



## Research article

## Improving land-use change modeling by integrating ANN with Cellular Automata-Markov Chain model

Anne Gharaibeh<sup>a,\*</sup>, Abdulrazzaq Shaamala<sup>a</sup>, Rasha Obeidat<sup>b</sup>, Salman Al-Kofahi<sup>c</sup><sup>a</sup> Department of City Planning and Design, College of Architecture and Design, Jordan University of Science and Technology, Irbid, 22110 Jordan<sup>b</sup> Department of Computer Science, College of Computer Information Technology, Jordan University of Science and Technology, Irbid, 22110 Jordan<sup>c</sup> Department of Land Management and Environment, Faculty of Natural Resources and Environment, The Hashemite University, Zarqa, 13133 Jordan

## ARTICLE INFO

## Keywords:

Environmental science  
 Computer science  
 Geography  
 Land use planning  
 Land use change  
 Urban growth  
 Machine learning  
 Urban planning  
 Modeling  
 Artificial intelligence  
 Cellular Automata  
 Markov Chain

## ABSTRACT

Urban growth and land-use change are a few of many puzzling factors affecting our future cities. Creating a precise simulation for future land change is a challenging process that requires temporal and spatial modeling. Many recent studies developed and trained models to predict urban expansion patterns using Artificial Intelligence (AI). This study aims to enhance the simulation capability of Cellular Automata Markov Chain (CA-MC) model in predicting changes in land-use. This study integrates the Artificial Neural Network (ANN) into CA-MC to incorporate several driving forces that highly impact land-use change. The research utilizes different socio-economic, spatial, and environmental variables (slope, distance to road, distance to urban centers, distance to commercial, density, elevation, and land fertility) to generate potential transition maps using ANN Data-driven model. The generated maps are fed to CA-MC as additional inputs. We calibrated the original CA-MC and our models for 2015 cross-comparing simulated maps and actual maps obtained for Irbid city, Jordan in 2015. Validation of our model was assessed and compared to the CA-MC model using Kappa indices including the agreement in terms of quantity and location. The results elucidated that our model with an accuracy of 90.04% substantially outperforms CA-MC (86.29%) model. The improvement we obtained from integrating ANN with CA-MC suggested that the influence imposed by the driving force was necessary to be taken into account for more accurate prediction. In addition to the improved model prediction, the predicted maps of Irbid for the years 2021 and 2027 will guide local authorities in the development of management strategies that balance urban expansion and protect agricultural regions. This will play a vital role in sustaining Jordan's food security.

## 1. Introduction

Urbanization has been expediting worldwide in recent decades, threatening natural resources, and landscape character (Gharaibeh et al., 2017). Urban growth is a complex process linked to many influential factors that play a significant role in the temporal growth (Lavelle et al., 2001). This triggered the need to understand urban growth patterns and trends in order to consider the appropriate mitigation measures dealing with and directing this growth (Aburas et al., 2016). Prediction of urban growth trends became a fundamental constituent to ecosystem preservation and sustainable development (Aburas et al., 2016). In urban growth simulations, decisive factors and the chronology of urban growth must be considered to understand the temporal and spatial relationship accurately (Musa et al., 2016; Aburas et al., 2017). Thus, improving a simulation model to take the driving forces into account is expected to

enhance model prediction capabilities. This study aims to improve the modeling of land-use change predictability using AI methods by incorporating driving forces. The results are expected to enhance planning strategies and direct urban growth and future land-use change plans. This is applied on a case study to simulate future land-use change for the fast growing city of Irbid, Jordan.

There are several techniques to study urban growth and land-use change, such as Remote Sensing (Arsanjani et al., 2013) and Geographic Information System (GIS). Several models have been developed to perform land-use change prediction and urban growth expectations including, but not limited to, Cellular Automaton (CA) (Syphard et al., 2005), CA-Markov (CA-MC) model (Memarian et al., 2012), Logistic Regression (LR) (Hu and Lo, 2007), and Artificial Neural Network (ANN) (Wang and Mountrakis, 2011) (Table 1).

\* Corresponding author.

E-mail address: [dr-anne@just.edu.jo](mailto:dr-anne@just.edu.jo) (A. Gharaibeh).

**Table 1.** Applications of various models for simulating and predicting land-use change.

Model	Author	Strength	Limitation
CA	(Vaz et al., 2012) (Yang et al., 2008)	Has an open structure that easily integrated with knowledge-driven models.	Only dependent on spatial data. Not appropriate to make a realistic simulation.
Sim-Wight	(Bununu, 2017) (Sangermano et al., 2010)	A suitable model for understanding the relationship between the variables.	
SLEUTH	(Saxena and Jat, 2019) (Nahavandya et al., 2017)	Helpful to assess the effect of different scenarios of policies.	The simulation process restricted by fixed factors that cannot incubate or change.
Support Vector Machin (SVM)	(Karimi et al., 2019) (Shafizadeh-Moghadam et al., 2017a)	Reliable for studying complex relations. It is integrated with other models easily.	The model does not explain the weights of the driving forces.
CA-Markov	(Aburas et al., 2017) (Jafari et al., 2016) (Memarian et al., 2012)	Modeling spatiotemporal dynamic. Good accuracy result.	The model does not address the driving forces of the land change.
Land Transformation Model (LTM)	(Pijanowski et al., 2002) (Pijanowski et al., 2005)	High accurate results for predicting land change.	The model Still needs more development to be easy to use for researchers.
ANN	(Megahed et al., 2015) (Shafizadeh-Moghadam et al., 2017b)	Integrates with other models easily. ANN can detect potential interdependencies through the implied driving forces	

CA-based models for urban growth simulation are first employed in the 1980s (Batty and Xie, 1994; Santé et al., 2010). CA model can simulate urban growth depending on the presumption that future patterns of urban growth are affected by past local interaction between land-uses. Among the advantages of CA model are its flexibility and simplicity. Additionally, CA model has the flexibility of being integrated with other models (Aburas et al., 2016).

However, traditional CA is not appropriate to make a realistic simulation for urban growth due to the limitations in the individual model technique where it is only dependent on spatial data (Arsanjani et al., 2013). Additionally, CA model is limited in implementing driving forces for land-use change which is difficult for this model to process (Mohammady et al., 2014). Consequently, it is recommended to modify and integrate the traditional CA model with a quantitative and spatio-temporal model such as Markov Chain (MC) model to achieve a better result and to overcome these limitations (Couclelis, 1997; White and Engelen, 2000; Aburas et al., 2017).

The Markov chain (MC) analysis is a stochastic modeling approach that has been used widely in urban growth modeling (Halmy et al., 2015). It works under the physics assumption that future state depends only on the current state (Bell and Hinojosa, 1977). The MC method monitors the temporal change in land-use type depending on transition matrices (Guan et al., 2011). In CA-MC combined model, MC controls the temporal changes in land-use (Guan et al., 2011), while the spatial changes are determined by a spatial filter of the CA model (Nouri et al., 2014). Although the potential of CA-MC model has been recognized by previous studies, the realistic simulation needs to take into account the driving forces in terms of social, environmental, and economic driving forces. For this reason, the CA-MC model maybe integrated with other models to obtain a better understanding of changing growth patterns and to improve the model's prediction capability (Aburas et al., 2017).

To improve CA-MC model, a few studies have combined socioeconomic and environmental data for urban growth simulation (Guan et al., 2011). Aburas et al. (2017) integrated Analytical Hierarchy Process (AHP) and Frequency Ratio (FR) based on the CA-MC model for simulating urban growth model. Other studies integrate experts' opinions or Multi Criteria Evaluation (MCE) with CA-MC model to improve its prediction capabilities. However, due to the complexity of studying land change, these methods have limitations that include insufficient knowledge about the area of interest, subjectivity in weighting the variables, and reliability of the results (Park et al., 2011). Furthermore, due to the complexity of land change, it seems doubtful that experts have sufficiently detailed understanding of the process of land change to apply AHP and MCE effectively (Shafizadeh-Moghadam et al., 2017b). Another weakness of MCA is its ability to simulate change in a linear fashion.

Consequently, it assumes linear trends among the spatial-temporal process. Therefore, there is a need to create and implement models that do not face these limitations and rather introduce a better understating of land change process and more accurate results depending on Artificial Intelligence (AI) (Shafizadeh-Moghadam et al., 2017b).

Artificial Neural Network (ANN) is one of the most powerful models that depend on artificial intelligence. It can be defined simply as nodes or neurons that are managed in multiple layers (Mohammady et al., 2014). The order of neurons in layers and the connection patterns within these layers is called Architecture (Maithani, 2010). ANN can capture the non-linear relationships between factors and deal with complex patterns such as urban growth and changes in land-use with great efficiency. Moreover, its provision of non-linearities and its ability to deal with missing or fuzzy data as well (Aburas et al., 2019).

ANN networks train by a process of learning from correcting errors where the preferred results must be known; that process is called Back-Propagation (BP) algorithm (Zhou, 1999). The BP algorithm randomly selects premier weights and then calculates the variance between the expected and calculated output results. After that, the weights are modified according to a generalized delta rule (Rumelhart et al., 1985). The model repeats this process of feeding single and BP until achieving the desired results (Pijanowski et al., 2002).

For simulation purposes, ANN model identifies changes in land-use and other patterns using data that illustrate the behavioral dynamics of land-use phenomenon (Mohammady et al., 2014). Therefore, it can detect potential interdependencies through implied driving forces (Shafizadeh-Moghadam et al., 2017a). Moreover, the significance of using ANN model is that the model illustrates the effects of each driving factor used in the simulation operation and specifies which factors affect the land change more to give a clear understanding of the land change process (Park et al., 2011).

Considering the potentials of the three models (CA, MC, and ANN), this research aims to enhance the ability of the CA-MC model by integrating it with ANN model. It will improve its predictive power by incorporating the driving forces and comparing the accuracy results of the ANN-CA-MC model with models that depended on experts' opinions in previous studies.

### 1.1. Driving forces of land-use change

The main drivers of land-use change that are employed in simulation models mainly include slope, distance to roads and urban centers, and land fertility (Park et al., 2011; Guan et al., 2011; Memarian et al., 2012; Arsanjani et al., 2013; Musa et al., 2016; Aburas et al., 2017; Shafizadeh-Moghadam et al., 2017a,b). The following is a brief discussion of these drivers of land-use change.

The gentler a land slope is, the easier it is to have land-use changes (Jin et al., 2015; Şatir, 2016; Zhang et al., 2019). This is regardless of the type of change. Changing land-uses from agricultural to urban or vice versa are more likely to happen with lower land slopes (Gharaibeh et al., 2020).

High population density is becoming an attraction for further urban growth especially in developing countries with rural-urban migrations or countries with refugees (Liu and Yamauchi, 2014; Zhang et al., 2019; Zhou et al., 2020). There is a tendency to live among the matching social and ethnic groups. In addition, people try to associate with the areas that belong to their relative for social inclusion purposes. In other areas, high population densities act as repellants for new coming wealthy residents. Therefore, regardless of its impact on attracting or repelling urban growth, it is an important factor in land-use change.

Land fertility (soil fertility) is always attractive for more agricultural expansions. However, many countries are facing soil fertility degradation which impacts land-use change (El-Seedy and Saeed, 2019; Prishchepov et al., 2020). However, with the absence of firm urban and environmental policies, such valuable lands may be lost to urban changes (Prishchepov et al., 2020). This issue is of extreme importance in the case study of this research paper. Many of the fertile valuable lands are now within the city limits and policies of preservation of agricultural and fertile lands are not enforced (Gharaibeh et al., 2020).

Distance to main road is a major land-use driver (Zhang et al., 2019). Accessibility has been an encouraging factor of land-use change. It is attracting more urban uses and in some cases agricultural or industrial uses (Farah et al., 2019). It is a driver of investment. With the absence of strict policies, lands turn quickly to urban uses along the main roads creating linear towns and cities and linking urban areas (Prishchepov et al., 2020). This factor is negatively impacting landscape character as well (Gharaibeh et al., 2017).

Distance to commercial is also a driving force for urban land changes (Simwanda et al., 2020; Zhang et al., 2019). In some cases, this variable is the second strongest driver of land-use change (Simwanda et al., 2020). People like to live close to commercial services and it is one of the critical requirements of sustainable living environments. In addition, commercial land-uses are usually associated with better transportation systems making lands adjacent to commercial uses more accessible in general. Therefore, it is expected that commercial uses will attract change of adjacent uses (Gharaibeh et al., 2019).

Distance to urban center can be a very strong driver of change where the closer the land to urban centers the easier it is for land to change to urban uses. This variable is also linked to transportation and commercial uses in general (Zhang et al., 2019). In our case study, this variable together with the radial nature of the city plan are also expected to impact the urban land-uses. Even when the plan is not radial, urban centers are strong drivers of land change (Gharaibeh et al., 2019).

In many case studies, elevation variation can be a considerable driver of change (Zhang et al., 2019; Simwanda et al., 2020). This is especially true in places with rugged terrain and land-use variations.

The following section includes the methodology which contains the preparations for the study comprising the dataset and pre-processing of data, accuracy assessment, land classification, case study data sources, the integrative model (ANN-CA-MC) explaining each part of the integration alone and explaining them combined, and the model validation at the end of this section. The results section includes CA-MC simulation results, CA-MC based ANN simulation results, and model validation. The discussion section presents the model comparison, model characteristics, and the case study assessment.

