Land-use change dynamics and urban growth simulations in a medium-sized city of Mangaluru, India through CA-based SLEUTH urban growth model

Dhanaraj K (dhanarajk100@gmail.com)
Mangalore University https://orcid.org/0000-0002-9121-7314
Gaurav V Jain
Space Applications Centre
Dasharatha P Angadi
Mangalore University

Research Article

Keywords: Remote sensing, GIS, Spatial metrics, Cellular Automata, SLEUTH urban growth model, Mangaluru

Posted Date: March 16th, 2022

DOI: https://doi.org/10.21203/rs.3.rs-759867/v1

Abstract

In the context of rapid urban growth in the small and medium-sized cities of developing countries, the current work attempts to calibrate the CA-based SLEUTH urban growth model to and predict urban growth for the first time in a medium-sized city of Mangaluru in southern India. The city has experienced a rapid urban growth in recent times. The current study uses the mixed methodology approach by incorporating the application of remote sensing, GIS, spatial metrics and urban growth model to map, quantify, analyse and predict urban growth dynamics of Mangaluru during the period from 2000 to 2031. The analysis of classified historical urban growth during 2000 to 2020 shows that there is a consistent increase of urban area in Mangaluru. Further, the spatial metrics used to quantify the pattern of urban growth for the historical and predicted years shows that the city is growing aggregated with several growth centres around the city. The SLEUTH model, calibrated using the historical urban area of 2000–2016, to predict urban growth for the year 2031. The urban growth simulation from SLEUTH shows slope resistance, spread and road gravity are the foremost factors influencing urban growth in Mangaluru. The urban area is expected to increase by 6895Ha from 11984Ha in 2020 to 18880Ha by 2031. The growth is expected to reduce in the eastern part due to the resistance effect of slope. The validation of the model output establishes it as acceptable but found limitation to simulate the small patchy and scattered urban growth in the outskirt of the city. The use of spatial metrics along with the SLEUTH urban growth modeling can be useful for the better understanding of the urban growth process and would therefore aid urban planners to manage the future urban growth sustainably.

Introduction

The world is getting urbanised in an unprecedented manner, which according to the United Nations estimations, currently 55% of the world's population is urbanised and is anticipated to rise to 68% by 2050 (United Nations, 2018). Urban growth is a major force driving the land use and land cover changes across the world (Bhat, Shafiq, Mir, & Ahmed, 2017; Radwan, Blackburn, Whyatt, and Atkinson, 2019; Kindu, et al., 2020). The process of urbanisation has been the most drastic contributor to environmental change, destroying biodiversity, hydrological system, loss of agricultural land, etc. Studies show that urbanisation has also been the cause of several socio-economic and health problems in the cities. However, the economic development associated with urbanisation cannot be disregarded (Black and Henderson, 1999; Ioannides and Rossi-Hansberg, 2010). Urban growths were therefore has become a contentious issue sandwiched between the priorities of development and environmental protection.

Urban areas are characterised by a high concentration of population and non-primary economic activities accompanied by intense resource utilisation all within a relatively smaller spatial area (Bhatta, 2012; Bhatti and Tripathi, 2014). The unplanned urban growth of cities in developing countries result in haphazard and low-density development at urban fringes (periphery), commonly referred to as sprawl, which is characterised by lacks of basic services such as piped water supply, street lighting, drainage etc. (Sudhira, Ramachandra, and Jagadish, 2004; Bruegmann, 2005; Bhatta, 2010).

India in recent decades is becoming hotspots urban growth in the world. In India, the proportions of people living in urban area were 34.47% in 2019 (World Bank, 2019), besides India has the world's largest rural population of 893 million. Today about 34% of the Indian population lives in the urban area, and the expected growth of the urban population is 416 million by 2050 (United Nations, 2018). This brings an ideal opportunity for India to grow urbanised and at the same time to manage the urban growth by bringing in a sustainable intervention during this initial period. It is expected that the small and medium-sized cities would host the future urban population of India (Rana and Krishan, 1981; Duijne and Nijman, 2019), regardless of this the small and medium-sized cities in India are ignored. The role of these medium-sized cities in ensuring sustainable development goals is therefore immense (Shaban, Kourtit, and Nijkamp, 2020). Urban growth studies are associated with the social, economic and environmental implications (United Nations, 2018), urban growth prediction would help to predict the consequences and thus bring interventions to sustainably manage the inevitable urban growth.

The studies of urban growth and sustainable urban development necessitate the need to develop models (Sofeska, 2016). The urban growth models that generate the future growth scenario became popular since their ability to predict the future growth, which can be employed for future urban land-use planning and to guide policy framework. The necessities of urban growth models are to avoid undesirable future urban growth and to test the theories and concepts of changing land use and local interactions (Nugroho and Al-Sanjary, 2018). Urban growth projection has become an essential component of urban planning and sustainable development goals (Aburas, Ho, Ramli, and Ash'aari, 2016). Increased computational power has enabled the development of numerous methods and techniques to model urban growth dynamism and to simulate future urban scenarios (Batty and Xie, 1994; White and Engelen, 1997; Li and Yeh, 2000; Triantakonstantis and Mountrakis, 2012; Falah, Karimi, and Harandi, 2020). Models such as Cellular Automata (CA) (Cheng and Masser, 2004), Artificial Neural Network (ANN) (Maithani, 2009), Fractal models (Man and Chen, 2020), Logistic regression (Hu and Lo, 2007), Dynamic urban growth models (Miyao, 1987) etc.

CA models are said to be an efficient urban growth simulation model due to their simplicity, structure, its ability to evolve and to simulate complex urban forms and geographical phenomena (Batty, Xie, and Sun, 1999; Aburas, Ho, Ramli, and Ash'aari, 2016; Falah, Karimi, and Harandi, 2020). The concept of CA was first proposed by Ulam and Von Neumann in the 1950s and later introduced into urban modeling by Tobler, (1979) and further developed in future. A CA model consists of five elements; cell, the state, the neighbourhood, the transition and the time, A cell can assume any one of the states at a particular time from the given set of states. The neighbourhood defines the number of cells surrounding the cell in question. Von Neumann and Moore neighbourhood are two types of neighbourhoods in cellular automata. The transition rule defines the state of the cell based on the neighbouring cells state (Liu Y., 2009; Feng, Liu, and Batty, 2015). Cellular Automata (CA) is the most popular approach to model cities integrating with GIS technology (Li and Yeh, 2000; Santé, García, Miranda, and Crecente, 2010). The limitations of traditional standalone CA models in simulating urban growth can be overcome by integrating the CA models with other spatial models (White and Engelen, 2000; Aburas, Ho, Ramli, and Ash'aari, 2016; Gharaibeh, Shaamala, Obeidat, and Al-Kofahi, 2020). By the 1990s several CA-based urban growth models were developed such as those by (Batty and Xie, From Cells to Cities, 1994, White and Engelen, 1997) etc. One of the most popular CA-based models developed by (Clarke, Hoppen, and Gaydos, 1997) was SLEUTH urban growth model (Santé, García, Miranda, and Crecente, 2010.

SLEUTH is a CA-based model for urban growth modeling (Clarke, 2008). The SLEUTH stands for the abbreviation of Slope, Land use, Exclusion, Urban, Transportation network and Hill shade. The model consists of two sub-models; the Urban Growth Model (UGM) and Land-cover Deltatron Model (LCD) which runs on a set of predefined growth rules (Dietzel and Clarke, 2007). The urban growth model component of SLEUTH is more extensively used in studies across the world than the Deltatron land use sub-model (Clarke, 2008). The SLEUTH model considers the slope, land-use, exclusion layers, historical urban extent, and transportation network as the key driving forces of urban growth (Chandan, Nimish, and Bharath, 2019). The slope layer affects the spatial growth of urban areas with gentler slope supportive and steeper slope preventing the built-up growth. As a basic CA urban models predict urban growth on assumptions that the past landscape affects the future of urban growth (Gharaibeh, Shaamala, Obeidat, and Al-Kofahi, 2020), SLEUTH also simulates the future urban growth by learning from the past urban growth or seed layer. Bearing in mind the simplicity and robustness of the SLEUTH model, the study uses the CA-based SLEUTH model to simulate urban growth in the study area. The universal applicability of the SLEUTH model by not requiring locality specific urban growth determinants makes it a simple and popular urban growth model (Chaudhuri and Clarke, 2019).

The current study makes a collective approach involving remote sensing, GIS, spatial metrics and urban growth modeling to examine Spatio-temporal land-use change, the pattern of urban growth and to predict the future urban development in a dynamic medium-sized city of Mangaluru in India. The primary objectives of the study are at first to assess the urban growth in the study area during 2000-2020 and secondly to study the dynamics of the urban growth pattern of the historical and the predicted urban area using the spatial metrics, and then to calibrate and predict the future urban growth in Mangaluru for the year 2031 by implementing SLEUTH urban growth model, and finally to evaluate the performance of the SLEUTH model in effectively simulating the historical and future urban growth of Mangaluru using Kappa agreement, correlation coefficient statistics and visual comparison techniques.

Literature Review

Many studies integrating GIS, remote sensing and SLEUTH spatial modeling to understand the dynamics of urban growth can be found in the literature, (Herold, Goldstein, and Clarke, 2003; Herold, Couclelis, and Clarke, 2005; Sakieh, et al., 2015; Akın and Erdoğan, 2020). This integrated approach to model urban growth has been proven successful in capturing the dynamics of urban growth. The digital land use and land cover mapping with the advent of aerial photography and remote sensing satellites, has replaced the conventional maps has made the process coast effective and efficient (Treitz, 2004). Urban remote sensing techniques have been widely used in the mapping of an urban area which provides data inputs for the models in high temporal and spatial resolutions and similar analysis of urban growth can be achieved by Geographic Information System (GIS). The pattern and structure of urban growth can be quantified using spatial matrices which describes the Spatio-temporal changes in urban form, landscape and also the implications of policy scenarios on urban patterns (Herold, Scepan, and Clarke, 2002; Peng, et al., 2010; McGarigal, 2014; Magidi and Ahmed, 2019). Numerous application of the SLEUTH urban growth model can be seen successfully implemented in cities around the world to simulate the spatial extent of urban growth (Silva and Clarke, 2002; Clarke, 2008; Dezhkam, Amiri, Darvishsefat, and Sakieh, 2014; Zhou, Varquez, and Kanda, 2019; Ilyassov, Kantakumar, and Boyd, 2021). KantaKumar, Sawant, Kumar, (2011), Chandan, Nimish, and Bharath, (2019), Chaudhuri and Clarke, (2019), Saxena and Jat, (2020) etc. has successfully deployed the SLEUTH urban growth model in Indian cities. However, there is an absence of the application of the SLEUTH urban growth model in the medium-sized and small cities of India. In the present study, an attempt has been made for the first time to calibrate the SLEUTH model and to predict the urban growth in an unplanned, emerging and medium-sized city in the densely populated west coast of southern India.

Study area

The city of Mangaluru lies on the coastal plains of south-western Karnataka, slightly west of the rolling hills of the Western Ghats. Administratively the city is situated within the Mangalore taluk of Dakshina Kannada district in the southern Indian state of Karnataka (Fig. 1). The city is well connected by networks of roads, railway, and the airport and seaport. The presence of National Highway NH-16, NH-66, and NH-73 in Mangalore ensures easy connectivity of the city with the rest of the country. Apart from the geographical distinctiveness of the place, the region is known for the unique culture, language and traditions of its own. Mangalore was an important city of the erstwhile Tulu Kingdom (Bhatt, 1969). The region has been historically an agricultural society known for its trade relations across the Arabian Sea in Africa, the gulf and the far south-east (Benjamin, 2017). The city is known as the cradle of the Indian banking sector and also an educational hub in the region. The city of Mangaluru has emerged as an industrial sprout in the country facilitated by a well-connected seaport enabling easy transport of goods and raw materials. Besides the health care industry and educational sector is booming in the city. The rapid population growth and a corresponding increase in urbanisation are manifest in the city, giving scope for real estate development in the city. The large scale developmental activities due to industrial development and also the tertiary sector in Mangaluru have made the city a prospective metropolis in the region. The city is also been given Special Economic Zone status by the Government of India, to further supporting growth in the region. In the current study, the study area includes the Mangaluru urban agglomeration and further the administrative boundary of Mangalore taluk has also been considered expecting future urban growth beyond the city limits.

Data And Methods

Data sources

The data required for the study comprises the satellite data, toposheets, high-resolution Google earth images, City and taluk maps, transport network map, GPS survey points and ancillary non-spatial data, which were collected from various departmental offices and online websites. The satellite images used in the study for the year 2000, 2006, 2011, 2016 and 2020 were collected from multiple satellites (Table 1) due to the lack of temporal continuity of any single satellite mission imageries. The Landsat imageries used in the study were downloaded from the USGS earth explorer (https://earthexplorer.usgs.gov/). The LISS-III data of the year 2011 was obtained from the Bhuvan portal of ISRO (https://bhuvan.nrsc.gov.in/). The satellite data were collected at an approximate 5-year interval for the period from 2000 to 2020. The images were collected based on (i) availability, and (ii) cloud-free condition. Toposheets and high-resolution images from Google Earth were used as a reference for the image classification and accuracy assessment.

Table 1 Details of the satellite imageries used in the study

Mission - Sensor	Acquisition Date	Path/Row	Spatial Resolution
Landsat 7 - ETM +	20-12-2000	145/051	30 m
ResourceSat-1 / IRS-P6 - LISS IV	28-06-2006	(098/064, 097/064)	5.8 m
ResourceSat-1 / IRS-P6 - LISS III	18-11-2011, 23-11-2011	(098/064, 097/064)	23.5 m
Landsat 8 - OLI TIRS	15-02-16	145/051	30 m
Sentinel-2 - MSI	07-01-20	T43PDQ	10 m

The SRTM Digital Elevation Model (DEM) for elevation data has been downloaded from the USGS earth explorer. Similarly, the transport network of the study area for the different year has been downloaded from the open street map website and extracted from onscreen digitisation from toposheets. The processes in the study were performed using multiple software packages. The QGIS and ERDAS were used in pre-processing of Landsat data and classification of the satellite imageries. ArcGIS and QGIS software were used for the analysis of spatial data. The prediction was executed in the SLEUTH urban growth model in the Cygwin environment. SLEUTH Model (http://www.ncgia.ucsb.edu/projects/gig/index.html) (SLEUTH3.0_beta) is an open-source modelling package developed by Dr Keith C. Clarke under the Project Gigalopolis, USGS and is based on LINUX operating system. In the current study, the model was implemented using the Cygwin interface in the Windows environment.

