SYNERGY BETWEEN SHORELINE CHANGE DETECTION AND SOCIAL PROFILE OF WATERFRONT ZONES: A CASE STUDY IN ISTANBUL

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ABSTRACT:

Cities of today compete with each other in terms of functions, places and opportunities that they provide. Among these, waterfront activities and physical attraction of such coastal zones play critical roles in urban planning agenda. Especially, cities like Istanbul experience a high pressure on coastal zones and hence, the protection of those areas has become a hard task to solve. With these reasons, change detection of the shorelines and waterfront landuse categories are fundamental to a broad range of interdisciplinary studies undertaken by city planners, civil engineers or coastal managers.

This paper aims to analyze the changes in the shoreline boundary and the adjacent landuse categories in the coastal zone of Istanbul through time periods. Different approaches for change detection analysis are described and analyzed. In particular, a new interdisciplinary methodology is presented in which techniques in remote sensing, GIScience and urban planning are integrated through digital images, census based socio-economic data and spatial analysis.

A case shoreline-mapping project is carried out in the European side of Istanbul where mixed-pixel problem arise in the urban environment. Since spectral characteristics are not representative of any single land cover type in such areas, *Fuzzy Logic* will be applied to detect the boundary of the shoreline and analyse the change of waterfront landuse categories in different years. A GIS based vector data will also be used as ancillary data. In addition, census based socio-economic data will be integrated into the model to analyze the relationship between the shoreline change detection and the social profile of the waterfront zones in Istanbul.

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1. Introduction

Remote sensing imagery of a large variety of spaceborne and airborne sensors provides a huge amount of data about our earth surface for global and detailed analysis, change detection and monitoring (Benz et al., 2004). Advances in remote sensing science, and in our ability to analyze temporal changes in our landscape, hold great promise for putting to rest any questions of the relevancy of remote sensing to local land use decisions (Daniel et al., 2002; Owojori and Xie (3)). Management of the urban environment involves procedures of monitoring and modeling which require reliable analytical techniques and methods of visualization (Sim,2005).

"Urban areas represent a complex association of population concentrations, intensive economic activities, and diverse lifestyles. They are a microcosm of human activity, and frequently experience rapid changes that need to be monitored and understood" (Lindgren, 1974; 243). Today changes made on cities are more extensive and take place more rapidly than ever before. Not only the city centers but also the urban fringes are under pressure because of their environmental significance such as forestry areas, water resources etc. "At urban fringe, complex areas of land cover change are often found, including transformations from rural land uses to residential, commercial, industrial, extractive and recreational uses" (Quarmby, 1989; 953). Hence, if urban planning may be defined as the regulation and designing of the physical facilities of a city to meet the changing economic and social needs of a community then it can easily be recognized that the information about current and accurate land use in urban areas is very important for the management and planning of these areas.

Therefore, urban planners need a reliable mechanism to detect and monitor urban land use changes in time. "One of the most perplexing problems facing urban planners, managers, and analyst is the dearth of pertinent, timely, and reliable information." (Horton, 1974; 243). Remote sensing provides a variable source of data from which update land cover information can be extracted efficiently. "Remotely sensed data can be used as a tool to detect, monitor and evaluate changes in ecosystems to develop management strategies for ecosystem resources" (Mouat, Mahin and Lancaster, 1993; 39). At this point, land use change detection is a very important application of remote sensing data. The goal of this paper is to analyze the changes in the shoreline boundary and the adjacent landuse categories in the coastal zone of Istanbul through time periods. Different approaches for change detection analysis are described and analyzed. In particular, a new interdisciplinary methodology is presented in which techniques in remote sensing, GIScience and urban planning are integrated through digital images, census based socio-economic data and spatial analysis.

A case shoreline-mapping project is carried out in the European side of Istanbul where mixed-pixel problem arise in the urban environment. Since spectral characteristics are not representative of any single land cover type in such areas, *Fuzzy Logic* will be applied to detect the boundary of the shoreline and analyse the change of waterfront landuse categories in different years. A GIS based vector data will also be used as ancillary data. In addition, census based socio-economic data will be integrated into the model to analyze the relationship between the shoreline change detection and the social profile of the waterfront zones in Istanbul.

2. Literature Review and Methodology

Timely and accurate change detection of earth's surface features is extremely important for understanding relationships and interactions between human and natural phenomena in order to promote better decision making (IIASA,1998). There have been many studies on digital change detection techniques depending on the needs. We can group these techniques into two:

> "1) comparative analysis of independently produced classifications for change detection;
> 2) simultaneous analysis of multitemporal data" (Singh, 1989; 990).

Also, (Singh, 1989) has made a classification of change detection techniques (Table 1): "Digital change detection approaches may be broadly characterized by 1) the data transformation procedure (if any) and 2) analysis techniques used to delineate areas of significant alterations" (Singh, 1989; 990).

Furthermore, the type of the land cover/use is also as important as the change detection technique. Among other land cover/use categories, "urban" and its sub-classes are the most sensitive in land use/cover change. To obtain the urban land use/cover change, information is important for urban decisionmaking and sustainable development. At this point, having diffferent spatial resolution and spectral characteristics, different satellite images are used to understand urban land cover/use changes such as data obtained from Landsat, SPOT, Quickbird etc.

