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A Test of the Markov Prediction Model: The Case of Isparta

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Abstract

Projections and predictions of urban growth provide information that can lead to a certain level of preparedness for making cities resilient and sustainable. To ascertain the degree of confidence in predicting urban growth, this paper back-tests the Cellular Automata (CA)-Markov Prediction Model (PM) by comparing the results of the model for 2010 and 2020 with the actual land-use patterns and growth of Isparta for the same years. The data used are Landsat images for 1990, 2000, 2010, and 2020. The images were classified and used to perform the CA-Markov PM. The findings show that successive changes in land use in Isparta display average proximity to the CA-Markov PM results, with strong positive correlations of 0.8559 in 2010 and 0.8494 in 2020. It is therefore attested that amongst other models the CA-Markov PM can be used as a mathematical model for simulating urban growth in Isparta.

Keywords: *City planning, urban growth, cellular automata, Markov prediction model, RS & GIS, Isparta*

Markov Tahmin Modelinin Testi: Isparta Örneği

Öz

Kentsel büyüme ve arazi kullanımı değişikliklerinin öngörülmesi ve tahmini, kentlerin dayanıklı ve sürdürülebilir hale getirilmesinde belirli düzeyde hazırlıklı olmayı sağlayan bilgiler sunar. Kentsel büyümeyi ve arazi kullanım değişikliklerini tahmin etmede modellerin kullanımının uygunluk düzeyini tespit etmek için bu makale, 2010 ve 2020 yılları için Hücresel Otomatlar (CA)-Markov Tahmin Modelini (PM) Isparta kentinin gerçek arazi kullanım kalıpları ve büyümesinin geriye dönük bir testini aynı yıllar için yapmaktadır. Çalışma için kullanılan veriler 1990, 2000, 2010 ve 2020 Landsat görüntüleridir. Görüntüler sınıflandırılmış ve CA-Markov PM'nin uygulamasında kullanılmıştır. Bulgular, Isparta'nın arazi kullanımındaki ardışık değişikliklerin CA-Markov PM sonuçlarıyla ortalama yakınlık derecesine ve sırasıyla 2010 yılı için 0.8559 ve 2020 yılı için 0.8494'lük güçlü bir pozitif korelasyona sahip olduğunu göstermektedir. Bu nedenle; diğer modeller arasından CA-Markov PM'nin, matematiksel bir model olarak, Isparta kentinin kentsel büyümenin simülasyonunda kullanılabileceği belirlenmiştir.

Anahtar Kelimeler: *Şehir planlama, kentsel büyüme, hücresel otomat, Markov tahmin modeli, UA ve CBS, Isparta*

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1. Introduction

The future state of the city is one of the major concerns on the minds of decision-makers and professionals involved in city planning (Kresl, 2007; Raven et al., 2018; Thompson, Greenhalgh, Muldoon-Smith, Charlton & Dolník, 2016). It is important for planning professionals to make necessary plans and deploy necessary tools in readiness for the future, if they are supporting resilient and – most importantly –sustainable development (Schubert, 2019; Fan, Weng & Wang, 2007). These concerns add to the importance of forecasting, predicting, and estimating or projecting urban dynamics.

Issues affecting the future that are frequently discussed include the prediction and estimation of food supplies to ensure food security (Peng & Berry, 2019), and climate studies to mitigate global warming and make the earth resilient and sustainable (Porter et al., 2014; Eren, 2021). Land-use changes, to ensure sustainable land use and urban growth (Perveen, Kamruzzaman & Yigitcanlar, 2017; Ajiboye, 2021) worth also mentioning. In essence, “sustainability”, as often reiterated, sets a proper picture of the future of our cities. This enables the clarification of our understanding and ideas on how to make the city resilient (Eren, 2019).

In the planning discipline, understanding the dynamics of urban growth and changes in land use has a significant impact on the future (Regmi, Saha & Balla, 2014; Gashaw, Tulu, Argaw & Worqlul, 2017). For this reason, the topic has attracted the attention of numerous researchers, whose studies have focused on the causes and consequences of changes in land use and sustainability-centered responses (Foley et al., 2005; Zhao et al., 2006). Similarly, land-use changes have been listed among the major changes that are occurring in the global environment (Vitousek, 1994).

The adoption of Remote Sensing (RS) as a way of accessing Spatio-temporal data and the use of Geographical Information Systems (GIS) to process, analyze and present such data has facilitated the study of land-use changes (Bhatta, 2010). In parallel with the progress made in geospatial operations, models have gained importance and are being used increasingly in simulating land-use changes (Zheng, Shen, Wang & Hong, 2015; Mustafa et al., 2018). For Bhatta (2010), the models are theoretical abstractions built through consideration of keen physical principles that are logically operated and modified via experimental judgment and plain intuition. These models simulate urban growth and predict future urban dynamics (Bhatta, 2010).

Several models exist and the classification of these models is open to debate. Common examples of such classifications include micro and macro models, deterministic or probabilistic models, and cell-based and zone-based models, among others (Bhatta, 2010). The models have, however, been grouped more comprehensively into three classes – namely: (1) land use and transportation models; (2) urban dynamics models, and (3) cellular automata, agent-based, and micro-simulation models (Batty, 2001; Batty, 2009). Bhatta (2010) provided a further classification of these models by categorizing them as (1) Theoretical models; (2) Complexity science-based models, and (3) rule-based land use and transport models.