## 2. Methodology

### 2.1. Study area

This study is applied to the city of Irbid to test the model and accuracy. Irbid city is located at 32° N and 35.51° E Northern Jordan adjacent

to the Syrian borders. The city has 24 districts and it covers about 324 km<sup>2</sup>. Irbid is witnessing an increase in the population and urban growth over the past nine years due to the regional instability and the flow of Syrian refugees (Al-Kofahi et al., 2018, 2019). Due to the lack of restrictions and the absence of preserved land, many periphery villages are absorbed within Irbid city agglomeration. These are also included within the parameters of this study as well (Figure 1). In the future urban growth and land use change, it is additionally important for this case study to preserve agricultural land located in Irbid Governorate which together constitutes 15.6% of the national agricultural land and produces more than 30% of the food in the country (DOS, 2017).

### 2.2. Dataset and pre-processing

In this study, land classification followed first-level Anderson land-use/land cover classification (Wang and Hofe, 2008). We employ three land-use categories: urban land, undeveloped land, and agricultural land (Table 2). Our study is limited to consider these categories because other types of land-use such as rangeland, forest land, water, wetland, tundra, and perennial snow or ice, are not present by nature in the study area.

We used maps of the study area of the years: 2003, 2009, and 2015 due to the data availability of the study area maps for these years (Figure 2). The map of 2009 is acquired from Landsat-7 images; Enhanced Thematic Mapper (ETM+) sensor with a spatial resolution of 30 m. It is obtained from the Landsat archive at <https://earthexplorer.usgs.gov>. The identification number for the scenes is LE71740382009086ASN00. ENVI version 5.3—which is a software for processing and analyzing geospatial imagery—is employed to prepare the study area images. A shapefile of the study area is used to select the area from the satellite scene. Then a supervised classification method in ENVI software is used to classify land-use type. This study is using the band combinations order 3-4-1 of the satellite scene. Then, thirty testing samples were chosen for each land class where the Maximum Likelihood classification is applied to classify the satellite image. Finally, we applied a set of smoothing and aggregation operations to smooth class boundaries and combine small or isolated pixel areas in the image. This method is also applied by Bhatti et al. (2019) in his study of land cover change assessment based on satellite data.

Aiming to improve the accuracy, the output classification results are reviewed visually many times and then updated by adding more training sets. Different levels of smoothing and aggregation are also applied. The used smoothing and aggregation method was the one in ENVI 5.3 software. Smoothing and aggregation are post-classification algorithms that smooth class boundaries and combine small or isolated pixel areas. The process starts by specifying the smooth kernel odd size of 3. Thus the 3 × 3 square kernel center pixel takes the value corresponding to the majority class values in the kernel. Then an aggregate size of 9 × 9 pixels is selected. Any region with kernel sizes equal to or less than 9 × 9 are aggregated to the adjacent larger region. The output results (raster image for the land cover classes) are exported to GIS for accurately assessing and preparing the land cover map.

The other classified maps for 2003 and 2015 are excerpted from Al-Kofahi et al. (2018). They also followed the same process to classify land-uses which are reported with an overall land cover classification accuracy of 88% and 87% respectively.

#### 2.2.1. Accuracy assessment

Ninety sample points were randomly distributed over the classified study area images using GIS. True color high-resolution images were used for accuracy assessment and building the confusion matrices. Each point location was examined based on the polygon that it was dropped in and was compared with the reference image to know if either it was classified correctly or not. Kappa coefficient (Congalton and Green, 2009; Clevers, 2009), Overall Accuracies, and User and Producer accuracies were calculated based on the confusion matrix (Congalton, 1991; Liberte et al., 2004). The results showed that the Overall Accuracy for

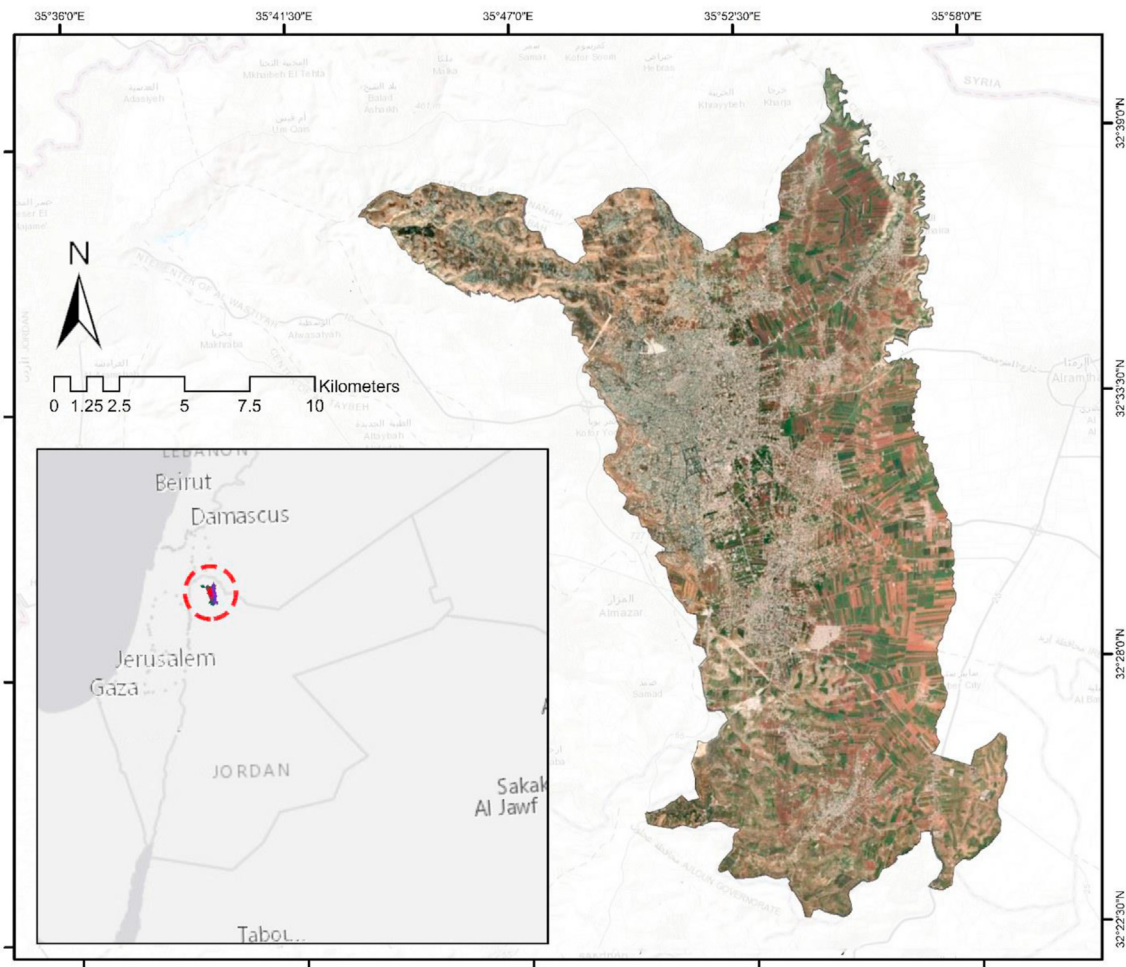


Figure 1. The study area of Irbid city located in Northern Jordan.

Table 2. Land-use classification categories based on Anderson land-use/land cover classification (Wang and Hofe, 2008).

Symbol	Land type	Included Areas
1	Undeveloped (Barren land)	Undeveloped Lands that are not built-up, uncultivated, and abandoned bare land.
2	Agricultural Land	Crops, orchards, and cultivated lands.
3	Urban or built-up land	Built-up area and street network

classification was 87.78% (Table 3). The confusion matrix calculated Kappa coefficient of 81.63% for this table.

This research employed land cover for Irbid city in three different years; 2003 and 2015 which were generated by Al-Kofahi et al. (2018); and 2009 which was generated by the researchers. The three maps (Figure 2) were prepared to be used in the next stage. Based on statistics done at the Department of Statistics in Jordan, the governorate population grew from 928,292 in 2003, to 1,064,400 in 2007, and well into 1,770,158 inhabitants in 2015 (DOS, 2004, 2009; and 2015).

Previous studies identified the significant factors that determine the potential urban growth and land-use changes (Park et al., 2011; Guan et al., 2011; Memarian et al., 2012; Arsanjani et al., 2013; Musa et al., 2016; Aburas et al., 2017; Shafizadeh-Moghadam et al., 2017a,b). These studies were dependent on the experienced opinions and reviews of previous studies. However, the main factors used in urban growth simulation models included slope, distance to roads and urban centers, and land fertility (Park et al., 2011; Guan et al., 2011; Memarian et al.,

2012; Arsanjani et al., 2013; Musa et al., 2016; Aburas et al., 2017; Shafizadeh-Moghadam et al., 2017a,b; Gharaibeh et al., 2020). In order to improve the prediction process, some studies recommended considering factors such as population density as the driving force for urban growth and land change (Shafizadeh-Moghadam et al., 2017a,b). In this study, researchers addressed all the factors above that were defined and recommended by most simulation studies.

Most of the data are obtained from Greater Irbid Municipality (GIM) (main road network, population density, land fertility (MoA, 1993; MoA, 1995), urban centers, land elevation (obtained from Digital Elevation Model (DEM)), commercial centers, slope (Table 4). The distances to main roads, urban centers, and commercial centers are calculated using Euclidean distance function in TerrSet 18.21 software (Figures 3 and 4). Euclidean distance is the straight-line distance between two points. Euclidean distance is used to calculate the closest and farthest on the maps. By this method, the model recognizes the area and calculates the influence of each factor on the land-use change based on distance.

### 2.3. ANN-CA-Markov model

ANN facilitates the automatic calibration of the CA-MC model and assists the incorporation of a variety of driving forces in the model (Figure 5). The sections hereafter explain each model (CA, MC, and ANN) separately. Then an assessment of this process of the modified model and its capabilities is applied based on the methodological flowchart (Figure 5).

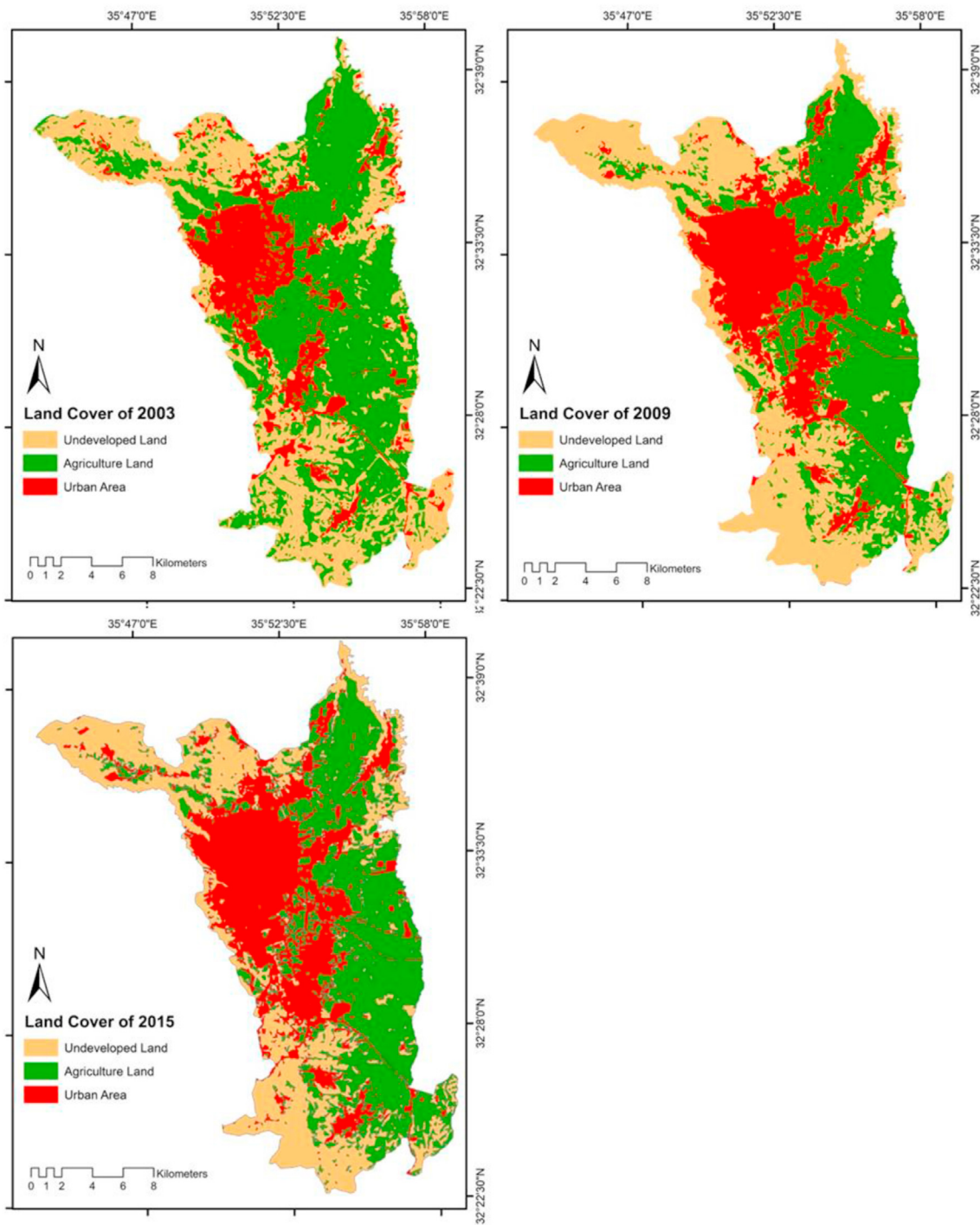


Figure 2. Irbid city land cover maps in 2003, 2015 (Al-Kofahi et al., 2018), and 2009 by the authors.

