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ORIGINAL ARTICLE

Monitoring the land use/cover changes and habitat quality using Landsat dataset and landscape metrics under the immigration effect in subalpine eastern Turkey

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Abstract Monitoring the land use/cover change (LUCC) is a vital part of the ecological planning in fast-changing regions. Fast industrial developments, local social dynamics like internal security problems and hard life conditions in rural places can impact LUCC directly. The purpose of this paper was to detect LUCC and its effects on landscape ecology using landscape metrics (LMs) in the Tatvan region of Turkey located in eastern Anatolia. Landscape of the Tatvan region has been transformed due to two main reasons: fast-developing industries in Turkey and security problems in the eastern Anatolian regions since 1985. Landsat 5 TM 1989 and Landsat 8 OLI 2013 satellite images were used to detect LUCC for 24 years. Additionally, landscape changes were evaluated based on LMs to observe the habitat quality change. As a result of the study, settlement areas were increased almost 100 % in 24 years because of immigration from rural to urban areas. At the same time, grasslands were transformed into agricultural lands, settlement and forestlands. Therefore, agricultural activities increased by 45 %. Animal production was the main income in the 1980s, but while the rural population decreased, agricultural activities and industrial income increased around the cities thus animal production lost importance after 2010. From the results of the edge density, mean core area, total core area, mean patch area, Shannon's diversity index and shape index values, it was observed that overall habitat quality decreased in 24 years.

Introduction

Landscape changes occurred as a result of natural and cultural activities. Climate suitability and natural hazards like floods and earthquakes are some of the natural impacts that effect landscape change (Correira et al. 1999; Kaya et al. 2005; Dugmore et al. 2007). Cultural effects on land use changes are unavoidable processes and planned actions by man. Accessibility, industrial development and tragic effects such as war or fast industrial development are the main cultural effects on landscape change (Antrop 1998, 2005).

Change detection techniques based on multitemporal satellite images are the most common methods to monitor landscape dynamics and human–landscape interactions. Two main change detection approaches were applied using optical remote sensing (RS) data as pre-classification and post-classification approaches. Pre-classification approaches are required for radiometric and atmospheric corrections and for the change threshold detection process. However, these techniques give very good results as they do not result in classification errors (Berberoglu and Akın 2009). In contrast, radiometric and atmospheric corrections are not vital for post-classification change detection techniques because each time is classified alone and landscape change is detected comparing two classified images. Change detection reliability of the post-classification approach completely depends on classification accuracies (Şatır and Berberoğlu 2012).

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Archive availability is the most important issue in change detection studies by RS. The Landsat satellite dataset was outshined in regional and local-scale studies because of a large archive, available spatial (30 m) and spectral (visible, near-infrared and shortwave infrared wave bands) resolutions (Özyavuz et al. 2011; Chen et al. 2015).

Landscape metrics (LMs) are measurements for characterizing land use patterns, including their composition, distribution and fragmentation. LMs have often been used for depicting the results of land use change, habitat quality assessments, human pressure identification on habitats, etc (Nagendra et al. 2004; Liu et al. 2010; Feng et al. 2011; Yang et al. 2015; Beekman 2015).

The purpose of this research was to determine the effects of immigration on LUCC in eastern Turkey in Tatvan Province scale and quantifying the habitat change using appropriate LMs. In this context, LUCC of the Tatvan Province was detected and these changes were related to the effects of immigration on LUCC.

Study area

Tatvan Province is located in the Eastern Anatolian region of Turkey, where agriculture, animal production and tourism are the most important sources of income. Elevation varies between 1283 and 2973 m. The region contains huge natural alpine and subalpine grasslands. Continental climate is dominant; however, the annual precipitation and mean temperature is 844 mm and 9 °C, respectively (TMSS 2015). The region consists of two important landmarks called the Van Lake (the biggest lake of Turkey) and the Nemrut Crater (the second biggest volcanic crater area of the world). The railway system which is supported by sea transportation connects the railways between Turkey and Iran; thus, the region has a key role in freight transportation. Regional forest areas are one of the limited natural forestlands of the Van Lake Basin. Oak and juniper are dominant species in the area. Additionally, black pine has been used in afforestation areas locally (Fig. 1).