Due to the complex character of the urban system – including its fractal dimensionality, self-similarity, spatial organization, and other emerging characteristics (Batty & Longley, 1994; Torrens, 2000) traditional urban models generally have their limitations when addressing important urban dynamics (Pooyandeh, Mesgari, Alimohamadi & Shad, 2007). For this reason, complex science-based models are often adopted in urban studies. Common complexity models are Cell-Based Dynamics Models (Cellular Automata CA), Agent-Based Models, Artificial Neural Network Based Models (ANN), and Fractal Geometry-Based Models (Bhatta, 2010).

In the present study, the CA Markov Chain Prediction Model (CA-Markov PM), which is a Cellular Automa-Based Model, was employed as a way of understanding the impact of urban dynamics and human-induced activities resulting in land-use changes. This approach hinges on the assumption that human activities and decisions, particularly natural and environmental, influence land-use changes and land cover in urban settings while creating problems in the environment (Brown, Walker, Manson & Seto, 2004; Ali, 2009; Memarian et al., 2012; Singh, Mustak, Srivastava, &Szabo, 2015). It is also assumed that political forces contribute to the vulnerability of such settings (Gibson, 2012).

The CA-Markov PM has been widely used in predictive land use studies. Liping, Yujun & Saeed (2018) used the model to predict the spatial pattern of land use in the Jiangle area of the province of Fujian, China, for the years 2025 and 2036. Behera, Borate, Panda & Behera (2012) employed the same model to analyze watershed dynamics in the Choudwar region of India. Wu et al. (2006) also adopted the Model and Regression Analyses together in investigating land-use change dynamics in Beijing.

The CA-Markov PM uses the principle of RS and relies on the accuracy of the data for the past and the present to understand and estimate future changes in land use and land cover (Öztürk, 2015). According to Sante, Garcia, Miranda & Crecente (2010), the CA-Markov Chain Prediction Model acts on the premise that the current state of a cell is dependent on its previous state as well as the state of the neighboring cell. The results of the Model can provide urban planners and policymakers with an early warning system for urban growth and assist them in making effective decisions (Parsa, Yavari &Nejadi, 2016).

On this basis, this study back-tests the CA-Markov PM to check how far the predictions of the Model for expected urban growth and land use and land cover change confirm the actual, observed urban growth and use of land in the city of Isparta. Isparta as a fast-growing city experiences transformation and land-use change, which should be closely monitored (Ajiboye, 2021). Data availability, proximity to the study area, and the growth tendencies of Isparta city as a medium-sized Turkish city also suggested her selection for the study (Eren & Ajiboye, 2020).

2. Material and Method

2.1. Study Area

The city of Isparta is the capital city of the Isparta Province. The city is located in the Lakes District of the Mediterranean Region of Turkey. Its location is between 271905mE, 4198605mN and 309045mE, 4160715mN. The Isparta Province borders the provinces of Konya to the East, Burdur to the West, Afyon to the North, and Antalya to the South. Isparta city's central district is one of the 13 districts in the Isparta Province. The city of Isparta borders the district of Eğirdir to the East, the district of Ağlasun to the South, Burdur Province to the West, and the districts of Gönen and Atabey to the North (Figure 1).

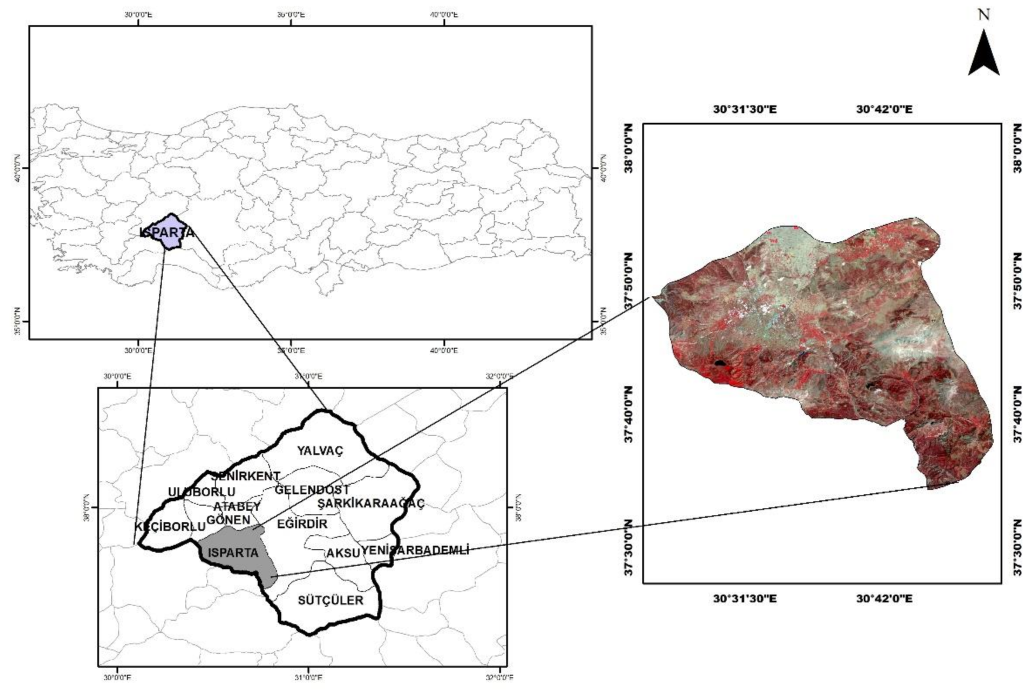

Figure 1. The city of Isparta, Turkey.

