Performing Multi-Temporal Spatial Data Analysis for Coastal Areas and Assessing Thematic Accuracy

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Abstract

It was used TM Landsat images from 1985, 1994, 2004 and 2014 and Object Based Oriented Analysis (OBIA) image classification techniques in order to study changes in land use and land cover for two cities: Passo de Torres and Balneário Gaivota at the south region of Brazil. Based on these analyses, four informational classes were chosen: Natural Vegetation, Water, Urban and Agriculture Use. Agriculture use includes croplands, livestock activities and reforestation areas. It was used post-classification multi-temporal analysis. The aim of this paper is to perform multi-temporal spatial data analysis in order to identify trajectories of changes on land use and land cover, during the last three decades. This paper also discusses an alternative methodology to assess the thematic accuracy in multi-temporal analysis. The multi-temporal analysis results show that this study area has considerably changed in the last three decades. The most frequent transition was due to the transformation of natural areas into cropland, livestock and reforestation ones, from the year of 1985 to 2014. It was observed that most of transition for urban class occurred from natural vegetated areas, while few transitions occurred from agricultural areas, even considering these classes as being more representatives in the whole study area. This transition was especially common in coastal urban division into plots of land. Besides understanding those processes of change, this study points out the importance of better planning, licensing and monitoring of urban coast division into plots of land to prevent the continuous loss of natural ecosystems and impoverishment of environmental quality. The accuracy assessment discussion shows the importance in choose a better classification strategy in order to perform the multi-temporal analysis in remote sensed data. Furthermore, it is observed that a considerable amount of research needs to be undertaken before the spatial characterization of thematic accuracy associated with multi-temporal analysis can be adequately reported in standardized format and legends.

I INTRODUCTION

Brazilian coastal areas have experienced fast changes in recent years, on form and model of occupation driven by geographical, economic, social forces and public policies. The multi-temporal analysis of changes on land use and land cover is a method focused on understanding, measuring and analysing spatial and temporal changes, both qualitatively and quantitatively.

On the other hand, it is widely acknowledged that classification of remotely sensed imagery has variable and often poor quality. The cause and nature of these errors has been the subject of extensive researches (e.g., Lu and Weng, 2007) in order to improve the accuracy of remotely sensed products.

The aim of this paper is to perform multi-temporal spatial data analysis in order to identify trajectories of changes on land use and land cover, during the last three decades. This study also discusses an alternative methodology to assess the thematic accuracy in multi-temporal analysis.

II STUDY AREA AND MATERIAL

The study area covers the municipalities of Passo de Torresand Balneário Gaivota in coastal southern state of Santa Catarina and covers an area of 25,030 hectares (Figure 1). The landscape can be considered homogeneous with elevation ranging from sea level to 30 meters. This study area is entirely composed of Holocene coastal sedimentary plain (Dieh and Horn Filho, 1996), originally covered by herbaceous marshes, typical of wetlands or fixative dunes, shrub or tree (Falkenberg, 1999; CONAMA, 1999). In addition to the native vegetation, the area has diverse types of land cover including family farms, monoculture timber species (*Pinus* and *Eucalyptus* cultivation), rice cultivation, livestock and urban areas at different stages of occupation.

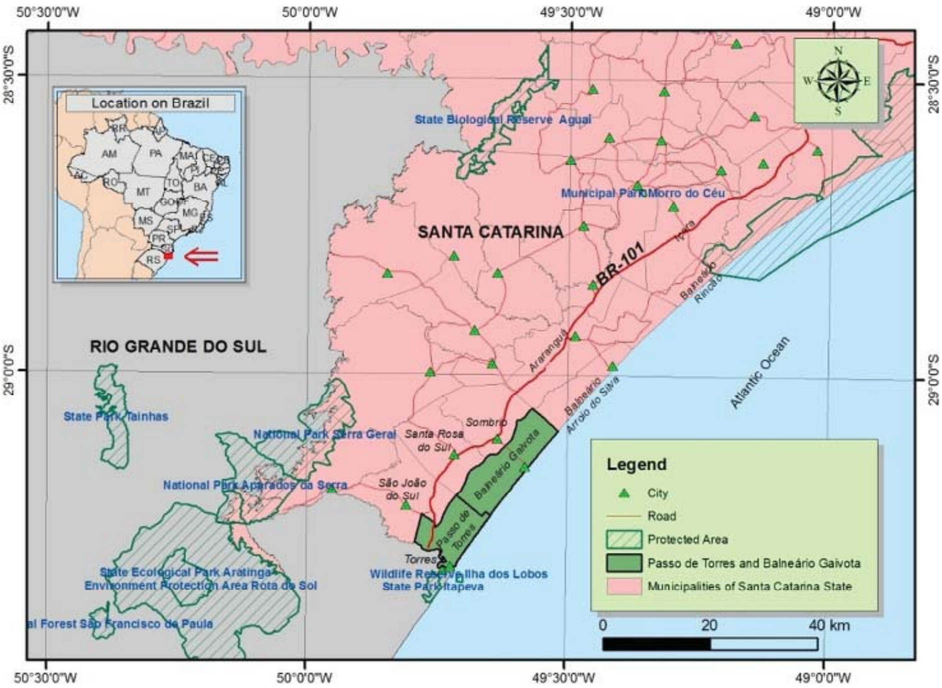

Figure 1: Study area location - municipalities of Passo de Torres and Balneário Gaivota.

