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Original Article

Automatic classification in Landsat images for the mapping of Otacílio Costa – SC

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Abstract
This paper aimed to compare digital classification methods (supervised, unsupervised, object - oriented) in Landsat images in order to map the changes in land use and occupation for the years 2007 and 2017 for the municipality of Otacílio Costa - SC. For this purpose, images of the Landsat-5 TM sensor and the Landsat-8 OLI sensor were used. After the digital processing of the images, the classes of use and soil coverage were defined and the samples generated, divided into 60% of training and 40% of validation. Finally, the classification accuracy statistics for each method were calculated. The unsupervised methods were inefficient in all analyzed years, while the supervised ones were superior to the others. On the other hand, the object-oriented classification presented a classification considered excellent in 2007 and very good in 2017. The performance of the classification by the SVM method (*Support Vector Machine*) was excellent in 2007 and 2017, and it was considered the best evaluated method. From this, the mapping of the classes of use and coverage revealed a reduction of 4.8% of agricultural areas and 2.3% of urban areas and an increase of 1% for vegetation and 1.5% for water bodies.
Keywords: Accuracy, Decision Trees, Remote Sensing.

Introduction

Changes in land use and cover influence the size of these classes and cause consequences for the environment. In this sense, knowing such changes are important for various purposes, such as deforestation, damage assessment, disaster monitoring, urban sprawl, land planning and management. The evaluation of the changes detection requires multi temporal data in the quantitative analysis of the results and in the spatial distribution of these changes (Attri et al., 2015).

Studies on the detection of changes in soil use and cover and purposes related to environmental and geomorphological aspects have been using and highlighting the efficiency of geotechnologies (Lima et al., 2017), such as Remote Sensing (SR). From this science, it is possible to obtain effective information on the use and coverage of the earth in a specific place by means of orbital data, enabling studies in this area to be developed (Attri et al., 2015).

One of the main applications of SR refers to image classification techniques, which allow obtaining land use information for economic and environmental planning (Li et al., 2014). The combined use of SR with the Geographic Information System (GIS) generated a wide range of possibilities related to the detection of changes in an area. An orbital image has qualitative data from small or large areas, minimizing field work. In this case, the data from the image are analyzed according to the characteristics and the restrictions of the different data generated by the accessible sensors (Natya and Rehna, 2016).

The classification of land use can be performed, analyzed and understood from orbital images. Therefore, the satellite sensors must have satisfactory characteristics regarding the spectral coverage (width and number of bands); radiometric resolution (number of bits); spatial resolution (pixel size) and temporal resolution (time for the sensor to revisit an area) (Natya and Rehna, 2016). This allows the digital classification of SR images to result in reliable information to be used for the management of these areas (Gaiad et al., 2017).

Abburu and Babu Golla (2015) and Silveira et al. (2016) conceptualize digital classification as the methodology that allows the observation of data in an image, in which labels are conferred for each class of use. With this, the pixels of an area with similar characteristics will be grouped.

Digital classification encompasses unsupervised and supervised methods, and the last one can be divided into parametric and non-parametric. Supervised methods require the user participation, a process known as a training sample. This step is very important and it is directly related to the method´s accuracy, since the samples will be used in two ways, as the following: to classify and to evaluate the method´s accuracy (Abburu and Babu Golla, 2015).

There is still the use of non-parametric algorithms, such as the Support Vector Machine (SVM) in the digital classification of images. These algorithms are also known as machine learning (AM) since they present decision trees (Andrade et al., 2014).

In the unsupervised classification, the image is segmented into a series of classes based on the natural groupings of the image values, without the aid of training data or prior knowledge of the study area (Puletti et al., 2014). The main unsupervised methods are K-Means and IsoData.

Currently, another method has been highlighted in studies related to classification: Object-Based Image Classification (OBIA). In this method, the models are based on objects and not on pixels, generating image objects through segmentation, classifying the image based on them (Myint et al., 2011).

The objective of this study was to compare methods of digital classification (supervised, unsupervised and object-oriented classification) in Landsat images and, using the best method, to map the changes in land use and occupation for the years 2007 and 2017 for the municipality of Otacílio Costa - SC.

