Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 5 August 2022 doi:10.20944/preprints202208.0119.v1

*Article*

# Simulation of Urban Sprawl by Comparison Cellular Automata-Markov and ANN

**Milad Asadi[1*], Amir Oshnooei-Nooshabadi[2], Samira-Sadat Saleh[3],Fattaneh-Habibnezhad[4], Sonia Sarafraz-Asbagh[5], John Lodewijk Van Genderen[5]**

[1] Department of Urban Planning, University of Daneshpajoohan, Isfahan 81747-47144, Iran (Miladasadi19908@gmail.com)
[2]Department of Geography, Lorestan University, Khorramabad, Lorestan/Iran; (oshnooei.a@lu.ac.ir)
[3] College of science, north texas University, USA; (SamiraalsadatSaleh@my.unt.edu)
[4]Department of geography and urban planning, Kharazmi University, Tehran/Iran; (habibnejad@ict.iau.ir)
[5]Department of Geography and Urban Planning, University of Tabriz/Iran; (sonia.sarafraz@tabrizu.ac.ir)
[5]International Institute for Geo-Information Science and Earth Observation (ITC), 7500 Enschede, Netherlands; (genderen@alumni.itc.nl)
* Corresponding author:
E-mail: SamiraalsadatSaleh@my.unt.edu
Tel : +98 (913) 275 64 36

**Abstract:** A correctly obtained Land-use/land-cover (LULC) prediction map is essential to understanding and assessing future patterns. In the study, the LULC map of Urmia/Iran in 2030 was produced using two different prediction methods CA-Markov and Artificial Neural Network (ANN). In general, the study followed a methodology consisting of three steps. In the first steps, Landsat satellite images acquired in 2000, 2010 and 2020 were classified with maximum likelihood algorithm and LULC maps were prepared for each year. In the second stage, to investigate the LULC prediction methods' validation (CA-Markov and ANN) the LULC prediction map of 2020 was produced using the LULC map of 2000 and 2010; In this step, the predicted LULC map of 2020 and the actual LULC map of 2020 were evaluated by correctness, completeness and quality indexes. Finally, The LULC map for 2030 was prepared using all two algorithms and the change map was extracted. The results show that the area of soil and vegetation decreased, and built-up regions increased during the research period. The methods validation results show that the two algorithms are much closer to each other. Nevertheless, in general, ANN has the highest completeness (96.21%) and quality (93.8%) and CA-Markov the most correctness (96.47). This study shows that the CA-Markov algorithm is most successful in predicting the future that had larger areas and a higher percentage in the region (urban and vegetation cover) and the ANN algorithm in predicting phenomena that had smaller levels with fewer percentages (soil and rock).

**Keywords:** LULC; prediction; artificial neural network; Urmia; CA-Markov

## 1. Introduction

Land cover is a crucial variable that affects the balance of the earth's energy, the hydrological and carbon cycles and the provision of natural resources and habitats (Bonan, 2008; Pflugmacher et al., 2019). Land use/Land cover (LULC) and its environmental impact have been a challenging issue since 1990 and it has become one of the most fundamental figures in global changes (Anderson et al.2017; Feddema et al., 2005; Luo et al., 2003; Liu et al., 2005; Wang et al., 2006; Maleki et al., 2020; Tang et al., 2020). Land-use land-cover change (LULCC) data have attracted the attention of the environmentalists due to the effects this issue has on the global environmental (Islam et al., 2018; Abuelaish and Olmedo, 2016; Subedi et al., 2013) Awareness of the environmental effects of the land use change (LUC) has caused the scientific society to support the policy makers in their activities and mind the amount of their changes and evaluate their impact on the environment (Pindozzi et al, 2017).

Land-use/land cover is a change on the surface of the earth created because of human beings' activities (Hamad et al., 2018; Roy et al., 2015), though climate change and natural disasters also have a significant impact. These changes result from the interactions between environmental, social, human, activities and economic factors (De Almeida et al., 2020). Mapping LULC change using remote sensing techniques provides a quantitative description of LULC that can help identify rates, extent, and patterns of LULC dynamics (Tadese et al., 2020).

Remote sensing is a rigorous surface monitoring tool specifically used for creating maps of LULC (Foody, 2002; Green et al., 1994; Hütt et al., 2016). Remote sensing is a practical tool for observing land surfaces and is widely used to extract data (Duan et al., 2020). Compared to measurements taken only from a specific location, remote sensing provides large-scale, high-resolution, continuous information for LULCs (Duan et al., 2020; Keshtkar et al. 2017). Therefore, LULC classification based on remote sensing has an essential role in evaluating the results of management interventions and how the changes will occur in the future (Kolli et al., 2020).

Changing natural environments, agricultural lands, etc. to urban areas is one of the most demanding environmental challenges in each and every country (Dadashpoor & Salarian., 2020). Spatial predictions are necessary to forecast and manage regional and global changes and to be able to improve environmental sustainability (Mc Cutchan et al., 2020). While some patterns are based on the prediction rate of change, others rather rely on spatial patterns that focus on required data and validation strategies (Veldkamp & Lambin., 2001). In recent years, some spatial models have combined remote sensing (RS) and geographic information system (GIS) to simulate and predict future scenarios of LULC (Mishra & Rai., 2016). For instance, Markov Chain (Arsanjani et al., 2013; Ziari & Zakerhaghighi, 2022), Ca-Markov (Kisamba & Li, 2022), logistic regression (Tayyebi et al., 2010; Buya et al., 2020), cellular automata model (Munthali et al., 2020; Wang et al., 2022), SLEUTH model (Jantz et al., 2004; Saxena & Jat., 2019), artificial neural network, (Kim et al., 2009; Al Rifat & Liu, 2022).

Many studies in the literature have applied the Fractal model (Chen, 2018; Chen & Huang., 2019), CA-Markov (Zhou et al., 2020; Baqa et al., 2021; Yi et al., 2022) and ANN (Malik & Bhagwat, 2021; Zare Naghadehi et al., 2021; Girma et al., 2022) Logistic Regression (Xu and Chen, 2019; Wang et al., 2020) Agent-Based modeling (Kaviari et al., 2019; Xu et al., 2020), which are popular in prediction studies separately for LULC. However, no studies are comparing these methods and evaluating their effectiveness comparatively using various validation techniques. The study’s scope was to determine the best Land-Use/Land-Cover prediction methods in Urmia, Iran through CA-Markov and ANN. For this purpose, the LULC map in 2030 was projected with the help of changes in land use in 2000, 2010, and 2020. In addition, the accuracy of the produced model was investi-gated with different validation methods such as correctness, completeness and quality indexes. Therefore, this paper can guide the use of appropriate methods by comparing the methods in this study for LULC prediction.

