MERGING MULTISPECTRAL AND PANCROMATIC BANDS OF LANDSAT USING COKRIGING

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ABSTRACT

Remote sensing data and imagery is used in countless applications, but their analysis and interpretation highly depends on the spatial and spectral resolution. Fusion has been defined as the process of combining relevant image(s) information in order to synthesize it into more informative and more suitable image(s) for visual perception or computer processing, particularly for interpretation or classification. Building upon these objectives, this study explores the application of ordinary cokriging and collocated cokriging to improve the spatial resolution of the multispectral bands from a Landsat ETM+ image based on its corresponding panchromatic image. The study region, located in the central part of Colombia, has different land uses and covers such as water, forest, crop and urban areas. The geostatistical methods allowed for the fusion of the Landsat's original bands into 'fused bands', which improved the visualization and characterization of the study area. The collocated cokriging results were slightly less satisfactory than those of ordinary cokriging, possibly because of the land cover heterogeneity of the region. The results indicate that the fused bands obtained through this generally available technique can provide valuable information in digital processing of Landsat images, such as land use and land cover classification.

Keywords: Image fusion, geostatistics, remote sensing, satellite

INTRODUCTION

The analysis and interpretation of remote sensing data and imagery highly depends on the spatial and spectral resolution. Data fusion processes combine data from multiple sources to improve data interpretation and to produce a high-quality visible representation of the data [1], [2]. In particular, image fusion has been successfully used to increase either the spatial or spectral resolution of the images involved [3], [4].

Several geostatistical methods have been proposed for spatial enhancement of low-resolution imagery [5]. For example, [6] performed preliminary experiments for the fusion of two remotely sensed data sets (ALI and Hyperion) based on cokriging. Later, [7] applied fusion for the purpose of pan-sharpening multispectral Landsat ETM bands by using cokriging. [8] and [9] also showed the utility of cokriging for increasing the spatial resolution of satellite sensor images. A more elaborated algorithm was developed by [10] to merge Landsat TM and SPOT-P images, which was based on direct sequential simulation with reference images and local coregionalization models. More recently, [11] proposed regression kriging to fuse multi-temporal images.

The main objective of this study is to improve the spatial resolution of multispectral bands from a Landsat ETM+ image using its corresponding panchromatic band by applying ordinary cokriging and collocated cokriging. The performance of these techniques is compared in an area located in the central part of Colombia, which exhibits a heterogeneous land use and land cover pattern.

STUDY REGION AND DATA SETS

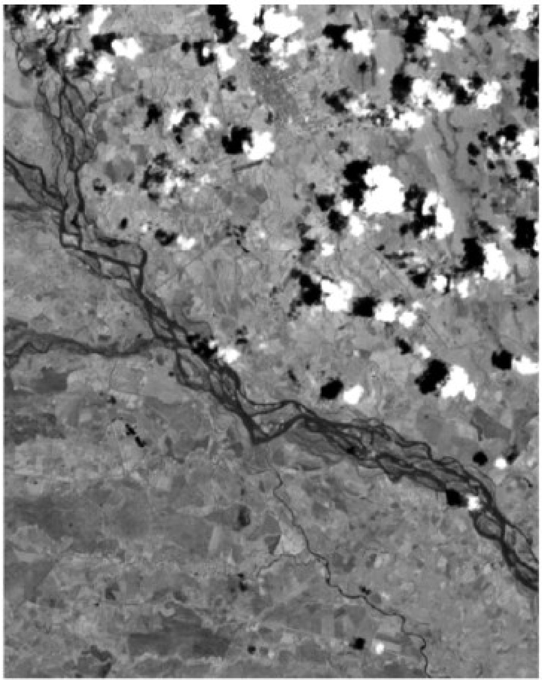
The study area has an extension of 153 312 square kilometres in the department of Meta, municipality of Granada, Colombia (Fig. 1). The region comprises different land uses and land covers, such as water, forest, crops and urban areas.

