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Forecasting urban sprawl in Dhaka city of Bangladesh

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Abstract
Dhaka, the capital of Bangladesh, is expected to be one of the five largest cities of the world by 2025 in terms of population. The rapid urban growth experienced by the city in the recent decades is one of the highest in the world. Urban expansion of Dhaka was slow in the 1950s, but strong growth followed the independence of Bangladesh in 1971. To understand Dhaka city growth dynamics and to forecast its future expansion by the year 2030, a self-modifying cellular automata Slope, Land use, Exclusion, Urban extension, Transportation and Hillshade model was used in this research using satellite images from 1989 to 2014. This model showed two interesting findings. First, approximately an additional 20% of the metropolitan area will be converted into built-up land by 2030 amounting to about 177 sq km. Second, the spatial trend of sprawl will be towards the north and north-west. The interpretation of depicting the future scenario as demonstrated in this research will be of great value to urban planners and decision makers, for the future planning of Dhaka.

Keywords
Urban expansion, Slope, Land use, Exclusion, Urban extension, Transportation and Hill model, growth prediction, urban sprawl, urban planning

Introduction

Urban areas are the most dynamic regions on earth. Their size has been constantly increasing during the past and this process will go on in the future. Especially in less developed countries, a strong trend towards concentration of people in urban areas can be observed (Moeller, 2005). Monitoring urban growth and accordingly anticipating urban extent is always recognized as a dynamic issue for any urban planning decision-making procedure. In the past 200 years, the world population has increased six times and the urban population has multiplied 100 times (Stalker, 2000). Due to the increase in world population and the progressive departure of national economies from merely agricultural systems, cities have been undergoing a rapid and often uncontrolled growth.

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Thus, urbanization is now one of the most common anthropogenic causes of arable land loss, the destruction of habitats and the decline of natural vegetation cover. In the last few decades, land use/cover conversion, due to human activities, occurred more rapidly in developing countries than in the industrialized world.

Like other developing countries, Bangladesh has experienced rapid urbanization. Dhaka, the capital of Bangladesh, is also the outcome of spontaneous rapid growth. Presently, Dhaka is the eighth largest city in the world in terms of population. Its population exceeds 15 million. If this trend continues, it will be the third largest city of the world in 2025 with a population of more than 20 million (World Bank, 2007a). On the other hand, in the process of urbanization, the physical characteristics of Dhaka city are gradually changing. Plots and open spaces have been transformed into built-up areas, open squares into car parks, low land and water bodies into reclaimed built-up lands, etc.

Dhaka is now attracting a significant amount of rural–urban migrants from all over the country due to well-paid job opportunities, better educational, health and other daily life facilities (Islam, 1999). This kind of increasing and overpopulation pressure is putting adverse impacts on Dhaka city such as unplanned urbanization, extensive urban poverty, water logging, growth of urban slums and squatters, traffic jams, environmental pollution and other socio-economic problems (World Bank, 2007a). If this situation continues Dhaka might soon become an urban slum with degraded living standards for the city dwellers. Thus, it is very important to project the future scenario of urban growth of Dhaka in order to understand how the city might expand. This may help planners to carry out their planning more efficiently based on computer simulation methods in addition to their expertise. In this case, land cover and land use change models are useful tools to analyse, understand and predict land cover changes and their consequences. Using these models, policy makers can analyse different scenarios of land use and land cover change and evaluate their effects, so models can support land use planning and policy (Veldkamp and Lambin, 2001).

Urban modelling was introduced in the late 1950s and now a number of analytical and statistical urban models have been developed based on such diverse theories as urban geometry and size, relationships between cities and economic functions. Some of these models explain urban growth patterns, instead of predicting future urban growth. For understanding the spatial consequences of urban growth, the dynamic modelling approach is preferred and has been used more often (Rafiee et al., 2008). Advances in remote sensing and geographic information science have brought about new spatial modelling approaches, such as cellular automata (CA) (Clarke et al., 1997), artificial neural networks (Pijanowski et al., 2002; Stathakis, 2009; Stathakis and Vasilakos, 2006), statistical models (Cheng and Masser, 2003), multi-agent models (Benenson, 1998) and fractal models (Batty et al., 1989). Among all documented dynamic models, CA are probably the most used approach in urban growth modelling (UGM) in terms of their flexibility, their simplicity in application and their close ties to remote sensing data and geographic information systems (Torrens, 2000). CA are discrete and dynamic systems. Their behaviour is exclusively specified in terms of the location relationships. The space is perceived as a uniform grid (an array of cells). Each cell can be in one of a finite number of possible states. The state of each cell is updated in a discrete time step based on local and identical transition rules and the status of the cells in the neighbourhood (Takayama and Couclelis, 1997).

CA were originally proposed by Ulam and Von Neumann in the 1940s to provide a framework for investigating the behaviour of complex and extended systems. CA refer to cellular space as the framework of analysis and automata concern the self-organizing behaviour of the cells (Torrens, 2000). The application of CA in geographical modelling was originally proposed by Tobler (1979). CA have become the most widely used approach in urban studies since the 1980s. Batty is one of the pioneers who developed an operational framework of CA in urban modelling (Batty et al., 1989) and later presented a class of urban models called dynamic urban evaluation modelling (DUEM). The dynamics of DUEM are based on theories of development associated with CA, with fine-grained data. The simulation of the model requires software that can handle an enormous array of spatial and temporal model outputs (Batty et al., 1999). The first attempt at a real simulation and prediction of urban growth was carried out in the early 1990s by White and Engelen (1993). A few years later, Engelen et al. (1995) developed the Island model which involved some advances on the first model.

Another application of CA in forecasting and simulation of urban growth was an UGM of the San Francisco Bay Area (Clarke et al., 1997). Wu (1998) offered a model that also involved a decision-making user-defined interface to reveal the outcome of the model. This model was called SIMLAND and provided an artificial environment to test the result of policies that was offered by decision makers. In other work, Li and Yeh (2000) applied CA to develop a model called the 'constrained cellular automata model'. This model is based on land suitability to explore urban form for sustainable development. This model can be used as a tool to help planners search for better urban forms. LEAM (land use evaluation and impact assessment model) is another CA-based model which was developed by Sun et al. (2005). LEAM has been developed as a comprehensive urban planning support system at a regional scale which simulates land use changes across time and space.

