Effects of Image Fusion Methods on Sugarcane Classification with Landsat-8 Imagery

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Abstract. The culture of sugarcane has great importance in the brazilian agribusiness. Remote sensing images have been tradicionally used on manual mapping of sugarcane fields. Manual classification is a laborious and time-consuming task, especially given the size of the territory, and it is still necessary to assess the quality of the maps. Image fusion can improve the identification and mapping of surface features. The computational data mining methodology demonstrates high potential for application in areas related to crop mapping and several classification techniques can be used. Most studies on fusion of remote sensing images have focused on the analysis of spectral and spatial quality of the products obtained by different algorithms, however, once classification is applied on these products, it is important to analyze the impact of fusion in the classification. In the literature there are few studies on this topic, especially considering the Landsat-8. In this context, we evaluated five pansharpening methods - Intensity-Hue-Saturation (IHS), Principal Components (PC), Gran-Schmidt (GS), Discrete Wavelet Transform (DWT) and DWT+IHS for the classification of sugarcane fields in a Landsat-8 image (bands 4, 5 and 6). The Support Vector Machine (SVM) algorithm was used to perform a target detection of sugarcane, using a binary classification. The samples used were selected based on a field survey realized on the study area. According to the Universal Image Quality Index (UIQI) and the Spatial Relative Dimensionless Global Error in Synthesis (SERGAS), the best fusion technique was the DWT+IHS. However, considering the effects on classification, the GS fusion showed better results than other methods.

Keywords: Pansharpening, Support Vector Machine, Image processing, Landsat-8, sugarcane classification .

1. Introduction

The culture of sugarcane has great importance in the brazilian agribusiness, representing a supply chain estimated in US$ 28.1 billion, that represented about 2 percent of Brazil´s GNP (Gross National Product) (NEVES; CONEJERO, 2010). Sao Paulo (SP) state is the main producer, with a planted area of 13.35 million ac (5.4 million ha) and an annual production of 404.5 million tons (IBGE, 2014).

Facing such expressiveness, remote sensing images have been used on manual mapping of sugarcane fields on SP state (RUDORFF et al., 2005). Thematic maps have been used as the basis for monitoring the harvest (AGUIAR et al., 2011); assessment of changes in land use and cover (ADAMI et al., 2012) and for the analysis of crop productivity (SUGAWARA, 2008). Although the manual classification by visual inspection is considered the most accurate, visual interpretation is a laborious and time-consuming task, especially given the size of the territory, and it is still necessary to assess the quality of the sugarcane maps (MELLO et al., 2012).

Image fusion can improve the identification and mapping of surface features, exploring different information content of the imaged targets and improving the interpretation of visual features, by rising the separability between classes when automatic classification is used (JOHNSON; SCHEYVENS; SHIVAKOTI, 2014). This technique consists on integrating the spatial resolution of the panchromatic band with the spectral resolution of other bands, producing colorful images that combine both characteristics (FONSECA et al., 2011).

Medium resolution images can be used on image fusion (POHL; GENDEREN, 1998). An example is the Landsat-8 satellite, which has the OLI (Operational Land Imager) sensor. It contains nine spectral bands with a spatial resolution of 30 meters and a panchromatic band with a spatial resolution of 15 meters. The images obtained are used in agricultural studies and the main application is related to crop mapping. However, for small agricultural areas, there might be difficulties in the extraction of desirable patterns for image analysis when using the multispectral imaging spatial resolution of 30 meters (JOHNSON; SCHEYVENS; SHIVAKOTI, 2014).

The computational data mining methodology demonstrates high potential for application in areas related to crop mapping and several classification techniques can be used. Some previous studies (BRUZZONE; CARLIN, 2006; JOHNSON; SCHEYVENS; SHIVAKOTI, 2014) found that incorporating spectral information from multiple image scales could lead to more accurate classification results using the Support Vector Machines (SVM) algorithm (CORTES; VAPNIK, 1995). SVM locates the optimal decision boundary between classes to minimize classification errors (BURGES, 1998), and its use in remote sensing was recently reviewed by Mountrakis, Im e Ogole (2011). One advantage of SVM is its relative insensitivity to high dimensional data sets when the number of training samples is high regarding to the number of classification variables (PAL; FOODY, 2010).

