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Analysis of permanent preservation areas surrounding springs through satellite images

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Abstract

The use of remote sensing and digital processing of images is increasingly present in the monitoring and analysis of environmental data, mainly due to the ease of obtaining orbital images and the advanced methods of image classification. Temporal evaluation of restoration of native vegetation surrounding springs is important for the protection of water resources. A project named Water Conserver (Conservador das Águas) was developed between 2005 and 2015, involving 380 springs in Extrema, state of Minas Gerais, Brazil, focused on the preservation of water sources. The present study was carried out to quantify and analyze Permanent Preservation Areas (PPA) surrounding these water bodies. Free orbital images with spatial resolution of 30 m were acquired from the satellites Landsat-7 and Landsat-8 in 2003 and 2021, respectively. Object-oriented classification was used to evaluate the total PPA of restored springs over 18 years. The success of the Water Conserver Project resulted in a total restoration of more than 82% of areas surrounding springs up to 2021.

Keywords: Springs; Brazilian Law 12,651/2012; Orbital Images; Landsat; Digital Image Processing.

Introduction

The use of orbital sensors and images and digital image processing techniques enabled the application of remote sensing to several study areas, including monitoring of soil use, deforesting, and reforesting, management of water resources, monitoring of catastrophic events, monitoring of soil degradation and erosion, and climate change studies (ANDRADE, 2011; LIU, 2015).

The constant evolution of remote sensing, combined with digital image processing, contributed to enhance techniques that assist in scientific research, such as the supervised object-oriented classification. This methodology is carried out for image segments (objects) considering not only spectral characteristics of each pixel individually, but also spectral characteristics of neighboring pixels that form the object (segment) (JENSEN, 2011).

Therefore, most information required for the management and conservation of natural resources can be extracted from images by digital process of object-oriented classification; the map resulting from this classification can be used in geographic information systems (GIS) for spatial analysis applied to environmental impact evaluations, monitoring of vegetation cover, and landscape studies (CAMPOS, 2005).

Permanent Preservation Areas (PPA) include protected forest areas surrounding springs, with the objectives of preserving water resources, promoting pluvial infiltration and drainage, contributing to the recharge of aquifers, and avoiding runoff and floods (FELIPPE, 2009). Thus, object-oriented classification can be used to quantify and evaluate PPA surrounding springs, which are essential elements in hydrological dynamics, responsible for the passage of underground water to the surface and formation of fluvial channels (FELIPPE, 2009).

Springs are perennial natural deep-water outcrops that start water courses, denoting the importance of preservation and recovery of surrounding vegetation for the maintenance of quality and quantity of water resources in basins to ensure stability of soils, serve as a fauna corridor, and avoid aggradation of water courses (BRASIL; FARIA, 2012).

In this context, actions for preserving springs are indispensable, since they are a natural resource of high economic, social, and environmental value (WINER, 2017). The mapping of PPA assists in their monitoring, facilitating their quantification and oversight, focused on meeting the standards established by the New Brazilian Forest Code (PESSI, 2018).

Considering the importance of preserving springs for water conservation, a project named Water Conserver (Conservador das Águas) was developed between 2005 and 2015, involving 380 springs in Extrema, southern state of Minas Gerais, Brazil. The main focus of the project was the recovery and maintenance of springs in Extrema; the project resulted in the planting of one million native trees, protection of 6,135 ha, and more than 180 contracts with owners of rural areas who adopted the project for the conservation of springs (PEREIRA, 2017).

Considering the high potential of using images obtained by sensors of orbital satellites to monitor and detect forest cover changes on large areas (MUCHONEY; HAACK, 1994), and the need for evaluation and quantification of recovered PPA surrounding springs involved in the project, the objective of the present study was to quantify the PPA surrounding springs in Extrema, southern state of Minas Gerais, Brazil, using orbital images and object-oriented classification.

Considering that the main purpose of the present work was to quantify the recovered PPA surrounding springs involved in the project, it was expected that the results obtained for the PPA of each spring were consistent with the guidelines determined by the New Brazilian Forest Code, which defines that they should have a minimum radius of 50 m (BRASIL, 2012).

