QUALITY EVALUATION OF MULTIRESOLUTION REMOTE SENSING IMAGES FUSION

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Odată cu disponibilitatea datelor multisenzor în domeniile de teledetecție satelitară şi imagistică computerizată, fuziunea senzorilor la nivel de pixel, trăsătură şi simbol reprezintă o nouă arie de cercetare. Scopul acestei lucrări a fost studierea schimbările de mediu ale zonei costiere româneşti a Mării Negre folosind diferite metode de fuziune de imagini aplicate seturilor de date satelitare multisenzor şi multispațiale. În scopul de a produce imagini fuzionate cu rezoluții spațiale şi spectrale foarte ridicate, în lucrare se analizează comparativ indicii de evaluare ai calității imaginilor fuzionate prin diferite tehnici aplicate datelor multisenzor şi multispațiale pentru zona costieră a Mării Negre în perioada 1985-2005.

With the availability of multisensor data in satellite remote sensing and computer vision fields, sensor fusion at the pixel or the so-called image, feature, and symbol level is a new research area. The aim of this paper was to study environmental changes of the Romanian Black Sea coastal zone using different image fusion methods applied to satellite multisensor and multispatial data sets.In order to produce the highest spatial and spectral resolution fused images, this paper examines the comparative quality evaluation indices provided by different techniques applied to multisensor and multispatial data over Black Sea coastal zone between 1985-2005 period.

Keywords : data fusion, satellite remote sensing, quality evaluation, coastal zone changes, Black Sea.

1. Introduction

Satellite remote sensing provides a means for locating, identifying and mapping certain coastal zone features and assessing of spatio-temporal changes. The Romanian coastal zone of the Black Sea is a mosaic of complex, interacting ecosystems, exposed to dramatic changes due to natural and anthropogenic causes (increase in the nutrient and pollutant load of rivers input, industrial and municipal wastewater pollution along the coast, and dumping on the open sea).

Nowadays, huge quantities of satellite images are available from many different Earth observation sites. Moreover, thanks to a growing number of satellite sensors, the acquisition frequency of a same scene is permanently increasing. Furthermore, the high spatial resolution of the sensors gives access to

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detailed image structures. The analysis of spatio-temporal structures is very useful to interpret and understand complex evolutions of coastal zones. Change detection, monitoring and validation of physical models by data assimilation constitute the most used analysis for information extraction. In many fields, there is a real need to transform growing databases into knowledge. The application of information technology has allowed the development of tools and techniques to handle coastal geospatial data and/or derived. With differences in scales, data, projections, formats, or resolution, the data are often difficult to handle and even more difficult to integrate.

To study environmental changes of the Romanian Black Sea coastal zone, different image fusion methods have been applied for fusing satellite multisensor and multispatial data. This paper examines the comparative quality evaluation indices of the fused images from different techniques applied to multisensor and multispatial data in order to produce images with the highest spatial and spectral resolution within the data set. Satellite Earth observation sensors provide a variety of data covering large domains of the electromagnetic spectrum, at various spatial, temporal and spectral resolutions. To fully exploit the potential of increased spatial resolution of remotely sensed imagery, several methods for combining datasets focus on the extraction of metadata with enhanced properties being referred to as multisensor image fusion.

2. Image fusion methods

Information fusion is a process of combining evidence from different information sources in order to make a better judgment. It plays an important role in many application domains. No single source of information can provide the absolute solution when detection and recognition problems become more complex and computationally expensive. However, complementary information can be derived from multiple sources. One of the important issues concerning information fusion is to determine how to integrate (fuse) the information or data.

Multisensor image fusion is a process dealing with the association, correlation and combination of data from multiple satellite sources, which is applied to digital satellite imagery in order to sharpen images, improve geometric corrections, provide stereo-viewing capabilities for stereo-photogrammetry, enhance certain features not visible in either of the single data alone, supplement datasets for improved classification, detect changes using multitemporal data, substitute missing information in one image with signals from another sensor image and replace defective data[1],[2],[3].

