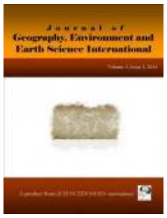

Journal of Geography, Environment and Earth Science International

10(4): 1-14, 2017; Article no.JGEESI.34604
ISSN: 2454-7352

Spatio-temporal Analysis of Land Cover Changes of Izmir Province of Turkey Using Landsat TM and OLI Imagery

Fatih Kara[1*]

[1]*Department of Geography, Fatih University, Buyukcekmece, 34500 Istanbul, Turkey.*

Author's contribution

The sole author designed, analyzed and interpreted and prepared the manuscript.

Article Information

DOI: 10.9734/JGEESI/2017/34604
Editor(s):
(1) Pere Serra Ruiz, Department of Geography, Universitat Autònoma de Barcelona, Spain.
Reviewers:
(1) Reeves M. Fokeng, University of Dschang, Cameroon.
(2) Awoniran Dauda, Federal University of Technology, Nigeria.
(3) Muringaniza Kudakwashe Collins Ralph, Midlands State University, Zimbabwe.
(4) P. A. Azeez, Sálim Ali Centre for Ornithology and Natural History, India.
Complete Peer review History: http://www.sciencedomain.org/review-history/19810

Original Research Article

Received 1st June 2017
Accepted 27th June 2017
Published 1st July 2017

ABSTRACT

Izmir province has experienced a tremendous increase in population such as other metropolitan cities of Turkey due to migration issues in last 30 years. Land use and land cover (LULC) of Izmir was affected from this unplanned population increase in province scale, natural ecosystems were destroyed by settlement, and agricultural activities of that doubled population. The aim of this study was determining LULC changes in Izmir and 30 m spatial resolution Landsat images were used as the main data along with geographic information systems (GIS) and remote sensing (RS) procedures. Satellite images from 1986 to 2015 were used to investigate LULC change patterns and a transition matrix was created. Object-based image classification technique was used for creating segments before classification. Segments, created by multi-resolution segmentation approach, were classified by visual analysis by the help of old maps, high-resolution imagery, Google Earth, and Landsat images. GIS-RS based hybrid method provided a very high accuracy (about 93%) in satellite image classification and maintained a transition matrix of changing dynamics. The results showed that increased impervious surfaces and decreased natural areas such as forests and meadows were the main features of LULC change in study area.

**Corresponding author: E-mail: msfkara@yandex.com;*

Keywords: Land use/land cover change; time series analysis; spectral segmentation; remote sensing; Landsat.

1. INTRODUCTION

Izmir province is the third largest province of Turkey in population and it is subjected to huge amount of population increase because of incoming migrations since the beginning of 1980's. Total population of the province was 1.976.763 in 1980 and it doubled in 30 years, became 4.168.415 in 2015 [1]. Izmir has several economical functions such as industry, trade, import/export, tourism, service sector and these economical resources attract many people especially from economically undeveloped rural areas whose economic resources are very limited. Land Use Land Cover (LULC) change progresses were already substantial in Mediterranean region [2] owing to historical development through agro-climatic supportive conditions for human settlement [3]. This rapid population increase demand in housing and converting green and undeveloped areas to residential units in the entire province including sub-provinces. Thus, expansion of massive amount of unplanned urban areas results reduction of agricultural areas, forests, and all other types of green areas [4]. Unplanned expansion of residential areas brings important environmental problems such as forest fragmentation, wasting of natural environment, habitat disturbance, increase of impervious surfaces, and soil loss [5].

Several studies have been conducted for analyzing LULC changes in large Mediterranean urban environments such as Rome [6], Athens [7], Lisbon [8], Madrid [9], Istanbul [10], and Barcelona [11] where urban sprawl and successive ecosystem and agricultural fragmentation very common. Maraccini et al. (2015) investigated common and different paths of land cover changes in six Mediterranean urban regions [2]. They declare urban expansion is mainly occurs on agricultural lands and results fragmentation of natural areas. They investigated direct changes to urbanization and indirect impacts on non-artificial land uses in six Mediterranean cities by using Landsat time series satellite imagery along with semi-supervised image classification method. Results displayed that significant change could be identified in small-medium cities and large metropolitan areas rather than according to north-south direction. While afforestation and abandonment of agricultural areas are the main feature of LULC changes in the Norther Mediterranean urban regions, Southern Mediterranean regions has mostly undergone transformation of natural areas to agricultural areas. There are also some studies on LULC transformations in semi-urban and rural areas of Mediterranean regions also. Salvati et al. [12] analyzed change in long-term spatial distribution of four basic land cover classes if there is a compact growth in rural gradients of Athens and explored relationships from 1960 to 2009. They used descriptive statistics, correlation analysis, and multivariate procedures for verifying their hypothesis and stated that there was similarities and differences in 'sprawl' or 'compact growth' phases in urbanized areas. They also indicated that croplands were the land cover class which undergone to change most.

LULC change is a global scale environmental issue [13] and changes in LULC are the major reason of ecosystem destruction and fragmentation [14]. Management of ecosystem services requires spatially explanation of changing patterns and interactions among ecosystem structures [15]. Temporal analysis of LULC changes are important tools for sustainable development, ecosystem monitoring, environmental change studies, and land management [16,17]. Satellite imagery and remote sensing techniques has been widely used in LULC analysis as their usefulness in revealing spatial patterns of LULC changes [18-19]. Landsat 5-7-8 imagery has been used for many earth observation and change detection analysis [20] studies due to its free availability, 16-day temporal resolution [21], and 30-m spatial resolution [22] hence these imageries allow effective monitoring LULC changes [23] as well as vegetation growth in forestlands [24], arid environments and Arctic areas [22].

