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COMPARATIVE ASSESSMENT BETWEEN PER-PIXEL AND OBJECT-ORIENTED FOR MAPPING LAND COVER AND USE[1]

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ABSTRACT: The traditional per-pixel classification methods consider only spectral information, and may be limited. Object-based classifiers, however, also consider shape and texture, firstly segmenting the image, and then classifying individual objects. Thus, a Geographic Object-Based Image Analysis (GEOBIA) was compared in conjunction with data mining techniques and a traditional per-pixel method. A cut of Landsat-8, bands 2 to 7, orbit/point 223/77, located between the municipalities of Cascavel, Corbélia, Cafelândia and Tupãssi, in the west part of the state of Paraná, from 12/18/2013 was used. In the GEOBIA approach was realized image segmentation, spatial and spectral attribute extraction, and classification using the decision tree supervised algorithm, J48. For the per-pixel method, we used the supervised Maximum Likelihood Classifier. Both approaches presented equivalent results, with Kappa Index of 0.75 and Global Accuracy (GA) of 78.97% for the approach by GEOBIA and Kappa Index of 0.72 and GA of 77.44% for the per-pixel classification. The classification by GEOBIA showed better accuracy for the soil, forest and soybean classes, and did not show the splash aspect, which visually improves the classification result.

KEYWORDS: GeoDMA, data mining, decision tree.

INTRODUCTION

Information about the land cover and use of a region are fundamental in studies such as mapping of deforestation and forest degradation, evaluation of the erosion risk, identification and estimation of areas with agricultural crops and analysis of urban expansion (Adami et al., 2012; Vieira et al., 2012; Maleky & Razavi, 2013; Souza et al., 2013a; Panagos et al., 2014). Based on this problem, data from orbital remote sensing represent a reliable tool for mapping the dynamics of land cover and use earth's surface on a large scale in different spectral, spatial and temporal resolutions (Bradley et al., 2007; Bioucas-Dias et al., 2013).

This range of sensors and resolutions from orbital remote sensing produces a huge amount of data. For example, optical satellites from the US, China, Brazil, India and Europe produced, in 2013, a data volume equivalent to that produced in 10 years by the Landsat-7 satellite (Körting et al., 2013). This shows a disparity between the ability to produce and to store this massive amount of data and the efficiency of conventional methods in analyzing them quickly and accurately (Wu et al., 2014).

In this context, Knowledge Discovery in Database (KDD) offers tools that can recognize and extract useful patterns or knowledge from extensive data sets (Fayyad et al., 1996; Liao et al., 2012). The KDD process, according to Fayyad et al. (1996), aims to identify in databases valid, potentially useful and easily to understand patterns. It consists of five stages (Figure 1), which are: 1) Selection of data; 2) Preprocessing; 3) Formatting/Transformation; 4) Data Mining; and 5) Interpretation/Evaluation.

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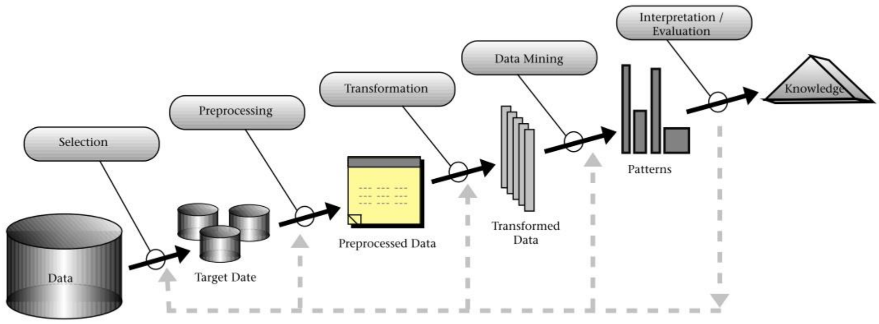

FIGURE 1. Overview of the steps of the KDD process (Fayyad et al., 1996).

The Data Mining (DM), one of the KDD stages, has machine-learning algorithms, such as the decision tree, that facilitate the process of extracting and recognizing patterns. Through these results, new knowledge is provided, which can be applied in the original data set, or in new data sets, aiming at solutions of problems like category classification (Cracknell & Reading, 2014).

