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Prediction of Land Use and Land Cover Changes from 2018 to 2042 Using CA-Markov: A Case Study from Türkiye

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Abstract

Aim of study: To determine the potential changes that may occur in land use classes in Akyazı Forest Enterprise for 2030 and 2042.

Area of study: Akyazı Forest Enterprise was selected as the study area.

Material and method: In this study, the Coordination of Information on the Environment (CORINE) land use land cover (LULC) datasets for the years 2006, 2012 and 2018 were used. The Markov model derived transition area and transition probability matrices (TPM) for 2018 based on the LULC maps derived from CORINE for 2006 and 2012. These matrices were used to predict LULC classes in 2018 through a 10-year simulation using the CA-Markov module.

Main results: A comparison was made between the projected LULC classes map and the land use class map derived from the 2018 CORINE data, and a similarity rate of 91.1% was found. For the 24 years from 2018 to 2042, the total forest area is predicted to increase by 3.8% or 581.5 ha.

Research highlights: The forecasted outcomes acquired for the future can aid in developing revised forest management strategies, particularly in ensuring the long-term viability of forest ecosystems.

Keywords: Forest Management, Sustainability, Simulation, Change Detection, Türkiye

CA-Markov Yöntemiyle 2018'den 2042'ye Arazi Kullanımı ve Arazi Örtüsü Değişimlerinin Tahmini: Türkiye'den Bir Vaka Çalışması

Öz

Çalışmanın amacı: Akyazı Orman İşletme Müdürlüğü'nde 2030 ve 2042 yıllarında arazi kullanım sınıflarında meydana gelebilecek potansiyel değişiklikleri belirlemektir.

Çalışma alanı: Çalışma alanı olarak Akyazı Orman İşletme Müdürlüğü seçilmiştir.

Materyal ve yöntem: Bu çalışmada, 2006, 2012 ve 2018 yıllarına ait CORINE arazi örtüsü veri setleri kullanılmıştır. Markov modeli, 2006 ve 2012 yılları için CORINE'den türetilen arazi kullanım sınıfları haritalarına dayanarak 2018 yılı için geçiş alanı ve geçiş olasılığı matrislerini türetilmiştir. Bu matrisler kullanılarak, 2018 yılındaki arazi kullanım sınıfları tahmini, CA-Markov modülü kullanılarak 10 yıllık bir simülasyon yoluyla gerçekleştirilmiştir.

Temel sonuçlar: Tahmin edilen arazi kullanım sınıfları haritası ile 2018 CORINE verilerinden türetilen arazi kullanım sınıfları haritası arasında bir karşılaştırma yapılmış ve %91.1'lik bir benzerlik oranı bulunmuştur. 2018'den 2042'ye kadar olan 24 yıl için toplam orman alanının %3.8 veya 581.5 hektar genişleyeceği tahmin edilmektedir.

Araştırma vurguları: Gelecek için elde edilen öngörülen çıktılar, özellikle orman ekosistemlerinin uzun vadeli sürdürülebilirliğinin sağlanmasında, revize edilmiş orman yönetim stratejilerinin geliştirilmesine yardımcı olabilir.

Anahtar Kelimeler: Orman Amenajmanı, Sürdürülebilirlik, Simülasyon, Değişim Tespiti, Türkiye

Introduction

Lands are a valuable natural resource that can be subject to degradation, primarily due to human activities. Additionally, it can degrade due to natural elements such as erosion, climatic conditions, and landslides (Nadaf & Gaonkar, 2021 ; Özdemir et al., 2020). Approximately 75% of the Earth's terrestrial surface has experienced anthropogenic alterations in the last millennium (Winkler et

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al., 2021). From 1990 to 2019, the amount of agricultural land available per person declined by 30 percent to 0.6 hectares (ha). This dynamic demonstrates that the productivity of agricultural land utilization improves as the population expands. During the same time frame, the total area of forests worldwide declined by 4%, reaching a value of 4.1 billion ha. The global agricultural area in 2019 was reported to be 4.8 billion ha, equivalent to one-third of the entire land area on Earth (FAO, 2021).

Changes in land use and land cover (LULC) are considered to be one of the critical environmental problems on a global scale (Singh et al., 2015 ; Chim et al., 2019; Sibanda & Ahmed, 2021; Hussain et al., 2022; Asif et al., 2023). Humans cause environmental impacts by changing various dynamics of LULC. Various natural and anthropogenic forces induce LULC changes within the constraints of socio-economic and political contexts (Hamad et al., 2018). The most common LULC changes at the global level include agricultural expansion, deforestation, and urbanization (Mubea et al., 2014; Asif et al., 2023; Xu et al., 2023). The investigation of LULC change provides a foundation for a more comprehensive understanding of worldwide change (Munthali et al., 2019). Significant changes in LULC have occurred in recent years, with critical forest regions becoming agricultural and urban areas rapidly encroaching on rural landscapes (Tariq et al., 2022). Information on monitoring the previous, current, and future status of LULC has an significant role in decision-making processes (Moghadam & Helbich, 2013; Beroho et al., 2023; Bulut, 2023). While monitoring and observation studies on LULC help to enhance our comprehension of historical tendencies, predictions about potential future developments are made possible with the help of modeling based on forecast simulation (Chim et al., 2019; Abdelkarim, 2023). The LULC model has been found to accurately forecast the future status and spatial arrangement of LULC by utilizing data from previous periods. (Nath et al., 2020). Geographic information system (GIS) methods and remote sensing (RS) data are considered suitable techniques for managing land cover and other natural resources (Atef et al., 2023). In particular, over the last two decades, various GIS and RS methods have been used to assess and model spatial and temporal LULC (Roy et al., 2015 ; Singh et al., 2015; Mansour et al., 2022; Beroho et al., 2023). Utilizing spatial and temporal resolution imagery from RS data enables the rapid identification of changes on the Earth's surface at a reduced cost and time compared to conventional field survey methods (Koko et al., 2020). Statistical models (Somvanshi et al., 2020), Markov chain (MC) models (Ahmad et al., 2017; Rimal et al., 2018), cellular automata (CA) models (Chen et al., 2014 ; Khan & Mohammad, 2022), logistic regression (Hoek et al., 2008; Buya et al., 2022) and artificial neural networks (Aksoy & Kaptan, 2022) are known as widely used models in the literature to predict LULC (Atef et al., 2023).

