the supervised classification, the generated map, in the format *raster*, with the classes of land use and occupation, was generalized in order to reduce the isolated pixels, in addition to reducing the number of converted polygons, of the format *raster* for vector. For the generalization, a CMU of 0.1 ha was defined in the vector format. In Figure 2, there is a sample that demonstrates the generalization made for the classification maps obtained for the study area.

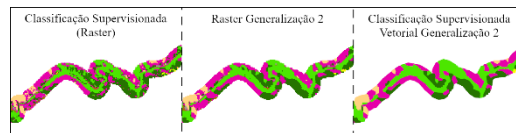


Figure 2 - Sample Format Generalization Step *raster* for vector

### 2.3.3 Thematic Accuracy Assessment

To assess the thematic accuracy of the maps obtained in the supervised classification, three essential steps were followed. Firstly, a reference sample was created with 194 random points, within the limits of the study area, where they were classified with the classes of land use and occupation, defined in the nomenclature. After each point was assigned to its reference class, the corresponding values were added, coming from the pixel class where each point was located, according to the supervised classification.

Secondly, a confusion matrix was created, where the raster values were assigned on the X axis and the reference values related to the classification of random points were assigned on the Y axis. In this matrix, the agreement and disagreement between the two variables is evaluated.

Thirdly and finally, the values of general accuracy were calculated. *overall accuracy* (OA), the producer accuracy (PA) values, i.e. the supervised classification model, and the user accuracy (UA) values, in which case they are the authors of this project. These parameters, presented in the confusion matrix, are calculated by Equations 1, 2 and 3, respectively (Caetano & Costa, 2023).

$$OA = \text{diagonal UACC} / TA \quad (1)$$

$$PA = UACC_{\text{class } x} / TA_{\text{class } x} \quad (2)$$

$$UA = UACC_{\text{class } y} / TA_{\text{class } y} \quad (3)$$

where:

UACC – Correctly Classified Sampling Unit,

TA – Sample Size.

## 2.4 Remote Sensing Metrics

### 2.4.1 NDVI

NDVI is an essential remote sensing metric that quantifies the density and health status of vegetation by measuring the difference between near-infrared light, which vegetation strongly reflects, and red light, which vegetation absorbs. This index contributes to several studies in ecology, epidemiology, among others (Carella et al., 2022) (Pettorelli et al., 2005). Used to assess the density and phytosanitary status of habitats, NDVI plays a decisive role in environmental monitoring, natural resource management and spatial planning, allowing the detection of changes between different time periods (Pettorelli et al., 2005).

In the present study, the NDVI values for the four mentioned dates were calculated, according to Equation 4, and the difference between the summer of 2023 and the summer of 2017, as well as the differences between summer and spring for the 2017 and 2023 projects, was then calculated using Equation 5. To observe the changes between these two variables, called "No Change" and "With Change", the conversion was performed using Equations 6 and 7.

$$NDVI = (Band\ 4 - Band\ 3) / (Band\ 4 + Band\ 3) \quad (4)$$

$$dNDVI = NDVI_2 - NDVI_1 \quad (5)$$

$$\mu - k\sigma < dNDVI < \mu + k\sigma \quad (6)$$

$$mNDVI = \text{Con}(dNDVI < (\mu - k\sigma), -1, \text{Con}(dNDVI > (\mu + k\sigma), 1, 0)) \quad (7)$$

where:

band 4 corresponds to Band 08 and band 3 to Band 04 in the original images,

$\mu$  – mean value obtained in dNDVI,

$k$  – is the scalar value (where  $k = 1$  has been used) that defines  $\sigma$ ,

$\sigma$  – is the standard deviation,

Con – condition tool that accepts the arguments, condition to be tested (dNDVI), value = 1 "if true" and value = 0 "if false".

To compare the differences in the riparian gallery between 2017 and 2023, a matrix was prepared to compare the supervised classifications of the projects in these years. Both classifications were carried out by analysing satellite images taken between the spring and summer of each respective year. The diagonal of this matrix corresponds to the agreement between the maps, and the remaining parameters are the disagreement between the classes obtained. In addition, both maps were also combined, thus obtaining a comparison of change between classes, and an attribute was created that allows distinguishing the places where the riparian gallery has undergone more changes in terms of area.

#### 2.4.2 LUI

The Land Use Intensification Index (LUI) aims to observe changes in land use for classes associated with landscape urbanization and agricultural practices. This index helps to quantify the level of exploitation of natural resources and to identify land use practices that may be sustainable or harmful to the environment. Recent studies have used LUI to better understand the implications of land use intensification on biodiversity (Meier et al., 2020). The LUI was calculated, through Equation 8, in order to evaluate the intensification of the landscape caused by anthropogenic activities, using the data from the supervised classification (Pace et al., 2022). The index was calculated for a single scale.

$$LUI = 5*(\% \text{artificial}) + 3*(\% \text{agriculture}) + 1*(\% \text{pastures}) \quad (8)$$

### 3 Findings

#### 3.1 Principal Component Analysis

In the first phase, it was decided to perform the unsupervised classification, but the results obtained did not guarantee a coherent and robust classification. Thus, it was decided to follow the supervised classification methodology.

Prior to the supervised classification, it was necessary to reduce the spectrum of bands to be used for the classification stage through PCA for the spring and summer images, and it was concluded that, in any of the hypotheses under study, Bands 08 and 04 were responsible for more than 99% of the variance of the data. Annex II presents a summary of the results obtained.

#### 3.2 Dendrogram Analysis

The difficulties underlying the discrimination between land use and occupation are reflected in the dendrograms (Annex III) which represent the distance between classes based on their spectral similarities. In this sense, the closest classes represent soil covers with similar spectral characteristics. For both years, there were short distances between 4 classes. However, the smallest distance occurred in the 2023 results, between "forest" and "bush", from which it can be deduced that the classifier had difficulties in discriminating between these two ground covers. It should be noted that the same phenomenon occurs in 2017. Other very close classes are: agriculture and artificial territory, forest and bush (in both years they appear as the two closest classes); pastures and bushes, pastures and riparian gallery (in 2017); agriculture and pastures, riparian gallery and bush (in 2023).

#### 3.3 Land Use and Occupation Classification

##### 3.3.1 Supervised Classification

The results obtained by the post-processing of the supervised classification reflect a significant variation in land cover on the two dates studied (2017 and 2023) and important differences depending on the river section Flavor. The Figure 3 Presents the result of the supervised classification in vector format for the years 2017 and 2023, and the boundaries defined for each of the three sections analysed (higher resolution in Annex IV).

In 2017, according to the comparison matrix (Annex VIII), the study area was mostly occupied by areas of Bushes (34.7%) and Riparian Gallery (24.2%), followed by Pastures with 9.6%, followed by Forest areas (8.5%) along with Agriculture areas (8.4%). Analysing the result of the supervised classification for 2023, a higher percentage of Matos (33.3%) was obtained, followed by Riparian Gallery (23.7%), followed in percentage terms by Pastures (11.2%), Forest and Bare

Rock (10.6% and 9.1%, respectively). These results are somewhat atypical, because the study area consists of a tiny fringe of the landscape - a buffer of 100m in relation to the Sabor River.

Annexes V and VI show the land occupations in the three sections studied. Briefly, it should be noted that Section 1 (coinciding with the headwaters of the Sabor River) has a greater concentration of areas with woods and a Riparian Gallery that is still very undeveloped. In turn, the Riparian Gallery reaches its greatest development in Section 2, gradually decreasing throughout Section 3. In turn, there is an increase in the areas of Agriculture and Pastures from Section 2 to Section 3. Finally, the Forest area is similar in Sections 2 and 3.

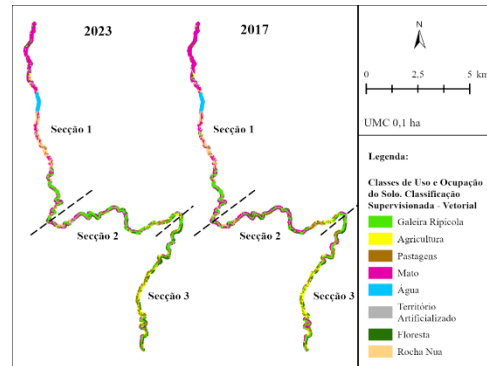


Figure 3 - Supervised ranking for the years 2023 and 2017

### 3.3.2 Thematic Accuracy

In the confusion matrix for 2023 (Annex VII), Water has the highest accuracy (100% AU), followed by the Riparian Gallery, which has a high accuracy (74% AU). Regarding Agriculture and Forestry, they have lower accuracy (AU of 47% and 32%, respectively), which may indicate some problems and overlaps in spectral characteristics, with influence on other classes. The same reasoning applies to Pastures and Bare Rock. It is only worth noting the Matos with a moderate accuracy (UA 66%). Overall accuracy is moderate (OA 58%).

On the other hand, the confusion matrix for 2017 reveals that the Riparian Gallery has a high accuracy (UA of 87%). Agriculture, on the other hand, has a moderate accuracy (AU of 67%) and Pastures and Artificial Territory a low accuracy (AU of 36% and 40%, respectively). The Matos area will have a moderate to high accuracy (AU of 65%). Finally, Water is the only one with an excellent accuracy (100% AU), which is common for bodies of water due to distinct features in satellite or aerial imagery. Overall accuracy is moderate (OA 59%).

