

PROPOSAL OF CHANGE DETECTION IN LAND COVER FOR PIPELINE MONITORING FROM RAPIDEYE AND IKONOS IMAGES

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ABSTRACT. The goal of this study was to improve and evaluate the applicability of a methodological procedure of pipeline monitoring to reveal indicators of third party activities that may interfere with the structural preservation of pipes and environmental damages. The procedure was developed from the technique of change detection through object-based classification of land cover, using high resolution satellite images applied to a section of the Guararema-Mauá – São Paulo pipeline, Brazil. In the seven-month monitoring period performed with RapidEye imaging, an area of 2.024 km² was identified as area of change, corresponding to 3.30% of the total area analyzed. For the monitoring performed with Ikonos imaging during a four-month period, changes were detected in an area of 0.187 km², which corresponded to 1.92% of the total area analyzed. The main changes in land cover were from Bare Soil to Grassland, due to changes related to the different stages of agricultural activity and reforestation areas, as well as the natural regeneration of vegetation over the pipeline and solid waste landfill. The results of the change detection of land cover from object-based classification were close to the technique reference limit for areas with great complexity and diversity of space occupation.

Keywords: structural preservation of pipes, object-based classification, high resolution satellite images.

RESUMO. Este estudo teve por objetivo avaliar a aplicabilidade de um procedimento metodológico de monitoramento de faixas de dutos que revelem indicativos de atividades de terceiros que podem interferir na integridade estrutural dos dutos e provocar danos ambientais. O procedimento foi desenvolvido a partir da técnica de detecção de mudanças na cobertura da terra pela classificação baseada no objeto, com utilização de imagens orbitais de alta resolução. Este procedimento foi empregado em um trecho da faixa de dutos Guararema-Mauá – SP, no monitoramento realizado por meio de imagens RapidEye. Em um período de sete meses, foram identificados 2,024 km² como área de mudança, que corresponde a 3,30% do total da área analisada. Para o monitoramento realizado a partir da imagem Ikonos, com período de quatro meses, foi identificada como mudança uma área de 0,187 km², correspondendo a 1,92% do total da área analisada. As principais mudanças ocorridas foram entre Solo Exposto e Vegetação Rasteira, devido às alterações ocorridas nos estágios de cultivo agrícola e áreas de reflorestamento, como também, estão associadas às áreas de regeneração da vegetação da faixa de dutos e aterro sanitário. Os resultados da detecção de mudanças da cobertura da terra pela classificação baseada no objeto atingiram acertos próximos ao limite de para esta técnica, em áreas com grande complexidade e diversidade de ocupação do espaço.

Palavras-chave: integridade estrutural dos dutos, classificação baseada no objeto, imagens orbitais de alta resolução.

INTRODUCTION

The installation and operation of a petrochemical industry brings many benefits to the region and the area of influence where it is installed, generating income, jobs and improvements to productive and road infrastructures. However, the environmental issue tends to be relegated to a secondary position behind economic efficiency, which seeks the optimization of refining facilities. Therefore, such facilities end up being concentrated in large complexes, generating a variety of social and environmental issues (Lora, 2002). The diagnosis of those issues must take into consideration the conflicts and potential changes associated with the land cover vegetation, water availability and demand, land use, environmental risks and the land occupation in the areas surrounding refineries and oil transportation facilities (Suarez, 1986).

New techniques have been employed to develop computational systems to analyze the risks to pipelines and their maintenance needs. The most utilized methods for monitoring pipelines include foot patrolling along the pipelines and aerial surveillance with small aircraft and helicopters (Zirinig et al., 2002). These inspections check for construction activity near the pipelines and maintenance of the service areas. The frequency of such inspections is determined by the intensity of human activity over the influence area of the pipeline (Roper & Dutta, 2005).

According to Hausamann et al. (2005), the changes in built-up, vegetation and bare soil areas were considered as indicators of third parties activities that may compromise the pipeline structural preservation. These indexes were the matter to be applied in the present study to improve the methodological procedure of pipeline monitoring developed from the technique of land cover change detection by using high spatial resolution satellite images.

Previous study (Marques et al., 2013) developed this procedure to the monitoring of ORBEL pipeline section from Rio de Janeiro to Belo Horizonte (Brazil). For the present research, this aforementioned procedure was improved and applied to the GASPAL/OSVAT pipeline for Guararema-Mauá section, in the State of São Paulo, Brazil. According to the Environmental Impact Report of the São Paulo State Secretary of the Environment, in the installation period the pipelines in São Paulo Metropolitan Area crossed areas of low building density. Currently unplanned land occupation near the pipeline service areas due to population growth, has resulted an increasing anthropic pressure on them (SEMA-SP, 2007).

Remote sensing (RS) products and techniques have proven to be fundamental in the diagnosis and monitoring of the occupation of space. The images serve as an important source of information regarding phenomena occurring on the land surface and are

essential for understanding and modeling the dynamics of changes in land use and cover, which helps to identify the elements that may constitute risks to the pipeline. The use of RS, as well as the geographic information systems (GIS), improves the capability to detect changes by enabling more frequent and systematic collection of information, and integration and analysis of spatial data (Roper & Dutta, 2005).

From literature, conceptually, change detection can be described as a process of identifying and quantifying changes in objects or phenomena based on multi-temporal observations (Singh, 1989; Coppin & Bauer, 1994; Seto et al., 2002; Lu et al., 2004). Despite it is not a general requirement to change detection analysis, the application of RS products in change detection must satisfy, if possible, the selection of images with the same spatial and spectral resolution, which makes it possible to identify features for comparison between images (Lu et al., 2004). High resolution satellite imagery is a rapidly evolving technology that provides spatial and temporal information regarding the different objects on the surface, with increasingly detailed and frequent resolutions, improving the efficiency for classification of specific features and identification of dynamic processes, as land use (Im et al., 2008). To evaluate the contribution of high spatial resolution sensors to the monitoring of pipelines, this manuscript used RapidEye images (acquired in Sep/2011 and Apr/2012) and Ikonos images (acquired in Nov/2011 and Mar/2012).

For Zirinig et al. (2001), change detection techniques can be useful tools for detecting changes in the area surrounding the pipeline, considering that in change detection, the data from one image are compared to corresponding data of the preceding image, based on each pixel of the images. Changes in the landscape are reflected in differences in the corresponding pixels. However, comparisons using this method can lead to problems due to natural changes in the vegetation, light, and surface conditions, such as snow or rain, which result in radiometric changes in the pixels. Thus, important corrections are necessary to reduce the high proportion of false changes generated by automatic detection based on RS images. According to Lu et al. (2004), the technique of comparing multi-temporal images using an array of changes after classification reduces atmospheric interference, and radiometric correction is not required.

The technique of change detection for digital images classification is based on the distinction and identification of different classes that have different spectral responses assigned, which allow their automated application to large areas. To the adoption of this technique, classification algorithms are applied to extract the features of interest from a multidimensional space, usually repre-

sented by the different bands, creating an unique level of thematic information: the classes (Lu et al., 2004).

The digital land use and land cover classification from those images is challenging, due to the spectral mixing of objects in the image, caused by the complexity of the elements found on the terrestrial surface (Eikvil et al., 2009; Pu & Landry, 2012).

Thus, the object-based image analysis is an approach increasingly used in classifying high spatial resolution remote sensing images (Liu et al., 2008). The first step for object-based image classification is the image segmentation into objects or image segments, and then classifies these objects based on their attributes and spatial relations, generating segments that are homogeneous in the spectral, geometric, texture and positional characteristics of the image elements (Ryherd & Woodcock, 1996; Shackelford & Davis, 2003).

The multiresolution segmentation algorithm approach uses the growth of regions in which adjacent regions are grouped according to the similarity criterion which considers the internal heterogeneity of the regions. In the definition of similarity, it is necessary to provide parameters of scale, form, tone, compactness, smoothness and spectral bands which also allow the use of a Thematic Layer (Baat & Schäpe, 2000).

