Theoretical and Empirical Researches in Urban Management
Volume 13 Issue 1 / February 2018

SIMULATION AND PREDICTION OF URBAN SPATIAL EXPANSION IN HIGHLY VIBRANT CITIES USING THE SLEUTH MODEL: A CASE STUDY OF AMMAN METROPOLITAN, JORDAN

A'kif AL-FUGARA
Department of Surveying Engineering, Faculty of Engineering, Al al-Bayt University, Mafraq, Jordan
akifmohd@aabu.edu.jo

Abdel Rahman AL-SHABEEB
Department of GIS and Remote Sensing, Institute of Earth and Environmental Sciences, Al al-Bayt University, Mafraq, Jordan
abdalshabeeb@gmail.com

Yahya AL-SHAWABKEH
Queen Rania Institutes of Tourism & Heritage, The Hashemite University, Zarqa, Jordan
yahya.alshawabkeh@hu.edu.jo

Hani AL-AMOUSH
Department of GIS and Remote Sensing, Institute of Earth and Environmental Sciences, Al al-Bayt University, Mafraq, Jordan
hani@aabu.edu.jo

Rida AL-ADAMAT
Department of GIS and Remote Sensing, Institute of Earth and Environmental Sciences, Al al-Bayt University, Mafraq, Jordan
rida.ali@aabu.edu.jo

Abstract

over the last decade, Amman's local authorities have faced challenges in meeting the needs of local populations due to unexpected rapid urbanization growth and the impact this has had on welfare and outdated urban infrastructure. Therefore, it is essential to model spatial dynamic growth to identify the land-use class of urbanized regions expansions to prepare for future urban demands. The present study addresses this need by exploring the application of the remotely- sensed data and cellular automation (CA) based SLEUTH model and its effectiveness in modelling of urban growth in highly Vibrant Metropolitan of Amman. the SLETUH model for Amman was successfully calibrated using the Optimum SLEUTH Metric (OSM) method based on archived remote sensing data from 1985 to 2015. The urban growth characteristics were determined using the urban rules derived from SLEUTH via calibration. SLEUTH's probabilistic image of future urbanized lands of historical trend-based urban growth scenario was employed as dynamic factors for urbanization suitability mapping and landscape pattern analysis of the year 2040. The SLEUTH model predicts that Amman's urban space will expand by 57km2 by 2040 (compared to 2015), resulting in a total area of 473.845 km2. Importantly, this research demonstrates that the issues experienced in Amman's urban locations today will continue into the next two decades unless steps are taken to improve urban growth strategies and increase both environmental and urban action. Findings of the present study cooperate the government's plan to demonstrate Jordan's commitment to modernisation through the creation a new administrative city for national-level civil servants and government ministries.

Keywords: SLEUTH; Urban growth; simulation; remote sensing; Amman.

1. INTRODUCTION

Urbanisation refers to the social process of physical conversion of rural land into urban space as a result of population growth either due to migration or conversion of peri-urban areas into cities (United Nations, 2015; UNFPA,2007). Urbanisation is therefore both socioeconomic and physical, although it is inclusive of land use changes, wherein areas categorised as rural become used for urban activities or constructions (Pham et al., 2011). Additionally, the 'urbanisation level' refers to the proportion of the total population residing in urban areas, expressed as a percentage; whilst the 'urbanisation rate' refers to the predicted average speed of urban population growth within a specific period (UNFPA, 2007).

Over the last 100 years, populations in developing countries have grown rapidly alongside increased urbanisation. In Jordan, large proportions of the rural population have migrated to urban areas in response to a series of significant political events and socioeconomic developments. Driven largely by the Syrian refugee crisis, Jordan has also absorbed above of 2 million new residents over the past five years. Consequently, Jordan has experienced urban growth at a faster rate than it has been equipped to cope with over the recent years. In 2014, Jordan demonstrated an annual urbanisation rate of 3.79%, with its urbanisation level rising to 83.7% (DOSJ, 2015). This has caused serious problems nationwide – for instance, scarcity of natural resources, environmental concerns, the creation of slum housing, road traffic congestion, and infrastructural pressure – due to rapid urban land growth (Al-Batoush, 2012).

Urban planners and key decision makers can only make effective decisions if they have access to the right data and forecasts regarding urban growth and land use, which necessitates continuous urban growth tracking and reporting (Cerreta and Toro, 2010). With effective and precise urbanisation modelling, effective planning and analysis can be carried out successfully (Al-shalabi et al,2012). In order to achieve accurate modelling, it is essential that the underlying methods and strategies are robust and up-to-date. Numerous statistics-based theoretical frameworks have been explored over the years, covering factors such as sociocultural patterns, economic functions, and urban geometry, for this purpose. However, such frameworks overlook spatial features, meaning that only regional economics and demographic characteristics are represented in the models built from these frameworks. Time series data gathered through the use of Digital Elevation Models (DEMs), geographic information systems (GIS) and remote sensing (RS) allow us to explore change dynamics (,Moeller, 2004), and analyse environmental changes such as hot spot changes, land use features, long-term monitoring, and land cover mapping. Spatial change analysis and modelling have therefore benefited greatly from the use of GIS and RS, and the high-quality satellite images, past spatiotemporal insights and reduced data costs they provide (Feng,2009).

Urban sprawl can be forecasted, modelled and mapped using the data provided by GIS, with remote sensing satellite images allowing for better tracking, design and execution of urban growth developments on both a temporal and spatial level. This supports sustainable development as a key element of regional planning (Bhatta, 2012). Urban research and management primarily adopts the use of remote sensing for the purpose of estimating urban growth variables (directly) and/or parameters (indirectly), as well as to map urban characteristics and regions. Using suitable remotely-sensed spatial and temporal data, GIS tools can be highly valuable given the vast body of RS imagery available; with RS itself having been found to be successful in obtaining and analysing different spatial data resolutions for the purpose of urban growth tracking. The Landsat Multispectral Scanner (Weismiller et al., 1977) was a pioneer in the movement towards the use of remotely-sensed data for urban growth monitoring; with Landsat TM, ETM+, and SPOT HRV (Al-Fugara et al, 2011; Quarmby and Cushnie, 1989) developed thereafter; and the more contemporary and higher spatial resolution sensors , e.g., Ikonos and Worldview making further headway in this field (Niebergall et al. 2007).