Image processing, classification and accuracy assessment

The pre-processing of satellite imageries removes redundancy and inaccurate data while making it suitable for operational use (Jensen, 2005; Narumalani and Merani, 2016). In remote sensing, reflected energy received at the sensors can be different from the actual radiance reflected from the object due to atmospheric scattering, refraction and absorption. To get correct ground radiance, the radiometric error must be removed by converting digital number (DN) values to radiance, then converting at-sensor radiance to the top of atmosphere (ToA) reflectance, and then converting the ToA reflectance to surface reflectance (Hall, Strebel, Nickeson, and Goetz, 1991). The radiometric correction was performed using the Semi-Automatic Classification Plugin (SCP) of QGIS (Congedo, 2016; Leroux, Congedo, Bellón, Gaetano, and Bégué, 2018). Similarly, Resourcesat-1 images were subjected to geometric correction and reprojection by ground-based registration to remove distortions in the image (NRSA, 2004; Dave, Joshi, and Srivastava, 2015). Then the multispectral composites of satellite imageries were created by stacking the respective bands of Landsat, Resourcesat-1 and Sentinel - 2 images of the study area.

The classification is performed using the reference spectra or signatures derived from the images in the supervised classification technique. The signatures were used to classify using the maximum likelihood classifier algorithm, which is one of the most commonly used algorithms of supervised classification (Strahler, 1980). The LULC classification scheme included six LULC categories viz. (i) urban / built-up area; (ii) water bodies; (iii) vacant land / bare soil; (iv) cropland; (v) plantation; and (vi) natural vegetation. Since classification algorithms do not produce perfect classification results, post-classification measures are applied to minimize the errors using the pixels recording function in ERDAS IMAGINE. Afterwards, the accuracy assessment was carried out to estimate how well the classified LULC image classes are identified corresponding to its reference image. The most popular way to represent the classification accuracy of the remote sensing data is through an error matrix (Congalton, 1991). The accuracy is described by Users' accuracy (error of commission), Producers' accuracy (error of omission), overall accuracy and kappa statistics (Congalton and Green, 2008). The raster images of LULC were converted into polygon to compute area statistics. Then using ArcGIS, urban polygon areas less than 4 Ha and non-urban polygon of less than 9 Ha was removed in the 'Eliminate' tool. As the usefulness of any classified map ultimately dependents on the production of output maps, tables and geospatial data (Lillesand, Kiefer, and Chipman, 2015), finally, maps and tables have been produced to show Spatio-temporal changes in land use and urban growth in Mangaluru during 2000-2020.

SLEUTH model description

CA-based SLEUTH urban growth model is coupled with the Clark Urban Growth Model (UGM) and the Land Cover Deltatron (LCD) sub-models (Clarke K. C., 2008; Jat, Choudhary, and Saxena, 2017). SLEUTH requires input layers of the slope, land-use, urban (seed layer), transportation and hill shade. The urban growth in the model is influenced by four sub-steps or growth rules determining different growth forms such as, spontaneous, new spreading centre (diffusive), edge (organic), and road influenced (Clarke, Hoppen, and Gaydos, 1997; Mahiny and Clarke, 2012). These growth rules are in turn determined by five parameters namely; diffusion, bread, spread, slope resistance and road gravity with a coefficient value ranging between 0-100 (Jantz, Goetz, and Shelley, 2003; Bajracharya, Lippitt, and Sultana, 2020). Diffusion coefficient determines the possibility of random selection of pixcels for new urban development, the bread index determines the growth probabilities in isolated pixel and its potentiality to develop new urban centre, the spread index influences edge growth of pixels, slope limits growth on steeper slope and road gravity index determines urban growth along the roads (Dietzel and Clarke, 2007). Table 2 describes the relationship between the growth types and growth coefficients simulating urban growth. The cell state (urban) in the CA environment is determined by the growth rules.

The SLEUTH is developed on a series of rules in a nested loop iteration in which brute force calibration using Monte Carlo simulation is used to produce growth parameters coefficient ranging in values between 0-100 for each controlling parameters in coarse, fine and final calibration phases to finally predict urban growth (Liu, Sun, Yang, Su, and Qi, 2012; Abedini and Azizi, 2016). Further, the behaviour of the model is determined by the user-provided excluded layers and slope gradient, in which locations having slope gradient higher than 21% cannot be converted to urban (Clarke, Hoppen, and Gaydos, 1997; Silva and Clarke, 2002). Finally, the model is controlled by self-modifying growth rules initiated by the critical-low or critical-high growth rate of the model which produces an S-shaped growth curve and prevents the model from simulating linear urban growth (Silva and Clarke, 2002; Dadashpoor and Nateghi, 2017).

The Leesalee metric generated during the final calibration of the model is used to choose the best-fit control parameters that best captures the pattern of urban changes and is used to predict urban growth (Chaudhuri and Clarke, 2019).

Table 2 Description of the relationship between growth types and growth coefficients for simulating urban growth

Growth rule	Growth coefficient	Description
Spontaneous growth	Diffusion, slope	Simulates random urban growth
New spreading centre (diffusive)	Bread, slope	New diffusion Centre
Edge (organic)	Spread, slope	Simulates edge growth of new or old urban centres
Road influenced growth	Bread, road gravity, spread, slope	Simulates new growth along roads

Model inputs

The SLEUTH model requires minimum spatial datasets as input layers in raster format such as slope, land-use, exclusion, urban, transportation and hillshade (Fig. 2). All the input data required for the model has been arranged using ARCMAP 10.3 software. The slope and hillshade layers were derived from SRTM DEM 30 m elevation data in ERDAS IMAGINE. The slope was calculated in percentage and the hillshade map of the study area was also prepared to be used as a background layer of the urban growth prediction map (Dietzel and Clarke, 2007). The land-use layer of the study area for the model is prepared using satellite imageries for the year 2000, 2011 and 2016. The exclusion layer was used to define areas not suitable for urban growth. The model requires a minimum of one excluded area layer, the excluded area layer was created by compiling all the water bodies Shapefile derived from the classified land use land cover map of the study area for 2000, 2011 and 2016 as there is less probability of water bodies converted for built-up purposes in future. The SLEUTH model requires a minimum of four historical urban seed layers (Liu, et al., 2019), the urban layers were extracted from satellite image classification as discussed in the image classification section, for the year 2000, 2006, 2011 and 2016. The urban extent layer is a critical input to the model which will be calibrated in phases for growth prediction (Dietzel and Clarke, 2007). Lastly, the transportation map was prepared for the year 2000, 2011 and 2016, which are digitised from toposheets and also downloaded from online sources (OpenStreetMap). The roads are categorised as national and state highways, then again as primary, secondary and tertiary roads, and residential roads. The entire layers used in the model were converted into Graphics Interchange Format (GIF) raster format with unsigned 8-bit pixel depth to use in the model. These layers were prepared with 30 meters and 100 meters spatial resolution to be used during coarse, fine and final phases of calibration. All the input layers were prepared with uniform arrays with the dimension of 30 m resolution data is 854×1388, whereas that of 100 m resolution data was 256×416. Then the implementation of the SLEUTH model follows three phases viz. test, calibration and prediction (Clarke, Hoppen, and Gaydos, 1997). The following sections briefly describe the calibration process implemented for urban growth prediction in Mangaluru.

Model calibration

The model calibration begins with the test. The test mode checks the reaction of the model to the input datasets by loading the input file directory. Once the test step is executed successfully the calibration procedure was started. The calibration process adjusts the modelled data with the historical input datasets. The calibration is done in three scenarios; coarse, fine and final, which produce the best coefficients (diffusion, bread, spread, and slope resistance road gravity) which is used by the model to determine the growth rule to effectively simulate the urban growth (Silva and Clarke, 2002). The calibration of growth coefficients is done using the brute force calibration technique, which produces output for every possible combination of coefficient values (Bihamta, Soffianian, Fakheran, and Gholamalifard, 2015; Bajracharya, Lippitt, and Sultana, 2020). The calibration process makes the model to get adapted to the local settings of the study area (Clarke, Hoppen, and Gaydos, 1996). In the coarse calibration, the scenario file was created with a wide range of parameter values of START-STEP-STOP (0-20-100) (Table 3), and the start date and end date of the calibration were set at 2000 and 2016 respectively. The output from the coarse calibration was assessed from the control statistics file to narrow down the best fit values corresponding to the top ten Leesalee indexes for the next phase of the calibration. The Leesalee index measures spatial fit between the historical urban growths with the modelled growth (Silva and Clarke, 2002). In the fine calibration, the range of parameters was narrowed down and Monte Carlo iterations were set according to the input raster resolution. The final calibration output from the previous calibration was used to further narrow down the values and was executed with 50 Monte Carlo iterations. The fine calibration provides the best fit coefficients from running the model on the historical urban growth to simulate the future urban growth (Rafiee, Mahiny, Khorasani, Darvishsefat, and Danekar, 2009). The best-fit prediction parameters for the end year (2016) urban layer were derived from the final calibration is used to forecast urban area in Mangaluru for the year 2031.

Prediction

For the urban growth prediction the best-fit prediction coefficients was used to execute prediction mode in SLEUTH for Mangaluru (Fig. 3). The prediction was executed using 100 m resolution raster input layers with 1000 Monte Carlo iterations. The predicted output GIF images were converted to .tiff image to use in the GIS environment for further analysis of the forecasted urban growth results.

Urban growth prediction validation

To confirm the accuracy of modelled urban growth in SLEUTH for Mangaluru, model validation was performed. In the current study, the model validation was performed by employing statistical measurements and visual inspection techniques. The Kappa index of agreement and correlation coefficient of observed and predicted urban growth pixels were computed to statistically measure the validity of the model (Sakieh, et al., 2015; Ilyassov, Kantakumar, and Boyd, 2021). The Kappa statistics is a measure of agreement between the actual urban area and the modelled urban area (Congalton and Green, 2008; Foody, 2002). The statistic is computed for pixels in the two maps as a percentage of agreement as;

$$\text{Kappa} = \frac{P_o - P_c}{1 - P_c} \quad (1)$$

Where, P_o is the proportion of the observed urban pixel and P_c is the expected proportion of correct urban pixels (Chaudhuri and Clarke, 2014). A Kappa value of 1 signifies that there is a perfect agreement in the data. However, the Kappa agreement is not the perfect method measurement of agreement (Foody, 2002). Then, the correlation coefficient between the historical observed and modeled urban pixels has been worked out for the year 2006, 2011, 2016 and 2020 (Sandamali, Kantakumar, and Sivanantharajah, 2018). Further, the visual association between the modeled and actual urban area was performed. For comparing the predicted growth with the observed growth of urban area classified LULC image of the year 2020 was used. The visual comparison of spatial association between the predicted and actual urban growth for the year 2020 was compared, in which areas of association, areas of over-predicted and under-predicted growth were spatially identified.

Landscape metrics

To quantify the Spatio-temporal dynamics of urban growth patterns spatial metrics have been used for both historical and predicted urban growth. The spatial metrics quantify spatial dynamics of urban patches and can be used as good indicators of urban form and morphology, planning scenario, ecology and socio-economic aspects (Herold, Goldstein, and Clarke, 2003; Alberti and Marzluff, 2004; Botequilha Leitão, Miller, Ahern, and McGarigal, 2006). The metrics quantify the physical dimensions of urban patches such as their shape, area, size, pattern and distances between the patches. The spatial metrics allows analysis of urban growth pattern. In the current study seven spatial indices measuring various aspects of urban patches were selected (Table 3). The urban patches for the year 2000, 2006, 2011, 2016 and 2020 of Mangaluru was derived from the classified maps by re-coding LULC classes into the urban and non-urban area and was compiled as binary maps in ArcMap. Later the same procedure was followed for the simulated 2031 urban map of Mangaluru. The metrics were calculated using the Fragstats 4.2 software (McGarigal, 2014).

Results And Discussion

Land use land cover classification and analysis

Land use and land cover map of Mangalore taluk area for the years of 2000, 2006, 201, 2016 and 2020 was prepared from Landsat, Resourcesat-1 and Sentinel-2 images using maximum likelihood classifier (Fig. 3). The LULC map consists of urban, barren land, water bodies, natural vegetation, agriculture and plantation classes. The LULC of Mangalore has undergone significant transformation over the years from 2000 to 2020. The incremental change in urban land use is particularly apparent. The urban land use was seen expanding primarily in a north-south direction along the coast. To assess the accuracy of these classified images the confusion matrix was constructed. The results of the accuracy assessment using the confusion matrix are shown in Table 4. The overall accuracy of the classified image for the year 2000, 2006, 2011, 2016 and 2020 was found to be 89.29%, 90.46%, 90.13%, 93.86% and 92.67% respectively. The overall Kappa coefficient value varies between 0.85% in 2000 to 93.86% for the year 2016. The Kappa agreement of the urban class was found to have a coefficient value varying from 0.87% to 0.97% in the study area. It can be observed from Table 4 that the Kappa value of the urban class displays an increase from the year 2000 to 2020. The classified LULC map is having an overall accuracy of 85% and more, which is considered qualifying for further scientific analysis (Anderson, Hardy, Roach, and Witmer, 1976).

The LULC area changes from 2000 to 2020 are shown in Table 5. It is evident from the table that natural vegetation and plantation are the dominant land cover in the region, which is followed by barren land, agriculture, urban and water bodies respectively. The abundance of vegetation is due to the favourable climatic condition in the region. However, the growth of urban land is most apparent in Mangaluru from 2462 ha in 2020 to 11984 ha in 2020. The impact of increasing urban land is felt in all land cover categories however the vegetation has received the maximum burn while water bodies are least affected. Decreasing traditional agricultural land can also be seen in Mangaluru, signalling the rapid urbanisation of the region. The change in the area of the LULC classes during the 2000-2020 periods is depicted in Fig. 4. The negative growth status of land cover and rapid expansion of built-up area can be seen in Fig. 4.

Urban growth analysis

The extent of the urban area was extracted from the LULC maps to understand the dynamics of urban growth in Mangaluru. The city of Mangalore has seen an exponential increase in urban area from 2000 to 2020. The various favourable pull factors in Mangalore have provided a unique opportunity for the expansion of the city beyond its traditional boundary. The spatial expansion of urban area during each period is shown in Fig. 5. The spatial expansion of the urban area in the north, north-east and southern part of the city is noticeable from 2000 to 2020. The expansion is more evident along with the transportation networks, where patches of urban areas have grown from the edges of previous growth patches. Similarly, patches that are grown spontaneously as a new growth centre over time can also be identified from the map. The concentrations of these newly grown urban patches were observed having higher intensity in the north and north-eastern part of the city. The new urban patches which have grown independent of the previous urban patches were mainly come up due to the emergence of new service centres or industrial establishments. The growth during 2016-2020 has mainly occurred in the areas away from the central business district and the fringe areas of the city. A major boom in urban growth has occurred during the 2011-2016 period as about 4000 Ha of the new urban area was added with an annual increase rate of 800 Ha.

