



# Climate-related spatial reduction risk of agricultural lands on the Mediterranean coast in Türkiye and scenario-based modelling of urban growth

Oznur Isinkaralar<sup>1</sup> · Kaan Isinkaralar<sup>2</sup> · Dilara Yilmaz<sup>3</sup>

Received: 10 April 2023 / Accepted: 7 August 2023 / Published online: 24 August 2023  
© The Author(s), under exclusive licence to Springer Nature B.V. 2023

## Abstract

The effects of urbanization and climate crisis due to warming and severe climate events are the primary critical developments that threaten agricultural production activities worldwide. The annual average surface temperature in Türkiye increased by 1.07 °C between 2010 and 2019, and it reached 1.4 °C in 2021. It is predicted that the temperatures will continue to grow in the coastal areas of the Mediterranean Region, where the annual average temperature is 18–20 °C. In countries with high climate risks, the sustainability of agricultural activities is a priority research topic in many respects, especially food safety. In this context, the spatiotemporal change in agricultural areas in cities located on the Mediterranean coast, one of the country's warmest regions, is estimated for 2040 via the Cellular Automata-Markov chain method. As a result of the simulation made in the IDRISI Selva program, two different estimations were made: the trend model reflecting the current trend model ( $M^T$ ) and the sustainable agricultural model ( $M^{AS}$ ), where agricultural areas are limited. In the  $M^T$ , the existing residential area will increase by 68.9% in 2040 and 208.1% in 2076. In the  $M^{AS}$ , it will be limited to an increase of 60.8% in 2040 and 194.5% in 2076.

**Keywords** Geographic information systems · Global warming · Sustainable environment · Spatial reshaping · Spatial modeling · LULC

## Abbreviations

CA	Cellular automata
GIS	Geographic information system
IPCC	Intergovernmental panel on climate change
LSE	Land surface emission
LST	Land surface temperature

---

✉ Oznur Isinkaralar  
obulan@kastamonu.edu.tr

<sup>1</sup> Department of City and Regional Planning, Faculty of Engineering and Architecture, Kastamonu University, 37150 Kastamonu, Türkiye

<sup>2</sup> Department of Environmental Engineering, Faculty of Engineering and Architecture, Kastamonu University, 37150 Kastamonu, Türkiye

<sup>3</sup> Department of Landscape Architecture, Graduate School of Natural and Applied Sciences, Kastamonu University, 37150 Kastamonu, Türkiye

LULC	Land use/land cover
$M^T$	Trend model
$M^{AS}$	Agricultural sustainable model
NDVI	Normalized vegetation difference index
USGS	United States geological survey

## 1 Introduction

Cities have ceased to be areas where only the physical environment is affected by climate change (Abbass et al., 2022; Olabi & Abdelkareem, 2022). Especially in metropolitan areas, where the population is high, climate change brings along socioeconomic problems (Bellezoni et al., 2022; Orsetti et al., 2022; Maskrey et al., 2023). Medium- and long-term changes in other sectoral structures, especially in the tourism and agriculture sectors, decrease in agricultural areas, the inadequacy of urban infrastructure, and access to healthy drinking water are among the most critical effects of climate events on the built environment in terms of adaptation and adaptation to climate change (O'Malley et al., 2015; Shirani-Bidabadi et al., 2019).

Climate change, which has started to show its effect, is felt intensely with the impact of greenhouse gas production due to human activities in urban areas, especially in densely populated cities (Purwanto et al., 2022; Yayla et al., 2022; Sulhan et al., 2023). While global climate change started to show its effect in the world in the 1980s, it began to show in Türkiye in the 2000s. Urbanization causes natural areas such as vegetation, water bodies, and agricultural lands to become impermeable surfaces (Ullah et al., 2023). This transformation causes a decrease in the evaporation and transpiration cycle obtained from the vegetation. At the same time, it causes an increase in the amount of energy consumed for the absorption and cooling of solar radiation, negatively affecting the climate on a local and regional scale, such as various health problems and air pollution (Yao et al., 2017; Dai et al., 2018; Yang et al., 2021).

The agricultural sector, heavily influenced by the climate, plays a crucial role in developing the national economy. This sector, which is present worldwide, plays an important role and contributes to the economic well-being of developed countries. This situation creates a resource value among developing countries. However, agricultural production depends on the climate prevailing in the region (Gornall et al., 2010; Banerjee & Adenauer, 2014; Ahsan et al., 2020). Weather and climatic conditions are the main factors affecting agricultural productivity. Global climate change is becoming a significant concern for activities in the agricultural sector (Howden et al., 2007; Ahsan et al., 2020; Istanbulu et al., 2023).

Predicting future climatic conditions has a significant role in the ability of cities to minimize the adverse effects of climate change and adapt to this process. By constructing various scenarios through these forecasts, strategies and targets are determined so that cities can be affected by the climate change process with minor damage. Urbanization is considered a global concern worldwide in the 6th Assessment Report published by the Intergovernmental Panel on Climate Change (IPCC) in 2022, one of these scenarios. According to the report, it is estimated that climate change will slow down economic growth in the short term, especially in cities where agriculture, fisheries, forestry, and tourism sectors are at the forefront. According to the report, it is predicted that cities with intense urbanization will be more affected by the increase in temperature, which is one of the intensifying

effects of climate change. With each global warming rise, extreme changes' impact grows larger. Every 0.5 °C increase causes many problems, such as heat waves, heavy rainfall, and agricultural and ecological droughts. These problems are thought to affect human health and economic development adversely. Another vital issue emphasized in the report is that the effects of climate change will increase gradually and result in more dangerous consequences with risks that will arise simultaneously and interact with each other (IPCC, 2022).

Considering these predictions, it is emphasized that cities should be prepared against the effects of climate change. It is stated that the irreversible effects of climate change will emerge as risks will increase with high temperatures. Considering that the trend of urbanization and urbanization will continue to grow, the increase in the pressures of the urbanization process on the climate system is among the possible consequences we will encounter as a significant problem. Therefore, this study aims to simulate and estimate the settled area effect on agricultural land use in the coastal cities of the Mediterranean Region, using the CA-based Markov Chain model, to more clearly demonstrate the interaction between climate change and urban growth from local scale and large-scale dynamics.

In this context, firstly, the literature on the impact of climate change on agricultural production and temporal spatial modeling is summarized. Then, the research area and the modeling method are explained comprehensively. The change in surface temperature and LULC in the region is presented spatially. A temporal and spatial model was developed with Cellular Automata (CA)-Markov chain to predict the change in agricultural land use in 2040 and 2076 in the coastal cities of the Mediterranean Region, which is a socioeconomically leading region in terms of agricultural land use in the country. The models are based on two different approaches, where the current trend continues and agricultural land can be sustained. Sustainability of agricultural lands can be achieved by applying the technique in different areas with high agricultural production potential and rapid growth behavior of urban settlements by spreading or leaping.

## 2 Literature review

Land use is shaped by human intervention to meet the basic needs of the people living in the city and increase the quality of life (Abera et al., 2021; Talukdar et al., 2021; Peyrev et al., 2021). Every intervention in land use land cover affects climate change (Ribeiro et al., 2021; Turner et al., 2021). Changes in land cover, such as deforestation, decrease in water bodies, and loss of cultivated lands, affect the ecosystem (Kouassi et al., 2021; Makwinja et al., 2021; Zheng et al., 2021). Due to the ongoing migration from rural to urban, urban problems such as housing problems, informal activities, and resource and energy depletion cause many environmental problems (Mestanza-Ramón et al., 2022). The population, which accumulates in urban areas, needs energy, such as fuel and electricity, especially for production, heating, and transportation (Ahmad et al., 2022; Su & Urban, 2021). As a result, the high level of carbon emissions reached in urban areas draws attention (Li et al., 2022a, b; Jayaratne et al., 2021). The settled areas within the land are expressed as carbon-producing areas, forests, water bodies, and cultivated-planted areas are represented as areas where carbon is captured (Hanssen et al., 2022; Ou et al., 2021). In particular, the Intergovernmental Panel on Climate Change (IPCC) reports that global warming will be 1.5 °C above pre-industrial levels by the year 2100 has led to an increase in research on surface temperature (Pörtner et al., 2022).

Land cover/use is considered the most dangerous factor affecting ecosystems, the environment, climate, and living things. Although urbanization and human activities provide economic benefits, they negatively affect land change and sustainability. The first of these effects is the increase in surface temperatures. Research shows that changes in land cover/use are one of the main reasons for the rise in surface temperatures (Denman et al., 2007; Friedlingstein et al., 2010; Fang et al., 2011; Basak et al., 2013; Jain et al., 2015; Wang et al., 2019; Kafy et al., 2021); Fattah et al., 2021; Tariq & Shu, 2020; Amir Siddique et al., 2021).

