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RESEARCH

Determining future scenarios of urban areas with cellular automata/ Markov Chain Model method; example of Ereğli District Konya-Türkiye (2030–2040)

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Abstract
As a result of the rapid increase in the world population, the earth surface has started to be damaged due to natural and artificial effects. The extent of the damage to nature can be determined by examining the temporal changes of land use and land cover (LULC). In order to offer healthier and more sustainable living spaces, scientists have produced many studies on the changes in nature. Within the scope of this study, 5 basic training classes were created with the help of Landsat satellite images and CORINE data, covering the period of 1985–2018 for Ereğli-Bor Sub-Basin, which is one of the 9 sub-basins of Konya Closed Basin located in the Central Anatolian Region of Türkiye. Landsat Satellite images, Google Earth Program and CORINE data were overlaid to create a basic training class as artificial areas, agricultural areas—pasture areas—forest areas and wetlands and these areas were classified by supervised classification method. The study was carried out on an area of approximately 331057 ha in and around Ereğli district. Modeling was carried out with the Cellular Automata (CA) Markov Chain Model to determine the urban development potential in the region. In order to estimate the modeling accuracy, the 2018 prediction model was created according to the 2018 reference map, and the validation between the two data was analyzed with the kappa statistics. According to kappa statistics values, it was determined that K_location and K_standard values were 0.9301 and 0.8935, respectively. As a result of the validation in sufficient standards, future prediction models were applied; future models and result maps were prepared for the years 2030–2040. According to the modeling results, it is estimated that the artificial area class in Ereğli district will reach 122.74 km^2 by 2030 and 142.24 km^2 in 2040. In addition, it was expressed in detail with the prediction results and maps that there will be a decrease in pasture, forest and agricultural areas in the region until 2030 and 2040. As a result, it is predicted that the ecological balance in the region will change and agricultural production may decrease as a result of the decline in agricultural pasture and forest areas. For this reason, it has been revealed that it is important for the future of humanity that plans such as environmental layout and master development plans to be made by regional manager in the region for the future should be planned in line with the results to be obtained as a result of future prediction models.

Keywords CA-Markov · GIS · Land use/land cover · Urban growth

Introduction

With the increase in the human population and the development of technology, land use/land cover (LULC) has started to be damaged due to natural and artificial factors. Changes in LULC in the world, especially in developing countries, have been quite common in recent years (Girma et al. 2022; Kafy et al. 2021; Gebreslassie 2014; Yirsaw et al. 2017). The increase in industrial areas has caused an increase in greenhouse gas emissions and, as a result, irreversible deformations on the earth. The occurrence of LULC and climate change has prompted scientists to investigate the effects of

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two concepts on the world. The development of computer technologies, the integration of Remote Sensing (RS) and Geographical Information Systems (GIS) have made it possible to examine changes in LULC in a shorter time, with lower costs and with better accuracy (Girma et al. 2022; Hassan et al. 2016; Rawat and Kumar 2015; Roy et al. 2015). Remote Sensing (RS) and Geographic Information System (GIS) technologies are utilized in LULC exchange studies. RS and GIS have a long history in map development and monitoring for different purposes (Matlhodi et al. 2019; Hathout 2002). There are many studies on the collection, classification of satellite images, detection and analysis of changes in images (Kundu et al. 2021; Redowan et al 2014). With recent advances in this technology, it is possible to access satellite data of hard-to-reach regions and to model and predict LULC changes (Matlhodi et al. 2019; Murayama et al. 2015).

Thanks to the developing satellite systems and images, the detection of earth changes, temporal analysis and future scenario studies have gained momentum. The rapid increase in the human population has led to an increase in urban areas, especially in developing countries, and it is stated in numerous papers that these increases have been obtained from agricultural, forest and pasture areas. In 2010, 5% of the Earth's surface consisted of urban areas (Al-Rifat and Liu 2022; Angel et al. 2011). One of the world's main problems in the future will be overpopulated cities, unbalanced population distribution, and unplanned cities (Valjarević et al. 2021). It is thought that by 2030, 60% of the human population in the world will live in urban areas, and urban sprawl will take place mostly in developing countries (Fadhil and Kurban 2022; Forte et al. 2019). Furthermore, the United Nations (2017) states that by 2050, 68% of the world's population will live in urban areas. It was stated in the previous studies that modeling the changes in LULC is important to protect land resources in a sustainable way and to take the necessary precautions (Girma et al. 2022; Regasa et al. 2021; Gebreslassie 2014).

The Corine land cover project is a system that dates back to 1985 and provides data for up to 38 countries, offering a detailed analysis through photointerpretation or data generalization. More recently, new and detailed Land Use/Cover services, such as High Resolution Layers (HRL) or Urban Atlas, provide a source of information. Modeling changes in LULC the Corine system is useful for the scholars (e. g. García Álvarez and Camacho Olmedo 2023).

Many modeling techniques have been introduced to monitor LULC in the earth surface, especially the urban areas, and to predict possible future growth and sprawl. Nowadays, many urban growth models have been developed that provide the opportunity to select models according to LULC characteristics of the area of interest and research questions (Hasan et al. 2020; Verburg et al. 2004; Reis et al. 2015). CLUE-S, Cellular Automata (CA), Markov Chain (MC), Cellular and Hybrid Models, LULC are some of the prediction models used for simulation of change dynamics (Girma et al. 2022; Kafy et al. 2021; Gharaibeh et al. 2020). Most of these models are experimental approaches based on change analysis algorithms using satellite image data (Girma et al. 2022; Rawat and Kumar 2015; Burnicki et al. 2010; Mas et al. 2014). Thus, past land transformations and transition dynamics help us to predict environmental changes and future land use scenarios (Girma et al. 2022; Wang et al. 2021; Eastman 2016). The SLEUTH, Markov Chain and Artificial Neural Networks (ANN) applications are the most popular among the LULC prediction models (Al-Rifat and Liu 2022; Kim and Newman 2019). The SLEUTH model predicts behavioral changes in LULC in the future (Kuo and Tsou 2017). The CLUE model determines Simulations of future LULC changes based on relationships between land uses and driving variables (Veldkamp and Fresco 1996).

The Cellular Automata-Markov Chain (CA-MC) model is one of the most effective methods widely used to model temporal and spatial changes in LULC (Girma et al. 2022; Yirsaw et al. 2017; Dey et al. 2021; Sang et al. 2011; Hamad et al. 2018). Furthermore, the Multi-Layer Neural Network Markov model is one of the best models for creating simulations of future LUCL (Al-Rifat and Liu 2022; Pahlavani et al. 2017; Sangermano et al. 2012). Multi-Layer Perceptron (MLP) algorithm is a very common application used in Artificial Neural Network applications (Al-Rifat and Liu., 2022; Sangermano et al. 2012). Multi-Layer Perceptron based Artificial Neural Network Markov hybrid model has been demonstrated to be highly efficient in accurately predicting LULC changes (Al-Rifat and Liu 2022; Mishra and Rai 2016; Ozturk 2015).

Within the scope of this study, the changes in Ereğli-Bor Sub-Basin, one of the 9 sub-basins of Konya Closed Basin which is located in the Central Anatolia Region of Türkiye and covers approximately 7% of the country's surface area, were examined. With the data obtained from Landsat satellite data, changes in LULC in a 34-year period were determined. For the classification maps to be prepared in the study covering the years 1985–2018, CORINE classification data were used and classification processes were carried out in 5 basic classes (*Agricultural Areas, Forest Areas, Pasture Areas* and *Artificial Areas*). In order to determine the urban development potential in the 34-year period, the urban sprawl of Ereğli district in the basin was modeled with the Cellular Automata-Markov Chain Model and future scenarios for the years 2030–2040 were made.

Materials and methods

Field of study

Konya Closed Basin, located in the Central Anatolia Region, is located at 36°51' and 39°29' north latitudes and 31°36' and 34°52' east longitudes of Türkiye (Aydın and Durduran 2021; Dervişoğlu 2018). The basin is a large region covering approximately 7% of Türkiye, having an area of 5 million hectares. Totally 3 million people live in the region while 45% (1.350.000 population) of the basin live in rural areas, 55% (1.650.000 population) of basin live in urban areas (Aydın, 2022; Topaloğlu 2014; Doğdu et al. 2007). It has been divided into 9 sub-basins by the State Hydraulic Works (DSI), Konya Regional Directorate, taking into account various properties such as groundwater recharge area, geological, hydrogeological and aquifer structures (Aydın and Durduran 2021; Tunçok and Bozkurt 2015). These sub-basins are Beyşehir-Kaşaklı, Konya-Çumra, Karaman-Ayrancı, Ereğli-Bor, Aksaray-Karapınar, Altınekin, Cihanbeyli-Kulu, Şereflikoçhisar, Niğde Misli sub-basins." (Aydın and Durduran 2021; Tunçok and Bozkurt 2015).

The modeling study was carried out on an area of approximately 331057 ha, covering Ereğli district, which is one of the oldest settlements in Anatolia within Ereğli-Bor Sub-Basin and an important location in terms of transportation between the Mediterranean and the Central Anatolian Region. Ereğli district is 153 km away from the city center of Konya province. Emirgazi is in the north of the district, Niğde is in the east, Karaman and Halkapınar are in the south, and Karapınar is in the west. It is located at an altitude of 1054 m above sea level. Since it has a continental climate, summers are hot and dry whereas winters are cold and snowy. At the core of the study, it is aimed to examine the urban development potential of the Eregli district, which is the important settlement of the region, and to determine the future scenarios (Fig. 1).