According to Dietzel and Clarke (2006), of all the CA models available, Slope, Land cover, Exclusion, Urbanization, Transportation, and Hillshade (SLEUTH) may be the most appropriate because it is a hybrid of the two schools in CA modelling. It has the ability to model urban growth and incorporate detailed land use data. Reasons for choosing this model are: (1) the shareware availability means that any researcher could perform a similar application or experiment at no cost provided they have the data, (2) the model is portable so that it can be applied to any geographic system at any extent or spatial resolution, (3) the presence of a well-established internet discussion forum to support any problems and provide insight into the model's application, (4) a history in the geographic modelling literature that documents both theory and application of the model and (5) the ability of the model to project urban growth based on historical trends with urban and non-urban data. SLEUTH incorporates two models: the UGM and the land cover deltatron model. The name SLEUTH has been derived from the image input requirements of the model: Slope, Land cover, Exclusion, Urbanization, Transportation, and Hillshade. In order to run the model, one usually prepares the data required, verifies the model functions, calibrates the model, predicts the change and builds probability maps. SLEUTH modelling can be implemented in different modes. In running the model, five coefficients including diffusion, breed, spread, slope resistance and road gravity are calculated followed by estimation of four growth rules consisting of spontaneous growth, new spreading centre growth, edge growth and road-influenced growth. The aim of this paper is to understand Dhaka city's growth dynamics and to forecast its future expansion by the year 2030 using SLEUTH.

Study area and data

Study area

The study area is Dhaka City Corporation and its surrounding areas shown in Figure 1. The study area is located in central Bangladesh. It covers the oldest core part of Dhaka city

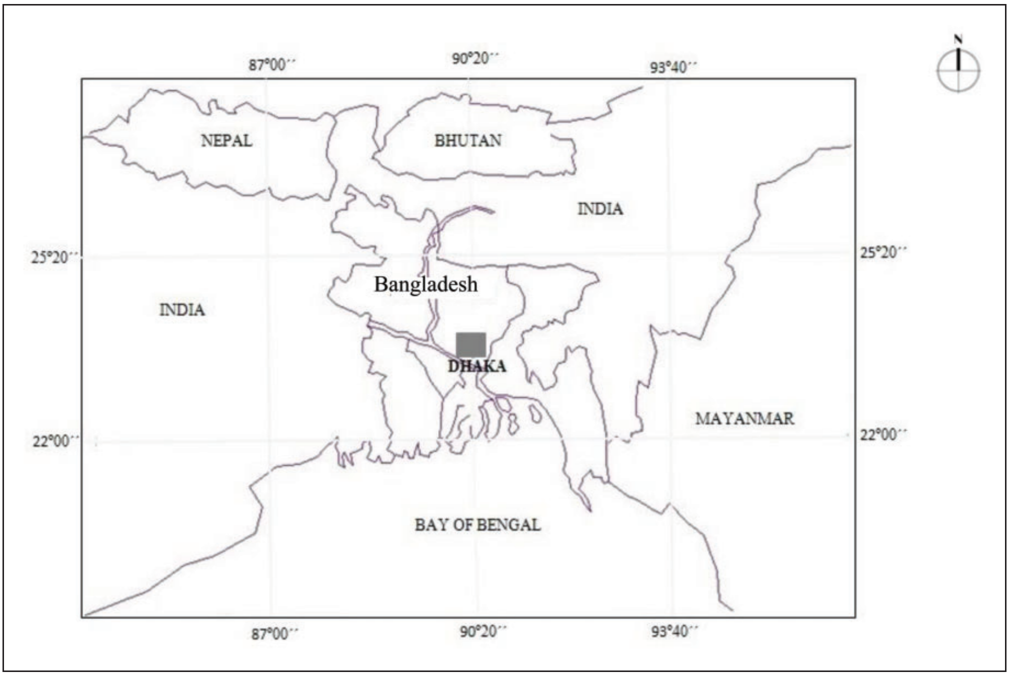

Figure 1. The grey rectangle corresponds to the study area (axes show geographic latitude and longitude in degrees).

(old Dhaka), the planned areas and even the unplanned new generation areas that are called 'Informal Settlements'. This area has great probability to be completely urbanized in the near future based on the current trend. Topographically, the area is flat with a surface elevation ranging from 1 to 14 m. Most urban areas are located at elevations ranging from 6 to 8 m (JICA, 1992). The city is surrounded by four rivers the Buriganga, Turag, Tongi and the Balu, which flow to the south, west, north and east, respectively. Average rainfall is high. The city has a humid sub-tropical monsoon climate and receives approximately 2000 mm of rainfall annually, more than 80% of which falls during the monsoon season from June to September. The occurrence of heavy monsoon rainfall combined with the low elevation flood water runoff from the rivers surrounding the city means that Dhaka is very prone to monsoon flooding.

In Figure 2, the increasing growth trend of Dhaka City in terms of area over time is shown. In the pre-Mughal and Mughal period (1205–1757) the area was only 10 sq km, with in the British (1758–1947) and Pakistan periods (1947–1971), the area was 22 and 85 sq km, respectively (Chowdhury and Faruqui, 1989). Now in the Bangladesh period, the area of greater Dhaka is 1530 sq km (World Bank, 2007b).

Data

Data preparation. The data preparation, calibration and prediction procedures followed here were mostly derived from the project Gigalopolis (http://www.ncgia.ucsb.edu/projects/gig/) and different previous work on the SLEUTH model. This study utilized data from various sources and topographic maps. The satellite data for the study area were developed from the USGS website and topographic maps from the Survey of Bangladesh. The SLEUTH model

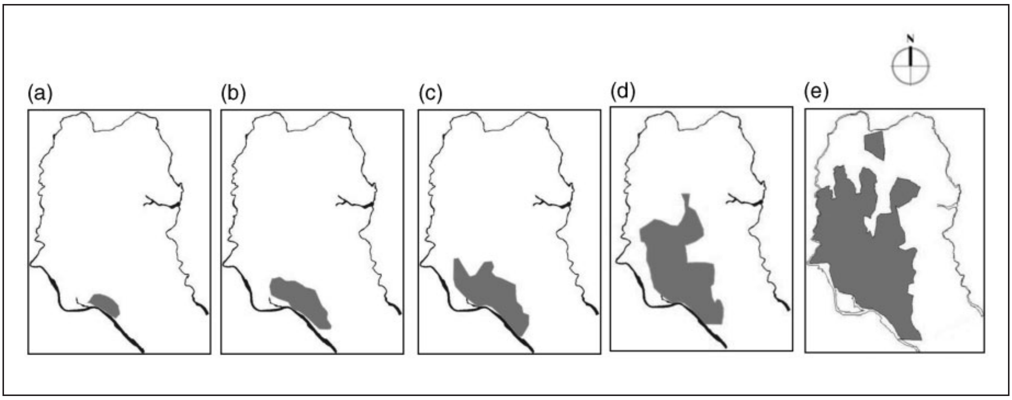

Figure 2. City boundary of Dhaka city over the year. (a) Pre Mughal (1205–1610), (b) Mughal (1620–1757, (c) British (1758–1947), (d) Pakistan (1947–1971) and (e) Bangladesh (1971 onward).

