INVESTIGATION OF CHANGES USING LANDSCAPE METRICS: THE CASE OF IZMIR GAZIEMIR

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ABSTRACT:

This study aims to create Land Cover/ Land Use (LC/ LU) maps of Gaziemir district in İzmir, Turkey based on an enhanced Urban Atlas nomenclature using Geographic Object Based Image Analysis (GEOBIA) techniques. Land changes occurred in the region for twelve- year period are investigated using landscape metrics created from LC/LU maps. 2006 dated Spot 5 image and 2018 dated SPOT 6 images were used as main Earth Observation data to create LC/LU maps. Open source geospatial data was also integrated into classification to better identify some LC/LU classes such as Discontinuous Medium Density Urban Fabric, Fast Transit Roads and Associated Land, Airport and to increase total classification accuracy. Overall classification accuracy of 2006 and 2018 dated LC/LU maps are 83.89%, 86.67% respectively. Several landscape metrics such as Total Class Area (TA), Number of Patch (NP), Core Area Percentage of Landscape (CPLAND), Mean Euclidean Nearest Neighbor Distance (ENN_MN), The Interspersion & Juxtaposition Index (IJI) metrics were calculated from highly detailed LC/LU maps and results were compared to better understand landscape changes occurred between 20016 and 2012.

1. INTRODUCTION

Most of the world's population lives in urban areas. Based on a report released by United Nations, 54 % of the world's population lives in urban areas and it is expected that this amount will reach up to 66 % by 2050. Continuous dynamic urban transformation processes, particularly the expansion of urban populations and urbanized areas worldwide, are affecting all natural and human systems at all geographical scales (Miller and Small, 2003; Thapa and Murayama, 2009). Similar to the global case, most of the population in Tukey is living in urban areas as a result of population growth, increase of industrial areas and development of transportation infrastructures in these regions. Monitoring urban areas and creating up-to-date and detailed thematic maps of urban areas are important to better understand urban environments, to support decision makers for future planning of urban areas and to comprehensively analyze ecological problems that could be caused as a result of urbanization (Thapa ve Murayama, 2009). Satellite images are widely used in different applications such as determination of urban, forest and agricultural areas, city planning, detection of plant species and diseases and monitoring the environmental problems (Sertel ve Ormeci, 2009; Akay, 2014). Use of high and very high resolution satellite images offer significant advantages, especially in urban mapping and analysis of spatial / temporal changes in urban areas (Sertel and Akay, 2015; Sertel et al., 2018). In the classification of very high- resolution images, Geographic Object Based Image Analysis (GEOBIA) is widely used and superior compared to traditional pixel-based technique in terms of obtaining more thematic classes with higher accuracy (Blaschke, 2010; Weng, 2012; Alganci et al., 2013).

LC/LU maps are used in various research and various areas. One of these areas is landscape pattern analysis by using landscape metrics. Landscape Metrics are different indices developed from thematic maps to characterize the geometric and spatial characteristics of the regions (McGarigal, 2002). These metrics provide information on the spatio-temporal arrangement of landscape components and help us to understand changes in landscape over the years from visual and ecological perspectives (Miller et al., 2005; Gökyer E.,2013; Sertel et al, 2018).

The main objective of this study is to evaluate the land changes in Gaziemir district of Izmir between 2006 and 2018 using landscape metrics created from high resolution LC/LU maps. For this purpose, SPOT images of obtained in 2006 and 2018 were pre- processed and classified. Object based classification is applied using various features and indices to create the two dated LC/LU map of the area. Open source geo-spatial data was incorporated into object-based classification to increase the classification accuracy and determine some LCLU classes. Totally 23 LC/LU classes were created based on an enhanced Urban Atlas nomenclature. Area-based accuracy assessment with 180 random areas was performed to determine the classification accuracy of two LC/LU maps. The overall accuracy of 2006 and 2018 LC/LU maps are calculated as; 83.89%, 86.67% respectively. For each year, class and landscape level landscape metrics were evaluated to better quantify land changes in the study region.

2. STUDY AREA AND DATA

2.1 Study Area

Gaziemir district of Izmir metropolitan city was selected as the study area. Izmir is the third most populated city of Turkey and is socio-economically important for the country (Url-1). Gaziemir is the greenest district of Izmir located in the center and attracts attention with the development of industry and trade in recent years. This district gained importance with its superior housing potential as well as its industrial and commercial power due to being located within the boundaries of the Aegean Free Zone and having International Adnan Menderes Airport (Url-2).

