Land-cover classification of an intra-urban environment using high-resolution images and geographic object-based image analysis: the case of APA *Mananciais do Rio Paraíba do Sul*

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Abstract. Protected areas of sustainable use such as the Environmental Protection Areas (APA) encompass urban areas. Because the characteristic urban spaces are under dynamic changes, they usually entail problems related to planning land cover. Such areas are fragile, especially when located inside protected areas, so it is necessary to monitor and evaluate them. Remote sensing data provides important information for urban planning and management issues, and have a great potential to assist conservation unit managers in monitoring such protected areas. Urban environments are characterized by high spectral and spatial heterogeneity and, consequently, most urban pixels in moderate resolution imagery contain multiple land-cover materials. The objective of this paper is to demonstrate the capability of RapidEye sensor data, for the intra-urban scale classification of land cover in protected areas, and to develop a semi-automatic classification method based on geographic object-based image analysis and data mining techniques, for efficiently identifying small changes in urban areas. The APA of "*Mananciais do Rio Paraíba do Sul*" (APA-MRPS), aimed to preserve the water sources for more than 15 million people, was selected as study site. The results showed that RapidEye data and the methodology used were effective in classifying constructed areas, enabling the identification of small changes in land cover. The data and methodology may be able to assist managers in the monitoring and evaluation processes of protected areas, especially APAs.

Keywords: Remote sensing, Image processing; Object based image analysis; Data mining; Image segmentation; Protected areas; APA Mananciais do Rio Paraíba do Sul.

1. Introduction

In the last century, particularly in recent decades, the concern with the environment has increased. Natural resources are becoming scarce and biodiversity have been reduced by human action, demanding a sustainable relationship between human needs and environment conservation, under penalty of compromising future generations. The creation and maintenance of protected areas are among the most effective instruments for environmental and territorial planning, contributing to the effective implementation of public policies related to environmental conservation (SÃO PAULO, 2009).

However, creating protected areas is not enough for achieving its purpose. Generating quality information about protected areas, seeking to monitor and assess how, and if, the objectives are being met and at which costs, is critical to its effectiveness. For this reason, monitoring and evaluating is a key strategic action adopted for protected areas worldwide (UICN, 2008). Monitoring refers to the regular gathering and analysis of information to determine whether or not the activities are working and explain why. It is usually done at regular intervals, so that over a cumulative time period trends in a particular situation become evident and measurable (TUXILL; NABHAN, 2001).

In the category of sustainable use, a particular type of protected area is the Environmental Protection Area (*Área de Proteção Ambiental* - APA). APAs are areas of planning and environmental management that contain ecosystems of regional significance, encompassing one or more environmental attributes, covering urban and rural areas and their inherent socioeconomic activities (BRASIL, 2000). Urban areas are characteristic spaces under dynamic changes, with problems related to planning land cover. Such areas are fragile, especially when they are located in protected areas, so it is necessary to monitor and evaluate the urban growth, reducing its potential injurious effects to the natural environment.

Orbital remote sensing data can be helpful to monitor and evaluate the impact of different types of human pressure and management strategies aimed at combating such pressure (NAGENDRA et al. 2013). Pinho et al. (2012) and Körting et al. (2013) concluded that geographic object-based image analysis (GEOBIA) allied to data mining techniques can be an appropriated method for classifying high-resolution images of urban areas.

The objective of this paper is to demonstrate the capability of RapidEye sensor data for intra-urban scale classification of land cover. A semi-automatic classification method based on GEOBIA and data-mining techniques was developed to efficiently identify small changes in urban areas, providing qualified information about protected areas for managers in their decision-making tasks.

2. Study area and data

Aiming to protect water resources of Paraíba do Sul river basin, the APA of *Mananciais do Rio Paraíba do Sul* (APA-MRPS) was created in 1982 also to protect the biological diversity, to guide the occupation process and to ensure the sustainable use of natural resources (BRASIL, 2010). The APA-MRPS is located in a highly anthropized region, with different socio-spatial formations, and has a non-continuous spatial arrangement, covering an area of 292,597.12 hectares of three states of southeastern Brazil: São Paulo, Minas Gerais and Rio de Janeiro. The unit of APA chosen for this study is located in the municipality of São José dos Campos, SP.

