URBAN GROWTH SIMULATION THROUGH CELLULAR AUTOMATA (CA), ANALYTIC HIERARCHY PROCESS (AHP) AND GIS; CASE STUDY OF 8th AND 12th MUNICIPAL DISTRICTS OF ISFAHAN

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Abstract:
Due to the models are basic tool of analysis for urban planners and the complexity of the urban growth process, in this paper, a model was developed based on CA, AHP and GIS for simulation of this phenomenon. At first, the factors affecting urban growth were determined and their weights were calculated by AHP. Then, a standalone CA was developed and simulation was performed for 2012 based on the data of 2005. By calculating the Kappa coefficient the accuracy of the model was demonstrated. The results suggested that the combination of indicated models can provide an appropriate tool for urban planners to profoundly analyze and predict urban growth process.

Key-words: *urban simulation, CA, AHP, GIS, 8th and 12th municipal districts of Isfahan*

1. INTRODUCTION

Nowadays, settlements which were small and isolated urban centres has become large and complex features that is called metropolis (Acevedo, Foresman & Buchanan, 1996). Moreover, population migration from rural to urban areas is one of the most important urban problem (Liu, 1965), which is resulted from regional imbalances and cause uncontrolled urban growth. The results of uncontrolled urban growth are urban sprawl, environmental damage (Zakerhaghighi, Majedi & Habib, 2010), and formation of informal settlements which suffer from social, economic, and physical problems (Ghaedrahmati & Heydarinejhad, 2009). “Faced with these severe negative impacts, there is an urgent need for urban planners to develop predictive models of urban growth, which not only provide an understanding of the urban growth process, but also provide realization of the numerous potential growth scenarios” (Maithani, 2010).

During the 1950s and 1960s, research on urban modelling attempted to build large scale urban models (LSUMs) (Mahiny & Golamalifard, 2007); these models are called spatial interaction models. Spatial interaction models are resulted from Reilly and Zipf attempts to model human activities and they are rooted in the gravity models such as Lowry model. These models are used to predict and analyze the interaction of urban subsystems, for instance: housing, transportation network, employment, population and land use subsystems (Clement, 1996).

However, the spatial interaction models had significant limitations, namely they are static in nature and require a lot of data (Maithani, 2010). It must also be noted that these modelling efforts try to shift urban planner’s point of view to the cities from an architectural phenomenon to a rational activity (Batty, 1994). Indeed, according to the comprehensiveness, complication and data requirements of spatial interaction models, they were criticized by planners and scholars (Lee, 1973).

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With respect to the fact that cities are complex combination of social and economic elements (Junfeng, 2003), application of conventional models is difficult, because they are static, aggregate and theoretically follow up, top to down approaches (Cheng, 2003). Hence, in the middle of 1980s, CA-based models were proposed as an alternative to conventional models (Couclelis, 1997; Torrens, 2000; Torrens 2001). CA-based models are simple, flexible, transparent (Sante et al., 2010), dynamic, bottom-up (Rezazadeh & Mirahmadi, 2007) and capable for combining with the other models (Philips, 1989).

Owing to the characteristics of CA-based models, they are vastly used for simulation of complex urban systems. Despite of the CA advantages, the original framework of CA is not appropriate to inform and support realistic urban dynamics (Wolfram, 1986). Determination of parameter's value in the urban growth process (Li & Yeh, 2002), constraint and simplicity of overall original structure (Sipper, 1997), as well as failure to consider the role of external factors which affect urban growth are some of the conventional CA limitations (Siethchiping, 2004).

Notwithstanding these restrictions, combination of conventional CA model with advanced models can remove these restrictions (Couclelis, 1989). There are some efforts for obviating to these limitations (*see:* Sui & Zeng, 2001; Almedia et al., 2003; Almedia et al., 2005*;* He et al., 2006; He et al., 2008; Al-Ahmedi et al., 2009). Engelen, White and Uljee (1997) proposed macro and micro integrated CA model in which various land uses were distributed based on socio-economic factors, while on the micro scale the assignment of the cells to the different land use types will be done. Wu (2002) developed a stochastic CA model in which the probability of modelling is extracted from observed temporal land use data. These researches confirmed that the capability of conventional CA model will increase if its components combine with the other models.

