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Predicting Urban Land Use Changes Using a CA–Markov Model

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Abstract This study employs a CA–Markov model as one of the planning support tools for analysis of temporal changes and spatial distribution of urban land uses in Anzali, located in Gilan province in the northwest of Iran. In the first step, area changes and spatial distribution of land uses in the town were analyzed and calculated using geographic information systems technology for a time span 1989–2011. In the next step, using the transition matrix, the spatial distribution of urban land uses in 2021 was simulated, the changes were predicted and the possible growth patterns were identified as well. The results showed a declining trend of 10.64 % in forest, 8.52 % in Anzali wetland and 11.54 % in barren land during 1989–2011, and also an increasing trend of 7.1 % in urban areas for a time span 1989–2021. Major expansions in urban areas were witnessed around western and eastern borders of the city, particularly close to the eastern border. Scattered expansions were also predicted in the Anzali wetlands registered in the Ramsar Convention (southern borders). This study provides an opportunity to define and apply better strategies for environmental management of land use to make an optimized balance between urban development and ecological protection of environmental resources.

Keywords CA–Markov · GIS · Land use change · Urban growth

الخلاصة

توظف هذه الدراسة نموذج ماركوف-CA بوصفه واحدا من أدوات دعم التخطيط لتحليل التغيرات الزمانية والتوزيع المكاني لاستخدام الأراضي في المناطق الحضرية في انزلي، الواقعة في مقاطعة جيلان في شمال غرب ايران. وتم في الخطوة الأولى تحليل التغيرات في المساحة والتوزيع المكاني لاستخدام الأراضي في المدينة وحسابها باستخدام تكنولوجيا نظم المعلومات الجغرافية (GIS) لفترة زمنية من 1989-2011. وتمت - في الخطوة التالية باستخدام مصفوفة الانتقال - محاكاة التوزيع المكاني لاستخدام الأراضي في المناطق الحضرية في عام 2021، وتوقع التغيرات و تحديد أنماط النمو الممكنة أيضا. وأظهرت النتائج اتجاها نحو الانخفاض من 10.64 ٪ في الغابات، 8.52 ٪ في أراضي انزلي الرطبة و 11.54 ٪ في الأرض القاحلة خلال الفترة من 1989 إلى 2011، و أيضا اتجاها متزايدا من 7.1 ٪ في المناطق الحضرية لفترة زمنية 1989-2021. وقد شهدت المناطق الحضرية توسعات كبيرة حول الحدود الغربية والشرقية من المدينة، وبخاصة على مقربة من الحدود الشرقية. و تم توقع توسعات متناثرة أيضا في أراضي انزلي الرطبة المسجلة في اتفاقية رامسار (الحدود الجنوبية). وتوفر هذه الدراسة فرصة لتحديد و تطبيق استراتيجيات أفضل للإدارة البيئية لاستخدام الأراضي من أجل إيجاد توازن أمثل بين التنمية الحضرية و حماية النظام البيئي من الموارد البيئية.

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1 Introduction

Today, urban development is one of the most important issues worldwide; accordingly, studying the change of urban structure as one of the new paradigms for sustainable development has received increasing attention from managers and planners involved in urban and environmental issues [1,2]. Furthermore, serious environmental and social risks which decrease quality of life in urban and non-urban communities, and uncontrollable changes in the spatial structure of cities are mainly due to the increasing unplanned physical development of cities; overpopulation (world population in-