### 3.4 NDVI Variation

To calculate the variation of the NDVI, based on the summer images (difference between 2023 and 2017), the area classified as Riparian Gallery was considered, resulting in a vector map with a clear definition between the areas where the degradation of the Riparian Gallery occurred (-1), maintenance (0) and an improvement in the development of the gallery (1), which is presented in the Figure 4. In Table 2 the variation of the NDVI is presented, considering only the areas of the Riparian Gallery.



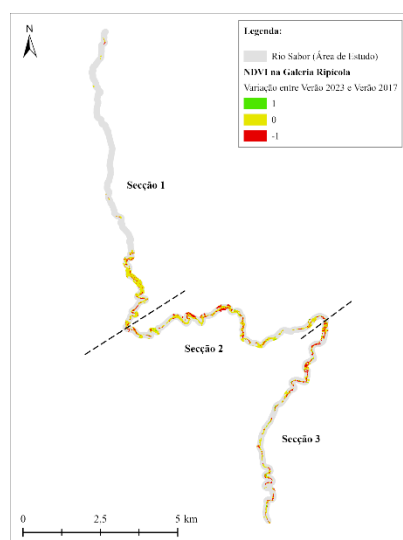


Figure 4 - NDVI of the Riparian Gallery, Variation between Summer 2023 and Summer 2017

The main changes in the riparian gallery occurred on both banks, with some important areas in Section 2, but with a greater incidence in the section between the villages of França and Rabal, coinciding with Section 3.

Table 2 – Variation of NDVI (2017-2023), by section of the Sabor River

	Section 1		Section 2		Section 3	
<b>Riparian gallery</b>	<b>Area (ha)</b>	<b>Area (%)</b>	<b>Area (ha)</b>	<b>Area (%)</b>	<b>Area (ha)</b>	<b>Area (%)</b>
Gallery Enhancement	0,1	0,3	1,4	2,3	2,0	5,1
Maintenance	30,2	83,2	43,1	72,5	22,1	56,2
Gallery degradation	6,0	16,5	15,0	25,2	15,2	38,7
<b>Total</b>	<b>36,2</b>	<b>100,0</b>	<b>59,5</b>	<b>100,0</b>	<b>39,2</b>	<b>100,0</b>

### 3.5 LUI Variation

The results of the supervised classification are not sufficiently robust, as evidenced by the confusion matrix of the 2023 and 2017 images (Annexes VII, VIII). This fact may interfere with a finer analysis of the evolution of the quality of the riparian gallery. Still, it presents itself in the Table 3, the LUI calculation, for both periods.

Table 3 - Calculation of LUI per section and per section analysed

<b>Sabor River</b>	<b>LUI (2023)</b>	<b>LUI (2017)</b>
Section 1	14,5	8,2
Section 2	27,8	64,2
Section 3	99,7	170,9
Thing	44,0	73,8

## 4 Discussion

### 4.1 Land Use Classification

According to the difficulties described in the results of the dendrograms, (Caetano & Costa, 2023) suggest that it is possible to apply some strategies to mitigate this problem, namely, increasing the number of training samples, investigating possible errors in the classification of the samples, and/or merging land cover classes. The merger of the bush and forest classes was considered, but this option was rejected, since the creation of this new class could imply greater difficulties of discrimination with the riparian gallery. Although there was a slight increase in training samples, this increase was not enough to improve the results. Future studies should take this aspect into consideration, suggesting a significant increase in the training samples of the most problematic classes to address the problems underlying the incorrect identification of classes.

### 4.2 Comparison Matrix

Regarding the object of study of this work, the riparian gallery, the comparison matrix (Annex IX) indicates that between 2017 and 2023, 11% (12.39 ha) of the riparian gallery was converted into forest, 7% (7.75 ha) into bush, 2% (2.31 ha) into agriculture, 1% (1.04 ha) into pastures and 1% (0.61 ha) into artificial territory. The spatial analysis of the change that occurred (Annex XI) indicates that most of the changes occurred in Section 3, and in the adjacent area of Section 2.

The most significant change (conversion from riparian gallery to forest) will most likely be due to classification errors, and will not be a true change between classes. It is not likely that a change of this kind, which involves the growth of trees, would have occurred in just 6 years. In fact, the difficulty in distinguishing wetlands from other types of land cover has been mentioned by other authors, who underline the notorious challenges associated with the process of their classification (Ozesmi & Bauer, 2002). In this sense, it can be speculated that in reality the riparian gallery maintained the 11% that appear to have been altered, or that in some sections the gallery was destroyed and was invaded by bushes, since forests and bushes will not have been well discriminated in any of the years.

### 4.3 Thematic Accuracy Analysis

The overall accuracy (OA) of the classification was very similar in 2017 and 2023, at 59% and 58%, respectively. Coincidentally, the classes with the most correct answers were the same for both years: water (UA and PA), riparian gallery (AU), and bare rock (PA). Regarding the classes with the fewest correct answers, agriculture and artificial territory (UA and PA) stand out. One of the possible sources of error could be the fact that the classification was carried out for a very specific strip of territory (the 100 m buffer in relation to the river), and that it includes a very small area of agriculture and artificial territory. Although the training samples were evenly distributed across classes (about 20 polygons per class), an area like the one in this study can represent an added challenge for the classifier. In this sense, it is suggested that a possible attempt to improve the accuracy of the classification is to classify a more extensive area, and only then to delimit the study area, segmenting the *buffer* in relation to the river axis.

### 4.4 NDVI

Within the scope of this work, the application of NDVI proved to be essential, since despite the lethality associated with one of the threats that hang over the riparian gallery – the *Phytophthora* sp. – Its effects on vegetation and landscape are not immediate. After the

infection of the fungus, it is expected that some trees will survive with their leaf area quite compromised, and that others will die progressively, although in some cases it can be relatively quickly (in a few years) (Perry, 2004). In this sense, NDVI is an extremely useful tool, as it enables the monitoring and quantification of the entire process of infection of the trees of the riparian gallery, allowing the design of a conservation and restoration strategy based on the evidence of this metric.

The visual analysis of the generated maps indicates that in 2017, both in spring and summer, the NDVI reached more positive values compared to 2023. The causes of the decline in the index can be associated with multiple factors, namely:

- Very low rainfall volume in 2023, compared to 2017;
- Changes in the agricultural regime of the study area, with lower production in 2023;
- Changes in the phytosanitary conditions of the riparian gallery, including infection and lethality of the trees that compose it.

However, analysing the agrometeorological and hydrological monitoring bulletins for 2017 and 2023 (Agrometeorological and Hydrological Monitoring, 2017) (Agrometeorological and Hydrological Monitoring, 2023) Rainfall in 2017 was even lower than in 2023, so the first hypothesis may be rejected.

In order to ensure that the NDVI changes analysed concerned exclusively the riparian gallery, this restriction was made, using the class previously delimited in the supervised classification. The visual analysis of the NDVI of the riparian gallery revealed the same pattern attributed to the rest of the study area, i.e., in the comparison between the NDVI of Summer 2017 and Summer 2023, there was a decrease in the values of this index, with special incidence for Sections 3 and 2. Although there are some affected areas in Section 1, this area was the one that showed the most stable values between the two years. Possibly, this difference between sections is due to the density of riparian gallery itself, which in Section 1, being a more mountainous area and hit by fires, is low.

The most detailed analysis of NDVI is revealed by the Table 2 whose values corroborate what had already been identified in the visual analysis of the map. For 70.9% of the study area, NDVI values remained the same, in 2.6% there was an increase, and in 26.6% there was a decrease. These values are quite expressive and may, in fact, indicate that the riparian gallery is already in regression and decline in some points. The analysis by Section revealed that the most affected area is Section 3, where there was a decrease in NDVI in 38.7% of the area, followed by Section 2, with 25.2%, and finally Section 1, with 6%. Coincidentally, the largest class changes recorded (Appendix XI) are at approximately the same places where NDVI assumes the lowest values (Appendix X).

Although the present work did not include field trips to validate the remote sensing metrics obtained, a contact was established with a specialist from the Polytechnic Institute of Bragança, who is very knowledgeable in the area of study. The specialist confirmed that the area of the riparian gallery most affected by *Phytophthora sp.*, and which is already in a state of decline, was the same as the one identified by this work – the northern area of Section 3 (Professor Amílcar Teixeira, personal communication). This confirmation validated the results obtained and gave more robustness to the main findings of this study.

#### 4.5 LUI

The results obtained indicate that 44% of the study area is somewhat intensified, with this result being more expressive for Section 3, moderate for Section 2 and low for Section 1. This result reflects the use of the territory, since Section 1 crosses a mountainous area of the Serra de Montesinho, with abundant rocky outcrops, and is therefore the wildest area in the entire study area. Section 3, on the other hand, is the most humanized area, as it is the area of lower altitude, and because it is closer to the city of Bragança.

Since it is not possible to determine a threshold to determine whether an LUI is very high, as the specific limits may vary based on regional ecological conditions, gallery vegetation types and the purposes of the analysis, it can be inferred from any level of LUI that significantly impairs the natural functions of riparian vegetation (pest control, filtration of nutrients and pollutants, carbon sequestration, control of river erosion and landslides, as well as the contribution of genetic resources) can be considered high. Thus, it should be noted that the highest values are always obtained in Section 3.

#### 5 Conclusion

The study reveals a worrisome regression in the quality of the riparian galleries of the Sabor River, evidenced by a degradation of the vegetation cover and by changes in the composition of the land use classes over the period studied. The results indicate that anthropogenic pressures, such as unregulated exploitation of river banks and indiscriminate felling of trees, together with the proliferation of pathogens such as *Phytophthora sp.*, may have contributed significantly to the degradation of this vital habitat. This decline threatens not only local biodiversity, including several species dependent on these ecological corridors, but also compromises the ecosystem services that these areas provide, such as water purification, erosion prevention and carbon sequestration.