Depending on the stage at which fusion takes place, it is often divided into three categories, namely, pixel level, feature level and decision level, as Fig.1 illustrates [4],[5]]. In pixel level fusion, the combination mechanism works directly on the pixels obtained at the sensors' outputs. Feature level fusion, on the other hand, works on image features extracted from the source images or the features which are available form different source of information. Decision level fusion works at an even higher level, and merges the interpretations of different objects obtained from different source of information. Several data fusion algorithms have been developed and applied, individually and in combination, providing users with various levels of informational detail in photogrammetry and remote sensing [6]. The choice of a suitable fusion level depends on the available information type: when the sensors are alike, one can opt for fusion at the pixel-level to take all data into account. When sensors or information are very different, decision-level fusion is more suitable and is also computationally more efficient. Feature-level fusion is the proper level when the features as found by the processing of the different sensors can be appropriately associated. The application of the fusion approach shows successes with techniques ranging from expert systems to probabilistic techniques. As there is no simple rule for selecting the proper fusion technique, a wide range of techniques has potential applicability. The process of selecting optimum algorithm for fusion is complicated by the fact that data analysis seeks to combine incomplete and missing data in a complex environment in real time. "Data fusion" is a formal framework in which are expressed means and tools for the alliance of data originating from different sources. It aims at obtaining information of greater quality; the exact definition of 'greater quality' will depend upon the application" [1]. In optical remote sensing, with physical and technological constraints, some satellite sensors supply the spectral bands needed to distinguish features spectrally but not spatially, while other satellite sensors supply the spatial resolution for distinguishing features spatially but not spectrally. For many applications, the combination of data from multiple sensors provides more comprehensive information.

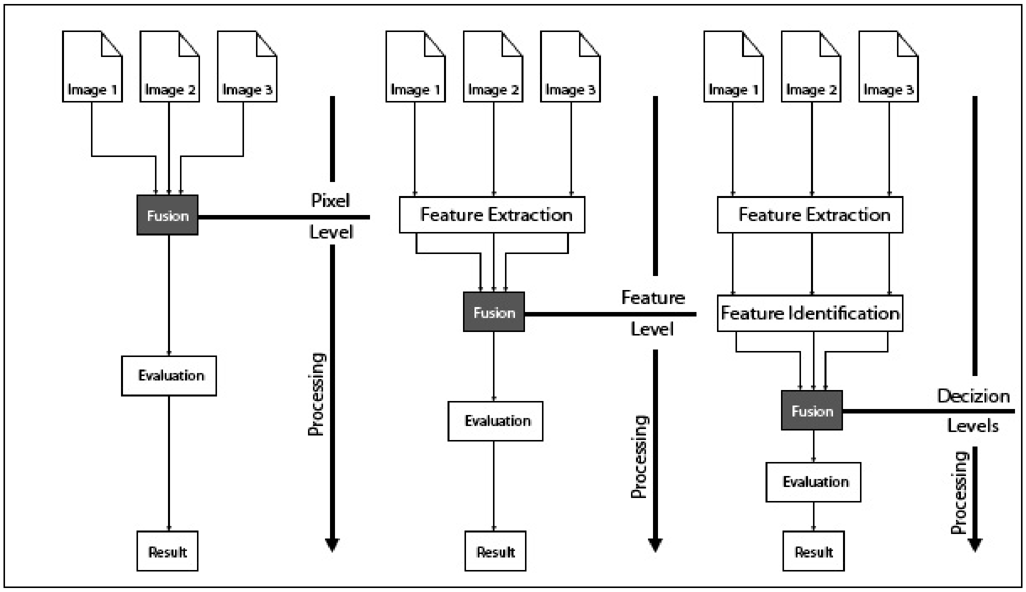

Fig. 1. Processing levels of image fusion

Developments in the field of remote sensing image understanding over the past four decades emphasized the requirements of an operational multisource thematic mapping process based on multispectral, hyperspectral and radar images analysis. It was suggested that the most practical approach is to analyze each data type separately, by techniques optimized to that data's characteristics, and then to fuse at the label level, as is illustrated in Fig.2. The most important is to derive practical labeling methodologies for effective thematic mapping from mixed data types to allow the synergy information contents of complementary datasets [7]. Data fusion is an operational method for multisource image analysis. Individual data types may be best analyzed separately, with combination occurring at the label level through some form of symbolic processing. Digital image fusion is very useful for environmental changes detection at local, regional and global scale.