Cellular automata (CA) models, which are built upon a GIS and RS image-based 2D cell grid wherein a specific land use and group of future transition rules are reflected in each individual cell, are useful in urban system and sprawl mechanism modelling as well as in gaining greater insight into urban theory and the impacts of urbanisation (Batty, 2005). Since its introduction (Tobler, 1970) as a model of Detroit's high-speed urban sprawl, many have adopted the CA approach for urban modelling; with others later applying CA theory to the relationship between individual behaviour and urban structure (Couclelis, 1985). Today, the CA approach is amongst the leading frameworks adopted in the exploration of sophisticated urban systems, with significant headway made in comprehending how geographic systems and urban dynamics relate to one another over the last 20 years (Clarke, 2008; Alfeld, 1995; Clarke and Gaydos, 1998; Batty, 2005). Consequently, CA models have been used for numerous purposes, including to model changes in land use and urban growth (Al-Shalabi et al, 2012; Mitsova et al, 2011), to explore patterns in ecological security (Gong et al, 2009), to track urban sprawl and growth (Al-Kheder et al, 2008; Al-Shalabi et al, 2012), and to forecast urban growth based on different variables (Mahiny and Gholamalifard, 2007).

During this time, a number of CA models have been established to simulate urban expansion. These include Shi and Pang's (2000) Voronoi-CA model; the dynamic urban evolution model (DUEM) (Ligtenberg et al, 2001); the Slope, Landuse map, Excluded area, Urban area, Transportation map, and Hillside area (SLEUTH) model (Clarke et al, 1997); the multi-actor-based land use modeling (MAS)-CA (Ligtenberg et al, 2001) ; the Markov-CA model (Vaz et al, 2012); the multi-criteria evaluation (MCE)-CA model (Wu, 1998); and the GeoCA-Urban model (Zhou et al, 1999). The SLEUTH model is the most commonly adopted. It allows for urban spread modelling to be performed over a specific time period whilst also supporting effective urban expansion prediction due to the high availability of input data, the minimal parameters required for calibration, and the accuracy of its simulation function (Al-Shalabi et al, 2012); Clarke et al, 1997; Silva and Clarke,2002). The SLEUTH model has been used in a number of developed countries to predict and simulate changes in land use and urban growth, with most adopting the model to predict urban growth so as to model the effects that future policy options would have on urban land use in certain socioeconomic scenarios (Batty, 2005; Clarke, 2008; Onsted and Clarke, 2012). Additionally, others have applied the SLEUTH model for urban growth in conjunction with other social/physical process models (Jantz, 2004; Oguz, 2007) or for the purpose of planning in the developing world (Badwi et al, 2014; Al-Shalabi et al, 2012; Kumar et al, 2011; Rafiee et al, 2009).

This paper describes the process of calibrating the SLEUTH model to adapt itself Amman governorate context. Amman, as Jordan's capital city, is home to 38% of its total population, with 42% of these individuals residing in Greater Amman and 82.6% residing in urban areas (Potter, 2009). Between 2004 and 2015, Amman's population more than doubled from approximately two to more four million, Driven essentially by the Syrian refugee crisis (DOSJ, 2016). like many other large cities, has witnessed the development of slums as a result of rapid urbanisation, with 19.6% of urban residents living in slum housing (Ajlouni, M 2011.) . The likely reason for this is unexpected population increase coupled with poor urbanisation planning, resulting in social stratification. For this reason, it is critical that steps are taken to better forecast urban growth in Amman. In order to achieve this, the SLEUTH model for urban growth analysis is adopted in this research. The prediction period ranges from 2015 to 2040, with a focus on forecasting the direction, magnitude and pattern of urban growth in Jordan's capital city. This model also allows the impacts of policy decisions to be analysed, as noted above. The SLEUTH model is adopted in this research due to its aforementioned popularity and widespread international usage as a predictive tool for changes in land use and urban growth. The selection of Amman as the case study city further allows for greater insight to be gained with regards to future changes in a city with unique

Theoretical and Empirical Researches in Urban Management
Volume 13 Issue 1 / February 2018

Theoretical and Empirical Researches in Urban Management
Volume 13 Issue 1 / February 2018

urban growth patterns, with the intention of supporting urban planning departments through the use of computerised simulation.

2. METHODS AND PROCEDURES

2.1. Study Area

As shown in Figure 1, Amman is located in Jordan's Hashemite Kingdom, serving as Jordan's most highly-populated city and the nation's centre of culture, politics and economy. The area spans 31˚25"N - 32˚1"N latitude and 35˚66"E - 36˚42"E longitude, and is situated in north-central Jordan. Amman has a land area of 1,680 km2, the elevation of Amman ranges from 700 to 1,100 m above the mean sea level. The topography of Amman consists of a series of steep hills and deep, and sometimes narrow, valleys. Whilst initial development was principally established on the upper slopes and crests and the lower slopes of this hill-valley system, the upsurge in urban development over the last 50 years expanded the urban development to the steeper mid-slope areas. During the 1900s. Over the space of one century, Amman has experienced extensive growth with regards to its geopolitical status, physical land and population (Potter, 2009). However, this has led to numerous environmental and infrastructural issues as a consequence of unexpected urban growth, creating a serious need for accurate forecasting for the future.