Material and Methods

The study area consisted of the municipality of Otacílio Costa, located in the State of Santa Catarina (Figure 1), with the coordinates for latitude 27º29'15" South and longitude 50º07'04" West, an altitude of 852 meters and an area of 846.58 km² (Ibge, 2017). According to Alvares et al. (2013), the climate is classified as Cfb, mesothermic moist and mild summer in the classification of Köppen. It presents a well distributed rainfall regime during the year, with annual average of 1519 mm, and average annual temperature of 16.1 ° C.

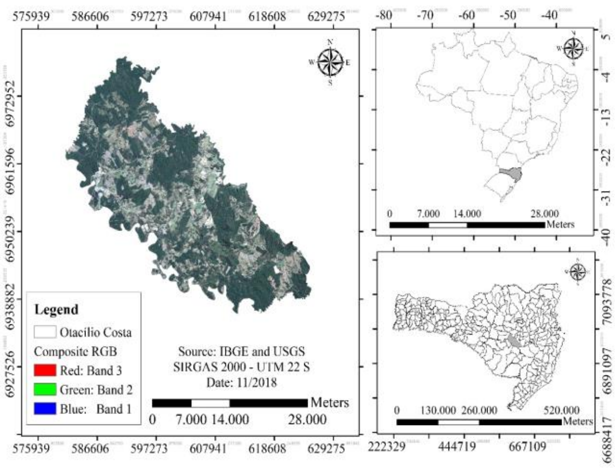

Figure 1. Location of the study area. Source: The Authors (2018).

Data Acquisition and Processing

The acquisition of the images was carried out for the years 2007 and 2017, acquiring an image for each year. For 2007, an image was taken from the TM (Thematic Mapper) sensor Landsat - 5 (Land Remote Sensing Satellite) orbit / point 221/079 on February 3rd, 2007. For 2017, a multispectral image of the OLI (Operational Land Image) sensor was obtained on board the Landsat - 8 satellite, orbit / point 221/079 on August 08th, 2017. Both images were purchased from the United States Geological Survey (USGS) (Usgs, 2017).

The shapefile of the municipality was obtained from the IBGE (Brazilian Institute of Geography and Statistics) portal using the reference system SIRGAS 2000 (Geocentric Reference System for the Americas). From this data, the study area was delimited.

Digital image processing involved preprocessing, processing and classification. Calibration, radiometric normalization and atmospheric correction in the images were performed using the FLAASH algorithm (Fast Line-of-sight Atmospheric Analysis of Spectral Hypercubes), available in the ENVI (Environment Visualizing Images) computational application.

Definition of training classes and samples

For the definition of the classes of use and ground cover, combinations of RGB bands (Red-Green-Blue) were made for both images in order to improve the visualization of the targets. It is important to highlight that, for the classification, only three bands of each sensor were used, as the following: red, green and blue for the 2007 image and near infrared, green and blue for the 2017 image. Therefore, we used compositions 5 (R), 4 (G) and 3 (B) for the 2007 image, and compositions 7 (R), 5 (G) and 4 (B) for the 2017 image. Thus, four classes of land use and land cover were defined, as follows:

- Agriculture and exposed soil: areas planted with annual crops/grasses or used by livestock; without vegetation or other crops;
- Urban area: areas with buildings, streets and roads;
- Water bodies: areas occupied by rivers, lakes, water courses;
- Vegetation: it covers all types of vegetation (native and planted) and in all stages of succession.

There was no greater discrimination of classes due to the spatial resolution of the images used (30 meters), which did not allow a better differentiation of the targets. It is worth mentioning that the first class presents characteristics of two different targets due to the difficulty of separating them in the images, caused by their spatial resolution (30 meters).

After the classes definition, the samples were generated. For this, 50 points were collected randomly and homogeneously in the image for each class, totaling 200 points in each image. The samples were collected in a way to contemplate the characteristic targets of each class, to guarantee the accuracy of the classification. The samples were then divided into 60% training and 40% validation using the Generate Random Sample tool, using the Ground Truth ROIs in the ENVI computational application.