## 2. Study Area

The Urmia city (37 o 33ˈN, 45o04ˈE) is the center of the West Azerbaijan province in the north west of Iran, which is located at a distance of 18 km from Lake Urmia (Khaledi et al., 2021). The climate of this region is cold, semi-arid with an average of 360 mm annual pre-cipitation and 11 ° C annual temperature (Chitsazan et al., 2019), making it one of the coldest cities in Iran (Abedini et al., 2020). Urmia is one of the most important historical and growing metropolises of Iran that has grown a lot in recent years (Abedini & Khalili, 2019). According to the 2016 census, it had about 750,000 population (Gharakhanlou & Hooshangi, 2020), which according to the 2018 census has increased to 800,000 (Mo-hammadi et al., 2020). The expansion of urbanization in this city has led to the reduction of

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 5 August 2022 doi:10.20944/preprints202208.0119.v1



plant and animal diversity, changes of natural environment of the village and finally to the climate change (Abedini et al., 2015; Abedini, 2018). Figure 1, shows the study area location.

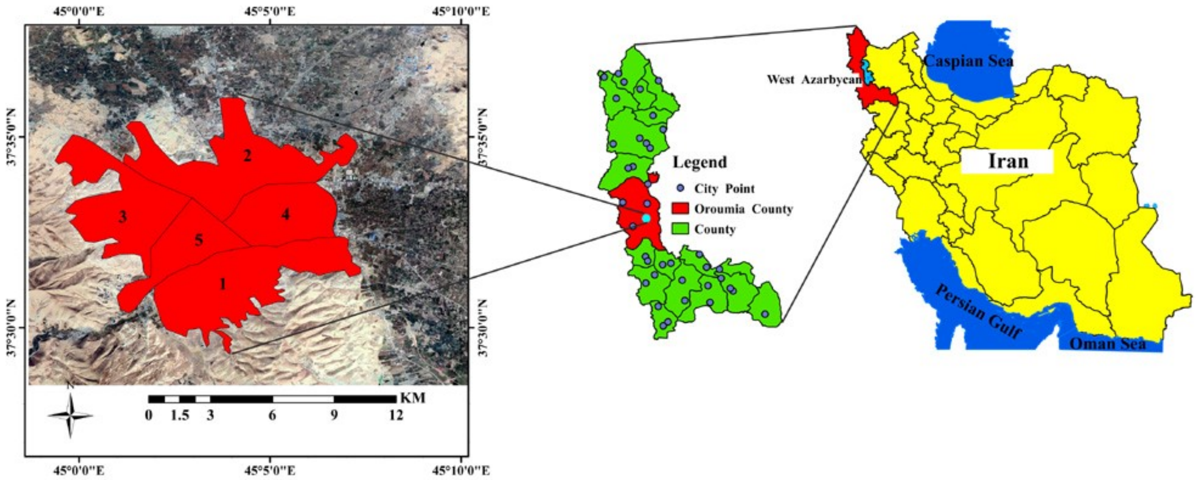



Figure 1. Study area

## 3. Data and Methods

Evaluating the rate of changes from one phase to another in a specific time and place of spatial data is significant for the prediction of future change scenarios (Takada et al. 2010). Using non-commercial satellite images is an inexpensive and fast method of predicting LULC which is by itself a rigorous tool for land planners. Landsat satellite series provide the longest record of satellite observations. Accordingly, Landsat is a precious source to monitor the global changes and it's the major source of observing the earth with medium-spatial resolution used in decision-making procedures.

In this study, Landsat images (7 and 8) covering Urmia were retrieved on 03/06/2000, 30/05/2010, and 02/06/2020. Initially, pre-processions steps such as geometric correction, radiometric correction, and etc. was carried out. Then, in the categorization stage, for choosing sample points from the old maps, high-resolution images (such as Google Earth, World Imagery), normalized difference built-up index (NDBI) and normalized difference vegetation index (NDVI) were used(sample points size are table 1). To extract the LULC map, the maximum likelihood method was applied because compared to some others, it provides the highest quality (Zare-Naghdaehi et al., 2020). Finally, prediction studies for the year 2030 were carried out with the methods detailed below and their accuracy was investigated.

**Table 1.** sample points size.

| Year | sample points size(pixel) | | | |
|---|---|---|---|---|
| | Build-Up | Rocky | Soil | Vegetation |
| 2000 | 2514 | 941 | 1542 | 3564 |
| 2010 | 2968 | 913 | 1317 | 3098 |

 doi:10.20944/preprints202208.0119.v1



| | | | | |
|---|---|---|---|---|
| 2020 | 3311 | 1072 | 1298 | 3012 |

### 3.1. CA-Markov

CA–Markov is a combined Cellular Automata/Markov Chain/Multi-Criteria/Multi-Objective Land Allocation (MOLA) to predict the LULCC trends and characteristics over time (Sang et al., 2011; Nouri et al., 2014 Hamad et al., 2018). CA model behaviors are under the influence of the uncertainty stemming from the interaction between the model elements, the structures, and the quality of the data sources that are considered model input. This is often focused on the local interaction of the local cells, distinct spatial and temporal properties and the rigorous computational ability of space that is proper for dynamic simulation and display with self-made features. Thus, CA model can be described as follows (equation 1):

$$S\ (t, t + 1) = f\ ( S(t), N) \qquad (1)$$

S is a collection of limited and discrete cellular models, N is a cellular field, t and t +1 stand for different times and f is the transformation of cellular states law in local space.

Markov chain is not sufficient to actively simulate or predict LULC because it doesn't consider the spatial distribution in each of the land categories or the spatial direction of the growth (Mansour et, 2020: Ghosh et al., 2017). On the other hand, CA-Markov is a Cellular Automata, Multi-Objective Land Allocation predicting method that adds elements of spatial proximity and the knowledge of spatial distribution to the Markov chain (Sang et al., 2011).

### 3.2. Artificial Neural Network

To detect the probability of LULC transformation, ANN uses several output neurons to simulate LULC changes. In the first step, the inputs of the neural network is defined for the simulation. The simulation is cellular-based (pixel-based) and each cell has a set of natural features (spatial variables) as input to the neural network, defined as follows:

$$X=[x1, x2, x3... xn]T \qquad (2)$$

Where xi is the ith property and t is the relocation.

Each correlation between the spatial variables is evaluated by the mutual comparison of raster, choosing the first raster from one variable and the second raster from the other. Next, LULC region and the changes related to each group are measured between initial and final time periods. In the next step, the probability of transformation through ANN is simulated. The structure of the neural network is created of three layers, meaning the input layers, latent layers and output layers. In the latent layer, the received signal by the j-th cell, (k,t)j network from the input layer for the k-th in t time is defined as follows:

$$net_j(k,t) = \sum_i w_{i,k}\, x_i'\ (k,t) \qquad (3)$$

In which wi,k is the weight between the input and latent layers; x_i^' is the i saleable attribute related to I neuron in the latent layer considering k cell in t time. The probability of relocation, minding the performance of the output of a neural network, is achieved as such:

$$P(k,t.1)=\frac{1}{1+e^{-net_j \quad (k,t)}}, \qquad (4)$$

Where P (k,t,l) is the probability of changing from the current state of l LULC for k cell in t time and wj,l is the weight between the latent and output layers (Rahman et al., 2017; Saputra & Lee, 2019).

*3.3. Model Assessment*

In this study, some indexes such as completeness, correctness, and quality have quantitatively assessed the forecast findings from these methods. The details of the indexes used in the study are described below.

