LAND COVER MAPPING USING OBJECT-BASED IMAGE ANALYSIS TO A MONITORING OF A PIPELINE

M. V. Ferreira[a]*, M. L. Marques[a], P. S. Riedel[a], S. P. Polizel[a], C. M. Bentz[b]

[a] UNESP, Instituto de Geocências e Cências Exatas, Rio Claro, São Paulo, Brazil - mateusvidotti@yahoo.com.br
[b] CENPES/PETROBRAS, Rio de Janeiro, Brazil - cris@petrobras.com.br

KEY WORDS: GeoEye; pipeline monitoring; image classification; eCognition; land use/cover.

ABSTRACT:

The diagnosis of land use/cover and its implication for the safety of pipelines was used to classify, by way of object-based analysis, for the purpose of mapping land use and land cover with a high spatial resolution GeoEye image, for monitoring a sector of industry pipelines in Rio de Janeiro-Belo Horizonte, located in the cities of Duque de Caxias and Nova Iguaçu - RJ. The algorithm for multiresolution segmentation was used to define objects in the image and for classification of land use/cover, according to the hierarchical network proposal, which was done using the algorithm Classification through the fuzzy membership functions. The results archived 81.33% overall and 0.79 Kappa coefficient. It is considered that the result of automatic classification by the o object-based method, has achieved values of accuracy close to the limit for the application of this technique for high resolution image data, with great complexity and diversity of space occupation. Thus, to achieve a better overall classification the manual editing of some segments that show misclassification must be done.

1. INTRODUCTION

The classification by object-based analysis was employed in the mapping of land use and cover with high spatial resolution images for the monitoring of a sector of industry pipelines in Rio de Janeiro- Belo Horizonte, located in the cities of Duque de Caxias and Nova Iguaçu, located in Rio de Janeiro state, Brazil.

It is considered that the diagnosis of land use and cover and its implications for the safety of pipelines is an essential factor to guide management decisions of the tracks.

The monitoring of the tracks is composed of sectors of internal and external duct inspections. The internal inspection sector is responsible for control of variables such as: pressure, flow, temperature, density and volume, during the process of transferring products. The external inspection sector is composed for aerial and ground observations that run the length of the right of way and adjacent areas, to check irregularities that may cause an increase of risks, such as erosion, mass movements, collapse, vehicle traffic and/or heavy equipment in the lane, growth of vegetation; drainage system failure in the lane; Fires; Lane occupation because of third parties working nearby; outcrop of the duct, crossing streams and road crossings, railways , power grids and the traffic conditions on access roads (ZIRNIG et al. 2002; HAUSAMANN et al., 2005).

The application of remote sensing techniques is essential in the diagnosis and monitoring of space occupation process. The images may be considering an important source of information about what occurs on the earth's surface and are essential to understand the land use and land cover, helping to identify elements that may constitute a risk to the pipeline (DUTTA and ROPER, 2005).

The complexity of the elements presented on the surface becomes a problem for digital classification of land use and land cover from high resolution images, since there is spectral mixture of objects in the image. Thus, the of object- based image analysis to define the objects through association of the spectral assign with spatial and context attributes, generating segments with homogeneous spectral, geometric, texture and position of elements in the image (ENCARNAÇÃO, 2004).

In classification of land use and land cover, through method of object-based, the structuring of classes requires the establishment of a hierarchical network based on semantics and physical characteristics of objects that compose a particular class. The semantic network represents a logical structure that relates objects or classes from their meaning and relationships (ANTUNES, 2003). According to Hofmann (2001), classes can be structured into three types of hierarchical networks: hierarchy with hereditary; hierarchy of groups and structured groups.

* Universidade Estadual Paulista – UNESP/Rio Claro
Caixa Postal 178 - 13506-900 – Rio Claro - SP, Brasil

2. METHODOLOGY

During the course of the study, a hierarchical network was created based on the physical characteristics of objects that make up the classes of interest in the mapping of land use/cover, using the GeoEye image (November/2009) acquired through band fusion and through spatial resolution of 0.5 m creating a hierarchy of groups. The Figure 1 shows the hierarchical network used and the Table 1 shows the interpretation key for the land use and land cover classes.

