

Assessment of land use and land cover change using spatiotemporal analysis of landscape: case study in south of Tehran

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Abstract In the recent years, dust storms originating from local abandoned agricultural lands have increasingly impacted Tehran and Karaj air quality. Designing and implementing mitigation plans are necessary to study land use/land cover change (LUCC). Land use/cover classification is particularly relevant in arid areas. This study aimed to map land use/cover by pixel- and object-based image classification methods, analyse landscape fragmentation and determine the effects of two different classification methods on landscape metrics. The same sets of ground data were used for both classification methods. Because accuracy of classification plays a key role in better understanding LUCC, both methods were employed. Land use/cover maps of the southwest area of Tehran city for the years 1985, 2000 and 2014 were obtained from Landsat digital images and classified into three categories: built-up, agricultural and barren lands. The results of our LUCC

analysis showed that the most important changes in built-up agricultural land categories were observed in zone B (Shahriar, Robot Karim and Eslamshahr) between 1985 and 2014. The landscape metrics obtained for all categories pictured high landscape fragmentation in the study area. Despite no significant difference was evidenced between the two classification methods, the object-based classification led to an overall higher accuracy than using the pixel-based classification. In particular, the accuracy of the built-up category showed a marked increase. In addition, both methods showed similar trends in fragmentation metrics. One of the reasons is that the object-based classification is able to identify buildings, impervious surface and roads in dense urban areas, which produced more accurate maps.

Keywords LUCC · Landscape fragmentation · Remote sensing · GIS · Tehran · Environmental impacts

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Introduction

Land use and land cover change (LUCC) is a major driver of global change which exerts a profound influence on humans and the environment. Although both natural and anthropogenic factors are responsible for LUCC, the role of humans in LUCC has become more prominent during the last few decades (Wijitkosum 2016; Rawat et al. 2013). Changes caused by human activities on the environment, especially in the arid zones, may have adverse impacts on biodiversity, water quality, soil degradation, wind erosion and carbon

cycling, as well as on the ability of biological systems to support human needs (Li et al. 2013; Vadrevu et al. 2015; Yu et al. 2011). Monitoring LUCC offers opportunity to enhance our understanding of the interactions between human activities and the environment (Lambin and Veldkamp 2001; Liang et al. 2014). Satellite remote sensing is the most common data source for detection, quantification and mapping of LUCC because of its repetitive data acquisition, digital format suitable for computer processing and accurate georeferencing procedures (Gómez et al. 2016; Lu et al. 2013).

Remote sensing systems differ in the level of detail or resolution they can capture. Spatial resolution is one of the most important factors which could affect LUCC information generated from remote sensing data (Soulard and Wilson 2015). Based on spatial resolution, satellite imageries can be categorized into low-, medium- and high-spatial resolution. Three types of these sensors have been used to analyse LUCC. Usman et al. (2015) used multi-temporal MODIS (low-spatial resolution) Normalized Difference Vegetation Index (NDVI) data for classification and Land use/land cover change detection in Pakistan from 2005 to 2012. Lu et al. (2010) used Quick Bird (high-spatial resolution) imagery to classify land cover in a complex urban-rural landscape in Lucas do Rio Verde, Brazil. Many researchers in the fields of remote sensing and geospatial sciences select images in a medium category because they have acceptable resolution for common requirements and relatively acceptable cost (some satellites owners provide free accessible images). Landsat satellite data is the most widely used data type for land cover mapping and has provided earth observation data to meet a wide range of information needs since 1972 (Gómez et al. 2016; Iqbal and Khan 2014). Rigorous calibration and consistency in the radiometry of the Landsat sensors, in particular the Thematic Mapper (TM), Enhanced Thematic Mapper Plus (ETM+) and Operational Land Imager (OLI), makes the Landsat image archive a strong example for the benefits of calibration and data interoperability. Given operational imperatives, other data sources (e.g. SPOT, IRS and ASTER) can be availed upon to offer complementary image coverage (Wulder et al. 2008).

In order to monitor LUCC from remotely sensed data, many changes in detection techniques have been developed and used, such as post-classification, image differencing, principle components analysis and vegetation index differencing (Mohamed and Mobarak 2016).

Post-classification change detection is the most well-used technique (Foody 2002). Post-classification comparison methods detect land cover change by comparing independently produced classifications of images from different dates (Yuan et al. 1998a, 1998b). Pixel-based and object-based classifications are two approaches for post-classification (Sertel and Alganici 2016). The most traditional pixel-based post-classification approaches are based exclusively on the digital number of the pixels itself. Thereby, only the spectral information is used for the classification. The situation is even more complicated when extracting certain features of interest only. As a result, it produces the salt-and-pepper-effect pseudo-colour layer (Sertel and Alganici 2016). To overcome the limitations of the pixel-based classification, the object-based classification has been suggested (Karami et al. 2015).

Object-based image analysis is quickly gaining acceptance among remote sensor scientists and users and has demonstrated great potential for classification and detection change of high-spatial resolution imagery in heterogeneous urban environments (Im et al. 2008). Object-based image analysis has been applied in various fields, especially for forest mapping and land use land cover classification (Kim et al. 2011). Object-based image analysis has generally had better success with narrow-band and high-spatial resolution data (Yang 2011). It has been proposed as an alternative analysis framework that can mitigate the deficiency associated with the pixel-based approach. Object-based image analysis approaches for analysing remotely sensed data have been established and investigated since the 1970s (Blaschke 2010). The classification process, in this case, begins with a segmentation of neighbouring pixels into homogenous units or objects. One of the advantages of segmentation is that it creates objects representing land use and cover types that may be spectrally variable at the pixel level. Another advantage is that objects can approximate real-world features better than pixels. A more detailed description of image segmentation and classification is given in Dingle Robertson and King (2011) and Jawak et al. (2015).

