

# A methodology for land use change detection of high resolution pan images based on texture analysis

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## Abstract

Since the black and white (B&W) aerial photographs came into existence much before the multispectral satellite imagery, they provide past information necessary for land use/cover studies. However, owing to the fact that they lack multispectral information, they cannot be used for automatic land use/cover classification. This shortcoming of air photos can be overcome by adding other information such as the spatial variation in pixel intensities also called texture features on the photos. The basic aim of this study is to add the texture feature and classify the historical B&W aerial photograph records thus rendering them usable for change detection studies.

**Keywords:** texture, classification, change detection, accuracy assessment, B&W aerial photographs.

## *Una metodologia per la identificazione dei cambiamenti dell'uso del suolo da immagini pancromatiche ad alta risoluzione basata sull'analisi tessiturale*

### **Riassunto**

*Le foto aeree in bianco e nero (B/N) sono disponibili da molto tempo prima delle immagini satellitari multispettrali pertanto possono fornire informazioni utili per studi di uso e copertura del suolo. Tuttavia, a causa della mancanza di una informazione multispettrale, le foto aeree non possono essere utilizzate per classificazioni automatiche dell'uso e copertura del suolo. Questo limite delle foto aeree può essere superato prendendo in considerazione altre informazioni come la variazione spaziale della intensità dei pixel, ovvero la tessitura della foto. L'obiettivo di questo studio è quello di utilizzare l'informazione tessiturale per classificare foto aeree storiche in B/N in modo da renderle utilizzabili per studi sulla identificazione dei cambiamenti di uso e copertura del suolo.*

**Parole chiave:** tessitura, classificazione, identificazione dei cambiamenti, stima dell'accuratezza, foto aeree B/N.

## **Introduction**

The remotely sensed satellite imagery is one of the widely used primary sources of data for land use/land cover classification and change detection analyses. Since the aerial photographs came into existence much before multispectral satellite imagery, they provide

past information with high spatial resolution which is invaluable in land use/cover change detection studies. However, although the aerial photographs usually have relatively high spatial resolution, they lack multispectral information [Tsai et al., 2005]. Hence this shortcoming of air photos is usually overcome by adding other information such as the texture/context, pattern, and lightness/darkness of the features on the photos.

Image texture, defined as a function of the spatial variation in pixel intensities (gray values), is a significant characteristics of remote sensing imagery. This characteristic provides information about the structural arrangement of objects and their relationship with respect to their local neighborhoods [Gong and Howarth, 1992; Caridade et. al., 2008]. The texture properties can be obtained in three ways: statistical, structural and spectral [Harklick, 1979; Chen, 1982; Unsen, 1991]. These methods have been successful in a variety of applications as automated inspection, medical image processing, and document processing and remote sensing. In remote sensing there are various examples of the use of texture features as an extra band for the land cover classification of different (ikonos, landsat, spot etc.) satellite imagery [e.g. Marceau et al., 1990; Sali and Wolfson, 1992; Zhang and Wang, 2001; Martino et al., 2004; Chen and Gong, 2004; Puissant et. al., 2005; Lu and Weng, 2005; Manian, et. al., 2005; Tsai et al., 2005; Safia et. al., 2007]. Most of these studies evaluate the importance of parameter selection for creation of texture bands and hence investigates the effect of parameter selection in classification result [Marceau et. al., 1990; Franklin et. al., 1996; Caridade et al., 2008]. Moreover, most of them examine the classification using supervised, unsupervised, wavelength, etc. methods [Zhu and Yang, 1998; Zhao et. al., 2008] and improvement of classification accuracy [Marceau et. al., 1990; Zhang and Wang, 2001; Puissant et al., 2005; Caridade et al., 2008] by the addition of texture parameters to the high resolution remote sensing images. Although most of the above mentioned studies focused on satellite imagery, a few also examined the classification of B&W imagery [Yu et al., 2005; Majumdar et al., 2007; Caridade et al., 2008; Xin et al., 2008]. However, the present study will not only focus on the classification but also assess the extent of change in space and time by post classification comparison. For this reason a texture-based approach to be used in historical B&W aerial photographs and Pan images is proposed. The textural approach chosen is based on the well-known co-occurrence matrix, which is a statistical measure derived from the work of Haralick and others in the 1973's. The output image generated by texture analysis is often classified directly or supplemented to the original data in classification [Hsu, 1978; Marceau et. al., 1990; Gong and Howarth, 1990; Marceau et al., 1990; Tsai et al., 2005]. In the proposed approach different texture bands are supplemented to the original B&W aerial photographs and the appropriateness of various texture bands are analyzed. The suitability of texture bands to be added to the Pan images is evaluated by creation and addition of texture indices for the Quickbird (QB) Pan image. The QB Pan image with added texture bands are classified by using supervised classification method. The result of classification is compared with classification result of QB multispectral (mss) image. The two data sets are classified into three different land use classes and the classification accuracy for each class is tested by the confusion matrix. After acquisition of sufficient accuracy with the additional bands in the Pan QB imagery and selecting the appropriate texture combinations by principal component analysis (PCA), the procedure is applied to the B&W aerial photos and Pan Image. To detect the changes in the study region, two independently classified land use/land cover maps of B&W aerial