Johann et al. (2013) used DM techniques in temporal NDVI profiles to identify spectrally homogeneous soybean areas. Delgado et al. (2012) carried out the spectral classification of sugarcane by decision tree and obtained good results. Nonato & Oliveira (2013) achieved good performances (accuracy rate of approximately 97% of the cases and a lower Kappa Index of 0.86) using DM techniques in Landsat-5 images to identify areas with sugarcane in the State of São Paulo.

Much of the analysis of the 1980s and 1990s of satellite images were based on per-pixel statistical algorithms. One of the algorithms most used for classification based on pixel analysis is the Maxver (Maximum Likelihood) and has been showing reliable results in the mapping of the soil use with satellite images (Santos et al., 2011; Sanhouse-Garcia et al., 2016).

These techniques represent the knowledge about patterns of soil use, considering a limited number of spectral parameters of the pixels, such as average and standard deviation (Blaschke, 2010). One of the major limitations of these algorithms is that the targets may have similar spectral patterns, such as regions with vegetation (agricultural areas and forest), resulting in confusing interpretations (Myint et al., 2011).

The Geographic Object-Based Image Analysis (GEOBIA) has shown a more efficient approach when compared to classifiers based on per-pixel classification (Chen et al., 2012). The GEOBIA can consider the classification of images based on the topological information (neighborhood, context) and geometric (shape, size) of the objects.

The GeoDMA (Geographic Data Mining Analyst) application, proposed by Körting et al. (2013), is used by GEOBIA for image classification, presenting the advantages of integrating image analysis tools and DM techniques into a single free and open source program. However, in most of the studies, the GeoDMA was applied in high spatial resolution images for classification of Urban Areas or extraction of patterns in deforestation structures (Maciel et al., 2012; Thompso et al., 2013; Körting et al., 2014).

The aim of this study was to compare two supervised classification methodologies to characterize the land cover and use in medium resolution images (Landsat-8), one using GEOBIA and DM techniques for obtaining the best parameters of the classification and another using the traditional per-pixel classification, through the Maxver classifier.

MATERIAL AND METHODS

The methodology adopted in this study follows the flowchart shown in Figure 2. The processes carried out in the selection of data, preprocessing of the images and evaluation of the classification accuracy were common to both classification methodologies. These approaches aim to characterize the land cover and use in seven classes. Soybean, Corn and Pasture represent the use related to agriculture; Native Forest represent the land cover, Reforestation represent the vegetation, besides the classes of Urban Area and exposed Soil.

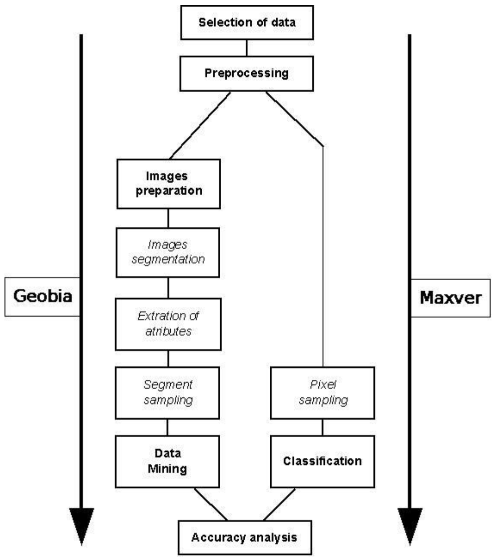

FIGURE 2. Flowchart of operations used to classify images using Geobia and Maxver.

Data Selection

An image of the Landsat-8 satellite, bands 2 to 7 of the Operational Land Imager (OLI) sensor was selected. The low cloud incidence (less than 5%) and the period in which the main annual agricultural crops of the region (soybean and corn) are close to their maximum vegetative development (Souza et al., 2015), were considered as criteria for the choice of the image of 12/18/2013 that belongs to the orbit/point 223/77. The bands used comprise the spectral regions of the visible, blue (band 2), green (band 3) and red (band 4); the NIR - Near Infrared (band 5); and SWIR - Short-wave Infrared 1 and 2 (bands 6 and 7, respectively). These bands have spatial resolution of 30 meters, 16-day temporal radiometric of 16-bit and are comprised between the wavelengths of 0.45 to 2.29 micrometers.