One of the direct consequences of LUCC is landscape fragmentation. Fragmentation occurs when large patches are divided into smaller patches by human activities such as construction of road networks, railroads, agriculture, urbanization and so forth (Anderson et al. 1976; Kizos et al. 2010). Landscape metrics are computed to quantify landscape fragmentation after image

classification that can be done by different methods and LUCC analysis. The application of landscape metrics in landscape fragmentation analysis has received an increasing attention in the recent years (Chouvardas and Vrahnakis 2009; Mitchell et al. 2015; Schindler et al. 2008). Landscape metrics are useful in applying the concepts of landscape fragmentation in landscape monitoring and planning (Barau and Qureshi 2015). Such an approach provides an objective description of different aspects of landscape structures and patterns (McGarigal et al. 2002).

The accuracy of the image classification and the capability of the classifier to produce highly representative thematic maps influence the reliability of the metrics produced to analyse the process of fragmentation. Although several studies have compared pixel- and object-based classification methods, few studies have compared the effect those methods may have on landscape metrics derived from thematic maps (Newman et al. 2011). Accordingly, this study compares a commonly used pixel-based method of image classification with an object-based method and examines the effects of these two methods on landscape fragmentation. The information on those changes is great importance to land use planners in order to act toward a better balance the effects of human activities and the environment.

To compare post-classification and capability in landscape studies, the objective of this study is providing a spatiotemporal analysis of LUCC by pixel- and object-based image classification methods and their effect on landscape fragmentation in Tehran and Alborz provinces, which demography and economy have been deeply modified by a massive rural exodus. Historically, LUCC in this area has been influenced by high human population density and caused severe environmental issues, among which dust storms resulting from wind erosion of abandoned agricultural lands. The causality relationship between LUCC and the increase of soil erosion by strong winds has however never been evidenced in this region of the globe.

Materials and methods

Study area

The study area covers approximately 4600 km² stretching from 35°N and 35°56'N in latitude, and 51°13'E and 51°30'E in longitude, which corresponds

to the south of Tehran and of Alborz provinces (Fig. 1). The elevation ranges from 800 to 1700 m above sea level. The study area is surrounded by mountains from southeast to northwest, while it is bounded by the Kavir Salt Desert in the south-southeast. However, more than 1800 villages remain in the study area, populated by farmers living from fertile soils (Talebi and Ardakani 2011).

The two provinces, Tehran and Alborz, are the most heavily populated in Iran. According to the latest census in 2012, Tehran and Alborz have a population of over around ten million inhabitants together. Rapid rural-urban migration and population growth in the city have significantly influenced urban fabric so that in the recent years, the area of green space is increasingly being less and land use change is happening on a large scale in these areas (Saeifar and Mohammadnia 2015). This would be the root cause for many socioeconomic problems among citizens as well as lots of environmental adverse consequences.

While in the past, the local rivers were primarily used to irrigate the agricultural lands, the share of surface water for agriculture has drastically decreased in the recent decades, mainly as a result of the construction of several major dams for drinking water and power generation, like the Latyan, Lar, Taleghan and Karaj dams (Motiee et al. 2001). As a dramatic result of chronic shortages in water supply, a large fraction of fertile lands have been abandoned by owners, or remained uncultivated, hence, potentially exposed to wind erosion. In addition, most of the agricultural lands in the vicinity of the cities were converted into residential or industrial areas. To make it easier to analysis and to have practical results in political boundaries, the study area was divided in three zones following the existing administrative boundaries: zone A consists in Karaj and Nazarabad; zone B includes the southwest part of Tehran region, namely Shahriar, Robot Karim and Eslamshahr and zone C consists in the south (Shahr-Rey) and southeast parts of Tehran (Pakdasht and Varamin) (Fig. 1).

Data

A set of Landsat-5 Thematic Mapper (TM) images acquired on May 1985 and May 2000, and Landsat-8 Operational Land Imager (OLI) images acquired on May 2014, were used to map LUCC changes in the study area (Fig. 1). All images were downloaded from

