Application of Genetic Algorithm and Cellular Automata for Simulation of Land Use and Land Cover Changes; Case of Karaj City, Iran

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Received: 26 November 2015 / Accepted: 01 January 2016 / Published online: 03 January 2015

Abstract

This study emphasized the ability of Genetic Algorithm and Cellular Automate to simulate urban land use changes by integrating adaptive model. The most important part of modeling is to define transition rules. In this research, a Cellular Automata model in DINAMICA EGO software was used coupled with genetic algorithm. According to disability of the software for manipulating large number of variables in Genetic Algorithm Tool in the software, a program implemented in Python language in order to carry out genetic algorithm for coefficients in the model to simulate human land use of Karaj City as a rapid urbanization area in Iran. Results revealed from the program had 67% similarity with Genetic Algorithm Tool. By using the results of the simulations have done. Finally, the results of the original status have been compared with the results of simulation based on genetic algorithm. The results show that proposed model provides a new way for the simulation of land use changes and demonstrated that there is no significant difference between results of original model and genetic algorithm simulation. Although it seems that genetic algorithm approach will lead to more optimal results but this is not guaranteed it has better outputs compared to original status.

Keywords: Land use planning; land cover changes; Genetic Algorithm; Simulation.

1- Introduction

One of the basic elements of management, especially at macro scale, is scenario-based studies that enable planners to predict forthcoming situations and finally set overviews and programs and eventually address the goals. Therefore planning support systems will be useful in this case. Computer simulation will help to model real world or an arbitrary position by computer in order to evaluate system performance. This is possible to predict system performance through changing the variables during simulation. In fact, computer simulation is a virtual approach for system performance studies (Banks *et al*., 2011).

Land use and land cover is changing rapidly due to the activities. This change has resulted divers modeling (KwadwoNti, 2013). One of the main conversion in land use and land cover changes is urbanization which eventually ended up to increasing non-productive land uses in the area and this will be a threat for food production in the future (Ellis, 2013).

Many researches have carried out using genetic algorithm in simulation of land use cover changes by cellular automata (Maleki, 2010;

Sarmadi, 2011; Zareyi and Al e Sheykh, 2012). Land evaluation models and modeling of the drivers of land use change enable policy makers to adopt preventive and restoration measures (Sakieh *et al*., 2015).

Remote Sensing Center of Universidade Federal de Minas Gerais (UFMG) has provided a software platform for modeling land use cover changes named DINAMICA EGO that using Cellular Automata method. DINAMICA EGO simulates landscape or land use cover changes through agent-base modeling or statistical approach and process changes as spatial patterns (KwadwoNti, 2013). According to the surveys, among all land use cover changes models and considering a number of factors such as estimated amount of changes, location of changes, change patterns production, model validation and professional simulations, this is concluded that performed models by DINAMICA EGO had better outcomes (Mas *et al*., 2007).

Land use cover changes models based on Cellular Automata, use transition rules and distinct parameters for modeling of changes from t1 to t2. In the real world these parameters and rules are not clearly known, therefore the modeler defines the rules according to the objectives and ignores other circumstances. In comparison of observed and simulated maps, the parameters and rules which have been entered to the model are evaluated and its uncertainty is measured. Therefore validation caused to the best effective coefficients in the model with their certainty will be characterized. Therefore one of the challenges is parameter and effective rules selection in calibration level whereas satisfaction level is approved. One of the current methods is increasing effective parameters in the model and finally led to model complexity and also this is possible that some parameters have synergetic effects on others and caused to skewness. In order to improvement of model result, different methods are addressed such as Monte Carlo, Genetic Algorithm and etc (KwadwoNti, 2013).

Genetic Algorithm is a powerful tool for land use cover changes modeling and will bring us better results (Eastman *et al*., 2005). Genetic Algorithm is an approach in which calculation resources are used too much according to Heuristic and Biologic Evolution in order to find general optimum solutions (Koza, 1998).

