Urban Growth Modeling using Integrated Cellular Automata and Gravitational Search Algorithm (Case Study: Shiraz City, Iran)

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Abstract

Cities are growing and encountering many changes over time due to population growth and migration. Identification and detection of these changes play important roles in urban management and sustainable development. Urban growth models are divided into two main categories: first cellular models which are further divided into experimental, dynamic, and integrated models and second vector models. In this study, an integrated urban growth model is proposed which is a combination of cellular automata and gravitational search algorithm (GSA). It has been implemented on Shiraz (Iran) to model the urban growth between 1990 and 2000. The proposed integrated model uses GSA to calibrate cellular automata transition rules. The Landsat satellite imageries in 1990 and 2000 with Digital Elevation Model (DEM) of Shiraz are used in this study. Five parameters including distances from major roads, urban neighborhood, slope, distances from attraction centers, and distances from parks and other green spaces are considered to be effective in the urban growth modeling. Based on the results, Kappa coefficient and overall accuracy of the model are 66.54% and 92%, respectively. By using GSA, calibration of cellular automata is facilitated and the proposed integrated model reaches optimal solutions in fewer iterations. The achieved results show that the proposed integrated model can be used for studying urban growth.

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1. Introduction

In recent years, analysis of land use changes in local and global scales have received more attention. The main purpose of land use analysis is the optimal use of lands and their limited and exhaustible resources [1]. Land use and land cover changes are connected to issues such as climate changes, carbon cycle, and soil erosion directly. In this regard, the sustainability of land has been threatened by the stresses and pressures caused by human activities [2]. Rapid and unbalanced population growth in urban areas caused problems such as chaos of the cities, marginalization and also increases the needs to housing, basic infrastructures, transport networks, accommodations, and service centers. The mentioned problems put too much pressure on the lands and resources in the crowded areas [3]. The urban growth phenomenon has a complex and dynamic nature [4]. Furthermore, it has spatio-temporal dimensions that are dynamically changing. Therefore, if this process is analyzed and modeled, the results will be useful for urban planning. Urban growth modeling is an efficient tool to understand and solve the problems of cities [5].

So far, numerous methods have been presented for urban growth modeling. The changes of urban structure can be studied from different viewpoints. Urban growth modeling methods are divided into two main categories including cellular and vector ones based on the modeling environment. Cellular models are subdivided into three categories including experimental, dynamic, and integrated models [6].

Experimental models are based on statistical methods. Some examples are Markov model, Artificial Neural Network, and Logistic Regression. Dynamic models show the interaction between agents, organizations, and their interaction environment. The Cellular Automata (CA) and also the Agent Based Model (ABM) are considered as dynamic models [5]. Integrated models are produced by combining dynamic models such as CA and optimization algorithms.

Cellular Automata (CA) is a dynamic and discrete system in space and time, which uses a set of transition rules on a regular grid of cells. In this system, the value of each cell changes as a function of the values of the neighboring cells and its own value. CA has five components including regular cellular network, a set of possible values for each cell, transition rules, neighborhood, and time [7]. Integrated models are presented to overcome the limitations of CA such as difficulty in its calibration and adding new parameters to it [8]. So far, using genetic algorithm (GA), fuzzy theory, and artificial neural network a few integrated models are proposed and implemented [9, 10, 11, 12, 13, and 14].

In 2012, an integrated model by using CA and GA was used for urban growth modeling of Isfahan city [15, 16]. Four parameters including urban land use and distances from streets and roads, green spaces, and rivers in the city were considered as effective parameters in the urban growing of Isfahan. The Kappa coefficient and the overall accuracy of the model were 72.38% and 86.28%, respectively.

In 2013, the integrated model of CA and Markov chain was used for urban growth modeling of Mumbai city [17]. Four parameters including distances from residential areas, roads, and wet areas, and slope were considered as effective parameters in the urban growing of Mumbai. The rate of urban growth of Mumbai was predicted to be 26% between 2010 and 2020 and 12% between 2010 and 2030.

In 2014, Artificial Neural Network was used for urban growth modeling of Sanandaj, Iran [18]. Six parameters including distances from main roads, residential areas, green spaces, and urban centers, slope, and elevation were considered as effective parameters in the urban growing of Sanandaj. Figure of Merit (FoM) and Percent Correct Match (PCM) of the model were 43.75% and 90.10%, respectively.

In 2015, Artificial Immune System (AIS) based on cellular automata model and logistic regression were used for urban growth modeling of Guangzhou, China [19]. Four parameters including distances from roads, railways, highways including provincial and national highways, and urban centers were considered as effective parameters in the urban growing of Guangzhou. FoM of the AIS based on cellular automata model and logistic regression were 26.10% and 20.47%, respectively.

In 2016, cellular automata modeling approaches were used to forecast urban growing of Adana, Turkey [20]. In this study urban modeling approaches including Markov Chain, SLEUTH, dynamic EGO modeling with the Logistic Regression (LR), Regression Tree (RT) and Artificial Neural Networks (ANN) were used. The overall Kappa accuracy of SLEUTH, Markov Chain, RT models, LR and ANN were 75%, 72%, 71%, 66%, and 66%, respectively. The SLEUTH model was the most accurate one to handle the variability in the present urban development.