The aim of LULC change models is to determine changes in LULC classes between two different dates [25]. The main aim of change detection studies is extracting change areas accurately and eliminating pseudo changes caused by extraneous factors such as atmospheric conditions, soil moisture, etc. [26]. Change analysis is carried out by comparison of 'before' (past) and 'after' (the latest) satellite imagery and detection of transformations from one LULC classes to another in these models. Various change detections techniques have been developed for LULC change analysis using remote sensing techniques [27] and these methods can be classified into two categories: post-classification comparison and pre-classification change detection [28]. Post-classification change detection approaches encompass comparison of independently classified LULC maps and quantify changing patterns by comparing maps [29] while pre-classification techniques identify changes by comparing unclassified multi-temporal satellite data directly [30]. Pre-classification techniques (image algebra, change-vector analysis, transformation) are designed to discover change or no change in the area of interest does not display type of transformation from one LULC classes to another [31].

In this study object-based change detection (OBCD) technique, a post classification method, has been used to detect changes among before (1986) and after (2015) Landsat imagery belong to Izmir province of Turkey. In this approach, before and after images are classified by object-based image analysis method (OBIA) and classified images subtracted each other for determining changes between dates. OBIA methods use contextual information such as texture and compactness for generating ‘image objects’ or ‘segments’ [32]. OBCD is a favorable method, which can be applied to medium or coarse resolution satellite imagery [33]. OBIA can provide more accurate classification results due to high resolution imagery [34] but pixel-based methods may give better classification results in some land cover classes also [35].

According to scales, there are three types of segmentation methods: fixed-scale, variable-scale, and multiresolution [36]. Multiresolution segmentation method creates segments in different scales for each land cover category comparing to one scale. Multiresolution segmentation uses a region merging technique starting from one pixel forming one image object or region. Image objects are merged and transformed to larger objects in each step according to local homogeneity criteria, which can be described as similarity of adjacent image objects [37]. The negative side of multiresolution segmentation is that it requires much efforts and time due to manually selection of segments for each category [38]. Image segmentation approach is widely used in classification of multi-temporal Landsat imagery [39,40]. This study describes LULC change information from 1986 to 2015, which is important due to proving green area fragmentation and environmental destruction in Izmir province of Turkey. The aim of this study is investigating LULC changes and environmental degradation in Izmir province using OBIA and post-classification comparison methods. Before and after images of study area were classified by OBIA and a change matrix were created by subtraction of after image from before image.

2. STUDY AREA

Izmir province has been chosen as study area in this study which is located between 26° 15’ - 28° 20’ E and 37° 45’ - 39° 15’ N on the shorelines of Aegean Sea with its large agricultural areas, olive farms, and pine forests along with dense population on seaside. Total areas of Izmir province are 12.007 km² and it has 30 sub-provinces including those located in metropolitan area of the city. Besides its large agricultural areas,hills and mountainous areas cover 60% of Izmir province. Mountains lie in West-East direction and Bozdag is the highest mountain with 2159 m altitude. There are three major rivers, which flow to Aegean Sea among mountain ranges named as Gediz, Kucuk Menderes, and Buyuk Menderes from North to South respectively (Fig. 1).

Mediterranean climate strongly influential in the entire province with seasonal mean temperatures between 8.9°C - 28.0°C and annual rainfall of 700-1000 mm. Winter is the rainiest season in Izmir and more than half of the precipitation occurs in winter season. In Mediterranean Climate, summers are very dry and about 1% of annual total precipitation in summer seasons. Due to these climate features, maquis plants are the main vegetation cover of Izmir province in lower altitudes than 700-800 m. Another Mediterranean plant, red pine (*Pinus brutia*), covers upper altitudes of the province unless there is no olive plant occupation on the area. Olive plantation is very common in the entire province due to suitable climate conditions.

3. DATA AND METHODS

This research includes OBIA and post-classification comparison methods of Landsat TM and OLI imagery. The data analysis is achieved in three stages: (1) image acquisition and pre-processing; (2) LULC map preparation for both before and after dates; and (3) LULC change detection and analysis.

Fig. 1. Google Earth image of Izmir province

3.1 Data

Cloud-free Landsat 5 Thematic Mapper (TM) imagery with 30 m spatial resolution have been used to create the before (1986) image of this study (path 181-row32/33; path 180-row 33), clear Landsat 8 Operational Land Imager (OLI) data were used to generate the after (2015) image in this work (path 181-row32/33; path 180-row 33). Only one Landsat scene is not enough to cover the entire study area and three scenes were required to create both the before and the after images (Fig. 2). All images captured in June/July were acquired from USGS Earth Explorer website. All Landsat scenes have very high geometric accuracy therefore geometric correction methods such as registration or rectification were not necessary to use.

3.2 Image Pre-processing

In case of multitemporal image analysis and comparison – analyzing images acquired in different dates – some pre-processing methods might be necessary due to different atmospheric and radiometric properties of dates in images acquired. Dark object subtraction (DOS) method was the first step of pre-processing of satellite images before classification for overwhelming different in situ atmospheric conditions of different acquisition dates [41]. This procedure assumes dark objects do not reflect light any value greater than zero comes from atmospheric scattering. This error is corrected by subtracting darkest pixel value of any band from every pixel value in the band. DOS is a simple technique which is effective for removing haze in multispectral imagery [42].

Satellite images were classified due to reflectance values of Landsat scenes thus in the second step of pre-processing reflectance values of each band were calculated. To calculate reflectance values, outgoing radiance (L) and incident irradiance (E) should be calculated [42]. Outgoing radiance should be calculated as;

$$L_y = \text{Gain} * \text{Pixel value} + \text{Offset} \qquad (1)$$

Based on this formula reflectance can be calculated as;

$$\text{Reflectance} = \rho = \frac{\pi L_\lambda d^2}{ESUN_\lambda \sin\theta} \quad (2)$$

Where:

L_y= Outgoing radiance in W/(m^2 * sr * μm),
d = Earth-sun distance in astronomical units,
$ESUN_\lambda$ = Solar irradiance in W/(m^2 * sr * μm),
θ = Sun elevation in degrees.

