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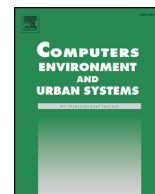
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Modeling an Indian megalopolis– A case study on adapting SLEUTH urban growth model

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1. Introduction

The rapid growth of India's urban population is one of the key processes affecting economic and urban development in Asia (Kundu, 2011). Studies of India's urban transition often suggest that the present pace of urbanization is unmatched by any other country (Kundu, 2011; Swerts, Pumain, & Denis, 2014). Between 2015 and 2050, India's urban population is projected to increase by 404 million, 30% more than China's projected urban growth and nearly twice that of any other country over the same period (UNDESA Population Division, 2014). The World Bank has estimated India's current demographic shift as the largest rural-urban migration of this century and the speed of urbanization presents unprecedented managerial and policy challenges for city planners (Christiaensen, De Weerdt, & Todo, 2013; Ghani, Goswami, & Kerr, 2012). Although these reports convey the enormous magnitude of India's urban growth, they have also contributed to an inaccurate impression that India's urbanization process has come to an apex. On the contrary, it is still a country that is dominated by villages and towns. Currently India's level of urbanization is 31% (Census of India, 2011) compared to China which is more than 50% urbanized (Swerts et al., 2014). Consequently, it is imperative to understand what factors influence the process of urbanization in India and where future urbanization is going to take place.

The magnitude of urbanization in India has been well studied (Denis, Mukhopadhyay, & Zérah, 2012; Pandey, Joshi, & Seto, 2013; Swerts et al., 2014; Taubenböck, Wegmann, Roth, Mehl, & Dech, 2009; Tian, Banger, Bo, & Dadhwal, 2014), but there is only limited information about the driving forces behind the urban growth. Previous studies have shown that at the national level factors like natural population increase, accessibility, rural-to-urban migration, industrialization and foreign direct investments have had major impacts on urbanization (Ablett et al., 2007; Denis & Marius-Gnanou, 2011; Gupta et al., 2014; Madsen, Saxena, & Ang, 2010; O'Mara & Seto, 2014; Sankhe et al., 2010). While there are many commonalities among the factors influencing urbanization throughout the country, it is important also to identify local or regional drivers to better understand the evolutionary process (Swerts et al., 2014). Land governance in India is a complex interaction of national and state level political government and multi-level planning bodies (Nagendra, Sudhira, Katti, & Schewenius, 2013; Sud, 2014). Policy is one of the crucial instruments that affects urban growth (Meyfroidt, 2016; Verburg et al., 2015). Except for a few national level urban policies, most factors that affect Indian urbanization are either local or regional. Individual state governments play a huge role in attracting new investments and reforming local policies to foster economic and urban development. As a result, there are vast disparities in the level of urban development throughout the country.

For the last two decades urban simulation models have been successfully used to understand the processes and patterns of urbanization (Magliocca et al., 2015; Paegelow, Camacho Olmedo, Mas, & Houet, 2013; Santé, García, Miranda, & Crecente, 2010). Among different types of simulation models, agent-based models are better for capturing the complex nature of social and land use systems, but cellular automata (CA) models have been arguably more popular due to their relative ease of application (Agarwal, Green, Grove, Evans, & Schweik, 2002; Batty & Xie, 1994). The SLEUTH model is one of the most popular CA- based urban simulation model and has been successfully used in many cities around the world (Chaudhuri & Clarke, 2013; Clarke, Hoppen, & Gaydos, 1997). In addition to the advantages of being a CA model, SLEUTH's open-source environment and ability to produce good results in a data sparse environment, have made its application popular. The SLEUTH model simulates and predicts urban growth based on the trend generated from the input historical data. In addition to the accuracy of the input layers, the model predictions are more reliable if the input data is from the recent past, predicted images are for the near future and the region being simulated has a medium to slow rate of development (Chaudhuri & Clarke, 2014). However, if the region being simulated has a high growth rate or the predictions are projected too far into the future then the accuracy decreases (Chaudhuri & Clarke, 2014). This is a serious challenge if the model is used to simulate cities in fast growing developing nations.

The objectives of this study were three-fold: (i) to evaluate the relationship between urbanization and its drivers in Kolkata; (ii) to evaluate the need to integrate urban driver information in the SLEUTH

urban simulation model; and (iii) to assess different approaches to integrate this information into the SLEUTH model to better forecast future urban growth. To address the first objective, a spatially lagged regression model was used (Anselin, 2013). To address the second and the third objectives, the SLEUTH model was run under different scenarios within which the standard SLEUTH simulation results were compared with the results generated from model runs that were modified by integrating the regression result. The model runs were then compared to draw conclusions on the performance and success of each run.

This study focused on the Kolkata Urban Agglomeration (hereafter called Kolkata UA). The Indian city system is not strongly hierarchical, but the spatial distribution of urban growth shows the historical dominance of the megalopolises of Delhi, Mumbai and Kolkata. Post-independence, Delhi and Mumbai continued to flourish and are well established as national powerhouses, but Kolkata's urbanization has lagged behind (Brar et al., 2014). Kolkata UA is the third largest megalopolis in India with a population of 14 million (Census of India, 2011). Since the late 1970s, state government has focused more on land reforms and agricultural development rather than industrialization. As a result, urban and economic development is plagued by inefficient land governance, defunct industries, highly politicized labor unions, and an unfriendly political environment for businesses and new investors (Guin, 2017; Roy, 2009; Sud, 2014). In the last decade, political changes at the state-level initiated new reforms to attract investment but their impact is still unknown. Thus, it can be said that urban growth in this region has been almost an organic process. Therefore, understanding the driving factors behind relatively slow but steady urban growth will provide better insight on the diverse process of urbanization in India.

The SLEUTH model simulates urban growth and land use change accurately but it does not incorporate socio-economic, demographic or ecological factors affecting the urbanization. In the last two decades, the modeling community has adapted SLEUTH toward different approaches to satisfy the respective goals of their studies (Chaudhuri & Clarke, 2013; Clarke, 2008). The three most common approaches used to adapt SLEUTH are: (1) coupling SLEUTH's Urban Growth Model (UGM) with other physical simulation models, regression based socio-economic models, and with multi-criteria analysis (Jantz, Drzyzga, & Maret, 2014a; Leao, Bishop, & Evans, 2004; Mahiny & Clarke, 2012; Rienow & Goetzke, 2015; Srinivasan, Seto, Emerson, & Gorelick, 2013); (2) using scenarios to evaluate alternate futures (Chaudhuri & Clarke, 2012; Onsted & Clarke, 2012); and (3) changing the model parameters, such as changing critical slope values, self-modification parameters, and custom growth parameters instead of using calibrated values to predict future growth (Clarke, Gazulis, Dietzel, & Goldstein, 2007; Leao et al., 2004). All these methods were applied in cities in different parts of the world and were successful in achieving their respective goals. Although 13 metrics are generated by the model to evaluate how accurately the input data is simulated, other than creating an uncertainty layer, the model does not provide any independent measure for the accuracy of the predicted output. A commonly used approach to evaluate the accuracy of the predicted maps is by conducting a pixel-by-pixel comparison between the simulated map and the observed map (Chaudhuri & Clarke, 2012). This second level of accuracy assessment is not always applicable for studies that focus on scenario-based modeling, however this is an important step for studies that aim to evaluate the drivers of growth and that then use the information for future planning and decision making.

The remaining sections of this paper follow the structure as described below. Section 2 provides a context for urbanization in India. Section 3 describes the study area, the physical location, administrative structure, socio-political scenario, and historical urban growth of the region. Section 4 provides a background on the factors influencing urbanization. This section is further subdivided into 4.1, that describes the data and methodology necessary to model drivers of urbanization,

and 4.2 that discusses the results. Section 5 provides background information about the SLEUTH model, and describes the different approaches adopted to incorporate local information in the existing literature. This section is further subdivided into 5.1 that describes data preparation and experiment set-up for SLEUTH modeling, 5.2 that describes the calibration, prediction, and validation of results from different approaches, and 5.3 that analyzes the results generated from the different approaches and the performance of the model. Finally, the paper concludes with a discussion section.

2. Urbanization in India

After 1990, economic reforms led to a rapid increase in India's formal economy. In 2005, the Indian government launched the Jawaharlal Nehru National Urban Renewal Mission (JNNURM) under which local and the national level policies were reformed to promote growth and development of 63 cities nationwide. A decade later the mission was deemed unsuccessful (Batra, 2009; IIHS, 2015; Sivaramakrishnan, 2011) but nevertheless it initiated a paradigm shift from a long tradition of rural focused development to urban development as a pathway to economic and industrial growth (Batra, 2009). Unlike older western cities that developed over centuries, the newer city regions in India are developing within a single decade.

Studies have shown that, unlike in China, Indian cities are experiencing horizontal growth with little vertical growth (Frolking, Milliman, Seto, & Friedl, 2013). This increase is happening at the cost of prime agricultural land, agrarian towns and villages mostly in peri-urban areas (Chaudhuri & Mishra, 2016; Seto, Fragkias, Guneralp, & Reilly, 2011; Taubenböck et al., 2012). The fast pace, scale and complexity of urbanization led to unmanaged growth and is likely to continue to impact negatively both to the local and global-level environment in the forms of biodiversity loss, energy use and GHG emissions (Ekholm, Krey, Pachauri, & Riahi, 2010; Gurney et al., 2015; Marcotullio, Sarzynski, Albrecht, & Schulz, 2012; O'Neill, Ren, Jiang, & Dalton, 2012). The research literature shows that in cities like Pune, Delhi, Surat, and Kolkata, rapid urban growth has resulted in a discernible urban heat island signature (Chakraborty, Kant, & Mitra, 2013; Chaudhuri & Mishra, 2016; Deosthali, 2000; Sharma & Joshi, 2014) but regionally it varies based on the type of land cover, distance from a major urban area, and size of the urban area (Chaudhuri & Mishra, 2016). Especially in tropical countries like India, the high heat challenges become multiplied in urban areas with overflowing population, poverty and poor informal infrastructure (Kovats & Akhtar, 2008). This rapid growth has resulted in uncontrolled and inefficient infrastructural development that threatens the sustainability of the environment due to a loss of biodiversity (Nagendra et al., 2013), deforestation and fragmentation (Nagendra, Sudhira, Katti, Tengö, & Schewenius, 2012), an increase in surface temperature and heat fluxes, degradation of the air quality, an increase in greenhouse gas emissions, variability in rainfall (Kishtawal, Niyogi, Tewari, Pielke, & Shepherd, 2010; Mitra, Shepherd, & Jordan, 2012; Niyogi et al., 2007), and water quality (Aggarwal & Butsch, 2011; Mohan & Kandya, 2015; Nagendra et al., 2013; Rao, Jaswal, & Kumar, 2004; Sharma, Chakraborty, & Joshi, 2015; Sharma, Ghosh, & Joshi, 2013; WHO, 2014) and an increase the vulnerability of the urban area to extreme weather related events (Parikh, Jindal, & Sandal, 2013; Revi, 2008; Suriya & Mudgal, 2012).