Table 4 Summary of the LULC classification accuracy assessment using error matrix for the year 2000, 2006, 2011, 2016 and 2020

Year	Accuracy	Classes						Overall Accuracy	Overall Kappa
		Urban	Water bodies	Vacant land	Agricultural	Natural Vegetation	Plantation		
2000	Reference Total	8	24	56	23	81	88	89.29	0.85
	Classified	9	24	56	21	90	80		
	Correctly Classified	8	23	50	17	75	77		
	User's Accuracy (%)	88.89	95.83	89.29	80.95	83.33	96.25		
	Producer's Accuracy (%)	100	95.83	89.29	73.91	92.59	87.50		
	Kappa	0.89	0.89	0.89	0.89	0.88	0.88		
2006	Reference Total	34	20	48	31	73	77	90.46	0.89
	Classified	32	21	50	31	77	72		
	Correctly Classified	21.00	19.00	48.00	26.00	66.00	69.00		
	User's Accuracy (%)	96.88	95.24	88.00	83.87	85.71	95.83		
	Producer's Accuracy (%)	34.00	20.00	48.00	31.00	73.00	77.00		
	Kappa	0.9506	0.9466	0.8448	0.9573	0.8022	0.9502		
2011	Reference Total	24	19	54	30	88	89	90.13	0.88
	Classified	22	20	55	30	93	84		
	Correctly Classified	21	19	48	25	80	81		
	User's Accuracy (%)	95.45	95.00	87.27	83.33	86.02	96.43		
	Producer's Accuracy (%)	87.50	100.00	88.89	83.33	90.91	91		
	Kappa	0.95	0.95	0.84	0.96	0.80	0.95		
2016	Reference Total	36	20	57	15	86	79	93.86	0.92
	Classified	36	20	53	18	86	80		
	Correctly Classified	35	20	51	13	79	77		
	User's Accuracy (%)	97.22	100.00	96.23	72.22	91.86	96.25		
	Producer's Accuracy (%)	97.22	100.00	89.47	86.67	91.86	97.47		
	Kappa	0.97	1.00	0.95	0.71	0.88	0.949		
2020	Reference Total	170.00	6.00	23.00	11.00	46.00	44.00	92.67	0.88
	Classified	168.00	6.00	26.00	8.00	48.00	44.00		
	Correctly Classified	166.00	6.00	22.00	7.00	38.00	39.00		
	User's Accuracy (%)	99.00	100.00	85.00	88.00	79.00	89.00		
	Producer's Accuracy (%)	97.65	100.00	95.65	63.64	82.61	88.64		
	Kappa	0.97	1	0.83	0.87	0.75	0.87		

Table 5 The classified land use land cover area of Mangaluru from 2000 to 2020 in Hectares

	Years				
Classes	2000	2006	2011	2016	2020
Barren Land	9481.14	9116.92	8701.20	7725.71	6522.69
Urban	2462.76	3252.81	4974.21	9027.32	11984.70
Water bodies	3193.47	3233.02	3102.71	3055.37	3003.36
Natural Vegetation	21350.79	20799.80	19779.11	17209.59	16171.60
Agricultural	1860.30	1854.11	1825.85	1751.55	1481.74
Plantation	18174.15	18263.10	18136.63	17753.83	17357.96

SLEUTH calibration and validation

The SLEUTH model run in three phases such as; coarse, fine and final was executed by applying the brute force calibration. The results of the top three optimal values of growth coefficients during different calibration phases are presented in Table 6. It can be noticed from the table that compare metric, which compares the modelled and real urban extent was high at 0.58, similarly, the least square regression score of 'Pop' for modelled and actual urban growth was high, 0.93. The metrics comparing the shape and form of modelled and actual urban growth; the Edge r^2 and R^2 cluster were higher as 0.77, 0.95 respectively. The average x and y values of modelled and actual urban cells were also high at 0.95 and 0.60 respectively. The indices for evaluating calibration show that the coefficients selected for growth modeling characterises the real urban growth in Mangaluru and therefore can be used in the prediction phase. After a successful test run of the SLEUTH model coarse calibration was executed using five controlling coefficients range in 0-20-100. In the following steps i.e. during fine and final calibration the top coefficients range are selected by averaging the values based on Leesalee metric as shown in Table 7. The Leesalee metric is the measure of spatial agreement between the modelled urban area and historical urban area, which was found to be 0.51 in the final calibration, is considered satisfactory in a random urbanised area (Mahiny and Clarke, 2012; Jat, Choudhary, and Saxena, 2017). From the final calibration, the best-fit coefficient was selected for the five parameters to be used in prediction.

Table 6 Top three optimal values of growth coefficients during coarse, fine and final phases of the SLEUTH model calibration

Coarse calibration																
Compare	Pop	Edges	Clusters	Size	Leesalee	Slope%	Urban	Xmean	Ymean	Rad	Fmatch	Diff	Brd	Sprd	Slp	RG
0.56	0.93	0.81	0.94	0.99	0.48	0.63	0.88	0.48	0.34	0.94	0.90	1	1	20	60	1
0.56	0.93	0.81	0.94	0.99	0.48	0.63	0.88	0.48	0.34	0.94	0.90	1	1	20	60	20
0.56	0.93	0.81	0.94	0.99	0.48	0.63	0.88	0.48	0.34	0.94	0.90	1	1	20	60	40
Fine calibration																
0.62	0.93	0.79	0.93	0.99	0.48	0.60	0.88	0.27	0.38	0.94	0.90	1	1	25	65	1
0.62	0.93	0.79	0.93	0.99	0.48	0.60	0.88	0.27	0.38	0.94	0.90	1	1	25	65	11
0.62	0.93	0.79	0.93	0.99	0.48	0.60	0.88	0.27	0.38	0.94	0.90	1	1	25	65	21
Final calibration																
0.58	0.93	0.77	0.95	0.96	0.51	0.05	0.91	0.95	0.60	0.93	0.92	1	1	29	63	25
0.57	0.93	0.77	0.92	0.97	0.51	0.04	0.91	0.96	0.62	0.93	0.92	1	4	29	66	17
0.58	0.93	0.77	0.98	0.96	0.51	0.23	0.91	0.95	0.60	0.93	0.92	1	1	29	60	17

Fig. 6 shows that the most important driving forces of urban growth in Mangaluru are coefficients of slope resistance (50), spread (34) and road gravity (27). The influence of diffusion (12) and bread (12) was relatively lower. This trend in growth coefficients indicates that the urban growth in Mangaluru will be largely limited by the rolling topography of the region. The deterrent effect of the slope would be more prominent towards the east and north-east where steeper slopes due to undulating terrain are prominent. The city is likely to experience edge growth or urban expansion from the current patches as the contribution of the spread coefficient is significant. The coefficient value of road gravity suggests that new urban growth tend to occur along with the transportation networks. However, the relatively less weightage of the diffusion and breed coefficient in the study area suggests that the simulation of the random spontaneous urban growth and emergence of new urban centres are having lesser chances. Nonetheless, the probability of the emergence of new urban centres and spontaneous urban growth is very much relevant along the transportation networks. Therefore, it can be supposed that the future urban growth in Mangaluru is determined by the development of transportation network and also investment in the creation and expansion of new infrastructure services which would act as new growth centres in the study area. The relative predominance of the slope resistance, spread and road gravity values suggest that the urban growth in Mangaluru is likely to be scattered and the existence of a transportation network would also facilitate the rapid urban sprawl from the previously grown urban patches (Mahiny and Clarke, 2012; Sakieh, Amiri, Danekar, Feghhi, and Dezhkam, 2015).

Table 7 The coefficients range selected for the SLEUTH calibration process based on Leesalee metric

Growth Parameters	Coarse			Fine			Final		
	Monte Carlo Iterations = 100			Monte Carlo Iterations = 25			Monte Carlo Iterations = 50		
	Total simulation runs = 7775			Total simulation runs = 1599			Total simulation runs = 1023		
	Start	Step	Stop	Start	Step	Stop	Start	Step	Stop
Diffusion	0	20	100	1	5	20	1	3	10
Spread	0	20	100	10	5	30	20	3	30
Bread	0	20	100	1	5	20	1	3	10
Slope Res.	0	20	100	50	5	70	60	3	70
Road Gr.	0	20	100	1	10	40	1	8	30

Analysis of urban growth prediction

Using the best-fit parameter coefficients from the SLEUTH model calibration of the historic urban growth of Mangaluru, the growth prediction for the year 2031 was executed. The city of Mangaluru has expanded from 2462 Ha in the year 2000 to 18880 Ha in 2031, which is an increase of more than 666 % urban area according to the SLEUTH model prediction. Fig. 7 show the observed historical urban growth area during 2000-2020 and the predicted growth for the year 2031 in hectares for Mangaluru. A steeper rise in the curves for the predicted urban area can be noticeable in the figure, and in general, the graph of urban growth preserves the current trend of urban growth in the city. During the period of the last ten years i.e. between 2020 and 2031, an increase of 6895 Ha of the urban land area can be noticed. The prediction output map of the urban growth of Mangaluru from the model is presented in Fig. 8. The simulation results show that the city is expected to expand its urban footprint. Extensive growth in the urban area in Mangaluru by the year 2031 will take place in the eastern and southern part of the city. The growth in the industrially dominant northern part was also seen increased in this period. A high growth probability (90%) can be expected in areas adjusting to the historic urban patches, which increases the built-up density near the city centre. A prominent growth can be seen along with the transportation network in the study area, particularly towards the east and in the north-south direction, where national highways pass through. Tiny patches of spontaneous new urban centres can also be seen sprouting influenced by proximity to the road. Some such bread points can be noticeable in the south-western corner of the study area and near Talipady village in the north-western part (Fig. 9). Fig. 9 compares the urban growth from 2020 to 2031 from the simulated map, in which the main urban centres and transportation network of Mangaluru is juxtaposed with the simulated urban growth layer. It can be deduced from the map that transportation is a major player in the urban growth of Mangaluru. The urban expansion and new urban centres along the highways is the characteristic feature of urban growth in the study area. Further, the existing urban centres away from the CBD of the city have also experienced widespread urban growth, which grows independently from 2020 and later merges with the larger urban patch of Mangaluru city by 2031. For example in the southern part of the city, the towns of Dheralakatte, Thokkotu, Someshwara and Ullal merge as at the tri-junction becoming an agglomeration by itself. Similarly, the industrial hotspot area of Surathkal expands spatially incorporating more of the surrounding area. The road tri-junction at Talipady and Kaikamba has seen rapid urban growth mainly at Kaikamba.

The urban growth simulation in Mangaluru shows that a major portion of future growth will take place in the southern part of the city. This can be associated with the rapidly developing education and health care industry in the region. The allocation of land for the IT-Special Economic Zone (SEZ) in the south-western part of the study area can also be seen as synonymous with this growth. Intensive growth by infilling development can be observed near the CBD of the city, where small patches of open land and, agriculture and natural vegetation has paved the way for built-up accretion. However, the city authorities could demarcate and limit urban growth over natural vegetation to promote sustainable development of the city. The highway centric growth toward the eastern part of the city highlights the future growth potential beyond the city limits, which would need larger administrative machinery to manage civic needs. Bearing in mind such forthcoming situations authorities could consider demarcating a larger city administrative area in line with the Bengaluru model. Fig. 10 plots the actual urban area for the year 2020 and simulated growth in 2031 extracted from 2 km multiple ring buffers around CBD of Mangaluru. There are a total of 15 buffer zones and the urban growth for 2031 increases steadily from the CBD area towards the outskirt. The higher growth can be seen in the distance between 6-16km distances from CBD due to edge growth, which largely constitutes the main urban area of the city. The zone between 16-18 km has seen unconventional growth which could be triggered due to the emergence of urban centres beyond the city limits. Zone 18 is expected to add 394 Ha of an urban area by 2031 also due to the expansion of the industrial area. However, the urban growth in the outskirts of the city is insignificant.

The SLEUTH urban growth prediction model has also produced different urban growth statistics in an avg log file that measures urban growth types for all the year from 2000 to 2031. Some important growth statistics for the year 2000 and 2031 are presented in Table 8 to compare the various urban growth statistics. Urban growth parameters in Table 8, shows an increasing trend, the urban growth pixel has increased from 227.45 in the year 2000 to 534.92 in 2031. The spontaneous urban growth (sng) has increased from 9.76 to 13.55 during the 2000 to 2031 period, suggesting the emergence of new urban centres though in small quantity. While the organic growth (og) has witnessed the highest growth from 199.14 to 501.88 during the period, as the edge growth is the predominant form of urban growth in Mangaluru. This is also reflected in the edge statistics which grew from 2247.84 to 4327.01 during 2000-2031. The road influenced growth has marginally decreased from 16.25 in 2000 to 15.27 in 2031 indicating that growth along the existing transport network would slow down and thus increasing road infrastructure would be crucial for future urban growth in the region. The increase in the five growth parameters of spread, bread, road gravity all indicates urban growth in the study area. However, increasing slope restraint from 3.2 to 3.87 in 2000-2031 periods indicates sprawling of the city towards the east where the presence of undulating topography limits the urban growth. The increasing radius of cluster (rad) value from 28.6 to 70.36 by 2031 suggests urban expansion by increasing the radius of the urban patch in Mangaluru. The declining rate of urban growth from 8.85 in 2000 to 3.44 in 2031 can be due to the increasing resistance offered by the slope in the east of the study area, which could push the growth beyond the study

area towards the south and northern direction along the coastal area. The possibility of vertical growth can also not be ruled out (Jat, Choudhary, and Saxena, 2017).

Prediction validation

The predicted image is prone to error, thus the accuracy of the predicted image is generally determined with an observed map (Chaudhuri and Clarke, 2019). The accuracy assessment of the modelled urban growth in Mangaluru is performed with statistical measurements such as Kappa agreement and correlation coefficient of the historical and predicted urban area and also through visual comparison of the spatial extent of actual and modelled urban area. The overall accuracy of modelled urban growth was found to be 88.06% while the Kappa agreement was 0.67 which is considered an acceptable value of accuracy and it indicates that there is an agreement between the modelled urban growth and reference historical urban area. The lower Kappa value of the model output indicates that the spatial match of the predicted urban area with the observed urban growth is lower. However, this could be due to the coarse spatial resolution of the modelled urban data in comparison to actual data and also due to missing ting urban patches in the modelled urban layer. The correlation between the modelled urban area and historical urban area in terms of pixels number is presented in Fig. 11. There is a high correlation, with an R^2 value of 0.93, between modelled and observed the number of urban pixels for the year 2006, 2011, 2016 and 2020. Thus it shows that the SLEUTH model is successful in accurately simulating the urban growth area of Mangaluru.