Radiometrically corrected bands were stacked and three multispectral Landsat scenes were created for the years of 1986 and 2015. While stacking Landsat TM bands, Thermal band (band 6) is excluded and only 30 m spatial resolution bands (bands 1-5, 7) were used for creating the “before” image. 30 m spatial resolution bands (bands 2-8) of Landsat OLI sensor were used to produce the “after” image by the year of 2015. After stacking images Landsat scenes were mosaicked based on histogram matching algorithm, which determines a lookup table that converts the histogram of one image to resemble the histogram of another (Hexagon Geospatial, 2016). Histogram matching algorithm was used to minimize color differences of adjacent Landsat scenes, which were acquired in different dates under different atmospheric conditions. This algorithm determines a master and a slave image, compare histograms and calculate histogram of slave image band-to-band. Mosaicked images were subset according to borders of Izmir province, which is updated by the help of Google Earth and ArcGIS base maps.

3.3 Image Classification

In this study, OBIA technique was used to classify images due to its capability in providing high accuracy in multispectral image classification although requirement of immense amount of time. Shape, size, and texture information is used to create image objects as well as spectral information in OBIA method [43]. eCognition software was used to create segments or image objects in this work. The software uses a region growing technique starts with region of one pixel according to spectral and spatial characteristics of the pixel. Then local homogeneity criteria are used to define merging regions of interest. This technique is named as ‘multi-resolution segmentation’ due to its product of primitive image objects at different resolutions [44]. OBIA includes four steps: (1) multi-resolution segmentation for generating image objects; (2) feature extraction and parameter assessments; (3) classifying image objects by iterative steps and; (4) accuracy analysis and evaluation [45].

According to Lillesand et al. [46] change detection studies require satellite imagery which are acquired by the same sensor because of different spatial and spectral properties of sensors. These different sensor features can make pixel by pixel comparison impossible. In this study Landsat scenes used to create before and after images were acquired by different sensors which have different spectral resolutions. Landsat scenes taken by Landsat 8 OLI sensor were rescaled from 16-bit to 8-bit for equalizing spectral properties of before and after

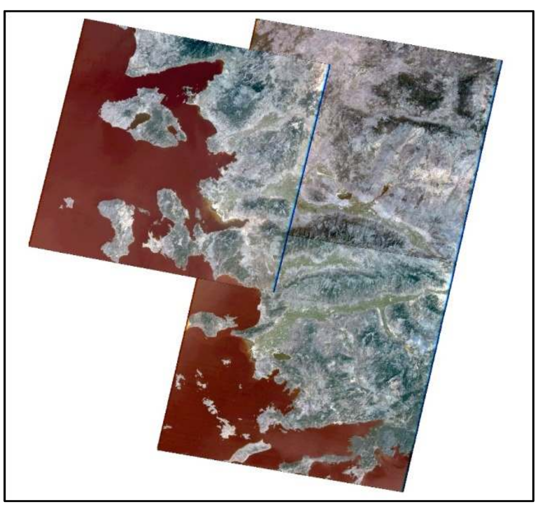

Fig. 2. Landsat scenes covering study area – Izmir province

images. At the beginning, multi-resolution segmentation creates thousands of image objects and usually number of segments are reduced by a secondary segmentation before classification of segments. Due to spatial resolution of satellite imagery secondary segmentation may produce undesirable large segments which have several LULC classes inside. Segments were classified by visual analysis directly after multi-resolution segmentation step because of aforementioned problem in this study. Visual analysis is a feasible and accurate of classifying segments [37] and both before and after images were classified by the help of cadastral maps, Google maps, ArcGIS base maps, and the images themselves.

Adapted USGS land-use/land-cover classification scheme [47,48] was used as the base for our classification, including agricultural areas, bare soils, forests, grasslands-meadows, high intensity residential, low intensity residential, and water (open water) (Table 1).

After classification of satellite images accuracy assessment procedure was applied an error matrix was created for determining quality of classification. Error matrix is the most appropriate way of assessment of classification accuracy quantitatively [49]. Error matrix shows number of sample units for each land cover class as compared to what really exists on the grounds [50]. Error matrix also provide calculated overall accuracy and kappa coefficient for each classification. Accuracy assessment procedure was applied to each classified image by total of 350 samples. These samples were distributed according to stratified random sampling algorithm for measuring classification accuracy of each LULC class. Validation of sample points was assessed by direct field observations, ArcGIS 10.2 base maps, and Google Maps.

3.4 LULC Change Detection and Analysis

After classification of images a multi-date post-classification change detection and analysis technique was applied for determination and quantify changes in LULC patterns from 1986 to 2015 based on producing a change matrix which allows identifying changes from one LULC class to another. The post-classification techniques give change information from one given date to another additionally calculated change statistics and maps [51]. Classified before and after images were compared in pixel scale. This method requires accurately classified images because accuracy of change map depends on accuracies of individually classified maps [52]. In this study accurately classified before and after images compared and change statistics and maps are created by ENVI software from 1986 to 2015. The results of change detection analysis were provided by cross-tabulation methods.

