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# Predicting spatial and decadal of land use and land cover change using integrated cellular automata Markov chain model based scenarios (2019–2049) Zarriné-Rūd River Basin in Iran ☆

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A B S T R A C T

Effective land use and land cover (LULC) change assessment requires tools to measure past, current, and based on them to create a future scenario. LULC changes are unavoidable in the world, particularly in developing countries. Since LULC are too dynamic and complicated without the identification of appropriate methods and approaches the future perdition will be less accurate. Therefore, the integrated Cellular Automata Markov chain (CA-Markov) model is known as a capable estimator. In this study, LULC changes in Zarriné-Rūd River Basin (ZRB) in Iran was analyzed based on different images and data extracted from satellite data in 1989 and 2019 to create the LULC scenario in 2049. The model was validated using actual and projected to 2019. The overall agreement on two extracted maps was 97.85% in 1989 and 96.55% in 2019. The more detailed analysis of validation of calibration based on the kappa showed the highest data reliability of 0.98 in 1989 and 0.95 in 2019, respectively. According to the transition matrix of probabilities, the most significant changes in the ZRB based on the past scenario (1989–2019) is in rainfed and built up land classes of LULC in 2049. Concurrently, the other classes continue to decline except irrigated agriculture and water bodies. The results obtained showed that the pasture and mountain LULC class had continued to reduce more than other classes. Furthermore, water resources and the amount of the precipitation in past and future are important to spatial and temporal expansion on LULC classes.

## 1. Introduction

Land Use and Land Cover (LULC) change has become a global concern, as their changes affect the global system (Di Gregorio, 2005; Hailu et al., 2020). Land use consists of all types of different use of land for different human needs. The most important prerequisites are the optimal use of land, knowledge of land use patterns, and knowing the changes of each over time. LULC change usually occurs in two forms (conversion) and change (Ildormi et al., 2015). LULC changes have a huge contribution to the different impacts of climate change (Keshtkar and Voigt, 2016).

The role of the human factor in reducing the physical quality of environmental resources is substantial and it can affect the environmental quality (e.g. water, soil, and air). The human impact in LULC resources appeared at locally, regionally, and globally (Bhattacharya et al., 2020), inland surface temperature rising (Gohin et al., 2020), rainfall distribution (Pielke Sr. et al., 2007). Hydraulic cycle and quality of groundwater (Scanlon et al., 2005), ecosystem services disturbance (Schilling et al., 2008), ecohydrological impacts (e.g. arid and semi-arid rivers basin) (Huang et al., 2020), extremes increase (FindellBerg et al., 2017), mitigation policies (Rice, 2010). Therefore, the quality of land cover is formed complex interactions between ecological, physical, and hydrological characteristics in particular area (Chemura et al., 2020). Assessing current spatial and temporal dynamics of LULC is vital to monitor the trend of changes for better future assessment.

The spatial and temporal impacts of rapid land-use change go beyond urban and rural boundaries (Kojuri et al., 2020; Kamran et al., 2020). The excessive use of LULC for different political and economic purposes can reduce the current and future capacities of the appropriate use of land. As a prime example, socioeconomic aspects of land-use change in the agriculture sector become a serious issue when the drought impacts have been followed by the expansion of roads and public trans-

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portation, which has made land abandonment in rural areas due to residents' easier and faster movements. Consequently, productivity reduction, unsustainable agricultural development, many environmental and socioeconomic issues with strong spatial and temporal impact appear (Shafieisabet, 2014). An effective current LULC assessment can reduce the future large numbers of land-lost farmers (Tang et al., 2020). On the other hand, rapid urban development can reduce the rural resources by a wide range of environmental impacts (e.g. habitat quality) (Dewan and Yamaguchi, 2009) as urban expansion and urban sprawl change arable lands to other urban land uses and threaten natural resources (He et al., 2013).

Appropriate current and future use of land is key to an effective assessment for standardization and compatibility between data sets and the possibility to map. In comparison to other, logistic regression models (is able to mix with other models but does not explain the weights of the driving forces). (Tayyebi et al., 2010), the Land transformation model (Li et al., 2012) the CA_Markov is a mixed model including the concept of both cellular automata (CA) (an open configuration that without difficulty integrated with knowledge-driven models) and Markov Chain (Modeling spatiotemporal dynamic high accuracy result). When, The Markov chain is made with a set of probability values that show the probability of converting user interfaces over a period of time, depending on the amount of change in the past. Theoretically, a certain part of the earth may change from one land use group to another at any time (Brown et al., 2000). Markov chain analysis uses matrices to analyze all land use changes among all unique groups available to display land uses. The accuracy and reliability of the Markov chain model have increased the application of this model for different LULC studies in the last three decades (Caswell and Etter, 1993; Nadoushan et al., 2015; Houet and Hubert-Moy, 2006). CA-Markov is used to assess transition probabilities of several land use interactions at different times. These transitions in different scales provide spatial domination of one or more one land uses in comparison to other land uses. In this method, the matrix the changes in the area indicate how much the number of pixels will change from one land use class to another in certain periods. In Markov chain analysis, coating classes have been used as chain states.