As Singh (2003) said, the combination of three elements, GIS, CA, and multi criteria evaluation method (MCEM) has several advantages: visualization of decision making, easier access to spatial information, and more realistic definition of transition rules in CA. On the other hand, among MCEMs, AHP has certain features which prepare this method for urban and regional planning (Zebardast, 2001). It must also be remembered that there are two approaches for application of CA model with GIS. In the first approach, the CA model is developed based on programming languages which are compatible with GIS, this kind of CA models runs within the GIS environment (Batty & Xie, 1994a*;* Batty & Xie, 1994b; Yeh & Li, 2001). In the second approach, modeller can develop a standalone CA model, in which the program can use GIS data according to file conversion protocols (Yate & Bishop, 1998). Therefore, in this paper, AHP, GIS and a developed standalone CA, were applied for simulation of urban growth in the study area.

2. MATERIALS AND METHODS

2.1. Study area

Over the last thirty years, 8th and 12th municipal districts of Isfahan expanded due to the population growth and allocation of unplanned land uses. These districts have the potential for attracting population which cause uncontrolled urban growth. In addition, these districts are located in the agricultural lands, and are experiencing the rapid urban growth phenomenon (Shahrokhane, 2007). It should be noted that in the study area all of the natural factors such as slope, elevation and soil type are appropriate for urban growth. For these reasons, 8th and 12th municipal districts of Isfahan were selected as the study area of this research (**Fig. 1**).

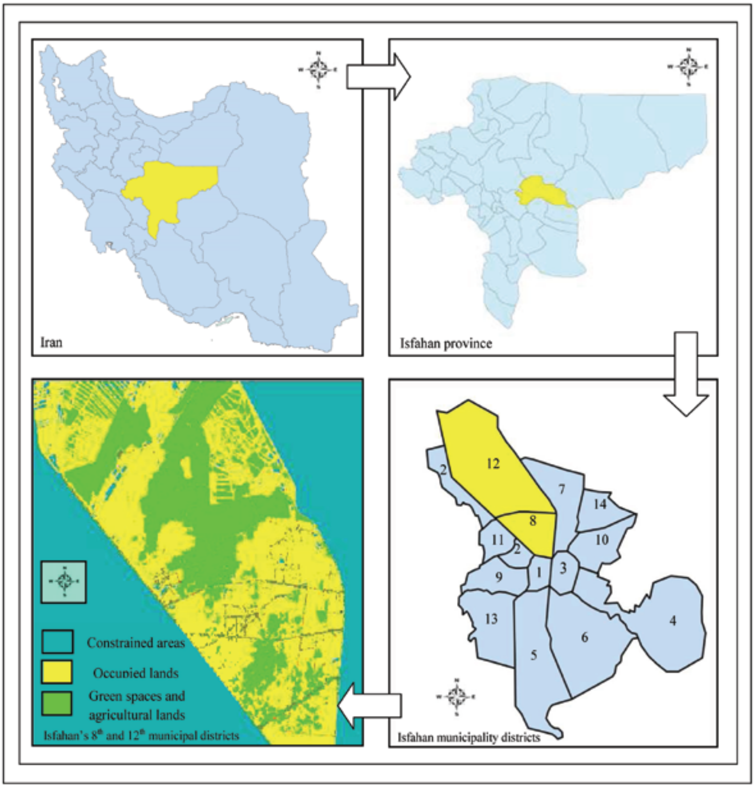

Fig. 1 Location of the study area.

The area of existent agricultural lands, open and green spaces and occupied areas subsequently equals 946 and 2323 hectares (**Table1**).

Table 1. The area of occupied and agricultural lands, green and open spaces in 2005.

Type of lands	Area (hectares)
Occupied lands	2323
Green and open spaces and agricultural lands	946

2.2. Introducing and selecting the factors affecting urban growth

Reviewing the literature about the urban growth showed that there are various factors which affect the urban growth process such as physical factors (i.e. slope and elevation), environmental factors, social factors (i.e. population density and social services), political factors (i.e. zoning policies), environmental factors, connection related factors (i.e. distance from roads and distance from highways), etc. These factors are introduced in **Table 2** in which factors that were used in previous studies are marked though the sign of star (*).

