Classification algorithms comparison for landslide scars

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Abstract. *Landslide inventory is an essential tool to support disaster risk mitigation. Using remote sensing images, it is usually obtained through pattern recognition. In this study, three classification methods are compared to detect landslides: Support Vector Machine (SVM), Artificial Neural Net (ANN) and Maximum Likelihood (ML). We used Sentinel-2A imagery, extracted and selected features for two areas in the Rolante River Catchment. The classification products showed that SVM classifier presented the best overall accuracy (OA) for Area 1 resulting in 87.143%; while for Area 2 ML showed the best OA equals to 86.831%.*

1. Introduction

Landslides are widespread natural geomorphologic processes and represent a gravity-driven component of erosion [Davies, 2015]. They are downward movements of slope material triggered by earthquakes, snow melting or heavy rain, which can also be caused or intensified by anthropic activities [Guzzetti *et al*., 2012]. These phenomena cause economic damages and loss of lives when occurred in occupied areas [Haque *et al.*, 2019]. The landslide inventory map consists on identifying mass movement scars, which can provide many information about past events, as location, types and patterns, assisting to build landslide susceptibility models [Ramos-Bernal *et al.*, 2018]. Thus, landslide inventory map is crucial to support urban planning and disaster risk reduction [Lupiano *et al*., 2019].

The inventory can be achieved by either conventional methods or state-of-the-art techniques. Conventional methods include field mapping and visual interpretation of remote sensing images; nevertheless, these methods are time and resource consuming [Qin, Lu and Li, 2018]. On the other hand, semi-automatic recognition of landslide scars and analysis of changes in the spectral signature of land surface can provide a rapid mapping [Guzzetti *et al*., 2012]. Support Vector Machine (SVM), Artificial Neural Network (ANN) and Maximum Likelihood (ML) are popular classifiers that are used to identify landslide scars. [Manfré *et al*., 2014] used SVM and ML to identify landslides in São Paulo State coast, in Brazil. The authors claim that SVM presented better performance than ML, especially when associated to the Normalized Difference Vegetation Index (NDVI). [Moosava, Talebi and

Shirmohammadi, 2014] compared ANN and SVM to mapping landslides and the results have shown no significant differences between both methods. Many researches have been made using ANN to attend landslides issues, for instance the results shown by [Chen et al. 2017] at Wanyuan area, China and by [Kalantar et al., 2018] at Dodangeh watershed, Iran.

In this context, the aim of this study is to compare different image classifying techniques: SVM, ANN and ML, in order to identify which of them presents better results concerning landslide scars detection.

2. Study Area

The Rolante River Catchment is located in the State of Rio Grande do Sul, Brazil (Figure 1), and it embraces three cities: Riozinho, Rolante and São Francisco de Paula. Its drainage area is 828 km², with altitudes varying from 19 to 997 m. This area is almost entirely located in the Serra Geral geomorphological unit, with a predominance of basaltic rocks and sandstone. According to [Rossato 2011], the climate is characterized as very humid subtropical, with precipitation regime distributed throughout the year, with annual averages between 1700 and 200 mm.

On January 5th, 2017, there was a landslide event in the upstream area of Rolante River Catchment triggered by an extreme precipitation event. The rains lasted for approximately four hours with local private measurers values estimated between 90 and 272 mm [SEMA, 2017]. These rains moved a large amount of material from the slopes, generating a natural dam on the Mascarada river, a tributary of the Rolante river with subsequent rupture of this barrier and consequent flash flood, reaching Rolante city.

Previous works identify approximately 300 landslide scars in this region [GAMEIRO *et al.*, 2019; QUEVEDO *et al.*, 2019a; QUEVEDO *et al.*, 2019b]. According to the landslide inventory, two areas of interest were chosen to be analyzed. The criteria to choose these areas considered that both of them contained a significant amount of landslide scars presented in the landslide inventory [QUEVEDO *et al*., 2019a]. The Area 1 contains 91 landslide scars with 39 ha whilst Area 2 contains 34 landslide scars with approximately 16 ha.