Image Preprocessing

In the preprocessing stage, the analyzes were subdivided into: atmospheric correction and cut of the image bands to the area of interest, making the false-color composition R5G6B4 to better identify the targets for training and making the image cubes with the OLI sensor strip cuts (band 2 to band 7) of the Landsat-8 satellite. The QGIS software was used to prepare the image used in the two comparative classification methodologies.

The correction for reflectance values was carried out using the QGIS "Geosud Reflectance TOA" plug-in, generating bands in 16-bit integer format, reducing the size of the images and improving the processing time in the software.

The cut covers an area of approximately 455.5 km², covering the municipalities of Cascavel, Corbélia, Cafelândia and Tupãssi (Figure 3), located in the western region of Paraná. This region is characterized by extensive agricultural activity, and consequently of great economic interest.

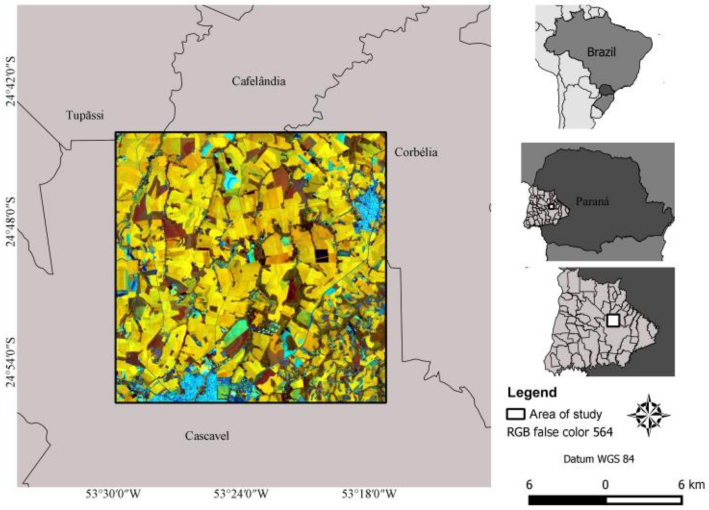

FIGURE 3. Location of the study area.

GEOBIA

The processes involving the GEOBIA approach were carried out using TerraView software. The image segmentation, attribute extraction and sampling for training were the stages performed specifically through the GeoDMA plug-in (Körting et al., 2013) of the software.

Preparation of images

The previously cut and corrected images were imported into the TerraView 4.2.2 software in a Microsoft Database (MDB), using the ACCESS, Database Management System (DBMS).

Image Segmentation

Through the GeoDMA, the segmentation process was carried out on the cube of the analyzed image. In this process, we used the algorithm that is based on the growing region, developed by Bins et al. (1996). The euclidean distance and the minimum area were used as parameters, with values of 30 and 20 respectively. These values returned the best image segmentation processes after carrying out several tests.

Extraction of attributes

After the segmentation process, the spectral and spatial attributes of the images were extracted (Table 1), using the GeoDMA tool, adapted from the methodology of Körting et al. (2013). According to Körting et al. (2013), the attributes based on segmentation include spatial and spectral metrics for describing each region (objects-based) stored in the database. Spatial attributes are related to all values of a region, including metrics for maximum and minimum values of pixels or texture properties, while spatial attributes measure the shapes of objects-based, such as length and width.

For the object-based approach, five variables referring to the standard deviations of the spectral values of the reflectance of each band in each object-based were taken, which did not influence the result of the classification.

TABLE 1. Attributes extracted from the segments by the GeoDMA tool.