Table 2. Factors affecting urban growth.

Researches	Distance to roads	Distance to urban centers	Agricultural value/ soil type	Social services	Hazard lands	Environmental factors	Slope	Elevation	Zoning	Urban suitability	Population density
(Al-Kheder et al., 2008)	*	*		*			*	*			*
(Caruso et al., 2005)	*			*		*			*		*
(Barredo et al., 2003, 2004)	*								*	*	
(White and Engelen, 2000)	*								*	*	
(Deadma, 1993)	*		*		*						

2.3. Introducing the AHP model

Generally, multi criteria decision making (MCDM) methods help decision takers solve problems through the knowledge of experts (Rafiyan & Sardari 2008). AHP is one of the MCDMs which were proposed by Saaty in 1980 (Zebardast, 2001), and is a widely used multiple criteria decision making tool (Vaidya & Kumar, 2006). The AHP has been developed as an emerging solution approach to large, complex and unstructured decision making problems (Carlsson & Walden, 1995; Albayrakoglu, 1996; Bahurmoz, 2006). It has been applied in many fields such as planning and management in which the appropriateness, validity and reliability of the model were confirmed (Libertore, 1987; Weiwu & Jun, 1994; Korpela, Tuominen & Valoho, 1998; Korpela & Lehmusvara, 1999;). The main procedure of AHP consists of four steps: 1) structuring the hierarchy, 2) prioritizing the criteria by pair-wise comparison, 3) pair-wise comparing the alternatives and synthesizing eigenvalues, 4) calculating the consistency index and determining the validity of judgments (Saaty, 1980) (for more information see: Saaty, 1996; Saaty, 2000).

2.4. Introducing the CA model

CA-based models are dynamic and discrete systems which behave according to the neighborhood relationships. In the CA, space is defined as a grid, each part of which is called cell (Ghaheribadr, Maybodi & Mahmoudi, 2008). CA models consist of four components: lattice, cell states, neighbourhood and transition rules (Batty, Xie & Sun, 1999). Lattice is a grid which can adopt various geometrical forms like square and hexagonal shapes (**Fig. 2a**).

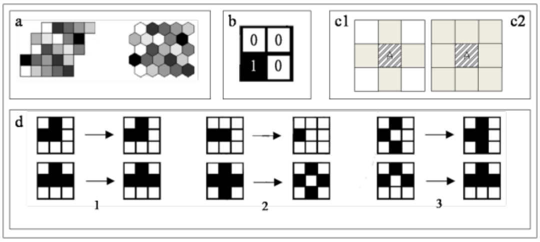

Fig. 2 Components of cellular automata model.

(Lee, Lei & Wu, 2009).

State of the cell shows the spatial variables related to each cell, like different types of land uses (**Fig. 2b**). Neighbourhood in CA models is the cells which are located around the central cell. In two dimensional CA, there are two ways for defining neighbourhoods: Van Newman and Moore neighbourhoods. In Van Newman neighbourhood (**Fig. 2c1**) four, and in Moore neighbourhood (**Fig. 2c2**) eight cells located around the central cell are considered for calculation and exploration of neighbourhood effects. Behaviours which occurred in the real world are apprehensible through transition rules in CA models. These rules let the CA models to become a dynamic model (Wu, 1998). The framework of the transition rules is a conditional if-then structure, making it possible to convert the complexity of the real world to the simplicity (Siethchiping, 2004) (**Fig. 2d**). According to Singh (2003), in cellular automata model, components and relationships between them can be shown as equation (1), where U is the lattice, T is the set of transition rules, S is the possible states, and N is the number of neighbours of each cell.

$$(U, S, N, T) \quad (1)$$

Singh also believes that we can represent the state of a cell at time (t+1) as a function of its state at time t, neighbourhoods and transition rules as equation (2):

$$S_{t+1}=f\ (S_t, N, T) \quad (2)$$

Where S_{t+1} is the state of a cell at time (t+1), S_t is the state of a cell at time t, and T is a set of transition rules followed by cells.