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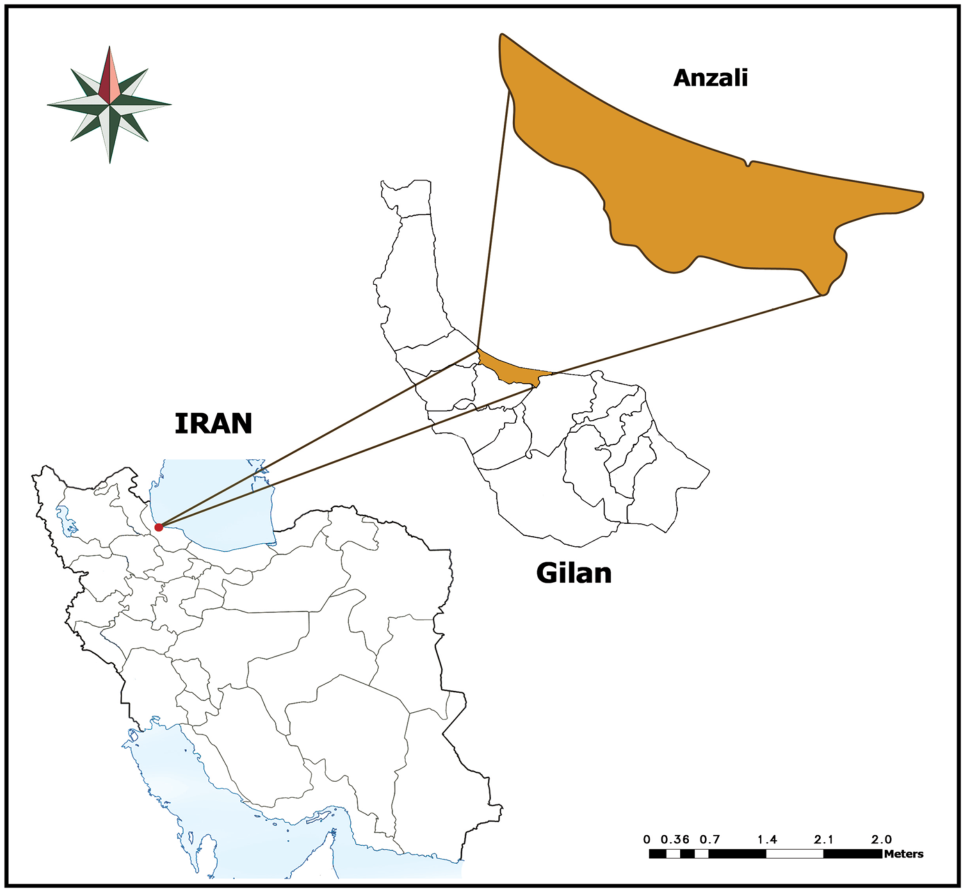

Fig. 1 Location of Anzali in Iran

Table 1 Description of land use/cover classes

Land use/class	Description
Built-up or residential	Residential, commercial, services and industrial areas, villages, asphalt and metalled roads
Agricultural	Agriculture, gardens, vegetables
Barren (lands with weak coverage and pasture)	Sandy land and coastal area, meadows out of the wetland area
Forest	Forest
Water bodies	Sea, swamp, rivers, big natural and artificial ponds, fish ponds
Wetland	Canebrake, wetland thick covers (lily, *Azolla* and shrubs), meadows inside the wetland

creased from 2.52 billion in 1950 to more than 7 billion in 2012 as reported by United Nations' Populations Division [3]); economic growth; and rural to urban migration [4–9]. Iran, as one of the developing countries, has recently encountered a rapid growth in both spatial and demographic terms in a way that the proportion of its urban population to total population has increased from 47 % in 1976 to 68 % in 2006.

Table 2 Evaluation of satellite image classification

Land use map	Kappa coefficient
TM 1989	0.82
ETM+ 2000	0.85
ASTER 2011	0.87

Given the fact that the dynamic process of urban development with its temporal–spatial dimensions cannot be prevented, modeling, simulation and prediction of cities' future growth would be applicable as one of the planning tools and policies to overcome the problems arising from rapid growth and development of urban areas, and to reach land use stability, understanding about interactions between the natural and man-made environments and finally the goals of sustainable

Table 3 Transition area matrix for land use change between 1989 and 2011

Land use in 1982	Land use type					
	A	B	F	U	W	We
Agricultural land (A)	0	362	6,999	0	0	0
Barren land (B)	6,751	10,093	0	23,182	5,536	4,805
Forest land (F)	1,935	0	5,914	33,848	15,314	16,218
Urban and built-up area (U)	0	76,968	0	0	0	0
Water body (W)	338	0	68	12,142	2,782	059
Wetland (We)	0	0	20,649	1,326	0	686,607

Table 4 Transition probability matrix for land use change between 1989 and 2011

Land use in 1982	Land use type					
	A	B	F	U	W	We
Agricultural land (A)	0.000	0.0491	0.950	0.000	0.000	0.000
Barren land (B)	0.134	0.2004	0.000	0.460	0.109	0.095
Forest land (F)	0.0264	0.000	0.080	0.462	0.209	0.221
Urban and built-up area (U)	0.000	1.000	0.000	0.000	0.000	0.000
Water body (W)	0.0212	0.000	0.004	0.759	0.174	0.041
Wetland (We)	0.000	0.000	0.190	0.012	0.000	0.797

urban development. Clarifying and predicting the changes in land covering and urban growth are keys to present the holistic and principled views on more efficient management of environmental resources, protection of suburban lands and adoption of long-term policies to minimize the impacts of urban development on the environment and even to appreciate the potential impacts on socioeconomic resources as well as people [10].