4. RESULTS

4.1 Accuracy Assessment

The accuracy assessment procedure was performed via examining truthfulness of classification of randomly selected points all over the imageries. Accuracy of classified images are usually calculated by ratio of correctly classified mapped area in comparison to reference data of total mapped area [53]. In total, 350 random points were selected randomly on both of classified images due to Lillesand et al. [46] definition as 50 random points for each

Table 1. Description of LULC classes

Land Cover Class	Description
Agricultural areas	Areas used for production of all types of agricultural products including fallow areas
Bare soil	Areas characterized by rock, gravel, sand, silt, clay, or other earthen material
Forests	Areas characterized by tree cover
Grasslands-meadows	Areas characterized by herbaceous vegetation or woody vegetation (maquis plants)
High intensity residentials	Highly developed areas with increased population
Low intensity residentials	Mixture of constructed materials vegetation. Constructed materials may account 30-80% of the cover.
Water	All areas of open water

Source: http://landcover.usgs.gov/classes.php/

LULC class. Stratified random sampling method was applied to select random points from all strata's (LULC classes) and error matrices were produced for each of the classified images. The overall classification accuracy levels for the two dates 1986 and 2015 are 92,82% and 93,36% respectively with Kappa statistics ranging from 0,90 to 0,91. These ranges are far above the minimum accuracy standards which Anderson et al. (1976) mentioned for imagery-based LULC maps. In comparison to the other LULC classes bare soils, water bodies, and low intensity residential areas have highest producer's accuracies both in 1986 and 2015.

4.2 Arealchanges in LULC

Comparative analysis of total areas of each LULC classes among two dates revealed that LULC classes altered noticeably in area (Fig. 2, Table 3). In 1986, Izmir Province covering 1205278,14 ha, was primarily made up by three LULC classes: Agricultural areas, forests, and grasslands/meadows. These three of seven classes cumulatively cover 95,93% of the entire province. In 2015, total area of Izmir province increased 726,53 ha and became 1206004,67 ha due to filling up some shoreline areas by construction materials and buildings. The same three LULC classes cover 92,98% of Izmir Province in 2015 also. Residential areas comprised 44322,47 ha and 70976,04 ha of study area by the years of 1986 and 2015 respectively and these amounts make 3.68% and 5,88% of Izmir Province. Bare soils are the LULC class which is the rarest in both years of 1986 and 2015.

Table 3 indicates that forests are the most common LULC class in both dates with 39,10% and 36,69% respectively. Area of forest have been decreased 28816,21 ha totally from 1986 to 2015 and this amount can be considered as acceptable regarding population growth in 29 years and other examples from Turkey. Grasslands-meadows are the second

Table 2. Accuracy assessment table of classified images

	Landsat TM - 1986			Landsat OLI - 2015		
	Producer's accuracy (%)	**User's accuracy (%)**	**Kappa statistics**	**Producer's accuracy (%)**	**User's accuracy (%)**	**Kappa statistics**
Agricultural areas	92,59	93,75	0,92	98,36	93,75	0,92
Forests	94,07	93,28	0,90	92,41	92,41	0,89
Grasslands-meadows	90	90	0,86	86,15	90,32	0,87
Bare soils	100	100	1,00	100	100	1,00
Low intensity Residentials	91,67	91,67	0,91	100	100	0,91
High intensity Residentials	94,44	94,44	0,94	94,74	100	1,00
Water	100	100	1,00	100	100	1,00
Overall classification Ac. (%)	92,82			93,36		
Overall Kappa statistics			0,90			0,91

Table 3. LULC classes and differences in Izmir province in 1986 and 2015

LULC classes	1986		2015		1986-2015 total gain or loss	
	Area (ha)	**Area (%)**	**Area (ha)**	**Area (%)**	**Area (ha)**	**Area (%)**
Agricultural areas	302885,9	25,1	347187,9	28,8	44302,1	14,6
Forests	471269,1	39,1	442452,8	36,7	-28816,2	-6,1
Grasslands-meadows	382123,2	31,7	331645,4	27,5	-50477,8	-13,2
Bare Soils	844,3	0,1	4421,1	0,4	3576,8	423,6
Low intensity residentials	9287,7	0,8	16182,3	1,3	6894,5	74,2
High intensity residentials	35034,8	2,9	54793,8	4,5	19759,1	56,4
Water	3833,2	0,3	9321,4	0,8	5488,2	143,2