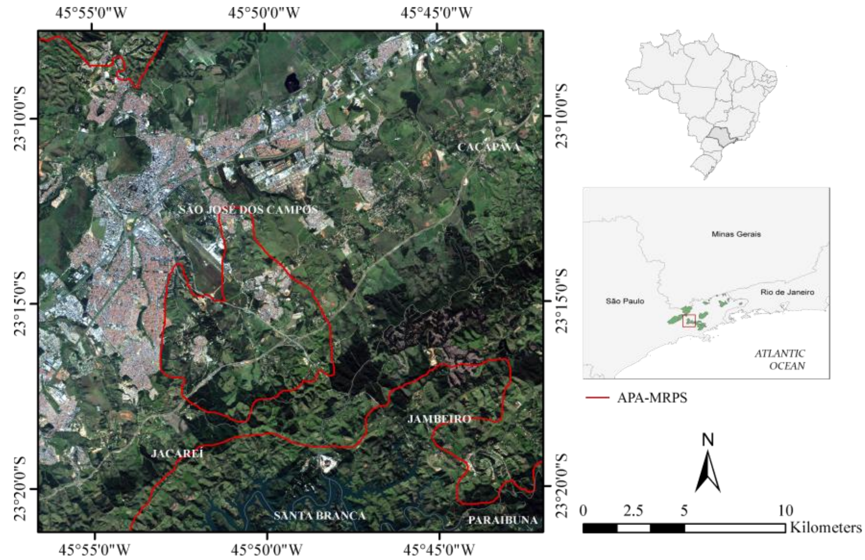


Figure 1 - Study area: APA-MRPS.

Recently, the number of very high spatial resolution (VHSR) commercial satellites provide new opportunities for the mapping of habitats in a much sensible spatial scale than was previously possible. Boyle et al. (2014) compared the classification efficiency of images in different spatial resolutions (i.e., Ikonos and Landsat), and the results suggested that very high resolution images are able to: (1) delineate more accurately the cover classes; (2) identify smaller patches; (3) maintain the shape of the features; and (4) detect narrow linear features.

Initially, the wider use of VHR images as a tool for environmental monitoring has been limited by high cost in acquiring images that covered these areas, however, recently these products began to be more frequently used in monitoring the earth's surface (NAGENDRA et al. 2013; BOYLE et al. 2014).

RapidEye mission offers image users a data source containing an unrivaled combination of large-area coverage, frequent revisit intervals, high-resolution and multispectral capabilities (Table 1). For the first time, there is a constellation of five earth-imaging satellites that contain identical sensors, which are in the same orbital plane and calibrated equally to one another, thus allowing the user access to an amount of imagery collected on a frequent basis (RAPIDEYE AG, 2009).

Table 1 - Characteristics of the very high-resolution sensors of the RapidEye mission.

Bands	Wavelength (µm)	Resolution (m)
Band 1 - Blue	0,44 - 0,51	5
Band 2 - Green	0,52 - 0,59	5
Band 3 - Red	0,63 - 0,685	5
Band 4 - Red limit	0,69 - 0,73	5
Band 5 - Near Infrared (NIR)	0,76 - 0,85	5

Source: RapidEye AG (2009).

The images of the sensors RapidEye (Table 2) are available for Brazilian governmental institutions by the Ministry of Environment (Ministério do Meio Ambiente - MMA) as part of the Environment Regularization Program, and represent an opportunity for the management of protected areas. The RapidEye data used in this study was acquired in the *Geocatálogo* - MMA.

Table 2 - Metadata of the images.

Id	Aquisition		Level
	Date	Time	
14465171	2012/07/03	14:09:18	3A*
14465215	2012/07/03	14:09:22	3A*

*RapidEye Ortho (Level 3A) are orthorectified products with radiometric, geometric and terrain corrections in a map projection.

3. Methods

For a better description of the methodological procedures in the intra-urban land cover classification, we defined five work phases, exposed in the Figure 2. These methodological procedures have been done in three softwares: (1) ENVI 5.0 (EXELIS, 2012), for the pre processing step; (2) eCognition (TRIMBLE, 2011b) for the segmentation, samples collection, classification and post classification; (3) and Weka (THE UNIVERSITY OF WAIKATO, 2014), for data mining process.

Pre processing → Segmentation → Data mining → Classification → Post classification

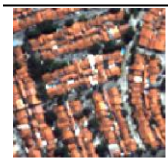
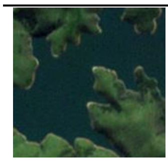
Figure 2 - Classification work breakdown structure.