Figure 1: Study area in the department of Meta, municipality of Granada, Colombia

Landsat 7 is a NASA's satellite carrying multiple remote sensor systems that periodically provides synoptic coverage of continental surfaces. The ETM+ sensor has an eight-band multispectral scanning radiometer providing ground sample distance, or pixel size, at three different resolutions [12]: 30 meters for spectral bands 1-5, and 7 (visible and infrared bands), 60 meters for band 6 (thermal band), and 15 meters for band 8 (panchromatic band).

The information used in the analysis corresponds to subsets of 931 rows per 735 columns of the panchromatic and spectral bands (Path: 007 – Row: 058) of a Landsat ETM+ image of the study area with date of collection 21/09/2002, available from the Global Land Cover Facility (GLCF, http://glcf.umd.edu).

The urban area of Granada (Meta) crosses the images (Fig. 2), which also show the Ariare River and different crops (southwestern part). The image also exhibits clouds and all these characteristics make it suitable for exploring the application of geostatistical methods for image fusion.



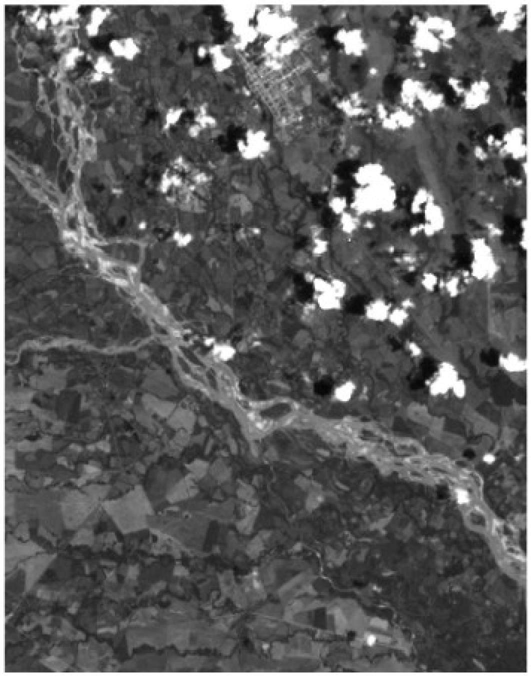


Figure 2: Landsat ETM+ scenes: panchromatic image (left), and RGB:321 composite image (right)

To determine which bands could be better spatially enhanced through cokriging techniques, we computed histograms, scatter plots (Fig. 3) and correlation coefficients between the bands with lower spatial resolution (B1-B5 and B7) and the panchromatic band (BP). For correlation purposes, the BP was generalized to the same spatial resolution of the other bands (30 meters).