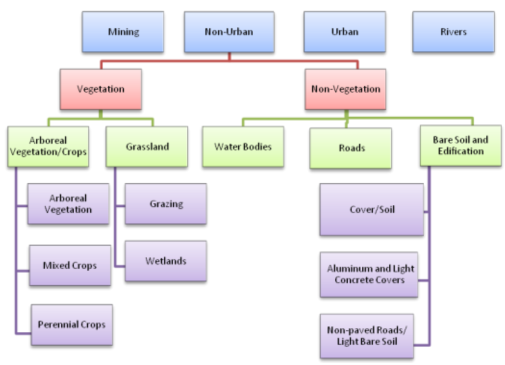


Figure 1. Hierarchical network.

To organize the hierarchical network, a generalized map of land use and land cover was developed, composed of the following classes Mining, Urban, Non-urban and Rivers (Figure 2). This thematic map was utilized as a reference in the creation of masks for image cropping, producing images in accord with the classes of the thematic map. At this stage, we chose to detail the classification of areas included in the non-urban class, because it occupies approximately 78% of the study area, with approximately 16.32 km^2 and is composed of natural vegetation, crops land, bare soil, buildings and access roads.

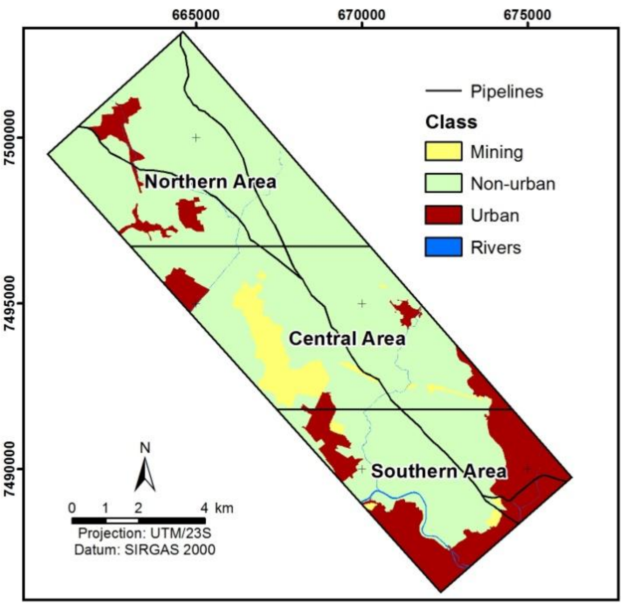


Figure 2. Generalized map of land use and land cover.

At the start of the image segmentation, it became necessary to divide the study area into three subareas: the Northern Area, the Central Area and the Southern Area, because of the limitations of the eCognition program to generate the number of segments required to target the entire area. Thus, the classification had to begin in the Southern Area and an algorithm for multiresolution segmentation was used. Segmentation tests were performed using a combination of different parameter values, noting that the parameter scale promoted greater interference in the formation of the segment. The parameters used in level I were 20 Scale, shape 0.2 and 0.5 Compactness, generating 559,161 segments. In Level II only the parameter was changed to 50 (90,000 segments). In Level III, with a parameter value range of 100 (24,010 segments), the segments did not outline the objects belonging to the vegetation and non-vegetation classes, which integrate the higher level of the hierarchical network. Thus, Level III was not used in the classification process.