The Markov chain model analyzes land use zoning images and provides an output in the form of a possible change matrix and an output image from a possible change matrix for the final year. A possible change matrix shows how likely each class of land use classification will change to another land use in the future. Markov chain and cellular automata model is one of the most effective land use change simulation models, which is known as a bottom-up approach. As a user-friendly model for future LULC prediction through the identification of dynamics of complex systems and prediction of the future spatial model. In addition, it is recognized as a useful two-dimensional method to show both the spatial and temporal dynamics of place and space dynamics (Stevens et al., 2007; Ye and Bai, 2007, August). Effectiveness of the Markov model has been proven in different scales and with high accuracy in tropical and subtropical areas (Gidey et al., 2017). Recent advancements in remote sensing and Geographical Information Systems GIS improve computing and modeling accuracy.

In this paper, we proposed a Cellular Automata-Markov Chain model (CA-Markov) as an alternative to simulate a counterfactual scenario. A Markov chain model is commonly used to quantify transition probabilities of multiple land cover categories from discrete time steps. These probabilities are then used with a CA model to predict spatially explicit changes over a certain period of time. The footstone of a CA-Markov model is an initial distribution and a transition matrix, which assumes that the drivers that produce the detectable patterns of land cover categories will continue to act in the future as they had been in the past (Briassoulis, 2000). This very assumption makes a CA-Markov model suitable for a counterfactual approach since we are interested to extrapolate the pre-intervention landscape into the future assuming no change in the form of intervention.

In this study historical and current analyzed to show future LULC changes in the Zarriné-Rūd River Basin (ZRB) of the North West in Iran. Due to the high concentration of agricultural activities in this area natural resources become a serious issue in (ZRB). The aim of this study is to simulate each LULC based on integrating cellular automata (CA) and Markov Chain in our study area in the (ZRB) which is a river in Kurdistan Province and West Azarbaijan Province. This paper is organized as follows. Section 2, preparation of data from 1989 to 2019 LULC map and using the Markov model to forecast, to increase simulation accuracy in 2049. section 3 introduces the methodology, tools, software, and support of the Markov model and cellular automata (CA) mix. Section 4 discusses findings of "the CA–Markov model simulation from "2019 to 2049″ and application approaches, and at the end concluded with pick points and summary of work with some recommendations.

### 1.1. Cellular automata

CA is a mathematical model that shows how different elements in terms of the time changing dramatically and effect of nearest neighbor values. In fact, CA tends to make homogeneous states and produces self-similar patterns. Generally, it uses for more investigation on self-organization and "chaos" in dynamic systems. (Wolfram, 1983). Furthermore, CA shows cell interactions also; it shows quantity and spatial change each value in different cells (Von Neumann, 1951; Arsanjani et al., 2011). Since LULC is very complex and dynamic, CA is dynamic models that are discrete in time, space, and state and mixable with other models. According to geometrical connections and spatial order, cells can change their state in time-space. These changes might be happening in the center of a group of cells or at the border. Usually and geographically, the changes in borders are so common but when the changes start from the center of the group of cells the impacts on the future will be significant (e.g. hydrologic changes). Computation of all these nonlinear dynamical transitions in cell value to another value clarifies negative and positive dimensions of quality of changes.

Alonso-Sanz, and Martín (Alonso-Sanz and Martín, 2004) mentioned CA considering a deterministic, transitional change, from a deterministic to a different type. *"Cellular Automata (CA) are discrete, spatially extended dynamic systems composed of adjacent cells or sites arranged as a regular lattice, which evolves in discrete time steps. Each cell is characterized by an internal state whose value belongs to a finite set. The updating of these states is made simultaneously according to a common local transition rule involving only a neighborhood of each cell* (Alonso-Sanz and Martín, 2004)." Automata considering historic memory of a mechanism when it beginning from a unit or a cell. The spatiotemporal pattern of this mechanism affected by the interaction between these neighboring cells. Where they start to push the other neighboring cells to change their behavior and make them similar.

CA model reliability make it as a popular and effective tool to address LULC changes with integration of the spatial and temporal of the dynamic procedure (Zhou et al., 2020; Karimi et al., 2018). This model adaptable to mix conditional and statistical rules and predict transition each class of land use in the calibrated spatial and temporal scale. Practically, modeler is able to use information influential factors involve to historical LULC changes. Finally, the CA model has to answer how sensitive model was about calibration, classification, parameter value, selected time and space. Also, how was the model performance in terms of simulation of LULC changes, presence and location (Jabbarian Amiri et al., 2017).