In the pre-processing, we first preceded the grey level balancing to match the statistics from one image to other and balance the data range between the different images. Gains and offsets has been calculated from one of the images and applied to adjust the other one, so it ends up with the same statistical range. After that, we were able to mosaic the two balanced images, and then subset according to the defined area of the study.

Next step was the construction of three new uncorrelated bands by the technique of principal components that transforms the original set of remote sensing data in a smaller and simplified form, which permit the interpretation of a set of uncorrelated variables that represent information contained in the original data set (GONZALEZ; WOODS, 2010). This technique reduces the correlation, geometrically transforming (by rotation) the connection between the bands, with a result that correspond to vectors that are linear combinations of the original band image. The first component contains more information about the grey level image, the second less and so on, while the latter components may be important in the differentiation of detail in the characteristics of an image. The technique was applied to bands 3, 4 and 5 of the RapidEye sensor. After the principal component procedure, we stacked the three components generated and the five original bands of RapidEye sensor.

Before starting the classification itself, we first selected the classes (objects) of interest to compound the 'Constructed area' class, based on the images visual interpretation. Different types of objects such as roofs, water and vegetation were identified, and organized in a typology key.

Table 3 - Typology of patterns in the study area.

Patern	Class	Abstract class	R3 G2 B1	Description
	Asphalt	Constructed area	Dark grey.	Occur on paved streets and parking lots. Retangular shape, nearly square (parking lots) or rectangular and narrow (streets).
	Ceramic roofs	Constructed area	Varying from orange to dark brown.	Located within blocks. Smooth, variable sizes, but with preferably rectangular.
	Bright roofs	Constructed area	White and variations of light blue.	Occurs on roofs of buildings, within blocks (in commercial and industrial areas). Size varies, but preferably with rectangular.
	Bare soil	Open space	Variations of light orange to brown	Located in open areas, within blocks in new or unused land allotments. Shape, texture and varying sizes.
	Grass	Open space	Variations of green.	Located in open areas and within blocks. Texture slightly rough to smooth.
	Trees	Open space	Variations of medium to dark green.	Located in open areas and within blocks. Rough texture, with variation in the size of textual elements, depending on the type of tree.
	Water	Open space	Blue to dark blue	Located in urban areas and open areas. Irregular shape and uniform texture.

The segmentation was used to share the image in its objects. A good segmentation increases the chances of success in the objects recognizing (GONZALEZ; WOODS, 2010). We used a segmentation based on Baatz & Schäpe (2000). The algorithm locally minimizes the average heterogeneity of image objects for a given resolution of image objects. This segmentation consecutively merges pixels or existing image objects. Thus, it is a bottom-up segmentation algorithm based on a pairwise region merging technique. The scale, shape and compactness parameters defined were respectively 160, 0.2, 0.5. These parameters have been defined empirically, trying to produce image regions as large as possible, and that still distinguishing different image objects.

Aiming to perform adjustments in the previous segmentation, we applied the Spectral Difference Segmentation. This algorithm merges neighboring image objects according to their mean image layer intensity values. Neighboring image objects are merged if the difference between their layer mean intensities is below the value given by the maximum spectral difference (TRIMBLE, 2011a). The maximum spectral difference parameter applied was 200. Figure 4b exhibits the final segmentation.

We adopted a supervised classification approach. First, we selected representative samples for each class already identified in the image. In total 650 samples were collected.

After the segmentation, the regions began to extrapolate the only spectral attributes, as in per pixel-based classification, and now have characteristics of geometry, texture, among others. To select the best attributes for describing objects to build the hierarchical network, we used data mining techniques. A classification method based on the decision tree algorithm was selected for the following reasons: (1) it does not require a significant amount of processing time; (2) the model is easily understood; (3) representative attributes are easily identified; (4) classification rules are simple, it does not require assumptions about statistical distributions or the independence of classes; (5) object attributes can be represented numerically and categorically, and it has produced good results in previous studies (PINHO et al., 2012; KÖRTING et al., 2013).

Several attributes of the regions were used, grouped into attributes of geometry, texture, and spectral. Geometry features are based on an image object's shape, calculated from the pixels that form it (i.e. area, perimeter, shape indexes). Texture features are used to evaluate the texture of image objects and include features based on an analysis of sub-objects helpful for evaluating highly textured data (i.e. homogeneity, contrast, entropy). Spectral features evaluate the first (mean), second (standard deviation), and third (skewness) statistical moments of an image object's pixel value and the object's relations to other image object's pixel values. Table 4 shows some additional spectral indexes that fed data mining.