Most studies on fusion of remote sensing images have focused on the analysis of spectral and spatial quality of the products obtained by different algorithms, however, once classification is applied, it is important to analyze the impact of fusion on the results. In the literature there are few studies on this topic, especially considering the Landsat-8 (JOHNSON; SCHEYVENS; SHIVAKOTI, 2014).

Given this context, the main goal of this paper is to evaluate the impact of different fusion methods on remote sensing images, for sugarcane classification in the region of Mogi Guaçu and Aguaí (SP), using the SVM algorithm.

2. Methodology

The study site is an agricultural area in Mogi Guaçu and Aguaí, located in São Paulo state. Figure 1 illustrates the region of the study. These municipalities are medium sugarcane producers, with an average production of 135,000 tons in an area of approximately 4942 ac (2000 ha) (IBGE, 2014).

A Level 1T (terrain corrected) scene of the OLI sensor, Landsat-8, corresponding to August 19, 2014, downloaded from the USGS EarthExplorer database (United States Geological Survey) was used (http://earthexplorer.usgs.gov/). A field survey was conducted in the study area in August 20th, 2014 in order to gather the required information of training and validation data for image classification. Multispectral images, corresponding to bands 4, 5 and 6 from OLI (Figure 2), were resampled from 30m to 15m by the nearest neighbor method. Using this interpolation, the brightness value of the closest pixel is assigned to each of the output pixels. It is a computationally efficient procedure and does not alter the pixel value during resampling (JENSEN, 2005).

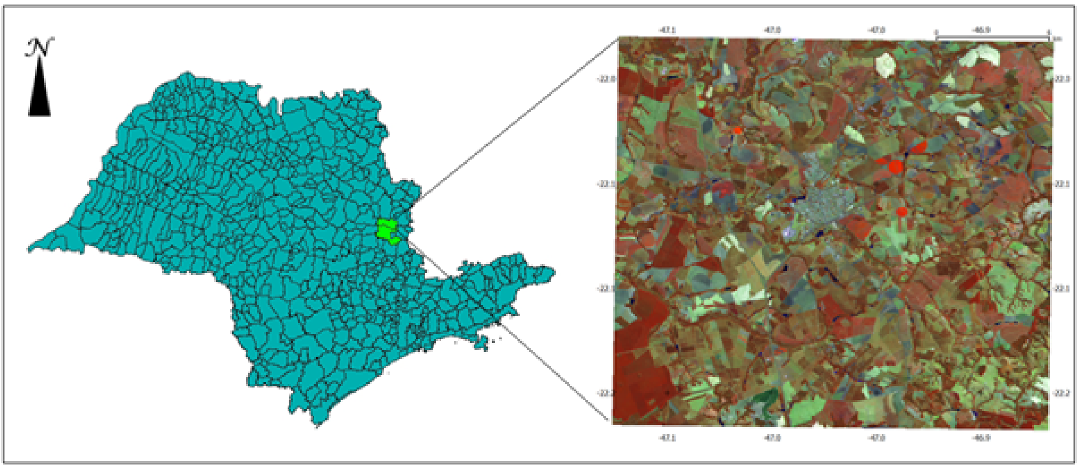

Figure 1: Map of São Paulo state showing the study area, with the Landsat-8 color composition (RGB 654).

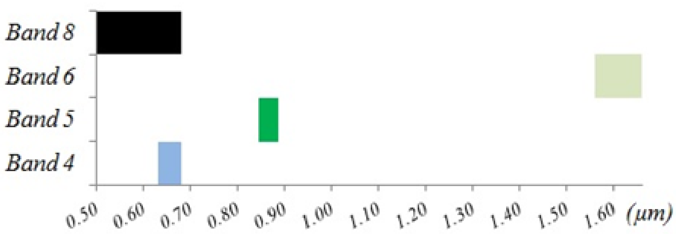

Figure 2: Relation of the wavelenghts of Landsat-8 used bands.