### 1.2. Markov chain model

A Markov chain is a random process of a limited condition in a system with transition probabilities pij, where that particular condition moving from point i to point j. These transitions between different parts of this system are different some of them in terms of the time remain

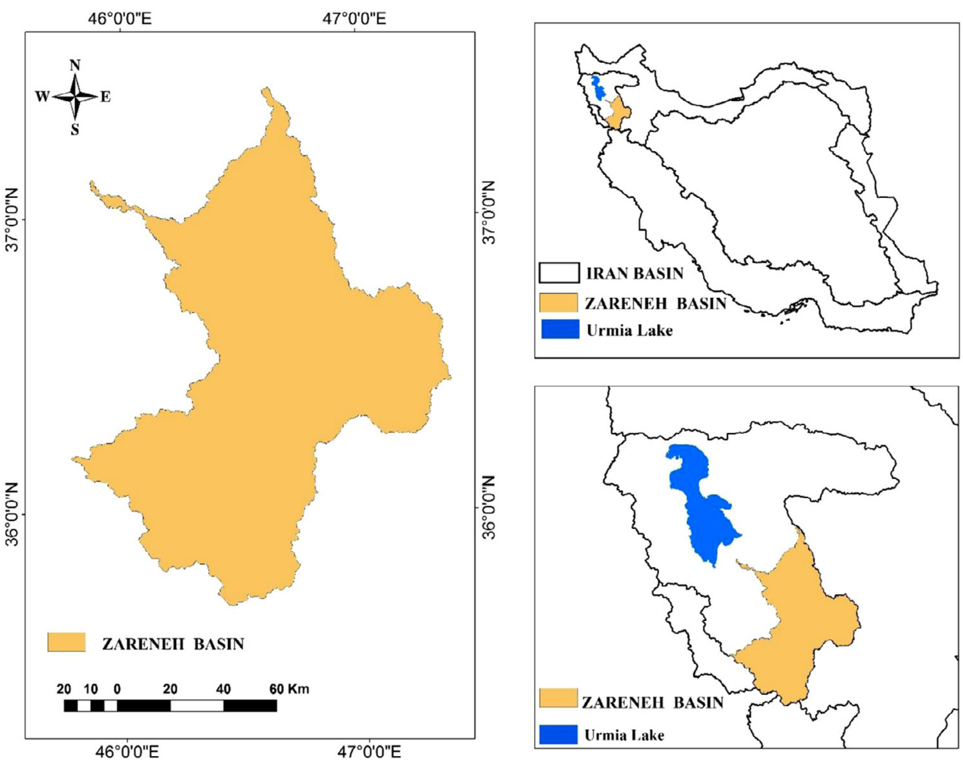


**Fig 1.** Geographical location of the study area.

the same and some of them change to other things. In land use studies, each identified class might remain the same for a long time and some of them change to the other class. That is how a matrix of actual transition probabilities can be used for predicting future land use change based on historical records of each class (Mondal and Southworthe, 2010; Imani Harsini et al., 2017). Due to its dynamic nature as well as its unique characteristics in modeling the natural and physical features of the earth's surface, the model of self-working cells has found wide application in predicting land use change (Alimohammadi et al., 2008).

The Markov chain is a sequence of random processes in which the result of each process at any given time depends only on the result of the process adjacent to it. Nevertheless, the distribution of their probabilities can be different, and each random variable in a Markov chain depends only on the variable before it (Behbahani and Heidarizadi, 2019). The following is a list of random variables:

$$x^{(0)}, x^{(1)}, x^{(2)}, \dots \quad (1)$$

The sample space of random variables in the Markov chain can be continuous or discrete, limited or unlimited. Assuming a limited discrete state for the sample space, any random variable can be represented by its probability distribution. We illustrate this distribution with a vector that holds the probability of each of the values of the sample space. Therefore, another display of the Markov chain is:

$$p_0, p_1, p_2, \dots p_i = \left[p\left(x^i = x_1\right), \dots, p\left(x^i = \bar{x}_n\right)\right] \quad (2)$$

According to the Markov chain definition, knowing the first - (i) of the component (1 –i) of the chain component and the interface that my component produces is enough to make the chain. The conversion of probability vector components by this function is obtained according to Eq. (3):

$$p\left(x^{i+1} = x\right) = \sum p\left(x^i = \tilde{x}\right) T_i(\tilde{x}, \bar{x}) \quad (3)$$

If in the Markov chain the relationship between successive random variables does not depend on their position in the chain, we call the chain homogeneous. The relationship shows 4 homogeneous chains:

$$T_i(\tilde{x}, x) = T_j(\tilde{x}, x) = T(\tilde{x}, x) \quad (4)$$

These relationships can be summarized as matrix 5:

$$T_{nn} = \begin{pmatrix} T\left(X_1, X_1\right) & \dots & T\left(X_1, X_n\right) \\ \dots & \dots & \dots \\ T\left(X_n, X_1\right) & \dots & T\left(X_n, X_n\right) \end{pmatrix} \quad (5)$$

In this analysis, two raster maps are always used called model inputs. In addition, in this model, the two produced maps, the time interval between the two images and the prediction is also considered. The output of the model also includes the possibility of changing the status, the matrix of the converted areas of each rank, and at the end of the images the conditional probabilities for the conversion of different uses. In fact, Markov chain analysis is the process of transition probability matrix for the second time assessment (Future) based on the first time assessment (Past and present) (Asadzadeh et al., 2018; Azizi Ghalati et al., 2016).