Material and methods

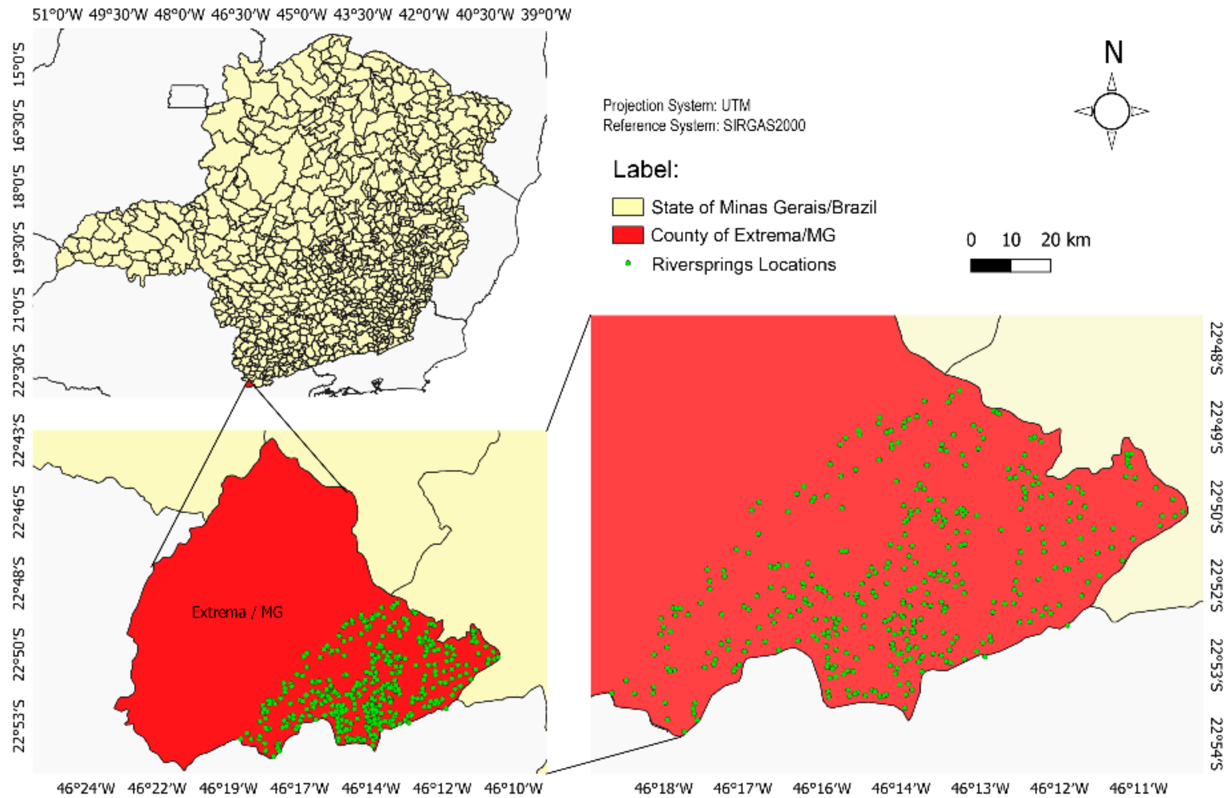
The springs involved in the Water Conserver (Conservador das Águas) Project, whose Permanent Preservation Areas (PPA) are the object of this study, are located in Extrema, southern state of Minas Gerais, Brazil (22°51’17”S, 46°19’06”W), bordering the state of São Paulo (Figure 1).

A flowchart was developed to determine the methodological sequence (Figure 2). Firstly, data referring to springs that were part of the Water Conserver Project were provided by the City Hall of Extrema to determine the correct location of the study area for later acquisition of orbital images of the area; a shapefile archive with the location of 380 springs involved in the project was acquired (Figure 1).

Orbital images of the area corresponding to the location of the springs were then acquired. As the objective of the work was to quantify and analyze the recovery of PPA as result of the implementation of the project, two orbital images with spatial resolution of 30 m were used: the first was from May 25, 2003, by the Landsat-7 satellite, date before the beginning of the project in 2005; and the second was from June 3, 2021, by the Landsat-8 satellite, six years after the end of the Water Conserver Project.

In this context, all images used for temporal analyses through orbital images should be acquired from the same satellite, due to specificities of each sensor. Regarding the images used in the present study, the OLI sensor of the Landsat-8 satellite has narrower spectral bands, improved calibration, higher radiometric resolution (12 bits), and more precise geometry, when compared to the Landsat-7 ETM (ROY, 2016).