Located on routes that connect Antalya to central Anatolia and the Aegean region, the city forms part of the transition zone between the warm temperate Mediterranean climate and the terrestrial climate of Central Anatolia. This provides a livable climate condition which attracts population from even abroad.

The city has an altitude of 1,050 meters and a total population of 262,255 people, who make up 59.56% of the population of the entire province. It has a population density of 49 people per kilometer (Türkiye Nüfusu, 2021). This density, when compared to other similar-sized cities, maybe low, however the rise in the last decade is relatively high (Ajiboye, 2021).

2.2. Data Collection and Research Methods

Four (4) Landsat images of the study area separated by ten-year intervals were used in the study. The three Thematic Mapper (TM) images for 1990, 2000, and 2010 and the Landsat Operational Land Imager (OLI) image for 2020 were sourced from the United States Geological Survey (USGS) (USGS, 2021) (Table 1).

Table 1. Landsat images

Satellite	Resolution (m)	Date of Acquisition	Path/Row
Landsat TM-5	30	02/08/1990	178/034
Landsat TM-5	30	05/08/2000	178/034
Landsat TM-5	30	25/08/2010	178/034
Landsat OLI-8	30	04/08/2020	178/034

The methodology used for the Markov test of the city of Isparta is outlined below. It consists of three phases – namely, (1) Land use analysis, (2) Markov prediction modeling, and (3) the comparison of the actual urban growth with the Markov Model Prediction.

2.2.1. Land use analysis

During the land use analysis phase, the historical satellite images of the city sourced from the USGS archives were processed in ERDAS Imagine 2015. The processing includes atmospheric correction, radiometric correction, the mask extraction or clipping of the area under study, the classification of the images into different land use classes, and an assessment of the accuracy of the classified images (Figure 2). The classification process involved the grouping of image pixels into categories of classes to generate a thematic map (Gecena & Sarpb, 2008, s.356). Hence, a pixel-based classification, of a supervised classification technique was employed due to the nature and resolution of the images. The pixel-based classification process extracts land use information based on the reflectance values of each pixel on the image (Wang, Sousa & Gong, 2004). The images were grouped into five categories: Built-up areas, farmland, forests, water bodies, and open spaces/bare surfaces to produce land use maps.