2.5. Developing a CA-based model for simulation of urban growth in the study area

The proposed model mainly consists of three modules. In the first module of the proposed model, the factors affecting urban growth in the study area were selected. Then, the analytical maps of each factor were prepared through GIS, by applying the buffer, conversion, union and reclassification functions. Finally, the weight of each factor was calculated through AHP, and analytical maps were overlaid based on the obtained weights of the previous step to achieve primary land suitability map. Second module of the model starts with calculation of probability map according to the AHP and direct probability (which is explained in proceeding sections) that is called final land suitability map, then the number of transforming cells was calculated; these are the inputs of CA model. The third module of the proposed model is definition of CA components (lattice, cell state, neighbourhood effects, and transition rules) and programming a standalone CA model (**Fig. 3**).

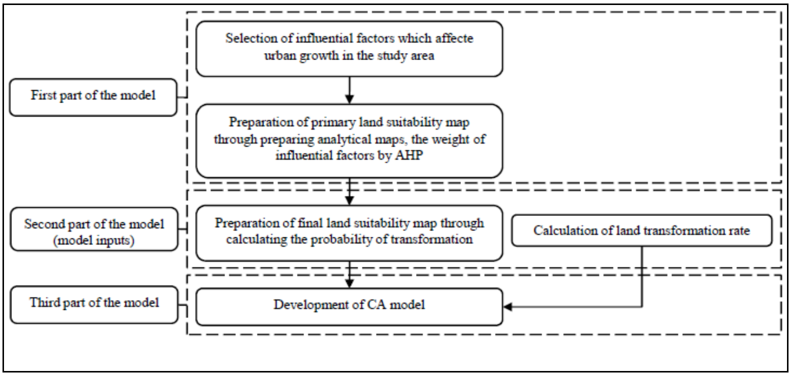

Fig. 3 The conceptual framework of proposed model.

2.5.1. Determining the factors affecting urban growth in the study area

Throughout this paper, distance from highways, distance from roads, distance from residential areas, distance from urban infrastructures and distance from educational land use were selected as the factors affecting simulation of urban growth, according to **Table 2**, geographical scale and comparative observation of temporal-aerial photos of the study area. It must also be noted that the urban growth in the study area is related to informal settlement. For this reason, political and institutional factors such as tax incentives don't have remarkable affect on the urban growth process than physical factors this fact that the residents of these areas are seeking to maximization of their accessibility to urban services.

2.5.2. Calculation of the factors affecting weight

Pair-wise comparisons of the affecting factors were conducted to obtain weight and the effect of each factor on urban growth process. For achieving the pair-wise matrices and appropriate points, Delphi technique was applied in which ten experts were asked to give their opinion on the weight of the affecting factors. Finally the weights of the affecting factors were calculated through the Expert Choice software (**Table 3**).

Table 3. Calculated weight of affecting factors.

Influential factors	Weight of each factors
Distance from highways	38.4
Distance from roads	21.9
Distance from educational land use	14.6
Distance from residential areas	6.40
Distance from urban infrastructures	6.20

2.5.3. Mapping primary land suitability map

After determining the influential factors and the weight of them, GIS map of study area in 2005 were taken from Isfahan municipality. Then, a model in GIS was developed for mapping primary land suitability, in which first the conversion function is applied for converting the format of input data (the input data comprised of selected affecting factors maps); second, the analytical map for each factor is produced through buffer and reclassification functions; third, the analytical maps converted to the shape files and a field were added to them. Then, the weight of each factor was multiplied to its value. After that the analytical maps were combined by union function and equation 3 (where s is the value of cell in each analytical maps, w is the weight of each factor and $\sum_1^n w_n \times s_n$ is the sum of values of the cell from combination of weights and the value of each cell on analytical maps) (**Fig. 4 and Fig. 5**). The results are shown in **Fig. 6**.

$$VPLSM = \sum_1^n w_1 \times s_1 + w_2 \times s_2 + ... + w_n \times s_n \qquad (3)$$