Table 1. Input data of SLEUTH model.

SLEUTH inputs	Map sources	Date acquired (day/month/year)	Sensor	Quality (100% cloud free)
Urban	LANDSAT	13/02/1989	Landsat 4–5 Thematic Mapper (TM)	7
	LANDSAT	24/11/1999	Landsat 7 Enhanced Thematic Mapper Plus ETM+)	9
	LANDSAT	26/10/2009	Landsat 4–5 Thematic Mapper (TM)	9
	LANDSAT	24/03/2014	Landsat 8 Operational Land Imager (OLI)	9
Road	Dhaka City Base Map (1989, 2001, 2009), Google Earth 2014			
Excluded	Google Earth, 2014			
Slope	DEM from USGS website			
Hillshade	DEM from USGS website			

requires data on Slope, Land use, Exclusion, Urban Extent, Transportation and Hillshade. In Table 1 the input data types and the year(s) of the data are shown.

Slope layer. The slope data were derived from the digital elevation model (DEM) of the Shuttle Radar Topography Mission (SRTM). SRTM is maintained by NASA. It provides digital elevation data (DEM) for over 80% of the globe.

Exclusion layer. The exclusion layer shows the area where urban growth would not occur without formal interventions. In this study, the excluded areas were identified as rivers, canals, airports, the zoo, botanical gardens, national monuments and parks which are not extensive. These areas occupy roughly 5% of the total city area.

Urban extent layer. Four historical urban maps were used for 1989, 1999, 2009 and 2014. This layer is the most important input of the model, so in preparing this layer special caution and attention was applied. Urban areas were derived by classifying LANDSAT imagery. To produce an accurate classification, the images were classified into five classes by supervised classification. Subsequently, these classes were reclassified into built and non-built classes with maximum likelihood classification as shown in Table 2.

Table 2. Details of built and non-built classes.

Major land classes	Detail sub classes	Description
Built-up area	Built-up area	All residential, commercial, industrial areas, settlements and transportation infrastructure
Non-built area	Water body	River, permanent open water, lakes, ponds, canals and reservoirs
	Vegetation	Trees, shrub lands and semi-natural vegetation: deciduous, coniferous and mixed forest; palms; orchard; herbs; climbers; gardens; inner-city recreational areas; parks and playgrounds; grassland and vegetable lands
	Low land	Permanent and seasonal wetlands, low-lying areas, marshy land, swamps, mudflats, all cultivated areas including urban agriculture; crop fields and rice-paddies
	Fallow land	Fallow land, earth and sand land in-fillings, construction sites, developed land, excavation sites, solid waste landfills, open space, bare and exposed soils

Table 3. Classification accuracy per year.

Year	Class name	Reference totals	Classified totals	Number correct	Producer accuracy (%)	User Accuracy (%)	Kappa for each category	Overall Kappa statistics	Over all classification accuracy (%)
1989	Built area	58	60	58	100.00	96.67	0.93	0.96	98.33
	Non-built area	62	60	60	96.67	100.00	1.00		
1999	Built area	58	60	57	98.28	95.00	0.90	0.93	96.67
	Non-built area	62	60	59	95.15	98.33	0.96		
2009	Built area	63	60	60	95.24	100.00	1.00	0.95	97.50
	Non-built area	57	60	75	100.00	95.00	0.90		
2014	Built area	61	60	60	98.36	100.00	1.00	0.98	99.17
	Non-built area	59	60	59	100.00	98.33	0.96		

The accuracy was tested by kappa statistics using stratified random sampling from two classes (60 samples from each class). The result was satisfactory. The kappa statistic showed very high scores for each year as shown in Table 3. The year wise classification error matrix per year is shown in Table 4.

Transportation layer. Four historical transportation layers were used for the years 2014, 2009, 1999 and 1989. The road networks in 1989, 1999 and 2009 were digitized from various transportation network maps of Dhaka city collected from the Survey of Bangladesh. The road network of 2014 was digitized from Google Earth.

Land use layer. An optional input to the SLEUTH model is land use. As already shown in Table 2, the LANDSAT images were first classified into five land classes in the process of

Table 4. Year wise classification error matrix per year.

Year	Classified data	Reference data (number of samples = 120)		
		Built-up area	Non-built-up area	Row total
1989	Built area	58	02	60
	Non-built area	00	60	60
	Column total	58	62	120
1999	Built area	57	03	60
	Non-built area	01	59	60
	Column total	58	62	120
2009	Built area	60	00	60
	Non-built area	03	57	60
	Column total	63	57	120
2014	Built area	60	00	60
	Non-built area	01	59	60
	Column total	61	59	120

preparing the urban extent layer. This land use layer has not been used in the model because it corresponds to the de facto land use on the ground that has a limited role in restricting urban sprawl in the area. Formal (de jure) land use plans are not available for this region.

Image processing. All of the data layers were projected to the Universal Transverse Mercator projection system. All the maps were resampled to 30 m resolution raster files. All of the data layers had 636 columns and 864 rows. All input layers of the model are shown in Figure 3.

Methods

The source code of the model was obtained from the Gigalopolis website (SLEUTH3.0beta_p01 version). The working process of the model is discussed below.

Model calibration

The goal of model calibration is to derive a set of values for the five growth coefficients that can effectively model the growth during the past time series. SLEUTH model calibration is performed in three phases: coarse, fine and final. Each coefficient is gradually modified through the Monte Carlo method (Clarke et al., 1997). Several test runs were made by changing the coefficient values. The output files and the images were examined by visual inspection. After testing the data, calibration was conducted using brute force. The general process of the brute force Monte Carlo method is that the range of values for each coefficient is first divided into four equal intervals in the coarse calibration. In other words, each coefficient has five possible values: 0, 25, 50, 75 and 100. SLEUTH simulates land use change with each probable set of values and evaluates the accuracy of simulated results. The best sets of values are then chosen by fine and final calibration. Commonly, the Optimal SLEUTH Metric (OSM) is used as a single goodness-of-fit metric (Chaudhuri and Clarke, 2013). The OSM is derived as a product of the compare, population, edges, clusters, slope, X-mean and Y-mean metrics.