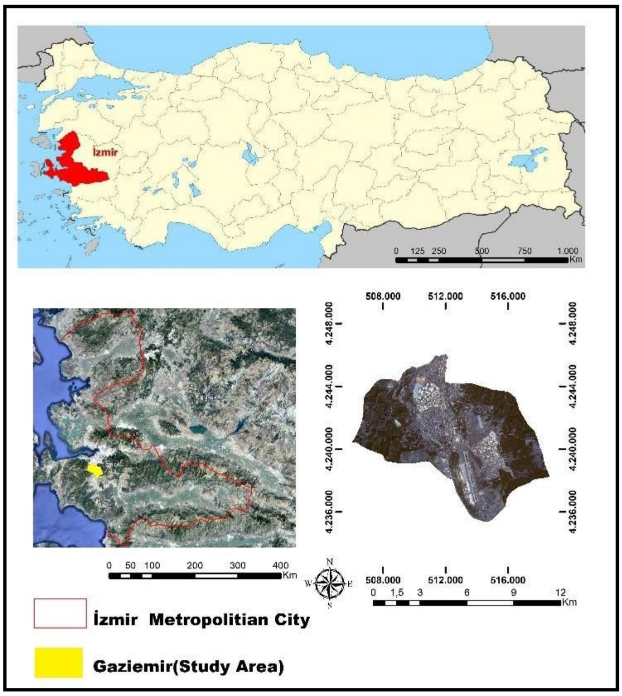

Figure 1. Study Area

Gaziemir's surface is approximately 75 km^2 and has various landscape characteristics such as agricultural areas, water bodies, and urban areas (Figure 1).

2.2 Data

SPOT 5 and SPOT 6 images were used in this study. SPOT 5 satellite was launched in May 2002 and it has multispectral sensors with 10 m spatial resolution in Green, Red, Near infrared (NIR) and Short-wave infrared regions of electromagnetic spectrum in addition to 2.5 m and 5 m resolution Panchromatic sensor (URL-3). On the other hand, SPOT 6 was launched in September 2012 and it has multispectral sensors with 6 m spatial resolution in Red, Green, Blue and Near-Infrared (NIR) regions of electromagnetic spectrum in addition to 1.5 m resolution Panchromatic sensor (URL-4).

In this research, SPOT 5 and SPOT 6 images acquired respectively on 09.09.2006 and 06.08.2018 were used as primary geographic data source for creating LC/LU maps. Vector data can be integrated into object-based approach as thematic layers for better segmentation and more accurate classification. Urban Atlas and CORINE nomenclature are used together for class definitions. Additionally, Open Street Map (OSM) vector data was used as a thematic layer for road extraction. Imperviousness maps were used for the extraction of artificial surfaces. The Imperviousness Density 2015 (IMD 2015) and 2006 (IMD 2006) maps were obtained from Copernicus website and used for the detection of the urban classes. Wikimapia was also used as a vector thematic layer for some of the artificial classes which are basically representing land use. Furthermore, opensource online maps (e.g. Google Earth, Google Street Viewer etc.) were used for visual interpretation of the study area to form further decision trees. Lastly, parcel data obtained from Ministry of Food, Agriculture and Livestock was used for accuracy assessment of the classification results.

PCI-Geomatica software was used for preprocessing of the SPOT images. QGIS software was used to organize vector data. eCognition Developer software was used for object-based classification. ArcGIS software was used for data conversion, accuracy assessment and visualization and lastly FRAGSTAT software was used for calculation of landscape metrics.

3. METHODOLOGY

After obtaining SPOT 5 and SPOT 6 images, different processes were applied to create land cover/land use maps for 2006 and 2018 years. Both satellite images were first pre-processed and geometrically corrected. Afterwards, object-based classification was performed using various spectral information, indices and features in order to create LC/LU map of the region. As a next step, area-based accuracy assessment was conducted to determine the accuracy of these two maps. Finally, Landscape Metrics were calculated and changes that occurred during 12 years were evaluated.

3.1 Pre-Processing

6 August 2018 dated SPOT 6 image was acquired as ortho-rectified and pan-sharpened to 1.5-meter resolution and 9 September 2006 dated SPOT 5 image was obtained as 10m multispectral (MS) + 2.5 panchromatic (PAN) data set. Each image was sub-setted by using Gaziemir district boundary.

A reference very high-resolution Pleiades image of the area was used for further improvement of geometric quality; which was geometrically corrected by using GCP coordinates obtained from Topographical Maps created by Turkish General Command of Mapping with 1m RMSE. In the first stage of the pre-processing, each image was geometrically corrected using the first order polynomial model and by use of homogenously distributed 25 ground control points (GCPs) collected from reference Pleaides image. During geometric correction, all RMSE (Root Mean Square Error) values were better than 2 m.