Table 4 - Indexes used as input to the data mining.

Index		**Description**
Normalized Difference Vegetation Index (NDVI)	$\frac{NIR - Red}{NIR + Red}$	Normalized difference of green leaf scattering in near infrared, chlorophyll absorption in RED.
Simple Ratio Index	$\frac{NIR}{Red}$	Ratio of green leaf scattering in near infrared, chlorophyll absorption in RED.
Red Edge Normalized Difference Vegetation Index	$\frac{NIR - Red\ edge}{NIR + Red\ edge}$	A modification of the NDVI using reflectance measurements along the red edge. Differs from the NDVI by using bands along the red edge, instead of the main absorption and reflectance peaks (SIMS; GAMON, 2002).
Modified Red Edge Simple Ratio Index	$\frac{NIR - Blue}{Red\ edge - Blue}$	A ratio of reflectance along the red edge with blue reflection correction. It differs from the standard SR because it uses bands in the red edge and incorporates a correction for leaf specular reflection (SIMS; GAMON, 2002).
Modified Red Edge NDVI	$\frac{NIR - Red\ edge}{NIR + Red\ edge - 2Blue}$	A modification of the Red Edge NDVI using blue to compensate for scattered light (SIMS; GAMON, 2002).
-	$\frac{Brightnes + Blue}{Red\ edge}$	Ratio of the sum of 'brightness and blue' and red edge (adapted from Leonardi [2010]).
-	$\frac{Brightnes + Blue}{Red}$	Ratio of the sum of 'brightness and blue' and red (LEONARDI, 2010).

In a classifier based on decision trees, thresholds are applied to object's features. Observations satisfying the thresholds are assigned to the left branch, otherwise to the right branch. In the final step, classes are assigned to the terminal nodes (or leaves) of the tree (KÖRTING et al. 2013). We used the J48 (C4.5) (Quinlan, 1993) decision tree algorithm that is freely available in the Weka software package.

Fully expanded decision trees often contain unnecessary structure, and it is generally advisable to simplify them before they are deployed (WITTEN et al. 2011). Although trees constructed by the divide-and-conquer algorithm perform well on the training set, they are usually overfitted to the training data and do not generalize well to independent test sets.

We controlled the decision tree size through the minimum number of instances in each leaf (pre-pruning). Various tree models were tested. The best result was the tree with 3 instances per leaf, Kappa coefficient value of 0.9354 (Table 5), and tree with 23 nodes. The pruned decision tree classifier obtained in data mining process can be seen in the Figure 3.

```
Mean PC 2 <= -1135.65876
|   Mean Blue <= 7523.010204
|   |   (Brgt+Blue)/Redge <= 2.585538
|   |   |   GLDV Ang. 2nd moment (45°) <= 0.020454
|   |   |   |   Skewness Red edge <= -0.180502: Bare soil (9.0)
|   |   |   |   Skewness Red edge > -0.180502
|   |   |   |   |   Standard deviation NIR <= 363.33118: Bare soil (4.0)
|   |   |   |   |   Standard deviation NIR > 363.33118: Ceramic roofs (156.0/2.0)
|   |   |   GLDV Ang. 2nd moment (45°) > 0.020454
|   |   |   |   Border length <= 572
|   |   |   |   |   (Brgt+Blue)/Redge <= 2.288286: Bare soil (46.0/2.0)
|   |   |   |   |   (Brgt+Blue)/Redge > 2.288286: Ceramic roofs (5.0/1.0)
|   |   |   |   Border length > 572: Asphalt (5.0)
|   |   (Brgt+Blue)/Redge > 2.585538
|   |   |   (Brgt+Blue)/Redge <= 3.397972
|   |   |   |   Standard deviation Red edge <= 533.53398: Asphalt (55.0)
|   |   |   |   Standard deviation Red edge > 533.53398: Ceramic roofs (4.0/1.0)
|   |   |   (Brgt+Blue)/Redge > 3.397972: Water (17.0)
|   Mean Blue > 7523.010204: Bright roofs (71.0)
Mean PC 2 > -1135.65876
|   Mean Red edge <= 3307.42053: Trees (171.0)
|   Mean Red edge > 3307.42053: Grass (107.0/1.0)
```

Figure 3 - The pruned decision tree model for land cover classification. Number of leaves: 12. Size of the tree: 23.