### 1.3. CA-Markov model

CA-Markov uses for time and purposes we do not have enough information or our knowledge is too limited by time and other physical barriers, which is the future. CA-Markov Chain model is widely used to show transitional probabilities several LULCs in different time spans. These probabilities used in the CA model to show significant spatial changes LULCs. Furthermore, these changes are correlated with the strong influence of drivers that have made such a pattern and they might continue the same changes in the future (Guan et al., 2011). This is very useful to understand the domination of future LULC and predict its impact on the environment, natural resources, and formation of landscape (Firozjaei et al., 2018). CA model alone is not capable to incorporate different dimensions of the environment in the simulation. However, CA's capability to mix with other models made it very interesting for modelers such as Markov Chain.

CA-Markov Chain model is an effective mixed model to simulate future LULC changes and natural complexity (Soares-Filho et al., 2002;

**Table 1**
SVM classification accuracy for land use.

| Images | SVM classification images | |
|---|---|---|
| | Overall accuracy | Kappa |
| 1989 (Landsat 5) | 97.85 | 0.98 |
| 2019 (Landsat 8) | 96.55 | 0.95 |

Moein et al., 2018; Mirzaeizadeh et al., 2015). The CA-Markov model considers time to show the tendencies and causes of their transitions that will appear in the future. This is how the cells' value changes give a new spatial pattern to the area and these changes associated with a cohesive transition in entire cells over and done with time and space, and this is how the CA-Markov cells change systemically by influence on adjacent neighborhood produces the spatial formation each class. Furthermore, reducing the influence of the center of a specific group of cells will make more influence from the other class and changes will happen very fast. Sometimes in different periods of the time, a group of cells might change to a few different classes this transitions and value of these classes in the whole system can show where and how positive and negative are making the transitions. Significantly, due to uniform transitions rules cells value to change the neighboring cells and turn to make them similar to themselves and these changes bring change in the whole system.

## 2. Materials and methods

### 2.1. Study area

The Zarriné-Rūd River Basin (ZRB) area is located between latitudes 45°48′5.16″E, and 46°12′22.28″E longitudes 36°53′59.37″N and 37° 7′2.16″N northwestern Iran and southeast of Urmia Lake. This area cover over 13,980 km3 (Fig. 1). The Zarriné-Rūd River originates in the northern slopes of the Chehel Cheshmeh Mountains near the Iraq border, and after collecting surface currents, a number of important tributaries such as Saruqchai, Khokhorhachai, Saqezchai and Ajrlou flow from the south to the north and eventually into Lake Urmia. The average annual rainfall of the Zarriné-Rūd River catchment area is estimated at 527 mm, the highest rainfall is in March to May, which covers about 47% of the annual rainfall, and only 7% of the rainfall is in June to October. The average annual temperature is 12.4 centigrade in Zarriné-Rūd dam location. It is estimated that from about −1.8 centigrade in February to 26.5 centigrade. Domination of agriculture activates in the Zarriné-Rūd river basin area made landscape maps in six classes: gardens, water body, built up land, irrigated agriculture, rainfed land, pasture and mountain (Fig. 1).

The ZRB with 11,738 ($Km^2$) area is the most important part of the Urmia Lake catchment area with an area of 51,876 ($Km^2$) area, which is located in the center of Urmia Lake. In terms of national political divisions, it includes the provinces of West Azerbaijan (46%), East Azerbaijan (43%) and Kurdistan (11%). The main watersheds that lead to Urmia Lake are the Zolachay, Nazlu Chai, Rozeh Chai, Shahr Chai, Barandoz Chai, Gadarchay, Mahabad Chai, Simineh Rud, “Zarrineh Rud”, Sufi Chai, Qaleh Chai, and Aji Chai watersheds. In the last two decades, the inflow of surface current to Urmia Lake has significantly decreased from the basins leading to the lake. The main reasons for this decrease are the decrease in the volume of water in the lake, continuous droughts, changing the pattern of cultivation to crops with high water requirements, developing aquaculture lands (Gardens), and increasing the use of surface and groundwater resources.