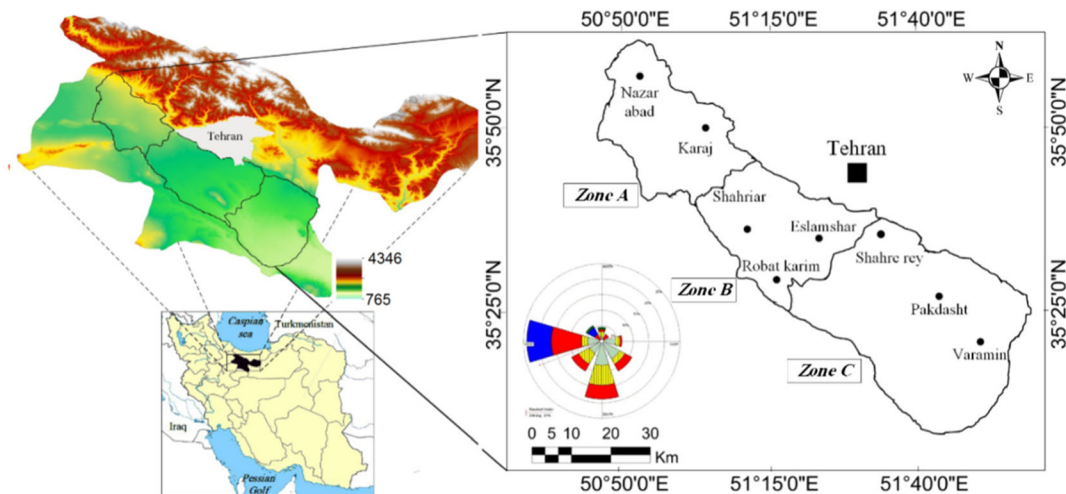


Fig. 1 Location of study area

the Earth Resources Observation and Science Center Earth Resources Observation and Science (EROS) (2014). Since the study area stretches over more than one scene, three scenes were acquired for each period of time. TM images were acquired in six spectral bands with a spatial resolution of 30 m. Landsat image 8 (OLI sensor) provided eight spectral bands with a spatial resolution of 30 m, one panchromatic band with a spatial resolution of 15 m and two thermal bands with a spatial resolution of 100 m which did not used in this study. More characteristics are presented in the Supplementary Table 1.

Additionally, a set of 150 ground control points were collected using a GPS for training sites (from Garmin, Model: Etrex Vista HCX). More recently, the Google Earth tool has quickly developed and has been widely used in many sectors. The high-spatial resolution images released from Google Earth, as a free and open data source, have been treated as ancillary data to collect the training or testing samples for land use/cover classification and validation or used as a visualization tool for land use/cover maps (Yu and Gong 2012). Therefore, in this study, in order to evaluate the ground control points, Google Earth has been used (Elkhrachy 2015).

Pre-processing

To start, a geo-correction was performed in three steps: the TM image was first registered to the Universal Transverse Mercator (UTM) zone 39°N with WGS84 (World Geodetic System) datum projection by using 40 ground control points, for which the total root mean

square error (RMSE) of 0.51 pixel was achieved. Then, the TM image was used as a reference and the rest of the images were co-registered using an image-to-image procedure with less than half pixel error. Finally, all images were resampled to 30 m using the nearest neighbourhood method (Johnson 2015).

At the next step, atmospheric correction was carried out using the dark object subtraction (DOS) method (Gilmore et al. 2015). Then, the study area was extracted from the mosaic image through an on-screen interoperation and digitizing. The optimum index factor (OIF) approach was applied in order to select the best band combinations among the spectral bands (Zhong et al. 2014). Based on the OIF results, the combination (2, 3, 4) was selected for 1985 and 2000 and (3, 4, 5) for 2014.

Image classification and spatiotemporal analysis

Land use/cover classification system presented in this article includes the most generalized first and second levels (Supplementary Table 2) (Anderson et al. 1976). Each image was classified into built-up, barren and agricultural land classes, using both pixel-based (ENVI 4.8) and object-based classifications (eCognition Developer 64). After the image classification, a post-classification comparison change detection algorithm was used to determine LUCC between 1985 and 2014, with six combinations of 'from-to' change information. The pixel-by-pixel nature of this change allowed to quantify both the areal extent and the spatial distribution of LUCC (Yang and Lo 2002).

Image classification methods

Pixel-based classification

The overall objective of pixel-based image classification approach is to automatically categorize all pixels in an image into land cover. Therefore, each image was subjected to a supervised classification. This method involves the selection of training samples for each class, which are homogenous groups of pixels representative of the land use category to be identified in the image (Matinfar et al. 2007). Training sites were used to generate spectral signatures for built-up, barren and agricultural lands classes. By using the maximum likelihood (Karakus and Karabork 2016), the most commonly used classification algorithm and all unclassified pixels were assigned to classes based on the probability that a pixel belongs to that particular class.

Object-based classification

Object-based image analysis comprises two parts: (1) image segmentation and (2) classification based on objects' features in spectral and spatial domains. Image segmentation is a kind of regionalization, which delineates objects according to a certain homogeneity criteria and at the same time, requiring spatial contingency (Zou et al. 2016). By segmentation, the image is divided into homogeneous, continuous and contiguous objects. Several parameters are used here to guide the segmentation result. The scale parameter determines the maximum allowed heterogeneity for the resulting image objects. The colour criterion defines the weight with which the spectral values of the image layers contributes to image segmentation, as opposed to the weight of the shape criterion. Smoothness is used to optimize image objects with regard to smooth borders, and compactness allows optimizing image objects with regard to compactness (Baatz et al. 2004). The parameters to guide the segmentation process were: scale factor 10, colour factor 0.8 and smoothness 0.5. Those parameter settings were decided after a visual check that the produced segments optimally represented the primitive earth objects. The segmented images were classified by standard nearest neighbour (NN) classifier using the same set of training samples as those used for pixel-based classification (Matinfar et al. 2007).

To describe the degree to which the derived image classification agrees with reality, classification accuracy

were used (Janssen and Vanderwel 1994). The error matrix is the most common method to assess the classification accuracy. Therefore, accuracy assessment using an error matrix was assessed for 1985 and 2000 and 2014 pixels, and object-based classification using four measures of accuracy: overall accuracy, user's accuracy, producer's accuracy and kappa coefficient. Overall accuracy is the simplest and one of the most popular accuracy measures. It is computed by dividing the total correct (i.e. the sum of the major diagonal) by the total number of pixels in the error matrix. Producer's accuracy indicates the probability of reference pixel being correctly classified; it is a measure of omission error. User's accuracy is the probability of classified pixel actually represents that category on the ground (Congalton 1991). The kappa coefficient measure attempts to control for a chance agreement by incorporating the off-diagonal elements as a product of the row and column of the error matrix (Cohen 1960).