CA and MC models are widely used to accurately simulate future LULC changes (Behera et al., 2012; Amini Parsa et al., 2016; Sibanda & Ahmed, 2021; El Haj et al., 2023). Cellular Automata-Markov Chain (CA-Markov) models offer suitable alternatives for modeling the spatial and temporal dynamics of LULC (Hua, 2017 ; Hyandye & Martz, 2017). Additionally, this model is widely used in modeling watershed management and describing forest cover and urban sprawl dynamics (Ghosh et al., 2017). Analyzing the change in LULC with the CA-Markov method has a significant role in forest management and land use planning (Nguyen et al., 2018). RS and GIS data sets are used to determine the initial conditions of the CA-Markov chain, parameterize the model, and calculate and define transition state probabilities (Nath et al., 2020). The basis of this method is the development of a TPM for LULC change between two different dates to use for predictions about the probability of specific LULC class pixels changing to another class or remaining in the same class (Yagoub & Al Bizreh, 2014; Surabuddin Mondal et al., 2019). After analyzing the zoning images, the MC model creates an output image with the potential change matrix for the previous year (Asif et al., 2023).

The basic CA-Markov flow is as follows:

1. Input Data (Historical LULC Maps)

Represent as a set of LULC maps over time (Eq. 1):

$$L(t_0), L(t_1), \dots, L(t_n). \quad (1)$$

2. Markov Chain Process

Use historical maps to calculate the transition probabilities between LULC categories (Eq. 2):

$$P = \{P_{ij}\}, \text{where } P_{ij} = P(L(t+1) = j(L(t) = i). \quad (2)$$

P_{ij} is the probability of transitioning from state i (e.g., forest) to state j (e.g., urban) in the next time step.

Calculate the expected area for each transition based on the probability matrix and the current state (Eq. 3):

$$A_{ij} = A_i X P_{ij}, \quad (3)$$

where A_i is the area of class i at time t.

3. CA Process

For each cell, define the neighboring cells, typically using a 3x3 or 5x5 window.

Apply transition rules that consider the transition probabilities and neighborhood effects to determine the likelihood of a cell changing state (Eq. 4):

$$C(x, y) = f(N(x, y), P_{ij}). \quad (4)$$

$C(x, y)$: New state of cell at location (x, y) based on the neighborhood $N(x, y)$ and transition probability P_{ij}.

4. Iteration of the CA Model :

Calculate the expected area for each transition based on the probability matrix and the current state (Eq. 5):

$$L(t+1) = CA - Markov(L(t)). \quad (5)$$

Continue iterating the CA process to refine spatial patterns of land use change.

5. Future LULC Prediction:

The final predicted LULC map at time T is generated by the model (Eq. 6):

$$L(T) = CA - Markov\ (L(T-1)). \quad (6)$$

The CA-Markov technique is often used in research to track variations in land use categories using various RS data (Choukiker & Dohare, 2021). Landsat imagery is often used as RS data (Zadbagher et al., 2018; Aksoy & Kaptan, 2021; Dey et al., 2021; Aksoy & Kaptan, 2022; Aksoy et al., 2022; Kaptan et al., 2022; Agudelo-Hz et al., 2023; El Haj et al., 2023; Badshah et al., 2024). Even so, several research in the literature analyze changes in LULC using CORINE land use data sets (Viana & Rocha, 2018; Alan et al., 2020; Kuleli & Bayazıt, 2022; Gull & Mahmood, 2022; Agudelo-Hz et al., 2023; Aydın & Durduran, 2024). The primary objective of this study is to generate land use/cover maps using CORINE land use data from 2006, 2012, and 2018. Additionally, it aims to examine the spatial and temporal variations in land use and to develop a model, namely the integrated CA-Markov model, to predict LULC changes for the years 2030 and 2042.

Materials and Methods

Study Area

Akyazı Forest Enterprise is located within the borders of Sakarya Regional Directorate of Forestry. The study area is between 280100-323300 eastern longitudes and 4483500-4523400 northern latitudes (Figure 1). The research area has a total size of 76406.7 ha. The elevation varies from 22 to 1716 meters above sea level. The average slope within the study area is 32%. The research region has an average annual precipitation of 484.2 millimeters and an average annual temperature of 20.6 ºC (Anonymous, 2015). The study area has a variety of tree species, including *Pinus sylvestris* L., *Pinus nigra*, *Fagus orientalis* L., *Abies*, *Castanea sativa*, *Fraxinus*, *Acer*, *Buxus* sp., and *Corylus avellana*.

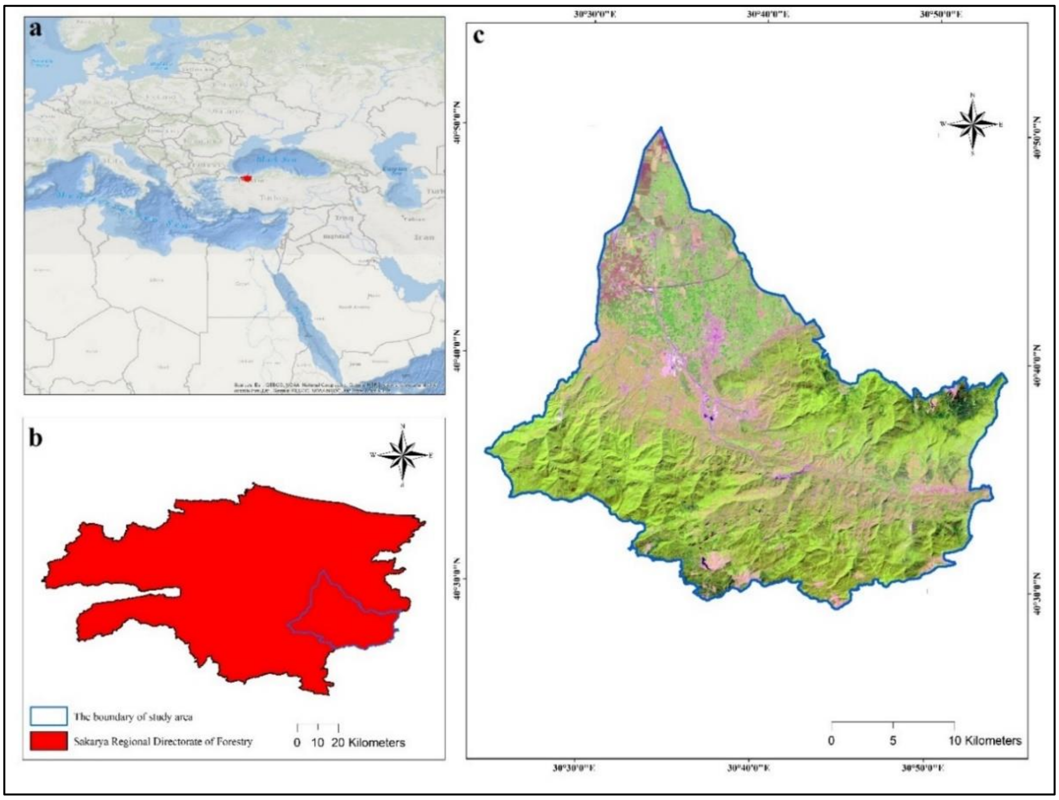

Figure 1. Location of the study area: a) location on the world, b) location on Sakarya Regional Directorate of Forestry, and c) Landsat 8 OLI satellite image (5, 4 and 3 band combination)

Database

In this study, the CORINE land cover datasets of 2006, 2012, and 2018 were used, and LULC maps were generated using Geographical Information Systems (GIS). Table 1 contains comprehensive information on the LULC types.