Table 8 Comparison of various urban growth statistics from SLEUTH between the year 2001 and 2031

Growth Metrics	2001	2031
Spontaneous Neighborhood Growth (sng)	9.76	13.55
Organic growth (og)	199.14	501.88
Road influenced growth (rt)	16.25	15.27
Area	2247.84	15551.99
Edges	2247.84	4327.01
Clusters	641.27	594.67
Radius of Clusters (rad)	28.6	70.36
Slope	3.2	3.87
Diffusion	12	16.17
Spread	34	45.83
Breed	12	16.17
Road gravity	1	15.72
Per cent urban	35.52	67.08
Growth rate	8.85	3.44
Growth pixels	227.45	534.92

Further validation of urban growth prediction was carried out by visually comparing the spatial association between urban extents of observed urban area in 2020 with that of predicted urban area of 2020 in GIS environment. Fig. 12 shows the overlay of predicted urban area layer of 2020 and observed urban layer. The correctly predicted areas i.e. areas of association mostly constitutes the main urban area of the city and some important secondary towns surrounding the city. It shows that the model has been successful in simulating core urban areas. The overestimated areas are largely areas surrounding the main urban patches. This could be due to the edge growth which the model might have exaggerated without considering environmentally protected areas and error during image classification of the base urban layer can also introduce fallacy. The model however fails to simulate tiny patches of scattered urban growth in the study area, particularly in the outskirts of the city, which has resulted in underestimation of urban growth. Overall the performance of the SLEUTH urban growth model can be considered as acceptable.

The pattern of urban growth

Several spatial metrics such as NP, CA, PD, LPI, FRAC_MN, CLUMPY and ENN_MN (Table 3) at the class level were chosen for urban growth pattern analysis in Mangalore for the historical and simulated urban area. The metrics were calculated for the year 2000, 2006, 2011, 2016, 2020 and the predicted year 2031 in Fragstats. The number of patches (NP) and patch density (PD) were seen (Fig. 13a and Fig. 13b) fluctuating with the increasing trend during the 2000-2006 period, due to rapid urban growth. And was seen decreasing from 2006-2016 and further increasing in the 2016-20 period due to scattered growth beyond the city core area. The simulated NP and PD for 2031were seen lowest as the small urban patches grew by merging and becoming larger urban centres. The PD has recorded the highest value in 2006, suggesting highly fragmented growth which by 2031 decreases to 0.13 as the urban patches became more even. The class area (CA) metric was on the other hand was seen increasing throughout the year, a steep rise in the curve can be noticed during the simulated period indicating urban expansion in Mangaluru (Fig. 13c). The LPI which is also an indicator of the presence of dense urban core area (Taubenböck, et al., 2014), was seen increasing for the historical urban growth period but slightly decreases in 2031suggesting increasing number of larger urban centres in the study area (Fig. 13d). The values of FRAC_MN increases initially suggesting dispersed urban growth and decreases further till 2031 except for an increase during

the 2016-2020 period (Fig. 13e). The decreasing mean fractal dimension index during the later period indicates compact urban growth and decreasing perimeter suggest the simplicity of patch morphology. The clumpyness index (CLUMPY) measures aggregation of patches ranges in value between 0-1 was seen having an increasing trend except during 2011-2016 period (Fig. 13f). This suggests increasing aggregation of built-up patches in the study area as the previous patches have expanded by edge growth. The higher clumpyness also reveals the concentrated growth of settlements surrounding an urban centre in Mangaluru. However, a small dip in CLUMPY value for the simulated year shows new urban growth away from the city. The isolation metric of the mean Euclidean Nearest Neighbour (ENN_MN), decreases for the observed urban area except for the period from 2006 to 2011(Fig. 13g). However, there is a steep rise in the mean ENN curve during the period of simulated urban growth again suggests the increasing distance between urban patches. The urban patches are coming together in a compact form in the central part of the city, while on the other hand the scattered patches at the outskirts of the city limits are aggregating and thus distances between them are increasing considerably. The infill development both within the city and along the suburban areas is visible.

Thus, the analysis of urban growth pattern during the observed and predicted period reveals that there has been considerable development of urban land in the study area during the 2000 to 2031 period. The most prominent growth has occurred during the 2011-16 period as reflected in the CA metric. The smaller and scattered urban patches in the region are expected to aggregate to form many clumps of urban centre across the study area by 2031, creating numerous growth points in Mangaluru. The significant reduction of scattered urban patches in the predicted year and decrease in the number of patches (NP) could be owed to the resistance of steeper slope towards the east. The LPI metric shows that the city has slowly developed the core urban area in the central-western part over the year and multiple centres also grew by the year 2031. In summary, more compact growth with decreasing urban patch complexity can be seen in general in Mangaluru over the years.

Conclusion

In the background of rapid urban growth in the small and medium-sized cities of developing countries, the assessment and forecast of urban growth are vital for planning and sustainable management of urban growth. However, in developing countries like India where, metropolitan driven urban development policies and lack of spatial data availability keeps the small and medium-sized towns out of academic discussions despite their potentiality. In the current study analysis of historical urban growth and prediction of future urban growth dynamics of a medium-sized city of Mangaluru in southern India was attempted. The present study makes use of a mixed methodology approach by incorporating the application of remote sensing, GIS, spatial metrics and urban growth model to study urban growth in Mangaluru from 2000 to 2031. It is extremely rare to use models to assess urban growth in a medium-sized city, in this study CA-based SLEUTH urban growth model has been calibrated for the local situation of Mangaluru and used to predict urban growth for the year 2031. The historical analysis of urban growth and its spatial pattern was carried out by making use of multi-temporal remote sensing data from Landsat, Resourcesat-1 and Sentinel-2 missions. The classification of LULC was realised with an overall accuracy ranging from 89% to 93% from the remote sensing imageries 2000, 2006, 2011, 2016 and 2020. These classified LULC maps were used for further analysis and modelling in SLEUTH.

The result of the study reveals a significant increase in the urban area in Mangaluru from 2000 to 2020 (3798 Ha – 11984 Ha) and a similar trend can be noticed for the predicted urban growth as well for the year 2031. There would be an expected increase of 6895 Ha of urban area in Mangaluru during the 2020 to 2031 period. The SLEUTH model has found that slope resistance, spread and road gravity are the major controlling growth types in Mangaluru. The new predicted urban growth is expected to occur along the highways and the current urban patches would spatially expand due to edge growth. Spatially the growth is anticipated to take place particularly in the northern and southern part of the city along the national highway. The southern part of the city would grow to become an important hub for the service sector in the city. Besides, infill and edge growth will make the existing urban areas become packed particularly in the core urban area. The slope resistance of the model restricts urban growth to the western part of the study area. The concentrated growth of urban land along the coastal area and the plane lands of the city cost dearly to the agricultural and wetlands lands in Mangaluru. The urban expansion also means large scale rural-urban transitions that would take place at Mangaluru, which must be therefore foreseen to manage the growth and achieve sustainable development of the urban agglomeration at Mangalore. The analysis of the spatial pattern of the urban area through spatial metrics suggests that the urban growth in the study area is increasingly becoming aggregated and also indicates the emergence of multiple growth centres away from the core city. The increasing PD, LPI, ENN and CLUMPY suggests a bigger urban patch and compact urban form in Mangaluru in future.

The integrated methodology approach for the analysis of urban growth, to quantify urban growth pattern and to model urban growth for predicting the future scenario was proven successful in the study area. The modeling studies on an emergent city like Mangaluru, which are expected to be the host of the future urban population of the country, would be useful for the land use and urban planning interventions to bring sustainable development of the urban area. Therefore with the proven applicability of the SLEUTH model in a small and medium-sized city, the study can be replicated for similar cities of developing countries. However, the evaluation of the model results shows that the SLEUTH model has not been able to capture the scattered urban growth in the peripheral area of the city. The study recommends that the results of the SLEUTH model can be further refined and improved by incorporating higher spatial resolution datasets and also by including a more elaborate exclusion layer and socio-economic data of the study area into the model.

Declarations

Funding: The research work is funded byUniversity Grants Commission, Ministry of Human Resource Development, Govt. of India, through doctoral research fellowship.

Conflicts of Interests: Authors declare no conflicts of interest with respect to the research, authorship and the publication of this work.

Acknowledgement

I would like to express my sincere thanks to the University Grants Commission, Govt. of India, for the financial assistance through the research fellowship. The first author is grateful to Dr Gaurav V. Jain, scientist, Space Applications Centre (SAC), Ahmedabad for the persistent guidance during the work. The opportunity provided by Dr S P Vyas, Head-ERTD, SAC, Ahmedabad to work with SAC is also gratefully acknowledged.

Data availability

All data generated during this study are included in this article and the same can also be requested from the corresponding author.

References

1. Abedini, A., & Azizi, P. (2016). Prediction of future urban growth scenarios using SLEUTH model: (Case study: Urmia city, Iran). *Int. J. Architect. Eng. Urban Plan, 26*(2), 161–172. doi:10.22068/ijaup.26.2.161
2. Aburas, M. M., Ho, Y. M., Ramli, M. F., & Ash'aari, Z. H. (2016). The simulation and prediction of spatio-temporal urban growth trends using cellular automata models: A review. *International Journal of Applied Earth Observation and Geoinformation, 52*, 380–389. Retrieved from https://doi.org/10.1016/j.jag.2016.07.007
3. Akın, A., & Erdoğan, M. A. (2020). Analysing temporal and spatial urban sprawl change of Bursa city using landscape metrics and remote sensing. *Modeling Earth Systems and Environment, 6*, 1331–1343. Retrieved from https://doi.org/10.1007/s40808-020-00766-1
4. Alberti, M., & Marzluff, J. M. (2004). Ecological resilience in urban ecosystems: Linkingurban patterns to human and ecological functions. *Urban Ecosystems, 7*, 241–265. doi: 10.1023/B:UECO.0000044038.90173.c6
5. Anderson, J. R., Hardy, E. E., Roach, J. T., & Witmer, R. E. (1976). A Land Use and Land Cover Classification System for Use with Remote Sensor Data. *USGS professional paper 964*, 138– 145. Retrieved from http://pbcgis.com/raster/anderson.pdf
6. Bajracharya, P., Lippitt, C. D., & Sultana, S. (2020). Modeling Urban Growth and Land Cover Change in Albuquerque Using SLEUTH. *The Professional Geographer, 72*(2), 181–193. Retrieved from https://doi.org/10.1080/00330124.2019.1674668
7. Batty, M., & Xie, Y. (1994). From Cells to Cities. *Environment and Planning B: Planning and Design, 21*(7), 31–48. Retrieved from https://doi.org/10.1068%2Fb21S031
8. Batty, M., Xie, Y., & Sun, Z. (1999). Modeling urban dynamics through GIS-based cellular automata. *Computers, Environment and Urban Systems, 23*(3), 205–233. Retrieved from https://doi.org/10.1016/S0198-9715(99)00015-0
9. Benjamin, S. (2017). Multilayered Urbanisation of the South Canara Territory. In E. Denis, & M.-H. Zérah, *Subaltern Urbanisation An Introduction to the Dynamics of Ordinary Towns* (pp. 199–233). New Delhi: Springer Nature. Retrieved from https://doi.org/10.1007/978-81-322-3616-0_8
10. Bhat, P. A., Shafiq, M. u., Mir, A. A., & Ahmed, P. (2017). Urban sprawl and its impact on land use/land cover dynamics of Dehradun City, India. *International Journal of Sustainable Built Environment, 6*, 513–521. Retrieved from https://doi.org/10.1016/j.ijsbe.2017.10.003
11. Bhatt, P. G. (1969). *Antiquities of South Kanara.* Udupi: Prabhakara Press. Retrieved from http://203.200.22.249:8080/bitstream/123456789/12240/1/Antiquites_of_south_Kanara.pdf
12. Bhatta, B. (2010). *Analysis of Urban Growth and Sprawl from Remote Sensing Data.* Heidelberg: Springer.
13. Bhatta, B. (2012). *Urban Growth Analysis and Remote Sensing A Case Study of Kolkata, India 1980–2010.* Dordrecht, Heidelberg: SpringerBriefs in Geography. doi:10.1007/978-94-007-4698-5_1
14. Bhatti, S. S., & Tripathi, N. K. (2014). Built-up area extraction using Landsat 8 OLI imagery. *GIScience & Remote Sensing*, 445–467.
15. Bihamta, N., Soffianian, A., Fakheran, S., & Gholamalifard, M. (2015). Using the SLEUTH Urban Growth Model to Simulate Future Urban Expansion of the Isfahan Metropolitan Area, Iran. *Journal of the Indian Society of Remote Sensing, 43*, 407–414. Retrieved from https://doi.org/10.1007/s12524-014-0402-8
16. Black, D., & Henderson, V. (1999). A Theory of Urban Growth. *Journal of Political Economy*, 252–284. doi:DOI: 10.1086/250060
17. Botequilha Leitão, A., Miller, J., Ahern, J., & McGarigal, K. (2006). *Measuring landscapes: a planner's handbook.* Washington, DC: Island Press.
18. Bruegmann, R. (2005). *S P R A W L: a compact history.* Chicago: The University of Chicago Press. Retrieved from https://doi.org/10.1086/509831
19. Chandan, M. C., Nimish, G., & Bharath, H. A. (2019). Analysing spatial patterns and trend of future urban expansion using SLEUTH. *Spatial Information Research, 28*, 11–23. Retrieved from https://doi.org/10.1007/s41324-019-00262-4
20. Chaudhuri, G., & Clarke, K. C. (2014). Temporal Accuracy in Urban Growth Forecasting: A Study Using the SLEUTH Model. *Transactions in GIS, 18*(2), 302–320. doi:10.1111/tgis.12047
21. Chaudhuri, G., & Clarke, K. C. (2019). Modeling an Indian megalopolis–A case study on adapting SLEUTH urban growth model. *Computers, Environment and Urban Systems, 77*. Retrieved from https://doi.org/10.1016/j.compenvurbsys.2019.101358
22. Cheng, J., & Masser, I. (2004). Understanding Spatial and Temporal Processes of Urban Growth: Cellular Automata Modelling. *Environment and Planning B: Planning and Design, 31*(2), 167–194. Retrieved from https://doi.org/10.1068%2Fb2975
23. Clarke, K. C. (2008). Mapping and Modelling Land Use Change: an Application of the SLEUTH model. In C. Pettit, W. Cartwright, I. Bishop, K. Lowell, D. Pullar, & D. Duncan, *Landscape Analysis and Visualisation* (pp. 353–366). Berlin, Heidelberg: Springer. Retrieved from https://doi.org/10.1007/978-3-540-69168-6_17
24. Clarke, K. C., Hoppen, S., & Gaydos, L. (1997). A Self-Modifying Cellular Automaton Model of Historical Urbanization in the San Francisco Bay Area. *Environment and Planning B: Planning and Design, 24*(2), 247–261. Retrieved from https://doi.org/10.1068/b240247