Data used

In this study, satellite data of Landsat 5 TM and Landsat 8 OLI-TIRS at 30 m resolution were obtained free of charge from *earthexplorer.usgs.gov* in order to observe the changes in LULC and to make regional analyzes. Height and slope maps were prepared from the Digital Terrain Model (DTM) data of the region. Data from the CORINE Classification Project system for the years 1990–2000-2006–2012 were used as a base in classification processes. Furthermore, the road network data required for the prediction models were obtained from *openstreetmap.org*. After these downloaded vector data were converted into a file with shapefile extension in the QGIS (ver. 3.2) program, distance analyzes were created for road networks using the Spatial Analyst-Euclidean Distance command in the ArcGIS (ver. 10.2) program. These analyzes have been made ready to be used in the prediction modeling to be done in the last part of the study. The flow chart for the processes carried out in the study is given in Fig. 2.

Methods used

Preprocessing and classification of satellite images

Erdas Imagine software was used to perform image preprocessing, enhancement techniques, classification processes, layer merging and multi-band transformations. While determining the classification criteria (training fields) in the study area, Level 1–2-3 data in the CORINE system were employed and 5 basic training classes were determined: Pasture Areas, Artificial Areas, Forest Areas, Wetlands and Agricultural Areas.

Similar studies show that these training classes are widely used. Abraham and Kundapura (2022) in the Meenachil and Manimala basins in Kerala, India, they categorized the education classes into 5 basic classes: water, building sites, wasteland, Agriculture and Forest areas.

It was aimed to increase the quality of classification with LANDSAT satellite images, CORINE and Google Earth software data (Table 1).

Digital images consist of combinations containing numerical values having different types of properties, depending on their natural spectral reflectance values. Groupings are performed between objects with the same spectral values. The aim is to divide the pixels in the satellite images into groups according to their spectral values and assign the reflectance values for each pixel to the corresponding cluster on the earth surface. According to the studies in literature, the classification process can be handled under two headings as pixel-based classification or object-based classification (Aydın and Durduran 2021; Oruç, 2003; Oruç et al. 2007).

Pixel-Based Supervised Classification: In this classification based on sample regions (test areas) representing the earth surface, property files with defined spectral properties are formed for each object to be classified. The property file in which the test areas are sampled is applied to the image data, and each image data is assigned to the class to which it is most similar (Ekercin 2007; Topaloğlu 2014). Pixel-based supervised (trained) classification method was used in this study. This classification method is divided into three different methods: Parallelepiped, Closest Distance and Maximum Likelihood classifications (Aydın and Durduran 2021; Oruç et al. 2007).

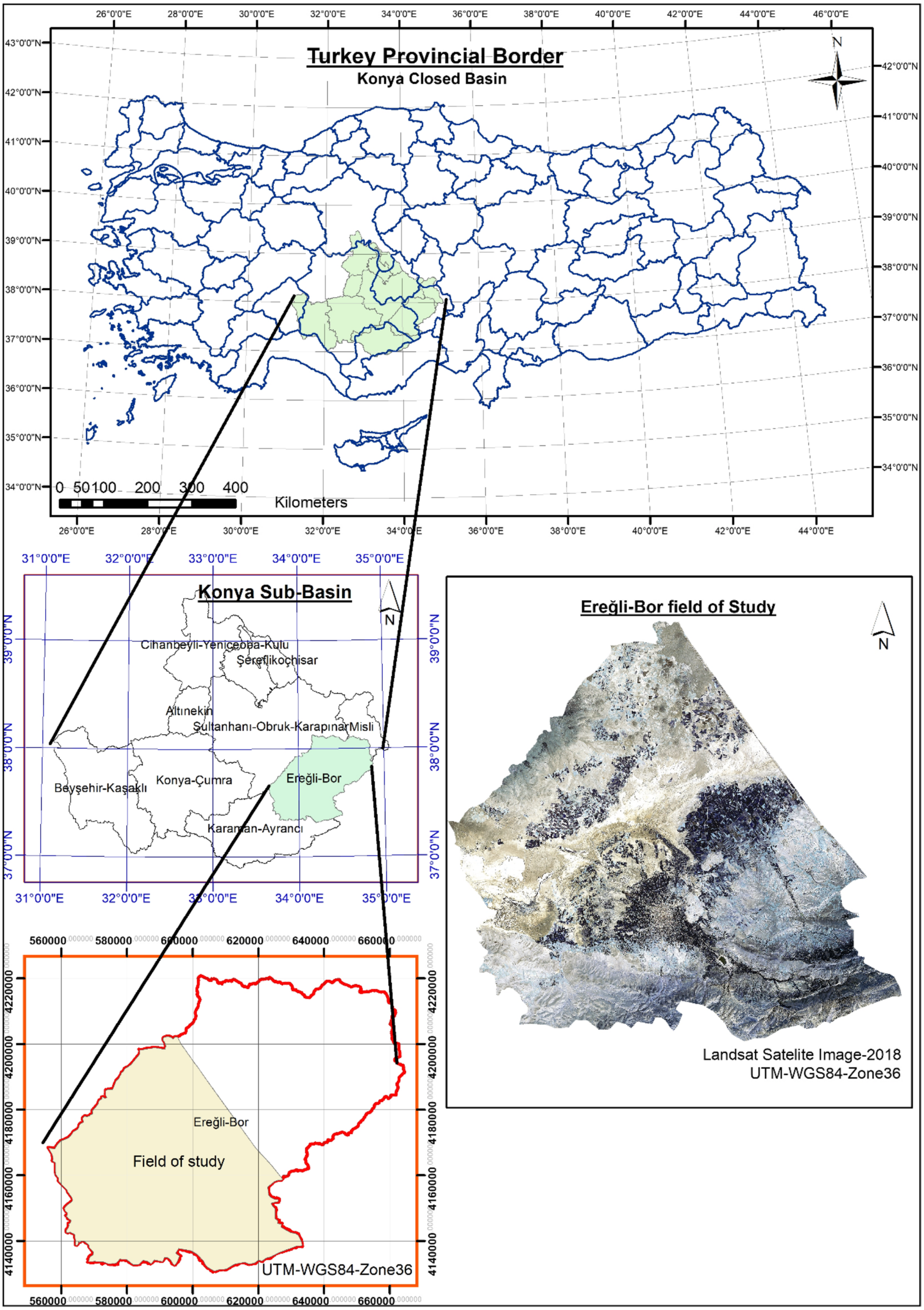

Fig. 1 Location map of the study area (Ereğli-Bor Sub-Basin)

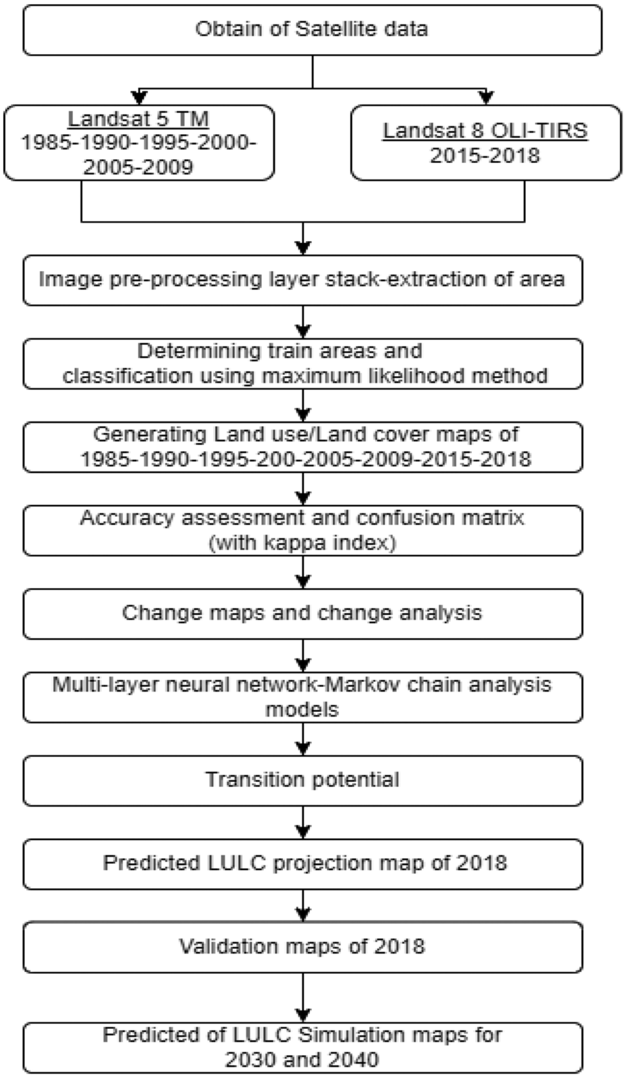

Fig. 2 Workflow process chart

Table 1 Landsat database information

Image Type	Date Acquired	Row and Path	Sensor ID
Landsat 5	22.08.1985	176/34	TM
	19.07.1990	176/34	TM
	2.08.1995	176/34	TM
	14.07.2000	176/34	TM
	12.07.2005	176/34	TM
	21.06.2009	176/34	TM
Landsat 8	24.07.2015	176/34	OLI-TIRS
	17.08.2018	176/34	OLI-TIRS

Maximum Likelihood Classification (MLC): It is one of the most commonly used supervised classifications. This method depends on the probability curves of the determined training classes and the assignment to the highest probability class according to the similarity of the pixels to be classified. The efficiency of this method depends on the correct prediction of the mean vector and covariance matrix in spectral classes (Aydın and Durduran 2021; Oruç, 2003). Maximum likelihood classification method was used in the study. Since the field of study has a large surface area, masking methods were treated in classification processes. The purpose of this method is to perform the classification process after the determined training areas are cut separately in cover type. Thus, the determination of how the land is used gives more accurate results, and on the other hand, higher classification results are acquired.