New perspectives and applications have been developed in recent studies to determine the relationship between land cover and surface temperature. Primarily due to the developments in remote sensing and related technology, it is now possible to evaluate the surface temperature with land cover changes and parameters. Markov chains, cellular automata, and artificial neural networks are some models developed. The Markov chains model, which is considered to reflect short-term values in a wide area more accurately, is frequently used (Araya et al., 2010; Adelabu et al., 2013; Omran, 2012; Tariq and Shu, 2020; Amir Siddique et al., 2021; Fattah et al., 2021; Isinkaralar and Varol, 2023). Changes in potential future land cover/use and simulation of the consequences of these changes on the environment and ecosystem are among the topics that have gained importance in recent years. Some studies focus on land cover/use and urban growth (Fadhil & Kurban, 2022; Isinkaralar, 2023). Others focus on land cover/use change and its impact on surface temperature (Wang et al., 2013, 2019). Some research focuses on the effect of different land covers and urban textures on the surface temperature. Studies focusing on the relationship between surface temperature and land cover/use emphasize that the surface temperature is higher in residential areas and lower in areas covered with vegetation. Correlation analysis, Ordinary Least Squares (OLS), and spatial regression models were frequently used in research in this area (Buyantuyev & Wu, 2010; Jeevalakshmi et al., 2017; Ning et al., 2018; Peng et al., 2018; Ullah et al., 2019; Parvin and Abudu, 2017; Chun and Guhathakurta, 2017; Yin et al., 2018; Aboelnour and Engel, 2018; Mia et al., 2017; Tran et al., 2017).

The prediction of urban land use and growth is a topic of discussion central to proactive planning and sustainable development goals. Thanks to temporal-spatial techniques, it is possible to analyze and forecast urban growth on a global and regional scale. These methods also determine urban growth dynamics (Lu et al., 2019; Baqa et al., 2021). Many models are used to analyze urban growth changes (Guan et al., 2011; Ghosh & Das, 2017; Azari et al., 2016; Shen et al., 2020; Dey et al., 2021). Among these methods, the CA-Markov chain model, which is an effective method for simulating urban growth change and transformation, has been developed by integrating the advantage of modeling spatial variation in complex systems of the CA model and the long-term prediction advantage of the Markov chain model (Isinkaralar et al., 2022). It is frequently used to predict and measure urbanization dynamics (Keshtkar and Voight, 2016; Baqa et al., 2021).

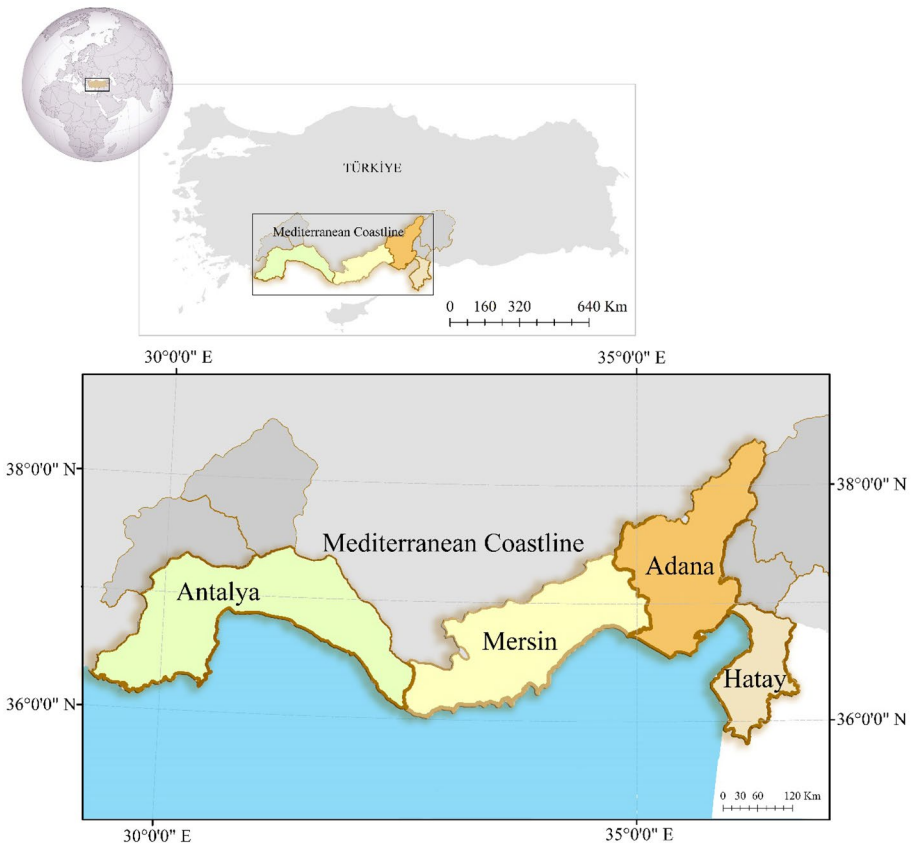
There are studies on the effects of climate change on agricultural production. Barati et al. (2023) examined the relationship between agricultural expansion and climate change with the structural equation modeling technique. Bedeke (2023) explores the vulnerability of farmers to climate change. It is emphasized that climate change, directly related to economic growth, threatens food security, especially in Africa (Pickson & Boateng, 2022). However, studies focusing on the effects of urban development on agricultural lands with the method of estimating the spatiotemporal change are pretty limited. Therefore, the research questions are defined as follows:

- RQ1: How can the pressure of urban growth on agricultural land be limited in the short and long term?
- RQ2: Can the effect of a sustainable agricultural approach on urban growth be modeled?
- RQ3: What are the key strategies for adapting the boundaries of sustainable urban growth to policy and practical outcomes?

### 3 Materials and methods

#### 3.1 Study area

The Mediterranean coastline in southern Türkiye was chosen as the study area—provinces in the selected region; Antalya, Mersin, Adana, and Hatay (Fig. 1). The Mediterranean Region is an essential region of Türkiye regarding tourism and agriculture. Cotton production, which cannot meet the high temperature, low humidity, and high sunlight needs of the cotton grown in the region between latitudes  $32^{\circ}$  and  $36^{\circ}$ , is one of the production forms at risk due to global warming. Due to its favorable ecological conditions, Türkiye owes all of its banana production and 88% of its citrus cultivation to this region.



**Fig. 1** The location of the selected Mediterranean coastline in Türkiye

### 3.2 Methodology of the modeling

The study aimed to reveal the firm area pressure on the agricultural land use of the coastal cities of the Mediterranean Region, which is essential for the agricultural sector in the climate change process between 2022 and 2040. The study consists of three main stages. First, the data for creating land surface temperature and land use maps were obtained. Then, surface temperature and land use changes between 2006 and 2022 were determined. In the third stage, the model was validated, and the agricultural and settled land use estimates for 2040 were made. The results obtained were evaluated by creating a transition area matrix (Fig. 2).

The land surface temperature (LST) map of the study area, 30\*30 resolution Landsat 8 satellite images provided by the United States Geological Survey (USGS), were used. Satellite images of two different years (2006–2022) were obtained to determine LST’s temporal and spatial changes. The climatic condition of the Mediterranean Region has been a determining factor in determining the dates of satellite images. In this context, August, when the region has the highest temperature values, was considered for the model.

#### 3.2.1 Converting reflection value to spectral radiance value

In Eq. (1) was used to convert the data of Band 6 of Landsat 7 and Band 10 of Landsat 8 into spectral radiance values:

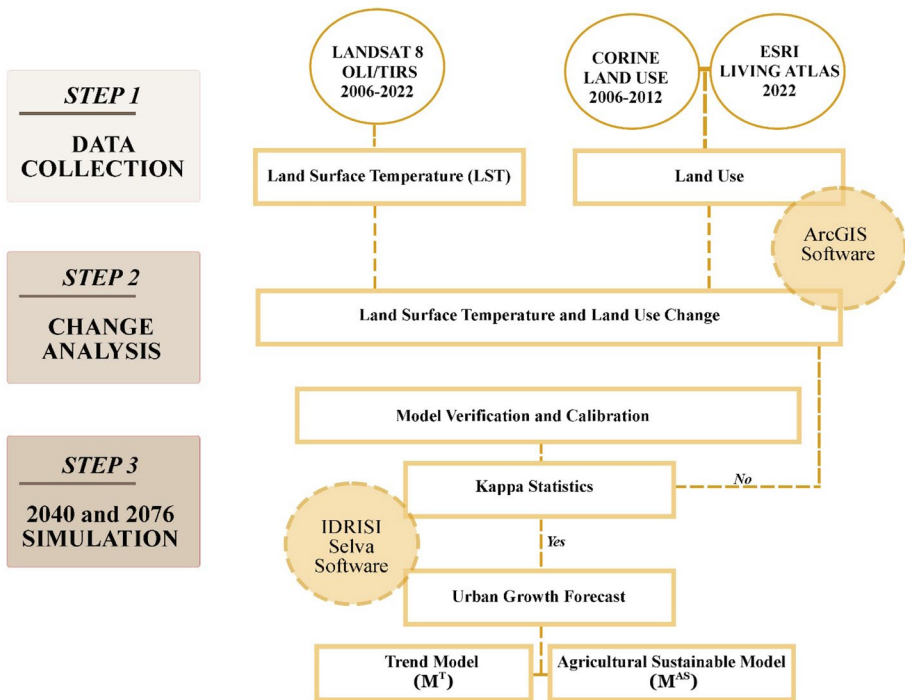


Fig. 2 Methodology steps of the study

$$L_{\lambda} = ML * Qcal + AL \quad (1)$$

where  $L_{\lambda}$ : TOA spectral radiance ( $\text{Watt}/(\text{m}^2 \times \text{srad} \times \text{m})$ ), ML: Radiance Mult Band (Band10), QCal: quantized and calibrated standard product pixel values: Band10, AL: Radiance Add Band (10). All of this information is obtained from the meta-data file of satellite images.

