

Markov CA, Multi Regression, and Multiple Decision Making for Modeling Historical Changes in Kirkuk City, Iraq

Najat Qader Omar · Mohd Sanusi S. Ahamad ·
Wan Muhd Aminuddin Wan Hussin ·
Narimah Samat · Siti Zubaidah Binti Ahmad

Received: 9 April 2013 / Accepted: 12 August 2013 / Published online: 11 October 2013
© Indian Society of Remote Sensing 2013

Abstract The cellular automata (CA) model is an important tool in land use change studies. Swift increases in population and long-term expectations of rapid urbanization have led to extensive land use change, and normal living conditions have affected the natural resources of the land. This paper highlights and analyzes the historical urban changes in Kirkuk City, Iraq, considering repeated changes undergone by the state such change as government infrastructures, wars, and economic blockade. In this paper, an integrated model,

built-in multi regression model, and multi-criteria evaluation were considered to improve the representation of CA transition rules. Environmental and socioeconomic factors were used to produce Suitable Maps (SMs). These SMs were practicalities to create factor layers and weight usage, rating method process for variance expert decision-making groups, and geographic information systems for the periods 1984, 1990, 2000, and 2010. The roots of the equation (R^2) values are compared and these values are chosen to produce a good model of suitable maps. The approach used in this study provides a mechanism for monitoring suitability maps in Kirkuk. Furthermore, the model Markov CA is implemented and evaluated. The results indicate that the model, its related concepts performs sufficiency

N. Q. Omar (✉) · M. S. S. Ahamad ·
W. M. A. Wan Hussin · S. Z. Binti Ahmad
Geomatic Engineering Unit, School of Civil Engineering,
Universiti Sains Malaysia, Engineering Campus, 14300
Nibong Tebal, Pulau Pinang, Malaysia
e-mail: nqo11_civ078@student.usm.my

M. S. S. Ahamad
e-mail: cesanusi@eng.usm.my

W. M. A. Wan Hussin
e-mail: cewan@eng.usm.my

S. Z. Binti Ahmad
e-mail: sitizubaidah86@gmail.com

N. Q. Omar
Civil Engineering Unit, College of Engineering,
Kirkuk University, Kirkuk, Iraq
e-mail: haneen7dc@gmail.com

N. Samat
Geography Section, School of Humanities, University Sains
Malaysia, Main Campus, 11800 Penang, Malaysia

N. Samat
e-mail: narimah@usm.my

Keywords Multi regression · Rating method ·
Suitability maps · Markov CA · Kirkuk City model

Introduction

Urbanization is a global trend that has been accelerated significantly since the 20th century. According to (Seto and Fragkias 2005), and depends on the United Nations report in 2002 half of the world's population resides in urban areas, and this percentage will continue to rise. Urbanization is the most dramatic form of irreversible land transformation, (Luck and Wu 2002) involving massive immigration of population to urban areas. The report of the United Nations in 2007 mentions the urban

population worldwide was approximated at 2.9 billion in 2000 and forecast to 5.0 billion in 2030. As an important process of population increase and urbanization, urbanization introduces a sequence of environmental issues such as the loss of agricultural land, emergence of heat island effect, regular changes in hydrological quality, and decreases in biodiversity.

Characterizing urbanization and landscape change includes the integration of various geospatial technologies to form technical support for data collection, processing, analysis, and production. Not limited to remote sensing (RS) and image analysis, these technologies include GIS and spatial analysis modeling. Furthermore, the last developments in RS, GIS, comprehensive computing, and forecasting techniques, simulation models have been developed to better understanding urban progress dynamically and to be confident regarding urban planning activities. In planning and management field, GIS is useful in land use, suitability mapping, and analysis (Brail and Klosterman 2001; Collins et al. 2001). The overlay actions occupy users in several GIS applications, as well as techniques that are in the front position of the advances in the land-use suitability analysis such as multi-criteria decision analysis (MCDA) (Malczewski 1999; Thill 1999). Given their cost-usefulness and technological reliability RS and GIS have been used more frequently to build up positive sources of information supporting decision-making in various urban applications.

The simulation and prediction of urbanization can give the input key to various environmental and planning models. In the last three decades, several urban models based on CA techniques were developed to improve understanding of urban evolution (Couclelis 1997; Wu and Webster 1998; Ward et al. 2000a, b; Li and Yeh 2004; Straatman et al. 2004; Herold et al. 2005). In the 1940s, CA model was developed by Ulam and was soon used by Von Neumann to study the logical nature of self-reproducible systems (White and Engelen 1993). CA has controlling capabilities and a high degree of reality when integrated with GIS for modeling (Li and Yeh 2002). In addition, CA has natural advantages in simulating and modeling a variety of spatio-temporal processes by using local interface rules. CA is conceptually clearer, more stable, and more complete than conventional mathematics. (Itami 1994). Cities become computable in various ways within the general framework of CA models.

CA models has been widely employed in the exploration of urban phenomena in the field of spatial and

urban modeling the core of a CA model its transition rules, for this reason CA model can be integration with other model and arrested consideration from international researchers and yet had many research outcomes, for example Wu and Webster proposed multi-criterion evaluation and cellular automata (MCE-CA) (Wu and Webster 1998), Clarke proposed the SLEUTH model (Clarke and Gaydos 1998), White put the weight matrices with CA (White and Engelen 1993), Wu setup logistic regression defined the transition rule in CA (Wu 2002), Li desgin neural networks with CA model (Li and Yeh 2002), and decision catalog trees (Li and Yeh 2004). through these methods, many criteria are collective for crucial transition rules. Each criteria is regularly related with a criterion that indicates its significance in the simulation and modeling process. These criteria significantly have an effect on outcomes of urban simulation (Wu 2002; Li and Yeh 2002). Two-dimensional CA is perhaps the simplest type of dynamic spatial model and consists of five points that are a very simple: lattice or array, a set of cell states, the neighborhoods definition, the transition rules, and the sequence of discrete time steps, (Torrens 2000).

The MCE method is based on the combination of several criteria to form a decision. Criteria can be divided into two kinds: factors, which enhance or detract from the suitability of a specific alternative for the activity under consideration; and constraints, which limit the alternatives under consideration. In the case of constraints, the solution usually lies in the union (logical function OR) or intersection (logical function AND) conditions. A detailed discussion concerning the MCE method can be found in (Eastman, J.R.2006). The rating method is a popular tool used by decision-makers to assess alternatives in problems that include not only definable and quantitative factors, but also indefinable and qualitative factors. The rating methods require the decision-maker to estimate weights depended on a predetermined scale (Malczewski 1999). Weighted linear combination (WLC), also identified as simple additive weighting, is a procedure that multiplies normalized criteria values of relative criteria weights for each alternative (Geldermann and Rentz 2007; Nyerges and Jankowski 2010). WLC can sum all weighted criteria values in a single step, or proceed hierarchically. The earlier mineral exploration example is analyzed using single-step WLC, showing criteria normalization and weighting, as well as the resulting map of aggregated suitability values. WLC supports full trade-off or

compensation among criteria values. Therefore, the method is at the midpoint of the risk tolerance continuum, between conjunctive and disjunctive approaches, and is considered a risk-neutral technique (Eastman, 2009). Fuzzy membership functions are used to standardize the criterion scores. Decision-makers must decide, based on their knowledge and fair judgment, which function should be used for each criterion. Regression is a technique to determine empirical correlations between a binary dependent and several independent categorical and continuous variables (McCullagh and Nelder 1989). Two essential approaches are used to assess spatial dependency within a regression model: first, the construction of an extra complex model incorporating an autoregressive structure (Anselin 1988); second, creating spatial sampling plot to increase the distance gap between sampled points. The goal of this article is to propose a new contribution framework for LULC modeling.

