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ORIGINAL ARTICLE

Sustainable urban growth boundaries for ecological protection via 2046 models of İzmir

Oznur Isinkaralar[1] · Kaan Isinkaralar[2]

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Abstract

Long-term sustainable development that urban lands threaten ecological security in developing countries has made it necessary to define urban growth boundaries in terms of spatial planning. Our study creates a framework to determine the boundaries of the urban structure in 1990 and 2018 in İzmir, which is rapidly developing in terms of its form in 2046. With the high immigration, preserving its existing natural structure poses an environmental problem. It estimates with the Cellular Automata-Markov Chain (CA-MC), based on interactions and constraints, with a multi-scenario approach. In the proposed framework, the validation of future predictions was supported by Kappa coefficients of K_{no}: 0.9922, $K_{location}$: 0.8747, and $K_{locationStrata}$: 0.8747. CA-MC model shows the urban area of İzmir district increased from 104.263 to 150.082 ha according to λ_{MSRA} and to 143.665 ha according to λ_{ARYA} during 2018–2046. While the λ_{MSRA} scenario predicts a built-up area of 12.63% by 2046, the λ_{ARYA} scenario limits it to 12.09%. According to the unique models, when the urban area is left to itself without restrictions, it grows more and pressures other land uses. Urban growth limits must be brought to the agenda for sustainable development and compact urbanization.

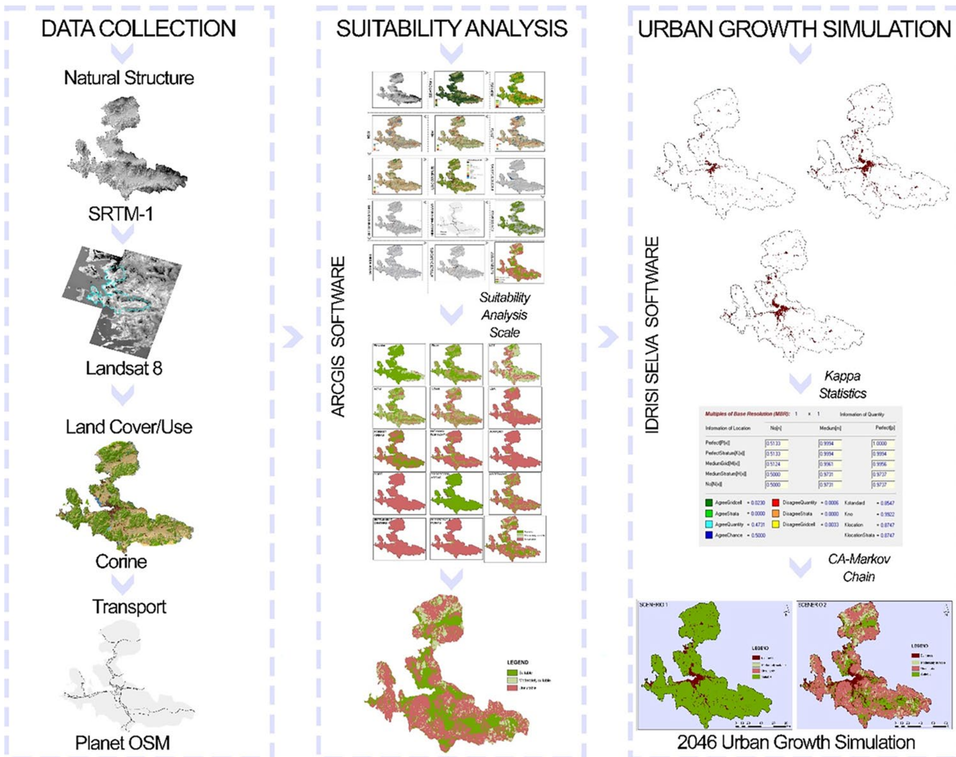
✉ Oznur Isinkaralar
obulan@kastamonu.edu.tr

Kaan Isinkaralar
kisinkaralar@kastamonu.edu.tr

1 Department of Landscape Architecture, Faculty of Engineering and Architecture, Kastamonu University, 37150 Kastamonu, Türkiye

2 Department of Environmental Engineering, Faculty of Engineering and Architecture, Kastamonu University, 37150 Kastamonu, Türkiye

Graphic Abstract



Keywords Land use · Ecological resilience · Environmental challenges · Urban planning; Spatial modeling; CA-Markov

1 Introduction

Urban sprawl, a driving factor for social development, causes an unexpected increase in the urban population. Today, a little more than half of the world's population lives in towns and cities—around 55%—according to Dijkstra et al. [1], while it is estimated that this rate will reach 68% in the next 25 years, according to Tan et al. [2]. Due to population growth, urbanization causes the expansion of the urban built environment and the destruction of natural lands [3]. While the vital benefits of ecosystems and the importance of ecosystem services are attracting increasing attention [4], the issue of effective management of land use dynamics in order to reduce destruction is on the agenda. It is advantageous to use urban growth boundaries (UGB) as a tool of spatial planning to limit irregular urban sprawl [5–8].

