Simulating urban growth in South Asia: A SLEUTH application

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Abstract

Megacities, especially in South Asia, poses significant challenge towards sustainable urban development. The sheer volume of population and unprecedented pace of growth demands a closer look at the process and pattern of urbanization. The present study used SLEUTH cellular model to simulate and forecast future urban growth in Kolkata Metropolitan region (KMR) in eastern India. With population of 14 million, KMR is one among the three megacities in India and has a significant influence in economic development of eastern and north-eastern India. The objective of this study to incorporate regional urban growth characteristics to simulate urban growth using SLEUTH model. Land use and urban maps of 1989, 1999, 2005, and 2010, and other GIS data to simulate historical pattern of growth using SLEUTH land use change model. The present study used two modifications, to better adapt the model to its regional characteristics. First, it used relative connectivity of the road as weights for modelling instead of pre-existing road classification; and secondly, it used socio-economic and physical drivers of urbanization to create an urban attractiveness surface to simulate and forecast urban growth. Urban growth was forecasted until year 2025. Primary results suggest that the future urban growth will increase in the northern part of the region following the existing cities and towns along the Hooghly river. Modelling and forecasting future urban growth can provide valuable insight on current trends of urbanization and its potential impact on the environment.

Keywords: urbanization, SLEUTH, South Asia

1. Introduction

Urban simulation models have been used in land use change (Magliocca et al. 2015) to understand the process and pattern of change. Among various approaches (Agarwal et al. 2002) to simulate urban growth, cellular automata models have been arguably most popular due to its relative ease of application (Batty & Xie 1994). Among the cellular automata models, SLEUTH (Clarke et al. 1997) have applied in number of cities in the world (Chaudhuri & Clarke 2013). Its open source nature and relatively low need for data has made its modifications and adaption popular in various parts of the world (Chaudhuri & Clarke 2013). In a deterministic model like SLEUTH, the underlying rules capture the historical pattern of growth and that information is used to predict future growth. However locally there are variety of factors in addition to the required layers that affect or determines future growth. There have been number of studies which used exclusion layer of the SLEUTH to develop scenarios (Chaudhuri & Clarke 2012; Onsted & Clarke 2012) and incorporate local knowledge that affect urban growth or make areas attractive to urban growth (Mahiny & Clarke 2012; Jantz et al 2015) for realistic predictions. The objective of this study to incorporate regional urban growth characteristics to simulate urban growth using SLEUTH model. The present study is currently experimenting with multiple approaches to address the aforementioned objective and the approach presented here is the one with relatively higher accuracy among others.

2. Study Area

The present study focuses on the eastern part of India covering an area of 25,137.9 sq.km in eastern India (Fig. 1). Administratively, the footprint corresponds to 9 districts in the state of West Bengal in India, and Kolkata Metropolitan region (KMR). This densely populated area with the elevation varying from 0 – 10m above mean sea level poses high risk from climate change impacts (Danda et al. 2011). The state-level HDI is 0.51 (Suryanarayana et al. 2011) with 19.8% of people living under poverty level (GoI-MoF 2015). The region is well connected to the rest of the country and the world by road, railways, air transport, and port, with relatively large proportion of population are employed in the secondary and tertiary sectors of the economy.

Figure 1: Location of Study Area

3. Data and Methodology

The study used SLEUTH cellular automata model (Clarke et al. 1997) to simulate and forecast urban growth in this region. The model used slope, land use, exclusion, urban, transportation and hillshade layers and sequential brute force calibration using behavioural rules to calibrate observed change

(Silva & Clarke 2002). The final calibration process generated an optimum metrics called OSM (0.65) (Dietzel & Clarke 2007) which determined the ability of the set of parameters to capture the observed change, and were used to forecast future urban growth until 2025 (Chaudhuri & Clarke 2014). For validation of the predicted images, Kappa simulation (Chaudhuri & Clarke 2014; van Vliet et al. 2011) was used and the observed urban map of 2011 was compared with simulated urban map of 2011.

Land use and land cover (LULC) maps of 1989, 1999, 2005, 2010, and 2011 (Chaudhuri & Mishra 2016), developed using ensemble tree-based classifier called Random Forest (RF) (Breiman 2001) were used in the model. The accuracy of the observed maps vary from 80%-85%. The hillshade layer was developed from SRTM data. In the exclusion layer, the Sundarban National Forest, which is a protected area, and waterbodies were excluded from future urban development.

The present study used 2 modifications in the road layer and the slope layer, to adapt the model to its regional characteristics. First, the road layer, was modified to represent a relative level of connectivity (Porta et al. 2006), to assign weights instead of pre-existing classification scheme. The relative connectivity was measured using degree centrality metric in a dual graph approach (Fig. 2) (Porta et al. 2006). It is assumed that roads with higher centrality makes the local area relatively more accessible, and thus will have higher influence on urban growth in that area.