Image fusion techniques can be grouped into two main classes, namely color related and statistical/numerical [1]. The first class comprises the color composition of three image channels in the RGB color space, as well as more developed color transforms (e.g. IHS). The second class refers to algorithms based on channel statistics, including correlation and filtering. Techniques such as principal components algorithm (PCA), Gram–Schmidt, local mean matching, local mean and variance matching, least squares and the Brovey transform belong to this group. A sophisticated numerical approach uses wavelets in a multiresolution environment. The method aims at the association of various input imagery through a multiresolution analysis procedure based on the combined use of successive lowpass and highpass filters, in order to extract a final fused image product with refined spectral and spatial properties.

The Hue Saturation Value (HSV) algorithm used in this paper for environmental changes analysis is an Image Fusion type and works at pixel level in order to allow for the combination of high resolution, panchromatic images with low resolution, multispectral images. The operation is conducted by keeping the spectral resolution while the spatial resolution of the lowest precision data is increased. In this way one is able to make use of the same information obtained before processing but at a greater degree of resolution.

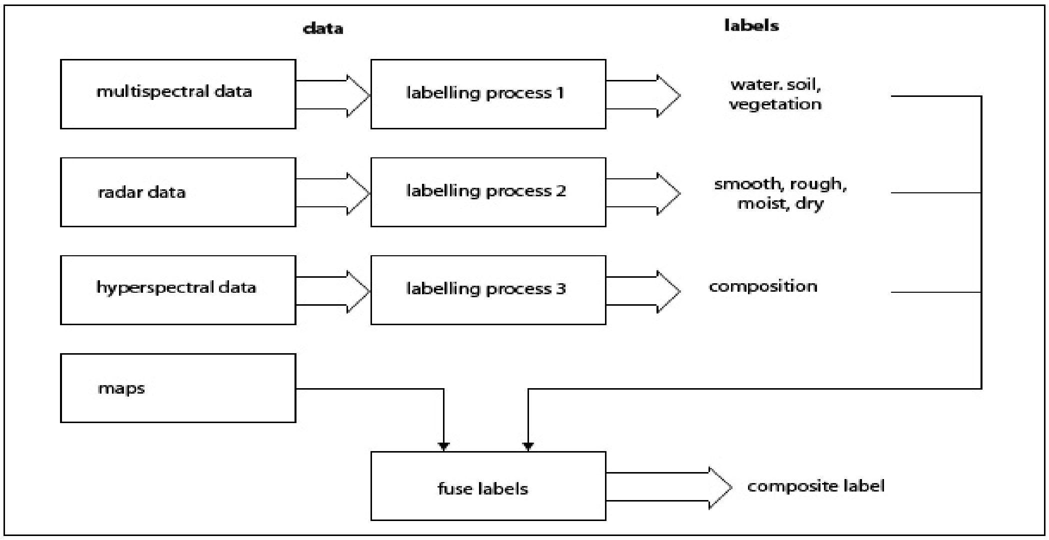

Fig. 2. Fusion of mixed data types at label level.

Before applying this method however, it is necessary to correct radiometrically and to geo-reference the images in order to make the relationship between the single pixels univocal. If however the data has the same spatial resolution, a simple co-recording can be carried out. HSV allows merging of RGB type images with panchromatic images, therefore only a limited number of bands (three with this method) may be employed. The different sensor channels are therefore associated with the three basic colors in order to generate a false colors image representing a physical reality. The principle on which this algorithm is based is to separate and extrapolate, starting from the false color image, the information relating to the intensity (I) to the saturation (S) and to the hue (H). From a strictly mathematical point of view, the system of coordinates (I,S, H) can be thought of as an Cartesian orthogonal system; given that the human eye treats the three components as if they were bound by an orthogonal type relationship and can be written [1] as follows (1):

$$\begin{bmatrix} I \\ V_1 \\ V_2 \end{bmatrix} = \begin{bmatrix} 1/3 & 1/3 & 1/3 \\ 1/\sqrt{6} & 1/\sqrt{6} & -2/\sqrt{6} \\ 1/\sqrt{2} & -1/\sqrt{2} & 0 \end{bmatrix} \cdot \begin{bmatrix} R \\ G \\ B \end{bmatrix} \tag{1}$$

$$\begin{cases} H = \mathrm{tg}^{-1}\left(\dfrac{V_2}{V_1}\right), \\ S = \sqrt{V_1^2 + V_2^2}, \end{cases}$$