Finally, 10-m resolution SPOT 5 multispectral data set was subjected to data fusion with 2.5-m resolution panchromatic data and a 2.5 m resolution pan-sharpened image was obtained. In this process, University of New Brunswick (UNB) algorithm, which maintains the spectral characteristics of multispectral data, (Zhang, 2004, Alganci, 2014) was used.

3.2 Classification

The object-based classification stage consists of two steps namely segmentation and classification. Some thematic layers were used as ancillary vector data during segmentation and classification processes to obtain better result s for some LC / LU classes. In this study, a harmonized LC/LU system consists of European Union CORINE and Urban Atlas nomenclature is used.

The most suitable segmentation parameters for each of the LC/LU classes were determined considering the difference and size of the spectral characteristics of the classes and illustrated Table-1. In order to obtain the most suitable objects for LC/LU classes with diverse characteristics, several multi resolution segmentations were performed.

Table 1: Multi-resolution segmentation parameters for 2018 and 2006

Class Name	Scale	Shape	Compactness
Inland waters	150	0.6	0.5
Artificial Surfaces sub-classes	1000,350,200, 100	0.9,0.8,0.3, 0.6	0.5, 0.6, 0.5 0.5
Agricultural Areas sub-classes	150, 100	0.7, 0.6	0.5, 0.4
Forest and Semi-natural Areas sub-classes	800, 500, 100	0.7,0.5, 0.6	0.4, 0.6, 0.5

Table 2: Classes in the study area (Used Classes).

Urban Atlas/ CORINE code	**Name**
11100	Continuous Urban Fabric
11210	Discontinuous Dense Urban Fabric
11220	Discontinuous Medium Density Urban Fabric
11230	Discontinuous Low-Density Urban Fabric
11240	Discontinuous Very Low-Density Urban Fabric
12100	Industrial, Commercial, Public, Military and Private Units
12210	Fast Transit Roads and Associated Land
12220	Other Roads and Associated Land
12230	Railways and Associated Land
12400	Airports
13100	Mineral Extraction and Dump Sites
13300	Construction Sites
13400	Land Without Current Use
14100	Green Urban Areas
14200	Sports and Leisure Facilities
21000	Arable Land
22000	Permanent Agriculture
23000	Pastures
24000	Complex and mixed cultivation
31000	Forests
32000	Scrub and/or herbaceous vegetation associations
33000	Open spaces with little or no vegetation
51000	Inland Waters

Different parameters can be used for each LC/LU class in the classification of each image. For example, for the determination of the Fast Transit Roads and Associated Land class within Artificial surfaces subclass which is one of the LC/LU classes in the study area, the scale parameter, shape and compactness are assigned as 100, 0.6, 0.5 respectively for both images. Additionally, scale parameter, shape and compactness values for Agricultural Areas are assigned as 150, 0.7, 0.5 respectively for 2006, 100, 0.7, 0.5 respectively for 2018 (Table-1).

In this study, classification of the urban areas are done according to the Urban Atlas, and agricultural and forest areas are defined by the CORINE nomenclature. There are totally 23 LC/ LU classes in the study area and the classes used are listed in table 2.

In the classification process, various spectral band ratios and differences, indices and functions explained in Table 3 were used for each year. In addition, a minimum mapping unit rule of 0.25 ha for Artificial Areas Surfaces and subclasses and a minimum mapping unit rule of 1 ha for all other classes were applied in both classification and segmentation procedures.

The classification phase was started with the determination of the Inland Waters. Firstly, the Normalized Differential Water index (NDWI) was used to determine the appropriate thresholds. Inland water class was successfully classified using NDWI index and area function.

Secondly, Fast Transit Roads and Associated Land, Other Roads and Associated Land, and Railways and Associated Land were determined using Open Street Map (OSM) vector data with a 10 and 1-meter buffers as suggested in the Urban Atlas Mapping Guide (Mapping Guide for Europe Urban Atlas, 2012). Because of the distinctive geometries of the members in this class, the geometric functions Asymmetry, Length /Width, Brightness were used in addition to the vector data.

At the third step, NDVI was used to distinguish vegetated and artificial surfaces areas at both dates (2018, 2006) in the study area. Industrial, Commercial, Public, Military and Private Units, Green Urban Areas, Sports and Leisure Facilities, Airports were identified using Wikimapia vector data including Shape index, Coordinate (X, Y Center) and Area functions.

After that, Continuous Urban Fabric, Discontinuous Dense Urban Fabric, Discontinuous Medium Density Urban Fabric, Discontinuous Low-Density Urban Fabric, Discontinuous Very Low-Density Urban Fabric classes were classified by using the vector layers of Imperviousness data and brightness values. IMD 2015 (Figure 3) was used to create urban related classes of 2018 whereas IMD 2006 was used for 2006 urban-related classes.

