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A GIs Based Weight of Evidence for Prediction Urban Growth of Baghdad City by Using Remote Sensing Data

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Abstract

The rapid growth of Baghdad city has an adverse effect on the environment; therefore, it is crucial to have a well-concerted plan for urban expansion. This paper presents the problem of urban growth in Baghdad city; hence, it is develop a methodology that combines remote sensing data and GIS with Weight of evidence to estimate the occurrence spatial distribution of urban extent. Accordingly, the required data for the proposed model building were identified by using satellite imagery of Landsat MSS/TM/ETM for years, 1976, 1990 and 2000 respectively. The satellite imagery is utilized for geometric correction, supervised and unsupervised classification, accuracy assessment, derivation of change detection and urban growth modeling. Three factors were considered in model building of urban growth in weight of evidence: environmental, social and economical factors. Geodatabase was digitized in ArcGIS and combined to develop statistical models relating land use to population density, distance from the center of the city, distance from highway, river and slope of study area. The work emphasizes spatial relationships between various geographic, land-use, and demographic variables to predict future urban extent. Based on the urban growth model in GIS, results show: the urban area in Baghdad is increased rapidly; the result of the work shows a rapid growth in built-up land between 1976 and 1990 from 100 km^2 to 380 km^2 and from 452 km^2 in 2000 to 610 km^2 in 2015. Finally, the case study demonstrated that GIS based weight of evidence is recognized to be used as a useful tool for prediction of urban growth by considering saving of money, time and effort.

Keyword: Weight of Evidence, GIS, Urban Growth.

1: Introduction

Urban growth being attributed to natural population growth and the rural-urban migration is expected to increase at an unprecedented rate in the coming decades and this will definitely lead to more changes in the urban environment (*M.E. Bauer, et al, 2006*). The rapid development of urban areas and the improvement in transportation networks have brought various land use problems in their wake, including urban diffusion and the phenomenon of urban sprawl. There is a strong need for accurate predictions of land-use change and future urbanization, as well as investigation of the appropriateness of present land use controls and the land use controls that will be required in the future, (*Kayoko Yamamoto ,2007*). Uncontrolled growth is a great menace to planning in settlements (both urban and rural). This is because uncontrolled growth could lead to overcrowding and its attendant's problems. These problems are greater if at the onset, the particular area had not been planned, (*Ufoegbune Gideon, 2005*). Remotely sensed data is the most important data source for environmental change study over the past 40 years. Since large collections of remote sensing imagery have been acquired in a time frame of successive years, it is now possible to study long-term spatial-temporal pattern of environmental change and impacts of human activities, (*Qiming Zhou1, et al, 2008*). Satellite images give urban planners synoptic views of large areas which allow them to lay plans for urban expansion effectively,(*Dr Abdullah Mah,2007*). Change detection technologies, which discover the change information on the surface of the earth by comparing and analyzing multi-temporal satellite images, can be usefully applied to the various fields, such as environmental inspection, urban planning, forest policy, updating of geographical information and the military usage, (*Miss Nang Mya Mya New, et al,2006*). Land use is an important explanatory variable in urban growth models, which explore the way various factors (e.g. geographic, economic, demographic etc.) interact to simulate urban growth. A serious problem for modeling urban systems has been the lack of spatially detailed data. Remote sensing and Geographical Information Systems have the potential to support such models, by providing data and analytical tools for the study of urban area, (*Nektarios Chrysoulakis,et al, 2004).* Land use models created with the aid of GIS are designed to predict the rate and direction of land use change resulting from economic aspects of human behavior. (*von Thünnen ,1966*). It is also essential that try to predict changes in land use that are likely to occur and the direction that is likely to be taken by future urbanization, examine whether the present land use controls are appropriate, and propose the kind of land use controls that will be required, (*Kayoko Yamamoto ,2007*). Planners must try to anticipate and try to visualize how big the city will grow or the extent of urban area over the next 10 to 20 years, and where the growth is likely to locate and what will be the likely impact of the expected growth if certain policy direction is undertaken. As urban land use system are complex systems which involves interaction between components, factors and agents from both human and the natural systems hence a more holistic approach need to be adopted through an integrated method in modeling and predicting future urban growth, (*Shamsaini Sh.,et al, 2007*). In order to understand past and predict future urban growth pattern, no single method is seen to be the most appropriate. Past studies have shown that various spatial modeling methods, such as statistical models (e.g. logistic regression, discriminated analysis, multiple regression analysis and linear programming methods), cellular automata model, rule based models with Geographical Information Systems (GIS) can be applied to understand, predict and simulate future urban spatial growth and pattern (*Shamsaini Sh.,et al, 2007*). Historical land use patterns, together with current trends in a region, are used to model future land use. Results from modeling urban growth and land use change can be used by the public, land use planners, and policy makers to anticipate and plan for the future. Land use change models can also generate alternative landscape predictions on the basis of different land use policies and environmental constraints, (*U.S. Geological Survey, 1999*).

2: Objective of the study

The rapid growth of Baghdad city has resulted very rapidly and has had an adverse effect on the environment and therefore multi temporal Landsat TM imagery for monitoring land use change has proven to be the best tool in this study. So, the main goal of this study is to use Arcgis9.2 software with weight of evidence method for predict future urban extent. Therefore, this study aims to:

1-To create a land use classification scheme

2-To determine the trend, rate and location of land use change.

3- To forecast the future pattern of urban growth in the area.

4- To investigate the relationships among social, economic, and environmental effects to predict urban growth.

5- To integration of statistical modeling technique via weight of evidence modeling with GIS technology in understanding and predicting urban growth pattern.

3: Study Area

Baghdad is the center city in Iraq. Baghdad city was trend for urbanization. It was as one of the most thickly populated countries will have a deep influence due its urban development. It is located between 33.332 to 33.329 latitude and 44.551 to 44.239 longitudes, covering an area of 380 km². The population of the city was 1 523 302 in 1965 census, 3 841 268 in 1987 census, and 5 337 684 in 2009 calculation with annual growth(1.51).The maps were digitized and incorporated within GIS (Arc Info), for creating thematic layers like river, road network, population density etc.