In 2016, neural network simulation was used for urban growing of Dongguan city, China [21]. In this study urban growth simulation was analyzed based on remotely sensed data of previous years and also the related physical and socio-economic factors. Figure of merit (FoM) was used to evaluate simulated map of 2014 that was 8.86% which can be accepted in the simulation and also be used in the prediction process.

Recently, the majority of methods used for urban growth modeling are placed in the category of integrated models. Attempts are made to present the integrated model of CA and Gravitational Search Algorithm (GSA) in the current study. GSA is one of the heuristic optimization algorithms inspired by the Newtonian laws of gravity and motion [22]. It is working for different optimization problems such as filter modeling in communication engineering [23], circuit designing [24], short term hydrothermal scheduling [25], data clustering [26], feature selecting [27, 28], image processing [29], optimizing binary encoded problems [30], and locating the electrical vehicle parking using GIS [31].

In this study, using Landsat satellite imageries and Digital Elevation Model (DEM), an integrated model of CA and GSA is used to model urban growing of Shiraz between 1990 and 2000. Radiometric calibration (radiance type) and atmospheric correction using Internal Average Reflectance (IAR) method were applied on the satellite imageries. Then corrected satellite imageries were classified into four classes including urban areas, roads and main streets, green spaces and agricultural areas, and other non-urban areas. The adopted classification method is the Support Vector Machine (SVM) [32]. Five parameters including distance from major roads, urban neighborhood, slope, distance from attraction centers, and distance from parks and other green spaces were considered as effective parameters in the urban growth modeling of Shiraz. Then, according to the mentioned parameters, transition rules were designed to create a cellular automata model which was calibrated using GSA. Thus, the integrated model of CA and GSA for Shiraz was designed. The Kappa coefficient and the overall accuracy were used to evaluate the integrated model.

In the second part of this study, gravitational search algorithm (GSA) is introduced and described. In the third section, the adopted method for urban growth modeling is described. Study area and data processing are expressed in the fourth section. In the fifth section, urban growing of Shiraz is modeled using the proposed model (CAGSA) and the results are presented and investigated. Conclusions are expressed in the final section.

2. Gravitational Search Algorithm (GSA)

In GSA, a set of N agents called objects are introduced to find the optimal solution by simulation of Newtonian gravity and motion laws [22]. The position of the i^{th} object is defined as follows:

$$X_i = (x_i^1, \ldots, x_i^d, \ldots, x_i^m) \quad , i = 1,2,\ldots,N \tag{1}$$

Where x_i^d is the position of i^{th} agent in the d^{th} dimension and m is the dimension of the search space. Based on [22], computing current population's fitness, the mass of each agent is calculated as follows:

$$q_i(t) = \frac{fit_i(t) - worst(t)}{best(t) - worst(t)} \tag{2}$$

$$M_i(t) = \frac{q_i(t)}{\sum_{j=1}^{N} q_j(t)} \tag{3}$$

Where $M_i(t)$ and $fit_i(t)$ represent the mass and the fitness value of the agent i at t, respectively and for a maximization problem, $worst(t)$ and $best(t)$ are defined as the minimum and maximum fitness function among all agents.

Total forces from a set of heavier masses that apply on an object should be considered to compute the acceleration of an agent based on the gravity law (Eq. (4)) which is followed by calculation of agent acceleration using the motion law (Eq. (5)). Afterward, the next velocity of an agent is calculated as a fraction of its current velocity added to its acceleration (Eq. (6)). Then, its position could be calculated using Eq. (7).

$$F_i^d(t) = \sum_{j \in kbest, j \neq i} rand_j G(t) \frac{M_j(t) M_i(t)}{R_{ij}(t)^{Rpower} + \varepsilon} (x_j^d(t) - x_i^d(t)) \tag{4}$$

$$a_i^d(t) = \frac{F_i^d(t)}{M_i(t)} = \sum_{j \in kbest, j \neq i} rand_j G(t) \frac{M_j(t)}{R_{ij}(t)^{Rpower} + \varepsilon} (x_j^d(t) - x_i^d(t)) \tag{5}$$

$$v_i^d(t+1) = rand_i v_i^d(t) + a_i^d(t) \tag{6}$$

$$x_i^d(t+1) = x_i^d(t) + v_i^d(t+1) \tag{7}$$

where $rand_i$ and $rand_j$ are two uniform random values in the interval [0, 1], ε is a small value, *Rpower* is the power of distances, and $R_{ij}(t)$ is the Euclidian distance between two agents i and j defined as $R_{ij}(t) = \|X_i(t), X_j(t)\|_2$. $kbest$ is the set of first K agents of the best fitness value and biggest mass. $kbest$ is a function of time, initialized to K_0 at the beginning and decreased with time. Here, K_0 is set to N (total number of agents) and is decreased linearly to 1. In GSA, the gravitational constant, G, will take an initial value G_0, and is reduced by time:

$$G(t) = G(G_0, t) \tag{8}$$

3. Methodology

This study uses an integrated model of Cellular automata and Gravitational Search Algorithm (CAGSA) for urban growth modeling. GSA is utilized to calibrate CA because it has a good performance in solving various engineering problems [23, 24]. Using GSA as an optimization algorithm in the proposed model, it becomes possible to compare CAGSA model with other integrated models. More specifically, with regards to the importance of transition rules in CA, GSA is used as an optimization tool to find the thresholds of the urban growth effective parameters in the transition rules. Figure 1 shows block diagram of the proposed model.