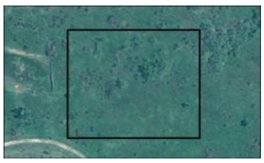
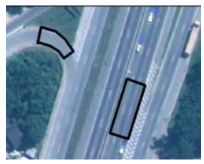
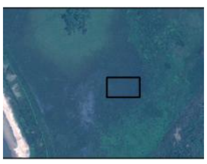
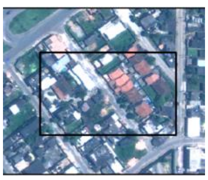
Classes	Description	GeoEye Image (visible composite – RGB 3,2,1)	Classes	Description	GeoEye Image (visible composite – RGB 3,2,1)
Arboreal Vegetation	Medium to tall trees found in forest and urban areas		**Covers/Soils**	Bright ceramic roofs and areas of bare soil with medium color tone	
Grazing	Areas composed of grasses and small shrubs		**Roads**	Highways and streets paved with asphalt	
Mixed Crops	Areas with many types of crops		**Non-paved Roads/Light Bare Soil**	Areas of unbuilt and no vegetation cover, with a light color tone and non-paved roads	
Wetlands	Areas temporarily covered by water		**Mining**	Mining areas	
Urban	Urban areas		**Rivers**	Rivers courses	
Aluminum and Light Concrete Covers	Light tone concrete or aluminum roofs and paved areas		**Water Bodies**	Water courses, lakes and reservoirs	

Table 1 – Interpretation key for the land use and land cover classes.

Level II was determined to be the most appropriate for implementation of the proposed hierarchical network and the acquisition of training samples for classes of use and cover. Starting from the analysis of histograms of attributes generated by the Sample Editor and through the specific responses of the classes, the most suitable attributes for separation of classes in each level of the hierarchy were defined. The attributes and thresholds defined the fuzzy membership functions were employed by way of the algorithm Classification in the image classification process. The Table 2 shows the membership fuzzy function used to classify each class.

Class	Attribute	Fuzzy membership	
Vegetation	Max. diference espectral		1.385 - 2.402
	Mean Band R		37.797 - 172.049
	NDVI		0.6078 - 0.8901
Non-Vegetation	Max. diference espectral		0.614 - 1.846
	Mean Band R		1 - 746.55
	NDVI		0.3059 - 0.8234
Arboreal Vegetation\Crops	Texture GLCM Homogeneity Mean das Bands		0.141 - 0.282
	Texture GLCM Homogeneity Band B		0.297- 0.494
	Texture GLCM Homogeneity Band G		0.17 - 0.33
	Texture GLCM Homogeneity Band R		0.062 - 0.156
	Texture GLCM Homogeneity Band NIR		0.231 - 0.415
	Stand. deviation Band NIR		37.50 - 131.81
Bare Soil and Edification	Texture GLCM Homogeneity Mean das Bands		0.019- 0.447
	Mean Band NIR		173.54 - 1473. 28
Roads	Brightness		401.32 - 520.44
	IHS - Intensity		0.2184 - 0.2874
	Length/Width		4.045 - 29.641
	Mean Band B		344.26 - 417.64
	Mean Band NIR		566.70 - 759.17
Grassland	Texture GLCM Homogeneity Mean das Bands		0.15 - 0.45
	Texture GLCM Homogeneity Band B		0.32 - 0.68
	Texture GLCM Homogeneity Band G		0.17 - 0.51
	Texture GLCM Homogeneity Band R		0.069 - 0.267
	Texture GLCM Homogeneity Band NIR		0.381 - 0.607
	Stand. deviation Band NIR		14.82 - 90.99
Water Bodies	Area		1 - 8098.7
	Brightness		144.32 - 243.57
	IHS - Intensity		0.076 - 0.151
	Length/Width		1 - 15.617
	Mean Band B		174.44 - 241.15
	Mean Band NIR		201.63 - 329.91
Grazing	Brightness		259.17 - 507.4
	IHS - Intensity		0.105 - 0.192
	Mean Band NIR		508.13 - 1355.32
Mixed Crops	IHS - Saturation		0.53 - 0.74
	Max. difference spectral		1.44 - 2.09
	NDVI		0.62 - 0.84
	Rate Band G/Sum Band (B, R, NIR)		0.239 - 0.321
Aluminium and Light Concrete Covers	Brightness		727.86 - 926.43
	Mean Band B		514.92 - 768.56
	Mean Band G		746.008 - 1070.39
	Mean Band R		434.31 - 596.26
Covers/Soils	Brightness		128. 8 - 476.36
	Mean Band B		165,67 - 345,88
	Mean Band G		150,86 - 487,73
	Mean Band R		22,35 - 278,09
Wetlands	Brightness		199,57 - 368,35
	IHS - Intensity		0,095 - 0,151
	Mean Band NIR		351,678 - 877,921
Arboreal Vegetation	IHS - Saturation		0.55 - 0.85
	Max. difference spectral		1.730 - 2.728
	NDVI		0.696 - 0.934
	Rate Band G/Sum Band (B, R, NIR)		0.158 - 0.296