Completeness: This index shows how many percentages of the features shown in the source data are considered so in the conclusion of the work. In this index, the feature units which is related to other features and distinguished wrongly, have no impact on the amount of this index. Therefore, this index is defined as follows:

Completeness = (TP/TP+FN)*100 (5)

Correctness: This index is used for the correctness of classification. It means how many percentages of the features that are detected in the results are the same as the reference features. In this index, feature units which exist in the source data but were not distinguished in the result did not influence on the amount of this index. This index is defined as follows:

Correctness= (TP / FP+TP)*100 (6)

Quality: It is an index that pertains to the evaluation of the findings of both correctness and completeness:

Quality = (TP/TP+FP+FN) *100 (7)

where:

True positive (TP) is the number of units of features that exist in the source data and in the findings or the number of features that have been successfully detected correctly as a feature.

False positive (FP) is the number of features that do not exist in the source data but have been identified in the conclusion as a feature.

False negative (FN) is the number of negative features that exist in source data but have not been identified in the conclusion (Maleki et al, 2017; Maleki et al 2017; Maleki et al, 2018).

## 4. Result and Discussion

This section presents the findings of the used methods. Firstly, the conclusions of the classification with maximum likelihood are presented. Figure 2 shows the LULC maps obtained as a result of classification for 2000, 2010 and 2020.

 doi:10.20944/preprints202208.0119.v1



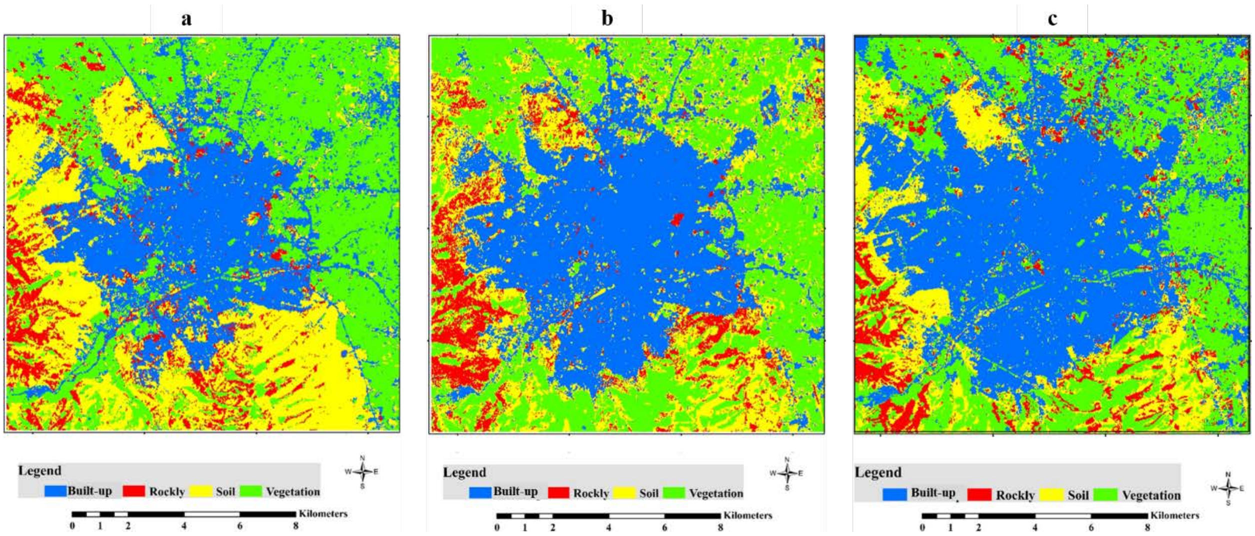



**Figure 2.** LULC maps (a,b,c) for the study region in the three analyzed intervals 2000, 2010 and 2020 respectively

Before using the achieved maps as the input of the LULC prediction methods, we should verify each class's classification. Table 2 depicts the result of the verification for the classification of each class in three studied periods. Based on table 2, the classification results in each of the three-period are proper for all classes. The Kappa coefficient in all of the three periods is higher than 90% and in the 2020 map, it is approximately 100%. The soil had less than 90% accuracy in 2 periods (2000 and 2010), which were nevertheless above 83% and acceptable.

**Table 2.** Classification results calculated for each year and class.

| Years | Accuracy Assessment | | | | | |
|---|---|---|---|---|---|---|
| | Build-Up | Rocky | Soil | Vegetation | Average | Kappa coefficient |
| 2000 | 94.36 | 96.13 | 83.59 | 99.72 | 93.63 | 91.49 |
| 2010 | 98.48 | 96.88 | 83.18 | 99.79 | 94.58 | 92.48 |
| 2020 | 99.51 | 99.42 | 97.91 | 99.51 | 99.21 | 98.94 |

Figure 3 shows the changes of the area of LULC in the studied periods in different pe-riods. Urban land use has changed from 5500 hectares in 2010 to more than 7100 in 2010 and exceeding to 8700 to 2020 which shows that every 10 years, almost 1600 hectares have been added to the area of the urban land use.

 doi:10.20944/preprints202208.0119.v1



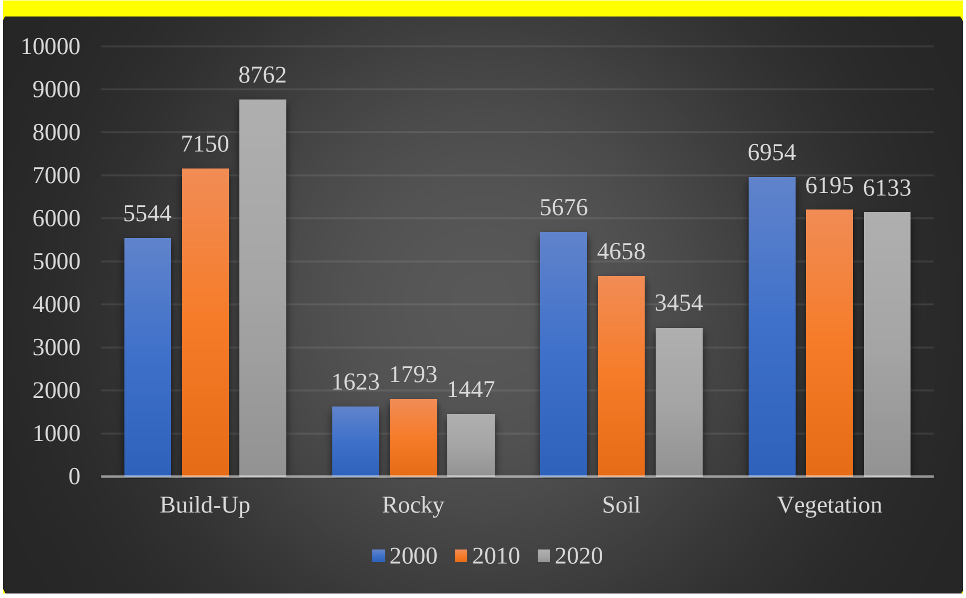



**Figure 3.** The graphic shows the spatial change of the Build-up, soil, vegetation and rocky areas (ha) for the years 2000, 2010 and 2020.