Classification of images

Next, the unsupervised (IsoData and K-Means), supervised (Maximum Likelihood Classification – MX and Support Vector Machine Classification - SVM) and object-oriented classification methods (OBIA) were tested in ENVI. The parameters considered for each classifier were the following: for non-supervised classification, 4 classes were considered, with 5 iterations with threshold change of 5%, with at least 1 pixel per class and minimum distance per class of 5 andmaximum error distance of 1; for supervised classifiers, in the case of SVM, the criteria were as follows: Kernel Type (Radial Basis Function), Gamma in Kernel Function of 0.17, Penalty Parameter of 100,000, Pyramid Levels of 0.00 and Classification Probability Thershold: 0.0. For MX, unique values were used, with a data scale value of 255.0. For OBIA, the scale level was 80.0 with edge algorithm and for the merge level, we used 80.0, the full lambda schedule algorithm.

The thematic maps were elaborated in GIS environment, on ArcMap software (Esri, 2017).

Abburu and Babu Golla (2015) list differences between classification methods. Supervised methods require the assistance of an analyst, through the creation of training samples, divided into the following categories: to classify and to evaluate the accuracy of the method. However, the approach of unsupervised methods comprises the use of pixel grouping techniques in the image in classes, which will be named from the analyst's evaluation. Finally, object-oriented classification is based on techniques and/or segmentation algorithms that perform the union of similar pixels into segments. In addition, it is possible to obtain information regarding the relative size and shape of objects.

Evaluation of the classification accuracy

The reliability of the classification of the methods tested was based on the error matrix, which according to Congalton (1991), consists of a set of numbers arranged in a square that are defined in rows and columns. This arrangement defines the number of units of each sampled class.

With these data, the following evaluation statistics were obtained for the accuracy of the mapping: Global Accuracy, Kappa Index, Tau Coefficient, Commission Error and Omission Error, User Accuracy and Producer Accuracy. All of them are described below.

The Global Accuracy presents the similarity of a measurement regarding its real value, and it was obtained by Equation 1:

$$P_o = \frac{\sum_{i=1}^{c} X_{ii}}{N} \quad (1)$$

In what: Po: Global Accuracy; Xii: elements of the main diagonal; c: number of classes present in the error matrix; i: number of columns; i: number of lines; N: total number of sample units.

Suggested by Cohen (1960), the Kappa Index relates how the baseline data and automatic classification differ and agree, and it was calculated by Equation 2 and Equation 3

$$P_c = \frac{\sum_{i=1}^{c} X_{i+} * X_{+i}}{N^2} \quad (2)$$

$$K = \frac{P_o - P_c}{1 - P_c} \quad (3)$$

In which: K: Kappa index; Po: global accuracy; Pc: proportion of units that agree by chance; c: number of classes present in the error matrix; Xi + and X + i: marginal totals of row i and column i, respectively; N: total number of sample units contemplated by the matrix.

Kappa index values were evaluated according to Table 1:

Table 1. Interpretation of Kappa Index values

Kappa value	Map Rating Quality
<0.00	Poor
0.00 – 0.20	Bad
0.21 – 0.40	Reasonable
0.41 – 0.60	Moderate / Good
0.61 – 0.80	Very Good
0.81 – 1.00	Great

Source: Adapted from Landis and Koch (1977).

The Tau methodology was proposed by Ma and Redmond (1995) to evaluate the accuracy of the mapping. Equation 4 illustrates the calculation of Tau:

$$T = \frac{P_o - \frac{1}{m}}{1 - \frac{1}{m}} \quad (4)$$

Where: T: coefficient Tau; Po: global accuracy; m: number of classes.

The Omission Error (Equation 5) corresponds to the number of samples that belonged to a certain class, but classified in another class by the method.

$$E_o = \frac{X_{i+} - X_{ii}}{X_{i+}} \quad (5)$$

In what: Eo: omission errors; Xi +: marginal of the line; Xii: diagonal of that line.

