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# Remote Sensing Data and SLEUTH Urban Growth Model: As Decision Support Tools for Urban Planning

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**Abstract:** Sri Lanka is experiencing speedy urbanization by converting the agriculture land and other natural land cover into built-up land. The urban population of Sri Lanka is expected to reach to 60% by 2030 from 14% in 2010. The rapid growth in urban population and urban areas in Sri Lanka may cause serious socioeconomic disparities, if they are not handled properly. Thus, planners in Sri Lanka are in need of information about past and future urban growth patterns to plan a better and sustainable urban future for Sri Lanka. In this paper, we analyzed the characteristics of past land use and land cover trends in Matara City of Sri Lanka from 1980 to 2010 to assess the historic urban dynamics. The land use change detection analysis based on remote sensing datasets reveal that the conversion of homestead/garden and paddy into urban land is evident in Matara City. The historic urban trends are projected into the near future by using SLEUTH urban growth model to identify the hot spots of future urbanization and as well as the urban growth patterns in Matara City up to the basic administrative level, i.e., Grama Niladari Divisions (GND). The urban growth simulations for the year 2030 reveal that 29 GNDs out of 66 GNDs in Matara City will be totally converted into urban land. Whereas, 28 GNDs will have urban land cover from 75% to 99% by 2030. The urban growth simulations are further analyzed with respect to the proposed Matara city development plan by the Urban Development Authority (UDA) of Sri Lanka. The results show that the UDA's city development plan of Matara will soon be outpaced by rapid urbanization. Based on the calibration and validation results, the SLEUTH model proved to be a useful planning tool to understand the near future urbanization of Sri Lankan cities.

**Keywords:** urban growth; urban planning; land use; land cover; SLEUTH model; Cellular Automata (CA); remote sensing; Sri Lanka

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## 1 Introduction

Urban areas are the hot spots of environmental change, since urbanization alters the land use and cover, biodiversity and hydrological systems from local to regional scales (Lambin et al., 2003; Grimm et al., 2008; Kuang, 2011; Butsch et al., 2017). Urbanization is positively correlated with economic development (Birch and Wachter 2011), but rapid and unplanned urbanization involves in breakdown of natural and social cohesion and can be regarded as a destructive process. Sri Lanka is experiencing a speedy urbanization over the last decades. According to a report (United Nations, 2012), the urban population of Sri Lanka will reach to 60% by 2030 from 14% in 2010. This rapid growth in urban population, unless handled properly, may create serious socio-economic disparities which are hard to fix. However, a well-planned and managed urbanization empow-

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ers the nation's economic development and provides better access to employment, education and health care to citizens. Thus, the Sri Lankan planners need new tools to monitor and project the urban growth into the near future to plan for better and more sustainable cites. In this context, remote sensing and Geographical Information Systems (GIS) can be used extensively to map and manage the rapidly growing urban areas (Bhatta, 2009; Kuang, 2012; Kantakumar et al., 2016). The urban growth models coupled with GIS can be useful to simulate the urban growth of cities to understand the pattern of urban growth (Batty et al., 1999; Stevens et al., 2007; Al-shalabi et al., 2013). Recent advancements in complexity science have given birth to a new age urban models based on Cellular Automata (CA) and Agent Based Models (ABM) (Sohl and Claggett, 2013). These models are capable of projecting the city growth into the near future both spatially and temporally. The CA models are an added advantage to ABM models, because of their simplicity and close resemblance to grids used in GIS (Su, 1998; Kantakumar et al., 2011). CA is a powerful simulation tool which assumes the land system is self-organized, heterogeneous and based on neighboring rules.