In calculating accuracy assessment, there were only ground control points for image classification in 2014, but none for 2000 and 1985. Any aerial photograph or other high-resolution image could be of use for deriving the previous land use reference data. In an attempt to overcome those problems, the identification and use of temporally invariant ground features as calibration and validation data for the classification of past dates of imagery were used. This approach addresses many of the challenges associated with retrospective mapping, while overcoming the limitations of signature extension by (a) only requiring one calibration and validation dataset for all images and (b) allowing each image to generate its own signature specific to its inherent spectral and spatial properties (Fortier et al. 2011).

To use this methodology, images from three separate dates spanning a 15-year period between 1985 and 2000 and 2000 and 2014 were selected for land cover classification. Using the imagery, temporally invariant samples were identified to create an invariant data set. This invariant data set was then applied to classify land cover in each image to test the plausibility of using invariant calibration data in a long-term retrospective (Fortier et al. 2011).

Landscape fragmentation analysis

In order to analyse fragment process, landscape metrics were calculated with FRAGSTATS 4.2 (McGarigal and Marks 2014). Many metrics can be used to quantify spatial heterogeneity. However, some metrics are

correlated with others, or respond to multiple components of spatial patterns, which make them difficult to interpret (McGarigal and Marks 2014). Five metrics were selected and calculated based on published studies (Botequilha Leitão and Ahern 2002; Corry and Nassauer 2005; Hargis et al. 1998; McGarigal et al. 2002; Tinker et al. 2003). They include the patch density (PD), edge density (ED), mean patch area (MPA), mean shape index (MSI) and interspersion and juxtaposition index (IJI) (Table 1). These indices were used to quantify fundamental and structural landscape characteristics. In brief, ED standardizes edge to a per-unit area basis that facilitates comparisons among landscapes of varying sizes. MPA and PD of a particular patch type reflect both the amount of a patch type (composition) and its spatial distribution (configuration). Because MPA and PD vary as a function of the spatial pattern complexity of the landscape, it is often more appropriate to consider those indices of landscape configuration. MSI measures the average patch shape, or the average perimeter-to-area ratio, for a particular patch type (class) or for all patches in the landscape. IJI measures the extent to which patch types are interspersed (not necessarily dispersed); higher values result from landscapes in which the patch types are well interspersed (i.e. equally adjacent to each other), whereas lower values characterize landscapes in which the patch types are poorly interspersed, i.e. disproportionate distribution of patch type adjacencies (McGarigal 2001).

Table 1 Fragmentation indices

Metrics	Description
Patch density (PD)	The number of patches per 100 ha (number/100 ha)
Edge density (ED)	The total length of patch edge per ha (m/ha)
Mean patch area (MPA)	The average area of the patches (ha)
Mean shape index (MSI)	Mean patch shape complexity equals to 1 when all patches are squared and increases without limit as patch shape becomes more irregular. It is the simplest and most straightforward measure of overall shape
Interspersion and juxtaposition index (IJI)	The adjacency of each patch with all other class types (%). Extent to which patches of different land uses/covers are interspersed

Results

Accuracy assessment

According to Table 2, the overall accuracy of the object-based classification was better than for the pixel-based classification. This was also the case for the overall kappa statistics. Overall accuracy ranged between 80.8 and 87% for pixel-based approach and 83.1 and 90.2% for the object-based one. The most accurate classification for both approaches was allocated to the year 2014, possibly due to the higher image quality and on-time training sample sites.

Additionally, relatively high accuracy for built-up area, both producer's one and user's one, is achieved by the object-oriented approach. The producer's accuracy and user's accuracy for built-up area by the object-oriented method are 89.5 and 81.1% for 1985, 91 and 90% for 2000 and 91.2 and 93.1% for 2014, respectively. While the corresponding producer's accuracy and user's accuracy by the pixel-based method are 77.5 and 80.8% (1985), 83 and 89.7% (2000) and 84 and 88.6% (2014), obviously, the object-oriented is more reliable to delineate built-up areas. Because of more accurate results from the object-based approach, the results of this approach only are presented in the LUCC section hereafter.

LUCC

Figure 2 shows the image classification following the pixel- and object-based approaches. The object-based classified images present a more homogenous appearance, while the pixel-based approach led to a less clear picture, in consistency with the studies of Karami et al. (2015). Statistics of LUCC from pixel- and object-based approach are summarized in Supplementary Table 3 based on the three above-defined zones A, B and C.

In zone A (Karaj, Nazarabad), the results of object-based image classification approach showed that the built-up category area increased by 7.6% (67 km²) together with the urban demography from 1985 to 2000, and an additional 10.4% (91 km²) moved to the built-up category from 2000 to 2014 (Fig. 3 a, b and Supplementary Table 3). Changes from agricultural and barren land categories (1985 to 2014) to built-up areas were 13 and 22.2%, respectively (Table 3). However, the classification results did not display a clear trend in this period for the agricultural and barren land

Table 2 Overall accuracy (%), kappa coefficient (%) and user’s (UA) and producer’s (Pro A) accuracies (%) for post-classifications using the pixel- and object-based classification

methodologies for 1985, 2000 and 2014 in Tehran and Alborz provinces. Rows: classification results; columns: ground truth