Accuracy analysis and error matrix

Evaluation and testing of classification accuracies are a prerequisite before detecting changes and making future predictions (Girma et al. 2022; Wang et al. 2021). In the study, 300 control points were placed with the accuracy analysis (Accuracy Assessment Function) of ERDAS software. Accuracy analyzes were completed with a homogeneous distribution, with at least 15 checkpoints for each training class. The accuracy of the checkpoints through the satellite images of Google Earth Pro and Landsat has been confirmed.

Change detection analysis

In the study, after the classification processes, change analysis was carried out in order to determine how and in which areas the change occurred within the training fields. Change detection was carried out with the matrix union module in ERDAS software. Aydın and Durduran (2021) study between 1985–2018 in land use changes on the cover and their results were expressed in Table 2 and Fig. 3.

Cellular Automata-Markov chain model

Markov chain (MC) is a term named after Russian innovator Andrea Markov. The Markov chain, which is a stochastic process, is based on predicting and interpreting the changes that will occur in the future. It follows a conditional probability distribution with step-by-step probability transitions in the process (Alsharif et al. 2022; Gagniuc 2017).

Cellular automata Markov improves accuracy of LULC projection due to consideration of user data. In many studies, the combination of RS and GIS is effectively used in the Markov model (Kundu et al. 2021; Cabral and Zamyatin 2009; Glenn et al. 1992).

After the LULC change analyzes in the field of study, a modeling study was carried out to analyze the directions in which the urban development of the region has increased from past to present and how it will develop in the coming years. Land Change Model (LCM) was used in TerrSet

Table 2 LULC change matrix for the years 1985–2018 (Aydın and Durduran 2021)

1985 year LULC	2018 year LULC					1985 Total (ha)
	Pasture Land	Artificial Land	Forest land	Wetland	Cultivated Land	
Pasture Land	40072.14	3083.94	6564.15	34.74	10236.78	59991.75
Artificial Land	383.4	8548.29	283.68	4.5	1211.58	10431.45
Forest land	16484.4	4768.29	237363.12	149.94	20836.08	279601.83
Wetland	2680.47	107.91	617.13	3639.96	203.04	7248.51
Cultivated Land	8075.34	8658.99	7277.49	74.52	224890.92	248977.26
2018 Total (ha)	67695.75	25167.42	252105.57	3903.66	257378.4	
Total Transformation	7704.00	14735.97	-27496.26	-3344.85	8401.14	

*Areas without change are underlined

software to detect the changes in LULC and to create scenarios. Since the urban development will take place mostly in the district center and its surroundings, Transition probability matrices were created, then model validation was performed and future prediction scenarios were created in an area of 331057 ha covering Ereğli region. The Cellular Automata -Markov Chain analysis module used for change detection for the years 1985 and 2018 and future predictions is explained by the equation below (Eq. 1).

$$S_{(t\,t+1)} = P_{ij}\ x\ S_{(t)} \quad (1)$$

In the equation, $S_{(t)}$ represents the state at time t and $S_{(t+1)}$ represents the state at time t + 1. $P_{(i\,j)}$ is calculated with the transition probability matrix given below (Eq. 2).

$$P_{ij} = \begin{bmatrix} P_{11} & P_{12} \ldots & P_{1n} \\ P_{21} & P_{22} \ldots & p_{2n} \\ P_{n1} & P_{n2} \ldots & p_{nn} \end{bmatrix}, (0 \le P_{ij} < 1) \quad (2)$$

Here P is the Markov probability matrix. P_{ij}, on the other hand, expresses the probability of transforming from the current state i to state j in the next time period. It will have a probability of 0 to 1 (Girma et al. 2022; Wang et al. 2021; Kumar et al. 2014).

Urban sprawl and geographical orientation

The geographical orientation of Ereğli district center in the period from 1985 to 2018 and the directions in which urbanization developed were determined. While the urban area of Ereğli district was 750 hectares as of 1985, it nearly doubled in 2000 and reached an area of 1420 hectares. Although the development rate during this 15-year period slowed down, the development continued gradually and reached an area of 1700 ha as of 2015 and 2670 ha as of 2018 (Fig. 4).

Although the district developed in every direction during the 34-year period, more changes are observed in the Northeast and South directions. This directional change was tried to be expressed more meaningfully by showing it spatially in tabular form and in radar chart environment (Fig. 5; Table 3).

Research results and discussion

Urban development and future prediction with the Cellular Automata-Markov Chain

Models were prepared with the Markov Chain in 3 different periods, covering the years 1985–2005, 2005–2015 and 1985–2015 from the classified satellite images, and the prediction model was compared with the 2018 LULC data selected as the test area. As a result of the high accuracy of the Markov chain model, a LULC model for the years 2030 and 2040 was created for the future prediction (Fig. 6).

Calculation of transition probability and transition area matrices

In order to determine the transition probabilities of changes in LULC to other classes over time, images classified in 3 different periods, covering 1985–2005, 2005–2015 and finally 1985–2015, were taken as a basis and 2018 transition probability matrix and transition area matrices were created.

Transition probability matrices express probable land use rates for the year 2018 in all 3 periods. If we examine Table 5, the transition probability in the class of artificial areas is 0.8286 in the 1st Period (1985–2005), while this rate increases to 0.9763 in the 2nd Period. This situation indicates that there is development in the class of artificial areas, i.e. in urban areas. The transition probability matrix is shown in Table 4.

LULC prediction and model validation

For prediction modeling, the 2018 prediction was carried out and compared with the 2018 reference data. Then, the

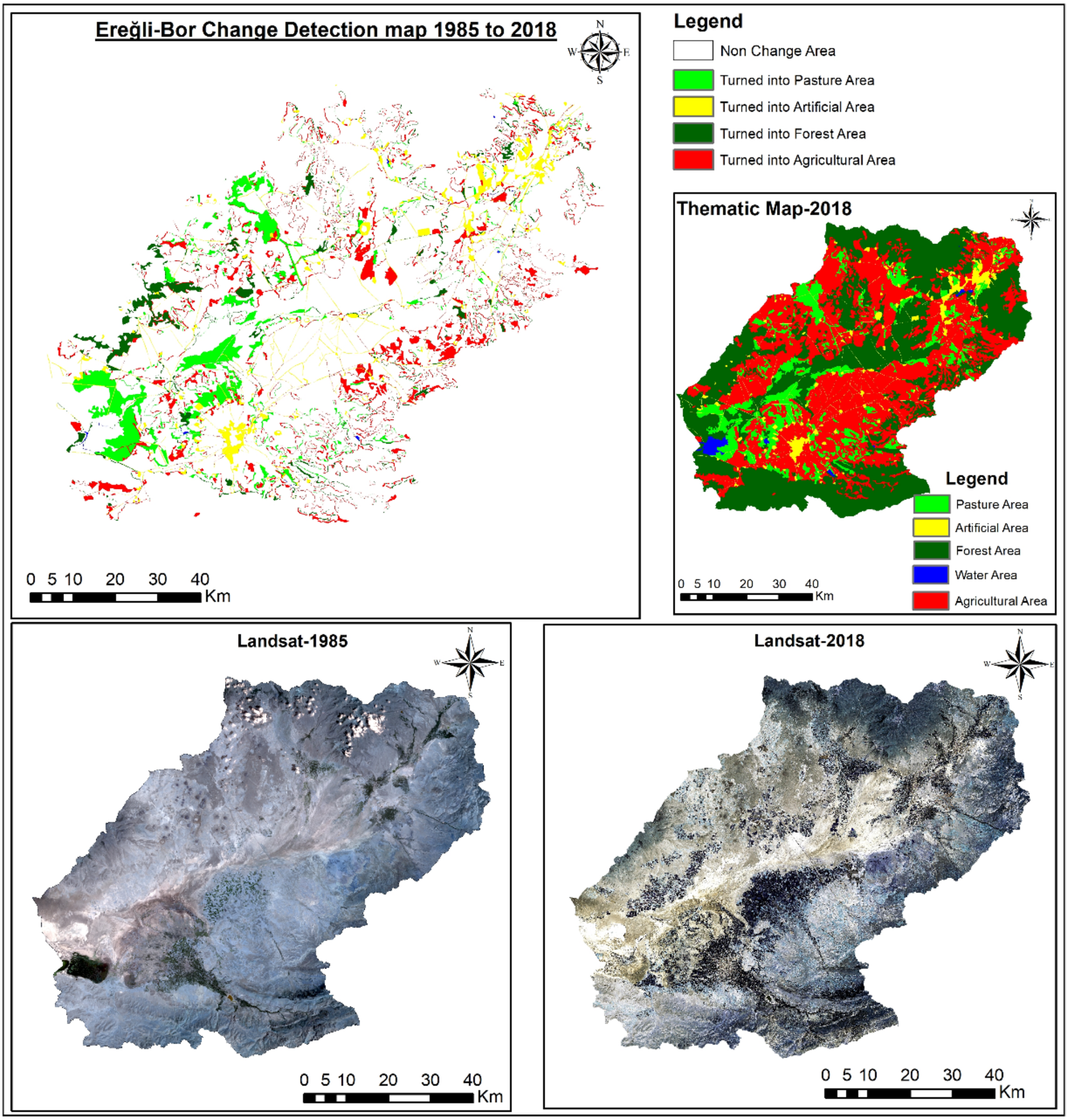

Fig. 3 Change analysis map for the years 1985–2018 (Aydın and Durduran 2021)

validation between the reference data and the predicted data was analyzed with the kappa statistics.