No atmospheric correction was performed because it is assumed that it does not improve the accuracy significantly (SONG et al., 2001).

The Intensity, Hue and Saturation fusion technique (IHS) corresponds to the transformation of three multispectral (MS) bands, initially in RGB (Red, Green, Blue) color space, to IHS, where the component I is replaced by the panchromatic image (PAN) and then, the reverse operation is performed to give the image fused (SCHNEIDER M. J.AND BELLON; ARAKI, 2003).

Principal Component (PC) pansharpening method starts with the transformation of the multispectral bands in the same number of uncorrelated components. A histogram match in the panchromatic band is performed to leave it as close as possible to the first principal component (PC1) to replace it in the multispectral image. After substitution, the inverse transformation is performed to obtain the merged image (PINHO C. M. D.; RENNO, 2005). The Gram-Schmidt (GS) fusion is similar to PC pansharpening method (RSI, 2003). The difference between GS transformation and PC is that the first principal component contains the majority information, other principal components contain less and less information; while information is average distributed among the components computed by GS transformation that are orthogonal (LIU; ZHANG, 2009).

There are also techniques based on wavelet transforms, which are mathematical tools that detect local features in signals, but may be extended to decompose an image at different levels of resolution. The wavelet-based (DWT) pansharpening methods (NUNEZ et al., 1999) involves spatially degrading the Pan band to approximately the same resolution as the MS bands, and then injecting spatial information given by the difference between the original and degraded Pan bands. The main strength of these methods are their high spectral quality (AMOLINS; ZHANG;

DARE, 2007; WANG et al., 2005), while their main weakness is their relatively lower spatial quality (TU et al., 2001). There are also variations that involve more than one type of technique, such as DWT and IHS, that showed great results (ZHANG; HONG, 2005).

For the fusion steps, we used IHS, PC, GS, DWT and the hybrid method DWT+IHS. Before the fusion procedures, we match the histograms between the PAN and the transformed images by the different methods, using a linear function for adjust means and variances, for reduces the spectral distortion between the images (SILVA, 2009). Finally, the hybrid images obtained by the fusion methods were evaluated. Besides visual perception, there are indexes that can quantitatively express the spectral and spatial quality of the fused images. We use the Universal Image Quality Index (UIQI), the Relative Dimensionless Global Error in Synthesis (ERGAS), Spatial Correlation Coefficient (SCC) and the spatial ERGAS (SERGAS) (SILVA, 2009). A good quality image is shown by low values of ERGAS and SERGAS, UIQI close to one and high SCC.

Both pansharpened and the original images were submitted to the classification process, considering the approach by pixel, using the SVM algorithm. Training polygons, based on the field survey, were digitized for two land cover classes, sugarcane and other classes, and pixels within these polygons were used as the training data for the classifications. The other class consisted of forested areas, other agricultural covers and bare soil.

There were a total of 25364 training pixels for the sugarcane class and 27757 for the other class in the Pansharpened images, 25% of these amounts were in the original MS image. The classes were prepared in order to have, approximately 50% of the total entries, which tends to lead to better results compared to other distributions (WEISS; PROVOST, 2001). The results were evaluated by Kappa statistics (COHEN, 1960) and confusion matrix indexes, such as accuracy, sensitivity (recall) and specificity (WITTEN; FRANK; HALL, 2011). The models were executed considering a 10-fold cross validation method, and the radial basis function (RBF) was the kernel type used on the SVM (JOHNSON; SCHEYVENS; SHIVAKOTI, 2014).

The results were obtained using the software packages ENVI (ENVI, 2009), SPRING (CAMARA et al., 1996), MATLAB (MATLAB, 2012) and WEKA (HALL et al., 2009).

3. Results and discussion

Figure 3 illustrates a target in images obtained by different fusion techniques. By visual analysis, comparing the original image with the pansharpening images, it is possible to observe that the GS and PC methods altered the spectral information in the red region of the spectra (630-680 nm), highlighting the contrast in this region.