Özdemir (2012) reviewed the short immigration background of Turkey periodically. Results of his study showed that the rural population of Turkey started to decrease in the 1950s due to developments in mechanized agriculture. During the time period our study was conducted in (1989–2013), the rural population decreased at a faster rate than before particularly in eastern Turkey. This fast change was an extraordinary situation in the 1990s relative to previous years. The main income source of the eastern Anatolian people in the region was animal production due to productive natural grasslands. In the 1990s, most of the natural grasslands were declared forbidden area because of security problems. However, security problems were not the only cause for immigration, but fast industrial development, more suitable transportation capabilities, education and other social factors were some other key reasons as to the steep increase in immigration, although security problems did accelerate immigration rate (Hurma 2003). The Tatvan region is located on a connection point between the north–south and the east–west transportation roads. So the region is affected directly from the regional changes, and it is a good indicator to monitor the immigration effects on LUCC. Rural population of Tatvan was 27,900 (34 % of total population) in 1989, and it decreased to 18,552 (22 % of total population) in 2013 due to dominant security problems and fast industrial development in the whole of Turkey. Security problems in the rural areas of eastern Turkey started in 1985. This situation caused permanent migration to safer regions of Turkey, particularly due to the migration of young population and reduction in rural manpower. The decline in the rural population stopped in the 2000s because region was more secure than in the 1980s. The total population of Turkey increased 35.8 % during the studied time period (1989–2013), of which the total population increase in the Tatvan Province was only 2.6 %, thus indicating that not only was there immigration from rural to urban areas but also from Tatvan City to other places (TSS 2014).

Data used

Landsat 5 TM 1989 and Landsat 8 OLI 2013 satellite images were used to evaluate LUCC and its effects on habitat quality for the duration of 24 years. Landsat was the most useful satellite in regional LUC mapping and monitoring studies (Hermosilla et al. 2015; Kamwi et al. 2015). Landsat dataset is provided by the US Geological Survey (USGS) freely for scientific studies. The Landsat 5 TM mission started on the March 1, 1984 and operational imaging ended in November 2011. Multispectral wave bands from the visible to shortwave infrared regions were used in this study. These wave bands have spatial resolutions of 30 m (0.09 ha) and thus can be used effectively in various terrestrial and aquatic studies from regional to global scale during its operating times (USGS 2015). Landsat 8 OLI was launched in February 2013. It has a spatial resolution of 30 m in a multispectral range and 15 m at the panchromatic band. Additionally, it contains coastal/aerosol and cirrus wave bands. Radiometric resolution of the Landsat 5 and Landsat 8 have 8 and 16 bit, respectively. Both images were classified separately, so radiometric and atmospheric corrections did not apply. Images had been already corrected geometrically by the USGS Landsat team.

The ancillary dataset was used in addition to the Landsat wave bands to improve LUC classification accuracy.
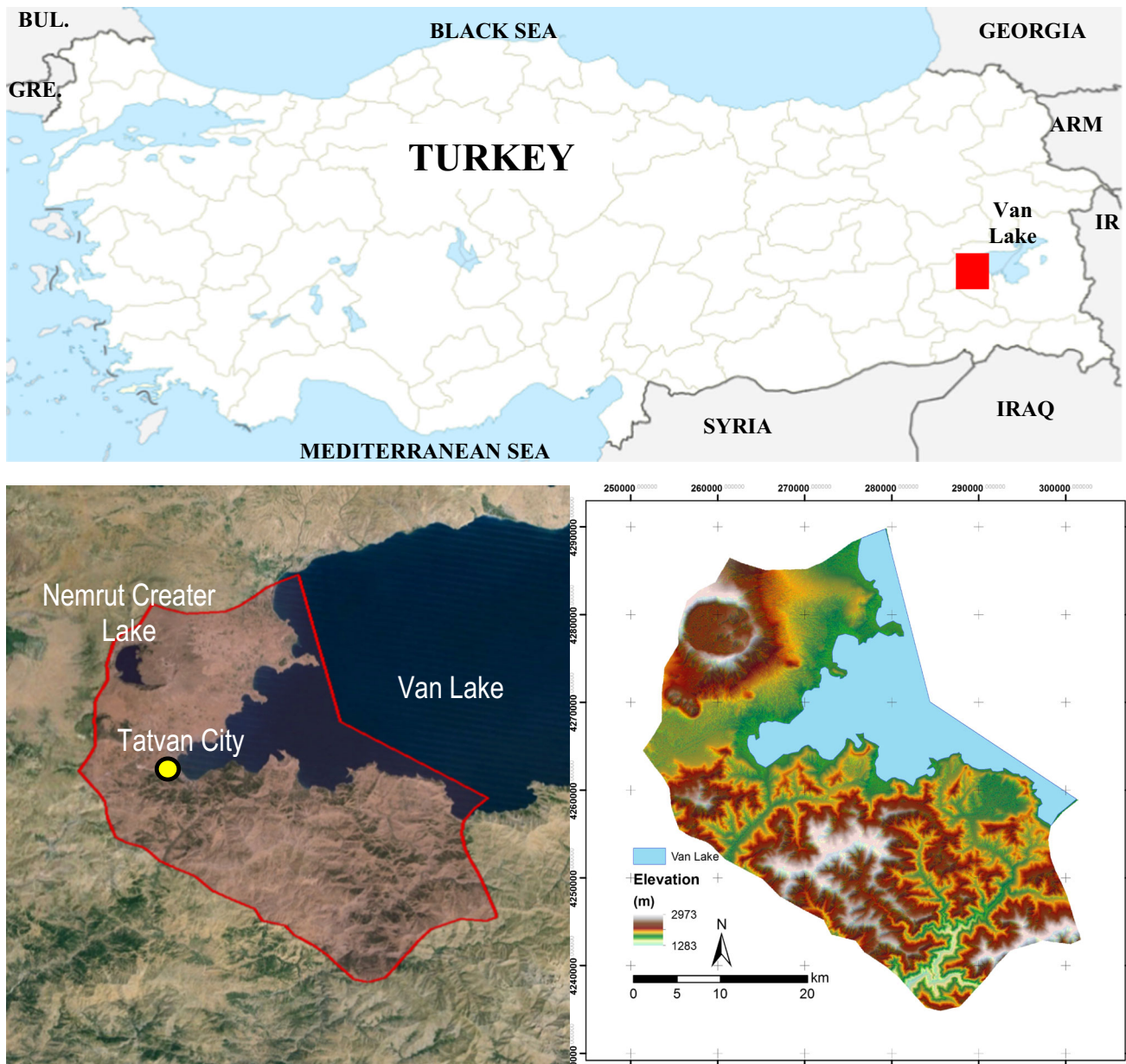
Fig. 1 Location of the study area

