LAND USE AND COVER IN THE URUGUAY RIVER BASIN CONSIDERING THE GEOBIA PARADIGM

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ABSTRACT:

This paper aims to contribute to this issue at two subareas in the South Region of Brazil by an implementation of Geographic Object-Oriented Image Analysis (GEOBIA) methods and techniques. We implemented a top-down hierarchical approach using decision rules and fuzzy membership functions. This approach appeared to be the most appropriate for classifying heterogeneous landscapes due to difficulties to discriminate spectrally some classes. The subarea A showed a great importance of PCA components and subarea B of LSM fractions, exposing the differences between these landscapes.

KEY WORDS: GEOBIA, Land use, Mapping, Remote Sensing.

1. INTRODUCTION

The land use and cover classification of heterogeneous and fragmented landscapes is a challenge even for medium spatial resolution data, e.g. Landsat-TM. This paper aims to contribute to this issue at two subareas in the South Region of Brazil by an implementation of Geographic Object-Oriented Image Analysis – GEOBIA methods and techniques (Hay and Castilla, 2008; Blaschke, 2010).

2. METHODOLOGY

2.1 Study area

The study area is composed by two sub-areas from Uruguay River Basin at Rio Grande do Sul State (Brazil) with distinct landscape characteristics (Figure 1).

The subarea A situated in the “Missões” region, the land use and land cover classes were identified as: forest, advanced secondary vegetation, native grasslands, silviculture, mixed semi-subsistence agriculture (heterogeneous rural landscape mosaics of pasture, crops and secondary vegetation), large-scale agriculture (intensive crops, mainly soybeans and wheat), urban and water.

In subarea B, located in the “Campanha” region, the land use and cover classes were: riparian forest, native grasslands, silviculture, large-scale agriculture, urban and water.

2.2 Digital image processing

We used in sub-area A four Landsat 5-TM images divided in: Mosaic 1 (path 223/79 and 223/80 of 04/11/2009) and Mosaic 2 (path 224/79 and 224/80 of 09/25/2009). In sub-area B we used three TM images: scenes 1 (224/80 of 09/25/2009), 2 (224/81 of 10/27/2009) and 3 (225/81 of 10/18/2009).

The geometric correction was based on orthorectified Landsat data projected in UTM-21S and WGS-84 datum of GeoCover Project that presented compatible displacements with the 1:50.000 cartographic base. We adopted an image-to-image registration based on a 1st polynomial procedure, nearest neighbour resampling and an RMS below 1 pixel. Two digital image processing were used: Principal Component Analysis (PCA) with the four first components; and Linear Spectral Mixture Models (LSM) with vegetation, soil and water fractions.

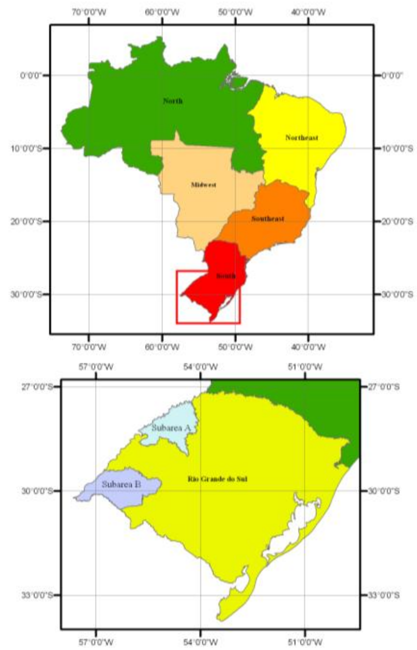

Figure 1: Subareas under study located in Rio Grande do Sul State (Brazil).

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2.2.1 GEOBIA methodology: The methodological implemented procedures were chosen after previous tests with a GEOBIA supervised classification based on nearest neighbour algorithm. In this paper, we adopted a hierarchical decision rules fuzzy membership functions approach (Navulur, 2007) based on visual and interactive data exploratory tools of the used software (Definiens, 2007).