Attribute Type	Name	Range	Unit
Spectral	Amplitude	≥ 0	pixels
	Dissimilarity	≥ 0	-
	Entropy	≥ 0	-
	Homogeneity	≥ 0	-
	Average	≥ 0	pixels
	Mode	≥ 0	pixels
	Standard deviation	≥ 0	pixels
Spatial	Angle	$[0, \pi]$	rad
	Area	≥ 0	$pixels^2$
	Box area	≥ 0	$pixels^2$
	Circle	[0.1)	pixels
	Elliptical adjustment	[0.1]	-
	Fractal Dimension	[1.2]	-
	Rotation Radius	≥ 0	pixels
	Length	≥ 0	pixels
	Perimeter	≥ 0	pixels
	Perimeter-area Ratio	≥ 0	$pixels^{-1}$
	Rectangular adjustment	[0,1)	-
	Width	[0,1)	pixels

Sampling for Training

For the classification process, it is necessary to obtain training samples, which consists in the selection of pixels or homogeneous regions that best represent each one of the classes. Based on these regions, the algorithms extrapolate to the rest of the image, thus carrying out the classification process.

The selection of the training samples was carried out on a false-color image R5G6B4 image, which visually accentuated the difference among the soybean, corn, forest and reforestation classes, which in other compositions may be similar. In this composition, the soybean presents yellow/orange tint and the corn presents brown/red tint (Figure 3), as reported by Mercante et al., (2012) when classifying soybeans in the Cascavel-PR region using the Landsat-5/TM composition R4G5B3 (equivalent to the false-color composition of R5G6B4 Landsat-8/OLI) of December 2008 and Souza et al. (2013b) when classifying four classes, including soybean and corn, in a municipality near Cascavel-PR. The forest and reforestation are brown in color, with a difference in texture. The reforestation has a more regular texture than the forest, because it is planted. The exposed soil and the urban area have cyan color and can be differentiated visually by the form, because in the urban Area it is possible to identify constructions. In the classification oriented by object-based, a sampling using the GeoDMA plug-in was carried out, considering the number of 17 samples (segments) for the reforestation class, 21 for forest, 25 for corn, 19 for soil, 17 for urban area and 21 for soybean.

Data Mining

The supervised algorithm J48 was used to classify the objects-based in the WEKA (Waikato Environment for Knowledge Analysis) software (Hall et al., 2009). The parameters used for generation and validation of the decision tree were cross-validation, with folds of 10. The choice of WEKA software to the GeoDMA software was due to the presence of a greater number of evaluation methods of the generated trees.

After obtaining the decision tree containing the rules that were used for the classification, the next step was its application to all objects-based. The classification based on segmentation was carried out with the application of the decision tree (generated by WEKA software) through the GeoDMA software to the other segments.

Per-pixel Approach

Considering the per-pixel classification, the sampling and the classification process were carried out through the SCP plug-in, present in the QGIS software. The Maxver algorithm was used in this stage.

Training Sampling

The training sampling consists of obtaining pixels belonging to each class. A total of 434 samples (pixels) were obtained for the reforestation class, 1321 for forest, 1608 for corn, 870 for soil, 1465 for urban area and 3938 for soybean. All selected pixels did not contain spectral mixing; only the characteristic pixels of each class were selected.

Classification

In the per-pixel classification, the Maxver classifier was used. All stages, from sample selection to algorithm application, were performed in the QGIS software, through the SCP plug-in, and several tests were carried out to find the parameters that would result in better classification.

Accuracy Analysis

To evaluate the accuracy of the classifications, the error matrixes were drawn from the random distribution of points (65 points per class). Through visual inspection of high-resolution images of Google Earth, and in some cases, in the false-color image R5G6B4 , allied to the interpreter's experience, it was verified which class each point belongs to. The process of distribution and visual inspection of the points was carried out through the QGIS software.

The Kappa Index, obtained by the error matrix, was used to evaluate the classification accuracy and the decision trees. The Global Accuracy (GA) was also used to evaluate the performance of the decision trees (Cohen, 1960; Congalton, 1991).

Producer Accuracy (PA) was also determined, which refers to the probability that a given pixel is correctly classified and the User's Accuracy (UA) indicating the probability that a pixel classified in the image represents that category in the field (Congalton, 1991). According to Johann et al. (2012), the producer error occurs with the inclusion of an object in a class to which it does not belong and the user error when an object is excluded from the class to which it belongs.