25. Clarke, K. C., Hoppen, S., & Gaydos, L. J. (1996). Methods and techniques for rigorous calibration of a cellular automaton model of urban growth. *Third International Conference/Workshop on Integrating GIS and Environmental Modeling* (pp. 1319–1328). Santa Fe, New Mexico: National Center for Geographic Information and Analysis. Retrieved from http://ncgia.ucsb.edu/projects/gig/Repository/references/SLEUTHPapers_Nov24/Clarke_Hoppen_Gaydos_1996.pdf
26. Congalton, R. G. (1991). A Review of Assessing the Accuracy of Classifications of Remotely Sensed Data. *REMOTE SENSING OF ENVIRONMENT*, 35–46.
27. Congalton, R. G., & Green, K. (2008). *Assessing the Accuracy of Remotely Sensed Data: Principles and Practices* (2 ed.). Boca Raton: CRC Press. Retrieved from https://doi.org/10.1201/9781420055139
28. Congedo, L. (2016). Semi-Automatic Classification PluginDocumentation. *Release, 4*(0.1), 29.
29. Dadashpoor, H., & Nateghi, M. (2017). Simulating spatial pattern of urban growth usingGIS-based SLEUTH model: a case study of eastern corridor of Tehran metropolitan region, Iran. *Environment Development and Sustainability, 19*, 527–547. Retrieved from https://doi.org/10.1007/s10668-015-9744-9
30. Dave, C. P., Joshi, R., & Srivastava, S. S. (2015). A Survey on Geometric Correction of Satellite Imagery. I*nternational Journal of Computer Applications, 116*(12), 0975 – 8887. Retrieved from http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.695.4354&rep=rep1&type=pdf
31. Dezhkam, S., Amiri, B. J., Darvishsefat, A. A., & Sakieh, Y. (2014). Simulating the urban growth dimensions and scenario prediction through sleuth model: a case study of RashtCounty, Guilan, Iran. *GeoJournal, 79*, 591–604. Retrieved from https://doi.org/10.1007/s10708-013-9515-9
32. Dietzel, C., & Clarke, K. C. (2007). Toward Optimal Calibration of the SLEUTH Land Use Change Model. *Transactions in GIS, 11*(1), 29–45. doi:10.1111/j.1467-9671.2007.01031.x
33. Duijne, R. J., & Nijman, J. (2019). India's Emergent Urban Formations. *Annals of the American Association of Geographers, 109*(6), 1978–1998. https://doi.org/10.1080/24694452.2019.1587285
34. Falah, N., Karimi, A., & Harandi, A. T. (2020). Urban growth modeling using cellular automata model and AHP (case study: Qazvin city). *Modeling Earth Systems and Environment, 6*, 235–248. Retrieved from https://doi.org/10.1007/s40808-019-00674-z
35. Feng, Y., Liu, Y., & Batty, M. (2015). Modeling urban growth with GIS based cellular automata and least squares SVM rules: a case study in Qingpu–Songjiang area of Shanghai, China. *Stoch Environ Res Risk Assess*, 1387–1400. https://doi.org/10.1007/s00477-015-1128-z
36. Foody, G. M. (2002). Status of land cover classification accuracy assessment. *Remote Sensing of Environment*, 185–201. Retrieved from https://doi.org/10.1016/S0034-4257(01)00295-4
37. Foody, G. M. (2020). Explaining the unsuitability of the kappa coefficient in the assessment and comparison of the accuracy of thematic maps obtained by image classification. *Remote Sensing of Environment, 239*, 111630. Retrieved from https://doi.org/10.1016/j.rse.2019.111630
38. Gharaibeh, A., Shaamala, A., Obeidat, R., & Al-Kofahi, S. (2020). Improving land-use change modeling by integrating ANN with CellularAutomata-Markov Chain model. *Heliyon, 6*(9). Retrieved from https://doi.org/10.1016/j.heliyon.2020.e05092
39. Hall, F. G., Strebel, D. E., Nickeson, J. E., & Goetz, S. J. (1991). Radiometric rectification: Toward a common radiometric response among multidate, multisensor images. *Remote Sensing of Environment, 35*(1), 11–27. Retrieved from https://doi.org/10.1016/0034-4257(91)90062-B
40. Herold, M., Couclelis, H., & Clarke, K. C. (2005). The role of spatial metrics in the analysis and modeling of urban land use change. *Computers, Environment and Urban Systems, 29*, 369–399. doi:10.1016/j.compenvurbsys.2003.12.001
41. Herold, M., Goldstein, N. C., & Clarke, K. C. (2003). The spatiotemporal form of urban growth: measurement, analysis and modeling. *Remote Sensing of Environment, 86*, 286–302. doi:10.1016/S0034-4257(03)00075-0
42. Herold, M., Scepan, J., & Clarke, K. C. (2002). The use of remote sensing and landscape metrics to describe structures and changes in urban land uses. *Environment and Planning*, 1443–1458.
43. Hu, Z., & Lo, C. P. (2007). Modeling urban growth in Atlanta using logistic regression. *Computers, Environment and Urban Systems, 31*(6), 667–688. Retrieved from https://doi.org/10.1016/j.compenvurbsys.2006.11.001
44. Ilyassov, A., Kantakumar, L. N., & Boyd, D. (2021). Urban growth analysis and simulations using cellular automata and geo-informatics: comparison between Almaty and Astana in Kazakhstan. *GEOCARTO INTERNATIONAL, 36*(5), 520–539. Retrieved from https://doi.org/10.1080/10106049.2019.1618923
45. Ioannides, Y. M., & Rossi-Hansberg, E. (2010). urban growth. In B. L. Durlauf S.N., *Economic Growth* (pp. 264–269). London: Palgrave Macmillan. Retrieved from https://doi.org/10.1057/9780230280823_33
46. Jantz, C. A., Goetz, S. J., & Shelley, M. K. (2003). Using the SLEUTH urban growth model to simulate the impacts of future policy scenarios on urban land use in the Baltimore Washington metropolitan area. *Environment and Planning B: Planning and Design, 30*, 251–271. doi:10.1068/b2983
47. Jat, M. K., Choudhary, M., & Saxena, A. (2017). Application of geo-spatial techniques and cellular automata for modelling urban growth of a heterogeneous urban fringe. *The Egyptian Journal of Remote Sensing and Space Sciences, 20*, 223–241. Retrieved from http://dx.doi.org/10.1016/j.ejrs.2017.02.002
48. Jensen, J. R. (2005). *Introductory Digital Image Processing A Remote Sensing Perspective.* London: Pearson Prentice Hall. Retrieved from https://dl.acm.org/doi/book/10.5555/526335
49. KantaKumar, L. N., Sawant, N. G., & Kumar, S. (2011). Forecasting urban growth based on GIS, RS and SLEUTH model in Pune metropolitan area. *International journal of geomatics and geosciences, 2*(2), 568. Retrieved from http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.421.9021&rep=rep1&type=pdf
50. Kindu, M., Angelova, D., Schneider, T., Döllerer, M., Teketay, D., & Knoke, T. (2020). Monitoring of Urban Growth Patterns in Rapidly Growing Bahir Dar City of Northwest Ethiopia with 30 year Landsat Imagery Record. *ISPRS Int. J. Geo-Inf., 9*(9). Retrieved from https://doi.org/10.3390/ijgi9090548

51. Leroux, L., Congedo, L., Bellón, B., Gaetano, R., & Bégué, A. (2018). Land Cover Mapping Using Sentinel-2 Images and the Semi-Automatic Classification Plugin: A Northern Burkina Faso Case Study. *QGIS and Applications in Agriculture and Forest, 2*, 119–151. Retrieved from https://doi.org/10.1002/9781119457107.ch4
52. Li, X., & Yeh, A. G.-O. (2000). Modelling sustainable urban development by the integration of constrained cellular automata and GIS. *International Journal of Geographical Information Science, 14*(2), 131–152. Retrieved from https://doi.org/10.1080/136588100240886
53. Lillesand, T. M., Kiefer, R. W., & Chipman, J. W. (2015). *Remote Sensing and Image Interpretation* (7 ed.). Westford: JohnWiley & Sons, Inc.
54. Liu, X., Sun, R., Yang, Q., Su, G., & Qi, W. (2012). Simulating urban expansion using an improved SLEUTH model. *Journal of Applied Remote Sensing, 6*.
55. Liu, Y. (2009). *Modelling urban development with geographical information systems and cellular automata* (Vol. 36). Boca Raton, Fla.: Taylor & Francis Group. Retrieved from https://doi.org/10.1201/9781420059908
56. Liu, Y., Li, L., Chen, L., Cheng, L., Zhou, X., Cui, Y.,. .. Liu, W. (2019). Urban growth simulation in different scenarios using the SLEUTH model: A case study of Hefei, East China. *PLoS ONE, 14*(11), e0224998. Retrieved from https://doi.org/10.1371/journal.pone.0224998
57. Magidi, J., & Ahmed, F. (2019). Assessing urban sprawl using remote sensing and landscape metrics: A case study of City of Tshwane, South Africa (1984–2015). *The Egyptian Journal of Remote Sensing and Space Science, 22*(3), 335–346. Retrieved from https://doi.org/10.1016/j.ejrs.2018.07.003
58. Mahiny, A. S., & Clarke, K. C. (2012). Guiding SLEUTH land-use/land-cover change modeling using multicriteria evaluation: towards dynamic sustainable land-use planning. *Environment and Planning B: Planning and Design, 39*, 925–944. doi:doi:10.1068/b37092
59. Maithani, S. (2009). A neural network based urban growth model of an Indian city. *Journal of the Indian Society of Remote Sensing, 37*, 363–376. Retrieved from https://doi.org/10.1007/s12524-009-0041-7
60. Man, X., & Chen, Y. (2020). Fractal-Based Modeling and Spatial Analysis of Urban Form and Growth: A Case Study of Shenzhen in China. *ISPRS Int. J. Geo-Inf., 9*(11), 672. Retrieved from https://doi.org/10.3390/ijgi9110672
61. McGarigal, K. (2014). Landscape Pattern Metrics. *Wiley StatsRef: Statistics Reference Online*. doi:10.1002/9781118445112.stat07723
62. McGarigal, K., & Marks, B. J. (1995). *FRAGSTATS: spatial pattern analysis program for quantifying landscape structure*. Portland: Department of Agriculture, Forest Service, Pacific NorthwestResearch Station. Retrieved from https://www.fs.fed.us/pnw/pubs/gtr_351.pdf
63. Miyao, T. (1987). Dynamic urban models. In E. S. Mills, *Handbook of Regional and Urban Economics* (pp. 877–925). Retrieved from https://doi.org/10.1016/S1574-0080(87)80008-1
64. Narumalani, S., & Merani, P. (2016). Digital Image Processing: A Review of the Fundamental Methods and Techniques. In P. S. Thenkabail, *REMOTELY SENSED DATA CHARACTERIZATION CLASSIFICATION, AND ACCURACIES* (pp. 197–216). Boca Raton: CRC Press Taylor & Francis Group.
65. NRSA. (2004). *RESOURCESAT − 1 : DATA USER'S HANDBOOK.* HYDERABAD: National Remote Sensing Agency. Retrieved from https://bhuvan.nrsc.gov.in/bhuvan/PDF/Resourcesat-1_Handbook.pdf
66. Nugroho, F., & Al-Sanjary, O. I. (2018). A Review of Simulation Urban Growth Model. *International Journal of Engineering & Technology, 11*(4), 17–23. Retrieved from http://dx.doi.org/10.14419/ijet.v7i4.11.20681
67. Peng, J., Wang, Y., Zhang, Y., Wu, J., Li, W., & Li, Y. (2010). Evaluating the effectiveness of landscape metrics in quantifying spatial patterns. *Ecological Indicators, 10*, 217–223. doi:10.1016/j.ecolind.2009.04.017
68. Radwan, T. M., Blackburn, G. A., Whyatt, J. D., & Atkinson, P. M. (2019). Dramatic Loss of Agricultural Land Due to Urban Expansion Threatens Food Security in the Nile Delta, Egypt. *Remote sensing, 11*(3). Retrieved from https://doi.org/10.3390/rs11030332
69. Rafiee, R., Mahiny, A. S., Khorasani, N., Darvishsefat, A. A., & Danekar, A. (2009). Simulating urban growth in Mashad City, Iran through the SLEUTH model (UGM). *Cities, 26*, 19–26. doi:10.1016/j.cities.2008.11.005
70. Rana, P., & Krishan, G. (1981). Growth of medium sized towns in India. *GeoJournal, 5*, 33–39. https://doi.org/10.1007/BF00185241
71. Sakieh, Y., Amiri, B. J., Danekar, A., Feghhi, J., & Dezhkam, S. (2015). Simulating urban expansion and scenario prediction using a cellular automata urban growth model, SLEUTH, through a case study of Karaj City, Iran. *Journal of House and the Built Environment, 30*, 591–611. doi:10.1007/s10901-014-9432-3
72. Sakieh, Y., Salmanmahinya, A., Jafarnezhad, J., Mehri, A., Kamyab, H., & Galdavi, S. (2015). Evaluating the strategy of decentralized urban land-use planning in a developing region. *Land Use Policy, 48*, 534–551. Retrieved from http://dx.doi.org/10.1016/j.landusepol.2015.07.004
73. Sandamali, S. P., Kantakumar, L. N., & Sivanantharajah, S. (2018). Remote Sensing Data and SLEUTH Urban Growth Model: As Decision Support Tools for Urban Planning. *Chinese Geographical Science, 28*(2), 274–286. Retrieved from https://doi.org/10.1007/s11769-018-0946-6
74. Santé, I., García, A. M., Miranda, D., & Crecente, R. (2010). Cellular automata models for the simulation of real-world urban processes: A review and analysis. *Landscape and Urban Planning, 96*(2), 108–122. Retrieved from https://doi.org/10.1016/j.landurbplan.2010.03.001
75. Saxena, A., & Jat, M. K. (2020). Land suitability and urban growth modeling: Development of SLEUTHSuitability Suitability. *Computers, Environment and Urban Systems, 81*, 101475. Retrieved from https://doi.org/10.1016/j.compenvurbsys.2020.101475
76. Shaban, A., Kourtit, K., & Nijkamp, P. (2020). India's Urban System: Sustainability and Imbalanced Growth of Cities. *Sustainability, 12*(7), 2941. Retrieved from https://doi.org/10.3390/su12072941
77. Silva, E. A., & Clarke, K. C. (2002). Calibration of the SLEUTH urban growth model for Lisbon and Porto, Portugal. *Computers, Environment and Urban Systems*, 525–552. Retrieved from https://doi.org/10.1016/S0198-9715(01)00014-X
78. Sofeska, E. (2016). Relevant Factors in Sustainable Urban Development of Urban Planning Methodology and Implementation of Concepts for Sustainable Planning (Planning Documentation for the Master Plan Skopje 2001–2020). *Improving sustainability Concepts in Developing Countries. 34*, pp. 140–151. Procedia Environmental Sciences. Retrieved from https://doi.org/10.1016/j.proenv.2016.04.014