III MATERIAL AND METHODS

Landsat TM scenes were selected at intervals of about 10 years, consisting in six spectral bands for each scene, for the images classification process (Table 1). It is important to note that the precise geometric correction process is crucial for the multi-temporal analysis (Morisette and Khorram, 2000; Mundia and Aniya, 2005; Singh, 1989). In order to perform this geometric correction procedure, it was used the image Landsat 8 / OLI 01/30/2014 as reference image (available with geometric correction by the United States Geological Survey - USGS). It was used a plane coordinates UTM system and the Datum WGS84. The resulting average quadratic error was less than 15 meters (half pixel) for all scenes. The resampling method used was the nearest neighbour, in order to maintaining the radiometric properties of the original images. After geometric correction, the four images were clipped using the feature IBGE municipal boundaries of the study area.

In addition, high-resolution images (e.g., SPOT and RapidEye Images) and photogrammetric data (Flights years 1978 and 1996) were used in the accuracy assessment procedures as reference data.

Satellite - Sensor	Date	Bands
LandSat 5 - TM	09/07/1985	1,2,3,4,5,7
LandSat 5 - TM	18/07/1994	1,2,3,4,5,7
LandSat 5 - TM	14/08/2004	1,2,3,4,5,7
LandSat 8 - OLI	30/01/2014	2,3,4,5,6,7

Table 1: Sensors, dates and bands used (orbit 220, point 080).

(i) Multi-temporal classification procedures

In the classification process, it was used an object oriented supervised classification method: OBIA (Object Based Image Analysis). According to Cohenca and Carvalho (2015) the OBIA method is based on image segmentation which consists of subdividing the image into homogeneous regions, called objects, which are the basic elements of the classification process (Benz*et al.*, 2004). Each object has spectral characteristics defined by its average value of pixel´s radiometry and also geometric characteristics such as: contextual information and texture. The segments are classified following a tree process, whose rules for the differentiation of the classes are defined by the interpreter (Francisco and Almeida, 2012).
For the whole set of bands were tested weights parameters, such as: scale, shape and compactness of the objects in each of the images, which define separability of objects and, consequently, the size and number of objects to be generated (Table 2).

Images	Scale	Shape	Compactness
TM -09/07/1985	10	0.1	0.8
TM-18/07/1994	10	0.1	0.9
TM-14/08/2004	10	0.1	0.9
OLI-30/01/2014	90	0.1	0.5

Table 2: Parameters used for segmentation of Landsat images.

The distinctive characteristics of atmospheric conditions on the acquisition of images and different sensors used, motivates each scene be classified separately. The evaluation of the quality of the segmentation was carried out through joint evaluation of the classification results (Darwish *et al*., 2003).

From field visits and analysis of high resolution images, were initially defined eleven thematic informational classes, considered representative of the diversity of types of coverage in the study area. In order to reduce source of imprecision and considering the objective of identifying the changes in coverage between native vegetation, areas of agriculture use and urban areas, regardless of the specific type of use in each segment, the initially defined eleven classes were grouped into four final classes: *Natural Vegetation, Water, Urban and Agriculture Use*. Agriculture use includes croplands, livestock activities and reforestation areas.

In order to assess the accuracy of the classification procedures, it was used the method proposed by Congalton and Green (1999). It was selected 200 pixels at random (50 samples per class with a minimum distance of 100 meters between samples), for each of these scenes independently (Korting, 2007). Comparing classification results and reference samples were generated confusion (or error) matrices, from which were derived indexes, such as: overall accuracy, Kappa and Conditional Kappa coefficients for each scene.

(ii) Multi-temporal analysis

It was chosen an overlay vector method for comparing the thematic classifications performed for each analysed stage, considering the complexity and diversity of land uses and types of land cover in the study area for the multi-temporal analysis of changes.

Data analysis was quantitatively performed globally as well as regionalized, using the limits of the different settlement pattern identified, based on the main type of use, property size and dynamics of occupation that have been mapped in historical survey of the occupation process. This mapping was crossed with maps of land use change, allowing identify settlement patterns that have undergone major change and what were these changes in different time intervals.

Thus, it was analysed the trajectory of multi-temporal land cover transitions in order to understand the changes detected between the studied decades, in both: global and regionalized manner.