2.2.2 Multiresolution segmentation and class hierarchy: The classification hierarchy was related with the multiresolution segmentation based specially on the scale parameter values (range from 10 to 50) with the shape and compactness features fixed in 0.1 and 0.5. The classification hierarchy was developed on the different segmentation levels with a greater diversification in the class hierarchy of large-scale agriculture due to multiple crops and development stages (bare soil, tillage, intermediate and advanced growth).

2.2.3 Decision rules and membership fuzzy functions: The decision rules and membership fuzzy functions were based in spectral attributes from the original data and generated products in most cases and also by shape and texture attributes (Tables 1-5). The hierarchy attribute (existence of super-objects) was used to unify the different classification levels in a top-down approach, i.e. the hierarchical classification followed a sequence from the higher to the lower levels (Figure 2). For evaluating of the classification performance was used the kappa coefficient (Congalton 1999), based in the several sampling plots obtained on the ground survey.

Class	Level	Attributes	Fuzzy	Rule
Forest	10	MN B4 MN B7 HOM	40 - 74[a] 11.2 - 24[a] 0.057 - 0.04[b]	AND
Native grassland	25	MN VEG_F MN B5 Y DIST_BOT	0.15 - 0.53[a] 77 - 120[a] >96000	AND
Silviculture	12	MN B7	8 - 12[a]	
Mixed agriculture	10	Unclassified		
Water	12	MN B4 MN B5	45 - 37[b] 39 - 32[b]	AND
Large-scale agriculture				
Bare soil	20	HOM MN SOIL_F MN SOIL_F	0.04 – 0.05[b] 0.23 – 0.33[b] 0.28 – 0.34[b]	AND OR
Intermediate 1	15	MN PCA4 MN B3	-11 - 2[a] 13 - 39[a]	AND
Intermediate 2	18	MN PCA2 MN PCA3 MN B4	2 - 25[a] -14 - 5[a] 30 - 55[a]	AND
Advanced	15	MN B4 MAX_DIFF	62 - 135[a] 0.95 – 1.1[b]	AND

[a] Distribution function initial and final values=0, mean value=1.
[b] Sigmoid function initial value=0 and final value=1.

Table 1: Segmentation levels, decision rules and fuzzy functions in subarea A (Mosaic 1). MN= mean, B4= e.g. Landsat NIR band, PCA= Principal Component Analysis, HOM= GLCM Homogeneity (all dir.), Y DIST_BOT = distance on Y from image bottom, VEG_F= LSM vegetation fraction, MAX_DIFF= maximum difference.

Class	Level	Attributes	Fuzzy	Rule
Forest	10	MN B3 MN PCA4 HOM	12 - 23[a] -4 - 3.2[a] 0.057 - 0.05[b]	AND
Native grassland	12	NDVI MN B5	0.4 - 0.65[a] 76 - 113[a]	AND
Silviculture	18	MN PCA1 MN PCA3	12 - 34[a] 4 - 16[a]	AND
Mixed agriculture	12	MN PCA1 MN PCA2 MN B5	-47 - 5[a] -20 - 20[a] 60 - 102[a]	AND
Water	12	MN B4	31 - 28[b]	
Large-scale agriculture				
Bare soil	20	MN PCA2 MN SOIL_F	-63 - -7[a] 0.2 – 0.3[b]	AND
Intermediate	15	MN PCA1 MN PCA3 SHP_IND	-30 - 17[a] -5 - 18[a] 3 – 2[b]	AND
Advanced	15	MN PCA4 MN SOIL_F MN B4	0.5 - 15[a] 0 – 0.35[a] 74 - 100[b]	AND

Table 2: Levels, decision rules and fuzzy functions in subarea A (Mosaic 2). NDVI= Normalized Difference Vegetation Index, SOIL_F= LSM soil fraction, SHP_IND= Shape Index.

