Influence of pre-processing tools on the results of svm image classification for environmental monitoring

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Abstract. Hydroelectric power plants reservoirs perform over 80% of Brazilian energy sources, requiring sustainable policies to avoid expanding their land surface domain. Remote sensing (RS) satellite images provide a useful tool for monitoring land cover to help establish conservation policies on reservoir expansion. Unfortunately, these images, frequently offered by many companies, are already pre-processed to enhance visual attributes, which distorts radiometric content. This study aims to compare the SVM (Support Vector Machine) classification results on a satellite image that passed through two different treatments. The first treatment evolved a pure satellite image and the second a pre-processed image, both from the same satellite sensor and evolving the same study area. Labeling process performed by the SVM classifier on these two images showed a little difference between Kappa Indexes (variation of approximately 0.03), but Confusion Matrix showed significant differences in some land cover classes. To validate differences between the obtained classification results, a McNemar statistical test was applied and stated that accuracies were significantly different. Photointerpretation was also done to complement classification accuracy evaluation. Although only the automatic identification of houses, rocks and water showed less quantitative accurate results in the pure image, accuracy evaluation reinforced that the pre-processed image generally presented less accurate results. Therefore, these results should be taken into account by people who sell or buy satellite images with visual attributes enhanced.

Palavras-chave: remote sensing, satellite images, reservoir, classification accuracy, visual properties.

1. Introduction

Hydroelectric power plants perform more than 80 % of Brazilian energy sources, and are a very important aspect of the country's development. Because this has brought serious social and environmental problems, these hydroelectric power plants must be provided with sustainable policies to avoid expanding their land surface domain (Maldonado et al., 2006).

Monitoring changes on the surface of the Earth, such as those aimed at the preservation of vegetated areas, is one of the many influences on the importance of Remote Sensing (RS) worldwide. Satellite images in RS systems provide a repetitive and consistent view of the earth which helps identify changes on the planet's surface (Schowengerdt, 2007). Data collected by satellites are most commonly transformed into information by multispectral image classification (Jensen, 1986).

Among many satellite image classification algorithms, Support Vector Machines (SVM) has shown very good results in the scientific community (Gualtieri and Cromp, 1999; Pal and Mather, 2004 and 2005). Many kinds of land surface experiments were made by SVM classification results, such as presence of roads, (Song and Civco, 2004), satellite images spatial texture variation (Wijaya, 2007) and classification accuracy compared to standard

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Maximum Likelihood (ML) classifier (Oommen et al., 2008; Pal and Mather, 2005). These studies pointed SVM as a potential classifier to be used in RS activities.

Satellite images, however, are generally pre-processed before the classification. This step includes correcting distortions that come from the data acquisition, like atmospheric effects, sensor calibrations and geometric rectification. Therefore, it is usually necessary to pre-process the remotely sensed data prior to its classification to improve the quality of the result (Jensen, 1986).

Although literature may point that a few and discrete pre-processing methods lead to more accurate image classification results (Bauer and Steinnocher, 2001; Lu and Weng, 2007; Velasco-Forero, 2009), the commercialization of this product frequently enhances only visual properties. This means that many companies sell images with pre-processing treatment that display only good visual properties, discarding the initial range of radiometric and spectral data. Although it is visually attractive, the loss of spectral and radiomatric data limits the spectral transformation possibilities, which are essential to image classification.

This study aims to compare the SVM (Support Vector Machine) classification results on a satellite image that passed through two different previous treatments. The first treatment started from the pure image (without any pre-processing) with all satellite bands and the second included the treatment already performed by the supplier, which enhanced only visual properties of the image. The results registered by this article may assist users who buy satellite images and perform classification processes to obtain thematic maps.

2. Materials and Methods

2.1 Study Area

The hydroelectric reservoir Luis Eduardo Magalhães, located in the Lajeado municipality in the state of Tocantins, Brazil, provides electric energy to Tocantins and other Brazilian states. Tocantins state is located between parallels 13°30'S and 14°30'S and meridians 50°45'W and 45°30'S. Lajeado's local municipality is shown in Figure 1.