Materials and Methods

Study Area

Kirkuk is a city in Iraq and the capital of the Kirkuk Governorate (formerly known as Tameem). It is built on the Khasa River, and lies on the geographical coordinates of Latitude 35° 28' 5" Northing, Longitude 44° 23' 31" Easting, approximately 350 m above sea level for a UTM reference project, zone 38 N (Fig. 1). It is located in the northern part of Iraq, 236 km northwest of Baghdad and 83 km south Erbil in the Kurdistan region. Furthermore, it is 149 km southeast of Mosul, 97 km west of Sulaymaniyah, and 116 km northeast of Tikrit. The topography of Kirkuk is generally very flat, with similar height terrain in the north, and is 786 km from the Arabian Gulf. Department of surveying and mapping, ministry of agriculture Kirkuk office 1987, Iraq. The Kirkuk region lies between the Zagros Mountains (northeast), the Zap and Tigris Rivers (west), the Hamrin Mountains (south), and Sir Wan (Diyala) River (southeast).

Based on national censuses, the area of AL-Tameem province is 9679 km² and represents 2.2 % of the total area of Iraq, including 13 administrative units (towns), forming four districts. The area of the Kirkuk district 797 km², and the population in 2010 was estimated at approximately 1,475,711 inhabitants. Population of

Kirkuk in 1997 was 753,171, comprising 3.4 % of Iraq's total population. In July and August, Kirkuk experiences normal temperatures at approximately 34 °C to 36 °C. These, along with June and September, are the driest months, with little to no rain. July also has the lowest average wind speeds. January and December are the coldest months with temperatures averaging 8 °C to 9 °C, but temperatures can reach as low as -2 °C. Similarly, the winter months are the wettest, with March is having the highest total rainfall with up to 711 mm of rain. The highest wind speeds are recorded in April, based on data from the Baghdad-based Central Organization for Statistics and Information Technology, Ministry of Planning and Development Cooperation.

Kirkuk is one of the ancient provinces in Iraq. With a distinguished history, it is inhabited by different ethnicities, and its significant geographic location links central and northern Iraq. It is an oil-rich province, with its oil renowned for its high quality. The last official master plan for the City of Kirkuk was completed in 1974, and last updated in 1986. Since then, the master plan and the development of the City of Kirkuk were politically influenced. Furthermore, since 2003, the city's growth and current situation have dramatically affected and altered the city.

Data and Pre-processing

Data

A temporal data of Land sat Thematic Mapper (TM) and Enhance Thematic Mapper (ETM) images are acquired for 24 June 1984, 30 April 1990, 16 April 2000, and 18 February 2010 were used as the primary data to measure spatial temporal urban growth pattern and acquired by The United States Geological Survey (USGS) URL: http://edc.usgs.gov/guides/landsat_tm.html#tm. The digital elevation model (DEM) data are obtained from the project Shuttle Radar Topography Mission (SRTM) and operated by the USGS ERDAS (1999). These DEM data are a part of the 1 arc sec (30 m) SRTM Digital Terrain Elevation Data (DTED). The data for the creation of the simulation, are accumulated from a number of different sources including: the cartography department of the physical planning, which supplied the majority of the data, including thematic and base map vector layers as well as the satellite imagery;

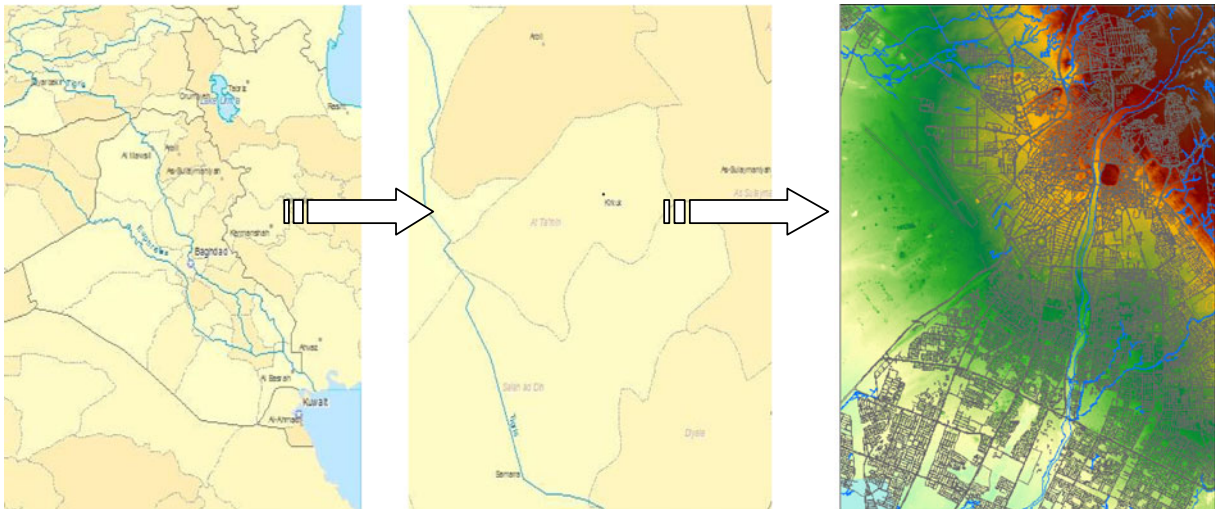


Fig. 1 Location of study area

Two sets of base map data covering the primary study area were obtained from the cartographic department: one set comprising of a series of seven maps in AutoCAD dwg format at a Scale of 1:10,000; which showed the locations of the boundary post markers that are used to denote the official border of the Kirkuk nature reserve. Thematic data layers (e.g. Soil types, geology etc.) Covering much the larger secondary study area were also obtained from the same department at a scale of 1:50,000. A number of thematic maps presenting the same information were also provided in a Windows bmp format (1:50,000) The water quality department of the Kirkuk, providing thematic vector layers and maps showing the hydrology and water quality of the region; The topographic sheet of 1:50000 used in the current study area has the following features: Land use/land cover, Contours and slopes, Road network, Administrative boundaries Survey of Iraq.

In addition to the GIS data summarized above, there are some additional CAD drawings available which display Public Open Spaces, Schools, Transportation and Residential.