The Commission Error (Equation 6) refers to the number of pixels not included in a class, but belonging to another.

$$E_{co} = \frac{X_{+i} - X_{ii}}{X_{+i}} \quad 6)$$

In what: E_{co}: commission errors; X + i: column marginal; Xii: diagonal of that column.

In terms of User Accuracy and Producer Accuracy, the first one was obtained by Equation 7 and the second one was obtained by Equation 8:

$$E_u = \frac{X_{ii}}{X_{i+}} * 100 \quad (7)$$

$$E_p = \frac{X_{ii}}{X_{+i}} * 100 \quad (8)$$

In what: I: accuracy to the user; Ep: producer accuracy; Xii: diagonal of that line; Xi +: marginal of the line; X + i: column marginal.

Results and Discussion

The statistic of the methods tested for the year 2007 (Table 2) revealed that the unsupervised methods were inferior to the other methods, presenting the lowest Kappa Indices and the largest errors of omission and commission. The supervised classification, in turn, presented the best results, superior to the object oriented classification.

Table 2. Accuracy of the classification methods tested for the municipality of Otacílio Costa - SC for the year 2007.

Statistic	IS	KM	MX	SV	OB
Kappa	0.64	0.46	0.94	0.97	0.92
Accuracy	0.86	0.75	0.98	0.99	0.97
Tau	0.81	0.67	0.97	0.98	0.96
Omission	21.4	34.6	12.4	5.9	6.3
Commission	40.7	49.9	2.5	2.4	9.1
User	59.2	50.0	87.5	94	90.8
Producer	78.9	65.3	97.4	97.3	93.6

In what: IS: IsoData; KM: K-Means; MX: Maximum Likelihood Classification; SV: Suppor Vector Machine Classification); OB: Object Oriented Classification.

In general, all methods presented misunderstanding in the classification of urban area classes and water bodies. This can be explained by the training samples provided. The class of water bodies had few features in the image, and the urban area class had a color similar to the agriculture class in some places. The agriculture class and the vegetation class had adequate representativeness and, for that reason, they were successful in the classification.

According to the Kappa Index, Global Accuracy and Tau Coefficient of supervised and object-oriented classification, the reliability of classification of these methods was excellent. For the IsoData method, the classification was very good and for K-Means it was moderate / good.

The excellent performance of the classification by the SVM (Kappa Index of 0.97 and Global Accuracy of 0.99) turns this method into the most appropriate to evaluate land use and land cover classes in 2007 for Otacílio Costa - SC.

The classification performed for the year 2017 (Table 3) revealed the superior performance of supervised classification over the others. Again, the unsupervised classification did not achieve satisfactory results, which can be explained by the accuracy of the supervised methods in relating training samples to the actual classes of the image.

Table 3. Accuracy of the classification methods tested for the municipality of Otacílio Costa - SC for the year 2017.

Statistic	IS	KM	MX	SV	OB
Kappa	0.63	0.15	0.95	0.97	0.75
Accuracy	0.75	0.41	0.96	0.98	0.95
Tau	0.66	0.22	0.94	0.98	0.93
Omission	19.7	48.8	2.4	2.6	3.6
Commission	31.7	63.8	2.7	2.0	2.7
User	68.2	36.1	97.5	97.3	89.2
Producer	84.2	51.1	97.2	97.9	89.3

In what: IS: IsoData; KM: K-Means; MX: Maximum

Likelihood Classification; SV: Suppor Vector Machine Classification); OB: Object Oriented Classification.