Table 1: Digital change detection techniques *(Source: Singh, 1989; 991).*

Analysis technique used to detect change	Raw data	Difference	Ratio	Vegetation index difference	Regression	Principal component analysis	Change vector	Post classification comparison
Standard deviation threshold		Ingram et al. (1981) Jenson and Toll (1982) Miller et al. (1978) Nelson (1983) Stauffer and McKinney (1978) Toll et al. (1980) Singh (1984, 1986)	Howarth and Wickware (1981) Nelson (1983) Todd (1977) Wilson et al. (1976) Singh (1984, 1986)	Angelici Et al.(1977) Banner and Lynham (1981) Howarth and Boasson (1983) Nelson (1983) Singh (1984, 1986)	Ingram et al. (1981) Singh (1984, 1986)	Byrne et al. (1980) Lodwick (1979) Richardson and Milne (1983) Toll et al. (1980) Singh (1984, 1986)		
Supervised	Banner and Lynham (1981) Williams and Hover (1976)	Anuta and Bauer (1973)						Gordon (1980) Howarth and Wickware (1981) Singh (1984, 1986)
Spectral (unsupervised)	Weismiller et al. (1977)	Anuta and Bauer (1973) Weismiller et al. (1977)						Joyce et al. (1980) Riordan (1980) Swain (1978) Weismiller et al. (1977)
Spectral-spatial (unsupervised)							Mailla (1980) Colwell and Weber (1981)	
Layered spectral/ temporal	Weismiller et al. (1977)							

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Among these satellite images, Landsat Thematic Mapper (TM) imagery can be used for educational and planning applications at both central and local levels. But more accurate land cover information is needed if we are to move beyond first generation impacts of educational programs and provide local end-users with information and products that can be easily and directly incorporated into land use plans and policies (Daniel et al., 2002). Since the objective of this paper is to analyze the general urban land cover/use of the shoreline zones of Europen Side in Istanbul (Figure 1), Landsat images of two years (1989 and 2001) will be used.
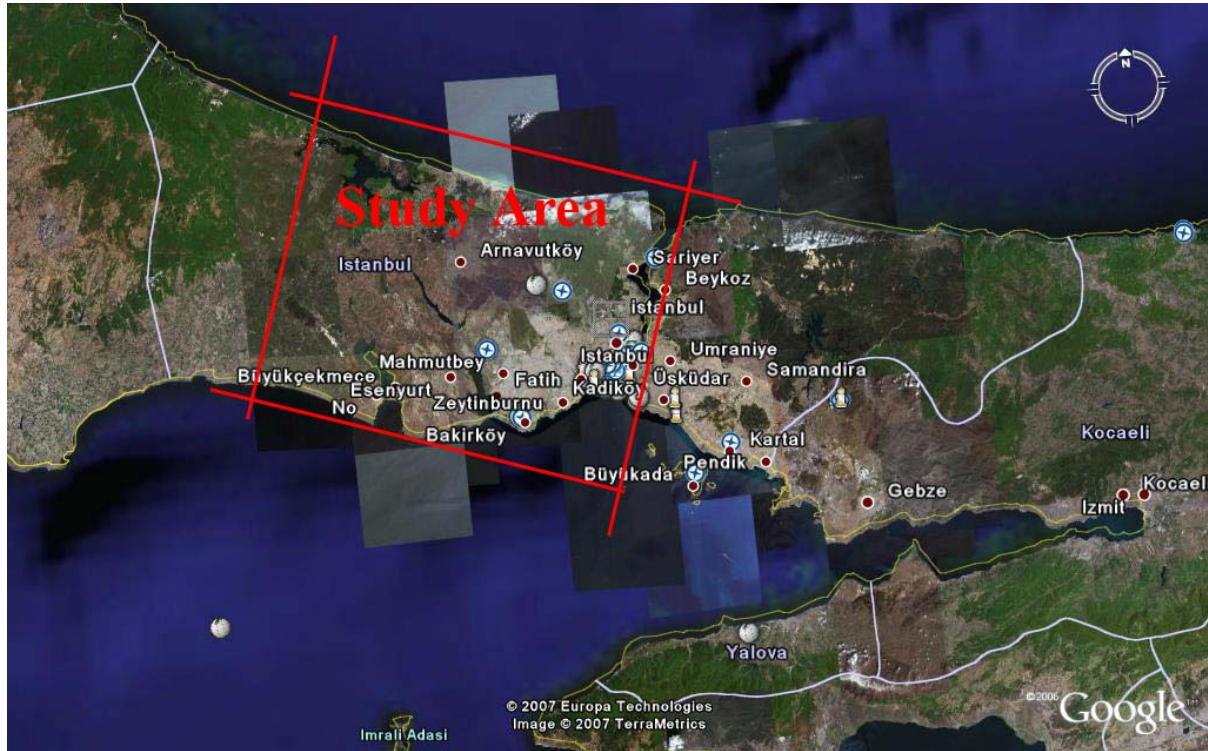
Figure 1: Study area – European side of Istanbul (source: Google Earth)

For this work, "eCognition software" is used to apply Fuzzy Logic algorithm on the two images. The eCognition software performs a first automatically processing - segmentation - of the imagery. This results to a condensing of information and a knowledge-free extraction of image objects. The formation of the objects is carried out in a way that an overall homogeneous resolution is kept. The segmentation algorithm does not only rely on the single pixel value, but also on pixel spatial continuity (texture, topology) (1).