UGBs are a complex decision-making problem that controls irregular construction for multiple land use/cover (LULC) functions [9]. However, it is one of the intervention types to manage the land with maximum rent and profitability and can be a guide to ensure sustainable urban growth in developing countries. In the inherently complex structure of urban growth, predicting boundaries based on comprehensive data is vital for ecological security. Predicting a UBG reduces pressure on land and can ensure efficient land use [10]. Nowadays, with the development of geographical information systems, it is possible to estimate UGBs with urban growth simulation (UGS) and scenario approaches [11]. However, urban development is a self-organizing, multi-layered process that includes many dynamics in a network structure. Potential areas are transformed into urban land with the supply–demand factors that direct urban land development and the decision mechanisms that manage this process. Therefore, it is crucial to consider the spatiotemporal structure. Past research has not evaluated land cover and comprehensive dynamic metrics in population and employment-based or housing market-based approaches [12]. Machine learning and algorithm techniques can be used to produce predictions. Cellular automata (CA), one of the oldest known prediction methods, works on the principle of rule algorithm produced through neighborhood relations [13]. However, since CA cannot integrate temporal processes, forecasting techniques provide more robust forecasts. The CA-Markov chain method is preferred in urban growth modeling by estimating temporal-spatial processes [14].

This study introduces a framework to predict UGB based on scenarios. The proposed framework defines urban growth's land use suitability (LUS) by considering areas under growth pressure and where urban growth should be limited, with a multilayered geographical analysis approach. While the LUS of urban growth includes an ecological approach, it also considers the dynamics of the city that trigger growth. Based on this, UGS and boundaries were applied in the İzmir Province of Türkiye, depending on the scenarios produced. Our city's number of people per square kilometer is 368 as of 2021, well above the Türkiye average of 110. İzmir is the third province with the highest population density in this area after İstanbul and Kocaeli, and the need for research on the urban heat island has been emphasized to develop planning and design strategies to achieve climate-resilient urban development [15]. According to 2021 data, İzmir received immigration from 131,400 people. While 4.26% of the built-up area was in 1990, the built-up area rate increased to 8.76% in 2018. While natural areas have large areas, defining the borders in the city, which has received significant investments, has become an important research topic. Therefore, we investigate further what is known about the generation of predictions using the CA-Markov chain method. While it provides sustainable growth for the city in practice, it includes an approach that can be adapted to different cities. The paper provides evidence of how limitations due to a city's internal dynamics affect urban growth.

1.1 Literature review of Urban growth

Studies on UGS generally focus on similar regions with rapid population growth. The aforementioned presents significant viewpoints regarding the PLUS, MOP, and CA-Markov models. The literature review indicates that existing research has focused mainly on ecology-based modeling. The main innovation in this research is the integrated approach of nature and interval dynamics and the future prediction of sprawl, as shown in Table 1.

2 Material and methos

The research includes scenario-based urban growth modeling to determine UGBs in İzmir. The study consists of data acquisition, suitability analysis, and UGS.

2.1 Study area

İzmir is situated in the Aegean Region in Türkiye, between 37° 45' and 39° 15' north latitude and 26° 15'–28° 20' east longitude. The area is 12,012 km^2, a coastal city facing a mountainous region. Approximately 40% of the province consists of forest areas. There are Madra Mountains north of the province, as shown in Fig. 1. These mountains, with a height exceeding 1250 m, create a significant elevation between the Burhaniye-Havran Plains in the north and the Bergama Plain in the south.

The total population of İzmir, Türkiye's third most populous city in terms of population, is 4,479,525 people, according to Turkish Statistical Institute 2023 data. Within the borders of the province are the Gediz Delta, Küçükmenderes, and Büyükmenderes rivers, which are among the essential natural resources of the Aegean Region. In the city, mountains extend perpendicular to the sea. Due to this situation, the sea affects the inland areas and causes the climate to be mild. In the city where the Mediterranean climate prevails, summers are hot and dry, and winters are warm and rainy.

2.2 Data collection

The first step in the research was to obtain natural data from the study area. In this respect, the SRTM 1 Arc-Second Global DEM data was downloaded from a USGS database to perform elevation and slope analyses. In this respect, satellite images from the Landsat 8 OLI/TIRS C2 with a spatial resolution of 30*30 m, specifically from path 139 and row 43, were derived from the USGS database for the analysis of LST, NDVI, NDWI, and LSA. Determining the date of the satellite imagery took into consideration the meteorological condition of İzmir. In this context, the execution of satellite imagery was performed on 28.07.2018. CORINE LULC change data from the Land Copernicus database was used for the LULC analysis for 1990, 2006, and 2018, which is necessary to determine LUS for the built-up area. Transportation data was obtained from the Planet OSM database.

2.3 LUS analysis of simulation experiments

A framework has been established to determine the suitability of urban growth. The classification made depending on the scenarios is given in Table 2. The first scenario is defined as a model that finds all areas suitable for growth from an urban perspective, including a salient range of affairs (λ_{MSRA}), and the second scenario is defined as a responsibility of yearning advice (λ_{ARYA}), which aims to grow according to LUS. Within the two scenarios, urban growth forecasts were made for 2046 using built-up area data from 1990 and 2018. A total of 13 maps were created for LUS, as shown in Figure S2.

Elevation and slope analyses for the suitability of residential areas are given in Figure S1 (see Supplementary Materials). The algorithms used to analyze LST and NDVI are defined by Barsi et al. [25] and Barbieri et al. [26]. The Landsat 8 OLI satellite image band 10 data were utilized to generate spectral radiance values using Eq. (1) [27].