The variables V1 and V2 are only and exclusively used to calculate H and S and have no direct connection to the image. The first of the three coordinates, that represents the intensity (I), is directly related to spatial position in that its value is bound to the type of surface analyzed, while the coordinates H and S supply additional radiometric information by describing its composition and degree of absorption.

Once the information is deconstructed, it is possible to substitute one of the three components with the information contained in a fourth channel, which has not undergone any kind of transformation. Generally it is the I component to be substituted with the intensity value obtained from the higher resolution image. Once this operation is completed, one proceeds to invert transformation (1) so as to obtain again an RGB type image. The formula that allows for such a passage is the following:

$$\begin{bmatrix} R \\ G \\ B \end{bmatrix} = \begin{bmatrix} 1 & 1/\sqrt{6} & 1/\sqrt{2} \\ 1 & 1/\sqrt{6} & -1/2 \\ 1 & -2/\sqrt{6} & 0 \end{bmatrix} \cdot \begin{bmatrix} I \\ V_1 \\ V_2 \end{bmatrix} \tag{2}$$

Before starting transformation (2), the information regarding saturation and color (S, H) is opportunely re-sampled by using linear type techniques and stretching techniques in order to adapt the multi-spectral bands to the band furnished by the highest resolution panchromatic sensor. HSV, therefore, is an evolution of the IHS algorithm, which has now become a standard in the procedure of Image Analysis.

Principal Component Analysis (PCA) used also in this paper for environmental changes analysis is very useful technique for image encoding, image data compression, image enhancement, digital change detection, multitemporal dimensionality and image fusion. It is a statistical technique that transforms a multivariate data set of intercorrelated variables into a data set of new un-correlated linear combinations of the original variables. It generates a new set of axes which are orthogonal [7]. The approach for the computation of the principal components (PCs) comprises the calculation of:

1. Covariance (unstandardised PCA) or correlation (standardized PCA) matrix
2. Eigenvalues, -vectors
3. PCs

An inverse PCA transforms the combined data back to the original image space. The use of the correlation matrix implies a scaling of the axes so that the features receive a unit variance. It prevents certain features from dominating the image because of their large digital numbers. Through applying the standardized PCA the signal-to-noise ratio (SNR) is significantly improved. Better results are obtained if the statistics are derived from the whole study area rather than from a subset area. Two types of PCA can be performed: selective or standard. The latter uses all available bands of the input image, e.g., TM 1- 7, the selective PCA uses only a selection of bands which are chosen based on *a priori* knowledge or application purposes [8]. In case of TM the first three PCs contain 98- 99% of the variance and therefore are sufficient to represent the information. PCA in image fusion has two approaches:

1. PCA of multichannel image replacement of first principal component by different images (*Principal Component Substitution*- PCS);
2. PCA of all multi-image data channels.

The first procedure follows the idea of increasing the spatial resolution of a multichannel image by introducing an image with a higher resolution. The channel which will replace PC1 is stretched to the variance and average of PC1. The higher resolution image replaces PC1 since it contains the information which is common to all bands while the spectral information is unique for each band; PC1 accounts for maximum variance which can maximize the effect of the high resolution data in the fused image [9]. The second case integrates the disparate natures of multisensor input data in one image. The image channels of the different sensors are combined into one image file and a PCA is calculated from all the channels. The PCA approach is sensitive to the choice of area to be analyzed. The correlation coefficient reflects the tightness of a relation for a homogeneous sample. However, shifts in the band values due to markedly different cover types also influence the correlations and particularly the variances.

