MONITORING LAND USE CHANGE BY MULTI-TEMPORAL LANDSAT REMOTE SENSING IMAGERY

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ABSTRACT:

This paper presents a methodology through utilizing remote sensing imagery, GIS-based neuro-fuzzy approach and variety of social and environmental factors for simulating land use change. Two historical Landsat imageries of Tehran Metropolitan Area with twenty year time interval and user-selected socio-economic and environmental variables have been employed in order to simulate land use change. All images were rectified and registered to Universal Transverse Mercator (UTM) WGS 1984 zone 39N. Supervised classification was used to classify the images to different land use categories. Four classes were identified: road, residential area, service centre, administrative area. This work introduces a simulation experiment on urban land use change in which a supervised back propagation neural network has been employed in the parameterization of the simulation model, while GIS is used to model and monitor land use change and perform spatial analysis on the results. This paper adapts land use change model which parameterized for Tehran Metropolitan Area and explores how factors such as road, 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 land use change layer. Parts of two datasets were used to train the neural network while full datasets were utilized to predict land use change modelling. In addition, the impact of training and prediction period on land use is examined. The creation of the GIS based neuro-fuzzy land use change modelling is the major contribution of this paper.

1. INTRODUCTION

A serious problem for modelling urban land use change has been the lack of spatially detailed data. GIS and remote sensing have the potential to support such models, by providing data and analytical tools for the study of urban environments. The work emphasizes spatial relationships between various geospatial, land-use, and demographic variables characterizing fine zones across and around regions. Land use change is a complex process that encounters sophisticated parameters. The interpretation of aerial photography provides a variety of ways to develop digital land use information which is basis for land use planning. For this reason, government is planning to develop land use maps on a regular timetable and store and manage this information in a GIS.

The proposed model in this paper relies on artificial neural network, GIS, fuzzy logic and remote sensing imageries from at least two time periods. Artificial neural networks arise as an alternative to assess such probabilities by means of non-parametric approaches. As stated by Fischer and Abrahart (2000), these mechanisms are able to learn from and make decisions based on incomplete, noisy and fuzzy information, and that is the reason why they can be suitable to handle spatial problems. This information is important for planners and resource managers in developing better decisions affecting the environment and local and regional economies. Land use change models attempt to project future changes in land use based on past trends and the drivers thought to determine conversions of land between different categories. The neuro-fuzzy approach was used to predict Tehran's future land use.

Li and Yeh (2001) conducted a simulation of land use change for a cluster of cities in southern China, using ANN embedded in a CA model upon a binary state basis (urban/non urban use). They further refined this model dealing with multiple regional land uses (Li and Yeh, 2002) and simulations for alternative development scenarios (Yeh and Li, 2003), however, their investigations did not ever scale down at the intra-urban level. A GIS-based Land Transformation Model (Pijanowski, et al., 2000) was developed to forecast land use change over large regions. Liu (2000) adapted a new method to detect the change from non-urban to urban land use through using artificial neural network (ANN). In land use change, (Pijanowskia et al., 2002) integrate both the artificial neural network and geospatial information systems for the purpose of forecasting the change in land use. The model (Pijanowski et al. 2000, 2002) couples GIS, customized data handling routines, a variety of parameter files and Artificial Neural Network (ANN) software to forecast land use changes.

The importance of accurate information describing the kind of land features for land use planning is increasing. Tehran Metropolitan Area exhibited accelerated rates of urban land use change over the last three decades. Being the capital city of Iran, Tehran has undertaken a great deal of economical and social developments in term of land use change and the rapid growth of infrastructure. The main objective of this paper is to implement the neuro-fuzzy concepts to create the land use

change of Tehran Metropolitan Area over a study period of two decades. Neural networks with SNNS software were trained using two datasets; and then predictions were made and the simulation results were compared to the real condition visually. For prediction, years 1980 and 2000 were used to train the network and then predicted land use change for the year of 2020 was accomplished. A series of simulation outputs for the case study town in the period 1980-2000 were produced.

This paper presents the development of land use change model by illustrating an application of remote sensing imageries, neuro-fuzzy and GIS as the inputs of this model. 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. The main objective of this paper is to exhibit how GIS and neuro-fuzzy can be used to forecast land use changes over selected region at a specific period. GIS is used to develop spatial data layers to be used as inputs to the ANNs while basic principles of neuro-fuzzy has been used for land use change modelling. The scheme of this work starts with design of the neural network and identify the inputs using a historical data, using subset of the inputs, the network was trained, then neural network testing was performed using the full data set of inputs and the final stage was to use the information extracted from the neural network to forecast land use changes. In this paper the development of land use change model for Tehran Metropolitan Area based on neuro-fuzzy was undertaken.