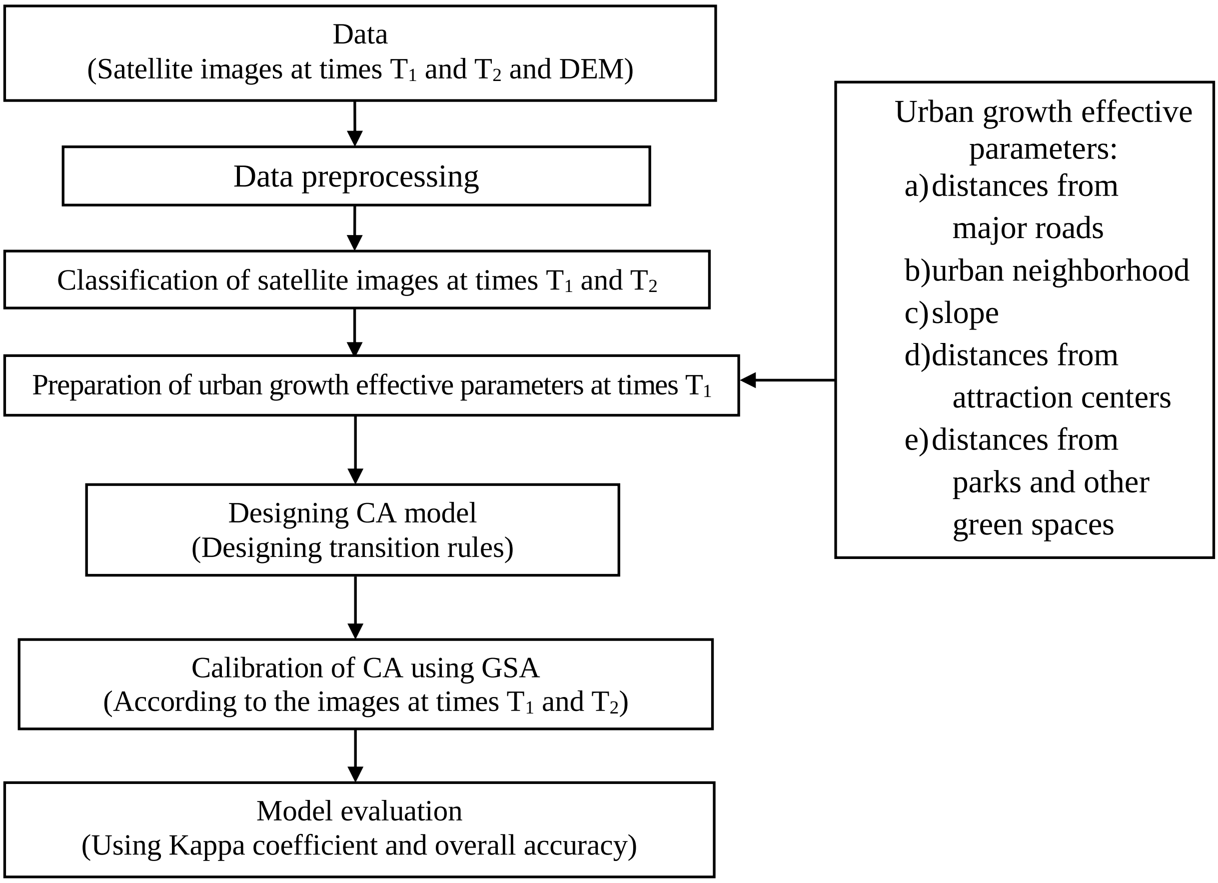

Figure 1. The block diagram of the proposed model (CAGSA)

According to the block diagram in Fig. 1, at first, Landsat satellite imageries at times T_1 and T_2 and Digital Elevation Model (DEM) of Shiraz are prepared. Then, data preprocessing including radiometric calibration (radiance type) and atmospheric correction are performed on satellite imageries. After preprocessing, using Support Vector Machine (SVM) classifier, corrected satellite imageries at times T_1 and T_2 are classified into four classes including urban areas, roads and main streets, green spaces and agricultural areas, and other non-urban areas.

Various factors including transportation, proximity to the urban areas and natural landscape are effective in the growth of a city. Reviewing [7, 18] suggests five parameters including distance from major roads, urban neighborhood, slope, distance from attraction centers, and distances from parks and other green spaces as effective parameters in the urban growth modeling of Shiraz. Distance from major roads and urban neighborhood are prepared from classified image of Shiraz at time T_1. Attraction centers and green spaces are prepared according to experts'[1] opinions. Slope map is prepared from the DEM of Shiraz using ArcGIS software.

According to the mentioned parameters, the offered CA transition rules are as the following:

If the target cell is urban, it stays urban, otherwise, for non-urban cells:

a) If the slope value is less than T_s, and the urban neighborhood is equal to or more than *n*, then transfer this cell to an urban cell.
b) If the slope value is less than T_s, distance from major roads is less than T_r, and distance from attraction centers is less than T_a, then transfer this cell to an urban cell.
c) If the slope value is less than T_s, distance from major roads is less than T_r, and distances from parks and other green spaces

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are less than T_g, then transfer this cell to an urban cell.