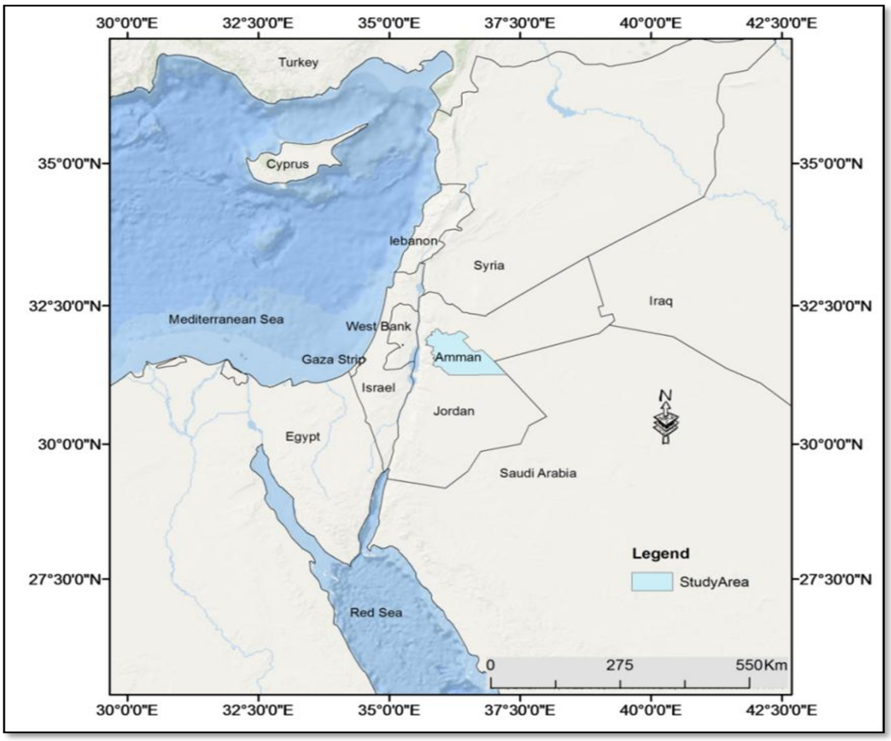

FIGURE 1 - AMMAN LOCATION FEATURES

2.2. SLEUTH Model

SLEUTH elements that comprise the model are the six variables (The Slope, Landus map, Excluded area, Urban area, Transportation map, and Hillside area) that determine the input of the model [Silva and Clarke ,2002, Clarke, 2008). Keith Clarke initially introduced the SLEUTH model at Santa Barbara’s University of California (Clarke et al, 1997), with CA used to model physical urban growth and land use dynamics in the form of a cell grid of growth rules. Using C programming language and usable on the LINUX or UNIX OS, the SLEUTH model is comprised of the Land Cover Deltatron (LCD) Model and Clarke Urban Growth Model (UGM). Whilst UGM simulates urban growth and is able to run on its own, the LCD Model simulates changes in land use and land transitions, run closely alongside urban code. The UGM and LCD model operate alongside one another, with the quantity of times the deltatron code is fired being reflected in the urbanised cell output. Land change potential decreases when urban growth reaches a standstill, and other inter-class transitions are generated when rapid urban expansion is associated with other land use classes (Clarke, 2008).

There are five coefficients that drive the SLUETH model’s urban growth rules, which are adopted in sequence as part of each individual cycle: the diffusion/dispersion, spread, breed, slope, and road-gravity coefficients (Clarke, 1997). The diffusion coefficient evaluates the way in which a newly-generated random separate settlement is to begin its growth cycle (Dietzel and Clarke, 2007). The spread coefficient determines the likelihood of a pixel being an element of a spreading centre. The breed coefficient evaluates the likelihood that a spontaneous growth pixel will form a new spreading centre. The slope coefficient dictates the level of urbanisation resistance to increasing steep slopes. Finally, the road gravity coefficient dictates the attraction of new urbanisation growth to roads. Essentially, every coefficient determines the urban growth roles present within the process of urbanisation, whilst also determining the model’s behaviour and influencing the mining of four key growth rules (spontaneous growth, new spreading centre growth, edge/organic growth, and road-influenced growth. The five coefficients can differ from one city to the next, and they represent an urban “DNA”. These coefficients are reflective of a group of integers with a range of 0-100, which have no dimensions. They reflect the influence of the parameter to which they are related to each urban system’s dynamic growth processes (Silva and Clarke, 2002; Silva, 2004)

Random land urbanisation, reflected as single pixels within the chosen area of analysis, is catalysed by spontaneous growth, which itself is determined by a diffusion coefficient that typically dictates the outward dispersive characteristics of new urban distribution growth. New spreading centre growth determines the likelihood that new urban spreading centres will be formed from new spontaneously-

Theoretical and Empirical Researches in Urban Management
Volume 13 Issue 1 / February 2018

urbanised cells based on the breed coefficient. The growth component that spreads outwards from spreading centres and urban infilling are simulated by edge-growth dynamics. This growth contributes to the formation of new growth centres and expansion of existing centres. It is determined by the spread coefficient, which impacts the likelihood of urbanisation in a non-urban cell that has three or more neighbouring cells. New development growth patterns are attracted to the transportation network by road-influenced growth, which is determined by the diffusion coefficient, spread coefficient, and breed coefficient. The SLEUTH model also contains self-modification growth rules that allow the model to change growth coefficient values to produce a more accurate typical S-curve urban development growth rate value. This brings greater robustness to the model, since it minimises the likelihood of different urban sprawl rates caused by a prediction of linear or exponential growth (Dietzel and Clarke, 2007; Clarke et al, 1997).

2.3. SLEUTH Input

In order to generate effective estimations, six types of gridded data inputs must be computed using the SLEUTH model: urban spatial extent, land use, transportation networks, excluded areas, slope, and hillshade. Additionally, four or more chosen periods of historic multi-temporal urban extent data must be inputted for the purpose of statistical calibration. The model also requires a historic transportation network from two or more selected periods, two land-use layers for each slope, terrain hillshading, and the specification of zones with no growth activity.

In this research, the above data were set with three resolutions, all sharing one projected coordinated system and extent. The multi-temporary input data covers the 1985-2015 period, and ArcGIS 10.3, PCI geomatica, ENVI, Erdas, and SLEUTH3.0_beta Software specifications were used to prepare the input data. Binary data representation is required for the SLEUTH model, with continuous data therefore converted into binary development extent maps based on a 10% impervious area threshold, since this threshold is effective in reflecting low-density built-up zones and urban growth (Hakan et al, 2007; Jantz et al,2004).

Five images of the Landsat Multispectral Scanner (MSS) and Thematic Mapper (TM) from 1985, 1995, 2005 and 2015 were used to obtain historic data on Amman metropolitan's land use and urbanisation. The images were sourced from the USGS website (United States A. Abedini, et al Geological Survey) and classified manually as cloudless images suitable for direct use in the Landsat Image Time Series, land use and urban area extraction, and as SLEUTH input data. All images represented the summer season, and were taken at the same time of day so as to achieve comparable radiometric attributions and lighting conditions, which negates the need for adjustments in the form of radiometric/atmospheric corrections (Roy et al, 2008). Once obtained, the images were applied to a Universal Transverse Mercator (UTM) coordinate system using WGS 1984 ellipsoid parameters (Zone 36 N).

Since each of the five images differed in terms of spatial resolution, the coarser resolution imageries (Landsat MSS – 60 m) were resampled to the finer imageries (Landsat TM - 30 m) in order to achieve the same spatial resolution across the Landsat Image Time Series. This being said, it should be noted that because the application of bi-cubic and bi-linear resampling methods averages out adjacent pixel values, this decreases image quality. Pixel dropout or duplication arises when using the nearest neighbour method for image resampling. Therefore, the pixel size of the images was not changed.

Layer stacking was then used to prepare the ETM images in order to map Amman's urban landuse or landcover for the four selected years (1985, 1995, 2005 and 2015). Here, we used the supervised classification of ERDAS Imagine's maximum likelihood algorithm. Land uses were categorised as urban, bare land (bare soil / rock) or agricultural. ERDAS Imagine's vector tools were used to create the three land use classes through visual interpretation of the images, allowing for optimum land cover/use map quality and precision of classification. The results produced by the supervised algorithm were enhanced through the inclusion of local knowledge, ancillary data, and a topographic map (scale = 1:50,000) along with other reference data. Mapping results for land use were then transformed into binary urban/non-urban form, as shown in Figure 2, to illustrate Amman's district features since 1985. This layer was then imported into ARCGIS 10.3, with binary rasters of 0 (non-urban) and 255 (urban). Amman municipality provided the 2005 transportation layer as a digital vector, with the layer adjusted with the exclusion of non-existing roads based on screen digitisation of November 2005 Landsat TM images (Fig. 2). GIS was then used to calculate the slope percentages and hillshade layers from SRTM 30-m as it has realistic accuracy (Al-Fugara, 2015).

