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EFFECTS OF PANSHARPENING METHODS ON DISCRIMINATION OF TROPICAL CROP AND FOREST USING VERY HIGH-RESOLUTION SATELLITE IMAGERY

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ABSTRACT

This paper assesses the effect of pansharpening process in classification of tropical crop and forest areas. Supervised classifications based on Support Vector Machine were adopted. Different pansharpening methods using bilinear interpolation technique have been used to merge very high spatial resolution Quickbird multispectral and panchromatic imagery. To develop this study, seven sub-areas were extracted and human segmentations data were created. The quantitative results based on the mean of Probabilistic Rand Index, Variation of Information and Global Consistency Error, computed for all sub-areas, showed similar results by using (0.92, 0.87, 0.87, 1.23, 0.2 respectively) and by not applying (0.93, 0.89, 0.86, 1.23, 0.21 respectively) pansharpening methods.

Index Terms— Land cover, Pansharpening methods, Classification, Remote Sensing, image processing

1. INTRODUCTION

Satellites such as Quickbird and IKONOS are able to take multispectral images (red, green, blue, and near-infrared bands) and panchromatic image with very high spatial resolution. The extracted information can be of great interest for the detection, identification, characterization and assessment of terrestrial objects and phenomena (e.g. land-use/land-cover, vegetation mapping, soil mapping).

In fact, undertaking identification studies in areas with complex structures requires the availability in a same image of high spectral and spatial resolutions. The inconvenient is that the actual spaceborne sensors do not provide this kind of data. To mitigate this issue, several pansharpening methods have been introduced to improve remote sensing datasets [1]. All these techniques allow fusing medium spectral with high/very high spatial resolutions images in order to obtain a single image that contains a good compromise between both information. However, it remains difficult to identify the most suitable technique able to produce an adequate image. In remote sensing, the use of very high/high spatial resolution fused data instead of coarser spectral images has become a very attractive option

for land cover classification. In fact, Hofmann [2] recommends using pansharpening methods as preprocessing step prior to classification task. However, little research has been done on studying the applicability of this kind of data to the classification problem [3]. On one hand, the general conclusion of studies that have examined the effect of resolution on classification accuracy show that spatial resolution could have a significant effect on classification accuracy [4]. On the other hand, Shaban et al. [5] have shown the importance of using pansharpening methods to maintain the radiometric characteristics by applying them as a preprocessing step before classification procedures. In this context, this work assesses the effects of the application of pansharpening methods for the separation between tropical crop and forest. To achieve this goal, firstly, we propose to use nine pansharpening techniques¹ that conserve good radiometric proprieties and may increase the classification accuracy. After the image fusion process, we applies support vector machine classifier (SVM) to evaluate the quality of fusion product by examining classification accuracy coefficients.

2. STUDY AREA AND DATA

2.1. Study area

The study site is located in the Capesterre-Belle-Eau municipality in the south-west of Guadeloupe Island, a French Caribbean Outermost Region. The study area is located at 16°02' N latitude and 60°33'W longitude, covering an area of approximately 103 km². Capesterre-Belle-Eau municipality has a quasi-flat topography. A large part of this area is dominated by agriculture and fruit culture, being the banana the most relevant crop. The remaining land cover is mostly occupied by forest. In order to test our methodological approach, seven sub-areas within this municipality have been selected. These areas represent different types of land-cover combinations (agricultural fields, grassland, bare soil and forest).

¹ Modified Intensity–Hue–Saturation (MIHS), Brovey Transformation (BT), Principal Component Analysis (PCA), Color Normalization (CN), Ehlers fusion (EH), Gram_Schmidt fusion (GS), High-pass Filter (HPF), Local Mean Matching (LMM), University of New Brunswick (UNB).

2.2. Data

The dataset used in this study includes four visible and near-infrared (VNIR) multispectral bands (red, green, blue and near-infrared bands) and a panchromatic image acquired by Quickbird satellite. These data were collected on April 11, 2007, at 15:03:39 local time. They show an irrelevant cloud cover (0.061%) over the study area, therefore, there are no visible atmospheric effects on the image.

To assess the accuracy of results, a human segmentation reference map was created using (1) photo-interpretation tasks; (2) the ecological map of Guadeloupe Island (1:75000 geographic scale), prepared in 1996 and provided by the National Forest Office/Guadeloupe National Park [6]; (3) field observation to validate both (1) and (2) training data components. We identified five main classes (forest², fruits plantations³, grassland and bare soil). A mask of narrow categories such as small human settlements, trails, roads and water streams was created, being classified in Figure 1 as “Errors” (white color).