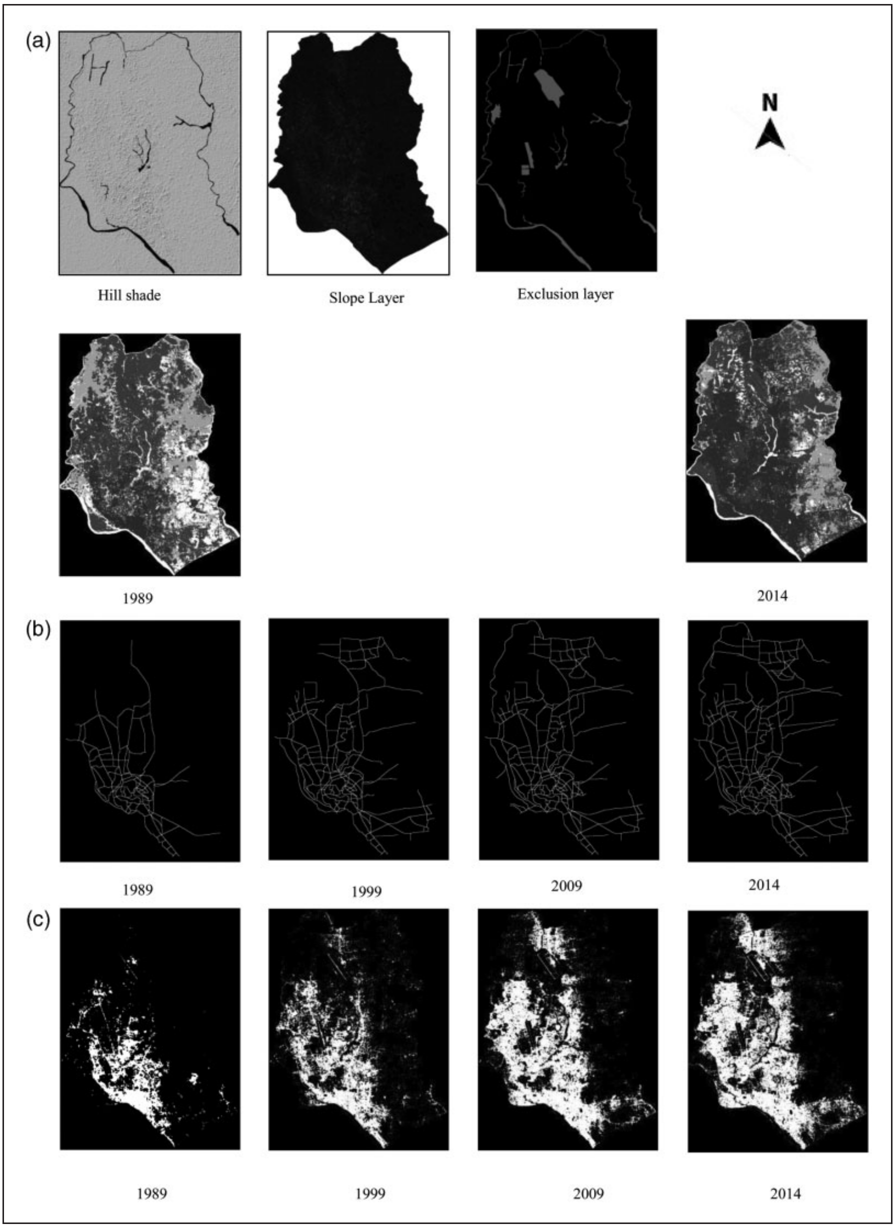

Figure 3. SLEUTH input layers. (a) Land use layer, (b) transport layer and (c) urban layer.

The definition of each statistic is as follows:

- Product: All other scores multiplied together;
- Compare: Modelled population for final year/actual population for final year, or IF $P_{modelled} > P_{actual}$ {1 – (modelled population for final year/actual population for final year)};
- Pop: Least squares regression score for modelled urbanization compared to actual urbanization for the control years;

Table 5. Calibration result and best fit value.

	Coarse		Fine		Final		Prediction best fit value
Growth co-efficient	Range	Step	Range	Step	Range	Step	
Dispersion	1–100	25	0–20	5	0–20	5	1
Breed	1–100	25	25–75	20	20–60	8	36
Spread	1–100	25	50–100	5	80–100	4	100
Slope	1–100	25	0–20	5	0–15	3	1
Road gravity	1–100	25	0–100	20	40–100	12	56
Monte Carlo iterations	5		8		10		
Run	3130		6480		6480		

- Edge: Least squares regression score for modelled urban edge count compared to actual urban edge count for the control years;
- Clusters: Least squares regression score for modelled urban clustering compared to known urban clustering for the control years;
- Cluster size: Least squares regression score for modelled average urban cluster size compared to known average urban cluster size for the control years;
- Lee-Sallee: A shape index, a measurement of spatial fit between the model's growth and the known urban extent for the control years;
- Slope: Least squares regression of average slope for modelled urbanized cells compared to average slope of known urban cells for the control years;
- % urban: Least squares regression of percentage of available pixels urbanized compared to the urbanized pixels for the control years;
- X-mean: Least squares regression of average x-values for modelled urbanized cells compared to average x-values of known urban cells for the control years.

Using the best OSM coefficients derived from calibration, SLEUTH is run for the historical time period to initialize forecasting. The coefficient values are shown in Table 5 as derived from the forecasting mode to predict the growth of the study area.

Urban growth prediction

The result of executing the prediction mode is a probabilistic map which shows the probability of each cell being urbanized in the future. Figure 4 shows the urban extent probability map of 2015, 2020, 2025 and 2030 of Dhaka city in cumulative percentage.

