



A Methodological Benchmark in Determining the Urban Growth: Spatiotemporal Projections for Eskişehir, Türkiye

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Received: 9 March 2023 / Accepted: 18 June 2024 / Published online: 10 August 2024
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Abstract

Urban growth changes spatial uses over time due to different dynamics. These processes cause many physical, environmental, and socioeconomic problems, such as climate change, pollution, and population-related events. Therefore, it is essential to predict future urban expansion to produce effective policies in sustainable urban planning and make long-term plans. Many models, such as dynamic, statistical, and Cellular Automata and Markov Chain (CA-MC) models, are used in geographic information system (GIS) environments to meet the high-performance requirements of land use modeling. This study estimated the growth of settled areas in Eskişehir city center using models developed using two different methods. In this context, settled areas in the city center were examined within the scope of 1990–2018, and the growth areas of settled areas in 2046 were predicted using the CA-Markov method in Model 1: Quantum GIS (QGIS) MOLUSCE plugin and Model 2: IDRISI Selva. While settled areas are continuously increasing, other urban areas are decreasing. Model 1 predicts an increase of 1195 ha in settled areas by 2046, while Model 2 predicts an increase of 45,022 ha. At the same time, it is concluded that settled areas will grow in a central location in Model 1, while they will spread in an east-west extension in Model 2. The study results show that QGIS-based modeling predicts more limited spatial growth than IDRISI Selva. The research interprets growth in terms of the staging of urban services, the population size of neighboring cities, distances, and income levels based on the internal and external dynamics of the city.

Keywords CA-markov · Molusce plugin · Urban growth · Simulation models · GIS · Spatiotemporal analysis · LULCC

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Introduction

Managing land use changes in the world, especially in crowded cities, is necessary for global sustainability (Chakraborty et al., 2022). Given the prediction that urbanization and urbanization trends will increase, it is inevitable that the urbanization process will increase the pressure on land use and land cover (LULC) (Lee & Kim, 2016; Sun et al., 2019; Hussein, 2021). As a result of this pressure, many environmental problems, such as degradation of land structure, loss of soil quality, and reduction of green vegetation cover, arise (Sarif & Gupta, 2021; Kadaverugu, 2023). These problems in urban areas due to LULCC reduce people's quality of life. Concerns about this issue are increasing globally (IPCC, 2023). Modeling of land use and land cover change (LULCC) is a complex issue involving many physical and environmental factors and has become increasingly important as a multidimensional research topic on a global scale in recent years (Kindu et al., 2018; Aburas et al., 2019; Weng et al., 2020; Dullinger et al., 2021; Isinkaralar et al., 2022). LULCC generally refers to physical changes on the Earth's surface. These transformations are often a result of human activities (Aburas et al., 2018).

Human activities are causing irreversible spatial changes with different impacts and magnitudes in all cities globally (Aithal & Ramachandra, 2016). LULCC constitutes a resource value for improving cities' social, environmental, and economic conditions (Hegazy & Kaloop, 2015; Singh et al., 2017; Amgoth et al., 2023). Sustainable development depends on LULCC, which is considered one of the most critical parameters causing environmental changes worldwide. Therefore, the spatio-temporal determination of LULCC is important (Padma et al., 2022).

LULCC can be determined by Cellular Automata (CA) models and Markov chain (MC). CA acts from neighboring cells and determines the spatial pattern transition potential maps for the period $t+1$ (Mostafa et al., 2023; Yue et al., 2024). The Markov chain has advantages in producing predictions based on past temporal dynamics (Firozjaei et al., 2019). As an integrated method, the CA-Markov chains compensate for each other. These models were developed to predict land use change. The Quantum GIS (QGIS) Molusce plugin model (Land Use Change Evaluation Module) created with the CA model is used to estimate possible LULCC (Alam et al., 2021; Muhammad et al., 2022; Kamaraj & Rangarajan, 2022; Amgoth et al., 2023). Another method frequently used by researchers in LULCC detection is the cellular automata integrated with the Markov model (CA-Markov) approach. CA-Markov is widely used to simulate the spatiotemporal variation of urban sprawl (Burstedde et al., 2001; Kamusoko et al., 2009; Yang et al., 2014; Halmy, 2015; Fu et al., 2022). This study aims to estimate the growth of settled areas that include artificial areas in CORINE classification in Eskişehir city center with models developed within the scope of two different methods. Within Model 1, the QGIS Molusce plugin, and Model 2, two different settled areas were estimated by choosing the CA-Markov method in the IDRISI Selva program. The two models applied in the research were applied in the sample area. The results offer an approach that can be applied to different cities and methodological implications. While this research considers LULC change, as in most current forecasting studies, it does not estimate the percentage change of different land uses or land cover over time. It focuses on understanding urban growth and the