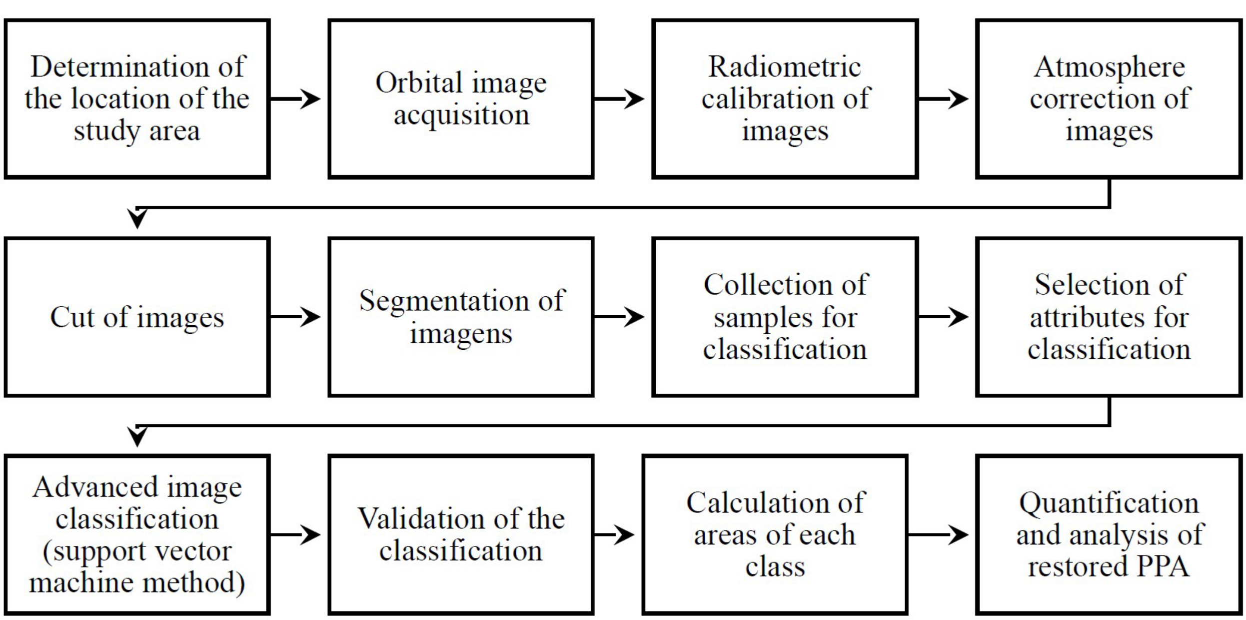
Figure 1 – Location of the study area in Extrema, southern state of Minas Gerais, Brazil.



However, the difficulty in using images of only one satellite is emphasized in the present work, since images of the Landsat-7 satellite after May 31, 2003 present scanner synchronism problems, also known as noises (ENGESAT, 2021).

Considering this problem, the use of images of two different satellites, Landsat-7 and Landsat-8, was needed. Images of the satellite Landsat-7 are available since 1999, but with problems of noises in images after May 31, 2003 (EMBRAPA, 2021), and images of the satellite

Figure 2 – Methodology followed in the work.



Landsat-8 are available since 2013. Thus, the images used were from the Landsat-7, from May 25, 2003, time before the noise problems and implementation of the Water Conserver Project; and from the Landsat-8, from June 3, 2021, time after the end of the project. The images from the Landsat-7 and Landsat-8 were acquired from catalogues of the Earth Explorer (USGS, 2021) and Brazilian National Institute of Space Research (INPE, 2021), respectively.

The images were subjected to radiometric calibration using the software ENVI 5.3. The objective of radiometric calibration is to transform digital numbers present in the images into reflectance values, adapting the data of the images for use in remote sensing (GOMES, 2020).

However, the reflectance values obtained through the radiometric calibration do not represent exclusively the object on the earth surface observed through the sensor, but a mixture of signs from the surface with atmosphere components, requiring atmospheric correction of images. The objective of this correction is to reduce the effect of interaction between atmospheric components with the sign detected by the sensor; thus, any evaluation of the image should be carried out only after the removal or decrease of effects caused by these components. The images acquired from the satellites Landsat-7 and Landsat-8 were subjected to atmospheric correction using the software ENVI 5.3 (SOARES, 2015).

The area of interest was then delimited encompassing all springs studied to optimize the processing. The cut of images was then carried out through the software ENVI 5.3. The images were corrected and cropped and, then, a segmentation was carried out through the software eCognition. The objective of this step was to fragment the image into objects (segments) based on elements of similarity and discontinuity of information from the image dynamics related to pixel form and texture or even spectral dynamics that a set of pixels can express (FARIA, 2017).

The multiresolution segmentation method was used in the segmentation process; it requires to determine some initial parameters, such as scale, form, and compacity. The scale parameter used was 15 m and the form and compacity criteria were 0.5. The next step consisted in determining the classes of interest for the object-oriented classification. Five classes were defined: Dense Vegetation, Ground Vegetation, Bare Soil, Building, and Water. Samples were then collected for each class, focusing on always selecting segments with a high purity, i.e., samples that better represent the class, since they would be used to classify all other segments of the image. Fifty reference samples were collected from each class in each image, except for the Water class, for which 30 samples were collected due to the low number of pure samples of the element analyzed.

Attributes that contributed to the classification of images were extracted using the software eCognition; they were selected from visual analysis considering all attributes available in the software and their dynamics regarding the different spectral bands of the images. Sixty-eight attributes that had more satisfactory visual results for the separation of the targets were selected in this analysis; they were grouped based on six spectral bands of the image as mean, mode, standard deviation, and quartile; and based on the pixel and some specific attributes as mean difference from neighbors (absolute), mean difference from the scene, ratio to the scene, area, volume, and width.