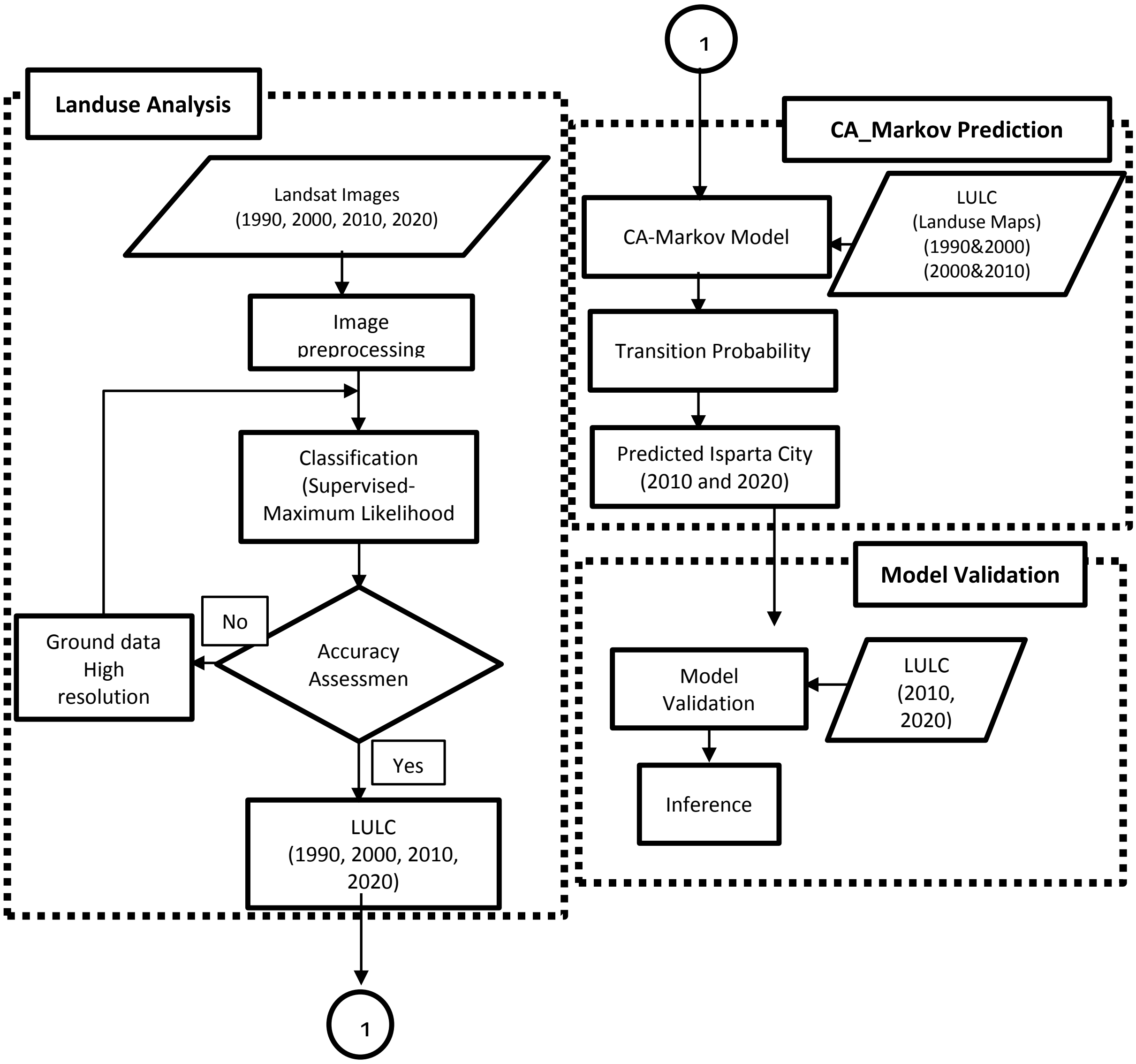

Figure 2. Workflow for back-testing the ca-Markov chain prediction model

An accuracy assessment was then carried out to determine the accuracy of the classification of the images. According to Roissiter (2004), accuracy assessment operations compare the classified images with available ground verification sources. For the accuracy assessment, 50 points from different land use areas were identified on Google Earth Pro 2021 to serve as corresponding references. Subsequently, the accuracy assessment was computed using a confusion matrix. The accuracy ratio was found to be 85.5% for 1990, 87% for 2000, 87.5% for 2010 and 89.5% for 2020. The classified images for all four years were then adopted as the data for the CA-Markov Chain Prediction Model.

2.2.2. Cellular automated (ca)-Markov chain prediction model

The CA-Markov Chain Prediction Model integrates the simulation ability of the CA Model and the predictive ability of the Markov Chain Prediction Model to present the expected growth of the city or changes in land use. In other words, the Models applied together are a combination of a transition matrix, a transition area matrix, and probability images (Eastman, 2012). The transition matrix is a reflection of the probability of changes/transitions from one form of land use or land cover to another. The transition area matrix, on the other hand, shows the pixels that are expected to transit to other uses, while the conditional probability image shows the probability of the land use or land cover in the years for which the prediction is made (Eastman, 2012).

The Markov PM assumes that to predict the future state of a city at time *t+1*, the state of the city at time *t* must be known (Lacono, Levinson, El-Geneidy & Wasfi, 2012; Eastman, 2012). This makes it possible to compute a time index showing the areas expected to transit to another land use (Lacono et al., 2012). In this study, the classified image of Isparta for 1990 was taken as *t*. The image of Isparta for 2020 was designated as *t+1*. Both were used to predict the expected condition of the city in 2010. The same process was employed in predicting the expected condition of the city in 2020. In the case of the 2020 prediction, the classified image of 2000 was taken as *t* while the classified image of 2010 was designated as *t+1.* This operation of the Model was performed in IDRISI software.

2.2.3. Correlating the actual growth with the predicted growth

At this phase, the result of the Markov-Chain Model (the expected urban growth of Isparta) was back-tested. The result obtained from each Markov Model figure calculation (for 2010 and 2020) was correlated with the observed growth/condition of the city in 2010 and 2020. Correlation analysis provides information on the closeness of two variables or explores the degree of association between study variables (Senthilnathan, 2019). In this study, the expected growth of the city of Isparta according to the 2010 CA-Markov Prediction Model was back-tested against the observed growth for the year 2010, and then the same process was repeated sequentially for the year 2020. This was done to validate the efficacy of the Markov PM and ascertain the discrepancies that might arise between the CA-Markov Chain Prediction Model and the actual physical growth of Isparta.

Correlation analyses were also performed for the CA-Markov Chain Prediction Model and the land use/land cover (LULC) for both 2010 and 2020. These analyses were carried out in a spreadsheet (MS-EXCEL). Correlation coefficients range from -1 to 1. Hence, results approaching -1 signify a non-correlation or a strong negative correlation, where +1 presents a strong positive correlation. The findings were used to draw inferences about the correlation between the CA Markov Prediction Model and the LULC.

As the major focus of interest was on urban growth, the built-up area was extracted from the CA-Markov Chain Prediction Model processed for 2010 and 2020. The built-up area of the LULC representing the actual urban growth of the city for the same years was also delineated. The built-up areas extracted from these two operations (CA-Markov Chain Prediction Model and LULC) were then correlated to identify areas of discrepancy.

3. Research Findings and Discussion

The images (Figures 3A, 6A) were pre-processed and classified as presented in Figures 3B and 6B. The statistics showing the areas of the different types of land use/land cover as per the classification results for the four images processed are given in Table 2. This table shows a constant increase in the expanse of the built-up area from 1,757.61 ha in 1990 to 1,823.22 ha in 2000, 2,429.19 ha in 2010, and 2,967.12 ha in 2020. Isparta is observed to be a compact and centralized settlement that has started expanding Northward along the Istanbul Road and leapfrogging towards the northeast. This finding fits in line with Eren and Ajiboye (2021)'s description of Isparta city growth.