In the next step, classification of Agricultural Areas was performed. After determining the appropriate segmentation parameter for each year, multi-temporal NDVI, Ratio of NIR, Mean value of NIR feature and indices, were used to define the class of Arable Land in both dated images. Afterwards, Permanent Agriculture fields were distinguished with the use of various Texture and Haralick features.

Texture functions used for this purpose are; Entropy, Homogeneity, Dissimilarity and Contrast in all directions. In addition, Shape Index and Rectangular Fit functions were utilized in the formal separation of both Arable and Permanent Agricultural Areas. Pastures, Complex and mixed cultivation LC/ LU classes were determined by the combination of NDVI, Maximum differences, Mean value of NIR and Standard deviation of NIR.

Table 3: Features and indices (; Sertel and Akay, 2015; eCognition© Developer – Reference Book, 2017; Sertel et al.,2018;).

Features/Indices	Explanations
NDVI	Normalized difference vegetation index; NDVI = (Layer 4 – Layer 1)/ (Layer 4 + Layer 1)
NDWI	Normalized difference water index; NDWI = (Layer 2 – Layer 4) /(Layer 2 + Layer 4)
Ratio of NIR	The amount that NIR contributes to the total brightness
Mean value of NIR	Mean intensity values in the NIR band
Brightness	Mean of the brightness values in an image
Maximum difference	Calculates the mean difference between the feature value of an image object and its neighbors of a selected class
Standard deviation of NIR	The standard deviation of the NIR band derived from intensity values of all pixels in this channel
Shape index	Measure of overall shape complexity
Border index	Describes how jagged an image object is; the more jagged, the higher its border index
Asymmetry	Compares an image object with an approximated ellipse around the given image object
Rectangular fit	Describes how well an image object fits into a rectangle of similar size and proportions
Density	The distribution in space of the pixels of an image object
Area	The total number of pixels in the object
Length/Width	The length-to-width ratio of the main line of an object
Coordinate (X, Y Center)	X-position and Y-position of the center of an image object. The calculation is based on the center of gravity (geometric center) of the image object in the internal map.
Related border to	Determines the relative border length an object shares with neighbor objects of a certain class
Distance to	The distance (in pixels) of the image object's center concerned to the closest image object's center assigned to a defined class
Texture after Haralick	Texture features are used to evaluate the texture of image objects. Texture after Haralick features are calculated from gray level co-occurrence matrix.

Next, after applying a bigger scale segmentation to the unclassified areas, classification of Forest was conducted by using NDVI Maximum difference and Standard deviation. Then, Scrub and/or herbaceous vegetation associations, Open spaces with little or no vegetation fields were determined with a smaller scale factor as shown in Table 1 and using NDVI, Area, Related border to, and Distance to features.

Finally, Industrial, Mineral Extraction and Dump Sites Construction Sites, Land Without Current Use were identified using NDWI, NDVI, Brigthness", "Border Index" and "Density functions. With these steps, most of the study area was classified into appropriate classes. However, at the final control stage, some manual corrections were conducted to separate some mixed LC/LU classes.

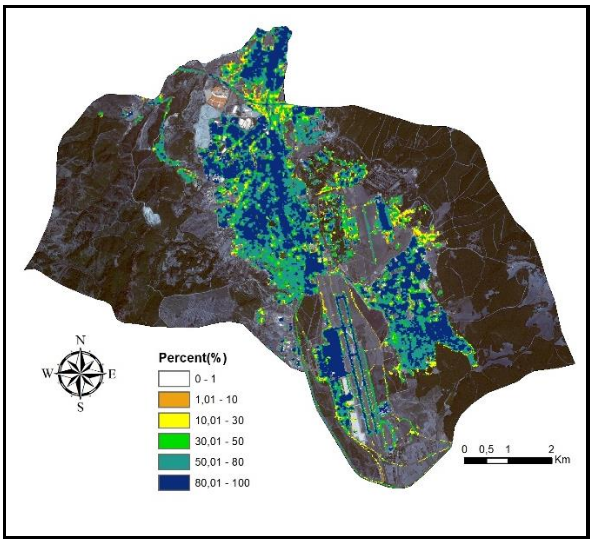

Figure 2. IMD 2015 for Gaziemir.

After classification processes, an error matrix was created by using 180 randomly selected reference areas for each year. Results were evaluated on the basis of producer's and user's accuracies and presented in section 4.