GIF images for the SLEUTH model were obtained through the conversion of input data layers, which were rasterised at a resolution of a30m to the Amman metropolitan spatial extent. The removed layer (Zarqa River, parks, mining zones, military bases, railways and airports, which were not urbanised) was rasterised on the Landsat image for 2015. Model calibration was then achieved by reassigning the input layers to the coarse (150 m), fine (90 m) and final (30 m) resolutions.

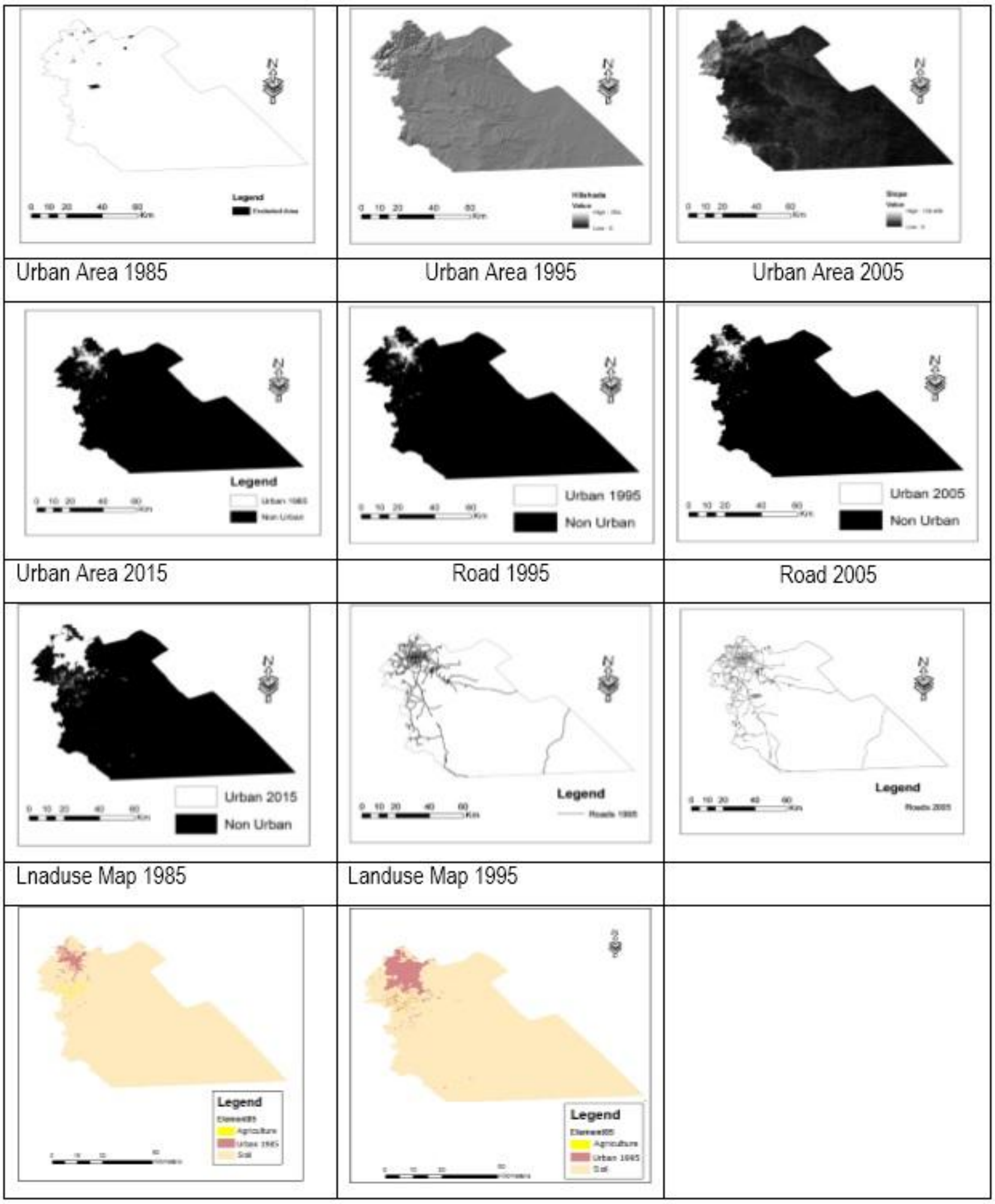

FIGURE 2 - AMMAN METROPOLITAN INPUT LAYER DATA

2.4. Implementation

2.4.1. Calibration

In order to enable the SLEUTH model to reflect the connections between the chosen urban growth variables during the selected period, calibration was necessary. This also allowed for good fit between the control and simulated years of analysis, therefore allowing for accurate predictions of future urban growth. Since growth rules are the urban “DNA” of the SLEUTH model, they are effective representations of urban growth in Amman, comprised of the key variables responsible for driving urban growth over a given time period. The brute-force Monte Carlo method was used during the UGM’s calibration stage. Here, each variable is assigned a range of values, with the SLEUTH model iterating every potential sequence of variables, permuting the five chosen control parameters from 1985 to 2015.

In order to determine appropriate parameters, the SLEUTH model was calibrated through the use of hierarchical spatial resolutions. This stage began with the coarsest resolution, decreasing the parameter range that best represented system growth, before reducing the values to a smaller set using a finer resolution. Thus, all 30-m resolution input data went through resampling four times, to 120-m resolution. Resampling to 60-m resolution was achieved during the fine calibration stage, where input data were resampled to double their initial resolution. During the final stage of calibration, input data were used in 10 Monte Carlo iterations with full input resolutions. The seed for the parameters was the first year of analysis (1985). This allowed Amman’s urban growth to be simulated from this year onwards, and it was resolved based on the control data. Here, the primary control parameter ranged from 1 (diffusion coefficient) to 100 for the diffusion, breed, spread, slope resistance, and road gravity coefficients at the point of calibration. Following each run of the calibration process, simulated and real growth were compared using the SLEUTH model’s 13 least-squares regression metrics (Silva, 2002). Various researchers have presented different methods for reducing the coefficient space, including the standard arrangement of all metrics, the weighting of certain metrics, and rendering all metrics equal (NCGIA, 2011). The Optimum SLEUTH Metric (OSM) (NCGIA, 2011; Dietzel & Clarke, 2007), which is the total of all least-squares regression metrics, was adopted to reduce the coefficient ranges. This being said, in most cases, growth is typically depicted using just a small subset of key metrics. This helps to simplify the sorting and description process impacting the regression score (Dietzel, and Clarke,2007; Lizhong et al., 200000). Table 1 provides a description of the indices subset adopted in this analysis for the purpose of assessing the fit of the SLEUTH model.