### 3.2.2 Conversion of spectral radiance value to luminosity temperature value

In the second step, temperature values will be calculated from the brightness values of the images. For this calculation, the inverse of the Plank function will be applied. Equatio (2) to be used is as follows:

$$T = K_2 / \ln(K_1 / L_{\lambda} + 1) - 273.15 \quad (2)$$

where  $T$ : Temperature degree (in Celsius),  $K_2$ :  $K_2$  Constant Band(10),  $K_1$ :  $K_1$  Constant Band(10),  $L_{\lambda}$ : Spectral Radiance. All of this information is obtained from the meta-data file of satellite images.

### 3.2.3 Normalized vegetation difference index (NDVI)

The following algorithm was used in the NDVI analysis. For Landsat 7 data,  $\text{NDVI} = (\text{Band } 4 - \text{Band } 3) / (\text{Band } 4 + \text{Band } 3)$ , for Landsat 8 data,  $\text{NDVI} = (\text{Band } 5 - \text{Band } 4) / (\text{Band } 5 + \text{Band } 4)$ , Band 3, 4, 5 represent the satellite image bands in formulas.

### 3.2.4 Land surface emission (LSE)

The emission value affecting the surface temperature is made using the NDVI (Normalized Vegetation Index). The following algorithms were used in the LSE analysis in Eq. (3):

$$PV = \left( (\text{NDVI} - \text{NDVI}_{\min}) / (\text{NDVI}_{\max} - \text{NDVI}_{\min}) \right)^2 \quad (3)$$

where PV: Vegetation rate, NDVI: NDVI analysis,  $\text{NDVI}_{\min}$ , max: Minimum and maximum value in NDVI analysis. After calculating the vegetation ratio, the LSE analysis was completed using the following algorithm.

$$\varepsilon = 0.004 * PV + 0.986 \quad (4)$$

where  $\varepsilon$  = Land surface emission, PV: Vegetation rate.

### 3.2.5 Land surface temperature (LST)

In the last step of the LST analysis, the analysis was completed using the following Eq. (5).

$$\text{LST} = T / (1 + (\lambda * T / c2) * \ln(\varepsilon)) \quad (5)$$

where  $T$ : Temperature degree (in Celsius),  $\lambda$ : Spectral Radiance wavelength (Landsat 8 band10, Landsat 7 band 6),  $c2$ :  $h * c / s = 1.43888 * 10^{-2} \text{mK} = 14,388 \text{mK}$ ,  $h$ : Planck's Constant:  $6.626 * 10^{-34} \text{J s}$ ,  $s$ : Boltzmann constant =  $1.38 * 10^{-23} \text{JK}$ ,  $c$ : velocity of light =  $2.998 * 10^8 \text{m/s} = 14,388$ ,  $\varepsilon$ : LSE.

Land use change consists of four steps. First, the data required for temporal and spatial change were obtained and arranged appropriately. Corine Land Cover data was used to determine the agricultural and settled land uses for 2006 and 2012. The database from ESRI Land Cover-Living Atlas database was used to determine the agricultural and settled land uses for 2022. The data downloaded in vector format was rearranged in ArcGIS 10.4.1 program within tiff format, and land use maps for each year were created. CA-Markov chains method was used for spatiotemporal modeling. CA-Markov integrates the Markov and cellular automata models in urban growth and land use prediction. It is an analysis that applies the transition probability to predict the future state based on the current and following conditions. The validity of the Markov chain in land use change situations is quite common (Guan et al., 2008; Chen et al., 2013; Yang et al., 2012; Sang et al., 2011) Markov estimation is made according to the following Eq. (6) (Isinkaralar et al., 2022):

$$S(t+1) = P_{ij} \times S(t) \quad (6)$$

where  $S(t)$  and  $S(t+1)$  mean row vectors at time step  $t$  and time step  $t+1$ ;  $P$  stands for the transition probability matrix for the previous time interval calculated with Eq. (7) as follows:

$$\|P_{ij}\| = \left\| \begin{array}{ccc} P_{11} & P_{12} & P_{1n} \\ P_{21} & P_{22} & P_{2n} \\ P_{n1} & P_{n2} & P_{nn} \end{array} \right\| \left( 0 \leq P_{ij} < 1 \text{ and } \sum_1^n P_{ij} = 1 \right) \quad (7)$$

$P_{ij}$  represents the probability of transitioning from land use type  $i$  to  $j$ . In the study, the future prediction was made in IDRISI Selva software using the CA-Markov model. Agricultural and settled land use estimates for coastal cities in the Mediterranean Region are estimated for 2040, based on the years 2006 and 2022.

## 4 Results

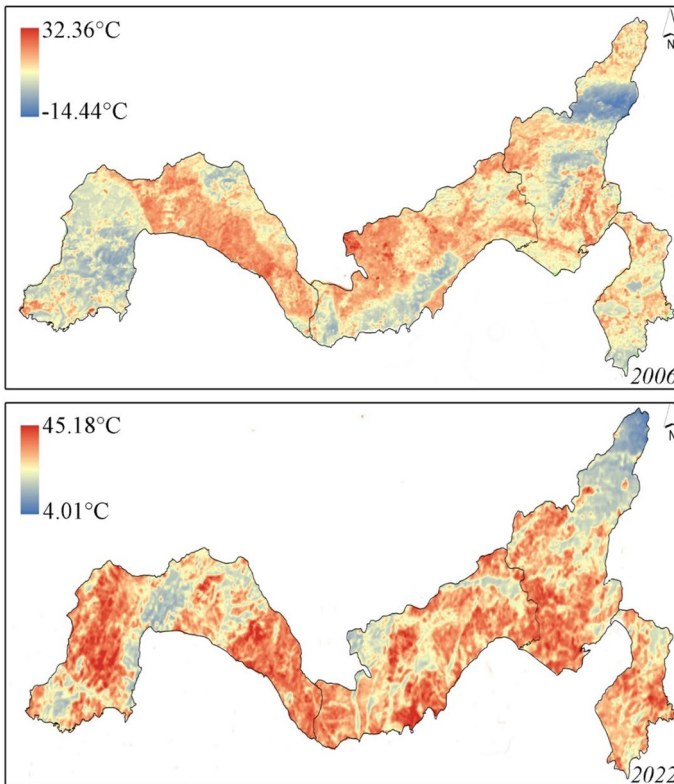
### 4.1 Land surface temperature change

The Mediterranean Region coastline's land surface temperature map was made using Landsat 7 ETM for 2006 and Landsat 8 OLI satellite images for 2022. If we look at the 2006 LST map, the temperature values were between  $-14$  and  $32$  °C, and by 2022, this value was calculated as between  $4$  and  $45$  °C. The highest surface temperature value increased by approximately  $13$  °C over 16 years. This clearly shows the impact of climate change on coastal cities (Fig. 3).

### 4.2 LULC change

When the change in land use in the coastal cities of the Mediterranean Region in the 2006–2022 period is examined, the difference in the settlement areas is striking. The increase in residential areas in 2006, 2012, and 2022 shows the pressure of residential areas on agricultural regions. The change in land cover was examined in 3 different periods. It is seen that the most change is from 2006 to 2022. While there is an increase in settled areas in every period, a decrease is observed in agricultural areas and indicates the pressure of populated areas on agricultural regions (Table 1).