Simulation based modeling has been used in different parts of the world to evaluate the impacts of urbanization on the environment. If the important drivers of urbanization can be captured by simulation modeling, the model forecasts will be able to produce better results. However, for a region like India where the availability of geospatial data is limited, it is difficult to best capture the different factors that affect urban growth. This study used openly available, census-based socio-demographic and locational factors and evaluated their relationship with urbanization. It is assumed that the selected variables will serve as a useful proxy for the drivers of urbanization. The present study
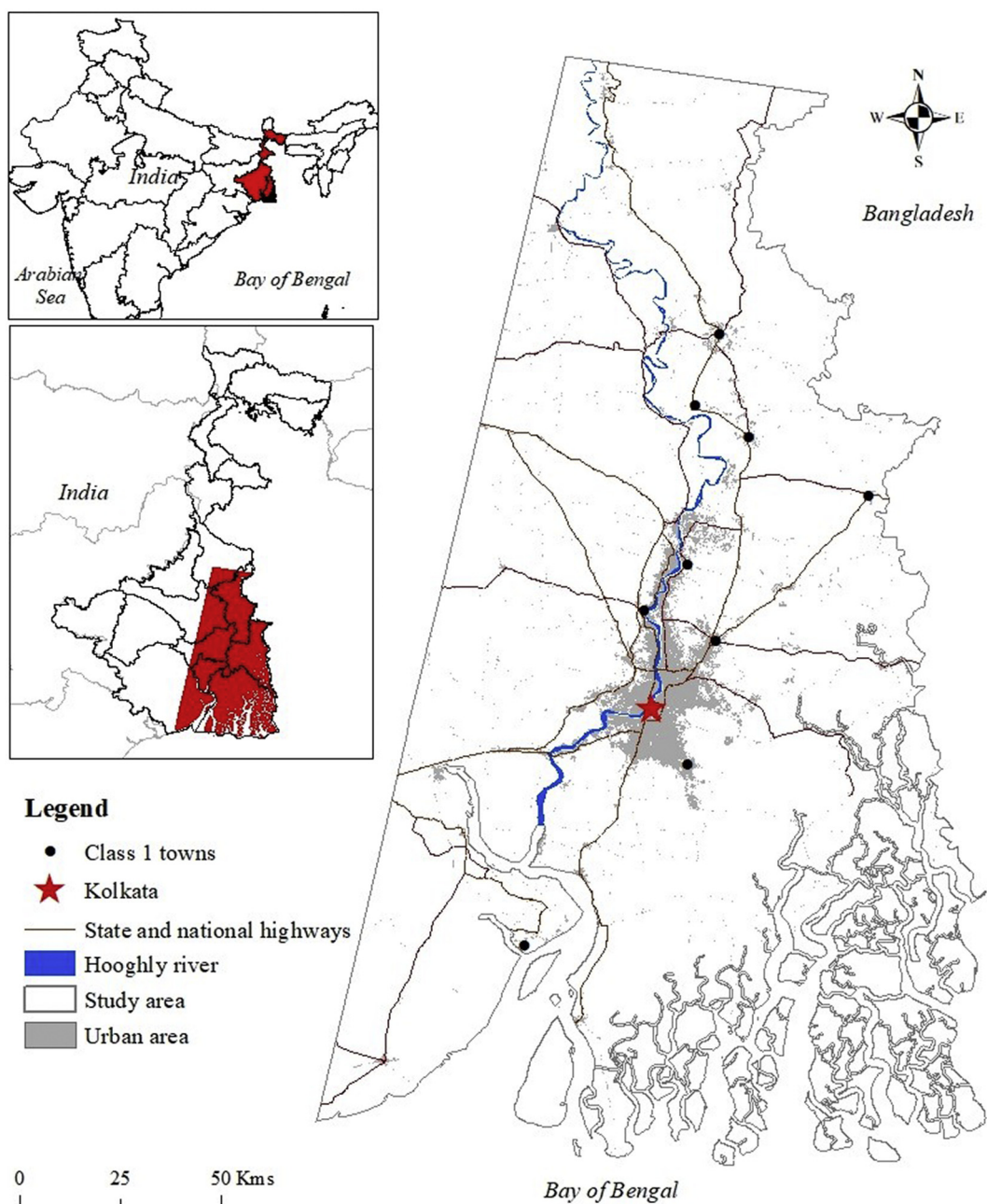
Fig. 1. Location of the study area.

used three scenarios to understand the need to integrate urban driver information into SLEUTH modeling. In the first scenario, the SLEUTH model was run using a default dataset which included 4 urban layers, 2 land use and transportation layers, 1 topographic slope, excluded, and hillshade layers, respectively. The excluded layer in this scenario included water bodies and reserved forests. In the second scenario, two experiments were run to integrate urban driver information, first via a modified excluded layer, and second via a modified slope layer. It is hypothesized that the modeling conducted using urban driver information will be better able to capture the impacts of urbanization, which will show in more accurate calibrations and more meaningful future simulations.

3. Study area

The Kolkata UA is located in the eastern part of India and is 25,138 sq.km in area (Fig. 1). The spatial extent of this study captures a bigger

area than the current footprint of the urban agglomeration to better capture the spatial heterogeneity of urbanization, and to anticipate future expansion. Situated in the low-lying coastal zone adjacent to the Bay of Bengal, this region is part of the Ganges-Brahmaputra delta in India and has one of the highest densities of population in India (Census of India, 2011; Chaudhuri & Mishra, 2016). Administratively, the footprint of the study area corresponds to nine districts (administrative sub-division of a state) in the state of West Bengal. Historically, the core urban area of Kolkata grew in tandem with its neighboring urban centers on both banks of the Hooghly River (Mukherjee, 2011). Post-independence, to restrict unplanned growth, the Kolkata Metropolitan Development Authority (KMDA) introduced the Basic Development Plan (BDP) (1966–86) that established a bi-polar growth model with the urban centers of Kolkata in the south and Kalyani in the north as two growth poles (Mukherjee, 2011). When Kalyani failed to attract growth during that time period, KMDA moved to a multiple-nuclei growth model with a number of urban centers within the region. This

strategy helped to decentralize urban growth and resulted in land use changes in the peri-urban areas, primarily by converting prime agricultural lands and rural areas into urban settlements (Chaudhuri & Mishra, 2016; Pandey et al., 2013). The urbanization pattern in this region is similar to McGhee's Desakota model (type 3). The region experienced high population growth, decline in the proportion of population engaged in agricultural activities, concurrent growth of small to medium-sized industries, and slower overall economic growth (Guin, 2017; Mondal, Das, & Dolui, 2015; Mukherjee, 2011; Sud, 2014). Unlike the Delhi and Mumbai urban agglomerations, the growth of Kolkata UA does not share the same degree of influence of colonial legacy (Guin, 2017). However, more than 300 years of urbanization, projected high economic growth (Brar et al., 2014), and the potential threat of sea-level rise (Satterthwaite, 2007) provide an opportunity to explore the local and regional drivers of urbanization and the future patterns of urban growth.

4. Drivers of urbanization in Kolkata UA

To understand the impact of urbanization, an evaluation of the influence of growth factors is important. Better insight on the driving forces of urbanization will be helpful for effective formulation and implementation of sustainable land use policies that will promote economic growth and minimize urbanization's environmental impacts (Seto & Kaufmann, 2003). In 2012, 54 metropolitan cities and their hinterlands (65 districts) accounted for 40% of India's GDP (Brar et al., 2014). These metropolitan regions throughout the country are diverse in their present and projected future growth rates. Existing literature shows that the economic and urban growth of these metropolitan regions are determined by geographical location, socio-demographic factors, historical trends of urbanization, economic status, and state-level policies that attract growth and infrastructural development (Brar et al., 2014; Meiyappan et al., 2017; Vishwanath et al., 2013). A 2014 McKinsey report (Brar et al., 2014) on the future of India's economic geography ranked the state of West Bengal as a 'Performing' state with per capita GDP (2011) between 0.7 and 1.2 times India's average.

Existing scholarship on urban growth uses biophysical factors, social factors, economic factors, and spatial policies as the drivers of urbanization (Li, Zhou, & Ouyang, 2013; Mondal, Das, & Bhatta, 2017; Poelmans & Van Rompaey, 2010; Shafizadeh-Moghadam & Helbich, 2015; Verburg, de Nijs, Ritsema van Eck, Visser, & de Jong, 2004). Both, locational and socio-demographic factors provide a measure of urban growth suitability and relative accessibility in a region. Based on the existing literature, this study evaluated selected locational and socio-demographic factors that have affected urban growth in the Kolkata UA (Brar et al., 2014; Meiyappan et al., 2017; Mondal et al., 2015). In regional scale spatial modeling, often the underlying factors involved in land change and the complexity of the system are not captured, either due to the lack of quality data or to follow the principle of Occam's razor (Engström et al., 2016). The lack of any or good quality spatio-temporal data is the biggest challenge in this region. The locational and socio-demographic factors used in our study were essentially the proximate factors to underlying causes that can be quantitatively mapped using open-source datasets and that represented spatial variations that attract or inhibit urban growth (Verburg, Soepboer, Espaldon, & Mastura, 2002).