Genetic algorithm has also been applied to optimizing land use change problems (Lockwood and Moore, 1993; Boston and Bettinger, 1999) and it is a powerful tool for land use cover changes modeling and will bring us better results (Eastman *et al*., 2005; Fonseca and Fleming, 1995; Jaszkiewicz, 2002). Much of this literature has dealt with the problem of characterizing the efficient solves by generating a population of efficient solutions, whereas for any given set of goal levels we seek the unique optimized solution which best approaches these goals. In one sense, the use of genetic algorithm to solve such problems is not really different to any single-criterion optimization (Stewart *et al*., 2004). Some other problems which can be appropriate for solution by genetic algorithms include timetabling and scheduling problems. Genetic Algorithm has also been applied to engineering science (Tomoiagă *et al*., 2013). Generally, genetic algorithms are often used in solving global optimization problems. Some of problems have been solved by genetic algorithms in other fields are: mirrors designed to funnel sunlight to a solar collector (Gross, 2013), antennae designed to pick up radio signals in space (Hornby *et al*., 2015), and walking methods for computer figures (Geijtenbeek *et al*., 2013).

Also, there is a Genetic Algorithm Tool in DINAMICA EGO for optimizing the results of the simulation. This tool is a very powerful way to apply genetic algorithm on land changes model because it uses Kfuzzy method for finding the fittest individual in any generation which is based on combination of fuzzy analysis and Kappa index. But it can only load and manipulate matrices with maximum length of 100 (Soares-Filho *et al*., 2013) and if we have a matrix with more length (in other words, if we have chromosomes with more than 100 genes), this tool is not able to use and we have to use another method for genetic algorithm.

Usage of genetic algorithm is able to fill the gaps of data scarcity. In DINAMIC EGO, Genetic Algorithm tool receives necessary data for implementation of genetic algorithm and simulation process for communities with distinct characteristics and defined generations will be done and recommend the best individual as an output (new matrix of weights of evidence) (KwadwoNti, 2013). Since this tool uses reciprocal similarity method, the results are more close to the real but it has some limitations which related to software implementation.

Furthermore, some authors (e.g. Ahadnejad-Roushti *et al*., 2010; KwadwoNti, 2013; Soares-Filho *et al*, 2012 and 2013; Sheng *et al*., 2012) have used fuzzy analysis for validation of simulation of land use cover changes. Their results confirmed by fuzzy analysis methods have high performance for validation of this type of simulation.

This study, present a new method to simulate urban land use changes based on developing a Python program for optimizing the results and investigating the efficiency of Genetic Algorithm tool in DINAMICA EGO and investigating its effectiveness. Also, another aim is to answer was if Genetic Algorithm always leads to better outputs or not.

2- Study area

Karaj city located in 35 kilometers in west of Tehran province and south of Alborz Mountains was considered as a study area (Figure 1). This area is located between latitude of Northern 35° 42" and 35° 53" and longitude of Eastern 50° 50" and 51° 03" (Strategic and structural planning for Karaj city, 2011).