The SLEUTH is a cellular automata based urban growth model (Clarke et al., 1997; Clarke and Gaydos, 1998). The name of SLEUTH is moniker of the input layers required to run the model. They are namely, slope, land use, elevation, urban, transport and hillshade. The SLEUTH model has been widely used to simulate the urban growth of several cities around the world (Chaudhuri and Clarke, 2013). It is successfully implemented in San Francisco, Chicago, Washington-Baltimore, Sioux Falls, Chesapeake Bay and south coast California in USA (Clarke et al., 1997; Goldstein, 2004; Jantz et al., 2004; Jantz et al., 2010). The first application of SLEUTH model outside USA was carried out by Silva and Clarke (2002) for Porto and Lisbon metropolitan areas (Portugal) in Europe. In Asia, SLEUTH model was calibrated to Chiang Mai (Thailand) and Taipei (Taiwan of China) cities by Sangawongse et al. (2005). The studies in the context of Asian cities are suggesting the need of some adaptations to the model code to attain good spatial accuracy and scale sensitivity (Sangawongse et al., 2005; Wu et al., 2009). In the context of south Asia, the SLEUTH model was first used to simulate the urban growth of Pune metropolitan area by Kantakumar et al. (2011). The SLEUTH model was loosely coupled with a Soil and Water Assessment Tool (SWAT) model to understand the impact of urbanization on water balance in the Pune metropolis, India (Wagner et al., 2016). Since, South Asian cities are different from the rest of Asian cities. There is a need to test the applicability of the SLEUTH model by calibrating and validating for more South Asian cities. No studies have been found in the literature used the SLEUTH model to simulate the urban growth of a Sri Lankan city. Thus, this study fills the gap by using remote sensing data and the SLEUTH model to understand and simulate the urban growth of Matara City in Sri Lanka.

Few scholars around the world are used the SLEUTH model to simulate urban growth of a city under different scenarios viz., historical trend, managed growth, ecologically sustainable growth scenarios (Jantz et al., 2004; Feng et al., 2012; Osman et al., 2016), diffuse or more compact growth (Solecki and Oliveri, 2004; Osman et al., 2016; Goodarzi et al., 2017). However, the assessment of the future simulations based on urban growth models with the city development plans are still missing. Such assessments will help planners to identify the gaps in the existing development plans and to device effective development plans. As the city development plans are blatantly ignored in developing countries (Butsch et al., 2017) due to the rapid urban growth of cities often outpaces the development plans (Kantakumar et al., 2016). Thus, this study evaluated the development plan of Matara City in Sri Lanka using the urban growth simulations of SLEUTH model. The objectives of the study are as follows: 1) to understand the land use and land cover change driven by Matara's urbanization; 2) to simulate the urban expansion of Matara City to provide an extra layer for the planner to plan for a sustainable urban Matara.

## 2 Materials and Methods

### 2.1 Study area

The Matara City (5°55′54″N–5°59′44″N, 80°30′05″E–80°37′44″E) is located on the southern coast in Sri Lanka. It is the administrative capital of Matara District and one of the main commercial centers in Sri Lanka. It is famously known 'Mahathota' means 'The great ferry'. The town contains many remnants of Sri Lanka's colonial period. The Nilwala Ganga (Blue River) drains through the center of the study area. The Matara City has tropical climate with an average annual precipitation about 2147 mm and the average annual temperature is 26.8℃. According to the 2001 census of Sri Lanka, Matara witnessed a 40% increase in population. As a result, 46 surrounding villages were merged into the administrative limits of Matara. The Urban Development Authority (UDA) of Sri Lanka declared Matara as a municipality in 2002. The Matara city being a major commercial hub in the southern coast of Sri Lanka can act as a catalyst for southern development. Thus, UDA initiated major infrastructure development projects, such as, the construction of Southern expressway with four lanes from Kottawa to Matara, railway track from Matara to Beliatta, Nilwala riverside park development as an urban forest to foster the urbanization in Matara. This development led to population growth in the suburbs of the study area. The Matara city, which includes Matara Municipal Council (MC) and surrounding fringe villages are chosen for the study (Fig. 1).

### 2.2 Data preparation

We used aerial photographs and multi-temporal Landsat datasets to prepare the land use and cover of Matara City. The orthorectified aerial photographs based on Kandawala Sri Lankan reference grid system were used to digitize the urban extent of Matara City in 1980. The multi-temporal Landsat datasets specific to Thematic Mapper and Enhanced Thematic Mapper + sensors were rectified to Kandawala Sri Lankan reference grid system. A maximum likelihood supervised classifier was used to prepare the land use and cover (LUC) maps for the years of 1990, 2000 and 2010 with five classes namely, built-up land (urban), homestead and garden, forest, marsh or paddy and water (Fig. 2). The main advantage of the maximum likelihood classifier is not only considering the mean vector of the pixels in one class, but also taking the variability of these pixels in multispectral feature space into account (Kantakumar and Neelamsetti, 2015). The accuracy of the LUC maps was evaluated with the help of survey department's toposheets and Google Earth. The overall accuracies of LUC maps for 1990, 2000 and 2010 are 87.69%, 84.35% and 89.64% respectively (Table 1). The spot heights data from the Sri Lankan survey department were used to create a Digital Elevation Model (DEM) of the study area. This DEM is used to prepare the percentage slope and hillshade maps of the study area (Fig. 3). The road layers used in this study are extracted from the aerial photographs (for 1980) and toposheets (for 2008).