The classification of land use and land cover from object-based analysis requires a hierarchical network elaboration in the class structure, which is based on the semantic network and the physical characteristics of the objects that compose a given class. The semantic network represents a logical structure relating the objects or classes to their meanings and relationships (Antunes, 2003), and may be classified in three kinds of hierarchical networks: inheritance hierarchies; group hierarchies and structured groups (Hofmann, 2001).

In object-based approach, the classification algorithms employ attributes to describe spectral properties, geometric characteristics and texture of the image objects. These attributes can be grouped into: (a) Spectral attributes (mean, standard-deviation, Gaussian distribution asymmetry, brightness, HSI transformation, algebra between bands, NDVI) – spectral bands set making up the image or the result of operations between bands, which discriminate objects by their tonality or statistical description; (b) Geometry attributes – describe objects as size, shape, width, length, area, and their relationships; (c) Position attributes – locate an object image relative to the entire scene, especially to geographically referenced data; (d) Texture attributes – estimate the texture of image objects. The texture is estimated by the Gray Level Co-occurrence Matrix (GLCM) or by Spatial Dependence Matrix. In Dependence Matrix is calculated spatial separation of one pixel

against another reference pixel (Definiens, 2009). The GLCM estimates the texture from the tabulation of the different combination of gray level in a scene. The calculation depends upon the feature angle: 0° , 45° , 90° , 135° for all pixels direction of an image object (Haralick et al., 1973; Haralick, 1979).

STUDY AREA

This study analyzed a section of the GASPAL/OSVAT pipeline between the Guararema Terminal and Mauá (RECAP). This segment crosses areas of the municipalities of Guararema, Mogi das Cruzes, Suzano, Ferraz de Vasconcelos, São Paulo and Mauá, in the State of São Paulo, Brazil. The Guararema-Mauá pipeline is represented in Figure 1.

For the test using the RapidEye image, covered area was 61.74 km^2 , Figure 1(a). For the Ikonos image test, total area covered was 9.75 km^2 , Figure 1(b). The RapidEye and Ikonos images had different buffers sizes, which were previously defined according to spatial resolution and costs for image scene.

MATERIALS AND METHOD

The REIS (RapidEye Earth Imaging System) sensor system collects images in five spectral bands: Blue ($0.44\text{-}0.51 \mu\text{m}$), Green ($0.52\text{-}0.59 \mu\text{m}$), Red ($0.63\text{-}0.685 \mu\text{m}$), Red-Edge ($0.69\text{-}0.73 \mu\text{m}$), which is sensitive to changes in the chlorophyll content in plants, and Near Infrared ($0.76\text{-}0.85 \mu\text{m}$), with an imaging area of 77.25 km . The satellite revisit time is 24 hours (off-nadir) and 5.5 days (nadir). The spatial resolution offered by this sensor is 6.5 m and 5 m for orthoimages and a 12-bit radiometric resolution (RapidEye, 2007).

The Red Edge band, which corresponds to the transition band between the Red and Near Infrared (NIR) bands, covers part of the spectrum where the vegetation reflectivity increases drastically from the Red band to the NIR band. The Red band is one of the areas where chlorophyll absorbs light, and the NIR band is where the leaf cell structure produces a strong reflection. Thus, variations in both the chlorophyll content and the structure of the leaf provide additional information contributing to the identification of plant types, nutrition and health, plant cover characteristics and abundance, among other resources (Weichelt et al., 2012).

The Ikonos (Advanced Earth Observing Satellite) satellite sensor is a high resolution satellite, encoded in 11-bit, with four multispectral bands: Blue ($0.44\text{-}0.51 \mu\text{m}$), Green ($0.52\text{-}0.59 \mu\text{m}$), Red ($0.63\text{-}0.69 \mu\text{m}$), Infrared ($0.76\text{-}0.90 \mu\text{m}$), 4 m resolution and one panchromatic band ($0.45\text{-}0.90 \mu\text{m}$), 1 m resolution. The application of Ikonos images is important for studies such as more

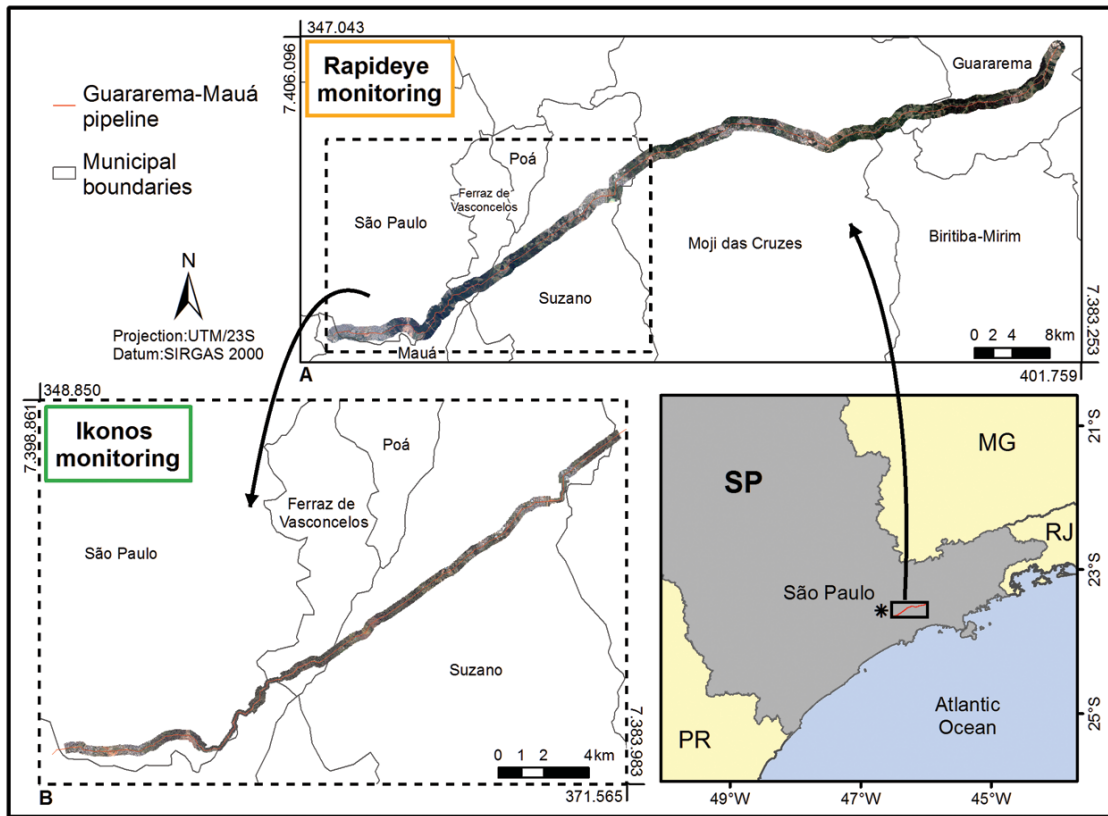


Figure 1 – Guararema-Mauá pipeline and area studied through RapidEye and Ikonos images.

detailed mappings of land cover and use, change detection, cartographic updating and monitoring environmental risks (Kalpoma & Kudoh, 2007). The acquisition parameters of RapidEye and Ikonos are described in Table 1. The use of the images was supported by a fellowship between IGCE/UNESP – Rio Claro and CENPES/PETROBRAS.

Pipeline Monitoring Procedures

The procedures for pipeline monitoring were developed through land cover classification for change detection from high spatial resolution images (Ikonos and RapidEye). These procedures were performed using ENVI, eCognition and ArcGIS softwares, following the methodological steps described below.

Table 1 – Description of acquisition parameters of RapidEye and Ikonos images.

