Application of image processing techniques for monitoring surface mining

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ABSTRACT

The purpose of this study is to examine whether change detection techniques can be applied to Landsat images of the mining sites located in Evia Island Greece, to detect the most significant changes in land use that provide essential information for proper planning, management and regulation of the mines restoration. Satellite data employed for this purpose were acquired 12 years apart by Landsat Thematic Mapper (TM) sensor. Two main techniques are explored: i) change detection applied to unclassified images and ii) change detection applied to classified images. Ratios and Principal Components are found to be suitable for qualitative interpretation. Post-classification comparison is found to be more appropriate for change detection than Principal Components Analysis and ratioing for these type of data. The reason for this is because areas covered by each class can be calculated quantatively. Both Supervised and unsupervised classification techniques were investigated for the purposes of land-use classification. However, there are many constraints which affected the classification accuracy such as the collapse of benches, small size of mines, fragmentation of the land, the mixed and multiple land uses.

Keywords: *Change detection, mining, PCA, post-classification comparison*

INTRODUCTION TO CHANGE DETECTION

The growing pressure of population coupled with increasing multiple requirements such as provision of adequate water and food, need for open space, sewage system, transportation, housing, streets, schools and health policy, and with environmental, social and land-use problems such as air and water pollution, widespread poverty, unemployment, underemployment and deterioration and limitation of land, have necessitated the optimum utilisation of land-cover of an area. Information on land-use and land-use change is essential information to proper planning, management and regulation of the use of the available resources (Spyropoulos, 1993). The importance of the available resources to economic development is clear particularly when a country strives for self sufficiency. Land use and land capability information such as the distribution of the soils and types of vegetation are necessary to determine the suitability for farming or range in many countries which much of their economic development effort is directly towards to agriculture and animal husbandry. On the other hand the land-use, urban and crops changes, pollution assessment of beaches and change of coastal environment are necessary information for countries which guide their development plans for the continued industrialization, improved land-use and quality of life in urbanized areas, water management and investment on agriculture including expanded assistance to the rural poor and placement of more land under irrigation (Kalivas et al., 2003).

Mining activity is only a temporary occupier of the land surface and, hence, is of a transient nature (Wagner, 1995). Although active mines at any particular time are not as widespread as other land uses, they dramatically change the landscape and tend to leave evidence of their past use. Thus, results of abandonment or closure become most conspicuous to the general public.

An important contribution of satellite sensors to land resource analysis is their potential to monitor changes that occur in land cover over an extended period of time. This measure of the change that has occurred can be obtained by comparing the brightness values (DN) for each pixel location in a scene with the corresponding values acquired for the same area, but on a different date (Fung, 1990). However, it is worth noting that differences in brightness values between dates can occur due to sources other than those originating from changes in surface materials, giving a potential error in these simple change-detection methods. Such sources include the differences in atmospheric conditions between the times of the two overpasses, scene differences introduced by seasonal conditions when non-anniversary data is being investigated, differences in sensor response between the dates involved and between sensors if data from different satellites are used. An ideally change detection method should be based on a satellite sensor system that:

- has a systematic period between over flights, for example 18 or 16 days,
- records imagery of the same geographic area at the same time of the day to minimise diurnal (sun angle) effects,
- maintains the same scale and look angle geometry,
- reduces relief displacements as much as possible and
- records reflected radiant flux in consistent and useful spectral regions.

If these conditions are satisfied (Spyropoulos & Granger, 1993), then it may be possible to analyse the spatial, spectral and temporal characteristics of the data to produce land-cover or land-use change statistics. Accurate spatial registration of two images is essential for all change detection methods. This necessitates the use of geometric rectification algorithms that register the images to each other or to a standard map projection. Resampling techniques can be used to register images from different dates and from different resolution. Atmospheric correction is also necessary to remove the unwanted effects of atmospheric scattering and absorption. Variations in the amount of water vapour, aerosol and dust present in the atmosphere, together with cloud cover will affect the magnitude of the radiometric values recorded by the system. These components absorb, scatter and re-emit incident solar radiation, as well as reflected excitant radiation. Therefore, the atmosphere can modify the apparent reflectivity of the unchanged ground targets giving higher or lower brightness values than they have normally and reducing the contrast between different cover types (Lu, 1988).