4: Remote Sensing Data Processing

This study seeks an efficient and practical methodology for Land use monitoring and spatial-temporal pattern analysis by integrating multi temporal remotely sensed data in a monitoring urban growth of Baghdad for 24 years. For the study, three multispectral remotely sensed images from Landsat MSS/TM/ETM of Baghdad city were obtained from Global Land Cover Facility (GLCF) an Earth Science Data Interface. Using Landsat imagery of Baghdad area, the paper demonstrates how to use Erdas software v9.2 in processing those images for urban planning and to monitor changes that took place over the 1976-2000 years. Initially, all images are rectified to the UTM WGS 1984 coordinate system. The best band ratio was selected for processing and classification. Ratio images using Landsat ETM(7,4,2) , TM(4,5,2), and MSS(1,3,4). From the original two full Landsat scenes, a sub-area covering Baghdad city was selected. In order to analyze the Landsat data from the two dates. The imagery was registered and geo-referenced based on the DEM map. The other images were then geometrically corrected and registered using image-to-image registration using previous corrected image. A total of 28 control points were collected with a RMS error of less than 0.6 pixels in both X and Y dimensions. This paper applies supervised (maximum likelihood method) and unsupervised classification to classify land use for all data imagery. Next, in order to improve image quality and advance image recognition degree, enhancement has been processed before classification, MSS imagery Landsat was enhanced using histogram equalizer and adaptive filter , ETM+ imagery was increased resolution using band 8 to 14.28 m resolution. After dataset being geometric corrected, subset and enhanced, the images were classified into twenty classes. By grouping these classes to 6 classes for MSS imagery (residential, high residential, green land, road, open land and river), and 8 main land use classes were derived for ETM/TM imagery include (residential, high residential, green land, road, open land, river, agriculture and transportation). The total classification accuracy was 80%. The classification results are shown in Figures (1), (2), and flow chart of image processing are shown in Figure (3).

5: Change Detection

Change detection is the process of identifying differences in the state of an object or phenomenon by observing it at different times (*Singh, 1989*). Change detection is an important process in monitoring and managing natural resources and urban development because it provides quantitative analysis of the spatial distribution of the population of interest, (*Zubair , et al,2006*). This is done by determining the difference between the land use classes in the datasets acquired at different date for a study area. The procedure allows an analyst to identify the areas where the land use has changed and the manner in which it has changed. After which the classified raster images are converted to vector maps. Suitable change detection techniques were developed in the ArcGIS and ERDAS environment. The results are shown in figure (4). The regions in green are locations of increased and the red pixels denote decreased.

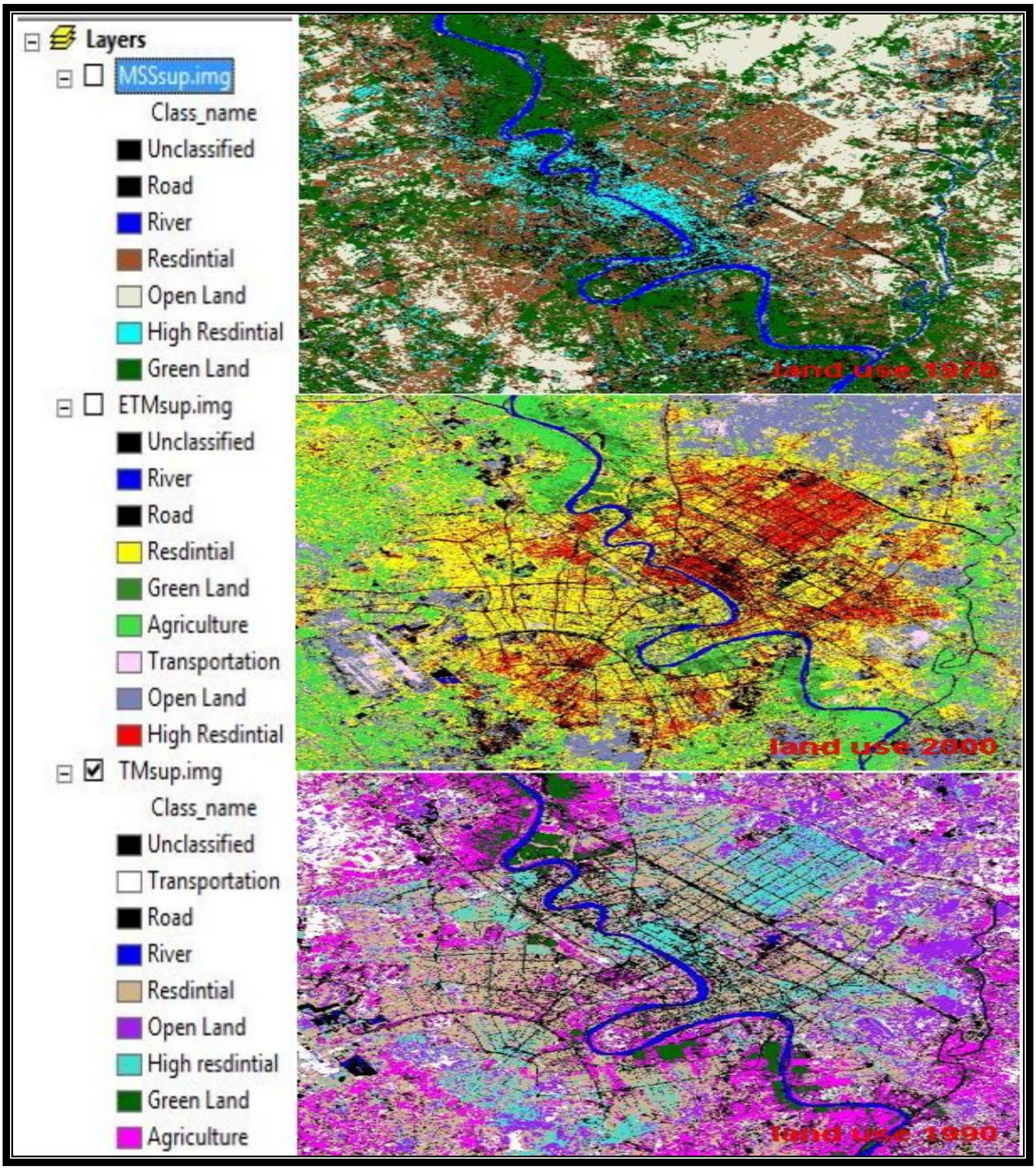

Figure 1: Supervised Classification of Multi Date Landsat of Baghdad City.

