Evaluation of two supervised classification techniques and the influences of thermal band application on target distinction: a case study of Santa Catarina Island - Brazil

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Abstract. Digital image classification is a useful process to characterize the land cover and the land use by analyzing target's spectral and spatial patterns. Digital image processing involves a manual or automatic process for the distinction of targets based on visual and statistical parameters. This study aimed to analyze the accuracy of two supervised classifications for OLI/Landsat 8 image featuring the island of Santa Catarina/Brazil applying two methods: the pixel-based approach by maximum likelihood classification with a post-processing step (majority filtering), and region-based approach by Bhattacharyya classification. Both classifications were submitted to an accuracy assessment through the validation of classes (urban, forest, pasture and bare soil, inland water and sand) based on references obtained from a high spatial resolution image (RapidEye). The highest agreement between classified image and the reference was achieved with the classification applying the region-based approach. This approach was then applied to evaluate the effects of the application of thermal band 10 (OLI/Landsat 8) in the classification process. Results revealed that the pixel-based approach and the region-based approach presented less accuracy in regions where the heterogeneity of the land cover is more complex and in addition, it was also revealed an agreement reduction between the classified data and the reference when OLI/Landsat 8 band 10 was used.

Keywords: Image Processing, Region-based Classification, Filtering, Thermal Band, Accuracy Assessment.

1. Introduction

Land use and land cover maps are based on visual interpretation or automatic classification techniques in order to distinguish types of surface's use and cover. The process of image classification consists in the recognition of patterns and homogeneous objects in the scene. Therefore, the aim is to simulate the interpreter behavior in the identification of these regions (CÂMARA et al., 1996). This technique can be separated onto two approaches: pixel-based and region-based. Independently of the use of pixels or regions as underlying units, the information within and among these units can be submitted to a variety of classification algorithms (DURO et al., 2011). Both of these approaches can be supervised or non-supervised.

Pixel-based classifiers use the spectral information for the recognition of homogeneous regions. Clustering is made based on a metric which expresses a similarity level. A basic premise is that the objects of interest must be bigger than the pixel size; otherwise, the mixing of different spectral components makes the classification pattern infeasible (KETTIG and LANDGREBE, 1975). The resulting thematic map can be submitted to a post-processing, such as the smoothing by a majority spatial filter. This filter compares the value of a central pixel inside a window with its "k-neighbors", and this value is substituted by the majority value of the k-neighborhood. The smoothness caused by filtering process aims to increase spatial accuracy apart from visual appearance (FIERENS and ROSIN, 1994).

In most of the cases, the semantic information that is useful for scene interpret is not represented in singular pixels but in scene regions (BAATZ and SHAPE, 2000). The segmentation process is defined by the total image partition in segments (adjacent and homogeneous pixel clustering, two-dimensionally spread in the image) not spatially

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overlapping. Therefore, segmentation methods follow two well-correlated principles: neighborhood and similarity (SCHIEWE, 2002) and can be classified in four strategies: measurement space guided spatial clustering, single linkage region growing schemes, spatial clustering schemes and split-and-merge schemes (HARALICK and SHAPIRO, 1985). The region growing scheme treats every pixel as a node in a graph, and neighboring pixels which obey the sentence "similar enough" are joined by an arc. The similarity condition varies from one algorithm to another. Amongst region growing classifiers, the Bhattacharyya algorithm intent to measure the statistical probabilities between each pair of spectral classes, calculated by the mean distance among the probabilities distributions of spectral classes (LEAO et al., 2007). According to Blaschke (2010), the segmentation process has the advantage of considering adding spectral information in each segment (from all pixels inside it) in comparison to singular pixels, although the main advantage is the spatial adding information into the objects.

Pixel-based and region-based classifiers use the spectral information to feature the pixel or object. Haralick and Shapiro (1985) suggest that pixels have a high correlation among bands, besides spatial redundancy in data. The choosing of input bands for classification influences the final result, and hence a selection criterion like less correlated bands is convenient. Visible, near infrared and short wave radiation bands, contain reflectivity and scattering information about the incident electromagnetic radiation in terrestrial targets. On the other side, the thermal infrared (TIRS band 10) band is located in the spectral range sensible to terrestrial emissivity. Therefore, it can be expected that the correlation between these bands is low.

Considering the aforementioned arguments, the aim of this work is to compare and evaluate two methods of supervised classification: the Maximum Likelihood Classification (a pixel-based approach) with a post-processing filtering, and the Bhattacharyya classification (region-based approach). Besides, the study will assess the influence of TIRS band from the OLI sensor (band 10) in classification to discriminate natural and anthropic targets in Florianópolis/SC.