Image	Date		Imaging Elevation Angle	Imaging Azimuth	Solar Elevation Angle	Solar Azimuth
RapidEye	September 2011	09/09/2011	86.63	2.79	84.12	2.47
		09/09/2011	86.63	2.79	84.13	2.51
		09/09/2011	86.63	2.78	84.13	2.43
	April 2012	04/19/2012	88.80	2.80	84.72	2.20
		04/12/2012	88.10	9.70	84.38	1.77
04/05/2012		86.75	9.81	84.22	2.37	
Ikonos	November 2011	11/25/2011	86.28	115.05	68.39	87.25
		11/25/2011	83.68	38.87	68.44	87.31
		11/25/2011	72.89	19.09	68.46	87.41
	March 2012	03/14/2012	73.39	320.05	56.35	54.73

Image Pre-processing

Pre-processing of the Ikonos images acquired on November 2011 and March 2012 was done according to the following procedures: (a) Geometric correction – The orthorectification was executed using RPC's (Rational Polynomial Coefficient), Digital Elevation Model (scale 1:2000) and control points obtained from digital aerial photographs (0.2 m resolution); (b) Image fusion – the multispectral bands (4 m) were fused with the panchromatic band (1 m), resulting in bands of 1 m resolution.

In this manuscript there were no radiometric correction, since according to Lu et al. (2004), the technique of change detection comparing multi-temporal images using an array of changes after classification, reduces atmospheric interference.

The RapidEye images required no further pre-processing procedure, since it was already orthorectified when acquired with a correction level A3 (RapidEye, 2007).

Elaboration of the Thematic Map T1

Land cover classes, presented in Table 2, were defined according to the identification of activities that may compromise the structure of the pipeline. From this definition, the classes were determined based on the spectral characteristics of the objects.

The object-based approach classification must be initiated with image segmentation. Segments were generated using a Multiresolution Segmentation algorithm that enables the identification of the image contents with different levels of detail (Baatz

& Schäpe, 2000). The parameters applied to images segmentation, considering RapidEye (Sep/2011) and Ikonos (Nov/2011), are showed in Table 3.

The classification of land cover was based on the spectral behavior, geometric characteristics and texture of the objects. Following the hierarchical class structure, training samples were obtained for each class of land cover. These samples are needed to describe the classes and the context in which they are inserted, making it possible the analysis of the histograms of attributes generated by the Sample Editor, to select the attributes for classification.

The maps of the initial land cover (T1) were drawn from the RapidEye images acquired on September 2011 and Ikonos images acquired on November 2011 through the classification algorithm Assign Class (Definiens, 2009). The parameters were described in hierarchical networks, illustrated in Figures 2 and 3. After that, classes were edited by visual interpretation.

Change Detection Procedure

The change detection process was carried on using eCognition software (Definiens, 2009), according to the steps described below.

Segmentation

In the searching for the best segmentation, tests were performed to obtain the parameters of scale, shape and compactness,

Table 2 – Land Cover Class Description.

Land Cover Class	Description
Shadow	Shadow of natural and built-up elements
Asphalt	Roads and streets paved with asphalt cover
Bare Soil	Areas without buildings or vegetation land cover
Arboreal Cover	Medium and tall trees in forested and urban areas
Grasslands	Areas covered by grasses and shrubs
Cover	Concrete, ceramic and asbestos roofs and concrete paved areas
Swimming Pools	Swimming pools
Flooded Area	Areas temporarily covered by water
Rivers/Reservoirs	Water streams, lakes and reservoirs

Table 3 – Segmentation process parameters for maps of the initial land cover (T1).

Land Cover Map T1			
Image		RapidEye (Sep/2011)	Ikonos (Nov/2011)
Segmentation Parameters	Scale	80	40
	Shape	0.4	0.4
	Compactness	0.5	0.5
	Band	B, G, R, N and RE	B, G, R and N

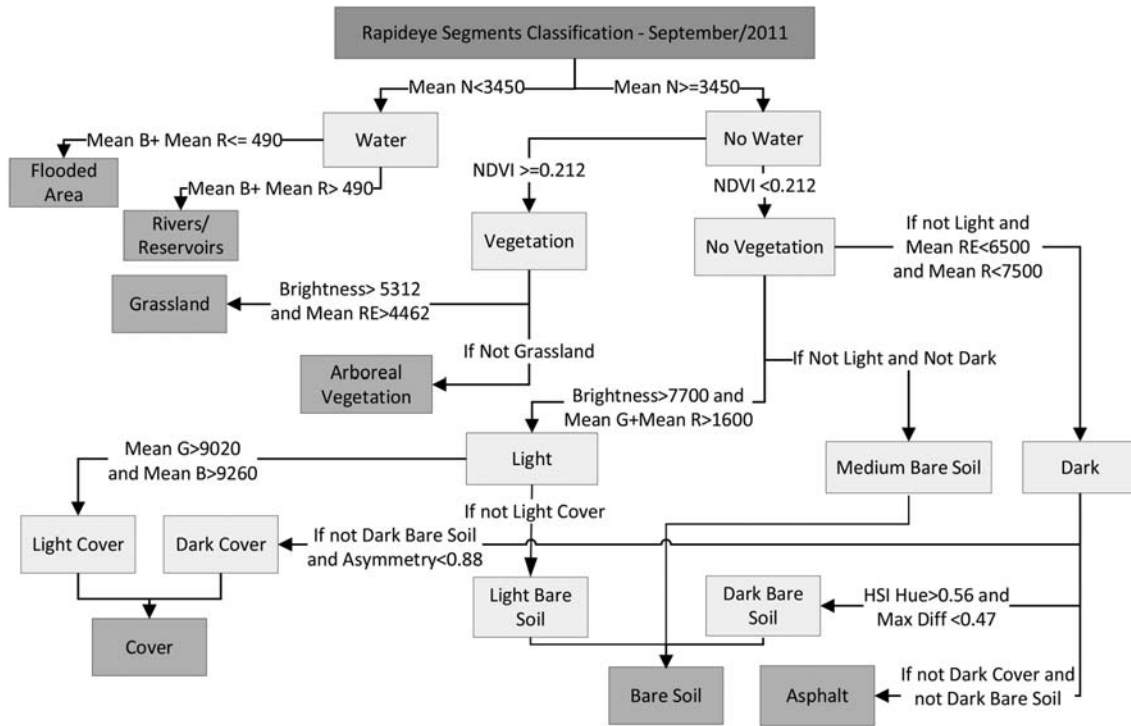


Figure 2 – Hierarchical network used in classification – RapidEye, Sep/2011 (T1).

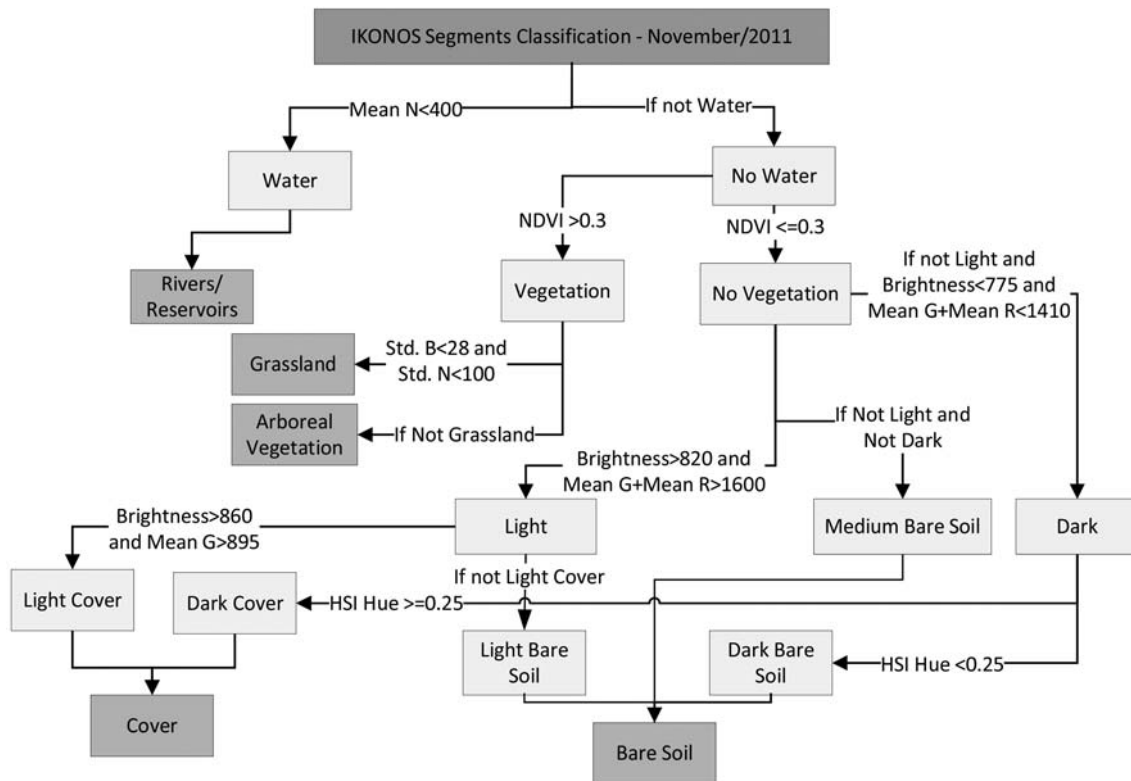


Figure 3 – Hierarchical network used in classification – Ikonos, Nov/2011 (T1).