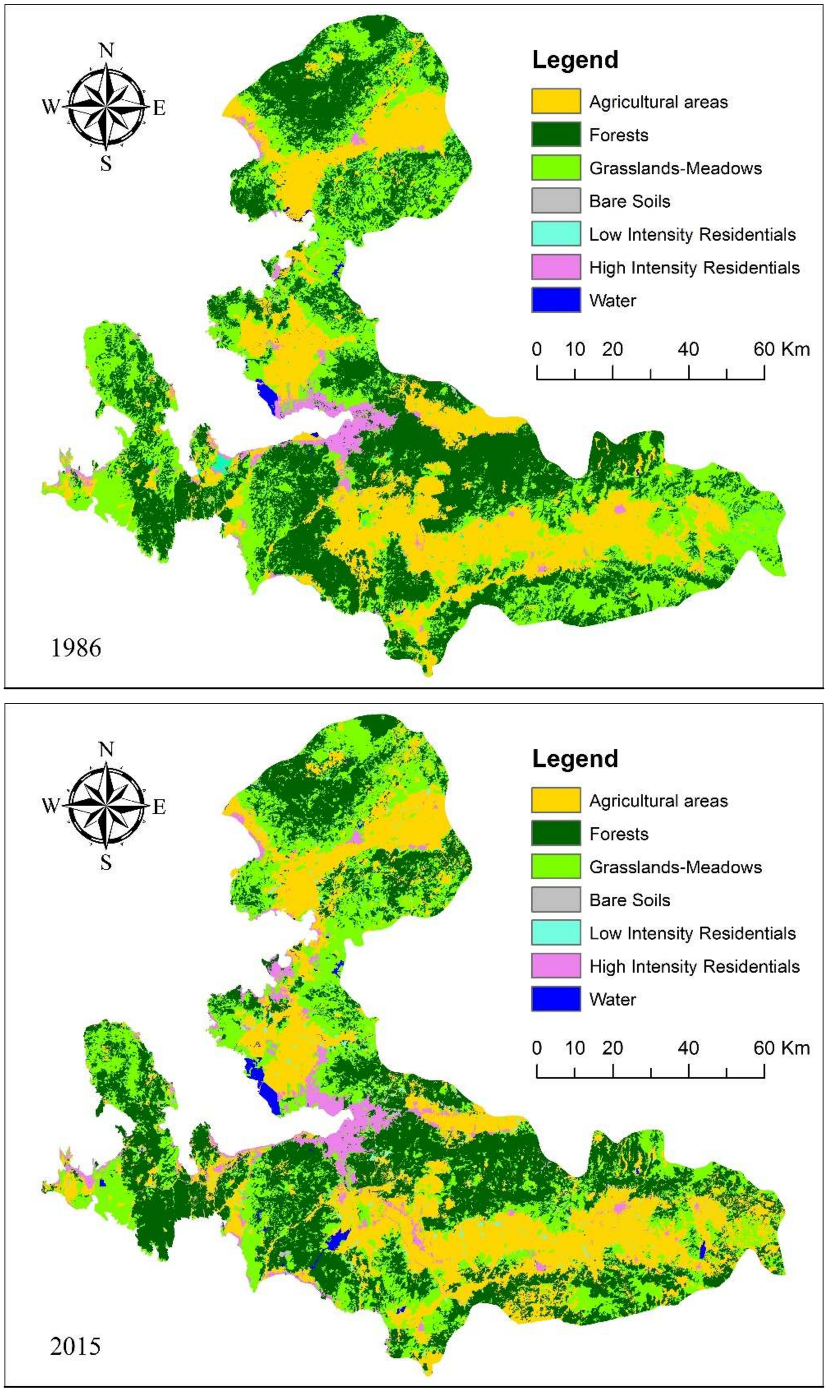

Fig. 3. LULC maps of Izmir province in 1986 and 2015

common LULC type in 1986 with 31,7% but these areas have become the third largest LULC type by 50477,81 ha loss in 2015 and this is the biggest area loose of any LULC class from 1986 to 2015. Agricultural areas increased 44302,02 ha between the dates due to mostly need of larger agricultural areas of growing rural population. Conversion of natural areas (forest/grasslands-meadows) to agricultural areas and settlements by rural population is a common environmental problem of rural areas in Turkey like other developing countries. Bare soils

Table 4. LULC change patterns in Izmir province from 1986 to 2015

Changed from	Changed to	Change (1986-2015)	
		Area (ha)	Area (%)
Agricultural areas	Forests	12744	4,2
	Grasslands-Meadows	20464	6,7
	Bare soils	348	0,1
	Low intensity residentials	6717	2,2
	High intensity residentials	12465	4,1
	Water	2451	0,8
Forests	Agricultural Areas	18235	3,9
	Grasslands-Meadows	94926	20,1
	Bare soils	2254	0,5
	Low intensity residentials	1738	0,4
	High intensity residentials	4125	0,9
	Water	606	0,1
Grasslands-meadows	Agricultural Areas	74959	19,4
	Forests	79205	20,5
	Bare soils	4234	0,3
	Low intensity residentials	4204	1,1
	High intensity residentials	11614	3,0
	Water	2628	0,7
Bare soils	Agricultural Areas	43	5,1
	Forests	55	6,5
	Grasslands-Meadows	321	38,0
	Low intensity residentials	0	0,0
	High intensity residentials	82	9,7
	Water	1	0,1
Low intensity residentials	Agricultural Areas	2672	28,8
	Forests	627	6,8
	Grasslands-Meadows	4204	17,1
	Bare soils	4	0,0
	High intensity residentials	1331	14,3
	Water	0	0,0
High intensity residentials	Agricultural Areas	2559	7,3
	Forests	1399	4,0
	Grasslands-Meadows	4204	12,0
	Bare soils	314	0,9
	Low intensity residentials	470	1,3
	Water	628	1,8
Water	Agricultural Areas	263	6,9
	Forests	16	0,4
	Grasslands-Meadows	177	4,6
	Bare soils	2	0,0
	Low intensity residentials	5	0,1
	High intensity residentials	102	2,7

were developed more than four times due to generally mining activities in study area. Low intensity and high intensity residential areas increased 74.23% and 56,4% by the years of 1986 and 2015 respectively because of rapidly growing population of the entire province. Open water areas increased 143,18% in study area where there are small amounts of natural lakes, due to dam construction from 1986 to 2015.

4.3 Analyses of Transitions in LULC

LULC change was quantified by cross-tabulation matrix of change detection tool of ENVI software. A cross-tabulation matrix is a major tool of LULC change analysis for displaying both amount of change and transitions between classes in different dates.