### 2.2. Data preparation for LULC change analysis

In the context of this study, Google Earth Engine used Satellite data search images to explain LULC changes. The spectral and spatial resolution, the ability to change the terrain, and the availability of these images used Landsat images, including images collected from the actual two satellite observes in 1989 and 2019. Since, the satellite data for the ZRB is exist based on different Landsat data collection in different routes 168 × 35, 168 × 34, and 167 × 35 for (1989 and 2019). This satellite provides high quality and accuracy of the maps which preprocessed both (atmospherically and geometrically).

The satellite maps validation prerequisites are known as guiding examples of the classifications in the study area, with the maps available in The State Organization for Registration of Deeds and Properties. The images transfer in ENVI software and we used the supervised classification of Support Vector Machine (SVM) for pre-identification of the accurate targeted classification. The supervised classification used for the images was classified by the Maximum Likelihood estimation was adopted to supervised classification provide pixel by pixel land use map of the ZRB. Finally, Terrasat software used to process in CA-Markov for predication of the LULC in ZRB for 30 years later. Therefore, six classes Gardens, Water body, Built up land, Irrigated agriculture, Rainfed agriculture, Pasture Mountain ranked as major LULC. To simulate future LLUC changes the accuracy of data was evaluated by Kappa index and shows data collected from Landsat 5 in 1989 at value 97.85 and in 2019 at value 0.95 from Landsat 8 are validated respectably (Table 1).

## 4. Results & discussions

### 4.1. Simulated LULC

#### 4.1.1. LULC transition probabilities and transition matrix of year 2019

After extraction of two different Landsat images in 1989 and 2019, combination of the two images was used to assess the possible quantity and percentage of land use change. The major land use changes in these 30 years of study in Table 2 indicates huge LULC changes in pasture and mountains, irrigated agriculture, and garden. As the collected data shows the pasture and mountain area are the biggest LULC in the ZRB with 74.17% in 1989 and 73.79% in 2019 and water body with 0.67% in 1989 and 0.39% in 2019 is the smallest LULC in the ZRB (Table 2).

The major LULCs changes in the ZRB as shown in Figs. 2 and 3 is followed by a 4.99% increase in rainfed agricultural lands, which is roughly 61.39 $km^2$ during 1898–2019. Similarly, there is a slow but sure increase in built up land by 0.52% during 1989 and 2019, which

**Table 2**
Trend of land use change perdition between 1989, 2019, and 2049.

| Class | 1989 | | 2019 | | 2049 | |
|---|---|---|---|---|---|---|
| | area($Km^2$) | Percent | area($Km^2$) | percent | area($Km^2$) | Percent |
| Gardens | 504.68 | 4.30 | 486.55 | 4.14 | 469.9376 | 4.00 |
| Water body | 78.27 | 0.67 | 45.38 | 0.39 | 44.84268 | 0.38 |
| Built up land | 73.52 | 0.63 | 134.91 | 1.15 | 205.7327 | 1.75 |
| Irrigated agriculture | 1687.01 | 14.37 | 1136.73 | 9.68 | 1162.203 | 9.90 |
| Rainfed | 688.25 | 5.86 | 1273.45 | 10.85 | 1772.205 | 15.10 |
| Pasture and mountains | 8706.82 | 74.17 | 8661.54 | 73.79 | 8083.63 | 68.86 |
| Total | 11,738.55 | 100.00 | 11,738.55 | 100.00 | 11,738.55 | 100.00 |