photos in 1998 and pan image of Spot in 2005 are compared.

### The methodology and data

The study adopted to follow a two step methodology (Fig. 1). In the first part of the study the methodology is tested in terms of the adequacy of addition of texture bands to the pan band. For the first part of the study QB mss and Pan Images are used. For the second part of the study pan images taken at two different dates are used. The imagery used in this first part of the study is a sub scene of Middle East Technical University (METU) Campus area in Ankara, Turkey, which is obtained for the year 2004 with 439 x 413 pixels (Fig. 2a). Eight texture bands are created from a 439 x 413 pixel sub scene of the original QB pan band at a spatial resolution of 64 x 64 cm. The QB pan image provides more spatial details than mss bands which has 2.4 m resolution. Then maximum likelihood classification (MLC) is used to characterize the urban structure with three different land use classes as: building, road and vegetation for both QB pan and mss bands. The classification results from mss data are compared with the pan data to determine suitability of adding texture information to pan images in land use classification. After analyzing the suitability of use of texture bands to pan image, in the second part of the study (Fig. 1), the same procedure is applied to the pan images taken at two different dates in Kumluca watershed of Bartın province in Turkey (Fig. 2b). The first image is the B&W aerial photo dates May, 1998 and the second data is the Pan band of Spot image dated at 2005. A sub scene of 465 X 472 pixels is extracted from the eight-bit images. Then the texture parameters are created for both of these single panchromatic images then the texture parameters are included to the related images as additional band information. MLC is applied to both pan images for both years for obtaining land use/cover classes then finally a change detection algorithm is applied to detect the changes in land use/cover between 1998 and 2005.

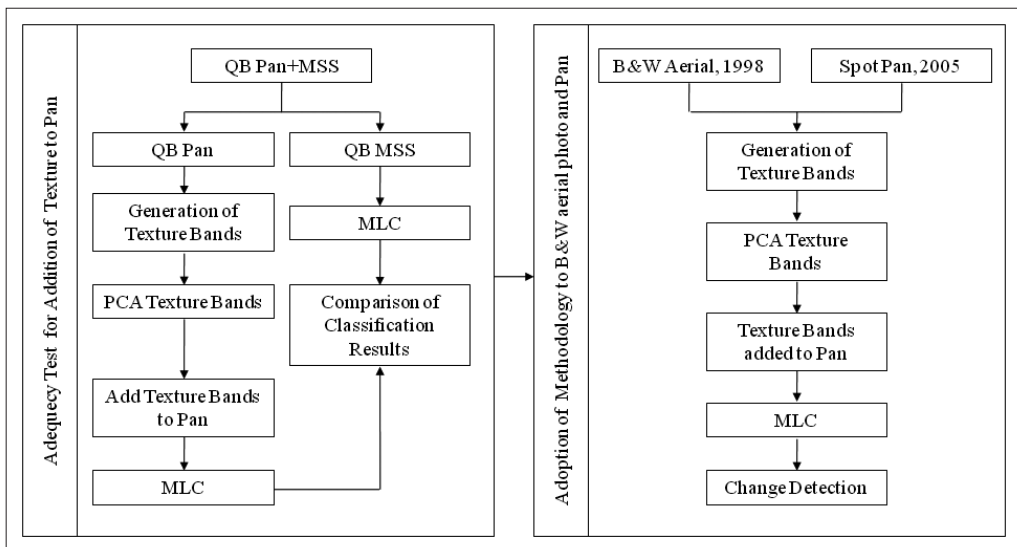
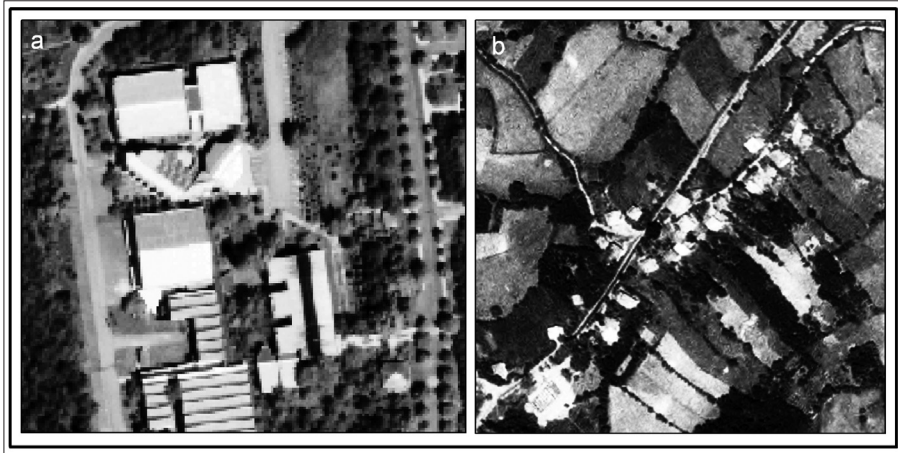