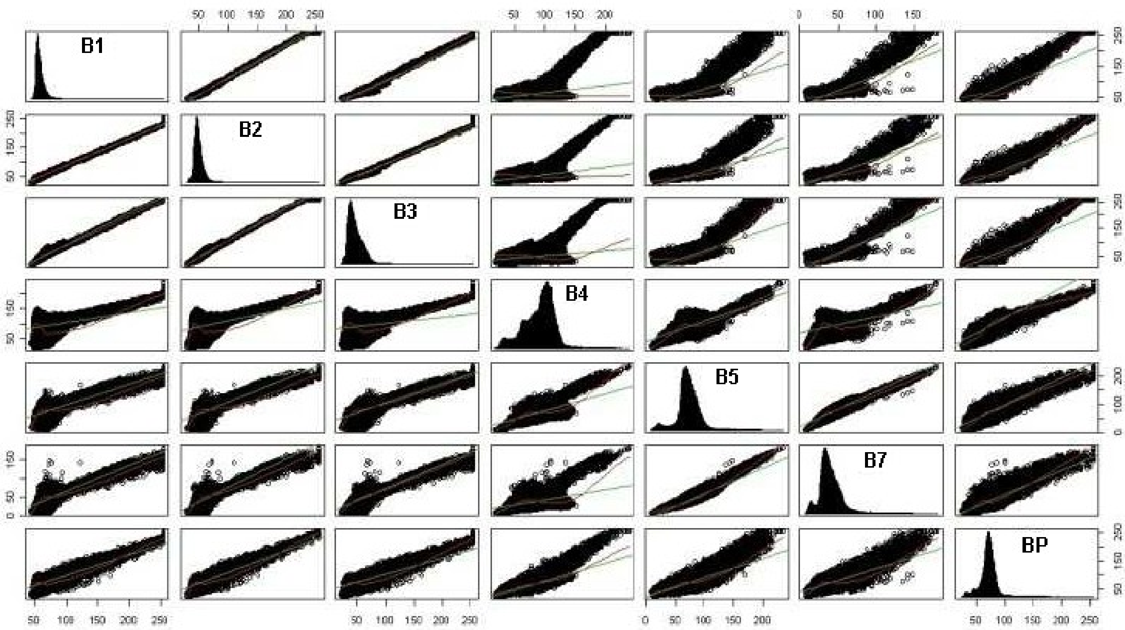


Figure 3: Histograms of single bands data and scatter plots between data from the bands 1-5 and 7 (B1-B5 and B7) and the panchromatic band (BP)

The bands of blue (B1), green (B2) and near-infrared (B4) have correlations above 0.80 with the panchromatic band, and its correlation with the band of red (B3) is slightly lower (0.78). Bands 5 and 7 have lower correlations with BP (0.77 and 0.75, respectively) and exhibit higher dispersion of values (Fig. 3). The bands with correlations with BP above 0.80 were considered appropriate to be spatially enhanced, and the band of red (B3) was also selected because it allows obtaining true color composites. Accordingly, the specific objectives of the analysis are to obtain enhanced bands of blue (B1), green (B2), red (B3) and near-infrared (B4) with 15 meters of spatial resolution (*fused bands*) using data from the panchromatic band.

COKRIGING METHODS

Geostatistical methods, known as kriging, provide unbiased estimates of spatial attributes using the estimated spatial covariance structure of the observed data [13]. Geostatistics has been successfully applied in several areas of the earth sciences such as mining engineering, environment, soil, agricultural and forestry sciences, hydrology, climatology, etc. The analysis of remote sensing images using geostatistics was consolidated in the late 1980s [5].

The term kriging covers a number of univariate and multivariate methods for spatial interpolation. A major advantage of multivariate techniques, such as cokriging, is that the prediction of the primary variable uses data from secondary variables that are more densely sampled. The primary variables considered here are the bands 1-4, and the secondary data corresponds to the panchromatic band. As discussed before, secondary data is spatially cross-correlated with the primary variables.

Cokriging estimators are but variants of the same linear estimator, which is usually expressed as a trend model plus a residual component [13], [14]. Several cokriging variants can be distinguished depending on the trend model adopted. The term cokriging usually refers to the ordinary cokriging estimator, which accounts for local variations of the means by limiting the domain of stationarity of both primary and secondary (unknown) means to a local neighborhood. Hence, the ordinary cokriging estimator uses secondary data falling within a local neighborhood of the location being estimated. Here, location values are the geographic coordinates of the pixel coordinates (data points) in the grid defined by the panchromatic image (15 meters resolution).

The panchromatic band provides exhaustive secondary information, because data is available at all primary data locations and all locations being estimated. Therefore, highly redundant secondary information might be included in the local neighborhood considered for prediction. In these situations, the collocated (ordinary) cokriging estimator might provide better results, because it retains only the secondary datum collocated to the location being estimated [13, p. 235].

The semivariogram model is assumed known, and should generate a positive definite covariance matrix. Typically, a semivariogram model with this property (e.g. exponential or spherical) is fitted to the experimental semivariogram values that are calculated from data, for given angular and distance classes.

After a thorough exploration of different models and parameters, we concluded that there are no significant differences in the parameters of the semivariograms for all individual and pairwise variables. These results are not surprising given the high correlation between the bands and the large amount of data in the database (684 285 records). The model that best fitted all experimental auto- and cross-semivariograms was the isotropic spherical model with the range equal to 550 meters and the sill equal to 350 (maximum semivariance).

Different search strategies were investigated to determine the local neighbourhoods considered for prediction using the ordinary and collocated cokriging methods. Prediction errors' statistics derived through cross-validation were used to assess the best search strategy, as well as to investigate the prediction performances of the two cokriging variants [14]. The best approach was then used in the final images generation. The prediction errors' statistics considered were the mean error (ME) and the root mean square error (RMSE). Given the strong similarity of results in the search strategies evaluated, we considered a maximum of five nearest neighbours (150 meters) to the location being estimated for all variables and cokriging variants.