It is suggested that conservation strategies by entities responsible for managing the NMP incorporate continuous monitoring technologies such as Remote Sensing (whenever possible complemented with *in situ data*), in order to assess the effectiveness of the conservation and restoration measures implemented.

In fact, the study's data suggest the need for more integrated environmental planning and policies that promote sustainable management of riparian galleries, more focused on restoring degraded habitats. The commitment to the conservation of these areas is crucial not only for the preservation of local biodiversity, but also for the well-being of human communities that depend on the natural resources and services that ecosystems provide. In conclusion, this study underscores the urgency of addressing the challenges faced by riparian ecosystems through a collaborative and sustained effort between government entities, environmental organizations, and the scientific community.

#### References

- 91E0—Alluvial forests of *Alnus glutinosa* and *Fraxinus excelsior* (Alno-Padion, Alnion incanae, Salicion albae). (2004). Natura 2000 Sector Plan. Natural and semi-natural habitat types in Annex I to Directive 92/43/EEC (mainland Portugal): Ecological and management characterisation sheets for the Natura 2000 sectoral plan. Report. Lisbon ICNB (Institute for the Conservation of Nature and Biodiversity). <https://www.icnf.pt/api/file/doc/5eb251e0990bdba7>
- About Copernicus / Copernicus. (2024). <https://www.copernicus.eu/en/about-copernicus>

- Almeida, J., Godinho, C., Leitão, D., & Lopes, R. J. (2022). *Red List of Birds of Mainland Portugal*. SPEA, ICNF, LabOR/UÉ, CIBIO/BIOPOLIS. <https://www.listavermelhadadasaves.pt>
- Arizpe, D., Mendes, A., & Rabaça, J. E. (2009). *Sustainable Riparian Areas—A Management Guide*. Ripidurable.
- Caetano, M., & Costa, H. (2023). *Remote sensing practicals, [ebook]*. NOVA Information Management School, New University of Lisbon.
- Land Use and Occupation Charter—2018. Directorate-General for the Territory*. (2022). [dataset]. <https://snig.dgterritorio.gov.pt/rndg/srv/por/catalog.search#/metadata/b498e89c-1093-4793-ad22-63516062891b>
- Copernicus Browser*. (2024a). Copernicus Browser. <https://browser.dataspace.copernicus.eu/>
- Copernicus Browser*. (2024b). Copernicus Browser. <https://browser.dataspace.copernicus.eu/>
- Copernicus Browser*. (2024c). Copernicus Browser. <https://browser.dataspace.copernicus.eu/>
- Copernicus Browser*. (2024d). Copernicus Browser. <https://browser.dataspace.copernicus.eu/>
- ESA - About the launch. (2024). [https://www.esa.int/Applications/Observing\\_the\\_Earth/Copernicus/Sentinel-2/About\\_the\\_launch](https://www.esa.int/Applications/Observing_the_Earth/Copernicus/Sentinel-2/About_the_launch)
- Jung, T., Orlikowski, L., Henricot, B., Abad-Campos, P., Aday, A. G., Aguin Casal, O., Bakonyi, J., Cacciola, S. O., Cech, T., Chavarriaga, D., Corcobado, T., Cravador, A., Decourcelle, T., Denton, G., Diamandis, S., Doğmuş-Lehtijärvi, H. T., Franceschini, A., Ginetti, B., Green, S., ... Pérez-Sierra, A. (2016). Widespread *Phytophthora* infestations in European nurseries put forest, semi-natural and horticultural ecosystems at high risk of *Phytophthora* diseases. *Forest Pathology*, 46(2), 134–163. <https://doi.org/10.1111/efp.12239>
- Kanoun-Boulé, M., Vasconcelos, T., Gaspar, J., Vieira, S., Dias-Ferreira, C., & Husson, C. (2016). *Phytophthora xalni* and *Phytophthora lacustris* associated with common alder decline in Central Portugal. *Forest Pathology*, 46(2), 174–176. <https://doi.org/10.1111/efp.12273>
- Mathias, M. D. L., Fonseca, C., Rodrigues, L., Grilo, C., Lopes-Fernandes, M., M. Palmeirim, J., Santos-Reis, M., Alves, P. C., Cabral, J. A., Ferreira, M., Mira, A., Eira, C., Negrões, N., Paupério, J., Pita, R., Rainho, A., Rosalino, L. M., Tapisso, J. T., & Vingada, J. (2023). *Red Book of Mammals of Mainland Portugal* (Number 1, pp. 1–371). FCIências.ID / ICNF. <https://repositorio.ul.pt/handle/10451/58108>
- Meier, E. S., Indermaur, A., Ginzler, C., & Psomas, A. (2020). An Effective Way to Map Land-Use Intensity with a High Spatial Resolution Based on Habitat Type and Environmental Data. *Remote Sensing*, 12(6), Article 6. <https://doi.org/10.3390/rs12060969>
- Agrometeorological and Hydrological Monitoring. (2017). Portuguese Environment Agency.
- Agrometeorological and Hydrological Monitoring. (2023). Portuguese Environment Agency.
- Pace, G., Gutiérrez-Cánovas, C., Henriques, R., Carvalho-Santos, C., Cássio, F., & Pascoal, C. (2022). Remote sensing indicators to assess riparian vegetation and river ecosystem health. *Ecological Indicators*, 144. Scopus. <https://doi.org/10.1016/j.ecolind.2022.109519>

Perry, E. J. (2004). Phytophthora—Root and crown rot in the garden. *Univ. Calif. Agric. Nat. Res.*

Pimenta, V., Barroso, I., Álvares, F., Correia, J., Ferrão da Costa, G., Moreira, L., Nascimento, J., Petrucci-Fonseca, F., Roque, S., & Santos, E. (2005). *Wolf Population Situation in Portugal, results of the 2002/2003 National Census. Technical Report* (p. 158). Institute for the Conservation of Nature / Grupo Lobo. <https://www.icnf.pt/api/file/doc/4f9c051e0e8f2808>

Rodrigues, A. (2008). *Nature Conservation Management in the Montesinho Natural Park: Theory and practice over 25 years*. Polytechnic Institute of Bragança.

Silva, L. (2010). *Evaluation of the ecological quality of lotic systems in the Sabor river basin (Douro Basin)*. Polytechnic Institute of Bragança.

## Annex I. Summary of Remote Sensing Project Milestones and Data

Steps		Description
1	Definition of the technical specifications of the map to be produced	Nomenclature: 8 defined classes (riparian gallery, agriculture, pastures, bush, water, artificial territory, forest, bare rock); Format: versions presented in raster and vector format; Minimum Cartographic Unit (CMU): raster 10x10 m and vector 0.1 ha.
2	Satellite and sensor selection and image acquisition	Sentinel-2 L2A satellite imagery; Format JPEG2000; Spatial resolution 10x10 m; Spectral resolution, band 2 (blue), band 3 (green), band 4 (red), band 8 (near-infrared); Temporal resolution, spring and summer images for 2017 and 2023 (19/04/2023, 18/07/2023, 05/04/2017, 29/07/2017).
3	Construction of the auxiliary database	<i>World Imagery</i> provided by ArcGIS Online; COS2018v2.0;
4	Satellite and sensor selection and image acquisition	Copernicus Browser (accessed on 08/05/2023 on <a href="https://browser.dataspace.copernicus.eu/">https://browser.dataspace.copernicus.eu/</a> );
5	Project Organization	3 different projects were carried out. The first, with satellite images from the summer of 2017 and 2023. The second, with satellite images from the spring and summer of 2017. The third, with satellite images from the spring and summer of 2023.
6	Preparation of exploratory images	The images were imported into the respective projects; The corresponding bands were joined into a single image (composite bands). In RGB432 band 4 corresponds to Band 08, band 3 to Band 04 and band 2 to Band 03. Band 02 was not used; The unified image was cropped only for the study area, in order to detail the analysis.
7	Creation of artificial bands	Composite bands 3 and 4 were placed and the NDVI was calculated using these; With the unified image, an image of core components was created.
8	Supervised classification	Training samples were created with several polygons where the corresponding classes were identified; spectral signatures were constructed with the bands of the principal components that indicated a higher percentage of eigenvalues; a dendrogram was created to observe the classes with the greatest differences and similarities; either the supervised model was created through the most influential bands of the principal components, as well as the assignment of land use classes;
9	Postprocessing	Generalization of the supervised classification raster; Conversion from raster to vector format and its generalization with the defined CMU.
10	Thematic Accuracy Assessment	Random points were generated that served as a reference to construct the confusion matrix; OA, BP of class x and UA of class x were calculated.
11	Map Comparison	The results of the supervised classification were compared between the 2017 project and the 2023 project, where, first, a comparison matrix was built with the areas of each class and then the maps were combined with the creation of a new attribute that indicates the change in the riparian gallery.
12	Metrics Analyzed	Calculation of the difference of NDVI and NDVI change; calculation of the LUI index.