The M(m) value, which determines the agreement between the comparison map and the reference data map, was found to be 0.9312. The fact that this value is higher than the M(p) value of 0.9136, which is expressed as the perfect information value, indicates that the agreement is quite successful (Table 6). In addition, low Quantitative Disagreement Value and Cell Disagreement Value are another indicator of successful agreement.

How well the cells overlap with the objects of their representation on earth surface is determined by the K_location value. This value was found to be 0.9301 in our study. In the study, the K_location strata value was determined as

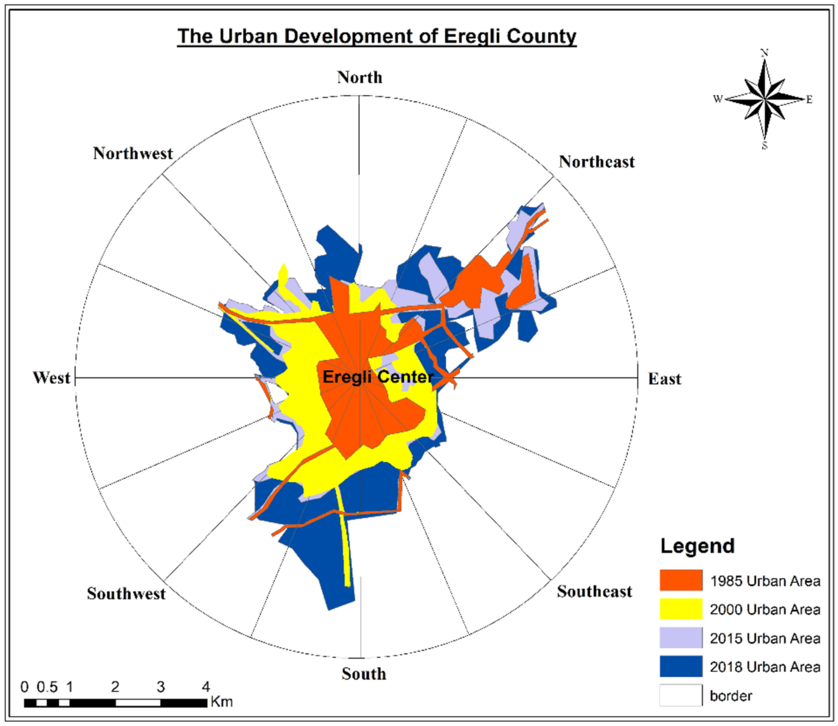

Fig. 4 Urban growth in Ereğli district

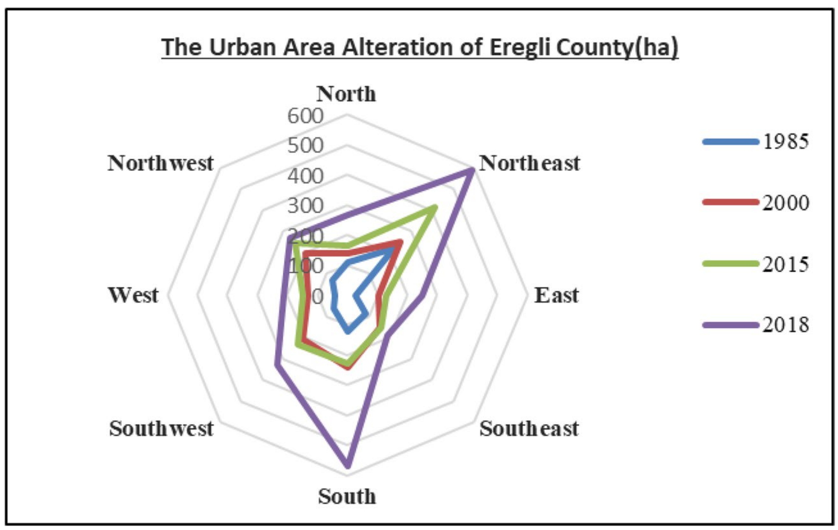

Fig. 5 Radar chart showing built-up area expansion (ha)

1.0000, which indicates that the overlap between the maps is very high. In addition, the K_standard value of the agreement between the reference map and the comparison map is 0.8935. The fact that all kappa index values are greater than 0.80 indicates that the agreement between the predicted and observed LULC maps is excellent (Table 6). The agreement and prediction modeling resulting from the validation ensure that the LULC results created for the future scenarios are accurately predicted. Based on the successful outcome of the modeling in the study, LULC maps and results of the field of study for the years 2030 and 2040 were presented. Agreement/disagreement values and Kappa statistics data results are given in Table 5.

Gains and losses in LULC

While the most gains were observed in Agricultural areas between the years 1985–2005, the highest gain was observed in Pasture Areas between the years 2005–2015. In both time periods, Agricultural, Forest and Pasture areas decreased and transformed into other land uses.

Table 3 Radar chart areal representation

Hectare(ha)	1985	2000	2015	2018
North	110.56	140.71	163.98	268.07
Northeast	222.83	250.48	413.73	586.78
East	29.09	105.93	128.33	248.63
Southeast	86.97	154.06	156.58	191.37
South	123.62	239.71	227.98	568.49
Southwest	65.81	206.94	231.67	330.97
West	40.1	130.98	146.28	212.93
Northwest	67.1	197.04	243.74	266.86
6Total Area (ha)	746.08	1425.85	1712.29	2674.1

While losses in Agricultural, Forest and Pasture areas progressed rapidly between the years 1985–2005, losses in Agricultural and Pasture areas between the years 2005–2015 tended to decrease compared to the previous period. However, losses in Forest areas continued (Fig. 7).

Between the years 1985 and 2005, Agricultural, Forest and Pasture Areas made the largest contribution to urban areas. 1.13% of Agricultural areas, 0.22% of Forest areas and 1.00% of Pasture areas transformed into urban areas. Between the same years, 29.61% and 1.09% of the pasture and water areas transformed into forest areas, respectively. A transformation was realized from pasture areas to agricultural areas at a rate of 8.45% (Fig. 8).

Between the years 2005 and 2015, as in the previous period, the transformation from Agricultural, Forest and Pasture areas to Urban areas took place. 0.50% of Agricultural areas, 0.40% of Forest areas and 0.82% of Pasture areas transformed into urban areas. Between the years 2005–2015, a gain of 6.88% from the forest areas and 2.56% from the water areas occurred (Fig. 9).

LULC prediction values for the years 2030 and 2040

According to the prediction results, while 2.75% of the region consisted of Artificial Areas in 2018, it is estimated that this rate will increase to 3.75% in 2030 and to 4.35% in 2040 (Table 6). It was observed that this increase in artificial areas has become more evident in the axes of the ring road connecting the provinces/districts as well as in the neighborhoods near Ereğli district center. While Pasture areas constituted 13.25% of the entire area as of 2018, it was estimated as a result of modeling that it will decrease to 13.07% in 2030 and to 12.97% in 2040. Regarding Table 6, it is estimated that there will be gradual decreases in agricultural and forest areas until 2030 and 2040.

In line with the statistical results and data obtained after the prediction modeling, future prediction maps were created and the geographical development of the region was expressed more descriptively with visuals (Fig. 10).

In the 2018 model map in the field of study;

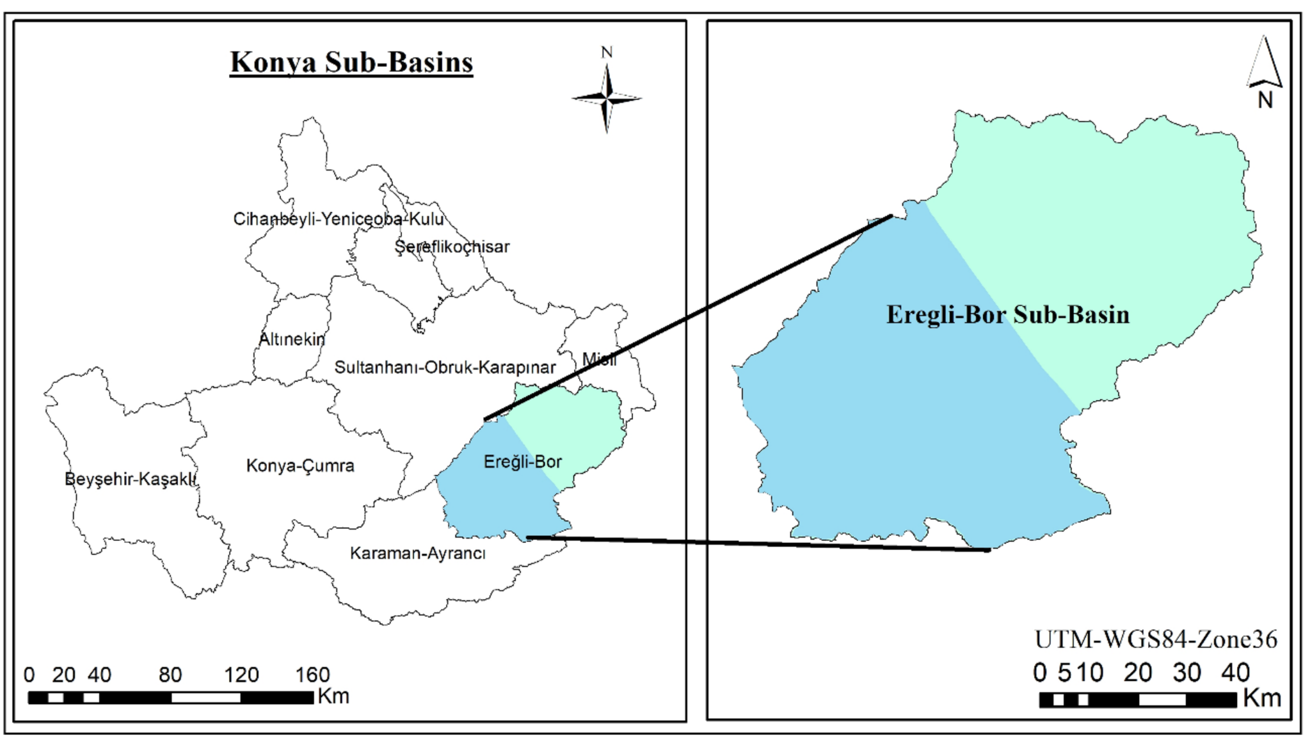

Fig. 6 Urban development modeling area

Table 4 Transition probability matrix (periods 1–2-3)