Image fusion is an important tool for environmental changes mapping and map updating in the provision of up-to-date information. Areas that are not covered by one sensor might be contained in another [8]. The optical data serves as reference whilst the radar data that can be acquired at any time provides the most recent situation. In addition the two data sets complement each other in terms of information contained in the imagery. Modern Earth resource satellites have the capability to collect spatially co-registered panchromatic (PAN) and multispectral (MS) imagery which can be merged to produce imagery with the best characteristics of high spatial resolution and high spectral resolution.

3. Quality evaluation indices

In order to assess the quality of the fused image with respect to the spectral information content, some quantitative assessment criteria have been defined by comparing the radiometry of the merged product and the low spatial resolution multispectral images [10]. If the two images are made to match each other, then it can be stated that their global statistical parameters such as their means and standard deviations should be very similar.

This study aims at the evaluation of data fusion methods applied to satellite data such as the IHS transform, PCA fusion method, through a set of various indicators. Besides subjective quality assessment (SQA) employing the human visual system (HSV) model , the successful quality measure is the objective quality assessment (OQA) using mathematically defined statistical indicators for quantitative evaluation in both spatial and spectral content of the fused images . Among available evaluation indicators, have been selected indicators which cover the statistical, physical and similarity based properties of the extracted fused imagery. Comments on fusion methods and evaluation indicators help users to select the appropriate data fusion method to enhance the spectral and spatial resolution of the imagery to meet the requirements of the specific application. If $p(x, y)$ represent the original PAN image, $A(x_i, y_j, k)$ represent original MS image of band k resampling to the same size as the PAN image and $F(x_i, y_j, k)$ result from a fusion algorithm, for evaluating fusion algorithms for image sharpening applications in change detection analysis have been introduced the following criteria:

a) Fidelity criterion: minimization of information loss in the fusion product with respect to original MS images [11]in terms of minimizing *Root Mean Square Error* –RMSE and maximizing Signal to Noise Ratio-SNR ,SNR*rms*, i.e., root mean square SNR, as in (3) and (4) and PSNR (5):

$$RMSE(k) = \sqrt{\frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}(F(x_i, y_j, k) - A(x_i, y_j, k))^2} \qquad (3)$$

$$SNR_{rms}(k) = \sqrt{\frac{\sum_{i=1}^{M}\sum_{j=1}^{N} F(x_i, y_j, k)^2}{\sum_{i=1}^{M}\sum_{j=1}^{N}(F(x,y,k) - A(x,y,k))^2}} \tag{4}$$

$$\text{PSNR} = 10\log\left(\frac{L^2}{\frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}(F(x,y,k) - A(x,y,k))^2}\right) \tag{5}$$

where the images are of size M x N, L is the maximum value of an image pixel.

b) Spectral criterion: minimization of spectral differences between *g(x, y, k)* and *f(x, y, k)* in terms of minimizing *Mean Absolute Error* -MAE, as in (6):

$$MAE(k) = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}\left|F(x_i, y_j, k) - A(x_i, y_j, k)\right| \tag{6}$$

c) Spatial criterion: maximization of spatial details in terms of maximizing the *Correlation Coefficient* between the high frequency components of the fusion product and the original PAN image, as in (7):

$$COR_h(k) = \frac{\sigma_{F_h p_h}(k)}{\sigma_{F_h}(k)\sigma_{p_h}} \tag{7}$$

where:

$$\sigma_{F_h p_h}(k) = \sum_{i=1}^{M}\sum_{j=1}^{N}(F_h(x_i, y_j, k) - \overline{F}_h(k))(p_h(x_i, y_j) - \overline{p}_h)$$

$$\sigma^2_{F_h}(k) = \sum_{i=1}^{M}\sum_{j=1}^{N}(F_h(x_i, y_j, k) - \overline{F}_h(k))^2$$

$$\sigma^2_{p_k} = \sum_{i=1}^{M}\sum_{j=1}^{N}(p_h(x_i, y_j) - \overline{p}_h)^2$$

$$\overline{F}_h(k)=\frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}F_h(x_i,y_j,k)$$

$$\overline{p}_h=\frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}p_h(x_i,y_j)$$

and the subscript h denotes the high frequency component of corresponding image using a 3x3 basic highpass filter [10].