Table 2 - Membership fuzzy function used to classify each class.

The assessment of the classified thematic map was done using error matrix and Kappa coefficient. The samples were collected by visual interpretation of the image. The sampler method was stratified random (CONGALTON and GREEN, 1999), being 50 acquired samples per class.

3. RESULTS

We observed that the process of classification was done allowing for the identification of limitations in the object-based approach in implementing the proposed hierarchical network. The first limitation identified in the production of map use and

* Universidade Estadual Paulista – UNESP/Rio Claro
Caixa Postal 178 - 13506-900 – Rio Claro - SP, Brasil

land cover is from the diversity of classes, which are composed of differently sized objects. Therefore, it is necessary to perform the classification in a more detailed level of segmentation, so that objects that take up a smaller area can be individualized. However, more detailed segmentation excessively subdivided the objects that occupy larger areas. Figure 3 shows the number of segments generated in different levels of segmentation. In Figure 3(A) we observed that grazing areas were outlined by only one segment in Level III and Level I, the more detailed, are subdivided into several segments. In Figure 3 (B) we can also observe the outline of ceramic tile object, which is considered to be the object with the smallest area in the proposed classification. In Level II of segmentation, this object is defined by a segment while at Level I is subdivided into various segments depending on the variation of shading on the roof.
The Error matrix and the statistical results of classification are observed in Tables 3 and 4. In the Figure 4 shows the resulting map of land cover and land use classification of the study area.

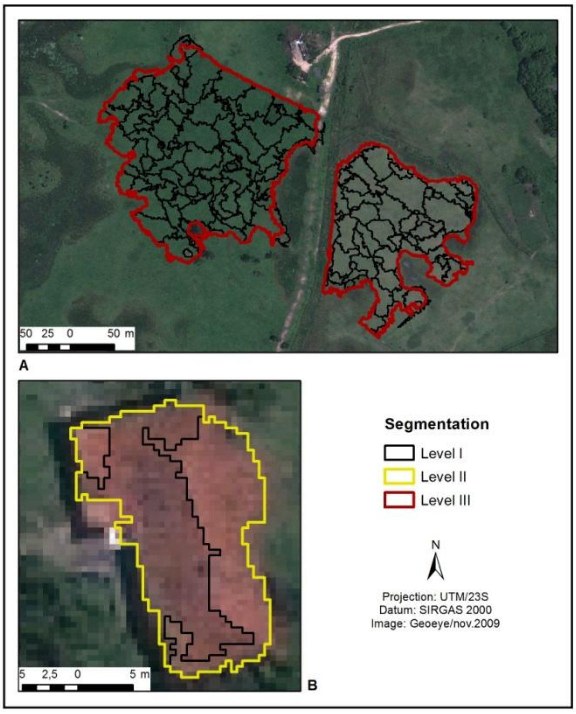


Figure 3. Comparison of segmentation in levels I, II and III. (A) grazing area, (B) ceramic roof tile.