Normalized difference vegetation index (NDVI), 1st principle component of the Landsat wave bands (PCA) and Aster global digital elevation model (GDEM) datasets were integrated to the classifications to improve classification accuracy.

Methods

The study consists of two main stages: (1) ancillary data integration, LUC classification and accuracy assessment, (2) change detection and habitat quality analyses by LMs (Fig. 2).

Ancillary data and LUC classification

Landsat imageries, which were taken in 1989 and 2013, were classified using the artificial neuron network (ANN) classification approach. ANN is one of the most popular nonparametric LUC classification techniques (Dreyer 1993; Rodriguez and Chica-Rivas 2012; Ni et al. 2015). Ancillary data, which was produced from a Landsat dataset as NDVI and PCA, were added to the classifications. Also Aster GDEM of the study area was used as another ancillary data to improve the classification accuracies.
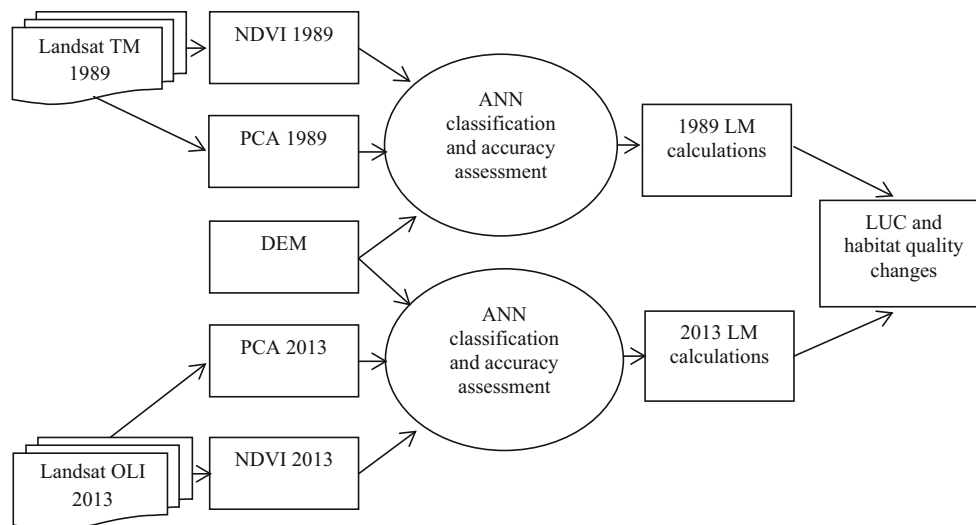
Fig. 2 Summary of the study

Ancillary data

NDVI is a ratio transformation which compares and contrasts the energy reflectance from a dead or senescent green cover (of the red band) with that from a healthy green cover (of the infrared band). The ratio ranges from −1 to +1 as greenness (and biomass) increases (Hassini et al. 2006). The vegetation index is a positive indicator of environmental quality. NDVI was used to improve vegetative area classification accuracies such as conifer and deciduous forestlands. NDVI was calculated using near-infrared (NIR) and red bands as follows (Rouse et al. 1973):

$$NIR - red/NIR + red. \tag{1}$$

PCA is mostly used as a tool in exploratory data analysis and for making predictive models. PCA can be done by eigenvalue decomposition of a data covariance (or correlation) matrix or singular value decomposition of a data matrix, usually after mean centering (and normalizing or using Z scores) the data matrix for each attribute (Abdi and Williams 2010). Basically, PCA merges the different variables (which in this study are wave bands) using the differences in each variable to create a new data which includes all of the variable's specification in one output.

