Monitoring the Urban Expansion by Multitemporal GIS Maps

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Keywords: Artificial Neural Network, Urban Expansion Model, Geospatial Information System, Fuzzy Set

SUMMARY

This paper presents a GIS-based neural-fuzzy approach for urban expansion modelling based on the utilization variety of social and environmental factors. Artificial neural networks not only can be used for pattern recognition development, but also examine the predictive capacity of the model, while GIS is used to model urban expansion and perform spatial analysis on the results. In this paper, two historical datasets with twenty year interval and user-selected socio-economic and environmental variables have been employed in order to simulate urban expansion. This paper adapts urban expansion model which parameterized for Tehran Metropolitan Area and explores how factors such as highways, slope, administrative space, service centre and residential area parameters can influence it. For each cell in the study area, the real change between the two time steps is determined and analyzed compared with the provided variables in order to produce a probability of urban expansion change layer. This dataset consists of a sequence of two land use acquired between 1980 and 2000 year. Two datasets were used to train the neural network for urban expansion modelling. In addition, the impact of training and prediction period on urban expansion is examined. The creation of the GIS based neural-fuzzy urban expansion model is the major contribution of this paper.

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1. INTRODUCTION

1.1 Background

The expansion of urban areas is determined by the interaction of three broad types of phenomena: the physical constraints of geography and environment, the demand for land by the households and firms who inhabit the city, and the policy constraints that govern land use and spatial interactions in the city. The most useful models for informing public action on the management of urban expansion will be those models that incorporate each of these factors in some way, and that evaluate the relative contribution of each factor to urban expansion.The importance of accurate information describing the kind of land features for urban expansion is increasing. The interpretation of aerial and satellite imageries is undertaken in a variety of ways to develop digital urban expansion information as a basis for urban expansion monitoring. For this reason, government is planning to develop urban expansion maps on a regular timetable and store and manage this information in a GIS. Urban growth is a complex process that encounters sophisticated parameters that interact to produce the urban growth pattern. Urban expansion models have been used to simulate urban development considering different results with consideration of a variety of factors. For this reason, we applied the urban expansion model which uses a number of factors such as transportation, population growth and proximity of important landscape features such as rivers, lakes, recreational sites, and high-quality vantage points as inputs to model urban expansion.

The model proposed in this paper relies on artificial neural network, GIS, fuzzy logic and urban expansion data from at least two time periods. The artificial neural networks are used to learn complex spatial association of factors that have contribution with urban development. The importance of this information related to planners and resource managers to develop better decisions that affect the environment and local and regional economies. The learning of the neural network has been carried out by feeding it with pairs of input and output vector. Historical information is used as input that can forecast future urban expansion. The neural-fuzzy approach was used to predict Tehran's urban expansion to assess the potential impact on Tehran's natural and built environment.

Li and Yeh (2002) presented a method for integrating Artificial Neural Network (ANN), GIS and Cellular Automata (CA) for the purpose of simulating different development patterns based on the planning objective. Pijanowskia et al. (2002) integrated the artificial neural network and geospatial information systems for the purpose of forecasting the change in land use. The neural network learning model approach constituted a new technique, complementary to dynamic systems analysis, for gaining insight into the problems of structure evolution (White, 1989). White developed a neural network model and applied it to urban structures. Li and Yeh (2001) implemented NN to determine the Cellular Automata simulation parameters through importing the values from the training of NN into the cellular automata models.

1.2 Statement of the Problem

Tehran Metropolitan Area exhibited accelerated rates of urban expansion over the last three decades. Being the main city in Iran, Tehran undergoes a great deal of economical activities and developments in term of urban expansion and the rapid growth of infrastructure. The main objective of this paper is to implement the neural-fuzzy concepts to create the urban expansion model of Tehran Metropolitan Area over a study period of two decades. Neural networks with SNNS software were trained using the two datasets; and then predictions were made and the simulation results were compared to the real condition visually. For prediction, data belonging to years 1980 and 2000 were used to train the network and then prediction of urban expansion for the year 2020 was accomplished.
This paper examines advantage of combining geospatial information systems (GIS) and artificial neural networks (ANNs) and fuzzy logic to predict urban expansion. The inputs of this model can be considered a variety of socioeconomic and environmental parameters. The use of neural networks has increased substantially over the last several years because of the advances in computing performance (Skapura, 1996) and the increased availability of powerful and flexible ANN software. This paper provides an update on the development of (Pijanowski et al. 1995; 2000) neural-fuzzy and GIS to model urban expansion. The main objective of this paper is to exhibit how GIS and neural-fuzzy can be used to forecast urban expansion over definite region at the available datasets. GIS is used to develop spatial data layers for use as inputs to the ANNs while basic principles of neural-fuzzy as we apply to urban expansion modelling. The scheme of this work starts with the design of the neural network and identify the inputs using a historical data, using a subset of the inputs to the network as training data, then neural network testing was performed using the full data set of inputs and the final stage was using the information extracted from the neural network to forecast changes. In this paper development of urban expansion model for Tehran Metropolitan Area based on neural-fuzzy was done.