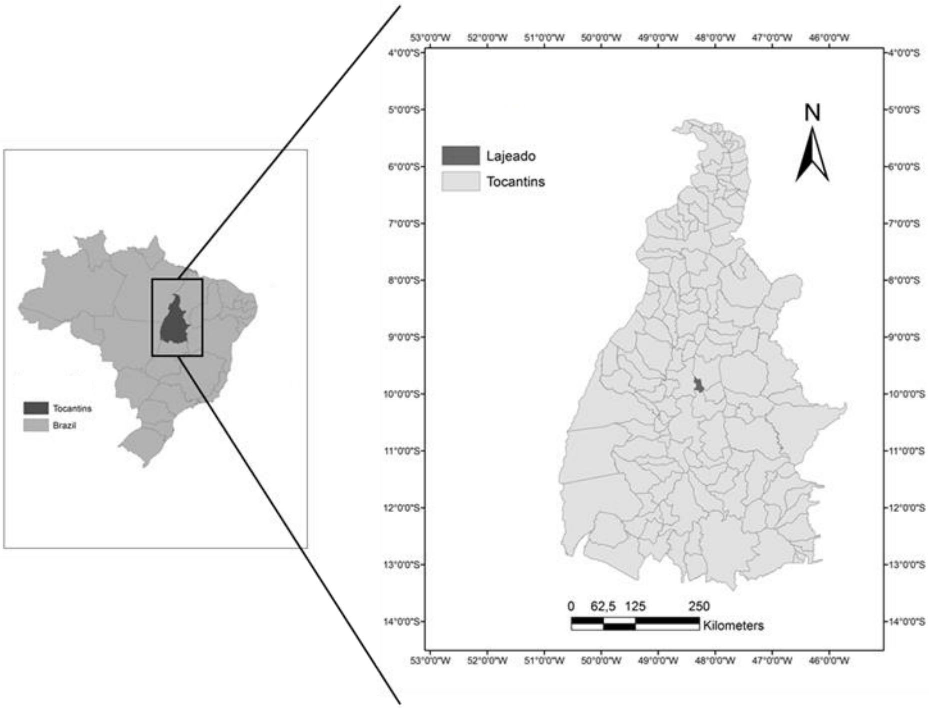

Figure 1. The Hydroelectric dam Luis Eduardo Magalhães.

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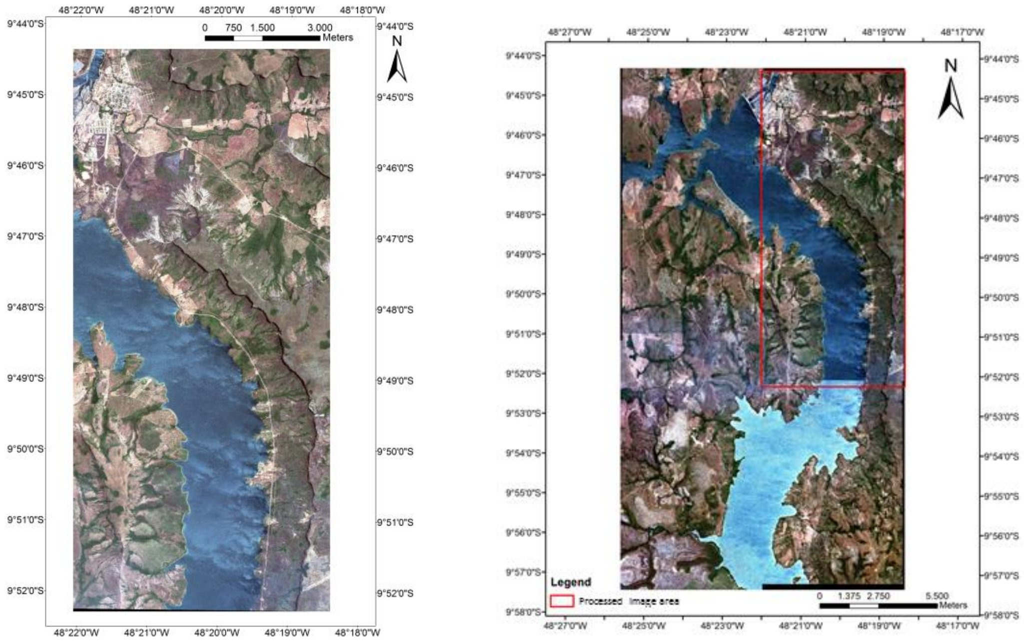
2.2 Materials

A GEOEYE satellite image of the study area was used but in two different ways: one had no pre-processing treatments while the other had some pre-processing techniques applied. The GEOEYE image dated in September 2010, with 0.5 meters spatial resolution. The application and the non-application of pre-processing techniques therefore resulted in two different images to be classified.

