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Assessment of SVM classification process for landslides identification

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Abstract

The Support Vector Machines (SVM) algorithm has been used for landcover classifications. The theoretical assumption of SVM indicates that the quality of the results increases with the use of more bands. This paper aimed to evaluate the accuracy of SVM algorithm applied over several bands compositions for the identification of landslides at Sao Paulo State Coast. LANDSAT images for the year 2000 were used. To minimize the effect of the shadows, the Normalized Difference Vegetation Index (NDVI) enhancement was calculated. We applied the SVM to the NDVI enhancement and to the following compositions: bands 1, 2; 3, 4; 1, 2, 3; and 1, 2, 3, 4. The NDVI based classification presented the highest Overall Accuracy and the Kappa Index. A huge difference in the Debris Flow areas was found, except NDVI based classification, all other overestimated this class. The NDVI presents the smallest percent of commission errors, and the best results for user accuracy. Therefore, depending on the natural conditions of the area, there are factors that are more important for the classification process with the SVM algorithm. The use of enhancements may facilitate the classification process and also produce better results than the use of a many of bands.

Keywords: Classification Assessment, Omission and Comission Errors, User Accuracy, Landslides Mapping.

1. Introduction

Support vector machine (SVM) is an algorithm that executes automatic separation of two classes. According to Vapnik (1995) it uses the support vectors (the most external samples of each class) for the math of the separation process. It establishes the best separating hyperplane, in other words, the greatest distance to the margin defined by support vectors (Burges, 1998). As the data is commonly distributed on a non-linear way, Boser *et al*. (1992) purposed the use of kernel functions to solve the problem on a higher dimensional space and allow the definition of the separating hyperplane.

Many authors are using this algorithm to monitor and identify land use changes with great results for medium and high spatial resolution images. Foody and Mather (2006), and Pal and Mather (2006) highlights that SVM classifier has the advantage of a lower sample effort comparing to other classifiers. The authors tested this assumption for an agricultural area at the United Kingdom. The results showed that if the support vectors of each class are well sampled, there is no need of a great amount of training areas.

The theoretical assumption of this algorithm shows that the quality of the results increases with the use of more bands (Vapnik, 1995). Although, some areas have problems like shadows and mists that difficult the land cover classification. There are some enhancement types that minimize those problems and facilitate the classification by the algorithms.

This paper aimed to compare the accuracy of SVM algorithm addressed for different bands compositions for the identification of landslide nearby an important road of Sao Paulo State Coast.

2. Methodology

A severe event at Piloes River happened in December 11 of 1999. Due to the high level of precipitation, typical of the tropical climate, the first scenes with no clouds over the landslide is of July of 2000. Therefore the SVM algorithm was applied on LANDSAT images for the year 2000.

To minimize the effect of the shadows and mists, the Normalized Difference Vegetation Index (NDVI) enhancement was calculated. The training areas were defined and used for all the compositions.

The training areas were sampled for the following classes: Debris Flow, Water, Urban/Roads, and Vegetation. The SVM algorithm was applied with the same training areas on the NDVI enhancement and to the following compositions: bands 1 and 2; bands 3 and 4; bands 1, 2 and 3; and bands 1, 2, 3 and 4.

As the spatial resolution of LANDSAT images is 30 meters, the reference data was sampled in GeoEye images (0.41 meter). The classifications were evaluated with the overall accuracy and the kappa index, confusion matrix, omission and commission errors, and the derived user and producer accuracy.

3. Results and Discussion

The Overall Accuracy and the Kappa Index obtained for each classification were: 82.54% and 0.76 for the NDVI based classification; 55.56% and 0.395 for the bands 1 and 2 based classification; 77.78% and 0.7 for the bands 3 and 4 based classification; 53.97% and 0.37 for the bands 1, 2 and 3 based classification; 79.89% and 0.73 for the bands 1, 2, 3 and 4 based classification. The results for the NDVI based classification were best, although, those numbers does not translate the great difference between the classifications.

This difference is evident when we compare the total area classified as landslides. The Table 1 presents the areas and the percentage of the land cover classes for each Classification.

Table 1: Percentage and Km² for each classification.

Classes	NDVI		1 and 2		3 and 4		1, 2 and 3		1, 2, 3 and 4	
	%	km²	%	km²	%	km²	%	km²	%	km²
Debris Flow	0.4	0.17	10.4	4.8	13.0	6.00	5.3	2.47	13.3	6.16
Water	1.5	0.68	0.0	0.0	1.6	0.71	0.2	0.08	1.7	0.78
Urban/roads	21.2	9.80	12.2	5.6	14.5	6.70	15.6	7.18	14.7	6.78
Vegetation	76.9	35.51	77.4	35.7	70.9	32.75	78.9	36.44	70.3	32.44

The NDVI based classification has 0.37% of the image area classified as land-slides, the bands 1 and 2 classification has 10.45%, the bands 3 and 4 classification has 12.99%, the bands 1, 2 and 3 classification has 5.34% and the bands 1, 2, 3 and 4 classification has 13.34%.

The Confusion Matrices for each classification are shown in Table 2 (NDVI), Table 3 (1 and 2), Table 4 (3 and 4), Table 5 (1, 2 and 3) and Table 6 (1, 2, 3 and 4).

Table 2: Confusion Matrix for the NDVI based classification.

Class	Debris Flow	Water	Urban/Roads	Vegetation	Total
Debris Flow	50	8	0	0	11.6
Water	13.89	74	2	0	22.8
Urban/Roads	36.11	18	98	1.89	38.1
Vegetation	0	0	0	98.11	27.5
Total	100	100	100	100	100

Table 3: Confusion Matrix for the bands 1 and 2 based classification.