3. METHODS AND RESULTS

In order to assess the effectiveness of Quickbird data and the effects of pansharpening methods on tropical crop and forest identification by using SVM supervised classifiers, 7 sub-areas representing different types of agricultural and forest land-cover combinations (agricultural fields, grassland, bare soil and forest) have been selected (Figure 1). After completing the classification step, the segmentation maps were generated and statistical criteria were computed to compare them with human segmentation maps.

3.1. Pansharpening techniques and quality assessment

Pansharpening methods allow merging multispectral images with medium/low spatial resolution (MS_b) and a panchromatic image with high/very high spatial resolution (PAN) in order to obtain a multispectral image with high spectral and spatial resolutions (MS_h^*). In this study, we used both Quickbird panchromatic and multispectral bands to produce MS_h^* . To evaluate the quality of the nine fusion products, consistency properties⁴ and synthesis properties⁵ were analyzed. Test 1 and 2 were performed by applying the extrapolation hypothesis [3]. In order to analyze and to assess the quality of the fused image, we used the Root Mean Square Error distance (RMSE) and the Global Quality index measure (GQ). Table 1 shows the three pansharpening methods that produce the best statistical values ($\mu \pm \sigma$). Ref. indicate ideal value. In fact, all pansharpening methods produced enhanced fused images. Nevertheless, PCA

method achieved a poorer quality when compared with BT and MIHS methods.

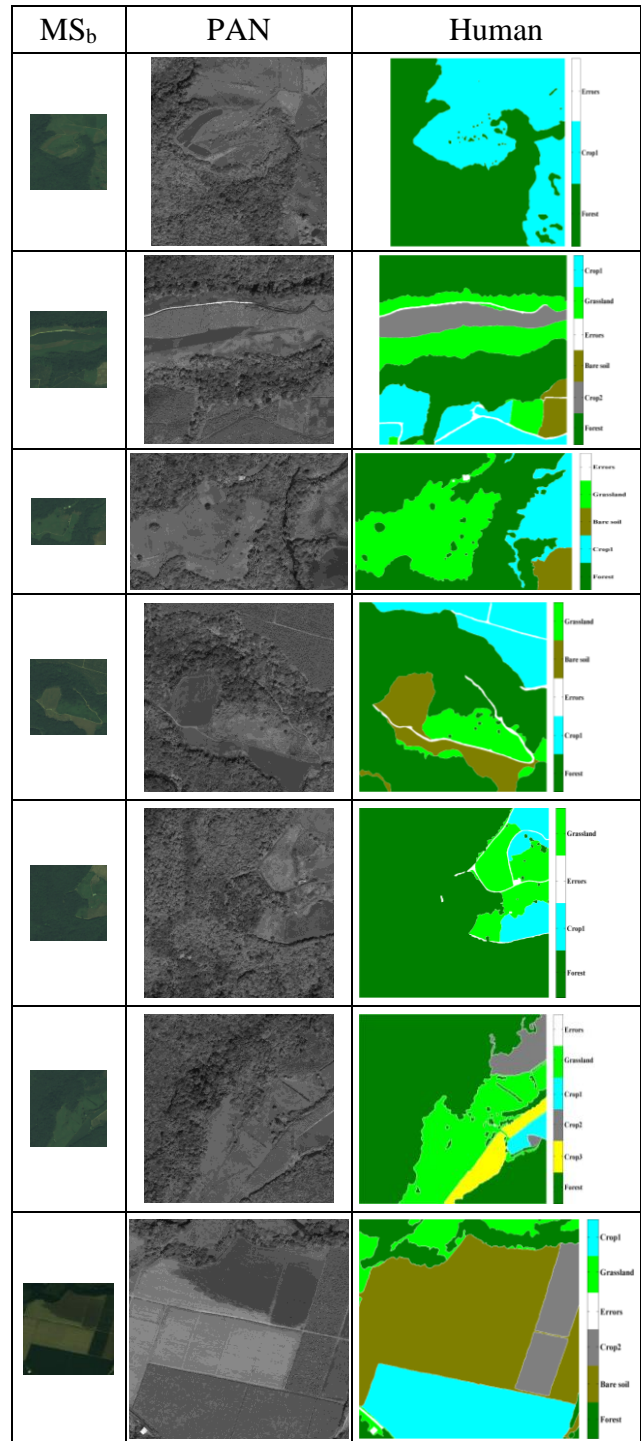


Figure 1. Left to right: multispectral, panchromatic original images and human segmentation maps.

² The forest class is composed by dense and/or scattered forest patches

³ Fruits plantations are labelled as two sub-classes: crop1 and crop2 (respectively grey and blue color in Figure 1).