seeking the best values of the parameters to extract the objects in the image, according to the classes of interest. After several trials three levels of segmentation were established, which parameters are described in Table 4.

Table 4 – Segmentation Process Parameters.

RapidEye Images: Sep/2011 and Apr/2012			
T1 Bands	T2 Bands	Parameters	Level III
B_T1	B_T2	Scale	80
G_T1	G_T2	Shape	0.4
R_T1	R_T2	Color	0.6
RE_T1	RE_T2	Compactness	0.5
N_T1	N_T2	Smoothness	0.5
Thematic Map T1		—	—
Ikonos Images: Nov/2011 and Mar/2012			
T1 Bands	T2 Bands	Parameters	Level III
B_T1	B_T2	Scale	40
G_T1	G_T2	Shape	0.4
RE_T1	RE_T2	Color	0.6
N_T1	N_T2	Compactness	0.5
Thematic Map T1		Smoothness	0.5

Identification of Change Areas (Change Map – CM)

Multi-temporal algebraic bands were applied to identify change areas, as proposed by Foresti (1986). Red bands ($[R_T2]-[R_T1]$) for both sensors (Ikonos and RapidEye) were used to evidence distinct spectral response assigned for different materials in the study areas. These bands allow better characterization of land cover changes in vegetated areas, as well as built-up areas (Jensen, 1983; Forster, 1985).

Table 5 – Thresholds used to determine change and no change areas.

RapidEye		Ikonos	
Class	Sep-Apr	Class	Nov-Mar
No Change	$-2620 \leq NC \leq 126$	No Change	$-350 \leq NC \leq -80$
Red Change	$RC > 126$	Red Change	$RC > 20$
Blue Change	$BC < -2620$	Blue Change	$BC < -350$

The output images were analyzed taking into account three change statements: No Change (NC), areas that remain unchanged; Red Change (RC), when the objects have lower spectral response in the T1 image than T2 image; Blue Change (BC), when the objects have higher spectral response in T1 image than in T2 image. From these statements, the thresholds were defined to determine change areas in the RapidEye and Ikonos images (Table 5).

Change map classification (Land Cover Map – LCM)

The areas identified as Red Change (RC) and Blue Change (BC) were grouped and labeled as Change Areas (CA). These CAs were classified according to the object-based approach. For the classification of land cover was employed the Assign Class algorithm, implemented in eCognition (Definiens, 2009). The attributes for classification were selected from training samples, which were obtained for each class of land cover. From these samples were generated histograms of the selected attributes used for classification of change areas in both RapidEye and Ikonos images. The parameters were described in hierarchical networks, as illustrated in Figures 4 and 5.

In the analysis and quantification of the land cover change areas, for each monitoring (RapidEye and Ikonos), classes with the same land use characteristics were grouped; thus, the Light, Medium, and Dark Bare Soil classes were grouped together to form the Bare Soil class, and the Light, Medium and Dark Cover classes were grouped together to create the land cover class.

Adjusted Land Cover Map – ALCM

The study identified Change and No Change areas with the purpose of analyzing activities that may interfere in pipelines operations. Although the four-month period used for the Ikonos images may be considered a short time to detect some changes, it is nevertheless adequate for the monitoring of the service as well as the influence areas of the pipeline, due to the need to prevent accidents and control third party activities. Considering that the frequency of observations should be proportional to the density of occupation along the pipeline influence area, some areas will be visited weekly, and even daily.

Therefore, to adjust for and control possible changes, some premises were considered. The first premise is related to the impossibility of arboreal development in such a short period. The second premise considers the land cover classes Rivers/Reservoirs, Asphalt and Swimming Pools to be constant. Lastly, the third premise determines that no change will occur for the Shadow class. Thus, after the automatic classification of the land cover classes of the areas defined as Change, some rules were applied in the classification process to limit the identification and classification of false changes (Table 6).

Generation of Thematic Map T2

After adjustments were done to obtain the ALCM, the land cover maps were updated with the changes identified in the period from September 2011 to April 2012 (RapidEye image) and from

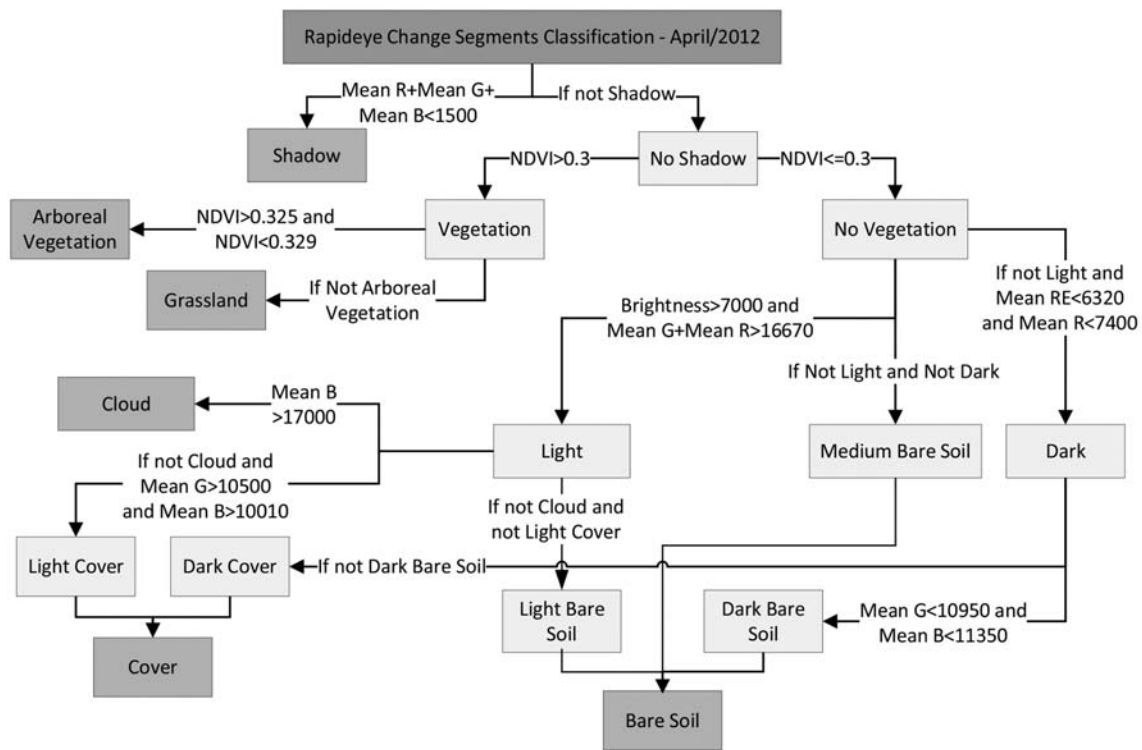


Figure 4 – Hierarchical network used in the classification – RapidEye.