The first image (named Pure Image in this study) was initially pure in all the four satellite spectral channels (Red, Green, Blue and Infra-red) with 16 bits of radiometric resolution and 0.5 meters of spatial resolution. The four GEOEYE satellite bands red, green, blue and infrared were used on Pure Image classification. The second satellite image (named Processed Image in this study) was pre-processed by the company that sold it and had only the RGB bands. According to the company, the Processed Image was orthorectified by SRTM DEM data to 90 meters, the georeferenced scenes were mosaic jointed and then converted to a radiometric resolution of 8 bits). Both Pure Image and Processed Image are shown in Figure 2.



(a) (b)

Figure 2. Pure Image on the GEOEYE RGB channel (a) and Processed Image area inside the red rectangle (b).

The classification process on both images were developed using ENVI 4.8 software. SVM classification was pixel-based and every band was included on each labeling process of Pure Image and Processed Image. There were no channel or pixel combinations in this study. ArcGis 10 was used to perform map layouts.

2.2 Methodology

The land cover classes were developed according to the hierarchy proposed by IBGE (2006) (Brazilian Institute of Geography and Statistics) with some adaptations following the CORINE (Bossard et al., 2000) hierarchy proposals. Thus, the land cover classes of natural areas were Water, Forest, Fields and Rocks and the land cover classes of non-natural areas (or anthropogenic sites) were Burned, Non-Vegetated, Concrete and Edifications. These eight classes data had good discrimination among them, confirmed by Jeffries-Matusita index (Richards and Jia, 1999) and were considered in the thematic map for classification process.

The Support Vector Machines (SVM) classification algorithm (Vapnik and Chervonenkis, 1971) was used to perform automatic mapping of the classes. To address SVM classification, Hsu et al. (2010) suggest the algorithm parameters to be calibrated by the cross validation method.

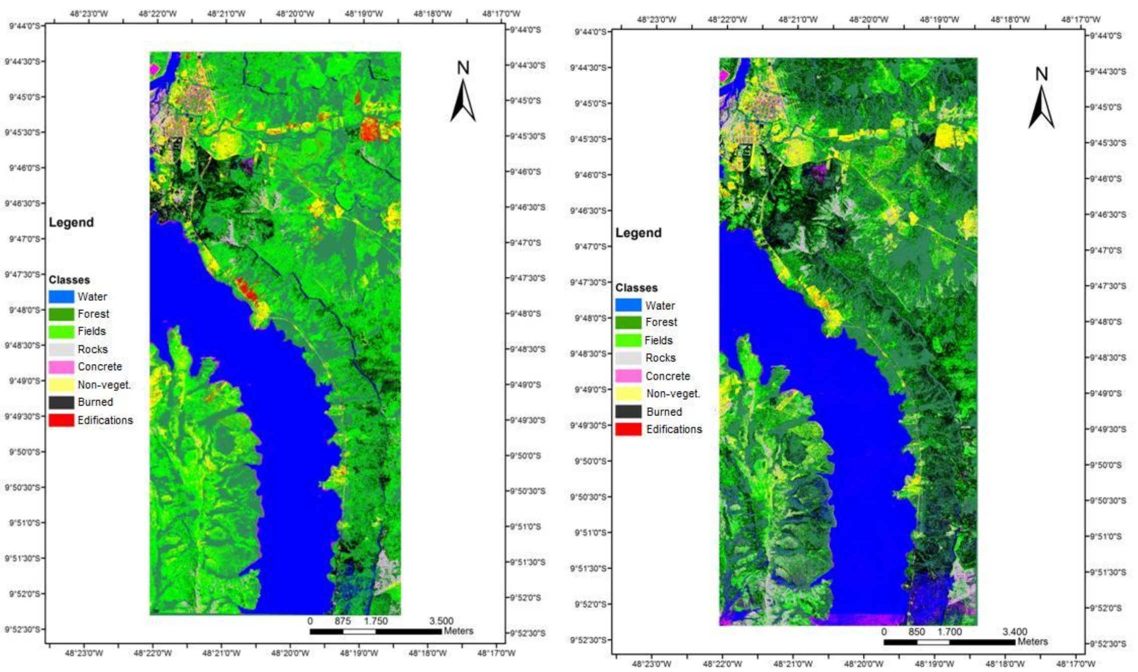
As SVM is a supervised classification method, the same training samples were used to perform classification on both images. Training samples acquisition were validated according to Campbell (2008), Mather and Koch (2011) and Foody and Mathur (2004) recommendations and Testing samples were also validated according to Congalton's (2005) requirements.