### 2.3 Land use change detection

Land use change detection was used to identify significant land use changes from imagery acquired at different points in time. In this study, post classification change detection (Shalaby and Moghanm, 2015; Yuan et al., 2005) was used to quantify the land use changes in Matara City. The post classification technique is a simple and effective method to quantify the land use change than other land use change detection techniques (Singh, 1989). The data input for the post classification change detection is two land use maps at two different points in time. The post classification technique uses pixel by pixel comparision to produce the land use change transtion matrix (Table 3 and Table 4). The land

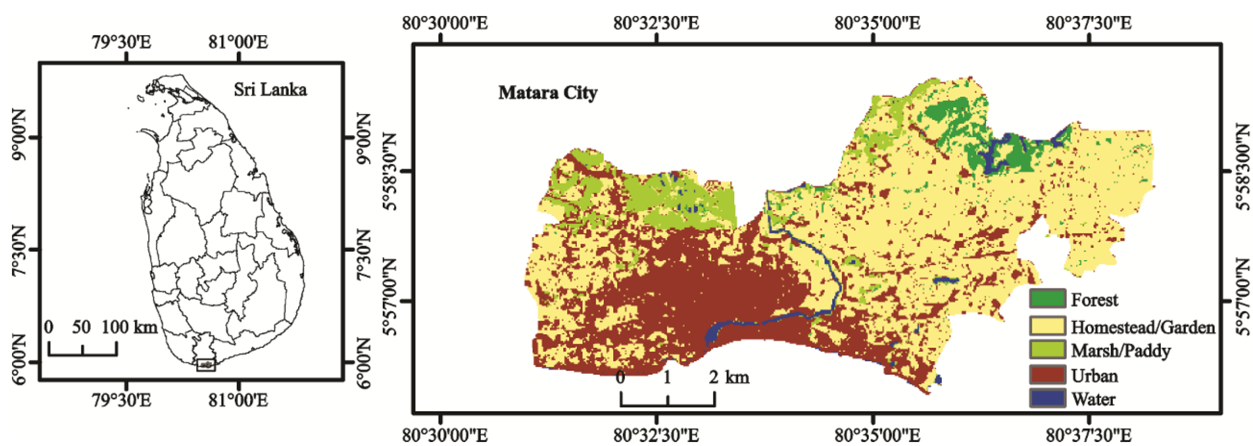


**Fig. 1** Study area map of the Matara City in Sri Lanka

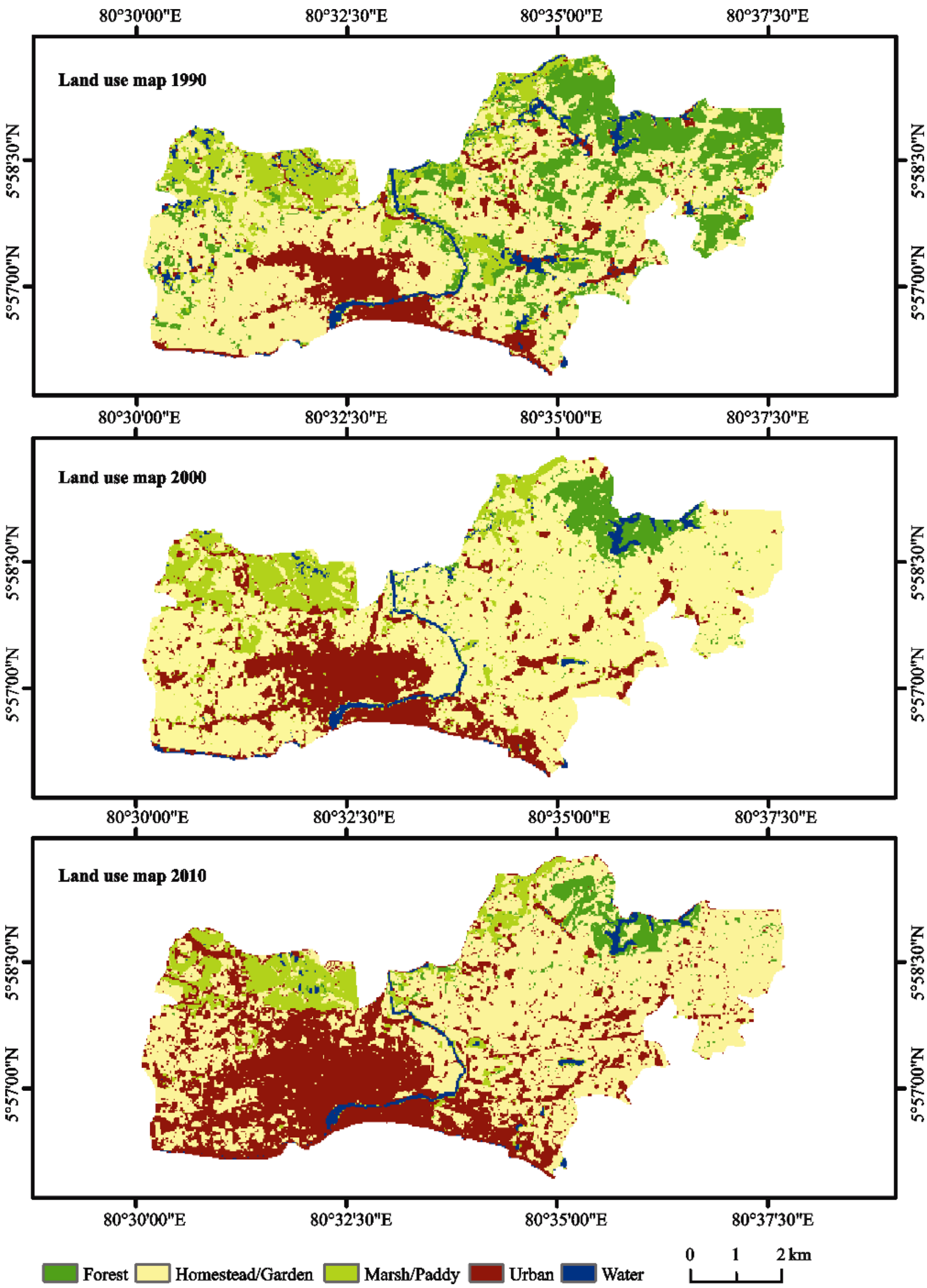


**Fig. 2** Land use and cover maps of 1990, 2000 and 2010 of Matara City in Sri Lanka

use change transtion matrix comprises detailed information about the size and distribution of changed areas and also provides the information about the percentages of other land cover classes that are contributing to the change in each land use class (El-Hattab, 2016). The accuracy of post-classification change detection can be approximated to the product of overall accuracies of the land use maps used (Coppin et al., 2004).

## 2.4 SLEUTH urban growth model

The SLEUTH model is a cellular automata based urban growth model which uses four types of growth rules namely spontaneous growth, new spreading center growth, edge growth, and road-influenced growth to simulate the urban expansion. These four growth types are applied sequentially during each growth cycle or year, and are controlled through the interactions of five