2. RECOMMENDED NEURAL-FUZZY APPROACH FOR URBAN EXPANSION MODELLING

Urban expansion for Tehran Metropolitan Area has been modelled using two urban maps, one from 1980 and the other from 2000. The urban expansion model follows four sequential steps including: (1) processing/coding of data to create spatial layers of predictor variables; (2) applying fuzzy logic for spatial layers; (3) integrating all input grids (4) analysis of the difference between model outputs and real change.

In Step 1, processing of spatial data, base layers were established within a GIS in which these base layers exhibit features in the landscape. In step 2, generation of inputs to neural network were achieved from fuzzifications of spatial layers that had been prepared in previous stage. In step 3, integration of predictor variables is required using ANNs method. Each integration procedure requires a different type of data normalization, while we only present information relevant to the ANN integration method. In step 4, spatial error analysis resulted from comparing output of the model forecasts against known urban expansion occurring during the same time interval. GIS has been used to overlay the forecasted model and known urban expansion.

3. METHODOLOGY

3.1 Study area and data sources

National Cartographic Centre (NCC) database (developed around 2000 from 1:50000 aerial photography) was used as the source of urban expansion data in this project for Tehran Metropolitan Area. Data on land use, transportation, natural features, public lands, digital elevation and political boundaries were incorporated into the Arc/Info 9.2 software. All urban expansion files were then rasterized at a resolution of 100*100 m. NCC line files, digitized from 1:50000 scale topographic maps were integrated with our database to represent the transportation network and locations of roads and highways to provide the appropriate inputs to the GIS-based model. Locations of recreational sites were obtained from published county road maps and stored as point coverage.

3.2 Predictor Variables in GIS Environment

After preparation of urban expansion maps for Tehran Metropolitan Area between 1980 and 2000 years, selection of appropriate parameters by experts with local considerations were performed. The first step in assessing the variables is to determine the factors affecting the suitable urban expansion modelling on the basis of an analysis of existing studies and knowledge. Input layers represent phenomena which may influence the model.

In our case, we assume that the following 5 drivers will influence urbanization in Tehran Metropolitan Area including slope and proximity to residential area, administrative place, service centre and highways. The variables will be different in each area and do not have to be "proximity to". They could also include such parameters as average yearly precipitation or elevation.

These parameters were inserted to ArcMap for specific calculations which were different due to variety of parameters. Distance function has been used for highway parameters. After these calculations different layers in ArcMap have been stored. *Exclusionary* cells are cells which are not going to be included in the analysis. Effective parameters require main considerations and criteria listed as follows:

Absorbing Excursion Spaces: Absorbing excursion spaces contain distance from administrative centres. The distance each cell was from the nearest absorbing cell was calculated and stored as a separate variable grids. It is assumed that the costs of connecting to current absorbing services decrease with distance from urban areas.

Transportation: It is another important factor which the distance of each cell had from the nearest highway cell calculated and stored in separate Arc/Info Grid coverage. The value of driving variable grids represented the potential accessibility of a location for new development.

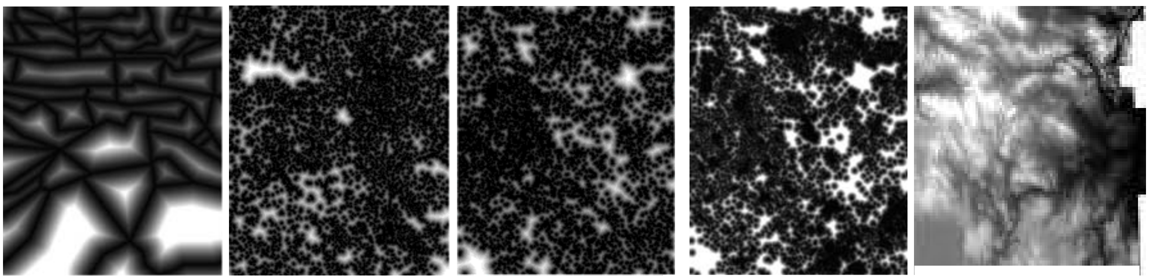
Landscape Features: Landscape topography is an influential factor contributing toward residential use. The amount of topographic variation surrounding each cell was estimated by calculating the standard deviation of all cell elevations within a 4 km square area. Cells containing larger values reflect landscapes that contain a greater amount of topographic relief around them.