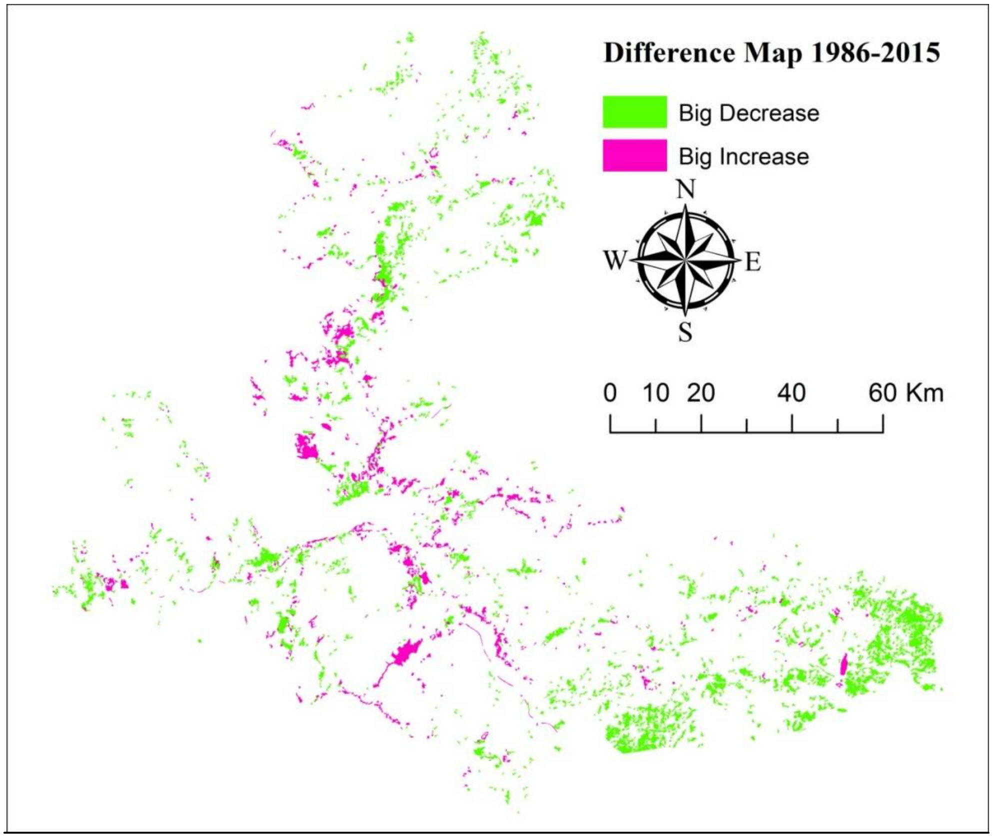

Fig. 4. Changed areas from 1986 to 2015

Table 4 displays LULC change transition patterns 29 years' time from 1986 to 2015 in borders of Izmir Province. According to table most of the agricultural areas remain same whereas there are still some change patterns. 4,2% of agricultural areas were converted to forests and plantation of olive trees could be the only explanation of this. Residential areas were covered 19182 ha (6,3%) of agricultural areas as an example of population growth. Rural population converted about 4% of forestlands to agricultural areas for having larger cultivatable lands. More than 20% of forests were converted to grasslands-meadows and this is the major example deforestation in study area. This conversion is usually the preliminary step of alteration of forested areas to agricultural areas. Almost 20% of grasslands-meadows were converted to agricultural areas by rural people for compensating their increased food demand in 29 years. Conversion of bare soils to another LULC class is a good example of land use management. In this case, 38% of bare soils were converted to grasslands-meadows and 9,7% of those empty areas were changed to highly developed residential areas. Some small amounts of bare soils were started to use agricultural activities and some other turned to forested lands.

Table 4 indicates high percentages of conversion from low intensity residential areas to agricultural areas and grasslands-meadows which cannot seem reasonable. The reason of this conversion is structural similarity among aforementioned classes and hardness of spectral and visual separability of them. Conversion from low intensity residentials to high intensity residentials is a natural result of rural population growth. More than 11% of water areas were converted to agricultural areas and grasslands-meadows in 29 years due to increased drought after 2000. These areas were either covered by natural vegetation or turned to cultivated lands.

4.4 Change Map

Change detection maps indicate more than 20% change in pixel values (digital number-DN). Thus, change maps which are created by comparing pixel values without classification, can give meaningful results and this technique is especially useful in determining high-value impervious surfaces. Change maps which are created by classified satellite imagery, do not have pixel information although they provide results according to user-defined order of land cover classes. Therefore, these maps may display areas where land cover class conversions-transitions occurred but give meaningful information about DN value change on a pixel. For instance, Fig. 4 water surfaces which were formed dam construction in some local areas, were indicated as “Big Increase” areas. Although water surfaces have very low DN values comparing bare soils, agricultural areas or developed surfaces. Change detection map of this study was used to show the places which change occurred. Fig. 4 states change all over the study area.

5. CONCLUSIONS

This study confirms effectiveness of satellite imagery in change detection analysis of both natural and developed areas in Mediterranean environment. Thematic maps derived from Landsat TM and OLI imagery successfully display deforestation, urban sprawl, land degradations, and habitat fragmentation [54].

Analysis of thematic maps by the years of 1986 and 2015 resulted total amount of changes in LULC classes and class conversions one to another in Izmir Province. First of all, increase of high intensity residential and low intensity residential areas in population growth especially in urbanized areas due to wealth of economic resources. Expansion of agricultural areas and narrowing of forests and grasslands/meadows are some other typical signs of population growth also in the study area. These signs of destruction and fragmentation of natural environment should be considered by central or local managers of the province. Furthermore, impacts of nature’s causes such as climate change, erosion, flood, and mining activities, should be analyzed and adaptation strategies should be developed. In total 64,2% of Izmir province was covered by natural environment either forests or grasslands-meadows in 2015 and this amount is far more ahead of Turkey's average. Transitions among forests and grasslands/meadows were considered evidences of both reforestation and deforestation or fragmentation. Conversions from natural areas (forests, grasslands/meadows) to semi-natural areas (agricultural areas) or impervious surfaces (roads, urban areas) are major information of environmental impact assessment and adaptation strategies [55].

This work also endorses applicability of Landsat imagery in change detection studies considering their time period and spatial resolution. Landsat TM and OLI imagery with 30 m spatial resolution, are available from 1984 and 2013 respectively and Landsat archive is the most used data source due to its free availability. Combination of spectral segmentation and visual analysis resulted highly accurate thematic maps (about 93%) using Landsat imagery and confirmed usefulness of 30 m imagery in change detection studies in large areas.

COMPETING INTERESTS

Author has declared that no competing interests exist.