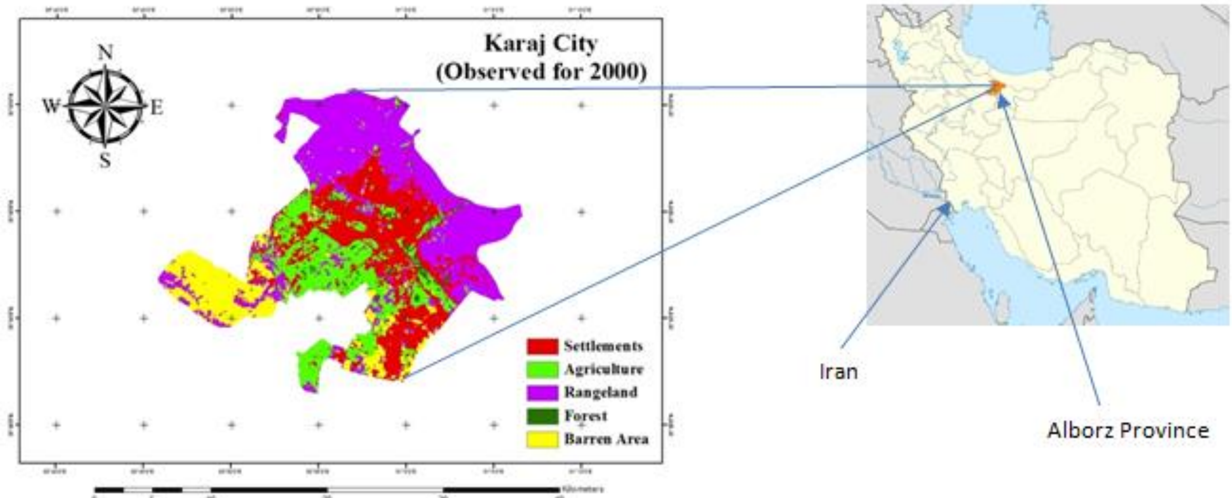

Figure 1. The location of study area

3- Materials and methods

In this study, Land use cover maps of Karaj were provided from satellite images of TM and ETM+ of Landsat from 1985 to 2000. These images were under three stages pre-process, process and post-process and different land use cover classes were derived and also all layers investigated in order to better certainty from coordination systems, by unique projection and same cell size (Makhdoom *et al*., 2001). Five land use cover classes including settlement, agriculture, rangeland, forest and barren area were surveyed. Also in this research, 12 auxiliary variables were used. Five variables include distance to each land use cover class and others including elevation, slope, aspect, and distance to road, distance to river, soil salinity and texture.

For model implementation of land use cover using cellular automata, there are different platforms, such as SLEUTH, LEAM and MOLAND which have only the ability to model binary changes. Many models such as SLEUTH are implemented in a distinctive framework and using predefined parameters. In this study, DINAMICA EGO, a raster based software that using cellular automata is utilized. This software not only is able to model unlimited changes of a class, but also the user could enter any amount of changes to the model. Also several tools are implemented in the software in order to facilitate for users with limited knowledge of computer programming to work with computation models for the purpose of spatial analysis (KwadwoNti, 2013).

In order to apply DINAMICA ECO, a model was created in which based on entered data, then probability maps of transitions were calculated using land use cover class maps in the previous step, simulation was done and new class were saved as new maps. Also in this software, there is a tool for comparison which characterized minimum and maximum similarity according to reciprocal similarity based on fuzzy analysis. In this tool, this is possible to determine moving window size on the maps. These dimensions are numbers between 1 and n and lead to compare patterns and structures of the maps. Changes in the dimension of moving windows caused to investigate border and area of cells of a class and truly are a kind of model proficiency analysis (KwadwoNti, 2013; Soares-Filho *et al*., 2013).

After determination of the original matrix of coefficients as main factor to run the model, modified matrix of coefficients was computed by the developed genetic algorithm program. In the next step, the new DINAMICA EGO model was run by using original and modified matrix separately and maps of land use cover changes were simulated. Finally, the results of model implementation were validated for two result maps and a comparison among original and genetic algorithm coefficients were done in order to clarify that genetic algorithm is useful or not for improvement of simulation results.

One of the limitations of Genetic Algorithm Tool in DINAMICA EGO is when the chromosomes are being created, it must use Calculate Map tool with an interior index between 0 and 99 (Soares-Filho *et al*., 2009). In this research, the numbers of layers related to chromosomes were 134. This is notable that layers related to chromosomes are including coefficients of variables in transitions which are investigated as genes in each chromosome.