After selecting all attributes, the advanced object-oriented classification was carried out in the software eCognition, which provides some classifiers, such as decision tree, random trees, support vector machine (SVM), and others. Thus, test classifications were carried out using these classifiers; SVM was that that had the best results. The SVM machine learning method improves the separation of points in their classes through a sequence of measurements. Firstly, a separation vector is created, which increases the maximum possible distance between points, considered as the ideal hyperplane, intensifying the separation margin between points of higher proximity, i.e., that are more susceptible to confusion (MEYER, 2017). When a non-linearity (nonexistence of linear separation) is found, the points are projected into an extra dimensional space, where they become effectively linearly separable through the Kernel technique. Finally, when the proximity persists, a low weight is attributed to the points of the overlapping region.

The classification quality was evaluated after classifying the images by the SVM; a confusion matrix was developed, including the correct classification and confusions between classes, and the Kappa and global accuracy indexes were calculated, which represent the total characteristics of the classification. The confusion matrix is a square matrix whose values are organized in rows and columns representing the sampling units attributed to a class, correlating them with reference classes (CONGALTON, 1991). The columns represent the references and the rows represent the generated classification. The confusion matrix depicts the classification precision based on its reference and errors (confusions) in each class. The global accuracy can be determined from values in the main diagonal of the confusion matrix, which represent the samples correctly classified (CONGALTON, 1983). These values are added and divided by the total number of samples classified, according to Equation 1; the result represents the general performance of the confusion matrix, which is the main method used for evaluating the classification precision.

$$\theta_1 = \frac{\sum \quad x_{kk}}{N} \qquad \text{Equation 1}$$

where:
θ_1 = global accuracy;
$\sum x_{kk}$ = sum of values of main diagonal samples;
N = total number of samples.

The Kappa index was calculated considering the whole confusion matrix, i.e., as the correct classification and errors of classification, different from the global accuracy, which considers only the main diagonal (CONGALTON, 1983). The Kappa index was calculated according to Equation 2.

$$K = \frac{\theta_1 + \theta_2}{1 + \theta_2} \qquad \text{Equation 2}$$

where:
K: Kappa index;
θ_1: global accuracy;
θ_2: random global accuracy.

The random global accuracy used to calculate the Kappa index was determined according to Equation 3.

$$\theta_2 = \frac{\sum \quad nti \times nit}{N^2} \qquad \text{Equation 3}$$

where:
θ_2: random global accuracy;
nti: number of samples evaluated in column *i*;
nit: number of samples evaluated in row *i*;
N: total number of samples.

The calculation of the Kappa index was used to evaluate the classification quality, according to Table 1 (LANDIS, KORCH, 1977).

The software eCognition does not generate the confusion matrix automatically; thus, it was developed manually by collecting new samples from the images from 2003 and 2021, different from the samples used for the classification, to analyze whether each object of the image was correctly classified. In this context, the collection of a satisfactory number of pure reference samples with maximum similarity to the reality

Table 1 – Kappa index values and performance of classification.

Kappa index	Performance
< 0	Very Bad
0 to 0.19	Bad
0.2 to 0.39	Reasonable
0.4 to 0.59	Moderate
0.6 to 0.79	Good
0.8 to 1	Excellent

Source: Adapted from Lands and Korch (1977).

found in the land is essential to adequately evaluate a classification (CONGALTON, 1991). The collection of at least 50 samples for each class is recommended for a set of five classes, as is the case of the present study (CONGALTON, 1991). Thus, new samples were collected and the confusion matrix and the Kappa and global accuracy indexes were defined using Microsoft Excel spreadsheets.

The results obtained in the classifications were used to analyze the Permanent Preservation Areas (PPA) surrounding springs of the Water Conserver Project, considering the PPA as a circle with radius of 50 m around the springs. The software QGIS was used to generate a buffer of 50 m around each point corresponding to the spring location, determining the PPA. The conditions of PPA were assessed based on the images from 2003 and 2021, considering the total area surrounding each spring that, theoretically, should be covered with native vegetation, corresponding to a buffer of 50 m. When the PPA were due protected, the buffer area was classified as Dense Vegetation; otherwise, the PPA would need restoration. The PPA that were protected and classified as Dense Vegetation increased because of the implementation of the Water Conserver Project. Thus, the restored area of the PPA was assessed through analyses in the software QGIS, correlating the classifications of images from 2003 and 2021 and the PPA buffers of 50 m.

Regarding the definition of the PPA, when the Water Conserver Project was developed in 2005, the old Brazilian Forest Code (Law no. 4,771 of September 15, 1965) was still current; according to the Article 2 of this law, preservation permanent areas are those with water springs, even intermittent ones, and those with waterholes, regardless of the topographic situation, in a minimum radius of 50 m (BRASIL, 1965).