impact of various dynamics. These: The staging of services was interpreted based on the distance between surrounding provinces, population, and average income.

Materials and Methodology

Study Area

Eskişehir province is located in the Central Anatolia Region of Türkiye, between the coordinates $39^{\circ} 45' 58.2948''$ N and $30^{\circ} 31' 36.1704''$ E. The central districts of the province are Odunpazarı and Tepebaşı. The average height of the city center is 1681 m, and it shows an east-west extension in the parts where the elevation is low in Fig. 1.

Dataset and Prediction Process

The growth of settled areas is predicted using three main steps, as shown in Fig. 2. Firstly, the data required for the spatiotemporal variation of the settled fields were obtained and arranged for the estimation phase. The accuracy of the growth prediction models was calculated using the Kappa values. In the last stage, forecast maps for the target year 2046 were produced within the scope of two different simulation models.

The settled areas covering the city center of Eskişehir were obtained from the Copernicus Land Monitoring Service database in vector format from CORINE layers. For the settled areas of 1990, 2006, and 2018, the study area is divided into two classes (settled areas and other urban areas). The maximum likelihood classification technique was used in the ArcGIS 10.4 program to correct the spatial resolution differences with the settled areas data for the classification process. After the classifica-

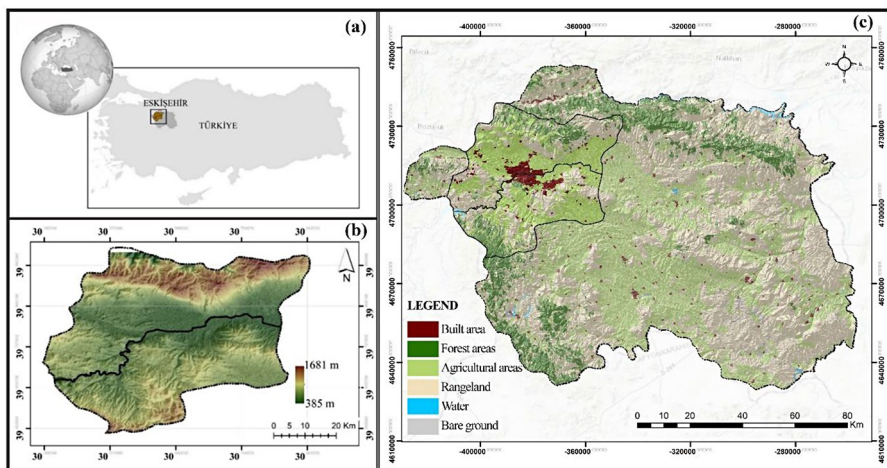


Fig. 1 Location and DEM map of the study area **a:** The location of the province in Türkiye, **b:** sea level rise of Eskişehir city center, **c:** land use of the province and location of city center in Eskişehir