According to performance and structure of genetic algorithm, a computer program was implemented by Python 2.7 programming language in which receive primary matrix of coefficients as input and finally optimized matrix of coefficients was revealed. Algorithm of implementation of this program is described in the following. Primary matrix of coefficients as first parent chromosomes was introduced to the program. Collection of amounts in the matrix was considered as gene. Then possible up and bottom limits for the purpose of jump were directed to the program. Some parts of chromosomes are released in the original manner and some its parts are randomly selected and jump process on its genes will be done. Therefore this is possible to define a chromosome as jumped parent chromosome (Reeves and Rowe, 2002). Then, the previous process is repeated using parent chromosome regarding to population size and therefore a new population is formed from the parent gene. According to natural selection criteria, this is concluded that in each population, the individuals with more adaptation in the ecosystem will have more chances for gene transfer to the next generation (Darwin, 1859; Fisher, 1930; Goldberg, 1991; Skiena, 2010). In the other hand, according to statistics, in each population the individuals with more frequent and therefore more presence possibility is located on the side of normal distribution (Lyon, 2014; Quine, 1993). Regarding to gene normal distribution and considering the dominancy of the genotypes with more frequency, in each population, mean of genes of the population which have located in the acceptable jump interval selected as indicator gene and the nearest individual with less distance to it will be selected as dominant chromosome in the population and transformed to the next generation as new parent (Koza, 1998; Back, 1996). With selection of new parent, next generation will be simulated and this process will be continued up to the distance between new and old parent will be less than convergence limit or the process will be repeated for a distinct number of generations (KwadwoNti, 2013; Reeves and Rowe, 2002). The main general trend of genetic algorithm has been shown in Figure 2.

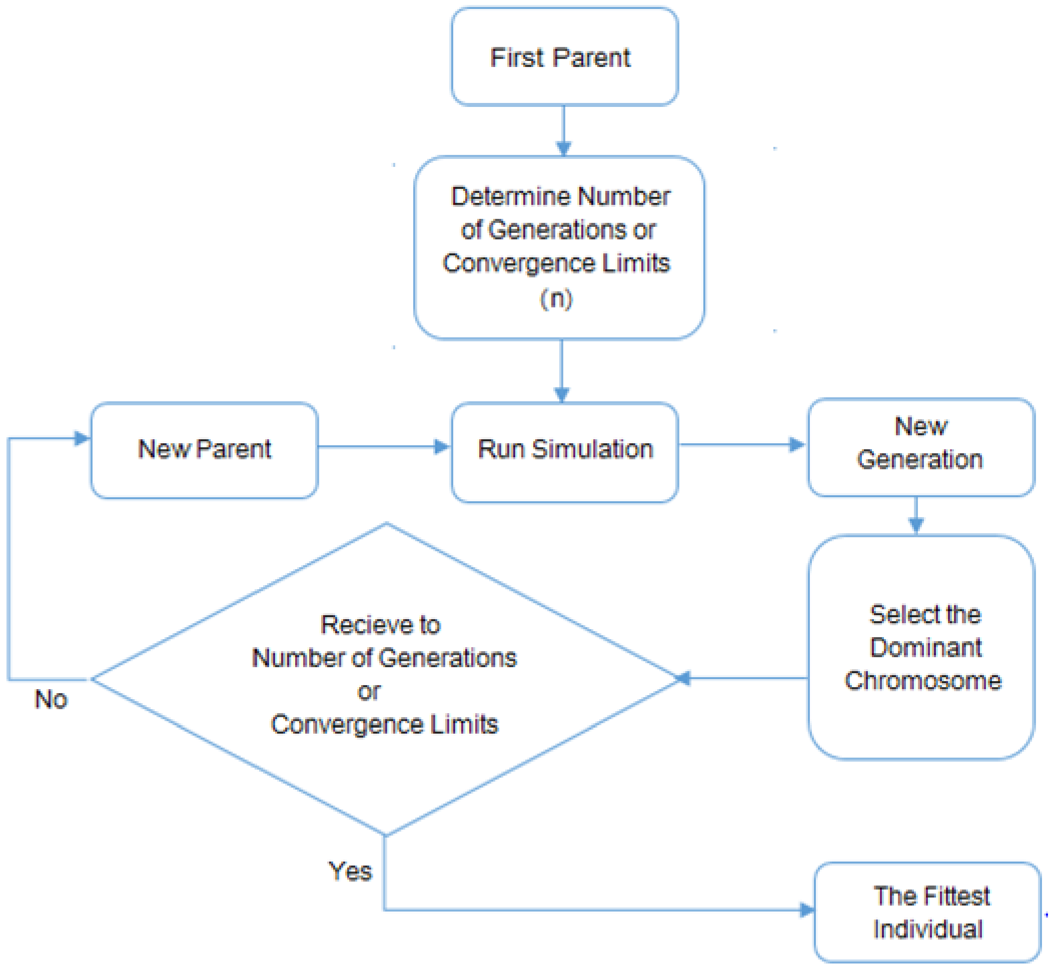

Figure 2) General main trend of genetic algorithm.