Table 1. CORINE LULC classes, description, and code in the study area

CORINE Level 1	CORINE Level 3	Code
Artificial Surfaces	112 - Discontinuous urban fabric	AS
	121 - Industrial or commercial units	AS
	122 - Road and rail networks and associated land	AS
	133 – Construction sites	AS
	142 – Sport and leisure facilities	AS
Agricultural Areas	211 – Non-irrigated arable land	AA
	212 – Permanently irrigated land	AA
	231 – Pastures	P
	242 – Complex cultivation patterns	AA
	243 – Land principally occupied by agriculture, with significant areas of natural vegetation	AA
Forest and Semi Natural Areas	311 - Broad-leaved forest	BF
	312 – Coniferous forest	CF
	313 – Mixed forest	MF
	321 – Natural grasslands	P
	324 – Transitional woodland-shrub	P
	331 – Beaches, dunes, sands	OS
Water bodies	511 – Water courses	W
	512 – Water bodies	W

Application of The CA-Markov Model

The process of modeling and simulating LULC was conducted using the Markov module inside the IDRISI TerrSet 2000 software. In order to achieve this objective, TPM were calculated during the first phase. The TPM quantifies the probability of land use classes transitioning to other classes during a specific time period. The transition area matrix displays the anticipated alteration in pixel values between different land use classes within a specific time interval. The resulting matrix is derived from multiplying the transition likelihood matrix by the number of pixels representing different land use classifications on a single date (Öztürk, 2013).

The Markov model derived transition area and TPM for 2018 based on the LULC maps derived from CORINE for 2006 and 2012. Using these matrices, the estimation of LULC in 2018 was conducted via a 10-year simulation using the CA-Markov module. The predicted LULC map for 2018 was compared to the actual LULC map acquired from CORINE for the same year. The validity and accuracy of the method were tested according to the similarity ratio method (Aksoy & Kaptan, 2022). With the Markov model, transition areas iteratively allocate pixels for each land use class for a determined number of years. The number of iterations continues for the years determined for the future projection. A neighborhood filter is used to determine the future state of each cell based on its neighboring cell and temporally previous state. In this study, a 5x5 neighborhood filter was used to define the neighborhood of the cells. The main reason for filtering is to reduce the fitness weight of cells that are far from a cell belonging to the land use class (Eastman, 2012; Aksoy & Kaptan, 2022).

The LULC maps obtained from CORINE for 2006 and 2018 were used to develop the LULC maps for 2030 and 2042. This was achieved by simulating 12 years using the CA-Markov model. Therefore, the statistical data and spatial distribution maps provided insights into the change direction. Figure 2. presents a comprehensive flow diagram illustrating the approach used in the investigation.

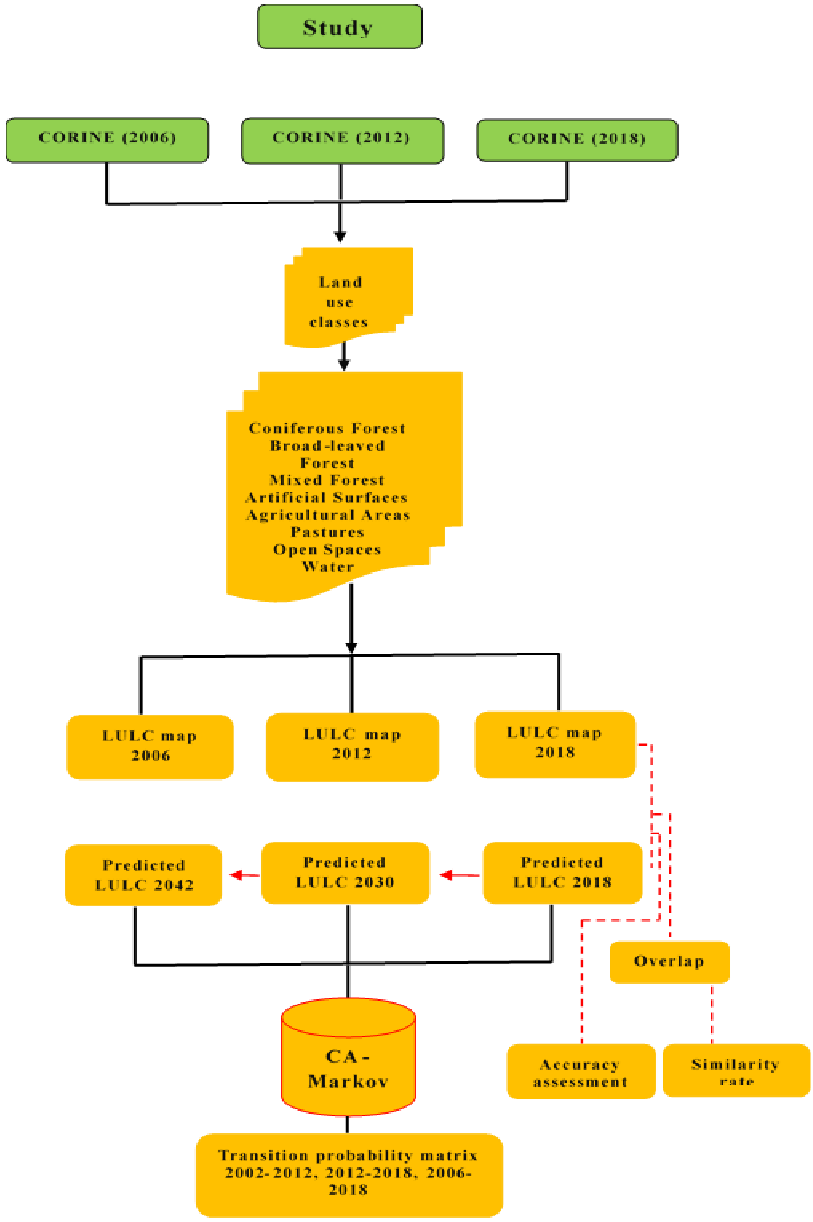

Figure 2. Flowchart of the methodology used in the study

Accuracy Assessment of CA Markov

The study conducted an accuracy evaluation comparing the LULC map estimated using CA Markov with the 2018 CORINE LULC map. Within this framework, 2000 sample points were strategically arranged on the CORINE LULC map. Subsequently, these locations were meticulously cross-referenced with the LULC map calculated using CA Markov. Therefore, the accuracy of producers and users, the overall success rate of classification, and the kappa value for each land use class were computed.