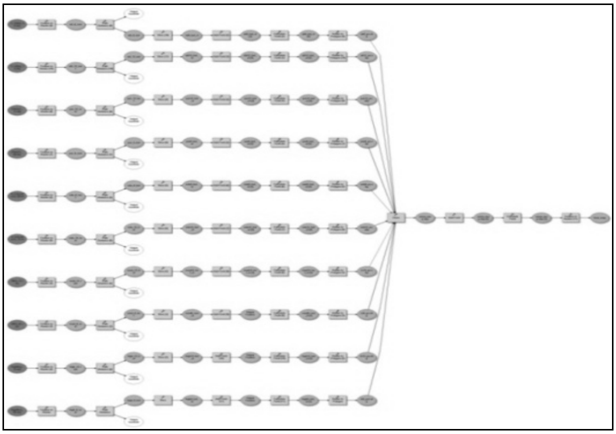

Fig. 4 Developed GIS model for mapping primary land suitability map.

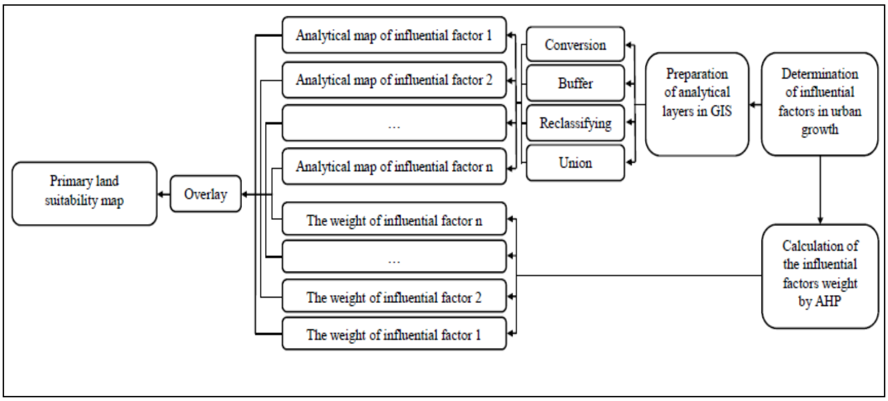

Fig. 5 Procedure of the first part of the proposed model.

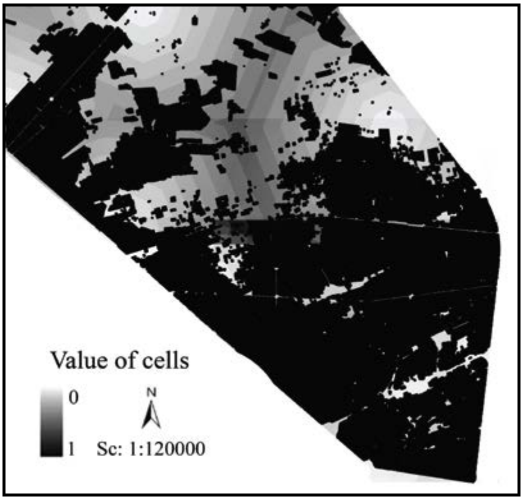

Fig. 6 Primary land suitability map.

2.5.4. Mapping the final land suitability map

In this part of the model, final land suitability map was drawn by calculating direct and weighted probability in which the probability of transformation for the cells from non-urban state to urban state were determined. The input of this part is primary land suitability map (**Fig 7**).

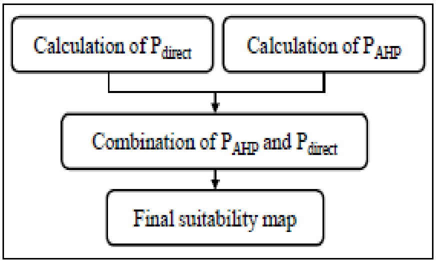

Fig. 7 Procedure of second part of the proposed model.