The spatial resolution of the sensor system is important because the instantaneous field of view (IFOV) governs the size of the area over which radiant flux will be integrated and recorded. The size of the picture element represent the minimum mapping unit. The 79m ground resolution of the LANDSAT multispectral scanner, for example, precludes the identification of individual houses or trees. The spatial resolution of the sensor must be sufficient to detect the appropriate changes.

A fundamental assumption of digital change detection is that there will be a change in the spectral response of a pixel on two dates if the land-use changes (Byrne, 1980). Consequently, the spectral resolution of the sensor is also very important and must be sufficient to record reflected radiant flux in spectral regions that best capture the most descriptive spectral attributes of the land. A further important issue is the temporal resolution. The user normally has in mind a time of period over which the change is to be monitored. Anniversary dates are often used because they minimise differences in reflectance caused by seasonal vegetation changes, soil moisture variation or sun angle differences. Conversely, with a 16 or 18 day orbital repeat cycle, it may not be possible to monitor environmental events such as bushfires and floods which usually occur in periods less than 16 days. Nevertheless, the effects of those events, such as burn scar left by the fire or the flush of ephemerals that follow the receding of a flood wave, will be detectable in the imagery.

A review of the remote sensing literature reveals that there are many and varied approaches to change detection use LANDSAT data employing both unclassified and classified imagery. Considerable success has been achieved by generating ratioed and differenced images for selected multi-spectral bands. Classification procedures have been performed which attempt to compare the results of two independent classifications on a pixel-by-pixel basis. Also transformed data sets such as Principal Components Analysis have been employed in change detection techniques with considerable success too. Several studies have also shown the use of satellite data in monitoring mining activity. These studies were mainly applied onto large exploitations where their mean area extent was around 50 sq. km., (Landsat Applications, 1993) and (Ganas, et al., 2004).

The objectives of the methodology stem from the hypothesis that is possible to discriminate and assess the spatiotemporal variability of mining land-use in small size exploitations (less than 10 sq. km) using satellite data and combining image processing algorithms. The main technologies we are concerned with are Satellite Remote Sensing and Geoinformatics. We are also concerned in a combination of PCA and Post Classification methodologies in a suitable way. The spatiotemporal distribution assessment of the mining land-use utilizing remotely sensed data is structured into the following three methodological tasks:

- Satellite data pre-processing
- Satellite data processing based on PCA and Post Classification Comparison

STUDY AREA AND DATA SET

The study area is occupying a 40km^2 mixed area of various land cover and land-use types, and located north of 39^0 35' and east of 23^0 35' (Figure 1). The sites are 80km north east of Athens. The climate is characterised by the Mediterranean bioclimate with mean annual rainfall less than 400mm. According to the Geological map of Greece (Institute of Geology and Mineral Exploration, Athens 1982) the open cast mining sites are characterized as stratiform deposits formed in the Lower Cretaceous, before the Cenomanian transgression. The deposit is a 1–40m laterite overlying ophiolitic rocks (mainly basaltic lavas and peridotites). Thick, Upper Cretaceous limestones of the Pelagonian isopic zone overlay the laterite. At places, Neogene lacustrine beds cover the limestones uncomfortably. Scattered Quaternary top soils also occur. Neotectonic faulting has heavily fractured all rocks. According to the soil map of Greece 1:250.000 (Soil and Fertilizer Institute of Ministry of Agriculture) the soils of the study area are Lithosoils and red-brown Mediterranean. The primary land cover in this region is a mixture of low dry vegetation with rocks and weeds (Chenopodium albus, Amaranthus sp., Cynopodium Dactylus, Lepidium draba).