	Pixel based				Object based			
	1	2	3	UA	1	2	3	UA
1985								
Built-up	38	6	3	80.8	43	9	1	81.1
Agricultural land	7	50	8	76.9	2	55	7	85.9
Barren land	4	5	51	85	3	6	46	83.2
Pro A	77.5	81.9	82.2		89.5	78.5	85.1	
Overall kappa		82.3				87.2		
Overall accuracy		80.8				83.1		
2000								
Built-up	44	2	3	89.7	45	3	2	90
Agricultural land	5	52	6	82.5	2	53	5	88.3
Barren land	4	5	49	84.4	3	4	49	87.9
Pro A	83	88	84.4		91	87.2	87.8	
Overall kappa		85.2				86.2		
Overall accuracy		87				87		
2014								
Built-up	39	1	4	88.6	41	0	3	93.1
Agricultural land	2	50	3	90.9	3	51	3	89.4
Barren land	5	7	58	82.8	1	6	60	89.5
Pro A	84.7	86	89.2		91.2	89.3	90.8	
Overall kappa		88				92.1		
Overall accuracy		87				90.2		

Classification results (in rows) and ground truth (in columns)

ProA producer’s accuracy in %, UA user’s accuracy in %, 1 built-up, 2 agricultural land, 3 barren land

categories. From 1985 to 2000, the agricultural land category area increased by 2%, but then decreased by 15.2% from 2000 to 2014 (Supplementary Table 3). On the opposite, barren land category area first decreased by -9.4% (-80 km²) between 1985 and 2000 but increased by 4.8% (42 km²) after the year 2000 (Fig. 3 and Supplementary Table 3).

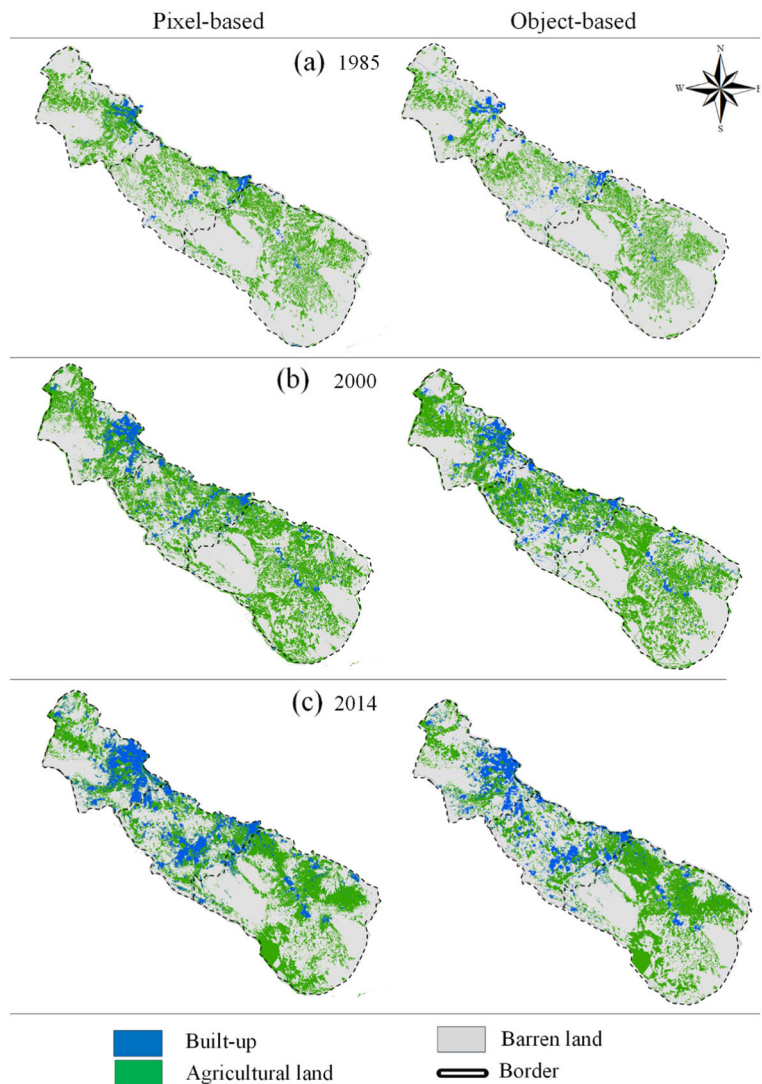
Zone B is characterized by large residential, industrial and commercial sites in the south of the Tehran and Alborz provinces. In this zone, change in agricultural and built-up categories had a similar pattern as in zone A. The agricultural and barren lands areas decreased by 69 and 141 km², respectively, and the area in the built-up category increased by more than 250 km² (Supplementary Table 3). Our results show that 20 to 25% of the agricultural and barren lands were changed into the built-up lands during 1985–2014 (Fig.3c and Supplementary Table 3).

Zone C (Shahr-Rey, Pakdasht and Varamin) did not experience a similar drastic increase of built-up areas than in zones A and B. According to Table 3, two third of zone C (66.7%) were classified as barren lands in 1985, while the built-up category area was negligible (2.3%). The built-up category also underwent the most minimal changes over the 30-year period, on the contrary of the agricultural and barren land categories (Table 3). In addition, barren land areas decreased by -426 km², while the agricultural land areas increased by 177 km² from 1985 to 2014.