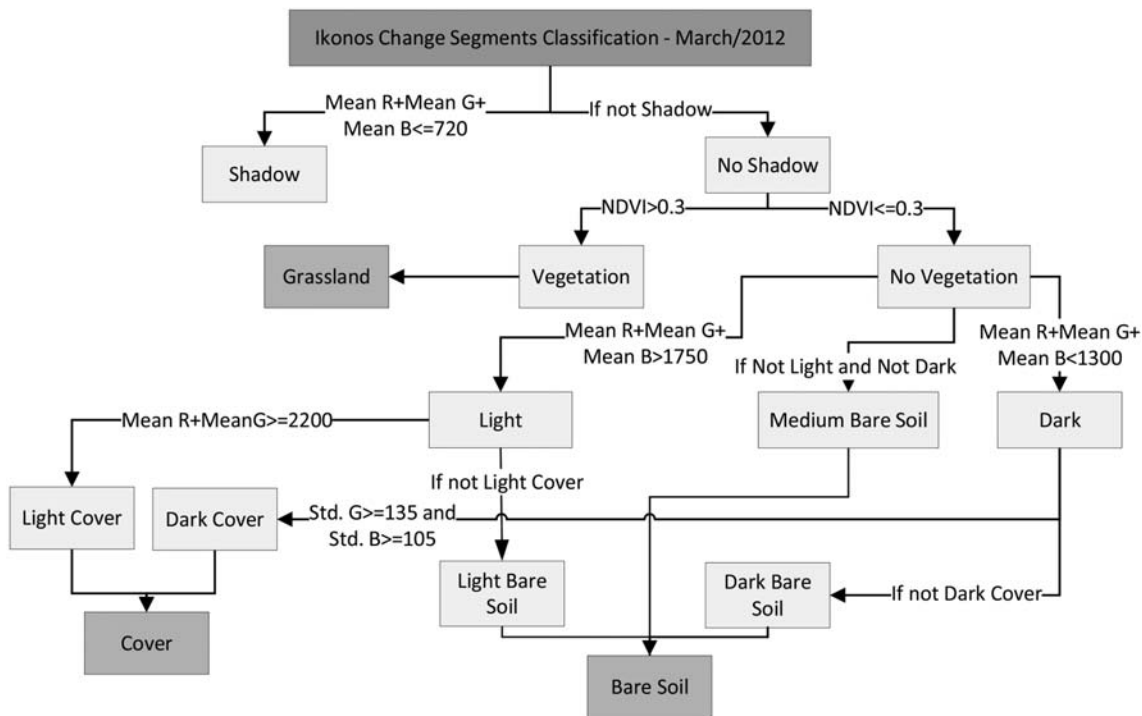


Figure 5 – Hierarchical network used in the classification – Ikonos.

Table 6 – Rules applied to the classification process to limit the identification of false changes.

LCM	Rule	T1 Object	ALCM
Arboreal Vegetation	T1 Object Present	Flooded Area	Grassland
Bare Soil	T1 Object Present	Cover	Cover
Arboreal Vegetation	T1 Object Present	Bare Soil	Grassland
Cover	T1 Object Present	Cover	No Change
Arboreal Vegetation	T1 Object Present	Arboreal Vegetation	No Change
Grassland	T1 Object Present	Arboreal Vegetation	No Change
Bare Soil	T1 Object Present	Bare Soil	No Change
Shadow	T1 Object Present	Shadow	No Change
Flooded Area	T1 Object Present	Flooded Area	No Change

November 2011 to March 2012 (Ikonos image). The new information was superimposed to the Thematic Maps T1 to generate the Thematic Maps T2.

Validation of the classification

The study used error matrices and the Kappa coefficient of agreement to determine the statistical accuracy of the results in Change and No Change areas, before and after the adjustment to limit false changes. The results obtained in the classification of changes in the land cover classes were also evaluated. The error matrix represents the mapping accuracy through analysis of the agreement between reference samples and the product of the classification (Congalton & Green, 2009). The stratified random sampling method was used to select validation samples. The reference samples were acquired based on visual interpretation of Rapid Eye and Ikonos images. This procedure was supported considering the features of the classes and the high resolution of the images, likewise adopted in Campos et al. (2005), Gamanya et al. (2007), and Platt & Rapoza (2008). One hundred samples of each image were acquired of each class of Change and No Change to evaluate the change areas. To validate the classification of the land cover classes, 50 samples of each land cover class were obtained in the segments defined as change areas, a number considered sufficient to determine the accuracy of change detection, according to Congalton & Green (2009). The exception was the class Arboreal Vegetation, where 18 samples were acquired of the RapidEye image but no sample from the Ikonos image was acquired, as there was no change detected in this class.

RESULTS AND DISCUSSION

The Figures 6 and 7 show the maps of the initial land cover (T1) outcome, respectively, from RapidEye and Ikonos images classification.

The results obtained from change detection using the Rapid-Eye images and those results obtained after adjustments to constrain false changes are showed in error matrices (Table 7). The percentage of correct values was 88 and 83%, and agreement Kappa coefficient was 0.76 and 0.66, respectively. The quality of classification is considered by the reference ranges values proposed by Landis & Koch (1977). The aforementioned coefficients for change areas classifications observed in the present study are qualified as a good agreement.

The change detection results from Ikonos images showed a percentage of 65% for correct values and 66% for the results observed after adjustments to constrain false changes. Both procedures showed an agreement Kappa coefficient of 0.31 and 0.32, respectively (Table 8), indicating a reasonable accuracy to the identification of the change areas.

Although the study area is located in a metropolitan region of accelerated socioeconomic dynamics, it showed few areas of change in the analyzed period. The monitoring done through RapidEye image during a seven-month period, identified a change area of 2.024 km², corresponding to 3.30% of the total area analyzed (61.29 km²). For the monitoring realized through the Ikonos image over a four-month period, the areas identified as change areas totaled 0.187 km², corresponding to 1.92% of the area analyzed (9.75 km²).

The main changes occurred between Bare Soil and Grassland, which are to a great extent explained by the different stages of agricultural activity and reforestation areas. Changes to Bare Soil are also associated with areas of vegetation regeneration over the pipeline and in the waste landfill. The analysis of these changes indicates that this area presents some limitations to the process of urban expansion, despite the proximity to the nucleus of the metropolitan region (Figs. 8 and 9).

As we can see in Tables 9 and 10, agreement Kappa coefficient for the land cover classification was 0.65 and the overall accuracy