Table 2. Isparta land use/land cover (1990, 2000, 2010 and 2020)

Class	1990	2000	2010	2020
Built-up area	1,757.61	1,823.22	2,429.19	2,967.12
Farmland	22,589.01	12,070.98	15,702.84	26,093.97
Water body	79.38	77.22	123.12	139.05
Bare surfaces	20,630.79	21,885.30	17,119.17	13,071.69
Forest land	32,420.16	41,620.23	42,102.63	35,205.12

The CA-Markov Chain Prediction Model (Figure 3C) classifies images for 1990 and 2000. And, these images were used as the input data to simulate the expected situation (land use/land cover) of Isparta in 2010. Table 3 shows the transition matrix of land use areas and Table 4 presents the probability matrix of the Model. The land-use transition matrix covers the areas (in hectares) expected to shift from one land use to another.

Table 3. CA-Markov transition areas of Isparta in 2010

	2010				
Cells in :	**Expected to transition to:**				
	Built-up area	**Farmland**	**Water body**	**Bare surfaces**	**Forest land**
Built-up area	1,667.88	329.49	0	213.66	218.16
Farmland	262.62	12,157.47	0.90	871.74	2,410.11
Water body	0	0	123.12	0	0
Bare surfaces	632.88	3,734.91	26.10	10,582.83	2,142.45
Forest land	168.30	1,350.63	11.97	2,791.44	37,780.29
TOTAL	2,731.68	17,572.5	162.09	14,459.67	42,551.01

As shown in Tables 3 and 5, the CA-Markov Chain PM predicts that the extent of the built-up area of Isparta in 2010 will be 2731.68 ha. Specifically, 262.62 ha of farmland, 632.88 ha of bare surfaces, and 168.30 ha of forest land are expected to transform into a built-up area. The water body is predicted to remain intact.

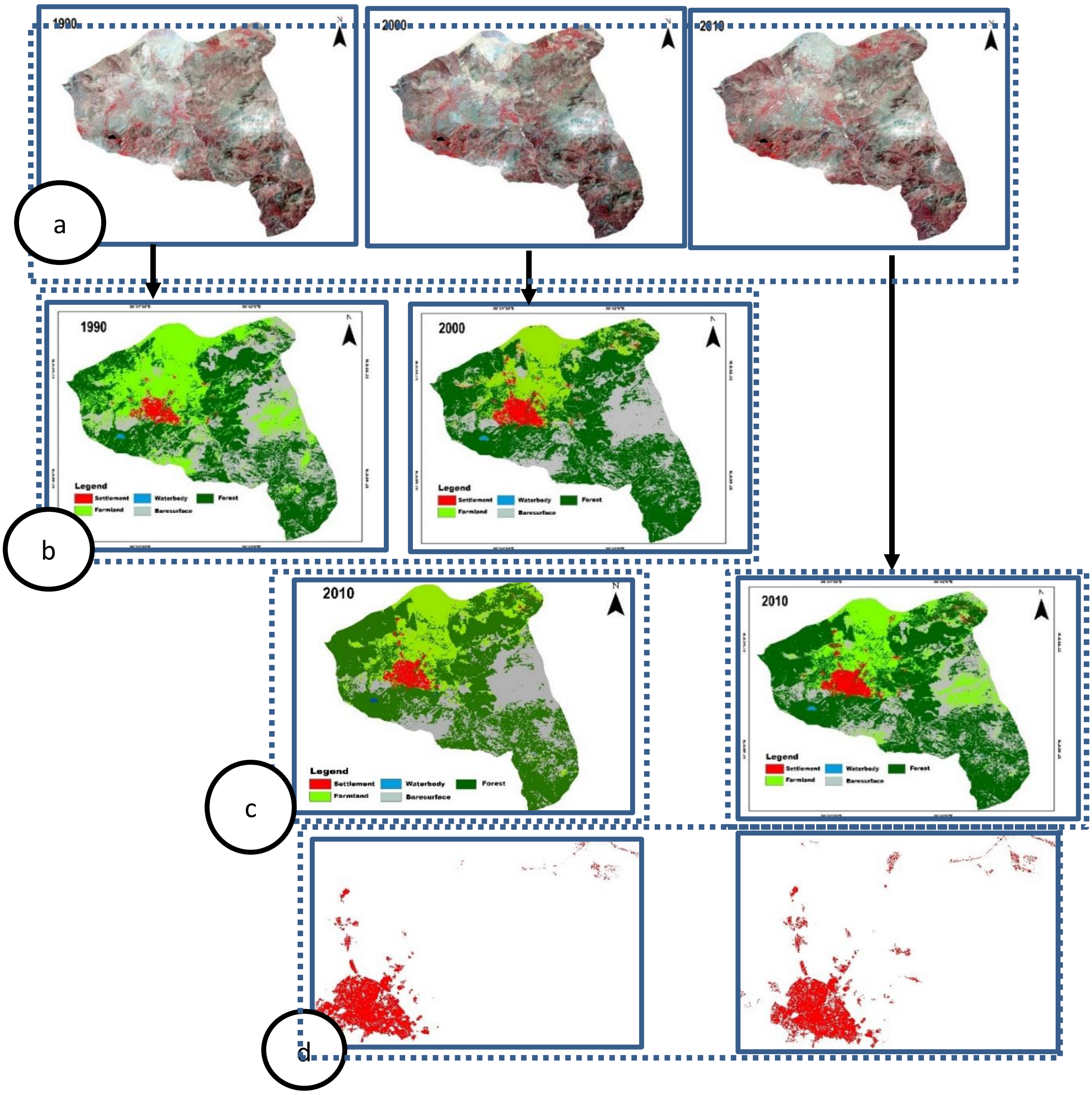

Figure 3. **a)** Landsat images (1990, 2000, and 2010), **b)** Land use/land cover maps (1990, 2000, and 2010), **c)** 2010 CA-Markov prediction model, **d)** extracted built-up areas