RESULTS AND DISCUSSION

The errors statistics of both interpolation methods indicate that they have a similar performance (Table 1), although collocated cokriging was slightly less accurate and more biased than ordinary cokriging. This could be explained by transitions in different covers of the earth surface in the study area. Ordinary cokriging uses more data from the panchromatic band than collocated cokriging, thus it captured slightly better the land cover heterogeneity. Hence, the fused bands were generated using ordinary cokriging.

Table 1: Prediction errors' statistics of ordinary cokriging (OCk) and collocated cokriging (CCk) for each spectral band

Band	**Method**	**Prediction errors' statistics**	
		Mean error (ME)	***Root mean square error (RMSE)***
Blue (B1)	OCk	0.0001	3.39
	CCk	0.0050	3.73
Green (B2)	OCk	0.0001	3.16
	CCk	0.0003	3.46
Red (B3)	OCk	0.0002	3.88
	CCk	0.0020	4.35
Near-infrared (B4)	OCk	0.0003	3.13
	CCk	0.0007	3.22

The spatially enhanced bands of blue (B1), green (B2), red (B3) and near-infrared (B4) with 15 meters of spatial resolution (fused bands) are shown in Fig. 4. The fused bands exhibit a better contrast than the original ones, thus the identification of land cover elements in the enhanced images has improved.