Table 3. Confusion matrix for land cover classification result for Irbid 2009.

		Reference Data				
Class		Urban	Agriculture	Undeveloped	Row Total	User's Accuracy
Classified Data	Urban	29	2	3	34	85.29
	Agriculture	2	26	2	30	86.67
	Undeveloped	1	1	24	26	92.31
	Column Total	32	29	29	90	88.09
Producer's Accuracy		90.63	89.66	82.76	87.78	(Overall accuracy)

**Table 4.** Data and data sources used in the analysis.

Data	Source	Image Date
Landsat-7 (ETM+)	USGS website <a href="https://earthexplorer.usgs.gov/">https://earthexplorer.usgs.gov/</a>	2009
Land cover maps	(Al-Kofahi et al., 2018)	2003, 2015
Digital Elevation Model SRTM 30m resolution	Greater Irbid Municipality	2012
Road Network	Greater Irbid Municipality	2015
Land Fertility	Greater Irbid Municipality and Ministry of Agriculture, Jordan	2015; based on 1993–1995 MoA soil fertility projects
Topographic Map	Greater Irbid Municipality	2012
Population Density	Greater Irbid Municipality	2015
Urban and Commercial Centers	Greater Irbid Municipality	2015

### 2.3.1. Cellular Automata

Cellular Automata (CA) is a spatial modeling technique that has been widely used in the simulation of urban systems. CA popularity comes from its ability to model the proximity, which is considered as an essential spatial element that reflects the dynamics of land-use changes. CA assumes that a region has a higher tendency to change to a land-use category if the neighboring regions belong to that category (Memarian et al., 2012) (Figure 6). The basic principle of CA is that the past urban development pattern affects future development through the local interactions which collectively constitute the global urban growth patterns (Santé et al., 2010).

In CA, the area is divided into a grid of cells. Each cell is equivalent to a pixel on the area map. The cellular state represents one of the land-use categories. The state of the cell in the next step depends on the cell's current state as well as the current states of the surrounding cells (the cell neighborhood) according to a set of transition rules. Von Neumann and Moore neighborhood types are the two most commonly employed in CA (Memarian et al., 2012). This study utilizes 5-by-5 Moore neighborhood filter to construct the transition rules to be used for predicting future land-use changes.

### 2.3.2. Markov Chain model and CA-Markov

Markov Chain (MC) is a stochastic process that describes a sequence of events in which the future event depends only on the current events and previous events without the need to consider the whole event history. The ability to express the temporal changes from a one-time period to another makes MC an appropriate tool for modeling land-use changes, thus form a basis to predict future changes.

MC model describes the possible transformation between different land-uses via a transition probability matrix. Each entry in the matrix represents the probability of changing a pixel state from one land-use to another. At least two different maps for the same area for two distinct timestamps are needed to learn the probability of transition between these two time periods. In this study, researchers used maps of the greater city of Irbid for the years 2003 and 2009. The transition matrix was generated using TerrSet.

However, this MC model is not able to produce model changes in spatial dimensions, i.e., it doesn't account for the influence of the neighboring cells. Consequently, MC per se has been rarely utilized to study urbanization and land-use change (Arsanjani et al., 2013). Driven by combining the strengths of CA and MC, CA-MC approach has been proposed to integrate both in a unified framework (Guan et al., 2011; Arsanjani et al., 2013; Shafizadeh-Moghadam and Helbich, 2013; Aburas et al., 2017). CA-MC is a strong approach that considers both spatial and temporal changes (Singh et al., 2015; Hamad et al., 2018). In addition, CA-MC has an open structure that facilitates incorporating a variety of external socio-economic and environmental factors that influence the urbanization processes, that is the transition rules of CA can be designed in many ways to account for these factors (Santé et al., 2010). The combination of both CA and MC makes the prediction stronger, but not sufficient.

### 2.3.3. Artificial Neural Network

Artificial Neural Network (ANN) is a machine learning technique that is used to model complex patterns and behavior. This study employs ANN to create potential transition maps-based on using historical data. These maps capture the effect of various environmental and socio-economic factors on land-use change. Several advantages make ANN stronger than the methods that have been previously used to incorporate the driving forces in simulating urban growth. First, it can efficiently model the complex system in which the relationship between the interacting variables is non-linear. Second, no prior knowledge of the data generating process or data distribution is needed to implement and train ANN (Anantwar and Shelke, 2012). Third, to some extent, it can cope with noisy, redundant, and inaccurate data (Guan et al., 2005). In the end, it does not ask for expert choice weighting and rather depends on adjustable coefficients that can be trained to reduce the error. Besides, and as a result of implementing this method, the researchers will be able to see the hierarchy of influential factors on land-use change.

This study employs a two-layer feedforward neural network. In addition to the input layer, the network has one hidden layer and an output layer. The input is a one-dimensional vector of size "m" that indicate the values of "m" environmental and socio-economic variables. The hidden layer is composed of "n" hidden nodes, each node is a neuron that uses a non-linear activation function to obtain a nonlinear mapping from inputs to outputs.

The output layer has one node to compute the probability that the land-use of a data point (a pixel on the map) will change to the type "t". Since we are dealing with three land-uses, we formulated three binary classification problems, thus, we trained three networks. The networks classified each data point into urban or non-urban, agricultural or non-agricultural and undeveloped or developed land-use, respectively.

The architecture of the ANN utilized in this work is shown in Figure 7. The lines represent weighted connections between the nodes in a layer and the subsequent layer. The ANN is trained using the Backpropagation algorithm (BP) to learn these weights using supervised learning, i.e., using already classified data points (Rumelhart et al., 1985). BP randomly chooses initial weights. Then the input representation of data points that are previously classified flow through the network. The input representation was multiplied by the weights and non-linear differentiable activation functions are applied. The output of the network and the actual class of the point were used to calculate the error. The error summarizes a set of data points that are misclassified. The error is backpropagated through the network in a backward direction to adjust the weights of the neural network. The weights were updated according to a learning rate using a (gradient descent)-based optimization function (Karayiannis, 1999). This process iteratively performs until the error stabilizes at a low level.

The training data is a set of points (pixels) that are randomly selected from the maps of 2003. Each pixel is represented by a vector that is composed of the values of the seven driving factors considered in this study (slope, population density, land fertility, distance to road, distance to commercial, distance to the urban center, and elevation). In addition, each pixel is assigned to a land-use type

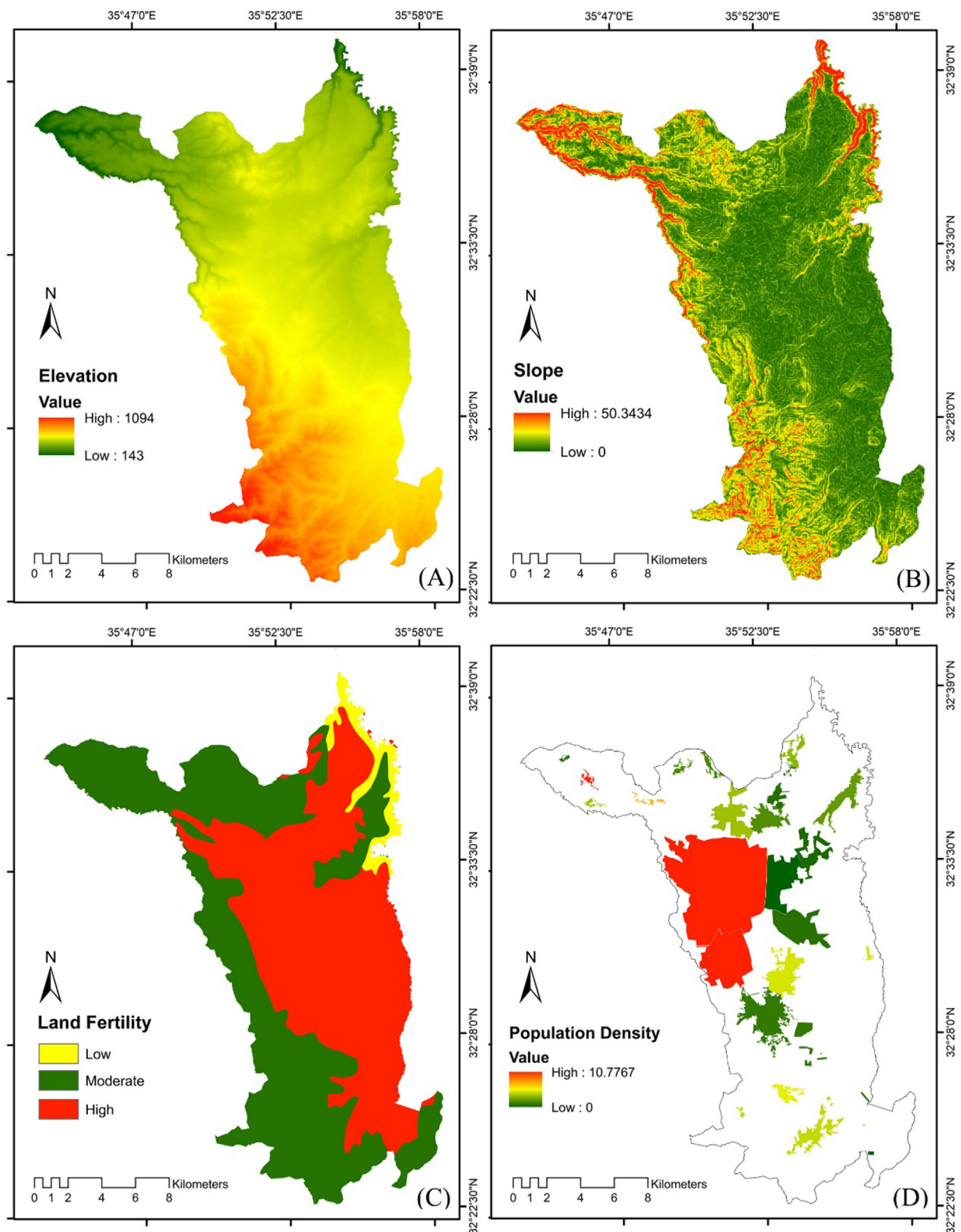


Figure 3. Factors used in ANN model (A) elevation (B) slope (C) land fertility (D) population density.

obtained from the corresponding map of 2009. The points are used to train three ANNs; one for each land-use and its complements. For example, one ANN is trained to decide whether each pixel in the map of 2009 is going to be turned into Urban or non-Urban, and so on). The probability maps are used as potential transition maps to improve CA-MC. Land Change Modeler (LCM) function in TerrSet software is

used to train the ANN and generate the potential transition map. Training the ANNs involved tuning a set of hyperparameters such as the number of hidden nodes and the learning rate. TerrSet applies an automatic method to choose the best values of the hyperparameters that produce the best performance on a hold-out data among a randomly selected set of values.

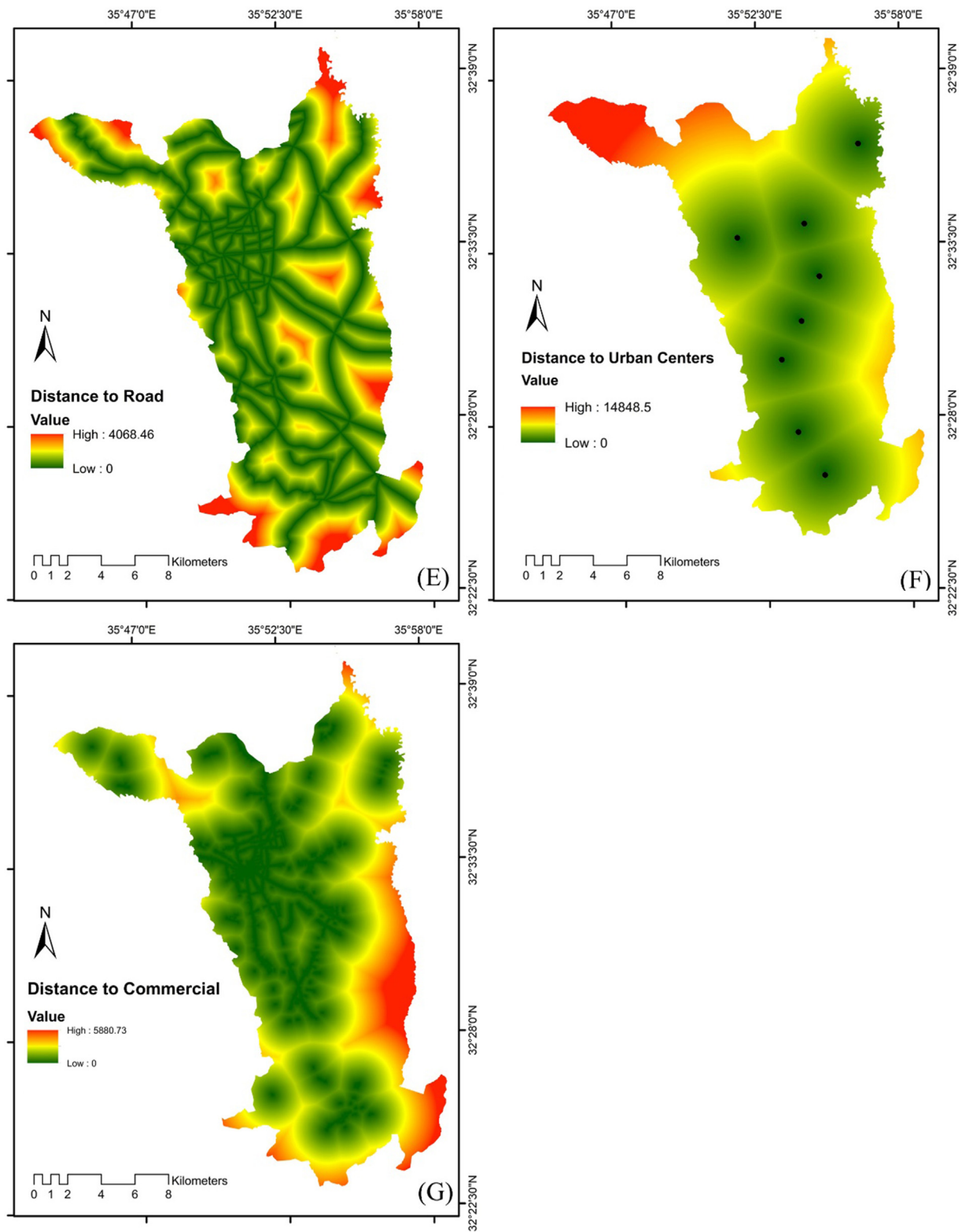


Figure 4. More Factors used in ANN model (E) distance to road (F) distance to urban centers (G) distance to commercial.