The statistics (Kappa Index, Global Accuracy and Tau Coefficient) suggest that the reliability of the supervised methods was excellent, as observed in the previous year, and the object-oriented classification was very good. The best method for the year 2017 was also the SVM. From the choice of the best method, it was possible to obtain the mapping of the classes of use and land cover for the analyzed period. Figure 2 illustrates the mapping for the year 2007 and Figure 3 for 2017:

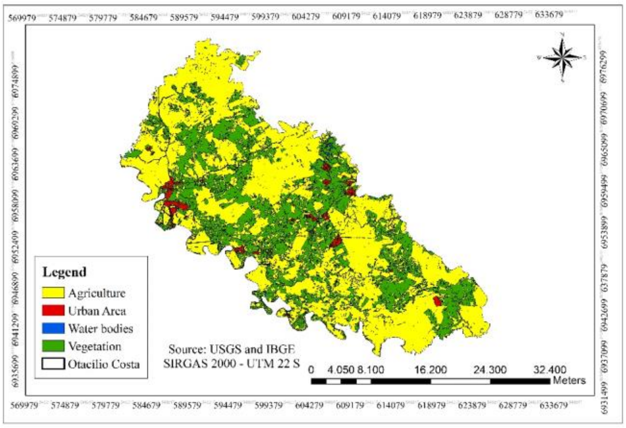

Figure 2. Map of land use and occupation of the municipality of Otacílio Costa - SC by the classification SVM for the year 2007.

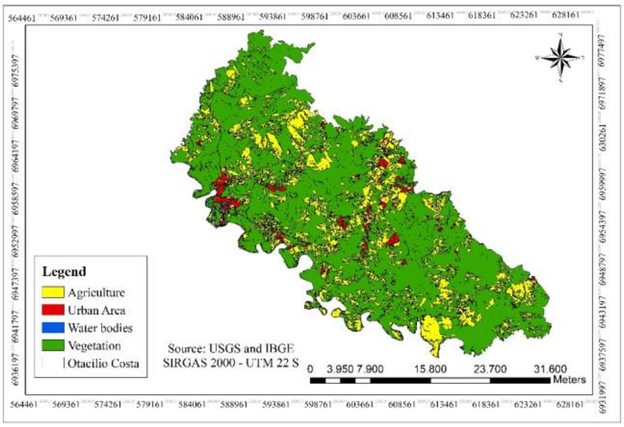

Figure 3. Map of the land use and occupation of the municipality of Otacílio Costa - SC by the SVM classification for the year 2017.

When evaluating the land use and land use maps generated by the SVM method for the interval analyzed, we can note the change in the areas of the classes. We can observe this process on Tables 4 and 5.

Table 4. Classification of the areas obtained with the supervised method SVM in the municipality of Otacílio Costa - SC for the years 2007 and 2017.

	2007		2017	
Class	**Area (ha)**	**Area (%)**	**Area (ha)**	**Area (%)**
Agriculture	22,257.4	26.3	18,162.5	21.5
Urban area	1,800.1	2.1	3,666.9	4.4
Water bodies	1.533.0	1.8	2,856.1	3.3
Vegetation	59,067.5	69.8	59,972,5	70.8
Total	84,658.0	100	84,658.0	100

The evaluation of the classes shown on Table 4 demonstrates that the greatest territorial extension belongs to the vegetation class, with 69.8% in 2007 and 70.8% in 2017. The agriculture class comes next, with 26.3% and 21.5% in the respective years, followed by the urban area class, with 2.1% and 4.4% in 2007 and 2017, respectively, while the water bodies' class presents the least extension in 2017, with 3.3% and 1.8%. In 2007, the anthropogenic areas (agriculture and urban area) occupied approximately 28.4%, while in 2017 there was a reduction of 2.5% in relation to the first year, being 25.9%. The vegetation class occupied 69.8% in 2007 and 70.8% in 2017, representing an increase of 1%. The water bodies' class represented 1.8% in 2007 and in 2017 it increased to 3.3%, an expansion of 1.5%.

During the analyzed time, an area loss of 4.8% occurred only in the agriculture class. The other classes had an increase, especially the urban area, which presented the highest growth (2.3%), followed by water bodies (1.5%) and vegetation (1%).

Table 5. Alteration of the areas classified by the SVM method for the municipality of Otacílio Costa - SC for the years 2007 and 2017.