The locational factors in this study included physical proximity to the city of Kolkata, Class 1 towns, railway stations, roads with varied degrees of centrality, and the Hooghly River. Urban growth in this region occurred mostly along the peri-urban areas of Kolkata and in class 1 towns (Shantipur, Krishnanagar, Ranaghat, Barasat, Bhatpara, Haldia, Rajpur-Sonarpur, Bongaon, Baidyabati). Over the years, the urban centers of Kolkata and class 1 towns grew independently and some merged with each other to become the Kolkata UA. For example, during the study period (1989–2010), the class 1 towns used in this study experienced urban growth ranging between 7.18% (Haldia) and

21.88% (Bhatpara) (Chaudhuri & Mishra, 2016). These class 1 towns also act as local markets and are the destination for rural migrants (Seto, 2011). Thus, physical proximity to these towns created a higher potential for urbanization. Historically, this region showed a clear trend of urban development along the river (Chaudhuri & Mishra, 2016). Especially, simultaneous growth of Howrah city on the other side of river, industrial growth and infrastructural development helped to favor urban growth near the river. Spatial proximity to railway stations, bridges and roads represent higher accessibility that makes an area favorable for urban growth. The Indian railway system is considered as one the key factors behind industrial development. Locations near railway stations have always attracted large-scale development in the peri-urban and rural areas in India (Bogart & Chaudhary, 2012; Vishwanath et al., 2013). In terms of the influence of roads, this study used the relative level of connectivity of individual roads as a factor attracting growth. Existing literature showed the centrality index as a determinant of accessibility, and that roads with higher centrality have a positive relationship with land use change (Chaudhuri & Clarke, 2015; Levinson, 2012; Levinson & Yerra, 2005).

The socio-economic factors included in this study, such as population density, proportion of workers involved in primary activity and the proportion of illiterate population, were also shown to affect urbanization (Chauvin, Glaeser, Ma, & Tobio, 2017; Denis & Marius-Gnanou, 2011; Gupta et al., 2014; Mondal et al., 2015; Sankhe et al., 2010). According to the Census of India, places with a municipality, corporation, cantonment board or notified town area committee, population density of at least 400 people per sq.km with a minimum population of 5000 and 75% and above male main working population engaged in non–agricultural pursuits, are designated as 'urban areas.' Since there are no reliable data on the boundaries of the local administrative units, population density and proportion of main workers in non-agricultural activities were used. The Census of India defines main workers as workers who worked for more than 6 months (180 days) in the reference period (Goverment of India, 2011). The locations indicating a higher proportion of non-agricultural workers and more literate population also corresponds to the areas with higher tertiary economic activities, industrial development, and thus a relatively higher potential for future urbanization.

Land use policies, migration and investments are three crucial factors that affect urbanization as well, but they were not included in this study. A lack of regional urban plans and the informality of existing restrictions on agricultural land conversion make land use policy an ineffective tool to rationally plan and manage land in this part of the world (Roy, 2009; Sud, 2014). For migration, the lack of detailed data on origin-destination of rural-urban migrants made it difficult and ineffective to use in this study. For investments, both domestic and foreign, the publicly available data are mostly at the national level and are not ideal for spatial modeling at the regional or urban agglomeration level.

4.1. Data and methodology for modeling drivers of change

The digital map shapefiles of class 1 towns, railway stations, roads, rivers, and administrative boundaries were retrieved from the DIVA-GIS data repository (www.diva-gis.org/Data) and were manually cleaned after crosschecking with high-resolution satellite imagery. In this study, the relative level of road connectivity was used to provide a measure of accessibility. The study area lacks a consistent source of road data from the Indian government. To develop consistent road data, data from the DIVA-GIS, Open-street map and high resolution imagery were combined and manually verified. Due to the high level of uncertainty in secondary and local roads, only the major roads, state highways, and national highways were used to develop the road dataset. Connectivity of a road was calculated using degree centrality in a dual graph approach, which measures the number of other roads connected a road (Fig. 2) (Porta, Crucitti, & Latora, 2006). Thus, if a road has many other
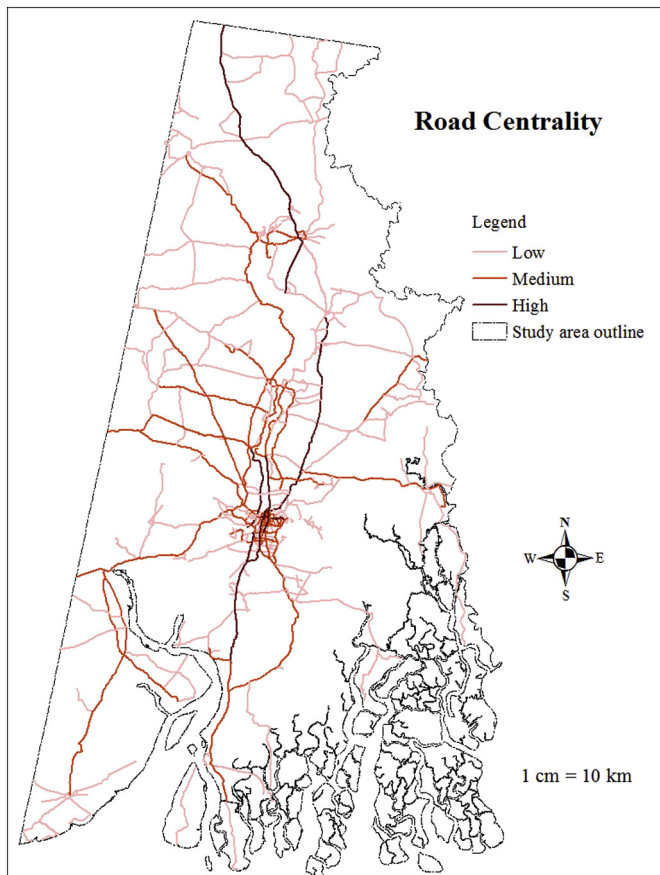
Fig. 2. Map of road centrality.

roads connected, it has higher degree centrality and vice versa. This also means, that roads which are long, such as national highways, connecting one city to another will have higher connectivity and local roads which are shorter in length have lower degree centrality. It should be noted that individual roads were defined by the road names used in the databases and not by their spatial syntax. Dual graphs are well documented in Porta et al. (2006) and the methodology to calculate degree centrality is explained in Chaudhuri and Clarke (2015). It was hypothesized that areas close to roads with higher centrality will have higher influence on urban growth and vice versa. Further, the centrality values were categorized into three classes to represent high, medium, and low road centrality (Fig. 2). To some extent, the roads with high centrality coincided with mostly national highways and some state highways, roads with medium centrality with the majority of the state highways, and low centrality were the major roads of each district, towns and class 1 cities.

The socio-demographic data on population density (popden), proportion of workers involved in primary activity (prop_pwork) and proportion of illiterate population (prop_ill) were retrieved from the 2011 tehsil-level (sub-division of a district) population enumeration dataset from the Census of India (Census of India, 2011) and converted into spatial format for mapping. The seven locational factors that were used to develop spatial proximity surfaces based on linear distance from each feature were: municipal boundary of Kolkata (dkol), class 1 towns (dclass1), railway stations (drail), the Hooghly river (driv), and roads with high (d_hird), medium (d_medrd), low (d_lwrd) centrality. All raster layers were at 100 m spatial resolution and were normalized so that they were comparable with the socio-economic variables. 100 m spatial resolution was used to make it compatible with the input data used in the SLEUTH model. In this study, the proportion of the urban area was used as dependent variable and was represented by the

proportion of impervious surface (W_perc_urb) in 2010. This study used the 2010 Global Man-made Impervious Surface (GMIS) Dataset from Landsat developed by Brown de Colstoun et al. (2017) as impervious surface data. The GMIS dataset (30 m) was resampled to 100 m spatial resolution to match the other datasets.

To better capture the interaction between urbanization and the drivers of urbanization, a spatial lag model was used (Anselin, 2013). A spatial lag model is formed when in a standard linear regression equation, spatial dependence is incorporated in the form of a spatially lagged dependent variable (Wy) (Anselin, 2013). In this study, the dependent variable that represented the proportion of impervious surface was spatially autocorrelated. Thus, a weighted spatial lag model was used in order to understand the type and strength of interactions between the dependent variable and the ten locational and socio-demographic independent variables, using the maximum likelihood estimation. A spatial lag model (also known as mixed regressive or spatial autoregressive model) can be expressed as:

$$y = \rho Wy + X\beta + \varepsilon \tag{1}$$

where y is a vector of observations of a dependent variable, ρ is a spatial autoregressive coefficient, Wy is the corresponding spatially lagged dependent variable for weights matrix W, X is a matrix of observations of the independent variables, β is a vector of regression coefficients, and ε is a vector of error terms (Anselin & Bera, 1998).

4.2. Results from regression modeling

Table 1 summarizes the results from the regression modeling. Among the proximity-based independent variables, proximity to a railway station had a significant higher negative influence than proximity to class 1 towns and Kolkata. Proximity to the river had insignificant weak positive influence. For roads with three categories of centrality, proximity to roads with low centrality had a significant strong negative relationship compared to roads with high centrality. Proximity to roads with medium centrality had a significant positive relationship and the level of influence was relatively higher than roads with high centrality and lower than roads with low centrality. Among the socio-demographic variables, population density, proportion of primary workers and proportion of illiterate people had significant negative relationships, but the influence of population density was higher than the other two (Table 1). The negative relationship of population density indicated sprawl in the peri-urban areas.

Overall, the higher proportion of urban area was highly influenced by closeness to railway stations, class 1 towns and Kolkata (in order of strength of influence). The city of Kolkata grew more organically by transforming the peri-urban areas and agricultural land around its edges to accommodate urban development. The class 1 towns also grew over time, and those adjacent to the Kolkata municipality merged to form the Kolkata UA. In terms of roads, proximity to roads with low centrality had a higher influence than roads with high or medium levels

Table 1
Regression model results.