		Pasture Area	Artificial Area	Forest Area	Agricultural Area
1985–2005 (1. period)	Pasture Area	0.8454	0.0105	0.0249	0.1182
	Artificial Area	0.0259	0.8286	0.0378	0.1072
	Forest Area	0.0045	0.0029	0.9676	0.0238
	Agricultural Area	0.0159	0.0120	0.0136	0.9584
		Pasture Area	Artificial Area	Forest Area	Agricultural Area
1985–2005 (2. period)	Pasture Area	0.9196	0.0031	0.0604	0.0169
	Artificial Area	0.0010	0.9763	0.0067	0.0158
	Forest Area	0.0414	0.0014	0.9541	0.0025
	Agricultural Area	0.0040	0.0024	0.0026	0.9909
		Pasture Area	Artificial Area	Forest Area	Agricultural Area
1985–2005 (3. period)	Pasture Area	0.9124	0.0049	0.0410	0.0415
	Artificial Area	0.0114	0.9636	0.0019	0.0230
	Forest Area	0.0247	0.0003	0.9746	0.0000
	Agricultural Area	0.005	0.0036	0.0016	0.9896

Table 5 Agreement/disagreement values of comparison maps (2005–2015) and reference map (2018)*

Information of Quantity			
Information of Location	P(n) = 0.5277	P(m) = 0.9746	P(p) = 1.0000
	K(n) = 0.4836	K(m) = 0.9312	K(p) = 0.9136
	M(n) = 0.4836	M(m) = 0.9312	M(p) = 0.9136
	H(n) = 0.4836	H(m) = 0.9312	H(p) = 0.9136
	N(n) = 0.1667	N(m) = 0.3544	N(p) = 0.3483
	Agreement Chance		0.1667
	Agreement Quantity		0.1878
	Agreement Strata		0.5768
	Agreement Gridcell		0.0000
	Disagreement Gridcell		0.0000
	Disagreeme Strata		0.0433
	Disagree Quantity		0.0254
	Kno (quantity)		0.9175
	Klocation (position)		0.9301
	Klocation Strata (location layer)		1,0000
	Kstandard (standard)		0.8935

*Studies of Aydın and Durduran 2021; Fadhil and Kurban 2022 were used for tables and equations

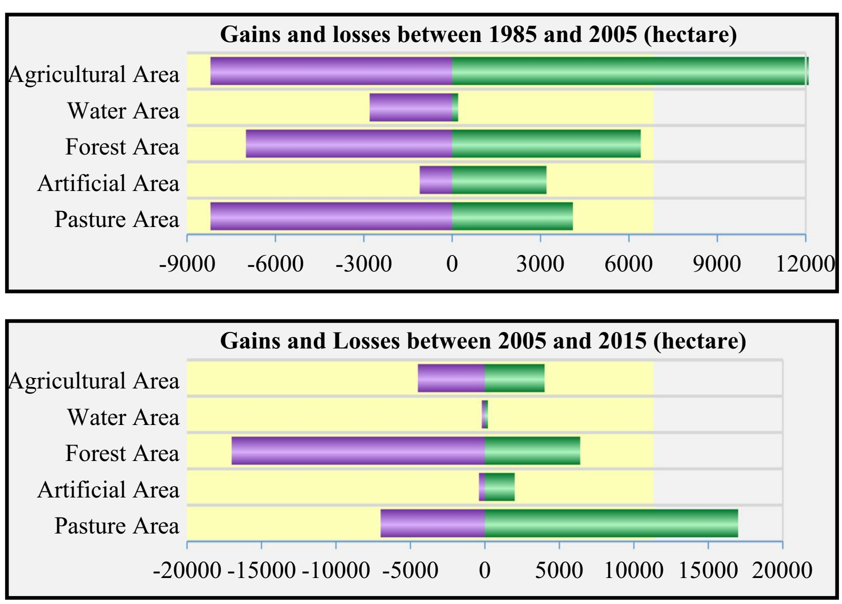

Fig. 7 Gains and losses between 1985–2000 and 2005–2015

- While the total surface area of the *Artificial Areas* is approximately 90 km^2, as a result of the modeling, the prediction model is expected to reach approximately 123 km^2 for the year 2030 and it is expected to reach approximately 142 km^2 for the year 2040.
- While the *Pasture areas* are 433 km^2 in total, as a result of the prediction model, it is estimated that there will be a decrease down to 427 km^2 in 2030 and down to 424 km^2 in 2040.
- While the *Forest areas* constitute 1320 km^2 of the field of study, it is estimated that this value will decrease to 1311 km^2 in 2030 and to 1304 km^2 in 2040 (Fig. 11).

As a result of the prediction model, it is estimated that the Alhan, Sarıtopallı and Kargacı neighborhoods in Ereğli district center will develop until 2030–2040 (Fig. 12).

Again, as a result of the modeling, it is expected that there will be development in the road axes connecting Ereğli district

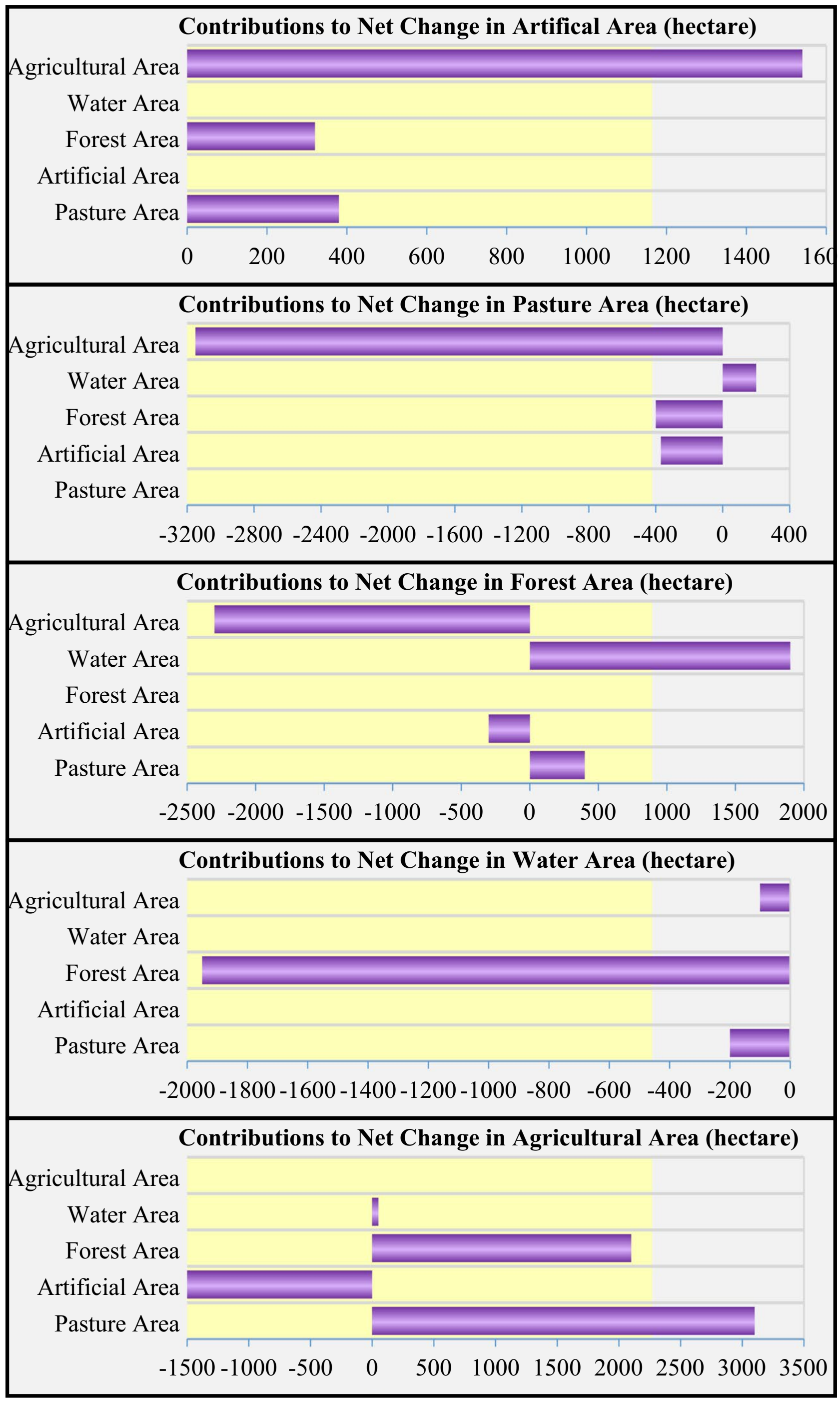

Fig. 8 Gains and losses in net change (ha) of Urban (1), Pasture (2), Forest (3), Water (4), Agricultural (5) areas between 1985–2005