**Table 1** Accuracy assessment results of land use maps of 1990, 2000 and 2010 for Matara City in Sri Lanka

| Land use category | User's accuracy of land use classification (%) | | |
|---|---|---|---|
| | 1990 | 2000 | 2010 |
| Urban | 97.87 | 93.99 | 85.31 |
| Homestead/Garden | 86.36 | 77.1 | 86.05 |
| Marsh/Paddy | 87.65 | 85.71 | 94.66 |
| Forest | 91.91 | 80.34 | 98.65 |
| Water | 65.31 | 88.55 | 94.74 |
| Overall accurcay | 87.69 | 84.35 | 89.64 |
| Kappa statistic | 0.84 | 0.79 | 0.86 |

growth coefficients: dispersion, breed, spread, road gravity, and slope (Clarke et al., 1997). The dispersion coefficent controls the spontaneous growth of a randomly selected non-urban pixel. The breed coefficent control the growth around newly urbanised pixels from spontaneous growth. The spread coefficent control the expansion of edges of the urban areas. The road gravity coefficent controls the growth along the transportation networks. The slope coefficent resists the urban growth on steep slopes. The growth rules used in SLEUTH model are scalable and universally applicable (Silva and Clarke, 2002). Thus, SLEUTH model is a dynamic and future oriented urban growth model conforming to the essential requirement of urban growth (Yang, 2010). It has been used to simulate the urban growth in more than hundred cities around the world (Chaudhuri and Clarke, 2013). Three modes namely, test, calibration and prediction are used to implement the model in the study area. The test mode verifies the suitability of the input datasets before performing calibration or prediction. Whereas, the calibration of the SLEUTH model aims to find the best possible combination of growth coefficients. The Prediction stage use these of growth coefficients to simulate the urban growth into the future.