VI RESULTS

Overall accuracies, derived from the confusion matrix, ranged between 84% and 88%, and the Kappa coefficients ranged between 0.793 and 0.836 (Table 3). These accuracies values can be considered very satisfactory. According to the conditional Kappa coefficients, the class with the highest accuracy rating was the class water, followed by urban class. The classes that had greater confusion were Natural and Agriculture Uses. This kind of confusion seems to be due to a lower separability of these classes. Figure 2 shows thematic images for the years of 1985, 1994, 2004 and 2014.

Classes	Images	1985	1994	2004	2014
Conditional Kappa	Water	0,973	0,947	1,000	0,895
	Natural	0,847	0,720	0,632	0,692
	Agriculture	0,783	0,636	0,803	0,787
	Urban	0,748	0,869	0,771	0,844
Kappa		0,836	0,793	0,800	0,807
Overall Accuracy		88%	84%	85%	85%

Table 3: Overall accuracies, Kappa and Conditional Kappa Coefficients.

The multi-temporal analysis results show that 19.8% of the study area has changed in the last three decades. Between 1985 and 2014, the most frequent transition (57.1% of changes) was due to the transformation of natural areas into agriculture use. The expansion of the urban class over natural areas responded for 24.3% of changes. The conversion of agriculture use into urban use responded for 5.1% of change, while conversion of agricultural areas to vegetation regenerated accounted only for 2.8% of change (Table 4).

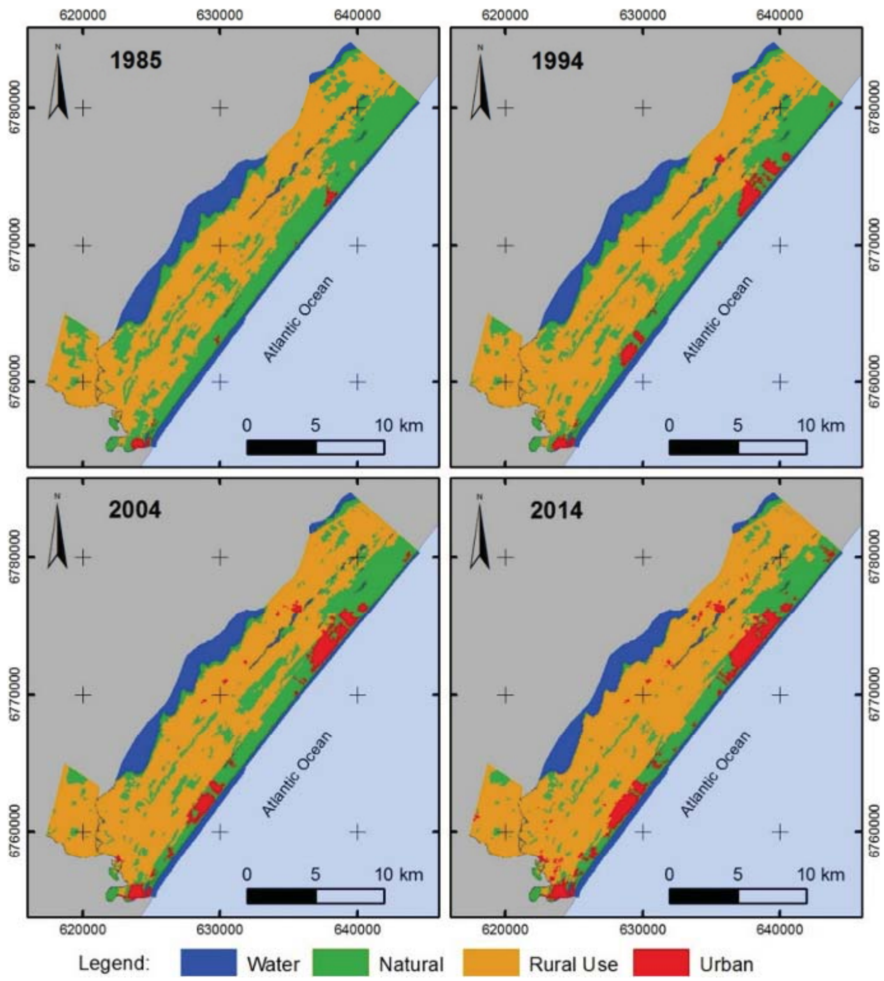

Figure 2: Image Classification results for the years of 1985, 1994, 2004 and 2014.

It was observed that 82% of the transition to urban class occurred from natural vegetated areas, while 18% occurred from agricultural areas, even considering these classes as being more representatives in the whole study area. This transition was especially common in coastal urban division into plot of land.

Remnants of natural class accounted for 17% of the study area in 2014, while in 1985 it was 32%, been particularly concentrated in these coastal urban divisions into plots of land.