The transition probabilities shown in Table 4 indicate the probabilities of changes in land use. The probability that farmland will become part of the built-up area in 2010 works out at 0.0167. The probabilities of forest land and bare surfaces becoming part of the built-up area are 0.004 and 0.037, respectively. The probability of the water body being added to the built-up area in 2010 is zero, implying that the water bodies will be conserved and not encroached upon by the built-up areas.

Table 4. CA-Markov transition probabilities of Isparta in 2010

	2010				
Class:	**Probability of changing to**				
	Built-up area	**Farmland**	**Waterbody**	**Bare surfaces**	**Forest land**
Built-up area	0.6866	0.1357	0	0.088	0.0898
Farmland	0.0167	0.7742	0.0001	0.0555	0.1535
Water body	0	0	1	0	0
Bare surfaces	0.037	0.2182	0.0015	0.6182	0.1251
Forest land	0.004	0.0321	0.0003	0.0663	0.8973

Following the application of the CA-Markov Chain PM, the difference between the simulated/predicted result of the Model for 2010 and the actual (observed) land use/land cover in 2010 were quantified (Table 5) and presented graphically (Figure 4). The difference between the two was obtained by subtracting the simulated/predicted result of the Model from the actual/observed land use/land cover and *vice versa*. The discrepancy in the built-up area turns out to be 12.45%. For farmland, it is 11.91%. Water bodies show the largest discrepancy, with 31.65%, and bare surfaces the second largest with 15.54%, while the discrepancy in forest land is the lowest at 1.07%.

Table 5. Discrepancies between the 2010 LULC and the 2010 CA-Markov prediction model results (ha)

Class	2010 LULC	2010 CA Markov	Difference	Difference (%)
Built-up area	2,429.19	2,731.68	302.49	12.45
Farmland	15,702.84	17,572.50	1,869.66	11.91
Water body	123.12	162.09	38.97	31.65
Bare surfaces	17,119.17	14,459.67	2,659.50	15.54
Forest land	42,102.63	42,551.01	448.38	1.07
TOTAL	77,476.95	77,476.95		

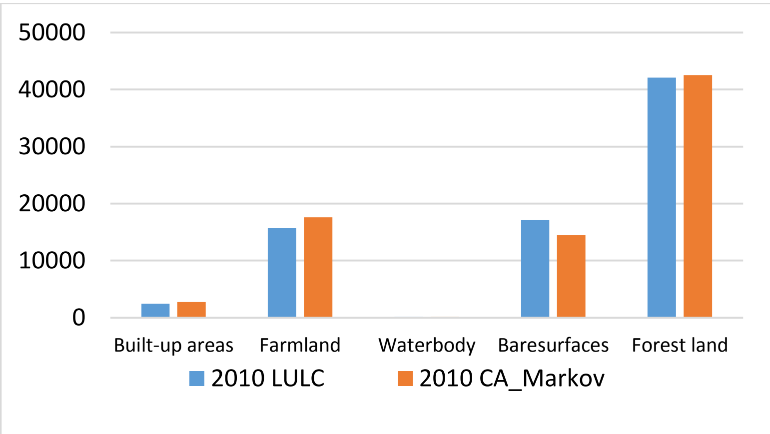

Figure 4. Differences between the observed LULC in 2010 and the predictions of the ca-Markov chain prediction model

Correlation analysis was used to ascertain an overall relationship or degree of conformity between the actual LULC and the results of the CA-Markov PM. The correlation values range from -1 to 1. The findings are given in Table 6. A value of -1 indicates a negative correlation or no correlation. A value of 1 or approaching 1 shows a positive correlation. The correlation result for the simulated and actual urban growth is figured as 0.856 (Table 6). This shows a strong positive correlation.

Table 6. Correlation Between the 2010 LULC in Isparta and the Prediction of the 2010 Markov prediction model

	2010 Actual growth	2010 CA_Markov
2010 LULC	1	
2010 CA_Markov	0.856	1

The CA-Markov PM prediction or simulation of the situation (land use/land cover and urban growth) of Isparta in 2020 is shown in Figure 5C. The classified images of Isparta in 2000 and 2010 constituted the input data (Figure 5A).