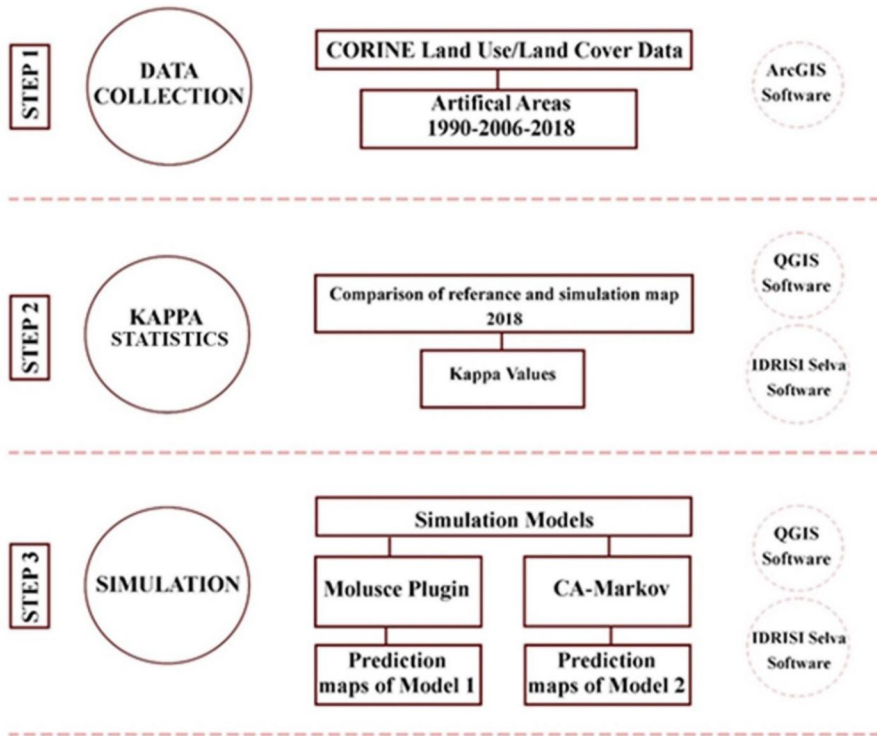


Fig. 2 Prediction process of the study

tion, the settled areas data were arranged in .geotiff format and ready for the IDRISI Selva program. Then, for the QGIS Molusce plugin, the LULC data was saved in raster format.

Model Validation

Two models were used to determine the spatial and temporal changes in the settled areas of the Eskişehir city center. While the QGIS 2.0.1 Land-Use Change Simulation (MOLUSCE) plugin was used in Model 1, the CA-Markov Chain method was used in the IDRISI Selva program in Model 2. Forecast processes are based on accepting spatiotemporal trends from past to present and the assumption that the entire city border can be opened to settlement. Settled areas were estimated for 2046 using the 1990 and 2018 maps, where the most significant and the most changes were experienced. The settled areas predicted for 2018 were verified by calculating the Kappa statistics from 1990 to 2006. In the QGIS program, the observed and simulated LULC were validated using multi-resolution, as shown in Fig. 3.

Kappa statistics results calculated with the QGIS Molusce plugin show that the maximum Kappa coefficient value is 0.97, and the maximum accuracy percentage is 98.49% throughout the study area in Table 1.

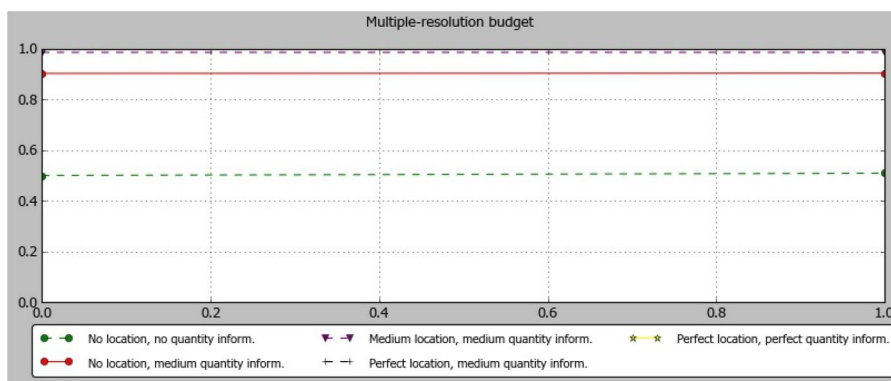


Fig. 3 Comparison of 2018 LULC observation data with 2018 forecast data in the QGIS program

Table 1 Different combinations of explanatory maps and Kappa coefficients

	Percentage of Kappa correctness (%)	Kappa coefficient
LULC	98.49	0.97

According to the results of Kappa statistics calculated within the scope of the CA-Markov chain method in the IDRISI Selva program, Location statistics are showing $K_{no} : 0.9915$, $K_{location} : 0.9958$, $K_{location\ Strata} : 0.9958$, and $K_{standard} : 0.9874$. Kappa statistic results calculated with Model 1 and Model 2 show that the settled areas simulation model is in excellent range for locating future change in Eskişehir city center.

