A COMPARATIVE CASE OF STUDY OF IMAGE SHARPENING

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KEY WORDS: Statistics, Fusion, Algorithms, Landsat, Spatial

ABSTRACT:

In this paper we present a comparative case of study of different methodologies for image sharpening. The evaluated methodologies are classic procedures such as Brovey (BR), Intensity Hue Saturation (FIHS), and Principal Component Analysis (PCA); two procedures based on wavelet transforms: Wavelet à Trous (WAT) and MultiDirection MultiResolution (MDMR); and one method of a geostatistical nature, Downscaling Cokriging (DCK). The comparison of the fused images is based on the quantitative evaluation of their spatial and spectral characteristics by calculating statistical indexes and parameters to measure the quality and coherence of the resulting images.
Synthesis of the obtained results shows that the algorithm fusions based on wavelet and DCK yielded better results than did the classical algorithms. Particularly, the DCK geostatistical method does not introduce artefacts in the estimation of the digital levels corresponding with the source multispectral image and, in this sense, can be considered the most coherent method. The MDMR method produces the merged images with the highest spatial quality.

1. INTRODUCTION

The arrival of new sensors and satellites in recent decades has notoriously favoured the availability of remotely sensed images with enhanced spatial and spectral resolution. In practice, a more effective use of this information entails the application of image fusion techniques in order to obtain a final product with improved spatial and spectral resolution suitable for a specific application.

The simplest fusion techniques are based on the direct substitution of some bands for visualization or in a simple arithmetic transformation, such as the Brovey (BR) method or the FastIHS method (Tu, 2005). Some other classic image fusion algorithms are more complex and involve transformations of the images and substitution of components, e.g. Principal Component Analysis (PCA) or Intensity Hue Sturation (IHS) transform.

A set of image fusion methods based on wavelet theory have recently been proposed (Amolins et al., 2007). These fusion algorithms may be considered as an extension of the High Pass Filtering (HPF) method, since they hold that spatial information is contained in the high frequencies. The wavelet transforms extract detailed information of the panchromatic image to integrate it in the multispectral image by means of methods based on the frequency or the spatial context. An advantage of these techniques is that the wavelet function can be modified to enhance specific features, which can be useful for a particular application (Amolins et al., 2007).

A further methodological alternative to the above is founded on geostatistical methods, which explicitly account for spatial variability characteristics of the images to be fused (Chica-Olmo and Abarca-Hernández, 1998). The geostatistical fusion model is based on the Cokriging method. One variant of this methodology is the Downscaling Cokriging method (DCK), proposed by Pardo-Iguzquiza et al. (2006), which considers relevant aspects for image fusion purpose such as pixel size (information support), the direct and cross-spatial correlations of the image digital values, and the point spread functions of the sensors.

Although several comparative studies of remote sensing image fusion methods have been published, there are only a few that include a detailed assessment of results obtained with a broad range of available techniques. The aim of this study is to perform a detailed comparative analysis of a set of image-fusion algorithms representative of the different methodological approaches. To this end, several classic methods based on arithmetic transformations or substitution of components were chosen: Brovey (BR), Fast IHS (FIHS) and Principal Component Analysis (PCA); two methods based on wavelet transforms: Wavelet à Trous (WAT) and MultiResolution MultiDirection (MDMR); and finally, a method of a geostatistic nature, Downscaling Cokriging (DCK).

2. RELATED WORK

2.1 Image sharpening approaches

Below we briefly describe the selected fusion algorithms that were chosen for comparative study.

BR Method: It is a very popular method of easy application, which is based on simple arithmetic applications, in which each band of the colour image is multiplied by the high resolution image and divided by the sum of the multispectral bands.

PCA Method: PCA is based on the application of a classic procedure of principal component analysis of the original bands

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of the mustispectral image. In the calculation of the principal components, the common information of the set of multispectral bands is contained, mainly, in the first component. This component is substituted by the panchromatic band, equivalent in radiometric information content, but having better spatial resolution. Inverse transformation allows the fused image to be obtained.

FIHS Method: The IHS is based on the transformation of the colour space, from RGB to IHS, and substitution of the resulting band intensity with the panchromatic image of high spatial resolution. By applying the inverse transformation after substitution, one obtains a multispectral image that is similar to the initial one, but has improved spatial resolution. The FIHS fusion algorithm is based on the same theoretical principals as the IHS, but the process of inverse transformation is simplified (Tu, 2005).