The IHS has also changed the information in NIR (845-885 nm) and SWIR (1560-1660 nm) regions, but preserved the image contrast. In the case of HSV (similar to the IHS, but implemented in ENVI), these changes were even more expressive. It is known that one of IHS methods limitations is the recomendation that the panchromatic band involves the wavelengths of the multispectral bands, which was not this case (see Figure 2), and this fact can be seen in the visual analysis of the results (Figure 3). These results so far corroborate those reported in the literature (SILVA, 2009; JOHNSON; SCHEYVENS; SHIVAKOTI, 2014).

Table 1 shows the calculated indices for evaluating the quality of hybrid images obtained by different fusion methods.

With respect to the indices, UIQI measures the similarity between two images, modeling image distortion as a combination of loss of correlation, radiometric distortion and contrast distortion. The closer to 1, the better. The ERGAS aims to globally quantify the spectral quality, considering a sum of pixels, weighted by the product of root mean squared error and the square average. The lower ERGAS value, the better the quality of the spectral fusion.

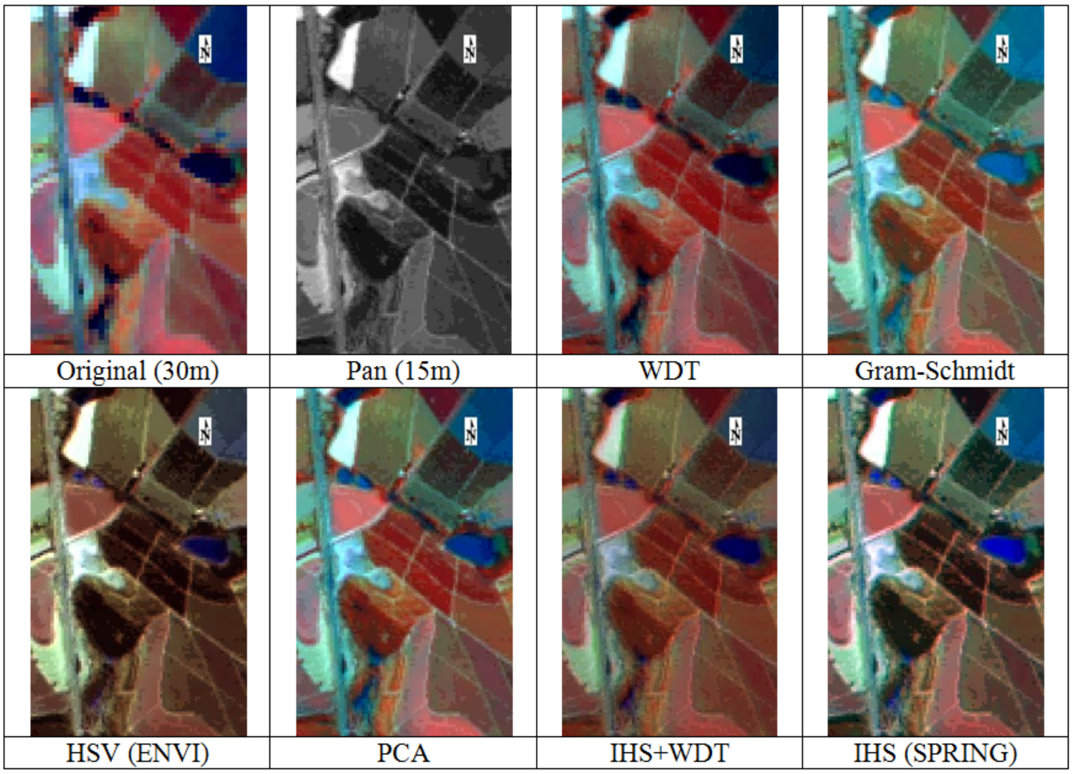

Figure 3: A target in the original color composition (RGB 654); panchromatic, and in pansharpened images by the different techniques.