Aster GDEM is a global elevation data provided from the ASTER satellite with a 30 m spatial resolution. This data were used as an ancillary dataset to improve classification results based on the fact that elevation and LUC are related with each other. Also vegetation dynamics, settlements and agricultural area usage change according to the elevation.

ANN classification approach and accuracy assessment

The multilayer perceptron (MLP) described by Rumelhart et al. (1986) is the most commonly encountered ANN model in data analysis and RS (because of its generalization capability), and this model is used in the current study (Satir et al. 2016).

ANN consists of three stages: training, allocation and testing. In training, pixel values are presented to the neural network, together with known class pixel values. The aim of network training is to build a model of the data-generating process so that the network in the testing stage can generalize and predict outputs from inputs it has not seen before. There are different types of learning algorithms for training the network. The most commonly used algorithm in RS is back-propagation, using the generalized delta rule (Rumelhart et al. 1986). Network weights are adjusted to minimize an error based on a measure of the difference between the desired and the actual feed-forward network output. This process is repeated iteratively until the total error in the system decreases to a pre-specified level or when a pre-specified number of iterations are reached. This threshold, which must be determined experimentally, controls the generalization capability and total training time.

Landscape metrics

Landscape ecology is a science that studies the structure and composition of the landscape elements along their changes overtime (Turner et al. 2001). Changes in the

landscape can be detected and quantified by the analysis of LUC images, which is called LMs (McGarigal and Ene 2015). They are useful for showing the spatial organization of a particular landscape. Pattern analysis of LMs makes sense when establishing relations with ecological processes such as biogeochemical cycles, genetic pathways and intra/inter-specific ecological interactions (Turner 1989; Li and Wu 2004).

Six LMs called Shannons diversity index (SHDI), edge density (ED), mean patch area (MPA), shape index (SI mean), total core area (TCA) and mean core area (MCA) were calculated for this study.

SHDI is a popular measurement approach to indicate the diversity of the population. In landscape studies, LUC diversity in a grid or plot area is referred to as the landscape complexity (heterogeneity) of an area, and there is a positive relationship between landscape complexity and biodiversity in general (Concepcion et al. 2008). ED equals the sum of the lengths (m) of all edge segments in the landscape, divided by the total landscape area (m^2), multiplied by 10,000 (to convert to hectares). This metric indicates landscape integrity, and if ED values are higher than before, it means that a landscape is more pieced than before. MPA calculates the mean patch size of all the landscape, and it is an indicator to assess the landscape integrity. SI evaluates class shapes according to the regularity, while LUCC based on human pressure forms a more regular landscape. TCA referred to the TCA size of the whole landscape, and if this value is smaller than before in change analyses, it means that the landscape regeneration ability has decreased. Big core areas have a very good resistance against outside effects like human pressure on natural landscapes. MCA is another core area analysis, and if a MCA change occurs twice it is referred to as land degradation. Information on calculation techniques of the LMs can be found in many literature (McGarigal et al. 2002; McGarigal and Ene 2015). Description of the metrics, usage purposes and units are shown in Table 1.

Results

This study was designed and conducted in stages: In the first stage, LUC classification with ancillary data and accuracy assessment of the August 1989 and 2013 data using ANN were completed because to calculate the LMs for overall habitat quality assessments, classified images must be obtained. Change detection statistics were derived in the second stage to see the areal change and LUC transformations under the immigration effect. LM calculations and overall habitat quality assessments have been done in the last stage to evaluate the immigration effect on habitats.

Ancillary data integration and LUC classification by ANN

Before the classification part, ancillary data were produced to integrate with Landsat images. NDVI and PCA images were produced from the Landsat dataset to enhance the class separation abilities of the ANN classification. NDVI values of conifer and deciduous trees were different from each other because of leaf area and chlorophyll contents. Additionally, NDVI may be used as an indicator of vegetation density and cropped agricultural land densities are higher than forest areas generally.

PCA of the Landsat wave bands were used as another ancillary data. According to the first component of the PCA, stable lands such as urban and water were referred with low values. Unstable lands such as agriculture and grasslands had taken high values.

DEM data were also integrated with the Landsat dataset in an ANN classification stage, so the elevation difference was considered when detecting LUC (Fig. 3).

The accuracy of an ANN is affected primarily by five variables: (1) the size of the training set, (2) the network architecture, (3) the learning rate, (4) the learning momentum and (5) the number of training cycles.