WAT Method: Wavelet transforms are considered as a bank of filters that, upon application to a sequence of levels of decomposition, divide the signal (e.g. satellite image) into high and low frequency components (Amolins et al., 2007). When decomposition at different levels is applied, we speak of multiresolution decomposition.

The transform denominated Wavelet à Trous, or WAT consists basically of the application of a series of consecutive convolutions for different levels of degradation. WAT calls for an iterative filtering process, in which a series of degradation filters are used to obtain the wavelet. Because it is not a decimal algroritm (with holes), the point of departure is an initial filter to which rows and columns are iteratively added, with zeros introduced between the rows and columns of the filter of the previous iteration, until the desired resolution is achieved.

The WAT method, unlike algorithms such as the pyramidal one of Mallat is characterized by the directional independence of the filtering process, without spatial compression of the different levels of degradation. Therefore, the image for each level of degradation has half the resolution of the previous one, but the same size, so that the information contained in each is redundant.

The wavelet coefficients $A^{kj}_{uj+n}(x)$ are calculated as the difference between two consecutive levels of degradation:

$$A^{k_j}_{u_j+n}(x) = DN^{k_j}_{u_j+n-1}(x) - DN^{k_j}_{u_j+n}(x) \quad (1)$$

DN represents the digital number of a pixel of location x = (x,y) belonging to spectral band k_j of the original image.

Following an additive criterion, if $DN^{kj}_{uj+n}(x)$ represents the successive degradations that contain the information of low frequencies of the original multispectral image, and $A^{kj}uj+n(x)$ the respective wavelet coefficients that contain the high frequency information, it is possible to obtain a fused image of high resolution by means of the sum of the low frequencies contained in the degraded multispectral image and the high frequencies extracted from the panchromatic image.

$$\widehat{DN}^{k_0}_{u_0}(x) = DN^{k_j}_{u_j+n}(x) + \sum_{k=1}^{n} A^{k_j}_{u_{j+n}}(x) \quad (2)$$

MDMR Method: The MultiDirection MultiResolution fusion algorithm (Lillo-Saavedra and Gonzalo, 2007) is a modification of the WAT that incorporates directional transforms. It is an algorithm meant to attain optimal equilibrium between the spectral and the spatial resolution of combined images, via the application of directional ellipsoidal filters.

The fusion process is virtually identical to that explained under the WAT method.

$$A^{k_j}_{\theta_n}(x) = DN^{k_j}_{\theta_n}(x) - DN^{k_j}_{\theta_n-1}(x)$$
$$\widehat{DN}^{k_0}_{u_0}(x) = DN^{k_j}_{\theta_l}(x) + \sum_{k=1}^{l} A^{k_j}_{\theta_n}(x) \quad (3)$$

However, we see that the level of degradation has been replaced by that of the directional filter of orientation θ. Unlike WAT, this is a highly anisotropic algorithm, which allows for trade-off between the desired spatial and spectral resolutions (see Lakshmanan 2004).

Downscaling Cokriging Method: The fused image of high spatial resolution obtained by means of this geostatistial method, DCK, is expressed as a linear combination of the experimental images (Pardo-Iguzquiza et al., 2006; Atkinson et al., 2008):

$$\widehat{DN}^{k_0}_{u_0}(\mathbf{x}_0) = \sum_{j=1}^{M}\sum_{i=1}^{n_j} \lambda^0_{ji} DN^{k_j}_{u_j}(\mathbf{x}_i) \quad (4)$$

where:
DN^b_a represents the digital number of a satellite image for the spectral band b and with a spatial resolution (pixel size) a and for a particular spatial location. The circumflex symbol above DN denotes that it is an estimated image or one fused by cokriging, whereas without the accent it is designated as an experimental image. Other annotations are:
$b=k_0$ spectral band whose spatial resolution should be improved.
$b=k_j$ experimental spectral band included in the process of fusion by cokriging.
$a=u_0$ spatial resolution or pixel size of the fused image.
$a=u_j$ spatial resolution or pixel size of an experimental image used in the fusion.
M: number of experimental bands used in the fusion.
n_j: number of pixels of the neighborhood used for the experimental image of the spectral band.
λ^0_{ji} : optimal weight applied to $DN^{kj}_{uj}(x_i)$ in the estimation of $DN^{k0}_{u0}(x_i)$.
The optimal weights given above are obtained by means of the resolution of a system of linear equations known as a cokriging system. This system is derived by imposing that the estimator be unbiased:

$$E\{\widehat{DN}^{k_0}_{u_0}(\mathbf{x}_0) - DN^{k_0}_{u_0}(\mathbf{x}_0)\} = 0 \quad (5)$$

and minimizing the variance of estimation

$$E\{[\widehat{DN}^{k_0}_{u_0}(\mathbf{x}_0) - DN^{k_0}_{u_0}(\mathbf{x}_0)]^2\} \rightarrow \min \quad (6)$$

where E{.} is the operator of mathematical expectation.