d) Textural criterion: minimization of textural differences between fusion product and original MS images in terms of minimizing the *Root Mean Absolute Local Variance Differences* (RMALVD) in a 5x5 moving window, as in (8):

$$\text{RMALVD(k)}=\sqrt{\frac{\sum_{\text{i}=2}^{M-3}\sum_{\text{j}=2}^{N-3}\left|\sigma_F^2(x_i,y_j,k)-\sigma_A^2(x_i,y_j,k)\right|}{\text{(M - 4)(N - 4)}}} \tag{8}$$

where:

$$\sigma_F^2(x_i,y_j,k)=\sum_{\alpha=-2}^{2}\sum_{\beta=-2}^{2}(F(x_i+\alpha,y_j+\beta,k)-\overline{F}(x_i,y_j,k))^2$$

$$\sigma_A^2(x_i,y_j,k)=\sum_{\alpha=-2}^{2}\sum_{\beta=-2}^{2}(A(x_i+\alpha,y_j+\beta,k)-\overline{A}(x_i,y_j,k))^2$$

$$\overline{F}(x_i,y_j,k)=\frac{1}{25}\sum_{\alpha=-2}^{2}\sum_{\beta=-2}^{2}F(x_i+\alpha,y_j+\beta,k)\quad \text{and}$$

$$\overline{F}(x_i,y_j,k)=\frac{1}{25}\sum_{\alpha=-2}^{2}\sum_{\beta=-2}^{2}F(x_i+\alpha,y_j+\beta,k)$$

The performance of a fusion algorithm can be evaluated according to these statistical indicators in corresponding bands k. In this paper we used also the following quality indices:

The Relative Difference of Means between the fused product and the original low spatial resolution multispectral image:

$$\frac{\overline{F}-\overline{LR}}{\overline{LR}} \tag{9}$$

where F is the mean value of the fused image and LR is the mean value of the original low spatial resolution image.

Universal Image Quality Index –UQI**,** for $A(x_i, y_j)$ the original image and $F(x_i, y_j)$ the fused one is defined by relation (10), where the means of images are rdefined by relations (11):

$$Q = \frac{\sigma_{FA}}{\sigma_F \sigma_A} \frac{2\overline{F}\overline{A}}{(\overline{F})^2 + (\overline{A})^2} \frac{2\sigma_F \sigma_A}{\sigma_F^2 + \sigma_A^2} \tag{10}$$

$$\overline{F} = \frac{1}{MN} \sum_{i=1}^{M} \sum_{j=1}^{N} F(x_i, y_j) \tag{11}$$

$$\overline{A} = \frac{1}{MN} \sum_{i=1}^{M} \sum_{j=1}^{N} A(x_i, y_j)$$

$$\sigma_F^2 = \frac{1}{(M-1)(N-1)} \sum_{i=1}^{M} \sum_{j=1}^{N} \left[F(x_i, y_j) - \overline{F}\right]^2$$

$$\sigma_A^2 = \frac{1}{(M-1)(N-1)} \sum_{i=1}^{M} \sum_{j=1}^{N} \left[A(x_i, y_j) - \overline{A}\right]^2$$

$$\sigma_{FA} = \frac{1}{(M-1)(N-1)} \sum_{i=1}^{M} \sum_{j=1}^{N} \left[F(x_i, y_j) - \overline{F}\right]\left[A(x_i, y_j) - \overline{A}\right]$$

4. Implementation of fusion methods and evaluation of results

In this paper, objective image quality measures in OQA have been examined for the comparative evaluation of pixel-based fusion techniques used for coastal zone change detection analysis in sharpening the multispectral images. In order to understand the performance of image fusion algorithms, multiple criteria and statistical indicators regarding different aspects of image quality are presented for objective and quantitative evaluation of the fused images. ENVI 4.3 software and algorithms have been used.