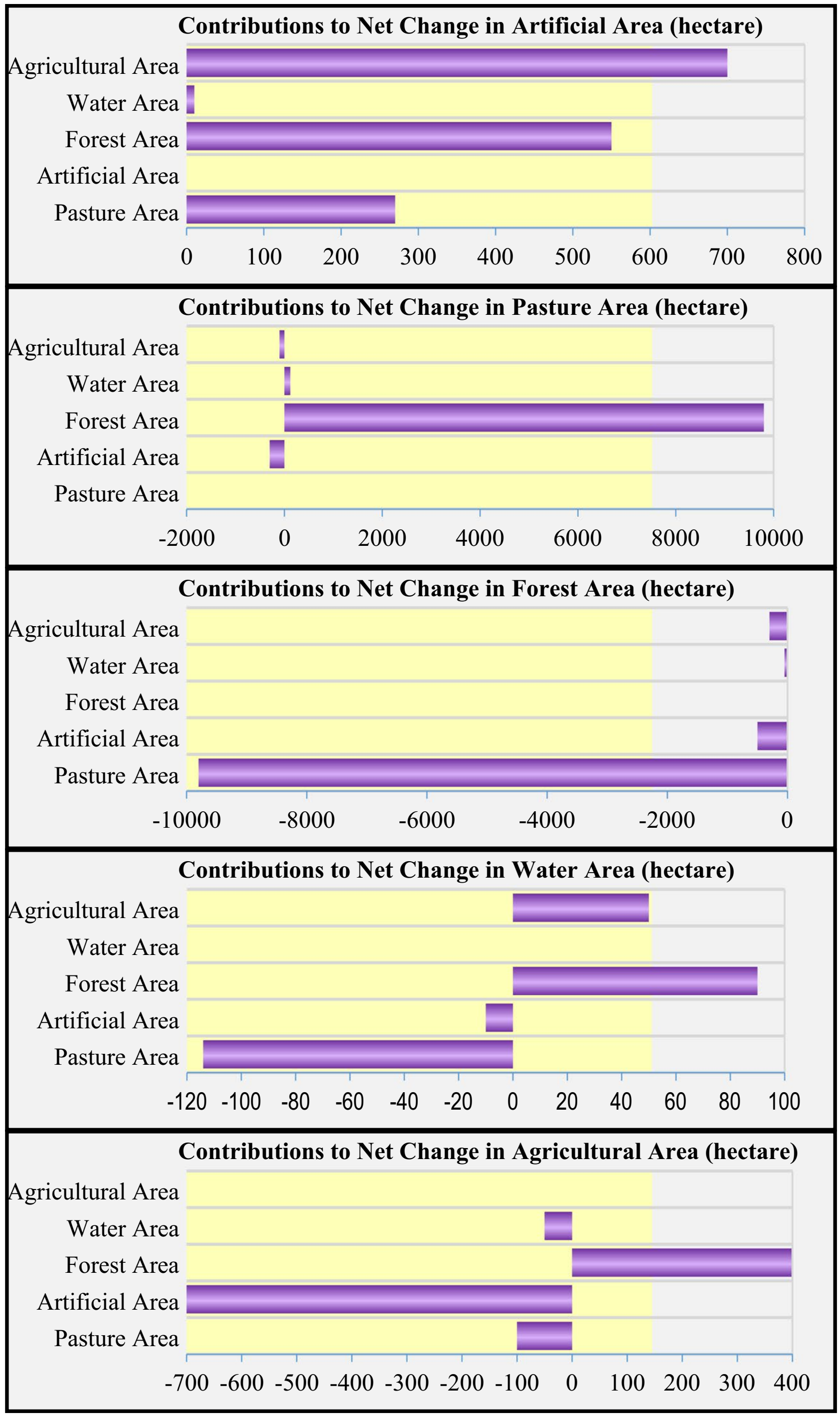

Fig. 9 Gains and losses in net change (ha) of Urban (1), Pasture (2), Forest (3), Water (4), Agricultural (5) areas between 2005–2015

Table 6 Class distribution of LULC for the years 2018–2030-2040 and prediction percentages (Aydın, 2022)

Classification	Years						YearsDifference in land use/cover change (%)		
	2018km^2	%	2030km^2	%	2040km^2	%	Δ% 2018–2030	Δ% 2030–2040	Δ% 2018–2040
Pasture Area	433.07	13.25	427.27	13.07	424.19	12.97	-1.36	-0.73	-2.09
Artificial Area	89.93	2.75	122.74	3.75	142.24	4.35	26.73	13.71	36.78
Forest Area	1320.49	40.39	1311.38	40.11	1304.64	39.90	-0.69	-0.52	-1.21
Agricultural Area	1425.76	43.61	1408.37	43.07	1398.83	42.78	-1.23	-0.68	-1.93

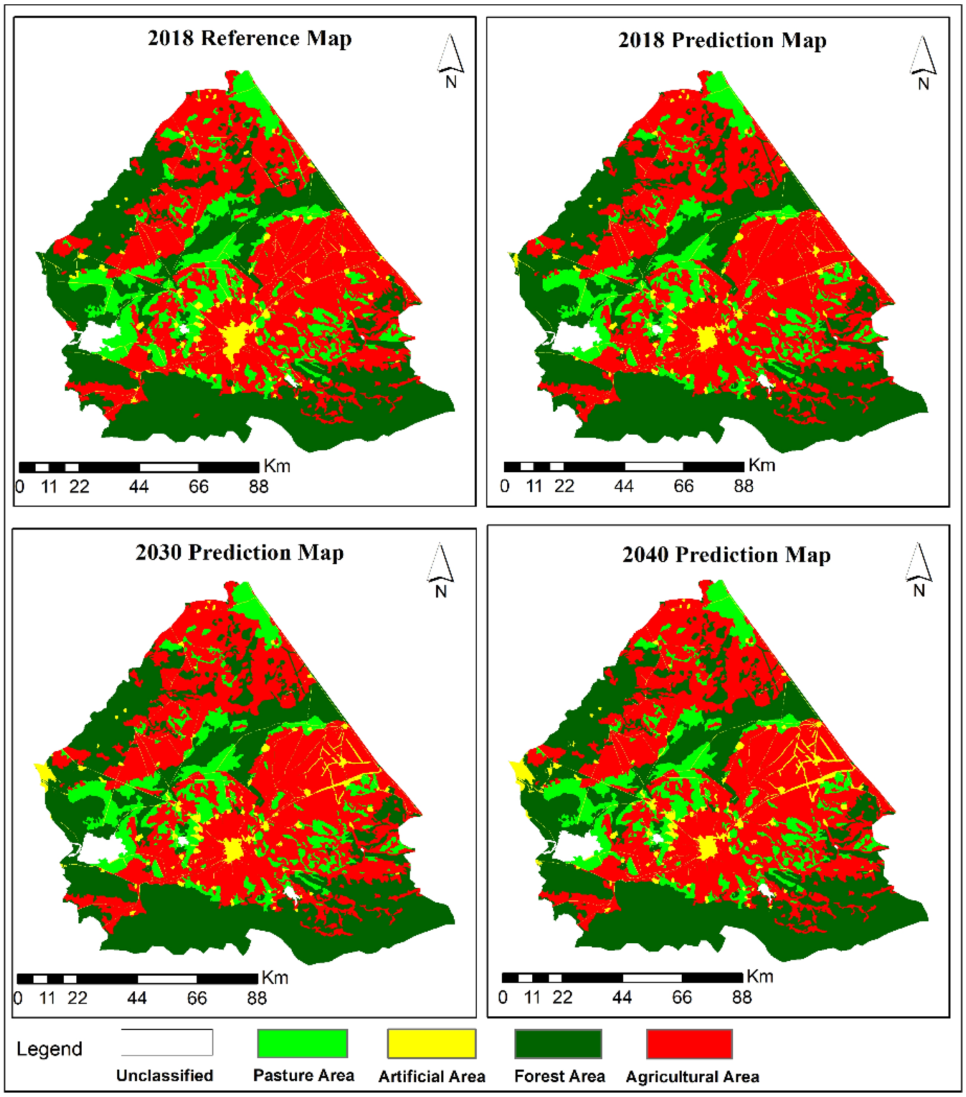

Fig. 10 2018 reference and prediction model map, 2030–2040 prediction map

to the cities of Aksaray and Niğde. Intercity roads in the region are thought to be a factor in this development (Fig. 13).

It is observed in the prediction modeling maps that there will be development until 2040 in Bulgurluk, Aziziye, Çakmak Bucağı, Acıkuyu, Tepeköy and Zengen neighborhoods located in the northeast geographical position, 20 km from Ereğli district, which is located at the intersection of Konya-Adana road and Adana-Aksaray road connecting Ereğli district to the cities of Aksaray, Niğde and Adana (Fig. 14).

Land Change Modelers are used to predict changes in LULC. As a guide to studies conducted for urban areas, simulations made with these models can provide information about the changes that may occur in the future under the current situation and conditions (Hasan et al. 2020; Ozturk 2015; Demirel et al. 2008). CA-Markov is an expert-driven process that spatially presents future LULC using categorized suitability maps (Gidey et al. 2017; Paegelow et al. 2014).