The cokriging system also accounts for three key aspects of fusion: the size of the pixel of the experimental images (support effect), the direct and crossed variograms of the radiometric bands, and the point spread functions of the sensor. (For a more detailed description of the cokriging system see Pardo-Iguzquiza et al., 2006; Atkinson et al., 2008).

2.2 Evaluation approaches

A set of statistical parameters and indexes were calculated to quantify the differences between the spectral information of the compared images, and, moreover, to measure the spatial and spectral quality overall:

-Correlation coefficient between the original multispectral image and the fused images.

-Mean Error and Root Mean Square Error of the original and the fused image.

-The ERGAS index (Erreur Relative Globale Adimensionnelle de Synthèse) (Wald 2000):

$$ERGAS_{spectral} = 100\frac{h}{l}\sqrt{\frac{1}{N}\sum_{k=1}^{N}\frac{\left(RMSE_{spectral}(B_k)\right)^2}{M_k^2}} \quad (7)$$

where h/l is the ratio between the resolution of the panchromatic image and the multispectral image, N is the number of spectral bands (B_k) of the fused image, M_k is the mean value of each spectral band, and RMSE is the Root Mean Square Error calculated between the fused image and the multispectral original.

To measure the spatial quality of fused images, authors Lillo-Saavedra et al. (2005) put forth a modification of the classic spectral ERGAS, referred to as the spatial ERGAS:

$$ERGAS_{spatial} = 100\frac{h}{l}\sqrt{\frac{1}{N}\sum_{k=1}^{N}\frac{\left(RMSE_{spatial}(B_k)\right)^2}{P_k^2}} \quad (8)$$

This index differs from the previous one in that it uses the original panchromatic band (P_K) instead of the multispectral one.

-The Image Quality Index, proposed by Wang and Bovik (2002) as an alternative to the Mean Square Error. It models the differences between two given monochromatic images as a combination of three separate factors: loss of correlation, luminance distortion, and contrast distortion.

$$Q = \frac{4\sigma_{OF}\bar{O}\bar{F}}{\left(\sigma_O^2 + \sigma_F^2\right)\left[\left(\bar{O}\right)^2 + \left(\bar{F}\right)^2\right]} \quad (9)$$

where and are the mean of the original and the fused images, respectively, σ^2_O and σ^2_F are the variances, and σ_{OF} is the covariance between the original image and the fused one.

- Index of spatial quality proposed by Zhou et al. (1998). This index measures the spatial quality of a fused image in relation with the spatial information provided by the panchromatic image. The algorithm applies a Laplacian filter to extract the high frequency information and compute the correlation coefficient between the sharpened image and the original panchromatic one.

-The "coherence measure" between the fused images and reality was obtained by calculating the correlation coefficient and the real errors (Mean error, ME and Root Mean Square Error, RMSE; (see Figure 2).

3. RESULTS AND DISCUSSION

The study is illustrated using a sector of a multispectral Landsat7 ETM+ scene of 944 km^2 (1024x1024) and its corresponding panchromatic image, with a spatial resolution of 30m and 15m, respectively. The image was acquired on 20 July 2002 over the metropolitan area of Granada, in southeast Spain. The scene corresponds to path 200 row 34 of the Landsat Worldwide Reference System (WRS) (figure 1).

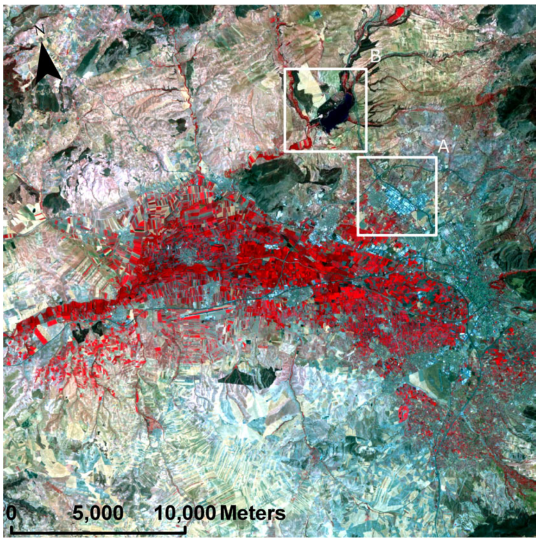

Figure 1. False colour composition image of the study area. Boxes A and B are two sectors of different land cover context.