2. Methods

2.1. Study area

The study area is the island of Santa Catarina, where is located a fraction of Florianópolis city (Figure 1), with an area of 424.4 km², between the geographical coordinates 48°21' to 48°35'W longitude and 27°22' to 27°51'S latitude.

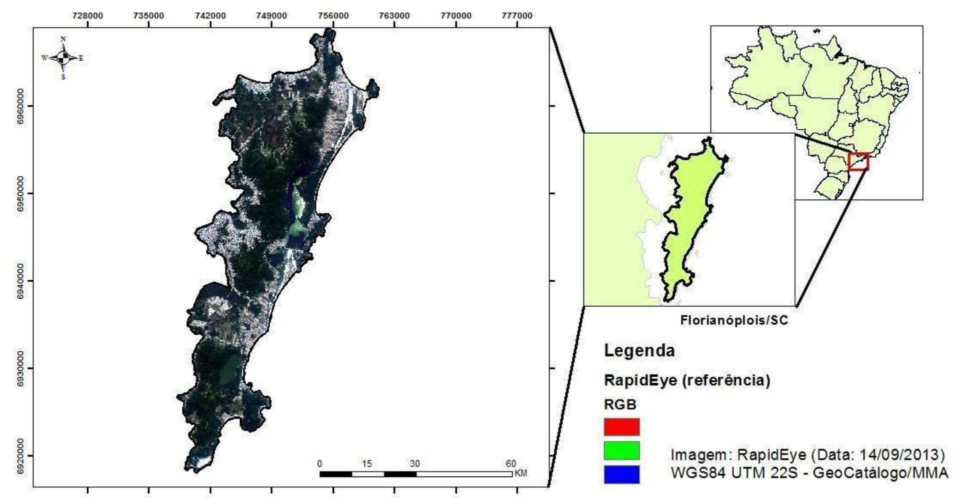


Figure 1. Location of the Santa Catarina Island.

The methodology (Figure 2) is divided into two analysis: 1º) Comparison of global accuracy between the pixel-based classification (maximum likelihood method) using spatial majority filter and the Bhattacharyya classification using segmentation method; and 2º) Evaluation of using the thermal band in support for classification.

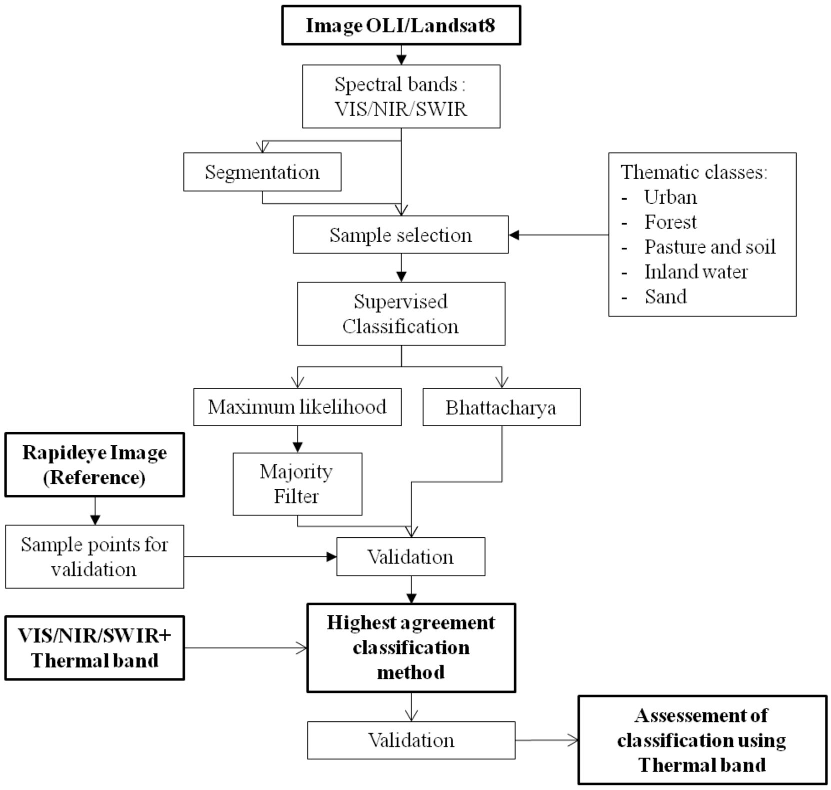


Figure 2. The methodology of the study.

2.2. Supervised classification using maximum likelihood and spatial filtering, and using Bhattacharyya and segmentation methods.