Table 1 Scenario-based urban growth literature

Authors	Search Criteria	Study site	Modeling methodology	Main Results
Li et al. [16]	UGS	Jiangsu Province in China	The FLUS model	Maintaining diverse land functions will considerably affect the number, spatial distribution, and landscape features of the UGB
Wei et al. [17]	A multi-scenario analysis of land use simulation	Kashgar region of Xinjiang	The MOP-PLUS-ESV model	It highlights the need to protect ecosystems
Deng et al. [18]	Scenario Simulation of LULC	Chang-Zhu-Tan Metropolitan Area, China	The ESP-PLUS model	Enlargement of the building has happened due to transportation and access to government sites and will surely contribute to the reduction of forests and cultivated areas in the future
Chen et al. [19]	Urban Agglomeration	Yellow River Basin in the northwest inland of China	the MCR-MOP- Dyna-CLUE model	The ecological optimization scenario provides a more rational land use pattern
Wang et al. [20]	Land Use Planning and the City's Spatial Heterogeneity	Beijing	the PLUS model	It was discovered that the zoning method can increase the precision of the LULC simulation
Li et al. [21]	Patch cellular automata models	Wuhan, China	The MOP model	Urban development that is low-carbon maximizes carbon storage in land use
Guo et al. [22]	Coupled MOP and PLUS-SA Model Research	Zhengzhou Metropolitan Area, Central China	The MOP and PLUS-SA Model	In contrast to the conventional PLUS and FLUS models, the proposed model exhibited superior simulation accuracy in Zhengzhou
Yu et al. [23]	UGB delineation	Ningbo, China	The CA model	It demonstrates that from a human-centered and low-carbon perspective, the context under multi-objective constraints is credible and more extensive than the context without constraints
Feng et al. [24]	The perspective of landscape pattern	Shenyang city	Resilience scale	Spatial development is an important factor affecting the flexibility of scale
In this study	Deciphering the Complex Spatial Change and Delineation of Sustainable UGB	İzmir, Türkiye	The CA–Markov model	Original models suggest that when left to its own devices without any constraints, the urban area grows more, putting pressure on other land uses

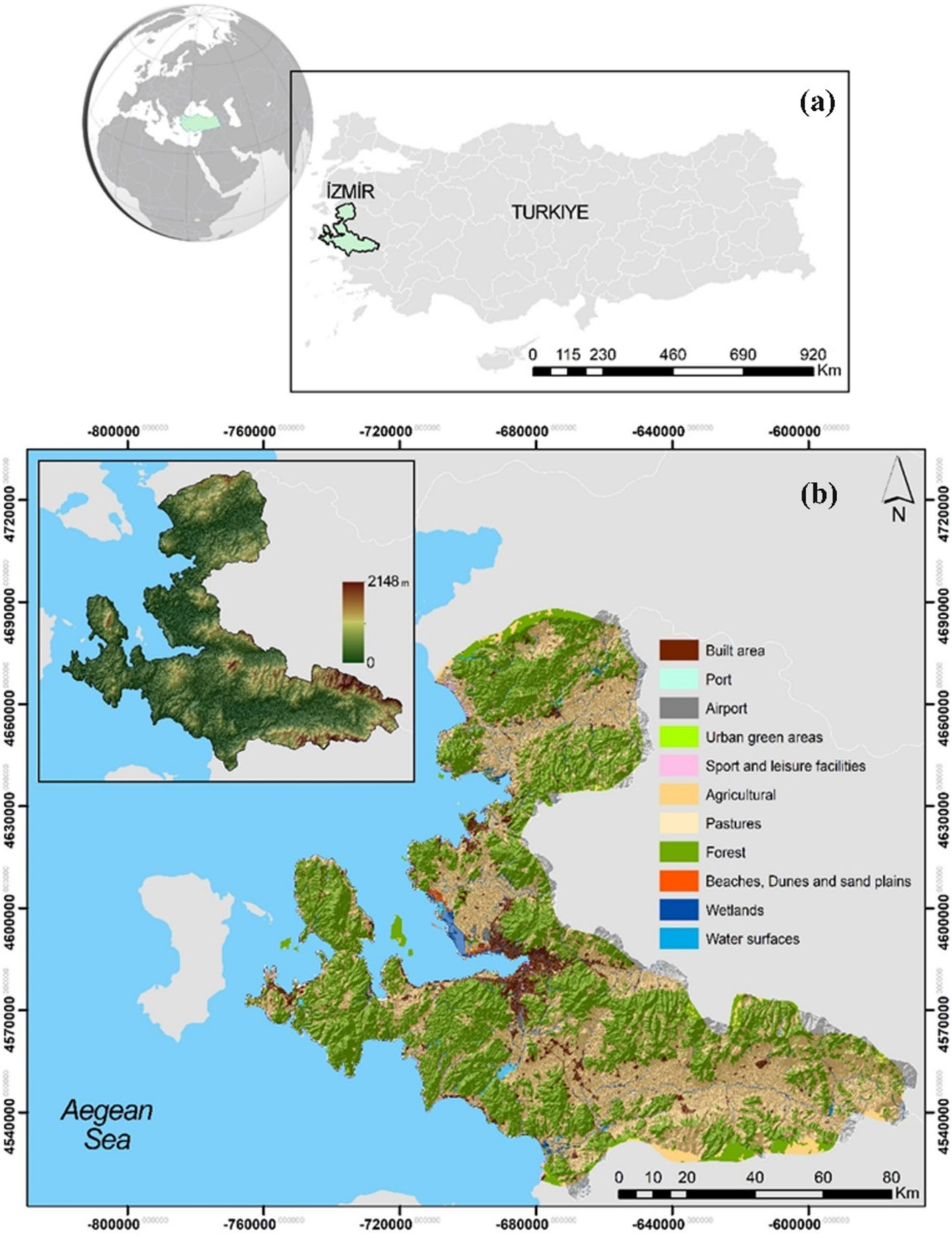


Fig. 1 Location map of the study area (**a**: Location map of İzmir in Türkiye, **b**: Land use of İzmir City)

$$L_\lambda = \left(M_L * Q_{cal}\right) + A_L \tag{1}$$

L_λ and λ present Top-of-Atmosphere (TOA) spectral radiance (unit: W m^{-2} sr^{-1} μm^{-1}) and radiation intensity at wavelength. M_L, A_L, and Q_{cal} reflect Radiance Mult Band (Band10), Radiance Add Band10, and calibrated digital numbers derived from pixel values. All this information described above is taken from the meta-data file accompanying the satellite imagery.