79. Strahler, A. H. (1980). The Use of Prior Probabilities in Maximum Likelihood Classification of Remotely Sensed Data. *Remote Sensing Of Environment*, 135–163.
80. Sudhira, H., Ramachandra, T., & Jagadish, K. (2004). Urban sprawl: metrics, dynamics and modelling using GIS. *International Journal of Applied Earth Observation and Geoinformation*, 29–39. doi:doi:10.1016/j.jag.2003.08.002
81. Taubenböck, H., Wiesner, M., A, F., Marconcini, M., T, E., & Dech, S. (2014). New dimensions of urban landscapes: The spatio-temporal evolution from a polynuclei area to a mega-region based on remote sensing data. *Applied Geography*, 1–17. Retrieved from http://dx.doi.org/10.1016/j.apgeog.2013.12.002
82. Tobler, W. R. (1979). Cellular Geography. In O. G. Gale S., *Philosophy in Geography* (pp. 379–386). Dordrecht: Springer. Retrieved from https://doi.org/10.1007/978-94-009-9394-5_18
83. Treitz, P. (2004). Remote sensing for mapping and monitoring land-cover and land-use change. *Progress in Planning, 61*(4), 267. Retrieved from https://doi.org/10.1016/S0305-9006(03)00062-X
84. Triantakonstantis, D., & Mountrakis, G. (2012). Urban Growth Prediction: A Review of Computational Models and Human Perceptions. *Journal of Geographic Information System, 4*(6), 555–587. Retrieved from http://dx.doi.org/10.4236/jgis.2012.46060
85. United Nations. (2018, May 16). *United Nations*. Retrieved February 19, 2020, from Department of Economic and Social Affairs: https://www.un.org/development/desa/en/news/population/2018-revision-of-world-urbanization-prospects.html
86. White, R., & Engelen, G. (1997). Cellular Automata as the Basis of Integrated Dynamic Regional Modelling. *Environment and Planning B: Planning and Design, 24*(2), 235–246. Retrieved from https://doi.org/10.1068%2Fb240235
87. White, R., & Engelen, G. (2000). High-resolution integrated modelling of the spatial dynamics of urban and regional systems. *Computers, Environment and Urban Systems, 24*(5), 383–400. Retrieved from https://doi.org/10.1016/S0198-9715(00)00012-0
88. World Bank. (2019). *The World Bank*. Retrieved from Urban population (% of total population) - India: https://data.worldbank.org/indicator/SP.URB.TOTL.IN.ZS?locations=IN
89. Zhou, Y., Varquez, A. C., & Kanda, M. (2019). High-resolution global urban growth projection based on multiple applications of the SLEUTH urban growth model. *Scientific Data, 6*, 34. Retrieved from https://doi.org/10.1038/s41597-019-0048-z

Tables

Table 3 is available in the Supplementary Files section.

Figures

Figure 1

Location map of the study area (Mangalore)

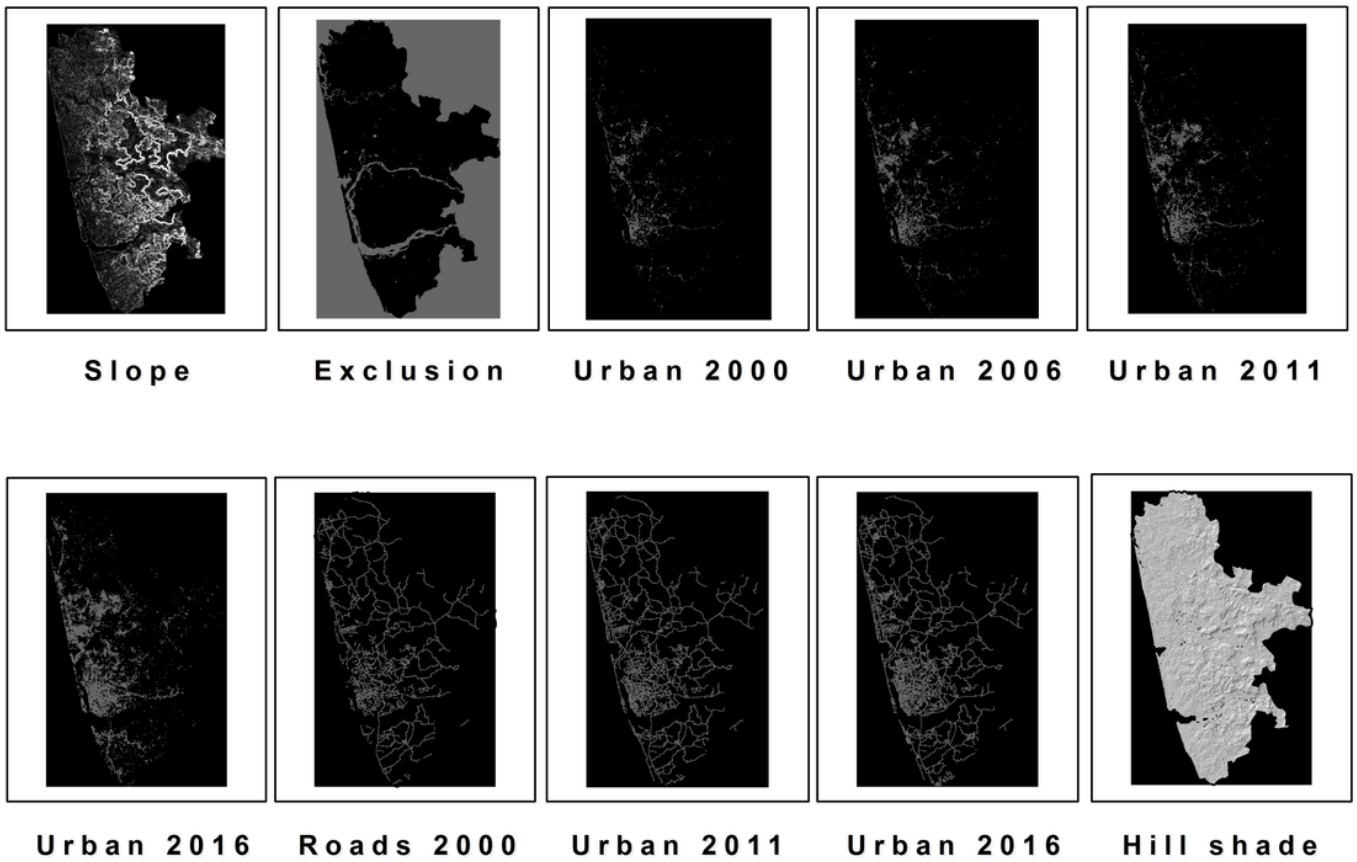

Figure 2

The input layers (other than Land use layer) in Graphical Interchange Format (GIF) used for the SLEUTH model

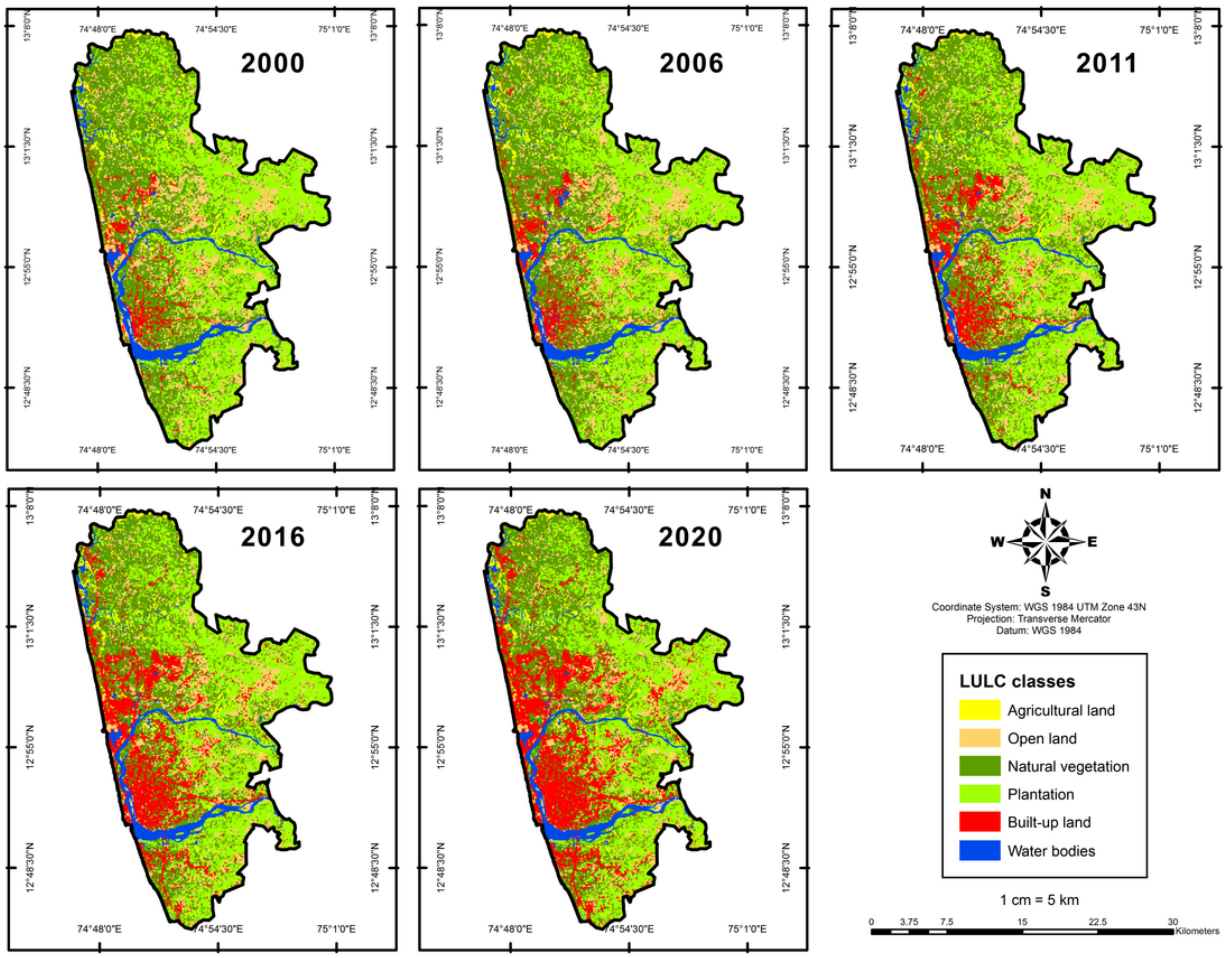

Figure 3

Land use and land cover map of Mangalore from 2000 to 2020

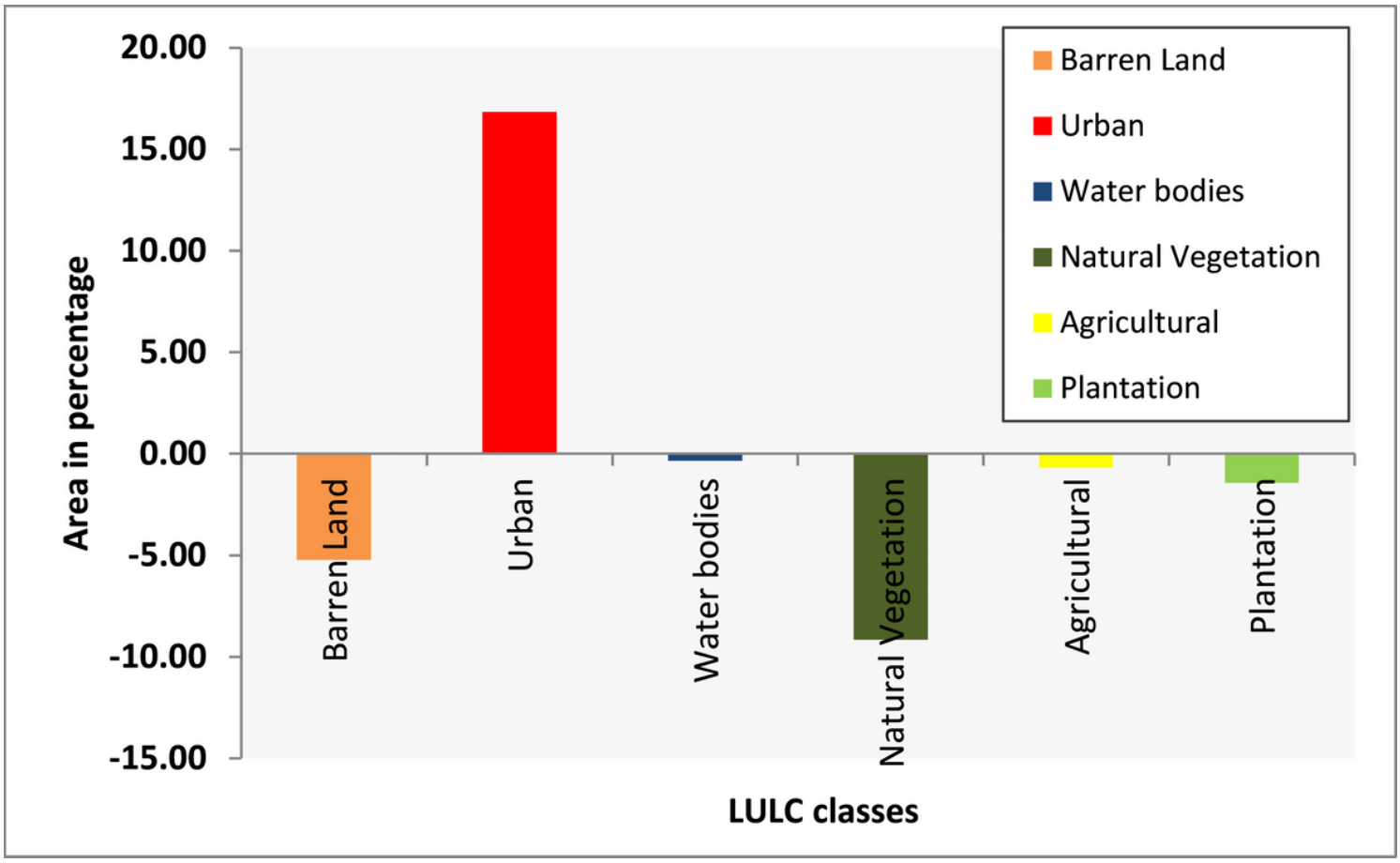

Figure 4

Fluctuations in area of land use and land cover classes during 2000-2020 in percentage