**Fig. 3** Surface temperature maps of 2006 and 2022

**Table 1** 2006–2022 Land use distribution and change

Land use distribution* (ha)	Land use change (ha)					
	2006	2012	2022	2006–2012	2006–2022	2012–2022
Settled areas	36	48	74	+ 12	+ 38	+ 26
Agricultural areas	362	342	297	– 20	– 65	– 45

\*Area calculations were calculated in the IDRISI Selva program. It represents approximate values

While the residential areas are constantly increasing, the decrease in agricultural areas is an essential indicator of the pressure of the residential areas on the agricultural areas. The transition area matrix was created seen that the highest conversion of agrarian regions to residential areas occurred from 2006 to 2022 (24.76 ha). It is seen a minor transformation from 2012 to 2022 (18.21 ha). The change from other urban areas to residential areas has a low rate in all three periods (Table 2).

**Table 2** 2006–2022 land use transition matrix

Land Use*	2006–2012	2006–2022	2012–2022
Settled -settled	26	42.24	48
Agricultural-settled	20.83	24.76	18.21
Settled-agricultural	1.37	0.30	0.23
Agricultural-agricultural	180	113.64	140.26
Other urban area-agricultural	160.63	183.06	156.51
Other urban area-settled	1.17	6.94	7.49

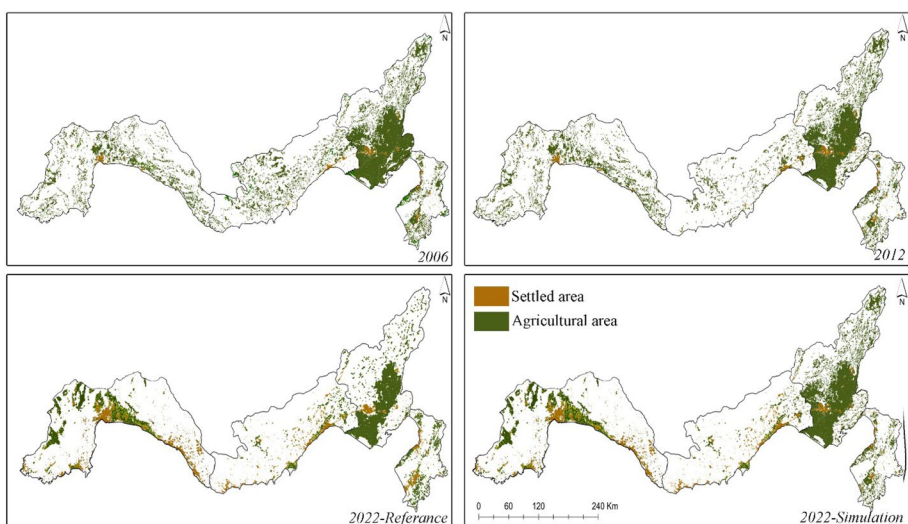
\*Area calculations were calculated in the IDRISI Selva program. It represents approximate values.

### 4.3 The CA-Markov urban land use simulation

#### 4.3.1 Model verification and calibration

Using the land use maps of 2006 and 2012, a forecast map for 2022 was made. When the 2022 reference map and the forecast map are compared, it is seen that the forecast map has a similar spatial pattern to the reference map (Fig. 4).

The Kappa statistics were calculated to evaluate the estimation results' accuracy numerically. It provides to measure the accuracy and reliability of comparisons between two variables. The study found location statistics as  $K_{no}$  0.9844,  $K_{location}$  0.9538,  $K_{location\ Strata}$  0.9538, and  $K_{standard}$  0.9338. The results show that the CA-Markov model is excellent in locating future change in Mediterranean coastal cities.



**Fig. 4** Current land use and forecast map for 2022

### 4.3.2 Land use simulation

Based on the 2006 and 2022 land use data, the predicted land use status for the Mediterranean coastline in 2040 and 2076 was estimated using the CA-Markov chain method within the scope of the “trend model:  $M^T$ ” and “sustainable agricultural model  $M^{SA}$ ”. In the trend model, it is seen that there will be an increase in residential areas in 2040 and 2076 while agricultural areas will decrease. As a result of the estimation made for 2040, it is predicted that there will be an increase of 51 ha in residential areas and a growth of 154 ha due to the estimate made for the year 2076. In the  $M^{SA}$ , the increase in the residential areas is taken under control by protecting the agricultural areas. As a result of the estimation made for 2040, it is predicted that there will be an increase of 45 ha in residential areas and a growth of 144 ha due to the estimation made for the year 2076. With the protection of the agricultural regions in the  $M^{SA}$ , the growth in residential areas is predicted to be less than in the  $M^T$  (Table 3).

The forecast map for the Mediterranean coastline of 2040 shows that settled areas will continue to grow, while agricultural areas will decrease simultaneously. It is estimated that the estimated populated regions will grow more toward agricultural areas (Fig. 5).

## 5 Discussion

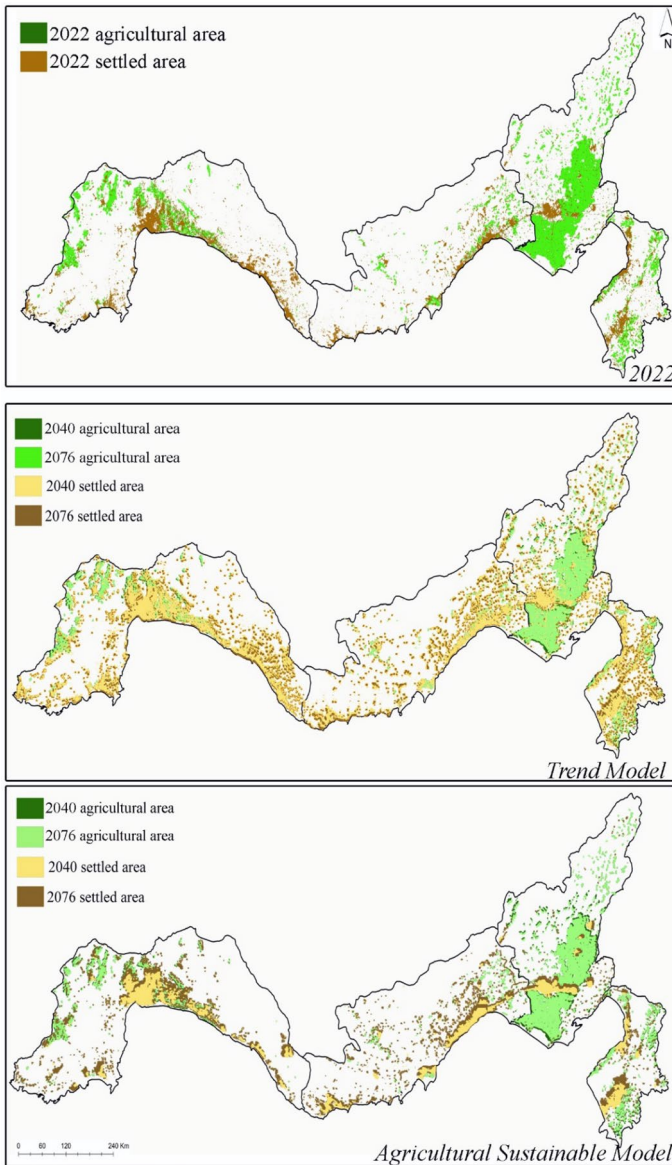
Thanks to the developments in the geospatial field, urban growth models facilitate the spatialization of many positive and negative situations to be foreseen in the future. In this study, the pressure of residential areas on agricultural areas during the climate change process, which is a significant threat on a global scale, is modeled in terms of time and space. The statistical accuracy of the forecast maps was analyzed by calculating the Kappa statistics. The Kappa coefficients calculated revealed that the Mediterranean Region’s coastline land use development followed specific growth rules due to the technique’s suitability and the accuracy of the forecast maps. Baqa et al. (2021) calculated the Kappa coefficient in the range of 0.86–0.90 in their simulations in Pakistan and as  $>0.9438$  in the simulation model they conducted in Kastamonu, Türkiye by Isinkaralar and Varol (2023). In this study, the Kappa coefficient was calculated as 0.9538.

Rapid urbanization and population growth lead to an increase in land use in cities. Changes in land use cause many environmental and climatic problems. Therefore, making estimations in land cover/use is of great importance in terms of early detection of both social, economic, and ecological issues and taking necessary precautions (Chen et al., 2012; Mulligan, 2013; Kuang et al., 2015; Huang et al., 2020a). When the transition

**Table 3** 2022–2076 land use distribution and change

		Land use distribution (ha)			Land use change (ha)	
		2022	2040	2076	2022–2040	2022–2076
$M^T$	Settled area	74	125	228	+51	+154
	Agricultural areas	297	215	171	–82	–126
$M^{SA}$	Settled area	74	119	218	+45	+144

\*Area calculations were calculated in the IDRISI Selva program. It represents approximate values.