Variables	Coefficient	Std. error	Z-value	Probability
dkol	−0.00387600	0.000236448	−16.3926	0.00000
dclass1	−0.00532191	0.000387118	−13.7475	0.00000
drail	−0.01003170	0.000680670	−14.7380	0.00000
driv	0.00021016	0.000445525	0.4717	0.63712
d_hird	−0.00970842	0.000475560	−20.4147	0.00000
d_medrd	0.01749700	0.000526286	33.2462	0.00000
d_lwrd	−0.03126890	0.000723364	−43.2271	0.00000
popden	−0.07208720	0.000454248	−158.6960	0.00000
prop_pwork	−0.01116070	0.000244633	−45.6222	0.00000
prop_ill	−0.01313360	0.000344031	−38.1755	0.00000
CONSTANT	9.32801000	0.042991900	216.9710	0.00000
W_perc_urb	0.77205300	0.000508512	1518.2600	0.00000

of centrality. For this study area, the roads which show low centrality were major primary roads within a district or town. The roads with medium centrality correspond to some major roads and mostly state highways and roads with high centralities mostly correspond to national and some state highways. The major primary roads with low centrality are mostly found in predominantly rural or suburban districts, outside the core urban area of Kolkata UA. These roads provide accessibility to secondary and tertiary roads in their respective areas. Studies on road centrality and land use at the city level suggested that high centrality values attract growth (Omer & Goldblatt, 2016; Rui & Ban, 2014). Our study showed that at the regional level and outside the Kolkata UA, higher proportions of urban areas were found in proximity to roads with lower centrality. Most of the national highways outside the urban agglomeration were built through the agricultural fields connecting towns and cities throughout the area. Thus, urban development is only found along the parts of national highways that are closer to class 1 towns and Kolkata UA, but not in other areas. India is not a car-based society yet, so areas close to national highways have rarely attracted growth. Urban land use in India is highly heterogeneous. The majority of the population live close to their workplace. Within the Kolkata UA, 80% of all trips for commuting are by public transit (Cervero, 2013). Some proportion of the population that commutes longer distance uses local trains, which is why there is high influence of proximity to railway station. National highways with higher centrality are mostly used for commercial purposes and not so much for daily commutes. However, there is a severe lack of literature that evaluates the relationship between travel behavior and urban structure in this region.

Based on the results, a predicted raster surface of the proportion of impervious surface was generated. The predicted surface from the regression is termed "urban attraction" based on the assumption that the proportion of predicted imperviousness corresponds to how attractive/unattractive that location is for urbanization. This layer was used in the SLEUTH modeling as both the exclusion and slope layers in experiments 1 and 2 respectively, as discussed in the next section. The advantage of using the predicted layer over the original GMIS dataset in SLEUTH experimentation is that the predicted layer provides an estimate of the proportion of impervious surface for both currently partially impervious and non-impervious pixels in the region. These values are based on the relationship with the independent variables as established in the model. Thus, the higher proportion of modeled impervious surface translates to a higher potential of urban growth and vice versa. Although there are no future estimates of data available for the socio-demographic variables used in this study, it is assumed that the nature and type of their relationship with urban growth will remain the same in the future.

5. SLEUTH model for urban simulation

Clarke's Urban Growth Model was tightly coupled with the Deltatron Land Use Change Model to develop the SLEUTH model, both based on cellular automata. The urban areas inside SLEUTH follow a set of transition rules that influence the changes of cell states within a set of nested loops (Clarke et al., 1997; Clarke et al., 2007). The model uses slope, land use, exclusion, urban extent, transportation and hillshade layers and sequential brute force calibration using behavioral rules to calibrate the model based on observed past changes (Silva & Clarke, 2002). The model calibrates with historical data to derive a set of five control parameters (dispersion coefficient, breed coefficient, spread coefficient, slope resistance factor and road gravity) that best capture the past urbanization trends (Chaudhuri & Clarke, 2012). The values of these coefficients influence the growth rate that determine the degree to which each of the four growth rules (spontaneous, diffusive, organic, and road influenced growth) influence urban growth within the system (Chaudhuri & Clarke, 2012). Additionally, there is a set of meta-level rules called the 'self-modification' rules, which respond to the aggregate

growth rate and change the growth control parameters in each of the growth cycles accordingly (Silva & Clarke, 2002) during periods of rapid or slow growth. The final calibration process generates an optimal metric called OSM (Dietzel & Clarke, 2007) that is used to select the final set of control parameters that best captures the observed change. These are then used to forecast future urban growth. Details about the calibration methods and applications of the model are well documented (Chaudhuri & Clarke, 2013; Clarke, 2008; Silva & Clarke, 2002). The SLEUTH urban growth model (Clarke et al., 1997) has been successfully applied in various parts of the world (Chaudhuri & Clarke, 2013), including in India (Chakraborty, Wilson, & Kashem, 2015; Kantakumar, Sawant, & Kumar, 2011; Srinivasan et al., 2013).

Being a stochastic model, SLEUTH does not need location specific driving forces to predict future urbanization. The generic nature of the model makes it globally applicable, but also demands close attention to the interpretation of its results. In the excluded layer of the SLEUTH model, the user can control where urban growth may occur in the future. The values in the excluded layer vary from 0 to 100, where 0 indicates that the pixel is available for urbanization and 100 where urbanization is completely excluded. Additionally, the excluded layer also allows partial or total exclusion of areas where urbanization may be restricted. A number of studies on model coupling and scenario-based modeling have successfully used weighted excluded layers for impact assessment and growth trend comparison under different scenarios (Chaudhuri & Clarke, 2012; Jantz, Drzyzga, & Maret, 2014b; Onsted & Chowdhury, 2014).

Slope is another layer that highly influences urban growth. Slope is one of the most important parameter for the UGM as part of the SLEUTH model due to its origin as a wildfire spread model (Clarke, Brass, & Riggan, 1994). All four types of urban growth captured by the model (spontaneous growth, new spreading centers, edge growth and road-influenced growth) are influenced by the slope parameter. Lower slopes are easier to build on than the steeper slopes, and eventually it is impossible to build when a critical slope value is reached, often around 25–30% slope. If the local slope (slope (i,j)) is below the critical slope, the slope coefficient determines the weight of the probability that the location (pixel) may be built upon (Clarke et al., 1997). Based on local knowledge, the user can determine a case specific critical slope value or can use the default value of 21%. The relative pressure to build upon steeper slopes is dynamic and related to the proportion of flat land available and the steeper area's proximity to an already established settlement (Clarke et al., 1997; Silva & Clarke, 2002). A recent successful application used a modified slope layer to understand the effect of uncontrolled urban growth in developing regions on environmental degradation (Li et al., 2018). The study used habitat quality information from the InVEST model to replace slope and assess the impact of urbanization.

The topographic slope layer is not effective when modeling urban areas that are located in flat land with no natural physical barriers that restrict urban growth. The topographic elevation of Kolkata UA varies from 0 to 10 m above mean sea level and therefore slope does not restrict urban growth. The study first ran the SLEUTH model with a standard excluded and topographic slope layer to show the need to integrate the urban attraction layer to improve simulation results. Then the study experimented with integrating urban attraction layer, first via the excluded layer and secondly via the topographic slope layer to assess their effectiveness. In the first experiment (experiment 1), the urban attraction layer from the regression result was integrated with the excluded layer (which also contained Sundarban Forest and waterbodies) and the slope layer represented the topographic slope, and in the second experiment (experiment 2), the urban attraction layer was used as the slope layer and the excluded layer only consisted of the Sundarban Forest and waterbodies. In the SLEUTH model, the excluded layer uses weights from 0 to 100 and forecasts linear urban growth during the prediction process, but the slope layer has both non-linear weighting and a critical level above which there is no influence. It is

hypothesized that the urban growth predicted by using urban attraction via the slope layer will be more spatially restricted and temporally delayed than that predicted by using the excluded layer.

5.1. SLEUTH data preparation and experiment set-up

The study area footprint aligns with part of the Landsat satellite image tiles 138/44 (path/ row) and 138/45 (path/ row) and covers an area of 25,137.9 sq.km. The present study used land use and land cover (LULC) maps from 1989, 1999, 2005, and 2010 produced by a previous study (Chaudhuri & Mishra, 2016) to develop the 2 LULC and the minimum 4 urban layers required by the SLEUTH model. The 2011 and 2017 urban extent maps were produced for accuracy assessment of the predicted images. The overall accuracy of the classified land use images varied from 80%–87%. The LULC classes included urban (high density built-up area with concrete surface), rural (low density built up area with either concrete or red-roof surface and intermittent patches of tree cover), agriculture (cropland, plantation and fallow land), forests (natural forest, swamps, mangroves, and forest plantations), barren (includes salt affected land, coastal and riverine sandy areas, and scrubland), and water (inland wetlands, ox-bow lake, cut off meander, waterlogged areas, rivers, streams, canals, aquaculture, lakes/ponds, and reservoir/tanks). The topographic slope and the hillshade layers required for modeling were developed from SRTM data. Finally, the road layers of 2004–2005 and 2010 were developed from existing shapefiles, and onscreen digitization using high-resolution satellite basemaps in ArcGIS 10.5 desktop. Given the large spatial extent of the study area and processing power required by the SLEUTH model, all raster layers were resampled to 100 m spatial resolution with an image size of 1575 × 2765 (rows and columns). All input data except the urban attraction layer are shown in Fig. 3.

First, SLEUTH was run using a standard dataset. The excluded layer only included water bodies and Sundarban reserved forest, and the slope layer included the topographic slope of the study area. This model run will be henceforth termed the unmodified SLEUTH run. Next, in experiments 1 and 2, the urban attraction layer was integrated with the SLEUTH model. The urban attraction layer showed the relative level of