A significant portion of the area is an evergreen xerophile, extremely thorny, scrubby formation, oriental type called phrygana together with Quercus coccifera, Sarcopoterium spinosum, euphorbia acanthothamnos. Urban land use is predominantly residential with specific industrial or commercial units and port areas. Digital satellite image data covering the study area were acquired several years apart. Particularly an archive image containing LANDSAT TM data captured in May 1986 was selected. A LANDSAT TM scene, acquired in June 1991 and April 1997, was also selected. A subscene including only the study area (mining sites) was extracted from three images. The TM image of 1997 that was closer to the present date was geocoded according to Hellenic Geodetic Reference System (EGSA '87). This reference system is a UTM grid system based on GRS80 ellipsoid.

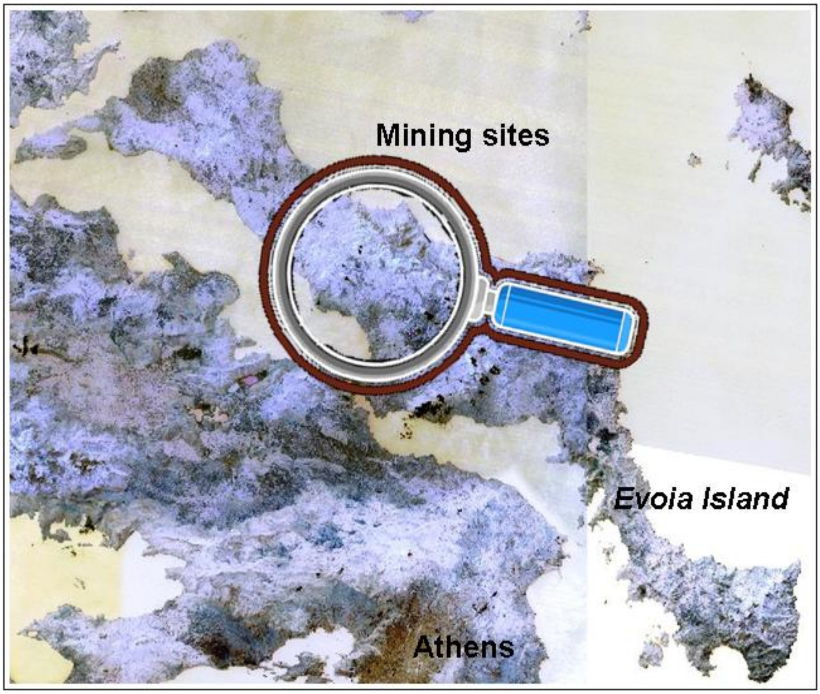

Figure 1: Map showing the location of the study area in Central Greece.

The data used for the identification of cover types was the Hellenic Military Geographical Service land-use land cover map of Psachna (scale 1/50.000). A series of B/W aerial photographs at scales of 1/20,000 and 1/25.000 were provided by the same Military Authority. Also a geological map of the study area was provided by the Institute of Geological and Mineral Exploration of Athens. In addition a KVR-1000 Russian black and White image was also acquired (1992) for delineating subtle information.

DATA PRE-PROCESSING

In this study the geometric correction is done by using image to image registration. Therefore, the TM image of 1997 was selected as the master to which the TM images of 1986 and 1991 were registered as the slave images (Spyropoulos, et al., 2010). Seventeen ground control points (G.C.Ps) were selected from the same positions on the false colour composite images. These were distributed in a uniform manner along the area of interest.

Pixels from TM images were resampled to 30m using a nearest neighbour algorithm that does not alter the original pixel values in contrast to most convolution resampling algorithms. This was important for the subsequent classification procedures. The RMS error was kept close to one pixel in X and Y direction.