**Fig. 5** Mediterranean coastline land use forecast for 2040

probability matrices are evaluated, it shows large conversions between land uses. The most significant change in the area is the conversion of most of the agricultural lands into residential areas. This result is also consistent with the results of the previous studies in the literature (Xie et al., 2007; Gong et al., 2015; Rimal et al., 2018; Huang et al., 2020b; Wang et al., 2021). The results of this study reveal the pressure of settled areas on agricultural lands in temporal and spatial terms, together with the significant differences in the Mediterranean coastline. Overall, the predicted results indicate that residential and agricultural

areas will likely maintain similar trends in the past analyzed periods. The most obvious change is the increase in residential areas and the transformation of agricultural areas into residential areas.

With the increase in the world population due to globalization and the technological developments it brings, the city forms have changed, and the handling of the cities has also changed. Today, urbanization and population growth are accepted as the most critical socio-ecological problems that trigger climate change on a global scale. Human-induced activities and the urbanization phenomenon that it brings play an essential role in the basis of climate change, which is accepted as one of the biggest environmental problems in the whole world. Human carbon emissions are known to affect climate worldwide with potentially devastating consequences (Hornsey & Fielding, 2019). Since the beginning of the 21st century, new methods have begun to be developed in the handling of cities, especially as a result of the developments in geospatial analytics. Statistical models are preferred in the preparation of growth models, especially on land cover changes (Hyandye et al., 2015), artificial neural networks (Guan et al., 2005; Maithani, 2009), logistic regression (Salem et al., 2021; Diep et al., 2022), cellular Many different techniques are applied, such as self-processing (Shafizadeh-Moghadam et al., 2021; Li et al., 2022a, b) and Markov chain (Yu et al., 2021). The advantages and disadvantages of the models are often discussed. Therefore, integrating the principles is preferred in current research (Mallick, 2021; Isinkaralar et al., 2022).

## 6 Conclusion, limitations and prospects

Land cover change models provide a dynamic dataset for examining environmental degradation and controlling the impact of planning and management on land use change. As a result of the research, depending on the temporal-spatial increase trend, the pressure of urban growth on agricultural areas emerges. The expansion of the residential regions causes a significant decrease in agricultural areas. When the development estimation maps for the Mediterranean Region coastline, which constitutes a considerable resource value for Türkiye's agricultural economy and tourism, are evaluated, it is predicted that the existing urban spot will grow linearly. In these areas, where agricultural areas are predicted to decrease significantly, it is thought that the plan decisions and the spatial development of the Mediterranean coastline may be effective in the process. While preparing the physical plans, establishing university-local government cooperation would be a helpful approach by ensuring that the academic literature on the field is examined. The research is considered to be entirely guiding for decision-makers in revealing the temporal process of land losses and showing the development aspects spatially.

This research is limited to four provinces in the Mediterranean region due to the size and scale of the area. In determining the borders, the region's place in the country's economy was considered. In additional research, coastal regions forming the three sides of the country or cities with high agricultural production potential can be studied. ArcGIS and IDRISI Selva were preferred for software. Different software can be tried to obtain efficient results regarding future predictions. Another modeling technique based on cellular automata can be used for prediction. Two models were used to produce the forecasts with an agriculturally sensitive approach. In future research, different land covers can be included in the model for more ecological sustainability goals.

**Author contribution** Oznu Isinkalar: Processing analysis, data interpretation, methodology, writing original draft, data curation, processing analysis and interpretation. Kaan Isinkalar: Processing analysis, data interpretation, writing original draft, data curation. Dilara Yilmaz: Conceptualization and visualization.

**Funding** There is no financial support and commercial support.

**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.

**Ethical approval** Not applicable.

**Consent to participate** Not applicable.

**Consent to publish** Not applicable.

## References

- Abbass, K., Qasim, M. Z., Song, H., Murshed, M., Mahmood, H., & Younis, I. (2022). A review of the global climate change impacts, adaptation, and sustainable mitigation measures. *Environmental Science and Pollution Research*, 29, 42539–42559. <https://doi.org/10.1007/s11356-022-19718-6>
- Abera, W., Tamene, L., Kassawmar, T., Mulatu, K., Kassa, H., Verchot, L., & Quintero, M. (2021). Impacts of land use and land cover dynamics on ecosystem services in the Yayo coffee forest biosphere reserve, southwestern Ethiopia. *Ecosystem Services*, 50, 101338. <https://doi.org/10.1016/j.ecoser.2021.101338>
- Aboelnour, M., & Engel, B. A. (2018). Application of remote sensing techniques and geographic information systems to analyze land surface temperature in response to land use/land cover change in Greater Cairo Region, Egypt. *Journal of Geographic Information System*, 10(1), 57–88. <https://doi.org/10.4236/jgis.2018.101003>
- Adelabu, S., Mutanga, O., Adam, E., & Cho. (2013). Exploiting machine learning algorithms for tree species classification in a semiarid woodland using RapidEye image. *Journal Of Applied Remote Sensing*, 7, 073480. <https://doi.org/10.1117/1.JRS.7.073480>
- Ahmad, U. S., Usman, M., Hussain, S., Jahanger, A., & Abrar, M. (2022). Determinants of renewable energy sources in Pakistan: An overview. *Environmental Science and Pollution Research*. <https://doi.org/10.1007/s11356-022-18502-w>
- Ahsan, F., Chandio, A. A., & Fang, W. (2020). Climate change impacts on cereal crops production in Pakistan: Evidence from cointegration analysis. *International Journal of Climate Change Strategies and Management*, 12(2), 257–269. <https://doi.org/10.1108/IJCCSM-04-2019-0020>
- Amir Siddique, M., Wang, Y., Xu, N., Ullah, N., & Zeng, P. (2021). The spatiotemporal implications of urbanization for urban heat islands in Beijing: A predictive approach based on CA–Markov modeling (2004–2050). *Remote Sensing*, 13(22), 4697. <https://doi.org/10.3390/rs13224697>
- Araya, Y. H., & Cabral, P. (2010). Analysis and modeling of Urban Land cover change in Setúbal and Sesimbra, Portugal. *Remote Sensing*, 2(6), 1549–1563. <https://doi.org/10.3390/rs2061549>
- Azari, M., Tayyebi, A., Helbich, M., & Reveshty, M. A. (2016). Integrating cellular automata, artificial neural network, and fuzzy set theory to simulate threatened orchards: Application to Maragheh, Iran. *GIScience & Remote Sensing*, 53(2), 183–205. <https://doi.org/10.1080/15481603.2015.1137111>
- Banerjee, C., & Adenauer, L. (2014). Up, up and away! The economics of vertical farming. *Journal of Agricultural Studies*, 2(1), 40–60. <https://doi.org/10.5296/jas.v2i1.4526>
- Baqa, M. F., Chen, F., Lu, L., Qureshi, S., Tariq, A., Wang, S., Jing, L., Hamza, S., & Li, Q. (2021). Monitoring and modeling the patterns and trends of urban growth using urban sprawl matrix and CA–Markov model: A case study of Karachi, Pakistan. *Land*, 10(7), 700. <https://doi.org/10.3390/land10070700>
- Barati, A. A., Azadi, H., Movahhed Moghaddam, S., Scheffran, J., & Dehghani Pour, M. (2023). Agricultural expansion and its impacts on climate change: evidence from Iran. *Environment, Development and Sustainability*, 1–27. <https://doi.org/10.1007/s10668-023-02926-6>

