Markov-CA model using analytical hierarchy process and multi-regression technique

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Abstract. The unprecedented increase in population and rapid rate of urbanisation has led to extensive land use changes. Cellular automata (*CA*) are increasingly used to simulate a variety of urban dynamics. This paper introduces a new *CA* based on an integration model built-in multi regression and multi-criteria evaluation to improve the representation of *CA* transition rule. This multi-criteria evaluation is implemented by utilising data relating to the environmental and socioeconomic factors in the study area in order to produce suitability maps (*SMs*) using an analytical hierarchical process, which is a well-known method. Before being integrated to generate suitability maps for the periods from 1984 to 2010 based on the different decision makings, which have become conditioned for the next step of *CA* generation. The suitability maps are compared in order to find the best maps based on the values of the root equation (R^2). This comparison can help the stakeholders make better decisions. Thus, the resultant suitability map derives a predefined transition rule for the last step for *CA* model. The approach used in this study highlights a mechanism for monitoring and evaluating land-use and land-cover changes in Kirkuk city, Iraq owing changes in the structures of governments, wars, and an economic blockade over the past decades. The present study asserts the high applicability and flexibility of *Markov-CA* model. The results have shown that the model and its interrelated concepts are performing rather well.

1. Introduction

In recent times, there has been a rapid increase in urbanization all over the globe. The approximate world population in 2000 was 2.9 billion and predicted to be 5.0 billion in 2030 (United Nations, 2007). This ratio will increase to over 72% by 2050 (United Nations, 2012). The unprecedented increase in population and rapid rate of urbanisation can lead to extensive land-use changes.

The rapid urbanization in Asia and West Asia, both has exhibited a process distinctively different in late 20th Century [1]. Many researchers have studied land-use and land-cover change (*LUCC*) since the end of the 20th century [2]. The input issues outlined by *LUCC* agenda include the study of integrated global and regional models and the evaluation of databases land-use and land-cover change is a complex process involving both environmental and socioeconomic factors. Land-use and land-cover change research increasingly takes the form of integrated land-use change research, important to this change is human activity that impinges on land-use systems and surface features, known as land use and land cover change (*LUCC*) [3].

Monitoring land-use and land-cover change help to develop an understanding of past trends, while simulation based modelling can provide insights into potential future developments. Both complementary approaches are necessary strategies for implementing appropriate actions including formulating better land use policies, providing infrastructure, identifying future development pressure points, and developing previous visions of urbanization process implications. [4].

Therefore, knowledge concerning past, current, and future growth plays an important role in the decision-making process [5, 6]. The simulation and prediction of urbanization can give input to various environmental and planning models. In the last three decades, urban models based on *CA* techniques were developed for improved understanding of urban evolution .The core of a *CA* is a transition rule that has been represented either using weight matrices [7], *SLEUTH* model [8], multi-criterion evaluation (*MCE*) [9], logistic regression [10], neural networks [11], and decision catalogue trees [12]. In these methods, many variables are mixed up for defining transition rules. Every variable is usually connected with a criterion that indicates its importance in the simulation process. These criteria significantly have an effect on outcomes of urban simulation [10, 11].

The cellular automata (*CA*) model is regularly employed in land utilities research. The grid cell in *CA* is similar in its spatial description to remote sensing images and raster data of geographic information systems (*GIS*), which frequently support the land utilities data [13]. The *CA* model also open managing of dynamic spatial models with time [14]. The setting of *CA* is in the simulation processes of adjacent interaction cells. This method is similar to land use activities that are frequently characterized by the interaction of adjoining landscape patterns.

The integration of various geospatial technologies in the form of technical support for data collection, processing, analysis, and production [15]. With developments in remote sensing (*RS*) and *GIS*, comprehensive computing, and prophecy techniques, simulation models have been developed to better understand urban progress dynamics and to be hopeful of urban planning activities [16]. Significant contributions in the urban field have been established thanks to the advancement of *GIS* and *RS* [6, 17] both of which have been used to relate land-use and land-cover change to urban growth models [18] 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*) [19]. RS and GIS, given their cost-usefulness and technical reliability, have been used progressively to build up positive sources of information supporting decision making in various urban applications [20]. *MCE* is based on the combination of several measures to make a conclusion. Criteria can be of two kinds: factors and constraints [21]. The AHP is a mathematical method of analysing complex decisions problem with multiple criteria. It is based on three principles: decomposition, comparative judgment, and synthesis of priorities. For this purpose, (Saaty, 1980) has used and developed the Par wise Comparison Method (*PCM*).

The *PCM* is based on forming judgments between two particular elements rather than attempting to prioritize an entire list of elements [22]. It allows users to estimate the relative weight of multiple criteria against giving criteria in an intuitive method. If the quantitative evaluations are not available, decision makers can nevertheless realize whether one criterion is (equally important, extremely important, or less important) than another depending on the scale. A spreadsheet package, EXPERT CHOICE is based on *AHP* and used in calculating weight for respective layering. It has an ability to compute weights for multiple criteria with par wise comparisons. Weighted linear combination (*WLC*) or simple additive weighting is a procedure that multiplies normalised criteria values of relative criteria weights for each alternative [23-25].

Fuzzy Membership Functions are used to standardize the criterion scores. Decision makers have to decide based on their knowledge and fair judgment the function to be used for each criterion. Regression technique determines the empirical correlations between binary dependent and several independent categorical and continuous variables [26].

Kirkuk is one of the ancient provinces in Iraq inhabited by different ethnicities and characterized by a rich culture with a distinguished history It is heritage of about 5,000 years and significant geographic location linking between central and northern Iraq. It is an oil-rich province having one of the top quality oils in the world .The last official master plan for the City of Kirkuk was completed by *Doxiadis* in 1974 and last updated on 1986. Since then, the Master Plan and the development of the City of Kirkuk were politically influenced, and since 2003, the city's growth and current situation have dramatically affected and altered the city to the   challenge by many difficulties such as unplanned environmental pollution and other socioeconomic problems. (Kirkuk Government, 2001).In addition owing to changes in government structures, political, wars, and economic blockade over the past three decades. In this respect, it is a good deal needed to study the land-use and land-cover changes and anticipate the future maps of Kirkuk city. In this paper, an incorporated model was developed based on multi-regression model and multi-criteria evaluation to improve the representation of *CA* transition rules as a new contribution framework . The objective of this article is to present analyses that are complete by *GIS* and *RS* of the period from 1984 to 2010 and depict the implementation of a validation procedure, which show how uncertainty affects the simulation results then predictive for future land use land cover change   model in Kirkuk city in 2020,2030 and 2040 based on the past trend (from 1984 to 2010) using a method called *Markov-CA* along with transition probability maps taken into account by *MCE*.