In recent years, the rapid and unprecedented growth of technologies such as remote sensing (RS) and geographic information systems (GIS) and their use in urban and environmental planning have resulted in both the formation and presentation of spatial modeling methods as a decision support tool, such as cellular automata [11], neural networks [12] and statistical models [13]. These models are capable of presenting a quantitative tool to assist in making decisions for urban and environmental planning, capability management and for assessing the suitability of land for development [14]. Numerous studies have revealed that the CA–Markov model, which efficiently matches with GIS and RS, is able to devise an appropriate approach in dynamic temporal and spatial modeling of cover/land use changes [13,15]. In this model, a Markov chain process controls the temporal changes in land use classification based on conversion probabilities [13,16], while the spatial changes are controlled by local rules determined by CA spatial filter or suitability maps [17,18]. In the meantime, GIS is employed to define the initial conditions, determine model parameters and calculate probabilities and to determine neighborhood rules [19].

The simulation of Anzali's future growth is the main objective of this study. For this purpose, Anzali's growth by 2021 was simulated and predicted using a CA–Markov model, and the analysis of temporal and spatial changes of its land uses from 1989 to 2011 was carried out using satellite imaging and GIS.

2 Materials and Methods

2.1 The Study Area

Anzali, with an approximate area of 304.7 km^2 (2.1 % of the total area of Gilan province) is located in the northwest of Iran in a plain area between latitudes 37°20′ and 37°34′N and longitudes 49°15′ and 49°48′E. This town is connected to the Caspian Sea in the north, to Someesara in the south, to Rasht in the east and to Rezvanshahr in the west. Relatively, high rates of precipitation and humidity in all seasons, especially in fall and winter (annual precipitation of about 1,892 ml and relative humidity of about 84 %), minor difference between day and night temperatures and extensive vegetation coverage are among the most important characteristics of this region. The Caspian Sea with a coastline of about 40 km on the one hand and the valuable ecosystem of the Anzali wetlands on the other hand contribute to the natural environment of the town.

Anzali houses around 133,000 people (according to population and housing census in 2010) with its 85.4 % of male