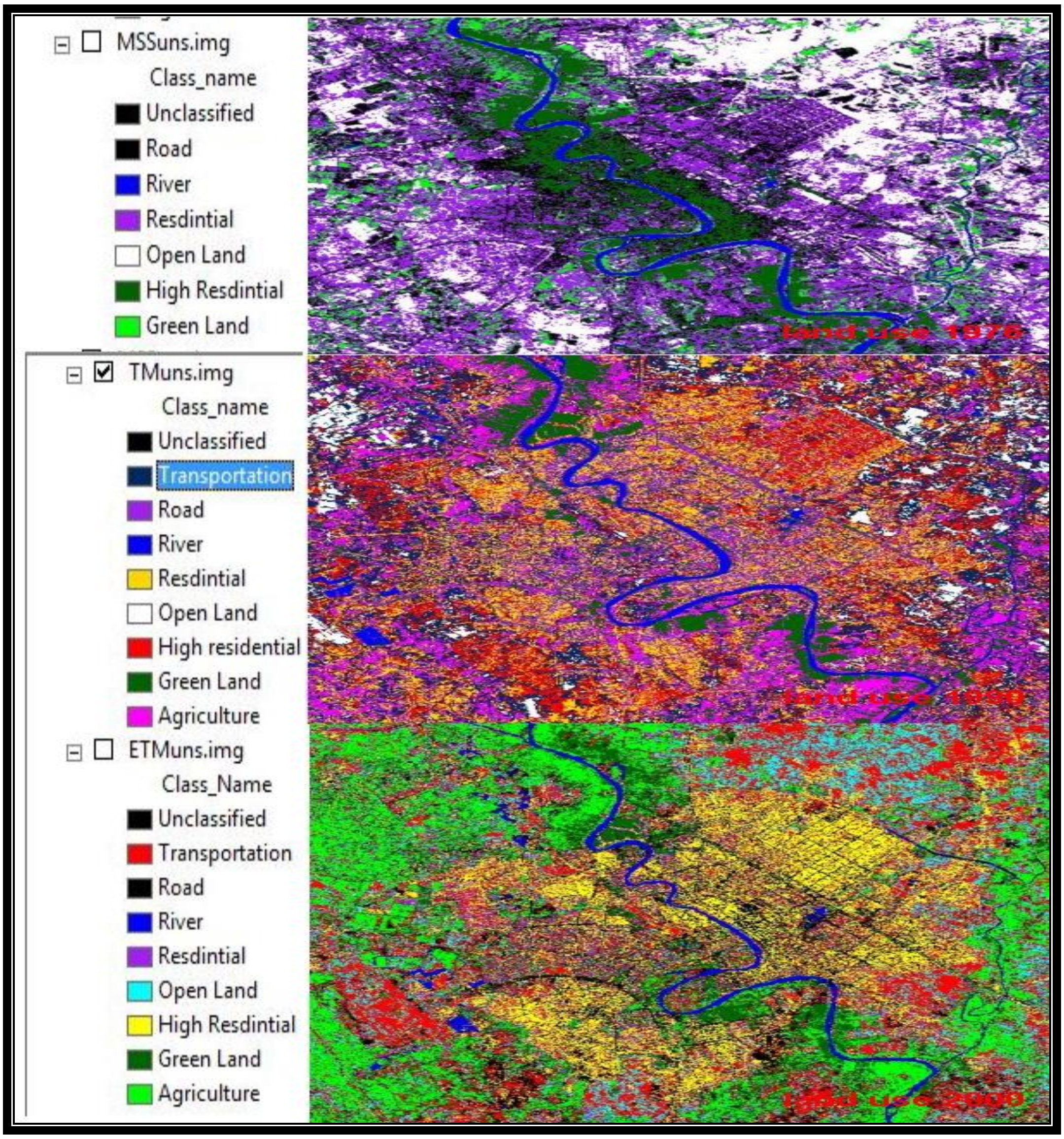

Figure 2: Unsupervised Classification of Multi Date Landsat of Baghdad City.

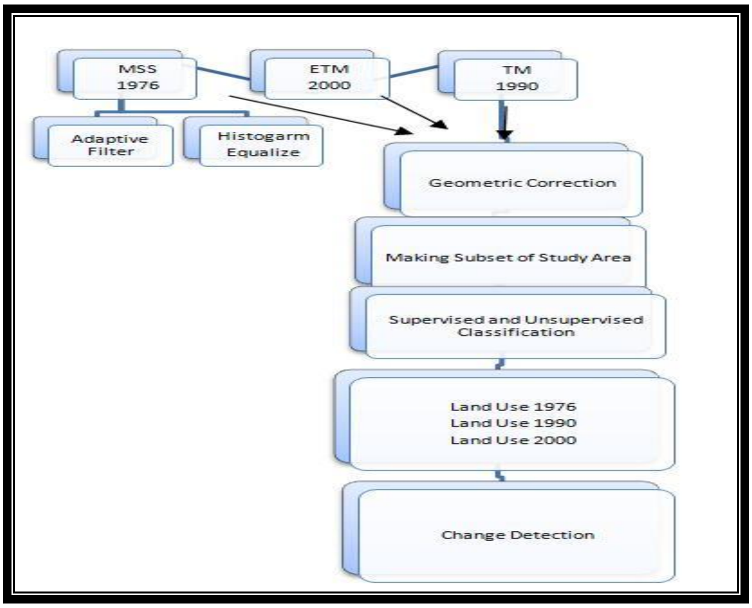

Figure 3: Flow Chart of Image Processing.