Figure 1 – Flow chart of the methodology.



**Figure 2 - (a) Test data, QB Pan image of the study region with 0.64 m spatial resolution. (b) B&W aerial photo in Kumluca watershed of Bartın province in Turkey (May, 1998).**

### ***Creation of texture bands***

Texture is one of the important characteristics used for the image interpretation and to identify objects of interest in an image [Zhang and Wang, 2001]. The spectral features, describe the average tonal variation in the various bands of an image however B&W aerial photos lack in this feature.

For this reason, feature extraction by using B&W aerial photos requires some additional information like the texture bands. Textural features contain information about the spatial distribution of tonal variations within a band. It considers the relationships between grey levels and the variation of neighborhood pixel values.

In this study, the texture analyses are based on the Gray Level Co-occurrence Matrix (GLCM) algorithm as described in Haralick et al. [1973]. GLCM matrix measures relative spatial frequency with which two neighboring pixels occur on the image [Marceau et al., 1990]. Using a moving window, neighborhood of the pixel is defined and texture features for each pixel in an image is computed [Zhang and Wang, 2001]. The window size cannot be bigger than the size of the object which is attempted to be identified. For this study, a 7x7 moving window is kept constant and found to be generally appropriate. Then the various texture measurements are calculated for each pixel. The inter pixel distance and angle between the pixels during the co-occurrence computation is kept constant at 1 and 0°, respectively [Caridade et al., 2008]. Eight texture features are calculated from the second-order statistics of the grey level co-occurrence matrices. They are Homogeneity (HOM), Contrast (CON), Dissimilarity (DISSIM), Mean (MEAN), Standard Deviation (STDDEV), Entropy (ENT), Angular Second Moment (ASM) and Correlation (COR) which is defined in Equations 1-8, respectively.

$$HOM = \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} \left( P(i,j) / (1 + (i - j)^2) \right) \quad [1]$$

$$CON = \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} P(i,j) * (i - j)^2 \quad [2]$$

$$DISSIM = \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} P(i,j) * |i - j| \quad [3]$$

$$MEAN = \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} i * P(i,j) \quad [4]$$

$$VAR = \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} P(i,j) * (i - MEAN)^2 \quad [5]$$

$$STDDEV = SQRT(VAR)$$

$$ENT = \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} -P(i,j) * \ln(P(i,j)) \quad [6]$$

$$ENT = \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} P(i,j)^2 \quad [7]$$

$$COR = \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} (P(i,j) * (i - MEAN_i) * (j - MEAN_j)) / SQRT(VAR_i * VAR_j) \quad [8]$$