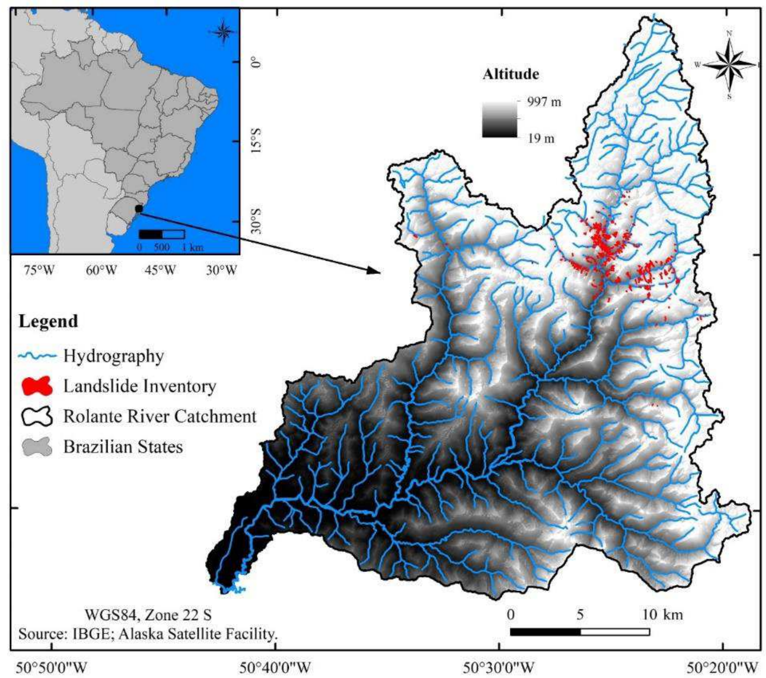

Figure 1. Location map of the study area.

3. Methodology

To fulfill the proposed objective, we used thirteen attributes (Sentinel Bands: 02 - Blue, 03 - Green, 04 - Red, and 8 - NIR; Sentinel TCI: Blue, Green and Red; NDVI; PCA 1 and PCA 2; Texture Variance and Texture Mean (Band 08); Slope). All the features were ranked in order of importance via Weka software and, then, we applied three image classifiers: SVM, ANN and ML. The methodological process of this study is exposed in the Figure 2.

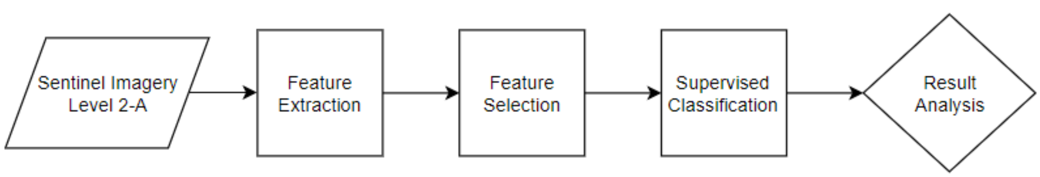

Figure 2. Flowchart of the methodology.

The identification of landslide scars usually present better results when high spatial resolution images are used [Karen *et al*., 2009]. Considering that, Sentinel 2A Level-2A imagery was chosen, especially because it provides orthorectified reflectance products of Bottom-of-Atmosphere (BOA). For the purpose of this study, among all products available for Level-2A, only 10 m spatial resolution data were used, discarding AOT maps. The Sentinel scene selected is from February 09th, 2019. The original image was clipped in for the two areas of interest, each one containing 6 km² (Figure 3).