TABLE 1 - GOOD FIT EVALUATION INDICES SUBSET ((SILVA & CLARKE,2002)

Index	Descriptio
Compare	Compares modelled and actual final urban extent pixels
R2 Cluster	Least-squares regression of modelled and actual urban extent clustering for the control period
Populationr2	Least-squares regression value for modelled and actual urban extent over the control period
Edges r2	Least-squares regression of modelled and actual urban edge pixel quantity over the control period
Xmean r2	Least-squares regression of modelled and actual urban pixel average x counts over the control period
LeeSallee shape index	Measures spatial fit in terms of modelled and actual urban extent over the control period

Theoretical and Empirical Researches in Urban Management
Volume 13 Issue 1 / February 2018

Theoretical and Empirical Researches in Urban Management
Volume 13 Issue 1 / February 2018

A step value of 20 with 5 Monte Carlo iterations was used for coarse calibration, whilst a step value of 5 with 10 Monte Carlo iterations was used for fine calibration. A step value of 1 with 20 Monte Carlo iterations was used for the final calibration. The highest set of comparison scores determined the range of values for the next calibration stage at the end of each previous stage. The 'control_stats.log' file can be executed to locate the top 50 best fit values using the OSM code, which assists in determining which values should be used in the following stage (Dietzel and Clarke, 2007). Following the calibration stage is the prediction stage. The parameter values were altered through a run from the starting year to the latest year, with the most suitable calibrated parameters of the ending date selected, as a result of the SLEUTH model's self-modification feature. In order to optimise parameter stability, a smaller range was adopted. A set of end date parameters were used for prediction purposes, with this set of parameters obtained through the use of best parameter values for the chosen time period (obtained through the calibration stage and following steps (Rafiee et al, 2009).

2.4.2. Model predictions

The modelling of future urban growth from the current date is achieved through urban predication. Numerous systems exist for predicting future urban growth based on specific policy decisions. These include the controlled growth and uncontrolled growth / historical growth systems (Silva and Clarke, 2002; Yang and Lo, 2003). The SLEUTH model forecasting stage is characterised by a single run, which produces images and statistical representations for growth forecasting. Whilst the SLEUTH model allows all policy decisions to be simulated, the current study focuses only on simulating Amman metropolitan urban growth based on a given historical growth scenario (HGS), wherein it is taken that historical patterns will be repeated in the future (Rafiee et al, 2009).

Here, the SLEUTH model's prediction function was used. The Monte Carlo iterations were calibrated to 100 or above, with best fit growth coefficients used based on the results of the calibration stage. During the final calibration stage, the 'avg.log' file was generated, producing the best fit prediction values (Table 2). Here, sorting was only performed on the OSM. A probability threshold of 75% was set for the sorting of probability images created by the SLEUTH model in order to produce binary images of urban extent whilst also determining a non-urban grid cell likely to undergo urbanisation. The following section presents and discusses the results of the SLEUTH model, with the following sections outlining the results of the calibration.

3. RESULTS AND DISCUSSION

3.1. Calibration

Historic growth data from 1985 to 2015 was used for coarse calibration. The growth coefficient value range (0-100) was assigned to the coefficient across 4,218 Monte Carlo iterations at steps of 20. The OSM was used to assess the results of the coarse calibration stage, with ranges chosen from the top 5 results. The remaining results were then utilised to determine the starting coefficient ranges for the next (fine) calibration stage. Here, a total of 8 iterations and 4,355 runs were carried out. The final calibration involved 10 iterations and 6,479 runs. The predict function of the model utilised the final growth parameters generated through the calibration stage, with the OSM used as the sum of the best fit metrics (Compare, Cluster, Population, Edges, Xmean, and Lee Sallee). Analysis of the values was performed using the OSM, with the top 5 OSM scores used to determine the ranges for the following stage in order to reduce the range of coefficients (Dietzel and Clarke, 2007). Table 2 outlines the top set of OSM best fit values for 2015.

TABLE 2 - AMMAN CALIBRATION RESULTS

Least-squares regression metrics	Coarse resolution	Fine resolution	Final resolution
1. Compare	0.972	0.984	0.987
2. Cluster	0.987	0.989	0.992
3. Population	0.978	0.982	0.987
4. Edges	0.951	0.956	0.964
5. Xmean	0.976	0.982	0.992
6. Lee Sallee	0.486	0.496	0.514
7. OSM	0.422	0.445	0.481
Growth Parameters			
1. Diffusion	22	23	25
2. Bread	24	27	27
3. Spread	24	27	27
4. Slope	2	3	3
5. Roads	27	30	32

A good OSM value of 0.422 for the coarse calibration was achieved (Table 2) and converted to 0.445 during the fine calibration stage, and 0.481 during the final calibration. A value of 1 is achieved when a perfect spatial match is produced, but this is not likely when using the OSM metric (Dietzel, and Clarke, 200607). The least-squares regression metrics were computed to assess the SLEUTH model's accuracy in modelling Amman's urban growth (see Table 2). A strong correlation was demonstrated through a comparison in these metrics, between modelled and actual urbanisation during the chosen years. The final correlation coefficients were 0.987 (Compare), 0.992 (Cluster), 0.987 (Population),

Theoretical and Empirical Researches in Urban Management
Volume 13 Issue 1 / February 2018

0.964 (Edges), 0.992 (Xmean), and 0.514 (Lee Sallee). Thus, the results indicate that the SLEUTH model provides relatively accurate predictions of urban growth based on historic data and the refined values generated during calibration. The Lee Sallee metric (the shape index measuring the level of similarity between the shape characteristics of modelled and actual growth) was at an acceptable level of 0.514 (KantaKumar et al, 2011). The above points indicate that the calibration was effective in representing real urban growth in Amman over the selected historic time period. The top values obtained through the final calibration stage were set as the initial values for the five chosen control coefficients. This allowed for urban growth to be modelled during the derive stage. In order to reduce error, a higher number of Monte Carlo iterations (1,000) were performed. The SLEUTH model's mean function was used to obtain average values. Table 2 illustrates the results of the three calibration stages, which indicate increasing parameter development determining system behaviour during each calibration stage. The control coefficients' final values were 25 (diffusion coefficient), 27 (breed coefficient and spread coefficient), 3 (slope resistance), and 32 (road gravity), with each relevant to a specific form of spatial growth. With a low diffusion coefficient, dispersive growth is unlikely in the study area, with a medium level of growth scatter across the Amman metropolitan area. This also supported by the low breed coefficient, with a medium level of opportunity for the development of new detached urban settlements in the Amman metropolitan area. The spread coefficient represents outward and inward growth from the spreading centre, indicating the quantity of residents moving from cities to suburban areas (Gandhi et al, 2012). The greatest coefficient is road gravity, indicating that Amman's transportation network has a considerable impact on growth in the city, and suggesting the attraction and diffusion of urbanisation around Amman's roads. The low slope resistance coefficient value also indicates that growth is not highly impacted by topography, which is logical given the four-storey height restriction for residential buildings in Amman. This being said, there are no storey limits on buildings placed on sloping hills if a street connects to the top of the site. Here, buildings are only restricted in that they can extend to no more than four storeys above the higher area of the slope. Naturally, this results in expensive land prices. Overall, it appears that the SLEUTH model can estimate future growth using the values outlined. This finding is impacted by the selected parameters and values, however. Additionally, further research is needed to explore the SLEUTH model in greater detail, and in different parts of the Mediterranean.