In the above rules, T_r is the threshold for the distance from major roads, *n* is the threshold for the urban neighborhood, T_s is the threshold for the slope value, T_a and T_g are the thresholds for the distances from attraction centers, and distances from parks and other green spaces, respectively.

Designing cellular automata model in MATLAB, it should be calibrated to reach its best accuracy. The appropriate thresholds of urban growth effective parameters in transition rules are determined through calibration. The determination of thresholds is difficult due to many different values that can be assigned to them. The evaluation of various threshold values is time-consuming and hard, and the trial and error method is not used to calibrate the cellular automata. In general, the thresholds are determined empirically. In the proposed model, the calibration of transition rules of CA is performed using GSA in order to optimize and facilitate the calibration.

Using classified images at times T_1 and T_2 in MATLAB, GSA determines the threshold values of urban growth effective parameters. In the proposed method, the Kappa coefficient is selected as a fitness function and the goal is to maximize this function. For threshold optimization using GSA, a five-dimensional search space is defined according to the five thresholds of T_r, *n*, T_s , T_a , and T_g. The position of an object in each dimension is the threshold of parameter related to that dimension. For example, the position of an object in the third dimension is the threshold of the slope parameter. The position of each agent in all dimensions (thresholds) are extracted and set to the CA model to assess purposes. Then the Kappa coefficient is computed for that model.

At each iteration, all objects are assessed, the values of G, $best$ and $worst$ are updated, and according to equation 3, the mass of each object is computed. Then using Eqs.4 to 7, the force exerted on each object, the acceleration, the velocity, and the new position of objects are computed. This process is repeated until reaching the stopping criteria. After predefined iterations for GSA, the position of the object that gets the highest kappa coefficient (the position of the heaviest mass) is the sub-optimal solution for thresholds of the CA model.

The Kappa coefficient and the overall accuracy are used to assess the proposed model. For this purpose, error matrix is computed as shown in Table 1 [33, 34].

Table 1. Error matrix to compare the model results with the reality

Reali / Model	Urban	Non-urban	Total
Urban	A	B	A+B
Non-urban	C	D	C+D
Total	A+C	B+D	A+B+C+D

In Table 1, A refers to the number of cells belonging to urban areas in reality and also in the model. B refers to the number of cells belonging to non-urban and urban areas in reality and in the model, respectively while C refers to the number of cells belonging to urban and non-urban areas in reality and in the model, respectively. D refers to the number of cells belonging to non-urban areas in reality and also in the model. The Kappa coefficient and the overall accuracy are computed using the Eqs. 9 and 10 [33, 34].

$$Kappa = \frac{2(AD - BC)}{B^2 + C^2 + 2AD + ((A+D)(B+C))} \tag{9}$$

$$\text{Overall Accuracy} = \frac{A+D}{A+B+C+D} \tag{10}$$

4. Numerical Experimentation

In this section, the study area and the data preprocessing are described in details.

4.1. Study area

Study area is Shiraz city (Iran) located at the eastern longitude of $52^\circ 33' 30''$ and the northern latitude of $29^\circ 37' 30''$. Area and average elevation of Shiraz city are 240 Km^2 and 1486 m, respectively [7]. The population of Shiraz city has increased from 848,289 to 1,053,025 people from 1990 to 2000 [7].

4.2.Data and data preparation

In this study, Landsat satellite imageries and Digital Elevation Model (DEM) of Shiraz city which were obtained from USGS[1] website are raw data. The specifications of Landsat satellite imageries and DEM of Shiraz city are shown in Tables 2 and 3, respectively.

1 http://earthexplorer.usgs.gov

Table 2. The specifications of Landsat satellite imageries of Shiraz city

Imaging date	Satellite	Sensor	Spatial resolution	Datum	Projection system	Geo-referencing precision (RMSE)
1990-06-06	Landsat5	TM	30m	WGS84	UTM, Zone39	4.419m
2000-05-08	Landsat7	ETM+	30m	WGS84	UTM, Zone39	3.297m

Table 3. The specifications of DEM of Shiraz city

Satellite	Sensor	Version	Spatial resolution	Datum	Projection system	Absolute elevation precision
Terra	ASTER	2	30m	WGS84	UTM, Zone39	8.68m

The satellite imageries of Shiraz city in 1990 and 2000 are shown in Figure 2.

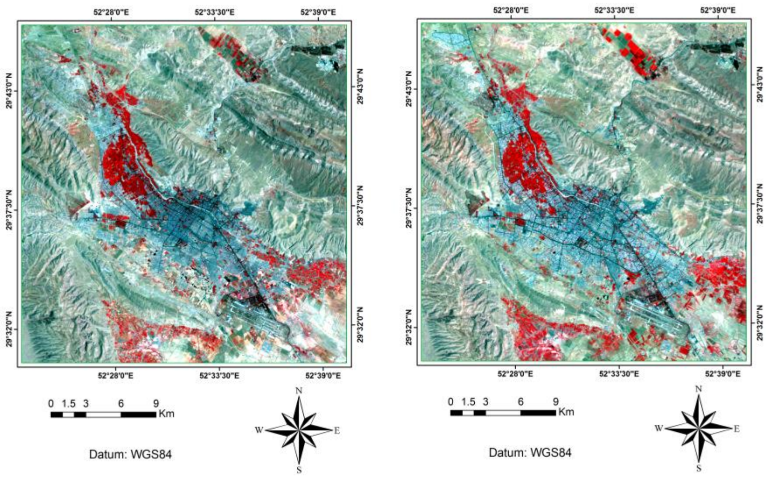

Figure 2. The satellite imageries of Shiraz city in 1990 (on the right) and 2000 (on the left