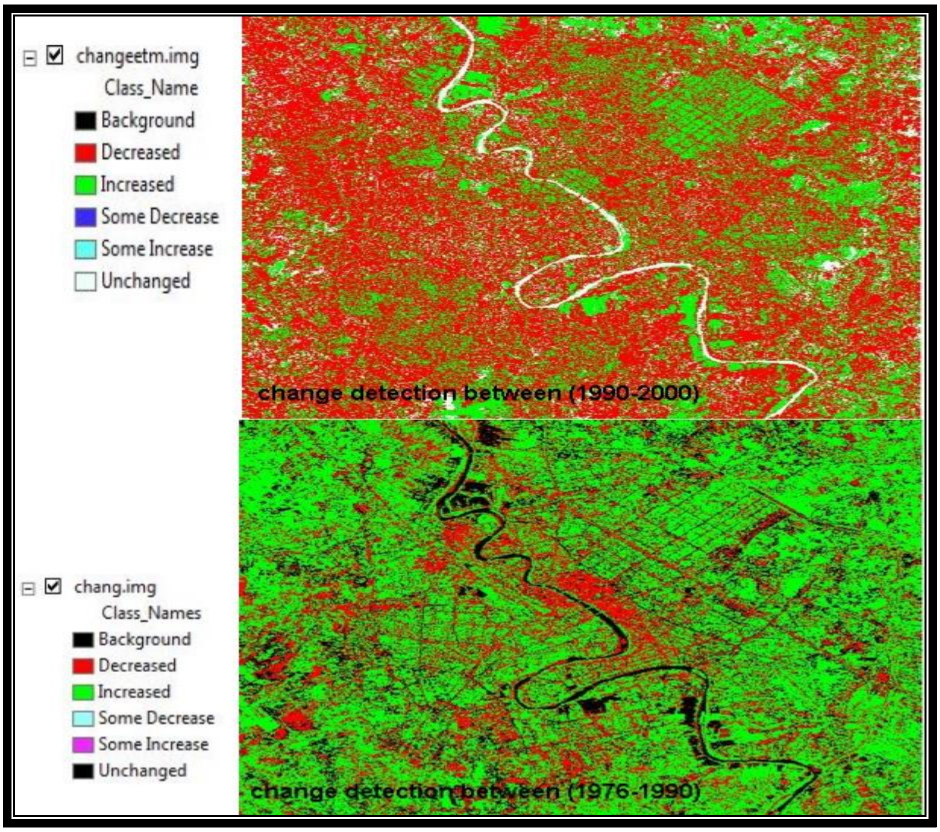

Figure 4: Change Detection of Baghdad City

6: Spatial Data Modeler Method (ArcSDM)

A weights-of-evidence software package, *Spatial Data Modeler* (*Kemp et al. 1999*), was recently developed to run with the ArcGIS *Spatial Analyst* extension (ESRI, Redlands, CA). Spatial Data Modeler, SDM, is a collection of tools for adding categorical maps with interval, ordinal, or ratio scale maps to produce a predictive map of where something of interest is likely to occur, (*Sawatzky, D.L, et al, 2008*). ArcSDM and its documentation are available for download at: http://ntserv.gis.nrcan.gc.ca/wofe. Spatial modeling uses multiple layers or themes related to the object or occurrence being searched for to statistically predict areas where it is most likely to be found. The key to the success of spatial data modeling is related to the way it takes into account of how strongly a particular theme is related to the occurrences being modeled, (*www.kenex.co.nz*). This paper highlights the integration of statistical modeling technique via weight of evidence modeling with GIS technology in understanding and predicting urban growth pattern. Information derived from historical land use change is one of the most important factors used to forecast future trends and patterns. The model can also be used to help understand what factors are most important to land use change, (*M.E. Bauer, et al , 2006*). However, the GIS alone cannot serve all needs of planning. For this, it is required to incorporate other tools like spatial data modeler as a tool to predict future urban extent. In this analysis, various maps are used to explore the role of different spatial information in land use occurrence. Used spatial information will be weighted with known land use occurrences. Four main steps are necessary to build a weights-of-evidence model and run an analysis (*KEMP et al., 1999*):

1. Building a spatial database.
2. Extracting predictive evidence.
3. Calculate weights for each evidential theme.
4. Combine the evidential themes to predict the land use occurrence.

7: Weights of Evidence modeling

ArcSDM is a free extension of ArcGIS, which provides tools for weights of evidence, logistic regression, fuzzy logic and neural network analysis. Weights of evidence model is used to predict a hypothesis about occurrence of an event based on combining known evidence in a study area where sufficient data are available to estimate the relative importance of each evidence by statistical methods. Although this method has been designed specifically for mineral potential mapping, it can also be used for other types of spatial prediction, (*Cheng, 2004*). A weight of Evidence s a Bayesian statistical approach that allows the analysis and combination of data to predict the occurrence of events. It is based on the presence or absence of a characteristic or pattern and the occurrence of an event, (*www.kenex.co.nz).* The Bayesian weights-of-evidence approach requires a set of *training points,* in this case; urban sites, a set of *evidential themes* or variables that are assumed to be predictive of training point location, and a spatially defined study area. Training points are then compared with the evidential themes to calculate a *weight* assessing the spatial association between the points and each class within the theme. A positive weight indicates the class is present; a negative weight if the class is absent. The strength of a correlation is measured by its contrast (W+-W-). Positive contrast values suggest that more training points occur within that class than would be expected by chance. Negative contrasts indicate that fewer training points within that class than would be expected by chance, (*www.blm.gov).* After weights have been calculated and re-classified into a binary evidentiary theme, they are combined to create a *response theme* that calculates a *posterior probability* for all cells within each unique group of binary combinations. Posterior probabilities that is higher than the prior probability suggests a non-random distribution within that intersection of evidential themes,(*www.blm.gov).*

7.1: Evidential Themes

Urbanization analysis required the compilation of a number of evidential themes that could be used in ArcSDM package. Geodatabase required for model include a defined study area, preparation of data for use in evidential themes, exploration of spatial association between potential evidential themes and training points, and the generalization of evidential themes. This study aims to use the maps and spatial analysis offered by GIS to building evidential theme that will be used in an urbanization prediction model that can reflect the influence and neighboring relationship of land use in neighboring areas. In order to make the image data comparable at the same spatial resolution, all the images need to be resample to a 14.28m resolution. The evidential themes used in the model as follows and are shown in Figures (5):

1) Highway

Transportation systems and land use patterns influence each other. Roads, transit, and other transportation elements shape land development, while the distribution and types of land uses affect travel patterns and transportation facilities, (*www.lcd.state.or.us*). Transport network has a strong guiding role in the urban development.