According to figure 3, the rocky and vegetation areas have changed little over the 20-year period. However, there have been serious changes over time in soil areas and build-Up areas. Soil class has shirked from 5700 hectares to 4650 in 2010 and to 3450 hectares in 2020. According to figure 3, the rocky areas do not present substantial change over the last 20-years, while the vegetation areas decreased significantly in 2010 with no significant reduction observed in the period 2010-2020.

Figure 4 shows the comparison of the LULC for the 2020 map (a) obtained as a result of classification with LULC prediction maps for the 2020, produced by CA-Markov (b) and ANN (c) method.

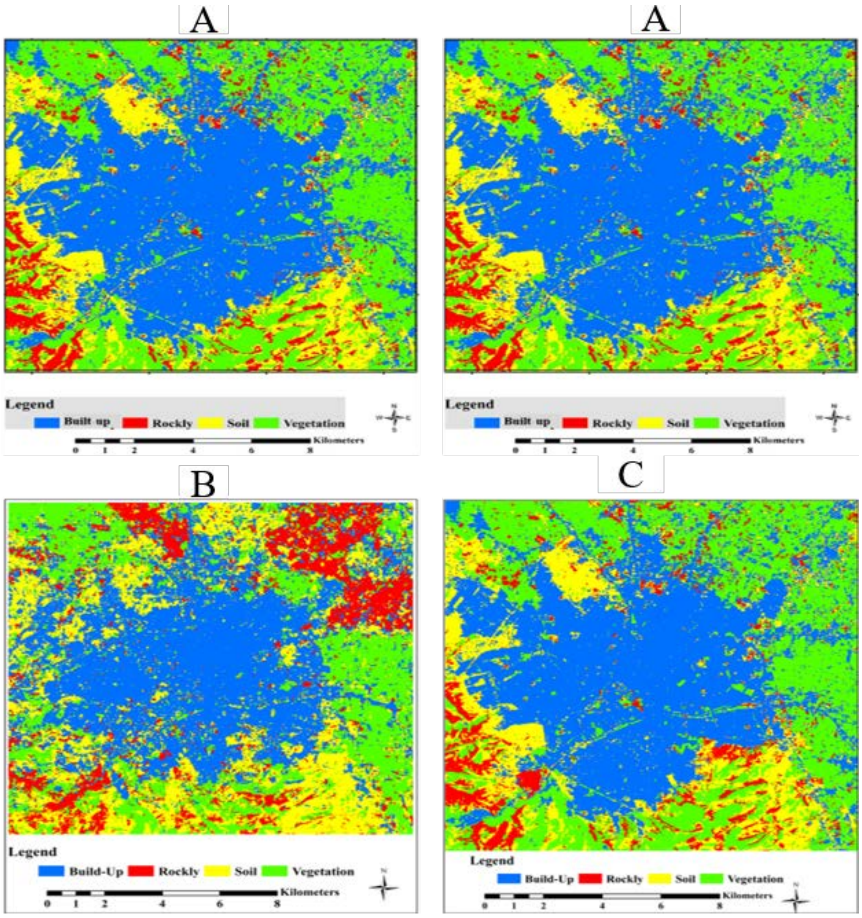



**Figure 4.** Comparison of LULC map under the current state (a) and LULC map produced by the classification method using CA-Markov(b) and ANN(c) method

According to the LULC classes shown in figure 4, we notice that the appearance of the CA-Markov and ANN are pretty similar to the current situation. To better understand and compare the methods with each other, the indicators of completeness, accuracy and quality were used, the results of which are shown in table 3.

**Table 3.** Evaluation of the role of the methods in simulating the LULCs

| Algorithm | Validation method | Land-use/Land-cover | | | | |
|---|---|---|---|---|---|---|
| | | Build-Up | Rocky | Soil | Vegetation | Average |
| CA-Markov | Completeness | 96.34% | 98.11% | 91.13% | 98.79% | 96.09% |
| | Correctness | 97.36% | 91.77% | 98.28% | 98.47% | 96.47% |
| | Quality | 93.99% | 89.89% | 94.63% | 96.16% | 93.67% |
| ANN | Completeness | 95.63% | 95.23% | 95.77% | 98.18% | 96.21% |
| | Correctness | 98.06% | 95.31% | 96.29% | 95.62% | 96.32% |
| | Quality | 93.85% | 92.11% | 94.79% | 94.44% | 93.8% |

Table 3 represents the completeness, correctness and the quality of the validation methods in order to evaluate and compare the consequences of the LULC prediction with the maximum likelihood classification method for 2020. The numbers shown in blue show the satisfactory result in this table. Accordingly, in LULC prediction models, the best accuracy results were obtained with the ANN technique while CA-Markov technique has ac-

 doi:10.20944/preprints202208.0119.v1

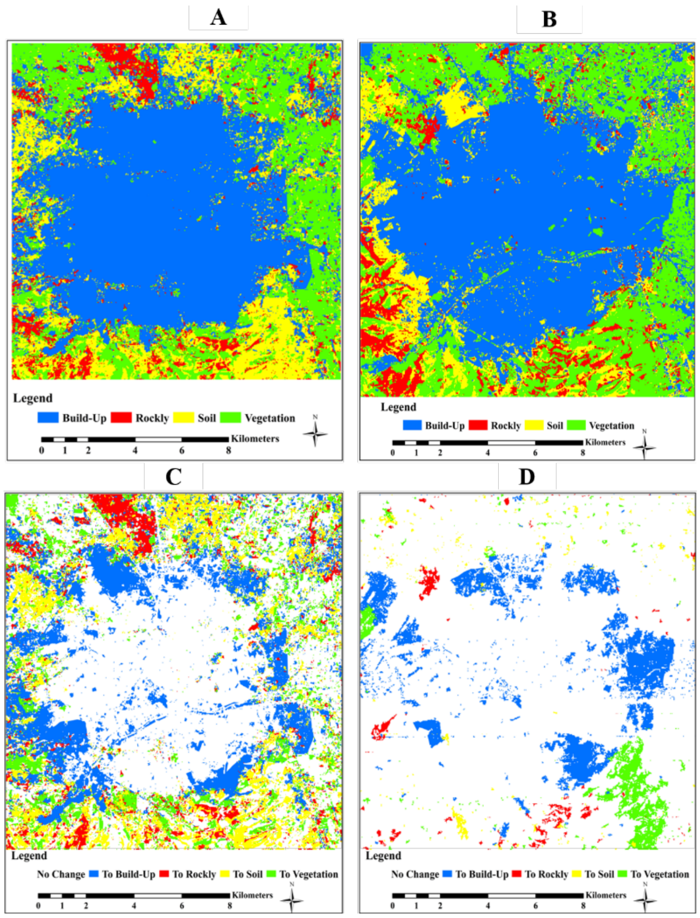


curacy values close to the ANN technique. The ANN technique map has the lowest vicinity of rocky lands. Although it has the lowest completeness, but correctness and the quality of forecast are highest.