While this study maintains its subjectivity due to the absence of similar investigations in the region, a comparison with findings from analogous studies conducted in different regions reveals that the results are not significantly different. Much like this paper, other studies draw conclusions regarding changes in land class and future scenarios in specific regions, unveiling the underlying reasons for these land changes (Yenibehit, et al. 2024; Koranteng et al. 2023; Aniah et al. 2023; Viana and Rocha 2020; Addae and Oppelt 2019; Abass et al. 2018; Braimoh and Vlek 2004;).

In numerous papers of a similar nature, comparisons between artificial zone classes (urban areas, residential areas, etc.) and other zone classes often lead to the general conclusion that there is an increase in artificial areas accompanied by a decrease in agricultural, forest, and pasture areas (Abraham and Kundapura 2022; Moghadam and Helbich 2013).

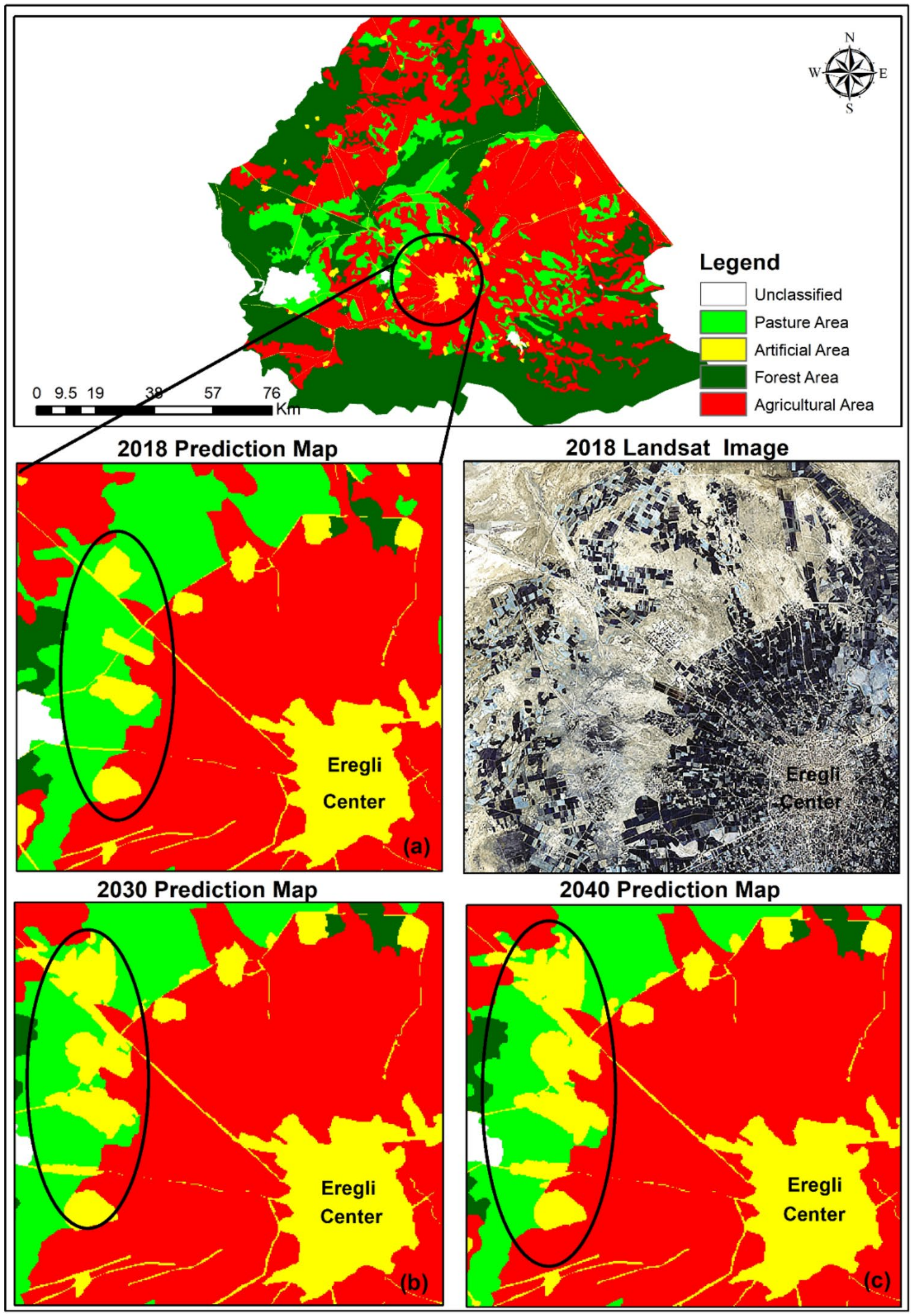

Fig. 11 Ereğli district change and prediction map; example-1 2018 (**a**), 2030 (**b**), 2040 (**c**)

This study employed the CA-MC modelling method to conduct an urban development analysis of the Ereğli district and its surroundings. The analysis identified decreases in agricultural, forest, and pasture areas, accompanied by increases in urban areas. The results reveal anticipated development trends in the northwest and northeast neighbourhoods of the region.

Conclusion

In this manuscript, satellite data of Landsat 5 TM and Landsat 8 OLI-TIRS at 30 m resolution were obtained from *earthexplorer.usgs.gov* (USGS) in order to observe the changes in LULC and to make regional analyzes. Height and slope maps were prepared from the Digital Terrain Model (DTM) data of the region. Data from

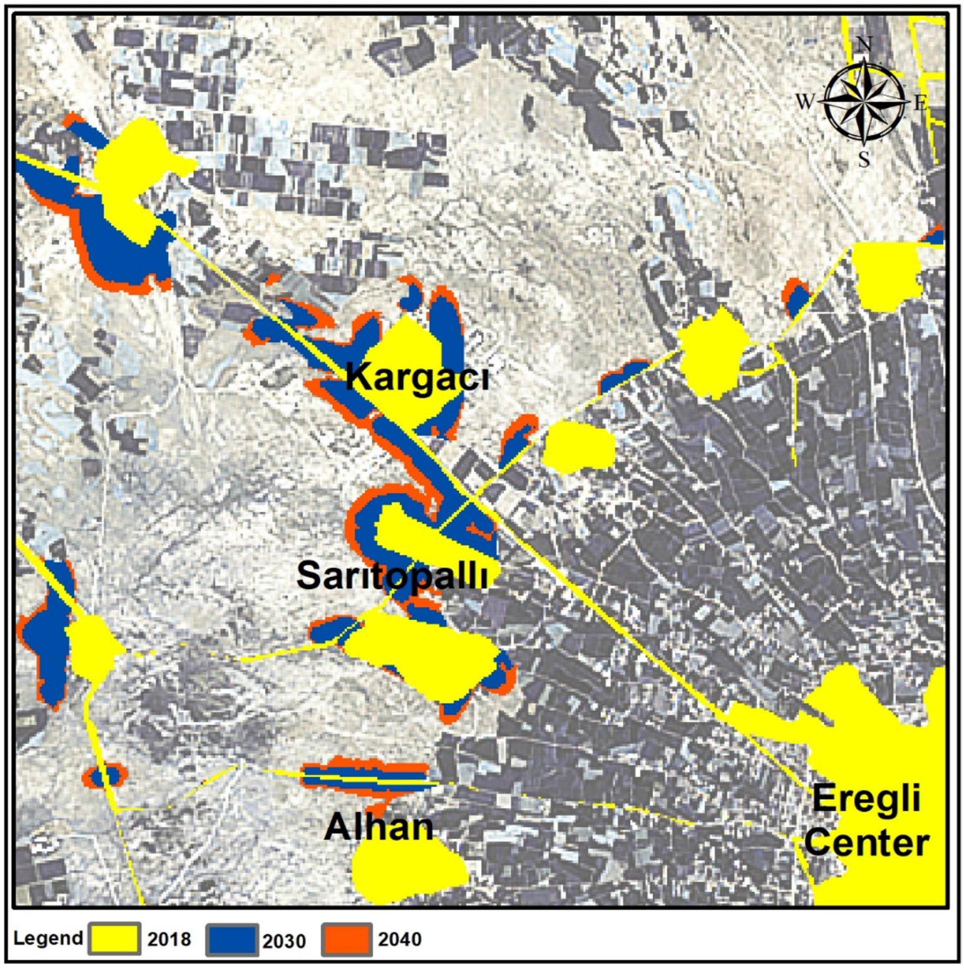

Fig. 12 Ereğli district center developing regions-1

the CORINE Classification Project system for the years 1990–2000-2006–2012 were used in classification processes. Furthermore, the road network data required for the prediction models created were obtained freely from *openstreetmap.org*. Modeling techniques were used to analyze temporal changes in the study area and make predictions about future years with the help of RS and GIS techniques. The Markov chain model predicts the future with the help of current probabilities. LULC in the Ereğli region, which change over time, were cross-tabulated with land categories and probability matrices of transition areas were calculated according to the situation of the region at different times. Briefly, the modeling is analyzed the connection of data cells with neighboring cells and it is explained whether the behavioral state of this connection will continue in the future.

In this study, in order to determine the changes in LULC in the period covering 1985–2018 in the Konya Eregli-Bor Lower Basin by using the Landsat TM satellite images and CORINE classification data, 5 basic training classes were identified and classified by supervised classification techniques. Then, modeling was carried out with the Cellular Vending MC Model to determine the urban development potential of the region and monitor the change in artificial regions. As a result, this study was conducted regionally for the first time. The change in LULC in the study area and future prediction models have produced new original results for both natural areas and artificial areas.