Performing multi-temporal spatial data analysis operations on data of unknown accuracy will result in a product with low reliability and restricted use in the decision-making process, while errors deriving from one source can propagate through the database via derived products. Moreover, current accuracy assessment methods are based on non-spatial statistics derived from the confusion or error matrix, which compares the output of a classifier against known reference data. Although these measures are in widespread use, none of them considers the spatial distribution of erroneously classified pixels, either implicitly or explicitly.

Transitions \ Period	1985-1994		1994-2004		2004-2014		1985-2014	
	Area (ha)	**%**	**Area (ha)**	**%**	**Area (ha)**	**%**	**Area (ha)**	**%**
Natural → Agriculture Use	1090	49,2	815	63,5	1370	72,0	2822	57,1
Natural → Urban	522	23,5	322	25,1	346	18,2	1200	24,3
Agriculture Use → Urban	60	2,7	74	5,7	127	6,7	250	5,1
Agriculture Use→ Natural	411	18,6	58	4,5	26	1,4	138	2,8
Other Transitions	134	6,0	14	1,1	33	1,7	532	10,8
TOTAL	2217		1282		1902		4942	100

Table 4: Frequent transitions in land coverage.

Vieira and Mather (2001) presents one possible way to characterize the spatial distribution of the errors in a thematic classification is by generating a *distance image* showing the distance from individual pixels to the multivariate means of the classes to which they have been assigned (Figure 3c). Either the Euclidean distance or the Mahalanobis distance measure can be used. The former, however, implies spherical clusters in feature space, while the latter takes into account the covariance between the features on which the classification is based. The individual distances are scaled onto a 0-255 range, and displayed as a grey scale image. Darker pixels are spectrally "nearer" to their class centroid (in the sense of statistical distance), and are thus more likely to be classified correctly. On the other hand, pixels with higher distance values are spectrally further from the centroid of the class to which they were assigned, and are thus more likely to be misclassified. This process (presented in Figure 3b) allowed to get known the thematic uncertainties associated for each pixel of the classified image.

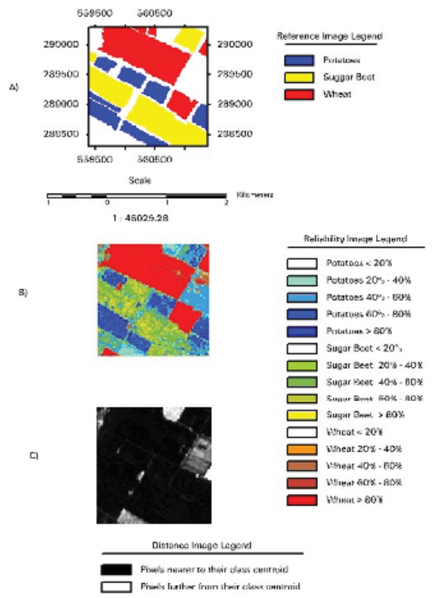

Figure 3: Spatial characterisation of classification errors using thematic image generated by Maximum Likelihood Classifier (100 by 100 pixels). A) Reference Image; B) Reliability Image; C) Distance Image.

Another possible way to characterise the spatial distribution of the errors in a thematic classification is by directly comparing thematic images with their respective ground truth maps. One of the products of this comparison should be an *error binary image* (Figure 3b), in which each point takes the value 0 (correctly labelled) or 1 (erroneously labelled).
On-going researches has been developed in order to propagate these uncertainties through the multi-temporal analyse model and a thematic uncertainty map could be generated, as suggested by Vieira and Mather (2001).

V CONCLUSIONS

The multi-temporal analysis results show that has considerably changed in the last three decades. Between 1985 and 2014, the most frequent transition was due to the transformation of natural areas into agricultural, livestock and reforestation ones. The expansion of the urban class over natural areas responded for 24% of changes. The conversion of agricultural use into urban one responded on exceeding of 5% of change, while conversion of agricultural areas to vegetation regenerated accounted only for less than 3% of change. It was observed that most of transition for urban class occurred from natural vegetated areas, while few transitions occurred from agricultural areas, even considering these classes as being more representatives in the whole study area. This transition was especially common in coastal urban division into plots of land. In 2014, remnants of natural class accounted for 17% of the study area, while in 1985 it was 32%, been particularly concentrated in these coastal urban divisions into plots of land.

Besides understanding those processes of change, this study points out the importance of better planning, licensing and monitoring of urban coast division into plots of land to prevent the continuous loss of natural ecosystems and impoverishment of environmental quality.

The accuracy assessment results point out the importance in choose a better classification strategy in order to perform the multi-temporal analysis in remote sensed data. Furthermore, it is also shown that a considerable amount of research needs to be undertaken before the spatial characterization of thematic accuracy associated with multi-temporal analysis can be adequately reported in standardized format and legends.

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