As it can be seen in Figure 2, the original coefficients will be imported to the Genetic Algorithm as first parent. By determining the number of desired generations or convergence limits, the model will be run and make new generation individuals. One of simulated individuals by using concepts that reviewed in previous paragraphs will be chosen as dominant chromosome. If number of generations or convergence distance to limits exceed from the criteria, the dominant chromosome will be returned as the fittest individual, else the Genetic Algorithm will continue by using the dominant chromosome as a new parent. Both of the Genetic Algorithm Tool and the developed Python program use the described framework. All levels are conceptually same for two approaches, except in “Select the Dominant Chromosome” level. In this step, in Genetic Algorithm Tool, the dominant chromosomes was chosen based on Kfuzzy method on image data and the output of this level is a new map that we can say it is the child of the parent map that consist a matrix of coefficients. But, in developed Python program, we ran optimization on numerical matrix data by using the statistical approach and the output was a matrix of coefficients that would be used for generating a new map from the parent one.

4- Results

Since initial land use cover map of Karaj belonged to 1985 and the map which used for model calibration produced in 2000, the number of repeats equaled to 15 and land use cover maps of Karaj from 1985 to 2000 were simulated. Land use cover simulated map of 2000 was considered as output of the model. Simulated map of 2000 is shown in figures 3 (the observed map of 2000 has been shown in figure 1).

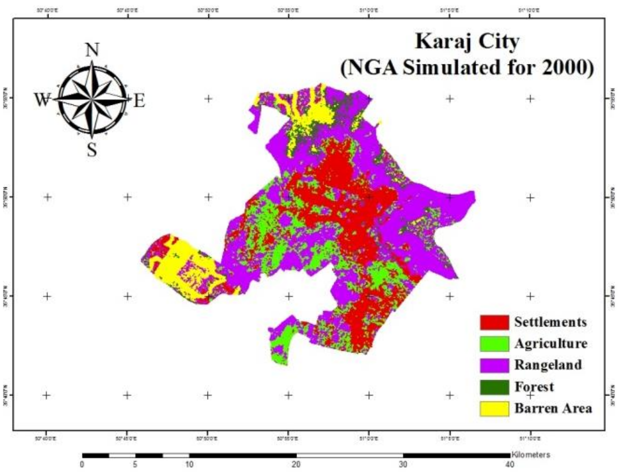

Figure 3) Simulated land use cover map of Karaj without using genetic algorithm (2000).

After model calibration, validation process among observed and simulated maps of 2000 was carried out using Reciprocal Similarity Tool. In this research, the size of moving window varied from 1 to 33. Considering the scale of used maps and corresponding size of each cell on the earth, window size 1 and 30, are equivalent to square areas with 30 and 990 meters long on the earth respectively.

Each moving window with distinct long, minimum similarity among two maps has characterized 0 to 1. Value 0 is equal to non-similarity and value 1 is equal to complete similarity. The results of this step are illustrated in figure 4.

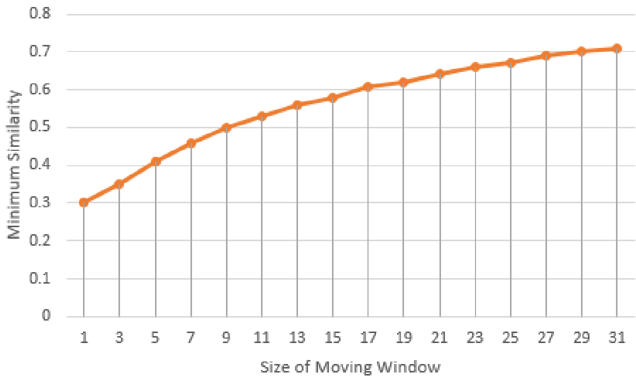

Figure 4) Minimum similarity between observed and simulated land use cover maps of Karaj in 2000 without using genetic algorithm.