Furthermore, eCognition supports different supervised classification techniques and different methods to train and build up a knowledge base for the classification of image objects. The frame of knowledge base for the analysis and classification of image objects is the so-called class hierarchy. It contains all classes of a classification scheme. The classes can be grouped in a hierarchical manner allowing the passing down of class descriptions to child classes on the one hand, and meaningful semantic grouping of classes on the other. This simple hierarchical grouping offers an astonishing range for the formulation of image semantics and for different analysis strategies. The user interacts with the procedure and based on statistics, texture, form and mutual relations among objects defines training areas. The classification of an object can then follow the "hard" nearest neighborhood method or the "soft" method using fuzzy membership functions. Multilevel segmentation, context classification and hierarchy rules are also available (Manakos, 2001).

Class descriptions are performed using a fuzzy approach of nearest neighbor or by combinations of fuzzy sets on object features, defined by membership functions. Whereas the first supports an easy click and classify approach based on marking typical objects as representative samples, the later allows inclusion of concepts and expert knowledge to define classification strategies (Baatz et al., 2001).

2.1. Segmentation of LANDSAT images before the classification

The basic processing units of object-oriented image -analysis are segments, so-called image objects, and not single pixels. Advantages of object-oriented analysis are meaningful statistic and texture calculation, an increased uncorrelated feature space using shape (e.g. length, number of edges, etc.) and topological features (neighbor, super-object, etc.), and the close relation between real-world objects and image objects.

As Hájek mentioned (2); in the segmentation process, size and shape of desired objects are defined by the calculation of heterogeneity between adjacent pixels, where scale is the main input parameter. Shape factor (colour/shape ratio) and spatial properties (smoothness/compactness ratio) are other variables to define homogeneity of object primitives. For this study, segmentation was conducted stepwise on several levels using different scales to construct the hierarchical image object network. Moreover, segmentation is processed using scale parameter of 5. The shape factor was set to higher value for the coarse segmentation and lower value at finer scale (higher influence of spatial properties). (2). Therefore the shape parameter is choosen as 0.3. Segmentation result is given in Figure 2.
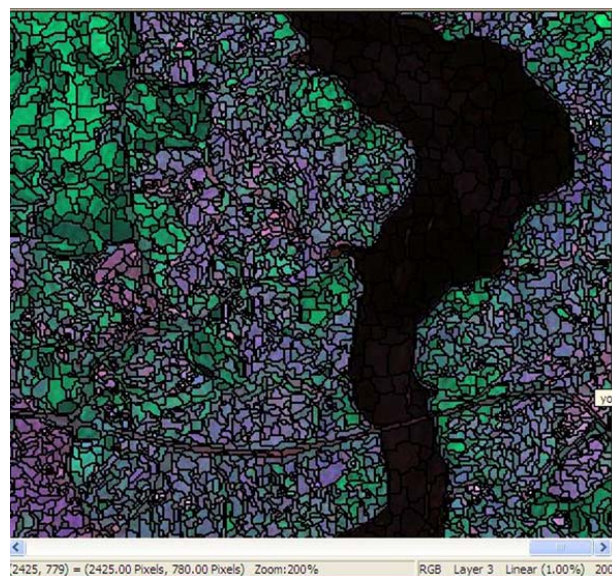

Figure 2: Segmentation result

2.2. Classification

As a first step of the classification, the major land use/cover categories are defined and then a class hierarchy is proposed as in Figure 3.
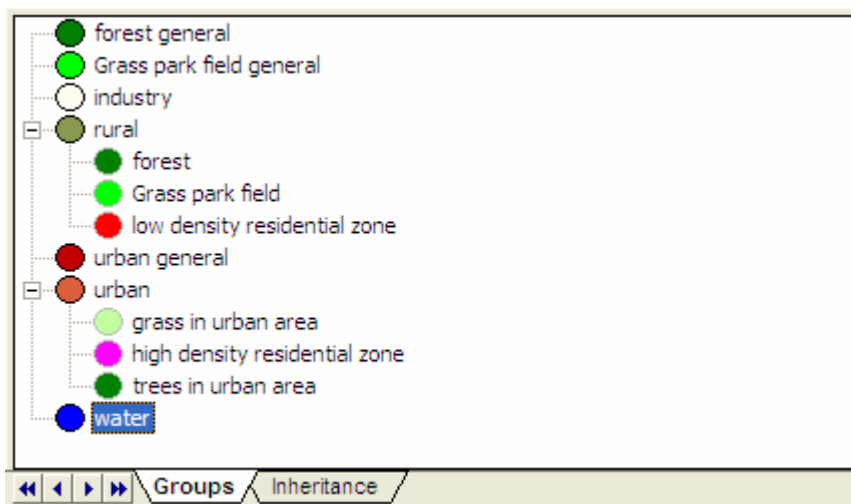

Figure 3: Class hierarchy

Among the land use/cover categories, "forest general, grass-park-field general and industry" are determined as 1st level in the class hierarchy. These categories are obtained through the training areas selected in eCognition and nearest neighbourhood method. Next, "forest, grass-park-field, grass in urban areas and high density residential zone" are determined as 2nd level class.