In the case of build-up, the highest completeness and quality are related to the CA-Markov method, and the highest correctness is related to the ANN method. In soil, the highest completeness and quality are related to the ANN method, and the highest correctness is related to the CA-Markov method. Also, in the case of vegetation, the best statistics are for the CA-Markov method. In terms of average (all LULCs), the highest completeness and quality were related to the ANN method and the highest correctness was associated with the CA-Markov method.

In conclusion, the results of the indices and subsequently the typical mean of the two algorithms ANN and CA-Markov, are very close to each other, but the ANN technique had the perfect mean in the two indices of completeness and quality and the CA-Markov algo-rithm had the easiest imply correctness. Therefore, the urban and vegetation LULCs in the CA-Markov algorithm and the soil and rock LCs in the ANN algorithm are better simulat-ed, the most vital factor that can be deduced from table 3. the biggest result of this research is the CA-Markov algorithm has been greater profitable in figuring out phenomena with wider and more continuous surfaces, and the ANN algorithm has covered the locations in simulating phenomena that is smaller areas in the map and include a less percentage of the area.

Figure 5 of the LULC prediction map for 2030 by CA-Markov and ANN, is shown in the pinnacle row and the map of changes in the duration 2020-2030 is proven in the bottom row. The change map is obtained of comparing of the map predicted by the algorithms (for 2030) and the LULC map for 2020 using the maximum likelihood algorithm.



Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 5 August 2022 doi:10.20944/preprints202208.0119.v1



**Figure 5.** LULC prediction map for 2030(a; CA-Markov b; ANN) and the 2020-2030 changes (c; change map by CA-Markov d; change map by ANN)

According to figure 5, it is shown that the CA-Markov reveal more changes compared to ANN. In both methods, the East side changes more than the West side of the studies re-gion. In accordance with the presented map, CA-Markov shows more changes. To de-pict the degree of the LULC change, the area of each LULC in 2030 is shown in Figure 6.

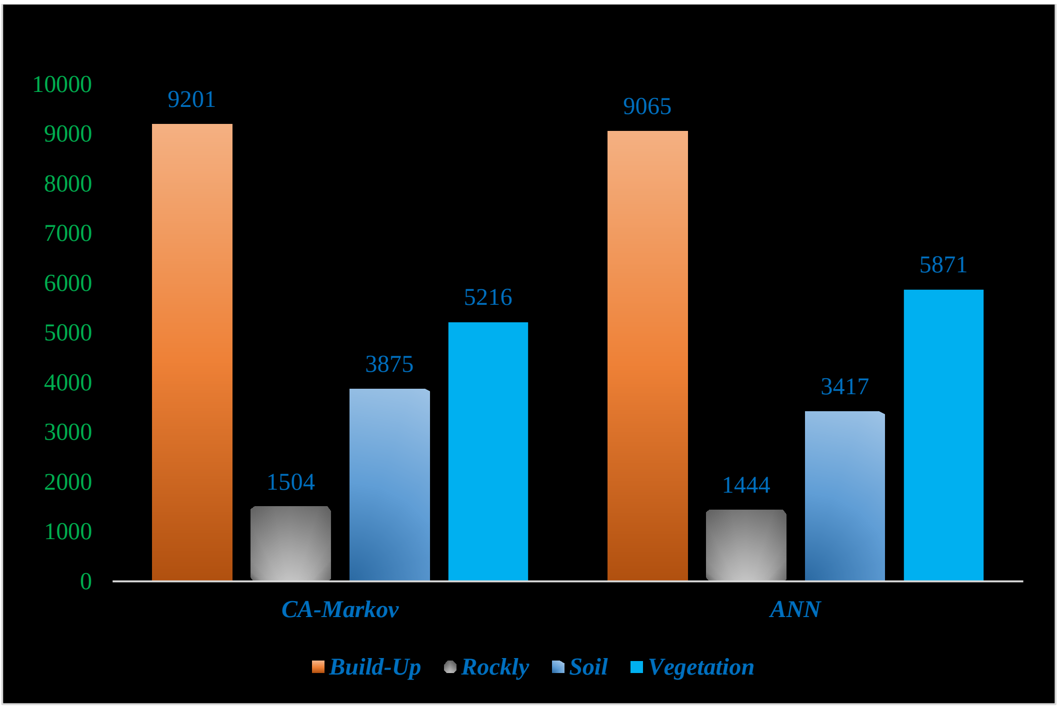



**Figure 6.** The diagram of LULC areas (ha) in 2030

According to Figure 6, the built-up's LU area in this study area will reach more than 9,000 hectares in 2030, which considering this issue in 2000, the area of this land use was less than 6,000 hectares, shows that the city of Urmia and Its habitat for environmental factors will extend by 50% over the in 30 years. Based on the data presented in table 3; it can be guessed that the area and the map of LULCs of urban (built-up) and vegetation are done through CA-Markov and the map and area of soil and rocky lands occur through ANN methods. According to Figure 6, it is proved that LULCs are similar in area are more reliable in terms of evaluation parameters (smaller zones in ANN and larger zones in CA-Markov).

The built-up areas were growing in each two methods, which decreased the area of vegetation. The largest difference in area between land uses derived from 2030 forecast algorithms is related to soil LC; this can be understood from the validation results of table 3 since the precision, quality and completeness statistics of this land use are lower than those of other land uses and are the greatest statistical discrepancy in the use of this land with other algorithms.

This investigation pointed that the Urmia urban area too expanded (Lotfata & Lot-fata, 2018). This indicates that the built-up areas will occupy many natural and ag-ricul-tural resources and this land change situation poses a threat to natural life (Mo-baraki et al., 2012). In addition, the performances of the methods were compared by ap-plying dif-ferent prediction methods such as, CA-Markov, and ANN. This type of LULC prediction study has been investigated in many other regions all over the world includ-ing Thimphu

 doi:10.20944/preprints202208.0119.v1



city, in Bhutan (Wang et al., 2021), Majang Forest Biosphere Reserves of Gambella in Southwestern Ethiopia (Tadese et al., 2021), Orkhon Province in Mongolia (Vandansambuu et al., 2020) and the north-east of the Iran (Rahnama, 2021). However, unlike these studies, the present study, which was conducted in the Urmia city, two pop-ular LULC prediction methods, which are widely used in the literature, were imple-mented and compared in a single study. Thus, this study regarding the comparison of LULC prediction methods in Urmia city significantly contributes to the literature.

**5. Conclusion:**

Getting a proper land-use map will pave the way for local planners' management survey decisions, monitoring environmental hazards such as soil erosion, flooding, landslides, degradation of pastures, and so on. Landsat images with a long imaging rec-ord can be an excellent archive to research the shift in an area's land-use land cover. Suburban change is more vulnerable in terms of changes in human exploitation than other places, particularly to the profiteers of the city, and is more subject to change.

Urmia has been Iran's top city in terms of development in recent decades and accordingly, analyzing its land-use land-cover changes is significant. More importantly, predicting the urban development pattern and the region's changes can be crucial for urban investors, local residents and landowners. Various algorithms exist to forecast land use and are slightly or generally different from each other in their structures. Knowing this issue that which algorithm functions better helps the researchers use the most efficient one in their future research.