3.3 Landscape Metrics

In this study, class level metrics and landscape level metrics were used to determine the spatial structures of the study area and for investigation of changes occurred in 12 years. To understand and evaluate the landscape patterns, the most meaningful class level and landscape level metric groups were created.

Landscape metrics used in this study are Number of Patches (NP), Patch Density (PD), Largest Patch Index (LPI), Total Edge (TE), Edge Density (ED), Total Class Area /(TC/CA), Area-Weighted, Mean Shape Index (SHAPE_AM), Mean Patch Shape Index (SHAPE_MN), Euclidean Nearest Neighbor Distance Area Weighted Mean (ENN_AM), Interspersion& Juxtaposition Index, Contagion Index(CONTAG). These metrics are described in Table 4 and metrics values were calculated using 8 × 8 m cell neighborhood rule in FRAGSTAT (McGarigal, 2002) software for each year.

Table 4: Used Landscape Metrics and Description (McGarigal et al.,2002; Aksu 2012, Plexida et al.,2014, McGarigal et al., 2015; Simsek and Sertel, 2018; Sertel et al.,2018; Luo et al., 2019).

Metric	Type	Description
Percentage of Landscape (PLAND)	Class	The percentage of the landscape comprised of a particular patch type
Number of Patches (NP)	Class	Number of patches of corresponding patch type (class)
PatchDensity (PD)	Class	Number of patches of corresponding patch type (class) per unit area
Largest Patch Index (LPI)	Class	The area (m^2) of the largest patch in the landscape divided by total landscape area (m^2)
Total Edge (TE)	Class	The sum of the lengths (m) of all edge segments in the landscape
EdgeDensity (ED)	Class	The sum of the lengths (m) of all edge segments in the landscape, divided by the total landscape area (m^2)
Total Class Area /(TC/CA)	Class	The sum of the class areas.
Area-Weighted Mean Shape Index (SHAPE_AM)	Class	Weighting patches according to their size, on contrary to LSI in which the total length of edge is compared to a landscape with a standard shape (square) of the same size and without any internal edge
Mean Patch Shape Index (SHAPE_MN)	Class	The shape index measures the shape complexity of the patch compared to the standard shape (square) of the same size.
Euclidean Nearest Neighbor Distance Area-Weighted Mean (ENN_AM)	Class	Shortest straight-line distance (m) between a focal patch and its nearest neighbor of the same class
Interspersion&Juxtaposition Index (IJI)	Class	It is the amount of scattering observed with the maximum possible scattering for the patch type in a given number.
Contagion Index (CONTAG)	Landscape	To the full likelihood that the cell of a particular type of patch will be adjacent to the same type of cells

4. RESULTS

4.1 Classification results

LC/LU maps of 2018 and 2006 years were produced according to enhanced Urban Atlas nomenclature by applying OBIA technique on multi-temporal SPOT 6 and SPOT 5 images. Figure 3 shows the original images and classification results.

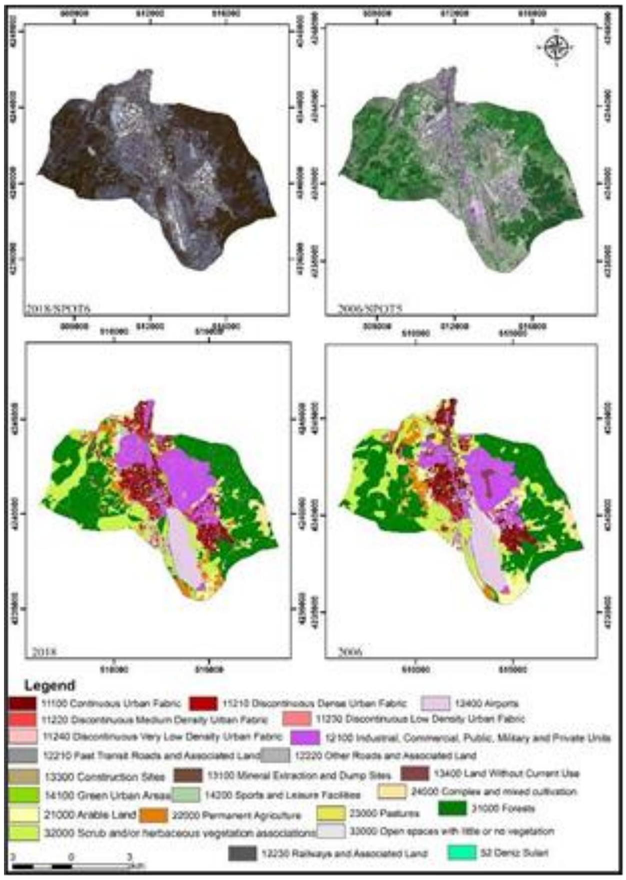

Figure 3. Classification results.