The secondary important data were obtained via the AHP questionnaire and Demographic Data, the questionnaire included interviews for decision-makers. The selections of growing criteria for evaluating suitability maps followed the literature review, and discussion with academic staff, experts engineer and members of the city planning groups in Kirkuk city. Among the 11 criteria (Distance to road accessibility, Distance to railway, Distance to airport, Distance to urban centers,

Social services, Slope, Elevation, Environmental factors, Hazard lands, Agricultural value/soil type, Urban suitability, Zoning, Population density, Land value, Water supply, river, water bodies, Social housing.. Etc.) Only five were chosen to determine the best suitability map. Our group of decision-makers comprised 27 professionals and amateurs. We used their expert opinions to identify and assign weights to the factors that best define the general parameters. And the Demographic Data details from Primary depended on the Census abstracts for 1957, 1977, 1987 & 1997 Directorate of census operations, Census of Iraq.

Software Used

Expert choice (EC) and Microsoft Excel obtained the relative importance weights, ERDAS. Imagine 8.5 was used to register the satellite data and cut the study area. ARC GIS 9.3 was used to prepare the data, digitizing all layers for criteria, then converting to raster. GIS IDRISI Andes was used to resample the resolution, enhance images, standardize all strata image criteria, map calculation (MCE), statistical Markov change, Markov cellular automata, and validation.

Base Map Development

The image consists of remote sensing, with considerable numerical values. Three parameters are used to control the number of numerical values in the image: the region, an area covered by the resolution, and the

number of spatial bands used in the photograph. To reduce the period and effort to complete the supply and treatment operations, cutting part of the image is the first step (ERDAS 1999), which covers the area to be studied in the minimum coordination (3933427.13539, 432502.457664). Images corresponding to the maximum coordination (3903144.38623, 459357.992169) are used to create land cover maps for the Kirkuk area, covering 827 km² cut off beyond the administrative city boundaries.

In the second step images from different sensors (TM image comprising seven bands with a spatial resolution of 30 m to 120 m and ETM image comprising eight spectral bands with resolutions from 15 m to 30 m) has a variance spatial resolution. Documented problems include resampling higher resolutions of 120, 90, and 60 to the lower 30 (Bhatta 2009).

Third step: the supervised maximum likelihood classification for each pixel with equal probabilities was classified into nine classes: urban (Residential, Commercial, Industrial, Public Services, Etc.), Mountain area, petrol area, mineral land, wetland, pastures, bodies of water, cultivated land, and vacant land (Eastman, J.R. 2009). Digitized training sites for each class delimited a visual interpretation of true-color composites, imagery for each year, multi temporal imagery via Google Earth, field observation, and topographic maps (Department of surveying and mapping, ministry of agriculture Kirkuk office, 1987, Kirkuk/Iraq) on a 1:50,000 scale. The signature of all classes was then collected. Finally, we used the kappa index to measure the overall classification accuracy of the four maps indicated in 0.74, 0.78, 0.77, and 0.82, respectively.

Parameter Specification

Theses provides a summary of input data sources and operations applied to the data to generate the necessary layers as input to the MCE model. The main input digital map data factor or constraints map (Fig. 2), were those from 1984, 1990, 2000 and 2010, which were digitized based on Land sat imagery and the Kirkuk land use\land cover map (Department of Surveying and Mapping, Ministry of Agriculture).

The derived population density layer is dependent on the total population in Kirkuk for each zone in all year. We compare the estimated population data with the latest census population data of 1997.

After digitizing the road network, the Khasa River, and the central business district (CBD), the map layer

through this data source is constructed. In addition, the layer of three constraint maps, water bodies, military area, and oil area are created.

All GIS data should be converted to the same projection and raster maps have to be standardized to the same cell size and grid dimensions (number of rows and columns). Creation of predictor maps can be accomplished by using most GIS software packages. We use Arc GIS Spatial Analyst to calculate predictor variables such as distance to roads and slope.

Euclidean distance from each cell to its nearest road network, Khasa River, and the central business district (CBD) was calculated using a Euclidian distance function in Arc/Info, and this distance is used to represent the minimum distance from the cell to its nearest road network, Khasa River, and the CBD. This is a normal procedure to all input data layers, which are then converted to a resolution of 30 m. The SRTM DEM data are resampled from its original resolution of 30 m. The slope (in percentage) map is derived from the DEM data. All geographic data are projected to the Universal Transverse Mercator (UTM) coordinate system, with the parameters associated with WGS84 zone 38 N

A Model Approach

To standardize the factor maps, the scaling of minimum and maximum ranges of the cell values as a standard numerical range (0 to 255) was applied by fuzzy set membership function. The Boolean logic function map was derived as constraint maps between (0, 1), to ensure comparability with MCE model.

The important relative weights were established by rate method matrix (Table 1). The three decision-makers, comprising planners, engineers, and academics, were used in Weighted linear combination (WLC) (Fig. 3). The overlay process summation for each factor map is multiplied by each factor weight; the result is indicated in GIS suitability maps (Fig. 4) in combination with Boolean maps for constraint layers. The rating process ranks and reclassifies all factors in the four suitability maps for each year. The rating method starts by assigning an arbitrary weight to the most important criterion, as identified by one of the ranking methods. A score of 100 is assigned to the most important criterion. Proportionately, smaller weights are given to criteria lower in the order. The procedure is continued until a score is assigned to the least important criterion. The