By combining the transition rules of CA, the transition matrix of MC model, and the potential maps that are produced by the ANN, our approach ANN-CA-MC considers both spatial and temporal dynamics of the urban growth as well as incorporating the impact of the driving forces.

#### 2.4. Models validation

land-use map of 2015 was used in model validation. The two models CA-MC and ANN-CA-MC will be validated by measuring their accuracy and comparing the results. Satisfactory validity is usually associated with



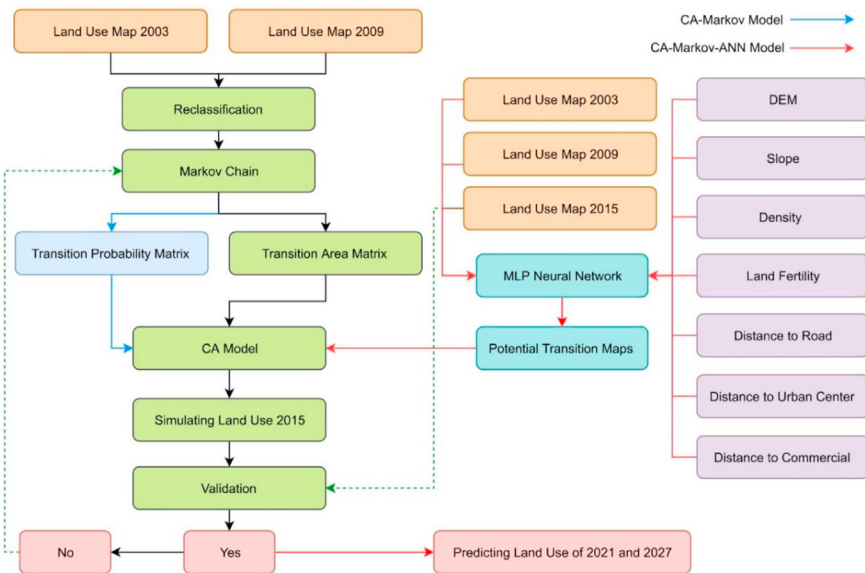


Figure 5. Flowchart of the study methodology.

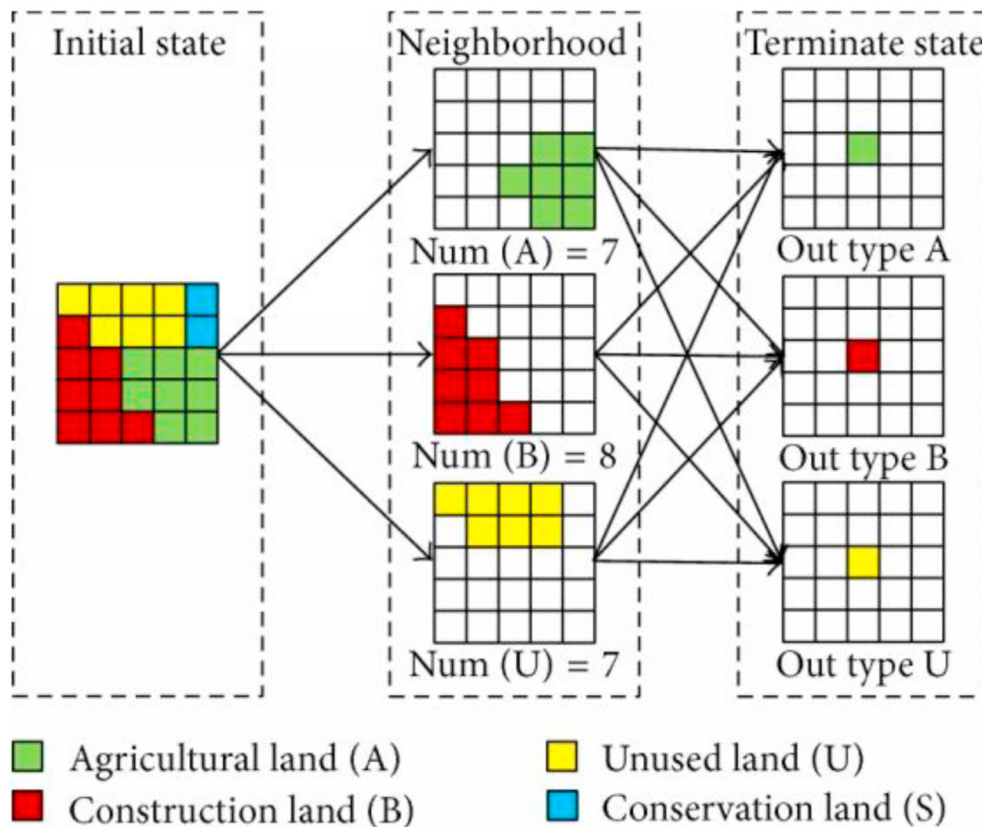


Figure 6. CA modeling for land-use change in a neighborhood (Yang et al., 2016).

values greater than 75% (Mitsova et al., 2011) or 80% (Eastman, 2006, 2012). The validation function on TerrSet software is employed using the real known map of 2015 to calculate Kappa indices. The validation model determines the agreement and disagreement between the simulated and the reference (existing) maps. Quantity disagreement occurs when cells quantity of a category of the simulation map is different from the same category in the reference map. Location disagreement happens when a cell's location of a category of the simulation map is different from the same category in the reference map. This methodology was calculated

based on an approach that was developed by Pontius and Millones (2011). Moreover, crossing and comparing with the real map method was used to calculate Kappa coefficient using the confusion matrix.

### 3. Results

Since the aim of this research is to improve predictive models of simulation, it will focus on the methods specifically, then review the results of the prediction. The results will explain CA-MC model

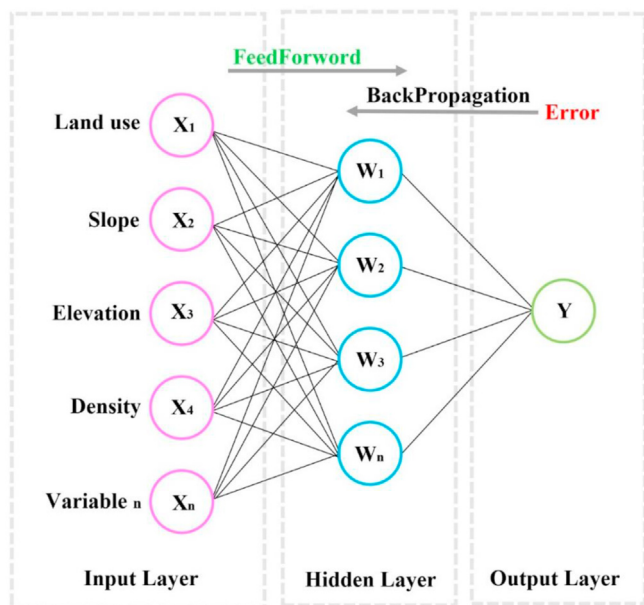


Figure 7. Multilayer neural network architecture.

simulation process, CA-MC based on ANN simulation, validation of the models, and predicted land-use change for 2021 and 2027.

### 3.1. CA-MC model simulation

The calibration of CA-MC model for 2003–2008 to predict the year of 2015. The results of the transition probability matrix illustrate the likelihood of the land-use type prospective to change to other land-use types (Table 5). In the table, class 1, class 2, and class 3 presented undeveloped land, agricultural land, and urban land-use, respectively. For example, Class 2 (agricultural land) is prone to change to Class 3 (urban land-use) by 20.12% (Table 5) and this corresponds with a prospective area change of about 28.334 km<sup>2</sup> (Table 6). The area matrix also registers the pixels prone to change from land-use/cover to another within the designated period of time (Table 6).

The conditional likelihood images present the prospective of each land-use class found at each pixel within the time period (Figure 6). The CA-MC simulation model showed the projected map for the study area (Figure 7). The map illustrated the three classes where urban areas and undeveloped land increased by 33.6 km<sup>2</sup> (3.52%) and 22.94 km<sup>2</sup> (3.84%) respectively, while the agricultural land lost about 56.55 km<sup>2</sup> (5.91%) (Figure 8). The final map is illustrated in Figure 9.

### 3.2. CA-MC based on ANN simulation

The ANN model showed the gains and losses between 2003 and 2009 for each land-use type. The analysis illustrated that the urban area (class 3) gained 2.49% while agricultural land (class 2) lost about 4.20%. In addition, undeveloped land (class 1) gained about 1.70% of the total area (Figure 10). When ANN was implemented to model transition maps for the undeveloped land class, there were two maps as a result; the first was

Table 5. Markov transition probability matrix of the period from 2003 to 2009.

Cells in	Expected to transit to		
	Class 1	Class 2	Class 3
Class 1	0.7122	0.2115	0.0763
Class 2	0.2010	0.5977	0.2012
Class 3	0.2362	0.0376	0.7262

Table 6. Markov transition area in square kilometers matrix of the period from 2003-2009.

Cells in	Expected to transit to		
	Class 1	Class 2	Class 3
Class 1	94.990	28.203	10.182
Class 2	28.303	84.153	28.334
Class 3	20.273	32.25	62.338

for prospect areas that have the potential to become agricultural land, and the other was for undeveloped land that has the potential to become an urban area.

The accuracy rate for this model is 84.98% and based on Eastman (2006) any accuracy rate should be at least 80% to accept the training result (Eastman, 2006, 2012) (Table 7). The skill statistic varies from -1 to 1 where skill of 1 means perfect forecasting, while a skill of -1 means worse than chance. The skill measure in this study achieved 0.6997 (69.97%) (Table 7). The analysis shows that applying appropriate variables is affecting the model learning accuracy, and by 84% model accuracy is means that the driver forces helps the model to predict more accurately.

#### 3.2.1. Forcing a single independent variable to be constant

We trained the model using all the variables, then determined which variable was the most influential and which one was the least influential. This is done so that var. 1 through 7 are: 1. distance to main roads, 2. slope, 3. distance to urban center, 4. distance to commercial, 5. Land fertility, 6. population density, and 7. elevation. To give an example, Table 8 shows the transition from undeveloped land to agricultural land. In this example test, variable 2 (slope) was the most affecting variable for the transition from undeveloped land to agriculture while variable 1 (distance to main road) was the least influential (Table 8).

The model then tested every possible pair of variables to figure out which pair had the least effect on the skill when held constant. It continued in this fashion, progressively holding another variable constant until only one variable was left. The results showed the accuracy and skill measure for every variable constant process (Table 9).

#### 3.2.2. Backwards stepwise constant forcing

The backward stepwise analysis worked by removing a chosen variable each time and testing the model because sometimes the skill of the model slightly increased as some of the variables were removed. Therefore, there is no need to further remove any of the variables (Table 10). After ANN training model was finished, the model created a transition map that showed the potential areas for agriculture (Figure 11).

Finally, this step was applied to the other three classes (Figure 12). The CA-MC model based on the ANN created the projection map for the study area in 2015 (Figure 13). The map featured the three classes where the researcher used this map in the validation stage to test the accuracy of the new modified model.

The process resulted with most effective driving forces as well. It showed that population density, slope, distance to commercial centers and land fertility are the most effective factors in the land change process (Table 11).