For 1989 Landsat image, results of maximum-likelihood classification are used in the 1st level categories except "water" (Figure 4).
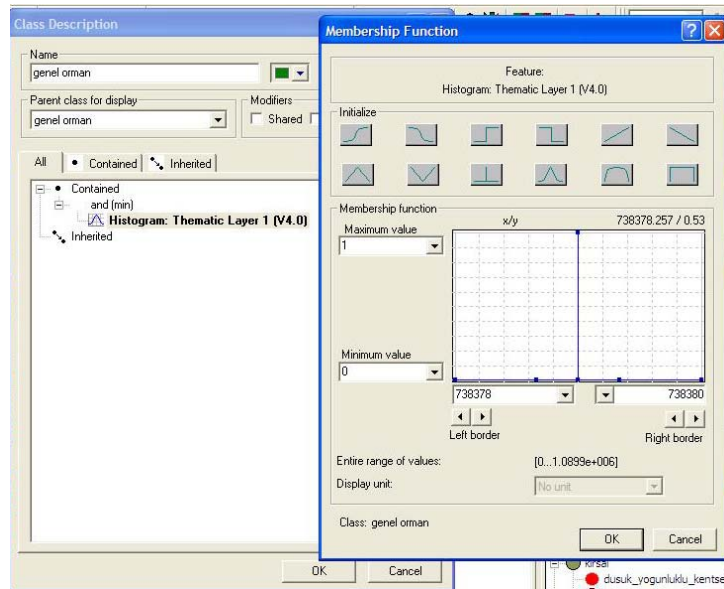
Figure 4: Classification by using thematic layers except water

Furthermore, "singletone" is used for the fuzzy membership function. For "water" category, as it is shown in Figure 5, fuzzy classification is applied and ratio Landsat band 1 is used. This means that the feature value range (between 0-1) is obtained through a ratio of the mean value of Band 1 to the sum of all mean values of other bands. This differentiates the "water" as a separate category from the others. It is shown in Figure 5 that the function "larger than" is applied during the classification and 0.36-0.72 range is used for the ratio -1. The selection criteria of these values are based on the interactive feature view option of the eCognition software.
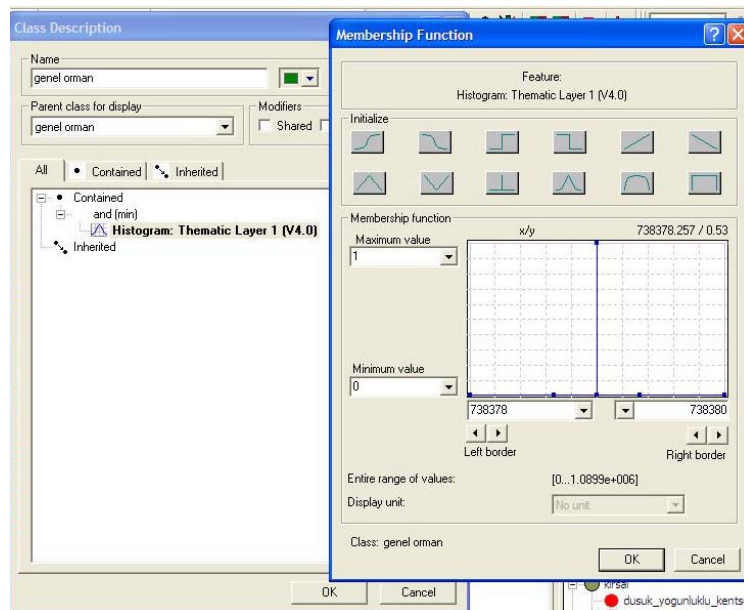

Figure 5: Membership function of water

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For the Level II categories of 1989 and 2001, the same rules are applied (Table 2). At the end of the classification, the accuracy test showed that for 1989 and 2001 images, an overall accuracy of 0.83 and 0.87 are obtained.

Table 2: decision rules

Class	Rule	Used membership function	Range
Forest	Relative area of neighbor urban (10)[1]	Smaller then	0.6-0.7
Grass-park-field	Relative area of neighbor urban (10)	Smaller then	0.6-0.7
Low density residential zone	Area[2]	Larger then	350-400
	Relative border to rural[3]	Larger then	0.99-1
Grass in urban area:	Relative area of neighbor urban (10)	Larger then	0.5-0.6
High density residential zone	Not low density residential zone		

Results of the two images are provided in Figures 6 and 7. According to these figures, shoreline zone of Istanbul in the European side has shown dramatic change. This change especially occurred between the categories of forestry areas to urban residential areas which points out to the deterioration of environmentally sensitive areas of the city. Within this zone, six areas are selected as case areas where the social profile is also analyzed to understand the urban dynamics of the change. For this purpose, 2001 census data at "mahalle" level, the smallest administrative unit where the census data are collected by the Turkish Institute of Statistics, are used. As a methodology, selected variables of the census data are subjected to the Principal Component Analysis (PCA) to understand the relationship between them. Next section provides the results of this analysis.