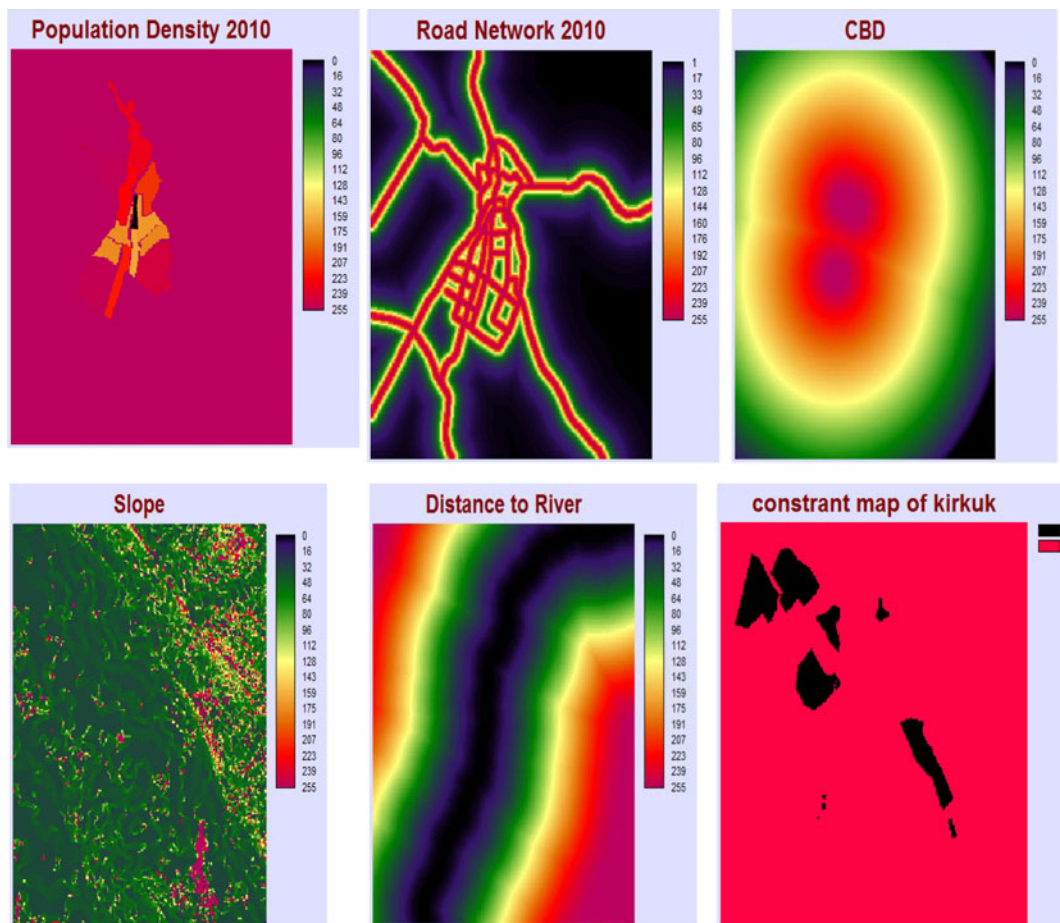


Fig. 2 factors and constraints maps

score assigned to the least important attribute is taken as an anchor point for calculating the ratios. Specifically, the score for the least important criterion is divided by the score for each criterion. The ratio is equal to W_j/W^* , where W^* is the lowest score and W_j is the score for the j th criterion. The ratio expresses the relative desirability of a change from the worst level of that criterion to its

best value, in comparison. This procedure is repeated for the next most important criterion, until weights are assigned to all criteria. Finally, the weights are normalized, by dividing each weight on the total weights.

Multi regression techniques could be applied to statistical analysis by ANOVA table, which shows that the value of alpha p was higher than 0.05, was significant at

Table 1 Average weights by Rating method for variance decision making (DM) groups

Criteria	Normalized Weight/ Total	Normalized Weight/ Planner	Normalized Weight/ Engineer	Normalized Weight/ Academic
Population density	0.3125	0.3125	0.3125	0.3125
Topographic	0.1969	0.2469	0.1594	0.1969
Accessibility to (C.B.D)	0.0844	0.1594	0.0844	0.2469
Distance to road	0.1594	0.0844	0.1969	0.0844
Distance to river	0.2469	0.1969	0.2469	0.1594
Total weight	1.0000	1.0000	1.0000	1.0000

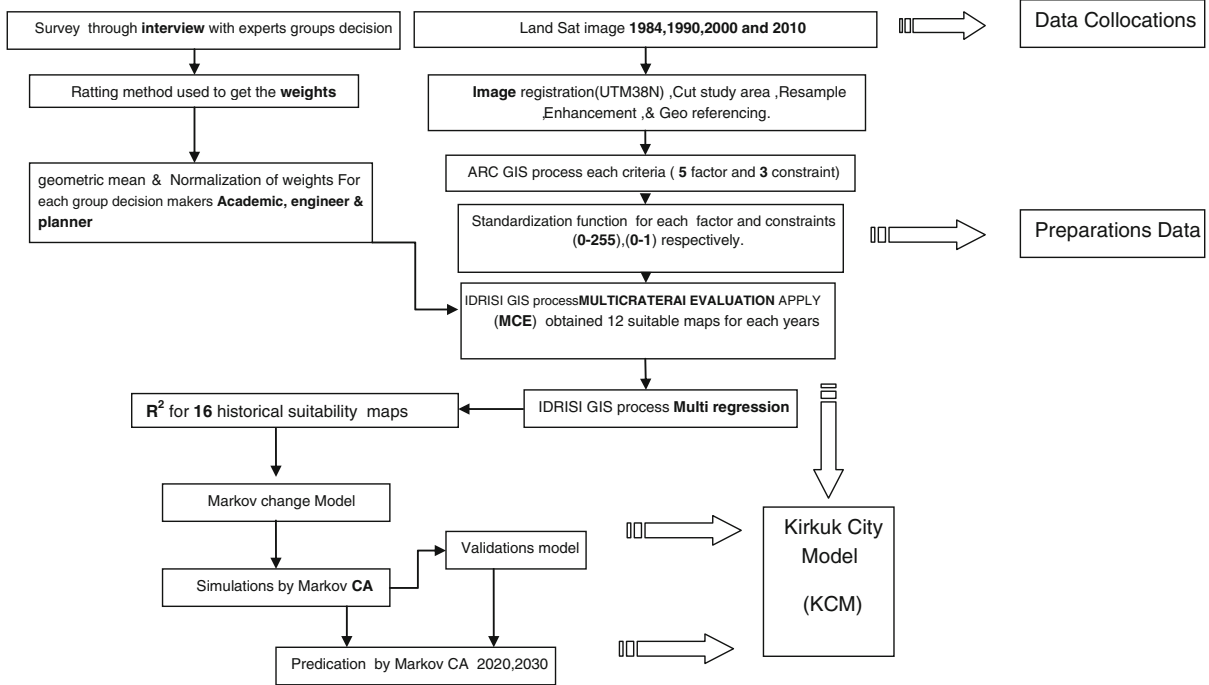


Fig. 3 Flow chart of modelling process for land use change analysis and prediction

1.00, and the weight of the three groups and the total weighted p value 0.85 were found to be dissimilar. The significance of the R^2 coefficient to choose the best-of-fit model indicated in the total suitability map for 2000, was 0.932, compared with the planner weight of the same year at 1.000. The result of the regression analyses is shown in Tables 2 and 3 (McGarigal et al. 2002).

The Markov Change model (MCM) in the land use in a sequence of dates detected by classifying comparison. The classified comparison leads to a categorical map that indicates the land use classes at the two subsequent examination years for every pixel. (Lunetta and Elvidge 1999). The MCM is a stochastic process that describes the probability of one state changing to another state (Mousiv et al. 2007) via the transition of possible matrix (Table 4), and each transition is defined as a step (Zhang et al. 2011).

The Markov CA model used for simulation and prediction of land use, land cover project and the map result consist of all classes (Fig. 5). The cellular automata complex model depends on many researchers, where space and time are discrete and engaged in interaction. The change in land use, land cover occurs according to the specific transition rules in CA model. The rules are mathematical calculations that rule changes in the cell state. A self-reproductive cell is a location of the raster

grids that is intelligent to assume a finite numeral of different states based on the decided transition rule which may be interacting with the states of the critical neighbors on the same raster grids.

The urban simulation model offered in this research incorporates cellular automata, Markov chain analysis, Multi regression equation and multi-criteria evaluation techniques. We use (CA MARKOV) model in IDRISI, Andes (Eastman J.R. 2006) to simulate the historical change in the study area. The module allows the gradual simulation of a class of land use and land cover categories. The MARKOV CA module requires a land use, land cover data set to distinguish the original states, a Markov transition matrix, a group of suitable images and a contiguity filter. The transition rules are set up, using a multi-criteria evaluation and fuzzy membership functions to put together the suitability maps for each simulated land use, land cover class (Eastman J.R. 2006).