Then, based on image brightness, the temperature values have been calculated. This was made in accordance with the following Eq. (2):

$$\mathrm{TB} = \frac{K_2}{In\left[\left(\frac{K_1}{L_\lambda}\right)\right] + 1} - 273.15 \tag{2}$$

where TB refers to brightness temperature (Celsius °C unit), K_1 and K_2 show calibration constant Band(10). L_λ tells the spectral radiance of the thermal band (unit: W m^{-2} sr^{-1} μm^{-1}). The metadata file of specific images contains this information.

The Normalized Vegetation Difference Index (NDVI) analysis was calculated using Eq. (3) from the 4th and 5th bands of Landsat 8 satellite imagery (Figure S3) [28].

$$\mathrm{NDVI} = \frac{(Band5 - Band4)}{(Band5 + Band4)} \tag{3}$$

Bands 4 and 5 represent satellite image bands to explain NDVI behavior patterns due to the different responses of the bands.

After carrying out the NDVI analysis, the vegetation cover ratio is calculated. This is obtained from the NDVI analysis. Equation (4) was utilized in calculating the vegetation cover ratio:

$$\mathrm{PV} = \left(\frac{(NDVI - NDVImin)}{(NDVImax - NDVImin)}\right)2 \tag{4}$$

where PV: Vegetation rate, NDVI: NDVI analysis, NDVImin, max: Minimum, and maximum value in NDVI analysis.

Then, the LSE analysis was completed using the algorithm in Eq. (5) after calculating the vegetation ratio:

$$\varepsilon = 0.004 * PV + 0.986 \tag{5}$$

where ε = Land surface emission, PV: Vegetation rate.

Already in the final step of the LST analysis, as conducted by Stathopoulou and Cartalis [29], the study was completed by applying the following Eq. (6).

$$LST = \frac{BT}{1 + \frac{\lambda(BT)}{p} * In(\varepsilon)} \tag{6}$$

where the LST unit is °C, and BT is °C. λ (11.5 μm) presents the spectral radiance wavelength of emitted radiance ($p = h*c/\sigma = 1.438*10^{-2}$mK) (Landsat 8 band10, Landsat 7 band 6), that here, h is Planck's Constant:$6.626*10^{-34}$ J, σ is the Stefan–Boltzmann constant = $1.38*10^{-23}$JK, c = velocity of light = $2.998*10^{8}$ m/s = 14,388, and ε is the land surface emissivity (LSE).

Equation (7) was used for the NDWI analysis.

$$\mathrm{NDWI} = \frac{(Band5 - Band6)}{(Band5 + Band6)} \tag{7}$$

In performing the LSA, the DN values of the Landsat satellite image band2, band4, band5, band6 and band7 were first rescaled to the TOA value using the range 0–1. Then, the analysis was completed using the scaled bands and Eq. (8). The produced NDWI and LSA maps are shown in Figure S3.

$$(0.356 * \text{band2} * \text{band4} * \text{band5} + 0.085 * \text{band6} + 0.072 * \text{band7} - 0.0018)/1.016 \tag{8}$$

LULC data, supplied in vector form, have been taken into the ArcGIS 10.4 software and edited. In the scope of the regulation, LULC was classified into 11 groups Figure S4. The protected areas and attraction points were determined using Google Earth and the LULC pattern Figure S5. The transportation data, supplied as a vector from the Planet OSM database, were edited in the ArcGIS program Figure S6. After the maps were developed, distance analyses and classifications were carried out in the ArcGIS. During the distance analysis, the required analyses were carried out by placing 800–1200 m distances to the areas given in Table 1. In the classifications, the natural breaks method was preferred. After completing the analyses, the LUS map was produced using the Weighted Overlay method. Figure 2 shows the mapping of land suitability for urban development. The classification of land-use suitability classes influencing urban growth has been divided into three classes (3–2–1) and ranges from highly suitable to unsuitable.

2.4 Principle of UGS

To estimate the growth of the residential area in the city of İzmir, CAMarkov chains were also applied. CA-Markov is the method that couples the Markov chain model with CA. CA-Markov has been applied in urban growth and land-use prediction. This is a present-state and next-state approach when transition probability is applied in order to predict the future state. The application of Markov chains within the contexts of land-use change is well documented for example, Guan et al. [30], Yang et al. [31], Sang et al. [32],