Results and Discussion

Spatiotemporal Change Analysis

Settled area maps and spatiotemporal change rates are shown in Table 2; Fig. 4. When the changes in settled areas between 1990 and 2018 are examined, it is seen that there is a continuous increase, while other urban areas are experiencing a decrease. In the period between 1990 and 2018, it is observed that there was continuous growth in the east-west extension of the city center in general in settled areas.

2046 Simulations of Settled Areas

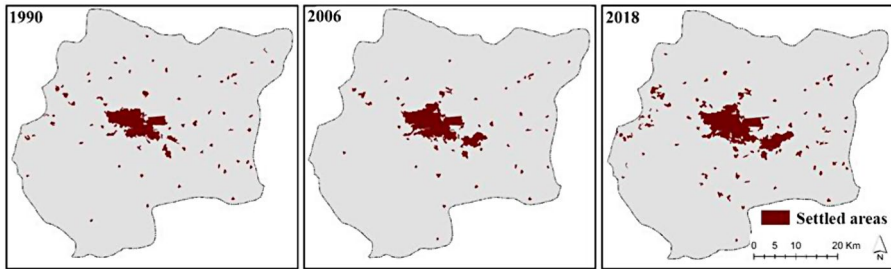
Within the scope of Model 1, in the settled areas estimation made for 2046 using the Molusce plugin of the QGIS program, the growth rate is predicted to be approximately 8.94% (1195 ha) compared to 2018. In the settled areas estimation made for the year 2046, which is estimated by using the CA-Markov chains method in the IDRISI Selva program within the scope of Model 2, the growth rate is predicted to be approximately 24.29% (45,022 ha) compared to 2018 in Table 3.

In Model 1, it is predicted that settled areas will grow in a central location, while in Model 2, it is predicted that the growth will be primarily east-west extension. This

Table 2 Spatiotemporal changes in settled areas

CORINE Data	AREA*	1990		2006		2018	
		ha	%	ha	%	ha	%
	Settled areas	9542.07	3.80	12086.51	4.80	14160.74	5.62
	Other urban areas	241,503	96.20	239,863	95.20	237,789	94.38
Model 1	AREA*	1990		2006		2018	
		ha	%	ha	%	ha	%
	Settled areas	9116.00	6.38	12,142	4.81	13,358	5.30
	Other urban areas	133,580	93.61	239,793	95.18	238,577	94.69
Model 2	AREA*	1990		2006		2018	
		ha	%	ha	%	ha	%
	Settled areas	134,448	36.09	147,309	38.35	185,276	44.29
	Other urban areas	238,045	63.90	236,759	61.64	232,962	55.70

*Calculations were calculated in the IDRISI Selva program. It represents approximate values

**Fig. 4** Changes of built areas depending on the years 1990, 2006, and 2018**Table 3** 2018–2046 settled areas change

Model 1	2018		2046		2018–2046	
	ha	%	ha	%	ha	%
QGIS Molusce Plugin	13,358	5.3	14,553	5.80	+1195	+8.94
	238,577	94.69	236,543	94.20	-2034	-0.85
Model 2	2018		2046		2018–2046	
	ha	%	ha	%	ha	%
IDIRSI Selva CA-Markov Chains	185,276	44.29	230,298	50.20	+45,022	+24.29
	232,962	55.70	228,460	49.80	-4502	-1.93

situation reveals that the development of settled areas in the city center will continue in Fig. 5.