Transportation planning decisions influence land use directly, by affecting the amount of land used for transport facilities, and indirectly, by affecting land use accessibility, (*Todd Litma, 2009*). Integrating land use and transportation more effectively can help shape priorities for transportation investments and ensure that new transportation projects and land use plans support and reinforce each other (www.lcd.state.or.us/tgm). Examining effects of highway and relationships it to urban growth was done by buffered highway at intervals of 200, 400, 800 and 1200 meters. Buffered shapes were then converted into grids for each analytic unit.

2) Population

Population growth is one of factors that affect urban extent; population is reclassifying to 8 categories and treated as categorical measurement in ArcSDM.

3) Slope

Is one of the most important elements for impacting urban development, which not only affects the spatial structure within the city layout, but also to the economic investment and engineering measure, (*Luo Lingjun, et al, 2008*). Slope is derived from DEM map and reclassify to 8 classes by using spatial tool in ARCGIS.

4) CBD

The central city of Baghdad County has the greatest impact on the development of the surrounding area and the affected range is widest. CBD is the main center gathering region of socio-economic elements, the location, size and grade of which play a decisive role on the distribution of future population. In order to examine effect of CBD on the model, CBD is distance using Euclidean distance tool in spatial analysis.

5) River

River is one of environmental criteria which influence the spatial allocation of predicted land cover probabilities. To show this affect, river is distance using Euclidean distance tool in spatial analysis.

7.2: Training point

The Bayesian weights-of-evidence approach requires a set of *training points,* in this case; urban sites. Land use map is classified to two classes to identify urban area and non-urban areas, this is done by converted classes (residential, high residential and highway) to urban area and other classes where converted to non-urban area. Training point derived from converted urban area raster to urban polygon feature by using spatial analysis tool, then converted polygon feature to point feature using XToolsPro extension and saved as site training point. ArcSDM require one training point per 1km unit area. SDM will automatically show errors when any duplicate training points within a cell so that there are no more than one training point (site) per unit area.

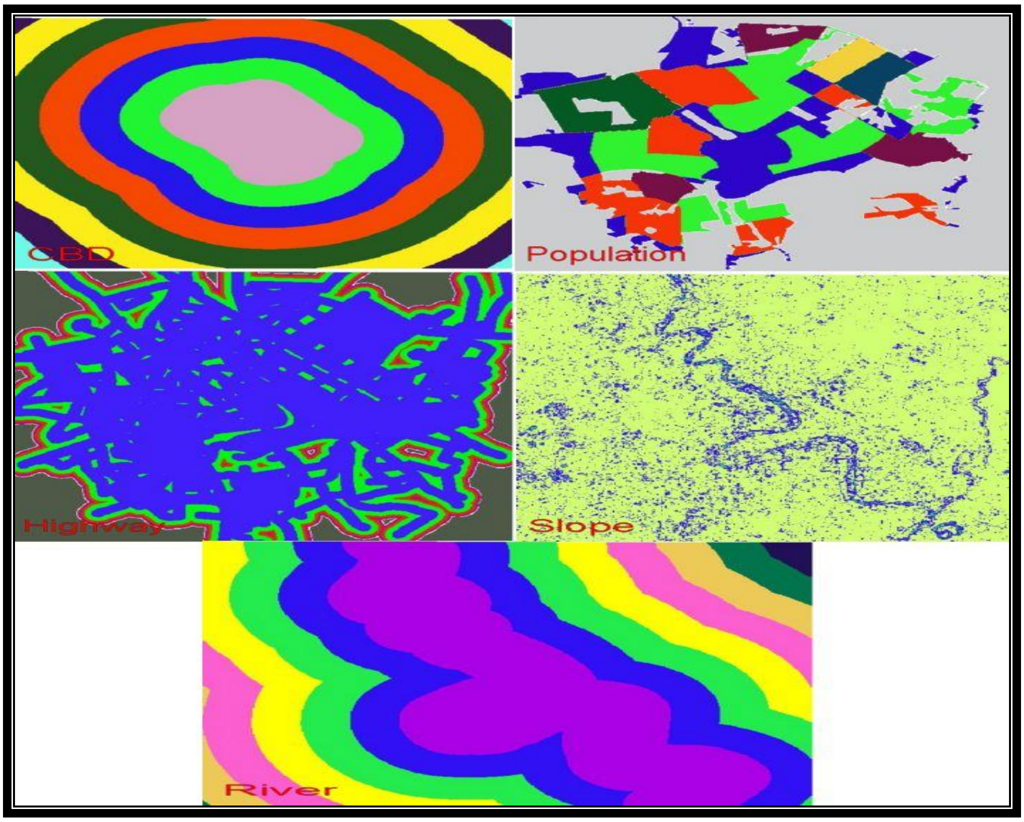

Figure 5: Evidential Theme of Urban Growth Model.