1. *Size of training dataset* Minimum 150 training and 150 testing pixels per class were used in 1989 and 2013 classifications. Total training pixel counts of the 1989 and 2013 classifications were 1028 and 1052, respectively, for the train network. Testing pixel counts of the 1989 and 2013 were 1032 and 1053 to calculate the testing root mean square error (RMSE). Training accuracy of the 1989 and 2013 were derived as 96.6 and 94.3 %, respectively.

2. *Network architecture* The number of input units was nine for 1989 and ten for 2013. In 1989, six Landsat TM wavebands, NDVI, PCA and DEM images were defined as inputs of the networks. In 2013, an additional Landsat 8 waveband (cirrus wave band) was added as an input. The neural network architecture that results in the most accurate output in network architecture can only be determined experimentally, and this can be a lengthy process for large classification tasks. This is often seen as a limitation of ANN. However, some geometrical arguments can be used to derive heuristics to set an approximate network size (Paola and Schowengerdt 1997). In the majority of cases, a single hidden layer is sufficient. The dominant factor is the number of the units within the hidden layers, as the number of hidden layers has a secondary effect. Ideally, the first hidden layer of a network should contain two to three times the number of input layer units. In the present case, the network

Table 1 Characterization of landscape metrics and usage purposes in this study

LM	Unit	Information	Usage purpose in this study
SHDI	Value	SHDI is a popular measure of diversity in community ecology. SHDI starts from "0" to positive way, without limit. Low value refers homogeneous landscape	Landscape complexity and biodiversity are related each other in correct proportions (Moser et al. 2002; Concepcion et al. 2008). This index is used to see biodiversity loss between 2 years as an indicator
ED	m/ha	ED reports edge length on a per unit area basis that facilitates comparison among landscapes of varying size	ED is referred landscape fragmentation. If landscape integrity of a natural area is broken, regeneration ability of the area is damaged. ED was used to compare landscape integrity in two times
MPA	ha	MPA is an area metric, and size of the each class in different location of the study area is calculated by dividing the total counts of the class patch	MPA is a very good indicator to evaluate landscape integrity
SI (mean)	Value	SI calculates each class or all classes boundary shapes according to the regularity. High value refers irregular shape boundaries	Natural landscapes have more irregular boundaries than human-made landscapes. This metric was used as an indicator to monitor the landscape naturalness
TCA	ha	TCA is an important metric to derive the landscape degradation	Core area quantity is an indicator of the landscape integrity and degradation
MCA	ha	MCA is another metric like TCA, but this metric also shows each core area increase or decrease	Size of the each core area is important for the regeneration and removal capacity of the landscapes. When this value is smaller than before its mean that landscape is more sensitive against outside effects anymore

architecture consisted of a single hidden layer with 19 nodes for 1989 and 21 nodes for 2013.

3. *Learning rate* The learning rate determines the portion of the calculated weight change that will be used for weight adjustment. This acts like a low-pass filter, allowing the network to ignore small features in the error surface. Its value ranges between 0 and 0.99. The smaller the learning rate, the smaller the changes in the weights of the network at each cycle. The optimum value of the learning rate depends on the characteristics of the error surface. The network was trained with a learning rate of 0.1 as this resulted in the most accurate classification. However, this rate requires more training cycles than a larger learning rate.

4. *Learning momentum* Momentum is added to the learning rate to incorporate the previous changes in weight with the current direction of movement in the weight space. An additional correction to the learning rate was conducted by adjusting the weights and ranges between 0.1 and 0.9. The network was trained with a back-propagation learning algorithm and a learning momentum value of 0.5.

5. *Number of training cycles* The network was trained until the RMSE reduced to a constant value that was considered acceptable (lower than 0.1). This is one of the most important issues in the design of an ANN as it is easy to over train, thus reducing the generalization capability of the network. The network was trained with 9126 cycles for 1989 and 18,991 cycles for 2013. The training dataset was divided into two parts: training and testing in training stage. When the

accuracy rate reached the optimum, training was stopped in an appropriate cycle. The training dataset was divided into two parts and the accuracy of each of the training processes was calculated. When the RMSE was lower than 0.1, the training progress was stopped to avoid system overtraining and memorization.

Classification results were tested applying kappa accuracy analysis using ground control points that were derived from detailed forest maps (1/25,000), topographic maps (1/25,000) and field trips. Old topographic maps (1987) and forest maps (1986) were used to validate the 1989 classification. Field trips and new forest maps (2014) were used to test the 2013 classification. Ground control points were selected stratified randomly and a minimum of 15 points per class were used. In total, 200 ground control points were used for accuracy assessment. Overall kappa accuracy coefficients were detected as 0.92 for 1989 and 0.91 for 2013 LUC classification. The kappa value varies between 0 and 1 and 1 refers to an almost perfect accuracy (Fig. 4).