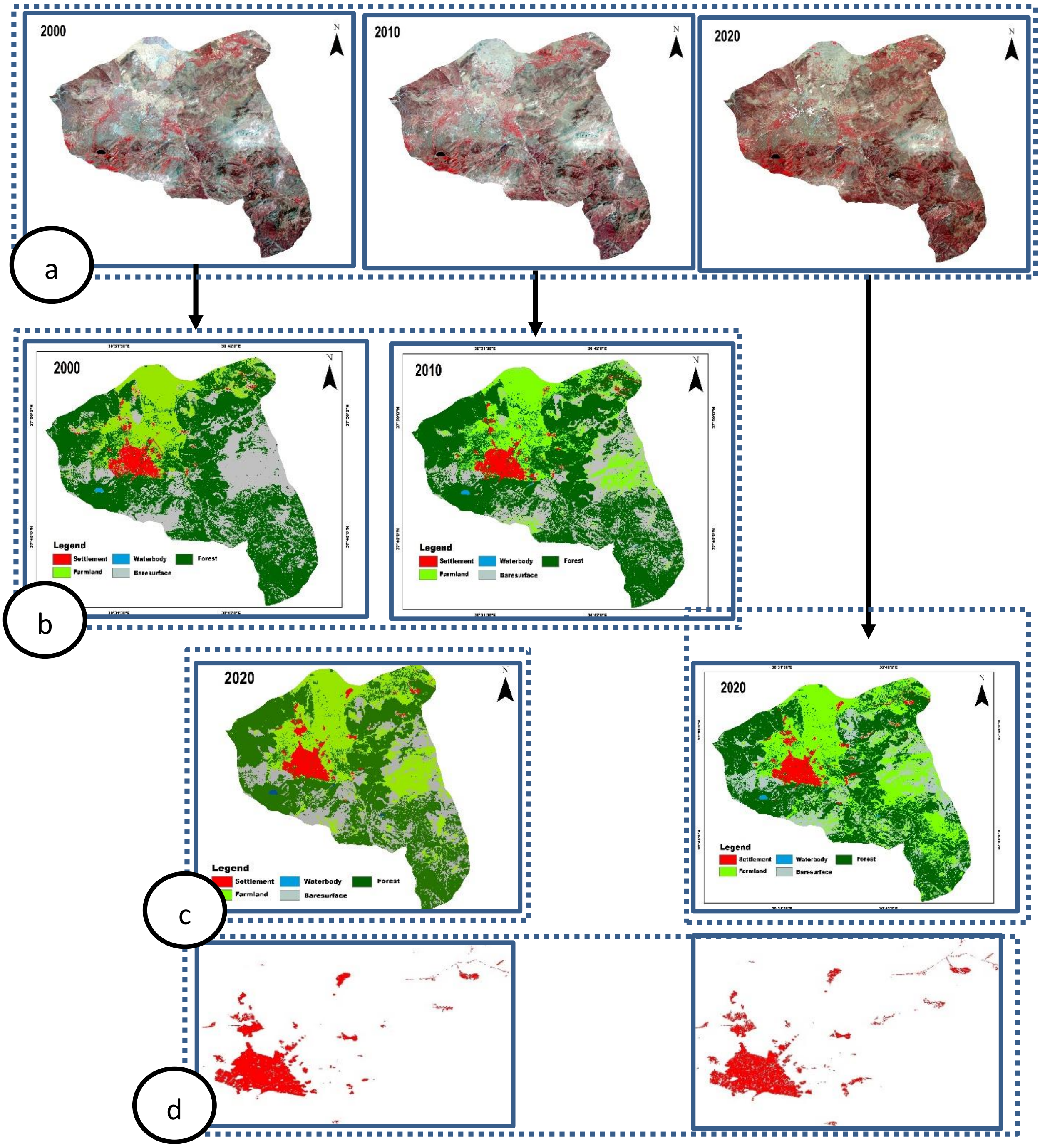

Figure 5. a) Landsat images (2000, 2010 and 2020), **b)** land use/land cover (2000, 2010 and 2020), **c)** 2020 CA-Markov prediction model, **d)** extracted built-up areas

In 2020, according to the Model, 823.6 ha of farmland is predicted to be added to the build-up area at a transition probability of 0.0316. The water body is not predicted to lose any acreage to the built-up area, so the transition probability is zero. Meanwhile, 136.71 ha of bare surfaces are determined to transform into built-up areas, with a transition probability of 0.0105. Finally, 236.34 ha of forest land is expected to join the built-up area, with a transition probability of 0.067 (Tables 7 and 8).

Table 7. The CA- Markov chain prediction model transition areas of Isparta in 2020

2020					
Cells in :	**Expected to transition to:**				
	Built-up area	**Farmland**	**Water body**	**Bare surface**	**Forest land**
Built-up area	2,455.11	277.92	0.09	67.05	166.95
Farmland	823.50	20,071.98	2.07	3,144.60	2,051.91
Water body	0	2.97	119.7	0.63	15.75
Bare surfaces	136.71	6,495.03	6.75	5,434.83	998.37
Forest land	236.34	4,413.96	19.08	3,349.89	27,185.76
TOTAL	3,651.66	31,261.86	147.69	11,997.00	30,418.74

Table 8. The CA-Markov prediction model transition probabilities of Isparta in 2020

2010					
Class:	**Probability of changing to:**				
	Built-up areas	**Farmland**	**Water body**	**Bare surfaces**	**Forest land**
Built-up areas	0.8274	0.0937	0	0.0226	0.0563
Farmland	0.0316	0.7692	0.0001	0.1205	0.0786
Water body	0	0.0212	0.8611	0.0044	0.1133
Bare surfaces	0.0105	0.4969	0.0005	0.4158	0.0764
Forestland	0.0067	0.1254	0.0005	0.0952	0.7722

Apart from the built-up areas, which naturally remain built-up areas, farmland is most likely to be added to the built-up area, followed by bare surfaces. In other words, it is predicted that more farmland and open spaces will be lost to the built-up area by 2020. On the other hand, no water body will be lost in built-up areas.