Class	Level	Attributes	Fuzzy	Rule
Riparian forest	15	NDVI MN PCA1 SHP_IND	0.33 – 0.7[a] -30 - 12[a] 1.3 - 1.7[b]	AND
Native grassland	15	Unclassified		
Silviculture	15	Manual		
Water	15	MN WAT_F NDVI	-1 - 1[b] -1 – 0.1[a]	AND
Large-scale agriculture				
Bare soil	20	MN PCA4 MN B3 MN VEG_F BRIGH MN PCA3	-33 - 12[a] 34 – 87[a] 0.01 – 0.38[a] 118 – 122[b] 2 - 15[a]	AND OR OR
Rice	20	MN B5 NDVI	15 - 88[a] 0 – 0.42[a]	AND
Advanced	20	MN PCA1 MN B5 MN B7 BRIGH MN B4	0 - 53[a] 51 – 91[a] 16 - 45[a] 60 – 50[b] 75 – 85[b]	AND OR AND

Table 3: Levels, decision rules and fuzzy functions in subarea B (Scene 1). WAT_F = LSM water fraction, BRIGH = Brightness.

Class	Level	Attributes	Fuzzy	Rule
Riparian forest	20	MN B5 MN PCA2	49 – 92[a] -46 - -10[a]	AND
Native grassland	20	MN VEG_F	0.4 – 0.86[a]	
Silviculture	35	INH RIP SHP_IND	2.5 – 2 [b]	AND
Water	25	MN WAT_F MN SOIL_F SHP_IND	0.3 – 0.35 [b] 0.1 – 0.07[b] 3 – 4[b]	AND
Large-scale agriculture				
Bare soil	35	MN B4 MN VEG_F MN PCA4 NDVI	34 – 38[b] 0.16 – 0.14 [b] -3.7 – -5 [b] 0 – 0.38 [a]	AND OR OR
Rice	20	MN WAT _F	0.23 – 0.92 [a]	
Advanced	50	MN PCA2 MN B5	-48 - -7 [a] 88 – 113 [a]	AND

Table 4: Levels, decision rules and fuzzy functions in subarea B (Scene 2). INH RIP = Inherited rules from riparian forest.

Class	Level	Attributes	Fuzzy	Rule
Riparian forest	20	BRIGH MN SOIL_F	21 – 32[a] 0.02 – 0.3[a]	AND
Silviculture	15	Manual		
Water	15	MN B4	0 – 46[a]	
Native grassland				
Shrub-herbaceous	20	MN B5	80 – 132[a]	
Herbaceous	20	MN VEG_F	0.07 – 0.33[a]	
Large-scale agriculture				
Bare soil	25	MN SOIL_F	0.6 – 0.7[b]	
Rice	35	MN PCA2	-43 – 0[a]	
Advanced	30	BRIGH MN PCA3	-26 - 40 [a] 0 – 40 [a]	AND

Table 5: Levels, decision rules and fuzzy functions in subarea B (Scene 3).

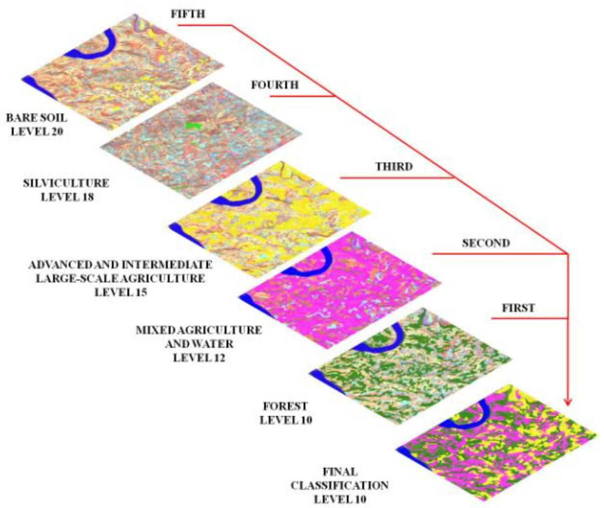

Figure 2: Top-down approach of the hierarchical classification with the multi-scale segmentation levels and the top-down order of classification.