⁴ degraded fusion product must be close to the reference product (Test 1)

⁵ fusion product must resemble to reference product, if it exists (Test 2)

The BT showed the lowest value of RMSE distance for the Test 1 and 2, and the highest value of GQ. Although spatial structures within MIHS and PCA fused images showed a general quality improvement, BT provided an image with higher spectral and spatial resolution.

Table 1. Quality assessment for best pansharpening methods.

	MIHS	Brovay	PCA	Ref
GQ	0.94±0.02	0.96±0.02	0.94±0.03	1
RMSE ^{TEST1}	6.26±1.58	4.20±2.11	7.05±2.82	0
RMSE ^{TEST2}	3.90±1.17	1.78±0.98	3.63±2.99	0

3.2. Classification algorithms

In remote sensing, image classification is widely applied. It is mostly used for land cover and vegetation mapping or to map other discrete categories from raw satellite data [7]. The supervised image classification process is generally expert-guided. To study the effects of the pansharpening methods on tropical crop and forest classification by using SVM classifiers, we computed a best model for the training set. The influence of changing parameters can be assessed through examining the classification accuracy. Only spectral bands were used for classification, before and after pansharpening methods were applied. The best models or parameters retained are then used to predict the association of each pixel to the most adequate class⁶. The classification results are compared with human segmentation maps using accuracy assessment measures.

3.3 Accuracy assessment

In remote sensing, the evaluation measures are generally, computed on error matrix defined by comparison between predicted samples and validation data [8].

Table 2. Classification accuracy for different pansharpening methods applied to all sub-areas using SVM classifier

Sub-areas		1	2	3	4	5	6	7	$\mu \pm \sigma$
MIHS	OAA	0.99	0.88	0.95	0.99	0.88	0.76	0.93	0.91±0.08
	OKCA	0.99	0.83	0.92	0.96	0.82	0.63	0.90	0.86±0.12
BT	OAA	0.98	0.92	0.96	0.98	0.89	0.78	0.94	0.92±0.07
	OKCA	0.96	0.89	0.93	0.96	0.82	0.65	0.91	0.87±0.11
PCA	OAA	0.95	0.91	0.94	0.99	0.90	0.76	0.5	0.85±0.17
	OKCA	0.90	0.89	0.90	0.97	0.84	0.63	0.93	0.87±0.11
Original (MS _b)	OAA	0.99	0.92	0.96	0.99	0.88	0.82	0.93	0.93±0.06
	OKCA	0.99	0.89	0.93	0.98	0.81	0.71	0.89	0.89±0.10

Table 2 shows the overall accuracy assessment⁷ (OAA) and overall kappa coefficient of agreement⁸ (OKCA) values

⁶ Best Parameters of SVM are radial basis function kernel, C=0, $\gamma=10^{-5}$

⁷ The OAA gives information about the effectiveness and performance of a classification. Values close to 1 indicate a good classification.

obtained by applying SVM classifiers on the training dataset extracted on original 7 sub-areas (MS_b) and on MIHS, BT, and PCA fused images (MS_h^{*}). According Table 2, the mean OAA computed on the original seven sub-areas is 0.93, showing a strong agreement and a good accuracy (mean OKCA=0.89). When using pansharpening methods, generally, the OAA results are slightly less accurate. The mean OAA and OKCA are 0.92 and 0.87 respectively by using BT. At overall level, our study has shown a small difference in accuracy when comparing both approaches. These results indicate that there is influence on the overall classifications resulting from the application of pansharpening methods, nevertheless those might be considered as low.

3.4 Region-based performance assessment

In the image processing and analysis domain, the evaluation measure is mainly related to the consistency between segmentations because there is no single human segmentation⁹. In this study, we use two human segmentation and apply three measures. The Probabilistic Rand Index (PRI) [9], the Variation of Information (VoI) [10] and the Global Consistency Error (GCE) [11]. The experiment has been conducted over the 7 sub-areas. The classification maps are shown in Figure 2 and error measures are presented in Table 3. These measures were computed on both MS_b and MS_h^{*} images. Table 3 and Figure 2 show that the classification maps obtained with MS_b images is very close to the classification maps computed on MS_h^{*} images. These results show once again that the use of pansharpening methods to improve spectral and spatial resolutions does not affect the classification maps.