The radiometric calibration (radiance type) is performed on the above satellite imageries to convert their grayscales to radiance using ENVI software. Then, atmospheric correction is performed using method of IAR through ENVI software. In this area, no certain atmospheric correction is required because there is not any certain atmospheric phenomena such as cloud cover or severe dust. IAR atmospheric correction method as a general atmospheric correction is used to reduce the effects of absorption and also limited atmospheric distribution.

According to [35, 18], method of SVM leads in better results compared with other methods of classification (especially maximum likelihood method). Here, corrected satellite imageries of Shiraz city in 1990 and 2000 have been classified into four classes including urban areas, roads and main streets, green spaces and agricultural areas, and other non-urban areas using SVM method in ENVI software. The classified images of Shiraz city in 1990 and 2000 are shown in Figure 3.

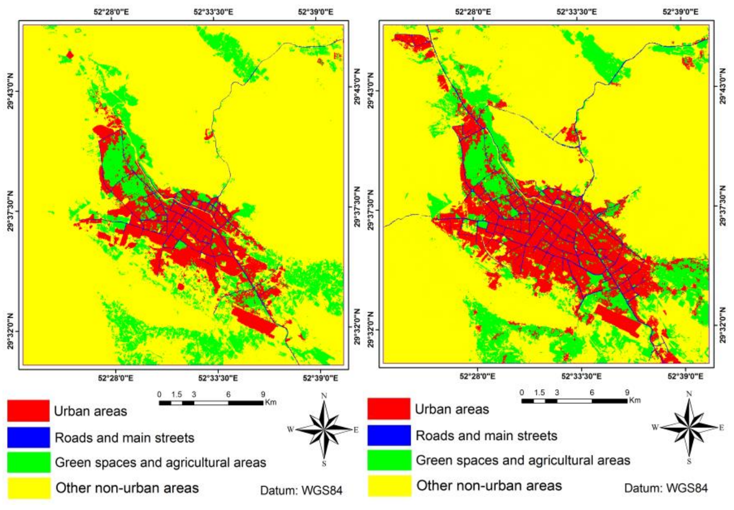

Figure 3. The classified images of Shiraz city in 1990 (on the left) and 2000 (on the right)

The Kappa coefficient and the overall accuracy which are shown in Table 4 are used to evaluate the above classification.

Table 4. The Kappa coefficient and the overall accuracy for the SVM classification.

Image time	Overall Accuracy	Kappa coefficient
1990	95.3975%	91.90%
2000	96.2025%	90.29%

5. Implementation and results

In this section, the integrated model of Cellular automata and Gravitational Search Algorithm is implemented between 1990 and 2000 for Shiraz city. The preparation of effective parameters in urban growing of Shiraz city and the results are presented in sequel.

5.1. Urban growth effective parameters of Shiraz city

Here, the effective parameters of Shiraz urban growth are prepared. Distances from major roads and urban neighborhoods (3×3 neighborhood size of Moore type) are obtained from the classified image of Shiraz city in 1990. The slope parameter is obtained from DEM of Shiraz city using ArcGIS software. The slope map of Shiraz city is shown in Figure 4.

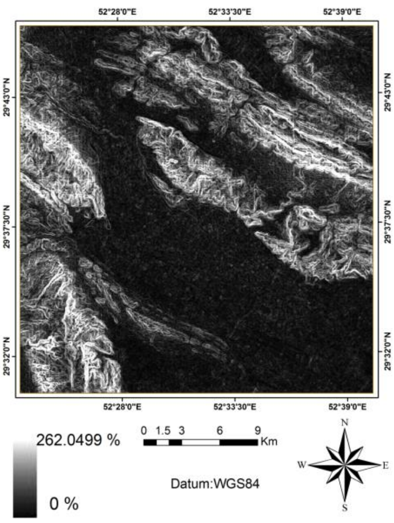

Figure 4. The slope map of Shiraz city

Using experts' opinions, the attraction centers and parks and other green spaces of Shiraz city in 1990 are identified in this study. Attraction centers of Shiraz city in 1990 included Shah Cheragh, gates of Isfahan, Kazeroon and Saadi, Zandie, Eram, old mall of Noor palace, Moshir Fatemi, Vakil market and Daryoosh street. Parks and other green spaces of Shiraz city in 1990 included Azadi park, Valiy-e-Asr (old house of carriage), green space of Quraan gate, Khatoon, Atlasi (Takht garden), green space around Saadi's tomb, green space around Hafez's tomb, Delgosha garden (Narenjestan), Eram garden and Afif abaad garden. Distances from attraction centers and parks and other green spaces of Shiraz city in 1990 are computed using ArcGIS software which are shown in Figures 5 and 6, respectively.