Validation techniques (Pontius 2000, 2002; Pontius et al. 2004) were used to determine agreement between the 1990, 2000, and 2010 urban land use reference maps and the 1990, 2000, and 2010 simulated urban land use maps. Furthermore, the techniques are used to compare the agreement between the reference map and the simulated map. The null model included parameters such as agreed between the 1990 and the 2000 reference maps.

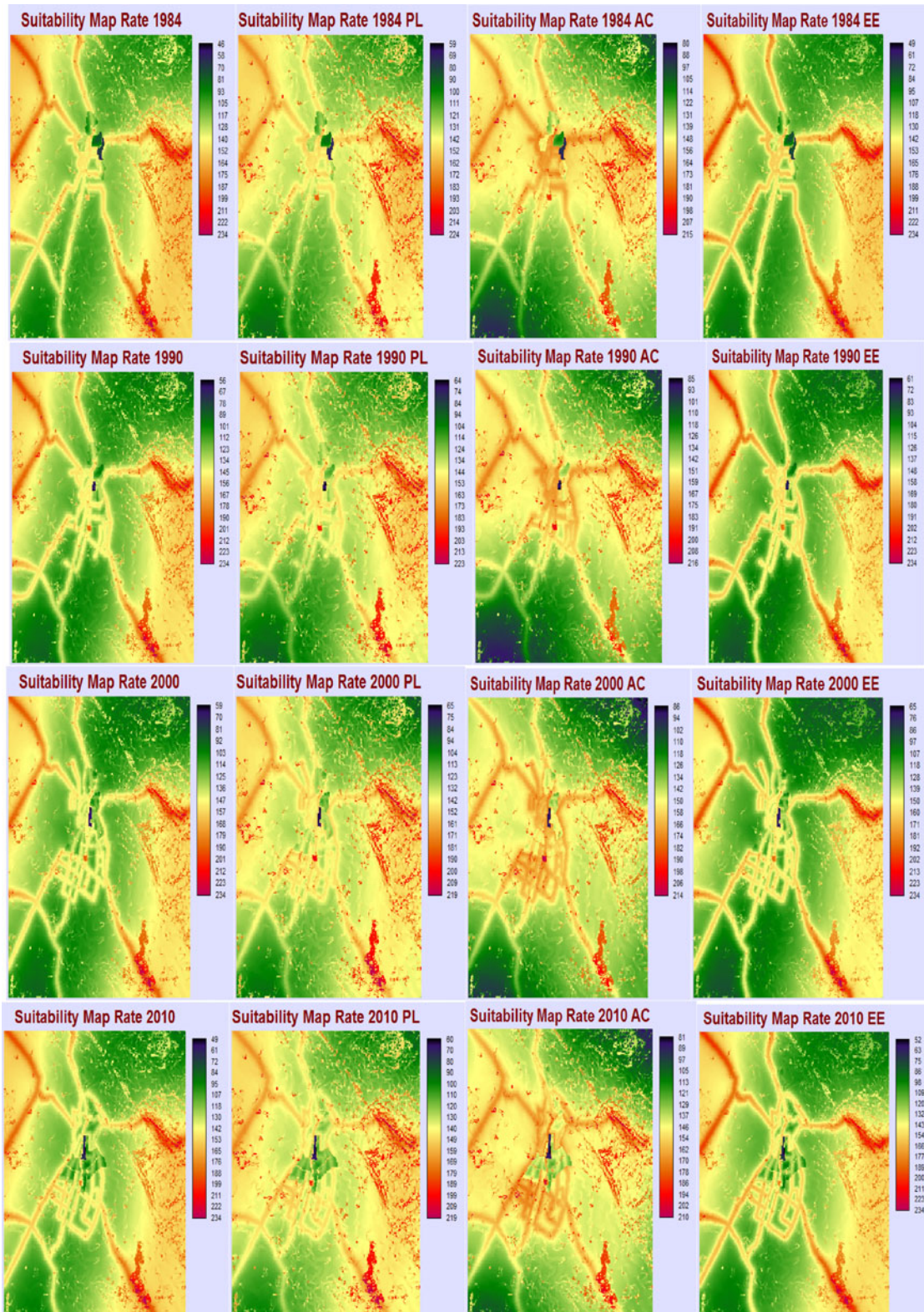


Fig. 4 Rating Suitability maps (*PL* Planner decision maker *AC* Academic decision maker *EE* engineer decision maker)

Table 2 Average weights by Rating method: rank sum, rank reciprocal and the rank exponent method

Criteria	Straight rank	Ratio scale	Original weight	Normalized weight
Population	1	100	10	0.3125
Topographic(slope)	3	63	6.3	0.196875
Accessibility to (C.B.D)	5	27	2.7	0.084375
Distance to road	4	51	5.1	0.159375
Distance to river	2	79	7.9	0.246875
<i>N=5</i>			32	1

Specifically, the validation technique, involving budgets, sources of agreement, and disagreement between the simulated map and the reference map, indicate a higher accuracy (Table 5). The precision of simulation or classification image results, pixel-by-pixel, is assessed via the kappa statistic index (Tables 5 and 6, respectively). This statistic measures the goodness of fit between two model predictions and reality, corrected for accuracy by chance (Bishop et al. 1975). Considering that using maps is categorical maps, kappa can be used to assess the goodness of fit between the simulation maps and the real land use map at the end of the simulation period (Foody 2002; Pontius 2002). Kappa values range from 1 to -1, where positive values are a sign of improved agreement, and negative values indicate insufficient agreement. The formulas for the summary statistics are:

$$\text{Kappa for no information} = K_{no} = \frac{(M(m)N(n))}{(P(p)-N(n))} \quad (1)$$

$$\text{Kappa for location} = K_{location} = \frac{(M(m)N(m))}{(P(m)-N(m))} \quad (2)$$

$$\text{Kappa for quantity} = K_{quantity} = \frac{(M(m)H(m))}{(K(m)-H(m))} \quad (3)$$

$$\text{Kappa standard} = K_{standard} = \frac{(M(m)N(n))}{(P(p)-N(m))} \quad (4)$$

Results and Discussion

In this study, we use cellular automata Markov chain model to simulate changes in nine classes as a result of historical urban changes presented in (Table 5) and shown in Fig. 5, indicating that simulation results are similar in terms of good model and provides a summary of the Markov probability matrix used for simulating the transitions between the initial cell state and the remaining nine cell states represented a land cover category. Table 5 indicates that during 1990–2010 there was a 5.5 % chance that mountain area, petrol area, mineral land, wetland, pastures, bodies of water, cultivated land, and vacant land pixels would transition to urban land. During the same period, there was a 4.2 % chance that wetland pixels would transition to pastures thus reducing the variance in these elements of the transition matrix. The transition rules allow the number and location of water pixels to remain unchanged, the wetland pixels to be preserved.