Results

The fitness metrics are shown in Figure 5. Most of the statistics present high values of goodness of fit, indicating the ability of the model to reliably replicate past growth. The result of model calibration is shown in Figure 6. It reflects a high score in the spread parameter (100) that indicates the dominance of urbanization outward from the existing urban centres. Another high score of road gravity (56) shows that urban growth has been affected by road networks significantly. Also, the breed parameter (36) scoring third position among the coefficients indicates the considerable importance of the establishment of new

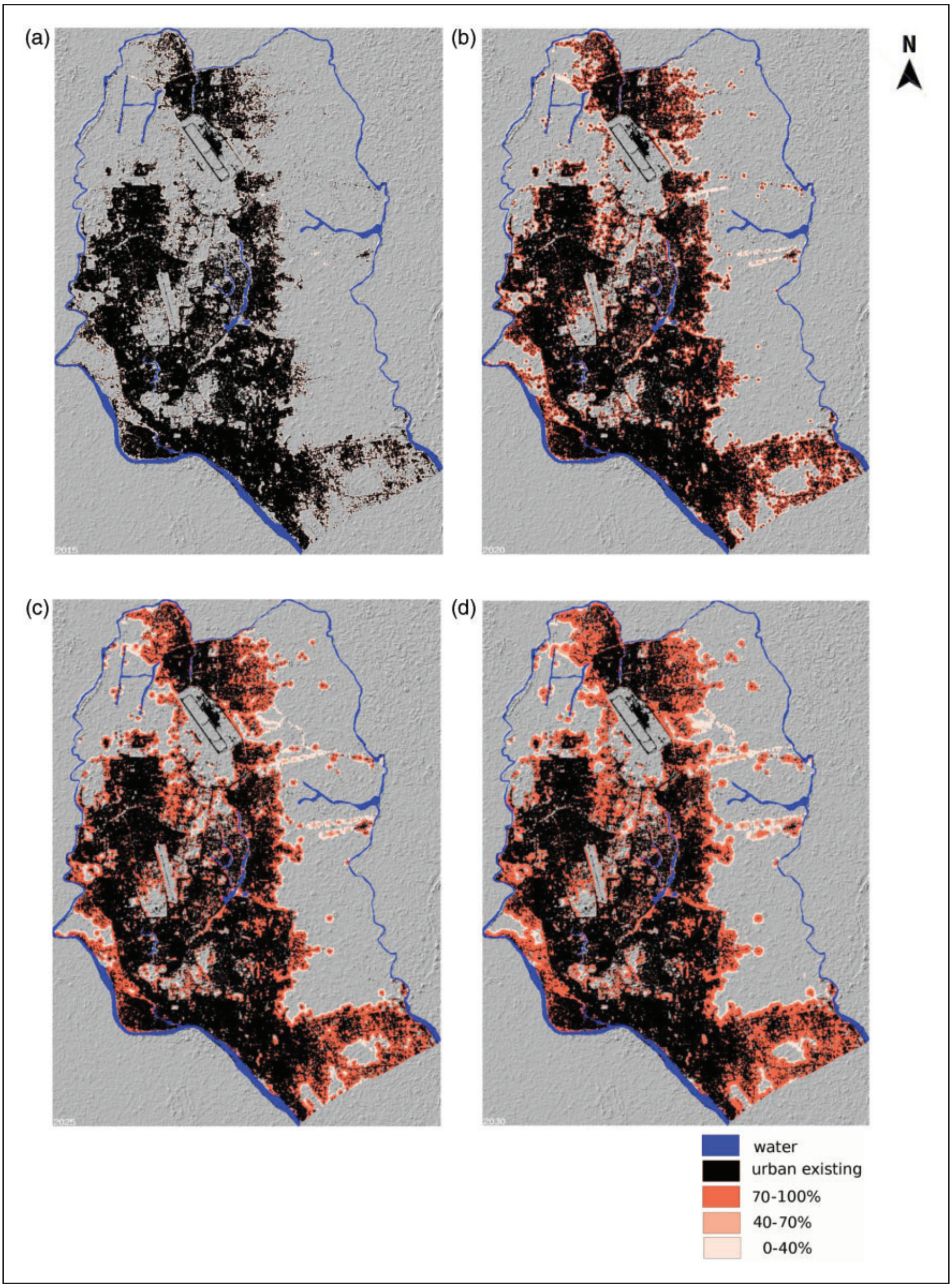

Figure 4. Urban extent probability map (2015–2030) in cumulative percentage. (a) 2015, (b) 2020, (c) 2025 and (d) 2030.

urban centres. The score for slope resistance is almost negligible verifying that topography is obviously not a limiting factor for urban sprawl in Dhaka city. Finally, the low diffusion coefficient shows that Dhaka city has a compact form of growth with its main urbanization occurring near the existing urban areas and urban cores.

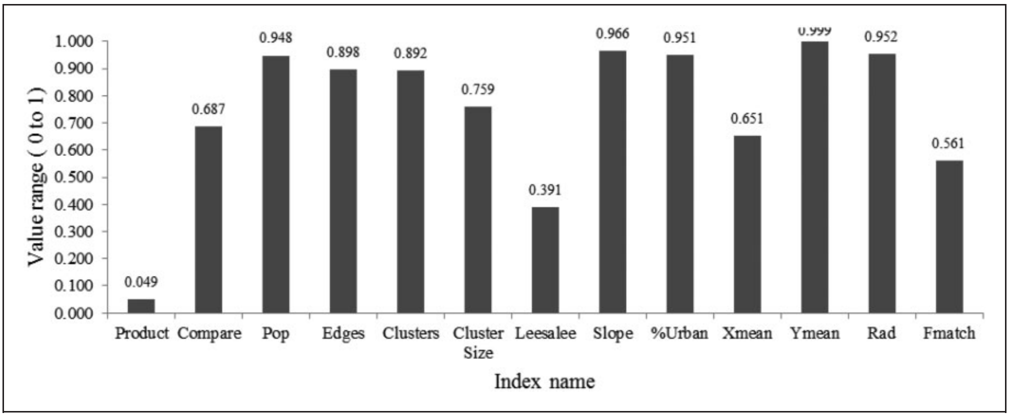

Figure 5. Statistics of the goodness-of-fit parameters (index) for modelling Dhaka city expansion (value range from 0 to 1, with 1 being a perfect fit).