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[1] The area of sungroup is divided by the total area of the ebtire object group. The relative area computes the amount of a specific image object type in larger set of image objects (eCognition 2003).
[2] The area of an image objects is the number of pixels forming it (eCognition 2003).
[3] The length of the image objects's common borders with the selected neighboring objects divided by the total border length of the image objects (eCognition 2003).
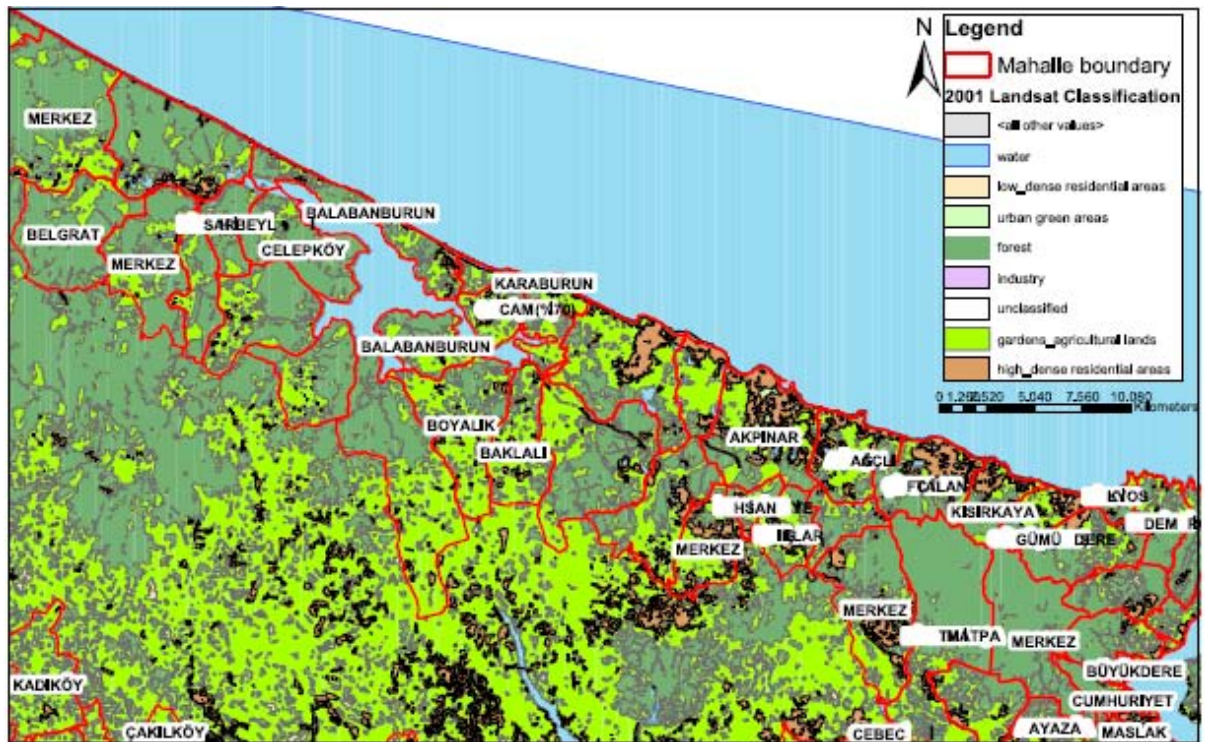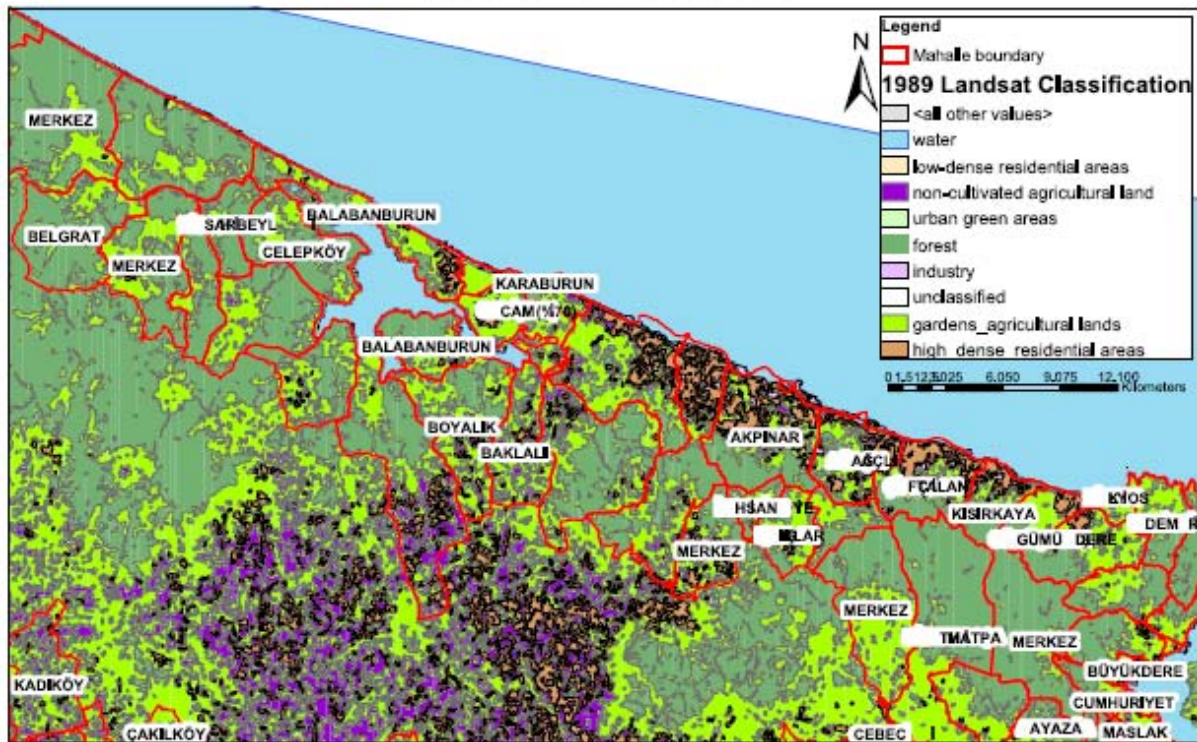
Figure 6: 2001 Land use classification