The MARKOV CA module in IDRISI Andes calculates the transition probabilities and outputs a text file with a transition probability matrix, a text file with the number of transitioning cells from one land use, land cover class to another, and raster lattice representing

Table 3 Assessing R² for suitability maps model at Rating method

Methods	Duration	Equations	R ²
Rating	1984	RATE84 = -0.0420 + 0.6174*RATE84EE + 0.0425*RATE84AC + 0.3461*RATE84PL	0.925
Rating	1990	RATE90 = -0.0311 + 0.6304*RATE90EE + 0.0239*RATE90AC + 0.3472*RATE90PL	0.926
Rating	2000	RATE99 = -0.0409 + 0.5650*RATE99EE + 0.0518*RATE99ACF + 0.3880*RATE99PL	0.932
Rating	2010	RATE10 = -0.0336 + 0.5331*RATE10EE + 0.0609*RATE10AC + 0.4087*RATE10PL	0.929

Table 4 Assessing R^2 for suitability maps model at variance decision making groups for Rating method

Decision maker	Duration	Equations	R^2
AC	1984	$RATE84PL = 0.2095 + 0.5291 * RATE84AC + 0.3400 * RATE84EE$	0.836
EE		$RATE84AC = 0.1909 + 0.6410 * RATE90PL + 0.3272 * RATE84EE$	0.802
PL		$RATE84EE = 0.0595 + 0.5156 * RATE90PL + 0.4514 * RATE84AC$	0.747
AC	1990	$RATE90EE = 0.0140 + 0.5892 * RATE90PL + 0.4000 * RATE90AC$	0.771
EE		$RATE90AC = 0.1785 + 0.6877 * RATE90PL + 0.2893 * RATE90EE$	0.819
PL		$RATE90PL = 0.2369 + 0.5301 * RATE90AC + 0.3285 * RATE90EE$	0.853
AC	2000	$RATE99PL = 0.1966 + 0.5624 * RATE99AC + 0.3139 * RATE99EE$	0.854
EE		$RATE99AC = 0.1367 + 0.6316 * RATE99PL + 0.3609 * RATE99EE$	0.859
PL		$RATE99EE = 0.0000 - 0.0000 * RATE99AC + 1.0000 * RATE99EE$	1.000
AC	2010	$RATE10AC = 0.1492 + 0.3572 * RATE10EE + 0.6310 * RATE10PL$	0.858
EE		$RATE10EE = 0.0350 + 0.4956 * RATE10AC + 0.4769 * RATE10PL$	0.811
PL		$RATE10PL = 0.1853 + 0.5702 * RATE10AC + 0.3106 * RATE10EE$	0.853

AC University Academician, EE Expert Engineer, PL Urban Planner

Markov transition areas. The Markov transition probability matrix is computed from a cross-tabulation of earlier and later land use, land cover images.

Markov transition areas are derived by multiplying each column representing a land cover category in Markov probability matrix (Table 5) by the number of cells of the same land cover class in the subsequent image (Eastman 2006). As a CA-Markov model set in motion, a standard 5×5 contiguity filter re-weights the suitability maps during each iteration increasing the suitability of pixels in close nearness to contiguous areas of the same land use land cover category. The reweighted maps experience a multi-objective land allocation process that resolves land share conflicts using the maximum suitability score (Eastman J.R. 2006).

During each iteration, pixels with the maximum transition probability and the maximum suitability score for an exacting class transition to a new class while pixels with minimum probabilities and minimum suitability scores remain unchanged. If the input consists of 10 iterations, the model allocates 1/10 of all cells expected to transition to another land cover class during each iteration (Eastman J.R. 2006) (Fig. 5) Illustrates Markov transition areas and suitability scores for nine land cover classes.

This Kappa index will assess the changes in the kappa statistics with various image resolutions and cell sizes. The prediction accuracy of the model was highly stable, with less than 1 % change in accuracy between the filters from 3*3 to 13*13. Furthermore, the model was suitable at the resolution image from 30 m to 120 m,

which is adequate for the remote sensing resolution of TM, allocating more time to simulate land use change (Wang et al. 2012).

The projections specify that approximately 15 % of the study area will be urbanized by the year 2030 and 2040, though the extent of urban development under academics and engineer's decision is slightly less than that under the planners' decision. The validity of the model results has been evaluated by comparing the projected land cover image with the existing land cover map. The overall Kappa statistics for the urban class in different years was 0.74–0.82 which indicated a very good agreement between observed and projected urbanized areas.

A separate Kappa statistic was calculated for the agreement between observed and projected built-up areas. Both kappa location and kappa location strata scores indicate that the model has improved performance over the regression model. The relatively low kappa information scores for academics, engineers, and planners in 1990 are caused by the appearance of certain large patches of this particular change in the same year. These are the results of one multi- decision makers. Thus, the simulated using a bottom-up technique, as used in CA very usefully.

However, the complete value of kappa is not a suitable measure for model results because it is highly dependent on the number of cells that change. A simulation with very little changing pixels will result in high kappa values, even if all newly allocated pixels are placed incorrectly. Therefore, this statistic can only be used to compare different results from the same case study.

