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 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 sugarcane 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. We evaluated five pansharpening methods - Intensity-Hue-Saturation (IHS), Principal Components (PC), Gran-Schmidt (GS), wavelet Transform (DWT) and wavelet + IHS (DWT+IHS) on sugarcane classification 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 correspond to a field survey realized on the study area. The best fusion methods were the DWT+IHS, DWT and IHS methods, which obtained higher Universal Image Quality Index (UIQI) values. However, when classification was performed, 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 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 this 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 was 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 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 to assist with the gathering of training and validation data for image classification.

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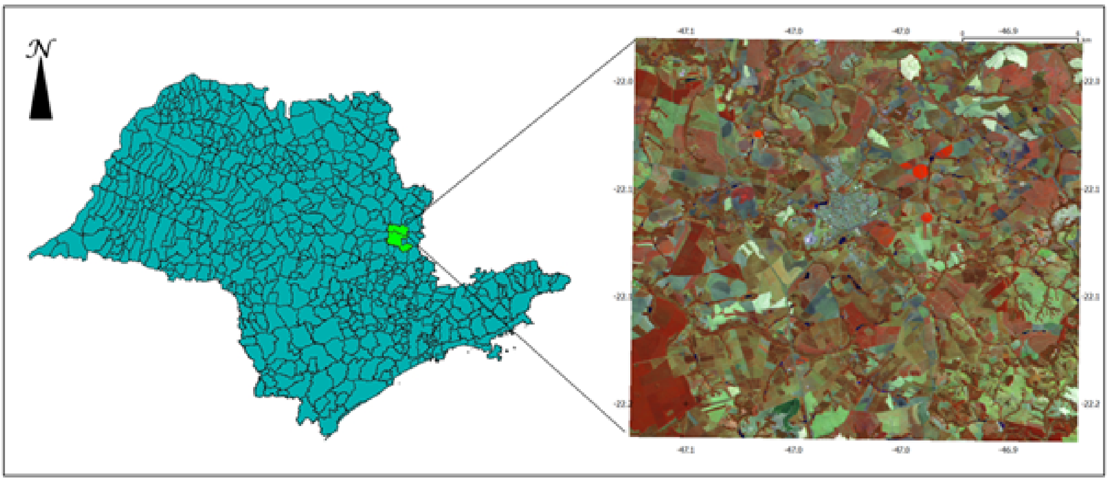

Figure 1: Map of São Paulo state showing the study area, with the Landsat-8 color composition (Bands 4, 5, 6 as blue, red, green).

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 closest brightness value to the pixel is assigned to the output. It is a computationally efficient procedure and does not alter the pixel value during resampling (JENSEN, 2005).

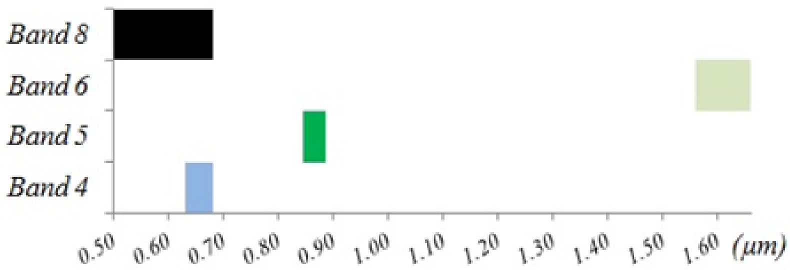

Figure 2: Relation of Landsat-8 used bands.

No atmospheric correction was performed because it does not improve the classification accuracy significantly when the training and evaluation data are in the same relative scale (SONG et al., 2001).

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

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 with 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 PCA 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 a 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 has show great results (ZHANG; HONG, 2005).

For the fusion steps, we used IHS, PCA, 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 BIAS, Standard Deviation of the Difference (SDD), Root Mean Square Error (RMSE), the Universal Image Quality Index (UIQI) and Spatial Correlation Coefficient (SCC) (SILVA, 2009).

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, and approximately 25% of these amounts 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 than 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 kernel type used on the SVM was the radial basis function (RBF) (JOHNSON; SCHEYVENS; SHIVAKOTI, 2014).

3. Results and discussion

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). Table1 shows the calculated indices for evaluating the quality of hybrid images obtained by different fusion methods.

It is possible to note that the images obtained by the IHS+DWT, DWT and IHS methods showed higher UIQI values, which reflects the quality of spectral fusion, since it would be expected values close to 1. However, when considering the SCC, which expresses the spatial quality of the merger, the Wavelet method showed an undesirable value. Figure 3 illustrates an enlarged target in images obtained by different fusion techniques.

The IHS method presented good results, but it is known that one of its limitations is the

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

	BIAS	SDD	RMSE	SCC	UIQI
HSV	24.34	37.387	44.72	0.899	0.583
Gram-Schmidt	-0.078	18.721	18.721	0.904	0.683
IHS	12.084	19.688	23.146	0.767	0.743
PCA	30.285	30.693	45.060	0.980	0.712
Wavelet	6.929	13.640	16.648	0.169	0.760
Wavelet+IHS	6.647	12.003	13.746	0.72	0.798

requirement that the panchromatic band involves the wavelengths of the multispectral bands, which does not happen in this case (Figure 2), and this fact can be seen in a visual analysis of the results (Figure 3). The results obtained so far corroborate those reported in the literature ((SILVA, 2009; JOHNSON; SCHEYVENS; SHIVAKOTI, 2014). However, more tests will be conducted in order to confirm the observed results and move forward with the classification.