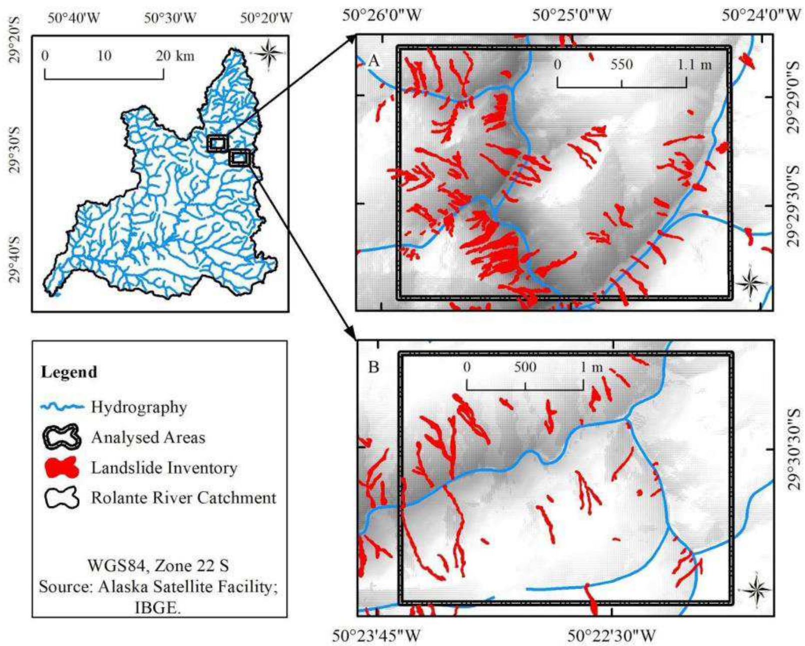

Figure 3. Location map of the two analysed areas. A) Area 1; B) Area 2.

After selecting the study area and clipping the scene, some statistics were used with the objective to identify heterogeneity of classes during the classification procedure. From the original images, a feature extraction process was performed, using features based on [Gerente et al, 2017a], [Gerente et al, 2017b] and [Karen et al, 2009]. This procedure was executed at ENVI 4.7 software. The first chosen feature is the NDVI which considers near-infrared and red wavelengths for its computation. The NDVI values are used to detect varying densities of vegetation coverage which could be used for natural disasters [Bhandari *et al.*, 2012].

The second used feature was the Principal Components 1 and 2, from Principal Component Analysis (PCA), shown in [Singh and Harrison, 1985], which computes eigenvalues and eigenvectors from a dataset. According to the authors, this approach aims the determination of underlying statistical dimensionality of a dataset, and it is usually applied to image enhancement, change detection and characterizing seasonal changes in land cover types.

Using QGIS 2.8 software, a slope has been extracted from the DEM of ALOS (Advanced Land Observing Satellite), PALSAR (Phased Array type L-band Synthetic Aperture Radar) sensor. Moreover, in the matter of characterizing heterogeneity of classes, textures are usually applied. This concept is related to spatial distribution of intensity values; hence it contains information regarding rugosity, regularity, contrast, etc. [Ruiz et al, 2004]. Among the statistic features, mean and variance have been used to characterize Texture.

[Hall, 1999] defines feature selection as a learning step that focuses on the most useful data aspects for analysis and feature prediction. The author adds that correlation-based feature selector approach eliminates non-relevant data and it may improve the performance of algorithms. This method takes into consideration feature-feature inner correlation as well as feature-class correlation. Using this approach, a rank of features is obtained, and the analyst defines the number of selected features. This approach was conducted using the Weka Software. All the features were ranked in order of importance and only the first four were selected. These four attributes were chosen to test whether only a quarter of the variables was able to map landslides scars and, consequently make the model more parsimonious. Furthermore, in order to be able to make a comparison between classifiers, the selected attributes were the first ones which were similar for both areas in Weka rank.

After selecting the most heterogeneous attributes, the supervised classification was conducted. The classification assessment was performed via holdout method where testing samples are given independently of training samples [Kim 2009]. The image size was 214x284 pixels and approximately 400 training samples and 100 testing samples were used for each class. The number of sampled pixels was defined after testing and finding a satisfactory result.

In order to assure our decision about the classes, high resolution images from different dates from Google Earth were consulted. It is assumed here that all bare soil classified is a landslide, once it was not detected significant presence of this type of land cover before the landslides event. Therefore, the classes were: Forest, Grass, Landslide, Shadowed Forest and Water.

3.1. Classification methods

The analysis of different classifiers for detecting landslides aims to present the best performance available in order to attend risk assessments in urgent situations. Considering that, it is important to take into account the computational efforts, time and feasibility of such methods.