It is known that the trend of urbanization and urbanization will gradually increase. The urbanization process, known to affect climate change and is a primary global concern, also causes many unfavorable social, environmental, and economic conditions in urban areas. Urban growth models facilitate the spatial determination of future projections. In this study, the problem of land degradation is emphasized by modeling the growth of settled areas in cities. The growth in settled fields between 1990 and 2018 also puts significant pressure on other types of LULC. While the

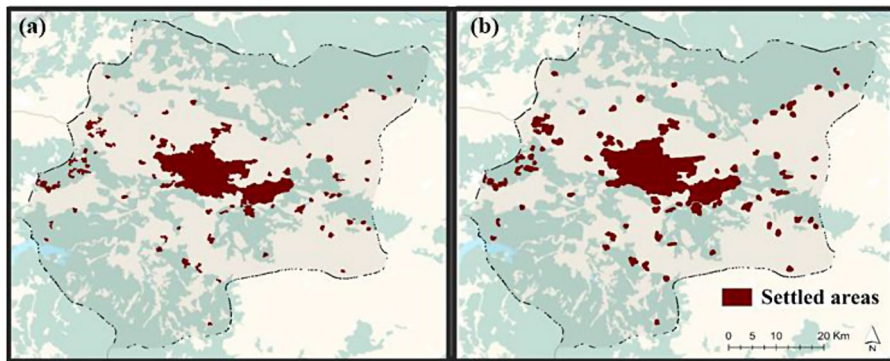


Fig. 5 2046 settled areas forecast map based on scenario a: Model 1, b: Model 2

increase in settled areas is one of the study's results, decreases in other urban areas are an essential indicator of this pressure. The descriptive results obtained using the settled areas maps of different periods show a continuous significant expansion in the settled areas, especially in 1990, 2006, and 2018. According to the estimation results for the 2046 settled areas, this situation is predicted to continue to increase. In other studies on a similar subject in the literature, attention was drawn to the pressure of built areas on other LULC types via QGIS (Wu & Zhang, 2012; Bose & Chowdhury, 2020; Mansour et al., 2020; Kamaraj & Rangarajan, 2022; Işınkaralar, 2023; Amgoth et al., 2023).

The triggering mechanisms that affect the expansion of a city are under the influence of a complex chain of vertical and horizontal networks. As in every city, there are many internal and external dynamics of urban expansion in Eskişehir, as shown in Fig. 6.

The assumptions of growth can be expressed from top to bottom as follows: (i) The most fundamental factor affecting the growth of the urban economy is the increase in national economic capital. The increase in national capital increases the urban economy, and the micro economy increases national income. Therefore, the city's location within the country and region is critical. (ii) One of the most fundamental factors governing urban morphology in developing countries is the central government's public expenditures and major investment decisions. The organized industrial zone, a significant employment area throughout the city, and the city hospital, which started operating in 2018, are located on the southeast axis, connecting with the capital, Ankara. (iii) Neighboring provinces may influence the direction of urban growth. Eskişehir is in the same nomenclature of territorial units for statistics (*nomenclature d'unités territoriales statistiques*, NUTS) class with the cities of Bursa and Bilecik in the TR412 region. Although it does not seem to be related to this classification in terms of staging of services, it serves surrounding cities such as Bilecik, Afyonkarahisar, and Kütahya. As a robust external dynamic, Ankara-oriented uses are supported by demands. (iv) The leaping spread of the city that emerged in this area was defined by zoning decisions on a macro scale. The political approach of the local government restricting urban density and new construction shapes the urban macroform. (v) One of the determinants effective in growth is natural thresholds. The limitation