2 . Material and Dataset
Kirkuk city in Iraq is the capital of the Kirkuk Governorate (formerly known as Tameem) located along Khasa River, within the geographical coordinates (Lat 35° 28' 5"N, Long 44° 23' 31"E) at 350m above sea level as shown in 'figure 1'. It is situated in the northern part of Iraq, 236 km in northwest of the capital Baghdad city, 83 km south of Erbil, the capital of Kurdistan Region, 149 km southeast of Mosul, 97 km west of Sulaymaniyah, and 116 km northeast Tikrit.

The topography of Kirkuk is generally very flat with common terrain heights in the northern part (786km from the Arabian Gulf). The Kirkuk region lies between the Zagros Mountains (northeast), Zap and Tigris River (west), Hamrin Mountains (south), and Sirwan (Diyala) River (southeast) (Google Maps Distance Calculator). All the geographic data for the study area were collected in two stages: primary and secondary phase.

2.1. Primary Data
   Group discussions, interviews, and reviews of existing studies conducted during the two field works (from the 15th of November 2011 to 01st of February 2012, and from the 21th of July 2012 to the 27th of September 2012), which provided the key information for identifying the driving criteria of urban growth in the last decade. The selections of urban growth criteria accorded through literature review [9, 27], academic knowledge, engineering expert, and members of the city planner. Synthesis of these data led to the derivation of five representative factors out of the 11 criteria identified, (Distance to road accessibility, Distance to railway, Distance to airport, Distance to urban centres, 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.).

Five factors closely associated with land-use and land-cover change forces were selected and incorporated into the transition potential calculation, and three constraints.

Figure 1. Location of the study area.

Ranging from socioeconomic to environmental, for further evaluation (table 1). These factors are populated , topography, accessibility to the Central Business District (*CBD*), Distance to the road, and Distance to the Khasa Rivers. Consequently, data pertaining to urban growth factors were obtained through a set of questionnaires was developed based on *AHP* technique, interviewed, in which the respondents stated the relative importance of each factor with respect to the others. The group of the decision making process uses 27 professionals where from their expert opinions weights to the genes that best define their preferences are obtained and assigned.

Table 1. The relative weights for different decision making groups.

Criteria	Normalized Weight Total	Normalized Weight PL	Normalized Weight EE	Normalized Weight AC
Population DENSITY	0.4650	0.4535	0.4431	0.4926
Topographic(Slope)	0.1438	0.1721	0.1220	0.1515
Accessibility To (C.B.D)	0.1101	0.1313	0.0860	0.1320
Distance To Road	0.1210	0.1004	0.1425	0.1075
Distance To River	0.1600	0.1426	0.2064	0.1165
Total Weight	1.0000	1.0000	1.0000	1.0000

2.2. Secondary Datasets

In this study four scenes of the land satellite "*LANDSAT*" images LANDSAT -5 Thematic Mapper (*TM*) and LANDSAT-7 Enhance Thematic Mapper (*ETM*) for path 169, row 35 covers the Kirkuk and the surrounding area , images were acquired on 24 June 1984, 30 April 1990 ,16 April 2000, and 18 February 2010. These images were downloaded one by one from the official website of the United States Geological Survey (USGS).

More details concerning the spectral ranges and spatial resolution of LANDSAT-5 can be referred to the *USGS* web site. The 30m spatial resolution of "*LANDSAT*" satellite images is sufficient to capture the characteristic scales of human development, and the spectral range of the tool is capable to recognize land -use of other types of land-cover change. The digital elevation model (*DEM)* data were obtained from the project Shuttle Radar Topography Mission www.glcf.umiacs.umd.edu/data/srtm (*SRTM*) operated by the US Geological Survey (*USGS*) Earth Resources Observation Systems (*EROS*) Data Centre (2006). *DEM* data were part of the 1 arc second (30m) SRTM Digital Terrain Elevation Data (*DTED*).

2.3. Software and Processing tools used

The work utilised various software for all the analyses, data preparation , image processing and analysis performed during the creation of the model of Kirkuk city expansion was accomplished using a combination of the following software sets:

Expert choice (*EC*) to determine the   relative weight of the factors (Expert Choice , 1982-2004). *AutoCAD* merged and edited the *CAD* (dwg extent file) data (Autodesk, 1982-2009). Microsoft excel in the arrangement of relative importance weights. *ERDAS* Imagine-8.5 (ERDAS, 1999) to register the satellite data, and then cut the interest area of studies. *ARC GIS 9.2* (*ESRI*) to set up the database and digitize all layers for criteria and convert to raster. *GIS IDRISI* (Eastman, 1987-2012) to resample enhancement of images, standardization of all strata image criteria, map calculation (*MCE*), statistical classification, Markova change, Markova cellular automata and validation. Lastly the Microsoft word for writing of the paper.

2.4. Base map

At   first, all "*LANDSAT*" images and *GIS* data needed for use in model, converted to the same projection and raster maps, standardized to the same cell size and grid dimensions (number of rows and columns), under a Universal Transverse Mercator map (*UTM*) projection system , referenced to the world geodetic system (*WGS*) 1984 coordinates system, Zone 38N.Secondly, for the purpose of ground-treating the base maps, they were registered them geometrically in the map projection system by using the image in 2005 as a basis. The Land sat images contain massive numbers of numerical values that signify information such as the region.

The region was encompassed by the resolution and the number of spatial band used. The effort in reducing supply and treatment operations in the computer was accomplished by partitioning the image (ERDAS, 1999), that covers the area of study to Minimum X and Y coordinate (3933427.13539o, 432502.457664o), Maximum X and Y coordinate (3903144.38623o, 459357.992169o) in decimal degrees using the WGS84 datum. The images used to create land cover maps for the Kirkuk area covers a surface area of 827 km2 representing the administrative boundary of the city. TM image has seven bands with a spatial resolution of 30m-120m, while ETM image has eight spectral bands with a resolution of 15m-30m. Images from different sensors will have a different spatial resolution.

Therefore one method of resolving this problem is to resample higher resolution i.e. 120m, 90m, and 60m to lower resolution of 30m, which is enough to capture spatial details and small enough to reduce computation time (Bhatta, 2009).The mean square error (*MSE*) is equal to 0.010734.