Fragmentation analyses

Landscape metrics are helpful tools in understanding the implications of human activities on the landscape and its fragmentation. Fragmentation not only creates great concerns in man-made areas, but it may also

Fig. 2 Land cover maps derived from **a** 1985 Landsat TM, **b** 2000 ETM+ and **c** 2014 OLI for pixel- (left) and object-based (right) approaches for the provinces of Tehran and Alborz



create a natural imbalance in terms of size, shape and distribution of a mosaic of patches. That observation could be the cause of significant impacts on the dynamics of species and materials in the landscape, under various ecosystems with unique structures and functions. This study attempted to quantify the effects of LUCC on determining landscape metrics (Fig. 4). The utility of the selected metrics is often assumed to be dependent on the quality of the classified images. Therefore, the pixel-based and object-based classification methods were used to determine their effects on landscape metrics.

In zone A, the PD resulting from the pixel-based approach remarkably increased from 1985 to 2014 for the three categories (Fig. 4a). But the PD results from

the object-based approach displayed a drastic increase for agricultural lands, from 0.2 number/100 ha in 1985 to 0.7 in 2014 (Fig. 4a), while built-up and barren land categories decreased from 2000 to 2014 after increment between 1985 and 2000. The most significant expansion of built-up land areas observed between 1985 and 2000 appears in correlation with the growth of man-made landscapes, together with a higher magnitude of anthropogenic activities, that caused reduction of natural and conventional landscapes (Shahraki et al. 2012). The results for the ED were similar than for PD, increasing from 1985 to 2014 in all categories for both approaches (Fig. 4b). In addition, the results for the MPA in the agricultural land category decreased from about 53 to 18 ha, from 1985 to 2014.

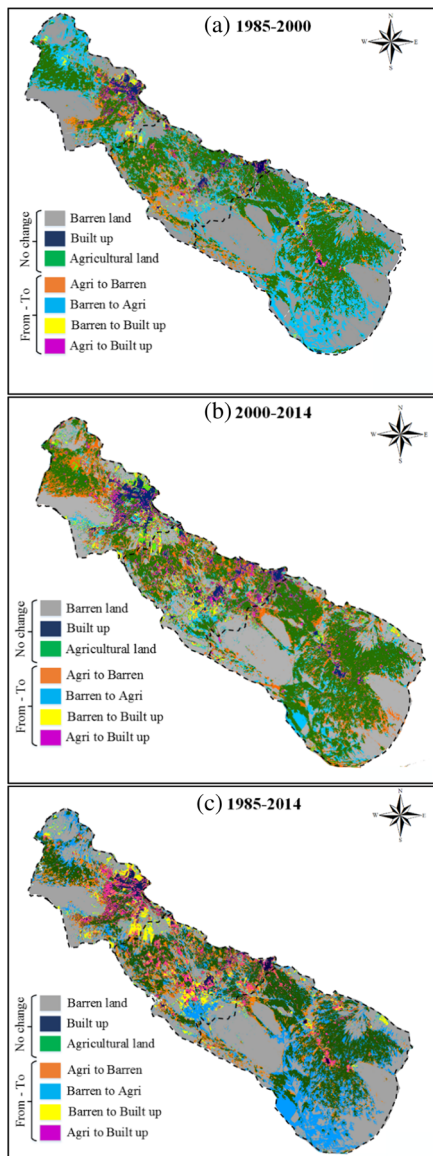


Fig. 3 Transition between land cover classes from **a** 1985 to 2000, **b** 2000 to 2014 and **c** 1985 to 2014 for object-based approach for Tehran and Alborz provinces

In zone B, from 1985 to 2014, the PD trends for the two classification approaches were similar. Built-up and agricultural land categories showed variations in time different than in zone A (Fig. 4a). For those two categories, after PD had increased from 1985 to 2000, it decreased from 2000 to 2014. PD also has the same trend in isolated patches of the barren land category (Fig. 4a). Interestingly, the built-up category designed from those two classification methods leads to clear differences. As it can be seen in Fig. 4a, PD of the

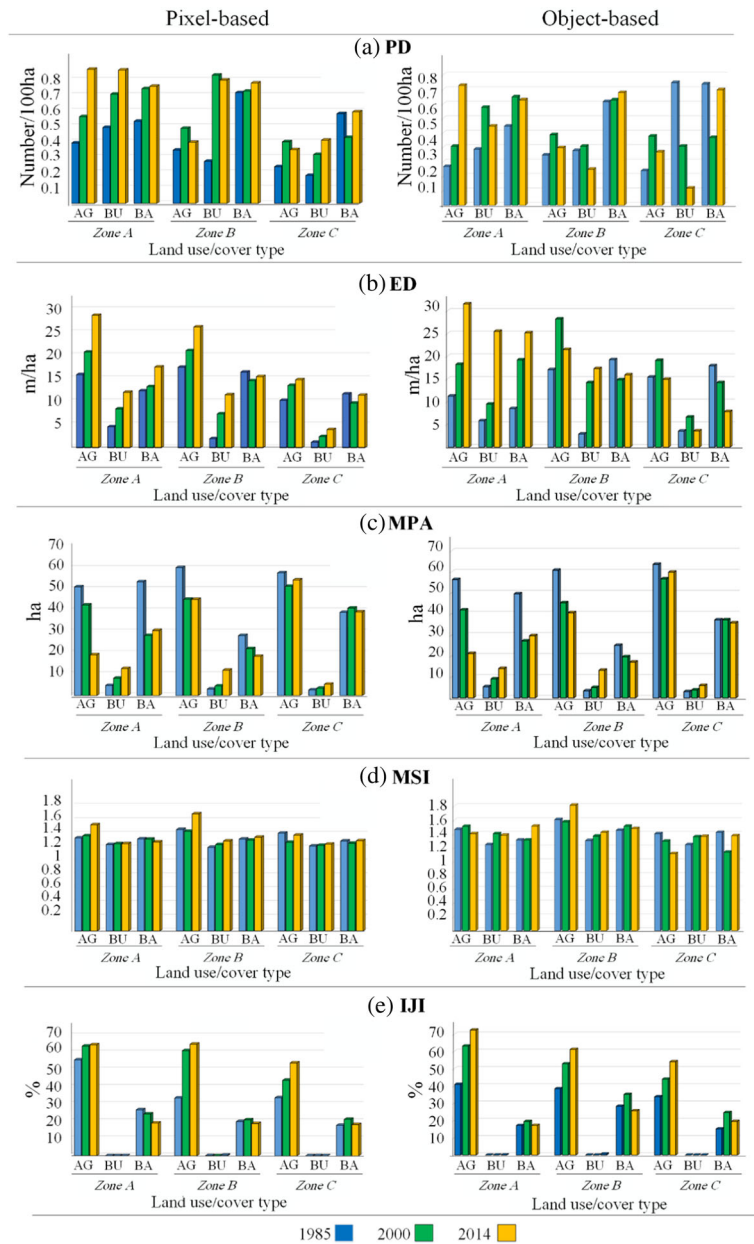
Table 3 Relative (%) areas for each land cover class for object-based post-classification approach in Tehran and Alborz provinces in 1985, 2000 and 2014. Net change is also shown