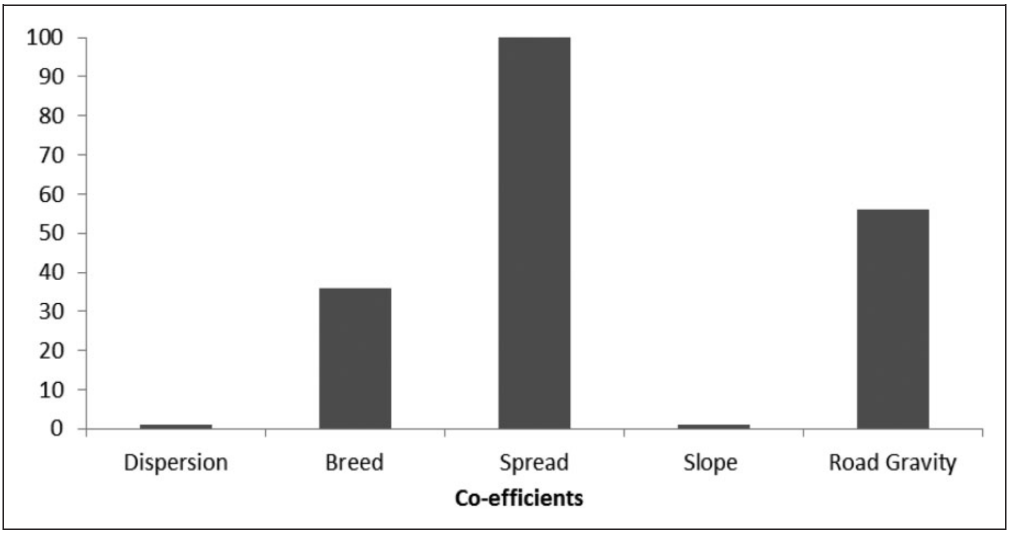

Figure 6. Best fit parameters for forecasting.

Figure 7 shows in a graph the increasing trend of urban expansion from 2014 to 2030 in terms of acreage. It is evident in this graph that urban extent is highly correlated with population. The correlation is very high ($r^2 = 0.99$).

Another interesting finding is that the model predicts that the city will expand towards the north and north-west directions. This is useful for policy makers who can get an idea about the city's future expansion direction.

A final finding is that in the year 2030 some activities will be affected directly or indirectly in the fringe areas of Dhaka city by land take. Among them agriculture, fisheries, recreation, flood control, etc. are mentionable. It is clearly shown in Figure 8 that approximately 20% of the present urban fringe area will be converted to built-up land.

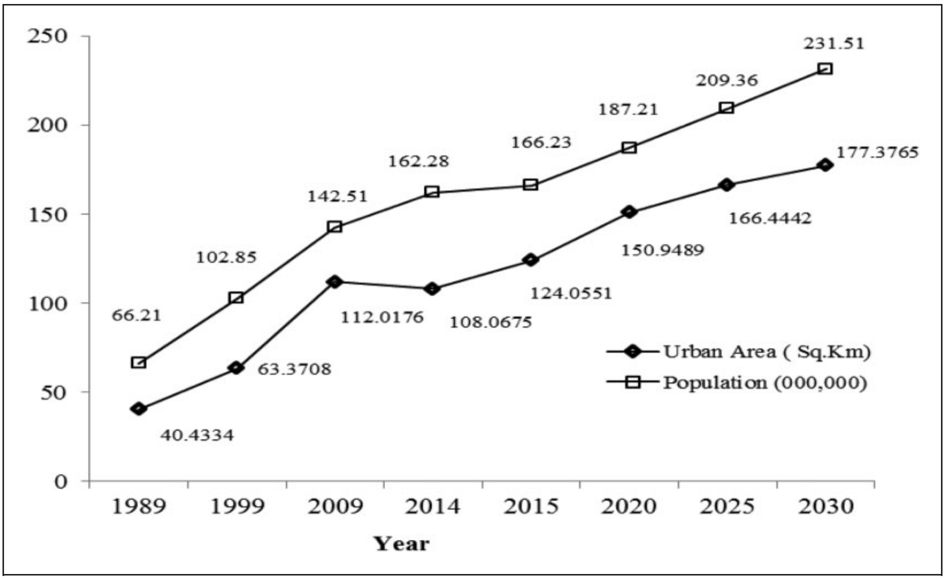

Figure 7. Increasing trend of urban expansion and urban population of Dhaka city (2014–2030).

In Figure 9, flood-prone areas are overlaid onto the probability map of 2030. The flood-prone zone has been digitized from a map of the Bangladesh Centre for Advanced Studies showing flooded areas during the 1998 flood (Cox, 2012). This severe flood affected two-thirds of the country and made 30 million people homeless. It is evident in Figure 9 that a lot of the foreseen urbanization pressure is within the flood-prone areas.

Conclusion

The application of SLEUTH in developing countries like Bangladesh is unique in multiple ways. Cities such as Dhaka expand rapidly and are unplanned while local data and know-how of planning models are limited. In that respect, SLEUTH is a very suitable approach because it can efficiently model urban growth dynamics, in a relatively straightforward manner, using a relatively minimal input dataset. Input data can currently be created even when local datasets are limited. In particular, land cover data can be derived from the LANDSAT sensor series, globally, for the past 40 years. Digital elevation data are obtained from SRTM or similar semi-globally available datasets. The transportation network can be based on online databases such as Google Maps or OpenStreetMap.org and completed with conventional historical locally available maps. For developing countries it is especially important that SLEUTH is provided at no cost while sufficient examples exist in the literature to aid newcomers in the field. This context shows why local planning authorities can indeed be equipped with such models. Another factor contributing to the uniqueness of applying SLEUTH in Dhaka is that the process of urbanization is very different compared to industrialized parts of the globe. For example, in the time frame of this study (1989–2014), the population of Europe (EU28) has increased by 6.5% whereas in Bangladesh the increase for the same period is almost 50%. In terms of car ownership, which clearly affects road gravity in the model, merely one in a thousand inhabitants in Dhaka owns a car when non-motorized vehicles are excluded (Mannan and Karim, 2001) whereas for Europe this is almost one in two.