3.2. Predictions

Once the model's accuracy had been confirmed, urban growth between 2015 and 2040 was simulated based on the average growth coefficient values obtained during the final calibration stage. Table 2 illustrates the best fit prediction values. Historic growth data were taken as grounds for predictions of future urban growth. This assumed a lack of growth restrictions, aside from the exclusion layer (government buildings, forestry, historical sites, mining sites, and military zones). In order to generate growth predictions, 100 Monte Carlo iterations were carried out. The results were produced in the form of an annual probability map to the year 2040, indicating the likelihood of urbanisation in each cell. With a threshold of 75%, all cells above this probability were classed as being highly likely to undergo urbanisation (Schwaninger, 2001) (Fig. 3). These probability maps were then exported for analysis in ArcGIS 10.3. The maps indicate that the south and west areas of the Amman metropolitan area are most likely to undergo urbanisation, potential due to greater land availability and cheaper land prices. Additionally, the results indicate an expansion of urban residences at an average annual rate of 2.29 km2, representing an increase from 416.432 km2 (2015, shaded in black) to 473.844 km2 (2040, shaded in grey). Figure 3 illustrates the t2040 urbanisation map was produced in GIF format, with the ESRI ArcGIS function utilised in order to convert pixels into km2.

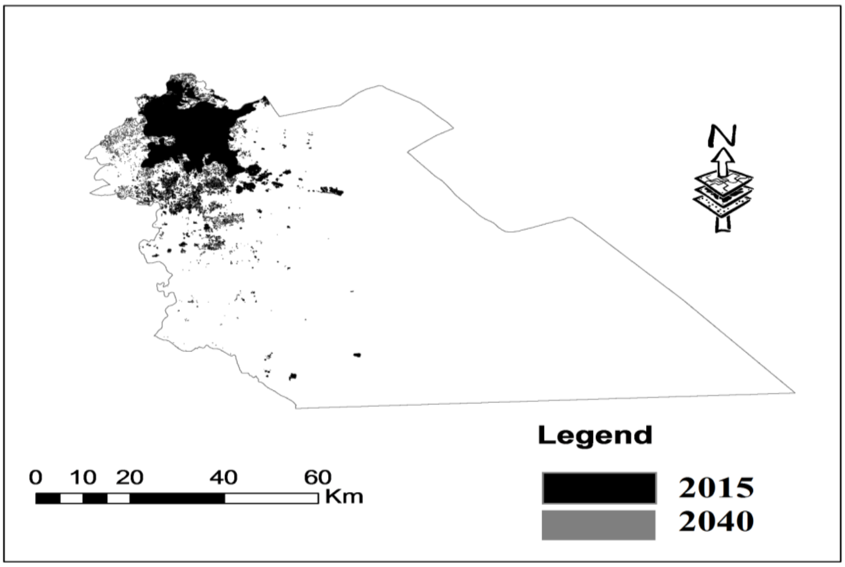

FIGURE 3 - 2015-2040 URBAN GROWTH PREDICTIONS

Figure 4 illustrates the S-shaped curve representing the initial, acceleration and terminal growth stages. This is useful for analysing the growth patterns of any given area. Currently, Amman is shown to be at the early middle growth stage. Urban sprawl rate can also be determined based on the S-shaped curve (Chen, 2012). Additionally, the SLEUTH model’s self-modification feature enables the adjustment of coefficients based on the urban growth rate, in the absence of this feature, only direct or exponential growth can be outputted (Clarke et al, 1997; Dietzel and Clarke,2007; silva & clarck, 2002). The actual growth demonstrated in urban areas is captured by the self-modification rules of the model, although the S-shaped urban growth curve is primarily used in the study of urbanisation in developed countries.

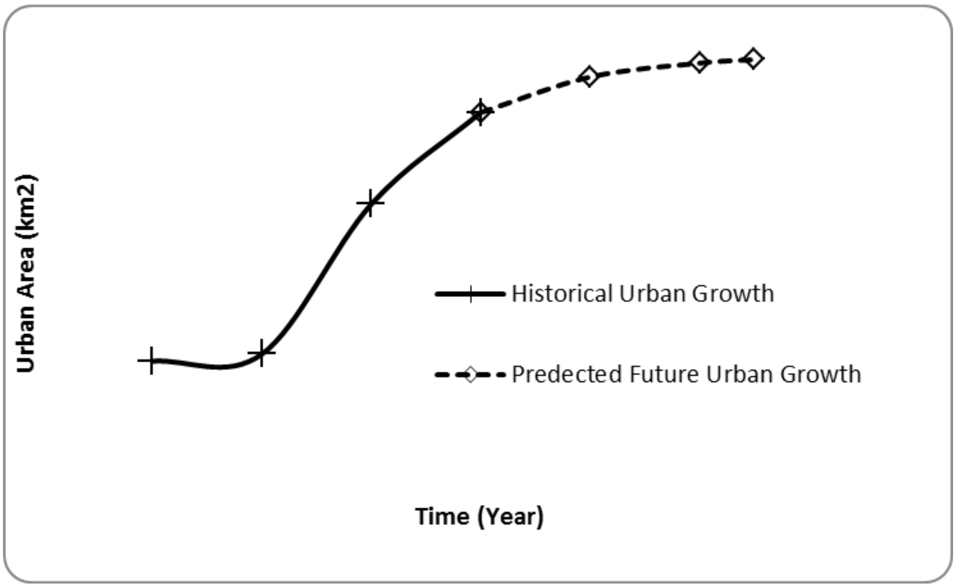

FIGURE 4 - HISTORIC AND FORECASTED URBAN GROWTH

The results of the current study are in line with those of other studies on developed countries, in this regard. The SLEUTH model's self-modification feature reflects growth patterns through the increase of diffusion, spread and breed values in line with an increase in urbanisation. This leads to the indication of urban growth being more likely. When the growth rate drops below a certain threshold, urbanisation slows, and the model provides a narrower distribution of urban growth as a result of a reduction in diffusion and breed parameter values.