The best reference for assessing the quality of a fused image is obviously the "true image" that the analyst wishes to obtain via the fusion method. In practice, this is however not feasible. For this reason, we designed an experiment in which the original multispectral and panchromatic images could be degraded (by a factor of 2) to resolutions of 120m and 30m, respectively, in order to obtain fused images with a resolution of 30m (figure 2). In this way we were able to compare the results of fusion with the "true" or "real" image (e.g., coherence measures).

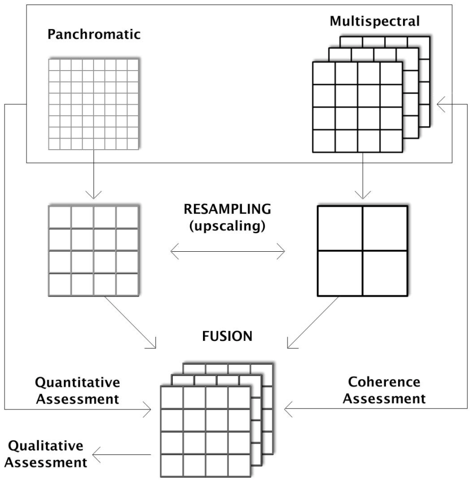

Figure 2. General scheme of the methodology used for comparative assessment of image fusion algorithms.

3.1 Application of the fusion algorithms

Classic methods: The classic fusion algorithms, BR, PCA or FIHS. These methods do not require definition of filters or the study of spatial variability between images, as required in the case of wavelet based and geostatistical based procedures.

Wavelet based:
WAT
In order to apply Wavelet à Trous fusion, a fusion ratio of 4:1 between the degraded multispectral Landsat image (120 m) and the degraded panchromatic image (30m) was considered. Two levels of degradation were applied to the multispectral image, so that two sets of wavelet coefficients were obtained, one containing detail between 120 m and 60 m and the other from 60 m to 30 m.

MDMR
In order to establish directionality and the optimal filter parameters, a great number of experiments were carried out applying different levels of degradation (l = 21, 22, 23, 24) for different combinations of a and b. The values of the filter parameters (a and b) were divided into two intervals. The first, defined between 0.1 and 0.5, using intervals of 0.1; and the second was ranged from 1 to 5 at intervals of 1. This gave a total of 100 different combinations for each partition frequency or degradation level (400 fused images). The resulting products of fusion were evaluated quantitatively using the ERGAS spatial and spectral indexes. For the selection of the best fused image by means of the MDMR algorithm, we determined the one in which the mean spatial and spectral ERGAS were lowest, and the difference between the two close to 0. This served as a guarantee of quality of the fusion, while affording balance between the spatial and spectral resolution of the fused image. According to the restrictions explained above, a filter with four directions and an adjustment of parameters a and b was selected which provided a fused image with a mean ERGAS equal to 2.15. Nonetheless, the values of a and b, together with the number of directional filters, can be adjusted to highlight the spectral or the spatial resolution so as to attain lower ERGAS values.

Geostatistical based (DCK): This method requires the variographic analysis of the multispectral and panchromatic images: the experimental and the induced models of the simple variograms of the different bands of the multispectral and panchromatic images, as well as the cross-variograms between these images. A linear model of corregionalization with two superimposed exponential structures was used: one of short range (45 m) and the other of long range (728 m). The practical ranges are 135 m and 2184 m, respectively. The sills of the simple and cross-variograms of the multispectral and panchromatic bands at point support level were all calculated using a process of numeric deconvolution and an adjustment of weighted squared minima.

Fusion by downscaling cokriging was done using two bands, the band whose spatial resolution we wished to improve, and the panchromatic one. The results of the Cokriging system provided the weights that were applied to the high and low spatial resolution images; that is, the multispectral and panchromatic ones, respectively.

3.2 Evaluation of the overall quality

In this section, we present the results of the fusions and the assessment of the spectral and spatial quality of the fused images.