8: Research Methodology

This paper takes use of remote sensing and GIS technology to study urban growth prediction. Using classified imagery and predictor's variable like factor of economic, social, and environmental factor which affect land urbanization evaluation through GIS analysis. Different prediction maps were produced by using the spatial Analyst Extension of ArcGIS for each of the different parameters including: the distance from the CBD, the distance from the highway network traffic, population, distance from the river and slope of the area. ArcWofE differs between maps with free data"and maps with „ordered data". Free data refers to data with a categorical or nominal measurement scale (e.g. a soils map), while ordered data is considered to follow an ordered measurement scale (e.g. elevation), (*Steffen Walther, et al, 2002*).Therefore, population raster was treated as categorical measurement scale while other maps were treated as ordered measurement scale (Cumulative-ascending calculation) in ArcSDM application. Through analyzing the various factors which impact on land prediction and the distribution of urbanization, the weight of the various factors which impact on the development of urban growth was shown in Table (1). Weight is mainly determined by spatial data modeler, to evaluate the land use factors to determine the direction of urban growth. A Land prediction is to integrate various factors for affecting the urban growth, add proper weight, and finally get comprehensive evaluation results of Land prediction. Figure (7) shows model of urban growth prediction. There is an expansion of the built-up area due to increase in the development of transport networks; that were developed over the recent years. The result map normalized posterior probability was then reclassified to reflect high, moderate and low probability of site occurrence, Figure (6) shows the predictive map of the area, the extent of urban areas for the year 2015 was mapped, the future urban growth areas will mostly be concentrated on the north-west. Another finding is that, a strong relationship between new development and proximity to highways and CBD. This means that the occurrence of urban use is higher in areas that are nearer to CBD center. According to the weight values, areas with medium population density, distances to highway and distance to CBD, distance to river and existing urban use have the greatest effects on urban development in the study area. This is anticipated , since, it is obvious that urban use always occur in areas near to highways and near existing developed areas. The classifications showed that the amount of urban or developed land increased from 100 km^2 to 380

km^2 of the total area between (1976- 1990), and from 452 km^2 in 2000 to 610 km^2 in 2015. The classifications have provided an economical and accurate way to quantify, map and analyze changes over time in urban extent.

Table 1: Summary Table of Weight for Prediction Variables.

weight of CBD

OID	CLASS	AREA_SQ_KM	AREA_UNITS	NO_POINTS	WPLUS	S_WPLUS	WMINUS	S_WMINUS	CONTRAST	S_CONTRAST	STUD_CNT	GEN_CLASS	WEIGHT	W_STD
0	1	93.118574	93.118574	26	0.4024	0.231	0.0597-	0.0943	0.4621	0.2495	1.852	2	0.2031	0.0905
1	2	195.201545	195.201545	52	0.3377	0.1619	0.1229-	0.1038	0.4606	0.1923	2.3945	2	0.2031	0.0905
2	3	331.664418	331.664418	95	0.438	0.1215	0.3883-	0.1287	0.8263	0.1769	4.6697	2	0.2031	0.0905
3	4	501.57534	501.57534	139	0.392	0.0998	0.9818-	0.2016	1.3738	0.2249	6.1083	2	0.2031	0.0905
4	5	668.237466	668.237466	161	0.2031	0.0905	1.9344-	0.4555	2.1375	0.4644	4.6027	2	0.2031	0.0905
5	6	759.554063	759.554063	166	0.0765	0.0878	7.1095-	10.0011	7.186	10.0014	0.7185	1	1.9344-	0.4555
6	7	799.07429	799.07429	166	0.012	0.0872	5.2968-	10.0065	5.3089	10.0069	0.5305	1	1.9344-	0.4555
7	8	806.793305	806.793305	166	0	0.0871	1.3507	14.1421	1.3508-	14.1424	0.0955-	1	1.9344-	0.4555

weight of highway

OID	CLASS	AREA_SQ_KM	AREA_UNITS	NO_POINTS	WPLUS	S_WPLUS	WMINUS	S_WMINUS	CONTRAST	S_CONTRAST	STUD_CNT	* GEN_CLASS	WEIGHT	W_STD
0	99-	117.562831	117.562831	3	0	0	0	0	0	0	0	99-	0	0
1	1	512.710476	512.710476	141	0.2026	0.0989	0.7773-	0.2279	0.9799	0.2484	3.9448	2	0.2026	0.0989
2	2	633.47743	633.47743	155	0.0448	0.0924	0.6146-	0.382	0.6594	0.393	1.6777	1	0.7773-	0.2279
3	3	665.553183	665.553183	162	0.0379	0.0903	1.9494-	1.0218	1.9873	1.0258	1.9373	1	0.7773-	0.2279
4	4	689.230473	689.230473	163	0	0.0896	1.172	14.1421	1.172-	14.1424	0.0829-	1	0.7773-	0.2279

weight of population

OID	CLASS	AREA_SQ_KM	AREA_UNITS	NO_POINTS	WPLUS	S_WPLUS	WMINUS	S_WMINUS	CONTRAST	S_CONTRAST	STUD_CNT	GEN_CLASS	WEIGHT	W_STD
0	99-	437.340377	437.340377	54	0	0	0	0	0	0	0	99-	0	0
1	1	103.629698	103.629698	24	0.367-	0.2329	0.1289	0.1303	0.4959-	0.2669	1.8582-	99	0.00005-	0.113198
2	2	102.553264	102.553264	29	0.0984-	0.2193	0.0368	0.1322	0.1352-	0.2561	0.5279-	99	0.00005-	0.113198
3	3	73.809361	73.809361	25	0.1633	0.2459	0.0424-	0.1276	0.2057	0.2771	0.7423	99	0.00005-	0.113198
4	4	33.819856	33.819856	15	0.6055	0.3461	0.0679-	0.1204	0.6734	0.3665	1.8374	99	0.00005-	0.113198
5	6	32.234954	32.234954	10	0.0333	0.3808	0.0032-	0.1186	0.0365	0.3988	0.0914	99	0.00005-	0.113198
6	8	10.881104	10.881104	4	0.2899	0.6287	0.0093-	0.1151	0.2991	0.6392	0.468	99	0.00005-	0.113198
7	9	12.524692	12.524692	5	0.4236	0.577	0.016-	0.1155	0.4396	0.5884	0.7471	99	0.00005-	0.113198