Support Vector Machine (SVM)

Based on statistical learning theory, SVM is a machine learning technique which transforms original input space into a higher-dimensional feature space to find an optimal separating hyperplane [Vapnik 1998; Kavzoglu and Colkesen 2009; Abe 2010]. The goal of the optimal separating hyperplane is a correct discrimination between two sorts of samples (though certain errors are allowed) while maximizing the classification margin [Huang, 2018]. A variety of authors have proven the efficiency of SVM for landslide susceptibility analysis [Lee et al., 2017]. According to [Feizizadeh *et al.* 2017], the resulting SVM classifications are affected by the choice of the kernel function and among the different possibilities of kernels available, the Radial Basis Function (RBF) have been found the most feasible and reliable to produce susceptibility maps. Based on that, it is our choice of using RBF in the classification by SVM.

Artificial Neural Network (ANN)

ANN is a supervised classification method, which is inspired on human brain functioning, composed of a variety of processing units, called neurons, that work in parallel classifying input data in output classes. Generally, a feed-forward multi-layer network is adopted. It typically consists of three layers—input, output, and a hidden layer between the first two—with a sufficient number of neurons in each layer [Aurora et al., 2004]. This method uses the error backpropagation algorithm [Rumelhart et al., 1986], which consists on minimizing the output errors.

Maximum Likelihood (ML)

ML is a supervised classification method determined by the Bayes theorem and employs a discriminant function to assign pixels to user-defined classes with the maximum likelihood [Pawluszek, 2018]. According to the author, ML continues to be the most widely used parametric classification algorithm. This method suits ellipses, so that the location, shape and ellipse size reflect the average variance and covariance of two variables [Duarte, 2018]. A probability function describes the distribution of reflectance values and evaluates the possibility of a pixel to belong to a certain category.

4. Results

From the Feature Selection, the software Weka ranked the 13 input attributes and we chose the first four ones which were similar, though not in the same order, for both areas (Table 1). It was not expected for the Feature Selection to choose Blue band instead of choosing either NDVI or NIR attributes, although the classification showed good results as can be seen herein.

Table 1. Feature Extraction and Selection for both studied areas

Feature Extraction	Feature Selection
Sentinel Band 02 (Blue)	
Sentinel Band 03 (Green)	
Sentinel Band 04 (Red)	
Sentinel Band 08 (NIR)	
Sentinel TCI (Blue)	Sentinel Band 02 (Blue)
Sentinel TCI (Green)	Sentinel Band 03 (Green)
Sentinel TCI (Red)	Sentinel TCI (Green)
NDVI (Bands 04 and 08)	PCA 2
PCA 1	
PCA 2	
Texture Variance (Band 08)	
Texture Mean (Band 08)	
Slope (DEM)	

One must highlight that, from all the classification approaches, SVM appeared to increase computational effort and it was not possible to perform it with all the extracted features. Therefore, Feature Selection has proven to be worthwhile for this study, otherwise no comparisons could be made.

The final classification products for both areas are shown in Figures 4 and 5. In order to standardize the classification figures for comparison, the classification labels of Area 2 were adapted to Area 1 classes, which means that Forest 1 and Forest 2, due to different spectral responses, were gathered into the same class, now called Forest. All three classifiers performed well in detecting landslide scars.

In Area 1, once the water pixels presented a relative similarity to the landslide in terms of spectral reflectance, some confusions between the two classes could be detected, as it can be visually noticed at the classification products. In the middle of this study area, there is a spot on the left bottom side which shows a saturation effect from the RGB image. This spot caused a variety of results provided from the classifiers. The ML classified it mostly as bare soil, while ANN mixed the area with some water pixels and SVM proposed it mostly as grass. On the other hand, in Area 2 no significant visual differences between the classifiers were noticed.

The classifications were evaluated by kappa index and matrix having different results as follows: for Area 1 SVM had a better kappa (0.8315) and ANN a better matrix, while Area 2 ML had a better kappa (0.8353) and SVM a better matrix. For Area 1 SVM presented an overall accuracy (OA) of 87.143%, while for Area 2 ML had an OA equals to 86.831%. It is important to point out that the overall accuracies for other classifiers in this area did not present significant difference from ML: both SVM and ANN with *kappa* equals to 0.8276 and OA of 86.21%. Further analysis of the results through commission and omission errors are developed in this session. [Gerente et al. 2017b] presented similar results concerning overall accuracy in landslides scar detection via Random Forest classification.