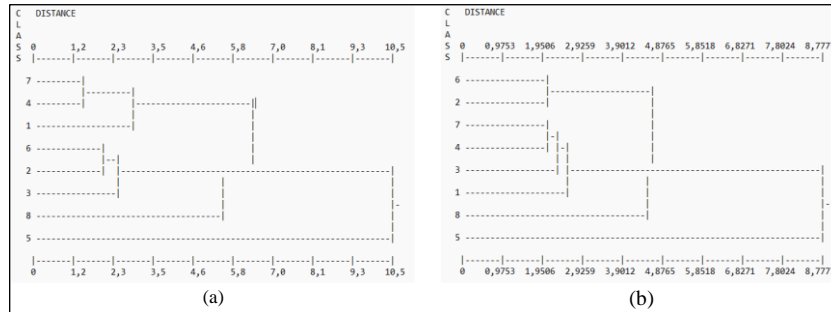
## Annex II. Results of Principal Component Analysis (PCA)

Gallery Riparian	Spring 2017		Summer 2017		Spring 2023		Summer 2023	
	Av <sup>1</sup>	AC <sup>2</sup>	Av <sup>1</sup>	AC <sup>2</sup>	Av <sup>1</sup>	AC <sup>2</sup>	Av <sup>1</sup>	AC <sup>2</sup>

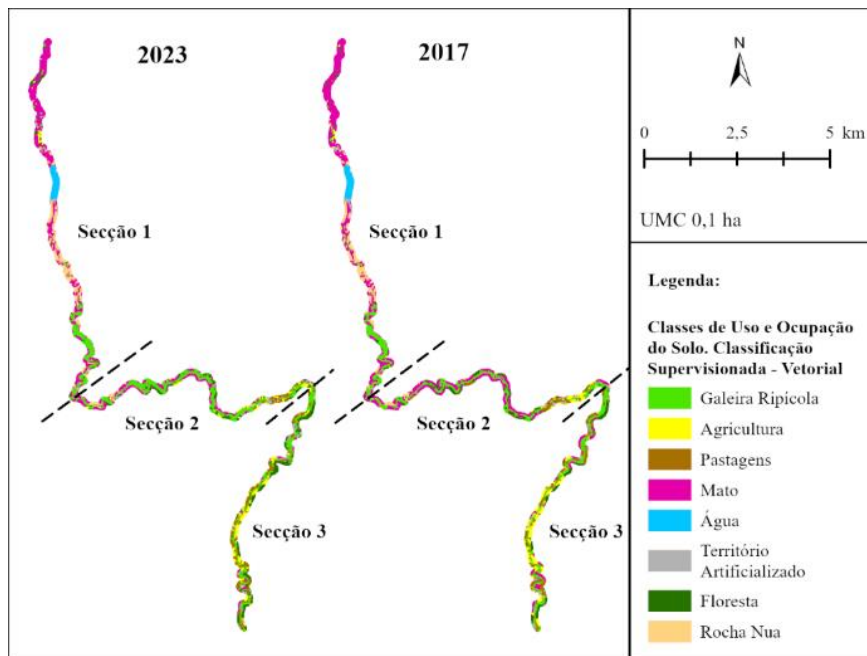
Band 8	79,3490	79,3499	<b>65,7315</b>	<b>65,7315</b>	79,9582	79,9582	<b>77,6671</b>	<b>77,6671</b>
Band 4	19,9280	99,2778	<b>33,4437</b>	<b>99,1752</b>	19,4103	99,3685	<b>21,8586</b>	<b>99,5258</b>
Band 3	0,5593	99,8372	0,6575	99,8327	0,4873	99,8558	0,3637	99,8895
Band 2	0,1628	100,000	0,1673	100,000	0,1442	100,000	0,1105	100,000

1 Eigenvalues. 2 Cumulative eigenvalues.

### Annex III. Dendrograms of the 2023 (a) and 2017 images (b)



### Supervised classification for the years 2023 and 2017 (vector format; UMC 0.1 ha)





**Annex V. Land Cover in the three sections (2017)**

Occupation	Section 1		Section 2		Section 3	
	Area (ha)	Area (%)	Area (ha)	Area (%)	Area (ha)	Area (%)
Riparian Gallery	38,7	17,1	51,0	29,3	48,6	28,4
Agriculture	2,4	1,0	11,0	6,4	34,5	20,2
Pastures	0,4	0,2	17,0	9,8	37,3	21,8
Bush	113,3	49,9	63,6	36,6	21,3	12,5
Water	17,9	7,9	-	-	-	-
Artificial Territory	5,7	2,5	5,3	3,1	7,9	4,6
Forest	7,7	3,4	20,3	11,7	20,6	12,1
Bare Rock	41,0	18,1	5,6	3,2	0,8	0,5
Total	227,1	100,0	173,9	100,0	170,9	100,0

**6 Annex VI. Land Cover in the three sections (2023)**

Occupation	Section 1		Section 2		Section 3	
	Area (ha)	Area (%)	Area (ha)	Area (%)	Area (ha)	Area (%)
Riparian Gallery	36,7	16,1	60,0	34,5	38,9	22,8
Agriculture	0,7	0,3	5,5	3,2	28,3	16,5
Pastures	4,5	2,0	18,7	10,7	40,9	23,9
Bush	109,2	48,1	56,0	32,2	25,5	14,9
Water	17,7	7,8	-	-	-	-
Artificial Territory	5,3	2,3	2,6	1,5	9,0	5,2
Forest	9,5	4,2	24,0	13,8	27,0	15,8
Bare Rock	43,6	19,2	7,1	4,1	1,4	0,8
Total	227,1	100,0	173,9	100,0	170,9	100,0

**Annex VII. Confusion Matrix (raster 2023)**

Class	1	2	3	4	5	6	7	8	Total	AU
1	43	1		5			9		58	74%
2		7	4	1		3			15	47%
3		9	7	1		1			18	39%
4	5	1	2	27		1	4	1	41	66%
5					4				4	100%
6	1			3		7		2	13	54%
7	9	2		3		1	7		22	32%
8	1			12				10	23	43%
<b>Total</b>	59	20	13	52	4	13	20	13	194	
<b>PA</b>	73%	35%	54%	52%	100%	54%	35%	77%		
<b>OA</b>	58%									

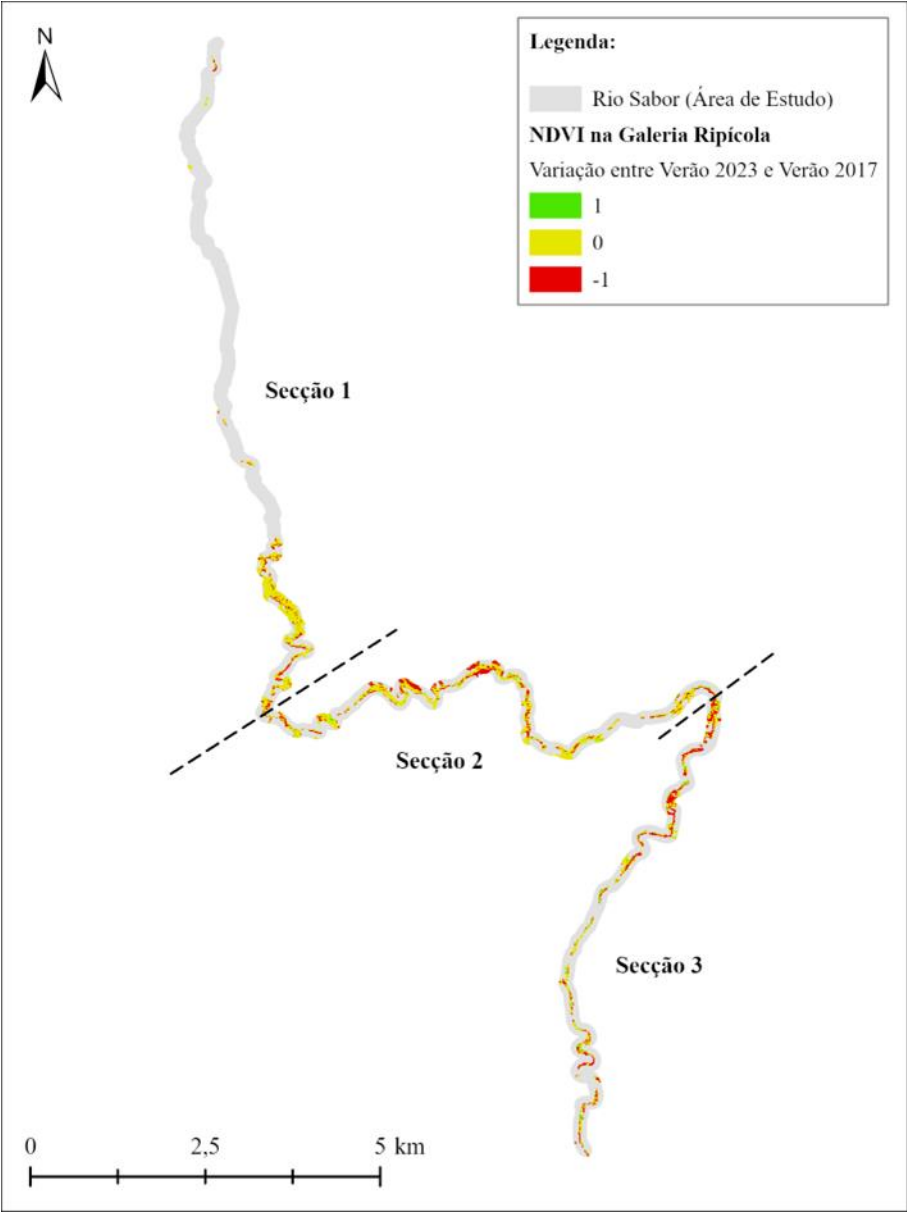
**Annex VIII. Confusion Matrix (raster 2017)**