In the next steps, the created model was run again using biological evolution rules and data optimization process through genetic algorithm. Since the data used in models were same except in matrix of coefficients which are the most effective factors on model performance that indicates the effectiveness level of each of variables on changes. From this point of view, result for matrix of coefficients from the previous step received as inputs and by a genetic mutation in coefficients according to biological evolution, new coefficients were produced by the developed Python program and finally the most worthy individual (which was one of simulated matrixes) would be introduced as genetic algorithm output.

With the use of output matrix of genetic algorithm, the simulated model with the main status was run again and the simulated map for 2000 was extracted which is shown in figure 5.

For further implementation of model, the only parameter which changed the results, matrix of coefficients, redefined and other parameters were as defined in the previous model.

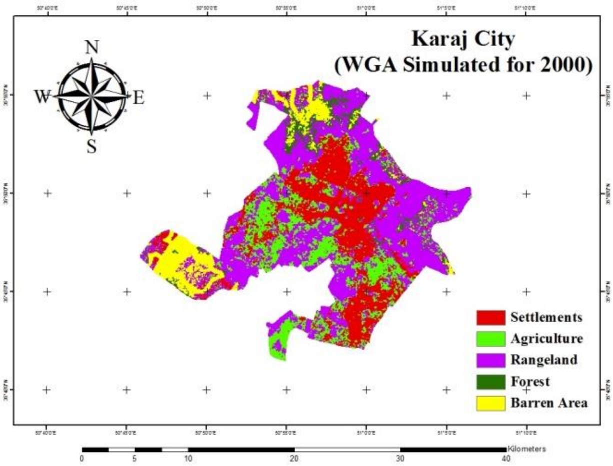

Figure 5) Simulated land use cover map of Karaj in 2000 using genetic algorithm.

In order to make results comparable for the purposes of model validation, all settings and related parameters for validation were same with no genetic algorithm conditions. The results of validation process are shown in figure 6.

As mentioned before, after model implementation using coefficients extracted form genetic algorithm, the results of validation of both approaches were compared together in order to specify the optimal approach. Therefore, the results of minimum similarity in validation process of both approaches were compared as shown in Table 1. This is concluded that application of genetic algorithm using developed program has ignorable effect on model implementation in this research.

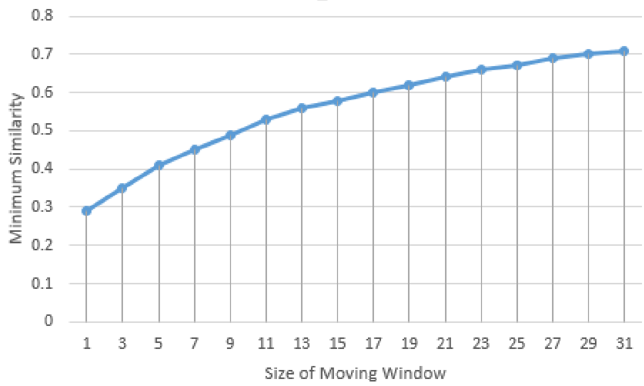

Figure 6) Minimum similarity between observed and simulated land use cover maps of Karaj in 2000 using genetic algorithm.

Table 1) Comparison of genetic algorithm results with original status.

Moving Window Size	Minimum Similarity for Original Status	Minimum Similarity for Genetic Algorithm Status
1	0.30	0.29
3	0.35	0.35
5	0.41	0.41
7	0.46	0.45
9	0.50	0.49
11	0.53	0.53
13	0.56	0.56
15	0.58	0.58
17	0.61	0.60
19	0.62	0.62
21	0.64	0.64
23	0.66	0.66
25	0.67	0.67
27	0.69	0.69
29	0.70	0.70
31	0.71	0.71

To assess developed program for genetic algorithm, a default calculation model in DINAMICA EGO was implemented and also developed program in same conditions run for 10 times. In this way, genetic algorithm of 100 generations with population size of 1000 individuals, 120% permissible limits for mutation and convergence limits of 97% was implemented by the developed program. Then, in each step, results were compared together and mean difference of two chromosomes (two matrices, one from developed program and one from Genetic Algorithm Tool) saved as indicator in each repeat and finally mean of all indicators demonstrated as mean convergence of results with outputs of Genetic Algorithm Tool in DINAMICA EGO which was about 67% .