Thirdly, by utilizing the widely used supervised maximum likelihood classification method, we separate the three images under a Nine-class (*C1-C9*), for each pixel equal probabilities which includes urban (consists the building's residential commercial industrial public serves road network and parking lots.), mountainous area, oil field area, mineral land, wetland, pastures water bodies, cultivated land and vacant land respectively [21]. Digitized training sites for each class were delimited by 1) comparing the visual interpretation of composites true colour imagery for each year with supervised classification images, 2) multi temporal imagery through Google earth, 3) field observation and 4) topographic map of 1987 (Department of survey and mapping, Kirkuk, 1987) at the scale of 1:50,000 before the signature of all grades are compiled. We calculate the overall accuracy and Kappa statistics were calculated for assessing the classification accuracy [28]. The results show that overall accuracies of the classification are 74 %, 78 %, 77 % and 82 % in 1984, 1990 , 2000and 2010 respectively.

2.5. Factors specification

The series of factors are prepared using *Arc GIS*, and they are transformed into a normalized scale before being input into the model. The "*LANDSAT*" imagery of 1984, 1990, 2000 and 2010, and topographic map of Kirkuk (Department of Surveying and Mapping, Ministry of Agriculture, Kirkuk, 2000) were used for digitised to creating vector layers by digitizing the road network, the Khasa Rivers and the Central Business District (*CBD*) for the mentioned years consecutively. The population density vector layer was digitized based on the entire population of the respective zones in Kirkuk for all the years and then the estimated population data was compared, with the last census population data in 1997. The Demographic Data details from Primary depended on the Census abstracts for 1957, 1977, 1987 and 1997 (National Census Bureau of Statistics, Kirkuk, 2005). The *SRTM DEM* data were re-sampled from its original resolution of 30m. The slope layer (in percentage) map is derived from the *DEM* data. Additionally, constraint vector data files such as water bodies, restricted military area, and oil producing area were created, which are stored in Shape file format.

3 . Modelling approach

3.1. Suitability maps

These suitability maps are organized based on Multi Criteria Evaluation (*MCE*) process. At present, the obtained weights can be computed automatically in Expert choice computer package software. The indicator score weights of factors in three aspects: First the Academic represent the theoretical aspect, second the Planner as the planning aspect, and the Expert Engineer as applied aspects of land-use and land-cover change is shown in (table 1) based on factors to compute the relative indicator score weights of decision makers. Thus, par wise comparison matrixes are calculated into Expert Choice determining priority weight. However, the normalisation of factors weight is (divide by the sums of the pillars, and average across rows to find the relative weights of each component).

Where, the vector layers converted to raster's fuzzy set membership is used for standardising criteria. The factors or land cover constraints which have been standardised to a continuous scale to minimum and maximum standard numerical range from 0 signify the least suitable to 255 signify the most suitable, the Boolean map for each land-cover type has been prepared. Then the images 'figure 2' for Boolean land-cover map were produced and compared with a model in a range from 0 to 1 [29]. The measurement unit was used is an international system (IS).

The distance images are created using a simple Euclidean distance function in *Arc GIS* which measures the distance between each cell from the featured image such as a road network, Khasa rivers, and *CBD* respectively. The lowest and highest values obtained from the distance image are used as the input for fuzzy set membership analysis. Then, the distance images have been standardised to the same continuous suitability scale (0-255) using fuzzy set membership analysis process. 'figure 2' provides a summary of the main input digital maps data (factors and constraints)to the *MCE* model.

We thus draw the following relative weights for the Five indicators. Factor as in (table 1) and for the three decision maker (Planner, Engineer, and academicians). Then, these will be entered in *Arc GIS* for spatial analysis to ascertain the suitability for development maps. These weights are used in the *WLC* as explained in 'figure 3'. In the overlay process, each factor map will be multiplied by its weight and the result is then summed up producing a suitable maps for consecutive years (2000 and 2010) as shown in 'figure 4'. The process involved constraint maps, where the suitability maps will be multiplied by each of the Boolean constraints to zero out the unsuitable area.
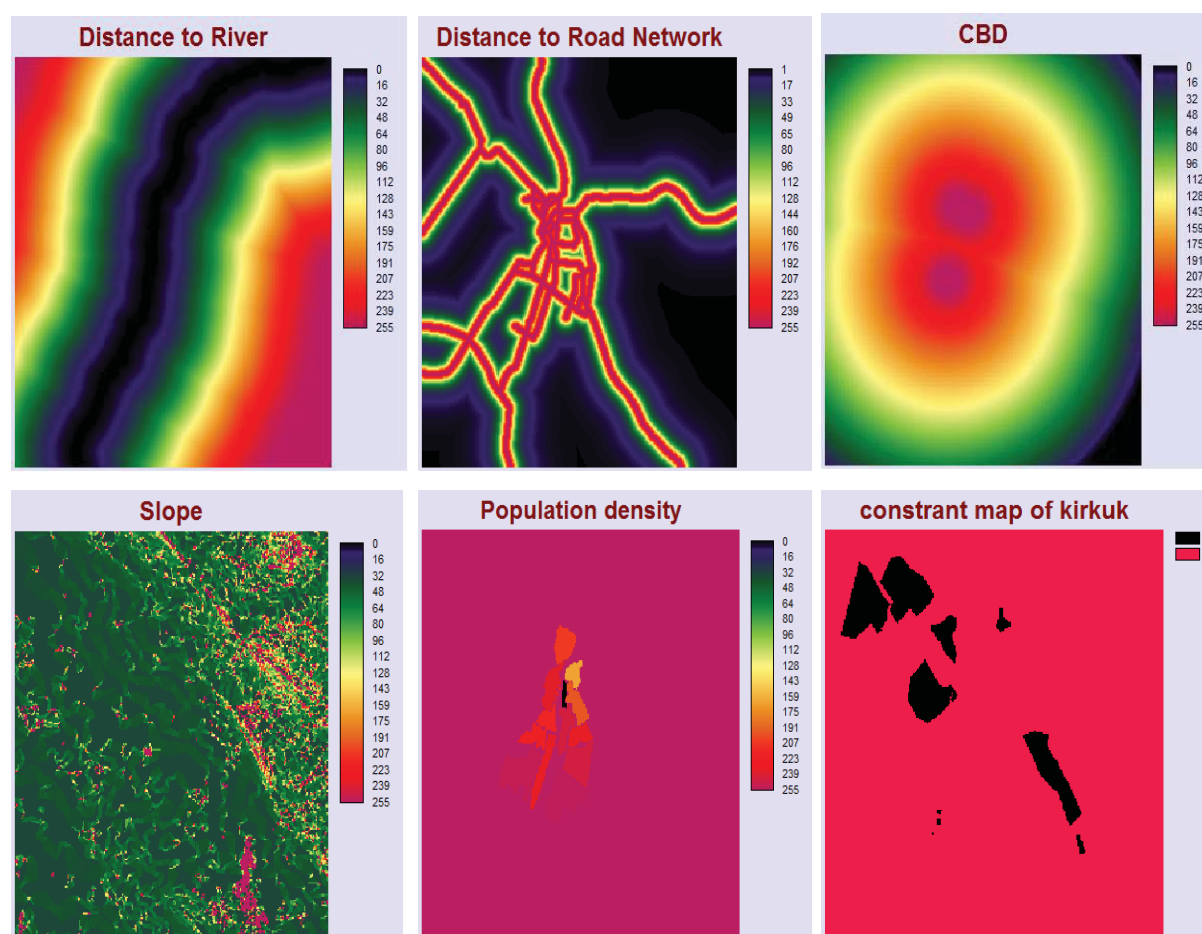