Table 2 LUS assessment scale

Variables		Gap	Classification*	Weight values λ_{MSRA}	λ_{ARYA}
Natural structure					
	Elevation	< 500 m 500–1500 m 1500 m <	3 2 1	–	10
	Slope	< 20% 20–30% 30% <	3 2 1	–	10
	LST	< 55 °C 55–63 °C 63 °C <	3 2 1	–	10
	NDVI	−0.31–0.15 0.15–0.29 0.29 <	3 2 1		10
	NDWI	−0.52–0.02 0.02–0.13 0.13 <	1 2 3		10
	LSA	−0.03–0.26 0.26–0.48 0.48 <	1 2 3		10
LULC	Forest areas	Forest area Not forest area	1 3	–	5
	Highway and Railways	< 800 m 800–1200 m 1200 m <	3 2 1	–	5
	Airport	< 800 m 800–1200 m 1200 m <	3 2 1		5
	Port	< 800 m 800–1200 m 1200 m <	3 2 1		5
	Protected areas (Wetlands)	Protected area Not protected area	1 3	–	5
	Waterways	< 800 m 800–1200 m 1200 m <	3 2 1		5
	Settlement Centers	< 800 m 800–1200 m 1200 m <	3 2 1	–	5
	Attraction points				
	University City hospital Shopping malls Organized Industrial Zone Beach Square Hotel Urban green areas Sport and leisure	< 800 m 800–1200 m 1200 m <	3 2 1	–	5

*3: Suitable, 2: Moderately suitable, 1: Unsuitable

and Huang et al. [33]. Forecasting by Markov processes is based on the following Eq. 9, according to Baqa et al. [34]:

$$S_{(t+1)} = P_{ij} x\ S_{(t)} \tag{9}$$

Equation 10 where St and St + 1 are the row vectors at time t at the next instant of time t + 1, whereas P denotes the transition probability matrix at time period t-1, which is defined by:

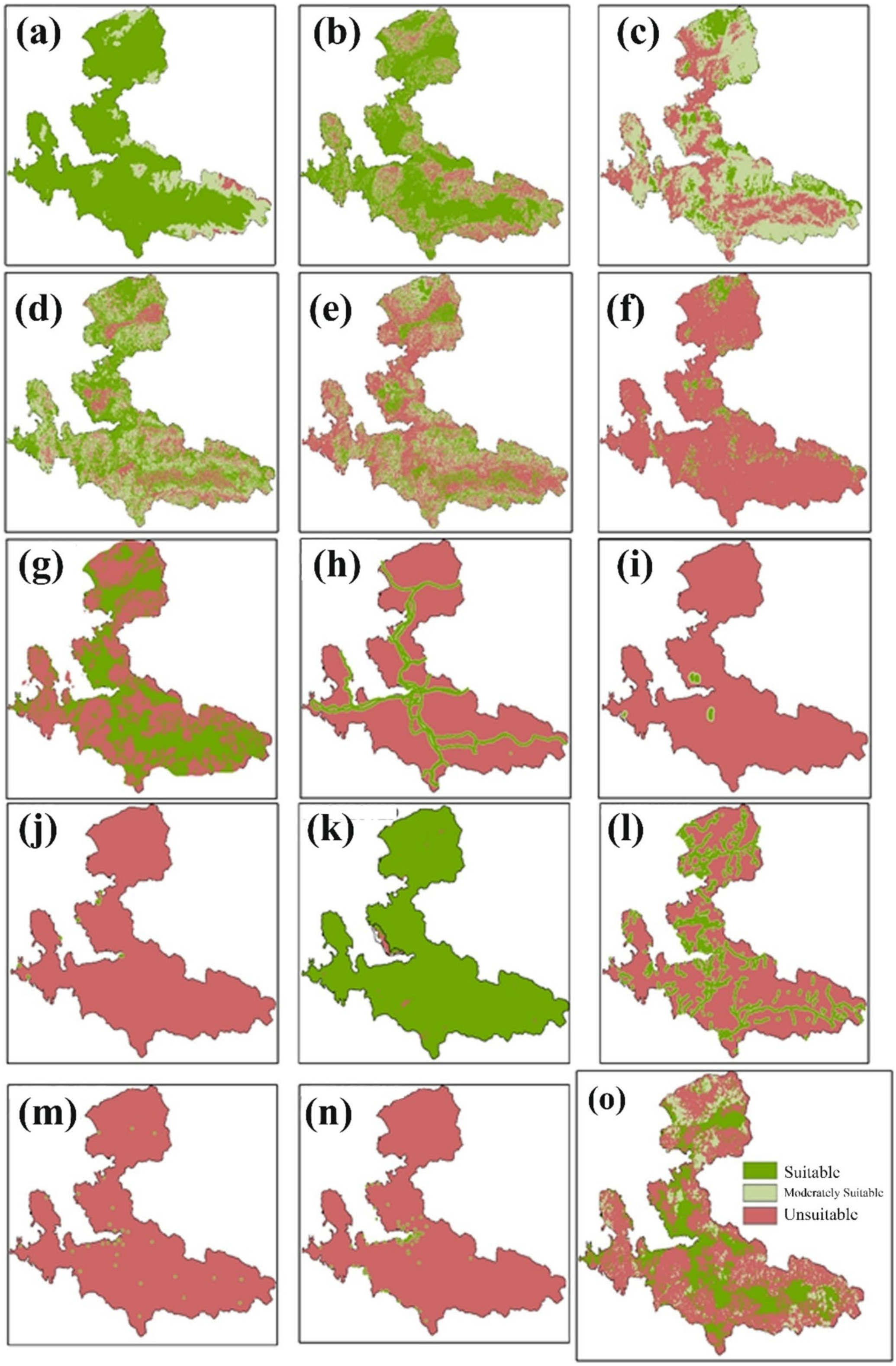


Fig. 2 Maps of LUS (**a**: Elevation, **b**: Slope, **c**: LST, **d**: NDVI, **e**: NDWI, **f**: LSA, **g**: Forest Areas, **h**: Highway Aras, **i**: Airports, **j**: Ports, **k**: Protected Areas, **l**: Waterways, **m**: Settlement Centers, **n**: Attraction Points, **o**: Suitability Map)

$$\|Pij\| = \left\| \begin{matrix} P_{11} & P_{12} & P_{1n} \\ P_{21} & P_{22} & P_{2n} \\ P_{n1} & P_{n2} & P_{nn} \end{matrix} \right\| (0 \leq Pij < 1 and \sum_{1}^{n} Pij = 1) \quad (10)$$

Pij, denotes the probability of transition from land use type i to j.