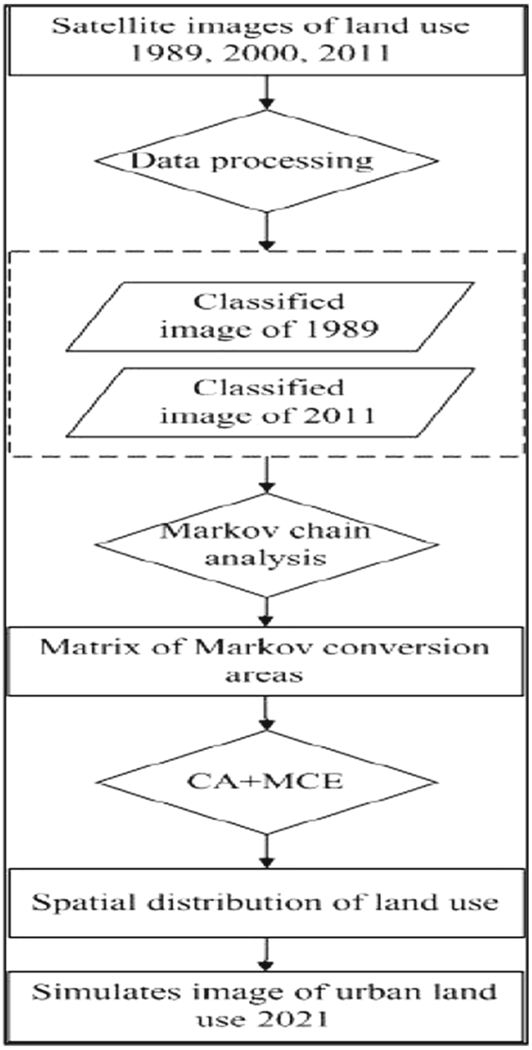

Fig. 2 Flowchart of simulating urban land use changes

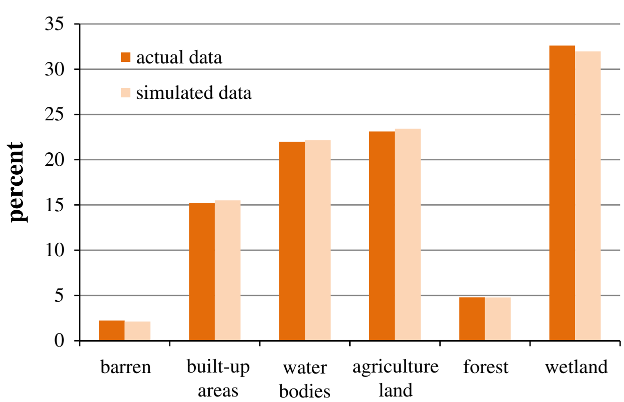

Fig. 3 Simulated change versus actual change of land use type in 2011

and 14.6 % of female labor force being employed. Most of the employees, i.e., 72 %, work in the private sector while 28 % of them are employed in the public sector. Out of the employed individuals in Anzali, 10.3 % are involved in the agricultural sector, i.e., agriculture, hunting, forestry and fisheries; 14.5 % in the industries and mining sector, i.e., mine, industry, electricity, gas and water; 10.8 % in the construction sector; and 64.4 % in services, i.e., wholesaling, hotels, transportation, dealership, real estate, education, health and other services activities. Figure 1 demonstrates the location of the study area.

2.2 Data

The present study used Landsat images (TM, ETM+) and Aster images taken in 1989, 2000 and in 2011, respectively. In the first step of the study, using ERDAS software, the satellite images were processed going through the pre-processing, classification, information processing and post-processing stages. After the pre-processing stage, composed of geometric correction and atmospheric effect correction, each image was classified separately; first using unsupervised and then supervised classification methods. Then, the primary land use map was extracted for each image. To classify the land cover, six classes of land uses/covers were determined accordingly: (1) built-up areas (including urban and rural, and transportation), (2) agricultural, (3) barren, (4) forest, (5) wetland, and (6) water bodies (Table 1).

Having finished the image classification stage, the accuracy of classification was determined and evaluated. To this end, 200 points were selected by stratified random sampling method. Then, based on the relative knowledge of the study area and using GPS in field studies, the classification accuracy was calculated for each image and the accuracy matrix was generated for each map. Classification accuracies of land use maps obtained from the studied images are listed in Table 2.

2.3 Methods

CA, due to its ability to fit complex spatial nature using simple and effective rules, has been widely and increasingly implemented to model the urban growth process in recent years [20]. Markov analysis is a statistical tool using transition probability matrix based on neighborhood effects in a spatial influence algorithm [15]. One inherent problem with Markov is that it provides no sense of geography. The transition probabilities may be accurate on per category basis, but there is no knowledge of the spatial distribution of occurrences within each land use category. To solve this problem, CA–Markov chain was developed to add a spatial dimension to the model using cellular automata. A cellular automaton is an agent or object that has the ability to change its state based upon the application of a rule that relates the new state to its previous state and its neighbor [11].

Markov is a tool for modeling land use changes for setting "current trends" scenario; because it uses evolution from $t-1$