The SLEUTH model requires a minimum of four historic urban extent maps along with elevation, slope, exclusion layers and two maps of transportation network representing early and later stages. The two land use maps are optional layers to run the model. Fig. 3 shows the inputs maps used to run the model. All the inputs maps are projected to the same extent with same spatial resoultion (30 m) as required by the SLEUTH model.

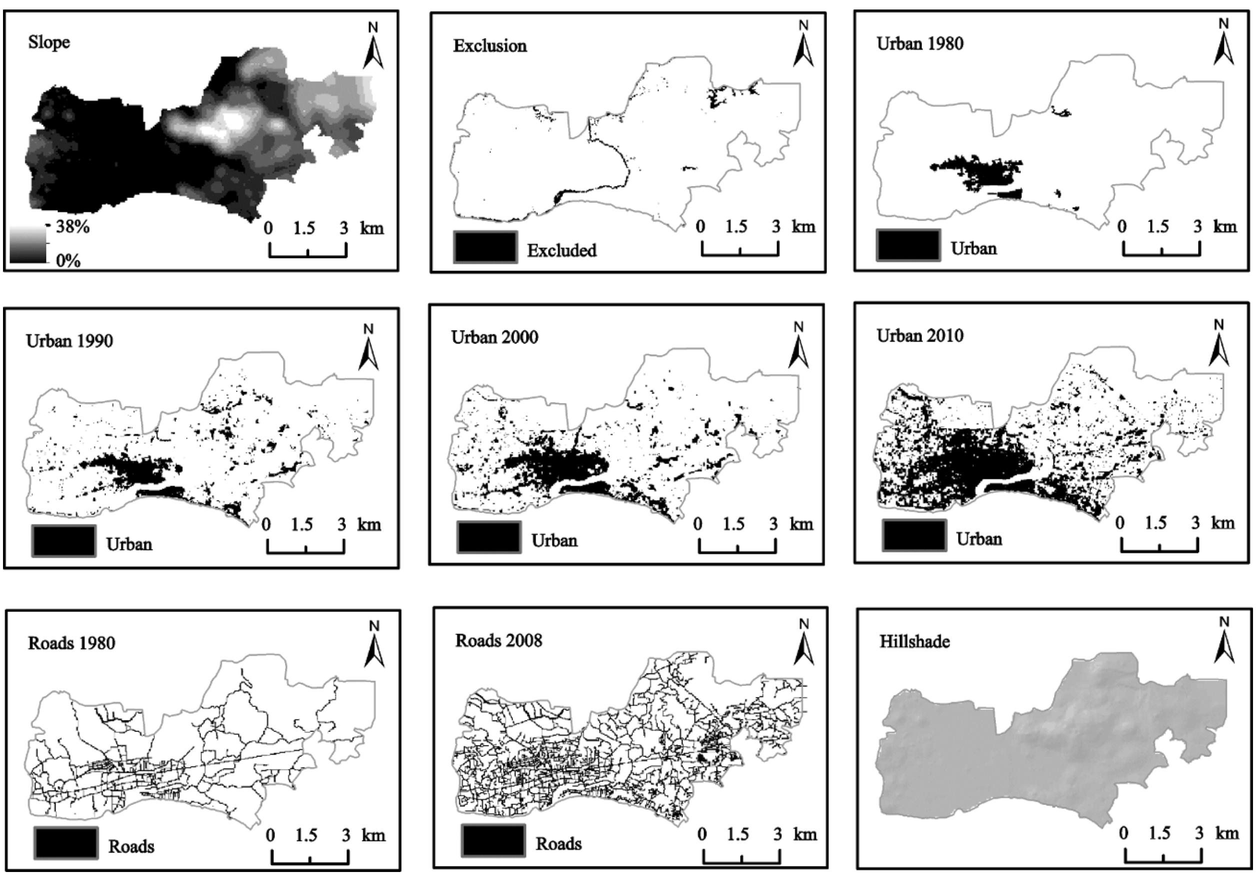


**Fig. 3** Input data layers used in SLEUTH urban growth model

### 2.5 Model calibration

The purpose of the model calibration is aimed to successfully replicate the historical urban expansion as presented in the input files. During the calibration, the statistical values which are best-fit to the historical urban expansion from all the possible iterations, are sorted to find optimum values for growth coefficients. The calibration of SLEUTH model is a computationally intensive process (Jantz et al., 2010). There are two methods available to carry out the calibration, they are brute force calibration and generic algorithm (Jafarnezhad et al., 2016). The brute force method uses a predetermined order of stepping through the coefficient space in an adaptive manner (Goldstein, 2004). In this study, brute force calibration method has been adopted to sequentially narrow down the ranges of coefficient values using the three phase calibration process: coarse, fine and final calibrations. The brute force calibration refers to the estimation of values for each parameter from known historical growth patterns, where the user indicates a range of values and the model iterates using every possible combination of parameters. For each parameter set combination, the model simulates growth multiple times in a Monte Carlo process and compares the simulated growth to actual growth by computing several least squares regression measures, including the number of urban pixels, the number and size of urban clusters, urban edge pixels, as well as other fit statistics.

The SLEUTH model can calculate these statistics internally and writes the results to log files. These log files are used to evaluate the performance of the different parameter sets (Abd-Allah, 2007). At the end of each calibration (i.e., coarse, fine and final) the model produces a 'control_stats.log' text file. The 'control_stats.log' text file contains thirteen least square regression estimates viz., compare (modeled final population), population (number of urban pixels), cluster (urban cluster edge pixels), edges (urban perimeter), Lee Sallee metric (shape index), average slope, *X*-mean (average *X* values) and *Y*-mean (average *Y* values) *etc*. These least square regression