- Basak, J. K., Titumir, R., & Dey, N. C. (2013). Climate change in Bangladesh: A historical analysis of temperature and rainfall data. *Journal of Environment*, 2(2), 41–46.
- Bedeke, S. B. (2023). Climate change vulnerability and adaptation of crop producers in sub-saharan Africa: A review on concepts, approaches and methods. *Environment Development and Sustainability*, 25(2), 1017–1051. <https://doi.org/10.1007/s10668-022-02118-8>
- Bellezoni, R. A., Seto, K. C., & de Puppim, J. A. (2022). What can cities do to enhance water-energy-food nexus as a sustainable development strategy? *Water-energy-food nexus and climate change in cities* (pp. 39–57). Cham: Springer International Publishing. [https://doi.org/10.1007/978-3-031-05472-3\\_3](https://doi.org/10.1007/978-3-031-05472-3_3)
- Buyantuyev, A., & Wu, J. (2010). Urban heat islands and landscape heterogeneity: Linking spatiotemporal variations in surface temperatures to land-cover and socio-economic patterns. *Landscape Ecology*, 25, 17–33. <https://doi.org/10.1007/s10980-009-9402-4>
- Chen, X., Chen, J., Shi, Y., & Yamaguchi, Y. (2012). An automated approach for updating land cover maps based on integrated change detection and classification methods. *ISPRS Journal of Photogrammetry and Remote Sensing*, 71, 86–95. <https://doi.org/10.1016/j.isprsjprs.2012.05.006>
- Chen, C. F., Son, N. T., Chang, N. B., Chen, C. R., Chang, L. Y., Valdez, M., Centeno, G., Thompson, C. A., & Aceituno, J. L. (2013). Multi-decadal mangrove forest change detection and prediction in Honduras, Central America, with landsat imagery and a Markov chain model. *Remote Sensing*, 5(12), 6408–6426. <https://doi.org/10.3390/rs5126408>
- Chun, B., & Guhathakurta, S. (2017). Daytime and nighttime urban heat islands statistical models for Atlanta. *Environment and Planning B: Urban Analytics and City Science*, 44(2), 308–327. <https://doi.org/10.1177/0265813515624685>
- Dai, Z., Guldmann, J. M., & Hu, Y. (2018). Spatial regression models of park and land use impacts on the urban heat island in central Beijing. *Science of the Total Environment*, 626, 1136–1147. <https://doi.org/10.1016/j.scitotenv.2018.01.165>
- Denman, K. L., Menon, S., Brasseur, G., Chidthaisong, A., Ciais, P., Cox, P. M., Dickinson, R. E., Hauglustaine, D., Heinze, C., Holland, E., Jacob, D., Lohmann, U., Ramachandran, S., Wofsy, S. C., & Zhang, X. (2007). *Couplings between changes in the climate system and biogeochemistry* United States.
- Dey, N. N., Rakib, A., Kafy, A., & Raikwar, V. (2021). Geospatial modelling of changes in land use/land cover dynamics using multi-layer Perceptron Markov chain model in Rajshahi City, Bangladesh. *Environmental Challenges*, 4, 100148. <https://doi.org/10.1016/j.envc.2021.100148>
- Diep, N. T. H., Nguyen, C. T., Diem, P. K., Hoang, N. X., & Kafy, A. A. (2022). Assessment on controlling factors of urbanization possibility in a newly developing city of the vietnamese Mekong delta using logistic regression analysis. *Physics and Chemistry of the Earth Parts A/B/C*, 126, 103065. <https://doi.org/10.1016/j.pce.2021.103065>
- Fadhil, A., & Kurban, T. (2022). Modelling urban sprawl with cellular automata markov chain method: The case of Kirkuk governorate. *Journal of Geomatics*, 7(1), 58–70. <https://doi.org/10.29128/geomatik.852900>
- Fang, J., Zhu, J., Wang, S., Yue, C., & Shen, H. (2011). Global warming, human-induced carbon emissions, and their uncertainties. *Science China Earth Sciences*, 54, 1458–1468. <https://doi.org/10.1007/s11430-011-4292-0>
- Fattah, M. A., Morshed, S. R., & Morshed, S. Y. (2021). Multi-layer perceptron-Markov chain-based artificial neural network for modelling future land-specific carbon emission pattern and its influences on surface temperature. *SN Applied Sciences*, 3, 359. <https://doi.org/10.1007/s42452-021-04351-8>
- Friedlingstein, P., Houghton, R. A., Marland, G., Hackler, J., Boden, T. A., Conway, T. J., Canadell, J. G., Raupach, M. R., Ciais, P., & Le Quéré, C. (2010). Update on CO<sub>2</sub> emissions. *Nature geoscience*, 3(12), 811–812. <https://doi.org/10.1038/ngeo1022>
- Ghosh, S., & Das, A. (2017). Exploring the lateral expansion dynamics of four metropolitan cities of India using DMSP/OLS night time image. *Spatial Information Research*, 25(6), 779–789. <https://doi.org/10.1007/s41324-017-0141-3>
- Gong, L., Ran, Q., He, G., & Tiyyip, T. (2015). A soil quality assessment under different land use types in Keriya river basin, Southern Xinjiang, China. *Soil and Tillage Research*, 146, 223–229. <https://doi.org/10.1016/j.still.2014.11.001>
- Gornall, J., Betts, R., Burke, E., Clark, R., Camp, J., Willett, K., & Wiltshire, A. (2010). Implications of climate change for agricultural productivity in the early twenty-first century. *Philosophical Transactions of the Royal Society B: Biological Sciences*, 365(1554), 2973–2989. <https://doi.org/10.1098/rstb.2010.0158>
- Guan, Q., Wang, L., & Clarke, K. C. (2005). An artificial-neural-network-based, constrained CA model for simulating urban growth. *Cartography and Geographic Information Science*, 32(4), 369–380. <https://doi.org/10.1559/152304005775194746>

- Guan, D., Gao, W., Watari, K., & Fukahori, H. (2008). Land use change of Kitakyushu based on landscape ecology and Markov model. *Journal of Geographical Sciences*, 18, 455–468. <https://doi.org/10.1007/s11442-008-0455-0>
- Guan, D., Li, H., Inohae, T., Su, W., Nagaie, T., & Hokao, K. (2011). Modeling urban land use change by the integration of cellular automaton and Markov model. *Ecological Modelling*, 222(20–22), 3761–3772. <https://doi.org/10.1016/j.ecolmodel.2011.09.009>
- Hanssen, S. V., Steinmann, Z. J., Daiglou, V., Čengić, M., Van Vuuren, D. P., & Huijbregts, M. A. (2022). Global implications of crop-based bioenergy with carbon capture and storage for terrestrial vertebrate biodiversity. *GCB Bioenergy*, 14(3), 307–321.
- Hornsey, M. J., & Fielding, K. S. (2019). Understanding (and reducing) inaction on climate change. *Social Issues and Policy Review*, 14(1), 3–35. <https://doi.org/10.1111/sipr.12058>
- SM, Howden, JF, Soussana, FN, Tubiello, N, Chhetri, M, Dunlop, & H, Meinke. (2007). Adapting agriculture to climate change. *Proceedings of the National Academy of Sciences of Sciences*, 104(50), 19691–19696. <https://doi.org/10.1073/pnas.0701890104>
- Huang, S., Zheng, X., Ma, L., Wang, H., Huang, Q., Leng, G., Meng, E., & Guo, Y. (2020). Quantitative contribution of climate change and human activities to vegetation cover variations based on GA-SVM model. *Journal of Hydrology*, 584, 124687. <https://doi.org/10.1016/j.jhydrol.2020.124687>
- Huang, Y., Yang, B., Wang, M., Liu, B., & Yang, X. (2020). Analysis of the future land cover change in Beijing using CA–Markov chain model. *Environmental Earth Sciences*, 79(2), 1–12. <https://doi.org/10.1007/s12665-019-8785-z>
- Hyandy, C., Mandara, C. G., & Safari, J. (2015). GIS and logit regression model applications in land use/land cover change and distribution in Usangu catchment. *American Journal of Remote Sensing*. <https://doi.org/10.11648/j.ajrs.20150301.12>
- IPCC. (2022). (IPCC Intergovernmental Panel on Climate Change). *Climate Change 2022*. Retrieved from, <https://www.ipcc.ch/report/ar6/wg2/>
- Isinkaralar, O. (2023). Bioclimatic comfort in urban planning and modeling spatial change during 2020–2100 according to climate change scenarios in Kocaeli, Türkiye. *International Journal of Environmental Science and Technology*, 20(7), 7775–7786. <https://doi.org/10.1007/s13762-023-04992-9>
- Isinkaralar, O., & Varol, C. (2023). A cellular automata-based approach for spatio-temporal modeling of the city center as a complex system: The case of Kastamonu, Türkiye. *Cities*, 132, 104073. <https://doi.org/10.1016/j.cities.2022.104073>
- Isinkaralar, O., Varol, C., & Yilmaz, D. (2022). Digital mapping and predicting the urban growth: Integrating scenarios into cellular automata—Markov chain modeling. *Applied Geomatics*, 14(4), 695–705. <https://doi.org/10.1007/s12518-022-00464-w>
- Istanbullu, S. N., Sevik, H., Isinkaralar, K., & Isinkaralar, O. (2023). Spatial distribution of heavy metal contamination in road dust samples from an urban environment in Samsun, Türkiye. *Bulletin of Environmental Contamination and Toxicology*, 110(4), 78. <https://doi.org/10.1007/s00128-023-03720-w>
- Jain, N., Bhatia, A., Pathak, H., Gupta, N., Sharma, D. K., & Kaushik, R. (2015). Greenhouse gas emission and global warming. *Introduction to environmental sciences* (pp. 379–411). TERI Press.
- Jayaratne, R., Thai, P., Christensen, B., Liu, X., Zing, I., Lamont, R., Dunbabin, M., Dawkins, L., Bertrand, L., & Morawska, L. (2021). The effect of cold-start emissions on the diurnal variation of carbon monoxide concentration in a city centre. *Atmospheric Environment*, 245, 118035. <https://doi.org/10.1016/j.atmosenv.2020.118035>
- Jeevalakshmi, D., Narayana Reddy, S., & Manikiam, B. (2017). Land surface temperature retrieval from LANDSAT data using emissivity estimation. *International Journal of Applied Engineering Research*, 12(20), 9679–9687.
- Kafy, A. A., Shuvo, R. M., Naim, M. N. H., Sikdar, M. S., Chowdhury, R. R., Islam, M. A., Sarker, M. H. S., Khan, M. H. H., & Kona, M. A. (2021). Remote sensing approach to simulate the land use/land cover and seasonal land surface temperature change using machine learning algorithms in a fastest-growing megacity of Bangladesh. *Remote Sensing Applications: Society and Environment*, 21, 100463. <https://doi.org/10.1016/j.rsase.2020.100463>
- Keshtkar, H., & Voigt, W. (2016). A spatiotemporal analysis of landscape change using an integrated Markov chain and cellular automata models. *Modeling Earth Systems and Environment*, 2, 10. <https://doi.org/10.1007/s40808-015-0068-4>
- Kouassi, J. L., Gyau, A., Diby, L., Bene, Y., & Kouamé, C. (2021). Assessing land use and land cover change and farmers' perceptions of deforestation and land degradation in South-West Côte d'Ivoire, West Africa. *Land*, 10(4), 429. <https://doi.org/10.3390/land10040429>
- Kuang, W., Dou, Y., Zhang, C., Chi, W., Liu, A., Liu, Y., Zhang, R., & Liu, J. (2015). Quantifying the heat flux regulation of metropolitan land use/land cover components by coupling remote sensing