Class	1	2	3	4	5	6	7	8	Total	AU
1	34			1		1	3		39	87%
2		10	2			3			15	67%
3	5	7	8		1		1		22	36%
4	5	1	3	32		3	4	1	49	65%
5					3				3	100%
6	2	2		2		6		3	15	40%
7	12			5			12		29	41%
8	1			12				9	22	41%
<b>Total</b>	59	20	13	52	4	13	20	13	194	
<b>PA</b>	58%	50%	62%	62%	75%	46%	60%	69%		
<b>OA</b>	59%									

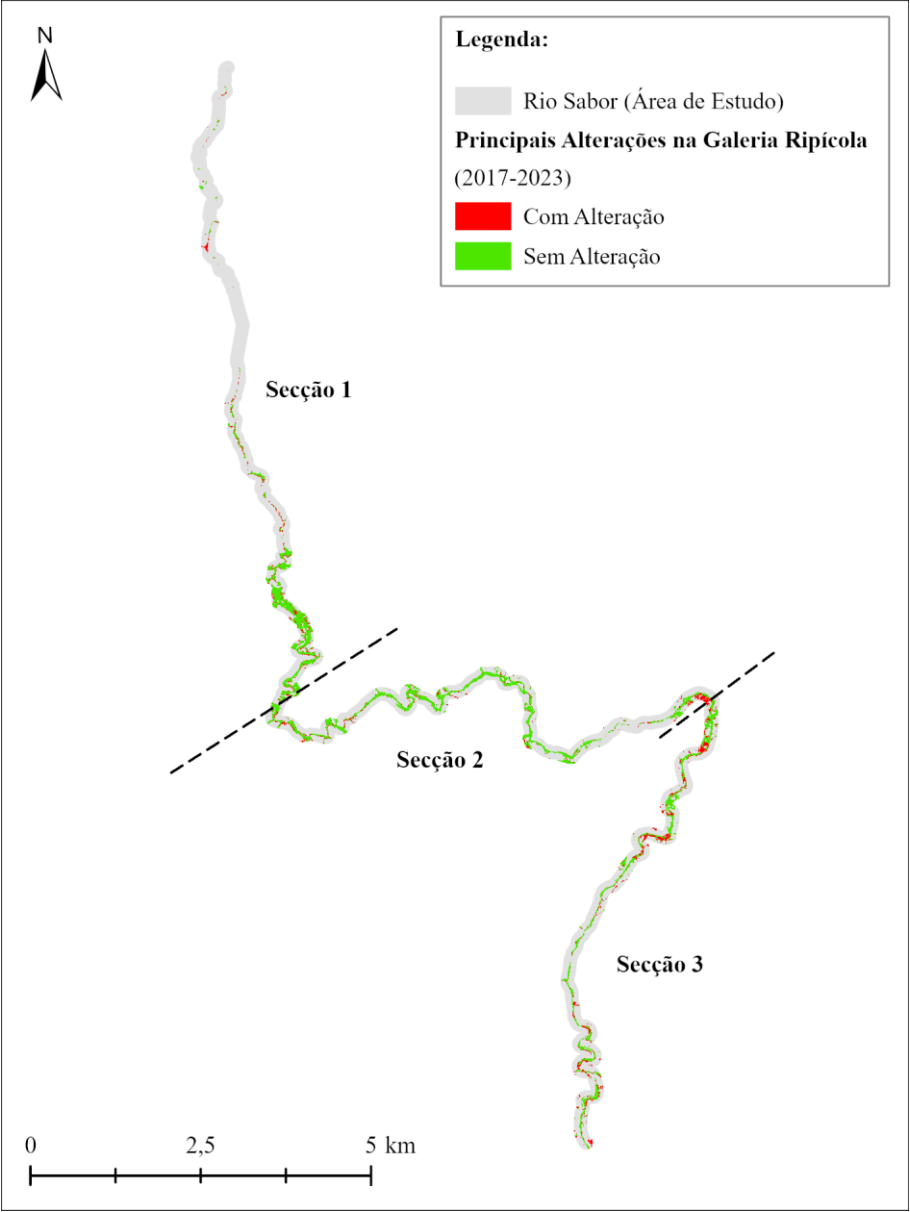
**Annex IX. Comparison Matrix (2017-2023)**

Class	1	2	3	4	5	6	7	8
1	91,11	0,81	6,98	14,14	0,04	0,4	21,75	0
2	2,31	23,79	10,56	3,2	0	2,97	2,39	0,01
3	1,04	15,27	26,68	3,99	0	3,16	1,89	0,04
4	7,75	1,13	5,01	130,88	0,07	2,79	8,14	4,43
5	0,07	0	0,62	0,05	17,11	0,07	0	0
6	0,61	2,89	3,24	9,33	0,03	11,93	0,24	4,14
7	12,39	0,69	8,87	25,54	0	1,16	36,02	0,02
8	0,01	0,03	0,24	10,03	0	2,73	0	45,14

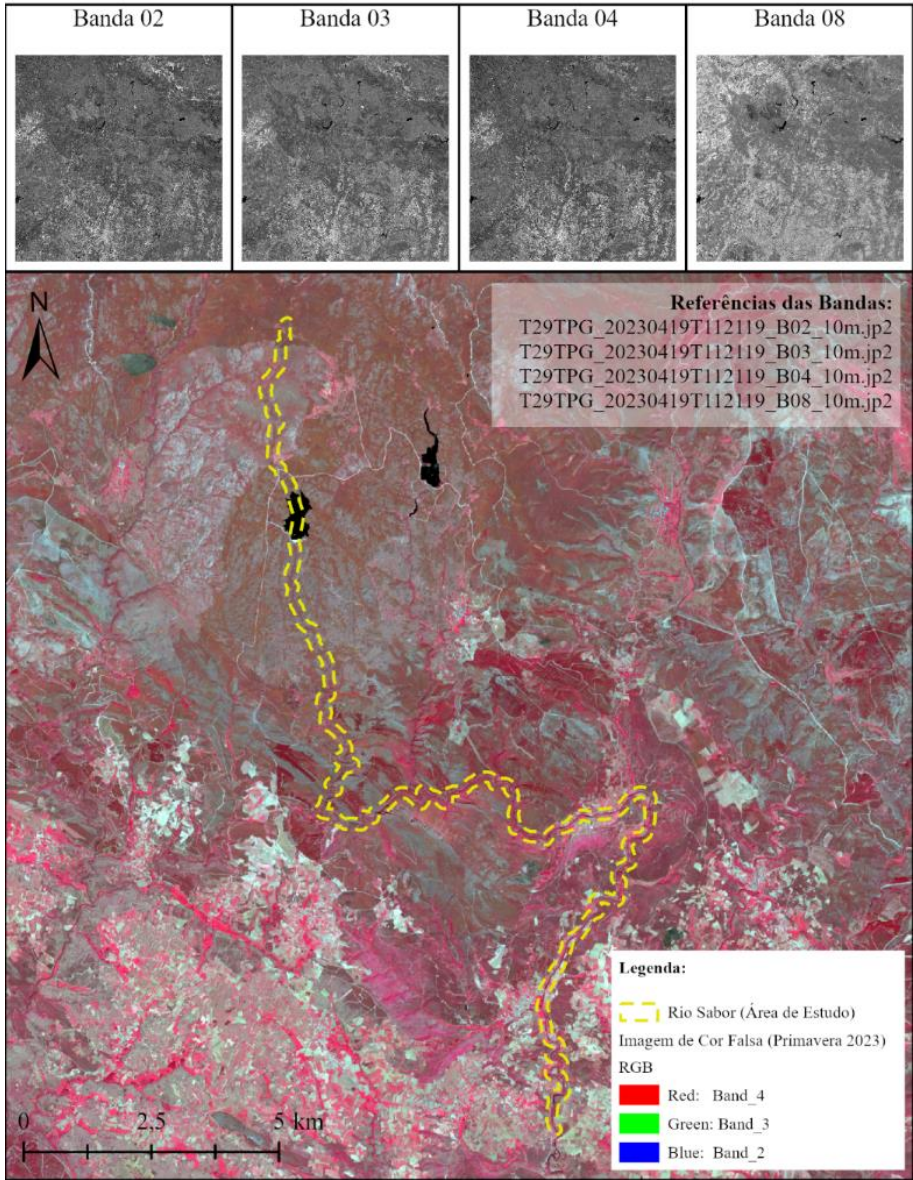
**Annex X. NDVI of the Riparian Gallery, Variation between Summer 2023 and Summer 2017**