2. DATA PREPARATION

2.1 Study area

Tehran Metropolitan Area located in North of Iran was selected for the purpose of this study. The city is considered as the largest and main economical city of Iran. Tehran is one of the most rapidly populated area and land use change regions in Iran. From 1980 to 2000, resident population in the Tehran nearly doubled. Tehran located on latitude 35° 45' N and longitude of 51° 30' E. Data on land use, transportation, natural features, public lands and digital elevation were integrated using Arc/Info 9.2 software.

2.2 Data Sources

Two Landsat TM images of the Tehran Metropolitan Area and surrounding areas were taken at 1980 and 2000. The images were geometrically registered and normalized. National Cartographic Centre (NCC) database developed around 2000 was used as the source of topographic data. NCC topographic data were integrated with our database to represent the transportation network and locations of roads to provide the appropriate inputs to the GIS-based model.

2.3 Data Pre-processing

The historical images were geometrically rectified and registered to the same projection namely, Universal Transverse Mercator (UTM) WGS 1984 to lay them over each other. Figure 1 shows the rectification and registration results as an example for the 1980 and 2000 images. Registration errors were about 0.5 pixel.
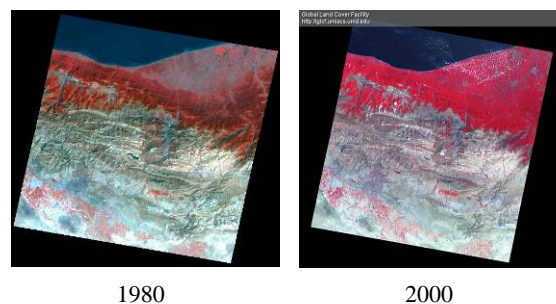

| 1980 | 2000 |

Figure 1. Rectification and Registration results for 1980 and 2000

2.4 Image Classification

The initial (1980) and final (2000) Landsat imageries were subjected to a classification of zones. Supervised classification was utilized to classify the images to different land use categories. In order to classify the rectified images, four classes of interest were specified in the images namely, road, residential area, service centre and administrative area. These classes were identified using sets of high resolution orthophotographs over the area and USGS land classification map as ground references. The overall testing accuracy for the classification of Landsat TM image (1980) was 82.14%, while it was 86.46% for Landsat TM image (2000) which Figure 2 shows the image classification results.
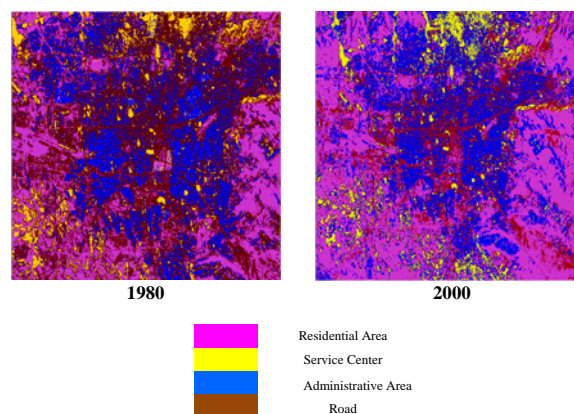

| **1980** | **2000** |

■ (Magenta) Residential Area
■ (Yellow) Service Center
■ (Blue) Administrative Area
■ (Brown) Road

Figure 2. Image classification results for 1980 and 2000

3. SIMULATING URBAN LAND USE CHANGE USING NEURO-FUZZY APPROACH

Land use change for Tehran Metropolitan Area has been modelled using two urban maps, one from 1980 and the other from 2000. The land use change 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, generation series of base layers were established within a GIS of exhibiting different land uses. In step 2, generation of inputs to neural network, achieved from fuzzifications of spatial layers that was prepared in previous stage. Step 3, integration of predictor variables is required using ANN method. Step 4, spatial error analysis

resulted from comparing output of the forecasted model against known land use changes. GIS has been used to overlay model forecasted and known land use changes to calculate the percentage of cells that the model correctly identifies as transition to urban area.