In this study, four uses of land, urban (constructed), rocky areas, vegetation cover and soil were identified in Urmia in 2000, 2010 and 2020 by satellite images and their land-use land-cover satellite images were taken. Nevertheless, since LULC prediction is more important and there are different prediction algorithms, this study compared CA-Markov, and ANN algorithms. Preliminary findings from the LULC map indicate that the city's growth was positive, while on the other hand the areas covered by soil and vegetation were limited and the rocky areas almost remained unchanged.

**6. finding:**

The results of the LULC forecast for 2020 for two algorithms were consistent with the current land-use map, which indicates that all other parameters in each two algorithms and parameters were higher than 90%. 96.47 correctness in the CA-Markov algorithm and 96.21 completeness and 93.8 quality in the ANN algorithm have demonstrated these algorithms' excellent region prediction. the CA-Markov algorithm had the highest com-pleteness for rock cover. but the ANN process, which shows rocky terrain a little less than reality, has low completeness but has high correctness and quality.

On the other hand, in soil land cover, the ANN method had the highest completeness and quality and the CA-Markov algorithm had the highest correctness, but in vegetation, all three statistics showed superiority CA-Markov method. In terms of average criteria used in all LULCs, the CA-Markov algorithm had the highest completeness and the ANN algorithm had the highest correctness and quality.

To sum up, both algorithms CA-Markov and the ANN perform good in a way that one cannot decide which algorithm excels over the other and thus more testing is required. Yet, as a result of this study it was obvious that the CA-Markov method is more efficient in predicting land-use land-covers with higher percentages of land, compared to the ANN method which presents a better prediction when it comes to a smaller area.

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 5 August 2022 doi:10.20944/preprints202208.0119.v1



**References:**


1. Abedini, A. (2018). “Measurement of Urban Sprawl Using Spatial-temporal Data (Case Study: City of Urmia)”. Motaleate Shahri, 7(25), 63-76.
2. Abedini, A. and Khalili, A., 2019. “Determining the capacity infill development in grow-ing metropolitans: A case study of Urmia city”. Journal of Urban Management, 8(2), pp.316-327.
3. Abedini, A., Khalili, A. and Asadi, N., 2020. “Urban Sprawl Evaluation Using Landscape Metrics and Black-and-White Hypoth-esis (Case Study: Urmia City)”. Journal of the Indian Society of Remote Sensing, 48(7), pp.1021-1034.
4. Abedini, A., Mosayebzade, A. and Shokrani, M., 2015. “Urban Physical Development of Urmia City by Quantitative Models”. Human Geography Research, 47(3), pp.411-422.
5. Abuelaish, B., Olmedo, M. T. C. 2016. “Scenario of land use and land cover change in the Gaza Strip using remote sensing and GIS models.” Arab J Geoscience 9 (274).
6. Al Rifat, S.A. and Liu, W., 2022. “Predicting future urban growth scenarios and potential urban flood exposure using Artificial Neural Network-Markov Chain model in Miami Metropolitan Area”. Land Use Policy, 114, p.105994.
7. Anderson, K., Ryan, B., Sonntag, W., Kavvada, A., & Friedl, L. 2017. “Earth observation in service of the 2030 Agenda for Sus-tainable Development.” Geo-spatial Information Sci-ence, 20(2), 77-96.
8. Arsanjani, J. J., Helbich, M., Kainz, W., & Boloorani, A. D. 2013. “Integration of logistic re-gression, Markov chain and cellular automata models to simulate urban expansion.” In-ternational Journal of Applied Earth Observation and Geoinformation, 21, 265-275.
9. Baqa, M.F., Chen, F., Lu, L., Qureshi, S., Tariq, A., Wang, S., Jing, L., Hamza, S. and 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), p.700.
10. Bonan, G. B. 2008. “Forests and climate change: forcing, feedbacks, and the climate bene-fits of forests.” Science, 320(5882), 1444-1449.
11. Buya, S., Tongkumchum, P., & Owusu, B. E. 2020. “Modelling of land-use change in Thailand using binary logistic regression and multinomial logistic regression.” Arabian Journal of Geosciences, 13, 437.
12. Chitsazan, M., Aghazadeh, N., Mirzaee, Y. and Golestan, Y., 2019. “Hydrochemical characteristics and the impact of anthropo-genic activity on groundwater quality in sub-urban area of Urmia city, Iran”. Environment, development and sustainability, 21(1), pp.331-351.
13. Dadashpoor, H., & Salarian, F. 2020. “Urban sprawl on natural lands: Analyzing and predicting the trend of land use changes and sprawl in Mazandaran city region, Iran.” Environment, Development and Sustainability, 22(2), 593-614.
14. De Almeida, A. S., Vieira, I. C. G., & Ferraz, S. F. 2020. “Long-term assessment of oil palm expansion and landscape change in the eastern Brazilian Amazon.” Land Use Policy, 90, 104321.
15. Duan, Y., Wang, X., & Wei, Y. 2020. “Land use change analysis of Daishan Island using multi-temporal remote sensing imagery.” Arabian Journal of Geosciences, 13(15), 1-9.
16. Feddema, Johannes J., Keith W. Oleson, Gordon B. Bonan, Linda O. Mearns, Lawrence E. Buja, Gerald A. 2005 Meehl, and Warren M. Washington. "The importance of land-cover change in simulating future climates." Science 310, no. 5754: 1674-1678.
17. Foley, J. A., DeFries, R., Asner, G. P., Barford, C., Bonan, G., Carpenter, S. R., ... & Helkow-ski, J. H. 2005. “Global consequences of land use”. Science, 309(5734), 570-574.
18. Foody, G. M. 2002. “Status of land cover classification accuracy assessment.” Remote sensing of environment, 80(1), 185-201.
19. Gharakhanlou, N.M. and Hooshangi, N., 2020. “Spatio-temporal simulation of the novel coronavirus (COVID-19) outbreak using the agent-based modeling approach (case study: Urmia, Iran)”. Informatics in Medicine Unlocked, 20, p.100403.
20. Ghosh, P., Mukhopadhyay, A., Chanda, A., Mondal, P., Akhand, A., Mukherjee, S., & Hazra, S. 2017. “Application of cellular automata and Markov-chain model in geospatial environmental modeling - a review.” Remote Sens Appl Soc Environ, 5: 64–77.
21. Girma, R., Fürst, C. and Moges, A., 2022. “Land use land cover change modeling by inte-grating artificial neural network with cellular Automata-Markov chain model in Gidabo river basin, main Ethiopian rift”. Environmental Challenges, 6, p.100419.
22. Green, K., Kempka, D., & Lackey, L. 1994. “Using remote sensing to detect and monitor land-cover and land-use change.” Photogrammetric engineering and remote sensing, 60(3), 331-337.
23. Chen, Y. and Huang, L., 2019. "Modeling growth curve of fractal dimension of urban form of Beijing". Physica A: Statistical Mechanics and its Applications, 523, pp.1038-1056.
24. Hütt, C., Koppe, W., Miao, Y., & Bareth, G. 2016. “Best accuracy land use/land cover (LULC) classification to derive crop types using multi-temporal, multi-sensor, and mul-ti-polarization SAR satellite images.” Remote sensing, 8(8), 684.
25. Islam, K., Rahman, M. F., & Jashimuddin, M. 2018. “Modeling land use change using cellular automata and artificial neural network: the case of Chunati Wildlife Sanctuary, Bangladesh.” Ecological indicators, 88, 439-453.
26. Jantz, C. A., Goetz, S. J., & Shelley, M. K. 2004. “Using the SLEUTH urban growth model to simulate the impacts of future policy scenarios on urban land use in the Balti-more-Washington metropolitan area.” Environment and Planning B: Planning and De-sign, 31(2), 251-271.
27. Chen, Y.G., 2018. “Logistic models of fractal dimension growth of urban morpholo-gy”. Fractals, 26(03), p.1850033.