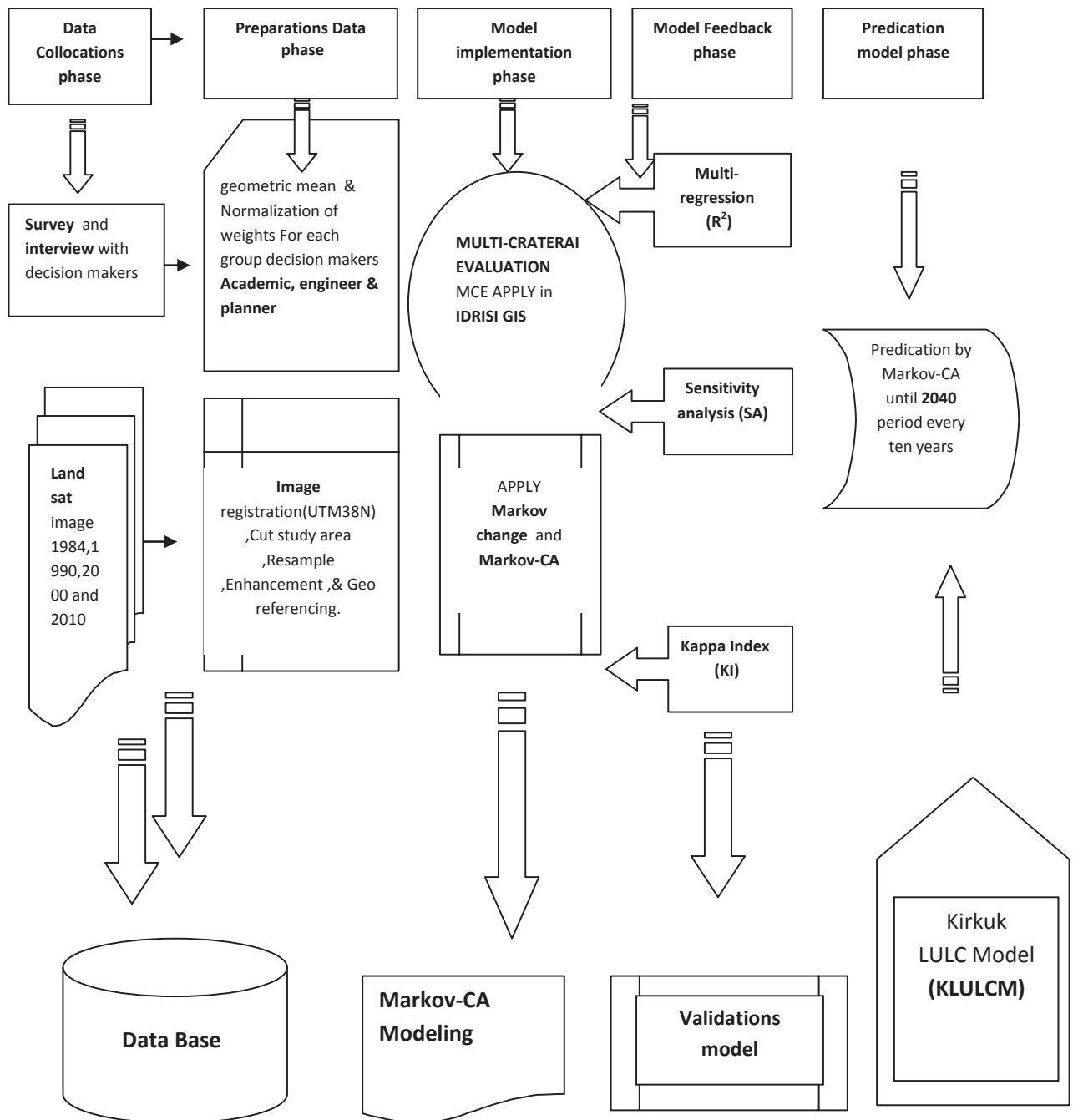**Figure 2 .** Criterion as a raster maps.

Figure 3. Flow chart modelling process for land-use and land-cover changes in Kirkuk city.

3.2. Multi-regression techniques

The suitability maps were analysed statistically in the form of a multiple regression model in *IDRISI* software. A stepwise regression building approach was used, which starts by including all the independent maps and then discarding those that do not have a significant role in determining the goodness or best fit suitability map. Hence, only maps that are significant in explaining variations in the dependent map are included. To deal with the problems of the potential non-linear relationship between the dependent and independent 16 maps in the models, the suitability change was transformed into common in *Markov-CA*. To show these changes the multi-regression analysis could be the best way to interpret the relationship between this map related to land use and land cover changes in the study area. Multi regression techniques were applied to the spatial statistical analysis variance (*ANOVA*).

This approach is based on the comparison of suitability maps obtained from active states in the simulation and in the actual city map through a set of spatial statistics. *ANOVA* tables show that the weights of the three groups are different. It is possible to better understand the similarities between suitability maps at different decision makers [30].By reference to the (table 2), the adjusted R^2 coefficient range (0.735 - 0.891) for the *AHP* method at different decision makers is a consequence of the high similarity in all the maps.

Table 2. Assessing R^2 for suitability maps model at different decision making for AHP method.