3.1 Variables of land use change in GIS environment

After preparation of land use maps for Tehran Metropolitan Area between 1980 and 2000 years, selection of appropriate parameters by expert people were performed. The first step in assessing the variables is to determine the factors affecting the suitable land use change on the basis of an analysis of existing studies. Input layers represent phenomena which may influence the model. In our case, we assume that the following 5 drivers will influence land use change in Tehran Metropolitan Area including: slope, proximity to residential area, commercial place, service centre and roads. Variables also include average yearly precipitation and elevation.

These parameters were inserted to ArcMap software. Distance function has been used for road 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. These driving predictor variables and the exclusionary zones were compiled in Arc/Info Grid format. Effective parameters require main considerations and criteria listed as follows:

Absorbing Excursion Spaces: Absorbing excursion spaces contain distance from administrative and service 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 road cell calculated and stored in separate 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 land use change 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.

3.2 Neuro-fuzzy approach to simulate urban land use change

This part shows that how the GIS based neuro-fuzzy approach has been used to simulate urban land use change. 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. Definition of fuzzy function which was used for fuzzification was performed.

A new Toolbox in ArcGIS has been developed to perform the requested calculations. Accordingly, outputs from GIS calculation are the input files for the neural networks, the same spatial features and spatial rules were applied. 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 3.

Fuzzy Distance to Road

Fuzzy Distance to Administrative Area

Fuzzy Distance to Service Centre

Fuzzy Distance to Residential Area
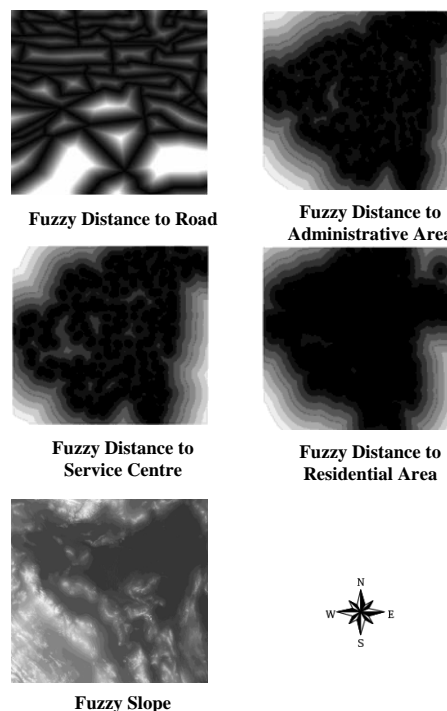
Fuzzy Slope

Figure 3. Fuzzy driving variable grids produced by the GIS

In order to perform 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 has been 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 land use change in four phases: (1) design of the network and of 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 extracted from the neural network to forecast changes. In this study, the proposed neural networks have only three layers each – the input layer, a hidden layer and the output layer which Simple Back propagation algorithm was used as the learning process. SNNS (Stuttgart's Neural Network Simulator) version 4.2 was used for design; training and prediction of the ANN (Zell et al., 1996) shown in figure 4. Difficult learning tasks can sometimes be simplified by increasing the number of hidden layers, but according to Gong (1996), a three-layer network can form any decision boundaries. 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.
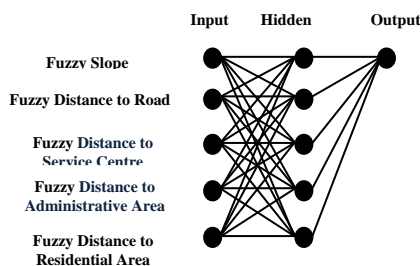
Figure 4. Application of neural nets in determination relationship between the driving variable grids, output and network files.

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 area.

The pattern file contained information from the 5 final input grids and one output file so that each line in the pattern file corresponds to one location. The output layer, on its turn, has only one neuron that corresponds to the map of transition probabilities for the considered type of land use change. In the training data set, the desired (target) value in the output layer is recorded as 1 for a cell that underwent a change in its land use, and 0 for a cell that had no change. In the extraction of the training data set for each network, large rectangles were delimited within the study area containing representative samples of the ranges of distances (for the maps of variables) and of land use change. In each cycle one complete presentation of all training cells to the network was performed, mean squared error generated by SNNS and each cycle was 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. It can be concluded that not only the number of iterations with neuro-fuzzy approach decreases, but also accuracy of land use change 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 ranging from 0.0 (no likelihood of changing to urban area) to 1.0 (highest likelihood of changing to urban area).