Results

Accuracy Assessment

The accuracy evaluation for LULC classes is shown in Table 2 The overall classification success rate is 0.98, with a kappa value 0.97. The producer accuracy values range from 0.94 to 1.00, while the user values range from 0.81 to 0.99. The results indicate that the accuracy of the map estimated using CA-Markov is highly satisfactory.

Table 2. Accuracy assessment derived by CORINE 2018 LULC map and CA-Markov predicted 2018 map

LULC classes	CF	BF	MF	AS	AA	P	S	W	Total	PA	UA	OA	K
CF	17		1						18	0.94	0.94	0.98	0.97
BF		553	1	1	7				562	0.98	0.98		
MF		4	415		1				420	0.99	0.98		
AS				32	8				40	0.96	0.80		
AA		1	2		868		1		872	0.97	0.99		
P	1	2				46			49	0.93	0.93		
S					3		20		23	0.95	0.86		
W						3		13	16	1.00	0.81		
Total	18	560	419	33	887	49	21	13	2000				

UA : User's Accuracy; PA : Producer Accuracy; OA : Overall Accuracy; K : Kappa Coefficient

LULC Changes Between 2006 and 2018

The information on LULC classes obtained from CORINE dated 2006, 2012, and 2018 is shown in Table 3, and the maps are shown in Figure 3. According to the results, AA is the LULC class occupying the most area in all three periods (2006, 2012, and 2018). In 2006, AA accounted for 45.5% of the whole area. BF (27.9%) and MF (20.5%) follow this in that order. During both periods, there was an increase in AS and W classes, while the AA class decreased.

Over 12 years, from 2006 to 2018, the area of AS expanded by 917.5 ha, representing a growth of 105%. Similarly, the area of W increased by 14.6 ha, showing a growth of 112%. Over this period, the AA class had a reduction of 699.6 ha, equivalent to a 2% decline. Another significant change took place in the S class. Over 12 years, the S class declined from 230.9 ha to 93.1 ha, resulting in a 60% reduction. There was no substantial alteration in the forest area, just a marginal 1% increase.

Table 3. Area values of LULC classes for the years 2006, 2012 and 2018

LULC Classes	2006		2012		2018	
	Area (ha)	%	Area (ha)	%	Area (ha)	%
Coniferous forest (CF)	1158.0	1.5	1161.4	1.5	1161.5	1.5
Broad-leaved forest (BF)	21345.1	27.9	21324.2	27.9	21268.1	27.8
Mixed forest (MF)	15621.9	20.5	16024.2	21.0	16024.2	21.0
Artificial Surfaces (AS)	867.2	1.1	1703.5	2.3	1784.7	2.4
Agricultural Areas (AA)	34721.4	45.5	34102.9	44.6	34021.8	44.5
Pastures (P)	2449.3	3.2	1970.6	2.6	2025.8	2.7
Open spaces (S)	230.9	0.3	92.8	0.1	93.1	0.1
Water (W)	13.0	0.0	27.2	0.0	27.6	0.0
Total	76406.8	100.0	76406.8	100.0	76406.8	100.0

The main factor influencing the expansion of forest areas in the study area is the effective implementation of afforestation activities by the purpose and goals of the General Directorate of Forestry. Reforestation initiatives were implemented in regions where forests had been cleared or degraded. Furthermore, with the implementation of the National Afforestation and Erosion Control Action Plan in 2008, GDF commenced afforestation endeavors with the primary objective of mitigating erosion. Implementing these action plans has resulted in a substantial increase in forest areas. The reduction in forest soil is also a consequence of the afforestation efforts conducted in S class as part of these activities (Demirel & Sivrikaya, 2023).

The population is an essential driver of the spatial and temporal dynamics of the forest environment (Alkan, 2014). Most AS in the study area are either inside the forest or on their periphery. Residents in this area lack socio-economic options and endure more challenging living circumstances than urban residents. Consequently, individuals relocate from rural areas to urban centers in anticipation of increased earnings and enhanced job opportunities. As the rural population decreased, the social pressure on forest areas decreased. Therefore, forests started regenerating in these areas with the spread and growth of forest tree seeds in abandoned agricultural areas. Furthermore, due to the movement from rural to urban regions, there has been a rise in AS areas and a corresponding decline in AA (Sivrikaya et al., 2007; Çakir et al., 2008; Kaptan, 2021). The primary factor contributing to the notable expansion of the W region within the research area is the establishment of the Acelle plateau pond.