DETECTION USING PCA AND CLASSIFIED IMAGES

Conventional per-pixel classification

Change detection was performed by comparing the individual classification of TM subscenes (1986, 1991 and 1997). The classifications were carried out firstly by supervised method (Figure 2) based on training areas and then by unsupervised method based on clustering.

Seven training areas for each class, on the F.C.C {TM741 ('97), TM741 ('91) and TM741('86)}, were chosen for classification categories. These training areas were helped with photographic documentation. Also their location and extend were noted on 1/50.000 topographic map. Maximum likelihood classification was performed on the corresponding bands TM1,2,3,4,5,7 (1986), TM1,2,3,4,5,7 (1993), and TM1,2,3,4,5,7 (1997) and the land-use class maps were displayed on a colour monitor screen. As classes, forests, artificial lake, roads and benches, dump sites, shadows and bed rock were determined from the TM subscenes. Then the classification maps were superimposed and displayed by colouring them differently. Then the quantitative estimation of the land-use change was calculated from the change maps. The results of the supervised classification were compared with the results of the unsupervised.

Finally the classification accuracy was evaluated by considering test areas that they were different from the training areas.

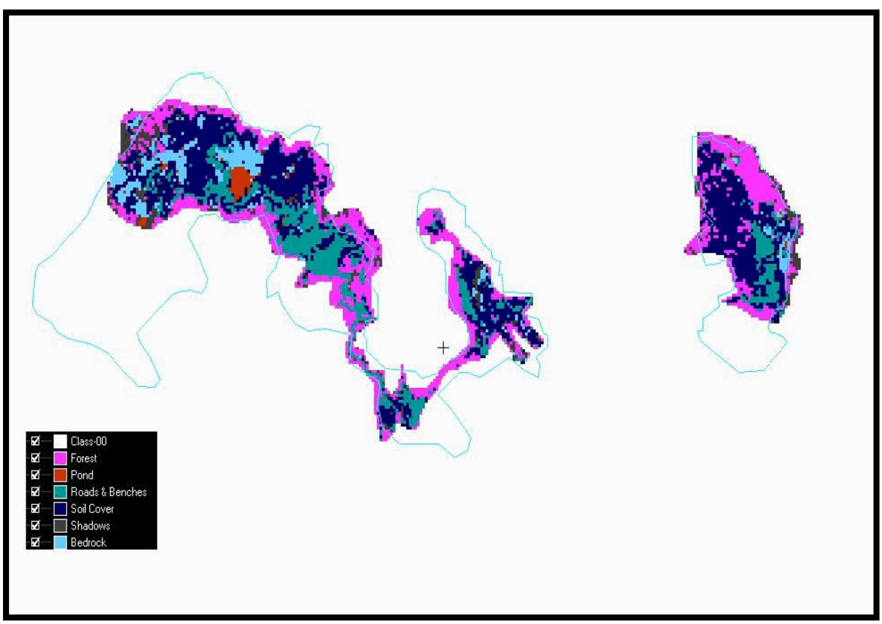

Figure 2: Supervised classification of the Landsat TM 1986 image. The cyan polygons are the outlines of the mining sites.