Land Use and Land Cover Classes		**Reference Data**									
		Grazing	Water Bodies	Mixed Crops	Aluminum and Light Concrete Covers	Covers/Soils	Wetlands	Arboreal Vegetation	Non-paved Roads/Light Bare Soil	Roads	**Total**
Classified Data	Grazing	47	0	0	0	0	15	1	0	0	63
	Water Bodies	0	25	0	0	1	0	0	0	0	26
	Mixed Crops	1	4	46	0	1	4	0	0	0	56
	Aluminum and Light Concrete Covers	0	0	0	36	0	0	0	0	0	36
	Covers/Soils	0	19	2	0	47	8	0	0	0	76
	Wetlands	0	0	0	0	1	23	2	0	0	26
	Arboreal Vegetation	2	0	2	0	0	0	47	0	0	51
	Non-paved Roads/Light Bare Soil	0	2	0	14	0	0	0	50	5	71
	Roads	0	0	0	0	0	0	0	0	45	45
	Total	50	50	50	50	50	50	50	50	50	**450**
Overall = (366/450) **81.33%** Kappa = **0.79**											

Table 3 – Error matrix.

Land use and land cover class	Producer`s Accuracy		Omission Errors (%)	Commission Errors (%)	User`s Accuracy	
	Samples	(%)			Samples	(%)
Grazing	47/50	94	6	25.4	47/63	74.6
Water Bodies	25/50	50	50	3.85	25/26	96.15
Mixed Crops	46/50	92	8	17.86	46/56	82.14
Aluminum and Light Concrete Covers	36/50	72	28	0	36/36	100
Covers/Soils	47/50	94	6	38.16	47/76	61.84
Wetlands	23/50	46	54	11.54	23/26	88.46
Arboreal Vegetation	47/50	94	6	7.84	47/51	92.16
Non-paved Roads/Light Bare Soil	50/50	100	0	29.58	50/71	70.42
Roads	45/50	90	10	0	45/45	100
Mean	**40.6/50**	**81.33***	**18.66**	**14.91**	**40.6/50**	**85.08**

* Standard deviation 20.42% and coefficient of variation 25.1%.