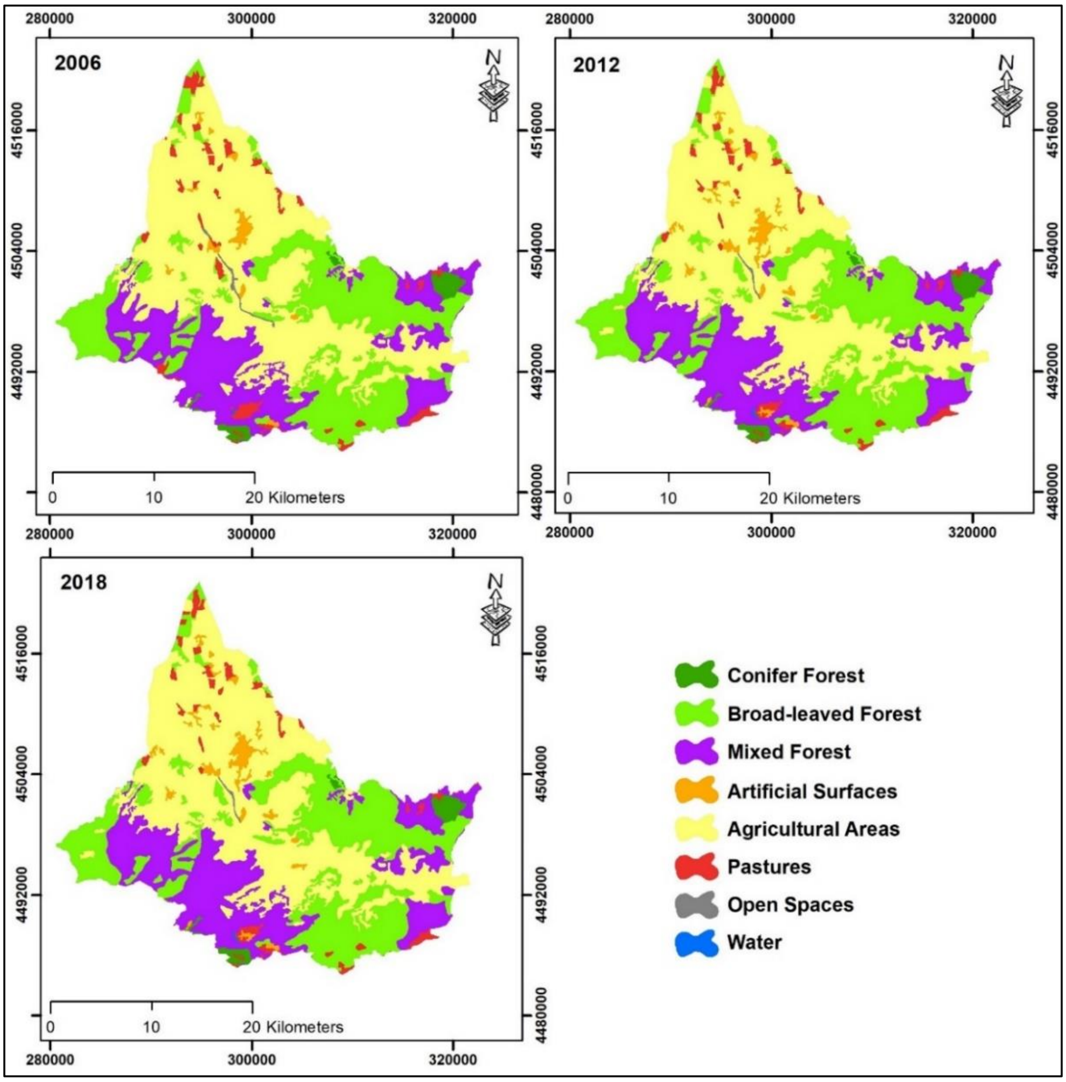

Figure 3. LULC maps of 2006, 2012, and 2018 based on CORINE LULC

CA-Markov Validation

The study generated TPM using the LULC maps derived from CORINE data for 2006, 2012, and 2018 (Table 4).

Table 4 displays the land use classes for the previous period in the rows and the land use classes for the next period in the columns. The diagonal values represent the likelihood of each class staying the same, while the off-diagonal values represent the likelihood of transitioning from one class to another. Upon examination of the TPM, it was found that 99% of the CF remained unchanged across classes, but only 38% remained unchanged in the S field from 2012 to 2018. From 2012 to 2018, no change was observed in any of the domains encompassing CF, MF, P, S, and W. From 2006 to 2018, about 95% of the CF, BF, MF, AS, AA, and W regions remained constant. The S region has the most significant variation among all the classes (Table 4).

Table 4. TPM of the study area from 2006 to 2018

Years	2012								
	Classes	CF	BF	MF	AS	AA	P	S	W
2006	CF	**0.9888**	0.0026	0.0033	0.0000	0.0000	0.0053	0.0000	0.0000
	BF	0.0001	**0.9808**	0.0062	0.0000	0.0107	0.0021	0.0000	0.0000
	MF	0.0004	0.0032	**0.9837**	0.0003	0.0119	0.0005	0.0000	0.0000
	AS	0.0000	0.0006	0.0001	**0.9832**	0.0140	0.0014	0.0007	0.0000
	AA	0.0001	0.0030	0.0136	0.0219	**0.9603**	0.0010	0.0001	0.0000
	P	0.0023	0.0941	0.0197	0.0344	0.0769	**0.7665**	0.0000	0.0060
	S	0.0000	0.0000	0.0000	0.0005	0.6183	0.0011	**0.3801**	0.0000
	W	0.0000	0.0000	0.0337	0.0000	0.0000	0.0048	0.0000	**0.9615**
Years	2018								
2012	CF	**1.0000**	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	BF	0.0000	**0.9974**	0.0000	0.0000	0.0000	0.0026	0.0000	0.0000
	MF	0.0000	0.0000	**1.0000**	0.0000	0.0000	0.0000	0.0000	0.0000
	AS	0.0000	0.0000	0.0000	**0.9978**	0.0022	0.0000	0.0000	0.0000
	AA	0.0000	0.0000	0.0000	0.0025	**0.9975**	0.0000	0.0000	0.0000
	P	0.0000	0.0000	0.0000	0.0000	0.0000	**1.0000**	0.0000	0.0000
	S	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	**1.0000**	0.0000
	W	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	**1.0000**
Years	2018								
2006	CF	**0.9888**	0.0026	0.0033	0.0000	0.0000	0.0053	0.0000	0.0000
	BF	0.0001	**0.9782**	0.0062	0.0000	0.0107	0.0047	0.0000	0.0000
	MF	0.0004	0.0032	**0.9837**	0.0003	0.0119	0.0005	0.0000	0.0000
	AS	0.0000	0.0006	0.0001	**0.9834**	0.0138	0.0014	0.0007	0.0000
	AA	0.0001	0.0030	0.0136	0.0243	**0.9580**	0.0010	0.0001	0.0000
	P	0.0023	0.0941	0.0197	0.0344	0.0769	**0.7665**	0.0000	0.0060
	S	0.0000	0.0000	0.0000	0.0005	0.6183	0.0011	**0.3801**	0.0000
	W	0.0000	0.0000	0.0337	0.0000	0.0000	0.0048	0.0000	**0.9615**

To assess the predictive accuracy of the CA-Markov model employed in the study, the areal similarity rate was calculated by comparing the CORINE 2018 LULC map with the 2018 LULC map forecasted by the CA-Markov model (Table 5). When analyzing Table 5, it is observed that the 2018 LULC maps generated using 2018 CORINE and CA-Markov exhibit the highest similarity rates in the AA (100%) and BF (100%) classes, while the lowest similarity rate is observed in the S class (52.2%). The similarity rate of the six classes (CF, BF, MF, AS, AA, and P) exceeds 90%. The least successful class in prediction is the S class, with 52%. Considering all classes, the overall similarity rate between the two thematic maps was 91.1%. The ratio indicates a significant level of similarity between the two maps, demonstrating that the CA-Markov model consistently produces precise results. Figure 4. displays the 2018 CORINE land use classes and the predicted LULC map 2018.