The Z test was used to test the statistical significance of the difference between Kappa indices. The significance of the difference between different Kappa coefficients can be evaluated by the deviation of the normal curve (Gleriani et al., 2005; Amaral et al., 2009; Cohenca & Carvalho, 2015). The null hypothesis posed by the Z test is that the different classifications have no significant difference (at 5% significance) as to their accuracy, versus the alternative hypothesis that there is a difference.

RESULTS AND DISCUSSION

The results found for the classifications were subdivided into objects-based classification and per-pixel classification.

Objects-based Classification

After the data mining stage, the initial database containing 69 spatial and spectral attributes extracted from the objects-based (segments) and the six bands of the Landsat-8 image was reduced. Of all the attributes considered for classification by GEOBIA, the decision rules considered relevant only three bands (2, 4 and 7) and two attributes of the spectral and spatial combinations (rp) of objects-based (Figure 4). The attributes considered are the mode of the rp values of bands 2 and 7 (rp_mode _B2 and rp_ mode_B7), and rp entropy of band 4 (rp_Entropy_B4).

The main attribute considered refers to the mode value of the combination of the spectral and spatial attributes of band 2 (blue), which has a lower degree of entropy. The attribute rp_Entropy_B4, responsible for the differentiation between the soil and urban area targets, represents the gray level disorder (Castejon et al., 2015), where high values of this attribute represent that the image has no uniform texture. The classes in which there was greater difficulty of differentiation were forest and corn, needing more nodes of the tree to differentiate them. Possibly this occurs due to the spectral similarity of the two classes.

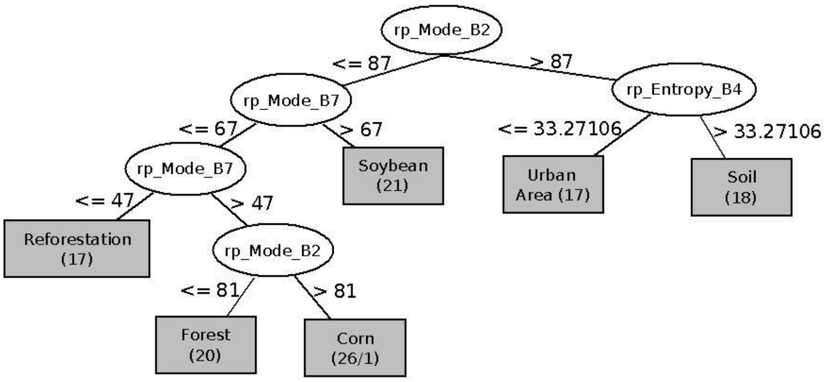

FIGURE 4. The decision tree, considering object-based classification.

The decision tree for objects-based showed, through the cross-validation process, a Kappa Index of 0.94 and GA of 94.96%, incorrectly classifying only one instance of the forest class as corn class (Figure 4). In the object-based classification (Figure 5), the predominance of the soybean crop is observed, occupying 65.85% of the region.

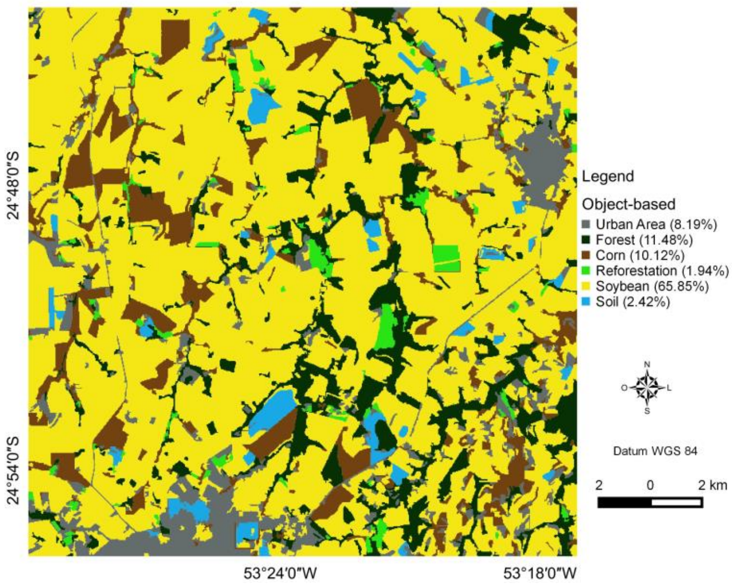

FIGURE 5. Classification considering the object-based approach

Per-pixel Classification

Considering the classification of the per-pixel approach (Figure 6), using the Maxver classifier, soybean cultivation predominated in the area (63.92%), similarly to the object-based classification. This high value is justified, because the image is from December, belonging to the period of the main agricultural crop of the state (Souza et al., 2015; Zhong et al., 2016).