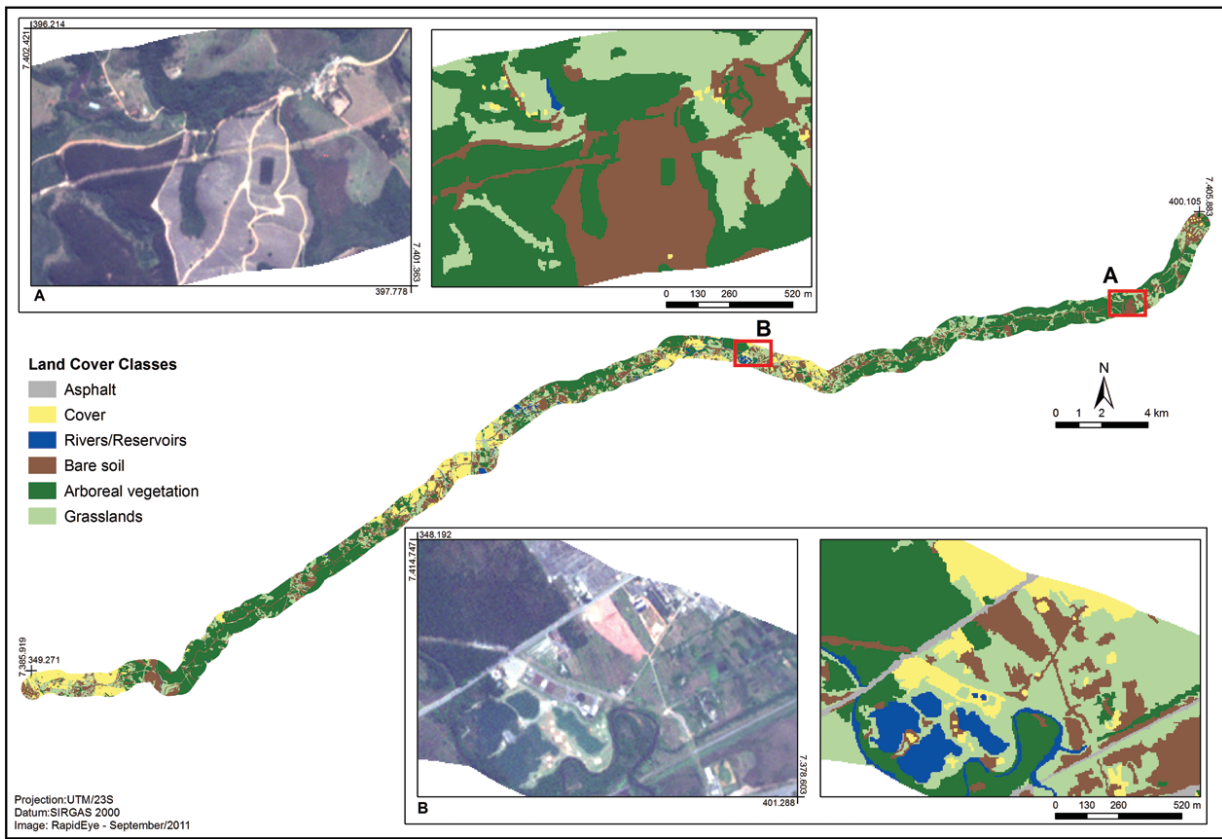


Figure 6 – Initial Land Cover Map (T1), elaborated from RapidEye image.

Table 7 – Change Areas Error Matrices in the RapidEye Monitoring.

Change Areas Error Matrix				Adjusted Change Areas Error Matrix			
Classified Data	Reference Data			Classified Data	Reference Data		
	Change	No Change	Total		Change	No Change	Total
Change	79	3	82	Change	67	1	68
No Change	21	97	118	No Change	33	99	132
Total	100	100	200	Total	100	100	200
Overall Accuracy	88%			Overall Accuracy	83%		
Kappa	0.76			Kappa	0.66		

Table 8 – Change Areas Error Matrices in the Ikonos Monitoring.

Change Areas Error Matrix				Adjusted Change Areas Error Matrix			
Classified Data	Reference Data			Classified Data	Reference Data		
	Change	No Change	Total		Change	No Change	Total
Change	33	2	35	Change	32	0	32
No Change	67	98	165	No Change	68	100	100
Total	100	100	200	Total	100	100	200
Overall Accuracy	65%			Overall Accuracy	66%		
Kappa	0.31			Kappa	0.32		

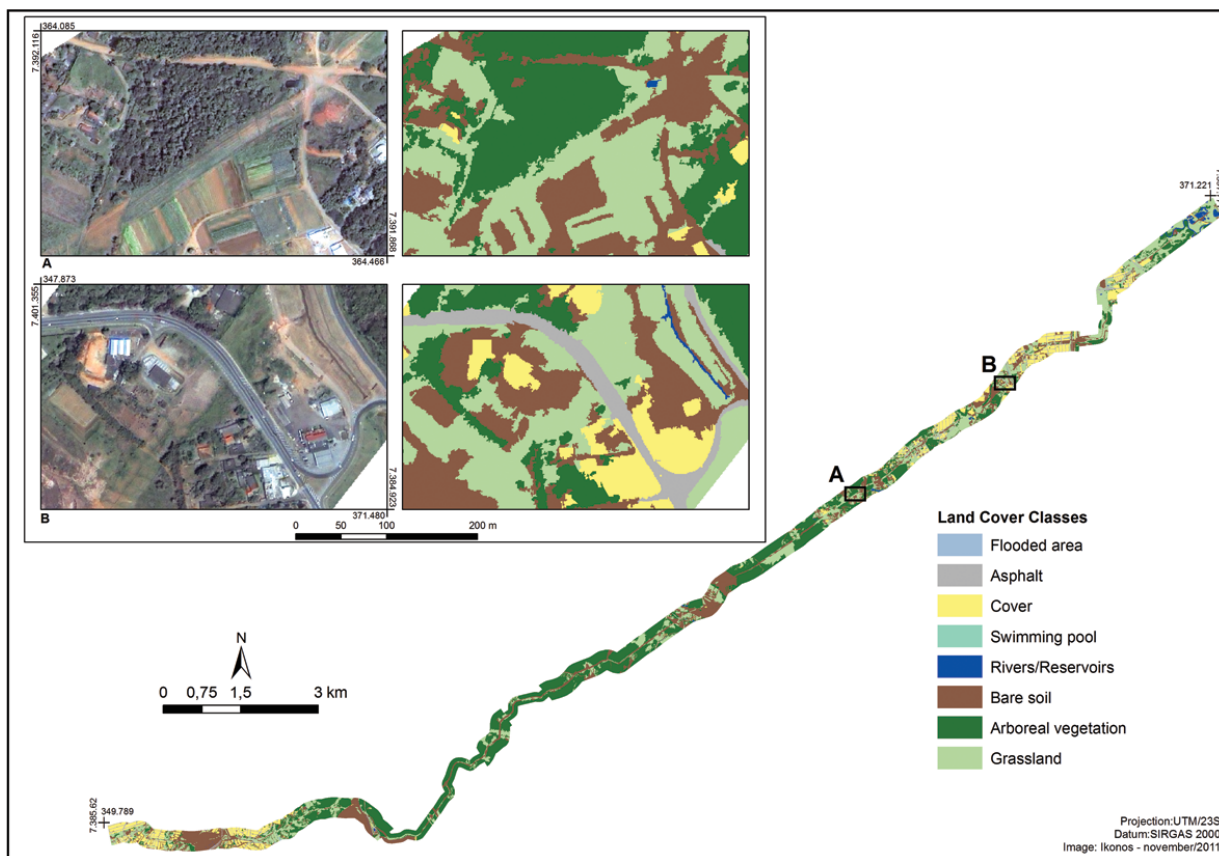


Figure 7 – Initial Land Cover Map (T1) elaborated from Ikonos image.

Table 9 – Land Cover Classification Error Matrix – RapidEye image.

Classified Data	Reference Data				Total
	Cover	Bare Soil	Arboreal Vegetation	Grassland	
Cover	37	8	0	0	45
Bare Soil	13	37	0	0	50
Arboreal Vegetation	0	0	3	0	3
Grassland	0	5	15	50	70
Total	50	50	18	50	168
Overall Accuracy = 76%					
Kappa = 0.65					

Table 10 – Land Cover Classes Change Areas and Conditional Kappa – RapidEye image.