### 3.3. Validation of the models

The result of the validated CA-MC map shows that the  $Kappa_{stander}$  was 86.29% which is an acceptable result for a simulation model (Pontius, 2000), when the  $Kappa_{no}$  was 89.25%. Therefore  $Kappa_{location}$  was 91.13%. On the other hand, the validation of CA-MC-ANN model map for 2015 showed that the  $Kappa_{stander}$  was excellent at 90.04% while the  $Kappa_{no}$  and the  $Kappa_{location}$  were 92.19% and 93.11% respectively. Figure 14 presents the successes and errors of the simulation. The result of the validation illustrated that the integration of

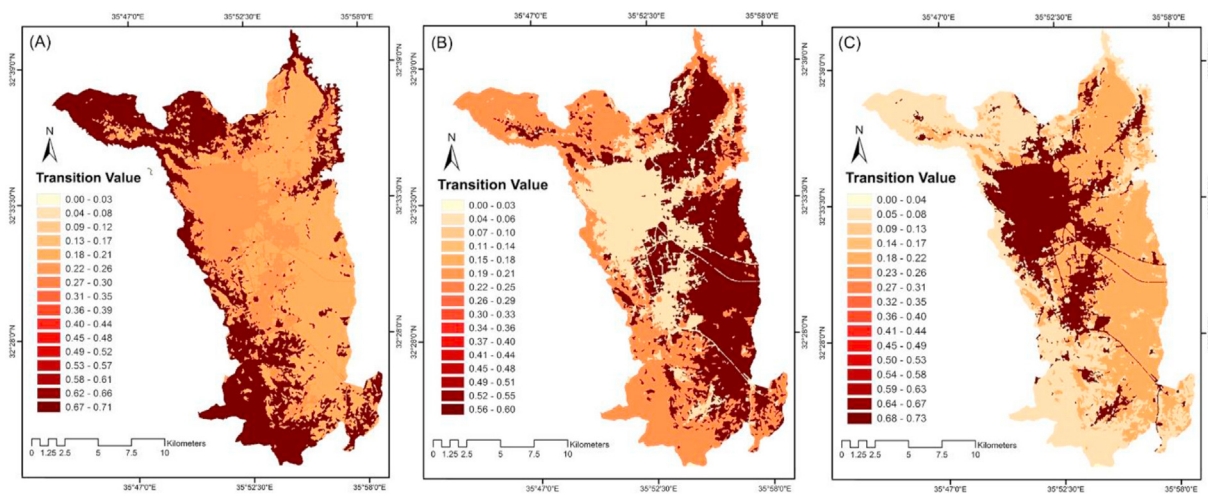


Figure 8. Markov conditional probability of being (A) class 1 (B) class 2 (C) class 3 in 2015.

ANN with the CA-MC model had successfully improved the model in terms of accuracy.

In addition, the kappa coefficient was calculated in order to compare the accuracy of this model to earlier studies' results. Google Earth maps from 2015 were used to assess the discrepancy in the projected map,

which was recorded in the confusion matrix. The kappa coefficient, overall accuracy, and user and producer accuracy were calculated using the confusion matrix (Table 12). The results showed that overall accuracy for the projected map was 94.44% when the calculated Kappa coefficient was 94.00% (Table 11).

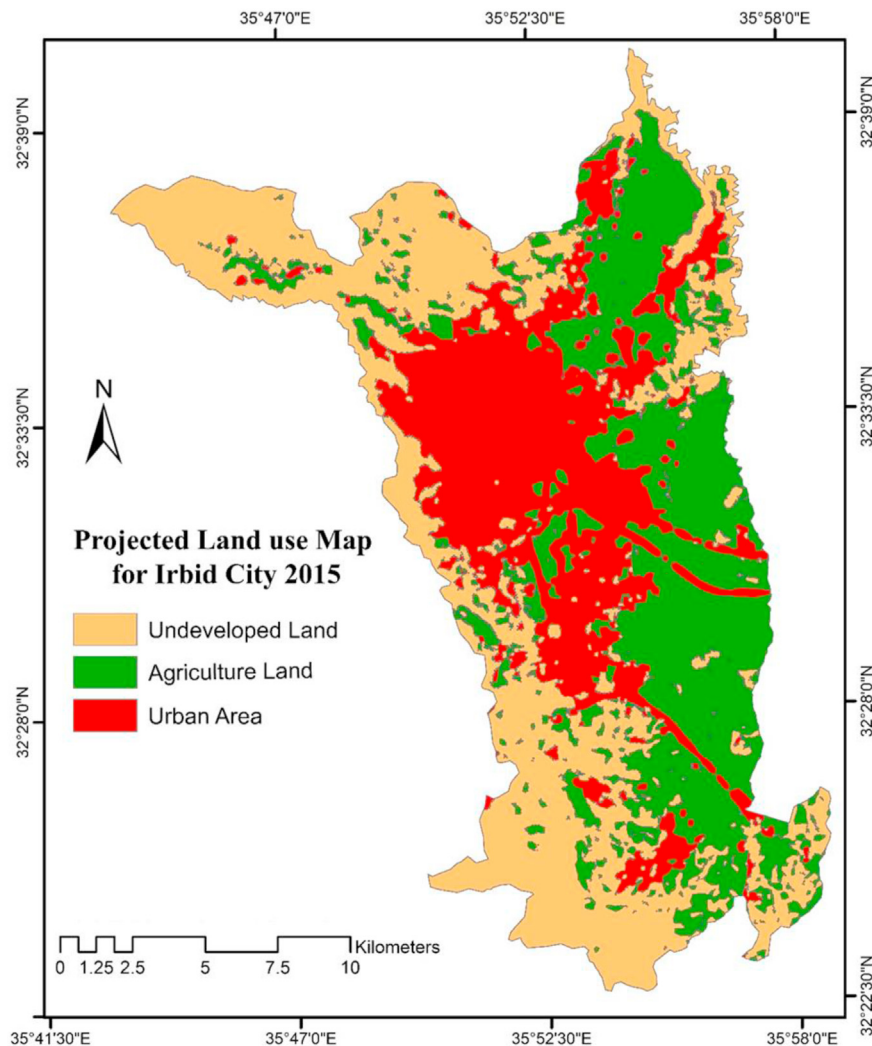


Figure 9. Projected land-use map of 2015 using CA-Markov.

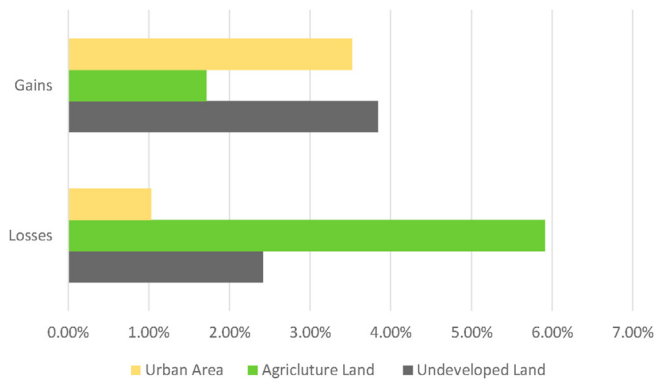


Figure 10. The gains and losses of lands between 2003 and 2009 by percentage of area.

Table 7. Parameters and performance of the model.

Input layer neurons	7
Hidden layer neurons	7
Output layer neurons	2
Requested samples per class	10,000
Final learning rate	0.0003
Momentum factor	0.5
Sigmoid constant	1
Acceptable RMS	0.01
Iterations	10,000
Training RMS	0.3242
Testing RMS	0.3275
Accuracy rate	84.98%
Skill measure	+0.6997

Table 8. The results of forcing a single independent variable to be constant. Testing the transition from undeveloped land to agricultural land.

Model	Accuracy (%)	Skill measure	Influence order
With all variables	84.98	+0.6997	N/A
Var. 1 constant	85.02	+0.7005	7 (least influential)
Var. 2 constant	75.75	+0.5150	1 (most influential)
Var. 3 constant	85.00	+0.7001	6
Var. 4 constant	79.64	+0.5929	3
Var. 5 constant	78.02	+0.5605	2
Var. 6 constant	84.96	+0.6993	4
Var. 7 constant	84.98	+0.6997	5

Table 9. The results of forcing all independent variables except one to be constant.

Model	Accuracy (%)	Skill measure
With all variables	84.98	+0.6997
All constant but var. 1	56.26	+0.1252
All constant but var. 2	73.52	+0.4704
All constant but var. 3	44.40	-0.1119
All constant but var. 4	67.60	+0.3519
All constant but var. 5	78.65	+0.5730
All constant but var. 6	48.88	-0.0224
All constant but var. 7	49.71	-0.0057

Table 10. Backwards stepwise constant forcing.

Model	Variables included	Accuracy (%)	Skill measure
With all variables	All variables	84.98	0.6997
Step 1: var.[1] constant	[2,3,4,5,6,7]	85.02	0.7005
Step 2: var.[1,7] constant	[2,3,4,5,6]	85.02	0.7005
Step 3: var.[1,7,6] constant	[2,3,4,5]	84.93	0.6987
Step 4: var.[1,7,6,3] constant	[2,4,5]	84.60	0.6920
Step 5: var.[1,7,6,3,4] constant	[2,5]	83.43	0.6685
Step 6: var.[1,7,6,3,4,2] constant	[5]	78.65	0.5730

### 3.4. Predicted land-use change for 2021 and 2027

The modified CA-MC model based on ANN was then calibrated to predict urban growth and land change for the study area in 2021 and 2027. The researchers predicted future maps based on the assumption that the pattern of land change will follow a similar pattern to that of the past and it will be affected by the same factors at the same level (Figure 15).

The predicted map for 2027 illustrated that urban areas would increase from 57.1 km<sup>2</sup> in 2003 to 144.7 km<sup>2</sup> in 2027 showing an area increase of 87.6 km<sup>2</sup>. On the other hand, the agricultural land would decrease by 74.7 km<sup>2</sup> when undeveloped land would also decrease by 12.8 km<sup>2</sup> when comparing 2003 with the predicted 2027 (Table 13). The future forecasting for Irbid land change showed that agricultural land will lose about 23.07% of its area compared to 2003. On the other hand, the total urban area in 2027 is expected to change by 27.03% compared to 2003 changing its percentage from 17.63% to an overwhelming 44.66% (Figure 16).

## 4. Discussion

The purpose of this research is to develop the AI models that simulate land-use change, namely, CA and MC models. This research integrates these models with ANN to improve the future land-use change prediction accuracy, incorporate more driving forces to aid in achieving more meaningful prediction, and compare the accuracy results of the ANN-CA-MC model with other models that depend on experts' opinions attained from previous case studies such as AHP. It is expected that this will help to overcome the shortcomings of the individual models by incorporating them in a hybrid model that has better potential for predicting land-use change. The following sections will compare the models, explain their characteristics, and discuss the case study findings.

### 4.1. Models comparison

Shafizadeh-Moghadam et al. (2017b) applied ANN, Weight of Evidence (WOE), and Fuzzy Multi-Criteria Evaluation models to predict future land-use where they achieved an accuracy of 85%, 75%, and 73%, respectively. Additionally, Maithani (2010) implemented a Logistic Regression Model and achieved an accuracy of 81%. In a more recent study done on Addis Ababa using CA-MC model, the overall accuracy showed 86%, 87%, and 87% for the years 2005, 2011, and 2015, respectively (Mohamed and Worku, 2020). However, in our research, the employment of ANN with CA-MC model resulted in higher overall accuracy (90.04%).

Shafizadeh-Moghadam and Helbich (2013) used CA-Markov model, with MCE to cover up the limitations of implementing driver forces of the original model and reported an accuracy level of 83%. Aburas et al. (2017) utilized the CA-MC model based on AHP and FR to simulate urban growth in Seremban, Malaysia. Their models succeeded in terms of addressing the most important factors that govern urban growth in the city and achieved 88.1% and 88.2% accuracy levels, respectively. However they incorporated subjective weighting of variables making the

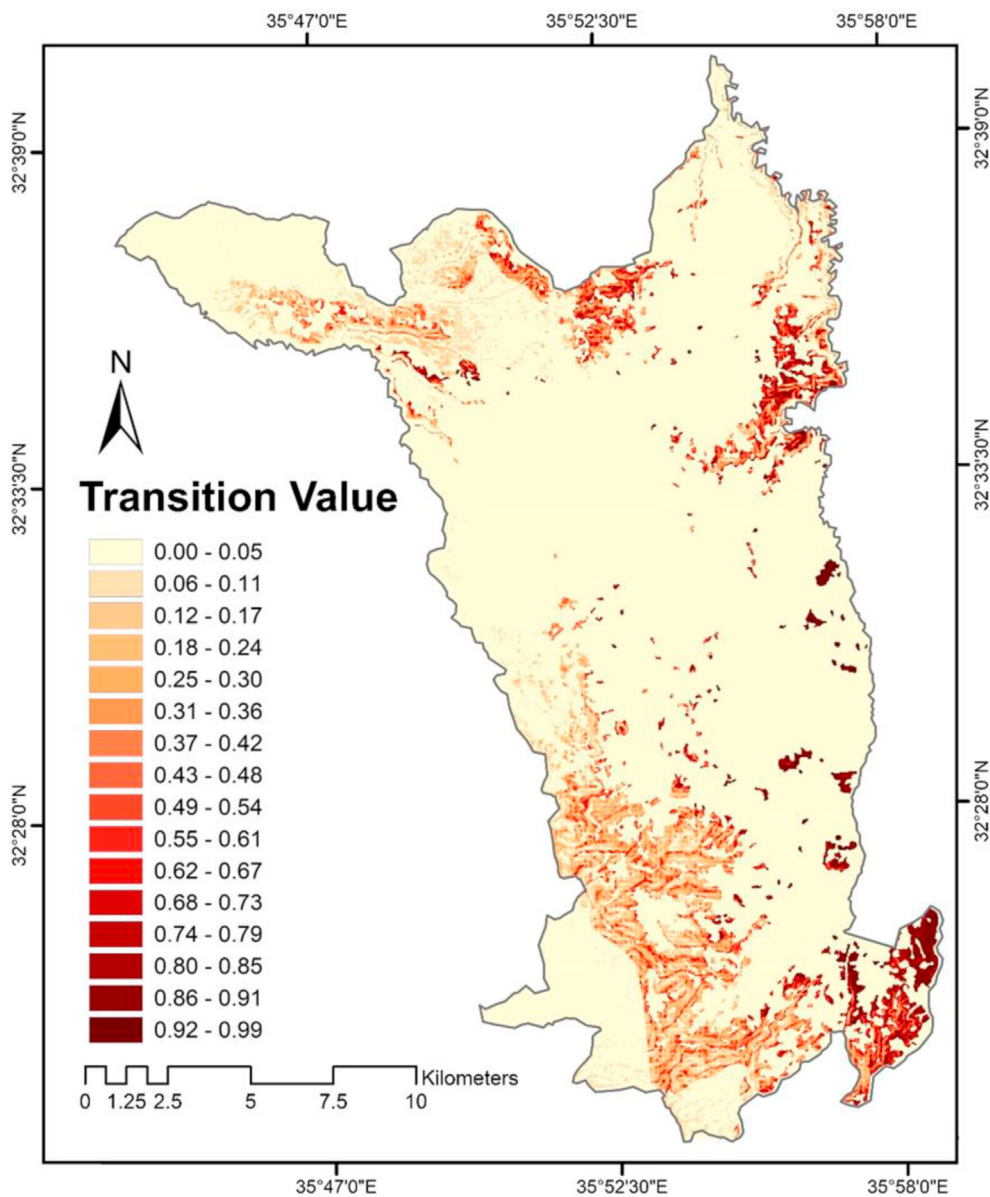


Figure 11. Potential area for transition from undeveloped to agricultural lands.