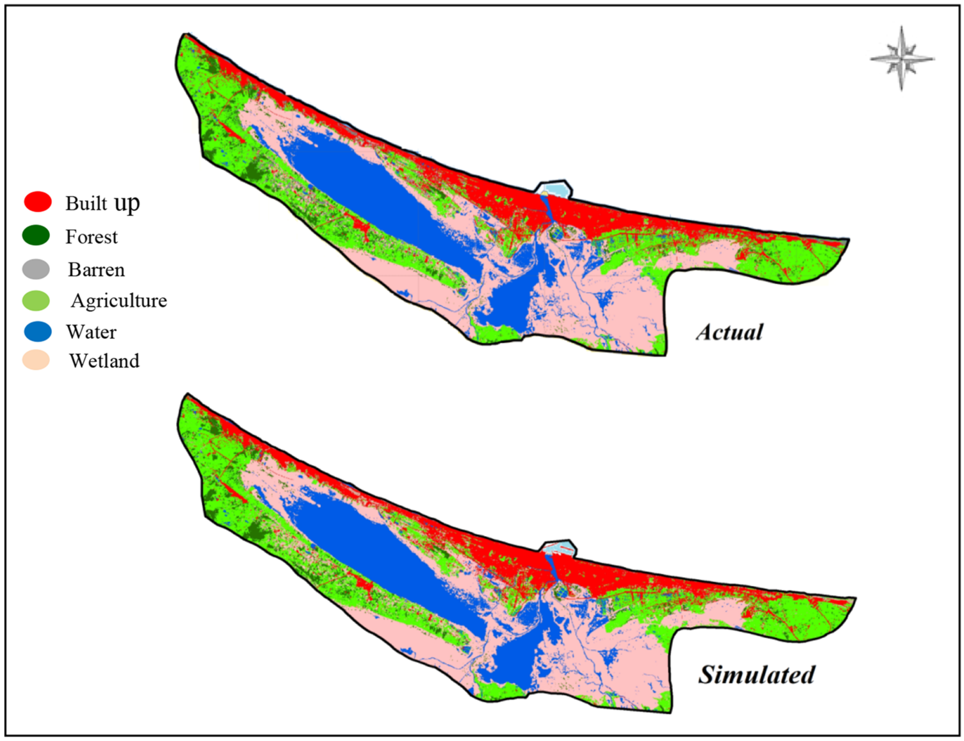

Fig. 4 Actual map and simulated map of land use type in 2011

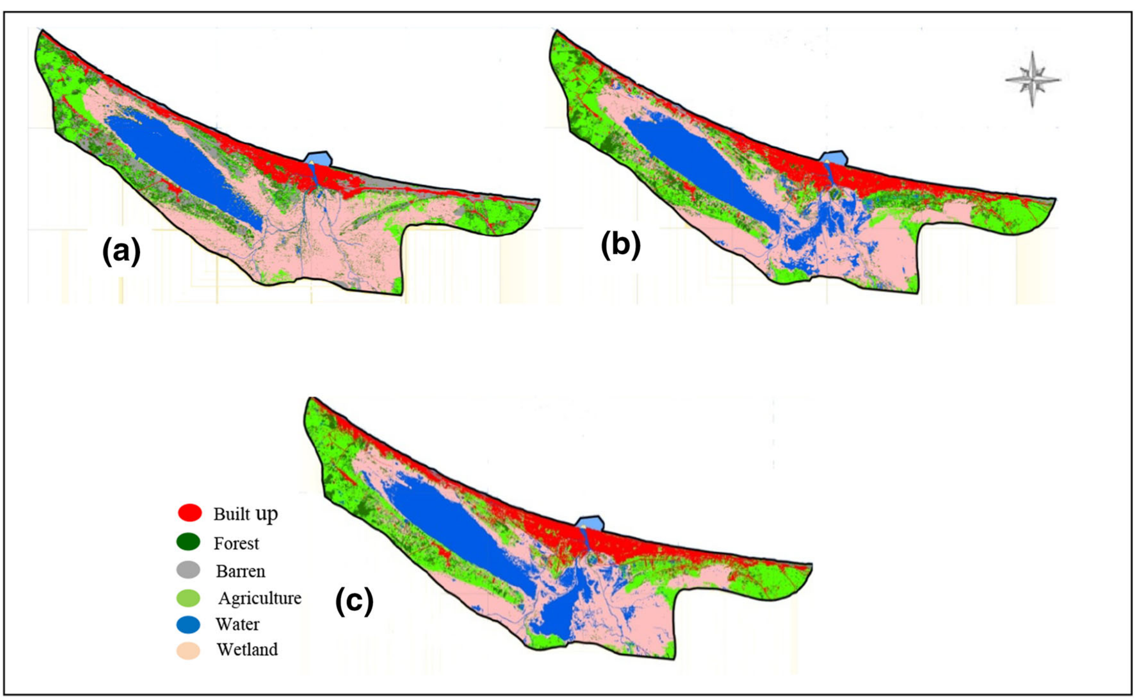

Fig. 5 Classified land use maps in Anzali; **a** 1989, **b** 2000, **c** 2011

Table 5 Percentage of land use/cover changes from 1989 to 2011

Land use	1989		2000		2011	
	Area (ha)	Coverage (%)	Area (ha)	Coverage (%)	Area (ha)	Coverage (%)
Barren	3,507	11.69	896	2.98	674	2.24
Built-up areas	2,942	9.85	3,732	12.48	4,561	15.21
Water bodies	4,185	13.96	5,951	19.85	6,591	20
Agricultural lands	4,163	13.88	6,083	20.29	6,931	32.12
Forest lands	3,579	11.93	2,828	9.43	1,441	4.80
Wetlands	11,599	38.69	10,485	34.97	9,777	32.61
Total	29,975	100	29,975	100	29,975	100

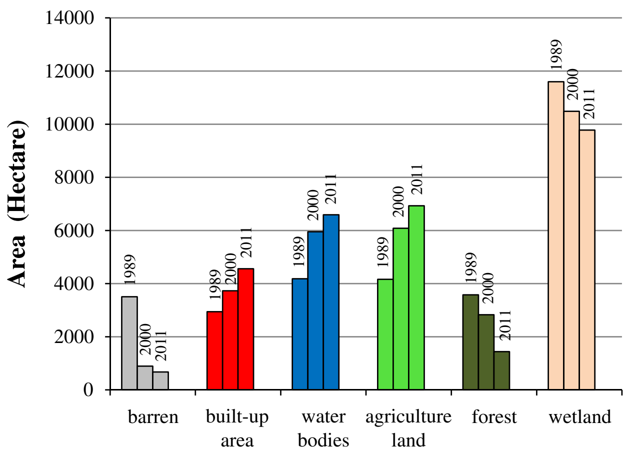

Fig. 6 Change in land use/cover classes during 1989–2011

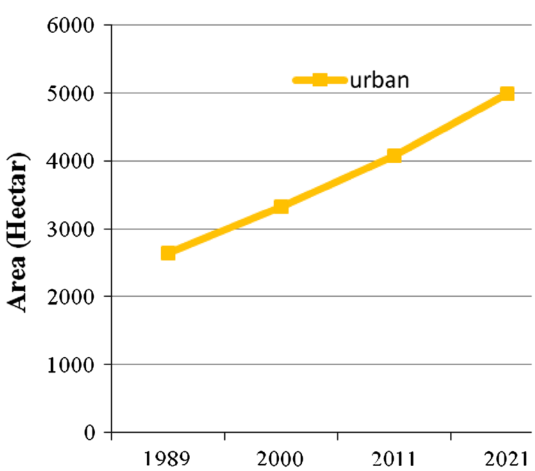

Fig. 7 Changes in urban land use class during 1989–2021

to t to project probabilities of land use changes for a future date $t + 1$ [20]. However, a stochastic Markov model is not appropriate because it does not consider spatial knowledge distribution within each category and transition probabilities are not constant among landscape states [21]. An hybrid Markov–cellular automaton (M–CA) model is an interesting approach to model both spatial and temporal changes: (a) the Markov process controls temporal dynamic among the cover types through the use of transition probabilities, (b) spatial dynamics are controlled by local rules through a CA mechanism considering either neighborhood configuration and transition probabilities, (c) GIS and remotely sensed data can be used to define initial conditions, to parameterize M–CA model, to calculate transition probabilities and determine the neighborhood rules [22]. They are particularly adapted when different processes interfere at different spatial and temporal scales.

The present study utilized a Markov chain model and a CA filter, jointly called CA–Markov, to predict and simulate the directions of future growth and development in Anzali. This model was based on using and evaluating land use layers of previous years and further predicting the spatial distribution of land uses in the future using GIS [21]. The simulated model of land use changes was developed in IDRISI software to monitor the patterns of spatial urban land use. This model comprises two main stages: (1) calculating conversion probability, including the conversion probability matrix, conversion area matrix and layers of conditional probability, using Markov chain analysis, and (2) spatial specification of land use coverage simulated based on CA spatial operator and multi criteria evaluation (MCE).