weight of river

OID	CLASS	AREA_SQ_KM	AREA_UNITS	NO_POINTS	WPLUS	S_WPLUS	WMINUS	S_WMINUS	CONTRAST	S_CONTRAST	STUD_CNT	GEN_CLASS	WEIGHT	W_STD
0	1	232.971373	232.971373	50	0.0534	0.1596	0.0222-	0.1039	0.0756	0.1904	0.3969	2	0.076	0.0883
1	2	409.079153	409.079153	93	0.1273	0.118	0.1418-	0.1295	0.2691	0.1752	1.5359	2	0.076	0.0883
2	3	556.152449	556.152449	127	0.1331	0.101	0.3406-	0.1743	0.4737	0.2014	2.3518	2	0.076	0.0883
3	4	675.033968	675.033968	153	0.1234	0.0919	0.8614-	0.2921	0.9849	0.3063	3.2158	2	0.076	0.0883
4	5	750.737495	750.737495	164	0.076	0.0883	1.9462-	0.7201	2.0222	0.7255	2.7874	2	0.076	0.0883
5	6	785.667088	785.667088	166	0.0334	0.0874	6.3045-	10.0024	6.3379	10.0027	0.6336	1	1.9462-	0.7201
6	7	801.216396	801.216396	166	0.0087	0.0872	4.9713-	10.009	4.98	10.0094	0.4975	1	1.9462-	0.7201
7	8	806.793305	806.793305	166	0	0.0871	1.3507	14.1421	1.3508-	14.1424	0.0955-	1	1.9462-	0.7201

weight of slope

OID	CLASS	AREA_SQ_KM	AREA_UNITS	NO_POINTS	WPLUS	S_WPLUS	WMINUS	S_WMINUS	CONTRAST	S_CONTRAST	STUD_CNT	GEN_CLASS	WEIGHT	W_STD
0	1	747.098818	747.098818	155	0.0105	0.0902	0.137-	0.3338	0.1474	0.3458	0.4263	1	0	0
1	2	55.195637	55.195637	9	0.2849-	0.3644	0.0191	0.0897	0.304-	0.3752	0.8102-	2	0	0
2	3	3.61106	3.61106	2	1.567	1.0586	0.0096-	0.0875	1.5766	1.0622	1.4842	3	0	0
3	4	0.641678	0.641678	0	0	0	0	0	0	0	0	4	0	0
4	5	0.176461	0.176461	0	0	0	0	0	0	0	0	5	0	0
5	6	0.039191	0.039191	0	0	0	0	0	0	0	0	6	0	0
6	7	0.023149	0.023149	0	0	0	0	0	0	0	0	7	0	0
7	8	0.00731	0.00731	0	0	0	0	0	0	0	0	8	0	0

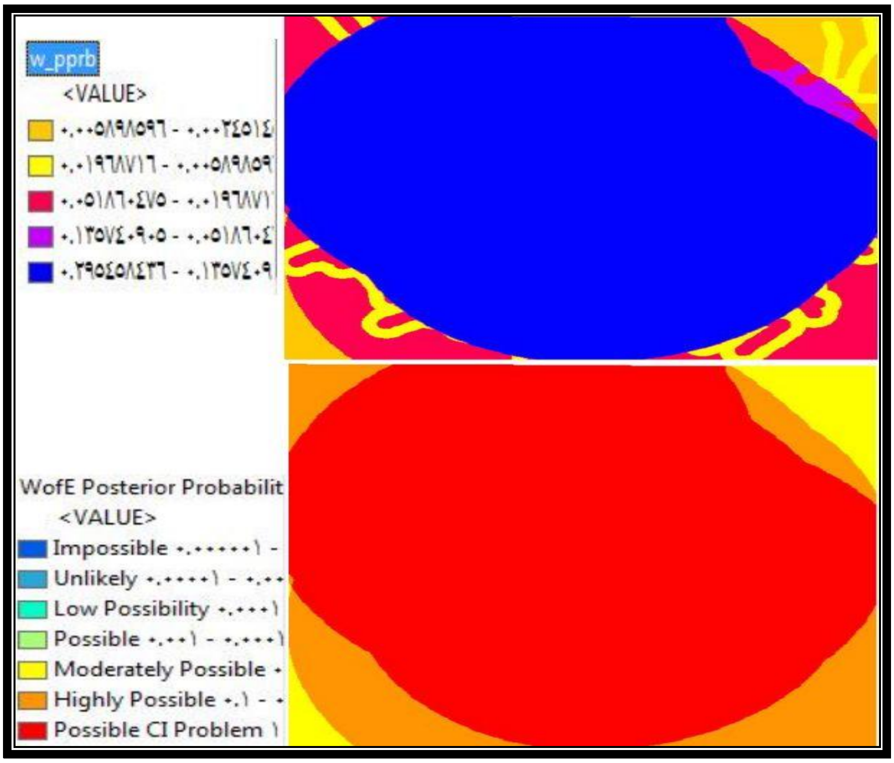

Figure 6: Predictive Urban Extent of Baghdad City.