DC	years	Equations	R^2
AC	1984	AHP84AC = 0.1998 + 0.1014*AHP84EE + 0.7662*AHP84PL	0.823
EE		AHP84EE = -0.0586 + 0.1802*AHP84AC + 0.8765*AHP84PL	0.787
PL		AHP84PL = 0.1477 + 0.5720*AHP84AC + 0.3681*AHP84EE	0.878
AC	1990	AHPAC90 = 0.1843 + 0.1061*AHPEE90 + 0.7701*AHPPL90	0.829
EE		AHPPL90 = 0.1478 + 0.3568*AHPEE90 + 0.5830*AHPAC90	0.879
PL		AHPEE90 = -0.0454 + 0.8583*AHPPL90 + 0.1932*AHPAC90	0.785
AC	2000	AHP99AC = 0.1962 + 0.7252*AHP99PL + 0.1393*AHP99EE	0.827
EE		AHP99EE = -0.0360 + 0.8509*AHP99PL + 0.1910*AHP99AC	0.827
PL		AHP99PL = 0.1324 + 0.5116*AHP99AC + 0.4378*AHP99EE	0.888
AC	2010	AHPAC10 = 0.2347 + 0.5099*AHPEE10 + 0.3302*AHPPL90	0.753
EE		AHPEE10 = -0.0036 + 0.7491*AHPAC10 + 0.3085*AHPPL90	0.735
PL		AHPPL10 = 0.1092 + 0.4291*AHPEE10 + 0.5266*AHPAC10	0.891

Where the AC is university academic staff , EE is expert engineer, PL is urban planner and DM is decision maker.

3.3. Markov Change model

To model the urban expansion with spatial models is a useful way to understand the land-use and land-cover process, with the results offering support to urban planning and management policies. Markov Change model (*MCM*) is clear as a set of land-use and land-cover states where the process begins with one of the states and moves consecutively from one state to another [31].

Each transition matrix is defined as a step for land-use and land-cover change, a transition areas matrix and a set of conditional probability images where analysing a number of qualitative land-use and land-cover changes from two different dates (1990 and 2000). It is a random process (illustrated in table 3) which shows how likely one state is to change to another state through the transition probability matrix [32]. In the tables , the rows represent the older land cover categories and the pillars represent the newer land cover categories. Markov Chain model Analysis also produces related conditional probability images with the help of transition probability matrices.

3.4. Markov-CA model

The *Markov-CA* model used to simulate and predict land-use and cover-maps for all classes are presented in 'figure 5'. These can be very effectively modelled using Cellular Automata (*CA*). A cellular automaton is a cellular entity that independently varies its new state based on its previous state and that of its immediate neighbours according to a specific rule.

Cellular automata consider the composition of associations of pixels around one pixel. Clearly there is a similarity between *MCM* and *CA* process. Both depend on the previous state, *CA* also upon the province of the local neighbourhood. So, combining both Markov Chain and CA (*MARKOV-CA*) will be much more accurate and logical for predicting the future land cover change for a certain domain.

Markov-CA is a powerful model for the state of several categories of a cell based on transition areas matrix; transitional suitability images and a user defined contiguity filter default a 5 x 5 mean have been utilised . The estimated years are 2020 (time 2), 2030 (time 3) and 2040 (time 4) that is based on the transitional years 2010 (time 1), 2000 (time 1) , 1990 (time 1) and 1984 (time 0). Therefore, for this research purpose, 10 iterations are considered for future prediction depending on years. In the final step , the transition area matrix, all the suitability maps, the 5×5 *CA* contiguity filter and the base map of Kirkuk city (2010) are used to predict the future land-use and land-cover images for 2020,2030, and 2040.

Table 3. Markov transitions probabilities matrix for 1984-1990.

Classes	Cl. 1	Cl. 2	Cl. 3	Cl. 4	Cl. 5	Cl. 6	Cl. 7	Cl. 8	Cl. 9
Class 1	0.4238	0.1804	0.0465	0.0682	0.0254	0.0347	0.1386	0.0378	0.0445
Class 2	0.0781	0.3207	0.0598	0.2241	0.0559	0.1018	0.0477	0.0722	0.0399
Class 3	0.0365	0.2187	0.0633	0.2851	0.0587	0.1495	0.0317	0.1277	0.0288
Class 4	0.0229	0.2247	0.0599	0.2817	0.0731	0.1668	0.0236	0.1169	0.0304
Class 5	0.0221	0.0784	0.0398	0.1615	0.1778	0.2752	0.0361	0.1491	0.0601
Class 6	0.0223	0.1329	0.0474	0.2148	0.1396	0.2391	0.0302	0.1251	0.0486
Class 7	0.1313	0.1709	0.0606	0.1515	0.1003	0.1312	0.1051	0.0787	0.0705
Class 8	0.0560	0.1732	0.0563	0.1981	0.0828	0.1736	0.0529	0.1649	0.0421
Class 9	0.0362	0.0969	0.0433	0.1645	0.1729	0.2491	0.0469	0.1255	0.0648

Where *C1, C2,C3,C4,C5,C6,C7,C8,and C9* to equal be the urban (consists the buildings residential commercial industrial public serves road network and parking lots.), mountainous area, oil field area, mineral land, wetland, pastures water bodies, cultivated land and vacant land respectively.

3.5. Kappa statistic index

   Validation techniques by [33] were used to determine the agreement between the 1990, 2000 and 2010 urban land use reference map with the1990, 2000 and 2010 simulated urban land use map. Furthermore, the techniques were used to compare the agreement between the reference map and the simulated map with the null model such as, agreement between the 1990 reference map and the 2000 reference map. Specifically, the validation technique described modest sources of agreement and disagreement between the simulated map and the reference map with higher accuracy as shown in (table 4).

The precision of the simulation or classification image results on a pixel by pixel beginning was assessed via the Kappa statistic index see (table 4). This statistic measures the goodness of fit or the best value between two model predication and reality, corrected for accuracy by chance [34]. Since land use maps are 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 [35, 36]. Kappa values range from 1 to -1, where positive values show sign of improved agreement than usual by chance, and negative values is agreement that is not good [21].

Table 4. Validation between actual and simulated maps in AHP for different decision makers.

Simulation Actual Maps	Methods	K no	K location	K location Strata	K standard
1990	AHP	0.9782	0.9865	0.9865	0.9739
	AC AHP	0.9775	0.9856	0.9856	0.9730
	EE AHP	0.9784	0.9867	0.9867	0.9740
	PL AHP	0.9778	0.9860	0.9860	0.9734
2000	AHP	0.9827	0.9867	0.9867	0.9782
	AC AHP	0.9819	0.9856	0.9856	0.9772
	EE AHP	0.9824	0.9863	0.9863	0.9779
	PL AHP	0.9822	0.9860	0.9860	0.9775
2010	AHP	0.9911	0.9893	0.9893	0.9893
	AC AHP	0.9915	0.9898	0.9898	0.9898
	EE AHP	0.9918	0.9902	0.9902	0.9902
	PL AHP	0.9912	0.9895	0.9895	0.9895

Where the K no is Kappa information, K location is kappa location, K location Strata is kappa location strata, and K standard is kappa standard.