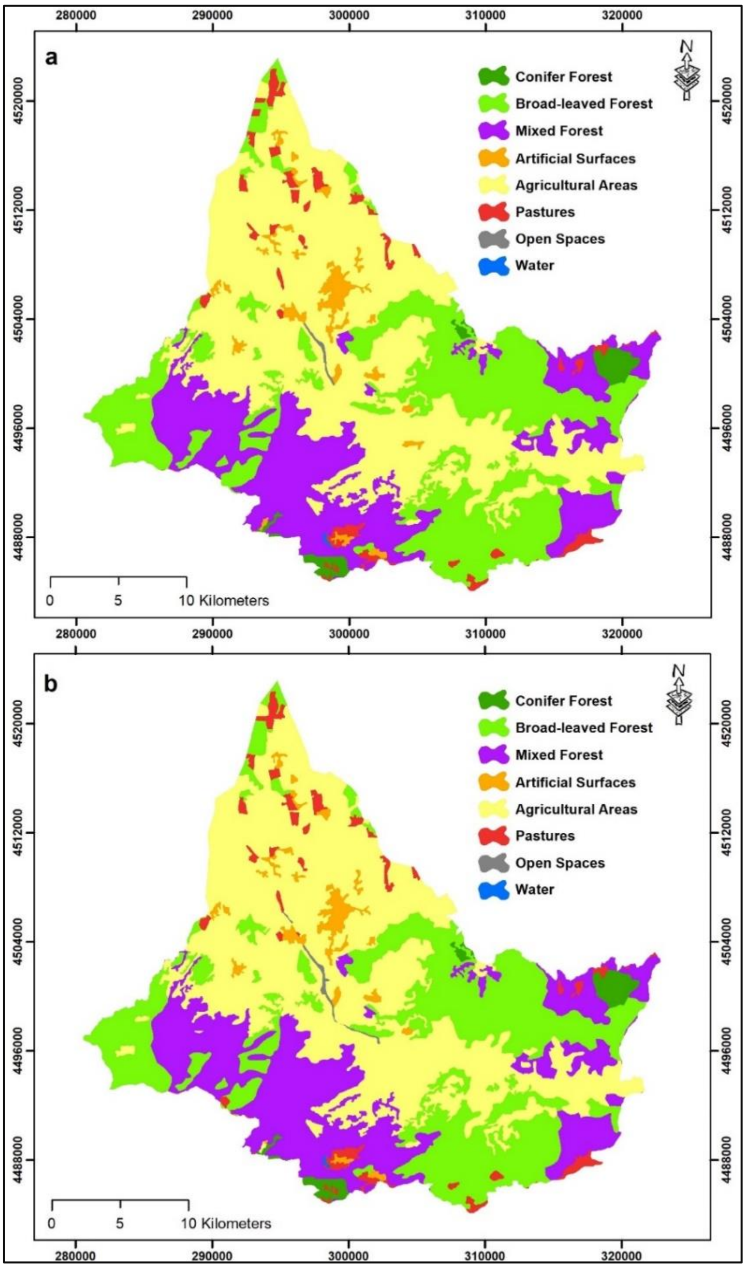

Figure 4. a) CORINE actual and b) CA-Markov estimated LULC maps for 2018

Table 5. Comparison of CORINE LULC and LULC produced with the CA-Markov model for 2018 and the similarity rate

LULC Classes	CORINE		Simulated		Similarity Rate (%)
	Area (ha)	%	Area (ha)	%	
Coniferous forest (CF)	1161.5	1.5	1160.4	1.5	99.9
Broad-leaved forest (BF)	21268.1	27.8	21277.8	27.9	100.0
Mixed forest (MF)	16024.2	21.0	16001.7	20.9	99.9
Artificial Surfaces (AS)	1784.7	2.4	1661.6	2.2	93.1
Agricultural Areas (AA)	34021.8	44.5	34021.5	44.5	100.0
Pastures (P)	2025.8	2.7	2081.4	2.8	97.3
Open spaces (S)	93.1	0.1	178.5	0.2	52.2
Water (W)	27.6	0.0	23.9	0.0	86.6
Total	76406.8	100.0	76406.8	100.0	91.1
Overall Average Similarity Rate					

CA-Markov Simulation

The TPM was estimated using CORINE LULC maps of 2006 and 2018, and LULC class areas were calculated for 2030 and 2042 with the CA-Markov model, and maps were produced (Figure 5 and Table 6). Upon analysis of the LULC maps projected for 2030 and 2042, it was forecasted that the study area will comprise 50.7% forest areas and 49.3% non-forest areas by 2030. Based on projections, the CF area will remain unchanged for 12 years. The BF area is forecast to decline by 0.1%, while the MF area is projected to expand by 0.5%. On the other hand, when the change in non-forest areas was evaluated as a percentage, an increase of 1.3% in the AS class, 1% in the AA class, 0.6% in the P class, and 0.1% decrease in the S class were estimated. Additionally, it is predicted that there will be no change in W class.

Based on the estimated results from the CA-Markov model for 2018-2042, forests are anticipated to cover 51.1% of the land, while non-forest regions will account for 48.9% in 2042. Out of all the classes in the forest area, just 1% were classified as CF, while 27.8% were classified as BF, and 21.8% were classified as MF. In contrast, in the non-forest area, 4.6% of the classes will be classified as AS, 42.4% as AA, and 1.9% as P. According to the 24-year (2018–2042) predicted LULC results obtained from the CA-Markov model, an increase of 3.8% in total forest area and 110.2% in AS, a decrease of 4.7% in AA, 31.5% in P and 90.3% in S, and there will be a 1.7% increase in W. The MF class will experience the most significant increase in the forest category, at 3.9% (616.3 ha), while the highest non-forest increase will be in the S class with 110.2% (1830.4 ha). It is evaluated that AA, P, and S classes will increase in both periods (2030 and 2042). Over the 24 years, AA will decrease by 4.7% (1597.8ha), P by 31.5% (654.7ha), and S by 90.3% (11.1ha).

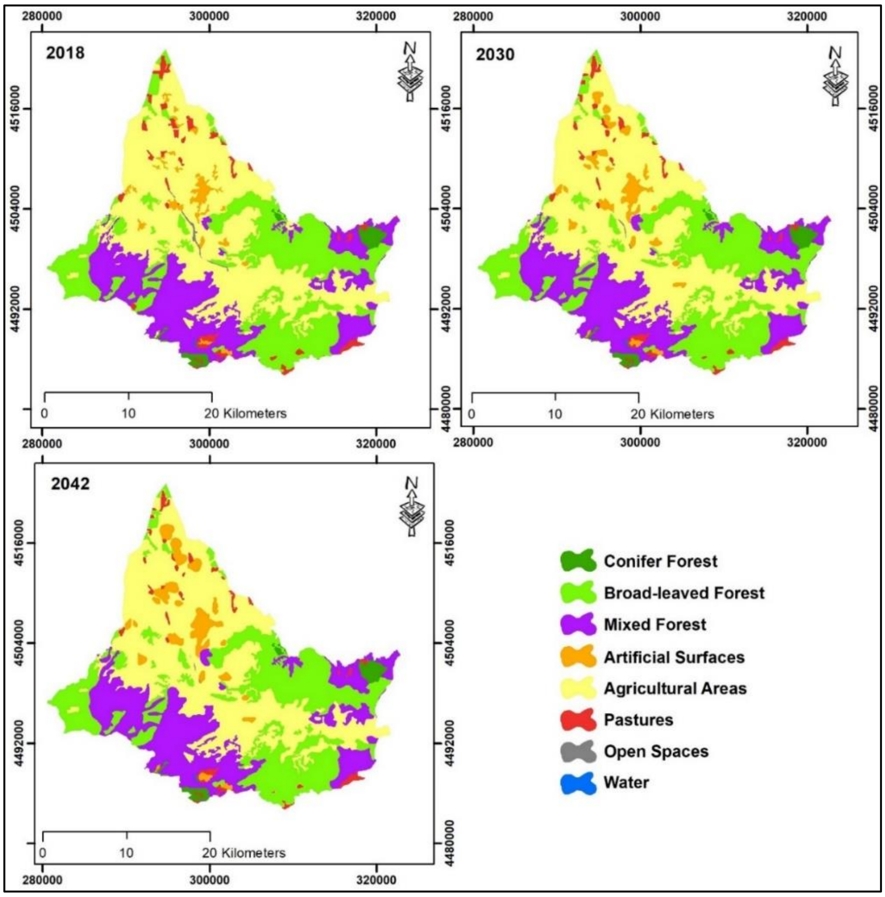

Figure 5. LULC maps of 2018, 2030, and 2042 simulated by the CA-Markov model

Table 6. Comparison of LULC for the years 2018, 2030, and 2042 simulated by the CA-Markov model