	Change 2007/2017	
Class	Area (ha)	Area (%)
Agriculture	-4,094.9	-4.8
Urban area	+1,866.8	+2.3
Water bodies	+1,323.1	+1.5
Vegetation	+905.0	+1.0

The use of the SVM algorithm should cautiously observe the Kernel Radial Basis Function (RBF) parameters, because it presents the best indications in the available literature (Pradhan, 2013). One of the factors that made SVM the best method in this study was the use of RBF.

Moreira et al. (2014) affirm that the SVM algorithm is named as a high-class classifier and it integrates the group of non-parametric classifiers. This algorithm acts in the minimization of classification inaccuracies, as well as in the isolation of classes by means of the decision surface, allowing separation among classes. On the other hand, Ruiz et al. (2014) affirm that algorithms like SVM need significant processing time and can be conceptualized as "black boxes", due to the complexity of the understanding of obtaining certain results.

The SVM method, superior in this study, was also chosen as the best method in the study of Andrade et al. (2014). Comparing supervised methods (Maximum Likelihood and Support Vector Machines) for vegetation physiognomy classification in high spatial resolution images, these authors concluded that SVM presented the best classification reliability, with a Kappa Index of 0.80.

Another excellent performance of SVM was obtained by Zheng et al. (2015) in the evaluation of the ability of this algorithm to discriminate crops using Landsat images and time series in Arizona. The accuracy of the classification was 90% for the nine major crops and the user and producer accuracies ranged from 57% to 100%. The authors associate these good results with the intelligent choice of training samples and the choice of images without the influence of clouds.

The study conducted by Souza et al. (2016) highlights the robustness of coffee mapping results in three regions of Minas Gerais using SVM, with Kappa Index of 0.80 and Global Accuracy of 0.85 in region one, 0.87 and 0.86 in region two and 0.84 and 0.88 in the last region, respectively.

Similar results were found by Gaiad et al. (2017) in the comparison of decision tree algorithms with Artificial Neural Networks (RNA) and Support Vector Machine (SVM) in the city of Mariana - MG. With Kappa Index of 0.979 and Global

Accuracy of 0.9832, SVM was the algorithm that showed the best performance.

Other authors have tested the efficacy of supervised methods. Oliveira et al. (2013) compared methods of supervised classification in Rapideye images to map forest fragments monodominated by Myracrodruon urundeuva in Tumiritinga, MG, concluding that Maximum Likelihood was the best method. Santos et al. (2017) evaluated the dynamics of land use and land cover from 1990 to 2015 in nine municipalities in the southern region of Tocantins, using classification supervised by visual interpretation. The results revealed the efficiency of the tested method and the high level of anthropization and conversion of areas belonging to the Cerrado in anthropic areas.

Marinho et al. (2017) used the Maximum Likelihood method to map class and soil cover changes in Sucupira - TO between 2007 and 2017. The Kappa Index was 0.97 for 2007 and 0.99 for 2017.

The performance of the OBIA method corroborates the results found by Nunes and Roig (2015). The Kappa Index found by these authors was 0.64, a value considered low and similar to the onde found in this study, for 2017 (0.75). The authors reported limitations and difficulties in the execution of this method that may have influenced the performance of the classification, such as non-individualized segmentation by feature, characteristics of the image used, heterogeneity of class segments and use of auxiliary data.

The OBIA method also revealed high dependence on the interpreter and a significant commitment to determine the criteria for classes' separability, which was affected by the spatial resolution of the images used (30 meters). In this way, it was not possible to distinguish aspects related to the shape and texture of objects, as it happens in high spatial resolution images.

Conclusions

The best classification method was the Suppor Vector Machine Classification (SVM) with Kappa Index of 0.97 for years 2007 and 2017. The study area presented a reduction of 4.8% for agriculture and 2.3% for urban areas. For the vegetation class there was an increase of 1% and 1.5% for water bodies. The greatest loss of area was observed for the agriculture class, with a reduction of 4.28%, and the water bodies' class was the one that showed the lowest representativeness.

It is important to highlight the efficiency of geotechnologies to map the changes occurring in the classes of use and land cover of the evaluated area. Such results may contribute to the proper elaboration and understanding of the activities related to the classes evaluated.

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