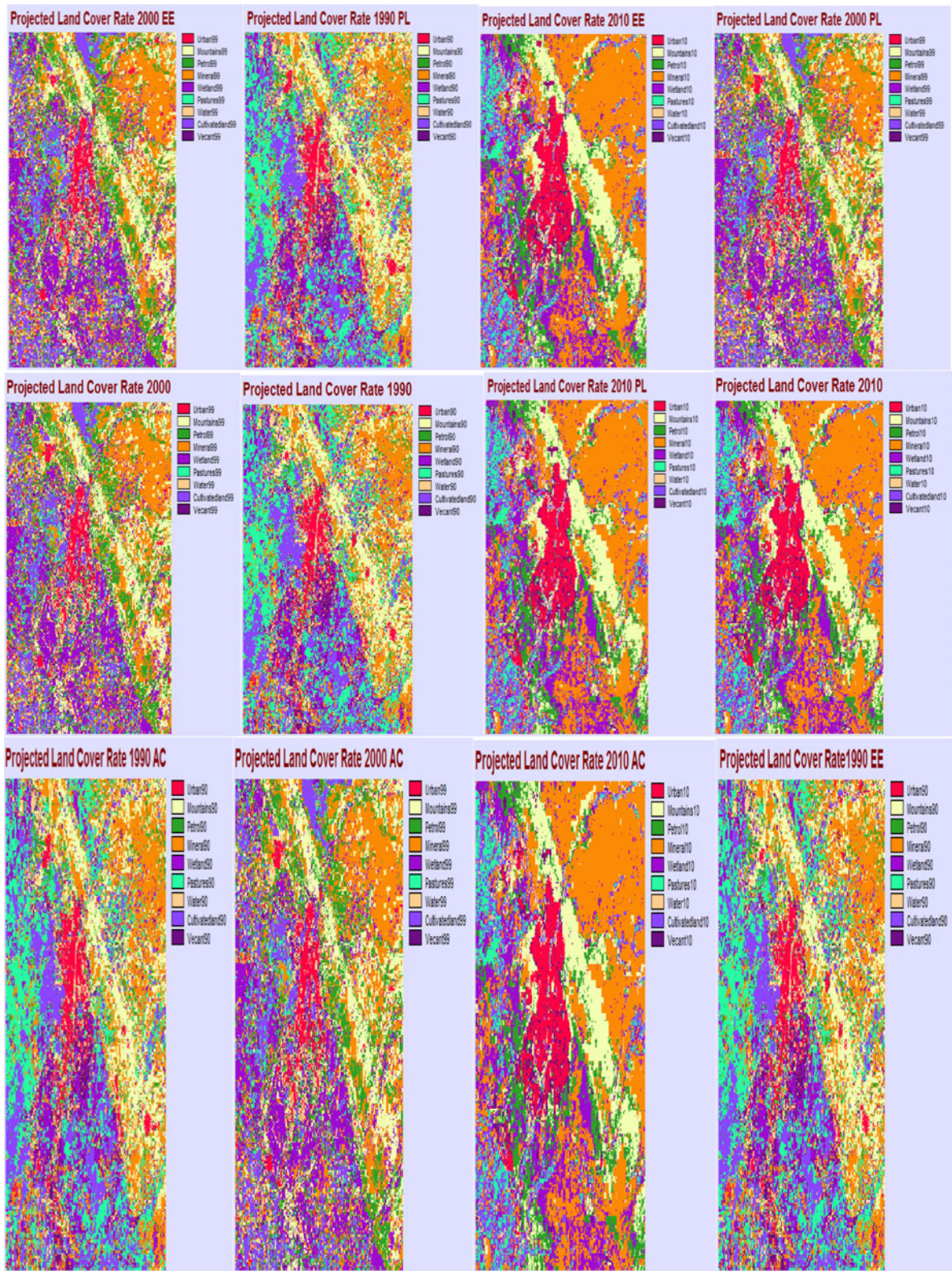


Fig. 5 1990,2000, and 2010 Land cover projection

Table 5 Markov transition probability matrix for 1999–2010

	Cl. 1	Cl. 2	Cl. 3	Cl. 4	Cl. 5	Cl. 6	Cl. 7	Cl. 8	Cl. 9
Class 1:	0.5491	0.1595	0.0264	0.0207	0.0067	0.0027	0.1609	0.0254	0.0487
Class 2:	0.0248	0.4153	0.1570	0.2609	0.0370	0.0055	0.0428	0.0272	0.0294
Class 3:	0.0272	0.1943	0.2649	0.2324	0.0939	0.0222	0.0598	0.0467	0.0586
Class 4:	0.0111	0.2104	0.1746	0.4138	0.0823	0.0163	0.0164	0.0580	0.0169
Class 5:	0.0076	0.0888	0.1201	0.1215	0.4164	0.0490	0.0233	0.1011	0.0721
Class 6:	0.0082	0.0692	0.1606	0.1828	0.3068	0.0719	0.0153	0.1452	0.0400
Class 7:	0.1587	0.1339	0.1307	0.0305	0.0804	0.0159	0.2324	0.0655	0.1520
Class 8:	0.0099	0.0646	0.1545	0.1972	0.2091	0.1003	0.0272	0.2040	0.0332
Class 9:	0.0725	0.1612	0.1561	0.0668	0.2135	0.0213	0.1262	0.0605	0.1219

Kappa values are considered relative to the results of the regression model. For example, the 2010 engineer land use model 2010 has an allocation of one of the actual academic models of variance decision-making groups for the rating method in 2010. This model indicates excellent results (Tables 2 and 3). Therefore, kappa was used (Hagen 2003; Hagen-Zanker et al. 2005). This statistic uses a linear distance decay role to account for slightly expatriate pixels.

Conclusions

A main goal of urban expansion modeling is evaluating potential for future paths improvement (Herold et al. 2005). In this paper, we develop and illustrate unusual

ways of measuring and managing the historical urban changes. In particular, we investigate a sampling method of criterion weight under three groups of decision makers: academic staff decision, expert engineer's decision, and planner decision maker, for five factors and three constraints. The approach based on Markov CA, Markov probability and multi-criteria evaluation allowed the simulation of nine land cover classes simultaneously and thus provide a basis for a significant examination of the land use land cover changes under different decision makers.

Setting transition rules in the form of suitable maps based on MCE allows for consideration of various factors that are commonly used in land use planning and decision-making such as changes in population density, topographical slope, proximity to network roads,

Table 6 Validation between simulated actual maps (reference map) and simulated map in Rating method for variance decision making groups

Simulation actual maps	Methods	K no	K location	K location strata	K standard
1990	Rate	0.9777	0.9858	0.9858	0.9732
	AC rate	0.9782	0.9865	0.9865	0.9739
	EE rate	0.9785	0.9869	0.9869	0.9742
	PL rate	0.9791	0.9876	0.9876	0.9750
2000	Rate	0.9832	0.9873	0.9873	0.9788
	AC rate	0.9818	0.9854	0.9854	0.9770
	EE rate	0.9829	0.9869	0.9869	0.9785
	PL rate	0.9824	0.9862	0.9862	0.9778
2010	Rate	0.9925	0.9910	0.9910	0.9910
	AC rate	0.9910	0.9892	0.9892	0.9892
	EE rate	0.9935	0.9922	0.9922	0.9922
	PL rate	0.9933	0.9919	0.9919	0.9919

Kno Kappa information, *Klocation* kappa location, *KlocationStrata* kappa location strata, *Kstandard* kappa standard

proximity to the CBD as well as protection riparian corridors of Kasha river, water bodies resources, military restricted area, and oil sensitive areas.

The group rating method is a useful decision-making tool that allows groups of decision-makers to conduct ratings depend on an important cause and select alternatives as a part of the group decision-making process. The method is easy for using, as well as the time and cost involved in generating weights are the major concerns.

The systematic evaluation in a GIS environment combined with opinion insight for decision makers and projections equipments land use planners with a useful tool that can integrate activities consistent with the urban expansion options. However the process for controlling and simplifying urban expansion model of integration with geographical information systems is mentioned in more researcher works (Wagner 1997; Clarke and Gaydos 1998; Wu 1998a, b; Ward et al. 2000a, b).

The analysis shows that the sample results between regression model and kappa index had been similarly indicated when choosing between three decision-makers. In addition, The performance of the model indicates its output and evaluation via Investigational application of the model to an imitation city produced realistic patterns of development, supporting the modeling approach.

Further studies will describe the results obtained from applying the model to Kirkuk, Iraq. A more appropriate and rigorous test of the model is required to validate its approach and output. [For example the paper shows the optimum suitability map used as a transition rule in CA model, that emphasizes the strength of our work: the ability to address multiple criteria with multiple decision makers for choosing the best model.

References

Anselin, L. (1988). *Spatial econometrics. Methods and models* (p. 284). Dordrecht: Kluwer Academic Publishers.

Bhatta, B. (2009). Modelling of urban growth boundary using Geo informatics. *International Journal of Digital Earth*. doi:10.1080/17538940902971383.