4. CONCLUSIONS

Environmental concerns have been raised as a result of rapid urbanisation around the globe. This is particularly prevalent in developing countries, where serious environmental and management issues are likely to occur if urbanisation continues to increase without proper planning. Therefore, it is essential to capture actual urban growth based on spatial and temporal growth patterns in order to understand the speed of growth as well its the societal, economic and environmental consequences. Urban planning departments and managers depend on accurate predictions of urban growth, not only in terms of growth patterns, but also in terms of specific area and magnitude. For this purpose, proven CA-based models such as the SLEUTH model adopted in this research are of critical importance. Whilst no simulation model can ever claim to predict with complete accuracy, they can be highly valuable in making predictions for the future based on certain variables and circumstances. With 42% of Jordan's population residing in its capital city, the need to accurately forecast urbanisation in Amman has become increasingly recognised, particularly due to the rapid speed and extent of growth witnessed over the last 30 years.

The research has demonstrated the value of RS data and the use of the GIS tool for simulating urbanisation in specific areas using historic growth information under the SLEUTH model. Remote sensing is able to generate relatively high quantities of data covering a significant area of land, which can then be analysed in GIS. This allowed for Amman's urbanisation to be mapped over a period of 30 years – something that would be infeasible without computerised data and tools. The GIS itself is also a key element, providing value to urban growth analysts at the input, preparation, calibration and evaluation stages. Further analysis and reporting was also simple due to the ease of importing SLEUTH model results into the GIS tool.

The OSM method was used to calibrate the SLEUTH model using historic growth data for Amman between 1985 and 2015, producing values comparable to other SLEUTH applications. The calibration process allowed urban DNA to be generated in order to obtain urban growth characteristics for the chosen area, which are presented as coefficient sets that capture the given urban system whilst also forecasting future urbanisation growth.

Initial parameter values for 2015, obtained through the calibration process, were 25 (diffusion), 27 (breed and spread), 3 (slope), and 32 (roads). Urbanisation patterns between 1985 and 2015 were used to confirm the SLEUTH model's accuracy, with these values then used for forecasting until 2040. The continuous urban sprawl growth demonstrated in Amman was simulated in the form of the urban scenario, with the SLEUTH model found to be accurate and useful in determining local features that impact future urban growth, with policy decisions factored into predictions.

The model predicted an increase in urban area from 416.432 km2 in 2015 to 473.845 km2 by 2040 based on historic data. Additionally, the model also predicted that the south and west areas of Amman would experience the most urban growth. The SLEUTH model only factors in slope, road gravity and other physical variables, even though the exclusion layer is effective in modelling the outcomes of conversation policy or regulatory changes. More accurate predictions of future growth can be achieved through the incorporation of regional development policies and socioeconomic factors as part of an adapted CA-based SLEUTH model. It is recommended that future research focuses on other areas undergoing rapid urban growth in the developing world, as this will support urban planners in making effective decisions with regards to urbanisation over the coming decades.

REFERENCES

Ajlouni, M. (2011). Jordan Health System Profile: Report Submitted to WHO, EMR, August, 2011, from http://ajlunihm.com/wp-content/uploads/2011/07/Jordan-HSP-2010- Final.pdf (Accessed on March 15 2017).

Al-Batoush, N. (2012). Recent trends of population growth in Jordan and their consequences: *Jordan Journal of Social Sciences*, Volume 5, Issue 1, pp. 111-124.

Alfeld, L.E. (1995). Urban dynamics-The first fifty years, *System Dynamics Review* 11(3): 199-217. John Wiley & Sons, Ltd.

Al-Fugara, A. (2015). Comparison and Validation of the Recent Freely Available DEM's over Part of the Earth's Lowest Elevation Area: Dead Sea, Jordan. *International Journal of Geosciences*, 6, 1221-1232, from https://doi.org/10.4236/ijg.2015.611096

AlFugara, A.M., Pradhan, B. & Mohamed, T.A. (2009). Improvement of Land Use Classification Using Object Oriented and Fuzzy Logic Approach. *Applied Geomatics*, 1,111-120, from http://dx.doi.org/10.1007/s12518-009-0011-3

Al-Kheder, S.A.M., Wang, J., Shan, J. (2008). Fuzzy inference guided cellular automata urban-growth modeling using multi-temporal satellite images: Al-kheder, S., Wang, J., & Shan, J. (2008). Fuzzy inference guided cellular automata urban-growth modelling using multi-temporal satellite images: *International Journal of Geographical Information Science* 22(11–12):1271–1293.

Al-Shalabi, M., Pradhan, B., Billa, L., Mansor, S., & Althuwaynee, O., (2012). Manifestation of remote sensing data in modeling urban sprawl using the SLEUTH model and brute force calibration: a case study of Sana'a city, *Yemen: Journal of the Indian Society of Remote Sensing*, 1–12. doi: 10.1007/s12524-012-0215-6.

Badwi, I. M., El-Barmelgy, M. M., & Ouf, A. S. E. D. (2014). Modeling and simulation of greater Cairo region urban dynamics using SLEUTH: *Journal of Urban Planning and Development*,10.1061/(ASCE)UP.1943-5444 .0000193, 04014032

Batty, M. (2005). Cities and complexity: Understanding cities through cellular automata, agent-based models, and fractals. Cambridge, MA: The MIT Press.

Bhatta, B. (2012). Urban growth analysis and remote sensing. Springer Briefs in Geography, A Case Study of Kolkata, India 1980–2010. *Springer Science & Business Media*, 2012, DOI: 10.1007/978-94-007-4698-5_2, 9-32.

Chen, Y.G. (2012). On the urbanization curves: Types, stages, and research methods: *Scientia Geographica Sinica*, 32(1), 12–17.

Clarke, K. C., Hoppen, S., & Gaydos, L. (1997). A self-modifying cellular automaton model of historical urbanization in the San Francisco Bay area, *Environment and Planning B*, 24, 247–261.

Clarke, K. C., & Gaydos, L. (1998). Loose coupling a cellular automaton model and GIS: Long-term growth prediction for San Francisco and Washington/Baltimore: *International Journal of Geographical Information Science*, 12(7), 699–714.

Clarke, K.C. (2008). *A decade of cellular urban modeling with SLEUTH: Unresolved issues and problems* (Ch, 3, 47–60).

Couclelis ,H. (1985). Cellular worlds: A framework for modeling micro-macro dynamics: *Environment and Planning A*, 1985 (17): 585–596.

Dietzel, C., & Clarke, K. C. (2007). Toward optimal calibration of the SLEUTH land use change model, *Transactions in GIS*, *11*(1), 29-45.

DOSJ, Department of Statistics Jordan. (2015). *Population Projection for the time period 2010-2030*. Retrieved from http://census.dos.gov.jo/wpcontent/uploads/sites/2/2016/02/Census_results_2016.pdf [Accessed March 15, 2017]

Feng, L. (2009). Applying remote sensing and GIS on monitoring and measuring urban sprawl: A case study of China: *Revista Internacional Sostenibilidad, Tecnología y Humanismo*, 4, 47-56.