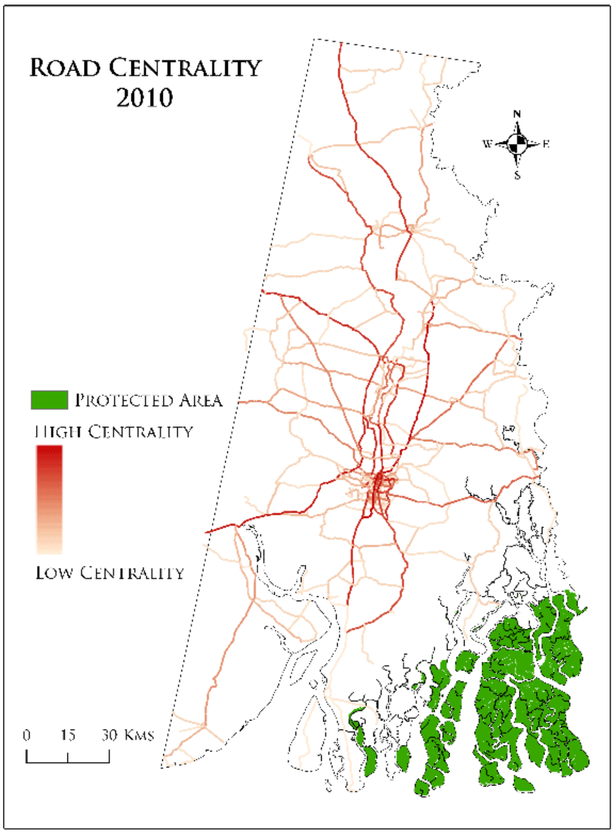

Figure 2: Road Centrality

Secondly, an urban attractiveness layer was developed and used instead of topographic slope (Fig. 3). The topographic slope of the study area is low and homogeneous, and thus it doesn't act as a physical barrier to future urban growth. Socio-economic factors such as population density, proportion of literate population, and proportion of primary workers; and locational factors such as proximity to market (Kolkata and other Class 1 cities (population >100,000)), proximity to road, proximity to railway stations, were used in a spatial error model, to understand their relationship with urbanization. The predicted output was used as the urban attractiveness layer, where each pixel represents the slope of urban development, and thus called modified slope layer. In the modified slope layer, the values vary from 0-100, and the critical slope of the model is 100. The low values represent areas which are socio-economically and physically attractive for urban development and thus likely to develop first compared to the less attractive steeper slopes, until a critical slope is reached at which building is impossible. The relative pressure to build upon a location which is socio-economically and physically unattractive to develop is dynamic and related to the proportion of attractive location available and the unattractive location's proximity to an already established settlement.

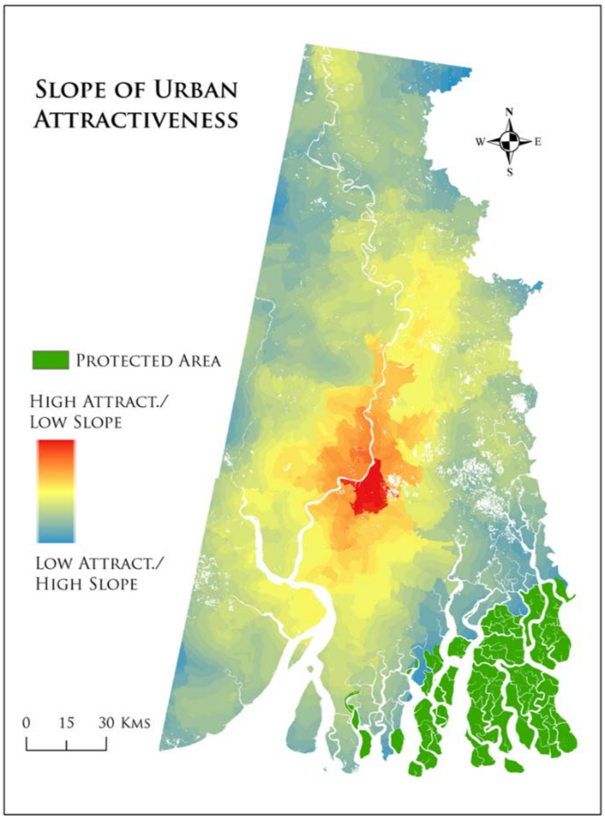

Figure 3: Modified Slope Layer of Urban Attractiveness

4. Results and Discussion

The probability map for future urban growth suggests that development will continue along the river and will most likely to increase in the north-eastern and south-western part of the region. The Kappa simulation results ($K_{simulation}$ = 0.832; $K_{Transloc}$ = 0. 881; $K_{Transition}$ = 0.945) suggests that the predicted image of 2011 was successful to capture the growth of the region. The results are relatively better than all the other approaches (multi-criteria analysis, logistic regression, and different variants of spatial error model). Enriching the model with local knowledge makes model prediction more realistic and thus useful for decision making and policy planning.

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