LULC	2018		2030		2042		Change 2018-2042	
Classes	Area (ha)	%	Area (ha)	%	Area (ha)	%	Area (ha)	%
CF	1160.4	1.5	1161.4	1.5	1161.5	1.5	1.1	0.1
BF	21277.8	27.9	21236.9	27.8	21241.9	27.8	-35.9	-0.2
MF	16001.7	20.9	16326.8	21.4	16618.0	21.8	616.3	3.9
AS	1661.6	2.2	2652.8	3.5	3492.0	4.6	1830.4	110.2
AA	34021.5	44.5	33263.0	43.5	32423.7	42.4	-1597.8	-4.7
P	2081.4	2.8	1699.6	2.2	1426.7	1.9	-654.7	31.5
S	178.5	0.2	39.9	0.1	17.4	0.0	-161.1	90.3
W	23.9	0.0	26.4	0.0	25.6	0.0	1.7	7.1
Total	76406.8	100.0	76406.8	100.0	76406.8	100.0		

Discussion

This study analyzed the LULC changes between 2006, 2012, and 2018 inside the boundaries of Akyazı Forest Management Directorate, utilizing the CORINE data set. Upon examining the LULC change between 2006 and 2018, it is observed that the forest area had grown from 38125 hectares to 38453.8 hectares. To clarify, the forest area experienced a net increase of 328.8 hectares over 12 years. Over this period, there was a rise in the size of AS and W class regions, while the size of AA, P, and S class areas fell. Svestac et al. (2020) analyzed the 1990-2018 CORINE data sets to investigate the alterations in LULC categories throughout this period. Upon evaluation of the results, it was observed that there was a decline in artificial and aquatic areas, while agricultural and forest areas experienced an increase.

The study undertaken by Üstün Topal & Kurt Konakoğlu (2023) utilized CORINE data sets from 1990-2018 to investigate changes in LULC categories over 28 years. Upon analyzing the results, it is evident that there has been a reduction in the extent of forest, semi-natural, and agricultural areas. This decline may be attributed to the expansion of artificial areas, which has occurred due to increased human activity and population growth over 28 years. Ayazli (2024) conducted a study in which CORINE analyzed changes in LULC categories based on data sets from 1990, 2000, and 2018. Upon analyzing the results, it was found that, in contrast to our study, there was a rise in residential areas but a decline in agricultural and forest areas throughout the periods of 1990-2000, 1990-2018, and 2000-2018. Cole et al. (2018) analyzed alterations in LULC categories by utilizing the 2000, 2006, and 2012 CORINE data sets. Upon analyzing the acquired results, it was observed that there was a decline in mixed forests during the period from 2000 to 2012, while artificial areas had an increase. Our investigation revealed comparable results about artificial areas. The study by Sibanda & Ahmed (2021) analyzed the alteration of LULC categories from 1984 to 2015 using Landsat satellite images captured at four distinct time points (1984, 1995, 2005, and 2015). Additionally, CA-Markov was employed to identify ten land types for 2025, 2035, and 2045. Estimations have been conducted about the categorization of LULC classes. The findings of the LULC research conducted from 1984 to 2015 revealed a decline in forest and wetland regions, which can be attributed to natural and human influences. This contrasts with the outcomes of our study. Furthermore, the study revealed that the kappa values ranged from 0.81 to 0.89, representing a high level of agreement. The classification success rate also ranged from 84% to 90%, demonstrating vital accuracy.

The study indicated that the CA-Markov model accurately forecasted the LULC classes map 2018, with a similarity rate of 91.1% compared to the existing LULC classes map. The significant resemblance between the two maps indicates that the CA-Markov model yields reliable and effective outcomes. While the similarity rate exceeded 90% in six classes, it was discovered to be below 90% in two classes. Işınkaralar (2023a) forecasted LULC for several LULC categories in 2056 based on the 1990, 2012 and 2018 CORINE data sets. The similarity ratio between the projected and observed LULC was 0.97. Alan et al. (2020) conducted a study in Ankara using the CA-Markov method and analyzed CORINE data sets from 1990, 2000, 2006, and 2012 to predict changes in LULC classes. The study found a 92% similarity rate for predicting LULC classes in 2012, using data sets from 1990, 2000, and 2006. The study carried out by Toplu (2024) utilized CA-Markov to evaluate spatial and temporal variations in LULC. The study analyzed the transition from 2009 to 2019 and used Markov chains to predict the LULC map for 2029. The study used the classification of Landsat imagery to establish LULC classes. The LULC classes that were classified and the existing LULC classes were compared, and it was determined that they overlapped with a similarity rate of 84.2%. The study performed by Zoncova & Masny (2022) analyzed changes in LULC classes between 1990 and 2012 utilizing CORINE data sets spanning the period from 1990 to 2018. The generated model was then compared to the actual changes in LULC classes over the subsequent period from 2012 to 2018. The analysis revealed that the similarity rate was 80%. The study conducted by Khawaldah et al. (2020) analyzed the alteration in LULC categories from 1984 to 2018 by utilizing Landsat satellite images captured at five different time points (1984, 1994, 2004, 2015, and 2018). The analysis determined an 80% similarity rate between the existing LULC class map and the projected LULC class maps for 2030 and 2050. Upon evaluating all studies, it becomes evident that outcomes compatible with our study are achieved.

This study examined the changes that may occur between 2018 and 2042 with the CA-Markov modeling technique. Within the scope of the research, the 12-year changes between the 2018-2030 and 2030-2042 periods were analyzed, and then the total 24-year changes during the 2018-2042 period were analyzed. In the 2018-2030 period, it was observed that CF did not change, BF decreased, and MF increased in the forest area class. In non-forest areas, it was determined that AS increased, AA, P, and S decreased, and W remained constant. In the 2030-2042 period, it was determined that CF and BF remained steady, but MF increased more than the previous period. On the other hand, it was determined that AA, P, S, and W showed similar changes compared to the last period. When evaluated throughout the 2018-2042 period, it was observed that there was a decrease in BF and AA LULC classes and an increase in other classes. However, it has been determined that these increases occur, especially in non-forest areas.