After generating the decision tree, it was translated into thresholds to compose a semantic network in and used to classify the image objects. Figure 4c is a highlighted subset of the classified image using the decision tree.

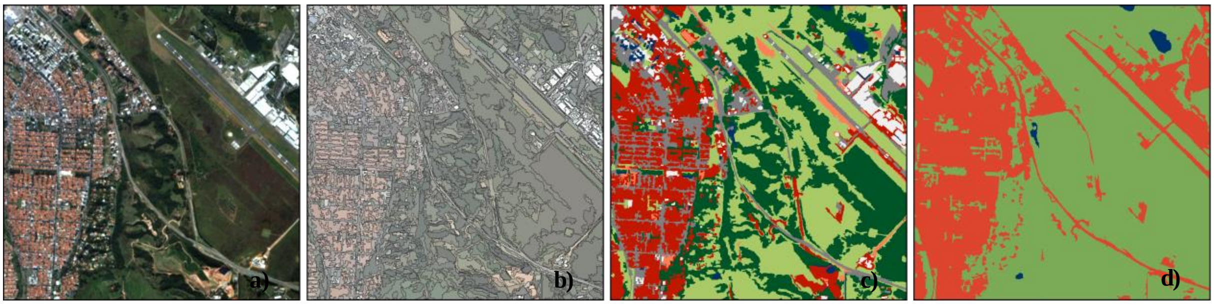


Figure 4 - Steps in this approach: (a) true color composition R3 G2 B1; (b) segmentation; (c) decision tree classification; and (d) post classification.

As can be seen in the confusion matrix (Table 6), due to similar spectral responses, it is common the confusion between 'Bare soil' and 'Constructed area', and between 'Water' and 'Shadows'. Previous studies have found similar results when trying to distinguish between bare soil and ceramic roofs, or water and shadows (SMALL, 2003; HEROLD et al. 2004; BRIGATTI et al. 2011).

This confusion was partially corrected through conditional thresholds that aimed to introduce the visual interpretation of user to classification. Threshold used was exemplified in Figure 5: segments smaller than 280 pixels, classified as water that had as immediate neighbors 'roofs', should be classified as constructed area. The same logical procedure assisted to correctly classify regions of bare soil on road borders. This process proved to be essential to refine the classification. Remaining classification errors were corrected manually through visual interpretation.

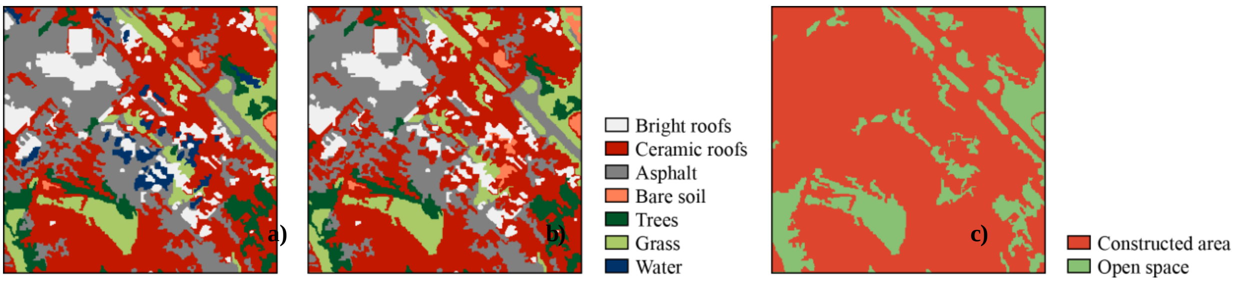


Figure 5 - Post classification process: (a) confusion between water and shadows; (b) corrected classification by conditional thresholds; and (c) merge of the classes corresponding to abstract classes 'Constructed Area' and 'Open Space'.

4. Results

Constructed area comprises 14.85% (92.84 km^2) of the total area of the scene (625 km^2). The smallest feature of constructed area that the RapidEye sensor recognized in this method was equivalent to 4 pixels, or 100 m^2.