Table 4 – Classification evaluation

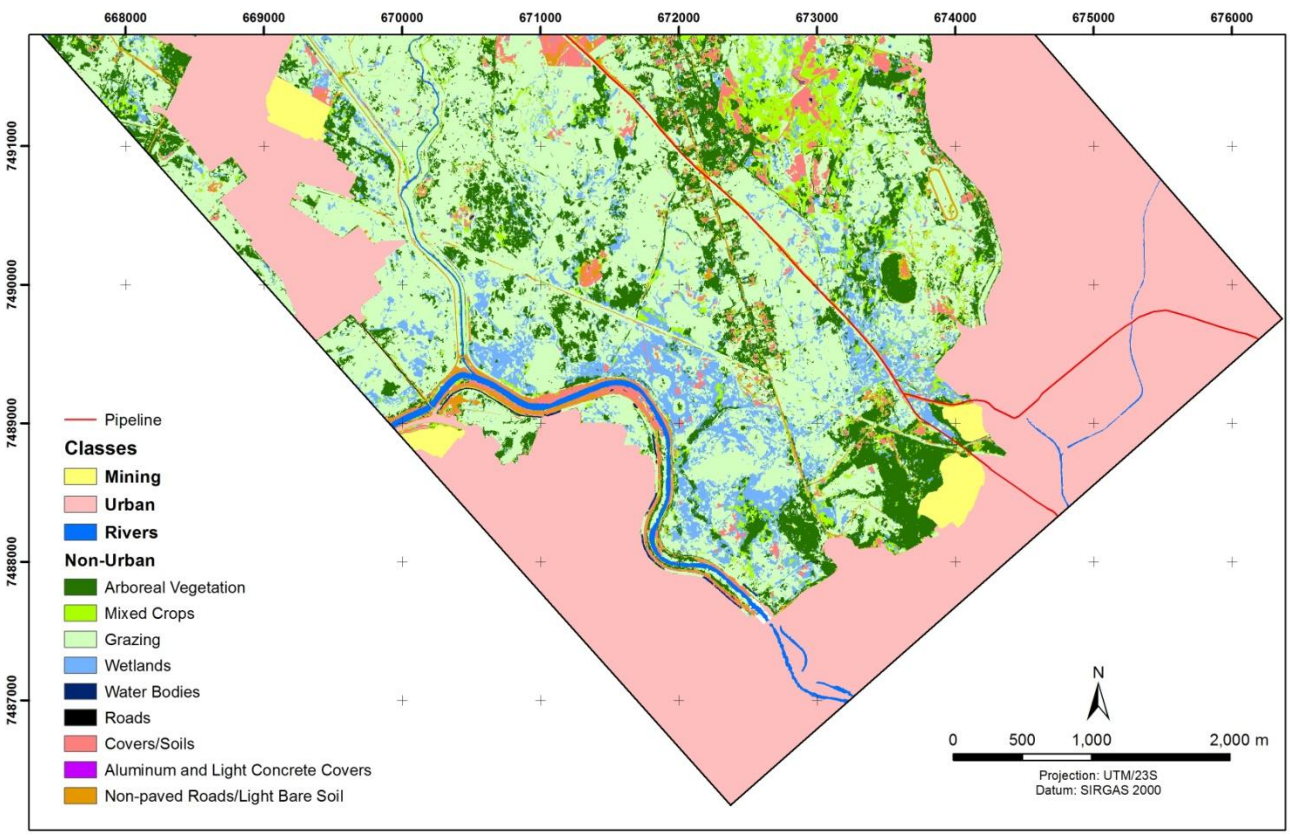


Figure 4. Land use and land cover map

The result of classification achieved 81.33% producer`s accuracy and 0.79 kappa index, considered by Landis and Koch (1977) a classification with strong agreement. This allows us to consider the land use and land cover classification through oriented-based approach satisfactory for this context.

In the analyses of Table 4 it was observed that the best producer’s accuracy occurred for Non-paved Roads/Light Bare Soil class, with 100% accuracy, however the same class showed 70.42% for user’s accuracy. Through Table 3 it is possible to identify that Aluminum and Light Concrete Covers objects were misclassified as Non-paved Roads/Light Bare Soil class. The histograms in Figures 6 and 7 show the spectral confusion using the classification descriptors, in which the meaningful overlaps of band means R, G and B descriptors, were observed.

The opposite situation occurs with the Water bodies and Wetland classes, that showed the worst producer’s accuracy results, 50% and 46% respectively, and high user’s accuracy, 96.15% and 88.46%. The results make sense because just wetland and water bodies were sampled with little influence from bare soil, vegetation and material in suspension, as it is observed in Figures 7 and 8.Thus, water object with influence from different material were not correctly classified.

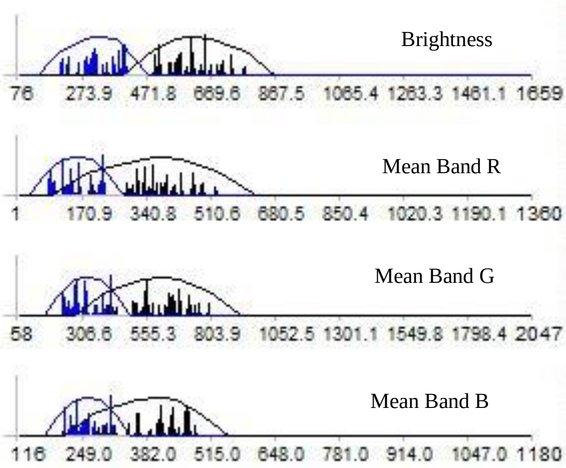


Figure 5. Histograms of attributes descriptors of Covers/Soils (blue) and Non-paved Roads/Light Bare Soil (black) classes.