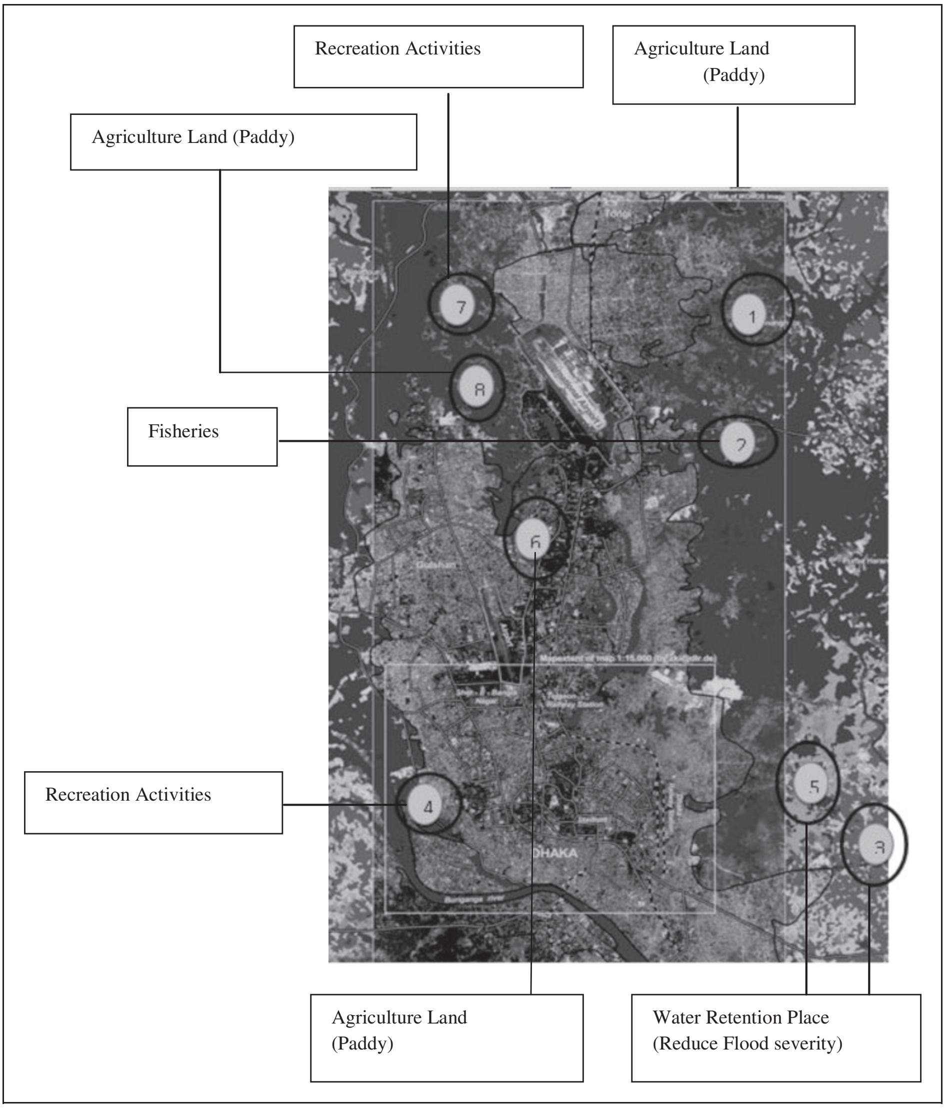

Figure 8. Mostly affected areas are shown in circle due to future urban expansion.

Overall, in the case of Dhaka, SLEUTH provided a very useful insight not only of the magnitude of future expansion but most importantly of its spatial pattern. This insight is crucial to maintain sustainable urbanization and control population density by balancing between population growth and urban expansion. In addition, the prediction of the spatial pattern of the pressure for urbanization can be combined with flooding plans and models as the area suffers from catastrophic floods during the rainy season that cause severe damage. Subsequently, expansion can be relaxed towards safer areas where water and drainage management plans can be prepared to continue the natural flow of water. Conversely, pressure for expansion in areas at risk can be anticipated based on SLEUTH's output and controlled so that land can be preserved for water runoff to reduce the over-flowing and flooding.

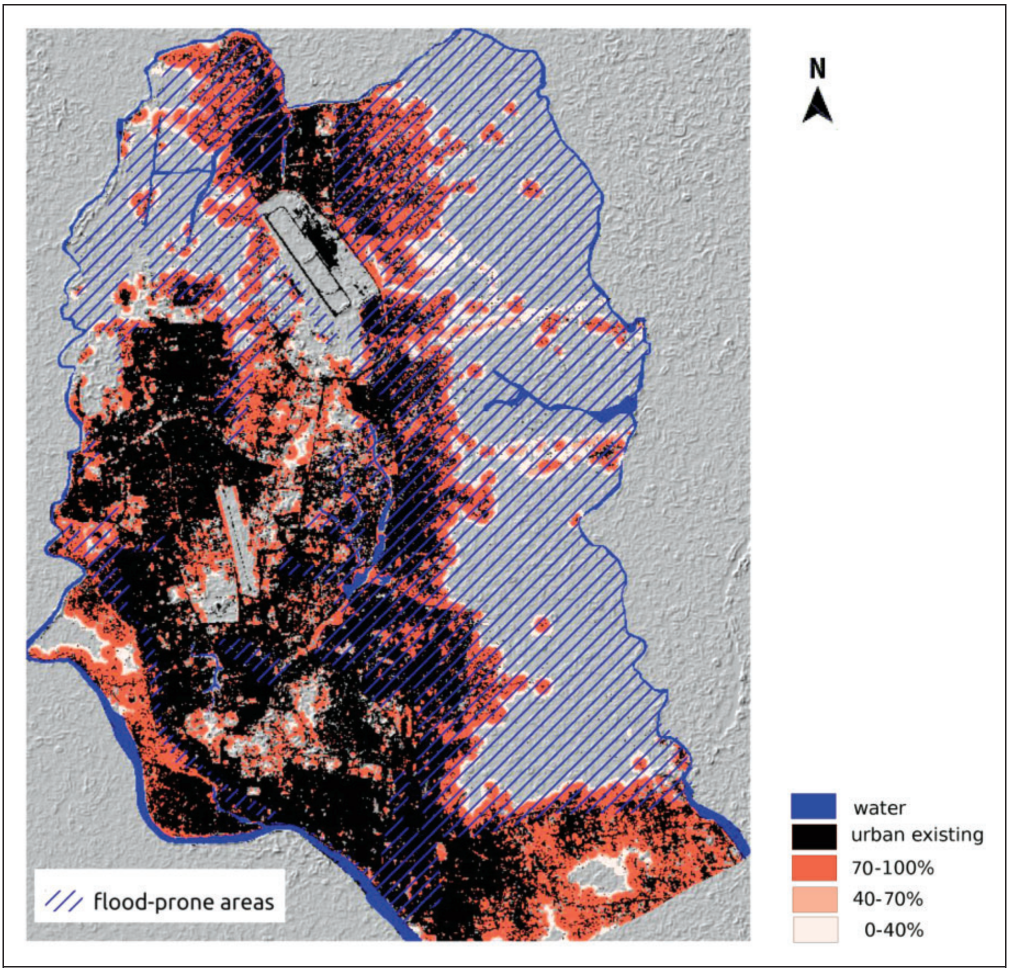

Figure 9. Flood-prone areas overlaid to the urban extent probability map for 2030. (Source: Bangladesh Centre for Advanced Studies for Dhaka flood-prone areas adapted from Cox, 2012).