In this context, a future prediction for the study was made using the CA–Markov model in IDRISI Selva. Estimation was done after calculating the Kappa statistics that tested the accuracy of the simulation model. The accuracy of the simulation model was tested using the 1990, 2006, and 2018 İzmir city built-up area maps. An estimation for the year 2018 was conducted utilizing built-up area maps from the years 1990 and 2006. The forecast map is juxtaposed with the existing map from 2018. This comparative analysis demonstrates that the prediction outcomes align with the reference map illustrated in Fig. 3.

Kappa statistics values were determined to verify the accuracy of the results numerically. Location statistics are: Kno: 0.9922, Klocation: 0.8747, KlocationStrata: 0.8747 and Kstandard: 0.8547. According to the findings, it can be said that the CA–Markov model is very successful in determining the location of future change in İzmir Figure S7.

2.5 CA-markov UGS results

While it is predicted that it will grow by approximately 43.94% within the scope of λ_{MSRA}, which expresses the natural growth of the built area without any restrictions, it is predicted to grow by 34.92% within the scope of λ_{ARYA}, which is limited by LUS assessment in Table 3.

Figure 4 shows the built-up area in 2018 and urban growth models for suitable areas according to two scenarios for 2046. In the built-up area change estimate of İzmir city, it is seen that there will be more growth in λ_{MSRA} than in λ_{ARYA}.

As a result of the prediction, it is assumed that the city will grow regardless of the interventions in λ_{MSRA}, and the irregular structure of the urban growth border and the growth in every direction of the city are predicted. In λ_{ARYA}, it has been determined that the city is less spread out. According to the models obtained, when the urban area is left to its

Table 3 The amount of built-up area 1990–2046

Years	The amount of built-up area (ha)*	The amount of built-up area (%)*
1990	50.665	4.26
2006	97.074	8.17
2018	104.263	8.76
2046 (λ_{MSRA})	**150.082**	**12.63**
2046 (λ_{ARYA})	143.665	12.09
2018–2046 (λ_{MSRA})	+45.819	+% 43.94
2018–2046 (λ_{ARYA})	+39.402	+% 34.92

*Area calculations were made using the IDRISI Selva program. It represents approximate values

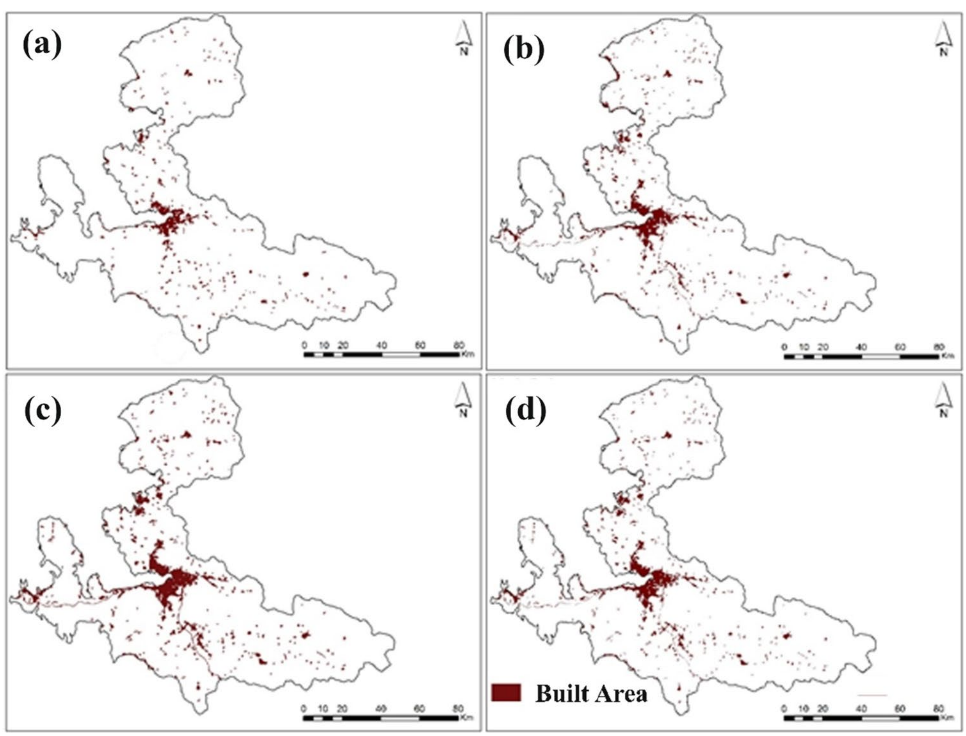


Fig. 3 Reference and forecast map for 2021 (**a**: 1990, **b**: 2006, **c**: 2018-Simulation, **d**: 2018-Reference)