The Kappa Index (Cong and Howarth, 1990) and Confusion Matrix (Congalton, 1991) were used for accuracy evaluation. As same test samples were used on both images, the McNemar test, described by Agresti (2007) and recommended by Foody (2004), was also applied to statistically validate if classification results were significantly different.

After classification accuracy evaluation by Confusion Matrix and Kappa Index and statistical difference validation by McNemar test, the two thematic maps obtained by both Pure Image and Processed Image labeling process were checked by human photointerpretation. This visual inspection is a qualitative accuracy evaluation method that complements the quantitative methods, especially when applied to the large amount of spatial and spectral data contained on the high resolution satellite images (BINAGHI, et al., 2003).

3. Results and Discussion

Hsu et al. (2010) cross-validation method resulted in coefficients C and γ equal to 100 and 2^{-5} in Pure Image and 2 and 0.25 in Processed Image. The results of the classifications are shown in Figure 3.



(a) (b)

Figure 3. SVM classification results for Pure Image (a) and Processed Image (b).

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Land cover classes statistics are shown graphically in Figure 4. It can be noticed by Figure 4 that the Fields, Rocks, Edifications, Burned and Concrete classes differed significantly. From these results, Pure Image suggests that the Lajeado dam presents a more favorable environmental situation than Processed Image, because more than 82 % of the first image, against 75 % for the second, was composed of natural areas.

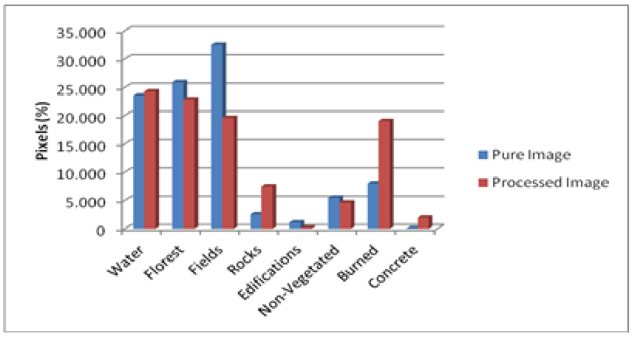


Figure 4. Graphic showing the percentage domain for each class in Images 1 and 2.

About these two resulted scenarios, which one is considered more relevant? Evaluating these results by post-classification methods, the Confusion Matrix and Kappa Index showed that Pure Image was a little more accurate than Processed Image. The Kappa Index was 0.8390 for Pure Image and 0.8066 for Processed Image and their respective Confusion Matrices in percentages are shown in Table 1.

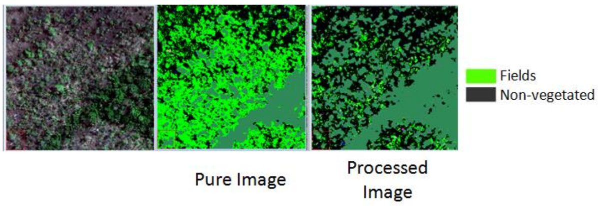
Table 1. Confusion matrix in percentages for Pure Image (Pu) and Processed Image (Pr).

Results / Test samples	Water	Forest	Fields	Rocks	Concrete	Non-vegetated	Burned	Edifications	Total
Water (Pu)	85.9	0	0	0	0.39	0	2.66	0.05	13.01
Water (Pr)	90.38	0	0	0	0	0	2.2	0.21	13.14
Forest (Pu)	0	100	0	0	0	0	0	0	10.87
Forest (Pr)	0.33	99.61	0.07	0	0	0	0.09	0	10.86
Fields (Pu)	0.15	0	78.16	2.24	3.65	0.01	10.73	0	7.54
Fields (Pr)	0	0	37.57	11.62	4.79	0.08	14.62	0.54	6.74
Rocks (Pu)	0	0	0	75.59	1.09	12.32	0	4.55	14.7
Rocks (Pr)	0	0	0.72	80.83	2.1	15.66	0.92	1.31	15.97
Concrete (Pu)	0	0	0	0	82.78	4.86	0	0	5.53
Concrete (Pr)	0	0	0	0	64.8	1.57	0	0	3.71
Non-vegetated (Pu)	0	0	0	0	10.83	82.71	0	0	15.65
Non-vegetated (Pr)	0	0	0.23	0	28.3	82.69	0	0.02	16.81
Burned (Pu)	0.73	0	21.84	9.24	0	0.07	86.61	0	13.63
Burned (Pr)	0.52	0.39	61.42	5.04	0	0	81.99	0.32	15.79
Edifications (Pu)	13.22	0	0	12.92	1.26	0.04	0	95.41	19.08
Edifications (Pr)	8.77	0	0	2.51	0	0	0.17	97.6	16.98
Total (Pu)	100	100	100	100	100	100	100	100	100
Total (Pr)	100	100	100	100	100	100	100	100	100