Cross-validation was performed to verify the accuracy of the classifier, where the original sample was randomly partitioned into 10 equal size subsamples. Of the 10 subsamples, a single subsample was retained as the validation data for testing the decision tree, and the remaining 9 subsamples were used as training data. The cross-validation process was then repeated 10 times, with each of the 10 subsamples used exactly once as the validation data. The 10 results from the folds were averaged to produce a single estimation, thus obtaining a more reliable measure of the ability of classifying the entire universe of data set model. Table 5 presents the cross validation summary from the data mining process using WEKA.

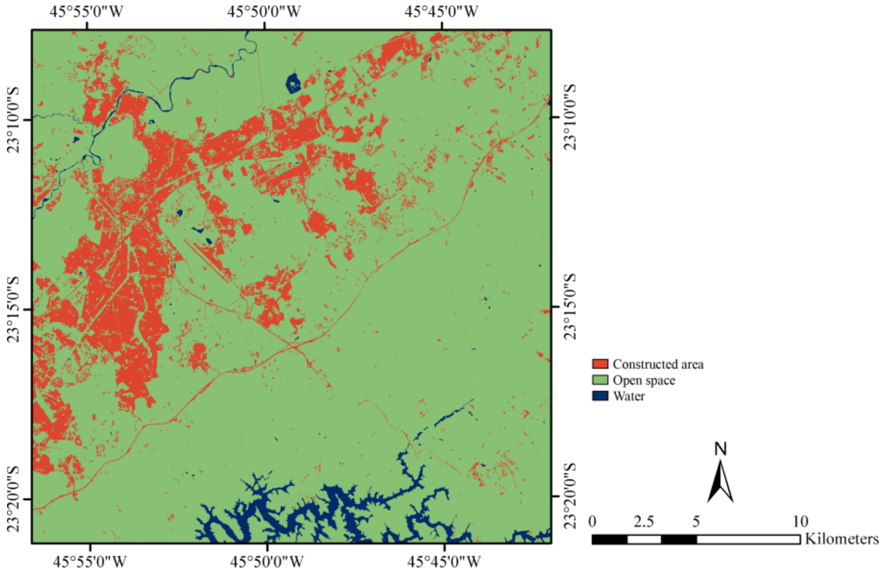


Figure 6 - Result of the final land cover classification.

To describe the degree of concordance between the classification with different subsamples, we use the Kappa index, based on the number of concordant responses. The closest of one is the Kappa index, stronger is the agreement or accuracy between the classification map and the samples manually collected.

Table 5 - Cross validation: summary.

Correctly Classified Samples	616	94,7692%
Incorrectly Classified Samples	34	5,2308%
Kappa statistic		0,9354
Total Number of Samples	650	

Vast majority of the samples were correctly classified (94.77%), which can be confirmed by a high kappa statistic (0.94). Table 6 shows the confusion matrix obtained in the classification.

Table 6 - Confusion matrix obtained in the classification.

Grass	**Water**	**Ceramic roofs**	**Trees**	**Asphalt**	**Bright roofs**	**Bare soil**	**← classified as**
105	0	0	1	0	0	0	**Grass**
0	14	0	0	3	0	0	**Water**
0	0	151	0	3	0	9	**Ceramic roofs**
0	0	0	170	1	0	0	**Trees**
0	0	2	0	59	0	0	**Asphalt**
0	0	1	0	0	70	0	**Bright roofs**
2	0	11	0	0	1	47	**Bare soil**

Among 34 samples incorrectly classified (5.23%), 14 samples (41.2% of the samples with errors) were classified as 'Ceramic roof', of which 11 samples have their origin as bare soil what is justified by the strong spectral correlation existing between these two information: roofs are generally made of clay or concrete, and these materials are present in the soil.

4. Conclusions

APAs are conservation units relatively lax in their use and land cover restrictions, encompassing urban, rural and natural landscapes. On the other hand, they are spaces of environmental planning and management that have great regional importance, as at APA-MRPS aimed to preserve the water sources that supply more than 15 million people. With these characteristics, APAs managers are faced with many challenges to manage such territories effectively.

This paper showed that RapidEye data and the methodology used were effective in classifying constructed areas, enabling the identification of small changes in land cover. The methodology presented in this paper succeeded to adapt the need to monitor small increases of constructed areas in protected areas. The data and methodology may be able to assist managers in the monitoring and evaluation processes of protected areas, especially APAs.

Future work will include a refinement of the methodology using new attributes, and other data mining methods to select the best attributes for composing semantic network. Furthermore, the field validation of the classification is necessary for a more effective verification of the methodology.

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