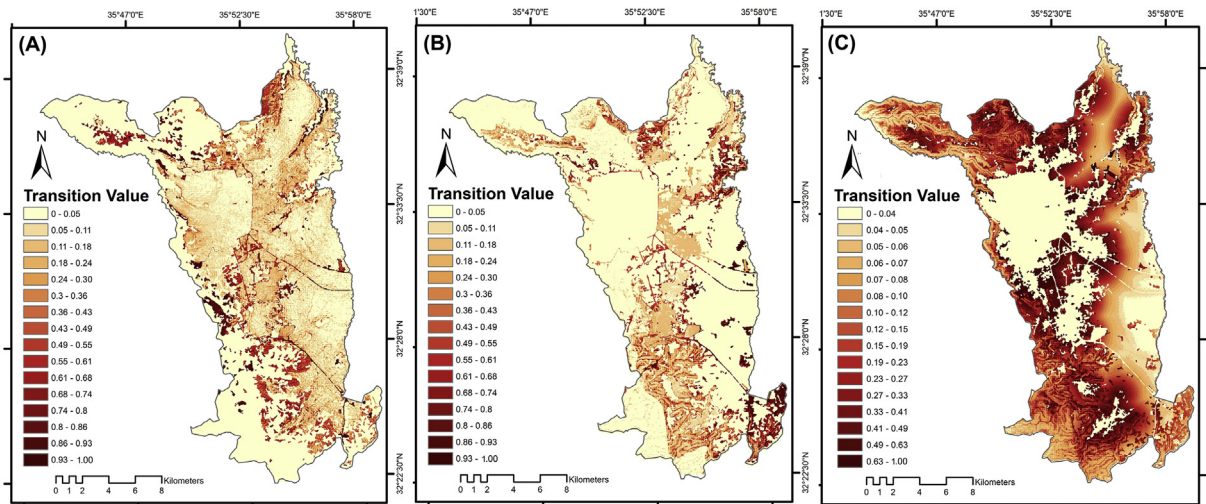


Figure 12. Potential transition area to (A) undeveloped land (B) agriculture land (C) urban area.

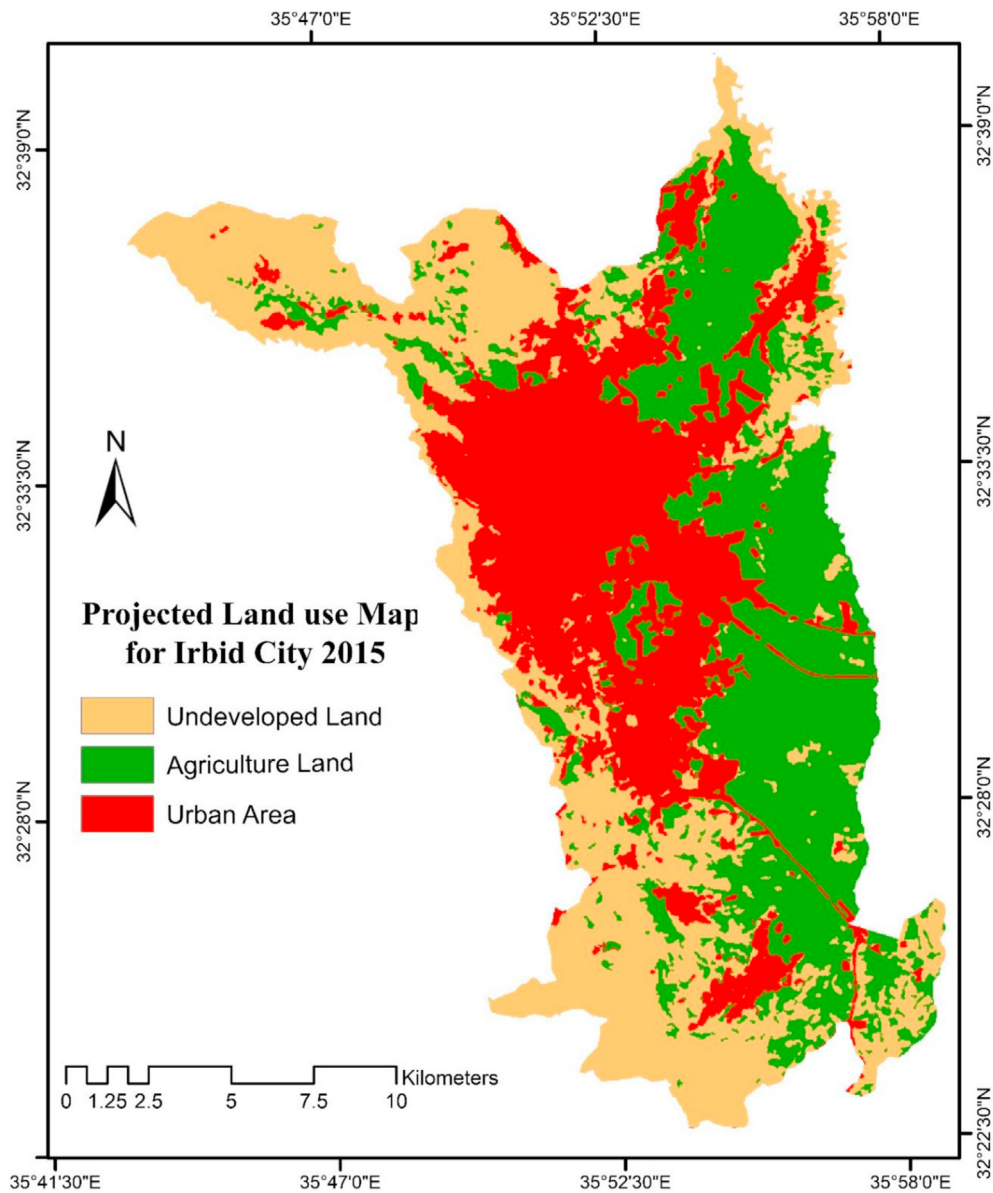


Figure 13. Projected land-use map for 2015 using CA-MC Model based on ANN.

Table 11. The influence of driving forces on land-use change.

Model	Influence order
Population Density	1 (most influential)
Slope	2
Distance to Commercials centers	3
Land fertility	4
Distance to Urban Centers	5
Distance to Main Roads	6
Elevation	7 (least influential)

results hard to reproduce when using other experts to weigh the driving forces (Park et al., 2011). Furthermore, due to the complexity of land change, it seems doubtful that experts have a sufficiently detailed understanding of the process of land change to apply AHP and MCE effectively (Cannemi et al., 2014; Shafizadeh-Moghadam et al., 2017b).

Therefore, despite the extensive efforts to minimize errors, there appear to be shortcomings resulting from subjective methods of

weighting the variables such as the one used in AHP. There are model limitations which, cannot incorporate nonlinear and qualitative variables, too. ANN substituted both shortcomings.

In more detail, applying AHP and MCE to develop the traditional CA-Markov model is successful in covering up the limitation of addressing the driving forces. These methods are flexible and can be easily integrated with the model and enable the researcher to use different opinions and achieve the ultimate goal more efficiently. However, a questionnaire survey is needed in such studies to calculate driving forces weights which are usually very subjective since AHP depends on subjective expert opinions. There is a limitation that when using AHP the results might not be repeatable, especially if the experts are changed each time (Cannemi et al., 2014; Labib, 2019).

These methods also show limitations where there is insufficient knowledge about the area of interest or when they fail in covering all aspects and variables affecting land-use change. Although adding more variables is preferable as it is expected to reduce errors, some of the data may not be accessible all the time.

On the other hand, ANN acts independently regardless of the statistical data distribution, or the lack of statistics for specific variables (Zhou

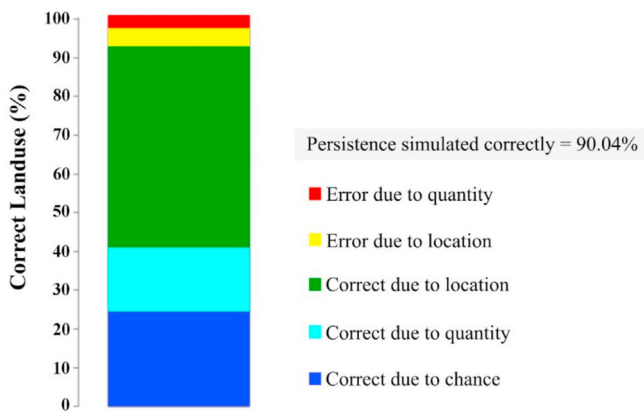


Figure 14. Component of agreement and disagreement for CA-MC model based on ANN.

et al., 2017). It has been reported that with little dataset training for the ANN model, accurate test results are possible (Lee et al., 2004; Paola and Schowengerdt, 2007; Park et al., 2011). The results of this study support ANN capability for training even with limited temporal inputs and

driving forces. In contrast with other methods, ANN allows for the detection of potential interdependencies. This is done through implied driving forces that are subject to adaptation in each significant case study (Shafizadeh-Moghadam et al., 2017b).

Adding ANN to the CA-MC model can internally compute weights in the hidden layers by incorporating nonlinear and qualitative variables. The integration of CA-MC with ANN allows the model to capture the different variables and dynamics behind land transformations, which significantly improves the CA-MC model's prediction capability. Thus, ANN can be considered an unbiased tool that is appropriate to assign weights that are derived with minimum prediction errors. As a result, it is fair to say that ANN approach reduces inaccuracy as well as the possibility of expert bias.

4.2. Model characteristics

In summary, CA model was useful in spatial change modeling, MC model enabled the modeling of temporal change, while ANN reduced the prediction error and incorporated the driving forces with the weights that achieved the most accurate optimization process. As a result, this research (ANN-CA-MC) enabled higher accuracy levels where its accuracy reached 90.04% while other models failed to reach this level of accuracy and had less reliability because it depended on expert choices. It

Table 12. Confusion matrix for projected map 2015.