Principal Components Analysis

Principal component analysis, also known as Hotelling, the Karhunen - Loeve transformation, or Eigenchannel transformation is mainly used to `pack' the information from two or more channels to a smaller number of channels. It is a powerful method for analysing, revealing and enhancing highly correlated multi-temporal data. An advantage of this method is that PCA can be performed on uncalibrated data set, saving cost by saving calibrating time on the computer. PCA is a linear transformation which rotates the axes of image space along lines of maximum variance (Spyropoulos & Granger, 1993). The rotation is based on the orthogonal eigenvectors of the covariance matrix generated from a sample of image data from the input channels. The output from this transformation is a new set of image channels (which are sometimes referred to as eigenchannels). Two type of data set was used in the PCA analysis. Landsat TM bands of 1986 and 1991 and Landsat TM bands of 1991 and 1997. Band 6 was not considered in the PCA analysis. In our case the new measurement axes are linear combinations of original measurement axes. Using the eigenvectors of the covariance matrix (resulted from PCA) of a data set as new measurement axes for that data set has two major effects: First, the new channels are orthogonal with respect to each other, which is not the case with most raw image data since channels are usually highly correlated (particularly the land-use inside the mining sites) and second, the variance (information plus noise) implicit in the original channels are “packed” in the new channels such that the eigenchannel (vector) with the highest eigenvalue (eigenchannel 1) typically contains considerably more variance than the second eigenchannel (Ingebritsen & Lyon, 1985). The same comparison holds for eigenchannel i and eigenchannel i+1. It has to be mentioned that a result of the principal component transformation is that the new midpoint for each eigenchannel is at 0, with approximately half the new data being negative and half positive. A separate, new midpoint can be specified for each selected eigenchannel.

RESULTS

There are numerous change detection techniques which make use of unclassified imagery, including image ratioing and image differencing of selected spectral bands, and Principal Components Transformation. The factor common to each of these approaches is that they require various "corrections" to be performed on the raw images prior to change detection. These include radiometric calibration, atmospheric correction and geometric correction.

Differencing methods enhance changes by subtracting selected single bands images. A similar effect is achieved by image ratioing, where the individual bands of multispectral images are divided by their multidate counterparts. Land-use and land-cover changes tend to show up as larger positive or negative differences or as the lowest and highest ratio values. However, using these approaches, effects such as atmospheric and radiometric changes must be taken into account.

Principal Components Analysis is often applied to multispectral, multidate images to transform them into a new set of uncorrelated images (Figure 3). By this method a new data set of coordinate axes is fitted to the image data, choosing as the first axis an orientation which maximises the variance accounted for by that axis (first eigen image). Subsequent axes account for successively smaller portions of the remaining variance. Therefore, land-use and land-cover changes are enhanced in medium-to high-order principal component (PC) images, whereas unchanged areas dominate the redundant temporal information in the low-order PC images. These methods involve transformations of the original spectral bands so as to enhance the land-cover changes (Spyropoulos, et al., 2010).

Change detection techniques using classified imagery often initially involve preprocessing procedures such as radiometric and geometric corrections to remove the unwanted effect of atmospheric scattering and geometric distortions which could lead to poor classification accuracy (shifting the mean of classes and affecting their variance).