The urban perimeters of the municipalities of Cascavel (in the south) and Corbélia (in the northeast) can be seen in both approaches (Figures 5 and 6). The forest class was classified in higher percentage for the per-pixel classification (Figure 6), compared to the classification by GEOBIA (Figure 5). Corn, reforestation, urban area and soybean were the classes that had larger areas in the classification by GEOBIA. Forest and soil had larger areas in the per-pixel classification

The splash aspect characterized by the presence of isolated pixels in the image, making the visual aspect of the per-pixel classification areas less homogeneous when compared to the object-based classification (Figure 5), as observed by Hao et al. (2015). According to Blaschke et al. (2014), the pixel-based classification is justified only when the objects of interest are smaller or similar to the spatial resolution.

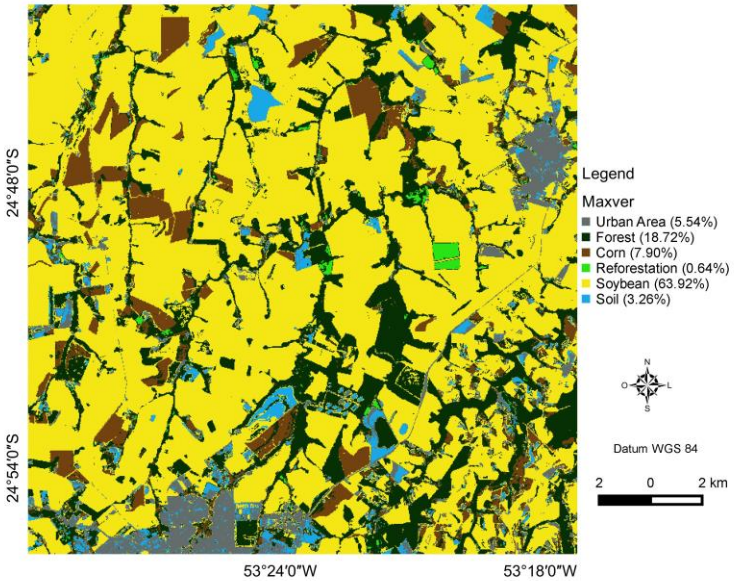

FIGURE 6. Classification considering the per-pixel approach

Accuracy

The confusion matrix (Table 2) was generated after crossing the 390 sampling points with the mapping obtained with GEOBIA classification. The Kappa Index found for this classification process was 0.75 and GA of 78.97%. The main source of error occurred in the classification of 25 urban area s as a soil category. The pattern found in this study is similar to that found by Zhang et al. (2014), which reports that the urban area classification presents few pure pixels due to the spectral mixture that occurs in these areas with regions of anthropic activity and vegetation in the same pixel, with spectral characteristics similar to the exposed soil, resulting in high confusion between these classes.

The corn and reforestation classes were erroneously classified as forest at 20 and 11 points respectively. Messias (2012) found similar results, which classified Landsat-5/TM images, obtaining great confusion between agricultural crops and the forest class.

TABLE 2. Error matrix for object-based classification.

		Reference						
		Urban Area	Forest	Corn	Reforestation	Soybean	Soil	TOTAL
Classification	Urban Area	40	0	0	0	0	25	65
	Forest	1	60	1	2	1	0	65
	Corn	0	20	42	2	1	0	65
	Reforestation	1	12	0	51	0	1	65
	Soybean	0	1	3	0	59	2	65
	Soil	3	0	4	0	2	56	65
	TOTAL	45	93	50	55	63	84	390

In the error distribution matrix, considering the per-pixel classification (Table 3), the soil class presented the greatest confusion, being classified in only 41 of the 65 randomly selected points. For this approach, a Kappa index value of 0.73 and GA of 77.44% were found. The Z test, among the classifications, returned a Z statistic of 0.52 and a p-value of 0.60, at 5% significance. Therefore, there was no significant difference between the GEOBIA and per-pixel approaches.