In the mentioned model, the land use map in 1989 and probability matrix from 1989 to 2011 formed the basic map and two main groups of data. In the first step, land use maps of 1989, 2000 and 2011 were extracted from the satellite images of TM 1989, ETM+ 2000 and ASTER 2011 using GIS technology. Likewise, the layers related to the years 1989 and 2011 (one belonging to the past and the other one belonging to the present time) were selected to be input into the model, to calculate matrices of conversion areas and conversion probabilities using Markov chain analysis (Tables 3, 4). In the next step, the conversion matrix was applied to provide a set of conditional probability data for the six determined main

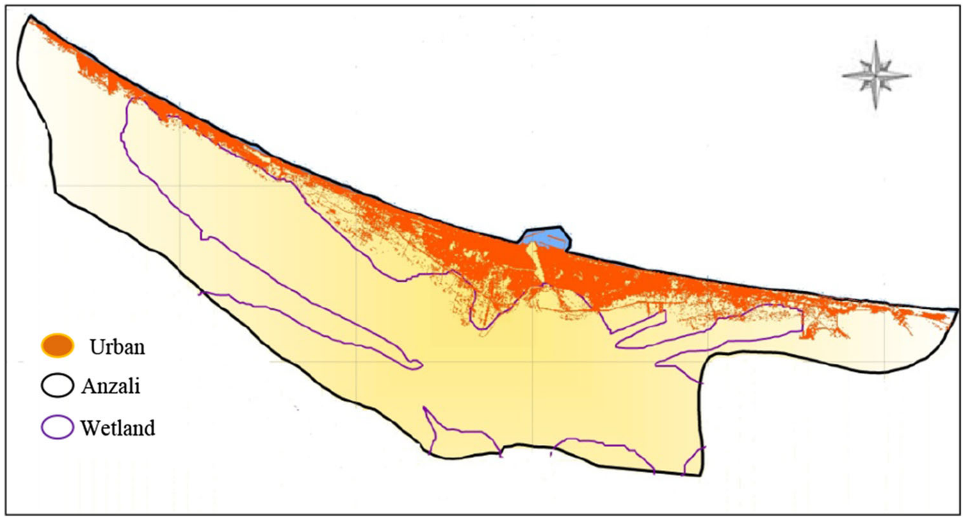

Fig. 8 Anzali simulated urban land use coverage in 2021

Table 6 Percentage of the predicted land use/cover based on CA–Markov model

Land use	2021	
	Area (ha)	Coverage (%)
Barren	45	0.15
Built-up areas	4,993	16.68
Water bodies	7,694	25.66
Agricultural lands	7,820	26.08
Forest lands	388	1.29
Wetland	9,035	30.14
Total	29,975	100

uses, i.e., built-up, agricultural, barren, forest, wetland and water bodies, from 1989 to 2011. The mentioned probability data set was, in fact, the result from calculated prediction of the two old and new (1989 and 2011) land use layers.

In the final step, to simulate the urban land use map of 2021, the land use map of 1989, as a base map, the matrix conversion probabilities of 1989–2011 and conditional probability data were integrated using the CA spatial operator in IDRISI software based on Markov chain analysis and MCE. Due to the temporal gap between 2011 and 2021, a repetition of ten times was assigned to CA model. Finally, at the end of each repetition, a new land use map was produced through overlapping the whole results obtained in the previous steps. The simulation of urban land use changes in Anzali is shown in Fig. 2.

3 Results and Discussion

3.1 Model Validation

For model validation, the simulated land use/cover maps for 2011 were compared with the actual satellite-derived land use/cover maps based on the Kappa statistic with GIS software using the land use maps for 1989 and 2000.

Although it was necessary to examine the similar periods to run the CA–Markov model twice to assess the validation, the limited accessing to the required satellite data made it inevitable to relay on a 10-year period for simulation of 2021 and on an 11-year period for CA validation in this study.

The results from testing the area change are shown in Fig. 3, which evidently indicates that six land use classes bear low relative errors of lower than 5 %. The best agreement was achieved in the forestland class, where the actual area was 1,440.62 ha, and the corresponding simulated area was 1,434.2 ha. The results from visual analysis indicate that forestland, water bodies and agriculture lands in the simulated land use/cover map are relatively close to the corresponding classes in the actual land use/cover map, while the bare land class was poorly simulated (Fig. 4). Meanwhile, the overall success of Markov–cellular automata's simulation was 0.83 % in 2011. The developed Markov model was also verified to effectively predict the area change of land use in future.