Two subsectors with different environmental context were chosen for detailed evaluation (figures 1 and 3). The fused images show considerable differences in visual quality depending on the integration technique applied. The BR and PCA methods have a negative impact on the colour of the image, decreasing contrast and increasing colour saturation. The FIHS and the WT methods achieve better spatial detail and give rise to sharper images, reflected most notably in the linear features present in the urban zones (figure 3 sector A). However, the greater the spatial enhancement the greater the spectral distortions and moreover, contrast is reduced, and an effect of radiometric homogenization is produced, which causes a loss of texture. This effect is particularly appreciable in the image obtained using the MDMR method, where the vegetation areas seem to be fuzzy. Finally, the geostatistical method (DCK) is the one that best conserves contrast, saturation and texture with respect to the original reference image, yet in certain areas, for instance in the urban ones, a coarser spatial resolution can be observed.

In order to quantify the quality of the images several indexes were calculated taking into account the original multispectral Landsat image, in the case of the spectral indexes, and the panchromatic image, in the case of the spatial indexes.

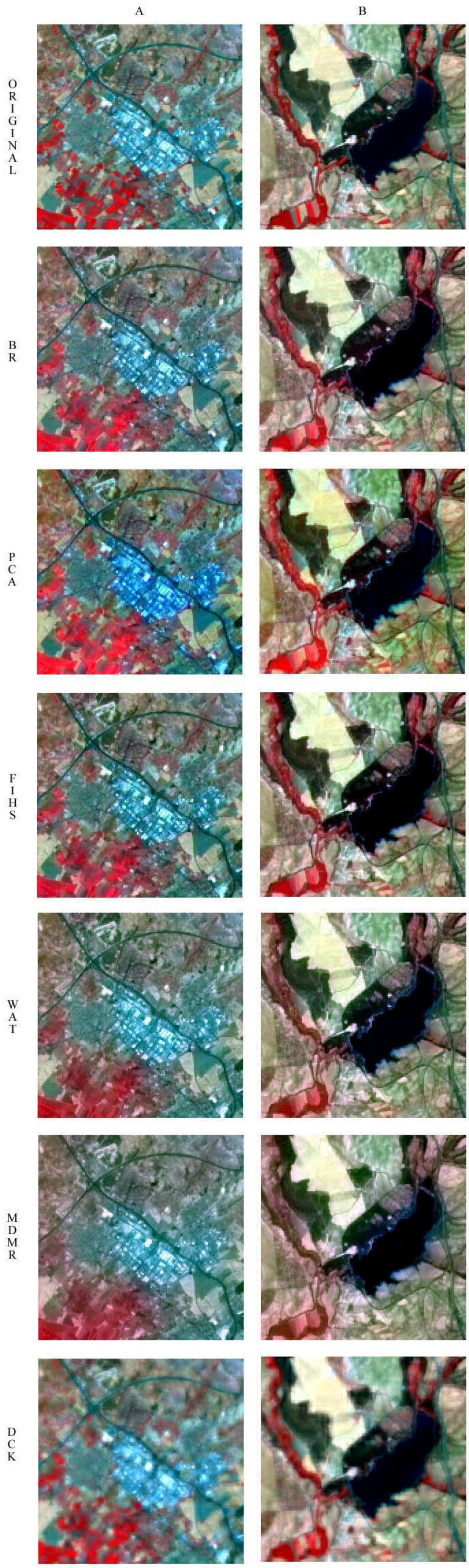

Figure 3. False colour compositions 432 (RGB) of the original multispectral image and the fused images for test sectors A and B.

In general, correlation coefficients indicate that a relatively large correlation in the near infrared (NIR) band exists for all the fusion methods analysed (0.896 to 0.958) (table 1). Correlations are however considerably larger for the green (0.940 to 0.962) and red visible (0.952 to 0.967) bands, due to a better spectral correspondence with the panchromatic band. With regard to image integration methods performance, PCA presents the smallest correlation coefficients for all the bands (0.896 to 0.955). In contrast, the DCK offers the best correlation with the multispectral image (0.958 to 0.967). Table 1 show that the RMSE are small for methods DCK, WAT and MDMR, while the rest of the algorithms present larger RMSE values, especially the BR method.