TABLE 3. Error matrix for the per-pixel classification.

		Reference						
		Urban Area	Forest	Corn	Reforestation	Soybean	Soil	TOTAL
Classification	Urban Area	42	7	1	0	0	15	65
	Forest	0	54	3	0	7	1	65
	Corn	0	6	55	0	0	4	65
	Reforestation	6	7	0	52	0	0	65
	Soybean	1	4	1	0	58	1	65
	Soil	8	6	3	0	7	41	65
	TOTAL	57	84	63	52	72	62	390

The soybean class obtained the highest PA (93.65%) in the GEOBIA classification (Table 4), not classifying 6.35% of the real area of the crop. The reforestation obtained the highest UA (92.31%), thus 7.69% of the area classified as reforestation is not reforestation. The urban area class had the lowest UA accuracy (61.54%), indicating a greater inclusion error (38.46%) among the classes of this approach. The largest error of omission (33.33%) occurred in the soil class (PA of 66.67%).

The reforestation class obtained 100% of PA for the per-pixel approach (Table 4), indicating that there was no omission error. The soybean class obtained the highest UA value (89.23%), indicating that there was an inclusion error of 10.77%, classifying other classes in this class. The largest error of omission (35.71%) occurred in the forest class (PA of 64.29%). The soil class obtained UA (63.08%), leading to the largest inclusion error (36.92%).

TABLE 4. PA and UA for GEOBIA and per-pixel classifications.

	GEOBIA		Per- pixel	
	PA (%)	UA (%)	PA (%)	UA (%)
Urban Area	88.89	61.54	73.68	64.62
Forest	64.52	92.31	64.29	83.08
Corn	84.00	64.62	87.30	84.62
Reforestation	92.73	78.46	100.00	80.00
Soybean	93.65	90.77	80.56	89.23
Soil	66.67	86.15	66.13	63.08

Souza et al. (2013b) in Landsat-5 classification, using the Maxver classifier, considering the classes of soybean, corn, forest and soil, obtained the highest PA for the soybean and forest classes and the highest UA for the classes of corn and soil.

The classes of forest, soybean and soil had better accuracy for the GEOBIA approach. In the per- pixel classification, the best accuracy was for the corn and reforestation classes. The urban area class obtained higher PA for the GEOBIA approach and a slightly higher value for UA in the per-pixel approach.

TABLE 5. Z test and p-value for comparison between GEOBIA and per-pixel classifications.

	Estatística Z	P-value
Urban Area	-0.36	0.716
Forest	1.60	0.109
Corn	-2.62	0.009*
Reforestation	-0.22	0.829
Soybean	0.29	0.770
Soil	3.02	0.002*

Considering the application of the Z test, at 5% significance, for each class of use (Table 5), the per-pixel approach obtained better classification for the corn class. The soil class, on the other hand, was more accurately differentiated by the GEOBIA approach. The other classes did not differ statistically in both approaches, considering the Z test at 5% significance.

The use of the segmentation process, together with the classification of the land cover and use by the decision tree for the medium resolution satellite images, showed results equivalent to the traditional approaches for the study area. Although the GEOBIA considers more information for classification, for some studies, such as Sarmiento et al. (2014) and Duro et al. (2012), the spectral attributes were determinant in the mapping of land use.

CONCLUSIONS

The results indicate that the process of classification of land cover and use by the GEOBIA method present efficiency equivalent to the per-pixel analysis. The classification by GEOBIA showed better accuracy for the Soil, Forest and Soybean classes, and the per-pixel approach presented better accuracy for the Corn and Reforestation classes. In the GEOBIA classification, the splash aspect was not found, which visually improves the classification result. The classification using Maxver required less processing time.

New approaches in future studies, considering different dates, sensors and algorithms are necessary to consolidate the use of the tool.

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