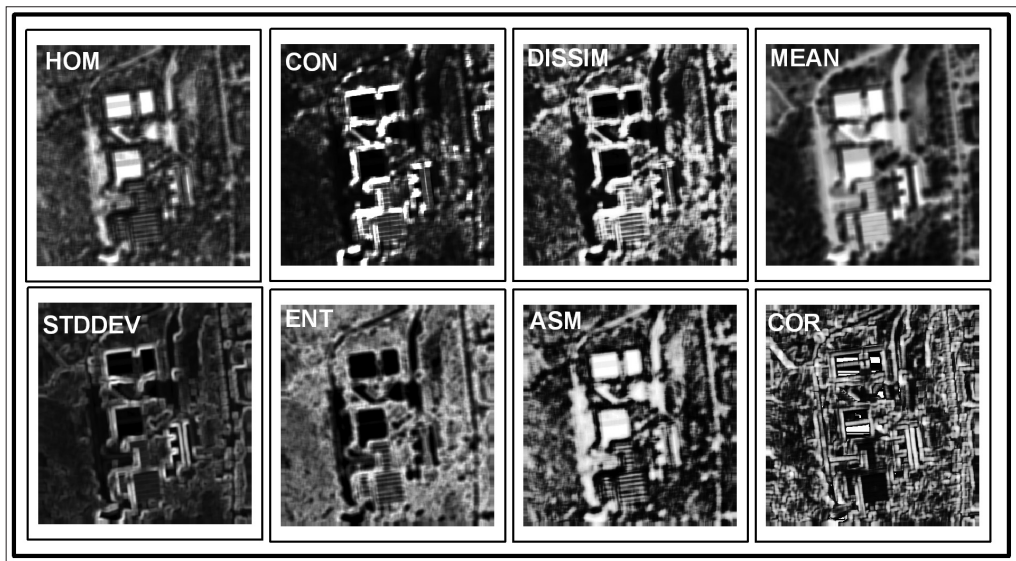
$$P = \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} P(i,j) = 1 \quad [9]$$

Where,  $N$  is the dimension of the co-occurrence matrix,  $P$  is the normalized symmetric GLCM of dimension  $N \times N$  and  $P(i,j)$  is the  $i$ th and  $j$ th entry of  $P$  in normalized grey-level co-occurrence matrix [Haralick et al., 1973].

### ***Addition of texture bands to pan images***

The eight texture bands described above are created (Fig. 3). The output texture images contain the raw texture measures which may have different ranges of values. The images are saved in 32-bit real channels to avoid information loss. The created texture images are then combined with QB pan band. As QB pan image is 16 bit unsigned, a radiometric transformation is applied to all texture images. When the texture bands in Figure 3 are investigated, it can be seen that homogeneity is high as GLCM concentrates along the diagonal. Similarly, entropy is high since the elements of GLCM have relatively equal values. Angular Second Moment which is the measure of local homogeneity yields high values when the GLCM has few entries of large magnitude and low when all entries

are almost equal. In order to reduce the redundancy in the texture bands, to determine appropriate texture features and to remove the correlation between input variables, the principle component analyses (PCA) technique is applied to the raw texture images. It is found that the first four numbers of the components have 98% explanation level of the variation. Hence the first four components are chosen for the maximum likelihood classification analysis.



**Figure 3 – The eight textures of the QB Pan image from left to right. Homogeneity, Contrast, Dissimilarity, Mean, Standard Deviation, Entropy, Angular Second Moment and Correlation.**

### ***Testing the performance of the methodology***

Maximum Likelihood Classification (MLC) which is a supervised classifier is used for classifying mss QB image and QB pan image with PCA components in textural channels. In the first step of the procedure the original QB mss channels are classified and the accuracy assessment is applied by the error matrix. In the second step of the procedures, the first four components of PCA bands are added into the QB Pan channel and classified. Then the accuracy of the classification is tested. In the third step the classification accuracies of QB mss classification result is compared with QB Pan with additional bands. For the classification procedure, selection of reliable training sites is important to have either spatial or spectral information about the pixels to be classified. Ground truth data which refers to the acquisition of knowledge about the study area from field work analysis is used in addition to the pan band of QB and different combination of channels in the selection of the training sets. The training sets are selected throughout the whole image until each of the land cover classes are all representative. The collected training set which is used for mss image is also used for the QB Pan and additional band combinations. Hence the training set band is merged to the QB Pan and texture combinations. For both of the classification procedures applied to mss images and pan images three different classes are selected in the training set

as: building, road and vegetation. The result of the classifications are shown in Figure 4a and 4b. When the classification result of mss bands of QB (Fig. 4a) is compared with the classification result of QB Pan combined with texture bands (Fig. 4b), the latter provide better classification performance for building class. The Figure 4a represents some spikes inside the classified zones, especially inside the building and vegetation classes whereas Figure 4b provides smoother result. This is mainly due to the high spatial resolution of pan image with additional texture bands.