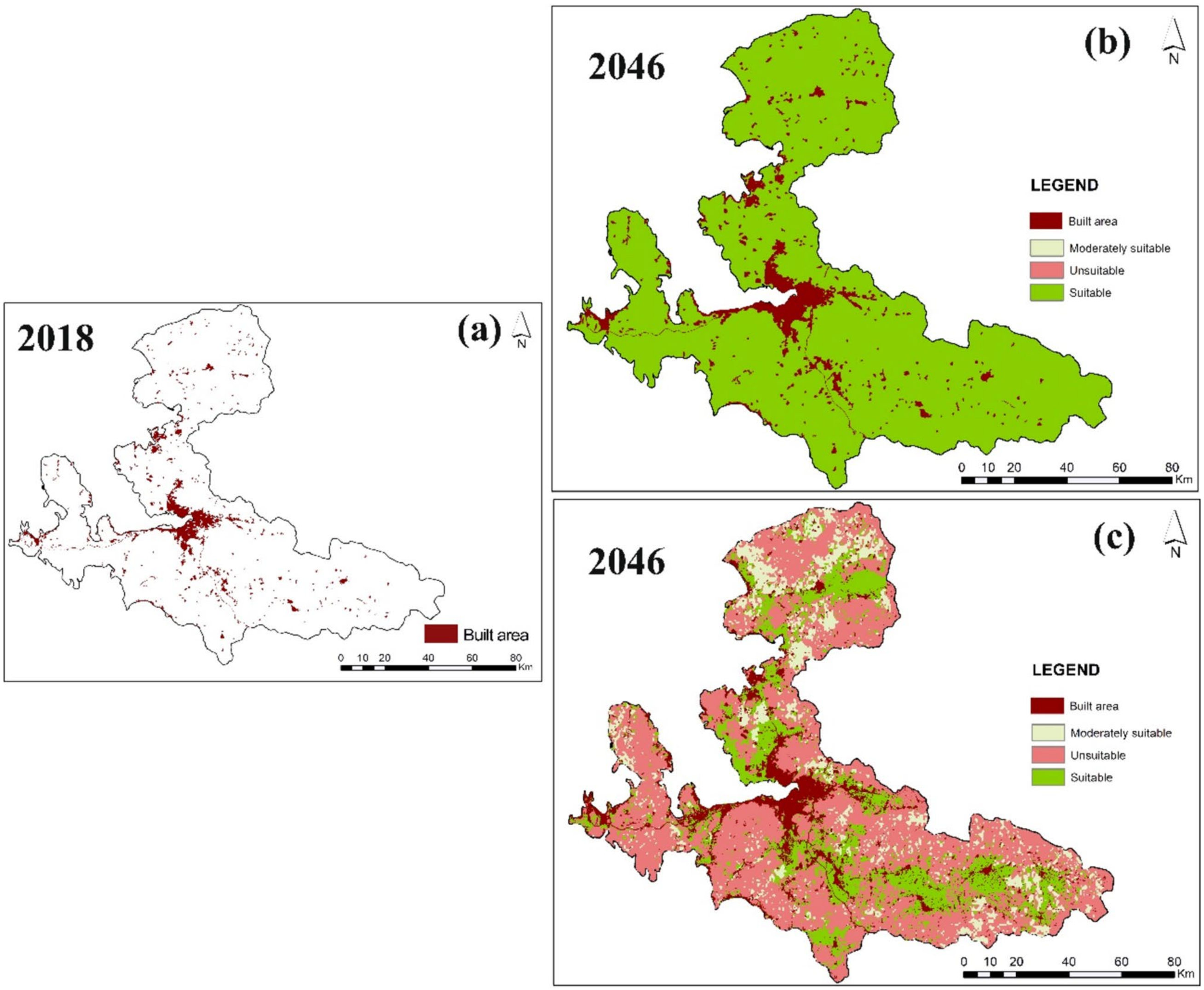


Fig. 4 Urban growth forecast of 2046 (**a**: 2018, **b**: $\lambda_{\mathrm{MSRA},}$ **c**: λ_{ARYA})

own devices without any restrictions, it grows more and puts pressure on other land uses in Fig. 5.

3 Discussion

Models that will direct and limit urban growth are necessary in order to keep the expansion brought about by country economies and population sizes under control [35]. It is quite clear that UGB is a critical tool to control urban sprawl when making urban planning decisions [36–38]. London's green belt can be considered the first urban growth boundary [39], and the need for boundaries arises from problems. This is why widespread studies on borders exist in developed countries such as China and the USA [40–42]. Determining the boundaries and rules for certain priorities from the beginning is a prerequisite for effective management, and traditional studies on UGBs in the literature to predict urban growth have used linear standard programming algorithms [43]. However, current research appears to use geographic information systems (GIS) technology more effectively. It is seen that land use modeling has been improved with the advantages provided by remote sensing. Li et al. [21] present a modeling approach combining MOP and Patch-Level CA models proposed in Wuhan, China, to optimize UGB under low-carbon development. The research by Isinkaralar [44] offers that a climate-sensitive approach in a framework links urban growth with the climate crisis. Chen et al. [45], in their results limiting urban growth with low carbon concerns, concluded that UGB can effectively reduce the wide range of carbon emissions. Wang et al. [46] presented approaches that represent space by setting targets with the ant colony algorithm. Several studies have the principle of multi-objective programming (MOP). Our research provides