It is revealed that urban development in Eregli district will be in the whole region but will show a more pronounced development especially in the neighborhoods of the Northwest direction, as well as the results of forecast modeling around road axes and development will continue. Despite the increase in artificial areas in the years 2030 and 2040 determined for the future scenario, it is noteworthy that there will be losses in agricultural, forest and pasture areas. Especially the losses to occur in pasture areas are higher than forest and agricultural areas. It should not be forgotten that these losses in pasture areas will damage the livestock sector and may cause the destruction of the most important food sources of the livestock.

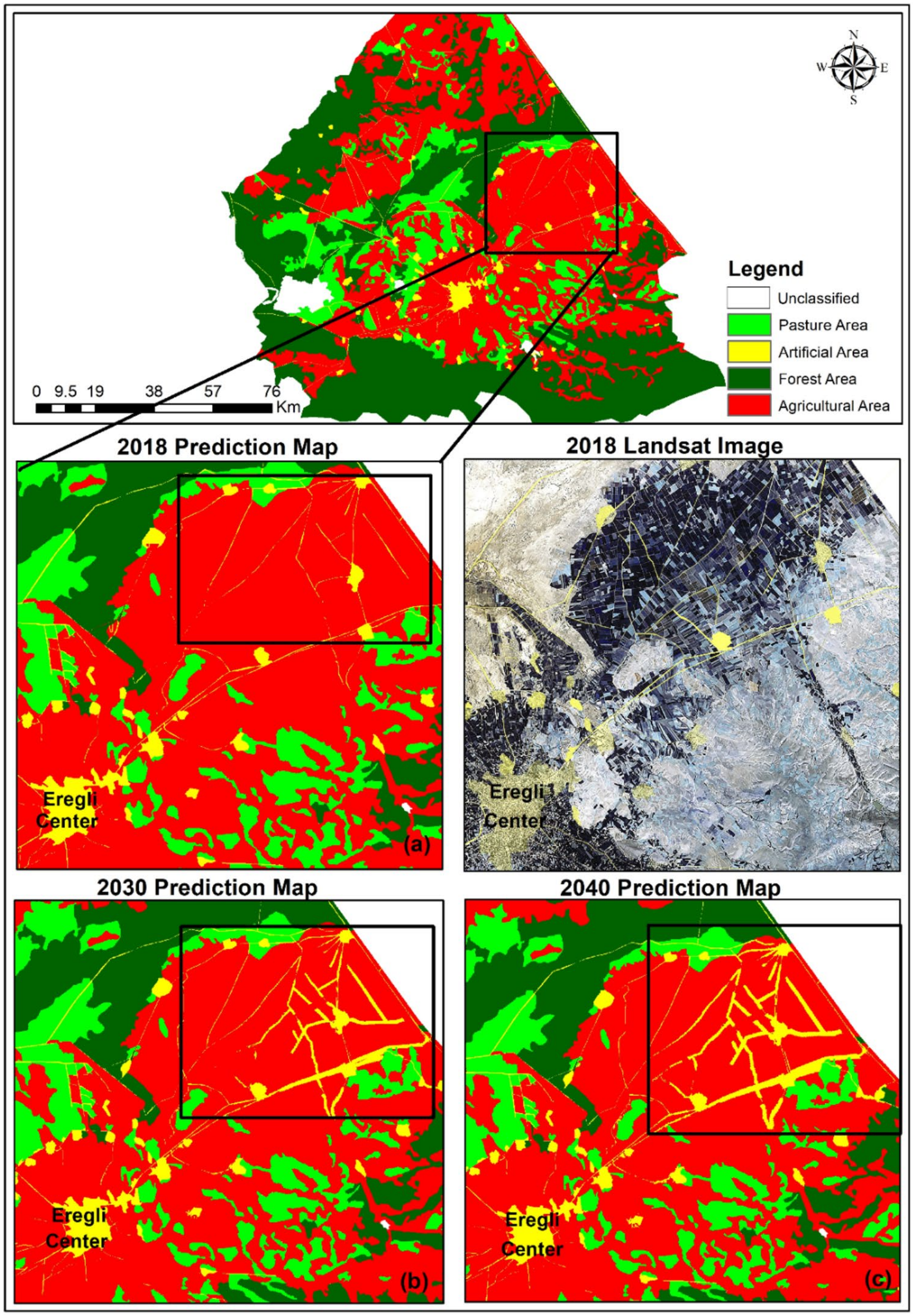

Fig. 13 Ereğli district change and prediction map; example-2 2018 (**a**), 2030 (**b**), 2040 (**c**)

In addition, agricultural areas have been transformed into artificial areas to meet the demand for housing. While the reduction of rural and agricultural areas causes negativities in terms of ecological balance and biodiversity conservation, the increase of urban heat islands also accelerates climate change (Akdeniz et al. 2023; Al-Kofani et al. 2018; Mansour et al. 2020).

Considering that nature has a unique balance, it is obvious that changes occurring on earth surface will cause a radical change in the ecological balance and cause irreversible losses. The region is one of the most important production regions of Türkiye in terms of agriculture. For this reason, it is necessary to prevent the unplanned and arbitrary use of the lands and to restrain the occupation of public lands and disruption of their characteristics. It is important to take into account the LULC of the region in the laws and regulations to be enacted by the authorized bodies in all kinds of future planning, and to control the planning with

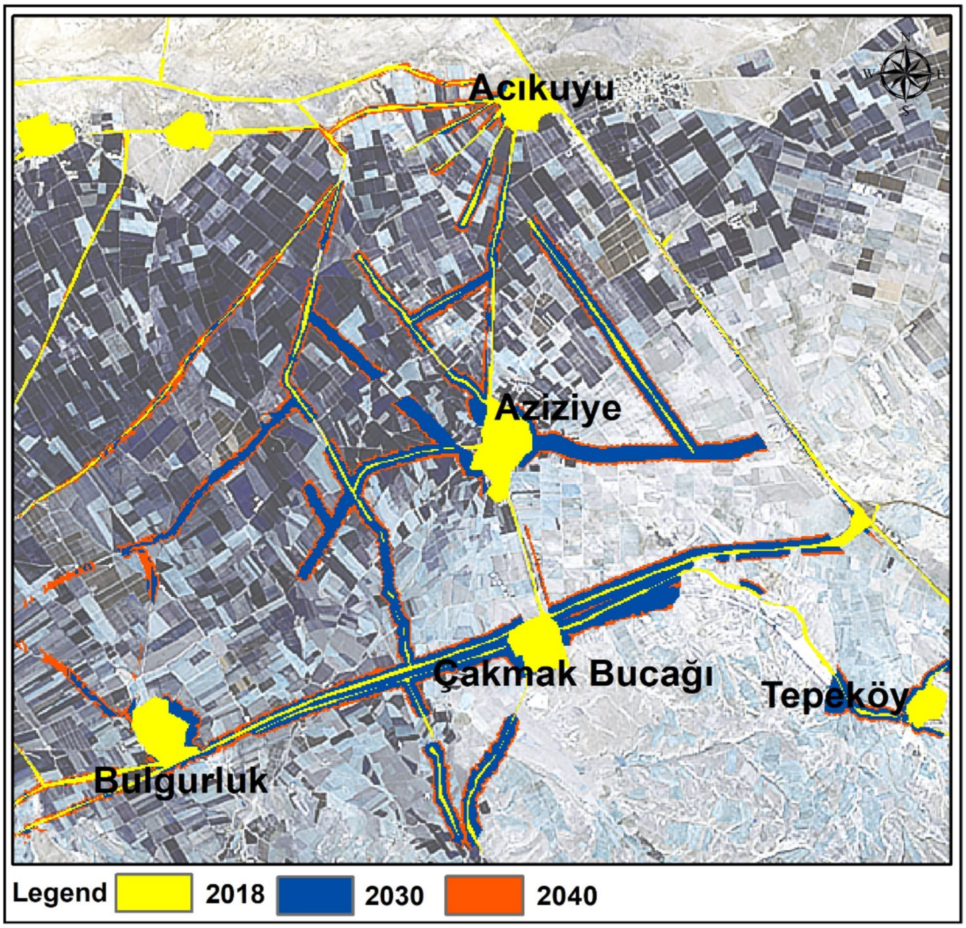

Fig. 14 Ereğli district center developing regions-2

future prediction models and analysis methods while planning residential areas, industrial areas and agricultural areas. Population increases, migration and socioeconomic conditions as well as political factors can cause environmental problems. Therefore, before the environmental plans, master development plans and implementary development plans prepared by local authorities are created, such prediction models should be prepared and city plans should be created in line with the development direction and speed of development of the region. Furthermore, comprehensive precautions should be taken to prevent construction in agricultural, forest and pasture areas, and deformations in these areas should be prevented. It will ensure that more sustainable living spaces are left for future generations by protecting and regenerating areas that have not been disturbed or can be rehabilitated.

Abbreviations ANN: Artificial Neural Networks; CA-MC: Cellular Automata-Markov Chain; DSI: State Hydraulic Works; DTM: Dijital Terrain Model; GIS: Gegraphical Information System; LCM: Land Change Model; LULC: Land Use Land Cover; MLC: Maximum Likelihood Classification; MLP: Multi Layer Perception; RS: Remote Sensing; USGS: United States Geological Survey

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The CORINE data used in the study were obtained free of charge from https://land.copernicus.eu/pan-european/corine-land-cover. In addition, satellite images were obtained free of charge from the US Geological Survey (USGS). We thank both institutions for their service.

Author contributions Taha Kağan Aydın, Fiction, data, applications, fieldwork and article writing and revision;

Süleyman Savaş Durduran, fiction, reviewed the manuscript.

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Data availability Datasets generated during the current study are available from the corresponding author on reasonable request.

Declarations

Competing interests The authors declare no competing interests.

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