		Reference Data				
		Urban	Agriculture	Undeveloped	Row Total	User's Accuracy
Classified Data	Urban	27	0	1	28	96.43
	Agriculture	0	33	2	35	94.29
	Undeveloped	2	0	25	27	92.59
	Column Total	29	33	28	90	94.44
Producer's Accuracy		93.10	100.00	89.29	94.44 (Overall Accuracy)	

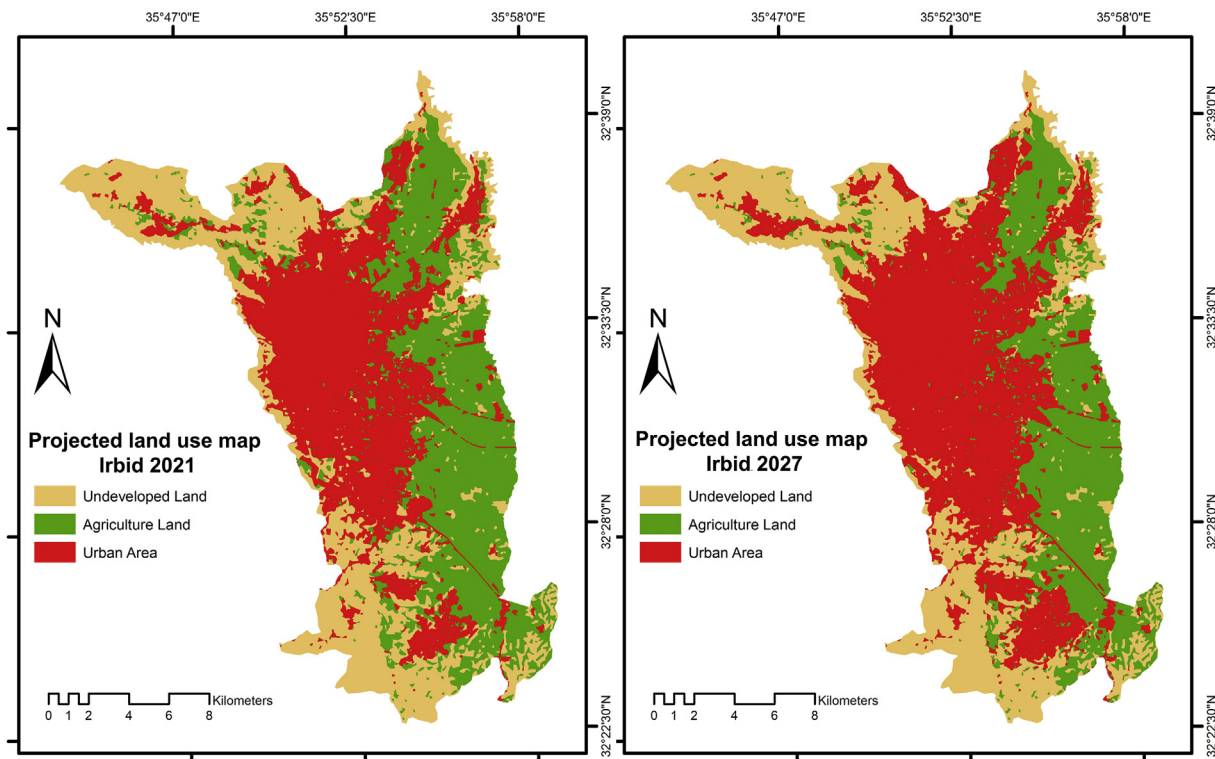
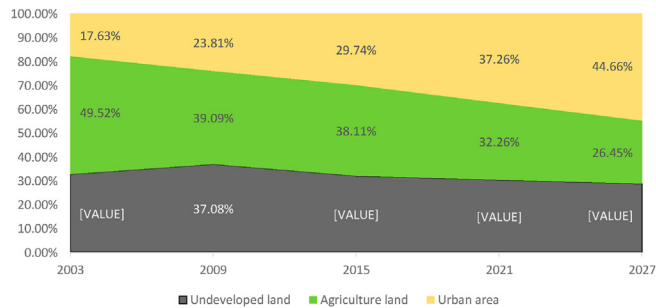


Figure 15. Projected land-use map for 2021 and 2027.

**Table 13.** Land change areas; actual and predicted.

	Undeveloped land km <sup>2</sup>	Agriculture land km <sup>2</sup>	Urban area km <sup>2</sup>	Total area km <sup>2</sup>
2003	106.4	160.4	57.1	324
2009	120.1	126.7	77.1	324
2015	104.1	123.5	96.4	324
2021*	98.7	104.5	120.7	324
2027*	93.6	85.7	144.7	324

\* Predicted areas.

**Figure 16.** Land area change from 2003 to the predicted year 2027. Grey: undeveloped land, Green: agricultural land, Yellow: urban land.

is worth mentioning that the improvement in the ANN-CA-MC model performance is not restricted to the output accuracy, but also exceeds that to the incorporation of driving forces during the prediction process.

Using such a model ensures accurate estimates for predicted land-use losses and land-use gains in each land-use in terms of percentage, area, and location (Table 13, Figures 15 and 16). It also enabled the comparison between driving forces to show which is more effective on the change in each scenario. Where the model illustrates that population density, slope, distance to commercial centers, and land fertility are respectively the most effective driving forces in the land change process in the case of Irbid city. This model is flexible and tolerates the incorporation of other future socioeconomic factors such as land value and population income. Adding more or less driving forces is usually site-specific or case sensitive. Our model is made so that the most important variables are incorporated.

This case study only had three types of land-uses. However, other case studies may have more variations in the land-uses such as preserved lands, water bodies, and other limiting land-uses which will surely enrich the model. These limitations are based on the available case study characteristics but they are not shortcomings of the research. When applying this model to other case studies, it will be an easy task to add more land-use types to the research model. It is expected that any future study will need to customize the model to benefit the most from its capability to predict land-use change. This model is made general to serve as a template that suits other cases around the world. Finally, this study will help planners to predict land-use change more precisely and also give them a more detailed understanding of the land-transformation process.

#### 4.3. Case study assessment

Based on the land-use change predictions for 2027 in the city of Irbid, agricultural lands will decrease by 46.6% changing its overall area from 49.52% in 2003 to 26.45% in 2027 (- 74.7 km<sup>2</sup>) (Table 13, Figure 16). The urban sprawl is quickly eating up agricultural land, however, it is still doubtful that the population will grow to fill up the expected urban land area growth by 153.4% (+87.6 km<sup>2</sup>) (Table 13, Figure 16). Based on the model, the selected driving forces successfully contributed to the predictability capacity of future land-uses since the accuracy level is greater

than 90%. The results highlight the major forces contributing to change especially population density, slope, distance to commercial centers, and Land fertility.

Population density is an impacting factor that cannot be ignored especially in this case facing many slowly incoming migrations such as many places around the globe (Liu and Yamauchi, 2014; Zhang et al., 2019; Zhou et al., 2020). However, the relationship between population projections and real estate growth is an issue that is worth investigating. The model is showing substantial urban growth which may impact the land-use balance.

Both gentle slopes and moderate ones can be attractive to land-use change (Jin et al., 2015; Şatir, 2016; Zhang et al., 2019; Gharaibeh et al., 2020). The slope maps show gentle terrains in the western and southern parts of the city of Irbid. In these areas, building is becoming more appealing to some in order to have a good view of the plains towards the east. In addition, places with low percentages of slope are easier to grow into and therefore, it is experiencing vast changes from agricultural land-uses to urban land-uses. Especially with the absence of enforced policies, this is growing out of hand in the city and the predicted future is no better than the current conditions (Gharaibeh et al., 2020). This is an alarming status for the future comprehensive plans of the city of Irbid.

Agricultural lands will be jeopardized and policies have to focus on limiting these expected land-use changes (Prishchepov et al., 2020). The concentration on ecological and agricultural protection policies should be given a priority in the city to limit the spatial changes leading to urban sprawl. The unplanned loss of agricultural and fertile lands will cause soil degradation as experienced in many parts of the world (El-Seedy and Saeed, 2019; Prishchepov et al., 2020). Food security is a major issue in the city of Irbid since these agricultural lands are the wheat fields that feed the nation (Gharaibeh et al., 2020).

Judging from the maps, areas adjacent to the main road network were more prone to change to urban areas. This result is also shared by previous research that focused on this variable as a driver of change (Farah et al., 2019; Zhang et al., 2019). This issue is also linked to distance to commercial land-use since this type of land-use is habitually located on the main road network (Simwanda et al., 2020; Zhang et al., 2019). With loose urban policies, this may lead to creating linearly expanding and connected cities and towns (Prishchepov et al., 2020). This is also jeopardizing the landscape character especially traveling from one place to another (Gharaibeh et al., 2017). Future agricultural land will be masked by the linear urban areas located on the main roads blocking the travelers' view. The easy terrain with mainly flat land may have contributed to this ease of horizontal expansion as well as changes (Jin et al., 2015; Şatir, 2016; Zhang et al., 2019).

#### 5. Conclusion

This study improved the capability of CA-MC model in simulation and prediction of land transformation. The performance of the model improved after integrating it with ANN model. The integrated approach was implemented to cover up the limitation of the original CA-MC model which is not utilizing the factors that drive the process of land change. On the other hand, ANN model can detect potential interdependencies



through the implied driving forces, which made it an ideal choice for this integration. A wide range of data and the most driving forces can be utilized in integrating ANN with original CA-MC. Based on the validation model, the original CA-MC and ANN-CA-MC models achieved 86.29% and 90.04% respectively. The ANN-CA-MC model improved the original model in terms of performance with no detectable limitations and more accurate results. ANN-CA-MC was calibrated to simulate urban growth for the years 2021 and 2027 in Irbid. Finally, ANN-CA-MC model will help planners and decision-makers to predict urban growth and give them a more detailed understanding of how the extent and pattern of the land-use change process takes place. It will surely support the efforts by authorities to sustain food security by protecting fertile lands and agricultural fields.

## Declarations

### Author contribution statement

A. Gharaibeh: Conceived and designed the experiments; Contributed reagents, materials, analysis tools or data; Wrote the paper.

A. Shaamala: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

R. Obeidat: Conceived and designed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

S. Al-Kofahi: Contributed reagents, materials, analysis tools or data; Wrote the paper.

### Funding statement

This work was supported by TA funding from Jordan University of Science and Technology. Research project number 675–2018 (Research Grant No: 20190014) Towards a Responsive Resilient Regional Environment for the City of Irbid.

### Competing interest statement

The authors declare no conflict of interest.

### Additional information

No additional information is available for this paper.

### Acknowledgements

This research received TA funding from Jordan University of Science and Technology. Research project number 675–2018 (Research Grant No: 20190014) Towards a Responsive Resilient Regional Environment for the City of Irbid.

## References

Aburas, M.M., Ahamad, M.S.S., Omar, N.Q., 2019. Spatio-temporal simulation and prediction of land-use change using conventional and machine learning models: a review. *Environ. Monit. Assess.* 191, 205.

Aburas, M.M., Ho, Y.M., Ramli, M.F., Ash'aari, Z.H., 2016. The simulation and prediction of spatio-temporal urban growth trends using cellular automata models: a review. *Int. J. Appl. Earth Obs. Geoinf.* 52, 380–389.

Aburas, M.M., Ho, Y.M., Ramli, M.F., Ash'aari, Z.H., 2017. Improving the capability of an integrated CA-Markov model to simulate spatio-temporal urban growth trends using an analytical hierarchy process and frequency ratio. *Int. J. Appl. Earth Obs. Geoinf.* 59, 65–78.

Al-Kofahi, S.D., Hammouri, N., Sawalhah, M.N., Al-Hammouri, A.A., Aukour, F.J., 2018. Assessment of the urban sprawl on agriculture lands of two major municipalities in Jordan using supervised classification techniques. *Arab. J. Geosci.* 11.

Al-Kofahi, S.D., Gharaibeh, A.A., Bsoul, E.Y., Othman, Y.A., Hilaire, R.S., 2019. Investigating domestic gardens' densities, spatial distribution and types among city districts. *Urban Ecosyst.* 22 (3), 567–581.

Anantwar, S.G., Shelke, R.R., 2012. Simplified approach of ANN: strengths and weakness. *Int. J. Eng. Innovat. Technol.* 1, 73–77.

Arsanjani, J.J., Helbich, M., Kainz, W., Boloorani, A.D., 2013. Integration of logistic regression, Markov chain and cellular automata models to simulate urban expansion. *Int. J. Appl. Earth Obs. Geoinf.* 21, 265–275.

Bhatti, N.B., Siyal, A.A., Qureshi, A.L., Bhatti, I.A., 2019. Land covers change assessment after small dam's construction based on the satellite data. *Civil Eng. J.* 5, 810–818.

Batty, M., Xie, Y., 1994. Modelling inside GIS: Part 1. Model structures, exploratory spatial data analysis and aggregation. *Int. J. Geogr. Inf. Syst.* 8, 291–307.

Bell, E.J., Hinojosa, R., 1977. Markov analysis of land-use change: continuous time and stationary processes. *Soc. Econ. Plann. Sci.* 11, 13–17.

Bununu, Y.A., 2017. Integration of Markov chain analysis and similarity-weighted instance-based machine learning algorithm (SimWeight) to simulate urban expansion. *Int. J. Unity Sci.* 21, 217–237.

Cannemi, M., García-melón, M., Aragonés-beltrán, P., 2014. Modeling decision making as a support tool for policy making on renewable energy development. *Energy Pol.* 67, 127–137.

Clevers, J.G., 2009. Russell G. Congalton and kass green, assessing the accuracy of remotely sensed data—principles and practices. *Int. J. Appl. Earth Obs. Geoinf.* 11, 448–449.

Congalton, R.G., 1991. A review of assessing the accuracy of classifications of remotely sensed data. *Remote Sens. Environ.* 37 (1), 35–46.

Congalton, R.G., Green, K., 2009. Thematic accuracy. *Assess. Accur. Remote. Sens. Data: Principles Pract.* 55–61.

Couclelis, H., 1997. From cellular automata to urban models: new principles for model development and implementation. *Environ. Plann. Plann. Des.* 24, 165–174.

DOS, 2004. Department of statistics, Jordan, general results of census. [http://www.dos.gov.jo/dos\\_home\\_e/main/population/census2004/group3/table\\_36.pdf](http://www.dos.gov.jo/dos_home_e/main/population/census2004/group3/table_36.pdf). (Accessed 25 May 2020).

DOS, 2009. Department of Statistics, Jordan, Jordan in figures report. <http://dosweb.dos.gov.jo/DataBank/JordanInFigures/2009.pdf>. (Accessed 25 May 2020).

DOS, 2015. Department of Statistics, Jordan, General Results of Census, the Population of the Kingdom by Administrative Divisions, According to the General Census of Population and Housing Result 2015. <https://www.citypopulation.de/en/jordan/admin/>. (Accessed 25 May 2020).

DOS, 2017. Summary of Agricultural Census in Jordan, 2017. Department of Statistics. Retrieved in August 17th 2020, from. <https://ammanchamber.org.jo/UploadedFiles/201891111538.pdf>.

Eastman, J.R., 2006. IDRISI Andes. Clark University, Worcester, MA.

Eastman, J.R., 2012. Idrisi Selva Tutorial, 45. Idrisi Production, Clark Labs-Clark University, pp. 51–63.