Areal change detections

Six LUC classes were classified as settlement, agriculture, conifer forest, deciduous forest, water bodies and alpine and subalpine grasslands. Changes between 1989 and 2013 were evaluated using a post-classification image comparison technique. According to the change results, the most dramatic changes were observed in the following order: settlements (96 %), deciduous forest (87.5 %) and agricultural areas (43 %) in positive way. When the rural

Fig. 3 Ancillary dataset used in classification of the 1989 and 2013 Landsat datasets
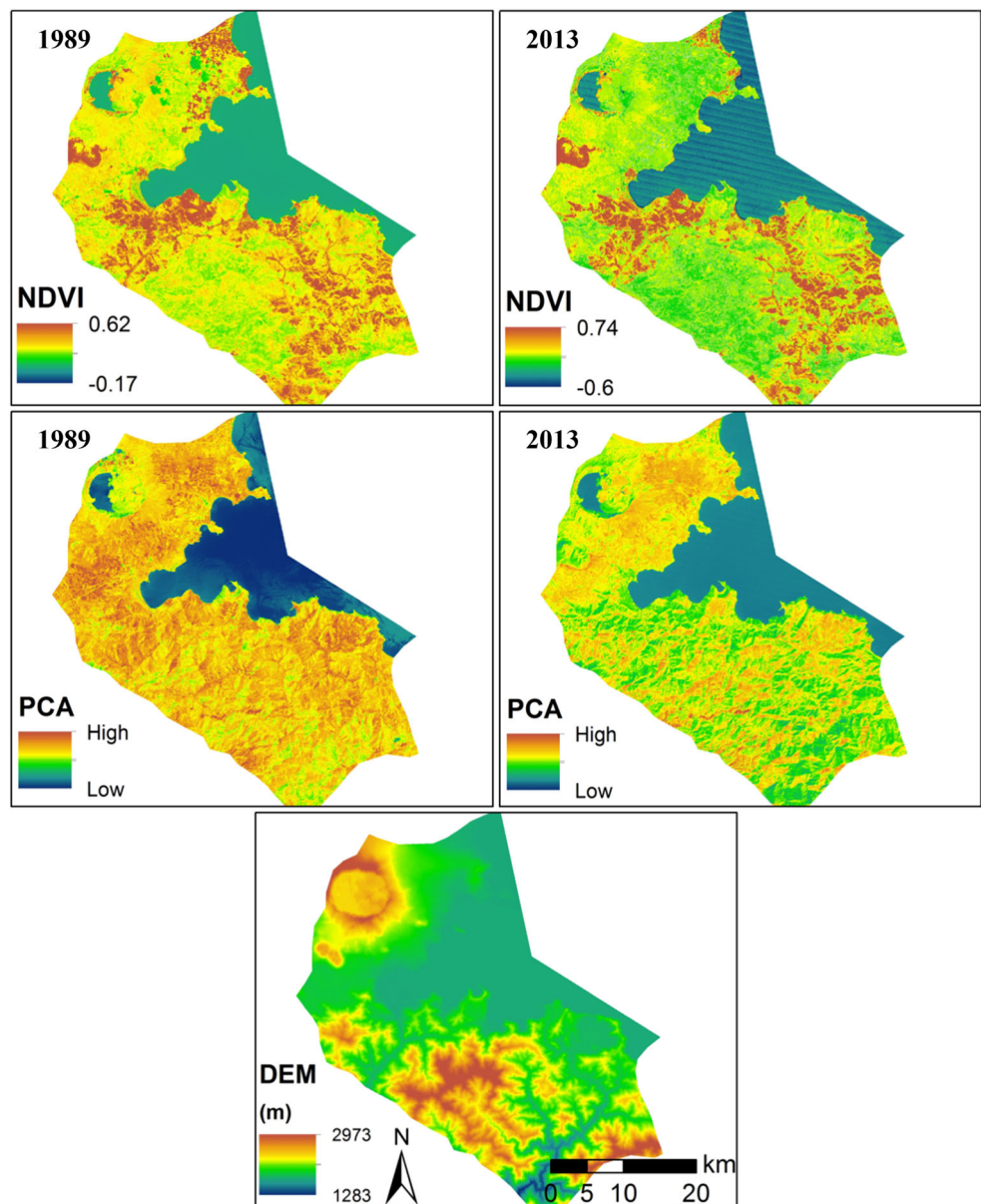
population of Tatvan decreased, people moved to the city center and other cities. Therefore, settlement areas increased. Animal production decreased because of security problems and population loss in rural areas so that pasturage also decreased, while the amount of natural deciduous forest areas started to rise because the highest pressure on forest regeneration was predominantly due to pasturage in the region. Another immigration effect was increasing farming areas. In 1989, especially people who resided in rural areas did not have permanent settlements. During the summer, they lived in the highlands in temporary tents or small buildings, and in winter they moved to villages or small towns and their income was primarily from animal production. However, this situation changed

in 24 years, and people started to settle more around the bigger cities and they started to do field farming instead of animal husbandry. Additionally, grasslands were transformed into agricultural land. Water bodies also decreased 231 ha from 1989 to 2013. Some of the water areas from the Van Lake were filled to build pavement roads next to the lake. All area changes of the region between two the periods due to the effects of immigration are shown in Table 2.