However, the New Brazilian Forest Code went into effect on May 25, 2012, substituting the Law no. 4,771/1965; it still defines PPA with a minimum radius of 50 m surrounding springs, regardless of the topographic situation. However, the Article 61 paragraph 5, determines that:

> In cases of consolidated rural areas within PPA surrounding springs, the maintenance of agrosilvopastoral, ecotourism, or rural turism activities will be accepted, being mandatory the vegetation recovery on a minimum radius of fifteen meters (BRASIL, 2012).

Consolidated rural areas were considered as those with any pre-existing change in local native vegetation for land use, human occupation, or practices of rural activities (TRENTINI, 2018) on July 22, 2008 (BRASIL, 2012). Thus, considering that the New Brazilian Forest Code was the current law by the end of the Water Conserver Project (in 2015), the conditions of PPA surrounding springs were analyzed from the image classified in 2021, also considering consolidated rural areas. All areas that were classified in any class other than Dense Vegetation in 2003, proving the suppression of native vegetation before 2008, were considered to determine these consolidated rural areas.

Results and discussion

Figures 3 and 4 show the results of the object-oriented classification by the SVM classifier for the images from May 25, 2003 and June 3, 2021, respectively. Some confusions in the classification of the classes Building and Bare Soil can be visually noticed in the image of 2003, as observed next to the region with higher concentration of water. Whereas the classification of the image of 2021 showed increases for the Dense Vegetation class, and occurrence of some confusions in the class Building, which decreased in areas of urban regions, being replaced by the Bare Soil and Ground Vegetation classes.

A confusion matrix was developed to validate the visual analyses of classifications.

Figure 3 – Classification of the image from May 25, 2003 in Extrema, southern state of Minas Gerais, Brazil.

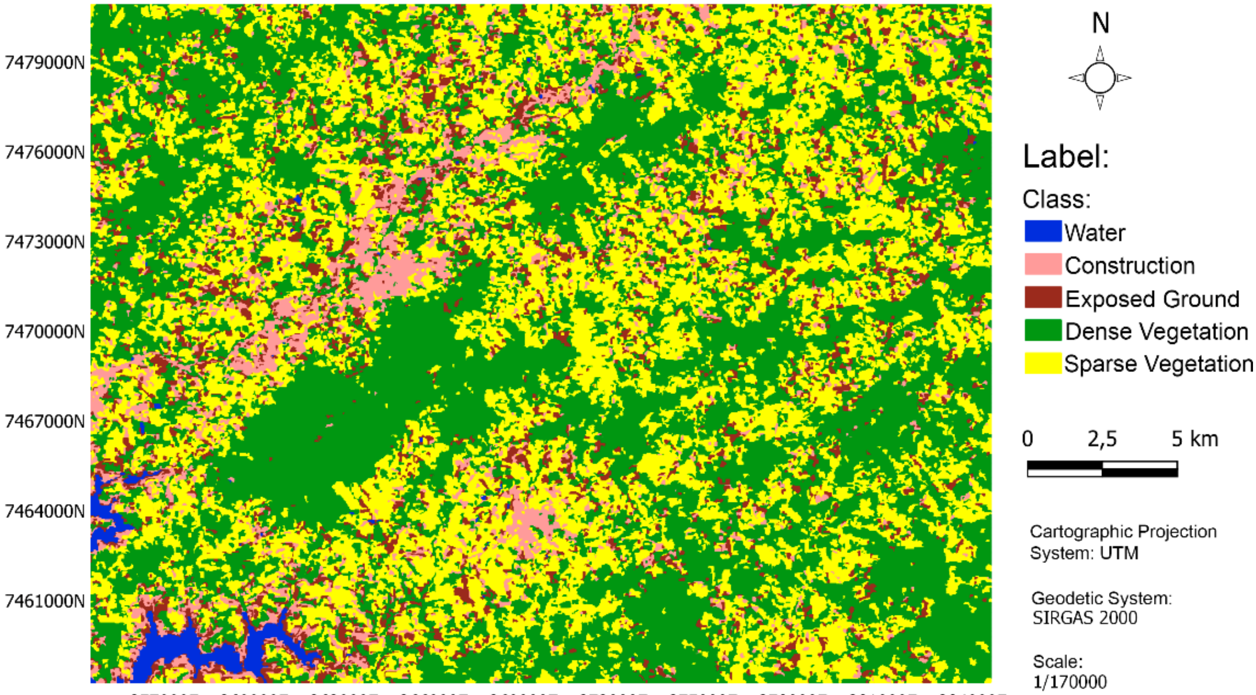
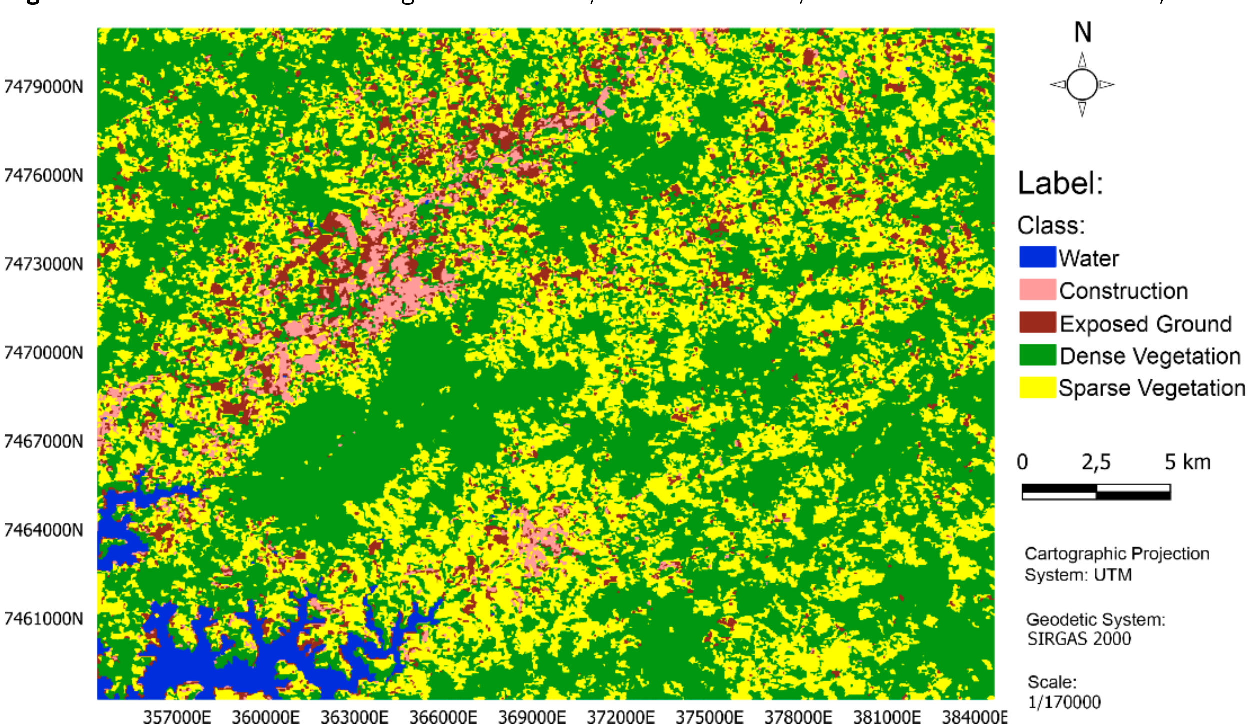