The results in Kappa Index were slightly different (about 0.03), suggesting that Pure Image was a little more accurate on SVM classification. McNemar statistical test although confirmed that classification results among the images were significantly diferent, as it pointed $X^2 = 6.68$, which is higher than $X^2tab(5\%) = 3.84$ and also higher than $X^2tab(1\%) = 6.64$.

When qualitative analysis was tried, made by visual interpretation of the image, a few findings could be stated to complement classification accuracy results evaluation. Figure 5 illustrates errors evolving Fields class that were noticed quantitatively and qualitatively.

According to visual inspection, the Burned (Figure 5.a) and Rocks (Figure 5.b) classes were over estimated once they generated some omissions errors in class Fields.



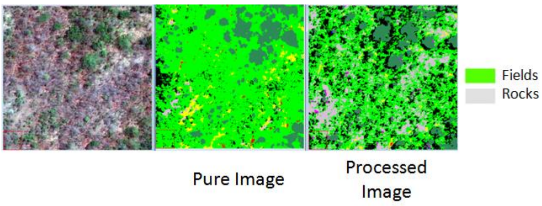


Figure 5. Omission errors of the Fields class occasioned by Burned in Pure Image and Processed Image (a) and by Rocks in Processed Image(b).

Confusion matrix indicates that class Rocks was more accurate in Processed Image while Figure 5.b by itself suggests that this class was more acurate on Pure Image. As test samples were validated according to Congalton's (2005) requirements, the fact showed in Figure 5.b doesn't contradict quantitative results of the Confusion Matrix. The reason is that errors illustrated in Figure 5.b occurred only in a small location (less than 2% of the study area) that had no Fields test samples.

Processed Image presented the Concrete class at over double the area when comparing to Pure Image. By qualitative inspection it was noticed that this class had many small commission errors in Processed Image, as illustrated in Figure 6.

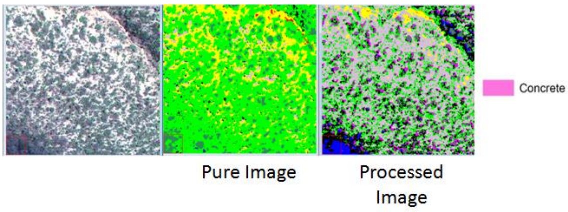


Figure 6. Commission errors of the Concrete class in Processed Image occurred in many small isolated areas.

Classification accuracy evaluation therefore stated different results between Pure Image and Processed Image, indicating that Pure Image's results were more accurate. As a significant amount of data was provided by the radiometric resolution (16 bits) and the Infrared band of Pure Image, it can be considered that such amount of data allowed a more accurate classification process.

The initial motivation for this study, namely the desire to better understand and evaluate land surface domains to help establish conservation policies on reservoir expansion aimed at hydro power generation, is influenced by different types of RS pre-processing. Therefore, conservation policies on hydroelectric reservoirs must carefully choose not only the satellite images but also the RS pre-processing treatments that come along with them. It should also be stated that unfortunately no similar studies of this investigation's outcomes were found for a cross-referencing literature.

This study was not focused on examining pre-processing elements and their respective consequences to labeling process, but rather the results that two different pre-processing treatments on the same image can generate on SVM classification. In this case, future work should also study the effects of each kind of pre-processing element on SVM satellite image classification process.

4. Conclusions

Pre-processing methods directly influenced satellite image classification, consisting of a RS element to be checked in automatic land cover mapping. The loss of some statistical parameters affected the task of labeling the pixels accurately by image classification. This study stated that a pure high resolution image presents more significant SVM classification results than a mosaic, orthorectified and radiometric converted RGB image.

The results presented in this paper should be taken into account by companies that sell satellite images. If they want to offer a product that is visually attractive, which comes with many pre-processing treatments, they should at least offer the satellite images in their original state (without any kind of pre-processing treatment). Along with the original state of the satellite images, these companies should also inform which were the specific pre-processed tools used in the image that had its visual properties enhanced.

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