When generated maps are evaluated, it can be seen class diversity is quite a lot in the region. Totally 23 classes are represented in the classification.

In general, thematically detailed highly diverse classes are hard to identify by using only satellite images. However, integration of thematic layers into the classification has facilitated the procedure and improved the classification accuracy. Moreover, some land use classes, such as Discontinuous Very Low-Density Urban Fabric, Industrial, Commercial, Public, Military and Private Units, Fast Transit Roads and Associated Land, which could not be directly deducted from SPOT could be successfully classified by means of open-source geospatial information. Further analysis of classification results were conducted with landscape metrics and presented in the upcoming sections.

4.2 Accuracy Assessment

To evaluate thematic accuracies of two LC/LU maps, an area-based accuracy assessment was utilized. A very high-resolution

Pleaides image of the study area and Google Earth (especially for 2006 LC/LU map) images were used to generate reference polygons to fulfill accuracy assessment.

Reference points were selected between 5-20 percent of the land cover / use class. A total number of 180 random areas which were obtained proportionally with 100m x 100m (1ha) dimensions and 50m x 50 m (0.25ha) were created and same areas were used for the accuracy assessment of two different year LC/LU maps.

Table 5. Accuracy assessment results of 2018 LC/LU map

Class Code	Producer's (%) Accuracy	User's (%) Accuracy
11100	81.82	100.00
11210	87.50	77.78
11220	80.00	80.00
11230	75.00	75.00
11240	100.00	75.00
12100	86.67	92.86
12210	83.33	100.00
12220	100.00	90.91
12230	100.00	100.00
12400	100.00	100.00
13100	71.43	83.33
13300	100.00	100.00
13400	100.00	60.00
14100	100.00	83.33
14200	100.00	100.00
21000	91.67	84.62
22000	57.15	80.00
23000	62.50	83.33
24000	85.71	66.67
31000	75.00	83.33
32000	73.33	61.11
33000	66.67	80.00
51000	100.00	100.00
Overall Accuracy	**86.67 %**	
Kappa Statistics	**0.859**	

Error matrix of each thematic map was created and results of the accuracy analyses are illustrated in Table 5 and 6.

Overall accuracy values of 2006 and 2018 were found as 83.89% and 86.67 %, respectively.

4.3 Landscape Metrics

After classification and accuracy assessment, landscape metrics were calculated in FRAGSTAT software for class and landscape levels. For two different years, class level metrics results are shown in Table 7,8, 9 and landscape level metrics are shown in Table 10.

Between 2006 and 2018, LC/LU classes, which have the largest area in terms of CA, are Forests and Scrub and/or herbaceous vegetation associations respectively. However, the decrease in the number of the Largest Unit (LPI), especially in the forest areas between 2006 and 2018, means that there is a serious fragmentation in this class. (Table-7/indicated by bold).

Metric values of Sports and Leisure Facilities class increased specifically for PD and CA. This means that the areas used for this purpose within the region are more in 2018 than in 2006 (Table- 7/indicated by bold).

PD metric for Arable Land and Permanent Agriculture class significantly increased between 2006 and 2018 which illustrated that more patches are observed in 2018 most probably caused by fragmentation and regional disconnections (Table-7/indicated by bold).

Table 6. Accuracy assessment results of 2006 LC/LU map

Class Code	Producer's (%) Accuracy	User's (%) Accuracy
11100	90.91	90.91
11210	75.00	85.71
11220	80.00	80.00
11230	100.00	80.00
11240	100.00	100.00
12100	80.00	92.31
12210	83.33	100.00
12220	100.00	83.33
12230	80.00	100.00
12400	100.00	100.00
13100	85.71	85.71
13300	100.00	100.00
13400	100.00	60.00
14100	100.00	83.33
14200	100.00	100.00
21000	91.67	84.62
22000	57.15	80.00
23000	62.50	83.33
24000	85.71	66.67
31000	75.00	83.33
32000	73.33	61.11
33000	66.67	80.00
51000	100.00	100.00
Overall Accuracy	**83.89 %**	
Kappa Statistics	**0.829**	

For both years, it is observed that the units of all classes do not have an appropriate geometric shape when the 23 LC/LU classes within the study area is interpreted according to SHAPE_AM and SHAPE_MN values. In the evaluation of the region for the selected period, it is evident that the changes are skewed in both years (Table- 8/indicated by bold).

One of the most important findings is that the value of Total Edge (TE) and Edge Density (ED) metrics reduced even though the increase of NP and PD metrics for Forest class (Table-7-8/indicated by bold). This shows that the units that are increasing in this time interval are not large enough to form the edge.