OLI/Landsat 8 images include 11 spectral bands, nine of which have 30m of spatial resolution (bands 1 to 7 and band 9), a panchromatic band (8) and two thermal bands (10 and 11) of the instrument TIRS have 100 m of spatial resolution. The imaged area is 170 x 183 km. In this analysis, bands 4, 5 and 6 (red, near infrared, and short-wave infrared I, respectively) will be used to perform the classifications.

The supervised classification is based on spectral training of classes provided by image interpreter and influenced by the number of samples, target heterogeneity, and interpreter's subjectivity. The maximum likelihood algorithm is the most applied to remote sensing data due to its simplicity of application. It's a parametric method with classes represented by a Gaussian multivariate model using training samples to establish the mean vector (m) and covariance matrix (s). The efficacy depends on reasonable accuracy to estimate m and s, which depends on pixel amount included in sample training (TISOT, 2005). This algorithm is also dependent on analyst's knowledge about the area to be classified in order to set representative classes (CROSTA, 1993).

Thus, for classification by pixel-based approach samples were collected considering the target heterogeneity and spatial distribution at the image. The classification result was refined by spatial majority filtering to remove the isolated pixels in the context of another class and for better delineation of classes' borders. The application of neighborhood filtering using the window of 3x3 pixels was evaluated by global accuracy, regarding the number of filtering repetitions, and the highest agreement classification was selected to be compared to the reference.

The segmentation process was tested using different similarity and area thresholds over image composed by OLI bands 4, 5 and 6. The visual assessment about performance using region growing segmentation conducted to define the similarity and area thresholds of 20 and 25, respectively. The supervised classification was performed by Bhattacharyya metric, in which spectral samples selected in the segmented image were the same samples used for maximum likelihood classification.

2.3. Use of OLI thermal band (TIRS 10) on classification.

The monitoring of thermal properties of several terrestrial surface features allows the distinction of targets as soil, urban area, vegetation and water (SILVA, 2015). Phenomena relating to thermal contrasts demonstrate thermal properties which aggregate information beyond the solar spectra.

This contrast is specially given by the urban elements properties, such as asphalt and concrete, by the heat retention and by the lack of green areas. Thus, the addition of the OLI thermal band to the set of band 4, 5 and 6 will be evaluated on the supervised classification, assessing its influence.

Once the focus of the application is the analysis of the classifier's performance due to the inclusion of TIRS band 10, the conversion of the digital level to temperature will not be performed. The classification method with the highest agreement level will be applied once again with the addition of TIRS band 10, and then the validated result will be compared to the classification using the solar spectra only.

2.4. Validation of classifications

The classifications were validated using 220 points randomly distributed over the reference image (RapidEye). The RapidEye is a system composed of five identical satellites on the same orbit. The swath is 77 km and extension of 1500 km, 5m of spatial resolution, 12 bits of radiometric resolution and 5 days of temporal resolution. The image was used as a reference for visual interpretation of land cover types in order to validate the classifications analyzed.

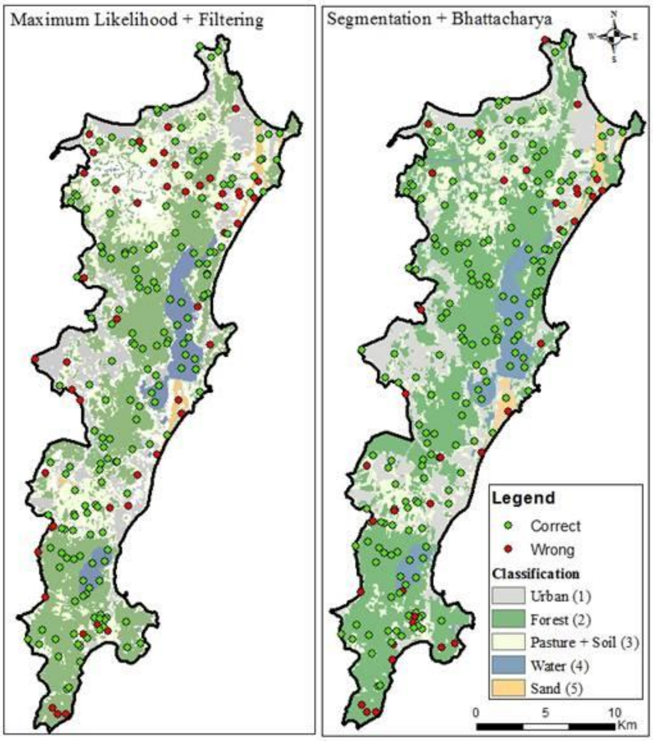
The land cover classes interpreted in the reference image were recorded as attributes of the random points and then, the points were crossed to the reference classes with classification to create the confusion matrix and to calculate the global accuracy of each method.