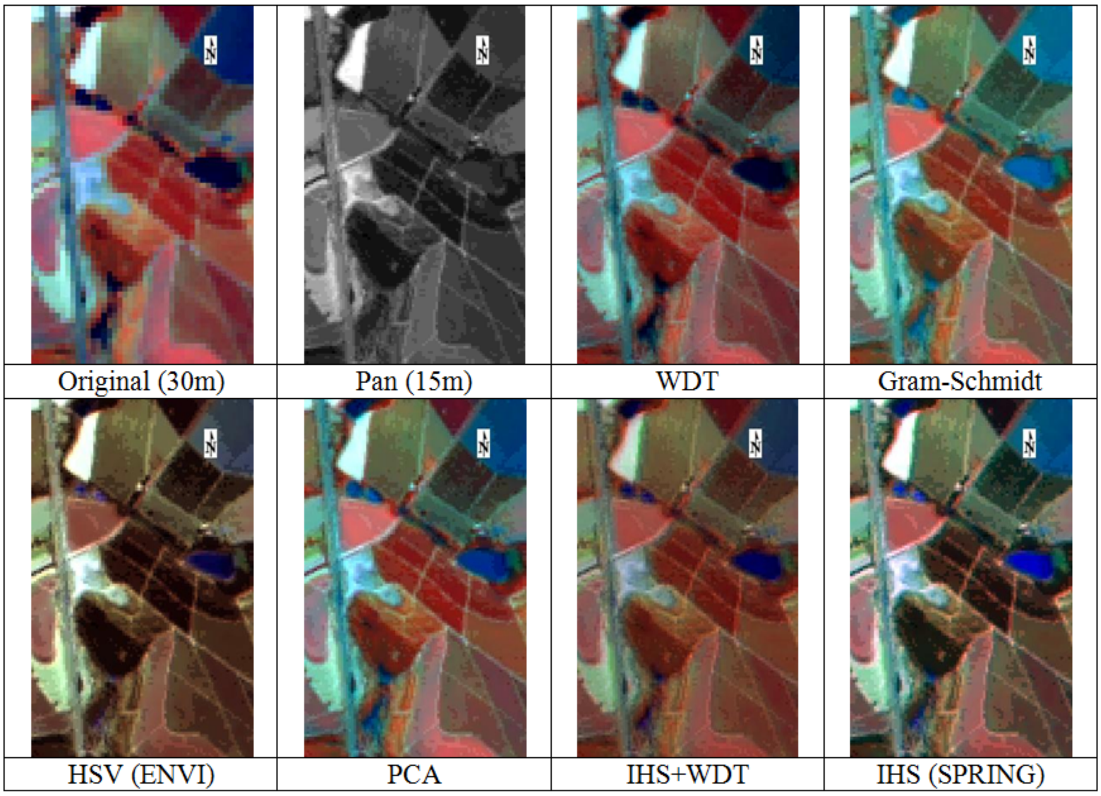

Figure 3: An expanded target in the original color composition; panchromatic, and in pansharpened images by the different techniques.

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 improvement over the original image (89.21%). The original image presented a low value of sensitivity when compared to the fusion images. The disadvantage of this value is the fact that more pixels from the class other were incorrectly classified as sugarcane. On studies that estimate the sugarcane area or parameters related (SUGAWARA, 2008; AGUIAR et al., 2011) this classification may bring more uncertainties than the GS fusion.

Table 2: Classification evaluation measures.

Measure	GS	IHS	IHS+WDT	PCA	WDT	Original
Accuracy (%)	91.66	90.37	90.00	91.30	91.29	89.21
Error (%)	8.34	9.63	10.00	8.70	8.71	10.79
Sensitivity (%)	91.05	90.73	92.11	91.37	90.83	85.97
Specificity (%)	92.22	90.05	87.70	91.25	91.71	92.16
Kappa	0.83	0.81	0.80	0.83	0.82	0.78
F-measure	0.92	0.90	0.90	0.91	0.91	0.89

The Kappa values were also considered on the evaluation of the best fusion according. The GS, WDT images obtained a better kappa index then the original image and the other methods.

4. Considerations

In this study, we evaluated the five different pansharpening methods on the classification of sugarcane in a Landsat-8 image. Techniques such as the (IHS), Principal Components (PC), Gram-Schmidt (GS), Discrete Wavelet Transform (DWT) and DWT+IHS and used Support Vector Machines (SVM) for sugarcane classification. Overall the best fusion methods were the IHS+DWT, DWT and IHS methods regarding to UIQI (Universal Image Quality Index) values, which reflects the quality of spectral fusion. However, when considering spatial quality the DWT presented a low value of the SCC (Spatial Correlation Coefficient). The fusion by GS showed better results among the other methods when classification was applied, the Kappa value was 0.83 and the accuracy was 91.66. Nonetheless, a improvement was noticed from the original image, which obtained accuracy of 89.21 and Kappa value of 0.78. The study provided an investigation of pansharpening for image classification, but much research on the topic is still necessary to determine whether the methods are suitable for classification. Future research is also needed to identify other pansharpening methods that work well in combination for image analysis.

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