Gong, J.Z., Liu, Y.S., Xia, B.C, & Zhao, G.W. (2009). Urban ecological security assessment and forecasting, based on a cellular automata model: a case study of Guangzhou China: *Ecological Modelling*, 220(24):3612–3620.

Hakan, O., Klein, A.G, & Srinivas, R. (2007). Using the SLEUTH urban growth model to simulate the impacts of future policy scenarios on urban land use in the Houston-Galveston-Brazoria CMSA. *Research Journal of Social Sciences* 2, 72–82.

Jantz, C.A., Goetz, S.J, & Shelley, M.K. (2004). Using the SLEUTH urban growth model to simulate the impacts of future policy scenarios on urban land use in the Baltimore-Washington metropolitan area. *Environment Planning: Plann. Des*. 31 (2), 251–271

Kumar, L. K., Nikhil, N., Sawant, G, & Shamita Kumar. (2011). Forecasting urban growth based on GIS, RS and SLEUTH model in Pune metropolitan area: *International Journal of Geomatics and Geosciences*, Volume 2, No 2, 2011.

Ligtenberg, A., Bregt, A, &Lammeren, R. (2001). Multi-actor based land use modelling: spatial planning using agents: *Landscape and Urban Planning* 56, 21–33.

Mahiny, A. S, & Gholamalifard, M. (2007). Dynamic Spatial Modeling of Urban Growth through Cellular Automata in a GIS Environment: *International Journal of Environmental Research*. 1, 272-279.

Cerreta, M, & Toro, P. (2010). Integrated spatial assessment for a creative decision-making process: a combined methodological approach to strategic environmental assessment. *International Journal of Sustainable Development,* Vol. 13, Nos. 1/2, 2010.

Mitsova, D., Shuster, W, & Wang, X. (2011) .A cellular automata model of land cover change to integrate urban growth with open space conservation, *Landscape and Urban Planning* 99(2):141–153.

Moeller, M. (2004). Monitoring long term transition processes of a Metropolitan Area with remote sensing. In: Proceeding of the IGARRS 2004: IEEE International Geoscience and Remote Sensing Symposium, Anchorage, AK, 3398-3401.

NCGIA. (2011). Project Gigalopolis, University Of California, Santa Barbara., USGS, from http://www.ncgia.ucsb.edu/projects/gig, accessed 02 Jun. 2011.

Niebergall, S., Loew, A, & Mauser, W. (2007). Object-Oriented Analysis of Very HighResolution QuickBird Data for Mega City Research in Delhi/India: Urban Remote Sensing Joint Event.

Oguz, H., Klein, A, & Srinivasan, R. (2007). Using the SLEUTH urban growth model to simulate the impacts of future policy scenarios on urban land use in the Houston-Galveston-Brazoria CMSA: *Research Journal of Social Sciences*. 2 (1), 72–82.

Onsted & Clarke. (2012). The inclusion of differentially assessed lands in urban growth model calibration: A comparison of two approaches using SLEUTH, *International Journal of Geographical Information Science*., 26 (5) (2012), pp. 881-89.

Pham, H. M., Yamaguchi, Y., Bui, T. Q. (2011). A case study on the relation between city planning and urban growth using remote sensing and spatial metrics: *Landscape and Urban Planning*, 100, pp. 223–230.

Potter, B. R., Darmame, K., Barham, N, & Nortcliff, S. (2009). Ever-growing Amman, Jordan: Urban expansion, social polarisation and contemporary urban planning issues. *Habitat International* 33, pp. 81–92.

Quarmby, N.A., & Cushnie, J.L. 91989). Monitoring urban land cover changes at the urban fringe from SPOT HRV imagery in south-east England, *International Journal of Remote Sensing* 10: 955 – 965.

Rafiee, R., Mahiny, A. S., Khorasani, N., Darvishsefat, A. A. & Danekar, A. (2009). Simulating urban growth in Mashad City, Iran through the SLEUTH model (UGM)", *Cities*, vol. 26, no. 1, pp. 19–26, 2009.

Roy, M. (2008). Planning for sustainable urbanization in fast growing cities: Mitigation and adaptation issues addressed in Dhaka, Bangladesh. *Habitat International* 13 (3), 276–286.

Schwaninger, M. (2001). Review of: Cities and regions as Self-organizing Systems. Models of Complexity. *System Dynamics Review* 17(4): 365-371. John Wiley & Sons, Ltd

Silva, E. A, & Clarke, K. C. (2002). Calibration of the SLEUTH urban growth model for Lisbon and Porto, Portugal. Computers, *Environment and Urban Systems*, 26(2002), 525–552.

Silva, E.A. (2004). The DNA of our regions: Artificial intelligence in regional planning. *Futures* 36, 1077–1094.

Tobler, W.R. (1970). A computer movie simulating urban growth in the Detroit region: *Economic, Geography*, 1970 (46): 234–240.

United Nations, Department of economic and Social Affairs, Population Division. (2015). World Population Prospects: The 2015 Revision. New York: United Nations. from (http://esa.un.org/unpd/wpp/Publications/Files/Key_Findings_WPP_2015.pdf).

UNFPA. (2007). State of the World's Population 2007: Unleashing the Potential of Urban Growth, United Nations Population Fund: New York).

United States Geological Survey. (2011). Earth explorer, from http://edcsns17.cr.usgs.gov/NewEarthExplorer, accessed 15 May 2011.

Vaz, E., Nijkamp, P., Painho, M., & Caetano, M. (2012). A multi-scenario forecast of urban change: a study on urban growth in the Algarve. *Landscape and Urban Planning*, 104, 201e211.

Weismiller, R. A., Kristof, S. J., Scholz, D., Anuta, P. E, & Momin, S. A. (1977). Change Detection in Coastal Zone Environments: Photogrammetric Engineering and Remote Sensing, 43 (12): 1533-1539.

Wu, F, & Webster, C.J. (1998). Simulation of land development through the integration of cellular automata and multicriteria evaluation: *Environment and Planning B* 25:103–126

Yang, X., Lo, C.P. (2003). Modelling urban growth and landscape change in the Atlanta metropolitan area, *International Journal of Geographical Information Sc*ience. 2003, 17, 463–488.

Zhou, C., Sun, Z, & Xie, Y. (1999). *Studies on Geo-Cellular Automata* (Geographical Information Science Series): Science Press of China, Beijing, pp. 52-74.

Shai, W, & Pang, M. (2000) . Development of Voronoi-based cellular automata -an integrated dynamic model for Geographical Information Systems. *International Journal of Geographical Information Science* 14(5):455-474. DOI.10.1080/13658810050057597

Sakieh, Y., Amiri, B., Danekar, A., Feghhi, J, & Dezhkam, S. (2014). Scenario-based evaluation of urban development sustainability: an integrative modeling approach to compromise between urbanization suitability index and landscape pattern. *Environment Development and Sustainability* 17(6). DOI10.1007/s10668-014-9609-7.