El-Seedy, M.E., Saeed, M.A., 2019. Tracking changes in soil fertility at North Nile Delta, Egypt using GIS techniques. *J. Soil Sci. Agricult. Eng.* 10 (10), 627–635.

Farah, N., Khan, I.A., Maan, A.A., Shahbaz, B., Cheema, J.M., 2019. Driving factors of agricultural land conversion at rural-urban interface in Punjab, Pakistan. *J. Agric. Res.* 57 (1), 55–62. [https://apply.jar.punjab.gov.pk/upload/1554058591\\_135\\_9\\_1353.pdf](https://apply.jar.punjab.gov.pk/upload/1554058591_135_9_1353.pdf).

Gharaibeh, A.A., Shaamala, A.H., Ali, M.H., 2020. Multi-Criteria evaluation for sustainable urban growth in an-Nuayyimah, Jordan; post war study. *Proc. Manufact.* 44, 156–163.

Gharaibeh, A.A., Jaradat, R.A., Okour, Y.F., Al-Rawabdeh, A.M., 2017. Landscape perception and landscape change for the city of Irbid, Jordan. *J. Architect. Plan.* 29 (1), 89–104. [https://cap.ksu.edu.sa/sites/cap.ksu.edu.sa/files/imce\\_images/jap\\_ksu\\_jan2017\\_e1.pdf](https://cap.ksu.edu.sa/sites/cap.ksu.edu.sa/files/imce_images/jap_ksu_jan2017_e1.pdf). (Accessed January 2020).

Gharaibeh, A.A., Zu'bi, A., Esra'a, M., Abuhassan, L.B., 2019. Amman (city of waters); policy, land-use, and character changes. *Land* 8 (12), 195.

Guan, D., Li, H., Inohae, T., Su, W., Nagaie, T., Hokao, K., 2011. Modeling urban land-use change by the integration of cellular Automaton and Markov model. *Ecol. Model.* 222, 3761–3772.

Guan, Q., Wang, L., Clarke, K.C., 2005. An artificial-neural-network-based, constrained CA model for simulating urban growth. *Cartogr. Geogr. Inf. Sci.* 32, 369–380.

Halmly, M.W.A., Gessler, P.E., Hicke, J.A., Salem, B.B., 2015. Land-use/Land cover change detection and prediction in the North-western coastal desert of Egypt using Markov-CA. *Appl. Geogr.* 63, 101–112.

Hamad, R., Baltzer, H., Kolo, K., 2018. Predicting land-use/land cover changes using a CA-Markov model under two different scenarios. *Sustainability* 10, 3421.

Hu, Z., Lo, C., 2007. Modeling urban growth in Atlanta using logistic regression. *Comput. Environ. Urban Syst.* 31 (6), 667–688. In this issue.

Jafari, M., Majedi, H., Monavari, S.M., Alesheikh, A.A., Zarkesh, M.K., 2016. Dynamic simulation of urban expansion through A CA-Markov model case study: Hyrcanian region, Gilan, Iran. *Eur. J. Remote Sens.* 49, 513–529.

Jin, G., Li, Z., Lin, Q., Shi, C., Liu, B., Yao, L., 2015. Land-use suitability assessment in low-slope hilly regions under the impact of urbanization in Yunnan, China. *Adv. Meteorol.* 2015, 1–9.

Karayannis, N.B., 1999. Reformulated radial basis neural networks trained by gradient descent. *IEEE Trans. Neural Network.* 10, 657–671.

Karimi, F., Sultana, S., Babakan, A.S., Suthaharan, S., 2019. An enhanced support vector machine model for urban expansion prediction. *Comput. Environ. Urban Syst.* 75, 61–75.

Labib, S.M., 2019. Investigation of the likelihood of green infrastructure (GI) enhancement along linear waterways or on derelict sites (DS) using machine learning. *Environ. Model. Software* 118, 146–165.

Laliberte, A.S., Rango, A., Havstad, K.M., Paris, J.F., Beck, R.F., McNeely, R., Gonzalez, A.L., 2004. Object-oriented image analysis for mapping shrub encroachment from 1937 to 2003 in southern New Mexico. *Remote Sens. Environ.* 93 (1–2), 198–210.

- Lavalle, C., Demicheli, L., Turchini, M., Casals-Carrasco, P., Niederhuber, M., 2001. Monitoring megacities: the murbandy/moland approach. *Dev. Pract.* 11, 350–357.
- Lee, S., Ryu, J.-H., Won, J.-S., Park, H.-J., 2004. Determination and application of the weights for landslide susceptibility mapping using an artificial neural network. *Eng. Geol.* 71, 289–302.
- Liu, Y., Yamauchi, F., 2014. Population density, migration, and the returns to human capital and land: insights from Indonesia. *Food Pol.* 48, 182–193.
- Maithani, S., 2010. A neural network based urban growth model of an Indian city. *J. Indian Soc. Remote Sens.* 37, 363–376.
- Megahed, Y., Cabral, P., Silva, J., Caetano, M., 2015. Land cover mapping analysis and urban growth modeling using Remote sensing techniques in greater Cairo region-Egypt. *Int. J. Geo-Informat.* 4, 1750–1769.
- Memarian, H., Kumar Balasundram, S., Bin Talib, J., Teh Boon Sung, C., Mohd Sood, A., Abbaspour, K., 2012. Validation of CA-Markov for simulation of land-use and cover change in the langat basin, Malaysia. *J. Geogr. Inf. Syst.* 4, 542–554.
- Mitsova, D., Shuster, W., Wang, X., 2011. A cellular automata model of land cover change to integrate urban growth with open space conservation. *Landsc. Urban Plann.* 99 (2), 141–153.
- MoA (Ministry of Agriculture, Jordan), 1993. The Soils of Jordan: Level 1 (Reconnaissance Survey), National Soil Map and Land-Use Project. Ministry of Agriculture, Jordan.
- MoA (Ministry of Agriculture, Jordan), 1995. Main Report. The Soils of Jordan, Report of the National Soil Map and Land-Use Project, 2. Ministry of Agriculture, Amman, Jordan.
- Mohamed, A., Worku, H., 2020. Simulating urban land-use and cover dynamics using cellular automata and Markov chain approach in Addis Ababa and the surrounding. *Urban Clim.* 31, 1–17, 100545.
- Mohammady, S., Delavar, M.R., Pahlavani, P., 2014. Urban growth modeling using an artificial neural network A case study of sanandaj city, Iran. In: *ISPRS - International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, XL-2/W3*, pp. 203–208.
- Musa, S.I., Hashim, M., Reba, M.N.M., 2016. A review of geospatial-based urban growth models and modelling initiatives. *Geocarto Int.* 32, 813–833.
- Nahavandya, S.K., Kumar, L., Ghamisi, P., 2017. Using the SLEUTH urban growth model to simulate the impacts of future policy scenarios on urban land-use in the Tehran metropolitan area in Iran. <https://arxiv.org/abs/1708.01089v1>. (Accessed 29 January 2020).
- Nouri, J., Gharagozlou, A., Arjmandi, R., Faryadi, S., Adl, M., 2014. Predicting urban land-use changes using a CA-Markov model. *Arabian J. Sci. Eng.* 39, 5565–5573.
- Paola, J.D., Schowengerdt, R.A., 2007. A review and analysis of backpropagation neural networks for classification of remotely-sensed multi-spectral imagery. *Int. J. Rem. Sens.* 16, 3033–3058.
- Park, S., Jeon, S., Kim, S., Choi, C., 2011. Prediction and comparison of urban growth by land suitability index mapping using GIS and RS in South Korea. *Landsc. Urban Plann.* 99, 104–114.
- Pijanowski, B.C., Brown, D.G., Shellito, B.A., Manik, G.A., 2002. Using neural networks and GIS to forecast land-use changes: a land transformation model. *Comput. Environ. Urban Syst.* 26, 553–575.
- Pijanowski, B.C., Pithadia, S., Shellito, B.A., Alexandridis, K., 2005. Calibrating a neural network-based urban change model for two metropolitan areas of the upper midwest of the United States. *Int. J. Geogr. Inf. Sci.* 19, 197–215.
- Pontius Jr., R.G., 2000. Quantification error versus location error in comparison of categorical maps. *Photogramm. Eng. Rem. Sens.* 66, 1011–1016.
- Pontius Jr., R.G., Millones, M., 2011. Death to kappa: birth of quantity disagreement and allocation disagreement for accuracy assessment. *Int. J. Rem. Sens.* 32, 4407–4429.
- Prishchepov, A.V., Schierhorn, F., Dronin, N., Ponkina, E.V., Müller, D., 2020. 800 years of agricultural land-use change in Asian (Eastern) Russia. In: *KULUNDA: Climate Smart Agriculture*. Springer, Cham, pp. 67–87.
- Rumelhart, D.E., Hinton, G.E., Williams, R.J., 1985. Learning Internal Representations by Error Propagation. California Univ San Diego La Jolla Inst for Cognitive Science.
- Sangermano, F., Eastman, J.R., Zhu, H., 2010. Similarity weighted instance-based learning for the generation of transition potentials in land-use change modeling. *Trans. GIS* 14, 569–580.
- Santé, I., García, A.M., Miranda, D., Crecente, R., 2010. Cellular automata models for the simulation of real-world urban processes: a review and analysis. *Landsc. Urban Plann.* 96, 108–122.
- Şatir, O., 2016. Mapping the Land-Use Suitability for Urban Sprawl Using Remote Sensing and GIS under Different Scenarios. InTech: Horwich, UK, pp. 205–226.
- Saxena, A., Jat, M.K., 2019. Capturing heterogeneous urban growth using SLEUTH model. *Rem. Sens. Appl.: Soc. Environ.* 13, 426–434.
- Shafizadeh-Moghadam, H., Helbich, M., 2013. Spatiotemporal urbanization processes in the megacity of Mumbai, India: a Markov chains-cellular automata urban growth model. *Appl. Geogr.* 40, 140–149.
- Shafizadeh-Moghadam, H., Tayyebi, A., Ahmadlou, M., Delavar, M.R., Hasanlou, M., 2017a. Integration of genetic algorithm and multiple kernel support vector regression for modeling urban growth. *Comput. Environ. Urban Syst.* 65, 28–40.
- Shafizadeh-Moghadam, H., Tayyebi, A., Helbich, M., 2017b. Transition index maps for urban growth simulation: application of artificial neural networks, weight of evidence and fuzzy multi-criteria evaluation. *Environ. Monit. Assess.* 189, 300.
- Simwanda, M., Murayama, Y., Ranagalage, M., 2020. Modeling the drivers of urban land-use changes in Lusaka, Zambia using multi-criteria evaluation: an analytic network process approach. *Land Use Pol.* 92, 104441.
- Singh, S.K., Mustak, S., Srivastava, P.K., Szabó, S., Islam, T., 2015. Predicting spatial and decadal LULC changes through cellular automata Markov chain models using earth observation datasets and geo-information. *Environ. Proces.* 2, 61–78.
- Syphard, A.D., Clarke, K.C., Franklin, J., 2005. Using a cellular Automaton model to forecast the effects of urban growth on Habitat pattern in southern California. *Ecol. Complex.* 2, 185–203.
- Vaz, E.D.N., Nijkamp, P., Painho, M., Caetano, M., 2012. A multi-scenario forecast of urban change: a study on urban growth in the Algarve. *Landsc. Urban Plann.* 104, 201–211.
- Wang, J., Mountrakis, G., 2011. A multi-scenario forecast of urban change: a study on urban growth in the Algarve. *Int. J. Geogr. Inf. Sci.* 25, 229–253.
- Wang, X., Hofe, R., 2008. *Research Methods in Urban and Regional Planning*. Springer Science & Business Media. [http://www.dos.gov.jo/dos\\_home\\_a/main/population/census2015/No\\_of\\_pop\\_depand\\_on\\_GOV.pdf](http://www.dos.gov.jo/dos_home_a/main/population/census2015/No_of_pop_depand_on_GOV.pdf). (Accessed 25 May 2020).
- White, R., Engelen, G., 2000. High-resolution integrated modelling of the spatial dynamics of urban and regional systems. *Comput. Environ. Urban Syst.* 24, 383–400.
- Yang, J., Su, J., Chen, F., Xie, P., Ge, Q., 2016. A local land-use competition cellular automata model and its application. *ISPRS Int. J. Geo-Inf.* 5 (7), 106.
- Yang, Q., Li, X., Shi, X., 2008. Cellular automata for simulating land-use changes based on support vector machines. *Comput. Geosci.* 34, 592–602.
- Zhang, D., Liu, X., Wu, X., Yao, Y., Wu, X., Chen, Y., 2019. Multiple intra-urban land-use simulations and driving factors analysis: a case study in Huicheng, China. *GIScience Remote Sens.* 56 (2), 282–308.
- Zhou, Q., Shao, Q., Zhang, X., Chen, J., 2020. Do housing prices promote total factor productivity? Evidence from spatial panel data models in explaining the mediating role of population density. *Land Use Pol.* 91, 104410.
- Zhou, W., 1999. Verification of the nonparametric characteristics of backpropagation neural networks for image classification. *IEEE Trans. Geosci. Rem. Sens.* 37, 771–779.
- Zhou, Y., Zhang, F., Du, Z., Ye, X., Liu, R., 2017. Integrating cellular automata with the deep belief network for simulating urban growth. *Sustainability* 9, 1786.