For calculating direct probability, all transformed cells (which means the cells with non-urban state in the past and urban state at the present time) and existent cells in each class were determined, then, the direct probability was calculated according to equation 4 where M_n is the number of transformed cells, S_n is the number of all cells that were located in class n and $P_{direct}^{n_{ij}}$ is the direct probability of the cell located in row and column on primary suitability map (Alimohammadisarab, Matkan & Mirbagheri, 2010):

$$P_{direct}^{n_{ij}} = \frac{M_n}{S_n} \tag{4}$$

The weighted probability was calculated through equation 4.

$$P_{AHP} = 1 - \frac{1}{VPLSM} \quad (5)$$

Finally, the weighted and direct probabilities were combined by equation 6 where Ω is the neighbourhood effect which depends on the number of the cells with the urban state around the cell, the value of Ω can be in the range of 1/8 and 1.

$$P_{total} = P_{AHP} \times P_{direct} \times \Omega \quad (6)$$

It should be noted that these calculations will be performed in the developed standalone CA model.

2.5.5. Calculation of transformation rate

The number of transforming cells in simulation years was predicted by regression model. First, the Pearson correlation coefficient (PCC) between the population of study area and the number of the cells with the urban state were calculated. The value of PCC equalled 0.97 which indicates the robust and direct relationship between these variables. Second, due to the value of PCC which demonstrates the correlation between population and transforming cells, a linear regression model was applied for predicting the number of transforming cells (**Table 4**).

Table 4. Prediction of transforming cells in the simulation years.

Year	Input value in the model
2012	3155
2022	3056
2032	3544
2042	3901

2.5.6. Definition of the CA components

As mentioned before, CA includes four components. In this part of the model these components were defined as follows:

Lattice: due to the similarity to square shape of raster data in GIS, square shape of lattice was selected in which the size of each cell equals 20 meters by 20 meters. Cell state: three cell states were defined in the proposed model, the urban state with the value of 1, constraint state with the value of 0 and the non-urban state with value between 0 and 1. Neighbourhood: in this study the Moore neighbourhood was considered. Transition rules: the defined transition rules are as below:

- If the state of a cell is urban, then the state of the cell will not be changed in simulation periods.
- If the state of a cell is constrained, then the state of the cell will not be changed in simulation periods.
- If a cell is closer to the affecting factors, then its probability for transformation to the urban state will increase.
- Cells with more urban state neighbours have more probability for transformation to urban state.

- If calculated P_{total} of a cell has the maximum value between the other cells then the state of the cell will transform to urban state (**Fig. 8**).