The results showed that similarity between observed and simulated maps go up with incensements in size of the comparison area (moving window size) for a period of 15 years in a way that it could be claimed that the results have convergence with the real data in minimum probability of 30% for regions with area of 900 square meters and minimum probability of 60% for regions with area of 32 hectares and minimum probability of 70% for regions with area of 98 hectares.

5- Discussion

Genetic algorithm considers evolutionary approach and addresses gene diversity and natural selection and simulates a population in order to make it sustainable through increasing gene diversity and facilitate worthy gene transfer to the next generation. Initially in land use cover changes studies; existing data are insufficient and maybe affect the structure of the model. Therefore, we have to use some methods such as genetic algorithm for model optimization and eventually improve model and its outputs. In this research, matrix of coefficients as chromosome is entered to the genetic algorithm and optimized matrix of coefficients revealed as the output. The optimized matrix of coefficients is entered to the main model and the model re-implemented with primary conditions in order to investigate the effect of the matrix on model performance improvement. In DINAMICA EGO, there is a tool for genetic algorithm computation which simulates for each chromosome and then validates the result with reciprocal similarity method and defines a suitability coefficient for each individual and finally introduces the most worthy one as the output. One the most important and fundamental disadvantages of Genetic Algorithm Tool is inability to load a chromosome with more than 100 gene's index. As mentioned before, in this research chromosomes are in fact matrix of coefficients and their genes are coefficients of variables in each transition. In this research, five class of land use cover and 25 transitions are defined in order to enter to the model. Also total number of all variables which entered to the model is 12 and therefore 300 different status of variable-transition is formed in the model. By implementation of correlation analysis and omitting not done transitions, totally 134 variable-transitions remained in the model and it caused to circumstances in which genetic algorithm tool is out of use. Therefore by the use of Python 2.7 language, genetic algorithm is applied on matrix of coefficients. Gene simulation was done for 100 population in each there were 1000 individuals, with permissible span on 120% and convergence limit of 97% and final optimal chromosome as the result of genetic algorithm entered to the model and then new simulation results were compared with the outputs of main model.

Also, reciprocal similarity method was used in this research for comparison which is a combination of Kappa accuracy coefficient and fuzzy analysis. In this method, some areas with same size on both maps were compared in the way that their similarity index was the amount of their differences with the base map. Therefore, in addition to considering similarity in cell scale, this is possible to investigate patterns in a region and specify the similarity of spatial patterns. This process was considered by changing in size of the comparison area. If this process carried out in calibration phase, it will lead to model improvement and truly primary results of the model will be used toward a better and more precise model. Validation analysis on data driven from final implementation of the model and comparison with existing data, will lead to assessment of the model. Both methods were addressed in this research.

6- Conclusions

In this research, model assessment using genetic algorithm demonstrated that there is no significant difference between results of main model and genetic algorithm application. It seems that genetic algorithm approach will lead to more optimal results but this is not guaranteed it has better outputs compared to original status. If in original model, effective variables are correctly addressed and data errors have been decreased and in fact if the model was accurately run, it will result in no applicability of genetic algorithm in model optimization. This does not mean that genetic algorithm is not efficient but accordance between original model and results of genetic algorithm will indicate proper accuracy and minimum error in the model.

In this research, structural similarity was calculated between simulated and observed data in regions with total area of 900 square meters to 98 hectares by using Kfuzzy method. The results confirmed that fuzzy analysis have high performance for validation of simulation of land use cover changes.

This is recommended to implement some tools in DINAMICA EGO for converting from Weights of Evidence to Lookup Table in order to enable unlimited usage of genetic algorithm tool in the software. Also this is recommended to change effective factors in genetic algorithm performance models under the conditions of less inputs in other researches to assess if genetic algorithm approach can enhance model with less effective variables or not.

Acknowledgments:

We aknowledge University of Tehran for providing resources.

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