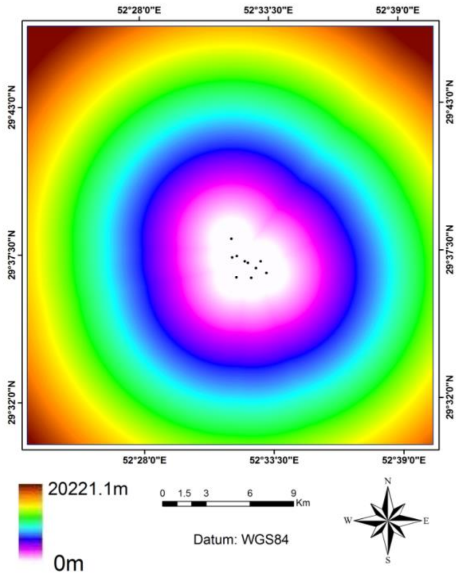

Figure 5. Distance from attraction centers of Shiraz city in 1990

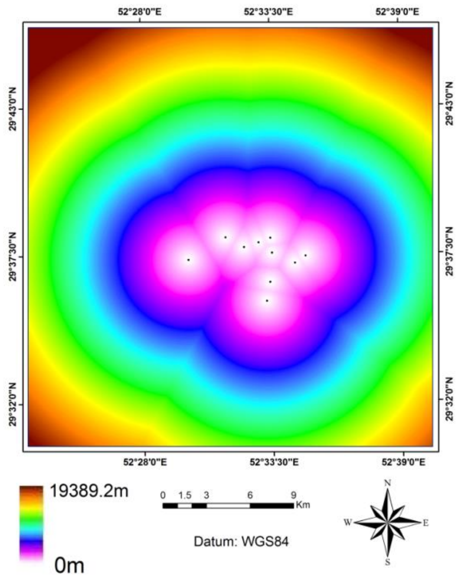

Figure 6. Distance from parks and other green spaces of Shiraz city in 1990

5.2. Threshold setting using GSA

Using mentioned parameters, CA model is constructed and GSA is utilized to set the thresholds of transition rules. In implementing GSA, the number of agents (N) is set to 50, the number of iterations is set to 30 and the initial gravitational constant (G_0) is set to 100. The number of variables (m) is 5 which is the number of target thresholds. The upper and lower values of each variable are shown in Table 5.

Table 5. The upper and lower values of each variable

Variable	**Lower value**	**Upper value**
distance from major roads (T_r)	0m	5000m
urban neighborhood (*n*)	0 cell	8 cells
Slope (T_s)	0%	15%
distance from attraction centers (T_a)	0m	5000m
distance from parks and other green spaces (T_g)	0m	5000m

It should be noted that a high number of agents slows the GSA speed. In this study the number of agents is adjusted experimentally. Also, the suitable value of the number of agents is considered to be 50 in numerous references [22,23,24].

The best thresholds of urban growth effective parameters of Shiraz city obtained by GSA are shown in Table 6.

Table 6. The best thresholds for urban growth effective parameters of Shiraz city obtained using GSA

Variable	**The best obtained Value**
distance from major roads (T_r)	1510.25m
urban neighborhood (n)	2 cells
Slope (T_s)	14.801%
distance from attraction centers (T_a)	2536m
distance from parks and other green spaces (T_g)	1650.9m

In the proposed model, calibration of cellular automata was optimized and facilitated using GSA. The proposed integrated model has reached optimal solution after 8 iterations. The modeled image of Shiraz city in 2000 is shown in Figure 7.

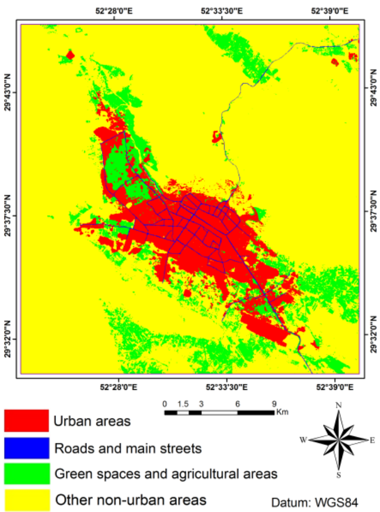

Figure 7. The modeled image of Shiraz city in 2000 obtained by CAGSA model

According to the modeled image and reality of Shiraz city in 2000, error matrix of the proposed model has been computed which is shown in Table 7.

Table 7. Error matrix of CAGSA model

Reality / Model	Urban	Non-urban	Total
Urban	85503	19174	104677
Non-urban	50568	737524	788092
Total	136071	756698	892769

According to the above table and using the Eqs. 9 and 10, the Kappa coefficient and the overall accuracy of the integrated model of CA and GSA are 66.604% and 92.19%, respectively. Cells being modeled correctly and incorrectly are used to calculate the Kappa coefficient. In other words the Kappa coefficient evaluates urban growth modeling cynically and in a strict way.

In general, the resulted value of 66.604% for Kappa coefficient in the proposed model is due to following reasons:

a) The relatively high irregular sprawl of Shiraz urban growth between 1990 and 2000.
b) The high complexity of urban growth phenomenon.

5.3. Comparison

The proposed model (CAGSA) is compared with an integrated model of Cellular automata and Genetic Algorithm (CAGA). The same CA design is optimized with both GA and GSA separately and their results are compared. In implementing GA, the number of agents (*N*) is set to 50, cross over probability is set to 0.9, mutation probability is set to 0.005 and the number of iterations is set to 30. The number of variables (m) is 5 which is the number of target thresholds.