	Object-based %		
	1985–2000	2000–2014	1985–2014
Zone A			
From barren land to barren land	53.2	78	64.9
From barren land to agricultural land	37.6	12.3	22.1
From barren land to built-up	9.2	9.7	13
From agricultural land to agricultural land	61.4	57	58.1
From agricultural land to built-up	18.5	11.3	22.2
From agricultural land to barren land	20.1	31.7	19.7
Zone B			
From barren land to barren land	61.2	61	53.1
From barren land to agricultural land	30.7	19.3	19.6
From barren land to built-up	7.1	19.7	27.3
From agricultural land to agricultural land	80.1	67.2	60.1
From agricultural land to built-up	5.1	15.5	24.7
From agricultural land to barren land	14.8	17.3	15.2
Zone C			
From barren land to barren land	60.9	80.7	69
From barren land to agricultural land	32.7	16.7	30.5
From barren land to built-up	6.4	2.6	1.5
From agricultural land to agricultural land	81.3	77.3	72.9
From agricultural land to built-up	5.4	4	10
From agricultural land to barren land	13.3	18.7	16.1

built-up category displays a decreasing trend between 2000 and 2014, after an increase between 1985 and 2000 in zones A and B.

In zone C, the PD and MPA of agricultural and barren land categories for both classification methods showed an inverse trend between the periods 1985 and 2000 and 2000 and 2014 (Fig. 4a). It could be due to the use of treated wastewater for irrigation and less urban

Fig. 4 Landscape metrics. **a** PD, patch density. **b** ED, edge density. **c** MPA, mean patch area. **d** MSI, mean shape index. **e** IJI, interspersion and juxtaposition index. *AG* agricultural land, *BU* built-up, *BA* barren land



expansion after the year 2000 (Saemian 2013). But the PD of pixel- and object-based approaches was totally different in the built-up category. While PD indicates an increase from 1985 to 2014 in the pixel-based approach, the object-based one shows an inverse trend. ED of the agricultural land category increased from 1985 to 2000 and decreased from 2000 to 2014. The ED of the barren lands also decreased from 1985 to 2014.

The MSI values, for all categories and both classification approaches, were greater than 1, which indicates

that the average patch shape in all categories was rather irregular (Fig. 4d).

Finally, the IJI points out identical patterns for land uses/covers (Fig. 4e). IJI indicates that the patch types became more interspersed from 1985 to 2014. IJI approaches 0 when adjacencies are unevenly distributed; IJI is equal to 100 if all patch types are equally adjacent to all other patch types (McGarigal and Marks 1995). The range of IJI values in all zones varied from almost zero to 65.03%. In all zones, IJI values for the

agricultural land category obtained were more than 30%, underlining that the agricultural land category, in particular, was highly interspersed.

Discussion

According to the results of this study, it was assessed that despite similar map accuracies, the object-based temporal analysis detected “from-to” change correctly, more often than the pixel-based analysis did. Additionally, the object-based classifier produced more uniform objects for easier interpretation in the structured urban environment, while the pixel-based maps had a salt-and-pepper appearance and were harder to interpret for LUCC change (Karami et al. 2015).

By comparing the overall kappa coefficients, the producer’s and user’s accuracies, it appears that the pixel- and object-based approaches did not display significant differences. But the built-up category was characterized from the object-based method by the highest rates of both kappa coefficient and overall accuracy, possibly due to the inclusion of roads (Goosem 2007). As previously mentioned, studies showed that the results from the object-based classification approach are more accurate than those obtained by the pixel-based one. Roads can be classified using a pixel-based method, but this is much more time-consuming and becomes increasingly difficult, and eventually impossible as the roads become hidden from aerial view (Riitters et al. 2004). Moreover, in most cases it is often difficult to classify roads in low-resolution images.