Figure 4 – Classification of the image from June 03, 2021 in Extrema, southern state of Minas Gerais, Brazil.



Fifty reference samples of each class were collected in each image, except for the Water class, for which 30 samples were collected due to the low number of pure samples. Tables 2 and 3 show the confusion matrices generated for the classification of 2003 and 2021, respectively.

Table 2 – Confusion matrix generated from the classification of the image from May 25, 2003.

	Reference					
Classes	**Dense Vegetation**	**Ground Vegetation**	**Building**	**Water**	**Bare Soil**	***nit***
Dense Vegetation	50	0	0	0	0	50
Ground Vegetation	0	50	3	0	0	53
Building	0	0	47	0	6	53
Water	0	0	0	30	0	30
Bare Soil	0	0	0	0	44	44
nti	50	50	50	30	50	230

nit = number of samples evaluated in the rows; *nti* = number of samples evaluated in the columns

Table 3 – Confusion matrix generated from the classification of the image from June 03, 2021.

	Reference					
Classes	**Dense Vegetation**	**Ground Vegetation**	**Building**	**Water**	**Bare Soil**	***nit***
Dense Vegetation	50	0	0	0	0	50
Ground Vegetation	0	50	1	0	0	51
Building	0	0	49	0	6	55
Water	0	0	0	30	0	30
Bare Soil	0	0	0	0	44	44
nti	50	50	50	30	50	230

nit = number of samples evaluated in the rows; *nti* = number of samples evaluated in the columns

Considering the confusion matrices of both classifications, there were some confusions in the class Building in the image from 2003, which was also found in the classification of the image from 2021, with a low confusion, and in the class Bare Soil for both images, confirming the visual analysis of classifications. However, no confusion was found for the Dense Vegetation and Ground Vegetation classes. Considering that the objective was to analyze the evolution of the Dense Vegetation surrounding springs, the classifications were considered adequate for the analysis of Permanent Preservation Areas (PPA) based on results of confusion matrix.