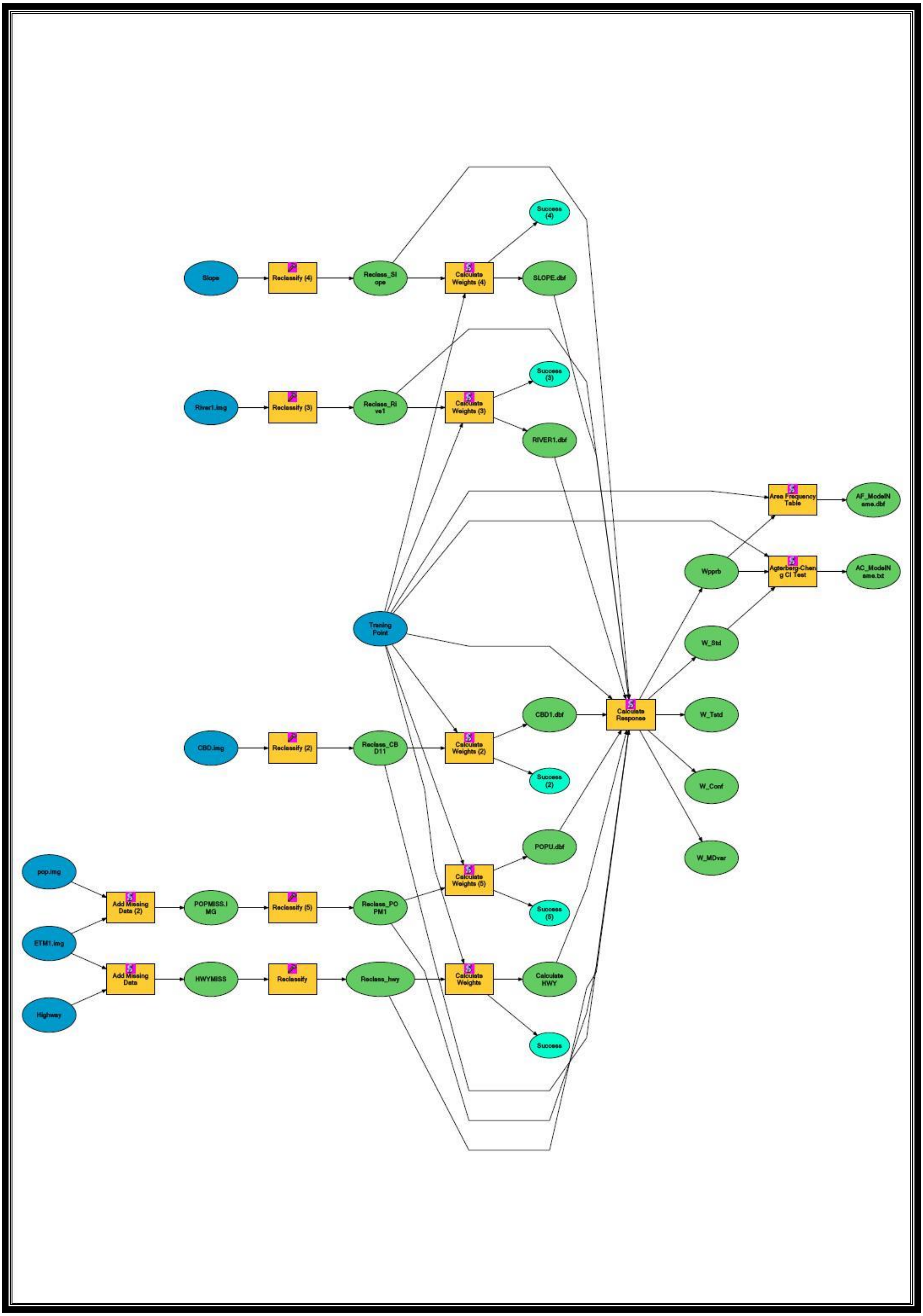

Figure 7: Model Prediction of Urban Growth.

10: Summary

Information from satellite remote sensing can play a useful role in understanding the nature of urban growth, where it is occurring, and projecting possible or likely future changes. In this study, it develops a methodology that combines remote sensing data and GIS with Weight of evidence to estimate the occurrence spatial distribution of urban area. The study above has shown that the model developed has enabled the prediction of future urban areas. It has also shown that areas with nearer to CBD and highway have strong influence on the occurrence of urban extent in the study area. The urban transition probability map generated from the weight of evidence model is use as the basis to map the extent of urban area for the predicted year. The result of the work shows a rapid growth in built-up land between 1976 and 2000 and it was also observed that change by 2015 may likely follow the trend in 1976/2000.

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تنبؤ النمو الحضري لمدينة بغداد بأستخدام بيانات الآستشعار عن بعد مسندا بطريقة أوزان الاثبات

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الخلاصة:

أن النمو السريع لمدينة بغداد له تأثير عكسي ومضرّ بالبيئة؛ لذا، فأنه من الضر وري أن تكون هناك خطة مدبّرة للتوسّع الحضري. تقدّم هذه الورقة مشكلة النمو الحضري في مدينة بغداد؛ لذلك، فهو يطوّر طريقة دمج بيانات الإحساس عن بعد ونظم المعلومات الجغرافية بطريقة أوزان الإثبات لتخمين توزيع الحدث المكاني للنمو الحضري. وفقا لذلك، فأن البيانات المطلوبة لبناء النموذج المقترح سيكون باستعمال صورة القمر الصناعي لاندسات MSS / TM / ETM لسنوات، 1976, 1990 و2000 على التوالي. باستخدام صورة القمر الصناعي تم عمل التصحيح الهندسي، تصنيف مشرف عليه وغير مشرف عليه، تقييم دقة، اشتقاق كشف التغيير وعمل موديل النمو الحضري. تم اعتبار ثلاث عوامل في بناء نموذج النمو الحضري في أوزان الإثبات وهي: العوامل الاقتصادية والاجتماعية والبيئية. تم تحويل وتجميع البيانات الرقمية في نظم المعلومات الجغرافية من اجل تطوير النموذج الإحصائي الذي يربط بين استعمال الأرض وكثافة السكان، البعد من مركز المدينة، البعد من شبكات الطرق والنهر وانحدار منطقة الدراسة. هذا العمل يربط علاقات مكانية بين متغيرات مختلفة، مثل جغرافية استعمال أرض، ومتغيّرات سكّانية لتوقّع المدى الحضري المستقبلي. وبالاستناد على نموذج النمو الحضري في نظم المعلومات الجغرافية. أظهرت النتائج بان: إنّ المنطقة الحضرية في بغداد متزايدة بشكل سريع؛ و نمو سريع في المناطق الحضرية بين عام 1976 -1990 من 100 كيلومتر مربع إلى 380 كيلومتر مربع ومن 452 كيلومتر مربع في عام 2000 إلى 610 كيلومتر مربع في عام 2015. أخيرا، بيّنت الدراسة الحالية بأنّه يمكن استخدام نظم المعلومات الجغرافية مع طريقة أوزان الإثبات كأداة مفيدة لتنبؤ النمو الحضري باعتبار توفير المال والوقت والجهد.

كلمات مفتاحية: أوزان الاثبات , نظم المعلومات الجغرافية , النمو الحضري