In the actual, observed situation in 2020, shown in Figure 5B, the built-up area of Isparta increased to 2,967.12 ha. The area of farmland increased to 26,093.97 ha, the water body to 139.05 ha, and the extent of bare surfaces to 13,071.69 ha. The forest land has declined to 35,205 ha. The spatial arrangement of the city of Isparta continued to be that of a centralized city, albeit with more pronounced leapfrogging development along the transportation routes (Figure 5D).

The discrepancies between the result simulated/predicted by the CA-Markov Chain Prediction Model for the year 2020 and the actual, observed land use/land cover of Isparta in 2020 are tabulated in Table 9 and shown graphically in Figure 6. They were found by subtracting the simulated/predicted results of the model from the actual, observed land use/land cover data and *vice versa*. There is a discrepancy of 23.07% in the built-up area, 19.81% in farmland, 6.22% in water bodies (the lowest discrepancy), 8.22% in bare surfaces, and 13.60% in forest land.

According to the correlation analysis undertaken to ascertain the degree of conformity between the Isparta 2020 LULC and the prediction made by the 2020 CA-Markov Prediction Model, the correlation between the simulated and actual land use was 0.849 (Table 10). This points to a high consistency and a strong positive correlation, confirming the reliability of the CA-Markov Chain Prediction Model in simulating/estimating the city's future development.

Table 9. Isparta 2020 LULC and 2020 CA-Markov prediction model correlation

Class	2020 LULC	2020 CA_Markov	Substition	%Diff.
Builtup	2967.12	3651.66	684.54	23.07
Farmland	26093.97	31261.86	5167.89	19.81
Waterbody	139.05	147.69	8.64	6.22
Baresurface	13071.69	11997	1074.69	8.22
Forestland	35205.12	30418.74	4786.38	13.60
	77476.95	77476.95	0	0

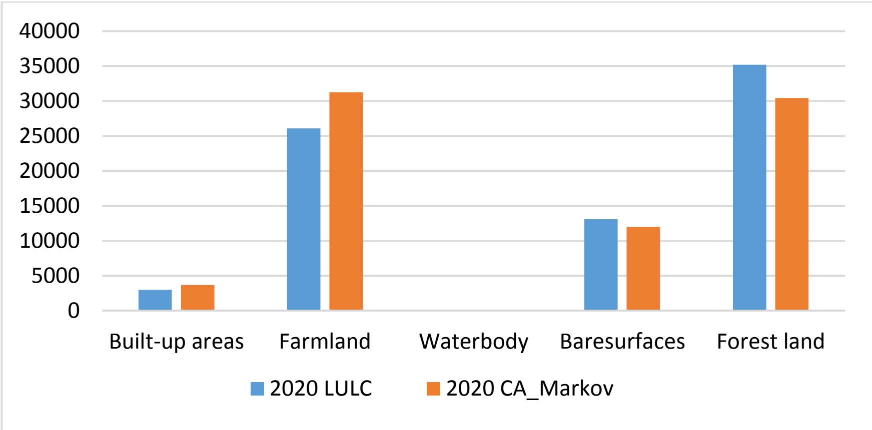

Figure 6. Differences between the observed LULC in 2020 and the predictions of the CA-Markov chain prediction model

Table 10. Correlation between the 2020 LULC in Isparta and The Prediction of the 2020 CA-Markov chain prediction model

	2020 Actual growth	2020 CA_Markov
2020 LULC	1	
2020 CA_Markov	0.849	1

4. Conclusion

Information about the future of a city is a treasure of which urban planners and decision-makers at all levels need to be cognizant. Various urban growth and land-use prediction models are used to predict and simulate the future growth of urban areas. This study has tested and explored the reliability of the CA-Markov Chain Prediction Model in the city of Isparta. Isparta's urban growth tendencies and acceleration and the emerging need to establish an effective growth predictive model suggested the backtesting of the CA-Markov Chain Prediction Model. This Model is selected here for its common use and ability to provide faster results. This research presented the applicability of the Model in the urban growth prediction of Isparta city.

Land use maps from different years (1990, 2000, 2010, and 2020) were used to predict the growth of Isparta for the years 2010 and 2020 and to test the accuracy of the predictions of the Model.

The positive correlation achieved from the calculations shows that the CA-Markov Chain Prediction Model is a reliable model for predicting and simulating Isparta city's future growth.

Back-testing the predictions made by the CA-Markov Chain Prediction Model for the city of Isparta for the years 2010 and 2020 by comparing them with the actual land use/land cover for the same years revealed a strong positive correlation between the predicted and observed growth of the city in both years. In 2010, the correlation coefficient was 0.8559 and in 2020, it was 0.8494. This confirmed that the CA-Markov Chain Prediction Model is a good model for forecasting future urban growth of this city and suggests its use as a powerful tool to inform urban planners and decision-makers in projecting, predicting, and simulating urban dynamics and growth.

This study has also presented that the processing of RS data using mathematical/statistical models is valuable in urban growth studies, prediction and simulations, and GIS techniques as a tool in tracking and assessing changes in urban spatial patterns and urban growth as stated by Guan et al. (2011); Jafari, Majedi, Monavari & Alesheikh (2016), Baqa et al. (2021), Jadawala, Shukla & Tiwari (2021).

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All authors contributed equally to the article, and there is no conflict of interest.

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