Overall habitat quality change analyses by LMs

LUC images of the two dates were assessed by the LMs to obtain the effects of LUC change on habitat quality
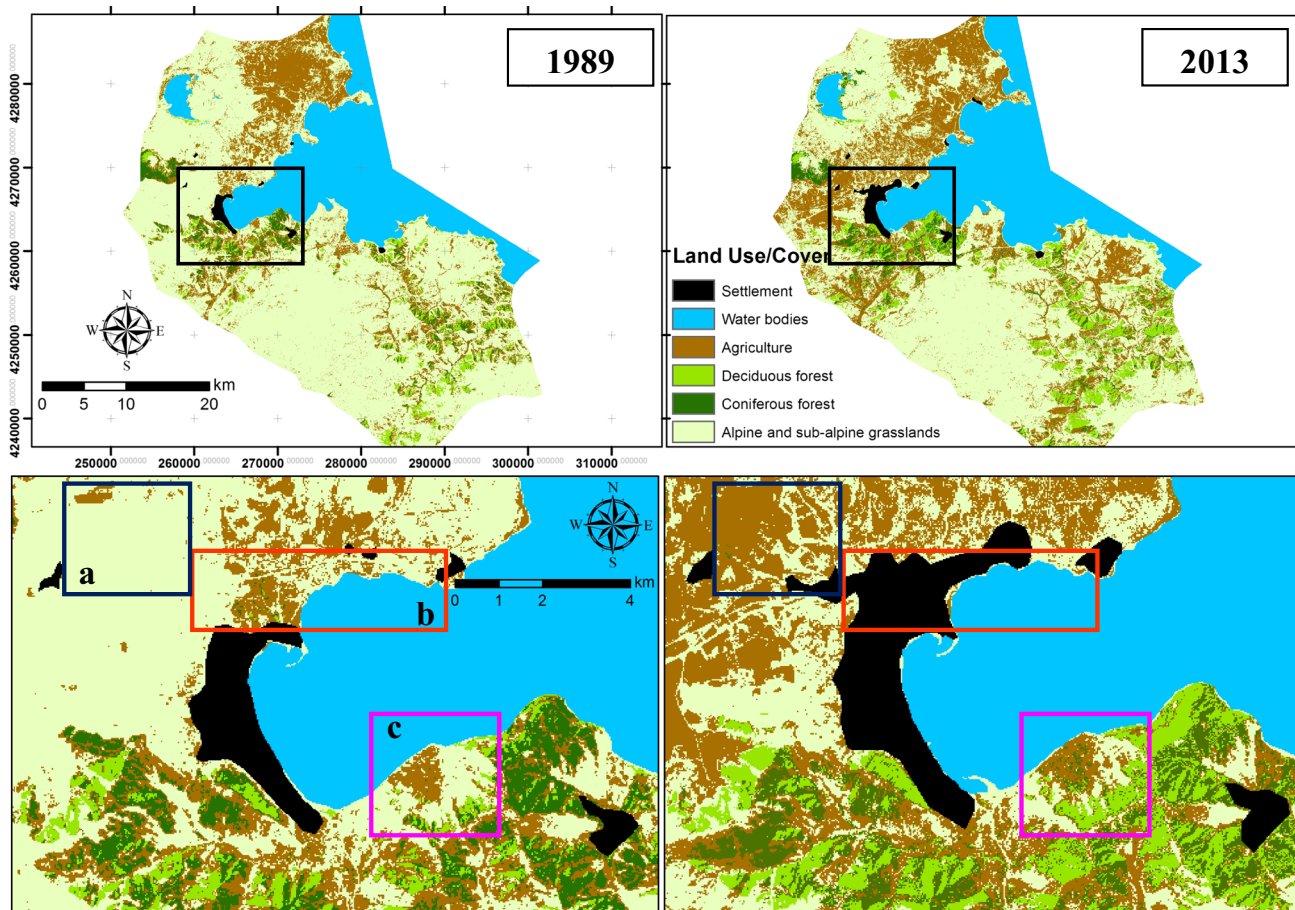
Fig. 4 ANN classification results and selected hot plots. **a** Grassland–agriculture transformation, **b** transformations–urban, **c** grassland–deciduous forest transformation

because of population diversity changes. LM specifications have previously been explained in Table 1 in the "Methods" section. LMs vary according to the research scale, from landscape scale (whole area assessments) to patch scale (small integrative areas). In this study, overall habitat quality was compared in the landscape scale between 1989 and 2013. In this frame, SHDI, ED, MPA, SI, TCA and MCA were calculated for each date (Table 3).