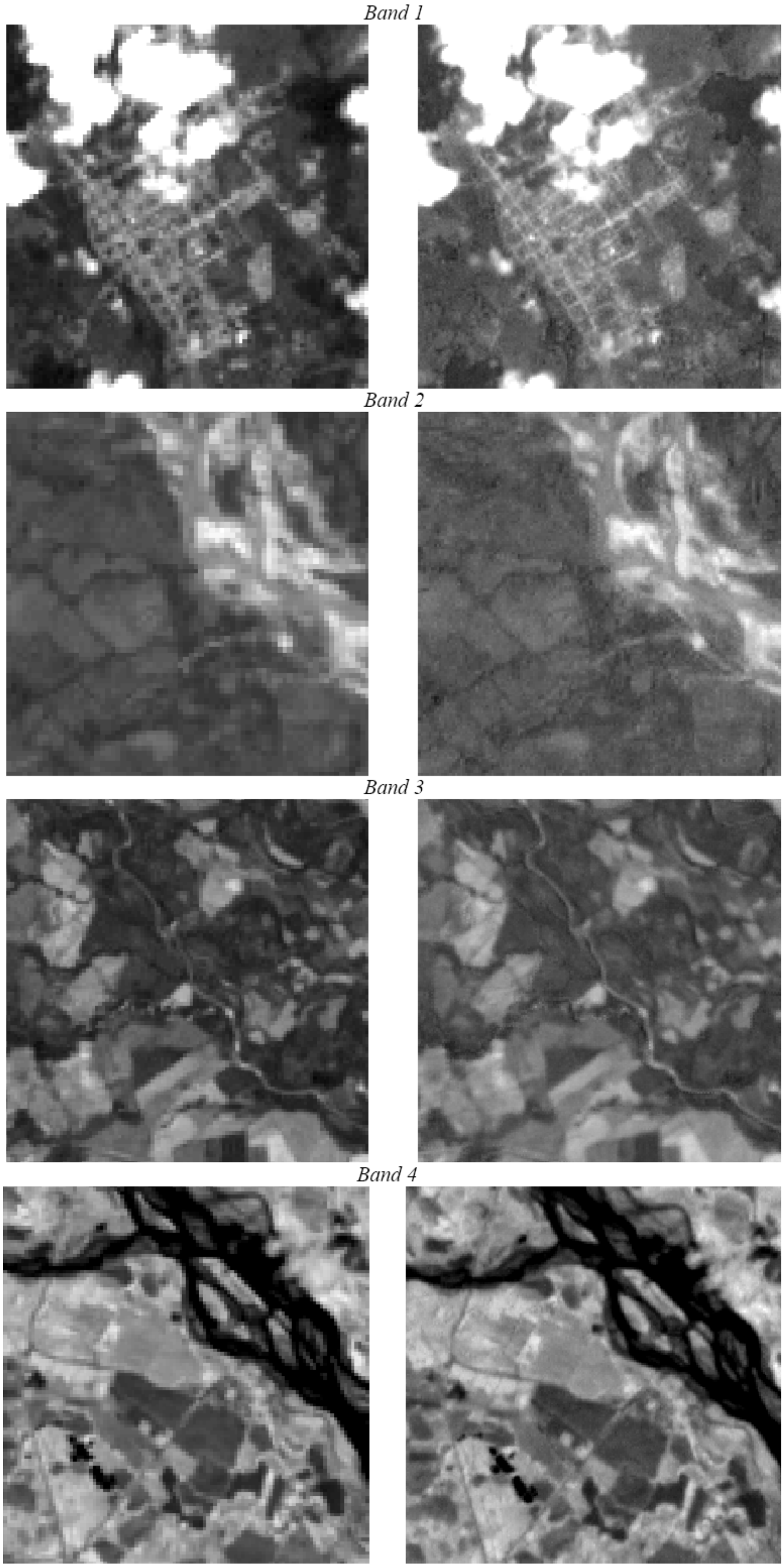


Figure 4: Images of the original bands (left) and the fused bands (right)

In the area with crops, in the central part of the study region, the true colour composites (RGB:321) of the original and fused bands reveal that the enhanced bands provide a better definition for the limits of crops, the river and the vegetation cover (not shown). The effect of the increase in the spatial resolution can also be observed in the urban part of the image (Fig. 5), where the definition of land parcels is more evident. Moreover, the roads inside the town are more sharpen in the composition of the fused bands. Therefore, the spatially enhanced bands provided more suitable images for visual perception.

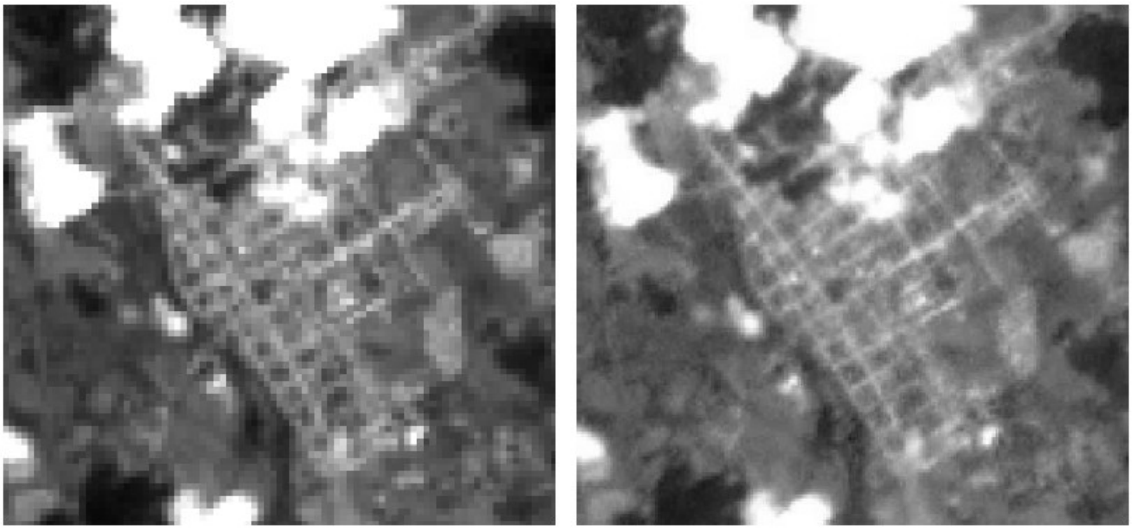


Figure 5: Image of the urban part of the study region in true colour composites (RGB:321) of the original bands (left) and the fused bands (right)

The topic of fusing images is relevant from an application viewpoint as the fused bands contribute to the understanding of the elements observed. The results indicate that the fused bands can support the digital processing of Landsat ETM+ images, such as interpretation or classification.

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