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References

Batty M, Longley P and Fortheringham S (1989) Urban growth and form: Scaling, fractal geometry, and diffusion-limited aggregation. *Environment and Planning A* 21(11): 1447–1472.

Batty M, Xie Y and Sun Z (1999) Modeling urban dynamics through GIS-based cellular automata. *Computers Environment and Urban Systems* 23(3): 205–233.

Benenson I (1998) Multi-agent simulations of residential dynamics in the city. *Computers, Environment and Urban Systems* 22(1): 25–42.

Chaudhuri G and Clarke KC (2013) The SLEUTH land use change model: A review. *The International Journal of Environmental Resources Research* 1(1): 88–104.

Cheng J and Masser I (2003) Urban growth pattern modeling: A case study of Wuhan city, PR China. *Landscape and Urban Planning* 62(4): 199–217.

Chowdhury AM and Faruqui S (1989) Physical growth of Dhaka City. In: Ahmed SU (ed.) *Dhaka: Past, Present and Future*. Dhaka: The Asiatic Society of Bangladesh, pp. 43–61.

Clarke KC, Hoppen S and Gaydos L (1997) A self-modifying cellular automaton model of historical urbanization in the San Francisco Bay area. *Environment and Planning B: Planning and Design* 24(2): 247–261.

Cox W (2012) Evolving urban form: Dhaka. Available at: http://www.newgeography.com/content/003004-evolving-urban-form-dhaka (accessed 10 July 2015).

Dietzel C and Clarke KC (2006) The effects of disaggregating land use categories in cellular automata during model calibration and forecasting. *Computers, Environment and Urban Systems* 30(1): 78–101.

Engelen G, White R, Uljee I, et al. (1995) Using cellular automata for integrated modeling of socio-environmental systems. *Environmental Monitoring and Assessment* 34(2): 203–214.

Islam N (1999) Urbanization, migration and development in Bangladesh: Recent trends and emerging issues. CPD-UNFPA Series 1. Dhaka, Bangladesh: Centre for Policy Dialogue.

Japan International Cooperation Agency (JICA) (1992) *Feasibility Study of Greater Dhaka Flood Protection Project, FAP 8A Interim and Main Reports*. Dhaka, Bangladesh: Flood Plan Coordination Organization (presently WARPO).

Li X and Yeh AG (2000) Modeling sustainable urban development by the integration of constrained cellular automata and GIS. *International Journal of Geographical Information Science* 14(2): 131–153.

Mannan MS and Karim MM (2001) Current state of the mobility of the urban dwellers in Greater Dhaka. Paper presented at the *94th annual conference and exhibition of air and waste management association*, Orlando, Florida, USA, 24–28 June. Available at: http://www.eng-consult.com/pub/mobility-paper.PDF (accessed 10 July 2015).

Moeller MS (2005) *Remote Sensing for the Monitoring of Urban Growth Pattern*, 11S, ASU. Tempe, AZ: International Institute for Sustainability, Arizona State University. Available at: http://www.isprs.org/proceedings/XXXVI/8-W27/moeller.pdf (accessed 10 July 2015).

Pijanowski BC, Brown DG, Shellitoc BA, et al. (2002) Using neural networks and GIS to forecast land use changes: A land transformation model. *Computers, Environment and Urban Systems* 26(6): 553–575.

Rafiee R, Mahiny AS, Khorasani N, et al. (2008) Simulating urban growth in Mashad City, Iran through the SLEUTH model (UGM). *Cities* 26(2009): 19–26.

Stalker P (2000) *Handbook of the World*. New York: Oxford University Press.

Stathakis D (2009) How many hidden layers and nodes. *International Journal of Remote Sensing* 8(30): 2133–2147.

Stathakis D and Vasilakos A (2006) Comparison of several computational intelligence based classification techniques for remotely sensed optical image classification. *IEEE Transactions in Geoscience and Remote Sensing* 8(44): 2305–2318.

Sun Z, Deal B and Pallathuchril WG (2005) The land use evolution and impact assessment model: A comprehensive urban planning support system. *URISA: Journal of the Urban and Regional Information Systems Association* 21(1): 57–68.

Takayama M and Couclelis H (1997) Map dynamic integrating cellular automata and GIS through Geo algebra. *International Journal of Geographical Information Science* 11(1): 73–91.

Tobler WR (1979) Cellular geography. In: Gales S and Olson G (eds) *Philosophy in Geography*. Netherlands: Springer, pp. 339–346.

Torrens PM (2000) *How Cellular Models of Urban Systems Work*. CASA Working Paper 28. London: Centre for Advanced Spatial Analysis, University College London.

Veldkamp A and Lambin EF (2001) Predicting land-use change. *Agriculture, Ecosystems and Environment* 85(1): 1–6.

World Bank (2007a) Dhaka: Improving living conditions for the urban poor. Sustainable Development Unit, South Asia Region, Report No. 35824-BD. Available at: http://siteresources.worldbank.org/BANGLADESHEXTN/Resources/295759-1182963268987/dhakaurbanreport.pdf (accessed 10 July 2015).

World Bank (2007b) *Dhaka metropolitan development plan: Strategic environmental assessment*. Washington, DC: World Bank. Available at: http://documents.worldbank.org/curated/en/2007/07/17207304/dhaka-metropolitan-development-plan-strategic-environmental-assessment (accessed 10 July 2015).

White R and Engelen G (1993) Cellular automata and fractal urban form: A cellular modeling approach to the evolution of urban land-use patterns. *Environment and Planning A* 25(8): 1175–1199.

Wu F (1998) SimLand: A prototype to simulate land conversion through the integrated GIS and CA with AHP derive transition rules. *International Journal of Geographical Information Science* 12(1): 63–82.

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