Bishop, Y., Fienberg, S., & Holland, P. (1975). *Discrete multivariate analysis: Theory and practice* (pp. 393–400). Cambridge: MIT Press.

Brail, R. K., & Klosterman, R. E. (2001). *Planning support systems*. Redlands: ESRI Press.

Clarke, K. C., & Gaydos, L. J. (1998). Loose-coupling a cellular automata model and GIS: long-term urban growth prediction for San Francisco and Washington/Baltimore. *International Journal Geographical Information Sciences*, 12, 699–714.

Collins, M. G., Steiner, F. R., & Rushman, M. J. (2001). Land-use suitability analysis in the United States: historical development and promising technological achievements. *Environmental Management*, 28(5), 611–621.

Couclelis, H. (1997). From cellular automata to urban models: new principles for model development and implementation. *Environment and Planning. B*, 24, 165–174.

Eastman, J. R. (2006). *IDRISI Andes*. Worcester: Clark University.

Eastman, J. R. (2009). *IDRISI Taiga: guide to GIS and image processing*. Worcester: Clark Labs.

ERDAS. (1999). *ERDAS field guide*. ERDAS LLC.

Foody, G. M. (2002). Status of land cover classification accuracy assessment. *Remote Sensing of Environment*, 80, 185–201.

Geldermann, J. & Rentz, O. (2007). Multi-criteria decision support for integrated technique assessment.

Hagen, A. (2003). Fuzzy set approach to assessing similarity of categorical maps. *International Journal of Geographical Information Systems*, 17(3), 235–249.

Hagen-Zanker, A., Straatman, B., & Uljee, I. (2005). Further developments of a fuzzy set map comparison approach. *International Journal of Geographical Information Systems*, 19(7), 769–785.

Herold, M., Couclelis, H., & Clarke, K. C. (2005). The role of spatial metrics in the analysis and modelling of urban land use change. *Computers, Environment and Urban.*, 29, 369–399.

Itami, R. M. (1994). Simulating spatial dynamics: cellular automata theory. *Landscape and urban. Planning*, 30, 27–47.

Li, X., & Yeh, A. G. O. (2000). Modelling sustainable urban development by the integration of constrained cellular automata and GIS. *International Journal of Geographical Information Science*, 14(2), 131–152.

Li, X., & Yeh, A. G. O. (2002). Neural-network-based cellular automata for simulating multiple land use changes using GIS. *International Journal of Geographical Information Science*, 16(4), 323–343.

Li, X., & Yeh A. G. O. (2004). Data mining of cellular automata's transition rules. *International Journal of Geographical Information Science*, 18(8), 723–744.

Luck, M., & Wu, J. (2002). A gradient analysis of the landscape pattern of urbanization in the Phoenix metropolitan area of USA. *Landscape Ecology*, 17, 327–339.

Lunetta, R. S., & Elvidge, C. D. (Eds.). (1999). *Remote sensing change detection. Environmental monitoring methods and applications*. Taylor & Francis: London.

Malczewski, J. (1999). *GIS and multi-criteria decision analysis*. New York: Wiley.

McCullagh, P., & Nelder, J. (1989). *Generalized linear models*. Boca Raton: CRC Press.

McGarigal, K., Cushman, S. A., Neel, M. C., & Ene, E. (2002). FRAGSTATS: Spatial Pattern Analysis Program for Categorical Maps. A computer software program produced by the authors at the University of Massachusetts, Amherst. Available at: <http://www.umass.edu/landeco/research/fragstats/fragstats.html>.

Mousiv & A. J., Alimohammadi Sarab, A., & Shayan, S. (2007). A new approach of predicting land use and land cover changes by

- satellite imagery and Markov chain model (Case study: Tehran). MSc Thesis. Tarbiat Modares University, Tehran, Iran.
- Nyerges, T. L., & Jankowski, P. (2010). *Regional and urban GIS: A decision support approach*. New York: Guilford Press.
- Pontius, R. G. (2000). Quantification error versus location error in comparison of categorical maps. *Photogrammetric Engineering & Remote Sensing*, 66, 1011–1016.
- Pontius, R. G. (2002). Statistical methods to partition effects of quantity and location during comparison of categorical maps at multiple resolutions. *Photogrammetric Engineering & Remote Sensing*, 68, 1041–1049.
- Pontius, R. G., Huffaker, D., & Denman, K. (2004). Useful techniques of validation for spatially explicit land-change models. *Ecological Modelling*, 179, 445–461.
- Seto, K. C., & Fragkias, M. (2005). Quantifying spatiotemporal patterns of urban land-use change in four cities of China with time series landscape metrics. *Landscape Ecology*, 20(7), 871–888.
- Straatman, B., White, R., & Engelen, G. (2004). Towards an automatic calibration procedure for constrained cellular automata. *Computers, Environment and Urban*, 28, 149–170.
- Thill, J.-C. (1999). *Multi-criteria decision-making and analysis: A geographic information sciences approach*. New York: Ashgate.
- Torrens P. M. (2000). "How cellular models of urban systems work", WP-28, Centre for Advanced Spatial Analysis (CASA), University College London; available at <http://www.casa.ucl.ac.uk/howcawork.pdf>.
- Wagner, D. F. (1997). Cellular automata and geographic information system. *Environment and Planning B: Planning and Design*, 24(2), 219–234.
- Wang, S. Q., Zheng, X. Q., Zang, X. B. (2012) *Accuracy assessments of land use change simulation based on Markov-cellular automata model priced Environmental Sciences* In process of 18th Biennial Conference of International Society for Ecological Modelling.
- Ward, D. P., Murray, A. T., & Phinn, S. R. (2000a). A stochastically constrained cellular model of urban growth. *Computers, Environ. Urban.*, 24, 539–558.
- Ward, D. P., Murray, A. T., & Phinn, S. R. (2000b). Monitoring growth in rapidly urbanizing areas using remotely sensed data. *Professional Geographer*, 52, 371–386.
- White, R., & Engelen, G. (1993). Cellular automata and fractal urban form: a cellular modelling approach to the evolution of urban land-use patterns. *Environment & Planning A*, 25, 1175–1199.
- Wu, F. (1998a). Simulating urban encroachment on rural land with fuzzy-logic-controlled cellular automata in a geographical information system. *Journal of Environmental Management*, 53, 293–308.
- Wu, F. (1998b). SimLand: a prototype to simulate land conversion through the integrated GIS and CA with AHP-derived transition rules. *International Journal of Geographical Information Science*, 12, 63–82.
- Wu, F. (2002). Calibration of stochastic cellular automata: the application to rural urban land conversions. *International Journal of Geographical Information Science*, 16(8), 795–818.
- Wu, F., & Webster, C. J. (1998). Simulation of land development through the integration of cellular automata and multi-criteria evaluation. *Environment and Planning B: Planning and Design*, 25, 103–126.
- Zhang, Q., Ban, Y., Liu, J., & Hu, Y. (2011). Simulation and analysis of urban growth scenarios for the Greater Shanghai Area, China. *Computers, Environment and Urban Systems*, 35, 126–139.