Class	Debris Flow	Water	Urban/Roads	Vegetation	Total
Debris Flow	50	2	0	7.55	12.2
Water	0	0	0	0	0
Urban/Roads	30.56	0	76	0	25.9
Vegetation	19.44	98	24	92.45	61.9
Total	100	100	100	100	100

Table 4: Confusion Matrix for the bands 3 and 4 based classification.

Class	Debris Flow	Water	Urban/Roads	Vegetation	Total
Debris Flow	66.67	18	16	3.77	22.8
Water	11.11	72	2	0	21.7
Urban/Roads	16.67	0	76	3.77	24.3
Vegetation	5.56	10	6	92.45	31.2
Total	100	100	100	100	100

Table 5: Confusion Matrix for the bands 1, 2 and 3 based classification.

Class	Debris Flow	Water	Urban/Roads	Vegetation	Total
Debris Flow	19.44	2	0	3.77	5.29
Water	0	0	0	0	0
Urban/Roads	33.33	0	88	0	29.6
Vegetation	47.22	98	12	96.23	65.1
Total	100	100	100	100	100

Table 6: Confusion Matrix for the bands 1, 2, 3 and 4 based classification.

Class	Debris Flow	Water	Urban/Roads	Vegetation	Total
Debris Flow	63.89	14	18	3.77	21.7
Water	11.11	78	0	0	22.8
Urban/Roads	19.44	0	78	1.89	24.9
Vegetation	5.56	8	4	94.34	30.7
Total	100	100	100	100	100

The data exposed from Table 2 to Table 6 shows that despite the higher accuracy of the NDVI based classification, the Debris Flow class had lower accuracy than the bands 3 and 4, and bands 1, 2, 3 and 4 based classification.

This result could induce the conclusion that the NDVI enhancement based classification provided worse result for the detection of landslides scars. Although, the Omission and Commission Errors, presented in Table 7 completes the information and contradicts this assumption.

Table 7: Percentage of Comission and Omission Errors for each classification.

Class	NDVI		1 and 2		3 and 4		1, 2 and 3		1, 2, 3 and 4	
	Com.	Om.	Com.	Om.	Com.	Om.	Com.	Om.	Com.	Om.
Debris Flow	18.2	50	21.7	50	44.2	33.3	30	80.6	43.9	36.1
Water	14	26	0	100	12.2	28	0	100	9.3	22
Urban/Roads	31.9	2	22.5	24	17.4	24	21.4	12	17	22
Vegetation	0	1.89	58.1	7.55	17	7.55	58.2	3.77	13.8	5.66

This analysis shows high commission errors for the Debris Flow Class for the three of the classification process. The lowest commission error for the Debris Flow Class was produced by NDVI based classification. Moreover, the analysis of the Table 1 induces finding that the Bands 1 and 2, Bands 3 and 4, Bands 1, 2 and 3 and Bands 1, 2, 3 and 4 based classifications overestimated the Debris Flow Class. This high average of errors might be related to shadows and to the rough of the terrain. The NDVI enhancement minimizes these effects and facilitates the classification process.

The results of the User and Producer Accuracy (Table 8) increments the assessment of the classification processes.

Table 8: Percentage of Producer and User Accuracy for each classification.

Class	NDVI		1 and 2		3 and 4		1, 2 and 3		1, 2, 3 and 4	
	Prod.	User	Prod.	User	Prod.	User	Prod.	User	Prod.	User
Debris Flow	50	81.8	50	78.3	66.7	55.8	19.4	70	63.9	56.1
Water	74	86.1	0	0	72	87.8	0	0	78	90.7
Urban/Roads	98	68.1	76	77.6	76	82.6	88	78.6	78	83
Vegetation	98.1	100	92.5	41.9	92.5	83.1	96.2	41.5	94.3	86.2

The analysis of Table 8 confirms that the NDVI based classification provided the best results to map the debris flow, once its User Accuracy was the highest. The User Accuracy represents the probability that a sample from land cover map actually matches what it is from the reference data (Story and Congalton, 1986).

However, it is important to discuss the low Producer Accuracy of the NDVI based classification. The Producer Accuracy describes the probability that a reference sample will be correctly mapped and measures the errors of omission (Story and Congalton, 1986). Therefore, it confirms that some Debris Flow areas were omitted.

Those omissions, according to the Table 2, were mainly converted to urban/roads and water classes. The explanation relies on the spectral behavior of non-vegetation in the NDVI enhancement. The NDVI is a measure of surface reflectance and gives a quantitative estimate of the vegetation growth and biomass (Hall et al. 1995).

4. Conclusion

Therefore, this paper shows that depending on the natural conditions of the area, there are factors that are more important for the classification process with the SVM algorithm. We can conclude that the use of enhancements may facilitate the classification process and also produce better results than the use of a large amount of bands. The characteristics of the aimed feature must be considered for the classification process, once it may have some similar spectral behavior, which may turn the classification process more difficult.

Furthermore, the identification of some specific land cover classes through medium spatial resolution images may be a complicated process. The use of complementary data is an alternative the reach a classification with higher accuracy.

We can also conclude that to assess a classification process and indicate the best result, a complete analysis of its statistics must be held. Many works evaluate the accuracy of the classification using only the Kappa Index. Although, depending on the objective of the classification, complementary analysis must be done. The User and Producer Accuracy and the assessment of the Omission and Commission Errors are important analysis and helps to identify the weakness of the results.

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