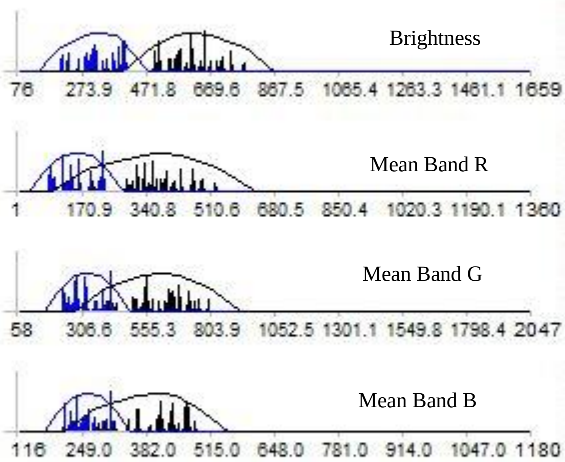


Figure 6. Histograms of attributes descriptors of Aluminium and Light Concrete Covers (blue) and Non-paved Roads/Light Bare Soil (black) classes.

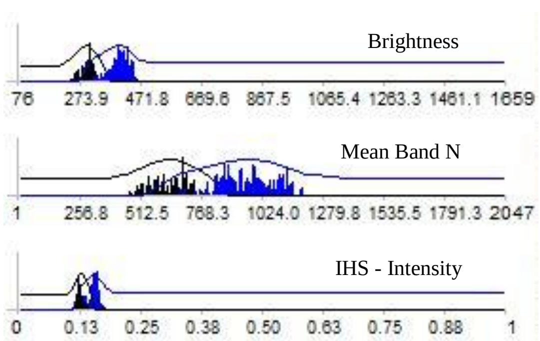


Figure 7. Histograms of attributes descriptors of Wetlands (blue) and Mixed Crops (black) classes.

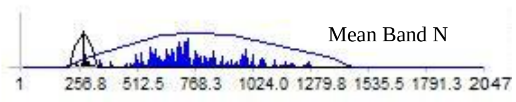


Figure 8. Histogram of attribute descriptor of Water Bodies (black) and Covers/Soils (blue) classes.

The other classes showed producer's accuracy above 72%. But it is important to note that despite the 81.33% producer's accuracy mean, the 20.42% standard deviation suggests a variance to the producer's accuracy, with a 25.1%.coefficient of variation. This coefficient does not suggest a high heterogeneity, but having a coefficient of variation higher than 10%, it also does not suggest a result with high homogeneity. However, the classification process was not susceptible to this level of variation, as evidenced by the Kappa coefficient.

When considering the performance by class, it was verified that the Aluminum and Light Concrete Covers and Roads classes have not included other classes (with 100% user's accuracy), demonstrating that the attributes parameters used by these classes were adequate. The classes that produced higher inclusion error were Covers/Soils (38.16%), Non-paved Roads/Light Bare Soil (29.58%) and Grazing (25%). In the Covers/Soils class an inclusion of Water Bodies class occurred, because of spectral responses similarity for the presence of materials in suspension in water and exposed soil in wetlands. The inclusions in the Non-paved Roads/Light Bare Soil class occurred by the spectral response similarity with the Aluminum and Light Concrete Covers and Roads classes, once the segmentation process used did not allow a consistent definition of these objects contours. The Grazing class showed a large inclusion of the Wetlands class because of the high frequency of flooding in grassland areas located in the lower regions of the land.

4. CONCLUSIONS

The details in the segmentation process produces a loss of shape and context attributes, making it difficult to differentiate objects. Thus, we intend to improve the border limits of objects in order to better portray the geometrical characteristics and location of features, so that we can deepen the exploration of software resources and features and also so that there can be a refinement of the classes of land use and land cover.

It is considered that the result of automatic classification by the o object-based method, has achieved values of accuracy close to the limit for the application of this technique for high resolution image data, with great complexity and diversity of space occupation. Thus, to achieve a better overall classification the manual editing of some segments that show misclassification must be done.

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