The previously mentioned image fusion methods HIS and PCA have been applied to some subsets of TM5 16/08/1985, Landsat ETM7+ 24/08/2005 and SAR ERS-2 (17/07/2000) and Landsat ETM7+ 12/08/2000 images for North-Western Black Sea coastal zone over the Cap Midia region and harbor of Constantza, Romania as are shown respectively in the figures :

3 (3a and 3b) and 4 (4a and 4b). The first subsets are of a coastal area at Black Sea and include vegetated areas, sandy beach and water, whilst the second subsets are of a largely urban area but also include an area of sea. Subsets were selected in order to include a variety of land use categories i.e.buildings, roads, sea, vegetation, grass and bare soil, delimited by multi-oriented edges.

Fig. 3. The two tested areas on Landsat TM5 16/08/1985 image: 3a) Cap Midia test area; 3b) Constantza harbor

The land use variety implies a variation in the respective spectral signatures that should be respected in the fused spectral bands, independent of the spectral range of the panchromatic band that is used during the fusion procedure. Moreover, edges on the fused images should be as clear as possible, independent of their orientation. A sample image for applied fusion methods on Landsat(TM5 16/08/1985) bandsTM1,2,3 and Landsat ETM7+ 24/08/2005 ,bands ETM 1,2,3, RGB-IHS-RGB transform over Cap-Midia test area on Black Sea coastal zone is presented in figure 5, showing the changes in a period of 20 years. Figure 6 is presenting principal components algorithm PCA 3/5/1 fusion method applied for Constantza harbor zone change analysis (very dark) map over1985-2005 period based on fused images TM5 16/08/1985 and Landsat ETM7+ 24/08/2005 . On figure 7 it can be seen the changes between 2000-2005 on Northern part of Constantza town on PCA analysis for images Landsat ETM7+ 12/08/2000 images and Landsat ETM7+ 24/08/2005 (dark areas represent changes in total amount of 6%).

Fig. 4. The two tested areas on Landsat ETM7+ 24/08/2005 image :4a) Cap Midia test area; 4b) Constantza harbor

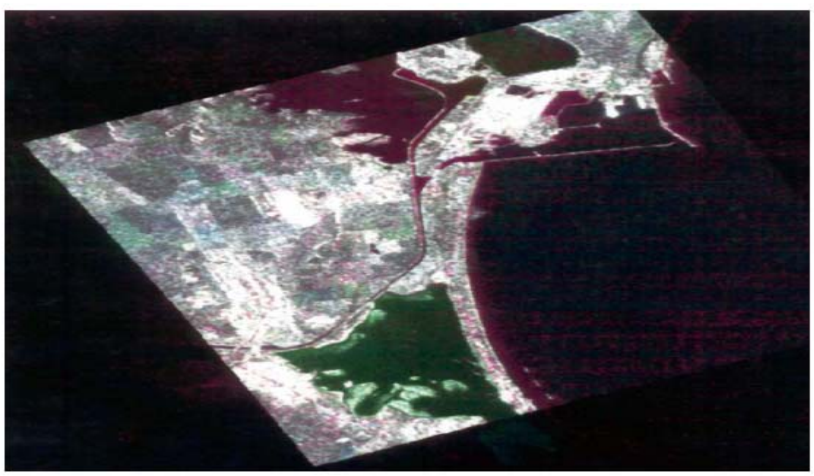

Fig. 5. RGB-IHS-RGB transform over Cap-Midia test area on Black Sea coastal zone: Landsat TM5 16/08/1985 and Landsat ETM7+ 24/08/2005, bands 1, 2, 3

5. Evaluation of results

The previously described statistical evaluation criteria (evaluation indicators) have been calculated independently for each test area and separately for each band.

Subsequently, mean values of the evaluation indicators have been calculated for all

bands and for both test areas, for image fusion methods HIS and PCA. Table 1 shows the average values of the evaluation indicators calculated for all bands for both test areas.

Table 1

Mean evaluation indicator values calculated for all bands for both test areas on Black Sea coastal zone

Fusion method	*COR*	*PSNR*	*UQI*	*RDM*
PCA	0.86	25.3	0.86	0.10
IHS	0.87	21.93	0.81	0.25

The fused images which will best preserve the spectral information of the original low resolution multispectral image is the one that has:

(a) the maximum correlation with the initial low resolution multispectral image;

(b) the smallest possible relative difference of means with the low resolution

multispectral image;

(c) the highest possible PSNR;

(d) the highest possible UQI.