estimates represent the measure of fit between simulated urban growths to the actual urban growth. Anyone metric or a weighted sum or the values derived from multiplication of several regression estimates can be used to derive optimum growth coefficients to represent historic growth of a city. Most of the previous studies used the Lee-Sallee metric as a measure to narrow down the coefficient space in calibration process (Silva and Clarke, 2002; Ayazli et al., 2014; Sakieh et al., 2015; Osman et al., 2016). Lee-Sallee metric is a measure of spatial fit between the modeled urban growths to the known urban extent (Dietzel and Clarke, 2007). Hence, we used the Lee-Sallee metric as primary measure to narrow down the coefficients space.

## 3 Results

### 3.1 Land use change detection

Land use statistics and transition matrices provide important information to analyze the changes in land use and cover. Land use change analysis is based on statistics extracted from three land use and cover maps of Matara City pertain to the years of 1990, 2000 and 2010. During the last two decades, it was observed that the urban area in Matara increased from 11% in 1990 to 31% in 2010 (Table 2). The rate of urbanization is high in the period of 2000 to 2010 as compared to the period of 1990 to 2000. The forest cover reduced to 4% of the study area in 2010 from 18% in 1990. Most of the losses in forest cover mainly occurred in the period of 1990 to 2000. Marshy or paddy area decreased from 12% to 9% from 1990 to 2010. It was observed that, the homestead/garden land use increased from 55% to 66% of the study area in the period from 1990 to 2000. While, the same was decreased to 55% of the study area by 2010.

**Table 2** Land use statistics of Matara City in Sri Lanka from 1990 to 2010

| Land use category | 1990 | | 2000 | | 2010 | |
|---|---|---|---|---|---|---|
| | Area ($km^2$) | Percentage (%) | Area ($km^2$) | Percentage (%) | Area ($km^2$) | Percentage (%) |
| Urban | 5.9 | 10.6 | 9.2 | 16.6 | 17.0 | 30.6 |
| Homestead/Garden | 30.4 | 55.0 | 36.6 | 65.9 | 30.8 | 55.5 |
| Marsh/Paddy | 6.7 | 12.1 | 5.9 | 10.6 | 4.7 | 8.5 |
| Forest | 10.2 | 18.4 | 2.5 | 4.5 | 2.0 | 3.6 |
| Water | 2.2 | 4.0 | 1.3 | 2.3 | 1.0 | 1.8 |
| Total | 55.5 | 100.0 | 55.5 | 100.0 | 55.5 | 100.0 |

The land use maps derived from multi-temporal satellite imageries from 1990, 2000 and 2010 show most of the homestead garden and paddy lands are converted to the built-up area during the last two decades (Fig. 2). The transition matrices of land use change detection are produced by using the intersect tool in ArcGIS. This method was use to characterize the land conversions for the periods from 1990–2000 and from 2000–2010 (Tables 3 and 4).