Figure 7: 1989 Land use classification

2.3. Social profile of selected case areas

To perform a socio-economic analysis for the case areas, as a starting point, the selected 30 variables from 2001 census data are exported from ArcGIS to Excel, to create labels for each variable. Then, the file is exported to SPSS, a statistical program which enables the user to do statistical analysis. Next step, is to calculate the percentages for each variable (this is necessary since the values of each variable are different like income level, education or household size, etc.).

After having calculated the percentage values for each variable, at the next stage, PCA is used to see the relation between different types of census data. The first step of PCA is to obtain the number of components (dimensions), which explain most of the data. To do this, the table of "Rotation sums of squared loadings" is used which is one of the resulting outputs of the PCA in SPSS (Table 3).

Table 3: Total Variance Explained in PCA

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	9,023	50,126	50,126	9,023	50,126	50,126	6,684	37,135	37,135
2	5,060	28,109	78,236	5,060	28,109	78,236	6,029	33,492	70,627
3	2,192	12,179	90,414	2,192	12,179	90,414	3,558	19,768	90,395
4	1,452	8,067	98,481	1,452	8,067	98,481	1,456	8,086	98,481
5	,273	1,519	100,000						
6	1,124E-15	6,243E-15	100,000						
7	9,751E-16	5,417E-15	100,000						
8	4,829E-16	2,683E-15	100,000						
9	2,807E-16	1,560E-15	100,000						
10	2,292E-16	1,273E-15	100,000						
11	9,164E-17	5,091E-16	100,000						
12	-1,885E-18	-1,047E-17	100,000						
13	-1,396E-16	-7,756E-16	100,000						
14	-1,441E-16	-8,004E-16	100,000						
15	-2,933E-16	-1,629E-15	100,000						
16	-3,412E-16	-1,896E-15	100,000						
17	-4,221E-16	-2,345E-15	100,000						
18	-9,532E-16	-5,296E-15	100,000						

According to Table 3, if only one component is used, 37.13 % of the data is explained. If the number is increased to five, then 70.62 % of the data is represented. A "Scree Plot" (Figure 8) is also used to see how many components to retain. From this graph, it is easily observed that four components are enough to represent the whole range of data.
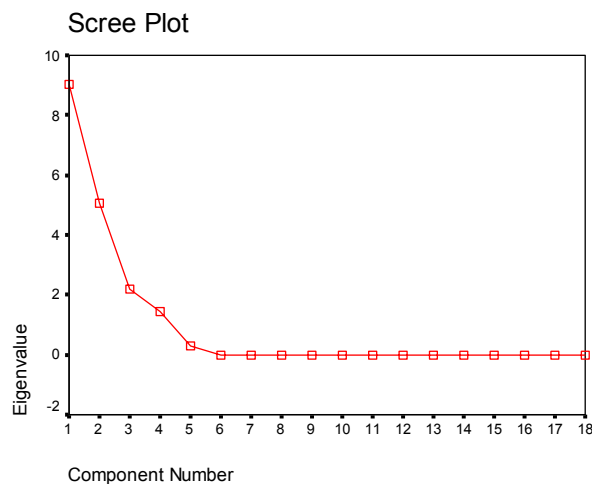

Figure 8: Scree Plot of PCA

After deciding the number of components to retain, the next goal is to understand the meaning of these components and to analyze which variables are explained in different components. To do that, "Rotated Component Matrix" is used (Table 4). According to this table, the variables "% total working male population", "% unemployment for male and female population", "% male and female population who can neither read nor write", "% people working in building construction", "% with bachelor degree or higher" are highly related to each other and are represented in component 1. Rotated Component Matrix is also useful to understand the variables that are positive or negatively related within each component. Therefore, it is observed that the variables "% unemployment for male population", "% male and female population who can neither read nor write" and "% total working male population" are positively related while "% total working female population", "% people working in building construction", "% household size 2" and "% with bachelor degree or higher" are negatively related.

Table 4: Rotated Component Matrix

	Component			
	1	2	3	4
% total working male population	,951	-,169	,211	8,898E-02
% total working female population	-,951	,169	-,211	-8,90E-02
% people working in agriculture	-6,18E-02	,842	-,524	9,484E-02
% people working in mining	,529	,838	,132	-7,31E-03
% people working in manufacturing	,308	-,486	,673	-,384
% people working in electric and technical	9,211E-02	,365	-,925	3,734E-02
% people working in building construction	-,925	-,184	,331	-1,70E-03
% people working in wholesale or retail	-4,83E-02	-,978	,146	-9,04E-02
% people working in transportation related work	,201	-,930	,129	,175
% people working in financial organizations	-,536	-,726	,336	,260
% household size 2	6,737E-02	1,373E-03	1,235E-02	,997
PCTHH2	-,825	-,431	-,142	,335
% household size 10 or more	-1,36E-02	1,222E-02	,991	,110
% unemployment for male	,751	,625	-,213	5,790E-03
% male population who can neither write nor read	,605	,766	,195	9,035E-02
% female population who can neither write nor read	,777	,259	,553	,151
% with bachelor degree or higher	-,917	-,256	,300	4,386E-02
% with education primary school	,492	,715	-,358	,159