The classification quality by the confusion matrix was evaluated by defining global accuracy and general Kappa index values for the classification of the images from 2003 and 2021 (Table 4).

The Kappa indexes obtained for both classifications were higher than 0.8; thus, the performance was considered Excellent, as shown in Table 1 (LANDIS; KORCH, 1977). The global accuracy found for the classification of the image from 2003 was 0.9609, i.e., 96.09% of the collected samples were correctly classified. Whereas the global accuracy found for the image from 2021 was 0.9696, i.e., 96.96% of correct classifications of the samples, also confirming good results.

Table 4 –Global indexes for the classifications of the images from 2003 and 2021.

Global Indexes	**Image from May 25, 2003**	**Image from June 03, 2021**
Global accuracy	0.9609	0.9696
Kappa Index	0.9507	0.9617

The comparison of the two classifications showed a decrease in Bare Soil and Ground Vegetation areas from 2003 to 2021 in the region of the springs of the Water Conserver Project and, consequently, an increase in local Dense Vegetation area. Despite some confusions found in the classifications in the region of these springs, they did not hinder the analysis of vegetation restoration. Figure 6 shows a better comparison between the images classified, highlighting the region of the springs, and Table 5 shows the areas of each class in 2003 and 2021.

Considering the area found for each class, the Dense Vegetation area increased 11.32% and the Bare Soil and Ground Vegetation areas decreased 11.71%, which is probably connected to the implementation of the Water Conserver Project.

The ideal area for PPA, defined by the buffers of 50 m surrounding each point corresponding to springs, was calculated before and after the implementation of the project for the analysis of PPA surrounding springs. In addition, the areas in the PPA of the 380 springs that are protected by native vegetation, considering a radius of 50 m surrounding each spring was determined by correlating the class Dense Vegetation in the images from 2003 and 2021 and delimitating PPA buffers (Table 6). This analysis confirms, numerically, the effectiveness of the Water Conserver Project, considering the 14.6% increase in the native vegetation area of the PPA surrounding the 380 springs, between 2003 and 2021.

The analysis of ideal and actual native vegetation areas surrounding springs in 2003

Figure 5 – Comparison between classifications of images from 2003 (A) and 2021 (B)

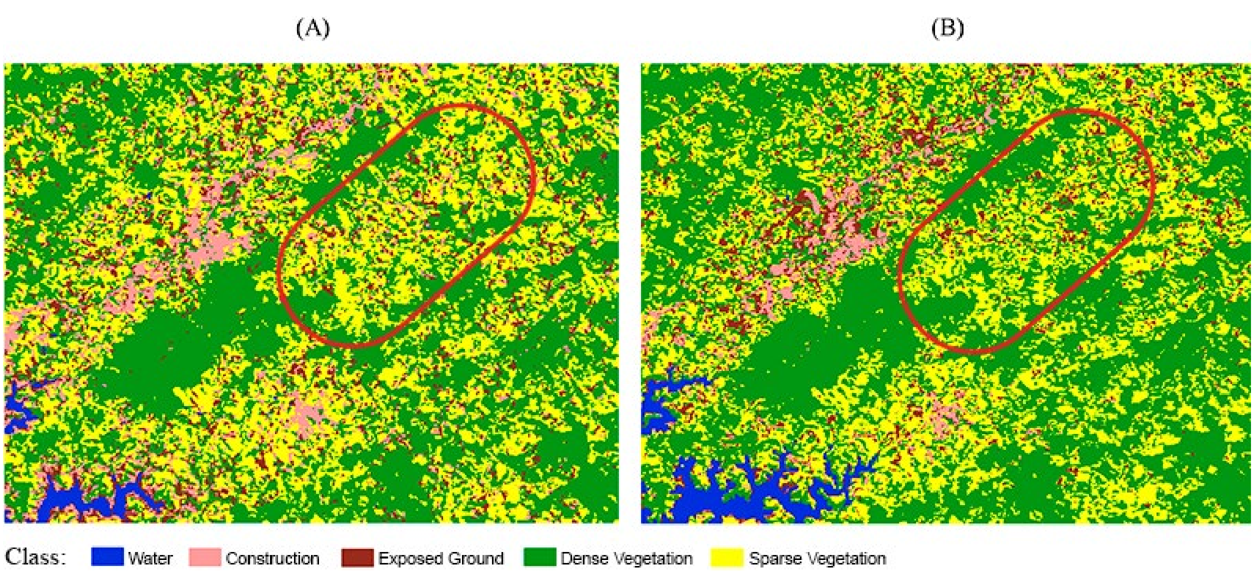


Table 5 – Area of each class for the classification of images from May 25, 2003 and June 3, 2021.