SHAPE_MN increased due to the decrease of NP metric of Fast Transit Roads and Associated Land and Other Roads and Associated Land (Table-7-8/indicated by bold).

ENN_MN is a metric showing the distance of a unit to the other unit with its own characteristics. This metric allows comments on the connectivity of landscapes over time. Changes in land use, have irreversible effects on the connectivity of the patches (Aksu,2012). There is a decrease in ENN_MN values for Industrial, Commercial, Public, Military and Private Units (Table-9/indicated by bold), with the increase of the construction in these areas; it can be said that the connectivity of the patch decreases while the fragmentation increases.

Table 7. Class Metrics with regard to Total Class Area, Patch Density and Number of Patch

Class Code	Class Level Metrics (Total Class Area, Patch Density and Number of Patch)							
	CA_2006	**CA_2018**	**NP_2006**	**NP_2018**	**PD _2006**	**PD _2018**	**LPI _2006**	**LPI _2018**
11100	468,06	438,45	3171	3294	23,51	24,31	0,12	0,04
11210	133,72	244,54	3658	3223	27,12	23,78	0,03	0,04
11220	17,77	32,90	1609	1192	11,93	8,80	0,01	0,01
11230	5,03	16,73	1080	586	8,01	4,32	0,01	0,02
11240	1,78	3,79	306	166	2,27	1,23	0,00	0,01
12100	828,41	1109,98	353	426	2,62	3,14	0,27	1,22
12210	40,65	46,92	**18**	**13**	0,13	0,10	0,25	0,30
12220	268,08	362,80	**1149**	**353**	8,52	2,61	0,92	1,28
12230	27,06	28,22	1	1	0,01	0,01	0,20	0,21
12400	530,57	435,31	25	21	0,19	0,16	2,99	2,97
13100	34,77	49,37	7	18	0,05	0,13	0,14	0,13
13300	5,42	5,85	36	7	0,27	0,05	0,01	0,01
13400	151,29	13,74	98	19	0,73	0,14	0,19	0,01
14100	44,46	53,87	54	92	0,40	0,68	0,03	0,07
14200	**8,08**	**36,45**	**8**	**10**	**0,06**	**0,07**	**0,02**	**0,14**
21000	336,20	160,83	198	1982	**1,47**	**14,63**	0,37	0,15
22000	224,50	329,17	51	1755	**0,38**	**12,95**	0,35	0,16
23000	96,31	46,34	54	173	0,40	1,28	0,16	0,09
24000	192,28	167,75	62	34	0,46	0,25	0,55	0,63
31000	**2332,81**	**2358,66**	**1549**	**359**	**11,49**	**2,65**	**6,27**	**2,14**
32000	**1231,42**	**1065,77**	1432	1141	10,62	8,42	**1,19**	**1,11**
33000	71,10	38,90	80	641	0,59	4,73	0,18	0,20
51000	**2,87**	**2,58**	5	1	0,04	0,01	0,01	0,02

Table 8. Class Metrics with regard to Shape

Class Code	Class Level Metrics (Shape Metrics)							
	TE_2006	**TE_2018**	**ED_2006**	**ED_2018**	**SHP_MN6**	**SHP_MN18**	**SHP_AM6**	**SHP_AM18**
11100	519955	520116	38,55	38,38	**1,46**	**1,46**	**2,78**	**2,04**
11210	235955	338919	17,50	25,01	**1,33**	**1,41**	**2,54**	**2,31**
11220	57645	64902	4,27	4,79	**1,26**	**1,28**	**2,21**	**2,37**
11230	28165	22491	2,09	1,66	**1,22**	**1,17**	**2,01**	**2,16**
11240	8385	5244	0,62	0,39	**1,22**	**1,14**	**1,47**	**1,65**
12100	319695	367311	23,71	27,11	**1,65**	**1,65**	**2,05**	**2,07**
12210	45113	50229	3,35	3,71	**2,31**	**2,82**	**14,28**	**15,43**
12220	1392863	1379997	103,28	101,84	**1,89**	**2,87**	**110,36**	**98,20**
12230	28000	27699	2,08	2,04	**13,43**	**13,02**	**13,43**	**13,02**
12400	49595	39660	3,68	2,93	**1,89**	**1,33**	**3,47**	**3,66**
13100	8860	14763	0,66	1,09	**1,66**	**1,68**	**1,79**	**1,77**
13300	3655	3243	0,27	0,24	**1,11**	**1,33**	**1,37**	**1,29**
13400	54195	9351	4,02	0,69	**1,41**	**1,49**	**1,69**	**1,48**
14100	28635	37260	2,12	2,75	**1,56**	**1,73**	**1,66**	**2,03**
14200	4020	8847	0,30	0,65	**1,36**	**1,36**	**1,27**	**1,45**
21000	104750	123312	7,77	9,10	**1,55**	**1,20**	**2,06**	**2,49**
22000	58520	193251	4,34	14,26	**1,68**	**1,23**	**2,50**	**2,71**
23000	39060	26142	2,90	1,93	**1,77**	**1,29**	**2,17**	**2,02**
24000	52600	51048	3,90	3,77	**1,54**	**2,00**	**3,49**	**3,33**
31000	**324983**	**402072**	**24,10**	**29,67**	**1,25**	**1,55**	**5,95**	**3,26**
32000	386330	389169	28,65	28,72	**1,35**	**1,50**	**3,23**	**2,88**
33000	31825	29004	2,36	2,14	**1,36**	**1,21**	**3,54**	**2,47**
51000	930	1014	0,07	0,07	**1,12**	**1,57**	**1,60**	**1,57**