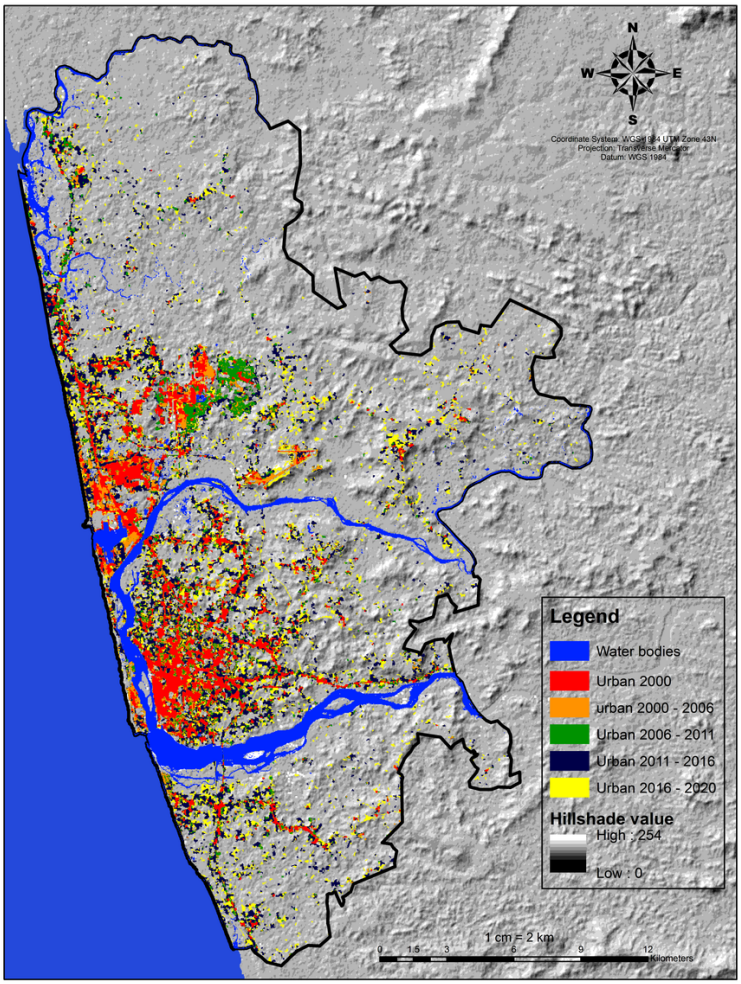

Figure 5

The Spatial expansion of the urban area in Mangaluru from 2000-2006, 2006-2011, 2011-2016, and 2016-2020

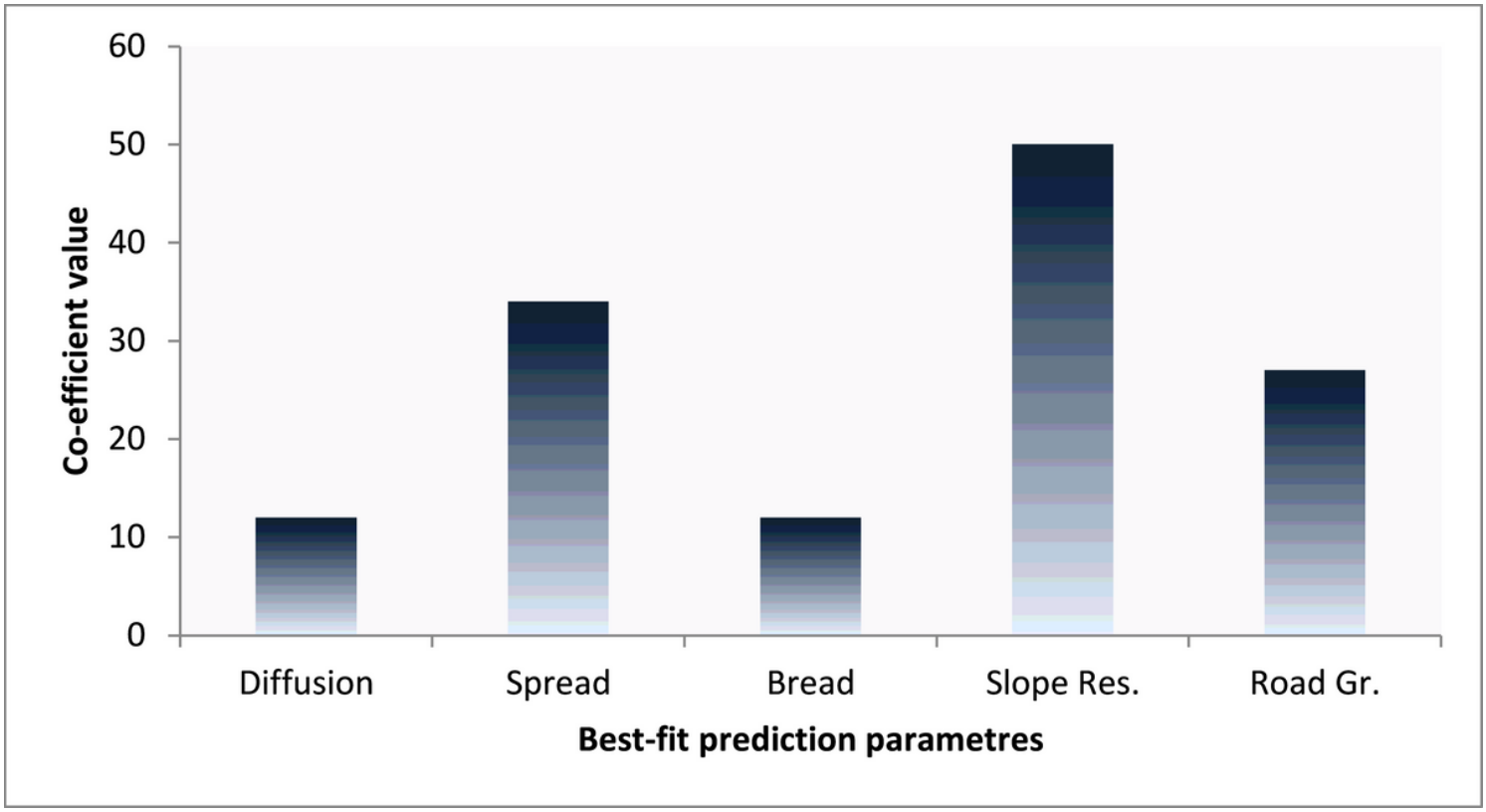

Figure 6

The best-fit growth parameters for urban growth prediction in Mangaluru

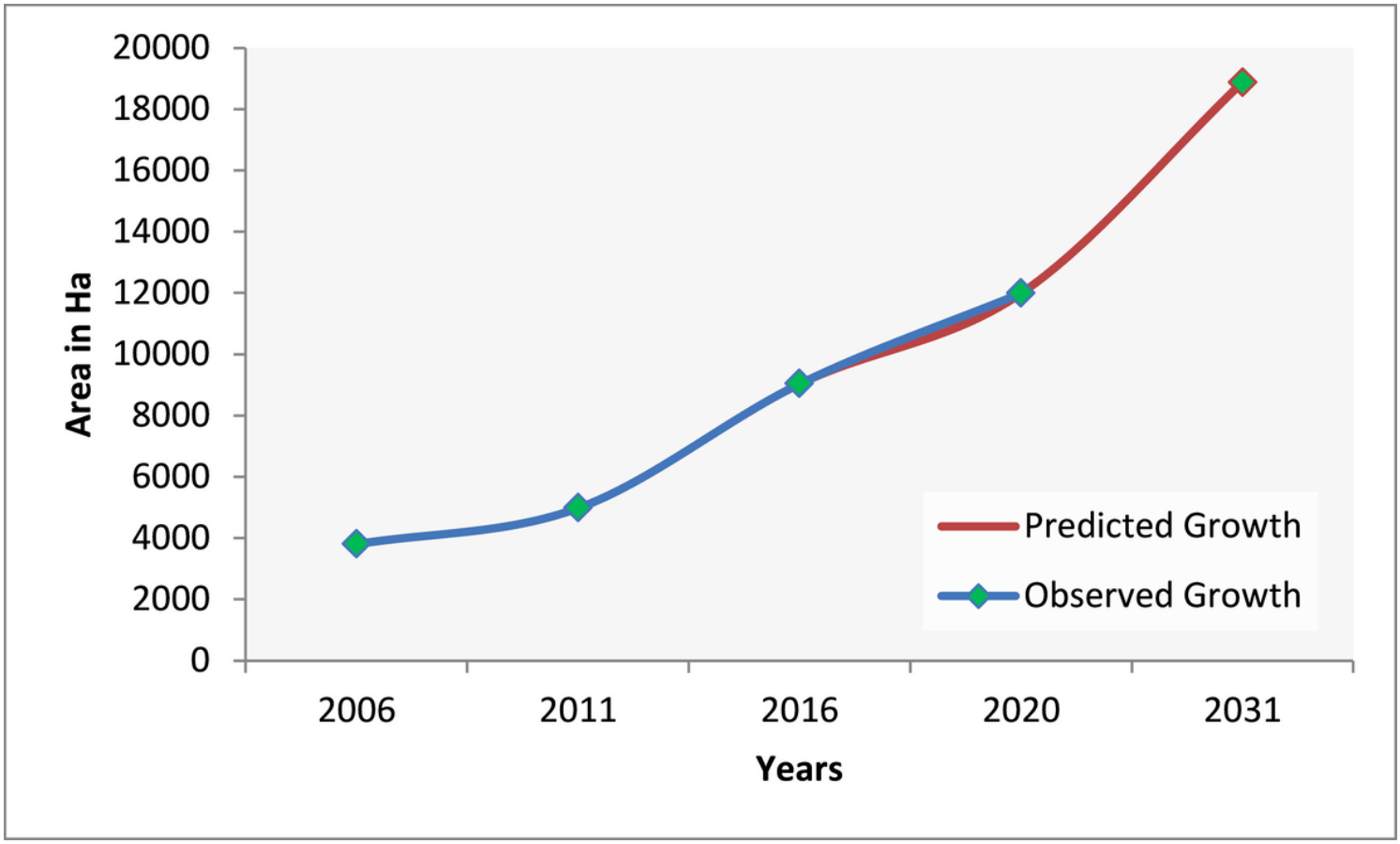

Figure 7

Shows the observed and predicted urban growth in hectares for Mangaluru during 2006-2031

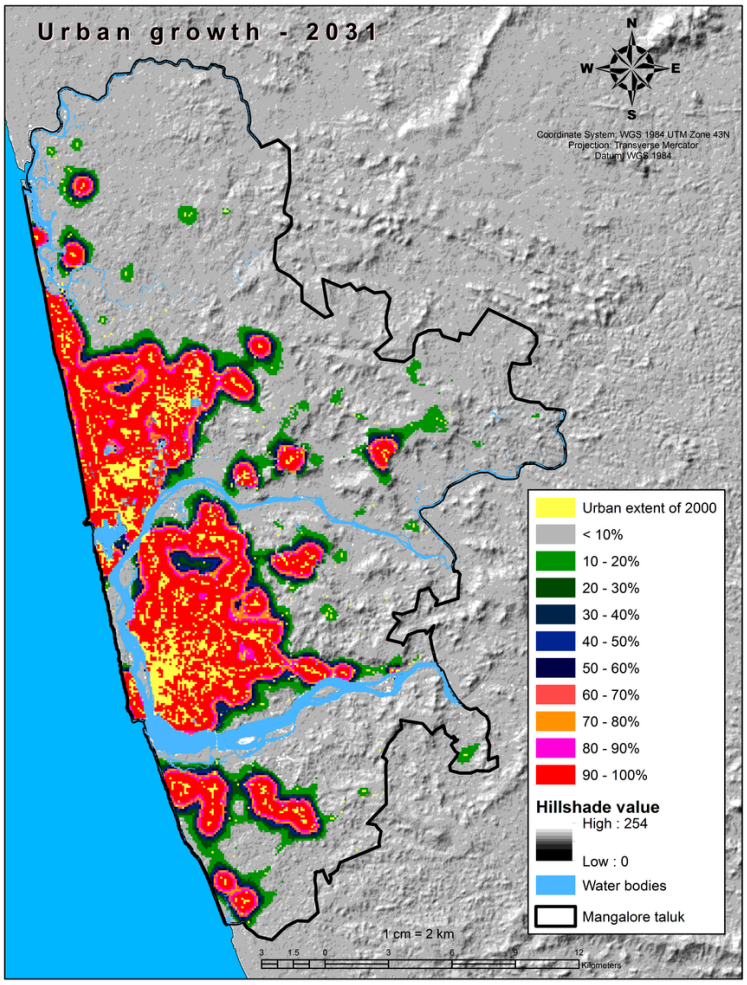

Figure 8

Predicted urban growth of Mangaluru for the year 2031 in proportions

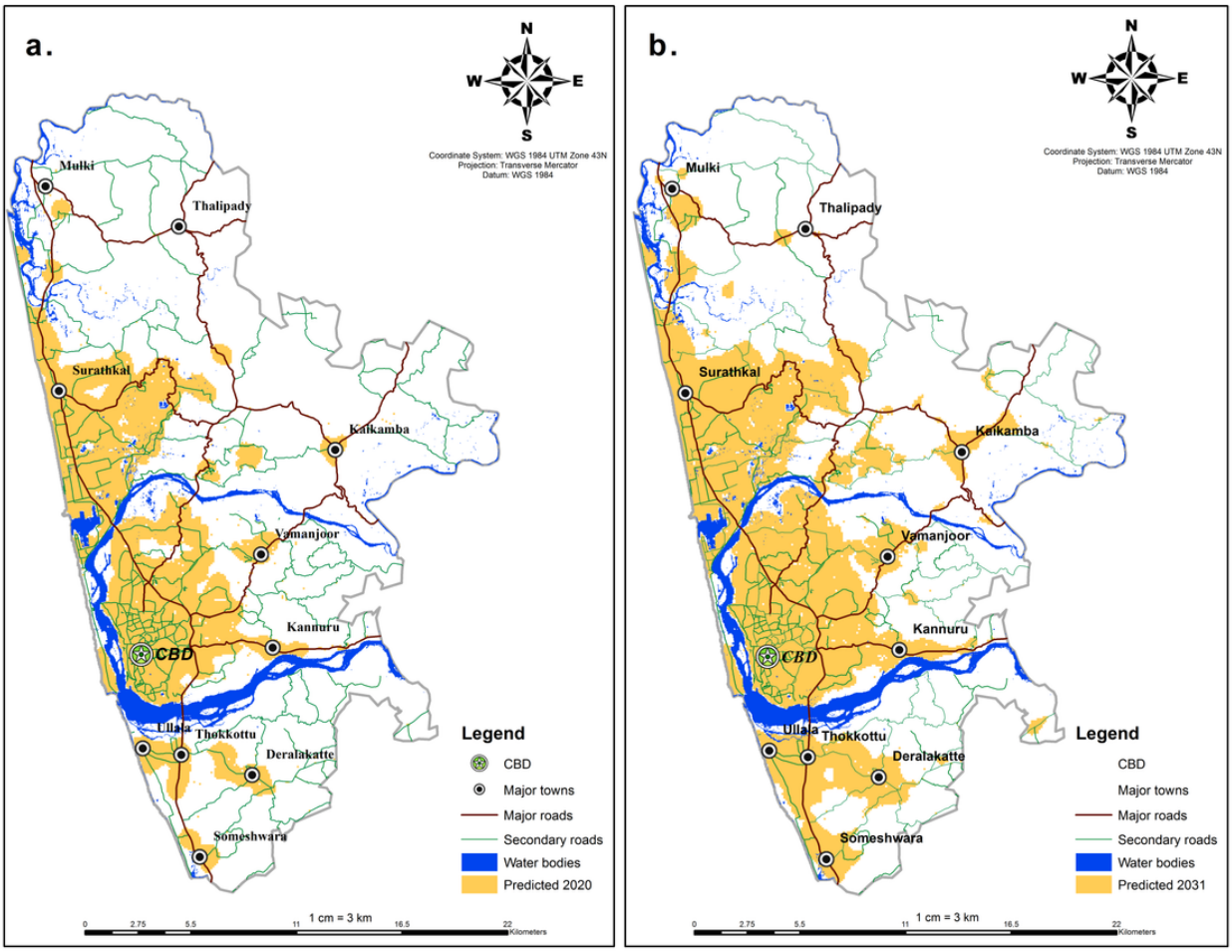

Figure 9

a-b The Urban growth comparison by juxtaposing road network and urban centres between the simulated year of a. 2020 and b. 2031