Classes	Image from May 25, 2003	Image from June 3, 2021
	Area (ha)	Area (ha)
Dense Vegetation	32,401.80	36,535.99
Ground Vegetation	24,852.35	23,333.31
Building	4,690.38	1,840.60
Water	717.25	1,833.69
Bare Soil	5,406.59	4,470.67

Table 6 – Comparison between ideal and actual areas covered with native vegetation in Permanent Preservation Areas (PPA).

PPA	Area (ha)	Percentage
Ideal area	288.34	100%
Actual area in 2003	131.31	45.5%
Actual area in 2021	173.46	60.2%

and 2021 showed that the PPA were often not fully protected, i.e., the buffer area of 50 m surrounding the springs were not in the Dense Vegetation class. However, parts of the PPA were often restored, which is a gain from the environmental point of view and a positive result of the Water Conserver Project. The number of springs that had PPA with up to 50%, between 50% and 100%, and 100% (fully restored) native vegetation, was calculated and is shown in Table 7.

The number of springs that had PPA with 50% native vegetation areas presented a significant decrease of 26%, when comparing the image from 2003 with that from 2021. Areas with more than 50% restored PPA increased 15.5%. Another important factor is the percentage of springs that were fully restored from 2003 to 2021, which reached 10.53% of the springs involved in the project.

The third analysis of the PPA considered consolidated rural areas, as defined by the Law no. 12,651/2012 (BRASIL, 2012). Firstly, the springs that fit the conditions for consolidated rural areas were defined, quantifying all springs in areas with Ground Vegetation in the image of 2003; 184 springs were identified as consolidated rural areas.

The PPA surrounding these springs were then defined considering a radius of 15 m; the ideal area of native vegetation surrounding these springs was then quantified, which corresponded to the area defined for the buffers, 15 m. As in the first analysis of PPA, the actual area covered with native vegetation surrounding these springs was defined by correlating the ideal native vegetation area and the class Dense Vegetation in the image from 2021 (Table 8).

Only 39% of the total PPA with a buffer of 15 m that should be covered with native vegetation was in fact protected in 2021 (Table 8). The main contribution of this analysis is to show the decrease in PPA as a function of consolidated areas by the New Brazilian Forest Code (BRASIL, 2021). According to the old Brazilian Forest Code, which considered a buffer of 50 m, the percentage of restored native vegetation would have been only 3.6%, and

Table 7 – Number of restored springs considering a Permanent Preservation Areas (PPA) of 50 m.

Image	<50%	>50%	100%	Total
2003	110	176	94	380
2021	11	235	134	380

Table 8 – Permanent Preservation Areas (PPA) surrounding water springs in consolidated rural areas.

Native vegetation area in the PPA	Area (ha)
Ideal area – buffer 15 m	12.80
Ideal area – buffer 50 m	139.44
Actual area in 2021	5.00

not 39%. It denotes how consolidated rural areas impacted the restoration of PPA, since the native vegetation area surrounding springs to be protected would be higher without them.

Table 9 shows the number of springs in consolidated rural areas that were fully restored (PPA with 100% native vegetation), partially restored (PPA with 50% to 100% native vegetation), and little restored (PPA with less than 50% native vegetation). In addition, it shows the numbers of PPA surrounding springs with a buffer of 50 m, as defined by the old Brazilian Forest Code. The results showed a significant number of PPA surrounding springs with less than 50% recovery, considering the consolidated rural areas. A total of 55 springs were fully restored considering the minimum radius of 15 m, as described in the New Brazilian Forest Code.

In addition, considering the old Brazilian Forest Code, the number of PPA with less than 50% area protected with native vegetation would be higher (128 springs). The number of PPA fully restored also would decrease, from 55 to 8 springs, which is worrisome from the environmental point of view.

Table 10 shows the PPA that should be found for the 184 springs that are in consolidated rural areas, added to the 196 remaining springs, and the PPA that was restored in the image from 2021, based on the New Brazilian Forest Code.

Conclusions

The use of remote sensing techniques, through object-oriented classification, using the SVM classifier and orbital images of the satellites Landsat 7 and 8, is applicable for environmental analyses, enabling to assess the restoration of Permanent Preservation Areas (PPA) surrounding water springs that were included in the Water Conserver Project.

The success of the Water Conserver Project resulted in a total restoration of more than 82% of areas surrounding springs up to 2021.

Further studies are recommended for the use of orbital images, with spatial resolutions better than 30 m, to quantify the restored areas surrounding springs more accurately.

Acknowledgements

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Table 9 –Number of springs restored in consolidated rural areas for the image from 2021.

Brazilian Forest Code	<50%	>50%	100%	Total
New (buffer of 15 m)	112	17	55	184
Old (buffer of 50 m)	128	48	8	184

Table 10 – Final analysis of permanent preservation areas (PPA) in 2021.

PPA	Area (ha)	%
Ideal area	161.5	100
Actual area / Image – 2021	132.8	82.23

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