Exclusionary Zones: This group includes limitations considered for urban expansion modelling in Tehran, which include existing urban areas, urban expansion plan, green spaces, historical and cultural centres, specific buffer for hospital and mosques, and other pious legacies mentioned in the comprehensive plan of Tehran.

3.3 Neural-Fuzzy Approach to Simulate Urban Expansion

This part shows that how GIS based neural-fuzzy approach can simulate urban expansion model. For this reason, output layers of previous stage were used as input for this stage. After the extended variables were introduced in different layers, we can apply fuzzy function in Spatial Analysis Tools for each layer separately. The main objective of this stage is fuzzification of layers that had been prepared in previous stage. At this stage, definition of fuzzy function which was used for fuzzification was performed.

Accordingly, outputs from GIS calculation are the input files for the neural networks, the same spatial features and spatial rules were applied area. For definition of fuzzy function, the views of some experts in addition to the parameters considered have been taken into account. For example, according to distance parameter, near distance fuzzy function was defined in ArcMap in spatial analysis tools while fuzzy driving variable grids are shown in Figure 1.



Fuzzy Distance to Highway | Fuzzy Distance to Administrative | Fuzzy Distance to Service Centre | Fuzzy Distance to Residential Area | Fuzzy Slope

Figur 1: Fuzzy driving variable grids produced by GIS

In order to perform the prediction in neural networks, training and testing phase should be done carefully. In training phase presenting input values and adjusting the weights applied at each node is considered. The testing presents a separate data set to the trained network independently to calculate the error rate. ANNs were applied to the prediction of urban expansion in four phases (Pijanowski et al., 2000): (1) design of the network and inputs from historical data; (2) network training using a subset of inputs; (3) testing of the neural network using the full data set of the inputs; and (4) using the information from the neural network to forecast changes. In this research ANN used has three layers including one input layer, one hidden layer and one output layer. Simple Back propagation algorithm was used as the learning process. Stuttgart's Neural Network Simulator (SNNS) version 4.2 was used for design; training and prediction of the ANN (Zell et al., 1996). The neural network has flexibility to choose optional number of inputs depending on the number of predictor variables presented to it, an equal number of hidden units as input units and a single output.
In order to prepare input files for SNNS software in the required format, all data layers need to be exported to ASCII files. Each cell in ASCII files was presented to the network will have a number assigned to it based on the cells relationship with the variables and the urbanization process. The higher numbers represent the neural network's prediction of a more likely transition of that cell to urban.

The pattern file contained information from the 5 final input grids and one output file so that each line in the pattern file corresponding to one location. The output of the ANN represents probability of urban expansion layer. The output layer contained binary data represented whether a cell location changed to urban (1= change; 0= no change) during the study period.
In each cycle one complete presentation of all training cells to the network were performed, mean squared error generated by SNNS and each cycle were stored in a file for analysis. Based on the analysis, it was concluded that about 6400 cycles were adequate to stabilize the error level to a minimum value. From results it can be discovered that not only the number of iterations with neural-fuzzy approach decreases, but also accuracy of urban expansion model improves. For testing, SNNS used the pattern file and the network file to generate an output file of activation values. The output file contains values ranged from 0.0 (no likelihood of changing to urban) to 1.0 (highest likelihood of changing to urban).

GIS was used to compare cells that were predicted to be the transition to urban (according to the model output) with the cells that actually did transition during the study period. For assessing the performance of the model, percentage of cells falling into this category was divided by the actual number of cells which have been transitioned to obtain a percent correct match (PCM) metric (Pijanowski et al., 2000)

GIS was used to determine that 1145 cells transitioned into urban class in Tehran Metropolitan Area during the 20-year period 1980–2000. Thus, 2073 cells were selected from the output file that had the greatest change likelihood values; these cells were then classified as new urban area. The test was completed by comparing those cells that were observed to transition, based on the data, with those cells with the highest likelihood of transition, based on the model.