The analysis of Table 2 allows the interpretation of results by the commission and omission errors of each classifier presented in percentage. For Area 1, the ANN classifier presented the best result. Among the five classes, ANN presented the lowest percentage of commission errors for Landslide (8,82%), Grass (17,39%) and Shadowed Forest (10,45%); while ML and SVM only presented best results for Forest (7,45%) and Water (0%). Regarding omission errors, ANN also revealed better results by keeping the minimum error compared to the others; however, the only class that ML and SVM had the best performance was Shadowed Forest (16,83%).

When it comes to Area 2, all the classifiers seemed to have similar classification, although SVM classifier showed the best performance. Concerning commission errors, it presented the lowest error percentage for the following classes: Forest 1 (14,29%), Landslide (0%) and Grass (20%). Regarding omission errors, it presented the best results for Landslide (20,41%), Grass (10,20%) and Forest 2 (1,08%).

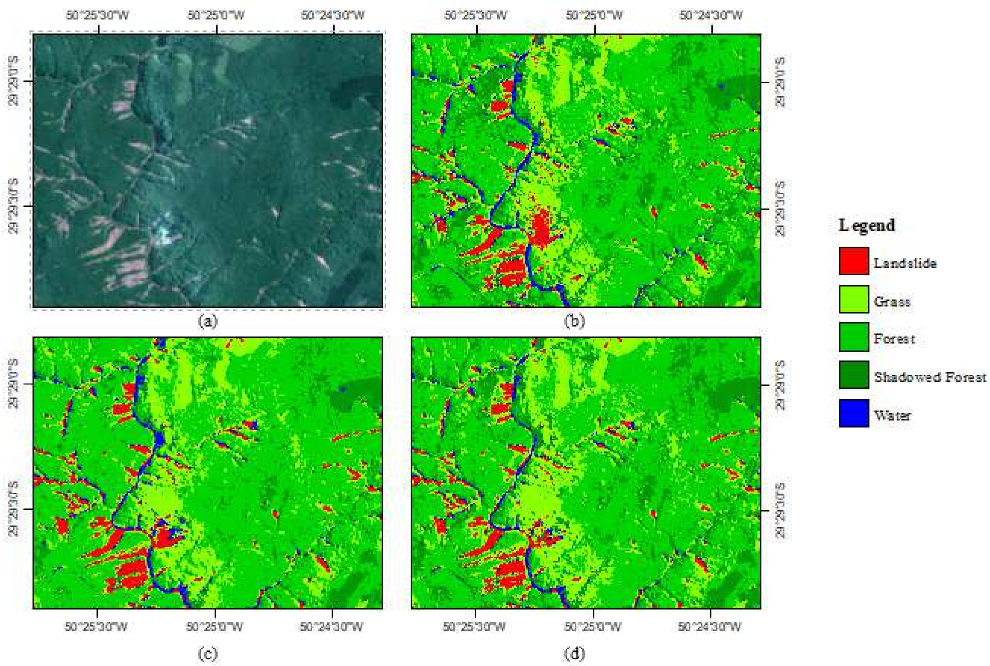

Figure 4. Classification products for Area 1. a) RGB composite; b) ML; c) ANN; d) SVM.