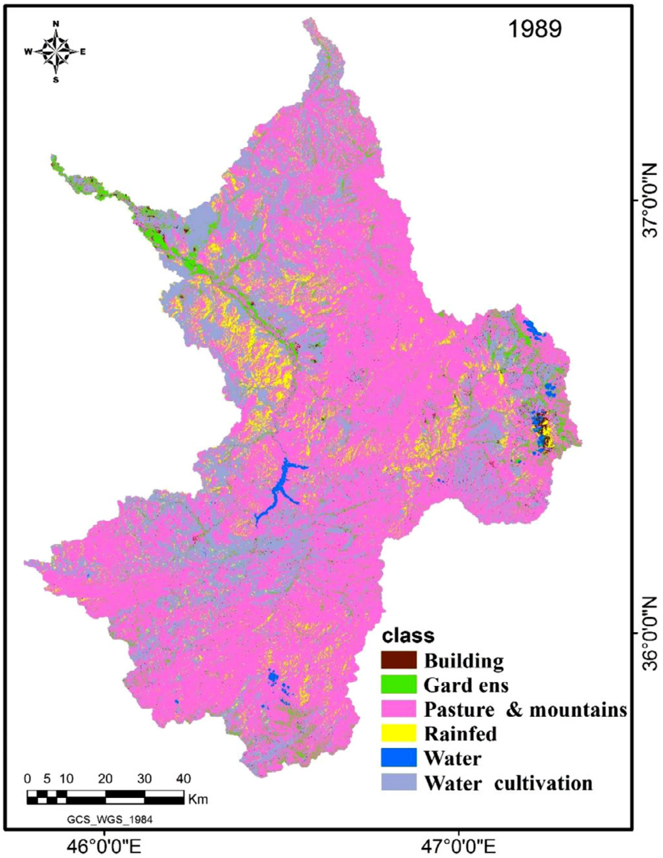


**Fig 2.** Land use map of 1989.

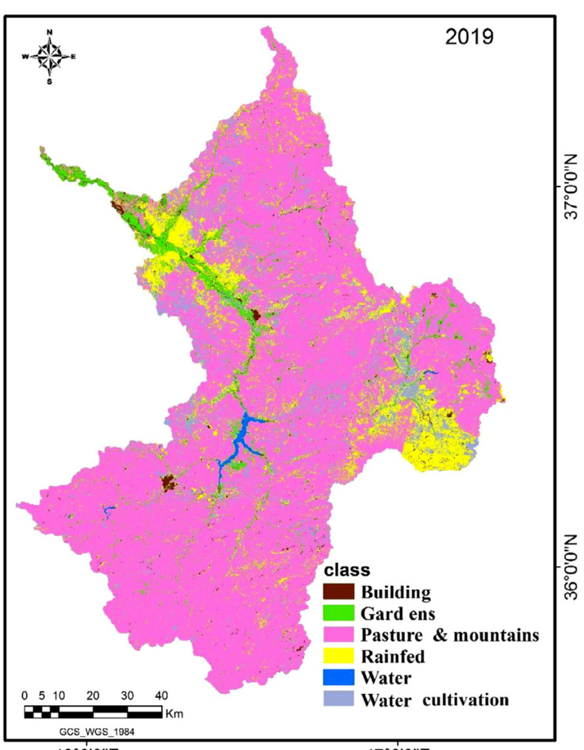


**Fig 3.** Extracted land use map of 2019.

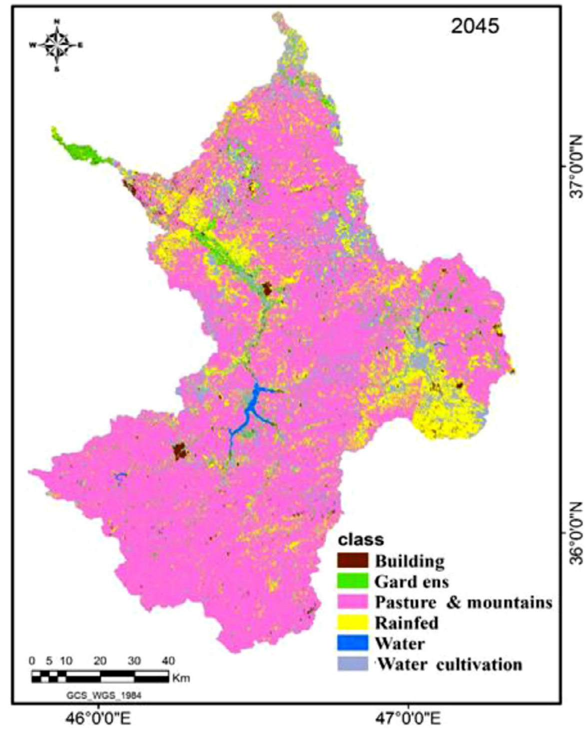


**Fig 4.** The Simulated LULC 2049 through the calibrated CA-Markov model of 1989–2019 period.

is almost 45 $km^2$. Spatially the main class changes are in the east part and the west part of the ZRB shifting from pasture and mountain class to rainfed agricultural lands and garden in the west and northwestern part of the region. In addition, there is huge LULC change from pasture and mountain to rainfed agriculture activities in the east part of the ZRB .

In contrast, irrigated agriculture lands shrank during 1989–2019 considerably about 4.69% equal to 550.28 $km^2$, as well as water body during 1989–2019 decreased 0.28% almost one third of pervious size, which was about 33.89 $km^2$. There are some slower decrease in pasture and mountain by 0.38% which is roughly about 45.28 $km^2$. In the same way, gardens reduced 0.16% approximately 18.13$km^2$.

*4.1.2. Model validation*

In many cases, it is necessary to calculate the amount of information matching the thematic map prepared with the real map of the region. In this way, the thematic map obtained from the classification of satellite images should be compared with the 2-subject map of terrestrial reality to measure the image accuracy. It is not possible to just measure two points in one or two classes to prove how the image is reliable. The LULC class changes in a specific area might be unchanged but the spatial distribution of LULC in the region significantly has changed. Therefore, in parallel with paying attention to the area of the class, their location should also be considered. Various methods have been developed for expressing the number of map readings and matching maps and based on the various, functions that have been provided to do this (Table 1 and Fig. 2 and Fig. 3). The general accuracy criterion shows the percentage of cells that have equal values on the map (depending on their location). Cells that do not match do not meet this criterion. In relation to the observed the accuracy of the error in the expected error matrix, it refers to the correct classification, which may be accompanied by a random agreement between the two images (Moein et al., 2018). Comparing 1898 and 2019 map based on selected classes look very reliable. The accuracy of results shows that decreasing and increasing in spa-