Component 2, on the other hand, keeps the variables "% people working in agriculture", "% people working in mining", "% people working in wholesale or retail" , "% people working in transportation" , "% people working in financial organizations" and "% male population who can neither write nor read". Among these, "% people working in wholesale or retail", "% people working in transportation" and "% people working in financial organizations" are negatively related with the other variables explained in component 2. The variables "% people

working in electric and technical related work" and "% people working in manufacturing" are explained in the third component and related negatively with each other. Furthermore, component 4 keeps the variable "% household size 2".

With the help of these results, the four components can be linked to shoreline change detection with four different meanings, which are described as follows:

- Component 1: Mostly explains about "unemployment" and "education"
- Components 2 and 3: Keeps the "economic sectors"
- Component 4: Explains the "household size".

When these components are mapped in the selected six areas (Avcilar Merkez, Sariyer Tarabya, Sariyer Buyukdere, Sariyer Zekeriyakoy, Eyup Kemerburgaz Ciftalan and Eyup Kemerburgaz Akpinar), it is observed that Zekeriyakoy has the most negative values for Component 1 and it is also the most sensitive area for the land use/cover change (Figures 9, 10 and 11).
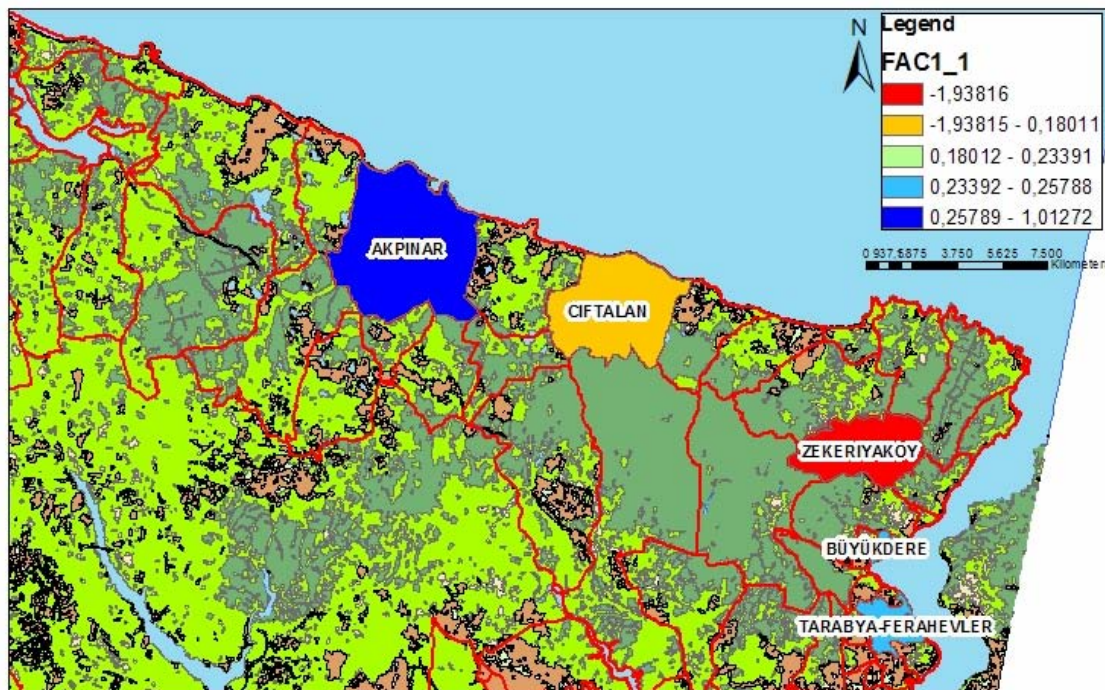

Figure 9: Component 1 in the selected case areas

3. Conclusion

This paper has made two significant contributions to the remote sensing applications in urban planning for the shoreline change detection. First, a change detection procedure is applied through the integration of supervised classification (maximum-likelihood) and Fuzzy Logic algorithms. Second, an attempt has been made to link the social profile of the community with the shoreline land use/cover change detection through GIS/RS integration. The methodology proposed in this work is tested only within a limited time period and case areas, however results shoed promising results indicating that there is a strong relationship between the physical land use/cover change of such waterfront zones and socio-economic variables.