attraction in each pixel. Thus, the lower values mean low-level of attraction and vice versa. Both the slope and excluded layer in SLEUTH takes values of 0–100, where 0 in both layers represents favorable pixels for urbanization. In experiment 1, the pixels values of predicted output from the spatial lag model were inverted and then scaled to create the excluded layer. Eleven classes were used at an increment of 10 units, with the last class of 100 including the forest and water bodies. Jantz, Goetz, Donato, and Claggett (2010) showed that the values below 50 in an excluded layer act as growth attractors whereas the values above 50 act as growth inhibitors. Following the same argument, the excluded layer in this study was categorized such that any value above 50 in the excluded layer corresponds to the values zero and below in the regression output. Thus, the values above 50 in the excluded layer represent very low or no relationship based on socio-demographic and locational factors. Thus, the areas with lower values in the excluded layer (0–50) have less resistance and therefore attract urbanization and vice versa (Fig. 4). In addition to the urban attraction/ prohibition, the water bodies and Sundarban reserve forest were completely excluded from development in experiment 1. The slope layer in experiment 1 represented topographic slope, with the default critical slope value of 21%. In experiment 2, the scaled urban attraction layer was used to replace the topographic slope layer (Fig. 4). In this case, the low values represent low resistance to urban development and thus are more likely to attract development compared to the less attractive areas with higher resistance, until the simulation reaches the critical attraction value at which urban growth is impossible. The relative pressure to build upon a location that is unattractive for development is dynamic and related to the proportion of attractive locations available and the unattractive location's proximity to an already established settlement. The topographic slope of a region is generally unchanged, whereas the urban attraction layer was developed based on the socio-demographic and location factors of 2010. The locational factors, except for the road centrality, did not change much in the region. The socio-demographic factors of each of the districts did change, such as increase in population density and decrease in proportion of illiterate people and primary workers. However, the relative spatial distribution of socio-demographic factors remained unchanged. It was hypothesized that inclusion
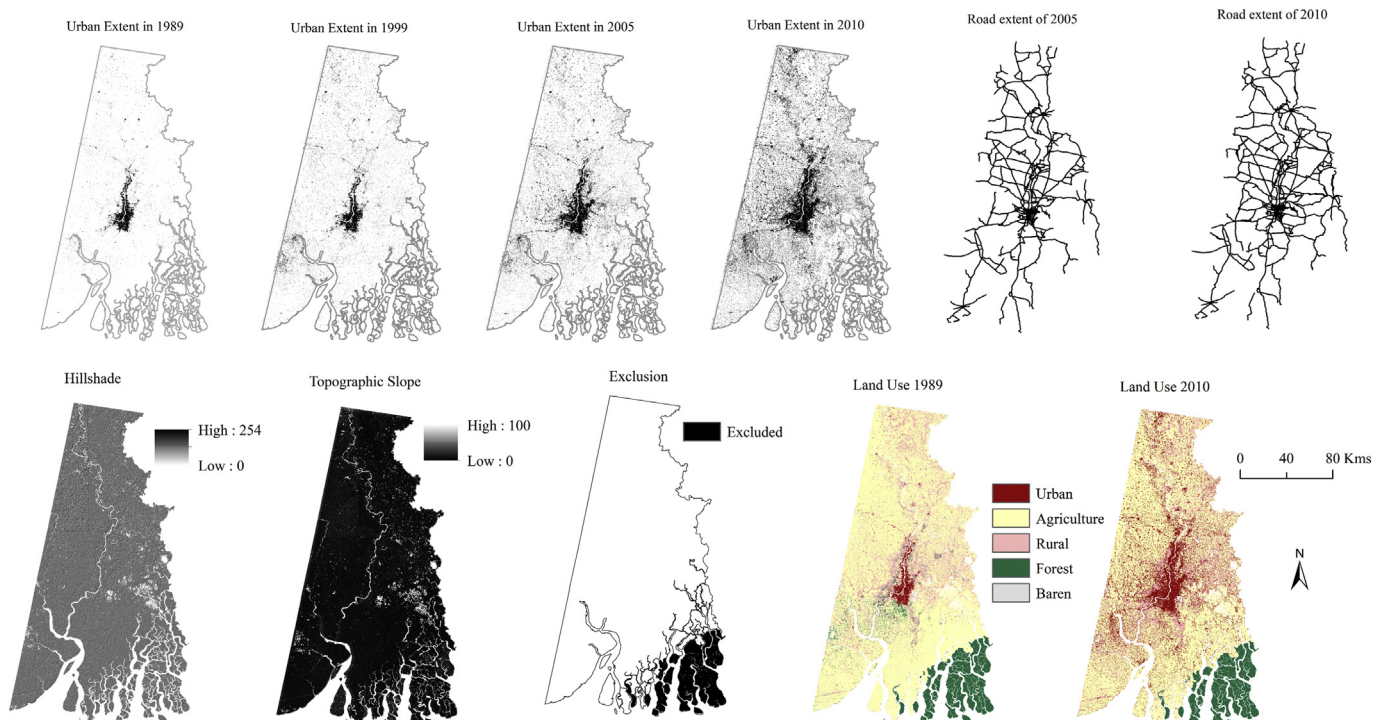

Fig. 3. Input data for the SLEUTH model (other than the urban attraction layer).
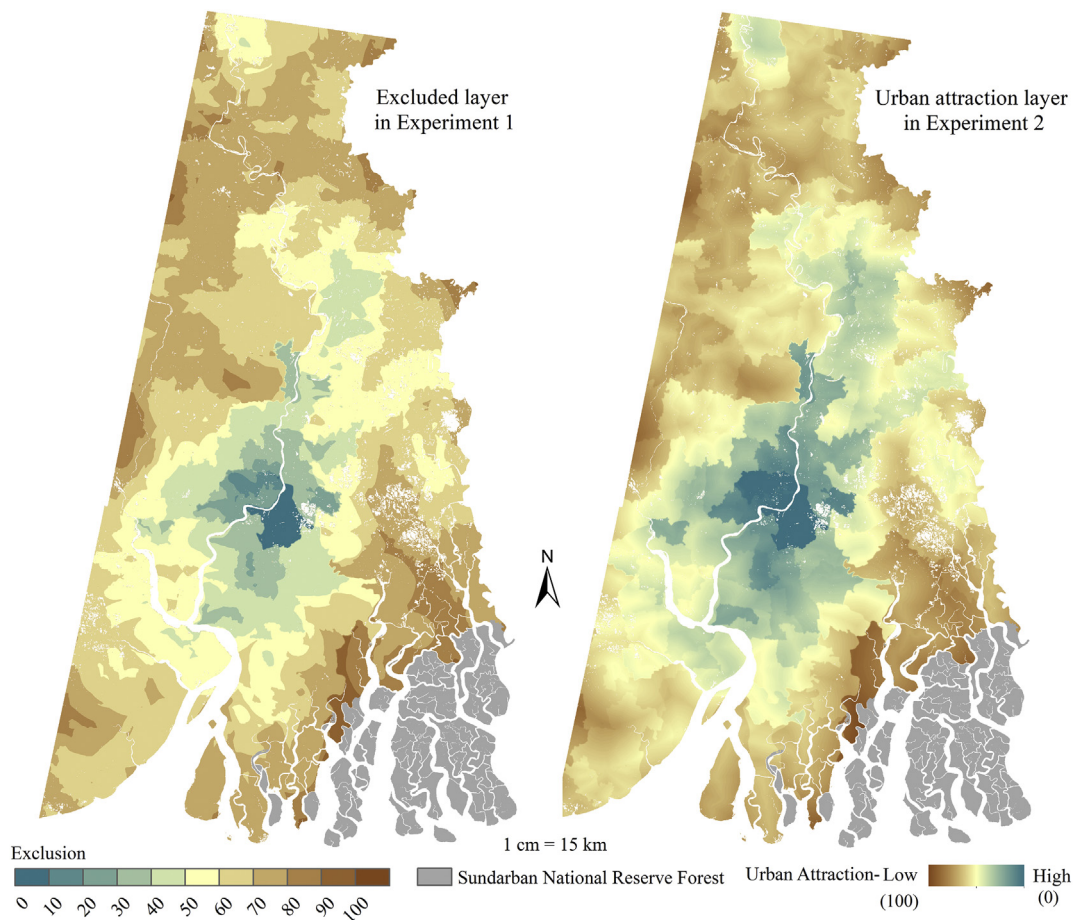
Fig. 4. Urban Attraction, used as the excluded layer in experiment 1 and slope layer in experiment 2.

of the urban attraction information in slope layer will be able to capture the dynamics of socio-demographic and locational factors and that the future growth will be guided by spatial variability of the degree of attractiveness of each pixel. The excluded layer for experiment 2 included only water bodies, and Sundarban reserve forest.

5.2. Calibration, prediction, and validation

For all model runs, three-stage brute force calibration was applied, the top parameter combinations were selected and averaged, and predictions run for 2011–2030 time period with 100 Monte Carlo iterations. In the unmodified SLEUTH run, the final step of calibration generated an OSM value (Dietzel & Clarke, 2007) of 0.61, and the coefficient values used for prediction were: Diffusion = 30; Breed = 33; Spread = 90; Slope = 14; Road gravity = 25. In experiment 1, the OSM value for the final calibration was 0.73. The coefficient values used for prediction were: Diffusion = 100; Breed = 100; Spread = 100; Slope = 76; Road gravity = 55.

In experiment 2, the slope-related coefficients were replaced by urban attraction values during calibration (Li et al., 2018). The model's default value of 0.1 was used for sensitivity to urban attraction. In this study, the critical urban attraction value was set through a trial and error process, testing with values ranging from 87 to 100. In the urban attraction layer, the values 87–100 corresponded to the values of zero and lower in the predicted output of the regression modeling. Thus, any value of 87 and above in the urban attraction layer meant very low or no potential to attract urbanization based on the relationship with socio-demographic and locational factors. From the trial and error process, the value 100 generated the best fit model, and was selected as the critical attraction value. Since the pixel values in the urban

attraction layer ranged from 0 to 100, therefore a critical urban attraction value of 100 means that all pixels have a potential to urbanize within the prediction period, if the conditions are suitable. For the present study area this means that the attraction to urbanize in an area will decrease as the values in the urban attraction layer get higher, but an unattractive location can be urbanized if there are no attractive locations available through self-modification. The final step of calibration in experiment 2 generated a lower OSM value of 0.48. The coefficient values used for prediction were: Diffusion = 95; Breed = 95; Spread = 95; Urban Attractiveness = 1; Road gravity = 19. The first three values are high, as before, which reflects the rapid rate and sprawled nature of the growth. The prediction was run twice with critical attraction values of 100 (same as calibration) and 87 under the assumption that future urban growth will avoid areas with low/no attraction. The methodological workflow for experiment 1 and 2 to integrate urban attraction layer is shown in Fig. 5.