Land Cover Class	Change Areas (km ²)	User's accuracy (%)	User's Kappa	Producer's accuracy (%)	Producer's Kappa
Cover	0.1563	82	0.74	74	0.64
Bare Soil	0.9875	74	0.62	74	0.62
Arboreal Vegetation	0.0018	100	1.0	17	0.57
Grassland	0.8787	71	0.59	100	0.79

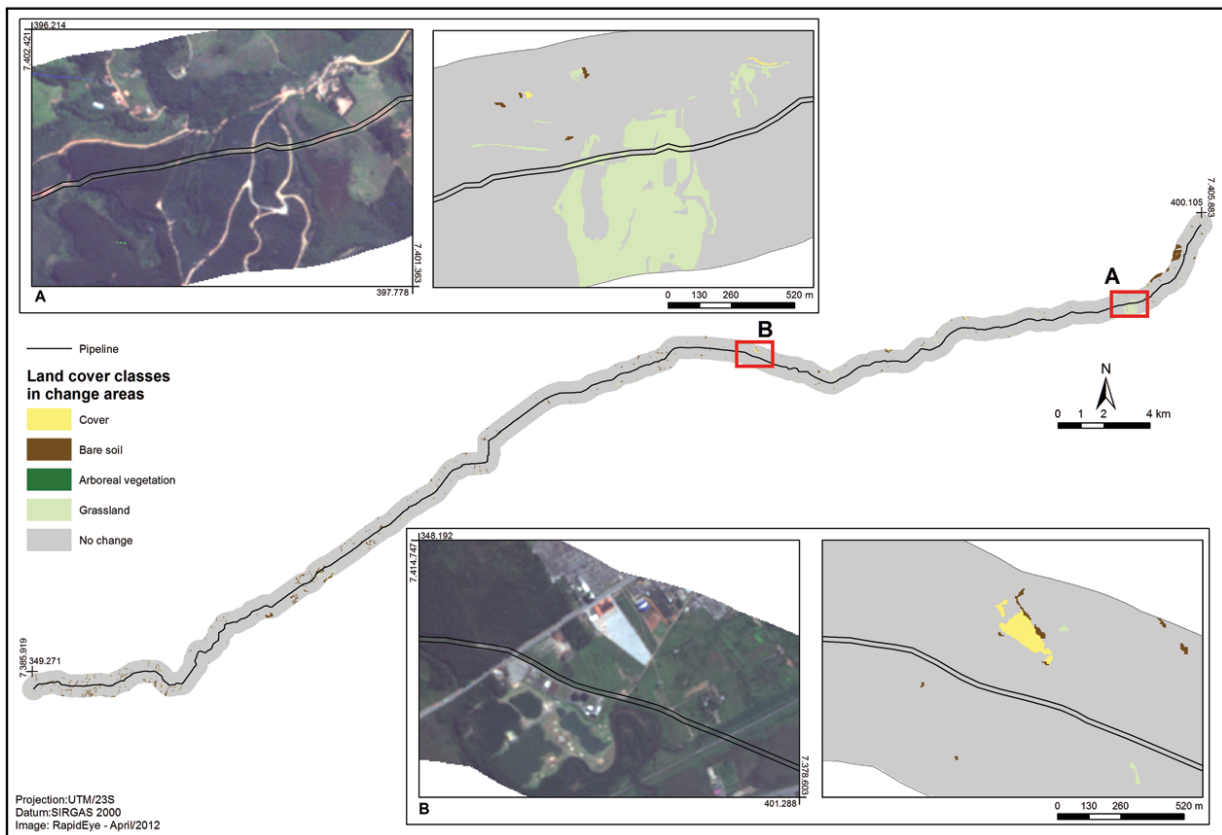


Figure 8 – Change Areas Classification – RapidEye monitoring.

was 76%, denoting a substantial agreement. This good performance of the classification can be verified in the change areas classified as Grassland, Cover, and Bare Soil. The exception was the Arboreal Vegetation class, which showed a low performance in the classification, obtaining a producer's conditional Kappa of 0.17%. This must be considered in order to avoid an incorrect interpretation of the vegetation growth.

The best performing class in the classification was Cover, with an overall of 82% and user's conditional Kappa of 0.74. Analyzing the performance of each class, we observed that the error of including the Arboreal Vegetation class in the Grassland class caused a lower user conditional Kappa (0.59).

The change detection process through the RapidEye images monitoring achieved a high level of agreement. According to the Z test, and considering a 95% confidence interval, the result of the RapidEye monitoring classification was better than random, since the Z value achieved (14.47) is higher than 1.96 (Table 11).

The results allowed identifying and quantifying land cover of the change areas in each monitoring, as shown in Table 10. In the study area with RapidEye monitoring, the classes that showed greater change were Bare Soil (0.9875 km²) and Grass-

lands (0.8787 km²), demonstrating that the changes in the seven-month period were not of great significance when compared to the total area analyzed.

Table 11 – Analysis of the individual Kappa in the RapidEye Monitoring Classification Error Matrix.

Error Matrix	Kappa	Variation	Z Test
RapidEye Classification	0.65	0.0020	14.47

The analysis of the results obtained in the study indicates that the procedure used for pipeline monitoring with RapidEye images was adequate. However, when Ikonos images were used, the results obtained had an overall accuracy of 56% and a Kappa coefficient of 0.34, which indicate a reasonable agreement coefficient (Tables 12 and 13).

The results obtained by the study indicate that for Grasslands the overall accuracy was 100% and the user's conditional Kappa for was 1.0.

The analysis of the Ikonos monitoring indicates that there were few changes in the four-month period analyzed, with small changes being detected in the classes Cover (0.0913 km²) and Grasslands (0.0858 km²).

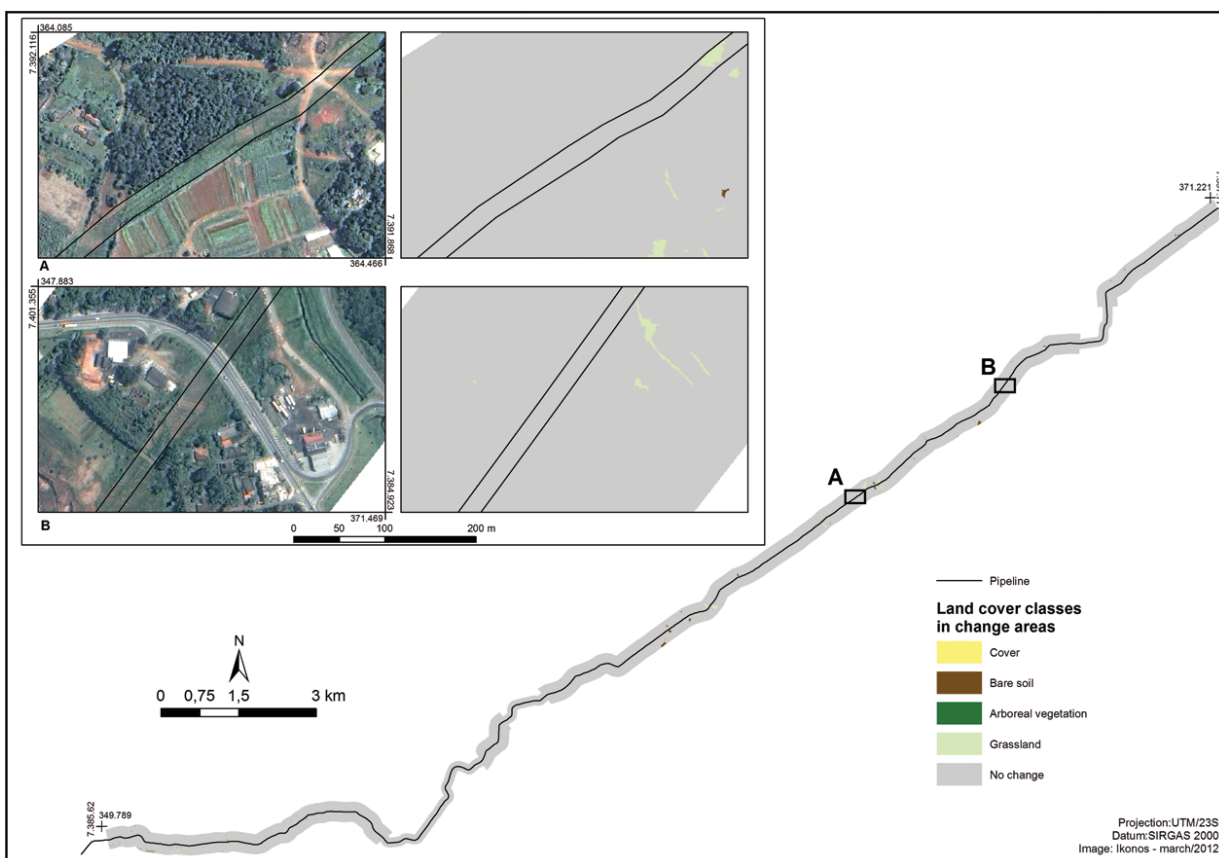


Figure 9 – Change Areas Classification – Ikonos monitoring.

Table 12 – Land Cover Classification Error Matrix – Ikonos image.