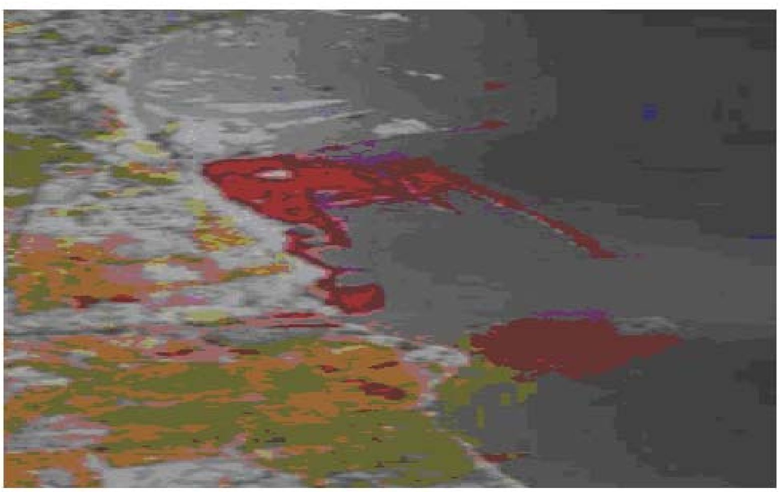

Fig. 6. Principal components algorithm PCA 3/5/1 fusion method applied for Constantza harbor zone change analysis (very dark) map over1985-2005 period based on fused images TM5 16/08/1985 and Landsat ETM7+ 24/08/2005

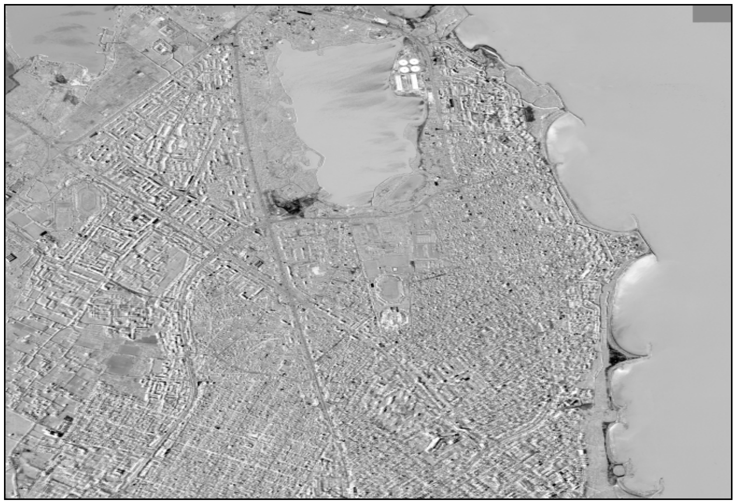

Fig. 7. Changes between 2000-2005 on Northern part of Constantza town on PCA analysis for images Landsat ETM7+ 12/08/2000 images and Landsat ETM7+ 24/08/2005 (dark areas represent changes)

6. Conclusion

Due to the inner details of the transform it uses, the PCA method has a better spatial than spectral response. The plain IHS transform attributes satisfactory spatial information, but strong spectral distortions aggravate the final fusion result; however, the combined use of the IHS transform with PCA transform ameliorates the spectral resolution of the fused image product for environmental changes analysis. When applying remote sensing to mapping, photogrammetric measurements, or for interpretation purposes, the spatial information of a fused image is just as important as the spectral information. In this analysis of the spectral and spatial quality of the fused image, was found some statistical differences between the original and synthesized images.

The results can be utilized as a temporal land-use change model for coastal zone regions dynamics to quantify the extent and nature of change, and aid in future prediction studies, which helps in planning environmental agencies to develop sustainable land-use practices. The change in the position of the coastline in Constantza area is examined and linked to the urban expansion in order to determine if the changes are mainly human induced or natural.

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