The predicted urban maps of 2011 and 2017, from all runs, were then compared with the observed urban maps of 2011 and 2017 using $K_{Simulation}$ metrics (van Vliet, Bregt, & Hagen-Zanker, 2011). $K_{Simulation}$ metrics have been used successfully in various land use change simulation studies (Chaudhuri & Clarke, 2014; van Vliet et al., 2011) and provide a robust measure of accuracy for simulated images. $K_{Simulation}$ is the coefficient of agreement between the simulated and the actual land use transitions. $K_{Simulation}$ can be further decomposed into $K_{Transition}$ that shows the agreement in the quantity of land use transitions and $K_{Transloc}$ that shows the degree to which the transitions agree in their allocations (van Vliet et al., 2011). The results for experiment 1 $K_{Simulation}$ metrics are shown below in Table 2. Accuracy assessment of the 2011 and 2017 predicted urban maps using $K_{Simulation}$ metrics from two prediction runs showed better accuracy of the images with the critical urban attraction
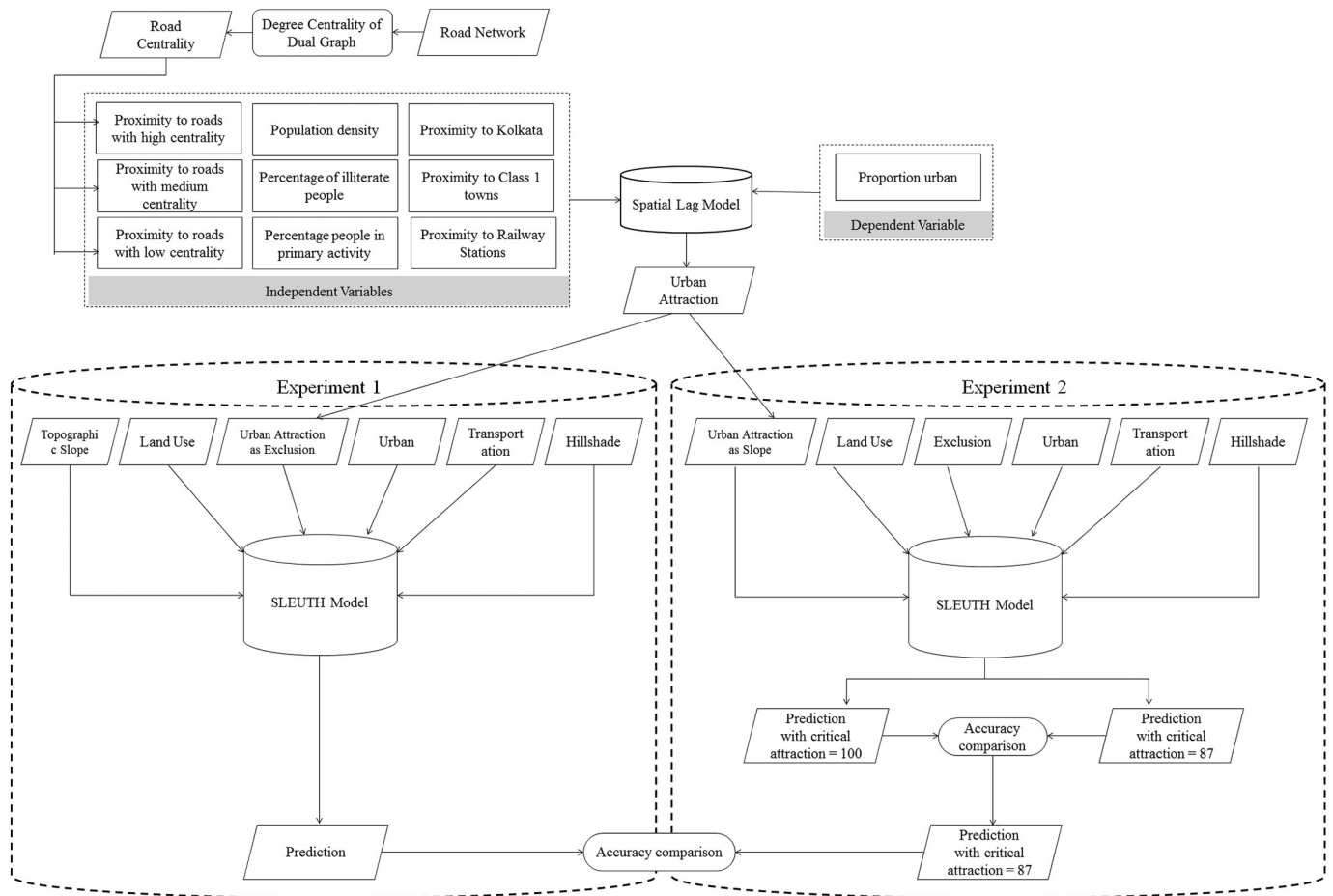
Fig. 5. Methodological workflow for experiment 1 and 2 to integrate urban attraction information.

Table 2
Accuracy analysis of 2011 and 2017 predicted images using $K_{Simulation}$ metrics.

Metrics	2011			2017		
	Unmodified	Exp. 1	Exp. 2	Unmodified	Exp. 1	Exp. 2
$K_{Simulation}$	0.787	0.822	0.853	0.149	0.214	0.274
$K_{Transition}$	0.991	0.961	0.913	0.332	0.515	0.749
$K_{TranLoc}$	0.794	0.855	0.934	0.450	0.415	0.366

value of 87, which are reported in Table 2.

5.3. Analysis of SLEUTH modeling results

During the calibration stage, experiment 1 generated higher OSM values than experiment 2 and the unmodified SLEUTH run. This suggested urban attraction as an excluded layer produced a better model fit with the input data. On the other hand, $K_{Simulation}$ metrics showed relatively better overall accuracy of the predicted images from experiment 2 (Table 2). The predicted images from the unmodified SLEUTH run had the least accurate images among all the model runs. In the predicted images, pixels with above 95% probability of urbanization were considered for analysis. Map comparisons among observed urban images of 2010, 2011, 2017 and simulated urban images of 2011 and 2017 showed how much the SLEUTH model under-predicted or over-predicted for years 2011 and 2017 in each run (Fig. 6). For 2011, the predicted images from experiment 1 and 2 under predicted urban pixels by around 13% and 6% respectively and the predicted image from the unmodified SLEUTH run over predicted urban pixels by around 1.5%. For 2017, the model under-predicted by 7% in experiment 2, and over-

predicted by 22% and 97% in experiment 1 and the unmodified SLEUTH run, respectively. Accuracy assessment of the 2011 simulated images showed that images from experiment 2 were more accurate in overall accuracy and allocation of newly urbanized pixels, except for the quantity of transition of land use classes (Table 2). For both 2011 and 2017, the $K_{Simulation}$ and $K_{TransLoc}$ values for the predicted images from the unmodified SLEUTH run were lowest. The unmodified SLEUTH run generated a more accurate quantity of newly urbanized pixels compared to all runs in 2011. For 2017 as well, the predicted images of experiment 2 were more accurate, except for the allocation of newly urbanized pixels (Table 2). The unmodified SLEUTH run generated more accurate allocation of newly urbanized pixels compared to all runs in 2017. Based on the $K_{Simulation}$ values of all runs, it can be said that the model performed better when information related to urban drivers was added in the simulation modeling.

The probability of urbanization (Fig. 7) from the unmodified SLEUTH run and experiment 1 showed that the majority of the study area will experience 90–95% urbanization by 2030, whereas the image from experiment 2 shows the southern part of the study area will experience 90–95% probability of urbanization in a linear pattern and in a more widespread manner in the central region. The right edge of the study area borders with Bangladesh. Being a closed border, it is highly unlikely that the adjacent areas along the border will experience a high level of urbanization. Bongaon is the only class 1 town that is located near the border and serves the Petrapol-Benapol land port between India and Bangladesh, which is the biggest land port in Asia in terms of volume and value of goods traded (Chaudhuri & Mishra, 2016). The model predicted urban growth near the border because there was no restriction added along the border. Ideally, a layer delineating restricted growth along the border would have resulted in better
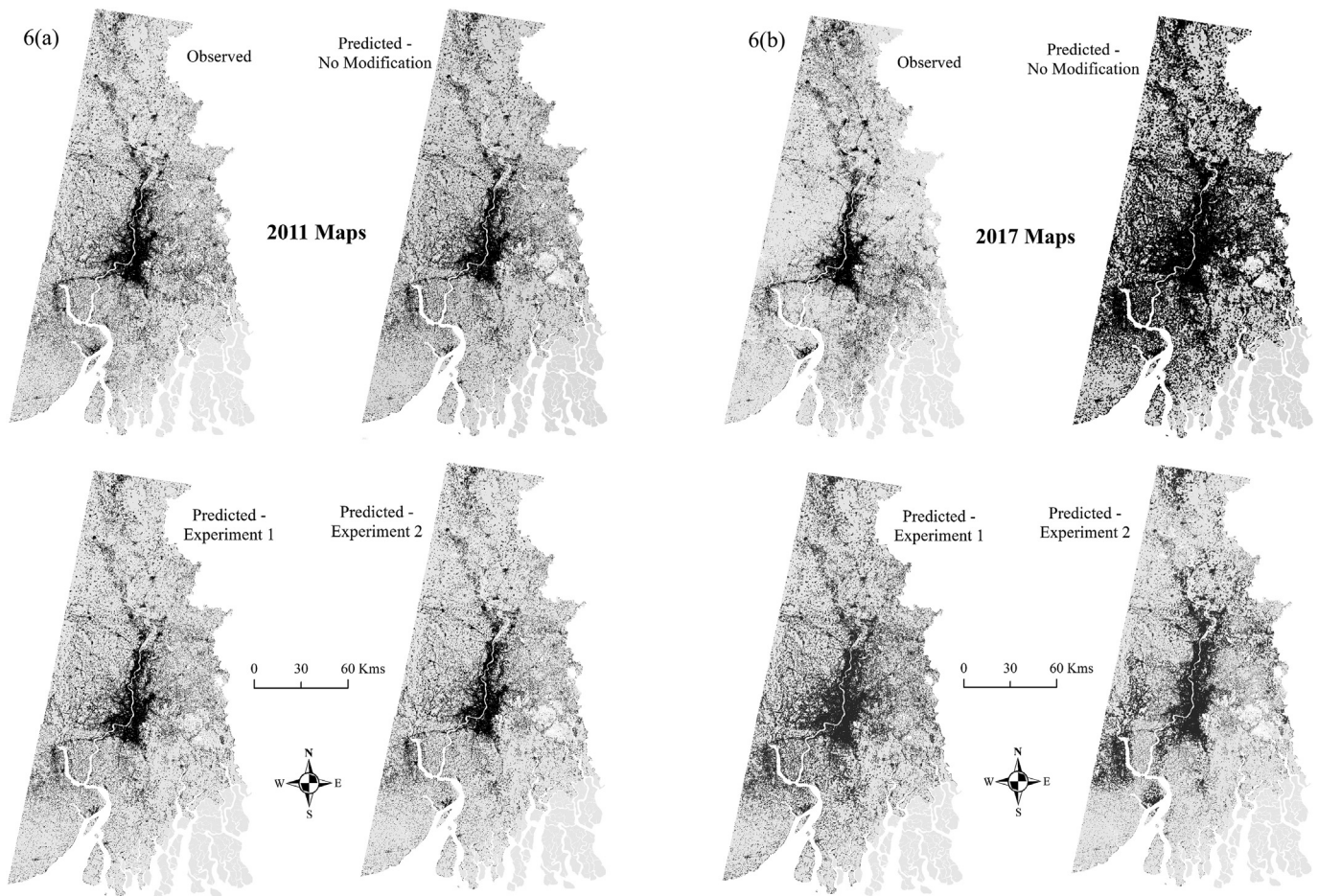
Fig. 6. Map comparison between observed map and predicted maps of 2011 (6a) and 2017 (6b) respectively.

prediction along those areas.