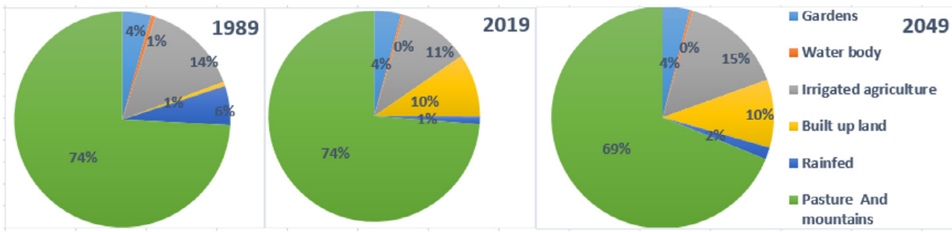


**Fig 5.** Trend of land use change perdition between 1989, 2019, and 2049.

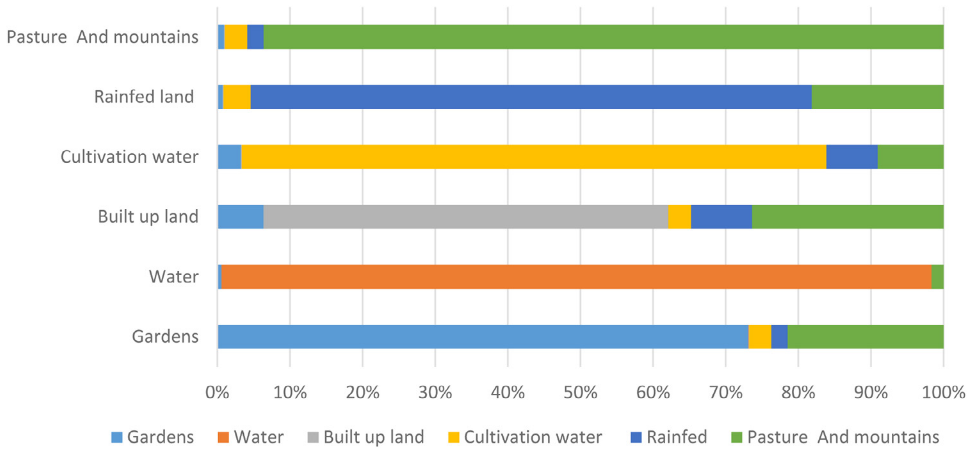


**Fig 6.** LULC transition class and their transition to the other class (Gardens1)، (water body 2), (built up land 3), (irrigated agriculture4), (Rainfed land 5, Pasture and mountains 6).

tiotemporal rate of each class trustworthy. Therefore, CA-Markov is a trustable model to predict the future LULC.

CA-Markov is a forecasting model based on historical data collection therefore it analyzes the combination of past tendencies and based on that provides future scenarios. However, CA-Markov does not involve any environment and socioeconomic aspects. Moreover, this model considers/analyzes the changes in the selected area and if there are some influential cells it cannot measure them (Von Neumann, 1951).

#### 4.1.3. LULC transition probabilities and transition matrix of year 2049

Since the CA-Markov model does not integrate all different socioeconomic and environmental facts, in this article we execute our calibration based on important socioeconomic and the most important socioeconomic and environmental changes. These changes have brought significant direct and indirect impacts on LULC changes in the region. Previous CA-Markov studies proved that scenarios perdition (Alonso-Sanz and Martín, 2004; Mirzaeizadeh et al., 2015; Gomes et al., 2019; Nouri et al., 2014) is a misleading land use simulation methods (Varga et al., 2019; Gohain et al., 2021; Hassan et al., 2016). Therefore, we identified in 1989 after the "1979 revolution" and war between Iran and Iraq and new political and economic policies that are perfect match for an effective assessment in the future. Yet, CA-Markov, as an estimator model, is not fully trusted but calibration based on significant socioeconomic changes can improve the truthfulness of future perdition of the LULC scenario.

The current and simulated LULC dynamics of the ZRB indicates that it is highly probable that the rainfed land and build up land LULC classes continue to take over other LULCs. As the human impact on the ZRB region is very significant due to huge use of water and soil resources for agricultural use. It seems any reducing and increasing of each LULC class in this region is highly related to the quality of one of them of both (Fig. 4). Simulation data shows the rainfed agricultural activities in the east part of the ZRB continue to change pasture and mountain lands. However, in the west and the northwest not only changes gardens and pasture and mountains also, it seems to provide a better situation for the expansion of irrigated agricultural lands. Furthermore, the transition of pasture and mountain in other parts of the region hints huge spatial potential of rainfed agriculture land expansion.