Table 9. Euclidean Nearest Neighbor Distance Area Weighted Mean (ENN_AM) and Interspersion&Juxtaposition Index (IJI).

Class Code	ENN_MN2006	ENN_MN_ 2018	IJI 2006	IJI 2018
11100	7,11	6,93	30,47	37,24
11210	10,47	9,64	42,16	54,50
11220	19,94	20,90	56,49	64,67
11230	20,99	28,27	55,59	70,56
11240	31,40	63,13	54,15	68,50
12100	**24,82**	**22,63**	52,21	41,53
12210	13,83	11,81	69,87	68,09
12220	13,42	18,00	69,93	68,34
12230	N/A	N/A	65,31	55,60
12400	25,71	28,44	42,33	44,58
13100	72,95	103,62	51,06	57,79
13300	**198,84**	**1031,77**	50,90	45,26
13400	136,48	393,29	67,64	45,26
14100	198,22	155,74	66,84	51,21
14200	230,07	848,47	59,18	61,65
21000	22,81	17,18	58,83	67,84
22000	27,44	20,20	55,01	62,45
23000	134,13	144,37	**74,96**	69,05
24000	**140,90**	**178,05**	57,34	51,51
31000	16,89	22,74	46,56	49,99
32000	20,45	19,77	57,96	56,65
33000	9,92	39,44	37,05	**78,31**
51000	1900,15	N/A	26,94	16,76

The significant raise in the ENN_MN value of Construction Sites (Table-9/indicated by bold) exhibits the decrease of fragmentation over the years. This might be inferring that the Construction Sites in the region either reduced or they are existing site areas in the area. On the contrary, increase of ENN_MN values for Complex and mixed cultivation between the years of 2006 and 2018 exhibits the increase of fragmentation (Table-9/indicated by bold). It indicates that the LC/LU class was scattered over the region within twelve years.

For two years, the IJI values of each LC / LU class ranges from 40% to 70%. However, it is seen that the IJI values of Pastures in 2006 and Open spaces with little or no vegetation in 2018 reaches 75% indicating the scattered structure of these classes (Table-9/indicated by bold).

CONTAG provides information on how fragmented the landscape s are or how they are aggregated. The values of CONTAG metrics for study area are 69,88 and 70,37 ha 2006 and 2018 respectively. (Table 10). The CONTAG metric value calculated for the whole region area shows that the heterogeneity in the region is close for two years.

Table 10. CONTAG metric results for two years

Landscape level metric	2006	2018
CONTAG	69,88	70,37

5. CONCLUSION&DISCUSSION

Thanks to the LC/LU maps produced using high-resolution satellite images, it is very easy to determine the development and change of cities and to learn about landscape and urban planning. In the use of the object-based classification method, open source geo-information, which has been checked for compatibility with high-resolution satellite images, can be a good source of data to improve results. Selection of the most appropriate landscape metric groups is an important subject for accurate information by LC/LU maps. Landscape metrics such as Number of Patches (NP), Patch Density (PD), Largest Patch Index (LPI), Total Edge (TE), Edge Density (ED), Total Class Area /(TC/CA), Area-Weighted Mean Shape Index (SHAPE_AM) are useful indicators to interpretation of city structure and changes. It is observed that almost all classes in the district of Gaziemir are scattered in the region and heterogeneity unchanged in twelve years. In particular, artificial areas (Continuous Urban Fabric, Discontinuous Dense Urban Fabric,,,,etc.) indicate there is no specific ground factor in the creation. Thanks to the metrics, it was possible to interpret the landscape and the change that cannot be visually understood for each land cover / use class in twelve-year period in Gaziemir.

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