The best thresholds obtained in CAGA are reported in Table 8.

Table 8. The best thresholds for urban growth effective parameters of Shiraz city obtained using GA

Variable	**The best obtained Value**
distance from major roads (T_r)	1844.9m
urban neighborhood (n)	2cells
Slope (T_s)	12.9%
distance from attraction centers (T_a)	2930.5m
distance from parks and other green spaces (T_g)	2700.8m

According to the above thresholds, the urban growing of Shiraz is modeled and the kappa coefficient and the overall accuracy of that are 66.54% and 92%, respectively. The evaluation results of the CAGSA and the CAGA models are shown in Table 9.

Table 9. The evaluation results of the CAGSA and the CAGA models

Model type	Kappa coefficient	Overall accuracy
CAGSA	66.604%	92.19%
CAGA	66.540%	92.00%

According to the above table, the CAGSA is slightly higher than the CAGA model.

5.4. Sensitivity Analysis

In this section, each parameter is eliminated and the CAGSA model is constructed with the four remaining parameters. Then, the Kappa coefficient is computed for that model. This way, the sensitivity of each parameter in urban growth modeling is investigated. Results are presented in Table 10.

Table 10. The Kappa coefficient value of CAGSA model according to the elimination of each parameter

The eliminated parameter	The Kappa coefficient value of CAGSA model
distance from major roads	66.47%
urban neighborhood	19.95%
slope	64.01%
distance from attraction centers	52.11%
distance from parks and other green spaces	52.11%

According to the above table, the least value for the Kappa coefficient of the model happens while the urban neighborhood parameter of the model is eliminated. Therefore, the urban neighborhood parameter has the greatest impact on the proposed model. Also, the highest value for the Kappa coefficient of the model happens while the parameter of distance from major roads is eliminated. According to these results, parameter of distance from major roads has the least impact on the proposed model for Shiraz city.

6. Conclusions

Urban growth modeling is an efficient tool to understand and solve problems in the cities due to the complexity and dynamic nature of cities. Urban growth modeling plays an important role in urban planning. It is required to use dynamic models in order to study the process of spatio-temporal changes of dynamic phenomena such as urban growth. In this regards, Cellular Automata is widely used because of its simplicity, dynamic structure and powerful spatial characteristics. This study presented an integrated model of CA and GSA for Shiraz city between 1990 and 2000. GSA was employed to tune the rule parameters. The kappa coefficient and the overall accuracy of this model are 66.54% and 92%, respectively.

It is suggested to take other parameters such as the economic value of land into account in order to improve the performance and results of urban growth modeling. Investigating the effect of changing the dimension of neighborhood in the proposed integrated model, and involving the changes of urban areas in urban modeling are also suggested. Another suggestion is to use the proposed integrated model for modeling non-urban areas such as jungles. Using satellite imageries with higher resolution is also suggested.

References

[1] Houghton, R. A. (1994), “The worldwide extent of land-use change,” BioScience, 305-313.

[2] Olson, J. M., Alagarswamy, G., Andresen, J. A., Campbell, D. J., Davis, A. Y., Ge, J., ... & Pijanowski, B. C. (2008), “Integrating diverse methods to understand climate–land interactions in East Africa,” Geoforum, 39(2), 898-911.

[3] Rabbani, A. (2011), “Assessment of Multi-Resolution Satellite Imagery in Urban Growth Modeling using Cellular Automata,” MSc thesis, Department of Geomatics and Surveying Engineering, Faculty of Engineering, University of Tehran, (in Persian).

[4] Xiao, J., Shen, Y., Ge, J., Tateishi, R., Tang, C., Liang, Y., & Huang, Z. (2006) , “Evaluating urban expansion and land use change in Shijiazhuang, China, by using GIS and remote sensing,” Landscape and urban planning, 75(1), 69-80.

[5] Tayyebi, A. (2010), “Prediction and Evaluation of Urban Land Use Change,” MSc thesis, Department of Geomatics and Surveying Engineering, Faculty of Engineering, University of Tehran, (in Persian).

[6] Hu, Z., & Lo, C. P. (2007), “Modeling urban growth in Atlanta using logistic regression,” Computers, Environment and Urban Systems, 31(6), 667-688.

[7] Javadi, Y. (2009), “Modeling Land Cover Changes Using Geospatial Cellular Automata,” MSc thesis, Department of Geomatics and Surveying Engineering, Faculty of Engineering, University of Tehran, (in Persian).

[8] Al-Kheder, S. A. (2006), “Urban growth modeling with artificial intelligence techniques,” Doctoral dissertation, purdueuniversity.

[9] Basse, R. M., Omrani, H., Charif, O., Gerber, P., & Bódis, K. (2014), "Land use changes modelling using advanced methods: Cellular automata and artificial neural networks. The spatial and explicit representation of land cover dynamics at the cross-border region scale," Applied Geography, 53, 160-171.

[10] Foroutana, E., Delavarb, M. R., & Araabic, B. N. (2012), "Integration of Genetic Algorithms and Fuzzy Logic for Urban Growth Modeling," ISPRS Annals of Photogrammetry, Remote Sensing and Spatial Information Sciences, 1, 69-74.