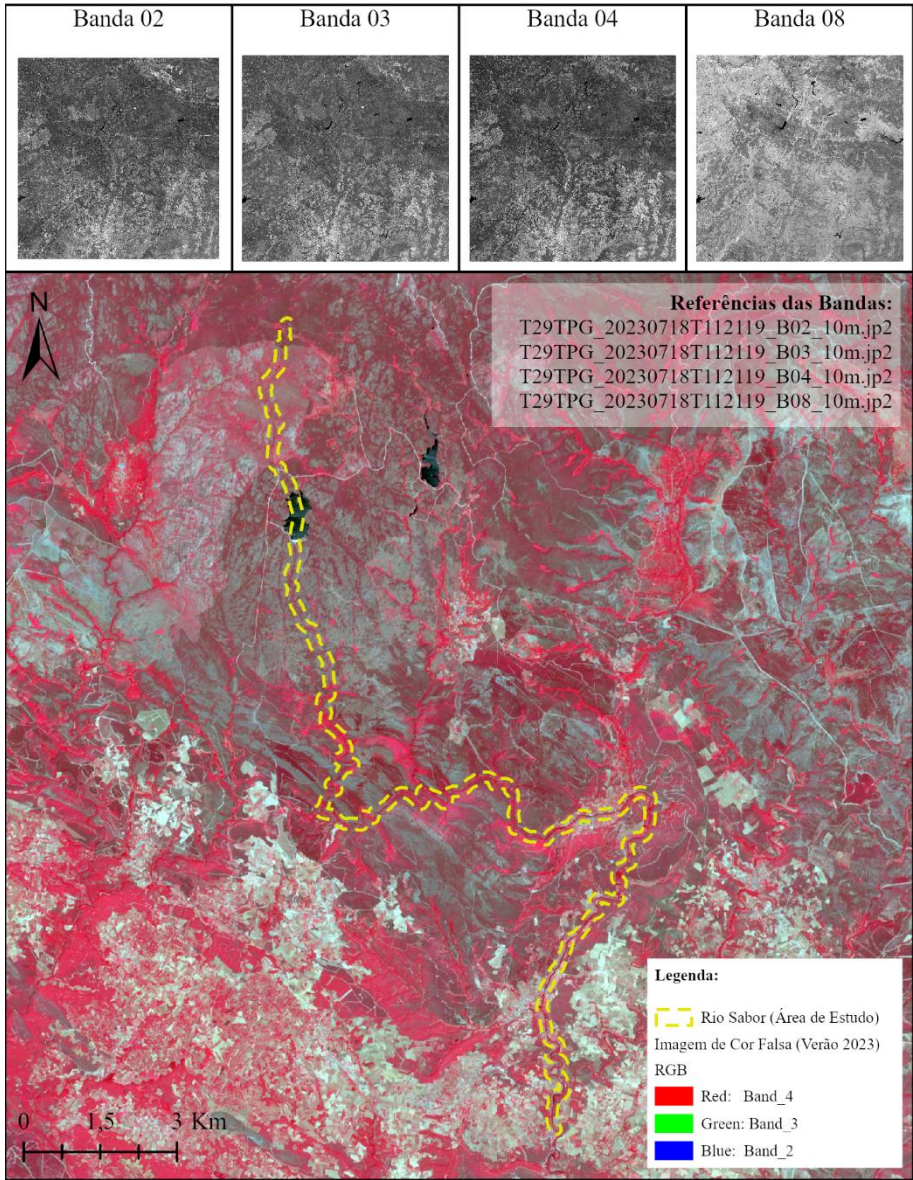
Annex XI. Major Class Changes. Alteration of the Riparian Gallery (2017-2023)