3.4 Accuracy Assessment of GIS Based Neural-Fuzzy Approach

In order to evaluate the results, the predicted land use changes were overlaid to the observed changes in land use from 1980 to 2000. A layer was created with the following codes at Table

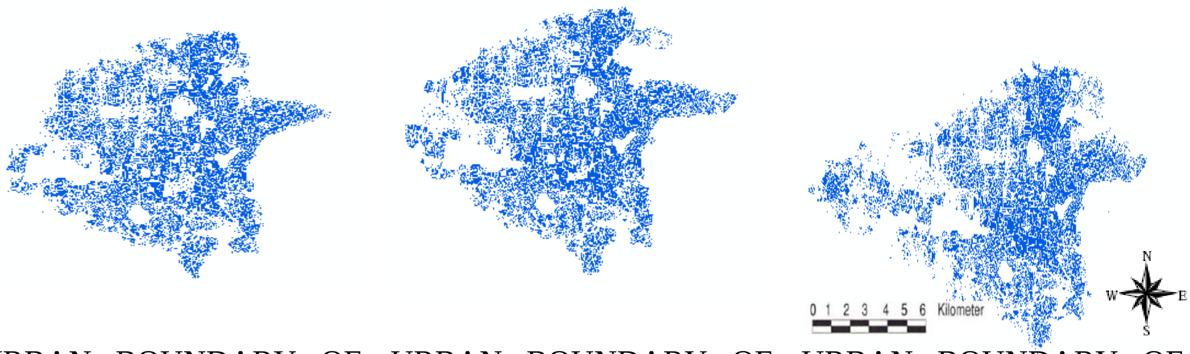
Table 1: Coding of predicted layer

0	No observed change and no predicted change	True Negative
1	Observed change but not predicted by the model	False Negative
2	No observed change but change predicted by the model	False Positive
3	Observed change and predicted change	True Positive

The Percent Correct Metric (PCM) is the number of 3's divided by the number of cells that were in transition. We typically picked the cycle which gives us the best PCM for our region. Neural-fuzzy approach undertaken reaches 55% accuracy.

4. RESULTS

The number of cells in transition is 9534. This number represents the number of cells which the program will pick as transition to urban area based on the highest "probabilities" in the result file. This number matches the number of cells between 1980 and 2000 that actually transitioned to urban and were not part of the exclusionary layer. The actual recorded urban growth to the neural network's prediction has been compared. Having urban expansion between 1980 and 2000 and considering the proposed urban land change and assuming the existence of the same rate of urban change, urban expansion of Tehran has been derived for 2020 (Figure 3). It is clear that extensive amount of urban expansion occurred at the west of Tehran Metropolitan Area for 2020 while it is noticeable that urban expansion was seen in south of the town.



URBAN BOUNDARY OF TEHRAN IN 1980 | URBAN BOUNDARY OF TEHRAN IN 2000 | URBAN BOUNDARY OF TEHRAN IN 2020

Figure 3: Urban boundary in Tehran Metropolitan Area from 1980 to 2010

5. CONCLUSIONS

This paper has focused on the development of an integrated approach of GIS based neural-fuzzy approach for urban growth study. This paper suggested GIS based neural-fuzzy approach which examines the relationship between 5 predictor variables and urbanization. The model performs with a relatively high predictive ability (55%) at a resolution of 100*100 m. By applying this methodology to the Tehran Metropolitan Area, urban growth, which resulted from predictor variables have been examined. The combined use of neural-fuzzy and GIS proves to be an effective tool for urban growth analysis. This linkage is based on the fact that land-use and land-cover data are the main input parameters for both urban growth analyses.

In order to simplify the model several assumptions have been made. First, we assumed that the pattern of each predictor variable remained constant beyond 1980 while difficulty lies in the fact that in practice factors are not held constant. Second, spatial rules used to build the interactions between the predictor cells and potential locations for transition are assumed to be correct and remain constant over time. Third, the neural network itself was assumed to remain constant over time. Thus, the relative affect of each predictor variable is assumed to be stable. Finally, the amount of urban per capita undergoing a transition is assumed to be fixed over time. Given the availability of data, it is possible to relax many of these assumptions in order to examine the potential effect each of these assumptions have on the performance of model forecasts.

It is clear that there is inconsistency in urbanization which probably we need to add/change other parameters. One reason is that the spatial resolution was set at 100m because of time constraints of the study, a higher spatial resolution would most likely yield better results for modelling urbanization. A separate population model forecasting the urbanization for specific years in the future based on 'business as usual' scenarios can be investigated.

ACKNOWLEDGEMENTS

The topographic maps provided by NCC are highly appreciated.

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