The obtained results specify that built up land will have gradual but continuous growth as it shows 0.63% in 1989, 1.15% in 2019, and 1.75% in 2049. Significantly, the growth in rainfed land not only keeps continuing for the calibrated period, but also is the main cause of other classes declines as it started with 5.88% in 1989, 10.88% in 2019, and 15.10% in 2049. On the other hand, the decline in other classes will continue with a slower rhythm of reduction in comparison to previous times. Pasture and mountains continue decline from 74.17% in 1989, 73.79% in 2019, and 68.86% in 2049 as well as gardens from 4.30% in1989, 4.14% in 2019, and 4.00% in 2049. Similarly water body, from 0.67% in 1989, 0.39% in 2019, and 0.38% in 2049. Remarkably, the irrigated agriculture lands with 14.37% in 1989, 9.68% in 2019, and 9.90% in 2049 as simulation CA-Markov shows it will have a gradual increase in comparison to the second evaluation in 2019 (Table 2, Figs. 3 and 5).

Integrating the other drivers' impact such as market influence, population growth and level of technology can shed light on accurate quantification of different LULC classes change. Usually, understanding major drivers in the region can help decision-makers and planners for sustainable use of land resources.

Comparing results under past, current, and future scenarios show agricultural activities play an important role in future LULCs. Importantly the most significant LULC classes' changes have happened in the northwest and the east part of the ZRB where agricultural activities are so concentrated. The spatial distribution of changed cells follows the big urban hubs and market gravity itself (Fig. 6). As changes in the number of cells show in the south and in the north part of the ZRB does not look any significant changes as is in the northwest and the east part of the region. Tabriz and Urmia city are the main causes of overuse of land and water resources in the north part and Tehran, Karaj, and Zanjan cities along with Guilin Province are the main cause of LULC class changed in the east part of the ZRB. The future changes follow by the same causes and any policies on sustainable use of land and water resources.

As shown in Fig. 6 LULC transition from a class of land to the other LULCs class shows water-related agricultural activities are the most influential classes from one class to another class. For that reason, the results obtained that first-class 4 (irrigated agriculture), second class 1 (gardens), are major classes that reduce other classes. However, water body itself does not show very big in comparison to the other classes but it plays a vital role in both classes 4 and 1.

The results obtained from the CA-Markov model seems are logically reliable to happen in the future. The only model that truthfully pass validation and calibration are reliable to use to the created a future scenario. Therefore, based validation and calibration of historical data which as mentioned above has been the greatest timespan for calibration. Moreover, as LULC is too complex and dynamic just CA-Markov strength spatial validation and calibration of all changes over time and space.

## 5. Conclusion

Understanding LULCs trends and directions in a region is very important to the sustainable use of natural resources. Rapid LULC changes the main cause of many problems such as drought, flood, erosion, and subduction. It is very useful to understand the most important current causes and assess the future impact of LULC change for sustainable use of land resources. The ZRB as part of the Urmia Lake catchment area and important region in food production. In the last two decades over pumping and overusing of land made many problems for the ZRB and surrounding areas such as Urmia Lake. This area is located in the most populated part of Iran and from the north Tabriz, Urmia, and other Azerbaijan cities and in southern parts close to Gilan, Tehran, Karaj, and Kurdistan cities made agriculture in the ZRB profitable. According to historical data, the transition of the different class of LULCs between 2019 and 2049 become faster than 1989–2019 due to water resources reduction in the ZRB. Apparently, water resources and the amount of precipitation play an important role in spatial expansion of each class of LULC.

CA-Markov does not integrate the socioeconomic and human dimensions of LULC change such as GDP, population, level of technology applied to extract or use the natural resources. It can quantify the spatial expansion of each LULC in calibrated time. These changes in the region are important to see how destructive have been human activities in selected LULC classes in the same region. Therefore, as CA-Markov is capable to take into account both time and space such as the ZRB, it seems a very practical model for other regions with the same settings. By comparing results based on different scenarios and address, logical use of natural resources can reduce harms and destruction in the future. Furthermore, to increase the validation of calibration (1989–2019–2049) in this study time selected based on the important socioeconomic decisions on the environment in Iran.

By comparing the extracted LULC map in 1989 and 2019, it shows that rainfed agricultural land expansion in the east part and at the same time irrigated agricultural development have made significant changes in northwestern of the ZRB. Therefore, tiny waterbodies 1/3 reduced from 78.27 in 1989 to 45.38 in 2019 due to agricultural activities and development. However, the simulated scenario for 2049 shows that these shift rainfed agriculture activities make water bodies more stable, and irrigated agriculture will have a gradual increase. Built up lands show significant growth from 73.52 (Km2) in 1989 to 134.91 (Km2) in 2019 in the central and the southern part of the ZRB and it will continue to 2049. On the other hand, pasture and mountain will reduce due to expansion of rainfed agriculture activities.

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