The results of LUCC showed that built-up category areas have increased in all three zones from 1985 to 2014, because of the rapidly increasing population, especially in the suburban areas. Thus, most of the rural structures were changed into peri-urban areas, characterized by the growth of infrastructures such as roads (Fig. 2). Elsewhere, neighbouring villages have combined to each other to result in small towns, characterized by a high growth rate over 1985–2014. After the Taleghan and Mamlou dams were constructed in 2000 and 2005, respectively, to respond to the growing urban needs, the share of water for irrigated agricultural lands in zone A (Karaj, Nazarabad), zone B (Shahriar, Eslamshahr and Robat Karim) and zone C (Pakdasht and Varamin) became significantly limited. As a consequence, from 2000 to 2014 in all three zones, water shortage together with economic issues were

aggravated, leading to the conversion of agricultural lands into barren and built-up lands (Jahani and Reyhani 2006; Saemian 2013). However, the observed increment in the amount of agricultural land between 2000 and 2014 may be due to the use of Tehran’s treated wastewater to irrigate and convert barren lands into agricultural lands in this zone (Saemian 2013).

According to the pixel-based approach of fragmentation analyses, in zone A, the PD and ED increment together with the reduction of MPA indicated that fragmentation was considerably strengthened in zone A during the whole period of study. Increasing MPA of the built-up category is an illustration of this category growth from 1985 to 2014 (Fig. 4c). Also, the increment of MPA of the barren land category from 2000 to 2014 occurred because of the agricultural land category conversion into the barren land category (Table 3).

ED and MPA in zone B display a similar trend as zone A: Agricultural lands had higher ED than barren lands (Fig. 4b). The reduction of agricultural land areas from 2000 to 2014 was probably caused by the abandonment of lands, or their conversion into built-up areas (Table 3). Additionally, the decrease of PD from the built-up category from 2000 to 2014 led to isolated patches of that category, although joined together. In general, joining patches occurs when corridors are eliminated between neighbouring patches and, accordingly, when connections between those patches increase, that is, when their edges join together (Kabba and Li 2011). Because of rapid population growth in the study area, villages were joined together and shaped into towns, then cities.

In zone C, PD, ED and MPA of the built-up category have an increasing trend from 1985 to 2014 and showed that the built-up category did not significantly change more than in zones A and B (Fig. 4).

Bigger values of MSI were obtained for agricultural land category in all zones, which suggests that the agricultural land category particularly underwent high fragmentation in all zones, and over the whole period. The IJI values of 33% in 1985 and 65% in 2014 illustrate that the agricultural land category became more even, and equally adjacent, to each other due to the usage of barren land for cultivation from 1985 to 2000, prior to the abandonment of those lands after 2000. The lowest IJI value was associated to the built-up category that ranged from almost zero to 0.4%, confirming that built-up category patches were not well interspersed or equally adjacent to all. MPA and MSI

and IJI metrics in both classification approaches are comparable. But one of the important points here is that the MPA and MSI in the object-based approach have lower values than that in the pixel-based one. Roads not only decreased the size of the largest patch but also greatly increased both the number and the total area of the patches in the medium-size classes.

Fragmentation studies have added the roads to land cover maps after image classification (e.g. Riitters et al. 2004). The object-based classification allows roads to be added as a separate layer to influence both image segmentation and classification. Also, the inclusion of roads in the object-based method significantly reduced the size of the largest patch and altered the forest-patch size distribution. Totally, the values of these five metrics varied significantly between the pixel- and the object-based methods, but as they are shown in Fig. 4, both classification methods overall produced similar patterns of fragmentation for the 30-year period. The results emphasize that using the pixel-based approach leads to a less-important fragmentation of the built-up category than with the object-based approach. Besides this simple test, roads have important implications on landscape assessment. They are important contributors to built-up fragmentation, and their impacts have been largely understudied (Goosem 2007).

Therefore, our results characterize the effects induced over a 30-year period by the expansion of built-up areas on the other categories. The growth of urban landscape, and consequently, the reduction of natural and conventional (e.g., agriculture) landscapes, is correlated to the anthropogenic activity rate. Interestingly, according to the results, the built-up category growth has occurred in separate patches in all zones and has presented threats to alter its neighbouring land uses/covers or caused to abandon them for financial reasons. Therefore, it is expected that more degraded and barren lands are susceptible to have negative impacts. For instance, wind erosion is a dramatic consequence which severely affects air quality in residential areas, especially in Tehran and Karaj cities.

Conclusion

This study has presented new results for the provinces of Tehran and Alborz in Iran. The pixel-based and object-based methods were used to classify Landsat imagery data to obtain a relatively more detailed land cover

mapping. The overall accuracy and the kappa coefficient were used to compare the two methods. The object-based classification method yielded to a higher accuracy in classification of images than the pixel-based classification method. Analysis of Landsat data of 1985, 2000 and 2014 evidenced that LUCC mainly affected the agricultural and barren land categories. It pointed out that the conversion from barren to agricultural lands was dominant between 1985 and 2000 and vice versa between 2000 and 2014. It finally illustrated the general increase of the built-up category over the whole period. Results of fragmentation analysis showed that in 2014, the landscape was more fragmented than in 1985. Fragmentation results for the agricultural and barren land categories showed a typical fragmentation process, characterized by an increase in PD and in ED and a decrease in the MPA. Thus, the result exhibited that barren and agricultural lands became highly fragmented as a result of the increase of anthropogenic activities. MSI values for all categories in all zones were greater than 1, indicating that the patch shapes in all categories were irregular. Also, IJI showed that the patch types in the agricultural and barren land categories became more interspersed and tended to be more fragmented and degraded with the increase of constant human disturbances. The inclusion of roads in the object-based method significantly reduced the size of the largest patch and altered the patch size distribution from the above classification and analysis, it has been established that eCognition (object-based classification) performed better in classifying and identifying different land cover classes.

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