In order to prevent natural and anthropical changes on the landscape to interfere with the assessment of classification methods, the OLI image and the RapidEye image used had near dates of image acquisition (30/01/2014 and 14/09/2013, respectively). Due to environmental restrictions of land cover on the island, changes in coverage are not significant in short time interval. Therefore, the given differences between image date acquisitions did not affect significantly the assessment and validation of classifications.

3. Results and discussion

3.1. Assessment of maximum likelihood classification using majority spatial filtering and Bhattacharyya classification using segmentation method

The OLI/Landsat 8 images were classified based on the proposed methods and the global accuracy was assessed from randomly distributed points using a high spatial resolution image as reference (Figure 3).



A - MaxVer Classification (%)

	Classes	Urban	Forest	Pasture and Soil	Water	Sand
Reference	Urban	59,09	2,27	38,64	0	0
	Forest	0	86,67	13,33	0	0
	Pasture and Soil	2,86	0	94,29	0	2,86
	Water	4,35	0	0	95,65	0,00
	Sand	27,27	0	0	0	72,73
Total (pixels)		31	92	64	22	9
				Global accuracy (%):		82,5

B - Segmentation + Bhattacharya Classification (%)

	Classes	Urban	Forest	Pasture and Soil	Water	Sand
Reference	Urban	79,55	4,55	15,91	0	0
	Forest	2,86	89,52	6,67	0,95	0
	Pasture and Soil	11,43	17,14	68,57	0	2,86
	Water	0	0	0	100	0
	Sand	18,18	9,09	0	0	72,73
Total (pixels)		44	103	38	24	9
				Global accuracy(%):		84,4

Figure 3. Land cover classification and distribution of validation points (Left), and Confusion Matrix for land cover classification using different templates: A - Maximum likelihood classification and majority filter; B - Segmentation and Bhattacharyya classification.

The maximum likelihood classification demonstrated concentration of errors in the northern region of the island due to high land cover heterogeneity and occurrence of small and isolated features classes such as pasture and bare soil, urban and forest. The spatial distribution of land cover classes in the northern region is a challenge for pixel-based classification once high diversity of land cover makes the majority filter an error source when it changes heterogeneous regions into homogeneous areas. The pixel-based classification demonstrated a high confusion on borders between distinct classes once spectral mixture in pixel generates different spectral patterns. This suggests that this classifier is sensible to the spectral mixture and spatial filtering is important to reduce spurious pixels in the context of another class and to smooth borders.

The highest agreement applying majority filter was obtained in the 3rd filtering repetition (82,5% of agreement) and this threshold was suggestive to preserve the heterogeneity of areas with a mixture of classes, such as urban area, and also to smooth borders. However, the urban class complexity given by its similarity with pasture and soil class resulted in lower accuracy (59,09%). The region-based classification demonstrated global accuracy greater than pixel-based classification with filtering. However, it also demonstrated less concordance on pasture and soil class and sand class. In the pasture and exposed soil areas, most of the pixels were classified incorrectly as forest and urban area, which can be explained by the fact that these classes often occur in the transition areas between forest and urban areas causing confusion in classification.

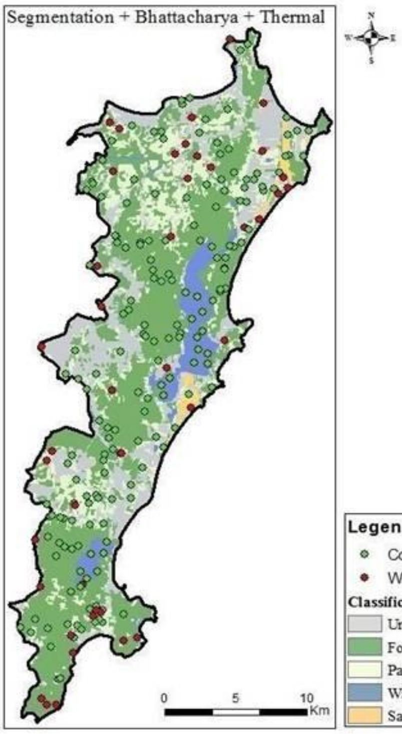
In sandy areas, the majority of pixels were classified incorrectly as the urban class, which is explained by the fact that spectral behavior of sandy area is similar to urban areas in the spectral bands chosen for classification. The method also presented confusion between sand and forest classes which may indicate a failure in the segmentation process. According to Haralick and Shapiro (1984), a limitation of region growing segmentation is its easiness to merge distinct regions.