4. Results and Discussion
The multi-regression analyses were carried out following the same methodology for all the metrics. Initially the value for each adjusted R^2 coefficient was calculated for each suitability map in all years at different decision makers. The first remarkable result of this analysis is the overall high adjusted R^2 coefficient obtained for most of the studied Suitability map.

The first sign most important suitability maps in explaining maps variations of urban planner decision maker in 2010 at *AHP* is 0.891 indicators of good fit models between 1984,1990,200, and 2010, although while comparing the weight of different decision making groups the same decision maker for 2000 the adjusted R-squared coefficient is 0.888 reasonably good degree correspondence between the evaluated Suitability map in mention yours. The result is shown in (table 2) and 'figure 4' respectively.

In this study, it is now possible to predict the land cover change map of Kirkuk city using *Markov-CA* modelling. 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 Markov transition areas. For example, (table 3) indicates that during 1984–1990 there was a 4.0 % chance the total pixels would transition.

The Markov transition probability matrix is calculated 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 3) by the number of cells of the same land cover class in the subsequent image [21]. As a *Markov-CA* 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 class[21]. 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[21].
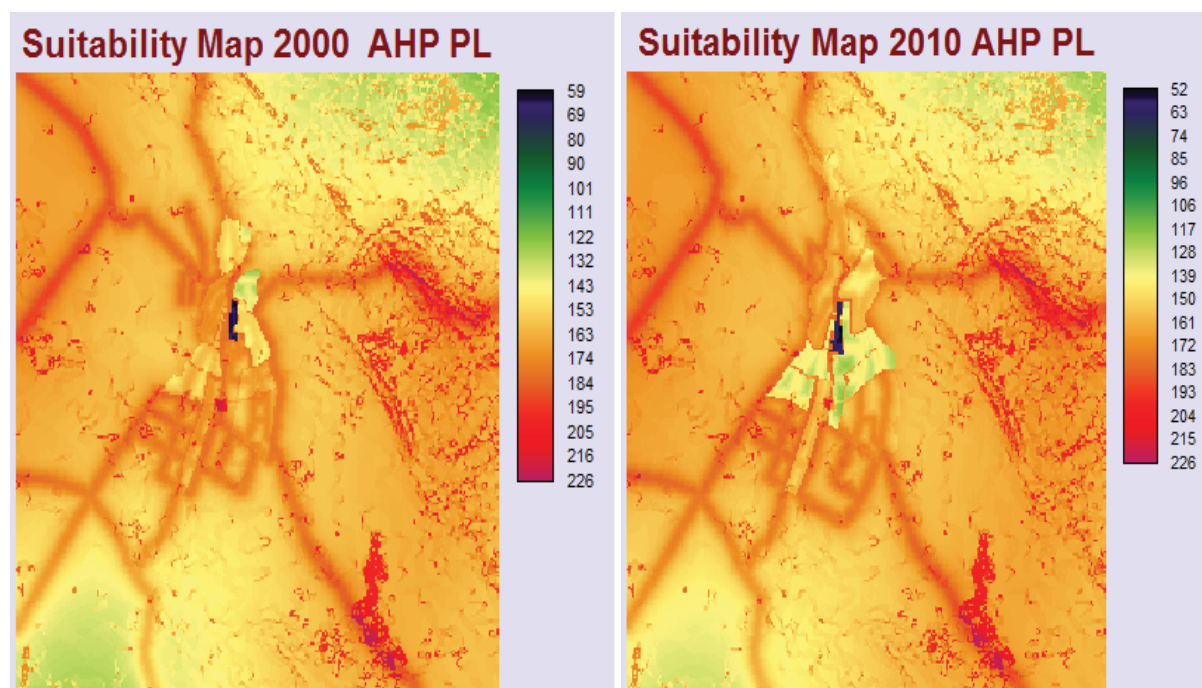

Figure 4. Suitability maps.

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 [37]. The projections specify that approximately 15 % of the study area will be urbanized by the year 2020,2030, and 2040, though the extent of urban development under academics and engineers 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 standard in different years was 0.97–0.99, which indicated a very good agreement between observed and projected land-use and land-cover see (table 4).

A separate Kappa statistic was calculated for the correspondence between observed and projected built-up areas [38]. Both kappa location and kappa location strata scores indicate that the model has improved performance over the multi-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 maker. Therefore, the simulated using a bottom-up technique, as used in *CA* very usefully. Nevertheless, Kappa values are taken as relative to the results of the multi-regression model. For instance, the suitability map in (table 2) shows the R^2 coefficient (2010) obtained for both maps is high as the previous as mentions 0.891 , although (table 4) representing Kappa Index was used to validate the simulation model, and the best kappa standard value for (2010) is 0.990. Thus, this model can be regarded as good results indicator of similarity between both maps. Kappa was used statistically as a linear distance decay role to account for slightly unfavourable pixels [39].
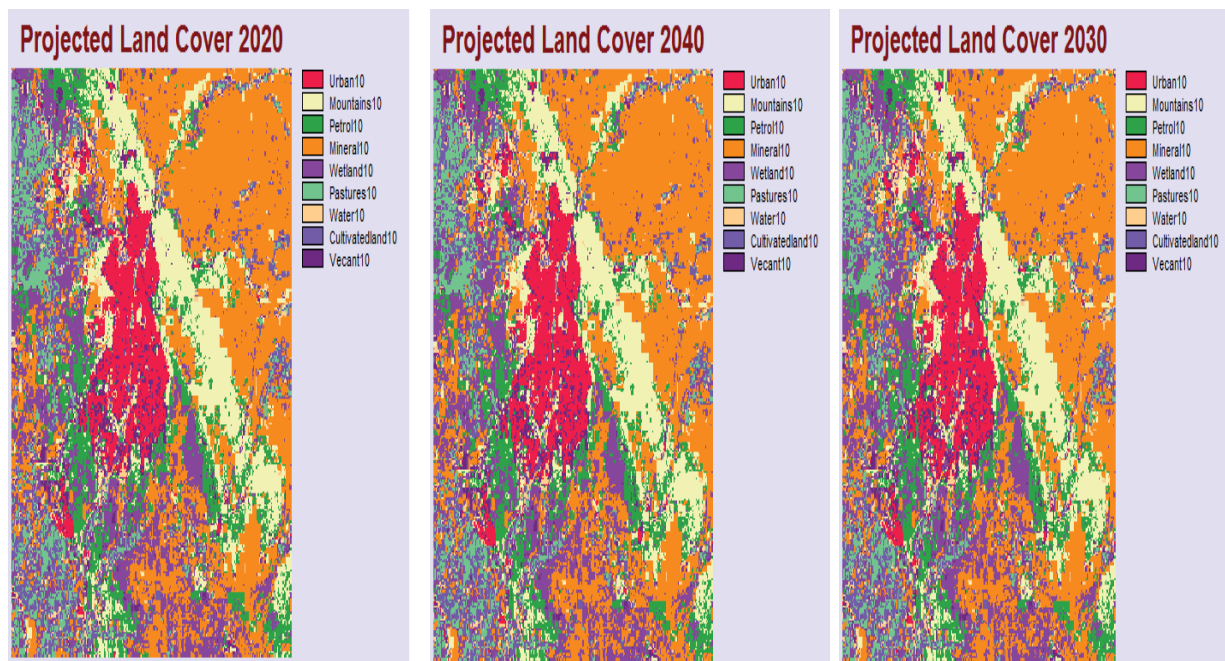