3.2 Analyzing Land Use/Cover from 1989 to 2011

According to Fig. 5 and Table 5, from 1989 to 2011, wetland, agricultural areas, water bodies and built-up areas constituted the main uses in the study area. During these period, built-up areas (urban) increased from 2,942 to 4,561 ha, which means that there has been an increase of 5.63 % in urban development within the past 23 years. Also, the major part of urbanization during the mentioned time interval has occurred around the eastern and western borders of the town, with a lower density at the southern border. Generally, a linear development has occurred due to having the Caspian Sea to

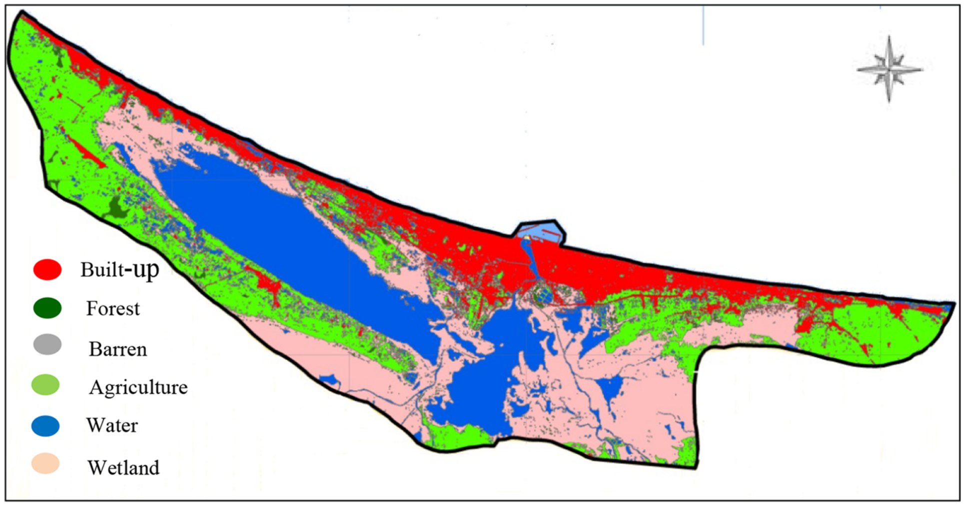

Fig. 9 Simulated land use coverage in Anzali in 2021 based on CA–Markov model

the north and the Anzali wetland to the south. The reduction of barren areas from 3,507 to 647 ha is the consequence of constructions during the past 23 years, especially from 1989 to 2000.

Despite the importance of the Anzali wetland as an international resource registered by the Ramsar International Convention, as well as the introduction of some protection and management plans; unfortunately, it has experienced a reduction of 6.08 % within the town. In addition, due to the increasing trend of urban construction, tree cutting and disregarding the measures for preventing further damage, forest areas have also faced a decrease of 7.13 % during 1989–2011 (Fig. 6).

During this period, agricultural lands and water bodies increased by 18.24 and 6.04 %, respectively.

3.3 Predicting Land Use/Cover Changes in 2021

Through this study, urban growth in Anzali for the year 2021 was simulated by land use /cover maps obtained from satellite images (1989, 2000, and 2011), physical data, and the CA–Markov model which is a combination of Markov chain analysis and CA models (Fig. 8; Table 5). Simulation of the spatial distribution of urban land use in Anzali, showed a growing trend in the built-up areas (Fig. 7). Thereby, based on the predictions, urban lands area will increase from 2,644 ha in 1989 to 4,993 ha in 2021. As shown in Fig. 8, the main development in the built-up areas is predicted to occur in the surrounding areas and suburbs of Anzali.

Based on the prediction of the simulation model in Table 6, forests will decrease from 4.8 % in 2011 to 1.29 % in 2021 and barren lands will also face a 2.09 % decrease in 2021. In contrast, water bodies which formed 20 % of the study area in 2011 will grow to constitute 25.66 % of the total area in 2021 (Fig. 9).

4 Conclusion

The results predicted by the CA–Markov model imply that rapid urbanization will occur around the western and eastern borders of Anzali town in 2021, especially close to the eastern border, which will be in the form of scattered parts of the Anzali wetlands registered in the Ramsar Convention (the southern border of the town). Therefore, reinforcement of the environmental protection plans at the eastern and western borders (such as those developed for the current agricultural lands in this area), specifically at the Anzali's wetlands to the south, should be given the highest priority by planners and decision makers.

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