Işınkaralar (2023b) conducted a study that analyzed LULC class changes using the 2006, 2012, and 2018 CORINE data sets. Additionally, a forecast map for 2030 was generated. Upon evaluation of the results, it was observed that there was a rise in residential, forest, and water areas, whereas agricultural areas had a decline during the period from 2006 to 2018. The study conducted by Kuleli & Beyazıt (2022) analyzed changes in LULC classes using CORINE land use data from 1990 to 2018. Additionally, forecasts were generated for the years 2034 and 2050 using CA-Markov. Upon analysis of the data, it is projected that forest areas will see a reduction of 53.4% by 2034 and 53% by 2050. Conversely, artificial areas are expected to increase by 4.5% in 2034 and 5% in 2050. According to the forecast map obtained in the study conducted by Işınkaralar (2023a), it was revealed that there will be an increase in artificial areas and a decrease in agricultural areas, wetlands, and water bodies between 2018 and 2056. Aksoy & Kaptan (2022) classified satellite images from Landsat 7 and 8. They created LULC maps for 1999, 2009, and 2019. The study generated prediction maps for 2029 using the TPM derived from the 10-year change matrices between 2009 and 2019. Additionally, prediction maps for the year 2039 were developed by employing the 20-year change probability between 1999 and 2019. According to the statement, the total forest area is projected to grow by 17.4% (11340.4 hectares) over 20 years (1999-2019). Nevertheless, the study revealed kappa values ranging from 80% to 95%. Tariq et al. (2022) investigated changes in LULC classes using Landsat imagery from five different years (1998, 2003, 2008, 2013, and 2018). They used CA-Markov to study changes in LULC classes for 10-year periods in 2018, 2028, and

2038. Upon analysis of the findings, it was found that the overall residential area noticed growth in 2018. Additionally, the afforestation project conducted from 2013 to 2018 led to an increase in forested areas. Furthermore, it has been shown that there will be a rise in both human settlements and forest areas from 2028 to 2038, mirroring our findings but in the opposite direction. The study revealed kappa values ranging from 85% to 88%. Badshah et al. (2024) conducted a study in Pakistan to analyze the changes in LULC categories from 1991 to 2021. They utilized Landsat imagery from four different time points (1991, 2001, 2011, and 2021) and employed CA-Markov modeling to provide predictions between 2031 and 2051. Upon analyzing the results, it was found that, in contrast to our study, there would be a decline in vegetated regions and an increase in urban areas by 2051. Additionally, forests are projected to decrease in 2051 compared to 2021. The investigation revealed a kappa value of 0.88 and an overall classification success rate above 90%.

The analysis undertaken by Toplu (2024) indicated the possibility of a decline in forested areas during a 10-year timeframe. According to reports, there would be a reduction of 5.6% in coniferous forests and 6.3% in deciduous forests, while mixed forests are projected to grow 6.1%. Our investigation showed comparable findings for mixed forests. Nevertheless, the study revealed kappa values ranging from 80% to 88%. Aydın & Durduran (2024) studied Konya using CA-Markov, CORINE, Landsat satellite images, and Google Earth data sets to predict future changes in LULC classifications. The study analyzed the alterations in LULC categories from 1985 to 2018 and projected future changes for 2030 and 2040. Upon evaluation of the results, it was determined that there would be a decline in agricultural and forest regions by 2030 and 2040, which contradicts our analysis. Jawaid et al. (2023) conducted a classification of Landsat imagery taken in 1989, 2000, 2009, and 2020. Based on this analysis, they drew predictions about LULC classifications for the year 2030. The study indicated that the map projected for 2030 predicts a 1.1% decline in forest areas and a 1.31% increase in residential areas. The same analysis showed a progressive reduction in the extent of barren land and aquatic bodies over time.

Hossein et al. (2023) examined the change in LULC classes using Landsat satellite images from different periods (1989, 1994, 1999, 2004, 2009, 2014, and 2019) and made predictions for 2030. When the results obtained from the study are examined, it is stated that the residential areas will constantly increase dynamically. In contrast, the water mass, agricultural land, and vegetation area will decrease. Guan et al. (2008) identified Landsat satellite images from four different periods (1990, 1995, 2000, and 2005) and used CA-Markov to estimate the change in LULC classifications between 2006 and 2050. When the data were evaluated, it was determined that contrary to our findings, there would be a 5.85% decline in forest areas and a 52.19% increase in residential areas. In the study conducted by Demir (2021) on the change of LULC classes using the 1990-2018 CORINE data sets, it was stated that artificial areas, agricultural areas, and water areas will increase the prediction made for 2040.

The study by Huang et al. (2020) on LULC transition in Beijing demonstrated the efficiency of using the CA-Markov model for LULC estimation. According to the results, a decrease of approximately 507.08 km^2 in agricultural lands and an increase of 262.57 km^2 in construction lands is predicted from 2012 to 2020. Aneesha Satya et al. (2020) used GIS resources, including the MC, to indicate the 2052 LULC scenario in the city of Warangal in the Telangana state of India. The research results revealed that economic and biophysical factors are significantly effective in expanding urban settlement areas and reducing vegetation and barren lands. Singh et al. (2015) used the Markov model and RS data to investigate and predict ten-year (1990-2020) LULC changes. The research results revealed that socio-economic and biophysical factors significantly affect the growth of agricultural areas and settlements in the region, and the predictions made for 2020 significantly contributed to LULC planners in creating policies for effective LULC. El Haj et al. (2023) made predictions about the trends of the 2019-2039 period using CA-Markov and Land Change Modeler in the Lakhdar

Morocco sub-basin study area. They used data and satellite images of the area for over 20 years. Study findings show that significant changes will affect forest areas, which will decrease in the coming years. With the effect of urbanization, there will be a 70% decrease in forest areas in the 2000-2039 period.

Conclusions

This study utilized the CA-Markov approach to assess the potential changes in LULC classes within the boundaries of the Akyazı Forest Management Directorate. Upon evaluation of the study's results, it was found that there were no changes in CF and BF in forest areas for the years 2030 and 2042. However, MF increased by 0.4%. Inon-forest areas, AS increased by 1.1%, while AA decreased by 1.1%. Additionally, there was a decrease of 0.3% in P and 0.1% in S. W, which remained unchanged. A 24-year assessment conducted from 2018 to 2042 projected a growth of 581.5 hectares in forested areas. These data can help explain the changes in land use classes. They can also be used to make informed decisions and create strategic plans for sustainably managing forests. Within this particular context, the knowledge provided will serve as a crucial foundation for future forest management strategies and significantly contribute to forest ecosystems' long-term viability. In future studies, it is believed that providing the areal values of land use classes and identifying the specific classes responsible for increases and declines through density analysis would considerably enhance the provision of more precise information for these classes.

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Author Contributions

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Conflict of Interest

The authors declare that they have no conflict of interest.

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