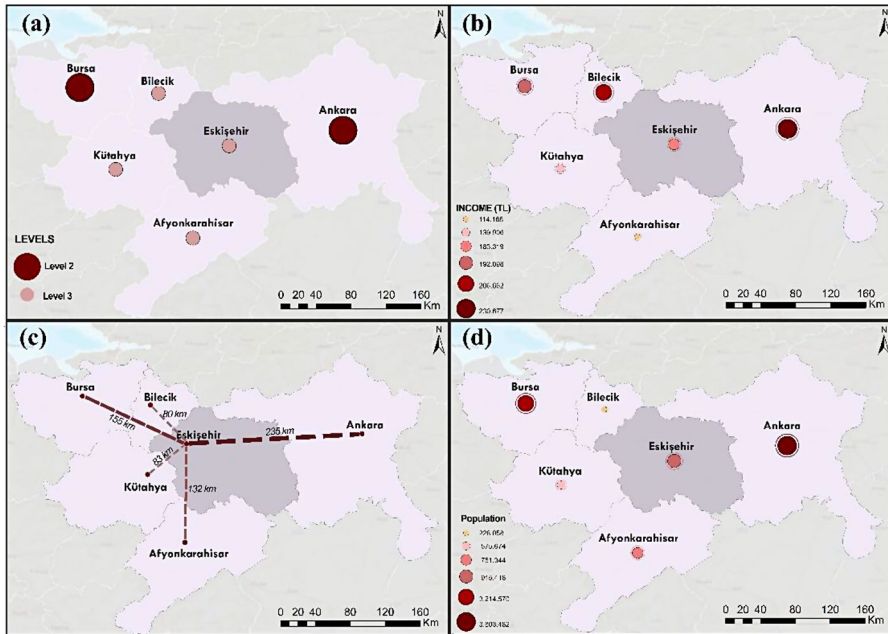


Fig. 6 Relationship **a:** The Nomenclature of territorial units for statistics (NUTS) zone classification level, **b:** income, **c:** distance, **d:** population with the close circle of Eskişehir

of the city to agricultural lands in the north-south direction effectively produced these decisions. Notably, the growth forecast is predominant in the southeastern direction, to dry farming areas. (vi) It is known that the city's student population is gradually increasing in terms of internal dynamics. In addition, the effective management of local touristic values has created a center of attraction in the city. Sectors supporting this, such as trade and daily tourism, trigger population growth in agglomeration economies. In summary, many general to local components are decisive regarding the city's growth rate and direction.

Conclusion and Future Work

This study contributes to developing research paths for LULC predictions by using two different techniques to observe the spatiotemporal changes of settled fields, one of the LULC types. Future LULCC simulation is a complex issue as it impacts the sustainability of the land use ecosystem. For this reason, it is possible to use it as an effective tool in ensuring sustainable development in urban planning. In the study, settled fields were modeled using only their physical properties. In future studies, the predictions of LULC change and growth can be enriched by including the environmental, physical, and socioeconomic characteristics and climate variables that affect the urban sprawl using the QGIS Molusce plugin and CA-Markov methods. Applying spatiotemporal data in a GIS and remote sensing environment is a powerful approach to evaluating urban growth models. In the QGIS Molusce plugin and IDRISI Selva

program, CA-Markov model techniques can be used to examine the growth pattern of any LULC species and to evaluate the spatial patterns of different cities.

Understanding the physical process of urban expansion and its factors is a requirement of urban planning, and predicting future land use provides critical clues. This situation will benefit decision-makers in producing appropriate policies to meet the future urban sprawl demand and reduce urbanization's adverse effects (Espindola et al., 2017; Osgouei & Kaya, 2017; Aburas et al., 2019). Along with the developments in geospatial analytics, spatial modeling methods that can be done with remote sensing and geographic information systems tools in urban planning are an essential advantage for researchers in determining urbanization and urban sprawl (Han & Jia, 2016; Aburas et al., 2021).

The study confirms the increasing pressure on other urban areas with the growth of settled areas. LULCC is a crucial point to consider in land use modeling studies. Urban growth models make it easier to make adequate plans to reduce the negative situations that urban sprawl will cause by spatializing future projections. It was concluded that there was and will be a continuous increase in settled areas in 1990, 2006, 2018, and 2046. This result may cause many future spatial problems in Eskişehir city center. The increase in settled areas and the fragmentation of other urban areas can put natural resources, the environment, food, and water security at risk. Therefore, the temporal-spatial and forward-looking simulation results will help protect the natural environment and promote sustainable development policies.

Funding There is no financial support and commercial support.

Open access funding provided by the Scientific and Technological Research Council of Türkiye (TÜBİTAK).

Data Availability The data supporting this study's findings are available from the corresponding author upon reasonable request.

Declarations

Ethical Approval Not applicable.

Consent to Participate Not applicable.

Consent to Publish Not applicable.

Competing interests The authors declare that they have no competing interests.

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