3.3 Accuracy assessment of the GIS based neuro-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. According to this overlay, four categories were achieved. In two categories one and four, there is no error; because observed changes and predicted changes have the same results. However, the other two categories, two and three, had same error, because the observed changes and predicted changes have contradicted results. For this reason, we need Kapa coefficient to assess accuracy of the mode which uses all of the four categories for assessment. Kapa coefficient was calculated for this model equal to 78% which seems reasonable. A layer was created with the following codes at Table 1:

1	No observed change and no predicted change
2	Observed change but not predicted by the model
3	No observed change but change predicted by the model
4	Observed change and predicted change

Table1: Coding of predicted layer

GIS was used to compare cells that were predicted to be the transition to urban areas (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 changed to obtain a percent correct match (PCM) metric (Pijanowski et al., 2000).

GIS was used to determine that 1145 cells changed 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 areas. The test was completed by comparing those cells that were observed as the changed areas, with those cells with the highest likelihood of the change, based on the model. The Percent Correct Metric (PCM) is the number of 4'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. Neuro-fuzzy approach undertaken reaches 72% thematic accuracy.

4. RESULTS

ANN proved to have the capability to model non-linear features and handles well the uncertainties of spatial data. The methodology described in this paper showed the potential of implementing NN algorithms as a tool to predict the land use change based on historical satellite images. The numbers of cells indicating land use change have been equal to 1145. 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. In the case of the Tehran Metropolitan Area, 800 km^2 of non-urban lands were converted to urban areas over the 20-year interval between 1980 and 2000.

Having urban land use change between 1980 and 2000 and assuming the existence of the same rate of urban change, urban land use of Tehran has been predicted for 2020. Based on a concurrent study in land use change detection in the Tehran Metropolitan Area between 1980 and 2000, it is clear that the land use change in this region for this time period is concentrated along west of the city. The land use change pattern to the south of the metropolitan area is also substantial but more dispersed (Figure 5).
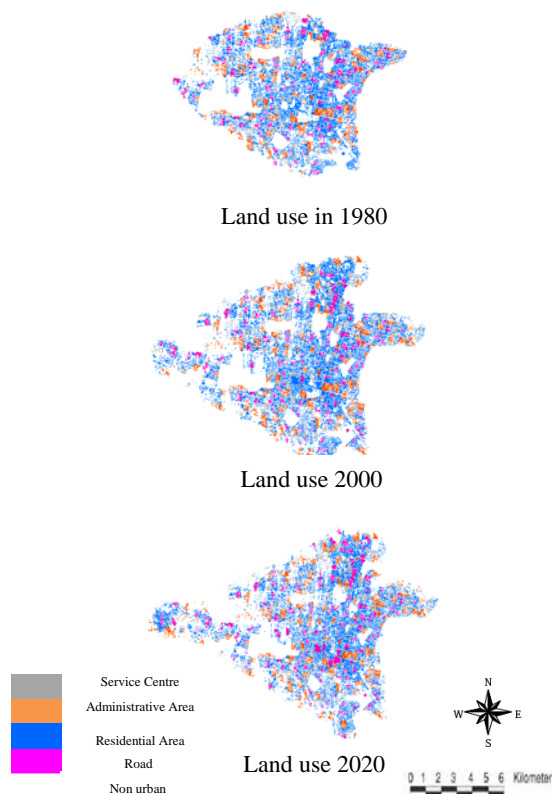
Land use in 1980

Land use 2000

Land use 2020

Service Centre
Administrative Area
Residential Area
Road
Non urban

Figure 5. Land use change in Tehran Metropolitan Area from 1980 to 2020

5. CONCLUSIONS

Models of land use change are tools to support the analysis of the causes and consequences of land use changes in order to better understand the functioning of the land use system and to support land use planning and policy. Models are useful for monitoring the complex suite of socio-economic and biophysical forces that influence the rate and spatial pattern of land use change and for estimating the impacts of changes in land use. This paper suggested a neuro-fuzzy approach which examines the relationship between 5 predictor variables and land use change. The model performs with a relatively high predictive ability (72%) at a resolution of 25*25 m. By applying this methodology to the Tehran Metropolitan Area, land use change, which resulted from predictor variables have been examined. The combined use of neuro-fuzzy and GIS proves to be an effective tool for land use change analysis.

In order to simplify the model, we made several assumptions. First, we assumed that the pattern of each predictor variable remained constant beyond 1980. Second, 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. The spatial resolution was set at 25m 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.

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