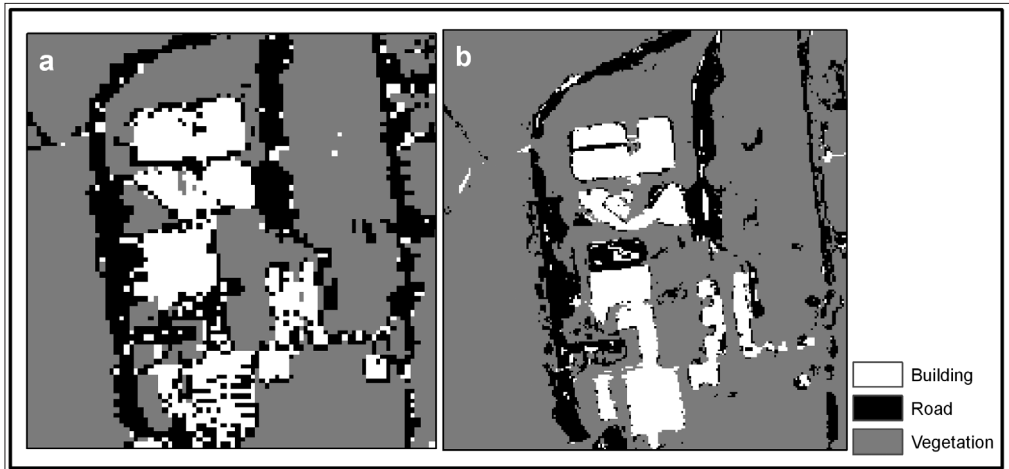


Figure 4 - (a) MLC result map of mss bands of QB image. (b) MLC result map of QB pan band with first four components of PCA for texture bands.

The accuracy assessment is performed on classification results. Random test pixels are selected from the classified images. These test pixels are obtained in such a way that they are proportional to the percentage of each class in the image. The classification results are then compared with the test pixels. The accuracy is assessed using the results of error (confusion) matrix (Table 1) and accuracy statistics. Reference data listed in the columns of the error matrix represents the number of correctly classified samples. Accuracy statistics lists different statistical measures such as producer's accuracy, user's accuracy and kappa statistics for each class. The overall accuracy of QB mss is found to be 86% with a kappa statistic of 71%. The overall accuracy of QB pan with additional features is found to be 84% with a kappa statistic of 68%. The producer's accuracy is calculated by dividing the total number of correct pixels in a category to the total number of pixels of that category as derived from the reference data [Jensen, 1996]. The producer's accuracy of building class yields 87% and 80% for mss QB and QB pan with additional texture bands, respectively. As the overall accuracy of the entire classification is 86% and 84% for mss QB and QB pan with additional texture bands, respectively (Tab. 1) it can be concluded that QB data with additional texture bands is quite adequate for identifying buildings in this area. However user's accuracy should also be considered. User's accuracy is calculated by dividing the total number of correctly classified pixels by the total number of pixels that are actually

classified in that category [Jensen, 1996]. The user's accuracy of building class yields 72% and 80% for QB mss and QB pan with additional texture bands, respectively (Tab. 1). Although QB mss classification have better accuracy level (97%) than QB pan with additional texture bands (91%), the accuracy level reached for QB pan with additional texture bands can be considered quite satisfactory. As can be seen from Table 1, both data sets have almost the same accuracy performance for road class. As a result, pan images with additional texture bands can be used for land use classification with satisfactory accuracy performance.