Figure 5. CA-Markov Projected Land-Use and Land-Cover Map of Kirkuk City (2020,2030 and 2040).

In the context , the result are summarized as follows: First, the integrated model has proven to be competent in monitoring and projecting the land-use and land-cover changes. Second, the future land use land cover map of Additionally , the value 0.990 for this index implies a high degree of similarity between both maps. From the point of view of their simulation model usually measure spatial configuration of land-use and land-cover , these techniques a powerful instrument for the comparison of suitability maps and simulated in the land use land cover change modelling.

The city will extend on the north-eastern, north-western and a few bit south- eastern parts in 2020,2030, and 2040. See (figure 5). Over the years land-use will increase intensively, while the land-cover will be diminished. Kirkuk city for the years of 2020,2030 and 2040 has been is predicted to increase at an annual rate of 3%. In spatially case , the newly increased land-use is most likely to expand around the vicinity of the city and mainly along a west–east axis and a north–south axis along the *CBD*.

5. Conclusions

The model is just a generalization of the reality. A goal of urban expansion modelling is evaluating potential for future paths improvement [40]. This paper, develops and illustrate new ways of assessing and managing the land-use and land-cover changes. In particular, it investigate a sampling method of criterion weight under three groups of decision makers: academic staff decision, expert engineer's decision, and planner decision makers, for five factors and three constraints. It is feasible and effective to build up a model to predict urban expansion trend through *Markov-CA*, Markov probability , multi-criteria evaluation and multi-regression which allowed the simulation of nine land cover classes simultaneously and thus furnished a basis for a significant examination of the land-use and land-cover changes under different decision makers. The analysis in this case has testified that the sample results in multi-regression to choose the best suitability map and kappa statistical index of the validation model indicates similarity between the choices of three decision makers. The transition rules were based on the score achieved by multi-regression.

MCE could not resolve this situation and therefore, some more is to be done to resolve this conflict. Setting transition rules in the form of suitable maps based on *MCE* allows for consideration of various components that are commonly used in land use planning and decision-making such as changes in population density, topography (slope), proximity to network roads, proximity to the *CBD* as well as protection riparian corridors of Kasha river, water bodes resources, military restricted area, and oil sensitive areas. The Group (*AHP*) is easy for usage , a powerful and useful decision-making tool that allows group decision makers to compare and select options as part of the group decision-making process However, the process for controlling and simplifying urban expansion model of integration with geographical information systems is mentioned in more researcher works [8, 9, 14, 41, 42]. In addition, the performance of the Kirkuk model indicates its output and evaluation via Investigational application of the model to an imitation city which produced realistic patterns of development, supporting the modeling approach. Iraq is one of the fastest growing country. After the year 1972, the unplanned appeared in many parts especially in Kirkuk . This research will add to the urban form of the city at first step in planning method. The decision makers: academic staff , expert engineer's as well the city planners can initiate appropriate plans based on the results. That will make the Kirkuk city a much more habitable and planned in the future.

Further studies can 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 Kirkuk model the optimum suitability map used as a transition rule in *CA* model. This emphasizes the intensity of our work, the ability to address multiple criteria with multiple decision makers in choosing the best model.

References

[1]   W. Bing Sheng and D. Z. Sui, "CA-based Simulation of Asian Urban Dynamics: A Case Study of Taipei Metropolitan Area, Taiwan," in *Geoscience and Remote Sensing Symposium, 2008. IGARSS 2008. IEEE International*, 2008, pp. V - 13-V - 16.

[2]   E. F. Lambin, M. D. A. Rounsevell, and H. J. Geist, "Are agricultural land-use models able to predict changes in land-use intensity?," *Agriculture, Ecosystems & Environment,* vol. 82, pp. 321-331, 2000.

[3]   D. R. Foley JA, Asner GP, Barford C, Bonan G, Carpenter SR, Chapin FS, Coe, D. G. MT, Gibbs HK, Helkowski JH, Holloway T, Howard EA, Kucharik CJ,, and P. J. Monfreda C, Prentice IC, Ramankutty N, Snyder PK., "Global consequences of land use.Science. 2005 Jul 22;309(5734):570-4," 2005.

[4]   H. Taubenböck, M. Wegmann, A. Roth, H. Mehl, and S. Dech, "Urbanization in India - Spatiotemporal analysis using remote sensing data," *Computers, Environment and Urban Systems,* vol. 33, pp. 179-188, 2009.

[5]   H. Shafizadeh Moghadam and M. Helbich, "Spatiotemporal urbanization processes in the megacity of Mumbai, India: A Markov chains-cellular automata urban growth model," *Applied Geography,* vol. 40, pp. 140-149, 2013.

[6]   J. E. Patino and J. C. Duque, "A review of regional science applications of satellite remote sensing in urban settings," *Computers, Environment and Urban Systems,* vol. 37, pp. 1-17, 2013.

[7]   R. White and G. Engelen, "Cellular automata and fractal urban form: a cellular modelling approach to the evolution of urban land-use patterns," *Environment and planning A,* vol. 25, pp. 1175-1199, 1993.

[8]   K. C. Clarke and L. J. Gaydos, "Loose-coupling a cellular automaton model and GIS: long-term urban growth prediction for San Francisco and Washington/Baltimore," *International Journal of Geographical Information Science,* vol. 12, pp. 699-714, 1998.

[9]   F. Wu and C. J. Webster, "Simulation of natural land use zoning under free-market and incremental development control regimes," *Computers, Environment and Urban Systems,* vol. 22, pp. 241-256, 1998.