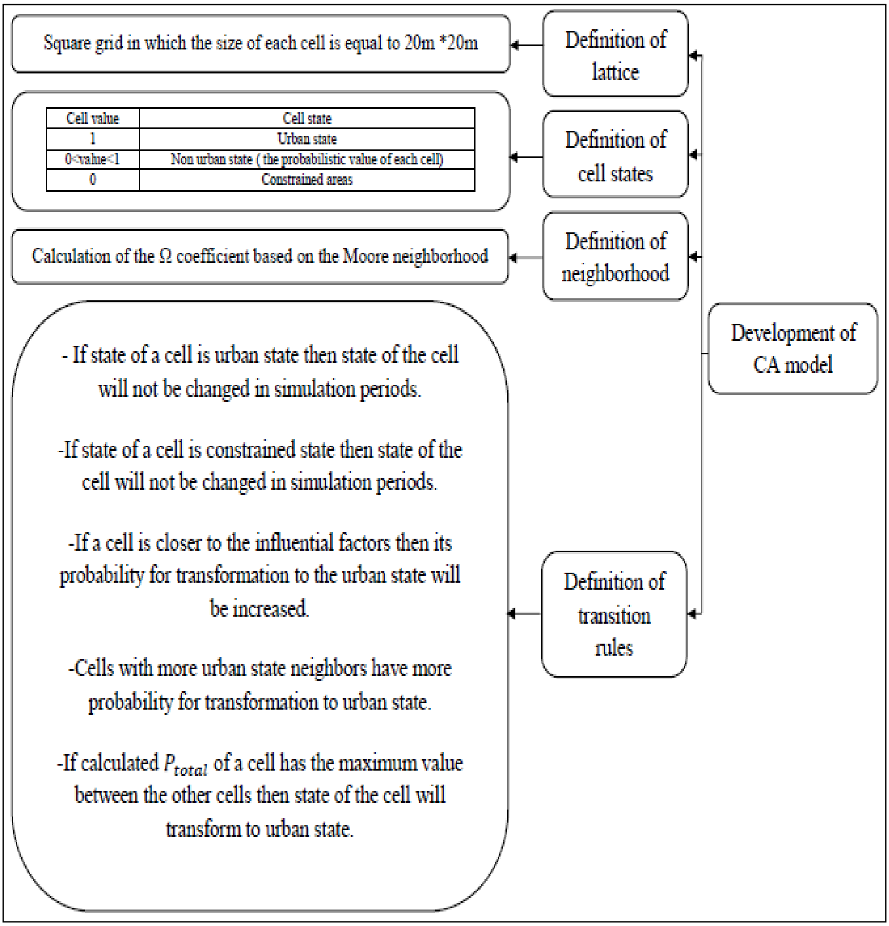

Fig. 8 Procedure of the third part of the proposed model.

2.6. Simulation of urban growth in the study area

Based on the previous sections of this paper, a standalone CA was developed through MATLAB programming language. Then simulation process was accomplished for 2012 based on the data of 2005. Then, the Kappa coefficient (KC) was calculated to check the accuracy and validity of the model. The value of KC equalled 0.885 which was acceptable according to the United States Geological Survey agency limit (i.e. 0.85 and more (Firouzabadi et al., 2009). Hence, it can be concluded that the developed model is accurate and capable of the simulation of urban growth. So it was applied for simulating urban growth in 2022, 2032, and 2042 (**Fig. 9**).

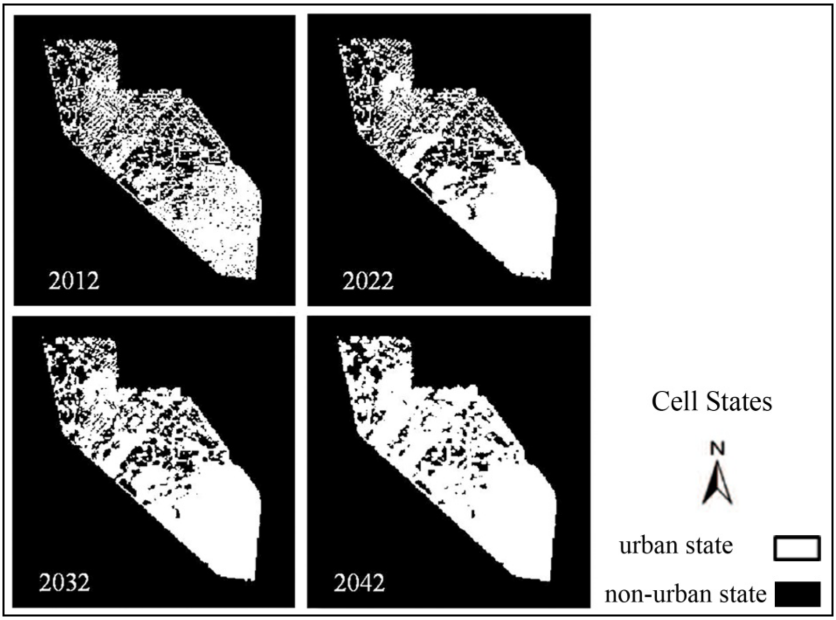

Fig. 9 Exports of the model.

3. CONCLUSION

Nowadays, cities are experiencing rapid urban growth which leads to destruction of agricultural lands, formation of informal settlement and irregular urban expansion. Therefore, there is a crucial need for realistic prediction of urban growth in the future, determination of the effects of various planning scenarios on urban growth process, and answer what-if questions. CA model is capable of responding these requirements, but there are some restrictions in conventional CA model. For this reason, in this paper, CA model were combined with AHP and GIS to ameliorate these insufficiencies. Then, the developed model was applied for simulation of urban growth in 2010 based on the data of 2005. For investigating the validity of the proposed model, the KC was calculated which indicated the acceptable accuracy of the model. Hence, it was applied for simulation of urban growth in 2022, 2023 and 2042. Consequently, combination of CA, AHP and GIS provide an appropriate tool for planners to assess their plans before implementation and better recognition of future state based on examination of different generated scenarios. In addition, in the proposed model, it is possible to add more variables and change their weights for observing the impact of each factor on urban growth process.

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