Annex XII. Bands and Their False Color Image for Spring 2023

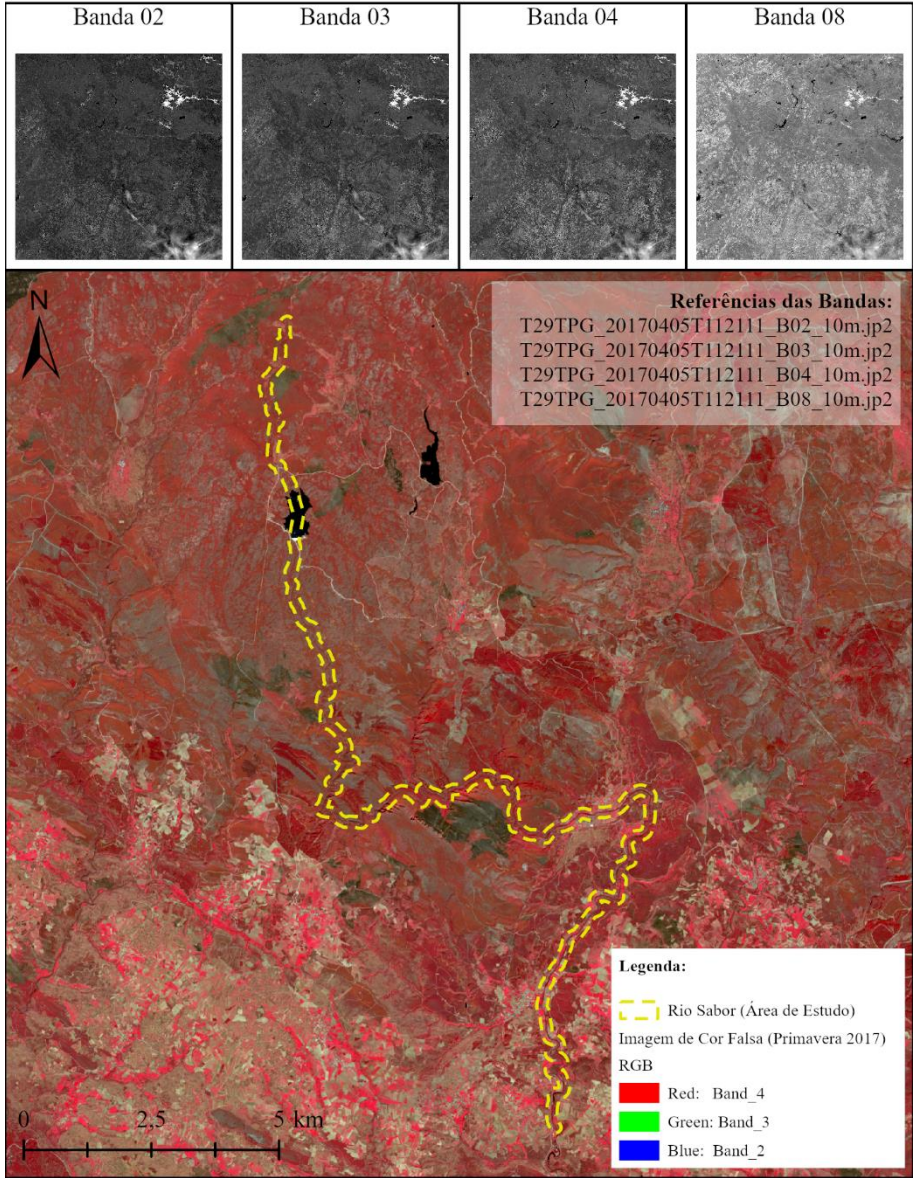


Annex XIII. Bands and Their False Color Image for Summer 2023

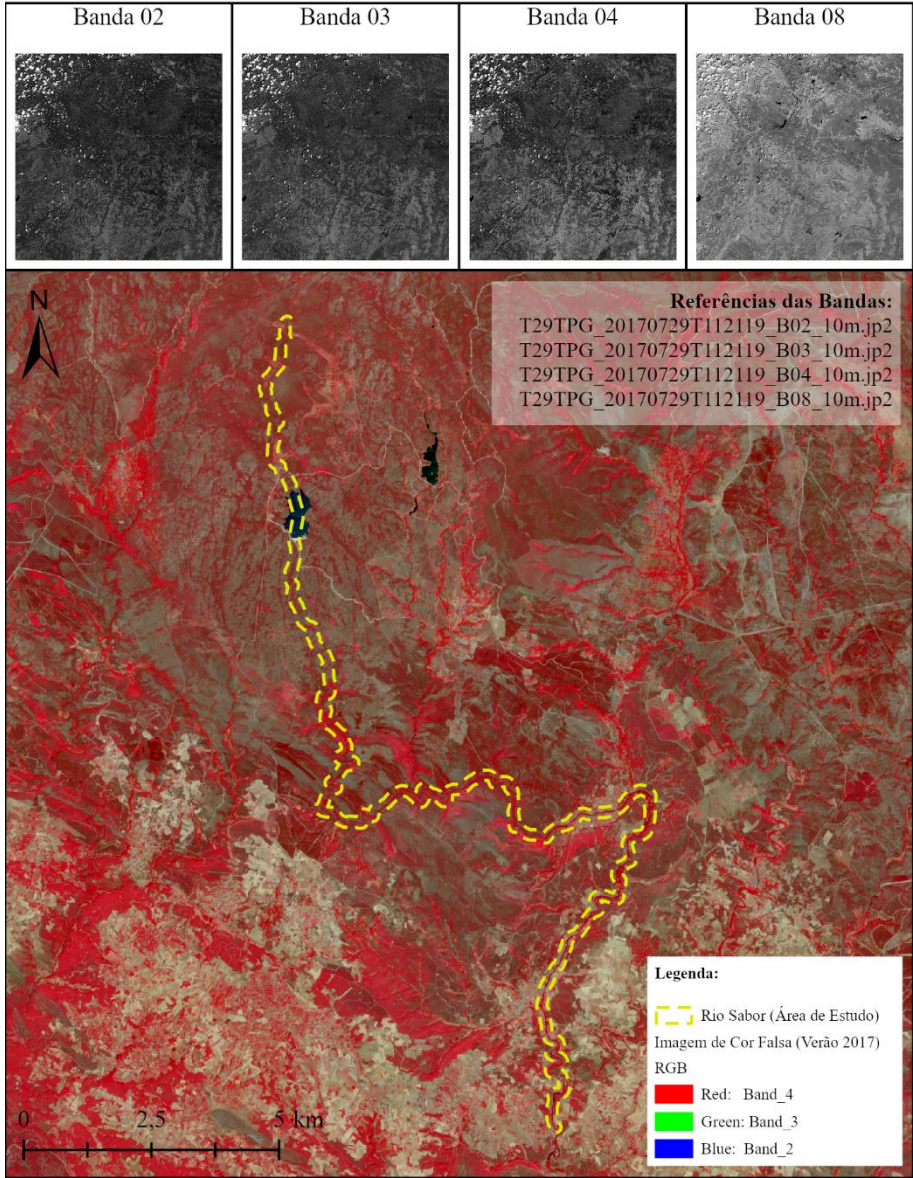




**Annex XIV. Bands and Their False Color Image for Spring 2017**

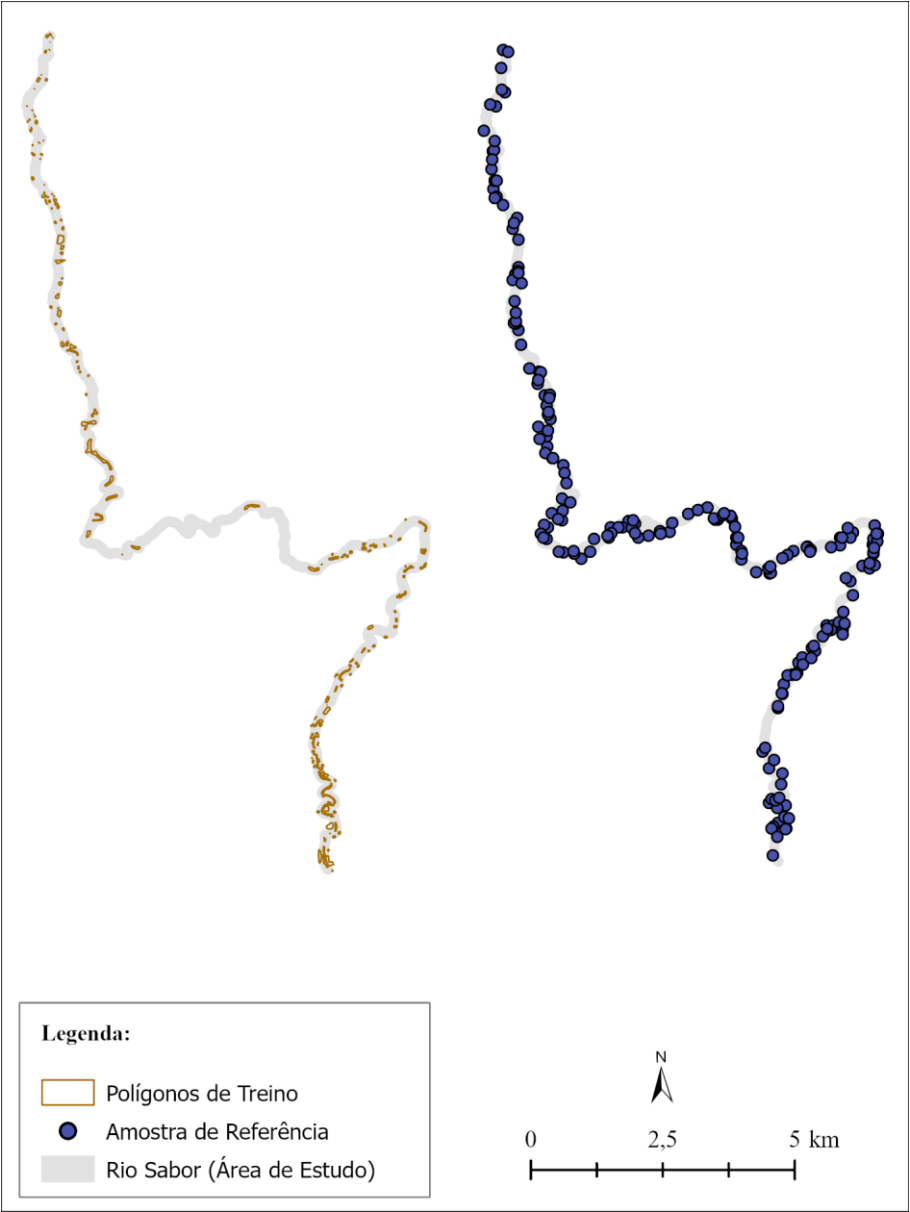


Annex XV. Bands and Their False Color Image for Summer 2023

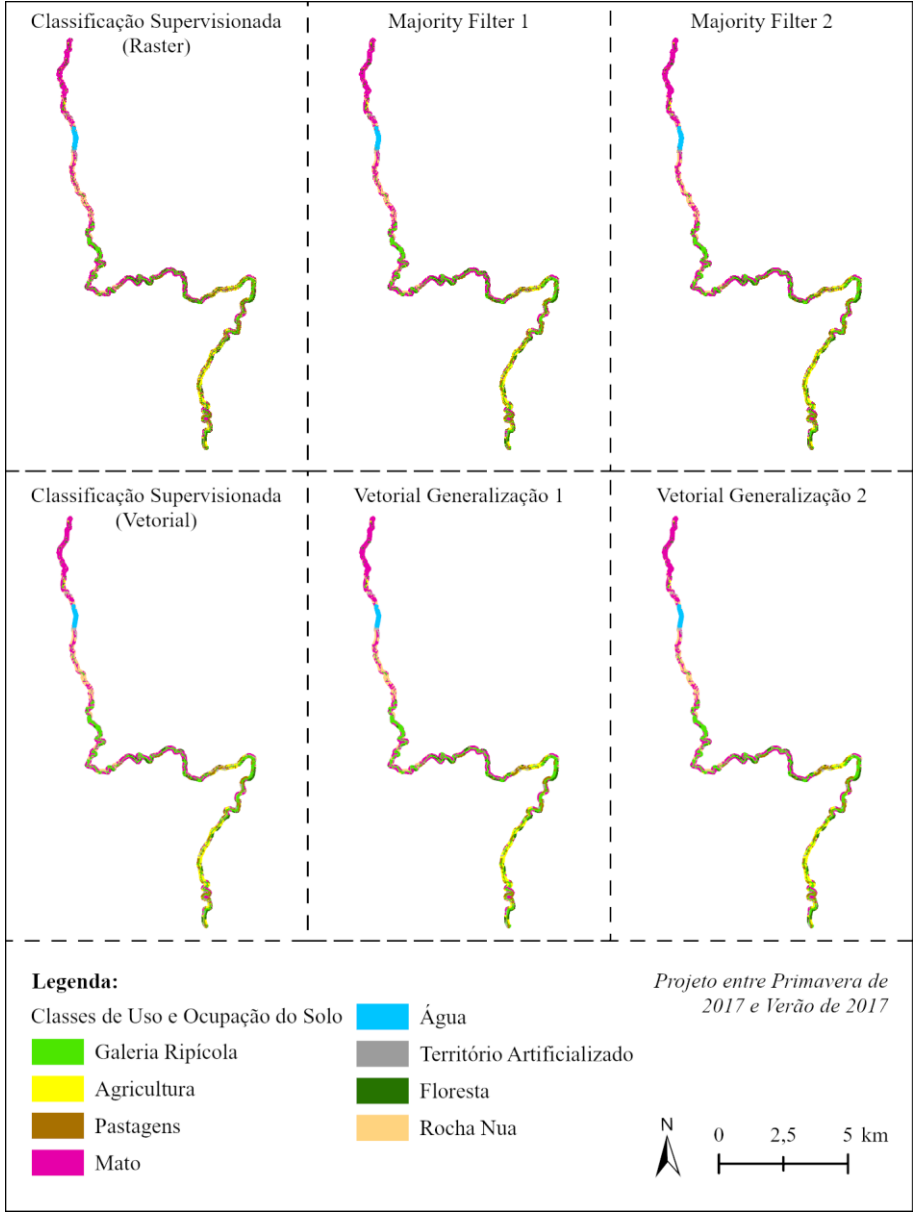




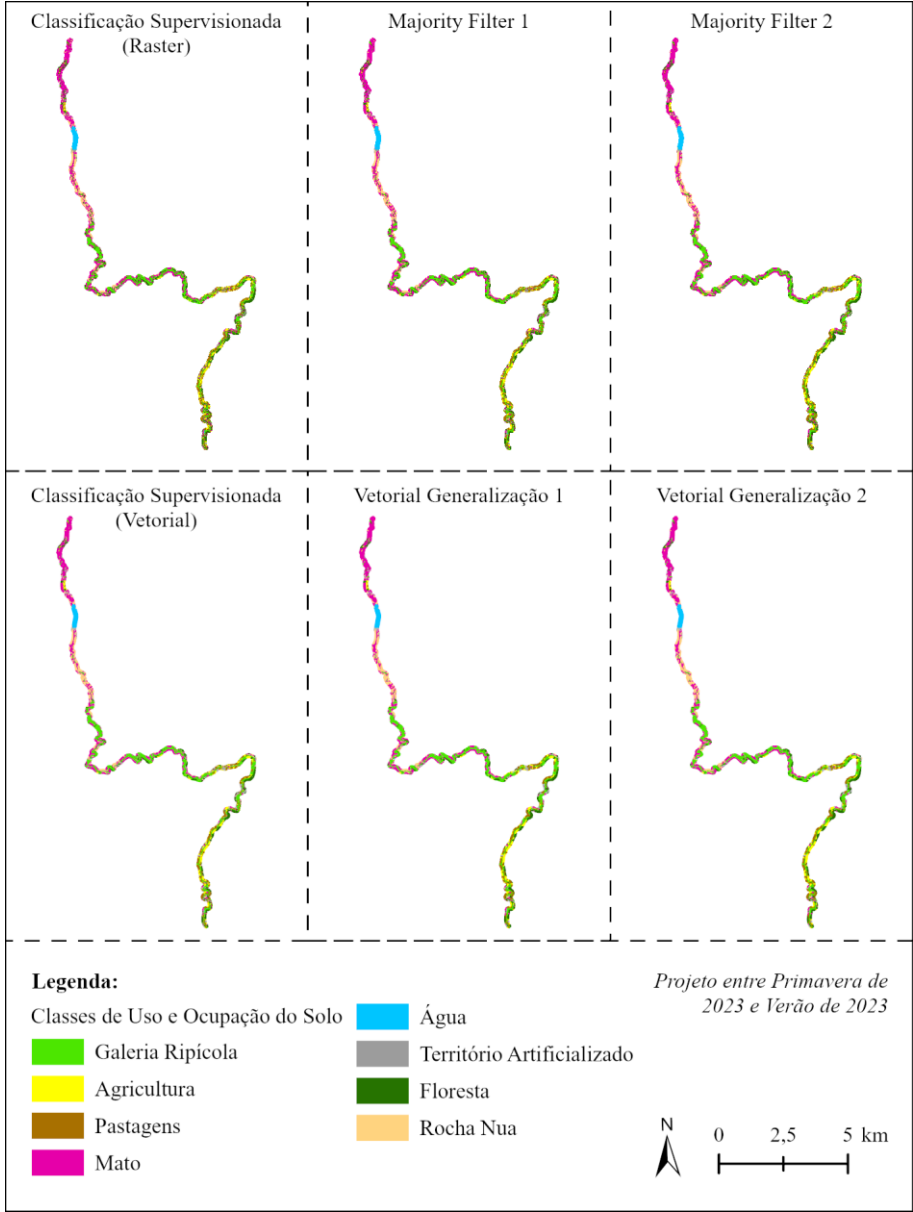
**Annex XVI. Training Polygons Used for Supervised Classification. Reference Sample Points for the Assessment of Thematic Accuracy**