[10]   F. Wu, "Calibration of stochastic cellular automata: the application to rural-urban land conversions," *International Journal of Geographical Information Science,* vol. 16, pp. 795-818, 2002.

[11]   X. Li and A. G.-O. Yeh, "Neural-network-based cellular automata for simulating multiple land use changes using GIS," *International Journal of Geographical Information Science,* vol. 16, pp. 323-343, 2002.

[12]   X. Li and A. Gar-On Yeh, "Data mining of cellular automata's transition rules," *International Journal of Geographical Information Science,* vol. 18, pp. 723-744, 2004.

[13]   A. M,nard and D. J. Marceau, "Exploration of spatial scale sensitivity in geographic cellular automata," *Environment and Planning B: Planning and Design,* vol. 32, pp. 693-714, 2005.

[14]   D. F. Wagner, "Cellular automata and geographic information systems," *environment and Planning B,* vol. 24, pp. 219-234, 1997.

[15]   Z. Yang, "PAML 4: phylogenetic analysis by maximum likelihood," *Molecular biology and evolution,* vol. 24, pp. 1586-1591, 2007.

[16]   I. Benenson and P. M. Torrens 2004, " Geosimulation: object-based modeling of urban phenomena," *Computers, Environment and Urban Systems,* vol. 28, pp. 1-8.

[17]   B. Bhatta, S. Saraswati, and D. Bandyopadhyay, "Quantifying the degree-of-freedom, degree-of-sprawl, and degree-of-goodness of urban growth from remote sensing data," *Applied Geography,* vol. 30, pp. 96-111, 2010.

[18]   J. Jokar Arsanjani, M. Helbich, W. Kainz, and A. Darvishi Boloorani, "Integration of logistic regression, Markov chain and cellular automata models to simulate urban expansion," *International Journal of Applied Earth Observation and Geoinformation,* vol. 21, pp. 265-275, 2013.

[19]   J. Malczewski, *GIS and Multicriteria Decision Analysis*: Wiley, 1999.

[20]   Q. Weng and D. A. Quattrochi, *Urban remote sensing*: CRC Press, 2007.

[21]   J. R. Eastman, *IDRISI Kilimanjaro: guide to GIS and image processing*: Clark Labs, Clark University Worcester, 2003.

[22]   T. L. Saaty, "How to make a decision: the analytic hierarchy process," *European journal of operational research,* vol. 48, pp. 9-26, 1990.

[23]   J. Geldermann, M. Treitz, and O. Rentz, "Towards sustainable production networks," *International Journal of Production Research,* vol. 45, pp. 4207-4224, 2007.

[24]   M. Treitz, H. Schollenberger, B. Schrader, J. Geldermann, and O. Rentz, "Multi-criteria decision support for integrated technique assessment," *RADTECH Europe 05: UV/EB-Join the Winning Technology,* pp. 153-160, 2005.

[25]   T. L. Nyerges and P. Jankowski, "regional and urban Gis," *A Decision Support Approach. New York,* 2010.

[26]   P. McCullagh and J. A. Nelder, "Generalized linear models (Monographs on statistics and applied probability 37)," *Chapman Hall, London,* 1989.

[27]   C. He, N. Okada, Q. Zhang, P. Shi, and J. Zhang, "Modeling urban expansion scenarios by coupling cellular automata model and system dynamic model in Beijing, China," *Applied Geography,* vol. 26, pp. 323-345, 2006.

[28]   S. Stehman, "Estimating the kappa coefficient and its variance under stratified random sampling," *Photogrammetric Engineering and Remote Sensing,* vol. 62, pp. 401-407, 1996.

[29]   T. L. Saaty, *The Analytic Hierarchy Process: Planning, Priority Setting, Resource Allocation*: McGraw-Hill, 1980.

[30]   K. McGarigal and S. A. Cushman, "Comparative evaluation of experimental approaches to the study of habitat fragmentation effects," *Ecological applications,* vol. 12, pp. 335-345, 2002.

[31]   X. Zhang, T. Kang, H. Wang, and Y. Sun, "Analysis on spatial structure of landuse change based on remote sensing and geographical information system," *International Journal of Applied Earth Observation and Geoinformation,* vol. 12, pp. S145-S150, 2010.

[32]   A. J. Mousivand, Alimohammadi Sarab, A., Shayan, S. , "A new approach of predicting land use and land cover changes by satellite imagery and Markov chain model (Case study: Tehran)." 2007.

[33]   R. G. Pontius, E. Shusas, and M. McEachern, "Detecting important categorical land changes while accounting for persistence," *Agriculture, Ecosystems & Environment,* vol. 101, pp. 251-268, 2004.

[34]   J. v. Vliet, R. White, and S. Dragicevic, "Modeling urban growth using a variable grid cellular automaton," *Computers, Environment and Urban Systems,* vol. 33, pp. 35-43, 2009.

[35]   G. M. Foody, "Status of land cover classification accuracy assessment," *Remote Sensing of Environment,* vol. 80, pp. 185-201, 2002.

[36]   R. G. Pontius and L. C. Schneider, "Land-cover change model validation by an ROC method for the Ipswich watershed, Massachusetts, USA," *Agriculture, Ecosystems & Environment,* vol. 85, pp. 239-248, 2001.

[37]   G. Wang, J. Song, B. L. Xue, X. Xu, and K. Otsuki, "Land use and land cover Cchange of hulun lake nature reserve in inner Mongolia,China: A Modeling analysis," *Journal of the Faculty of Agriculture, Kyushu University,* vol. 57, pp. 219-225, 2012.

[38]   R. G. Pontius Jr and M. Millones, "Death to Kappa: birth of quantity disagreement and allocation disagreement for accuracy assessment," *International Journal of Remote Sensing,* vol. 32, pp. 4407-4429, 2011.

[39]   A. Hagen-Zanker, B. Straatman, and I. Uljee, "Further developments of a fuzzy set map comparison approach," *International Journal of Geographical Information Science,* vol. 19, pp. 769-785, Aug 2005.

[40]   M. Herold, H. Couclelis, and K. C. Clarke, "The role of spatial metrics in the analysis and modeling of urban land use change," *Computers, Environment and Urban Systems,* vol. 29, pp. 369-399, 2005.

[41]   F. Wu, "SimLand: a prototype to simulate land conversion through the integrated GIS and CA with AHP-derived transition rules," *International Journal of Geographical Information Science,* vol. 12, pp. 63-82, 1998/01/01 1998.

[42]   D. P. Ward, A. T. Murray, and S. R. Phinn, "A stochastically constrained cellular model of urban growth," *Computers, Environment and Urban Systems,* vol. 24, pp. 539-558, 2000.