The accuracy analysis of the 2017 images showed that the level of accuracy is less compared to 2011 for both the experiments (Fig. 6), but was useful to identify the trends that the model was not able to capture. It is known that the prediction uncertainty increases as SLEUTH predicts further into the future (Chaudhuri & Clarke, 2014). The rate of decrease in overall accuracy varies based on the urbanization trend in the region and the accuracy of the observed urban images used for input and validation. All observed urban images in the study were generated from Landsat imagery. The observed map for 2017 was developed from Landsat 8 and had higher classification accuracy compared to the input data, which were developed from Landsat 5TM. This resulted in low level of accuracy in the 2017 simulated images. If the 2017 observed urban map was adjusted based on input data, then the accuracy level will increase to some extent. Map comparison between the observed urban images of 2010 and 2017, showed that the southern part of the study area experienced more widespread urban growth by conversion of rural areas, and whereas in the northern part growth was more concentrated along the road network and around the existing class 1 towns. The simulated image of 2017 from the unmodified SLEUTH run showed over-prediction of urban pixels throughout the study area. Map comparison between the observed urban image of 2017 and the simulated images of 2017 from experiments 1 and 2 showed similar changes, but edge growth around the small pre-existing urban clusters in the predominantly agricultural areas contributed to the low $K_{Simulation}$ value for the 2017 simulated images (Fig. 8).

Fig. 8 shows the predominance of edge growth in images from all runs. The unmodified SLEUTH run generated the largest number of pixels under edge growth until 2024 when compared to the two

experiments. However, from 2025 onwards for the last 5 years the number of pixels is lower than experiment 1 but higher than experiment 2. The quantity of pixels from edge growth was lowest in experiment 2. The edge growth is a function of the spread and slope coefficients. In both the experiments, the spread coefficient was higher, but the slope coefficient was very low in experiment 2, which was one of the reasons for fewer edge growth pixels in the simulated images from experiment 2. This helped us to conclude that in the input historical data the spread coefficient showed more influence, but in the future (rather than at present) the edge growth is only limited to the surroundings of the major urban centers and is not spatially uniform. This conclusion was also confirmed by the higher overall accuracy of the 2017 simulated images from a few test prediction runs with user defined spread coefficients (such as 40, 50, 60). Thus, the higher OSM value in experiment 1 but relatively better $K_{Simulation}$ values of predicted results in experiment 2 showed that the present (and future) trend of urban growth in this region is different from the past trend. Visual map comparison between the urban attraction map (Fig. 4) and the probability of urbanization maps in experiment 1 (Fig. 7) showed a direct correlation between relatively low attraction values and the 50–95% probability of urbanization. For this study, the accuracy analysis is based on urbanization with 95–100% probability of urbanization, so pixels with below 95% probability of urbanization were considered as low probability. There was no such linear correlation between lower attraction values and the probability of urbanization in experiment 2, in fact a majority of the study area showed lower than 50% probability of urbanization by 2030. Fig. 9 shows the growth rate during the prediction years and number of growth pixels from all runs. Similar to the trend seen in edge growth, the total number of pixels predicted was highest during the
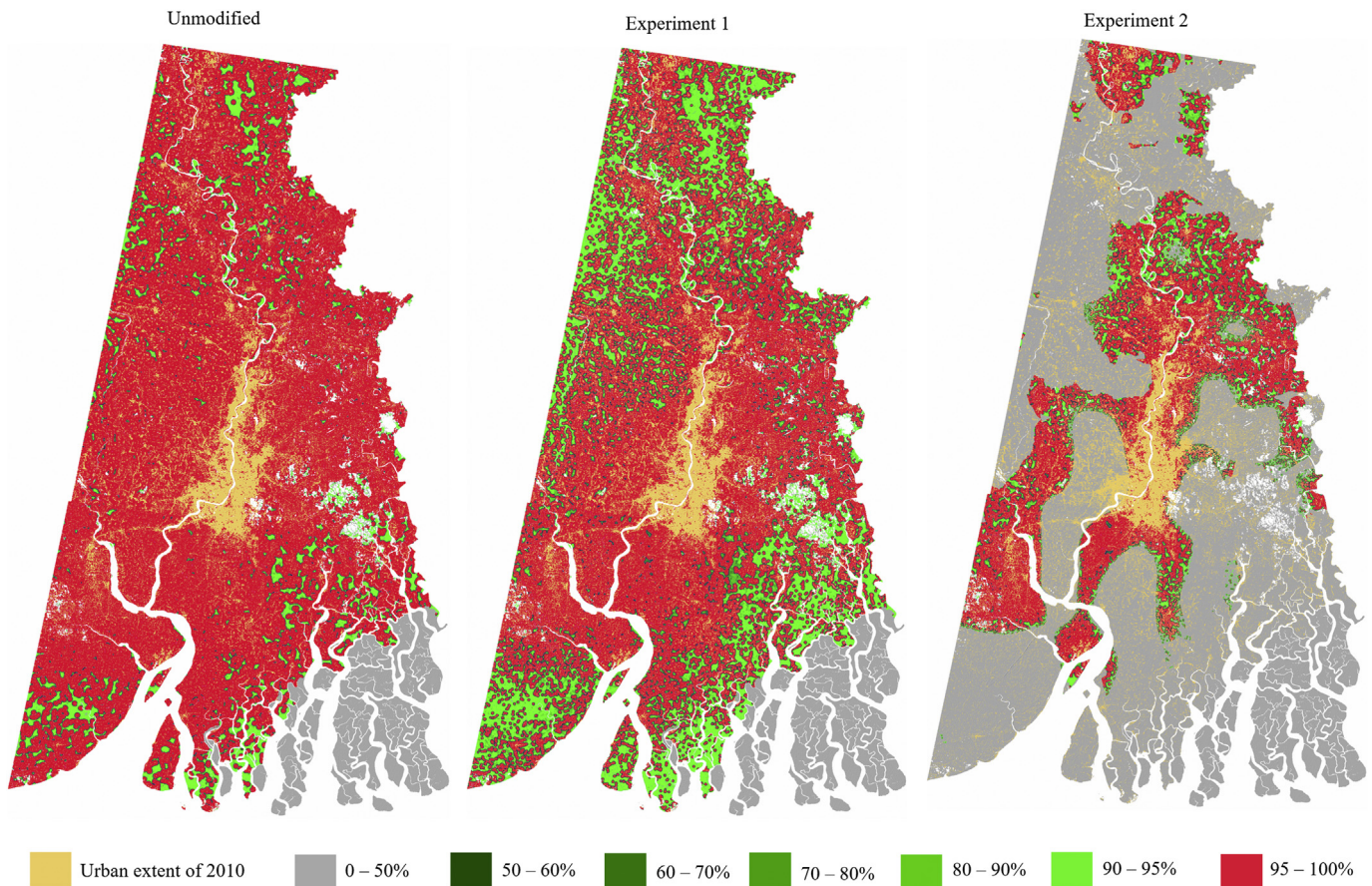
Fig. 7. Probability of urbanization in 2030 from unmodified SLEUTH run (left), experiment 1 (center) and 2 (right).
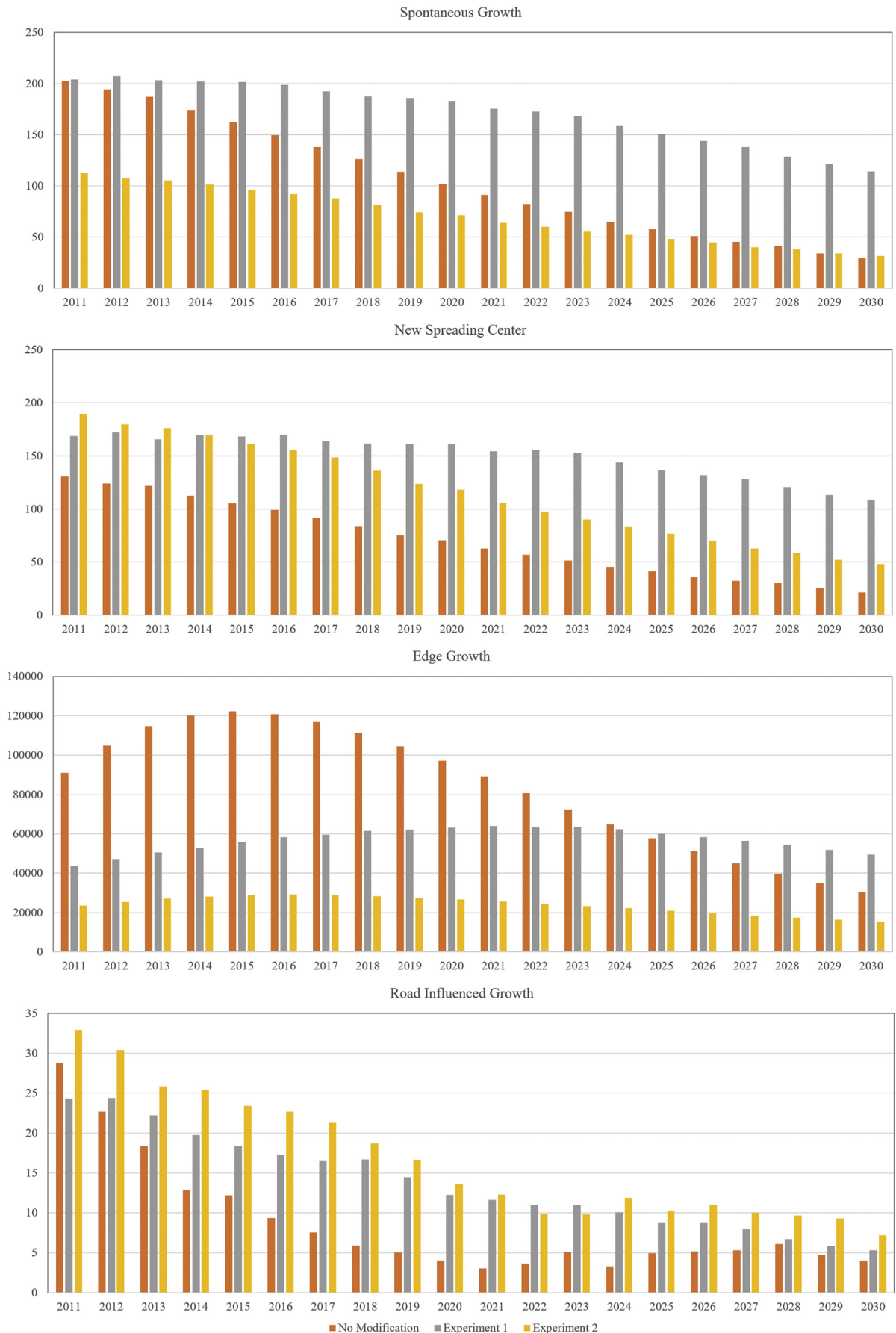
unmodified SLEUTH run until 2024. From 2025 onwards, the number of pixels from experiment 1 is the highest. The total number of growth pixels in experiments 1 and 2 are consistent throughout the prediction period but experiment 1 generated almost twice as many growth pixels as experiment 2. The growth rate for the unmodified SLEUTH run ranges between 2 and 20%, whereas for experiment 1, it ranges between 4 and 14% and for experiment 2, 2–6%. During 2020, the growth rate generated by the unmodified SLEUTH run drops below the growth rate from experiment 1 and for the last 4 years it is similar to the growth rate of experiment 1. The model calculates the growth rate during the calibration stage from the input images. The information is then used during the prediction stage and with the proportion of available pixels for urbanization. With each subsequent prediction year the number of available pixels decreases, which results in a decreasing growth rate in later periods. The restriction imposed by the excluded layer in experiment 1 and the urban attraction layer in experiment 2, helped to temporally distribute the number of growth pixels during the prediction period.