Furthermore, the analysis also indicated that the trend of the land use/cover change of the shoreline zones in Istanbul points out a high deterioration of forestry areas. To this end, it is not wrong to conclude that the rapid increase in urban settlement areas within such zones will not only decrease the amount of forests and green parks but also increase the pollution of drinking water resources of the city which will diminish the overall quality of life of all citizens.
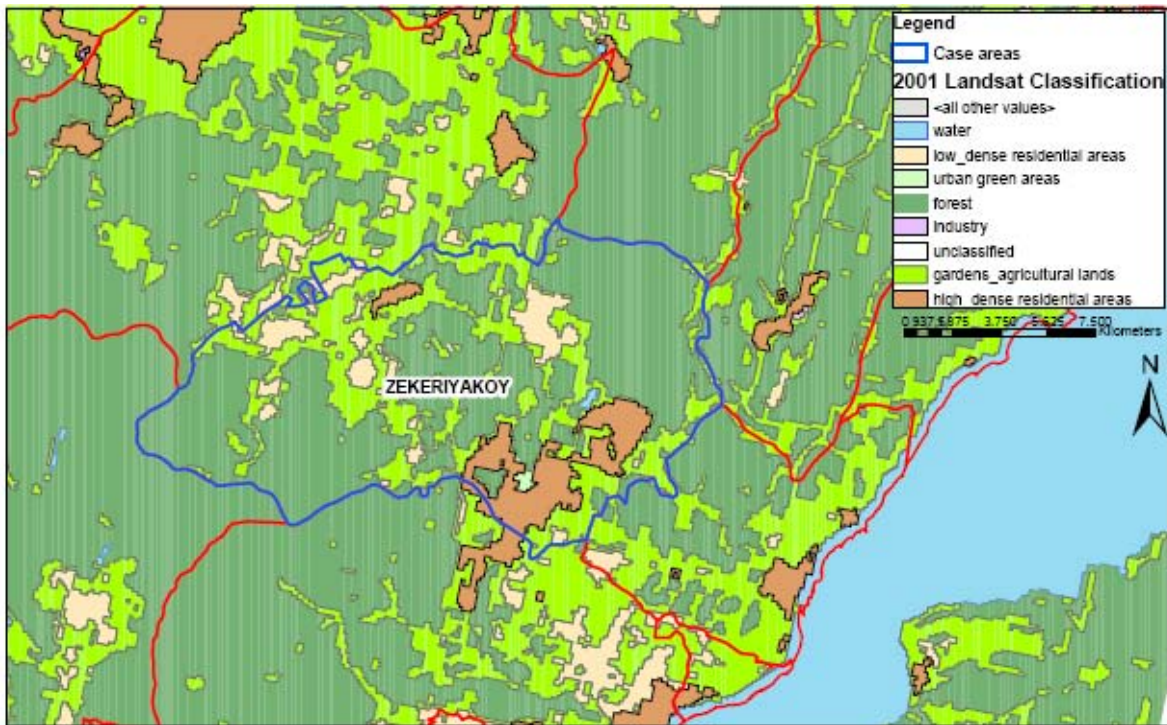
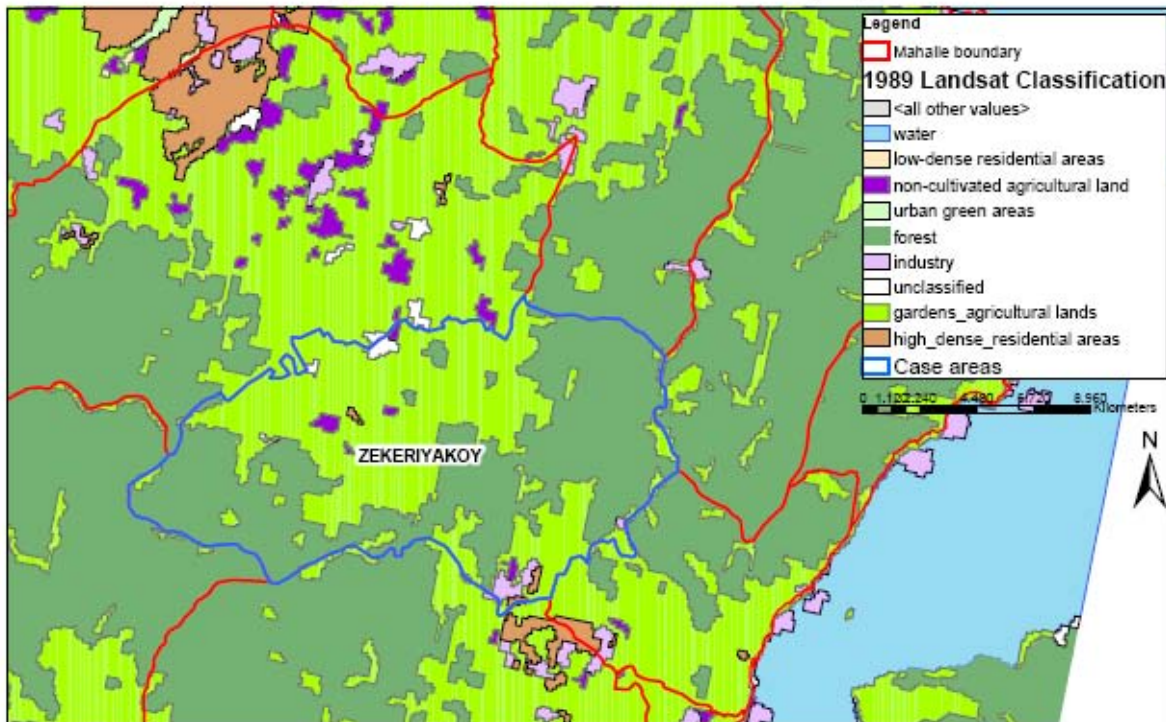Figure 10: 2001 Land use classification in Zekeriyakoy

Figure 11: 1989 Land use classification in Zekeriyakoy

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