**Table 1 - Error matrix and accuracy statistics of the classification map derived from QB data.**

QB mss data		Vegetation	Road	Building	Producer's Accuracy
	Vegetation	64	6	3	96.97%
Road	1	10	0	55.56%	
Building	1	2	13	80.00%	
User's accuracy	87.67%	90.91%	80.00%		
<b>Overall accuracy=86%, Kappa statistics=0.71%</b>					
QB Pan	Vegetation	61	5	0	91.04%
	Road	4	10	2	55.56%
	Building	2	3	13	86.67%
	User's accuracy	92.42%	62.50%	72.22%	
	<b>Overall accuracy=84%, Kappa statistics=0.68%</b>				

### Adoption of methodology to aerial photos and pan images

Identification of change in nature by measuring and assessing the extent of change in space and time is very important for monitoring natural resources. Generally it is difficult to obtain information from the past due to lack of data for the study region. In Turkey the B&W aerial photos were acquired for the whole country to prepare 1:25000 topographic maps. Hence these data are a significant source to obtain past information. One effective way to classify grayscale images is to make use of the texture information as additional bands. As it can be seen from the classification results, the combination of texture channels provide relatively better accuracy to the pan image of QB image. Therefore, in this study it is aimed to apply change detection by using pan images. The first pan image is B&W air photo acquired in 1998 and the second one is pan image of Spot 2005, which are the only available images for the study region. Therefore, the eight different texture parameters are created for both of the images. To remove the redundant information PCA procedure is applied to the created texture bands. The first two components of PCA which provide 98.37% and 98.94% explanation level, respectively for 1998 and 2005 images are selected for the classification procedure and added to the pan images. The region occupies three different classes including manmade features (building and road), forest and agriculture. Hence a supervised classification pattern recognition routine where minimum distance to means and maximum likelihood classifiers are run. The resultant classification maps are presented in Figure 5a and 5b for 1998 and 2005 years respectively.

The accuracy is assessed using the error matrix and accuracy statistics shown in Table 2.



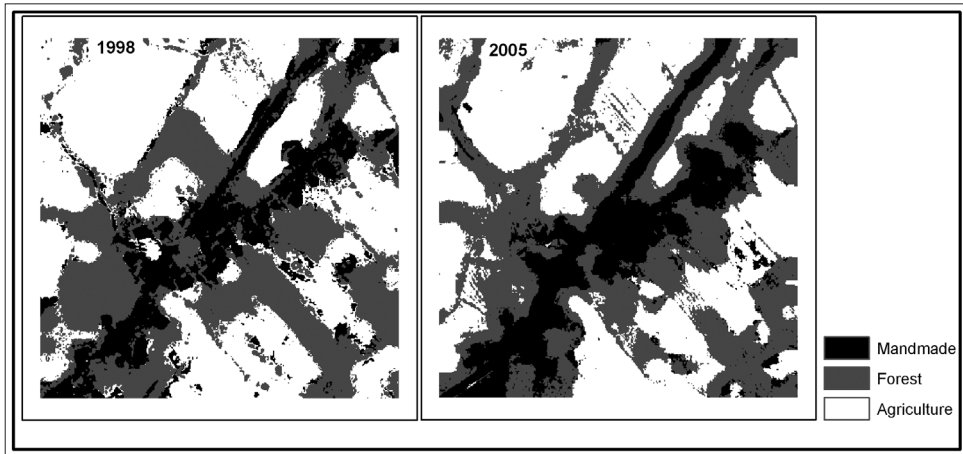


Figure 5 – (a) The supervised classification result map of B&W aerial photos and (b) Pan Image of Spot with the combination of additional components.

The final classification result of the images are appropriate with the 85% overall and 75% kappa statistics for 1998 and 90% overall and 84% kappa statistics for 2005 image.

Table 2 - Error matrix and accuracy statistics of the classification map for 1998 and 2005.

		Manmade	Forest	Agriculture	Producer's Accuracy
1998	Manmade	5	0	15	100.00%
	Forest	0	40	0	100.00%
	Agriculture	0	0	40	72.73%
	User's accuracy	25.00%	100.00%	100.00%	
<b>Overall accuracy=85%, Kappa statistics=0.75%</b>					
2005	Manmade	20	0	0	100.00%
	Forest	0	30	5	85.71%
	Agriculture	0	5	40	88.89%
	User's accuracy	100.00%	85.71%	88.89%	
<b>Overall accuracy=90%, Kappa statistics=0.84%</b>					