Table 3. Segmentation accuracy for different pansharpening methods applied to all sub-areas using SVM classifier

Sub-areas		1	2	3	4	5	6	7	$\mu \pm \sigma$
MIHS	PRI	0.81	0.87	0.89	0.98	0.82	0.76	0.94	0.87±0.08
	VoI	1.01	1.87	1.12	0.34	1.24	1.69	1.33	1.23±0.5
	GCE	0.20	0.32	0.18	0.05	0.20	0.22	0.22	0.2±0.08
BT	PRI	0.82	0.83	0.89	0.96	0.85	0.78	0.93	0.87±0.06
	VoI	0.95	1.82	1.13	0.36	1.27	1.67	1.39	1.23±0.49
	GCE	0.18	0.31	0.19	0.05	0.20	0.22	0.23	0.2±0.08
PCA	PRI	0.75	0.83	0.87	0.97	0.86	0.77	0.90	0.85±0.08
	VoI	1.16	1.84	1.25	0.31	1.20	1.75	1.59	1.3±0.51
	GCE	0.24	0.32	0.20	0.04	0.19	0.23	0.26	0.21±0.09
Original (MS _b)	PRI	0.78	0.83	0.87	0.97	0.84	0.80	0.94	0.86±0.07
	VoI	1.09	1.83	1.22	0.33	1.27	1.58	1.30	1.23±0.47
	GCE	0.22	0.32	0.21	0.05	0.21	0.21	0.22	0.21±0.08

⁸ The OKCA provides a measure of how much better the classification performed in comparison to the probability of random assigning of pixels to their correct categories. Values close to 1 shows a good classification.

⁹ The VoI is non-negative, lower values indicating greater similarity

4. DISCUSSION AND CONCLUSIONS

By comparing the classification maps derived from original (MS_b) and pansharpened images (MS_{h^*}) (Figure 2), we can state that for all MS_{h^*} there is some noticeable and detectable improvement in border regions. The pansharpened land cover classes are less pixelated and more representative after the application of MIHS method.

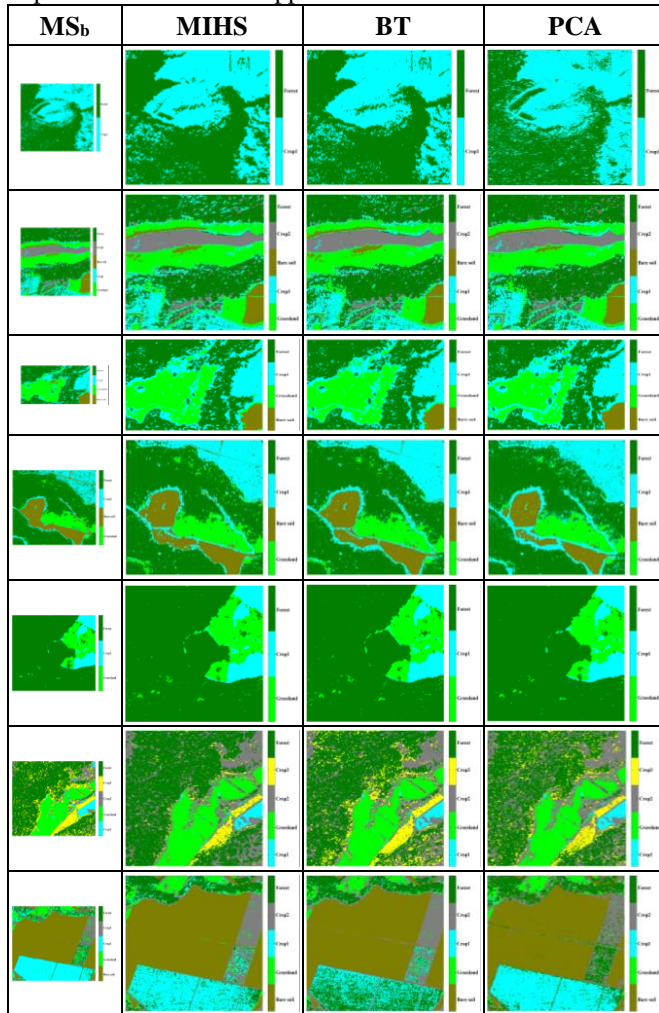


Figure 2. All sub-areas classification maps obtained by human and SVM classifier.

This difference is mostly apparent in the delineation of bare soil and grassland features. Tables 2, 3 and Figure 2 show that quantitatively and visually results are not significantly affected. In the case of the pansharpened sub-areas, the classification maps display significantly improved detail over the original sub-areas. The pansharpened classifications maps show better outlines for most land cover types, particularly in the case of bare soil and grassland. However, the PRI, VoI and GCE measures show the same values when comparing the MS_b and MS_{h^*} sub-areas.

The main goals of this work were to evaluate the effects of pansharpening methods on classification algorithms,

including a comparison with original multispectral images and their capacity to separate tropical crop and forest. The results indicate that the relevant increase in spatial resolution does not affect significantly the classification accuracy. In the same way, the classification maps obtained from pansharpened images showed similar accuracy and performance than classification maps derived from original imagery.

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