	BR	PCA	FIHS	WAT	MDMR	DCK
CC G	0.953	0.943	0.940	0.946	0.944	0.962
CC R	0.967	0.955	0.966	0.958	0.952	0.967
CC NIR	0.931	0.896	0.945	0.932	0.928	0.958
RMSE G	51.68	17.05	15.14	5.82	5.90	4.88
RMSE R	66.44	24.18	17.39	8.40	9.11	7.49
RMSE NIR	65.83	23.53	12.60	6.58	6.75	5.16
Spatial ERGAS	10.327	3.005	2.826	2.431	2.129	2.943
Spectral ERGAS	11.036	3.284	2.845	2.111	2.167	1.319
Average ERGAS	10.682	3.144	2.835	2.271	2.148	2.131
Q 8x8	0.647	0.875	0.881	0.871	0.860	0.879
Q 16x16	0.658	0.901	0.911	0.905	0.887	0.921
Q 32x16	0.665	0.914	0.928	0.925	0.907	0.940
Q 64x64	0.668	0.922	0.939	0.938	0.922	0.951
Q 128x128	0.670	0.926	0.947	0.948	0.935	0.960
Average Q	0.662	0.907	0.921	0.917	0.902	0.930
Zhou	0.972	0.972	0.995	0.997	0.996	0.857

Table 1. Values of the different parameters analysed to estimate the spectral and spatial quality of the fused images.

With regard to the spatial, spectral and mean ERGAS values (table 1), all the fusion methods, except the BR and PCA, generate good quality merged images. However, image fusion methods based on wavelet transforms (MDMR and WAT) and geostatistics (DCK) clearly outperform the rest of algoritms. MDMR and DCK are the ones providing larger spatial and spectral quality (2.129 and 1.319 respectively). DCK has a lower mean ERGAS than the others with a value equal to 2.131. The WAT method presents indexes of spatial and spectral quality that are better balanced (2.431 and 2.111 respectively). All the fusion methods, except BR, result in improved spectral quality with respect to the degraded multispectral image. The

DCK method yields the best results with an average Q equal to 0.930.

The Zhou spatial index (table 1) present high values in all cases, except under DCK, which gives a value of 0.857.

3.3 Assessment of coherence

The coherence of digital levels when comparing the target image and those estimated by means of the fusion algorithm has been considered in this study. We elaborated a "coherence measure" based on: mean error, Root Mean Square Error (table 2) and the correlation coefficient of each band estimated with respect to its corresponding "true" multispectral band (table 2). DCK is the most coherent, as it presents a maximum correlation coefficient (practically equal to 1) and it minimizes the RMSE for all the bands. The rest of the methods give correlation coefficients that are similar (all lower), whereas the RMSE and the ME of the classic methods are significantly less coherent than those of the wavelet methods.

	BR	PCA	FIHS	WAT	MDMR	DCK
ME G	-50.15	-15.73	-13.73	0.03	0.0341	-0.44
ME R	-63.25	-21.82	-15.69	0.03	0.0378	-0.45
ME NIR	-64.69	20.90	-11.08	0.04	0.0387	-0.44
RMSE G	51.40	16.31	14.17	3.00	3.6581	0.66
RMSE R	65.89	23.20	16.10	4.88	5.8669	0.69
RMSE NIR	65.59	22.98	11.45	3.65	4.3800	0.67
R G	0.98	0.97	0.97	0.98	0.9749	0.99
R R	0.99	0.98	0.99	0.98	0.9778	0.99
R NIR	0.97	0.92	0.98	0.97	0.9641	0.99

Table 2. Parameters of coherence between the true or real multispectral image and the fused images: mean error, Root Mean Square Error, and correlation coefficient.

4. CONCLUSIONS

The assessment of the global quality of all merged images has demonstrated that the algorithms based on wavelet transforms (WAT and MDMR) and the geostatistical algorithm, Downscaling Cokriging (DCK), produce better spectral and spatial results than the classic image fusion methods employed. These classic methods, with the exception of FIHS, introduce some colour distortions which can be observed in the visual analysis. The WT, along with FIHS method, enhance the spatial details of certain zones presenting specific patterns, such as the reticulate pattern of urban zones, although they introduce some distortions in more homogeneous zones such as areas covered with natural vegetation.
The assessment of the global quality of all merged images has demonstrated that the algorithms based on wavelet transforms and Downscaling Cokriging (DCK), produce better spectral and spatial results than the classic image fusion methods employed.

The analysis of the values of correlation coefficients, RMSE, spectral ERGAS and Q shows that the DCK method is the algorithm that best preserves the multispectral information of the original image. The MDMR method was the most efficient in increasing the spatial resolution of the image (as indicated by spatial ERGAS index and Zhou index). Finally, from the overall viewpoint of both spectral and spatial indexes, WAT is the method that presents the most balanced results.
The DCK is the most coherent method of those studied here, because it does not introduce artefacts in the estimation of the digital numbers.

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ACKNOWLEDGEMENTS

We are grateful for the financial support given by the Spanish MICINN (Project CGL2006-06845/CLI) and Junta de Andalucía (Group RNM122).