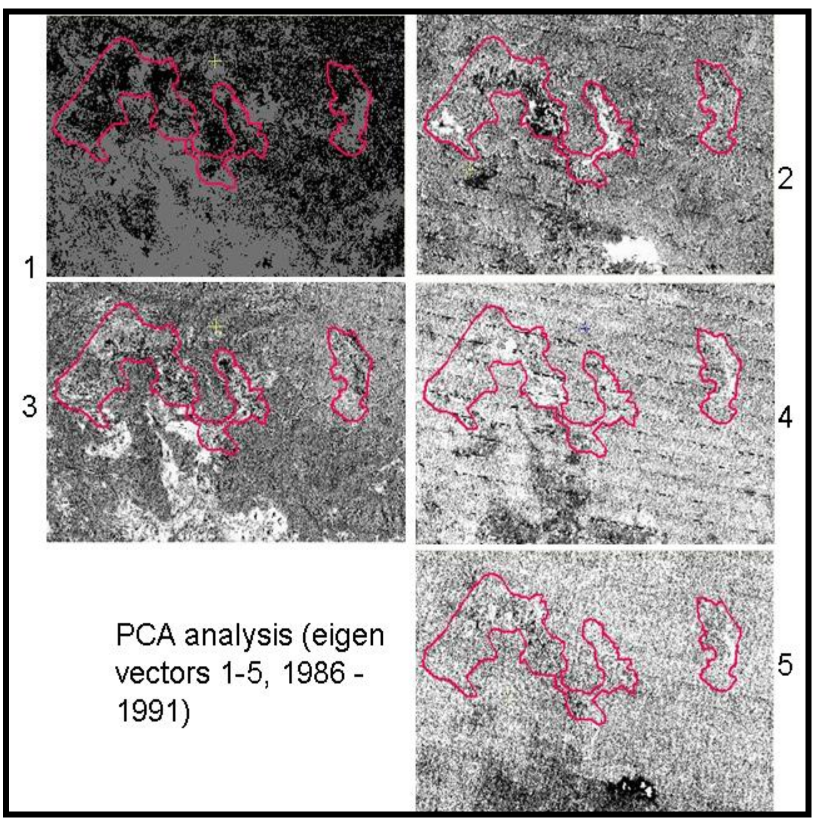

Figure 3: PCA analysis eigenvectors 1-5 produced by transforming Landsat TM bands 12,3,4,5 and 7 of 1986 and 1991 respectively. The red polygons are the outlines of the mining sites.

Three independent classifications were produced, one for each data set. The choice of supervised or unsupervised classification method depends on the availability of ancillary ("ground truth") data.

The results overlaid and compared pixel-by-pixel, so that the areas and types of change identified. The categories or class used in the three classifications were the same, as far as possible, so that direct comparison of these was carried out. These procedures allow areas of no change to be identified and, in cases where change has occurred, the nature of change to be determined. Post-classification comparison change detection, comparing each land-use separately can go beyond that can be achieved by band ratioing or Principal Components Analysis, generating detailed statistics of change (by using percentage change or confusion matrix), and not only identifying the nature of the change (Spyropoulos, et al., 2010). Figure 4 shows the bed rock map change from 1991 (red pixels) to 1997 (green pixels). The unaltered bed rock is shown with bluish pixels. Digital change detection, or more exactly, comparison between two images of the same area acquired at two different dates, is in practice an intricate task to perform accurately due to the operating characteristics of the satellites and the complexities of the environment which is being study. Spatial, spectral and temporal constraints affect the change detection procedure. If we assume that the imagery can be placed in a form that can allow digital analysis, then the most important task is the selection of the appropriate change-detection algorithm.

By comparison, Post-classification change detection methods are useful for giving detailed statistics of change, but only if an accurate land-cover classification can be obtained initially. Radiometric correction is also necessary for the successful implementation of this method.

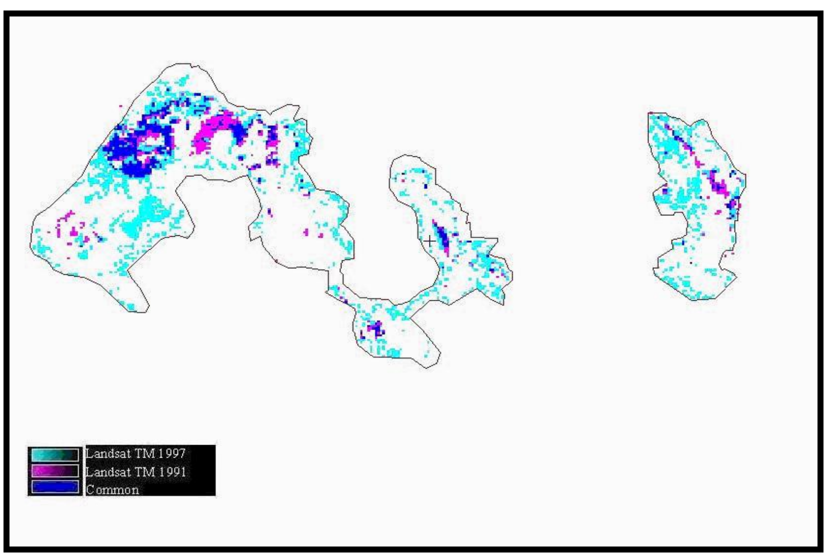

Figure 4: Bed-rock change map (1991-1997) resulted from post classification comparison.