- modeling with in situ measurement. *Journal of Geophysical Research: Atmospheres*, 120(1), 113–130. <https://doi.org/10.1002/2014JD022249>
- Li, Q., Feng, Y., Tong, X., Zhou, Y., Wu, P., Xie, H., Jin, Y., Chen, P., Liu, S., Xv, X., Liu, S., & Wang, C. (2022). Firefly algorithm-based cellular automata for reproducing urban growth and predicting future scenarios. *Sustainable Cities and Society*, 76, 103444. <https://doi.org/10.1016/j.scs.2021.103444>
- Li, Z., Wang, F., Kang, T., Wang, C., Chen, X., Miao, Z., & Zhang, H. (2022). Exploring differentiated impacts of socio-economic factors and urban forms on city-level CO<sub>2</sub> emissions in China: Spatial heterogeneity and varying importance levels. *Sustainable Cities and Society*, 84, 104028. <https://doi.org/10.1016/j.scs.2022.104028>
- Lu, Q., Joyce, J., Imen, S., & Chang, N. B. (2019). Linking socio-economic development, sea level rise, and climate change impacts on urban growth in New York City with a fuzzy cellular automata-based Markov chain model. *Environment and Planning B: Urban Analytics and City Science*, 46(3), 551–572. <https://doi.org/10.1177/2399808317720797>
- Maithani, S. (2009). A neural network based urban growth model of an indian city. *Journal of the Indian Society of Remote Sensing*, 37(3), 363–376. <https://doi.org/10.1007/s12524-009-0041-7>
- Makwinja, R., Kaunda, E., Mengistou, S., & Alamirew, T. (2021). Impact of land use/land cover dynamics on ecosystem service value—A case from Lake Malombe, Southern Malawi. *Environmental Monitoring and Assessment*, 193(8), 1–23. <https://doi.org/10.1007/s10661-021-09241-5>
- Mallick, S. K., Das, P., Maity, B., Rudra, S., Pramanik, M., Pradhan, B., & Sahana, M. (2021). Understanding future urban growth, urban resilience and sustainable development of small cities using prediction-adaptation-resilience (PAR) approach. *Sustainable Cities and Society*, 74, 103196. <https://doi.org/10.1016/j.scs.2021.103196>
- Maskrey, A., Jain, G., & Lavell, A. (2023). The social construction of systemic risk: Towards an actionable framework for risk governance. *Disaster Prevention and Management: An International Journal*, 32(1), 4–26. <https://doi.org/10.1108/DPM-07-2022-0155>
- Mestanza-Ramón, C., Ordoñez-Alcivar, R., Arguello-Guadalupe, C., Carrera-Silva, K., D’Orío, G., & Straface, S. (2022). History, socio-economic problems and environmental impacts of gold mining in the Andean Region of Ecuador. *International Journal of Environmental Research and Public Health*, 19(3), 1190. <https://doi.org/10.3390/ijerph19031190>
- Mia, B., Bhattacharya, R., & Woobaidullah, A. S. M. (2017). Correlation and monitoring of land surface temperature, urban heat island with land use-land cover of Dhaka City using satellite imageries. *International Journal of Research in Geography (IJRG)*, 3, 10–20. <https://doi.org/10.20431/2454-8685.0304002>
- Mulligan, M., Rubiano, J. R., Burke, S., & Van Soesbergen, A. (2013). *Water security in Amazonia*. Report for Global Canopy Programme and International Center for Tropical Agriculture as part of the Amazonia Security Agenda project. Retrieved from, <https://doi.org/10.1080/02508060.2022.2133815>
- Ning, J., Gao, Z., Meng, R., Xu, F., & Gao, M. (2018). Analysis of relationships between land surface temperature and land use changes in the Yellow River Delta. *Frontiers of Earth Science*, 12, 444–456. <https://doi.org/10.1007/s11707-017-0657-9>
- O’Malley, C., Piroozfar, P., Farr, E. R. P., & Pomponi, F. (2015). Urban Heat Island (UHI) mitigating strategies: A case-based comparative analysis. *Sustainable Cities and Society*, 19, 222–235. <https://doi.org/10.1016/j.scs.2015.05.009>
- Olabi, A. G., & Abdelkareem, M. A. (2022). Renewable energy and climate change. *Renewable and Sustainable Energy Reviews*, 158, 112111. <https://doi.org/10.1016/j.rser.2022.112111>
- Omran, E. S. E. (2012). Detection of land-use and surface temperature change at different resolutions. *Journal of Geographic Information System*, 04(3), 189–203. <https://doi.org/10.4236/jgis.2012.43024>
- Orsetti, E., Tollin, N., Lehmann, M., Valderrama, V. A., & Morató, J. (2022). Building resilient cities: Climate change and health interlinkages in the planning of public spaces. *International Journal of Environmental Research and Public Health*, 19(3), 1355. <https://doi.org/10.3390/ijerph19031355>
- Ou, L., Banerjee, S., Xu, H., Coleman, A. M., Cai, H., Lee, U., Wigmosta, M. S., & Hawkins, T. R. (2021). Utilizing high-purity carbon dioxide sources for algae cultivation and biofuel production in the United States: Opportunities and challenges. *Journal of Cleaner Production*, 321, 128779. <https://doi.org/10.1016/j.jclepro.2021.128779>
- Parvin, N. S., & Abudu, D. (2017). Estimating urban heat island intensity using remote sensing techniques in Dhaka city. *International Journal of Scientific & Engineering Research*, 8(4), 289–298. <https://doi.org/10.1029/2008/jd009916>
- Peng, J., Jia, J., Liu, Y., Li, H., & Wu, J. (2018). Seasonal contrast of the dominant factors for spatial distribution of land surface temperature in urban areas. *Remote Sensing of Environment*, 215, 255–267. <https://doi.org/10.1016/j.rse.2018.06.010>