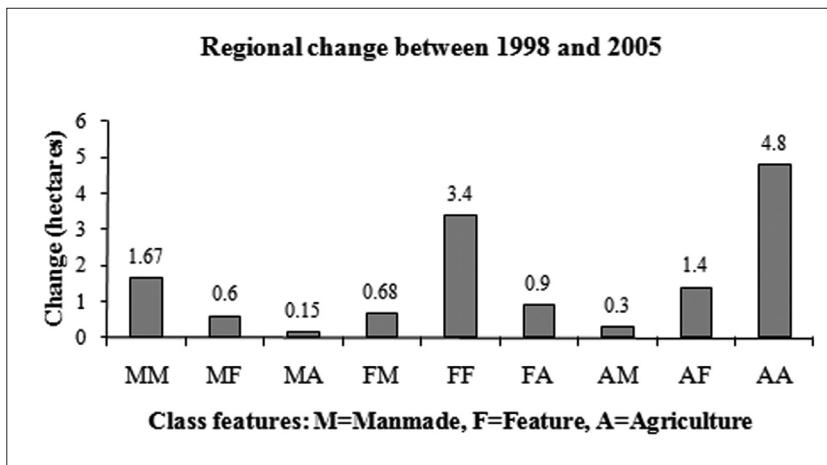
### Land use change detection from pan images

To detect land use/cover change in the study region multi-temporal Pan images are separately classified by using texture based approach as described above. Afterwards, the created thematic maps are compared by a pixel-by-pixel comparison to detect changes. To obtain the change in the land use/cover there are various algorithms which have been developed, applied or evaluated [Singh, 1989; Jensen et al., 1993; Jensen, 1996; Yuan et al., 1998; Ridd and Liu, 1998; Serpico and Bruzzone, 1999; Coppin et. al., 2004; Liu et. al., 2004; Lu et. al., 2004]. Generally two basic methods are adopted for change detection studies. The first one is detection of changes in the raw images (pixel-to-pixel comparison) and the other is comparing two classified images (post-classification comparison) [Martin, 1989;

Green et al., 1994; Dewidar, 2004]. This paper involves detection of change by comparing two independently classified land use/land cover maps from Pan Images covering the study area at different dates. The principal advantage of post-classification comparison lies in the fact that the bitemporal images are separately classified, thereby the problem of radiometric calibration between dates is minimized [Coppin et al., 2004]. Preprocessing analysis is required before implementing change detection algorithms [Lu et. al., 2004]. In this respect before the analysis, precise registration of multi-temporal images is applied to make sure that they properly align to each other. The thematic maps are compared pixel-by-pixel basis with a raster calculator to detect changes. In this case thematic map of 1998 is subtracted from, thematic map of 2005. As a result the following change detection matrix and histogram is obtained (Tab. 3 and Fig. 6).

**Table 3 - The change detection matrix showing the regional change in hectares between 1998 and 2005.**

1998/2005	M	F	A	Total
M	1.67	0.60	0.15	2.42
F	0.68	3.40	0.90	4.98
A	0.30	1.40	4.80	6.50
Total	2.65	5.40	5.85	13.90



**Figure 6 - Change detection histogram. The first letter represents the 1998 and the second one represents the 2005 class eg. MF: The amount of change from Manmade class in 1998 to Forest class in 2005.**

The change detection matrix and histogram clearly indicates regional changes in hectares between 1998 and 2005 for three different land use/cover categories. When analyzing the changes, it can be seen from the Table 3 that 1.58 hectare of forest regions were lumbered due to agricultural activities and in order to construct manmade features. Also 0.3 hectares of agricultural fields were built on and 1.4 hectares of agricultural fields became forest.

Both the man made and forest regions totally increased from 2.42 to 2.65 and 4.98 to 5.4 respectively. On the contrary, agricultural fields reduced from 6.5 to 5.85. As a result it can be concluded that the decrease of agricultural fields may be due to the mitigation from rural to urban areas. Moreover, the abandoned agricultural fields may become forest.

## Conclusion

This study demonstrates that employing spatial pattern (texture) analysis to extract texture features from a single panchromatic image and using them for classification has satisfactory performance. Therefore, aerial photos of the past can be incorporated in change detection algorithms by using the methodology explained in this study. Although in this study only three classification classes are studied, the methodology promises for higher number of classes. Hence the authors aim at applying the methodology to more number of classes in future studies. The approach proposed in this study suggests that use of texture parameters as additional bands in B&W air photos and Pan Images allow us to conduct land use/cover classification and change detection.

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