Table 1: Land-use change statistics from 1986, 1991 and 1997 (open cast mine areas only).

Type of classes	1986	1991	1997	Change 86-91		Change 91-97	
	m^2	m^2	m^2	m^2	%	m^2	%
Forest	1,849,500.00	2,138,400.00	2,290,500.00	288,900.00	115.62%	152,100.00	107.11%
Artificial lake	92,700.00	121,500.00	98,100.00	28,800.00	131.07%	-23,400.00	80.74%
Roads and benches	1,098,900.00	1,565,100.00	1,126,800.00	466,200.00	142.42%	-438,300.00	72.00%
Soil Cover	2,187,000.00	2,333,700.00	3,249,900.00	2,187,000.00	106.71%	916,200.00	139.26%
Shadows	446,400.00	53,100.00	480,600.00	-393,300.00	11.90%	427,500.00	51.10%
Bed rock	459,900.00	940,500.00	2,290,500.00	480,600.00	204.50%	1,350,000.00	243.54%
Total	6,134,400.00	7,152,300.00	9,536,400.00				

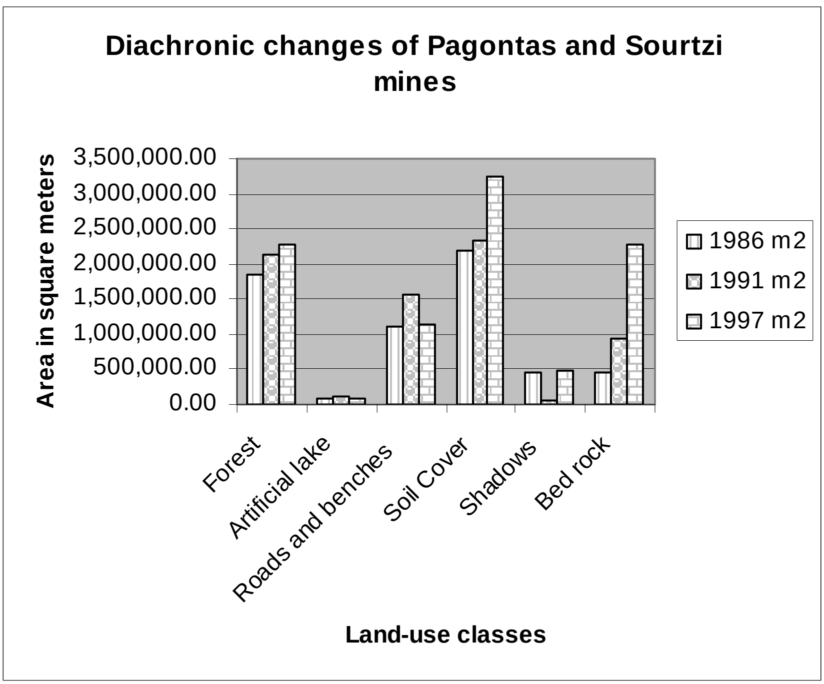

Figure 5: Diachronic changes of Pagontas and Sourtzi mining sites resulted from post classification comparison of Landsat TM images from 1986, 91 and 97 respectively.

CONCLUSIONS

In our study the different land-uses inside the mining sites were expanded from 6,13 square km in 1986 to 7,15 square km in 1991 and 9,53 square km in 1997 (Table 1 and Figure 5). The main changes evident in the mining sites are mine expansion and restoration. The first change is justified by the increase of roads areas and dump sites including also the bed rock whereas the second change is justified by the increase of forest and decrease of benches as a result of leveling. There are a lot of discrepancies identified such as the reduction of shadows from 1986 to 1991 which were justified as a collapse of dump sites due to slope failure. Post Classification comparison proved to be the more accurate method in assessing the land-use changes, since it provides the qualitative and quantitative analysis of diachronic change of each land-use.

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