REFERENCES

1. Turkish Statistical Institute (TSI). Population statistics; 2015. Available:https://biruni.tuik.gov.tr/medas/ (Accessed 01/11/2016)
2. Marraccini E, Debolini M, Moulery M, Abrantes P, Bouchier A, Chery JP, Sanz E, Sabbatini T, Napoleone C. Common features and different trajectories of land cover changes in six Western Mediterranean urban regions. Applied Geography. 2015;62:347-356.
3. Leontidou L. Postmodernism and the city: Mediterranean versions. Urban Studies. 1993;30(6):949-965.
4. Lu YH, Feng X, Zeng Y, Liu Y, Chang R, Sun G, Wu, B. A policy driven large scale ecological restoration: Quantifying ecosystem services changes in the Loess Plateau of China. PLoS ONE. 2012;7. Available:http://dx.doi.org/10.1371/journal.pone.0031782
5. Brueckner JK. Urban sprawl: Diagnosis and remedies. International Regional Science Review. 2000;23(2):160-171.
6. Frondoni R, Mollo B, Capotorti G. A landscape analysis of land cover change in the Municipality of Rome (Italy): Spatio-temporal characteristics and ecological implications of land cover transitions from 1954 to 2001. Landscape and Urban Planning. 2011;100:117-128.
7. Gounaridis D, Koukoulas S. Urban land cover thematic disaggregation, employing

datasets from multiple sources and Random Forests modeling. International Journal of Applied Earth Observation and Geoinformation. 2016;51:1-10.
8. Moeira F, Fontes I, Dias S, Batista eSilva J, Loupa-Ramos I. Contrasting static versus dynamic-based typologies of land cover patterns in the Lisbon metropolitan area: Towards a better understanding of peri-urban areas. Applied Geography. 2016;75:49-59.
9. Hewitt R, Escobar F. The territorial dynamics of fast-growing regions: Unsustainable land use change and future policy challenges in Madrid, Spain. Applied Geography. 2011;31(2):650-667.
10. Çakir G, Ün C, Baskent EZ, Kose S, Sivrikaya F, Keleş S. Evaluating urbanization, fragmentation and land use/land cover change pattern in Istanbul City, Turkey from 1971 to 2002. Land Degradation & Development. 2008;19(6): 663-675.
11. Molowny-Horas R, Basnou C, Pino J. A multivariate fractional regression approach to modeling land use and cover dynamics in a Mediterranean landscape. Computers, Environment and Urban Systems. 2015;54:47-55.
12. Salvati L, Sateriano A, Bajocco S. To grow or to sprawl? Land Cover Relationships in a Mediterranean City Region and Implications for Land Use Management. Cities. 2013;30:113-121.
13. Guan D, Li H, Inohae T, Su W, Nagaie T, Hokao K. Modeling urban land use change by the integration of cellular automaton and Markov model. Ecological Modelling. 2011;222:3761-3772.
14. Sala OE, Chapin FS, Armesto JJ, Berlow E, Bloomfield J, Dirzo R. Global biodiversity scenarios for the year 2100. Science. 2000;287:1770-1774.
15. Daily GC, Matson PA. Ecosystem services: From theory to implementation. Proc. Natl. Acad. Sci. USA. 2008;105:9455–9456.
16. Turner BL, Lambin EF, Reenberg A. The emergence of land change science for global environmental change and sustainability. Proceedings of the National Academy of Sciences of the United States of America. 2007;104:20666–20671.
17. Lambin EF, Meyfroidt P. Global land use change, economic globalization, and the looming land scarcity. Proceedings of the National Academy of Sciences of the United States of America. 2011;108(9): 3465-3472.
18. Peng J, Liu YH, Shen H, Han Y, Pan YJ. Vegetation coverage change and associated driving forces in mountain areas of Northwestern Yunnan, China using RS and GIS. Environmental Monitoring and Assessment. 2012;184: 4787–4798.
19. Zhang ZX, Wang X, Zhao XL, Liu B, Yi L, Zuo LJ, Hu SG. A 2010 update of National land use/cover database of China at 1:100000 scale using medium spatial resolution satellite images. Remote Sensing of Environment. 2014;149:142–154.
20. Ahmad S, Avtar R, Sethi M, Surjan A. Delhi's land cover change in post transit era. Cities. 2016;50:111–118.
21. Friedl MA, Sulla-Menashe D, Tan B, Schneider A, Ramankutty N, Sibley A, Huang X. Modis collection 5 global land cover: Algorithm refinements and characterization of new datasets. Remote Sensing of Environment. 2010;114:168–182.
22. Zhu Z, Fu Y, Woodcock E, Olofsson P, Vogelmann JE, Holden C, Wang M, Dai S, Yu Y. Including land cover change in analysis of greenness trends using all available Landsat 5, 7, and 8 images: A case study from Guangzhou, China (2000–2014). Remote Sensing of Environment. 2016;185:243-257.
23. Arvor D, Jonathan M, Meirelles MSP, Dubreuil V, Durieux L. Classification of MODIS EVI time series for crop mapping in the state of Mato Grosso, Brazil. International Journal of Remote Sensing. 2011;32:7847–7871.
24. Van Lier OR, Luther JE, Leckie DG, Bowers WW. Development of large-area land cover and forest change indicators using multi-sensor Landsat imagery: Application to the Humber River Basin, Canada. International Journal of Applied Earth Observation and Geoinformation. 2011;13(5):819-829.
25. Veldkamp A, Lambin EF. Predicting land-use change. Agriculture, Ecosystems and Environment. 2001;85:1e6.
26. Lu M, Chen J, Tang H, Rao Y, Yang P, Wu W. Land cover change detection by integrating object-based data blending model of Landsat and MODIS. Remote Sensing of Environmet. 2016;185:374-386.