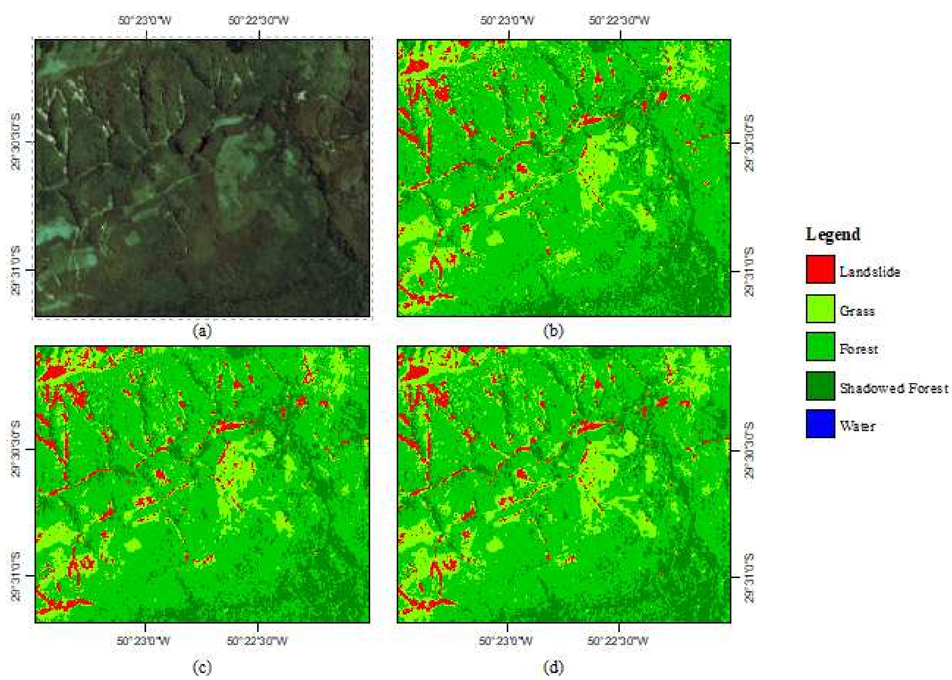

Figure 5. Classification products for Area 2. a) RGB composite; b) ML c) ANN and d) SVM.

A comment about the confusion between water and landslide pixels is valid; once the landslide scars are still exposed, having not been occupied by vegetation yet. Bare soil is constantly falling off the slopes into the river, mixing the water components with soil material. This phenomenon causes significant confusion on the water pixel value compared to the landslide pixel's value.

Table 2. Commission and Omission errors (in percentage) for the three classifiers in Areas 1 and 2

AREA 1	ML		ANN		SVM	
Class	Commission	Omission	Commission	Omission	Commission	Omission
Forest	7.45	10.31	19.64	7.22	7.53	11.34
Landslide	9.38	17.14	8.82	11.43	9	13.33
Grass	22.95	8.74	17.39	7.77	22.13	7.77
Shadowed Forest	10.64	16.83	10.45	40.59	11.58	16.83
Water	28.57	28.57	58.33	28.57	0	28.57

AREA 2	ML		ANN		SVM	
Class	Commission	Omission	Commission	Omission	Commission	Omission
Forest	15.66	27.84	16.47	26.8	14.29	31.96
Landslide	0	22.45	1.33	24.49	0	20.41
Grass	22.52	12.24	23.42	13.27	20	10.2
Shadowed Forest	18.85	1	18.85	1	20.83	5
Water	3.19	2.15	3.23	3.23	8.91	1.08

In addition, due to high reflectance values for both classes, grass caused confusion with bare soil, which was expected to be detected by NDVI attribute - not selected for the classification. However, the commission errors still presented satisfactory outcomes even though omission errors were large.

5. Conclusion

Feature Selection was mandatory to obtain our results, otherwise it would not be possible to perform the SVM classifier, due to computational efforts. In addition, the classification presented satisfactory results even though the number of used attributes was reduced from 13 to 4. This fact confirms that it is not necessary, whatsoever, to use a great number of attributes for classification. However, few features, such as NDVI still seem to be decisive for acquiring better classification results. Therefore, one should analyze and decide thoroughly the number of attributes.

When it comes to classification, all the resulted products have shown suitable outcomes, even though ANN has proven to be the best for Area 1 and SVM for Area 2, concerning the commission and omission errors perspectives. This fact shows that finding the most appropriate classifier is relative. However, one can be the best recommended for a specific study area. Therefore, one should always test the best option for their specific case.

Moreover, it is important to point out that the classes used must be chosen thoroughly as the supervised classification quality depends directly on that. Likewise, one must have a good training sampling mechanism and a truthful test sampling in order to achieve better outcomes.

For future studies, it is recommended to add a segmentation process before the classification and test other classifiers such as Random Forest and Decision Tree. Nevertheless, even though semi-automatic classification methods have proven to display satisfactory results, it does not exclude completely the importance of manual processing and the interpreter interference. Semi-automatic algorithms still show some problems, which can be better managed throw auxiliary data such as field work and visual interpretation corrections, in order to produce better classification results.

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