- Peyre, G., Osorio, D., François, R., & Anthelme, F. (2021). Mapping the páramo land-cover in the Northern Andes. *International Journal of Remote Sensing*, 42(20), 7777–7797. <https://doi.org/10.1080/01431161.2021.1964709>
- Pickson, R. B., & Boateng, E. (2022). Climate change: A friend or foe to food security in Africa? *Environment Development and Sustainability*, 24, 4387–4412. <https://doi.org/10.1007/s10668-021-01621-8>
- Pörtner, H. O., Roberts, D. C., Tignor, M., Poloczanska, E., Mintenbeck, K., Alegría, A., & Rama, B. (2022). IPCC 2022: Climate change 2022: Impacts, adaptation and vulnerability: working group II contribution to the sixth assessment report of the intergovernmental panel on climate change, 3056. <https://doi.org/10.1017/9781009325844>
- Purwanto, P., Astuti, I. S., Rohman, F., Utomo, K. S. B., & Aldianto, Y. E. (2022). Assessment of the dynamics of urban surface temperatures and air pollution related to COVID-19 in a densely populated City environment in East Java. *Ecological Informatics*, 71, 101809. <https://doi.org/10.1016/j.ecoinf.2022.101809>
- Ribeiro, S., Limoges, A., Massé, G., Johansen, K. L., Colgan, W., Weckström, K., ... & et al. (2021). Vulnerability of the North Water ecosystem to climate change. *Nature Communications*, 12(1), 4475. <https://doi.org/10.1038/s41467-021-24742-0>
- Rimal, B., Zhang, L., Keshtkar, H., Haack, B. N., Rijal, S., & Zhang, P. (2018). Land use/land cover dynamics and modeling of urban land expansion by the integration of cellular automata and markov chain. *ISPRS International Journal of Geo-Information*, 7(4), 154. <https://doi.org/10.3390/ijgi7040154>
- Salem, M., Bose, A., Bashir, B., Basak, D., Roy, S., Chowdhury, I. R., Als Salman, A., & Tsurusaki, N. (2021). Urban expansion simulation based on various driving factors using a logistic regression model: Delhi as a case study. *Sustainability*, 13(19), 10805. <https://doi.org/10.3390/su131910805>
- Sang, L., Zhang, C., Yang, J., Zhu, D., & Yun, W. (2011). Simulation of land use spatial pattern of towns and villages based on CA–Markov model. *Mathematical and Computer Modelling*, 54(3–4), 938–943. <https://doi.org/10.1016/j.mcm.2010.11.019>
- Shafizadeh-Moghadam, H., Minaei, M., Pontius, R. G., Jr., Asghari, A., & Dadashpoor, H. (2021). Integrating a forward feature selection algorithm, random forest, and cellular automata to extrapolate urban growth in the Tehran-Karaj Region of Iran. *Computers Environment and Urban Systems*, 87, 101595. <https://doi.org/10.1016/j.compenvurbsys.2021.101595>
- Shen, Y., Shen, H., Cheng, Q., Huang, L., & Zhang, L. (2020). Monitoring three-decade expansion of China's major cities based on satellite remote sensing images. *Remote Sensing*, 12(3), 491. <https://doi.org/10.3390/rs12030491>
- Shirani-Bidabadi, N., Nasrabadi, T., Faryadi, S., Larijani, A., & Roodposhti, M. S. (2019). Evaluating the spatial distribution and the intensity of urban heat island using remote sensing, case study of Isfahan city in Iran. *Sustainable Cities and Society*, 45, 686–692. <https://doi.org/10.1016/j.scs.2018.12.005>
- Su, C., & Urban, F. (2021). Circular economy for clean energy transitions: A new opportunity under the COVID-19 pandemic. *Applied Energy*, 289, 116666. <https://doi.org/10.1016/j.apenergy.2021.116666>
- Sulhan, O. F., Sevik, H., & Isinkaralar, K. (2023). Assessment of Cr and Zn deposition on *Picea pungens* Engelm. in urban air of Ankara, Türkiye. *Environment Development and Sustainability*, 25(5), 4365–4384. <https://doi.org/10.1007/s10668-022-02647-2>
- Talukdar, S., Eibek, K. U., Akhter, S., Ziaul, S. K., Islam, A. R. M. T., & Mallick, J. (2021). Modeling fragmentation probability of land-use and land-cover using the bagging, random forest and random subspace in the Teesta River Basin, Bangladesh. *Ecological Indicators*, 126, 107612. <https://doi.org/10.1016/j.ecolind.2021.107612>
- Tariq, A., & Shu, H. (2020). CA-Markov chain analysis of seasonal land surface temperature and land use land cover change using optical multi-temporal satellite data of Faisalabad, Pakistan. *Remote Sensing*, 12(20), 3402. <https://doi.org/10.3390/rs12203402>
- Tran, D. X., Pla, F., Latorre-Carmona, P., Myint, S. W., Caetano, M., & Kieu, H. V. (2017). Characterizing the relationship between land use land cover change and land surface temperature. *ISPRS Journal of Photogrammetry and Remote Sensing*, 124, 119–132. <https://doi.org/10.1016/j.isprsjprs.2017.01.001>
- Turner, B. L., Lambin, E. F., & Verburg, P. H. (2021). From land-use/land-cover to land system science: This article belongs to Ambio's 50th Anniversary Collection. Theme: Agricultural land use. *Ambio*, 50, 1291–1294. <https://doi.org/10.1007/s13280-021-01510-4>
- Ullah, S., Ahmad, K., Sajjad, R. U., Abbasi, A. M., Nazeer, A., & Tahir, A. A. (2019). Analysis and simulation of land cover changes and their impacts on land surface temperature in a lower himalayan region. *Journal of Environmental Management*, 245, 348–357. <https://doi.org/10.1016/j.jenvman.2019.05.063>
- Ullah, N., Siddique, M. A., Ding, M., Grigoryan, S., Khan, I. A., Kang, Z., Tsou, S., Zhang, T., Hu, Y., & Zhang, Y. (2023). The impact of urbanization on Urban heat island: predictive approach using google earth engine and CA-Markov modelling (2005–2050) of Tianjin City, China. *International Journal of Environmental Research and Public Health*, 20(3), 2642. <https://doi.org/10.3390/ijerph20032642>

- Wang, X., Lei, X., Fan, P., Hu, R. Q., & Horng, S. J. (2013). Cost analysis of movement-based location management in PCS networks: An embedded Markov chain approach. *IEEE Transactions on Vehicular Technology*, 63(4), 1886–1902. <https://doi.org/10.1109/TVT.2013.2285118>
- Wang, C., Li, Y., Myint, S. W., Zhao, Q., & Wentz, E. A. (2019). Impacts of spatial clustering of urban land cover on land surface temperature across Koppen climate zones in the contiguous United States. *Landscape and Urban Planning*, 192, 103668. <https://doi.org/10.1016/j.landurbplan.2019.103668>
- Wang, H., Liu, X., Zhao, C., Chang, Y., Liu, Y., & Zang, F. (2021). Spatial-temporal pattern analysis of landscape ecological risk assessment based on land use/land cover change in Baishuijiang National nature reserve in Gansu Province, China. *Ecological Indicators*, 124, 107454. <https://doi.org/10.1016/j.ecolind.2021.107454>
- Xie, Y., Fang, C., Lin, G., Gong, H., & Qiao, B. (2007). Tempo-spatial patterns of land use changes and urban development in globalizing China: A study of Beijing. *Sensors for Urban Environmental Monitoring Special Issue*, 7(11), 2881–2906. <https://doi.org/10.3390/S7112881>
- Yang, X., Zheng, X. Q., & Lv, L. N. (2012). A spatiotemporal model of land use change based on ant colony optimization, Markov chain and cellular automata. *Ecological Modelling*, 233, 11–19. <https://doi.org/10.1016/j.ecolmodel.2012.03.011>
- Yang, J., Menenti, M., Wu, Z., Wong, M. S., Abbas, S., Xu, Y., & Shi, Q. (2021). Assessing the impact of urban geometry on surface urban heat island using complete and nadir temperatures. *International Journal of Climatology*, 41, E3219–E3238. <https://doi.org/10.1002/joc.6919>
- Yao, R., Wang, L., Huang, X., Niu, Z., Liu, F., & Wang, Q. (2017). Temporal trends of surface urban heat islands and associated determinants in major Chinese cities. *Science of the Total Environment*, 609, 742–754. <https://doi.org/10.1016/j.scitotenv.2017.07.217>
- Yayla, E. E., Sevik, H., & Isinkaralar, K. (2022). Detection of landscape species as a low-cost biomonitoring study: Cr, Mn, and Zn pollution in an urban air quality. *Environmental Monitoring and Assessment*, 194(10), 687. <https://doi.org/10.1007/s10661-022-10356-6>
- Yin, C., Yuan, M., Lu, Y., Huang, Y., & Liu, Y. (2018). Effects of urban form on the urban heat island effect based on spatial regression model. *Science of the Total Environment*, 634, 696–704. <https://doi.org/10.1016/j.scitotenv.2018.03.350>
- Yu, J., Hagen-Zanker, A., Santitissadeekorn, N., & Hughes, S. (2021). Calibration of cellular automata urban growth models from urban genesis onwards—a novel application of Markov chain Monte Carlo approximate bayesian computation. *Computers Environment and Urban Systems*, 90, 1–14. <https://doi.org/10.1016/j.compenvurbsys.2021.101689>
- Zheng, Z., Ma, T., Roberts, P., Li, Z., Yue, Y., Peng, H., & Saito, Y. (2021). Anthropogenic impacts on Late Holocene land-cover change and floristic biodiversity loss in tropical southeastern Asia. *Proceedings of the National Academy of Sciences*, 118(40), e2022210118. <https://doi.org/10.1073/pnas.2022210118>

**Publisher's Note** Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Springer Nature or its licensor (e.g. a society or other partner) holds exclusive rights to this article under a publishing agreement with the author(s) or other rightsholder(s); author self-archiving of the accepted manuscript version of this article is solely governed by the terms of such publishing agreement and applicable law.