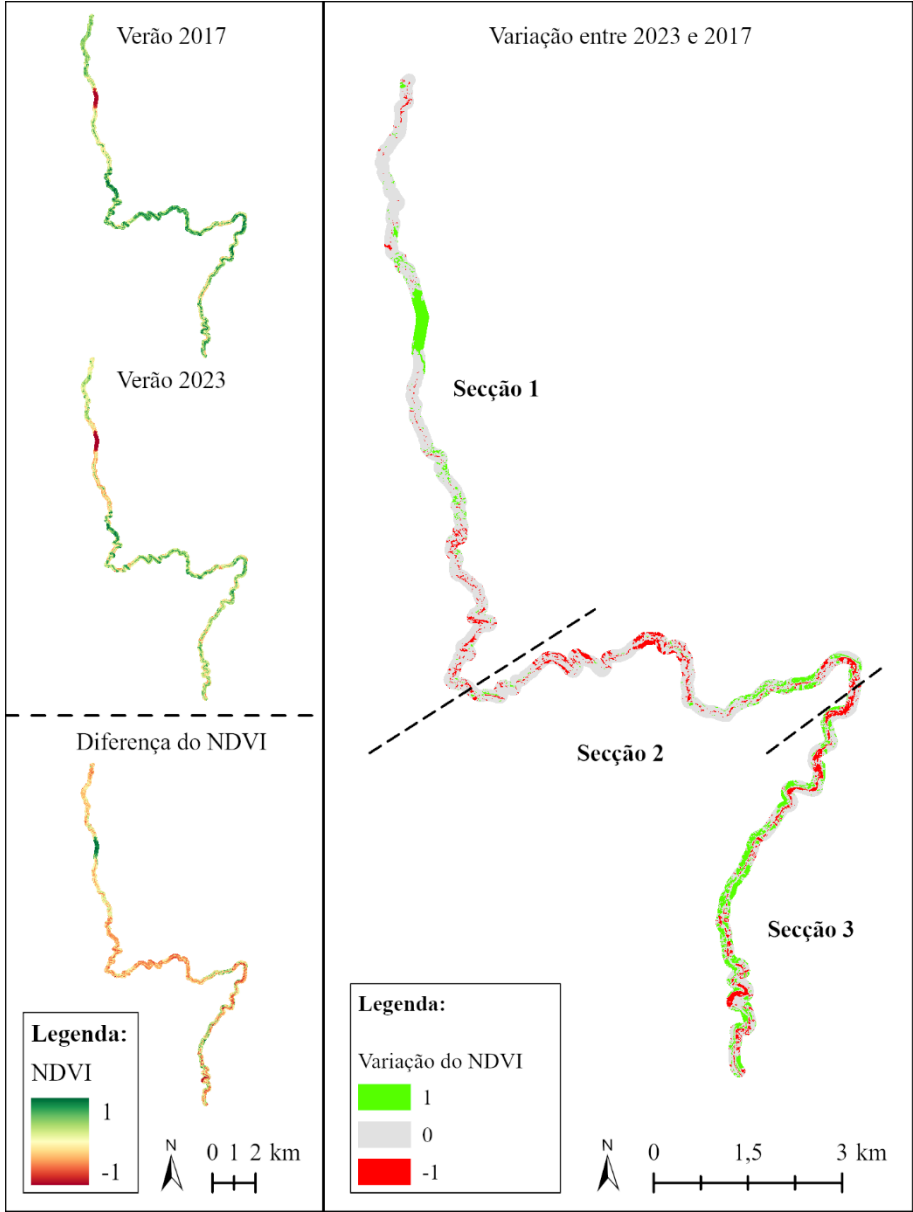
**Annex XVII. Post-Processing Stage for the Project between Spring 2017 and Summer 2017**



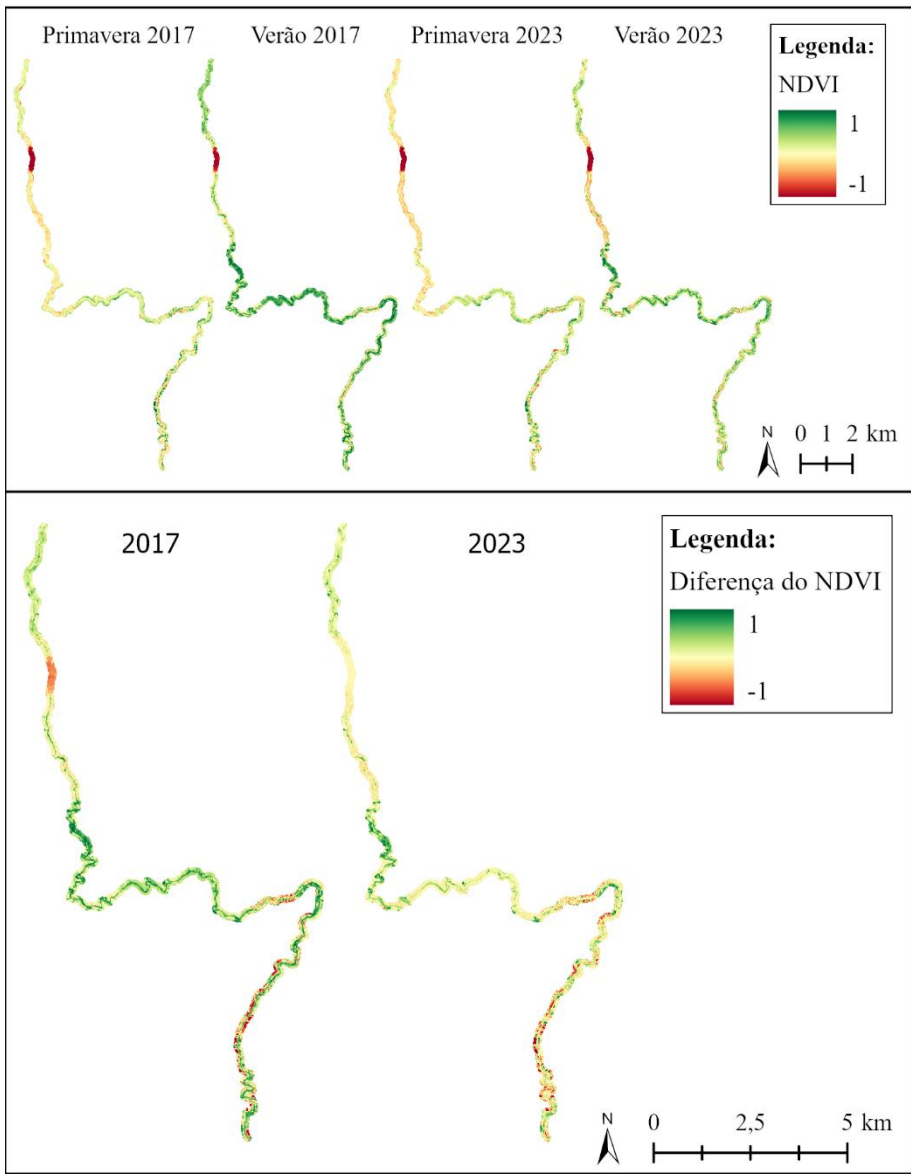
**Annex XVIII. Post-Processing Stage for the Project between Spring 2023 and Summer 2023**



**Calculation of NDVI through Bands 3 and 4 between Summer 2023 and Summer 2017 and Analysis of Their Difference and Variation**



**Annex XX. Calculation of NDVI through Bands 3 and 4 between Spring 2017 and Summer 2017 as well as between Spring 2023 and Summer 2023 and Analysis of the Respective Difference**



**Annex XXI. Analysis of the Respective Change between Spring 2017 and Summer 2017 as well as between Spring 2023 and Summer 2023**