In both classifying methods, errors were concentrated in the north, central-south, and south of the island due to a higher occurrence of transitions areas between coverage types, which demonstrates the technique limitation in areas with complex characteristics. The definition of the classification method requires a critical assessment by the analyst regarding the complexity degree of the land cover types in the study region and the goals of the study.

Lastly, despite the limitations of global accuracy metric, this criterion was considered sufficient to evaluate the classifications in this study in order to select the technique to be used at the classification of the image composed of OLI/Landsat 8 spectral bands 4, 5, 6 and 10. Therefore, the region-based classification approach was defined as the classifier technique to be applied in the next processing steps of this study.

3.2. Use of OLI/Landsat 8 thermal band (B-10) on classification

Due to its higher agreement on the results of the considered classes, the region-based classification approach was selected to evaluate the use of the thermal band as an auxiliary data to the multispectral bands (Figure 4).



C - Segmentation + Bhattacharya Classification + Thermal (%)

	Classes	Urban	Forest	Pasture and Soil	Water	Sand
Reference	Urban	70,45	15,91	13,64	0	0
	Forest	0,95	89,52	8,57	0,95	0
	Pasture and Soil	8,82	26,47	64,71	0	0
	Water	0	0	0	100	0
	Sand	9,09	9,09	9,09	0	72,73
	Total (pixels)	36	111	38	25	8
				Global accuracy(%):		82,1

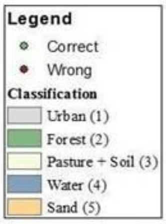


Figure 4. Land cover classification and distribution of validation points (Left), and Confusion Matrix for land cover classification using Segmentation and Bhattacharyya classification adding Thermal band 10 (Right).

Region-based classification using OLI spectral bands 4, 5, 6 and 10 led to the lowest global accuracy (82%) in comparison to the other classifications which used the multispectral bands 4, 5 and 6 only. This result demonstrates that the differences between targets' temperature patterns were insufficient to aggregate auxiliary information for the classification. It can be seen that the lowest agreement occurred on the pasture and exposed soil class, this fact, however, also occurs on the classification using the solar spectra bands only. Despite the existence of a relation between pixel digital levels at the thermal image and the targets' temperature, the temperature variations could not have been sufficient to cause a better performance of the classifier.

The expectation of the thermal contrast, between urban and natural areas, to assist the classifier on classes distinction were not achieved and the agreement proportion for the urban class was of 70,45% in comparison to 79,55% on the classification using the solar spectrum only.

In spite of this difference between validation values for the urban area, it cannot be argued securely that the thermal band does not contribute to a good classification, once this variation of values is susceptible to the sampling quality and quantity. Once the digital levels were not converted to surface temperature values, it must be stated that the thermal data was under atmosphere interference.

It is important to highlight that the predominance of green areas such as forest at urban area surroundings throughout the island favor the temperature attenuation of urban centers and reduce thermal differences represented on TIRS band. Furthermore, although band 10 image has a pixel size of 30x30m, the spatial resolution for the data acquisition by the sensor is 100m, causing the image of this band to be insensitive to urban areas of narrow spatial development, which tend to be obfuscated by the response of forests on their surroundings.

The sand class validation presented an agreement of 72,73% in all classifications. This can be explained by the fact that dunes areas are small and homogeneous, suggesting that the classifiers could find a relatively good similarity for these areas, beyond the fact that, given the small spatial area of dunes on the image, a reduced number of validation points were obtained for this class.

4. Conclusions

The supervised classification using segmentation revealed a slightly superior global accuracy in comparison to pixel-based classification with the filtering application. However, the global accuracy metric is simple and validation uncertainties influence the final value. The differences in performances between the classification methods are not significant for the study area. In this context, the maximum likelihood classification with filtering application is satisfactory due to the simple application in classifying the land cover classes in Santa Catarina Island.

The performance of both classification methods was reduced for high complexity land cover areas, which is also verified for Fierens and Rosin (1994), who suggest that the pre-processing data is a potential source for introducing errors and this risk is higher when the land cover is complex. Unquestionably, the definition of method of classification requires a critical evaluation by the analyst about the complexity level of the land cover types on the area of study.

The expectation of thermal band to support the classifier in the distinction of cover types was failed, and the accuracy rate for the urban class, for example, was lower than the classification with multispectral bands. This result demonstrates the differences between the target’s temperature patterns were not sufficient to induce a better performance of the classifier. However, the application of the thermal band should not be dismissed, once it’s necessary to consider the intrinsic variations of the thermal data, which change the temperature contrast among terrestrial surface targets.

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