There are 25 possible combinations for each time period. Since this study is focusing on the urban growth characterization, only 5 combinations related to urban land conversion, such as urban (no change), homestead/garden into urban, forest into urban and water into urban were selected for further analysis. The other combinations are merged into a single class (Table 5). The loss of the homestead/garden category has contributed to greater share of urban growth among other land use categories. During 1990 to 2000 urban land use had a net addition of 4.2 km$^2$ (7.6%) from the homestead/garden category and from 2000 to 2010 it was contributed to 8.6 km$^2$ (15.5%). From the transition matrices of land-use change (Tables 3 and 4), it was observed 1.4 km$^2$ in period of 1990–2000 and 1.8 km$^2$ urban area was converted into homestead/garden. This conversation might be due the misclassification of mixed pixels of urban and homestead/garden land use classes.

### 3.2 Calibration and validation

The goal of the calibration is to derive a set of values for the growth parameters that can effectively simulate the urban growth. In order to derive the best fit values for the growth coefficients, the historical urban extent data of Matara was calibrated in three successive calibration

**Table 3** Transition matrix of land-use change from 1990 to 2000

| Land use category/Extent (km$^2$) | Urban (km$^2$) | Homestead/Garden (km$^2$) | Marsh/Paddy (km$^2$) | Forest (km$^2$) | Water (km$^2$) | 2000 ( km$^2$) |
|---|---|---|---|---|---|---|
| Urban | 4.1 | 4.2 | 0.4 | 0.2 | 0.3 | 9.2 |
| Homestead/Garden | 1.4 | 24.4 | 2.5 | 7.7 | 0.6 | 36.6 |
| Marsh/Paddy | 0.3 | 1.5 | 3.4 | 0.2 | 0.5 | 5.9 |
| Forest | 0 | 0.3 | 0.1 | 2.0 | 0.1 | 2.5 |
| Water | 0.1 | 0.1 | 0.3 | 0.1 | 0.7 | 1.3 |
| 1990 | 5.9 | 30.5 | 6.7 | 10.2 | 2.2 | 55.5 |

**Table 4** Transition matrix of land-use change from 2000 to 2010

| Land use category/ Extent (km$^2$) | Urban (km$^2$) | Homestead/Garden (km$^2$) | Marsh/Paddy (km$^2$) | Forest (km$^2$) | Water (km$^2$) | 2010 ( km$^2$) |
|---|---|---|---|---|---|---|
| Urban | 7.0 | 8.6 | 1.1 | 0 | 0.3 | 17.0 |
| Homestead/Garden | 1.8 | 26.3 | 1.4 | 1.1 | 0.2 | 30.8 |
| Marsh/Paddy | 0.3 | 1.0 | 3.2 | 0 | 0.2 | 4.7 |
| Forest | 0 | 0.5 | 0.1 | 1.3 | 0.1 | 2.0 |
| Water | 0.1 | 0.2 | 0.1 | 0.1 | 0.5 | 1.0 |
| 2000 | 9.2 | 36.6 | 5.9 | 2.5 | 1.3 | 55.5 |

**Table 5** Other land use to urban land use conversions from 1990 to 2000 and from 2000 to 2010

| Nature of change | 1990–2000 | | 2000–2010 | |
|---|---|---|---|---|
| | Area (km$^2$) | Percentage (%) | Area (km$^2$) | Percentage (%) |
| Urban (no change) | 4.1 | 7.4 | 7.0 | 12.6 |
| Homestead/Garden into urban | 4.2 | 7.6 | 8.6 | 15.5 |
| Marsh/Paddy into urban | 0.4 | 0.7 | 1.1 | 2.0 |
| Forest into urban | 0.2 | 0.4 | 0 | 0 |
| Water into urban | 0.3 | 0.5 | 0.3 | 0.5 |
| Other combinations | 46.3 | 83.4 | 38.5 | 69.4 |