Table 1: Indices for assessing the quality of different fusion techniques.

	UIQI	ERGAS	SCC	SERGAS
HSV	0.583	21.106	0.899	25.459
GS	0.683	10.447	0.904	10.541
IHS	0.743	10.943	0.767	13.266
PC	0.712	21.134	0.980	27.084
DWT	0.760	8.975	0.169	9.626
DWT+IHS	0.798	6.525	0.720	7.785

Thus, we can conclude that, considering the combination of UIQI and ERGAS, the IHS+DWT and DWT methods showed higher spectral quality. When we consider the UIQUI, IHS is in third place, followed by PC, GS and HSV. However, when we look at the ERGAS, GS ranks third, followed by IHS, HSV and PC. We can visually perceive that GS has better spectral quality that IHS, but when considering the correlation observed by UIQI, this order is reversed, with IHS appearing in front of GS.

Considering the spatial quality, we found that looking at the SCC, which has aimed to estimate the spatial quality of the fused images by the correlation of the details in the images, PC is the best one, followed by GS. Thirdly comes HSV, then the IHS, IHS+DWT, and DWT in the last position. But when considering the SERGAS (spatial ERGAS), which aims to quantify globally the spatial quality of the fused image, we see that the relationship is reversed, and DWT and DWT+ IHS reappeared first, then GS, IHS, HSV and PC.

Table 2 shows the results of the classification considering the fusion and the original images. The accuracy of all fusions was very similar, near the 90%, which showed a litlle improvement over the original image (89.21%). The original image presented a lower value of sensitivity when compared to the fusion images. This value means that more pixels from the class other were incorrectly classified as sugarcane.

Table 2: Classification evaluation measures.

Measure	GS	HSV	IHS	IHS+DWT	PC	DWT	Original
Accuracy (%)	91.660	90.810	90.370	90.000	91.300	91.290	89.210
Error (%)	8.340	9,190	9.630	10.000	8.700	8.710	10.790
Sensitivity (%)	91.050	91.990	90.730	92.110	91.370	90.830	85.970
Specificity (%)	92.220	82.730	90.050	87.700	91.250	91.710	92.160
Kappa	0,833	0.816	0.807	0.799	0.826	0.825	0.78
F-measure	0.917	0.908	0.904	0.900	0.913	0.913	0.892

When we look at the classification results (Table 2), we see that considering the accuracy, error, Kappa and F-measure, we conclude that hybrid images obtained by the fusion techniques GS and PC performed better, while IHS + DWT and the original presented the poorest performances. Analyzing together the evaluation of the classifications (Table 2) with the quality assessment of the fusion techniques (Table 1), it is observed that the spatial correlation of fusion is essential for the classification combined with the globally spectral and spatial evaluation.

4. Considerations

In this study, we evaluated five different pansharpening methods for the classification of sugarcane fields in a Landsat-8 image: The Intensity-Hue-Saturation (IHS), Principal Components (PC), Gram-Schmidt (GS), Discrete Wavelet Transform (DWT) and DWT+IHS. The Support Vector Machines (SVM) algorithm was used for sugarcane classification. Overall according to combination of the UIQI (Universal Image Quality Index) and SERGAS (Spatial Relative Dimensionless Global Error in Synthesis) which reflects the spectral quality of fusion, the best fusion method was the IHS+DWT method. But when we considered the SCC (Spatial Correlation Coefficient), the PC and GS methods were better. However, the fusion by GS and PC showed better results among the other methods when classification was applied, the Kappa value was 0.833 and 0.826, and the accuracy was 91.66 and 91.3, respectively. A little improvement was noticed from the original image, which obtained accuracy of 89.21 and Kappa value of 0.78. These results also suggest that the spatial correlation of fusion is very relevant for the classification combined with the globally spectral and spatial evaluation. The study provided an investigation of pansharpening for image classification, but more research on the topic is still necessary to determine whether the methods are suitable for classification, considering more samples, for another areas and crops, as well the use of methods for accuracy assessment considering the impact on the classification of the edge pixels and small features.

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