[11] 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," International Journal of Applied Earth Observation and Geoinformation, 21, 265-275.

[12] 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," Ecological Modelling, 222(20), 3761-3772.

[13] Munshi, T., Zuidgeest, M., Brussel, M., & van Maarseveen, M. (2014), "Logistic regression and cellular automata-based modelling of retail, commercial and residential development in the city of Ahmedabad, India," Cities, 39, 68-86.

[14] Li, X., Lao, C., Liu, Y., Liu, X., Chen, Y., Li, S., ... & He, Z. (2013), "Early warning of illegal development for protected areas by integrating cellular automata with neural networks," Journal of environmental management, 130, 106-116.

[15] Foroutan, E., & Delavar, M. R. (2012), "Urban growth modeling using genetic algorithms and cellular automata; A case study of Isfahan Metropolitan Area, Iran," Proceedings of the GIS Ostrava, 23-25.

[16] Foroutan, E. (2012), "Urban Growth Modeling Using Cellular Automata and Fuzzy Integration Genetic Algorithms," MSc thesis, Department of Geomatics and Surveying Engineering, Faculty of Engineering, University of Tehran, (in Persian).

[17] Moghadam, H. S., & Helbich, M. (2013), "Spatiotemporal urbanization processes in the megacity of Mumbai, India: a Markov chains-cellular automata urban growth model," Applied Geography, 40, 140-149.

[18] Mohammady, S., Delavar, M. R., & Pahlavani, P. (2014), "urban growth modeling using an artificial neural network a case study of sanandaj city, iran," ISPRS-International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, 1, 203-208.

[19] He, Y., Ai, B., Yao, Y., & Zhong, F. (2015), "Deriving urban dynamic evolution rules from self-adaptive cellular automata with multi-temporal remote sensing images," International Journal of Applied Earth Observation and Geoinformation, 38, 164-174.

[20] Berberoğlu, S., Akın, A., & Clarke, K. C. (2016), "Cellular automata modeling approaches to forecast urban growth for adana, Turkey: A comparative approach", Landscape and Urban Planning, 153, 11-27.

[21] Zhang, X. (2016), "Urban Growth Modeling Using Neural Network Simulation: A Case Study of Dongguan City, China", Journal of Geographic Information System, 8(03), 317.

[22] Rashedi, E., Nezamabadi-Pour, H., & Saryazdi, S. (2009), "GSA: a gravitational search algorithm," Information sciences, 179(13), 2232-2248.

[23] Rashedi, E., Nezamabadi-Pour, H., & Saryazdi, S. (2011), "Filter modeling using gravitational search algorithm,"Engineering Applications of Artificial Intelligence, 24(1), 117-122.

[24] Shams, M., Rashedi, E., & Hakimi, A. (2015), "Clustered-gravitational search algorithm and its application in parameter optimization of a low noise amplifier," Applied Mathematics and Computation, 258, 436-453.

[25] Gouthamkumar, N., Sharma, V., and Naresh, R. (2015), "Disruption based gravitational search algorithm for short term hydrothermal scheduling," Expert Systems with Applications vol. 42, pp.7000-7011.

[26] Dowlatshahi, M. B., & Nezamabadi-pour, H. (2014), "GGSA: A grouping gravitational search algorithm for data clustering," Engineering Applications of Artificial Intelligence, 36, 114-121.

[27] Xiang, J., Han, X., Duan, F., Qiang, Y., Xiong, X., Lan, Y., & Chai, H. (2015), "A novel hybrid system for feature selection based on an improved gravitational search algorithm and k-NN method," Applied Soft Computing, 31, 293-307.

[28] Rashedi, E., & Nezamabadi-pour, H. (2014), "Feature subset selection using improved binary gravitational search algorithm," Journal of Intelligent and Fuzzy Systems, 26(3), 1211-1221.

[29] Rashedi, E., Nezamabadi-Pour, H., & Saryazdi, S. (2013), "A simultaneous feature adaptation and feature selection method for content-based image retrieval systems," Knowledge-Based Systems, 39, 85-94.

[30] Nezamabadi-pour, H. (2015), "A quantum-inspired gravitational search algorithm for binary encoded optimization problems," Engineering Applications of Artificial Intelligence, 40, 62-75.

[31] Aghaebrahimi, M., Toorani, M., ghasemipour, M. (2014), “Locating the electric vehicle parking using GIS information and Gamut of urban areas,” Computational Intelligence in electrical engineering, vol. 4, pp. 71-84, (in Persian).

[32] Cristianini, N., & Shawe-Taylor, J. (2000), “An introduction to support vector machines and other kernel-based learning methods,” Cambridge university press.

[33] Monserud, R. A., & Leemans, R. (1992), “Comparing global vegetation maps with the Kappa statistic,” Ecological modelling, 62(4), 275-293.

[34] Pontius, R. G., & Schneider, L. C. (2001), “Land-cover change model validation by an ROC method for the Ipswich watershed, Massachusetts, USA,” Agriculture, Ecosystems & Environment, 85(1), 239-248.

[35] Mondal, A., Kundu, S., Chandniha, S. K., Shukla, R., & Mishra, P. K. (2012) , “Comparison of support vector machine and maximum likelihood classification technique using satellite imagery,” International Journal of Remote Sensing and GIS, 1(2), 116-123.