3. RESULTS

The subarea A presents a higher landscape complexity resulting in a greater confusion between mixed agriculture, native grasslands and secondary vegetation (e.g. at Mosaic 1 mixed agriculture was assigned to the unclassified objects). The attributes with greater contribution (Tables 1 and 2) were PCA components, original bands averages and texture (homogeneity). The validation showed good results (k = 0.89, overall accuracy= 92.57%, n= 525) (Figure 2).

The subarea B has lower landscape heterogeneity. The attributes with greater contribution (Tables 3-5) were LSM factors, original bands averages and shape index. The map accuracy showed a good performance (k= 0.82, overall accuracy= 88.44%, n= 199) (Figure 3).

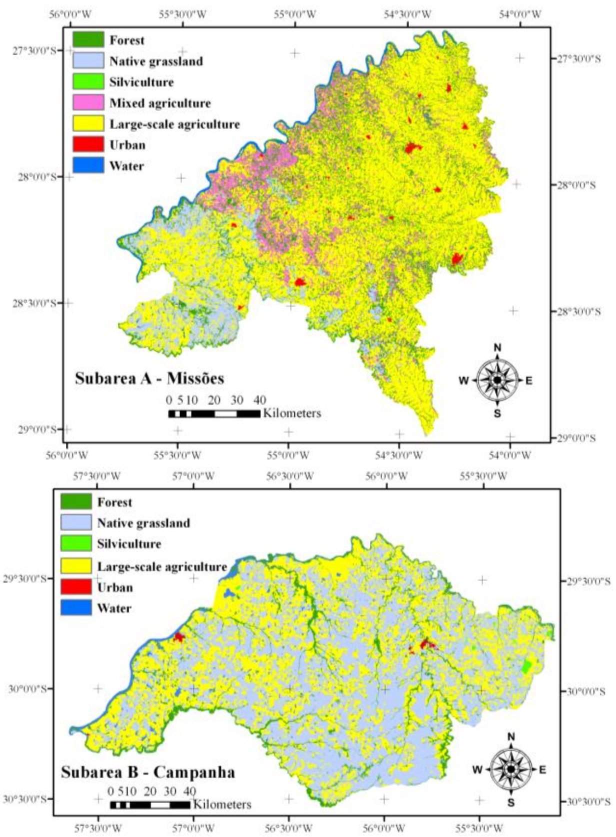

Figure 3: Classification of subareas A and B.

4. CONCLUSION

The implemented top-down hierarchical approach using decision rules and fuzzy membership functions appeared to be the most appropriate for classifying heterogeneous landscapes due to difficulties to discriminate spectrally some classes. The subarea A showed a great importance of PCA components and subarea B of LSM fractions, exposing the differences between these landscapes.

4.1 References and/or Selected Bibliography

Blaschke, T., 2010. Object based image analysis for remote sensing. *ISPRS Journal of Photogrammetry and Remote Sensing*, v. 65, p. 2-16.

Hay, G.; Castilla, G., 2008. Geographic Object-Based Image Analysis (GEOBIA): a new name for a new discipline. In: Blaschke, T.; Lang, S.; Hay, G. *Object-based image analysis: spatial concepts for knowledge driven remote sensing applications*. Berlin, Springer-Verlag, p.3-27.

Navulur, K., 2007. *Multispectral image analysis using object-oriented paradigm*. CRC Press, Boca Raton, 165p.

Shimabukuro, Y., 1987. Shade images derived from linear mixing models of multispectral measurements of forested areas (PhD Thesis) - Colorado State University, Fort Collins, CO.

4.2 Acknowledgements

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