According to the metric values, SHDI decreased 13.6 % meaning that landscape complexity in per area scale (this

size is variable based on the user and 150 × 150 m used in this study) decreased and the whole area landscape lost its biodiversity potential as landscape complexity and biodiversity has a positive relation (Moser et al. 2002; Concepcion et al. 2008). The ED value of Tatvan Province, in contrast, increased in the 24-year period. This result shows that landscape integrity was broken and more small pieces were created because of LUCC, and also TCA, MCA and MPA values supported this result. TCA size, mean size of the core areas and MPAs were reduced, and the landscape

Table 2 Areal changes in 24 years (1989–2013) in Tatvan Province

LUC	1989 (ha)	2013	Difference	Change (%)
Settlement	762	1500	738	96
Water bodies	30,578	30,347	−231	−0.75
Agriculture	22,943	32,809	9866	43
Deciduous forest	5197	9747	4550	87.5
Conifer forest	3983	4884	901	22.5
Alpine and subalpine grasslands	90,053	74,229	−15,824	−17.5

Table 3 Calculated metrics and differences

Metrics	Unit	1989	2013	Change (%)
SHDI	Value	1.54	1.33	−13.6
ED	m/ha	60.26	84.76	40.5
MPA	ha	7.79	5.1	−34.5
SI (mean)	Value	1.26	1.25	−0.81
TCA	ha	84,912	67,736	−20.2
MCA	ha	4.31	2.25	−47.7

in general was divided into pieces. When MCA decreased, the regeneration ability of the total landscape also decreased and thus external influences had a greater effect due to reduced rates of landscape regeneration. This loss mostly effected grasslands, because grasslands were the biggest land cover and unfortunately, they were reduced by 17.5 % in the 24-year period and the integrity of the areas were broken mainly due to agricultural land and settlement transformations. The SI index value also decreased; however, this situation was not as significant as other LMs. Finally, natural boundaries of the classes were more regular (like square) in 2013. Human activities had a direct impact on the class boundary type, and human-made systems are not irregular shapes such as agricultural lands and settlement areas.

Discussion and conclusions

This study focussed on the effects of human population movement on LUCC and habitat quality using a combination of RS science and LMs. Tatvan region was a good indicator to mainly see the effects of immigration on LUCC in the eastern Anatolian region of Turkey. Immigration has occurred because of different reasons all over Turkey, and changes on LUCC were related based on these reasons. For example, Özyavuz et al. (2011) investigated the effects of immigration on the European part of Turkey, specifically for the cities of Çorlu and Lüleburgaz, and found that the fast industrial development in İstanbul was the cause. As a result, field agriculture decreased as the younger population moved from rural areas to the cities. Agricultural lands were abandoned and transformed into the grasslands. Oppositely, the results in our studies showed decrease in grasslands in eastern Anatolia. Immigration effects on LUCC in industrial cities such as Adana, located in Southern Turkey, are different. Adana city population increased faster because of fast industrial development and population movement from eastern to western Turkey in the 1990s; thus, agricultural areas decreased because of fast urbanization in Adana city (Akın 2006).

In addition to the changes in LUC, overall habitat quality change was also observed by LMs. Particularly, landscape integrity of the area was disrupted in the last 24 years based on TCA, MCA and MPA metrics. Meanwhile, natural boundaries decreased according to the mean SI value difference. It was found that one of the most important reasons was determined due to security problems in the region (Hurma 2003), as most of the villagers had abandoned their homes in the 1990s and moved to the city centers. This situation ended at the beginning of the 2000s, but old villagers settled, and their life style, income type and social activities were transformed (Özdemir 2012). Decrease in rural population had already started in the 1950s because of agricultural mechanization, and it continued in the 1980s due to wrong rural development policies like giving subventions to mass tourism and industrial facilities instead of agriculture and animal production. Unfortunately, security problems encouraged villagers to migrate to cities.

In conclusion, migration from rural to urban areas in eastern Turkey affected LUCCs directly. The source of income of the local people changed in the 24-year period, and animal production lost its importance. Field agriculture increased instead of animal production because of the decrease in rural population. While settlement and agricultural areas increased, natural grasslands decreased in the region. Today, Turkey imports live animals from other countries like S. American Countries and Hungary. The government has been giving subventions to encourage animal production in eastern Turkey again, and government encouraged aims to encourage citizens to go back to rural areas (villages) by providing extra opportunities such as tax advantages, interest-free loans and grants. However, local people have already settled into city life, and policies were not sufficiently successful enough to change this situation.

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