At present, compared to the core Kolkata area, more growth is visible along the class 1 towns. Diffusion and coalescence of small and large urban municipalities, class 1 towns, and Kolkata UA is visible along the transportation network. Urban growth is spreading more to the north along the national highways, and south-western part near Haldia. Road based growth has increased with the development and improvement of the national highways and improvement in connectivity between growth centers within and outside of the study area. Although the economic and urban development in this region is not at par with fast-growing areas of India nevertheless it is experiencing profound economic transition, like the rest of the country. Thus, it is not surprising that the historical urban growth trend captured from the input urban map is different from the current urbanization trends.

6. Discussion

The goals of this study were to evaluate the relationship between urbanization and its driving forces, to evaluate the need to integrate urban driver information in the SLEUTH urban simulation model and to assess the most effective approach to integrate this information. Among the socio-demographic and locational factors included in this study, proximity to railway stations, roads with low centrality, a higher proportion of non-primary workers and a more literate population have a significant influence on urbanization. Comparison of model results between the unmodified SLEUTH run and modified SLEUTH runs (experiments 1 and 2) showed that the model benefited from adding the drivers of urbanization information. The two experiments set up to assess the best approach to integrate the drivers of change information brought forward new insights on the use of the excluded and slope layers on simulation and forecasting of urban growth in the study area. The OSM is calculated using 13 metrics generated by the SLEUTH model that show the parameters that best capture the historical growth. However, using that information to forecast future growth may not always produce the most accurate maps of the future. In our study area, this may be attributed to the change in pace and process of urbanization. This suggests that in developing nations with transitional economies, the basic assumption that the past is the best predictor of the future, may not work. Such trends have been called 'non path-dependent' (Houet et al., 2016) development. More research on the model application is required in different regions of the world that are going through similar urban transition. Knowledge gained through more applications will help to better understand the urban dynamics in transitional economies and efficient ways to simulate and forecast urban growth in these regions.

For this study, use of urban attraction as the slope layer generated

Spontaneous Growth

New Spreading Center

Edge Growth

Road Influenced Growth

No Modification   Experiment 1   Experiment 2

(caption on next page)

relatively better predicted maps than using urban attraction as the excluded layer. The integration approach using the slope layer was only possible because the study area is situated on a large delta and does not have any topographic barrier to restrict urban growth. In the excluded layer, partial exclusion/attraction is sensitive and its performance varies from one study to another (Jantz et al., 2014b; Onsted & Chowdhury, 2014). In our study, the spatial variability of urban attraction depicted by the partial exclusion of pixels was not able to simulate future growth effectively. When and where these partially excluded pixels are being urbanized within the predicted period in the study area needs further testing. This study also compared the results between a classified excluded layer (experiment 1) with an excluded layer that used continuous values ranging from 0 to 100 as shown in Mahiny and Clarke (2012). Both model runs generated similar results. The influence of urban attraction varies as slope is more dynamic, because the behavior is reactive. The relative pressure to build upon non-urban pixels with low urban attraction is related to proximity to an existing urban cluster and the proportion of attractive locations available. Therefore, if no attractive pixel is available and there is an existing urban settlement nearby, then a less attractive location will be urbanized. This dynamic behavior worked better for the study area. In order to urbanize, both exclusion and slope reflect an individual pixel's favorability, but slope is dynamic and considers the proportion of favorable land available and a location's proximity to an already established settlement. Hence, for this study the use of the slope layer to integrate information related to drivers of urbanization performed better for future prediction. This approach will not be applicable for cities where the topographic slope is a natural barrier to development. Furthermore, the choice of factors that are assumed as driving forces of urbanization and the method of evaluation of their relationship to urbanization will also affect SLEUTH results. More application of the same methodology to other cities, especially in highly urbanizing and fast growing cities in Asian deltas, will be beneficial to test the efficiency of this approach.

Two factors affected this study, data availability and simulation time. Any urban simulation model is challenged by its capability to capture implicit and explicit factors involving growth, and by data availability. Availability of open-source high quality multi-temporal geospatial data is very limited in this region. Consequently the choice of

independent variables that best represent drivers of urbanization is biased by data availability. Secondly, a large area (25,137.9 sq.km) was considered in this project to capture the megalopolis and its surrounding area. With six dedicated CPUs (2.60GHz), it took 30–60 days to complete all three phases of calibration. Therefore, in the future the model framework needs to be adjusted to utilize multi-core machines to simulate large urban areas. Use of multiple cores will heavily reduce the calibration time and will allow the testing of unique characteristics of large-scale urbanization, such as comparing the process in urban corridors between developed and developing nations and the growth of networks of cities.

Compared to Delhi and Mumbai, Kolkata UA experienced relatively slower growth in the past, but if the current state-level initiatives to attract economic development are successful, this region will grow faster in the future (Brar et al., 2014). At present, the high levels of haphazard urbanization results in a low quality of life and damaging environmental consequences. For sustainable urbanization in the future, an effective regional plan is necessary for Kolkata UA. Results generated by this study provide a glimpse of a possible future urbanization pattern based on the current relationship with socio-demographic and locational factors. Every urban area experiences different dynamics of growth at different time periods, so it is important to evaluate the drivers of urbanization in other Indian cities of different sizes to understand the growth dynamics. These approaches will also help to understand whether the second or third tier cities in India are following the same trends as the first tier cities or not, why so, and how regional economic disparities are affecting urbanization in the country. In India, phenomena like arbitrary zoning, ineffective policies, and the unpredictability of decision makers make it difficult to create accurate predictions (Cheng & Masser, 2003; Triantakonstantis & Mountrakis, 2012). However, simulation modeling can provide scenario-based possible outcomes, which can be highly effective tools for designing future plans. Additionally, the lessons learned from understanding the evolutionary process of present day Indian megacities will be of immense significance to plan for more sustainable megacities of the future in India.
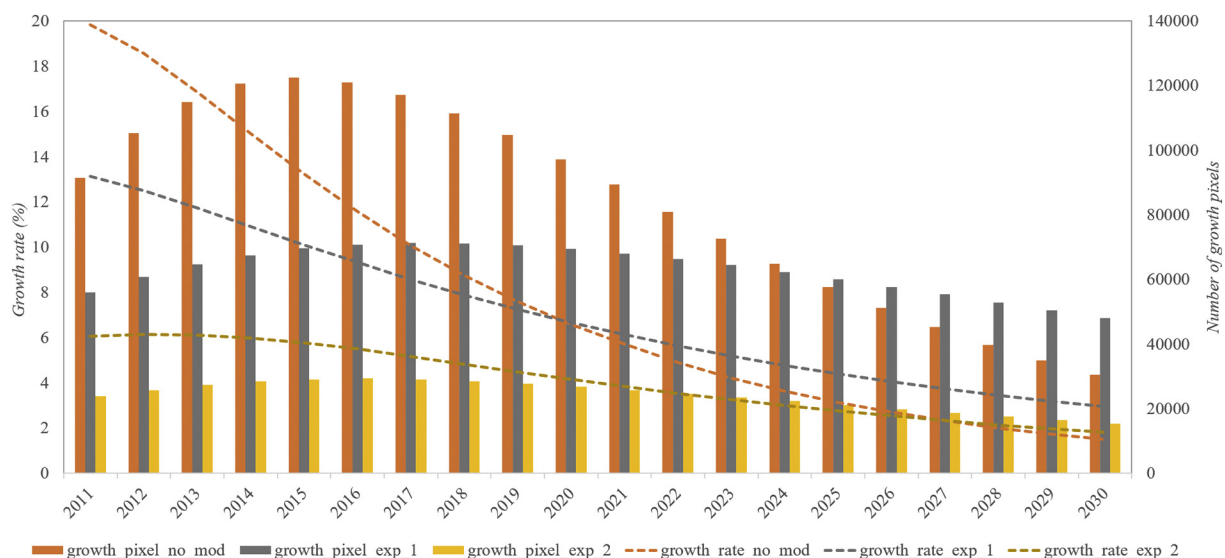
Fig. 9. Growth rate (dashed lines) and number of urban growth pixels (columns) in each predicted year.

Acknowledgment

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