27. Hussain M, Chen DM, Cheng A, Wei H, Stanley D. Change detection from remotely sensed images: From pixel-based to object-based approaches. ISPRS Journal of Photogrammetry and Remote Sensing. 2013;80:91–106.
28. Yu W, Zhou W, Qian Y, Yan J. A new approach for land cover classification and change analysis: Integrating backdating and an object-based method. Remote Sensing of Environment. 2016;177:37–47.
29. Deng JS, Wang K, Hong Y, Qi JG. Spatio-temporal dynamics and evolution of land use change and landscape pattern in response to rapid urbanization. Landscape and Urban Planning. 2009;92:187–198.
30. Eklundh L, Johansson T, Solberg S. Mapping insect defoliation in Scots pine with MODIS time-series data. Remote Sensing of Environment. 2009;113:1566–1573.
31. Berberoglu S, Akin A. Assessing different remote sensing techniques to detect land use/cover changes in the eastern Mediterranean. International Journal of Applied Earth Observation and Geoinformation. 2009;11:46–53.
32. Desclée B, Bogaert P, Defourny P. Forest change detection by statistical object-based method. Remote Sensing of Environment. 2006;102(1):1–11.
33. An K, Zhang J, Xiao Y. Object-oriented urban dynamic monitoring—A case study of Haidian District of Beijing. Chin. Geog. Sci. 2007;17:236–242.
34. Cleve C, Kelly M, Kearns FR, Moritz M. Classification of the wildland–urban interface: a comparison of pixel-and object-based classifications using high-resolution aerial photography. Computers, Environment and Urban Systems. 2008;32:317–326.
35. Flanders D, Hall-Beyer M, Pereverzoff J. Preliminary evaluation of eCognition object-based software for cut block delineation and feature extraction. Canadian Journal of Remote Sensing. 2003;29:441–452.
36. Zhang X, Du S. Learning selfhood scales for urban land cover mapping with very-high-resolution satellite images. Remote Sensing of Environment. 2016;178:172-190.
37. Baatz M, Schäpe A. Multiresolution segmentation: An optimization approach for high quality multi-scale image segmentation. Angewandte Geographische informationsverarbei- tung. 2000;8:12–23.
38. Zhou W, Huang G, Cadenasso ML. Does spatial configuration matter? Understanding the effects of land cover pattern on land surface temperature in urban landscapes. Landscape and Urban Planning. 2011;102:54–63.
39. Meddens AJH, Hicke JA, Vierling LA, Hudak AT. Evaluating methods to detect bark beetle-caused tree mortality using single-date and multi-date Landsat imagery. Remote Sensing of Environment. 2013;132:49-58.
40. Fu P, Weng Q. Consistent land surface temperature data generation from irregularly spaced Landsat imagery. Remote Sensing of Environment. 2016;184:175-187.
41. Moran MS, Jackson RD, Slater PN, Teillet PM. Evaluation of simplified procedures for retrieval of land surface reflectance factors from satellite sensor output. Remote Sensing of Environment. 1992;41(2–3): 169–184.
42. Harris Geospatial. SPEAR Atmospheric Correction, Dark object subtraction; 2016.
43. Benz UC, Hofmann P, Willhauck G, Lingenfelder I, Heynen M. Multi-resolution, object-oriented fuzzy analysis of remote sensing data for GIS-ready information. ISPRS Journal of Photogrammetry and Remote Sensing. 2004;58(3-4):239–258.
44. Forghani A, Cechet B, Nadimpalli K. Object-based classification of multi-sensor optical imagery to generate terrain surface roughness information for input to wind risk simulation. Geoscience and Remote Sensing Symposium (IGARSS), Barcelona-Spain; 2007.
45. Zeng Y, Zhang J, van Genderen JL, Zhang Y. Image fusion for land cover change detection. International Journal of Image and Data Fusion. 2010;1(2):193-215.
46. Lillesand T, Kiefer R, Chipman J. Remote sensing and image interpretation, Fifth ed. John Wiley and Sons; 2004.
47. Anderson JR, Hardy EE, Roach JT, Witmer RE. A land use and land-cover classification system for use with remote sensor data. Washington, DC: U.S. Government Printing Office, Geological Paper 964; 1976.
48. Lillesand TM, Kiefer RW. Remote sensing and image interpretation, Fourth Edition. New York, NY: John Wiley and Sons; 2000.

49. Congalton RG, Plourde L. Quality Assurance and accuracy assessment of information derived from remotely sensed data. In Manual of Geospatial Science and Technology, Edited by John Bossler. London: Taylor & Francis; 2002.
50. Congalton RG. How to assess the accuracy of maps generated from remotely sensed data. In Manual of Geospatial Science and Technology. 2nd ed. Boca Raton, FL: CRC Press. 2010;403–421.
51. Yuan F, Sawaya KE, Loeffelholz BC, Bauer ME. Land cover classification and change analysis of the Twin cities (Minnesota) Metropolitan area by multitemporal Landsat remote sensing. Remote Sensing of Environment. 2005;98:317–328.
52. Lambin EF, Strahler AH. Change-vector analysis in multitemporal space: A tool to detect and categorize land-cover change processes using high temporal-resolution satellite data. Remote Sensing of Environment. 1994;48(2):231–244.
53. Sewnet A. Land use/cover change at Infraz watershed by using GIS and remote sensing techniques, Northwestern Ethiopia. Intl. J. River Basin Management. 2016;14(2):133–142.
54. Pontius RG, Shusas E, McEachern M. Detecting important categorical land changes while accounting for persistence. Agriculture, Ecosystems and Environment. 2004;101:251–268.
55. Mei A, Manzo C, Fontinovo G, Bassani C, Allegrini A, Petracchini F. Assessment of land cover changes in Lampedusa Island (Italy) using Landsat TM and OLI data. Journal of African Earth Sciences. 2016;122:15-24.

Peer-review history:
The peer review history for this paper can be accessed here:
http://sciencedomain.org/review-history/19810