28. Keshtkar, H., Voigt, W., & Alizadeh, E. 2017. "Land-cover classification and analysis of change using machine-learning classifiers and multi-temporal remote sensing imagery." Arabian Journal of Geosciences, 10(6), 1-15.
29. Khaledi, S., Ghahroudi Tali, M. and Farahmand, G., 2021. "Measuring and Evaluating the Resilience of Urban Areas Against Urban Flooding (Case Study: Urmia City)". Sustainable Development & Geographic Environment, 2(3), pp.169-182.
30. Khedmatzadeh, A., Mousavi, M.N. and Mohammadi Torkamani, H., 2021. "An Analysis on Land Use Process Changes and Forecasting in Urmia City Using SVM Model and Neural Networks". Iranian Journal of Remote Sensing & GIS, 12(4), pp.53-72.
31. Kim, K. D., Lee, S., & Oh, H. J. 2009. "Prediction of ground subsidence in Samcheok City, Korea using artificial neural networks and GIS." Environmental Geology, 58(1), 61-70.
32. Kisamba, F.C. and Li, F., 2022. "Analysis and modelling urban growth of Dodoma urban district in Tanzania using an integrated CA–Markov model". GeoJournal, pp.1-22.
33. Kolli, M. K., Opp, C., Karthe, D., & Groll, M. 2020. "Mapping of Major Land-Use Changes in the Kolleru Lake Freshwater Ecosystem by Using Landsat Satellite Images in Google Earth Engine." Water, 12(9), 2493.
34. Hamad, R., Balzter, H., & Kolo, K. 2018. "Predicting land use/land cover changes using a CA-Markov model under two different scenarios." Sustainability, 10(10), 3421
35. Liu, J., Liu, M., Tian, H., Zhuang, D., Zhang, Z., Zhang, W., & Deng, X. 2005. "Spatial and temporal patterns of China's cropland during 1990–2000: an analysis based on Landsat TM data." Remote sensing of Environment, 98(4), 442-456.
36. Lotfata, Y. and Lotfata, A., 2018. "Effect of physical changes on the spatial structure of historical area, the Historical District of Urmia city as a case study". Journal of Sustainable Development, 11(4), p.174.
37. Luo, G., Zhou, C., & Chen, X. 2003. "Process of land use/land cover change in the oasis of arid region." ACTA Geographica Sinica-Chinese Edition, 58(1), 63-72.
38. Maleki, M., Tavakkoli Sabour, S. M., Zeaieanfirouzabadi, P., & Raeisi, M. 2018. "Compar-ison of optic and radar data for Terrain feature extraction." Journal of RS and GIS for Natural Resources, 9(2), 93-107.
39. Maleki, M., Tavakkolisabour, S. M., Arjmand, B., & Rahmati, M. 2017. "Simultaneous Analysis of Radar Look Angle and Placement of Features to Identification of Terrain Feature (Mianrahan Basin in West of Iran)." International Journal of Landscape Planning and Architecture, Vol. 3: Issue 1, pp 1-12.
40. Maleki, M., Tavakkoli-Sabour, S. M., Rahmati, M., & Arjomand, B. 2017. "Statistical Inte-gration of Radar and Optical Data for Geomorphological Feature Extraction." Interna-tional Journal of Image Processing and Pattern Recognition, 3(1), 1-10.
41. Maleki, M., Van Genderen, J. L., Tavakkoli-Sabour, S. M., Saleh, S. S., & Babaee, E. 2020. "Land Use/Cover Change In Dinevar Rural Area Of West Iran During 2000-2018 And Its Prediction For 2024 And 2030." Geographia Technica, Vol. 15, Issue 2, pp 93-105
42. Malik, A. and Bhagwat, A., 2021. "Modelling groundwater level fluctuations in urban areas using artificial neural network". Groundwater for Sustainable Development, 12, p.100484.
43. Mansour, S., Al-Belushi, M., & Al-Awadhi, T. 2020. "Monitoring land use and land cover changes in the mountainous cities of Oman using GIS and CA-Markov modelling tech-niques." Land Use Policy, 91, 104414.
44. Mc Cutchan, M., Özdal‐Oktay, S., & Giannopoulos, I. 2020. "Semantic‐based urban growth prediction." Transactions in GIS, 24(6), 1482-1503.
45. Mishra, V. N., & Rai, P. K. 2016. "A remote sensing aided multi-layer perceptron-Markov chain analysis for land use and land cover change prediction in Patna district (Bihar), India." Arabian Journal of Geosciences, 9(4), 249.
46. Mobaraki, O., Mohammadi, J. and Zarabi, A., 2012. "Urban form and sustainable devel-opment: The case of Urmia City". Journal of Geography and Geology, 4(2), p.1.
47. Mohammadi, A., Ghassoun, Y., Löwner, M. O., Behmanesh, M., Faraji, M., Nemati, S., ... & Miri, M. (2020). Spatial analysis and risk assessment of urban BTEX compounds in Ur-mia, Iran. Chemosphere, 246, 125769.
48. Mondal, M. S., Sharma, N., Garg, P. K., & Kappas, M. 2016. "Statistical independence test and validation of CA Markov land use land cover (LULC) prediction results." The Egyp-tian Journal of Remote Sensing and Space Science, 19(2), 259-272.
49. Munthali, M. G., Mustak, S., Adeola, A., Botai, J., Singh, S. K., & Davis, N. 2020. "Model-ling land use and land cover dynamics of Dedza district of Malawi using hybrid Cellular Automata and Markov model." Remote Sensing Applications: Society and Environment, 17, 100276.
50. Mustafa, A., Ebaid, A., Omrani, H. and McPhearson, T., 2021. "A multi-objective Markov Chain Monte Carlo cellular automata model: Simulating multi-density urban expansion in NYC". Computers, Environment and Urban Systems, 87, p.101602.
51. Nouri, J., Gharagozlou, A., Arjmandi, R., Faryadi, S. and Adl, M., 2014. "Predicting urban land use changes using a CA–Markov model". Arabian Journal for Science and Engineer-ing, 39(7), pp.5565-5573.
52. Pflugmacher, D., Rabe, A., Peters, M., & Hostert, P. 2019. "Mapping pan-European land cover using Landsat spectral-temporal metrics and the European LUCAS survey." Re-mote sensing of environment, 221, 583-595.
53. Pindozzi, S., Cervelli, E., Recchi, P. F., Capolupo, A., & Boccia, L. 2017. "Predicting land use change on a broad area: Dyna-CLUE model application to the Litorale Domizio-Agro Aversano (Campania, South Italy)." Journal of Agricultural Engineering, 27-35.
54. Rahman, M. T. U., Tabassum, F., Rasheduzzaman, M., Saba, H., Sarkar, L., Ferdous, J., ... & Islam, A. Z. 2017. "Temporal dynamics of land use/land cover change and its predic-tion using CA-ANN model for southwestern coastal Bangladesh." Environmental moni-toring and assessment, 189(11), 1-18.