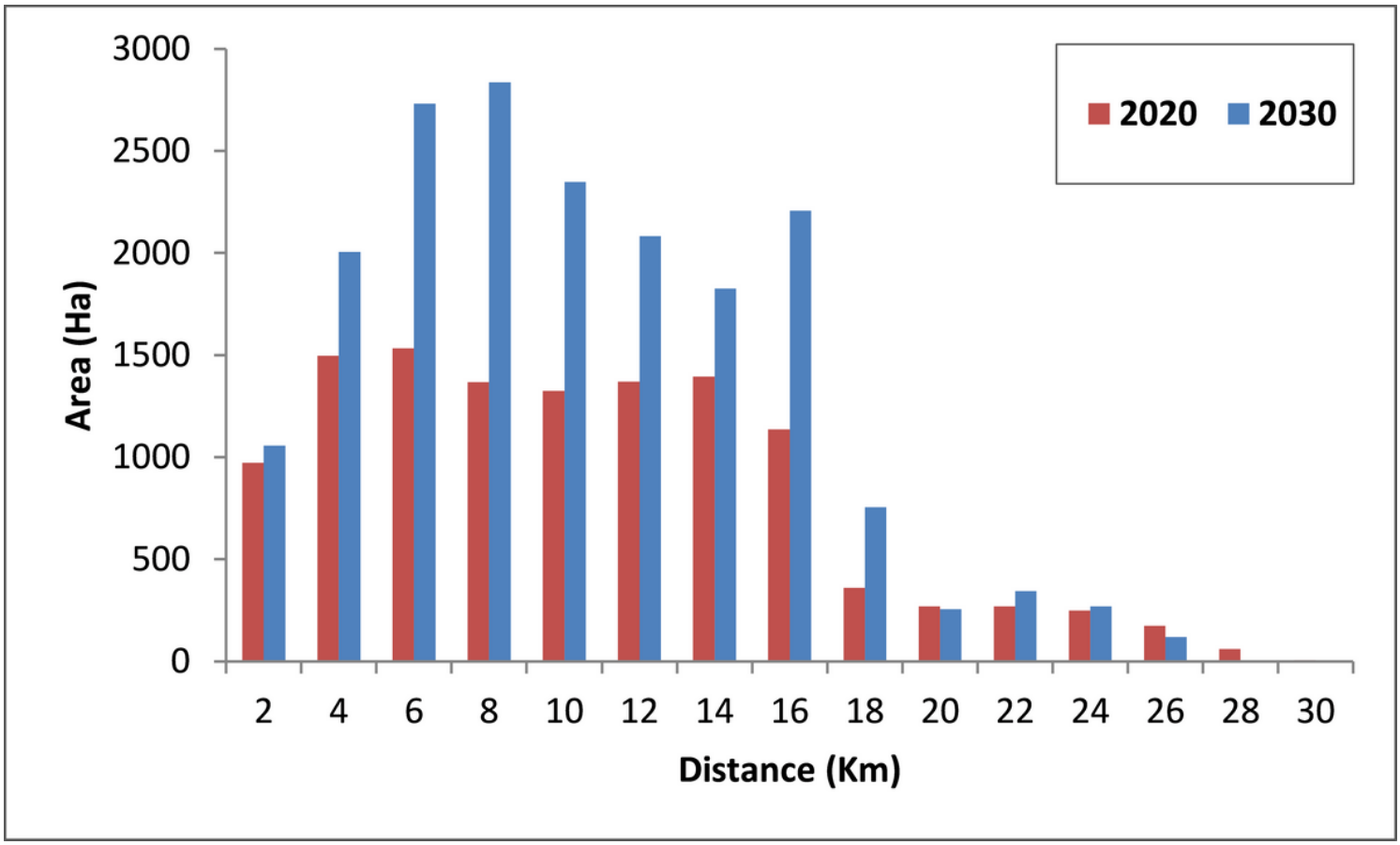

Figure 10

Buffer-wise comparison plot of urban area for the observed urban area in 2020 and the predicted urban area in 2031

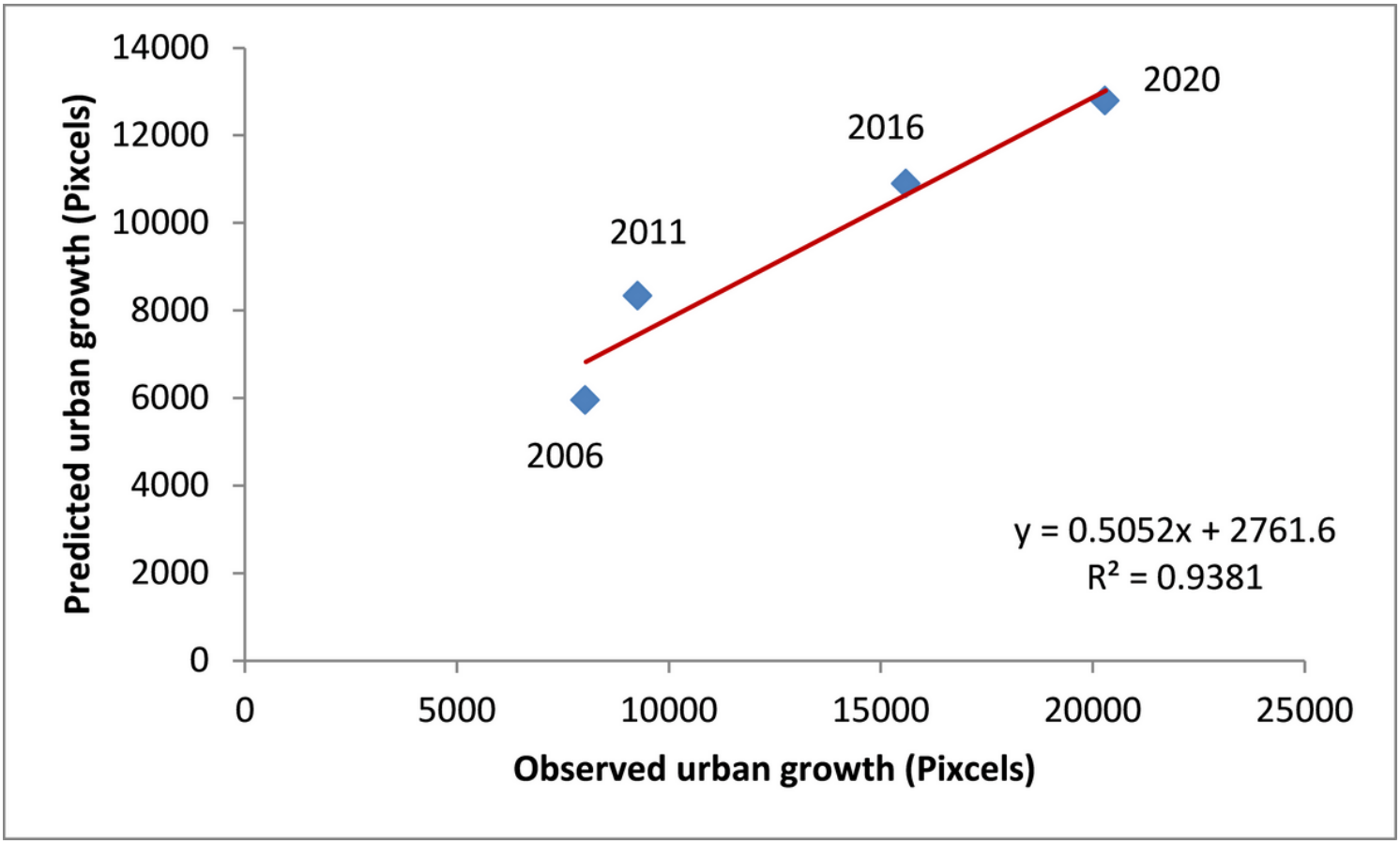

Figure 11

Shows the correlation between the predicted urban growth and observed urban growth in terms of pixels number

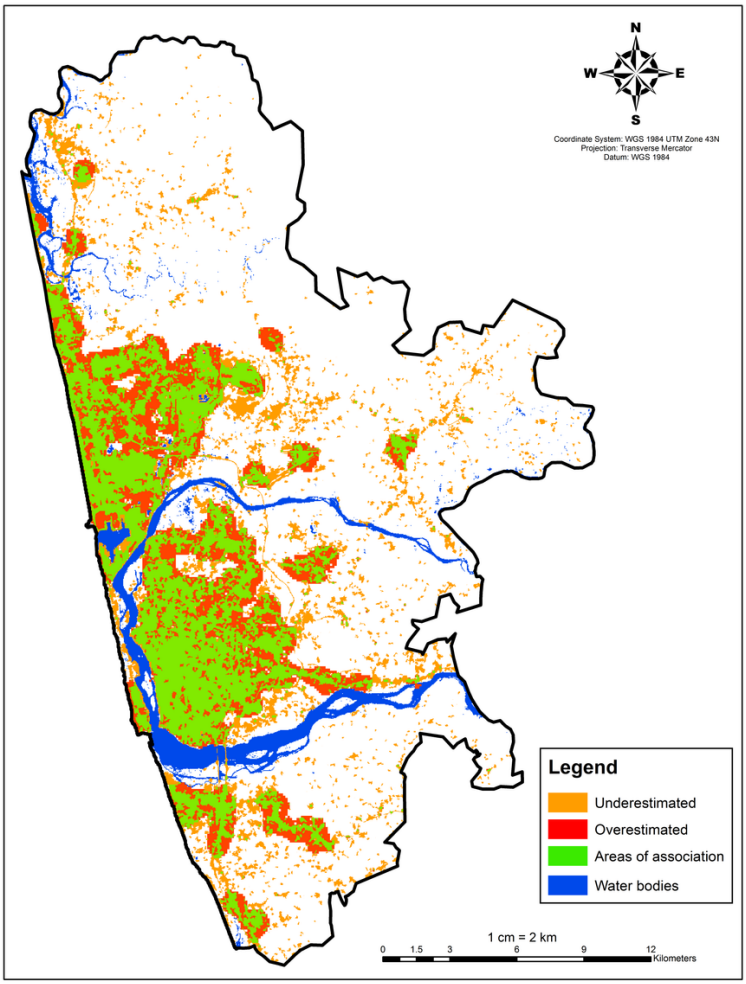

Figure 12

Shows the spatial association between the predicted and observed urban growth of 2020 by spatial overlay

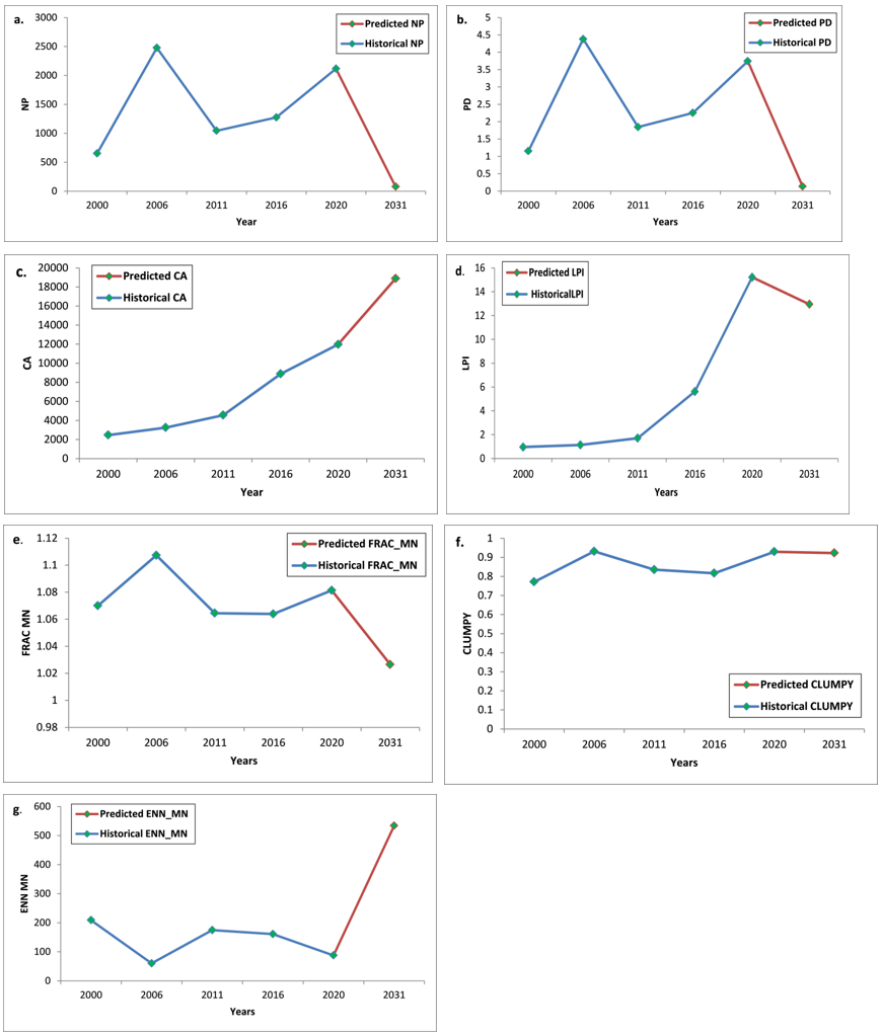

Figure 13

a-g Spatial metrics a. NP, b. PD, c. CA, d. LPI, d. LPI, e. FRAC_MN, f. CLUMPY, g. ENN_MN of historical and simulated urban area in Mangalore from 2000-2031

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- Table3SpatialmetricsusedtoquantifyurbanpatterninMangaluruduring2000.docx