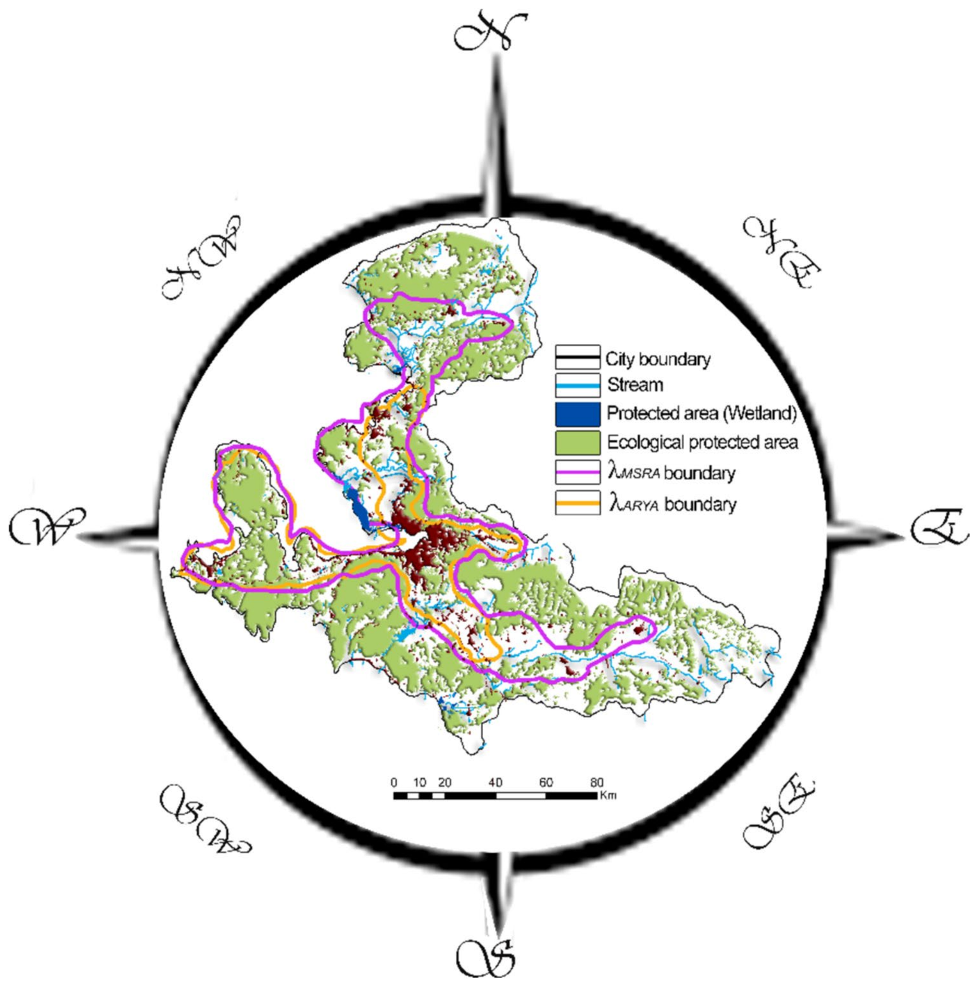


Fig. 5 UGB based on the scenerios

a framework that classifies land in terms of suitability for growth while simulating complex dynamics. If we consider the city's current structure and growth behavior trend, it is observed that many natural structures are at risk. However, the scenario considering specific criteria for urban growth modeling reveals that growth can be controlled. According to the research results, the hypothesis that the definition of UGBs limits the built-up areas in the estimates produced by the CA-Markov method, depending on the past trend of the city, was confirmed and coincides with previous research findings by Kisamba and Li [47] and Hussain et al. [48]. In summary, a framework is presented as a policy tool, and a border is defined as a precaution against ecological destruction.

3.1 Limitations and future prospects

In this research, CA-Markov models were produced and compared while making future predictions in the city of İzmir, depending on its internal dynamics and natural structure. However, the research topic has several limitations: (i) Most studies are based on defining boundaries in the current structure rather than focusing on the future city. (ii) Most of the research takes into account natural elements or focuses only on local dynamics, and there is limited interest in a combined approach. (iii) There is no systematic IGB structure defined internationally or protected by legislation at the national level. These identified limitations were addressed in the research. First of all, future simulations in which scenarios were included in the model development of UGBs. In addition, development suitability criteria were produced depending on the characteristics of the city. However, this research, which brings the importance of the UGB issue to the agenda, is limited to emphasizing a sanction power.

Additionally, the research is limited by the data sources available. Future research can be enriched by integrating data on ecosystems, wildlife, and species in terms of natural structure, which can be obtained at the provincial level and used numerically in spatial terms, and data such as tourism, transportation, employment, and socio-demographic structure in terms of dynamics. In addition, this research was based on two basic scenarios. Further research may diversify the scenarios. Finally, while the CA-Markov chain method is used in modeling, other research such as MOP, SLEUTH, FLUS, and QGIS can apply the methods with different approaches or by comparing them.

4 Conclusion

Achieving effective management of urban geography is possible with a conscious approach that meets the population's needs, supports development, and takes the ecological environment into consideration when deciding the future of land use. UGBs are practical tools for uncontrolled dissemination in the production of decision mechanisms. In light of these considerations, a balanced framework between the internal dynamics of the city and the natural structure. With its methodological advantages for sustainable urban management, it has a perspective that can be adapted especially to developing cities that have not reached construction maturity. The existing literature seems to be limited to internal dynamics or the natural structure of land cover and rarely considers it multi-dimensionally. Based on the above conclusions, our research evaluates this gap in the literature by comparing it with its self-organizing structure and intervention mechanisms to fill it from a scenario-based framework.

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Data availability The data that support the findings of this study are available from the corresponding author, upon reasonable request.

Declarations

Conflict of interest The authors declare that they have no conflict of interest.

Ethics approval All authors have read, understood, and have complied as applicable with the statement on “Ethical responsibilities of Authors” as found in the Instructions for Authors.

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