Classified Data	Reference Data			
	Cover	Bare Soil	Grassland	Total
Cover	1	1	0	2
Bare Soil	47	34	1	82
Grassland	2	15	49	66
Total	50	50	50	150
Overall Accuracy = 56%				
Kappa = 0.34				

Table 13 – Land Cover Classes Change Areas and Conditional Kappa – Ikonos image.

Land Cover Class	Change Areas (km ²)	User's accuracy (%)	Kappa (user's)	Producer's accuracy (%)	Kappa (producer's)
Cover	0.0016	50	0.25	2	0.01
Bare Soil	0.0258	41	0.12	68	0.29
Grassland	0.0858	74	0.61	98	0.96

According to the Z test, and considering a 95% confidence interval, the classification results of the Ikonos monitoring was better than random, since the Z value achieved (7.37) is higher than 1.96 (Table 14).

Table 14 – Analysis of the individual Kappa in the Ikonos Monitoring Classification Error Matrix.

Error Matrix	Kappa	Variation	Z Test
Ikonos Classification	0.34	0.0021	7.37

The results reached in the RapidEye images were adequate to the monitoring of the influence area of the pipeline allowing the identification of the main types of land cover in larger areas and also the understanding of the diversity into a geographic context.

For Eikvil et al. (2009), the manual classification is tough on high resolution images due the ambiguity among the objects. This fact shows that the resolution is near to the limit for small objects detection, like small buildings. Thus, the automated classification results show a performing nearby to visual interpretation and ratify the applicability of automated classification techniques.

In remote sensing, the scenes can be differently perceived or observed as spatial resolution image change, as a result of two interrelated problems: the scale and the zooming, which lead to different inference of the scene, simply because it could aggregated areal units physically and thus perceptually changed (Powers et al., 2012).

The Ikonos images were better suited for a more detailed monitoring of the pipeline, due to their higher spatial resolution (1 m). Thus, they allow for a better identification of objects in the classification process of change areas. However, it should be noted that the variation in the periods analyzed (September 2011 to April 2012 for RapidEye monitoring and November 2011 to March 2012 for Ikonos) causes differences in the detection of changes, especially in agricultural and reforestation areas, due to management and stages of cultivation.

The analysis of applicability of the pipeline monitoring through land cover changes detection procedures using RapidEye and Ikonos images also considered a quantitative evaluation realized from the estimated monitoring process execution time for each sensor employed (Table 15).

For a pipeline monitoring using optical images, it is necessary to observe the image acquisition characteristics covering the area to be analyzed. This is due to the possibility of the images being captured at different dates, which cause differences in the spectral response of the objects. In the test performed in the Guararema-Mauá/SP pipeline, it was possible to identify such spectral variation, especially in areas with vegetation cover. As we can see in Figure 10, the vegetated areas present a higher spectral response

in the visible bands (Blue, Green, Red and Red Edge) of the image shown on the left of Figure 10 (captured on 04/19/2012), while in the image on the right of Figure 10 (captured on 04/05/2012) the vegetated areas show a lower spectral response. We can also see that this variation generates differences in the values of the Normalized Difference Vegetation Index (NDVI) obtained from different dates. Thus, it is advisable not to make an image mosaic for pipeline monitoring for lengths requiring more than one image to be covered. In this way, the spectral characteristics produced by the different image acquisitions will be respected, facilitating the definition and estimation of attributes and thresholds of the classification process.

CONCLUSIONS

The methodological procedure of change detection and classification was adequate for monitoring the pipeline. Through the analysis of the results, it was possible to consider that in the segments analyzed no anthropic activities were detected that could compromise the pipeline structure or interfere with the maintenance of the service strip.

The accuracy to change detection analysis was 83% and 63% for RapidEye and Ikonos imagery, respectively. The monitoring with RapidEye images showed 3.3% of changes in the area, mostly occurred between Bare Soil and Grassland, which could be explained by the different stages of agricultural activity and reforestation areas. For the monitoring by Ikonos images, the changes of 1.92% of the area, detecting alteration between Cover and Grassland classes, while few changes were detected in built areas.

Regarding the use of object-based classification with high spatial resolution images for pipeline monitoring, we highlight the recommendation of not creating an image mosaic when the images are captured on different dates, once high resolution imagery increased the difficult to find attributes and thresholds to identify similar features into the area.

Levels of correctly classified land cover using the object-based method achieved are considered to be close to the limit of application of this technique with multi-temporal data of high complexity and diversity of space occupation. Higher overall levels could only be achieved by applying the manual edition to some segments that present classification errors. This limitation was also noted in literature, corroborating the need for development of specific rules and integration of user knowledge in the process to increase the precision of the change detection.

This study has presented the problem of aggregation of homogeneous units due to the variation of resolution. Despite using

Table 15 – Pipeline Monitoring Process.

Pipeline Monitoring Stages		Execution Time	
		RapidEye	Ikonos
Pre-processing	Orthorectification	Orthorectified product	4h/scene
	Fusion	—	1h/scene
Elaboration of Thematic Map T1	Supervised Classification	4h/scene	4h/scene
	Visual Edition	1h/km ²	10h/km ²
Change Detection	Segmentation, Change Detection and Classification of Change Areas	6h/scene	8h/scene

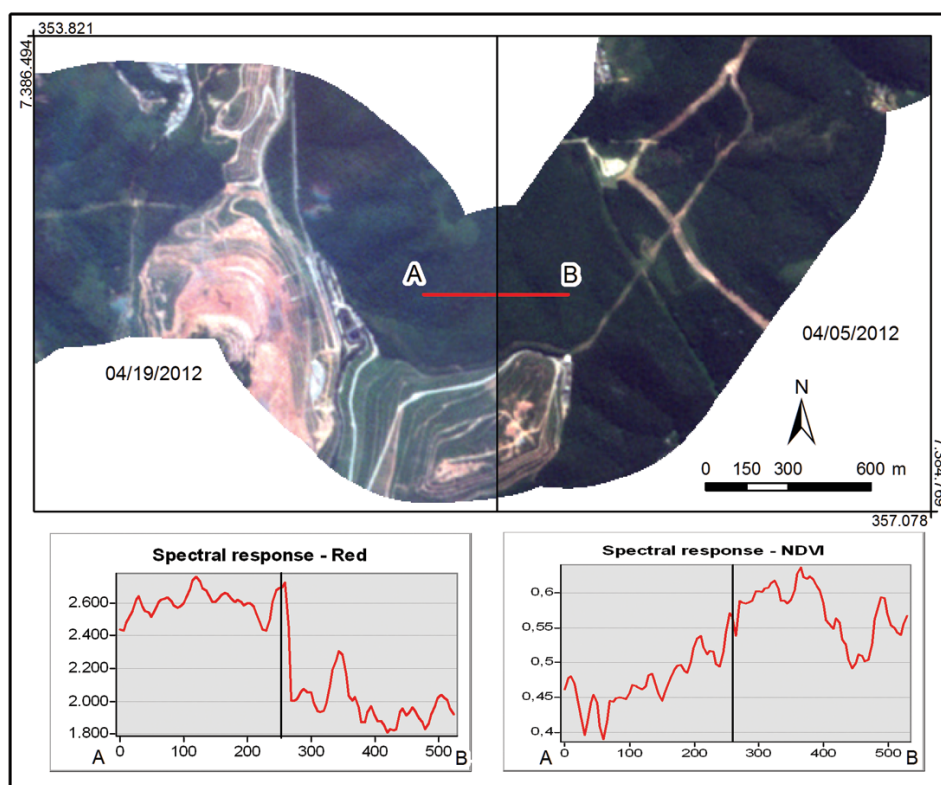


Figure 10 – Spectral response of vegetated areas in the RapidEye images captured in different dates.

high spatial resolution, differences have occurred in the number and size of the segments generated in Ikonos (1 m) and RapidEye (5 m) images. This requires caution in the selection of parameters and attributes to be used for image classification, they must be adequate to the spatial resolution of the specific image used in monitoring procedures.

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