55. Rahnama, M. R. (2021). Forecasting land-use changes in Mashhad Metropolitan area using Cellular Automata and Markov chain model for 2016-2030. Sustainable Cities and Society, 64, 102548.
56. Roy, S., Farzana, K., Papia, M., & Hasan, M. 2015. “Monitoring and prediction of land use/land cover change using the integration of Markov chain model and cellular auto-mation in the Southeastern Tertiary Hilly Area of Bangladesh.” Int. J. Sci. Basic Appl. Res, 24, 125-148.
57. 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 Comput-er Modelling, 54(3-4), 938-943.
58. Saputra, M. H., & Lee, H. S. 2019. “Prediction of land use and land cover changes for north Sumatra, Indonesia, using an artificial-neural-network-based cellular automaton.” Sustainability, 11(11), 3024.
59. Saxena, A., & Jat, M. K. 2019. “Capturing heterogeneous urban growth using SLEUTH model.” Remote Sensing Applications: Society and Environment, 13, 426-434.
60. Subedi, P., Subedi, K., & Thapa, B. 2013. “Application of a hybrid cellular automaton–Markov (CA-Markov) model in land-use change prediction: a case study of Saddle Creek Drainage Basin, Florida.” Applied Ecology and Environmental Sciences, 1(6), 126-132.
61. Tadese, M., Kumar, L., Koech, R., & Kogo, B. K. 2020. “Mapping of land-use/land-cover changes and its dynamics in Awash River Basin using remote sensing and GIS.” Remote Sensing Applications: Society and Environment, 19, 100352.
62. Tadese, S., Soromessa, T., & Bekele, T. 2021. “Analysis of the current and future predic-tion of land use/land cover Change using remote sensing and the CA-markov model in majang forest biosphere reserves of Gambella, southwestern Ethiopia.” The Scientific World Journal, 2021.
63. Takada, T., Miyamoto, A., & Hasegawa, S. F. 2010. “Derivation of a yearly transition probability matrix for land-use dynamics and its applications.” Landscape ecology, 25(4), 561-572.
64. Tang, J., Li, Y., Cui, S., Xu, L., Ding, S., & Nie, W. 2020. “Linking land-use change, land-scape patterns, and ecosystem services in a coastal watershed of southeastern China.” Global Ecology and Conservation, 23, e01177.
65. Tayyebi, A., Delavar, M. R., Yazdanpanah, M. J., Pijanowski, B. C., Saeedi, S., & Tayyebi, A. H. 2010. “A spatial logistic regression model for simulating land use patterns: a case study of the Shiraz Metropolitan area of Iran.” In Advances in earth observation of global change (pp. 27-42). Springer, Dordrecht.
66. Turner, B. L., Lambin, E. F., & Reenberg, A. 2007. “The emergence of land change science for global environmental change and sustainability.” Proceedings of the National Academy of Sciences, 104(52), 20666-20671.
67. Vandansambuu, B., Davaa, T., Gantumur, B., Purevtseren, M., Lkhagva, O., & Wu, F. 2020. “Spatiotemporal monitoring and prediction of land use/land cover changes using CA-Markov chain model: a case study in Orkhon Province, Mongolia”. In Remote Sens-ing Technologies and Applications in Urban Environments V (Vol. 11535, p. 115350E). International Society for Optics and Photonics.
68. Veldkamp, A., & Lambin, E. F. 2001. “Predicting land-use change.” Agriculture, Ecosys-tems and Environment 85, 1–6
69. Wang, S. W., Munkhnasan, L., & Lee, W. K. 2021. “Land use and land cover change de-tection and prediction in Bhutan's high-altitude city of Thimphu, using cellular automa-ta and Markov chain.” Environmental Challenges, 2, 100017.
70. Wang, X. Z., Zheng, Y. H., & Li, S. 2006. “Analysis of land use and landscape pattern change in west of Hainan Island.” Journal of Desert Research, 26(3), 409-414.
71. Wang, X., Li, J., Zheng, T., Diao, S., Zhang, X. and Tian, Y., 2022. “Constructing Land-scape Ecological Security Patterns of an Ancient Capital Based on Cellular Automata Theory”. Urban Science, 6(2), p.29.
72. Yi, S., Zhou, Y., & Li, Q. (2022). “A New Perspective for Urban Development Boundary Delineation Based on the MCR Model and CA-Markov Model”. Land, 11(3), 401.
73. Zare Naghadehi, S., Asadi, M., Maleki, M., Tavakkoli-Sabour, S. M., Van Genderen, J. L., & Saleh, S. S. 2021. “Prediction of Urban Area Expansion with Implementation of MLC, SAM and SVMs’ Classifiers Incorporating Artificial Neural Network Using Landsat Da-ta.” ISPRS International Journal of Geo-Information, 10(8), 513.
74. Zhou, L., Dang, X., Sun, Q. and Wang, S., 2020. “Multi-scenario simulation of urban land change in Shanghai by random forest and CA-Markov model”. Sustainable Cities and Soci-ety, 55, p.102045.
75. Ziari, K. and Zakerhaghighi, K., 2022. “Measuring the Effective Variables on Urban Ex-pansion and Physical Development Simulation of Hamadan City Using Integrated Mod-el of Cellular automata, Logistic Regression and Markov Chain”. Journal of Studies of Hu-man Settlements Planning.
76. Xu, E. and Chen, Y., 2019. "Modeling intersecting processes of wetland shrinkage and urban expansion by a time-varying methodology". Sustainability, 11(18), p.4953.
77. Wang, Y., Sha, Z., Tan, X., Lan, H., Liu, X. and Rao, J., 2020. “Modeling urban growth by coupling localized spatio-temporal association analysis and binary logistic regres-sion”. Computers, Environment and Urban Systems, 81, p.101482.
78. Kaviari, F., Mesgari, M.S., Seidi, E. and Motieyan, H., 2019. “Simulation of urban growth using agent-based modeling and game theory with different temporal resolu-tions. Cities, 95, p.102387.
79. Xu, T., Gao, J., Coco, G., & Wang, S. (2020). “Urban expansion in Auckland, New Zea-land: a GIS simulation via an intelligent self-adapting multiscale agent-based mod-el”. International Journal of Geographical Information Science, 34(11), 2136-2159.