phases namely, coarse, fine and final calibrations. In all the calibration phases the images with 30 m spatial resolution were used. In coarse calibration, all the five control coefficients start and stop values are set to the entire range of potential values from 0 to 100 with a step value of 25. To reduce the computation time, a minor value (4) is given for the number of Monte Carlo iterations. After completion of coarse calibration, the Lee-Salle metric is used to sort all the simulations runs to identify the top three simulations replicating the historic growth patterns (Table 6). The minimum and maximum values of each growth coefficients in top three sorted simulations using Lee-Salle metric are used as start and stop values for respective growth coefficients with higher number of Monte Carlo iterations than the previous stage of calibration in fine and final calibration process. The top 50 simulation from the final calibration are averaged to derive the final calibration coefficient values of growth parameters. These final calibration coefficients are used as start and stop values with a unit step increment and 100 Monte Carlo iterations to derive the best fit values for prediction. The results of the final calibration and best fit values for prediction are presented in the Table 7.

The SLEUTH model performance is validated by comparing the number of simulated pixels to the number of urban pixels presented in the urban extent layers, which are prepared from Landsat TM, ETM+ by using the maximum likelihood classification method. The Fig. 4 shows the relationship between modeled urban area by SLEUTH model to the observed urban area for the year 1990, 2000 and 2010.

### 3.3 Urban growth prediction by 2030

The urban extent of 2030 was simulated by initializing the SLEUTH model with the prediction best fit values from Table 7 and the urban extent of 2010 as seed layer. The graph showing simulated urban areas at five year interval form 2010 to 2030 presented in the Fig. 5. The results show that, if the historical urban pattern continues to be the same, the urban area in Matara will occupy about 82.8% of the total area by 2030. The city of Matara will gain at about 29 $km^2$ of urban area from 2010 to 2030. From the Fig. 6, we can notice that conversion probability of non-urban land to urban is likely to be very high ranging from 70% to 100%.

The information about historic urban growth patterns and future simulations at the basic administrative division (GND in Sri Lanka) scale will help the planners in the planning process to plan sustainable cities. Hence, we superimposed the urban growth probability map on GND boundary map to identify the GNDs that will be most probably witness the rapid urbanization by 2030 (Fig. 6). Further analysis has been carried out by con-

**Table 6** Sorting coefficient space in coarse calibration using Lee-Salle metric

| Run | Product | Least square regression estimates | | | | | | | | | | | Coefficient values | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Compare | Population | Edges | Clusters | Cluster size | Lee-Salle | Slope | Percentage Urban | *X*-mean | *Y*-mean | Rad | Diffusion | Breed | Spread | Slope | Road gravity |
| 346 | 0.00 | 0.83 | 0.98 | 0.99 | 0.99 | 0.94 | 0.41 | 0.62 | 0.98 | 1.00 | 0.02 | 0.98 | 1 | 50 | 75 | 100 | 25 |
| 216 | 0.02 | 0.74 | 0.98 | 0.99 | 0.98 | 0.96 | 0.41 | 0.67 | 0.98 | 0.98 | 0.11 | 0.98 | 1 | 25 | 75 | 75 | 25 |
| 246 | 0.01 | 0.76 | 0.97 | 0.99 | 1.00 | 0.39 | 0.40 | 0.65 | 0.98 | 0.99 | 0.10 | 0.98 | 1 | 25 | 100 | 100 | 25 |
| 221 | 0.02 | 0.73 | 0.98 | 0.97 | 1.00 | 0.93 | 0.40 | 0.67 | 0.98 | 0.99 | 0.11 | 0.98 | 1 | 25 | 75 | 100 | 25 |
| 470 | 0.00 | 0.93 | 0.98 | 0.97 | 0.98 | 0.97 | 0.40 | 0.59 | 0.98 | 0.99 | 0.01 | 0.98 | 1 | 75 | 75 | 100 | 1 |
| 595 | 0.01 | 0.98 | 0.98 | 0.96 | 0.88 | 1.00 | 0.40 | 0.61 | 0.99 | 0.99 | 0.04 | 0.98 | 1 | 100 | 75 | 100 | 1 |
| 222 | 0.03 | 0.74 | 0.98 | 0.94 | 0.94 | 0.99 | 0.40 | 0.67 | 0.98 | 1.00 | 0.18 | 0.98 | 1 | 25 | 75 | 100 | 50 |
| 445 | 0.02 | 0.77 | 0.98 | 0.98 | 0.99 | 0.89 | 0.40 | 0.66 | 0.98 | 0.98 | 0.15 | 0.98 | 1 | 75 | 50 | 100 | 1 |
| 320 | 0.03 | 0.69 | 0.98 | 0.96 | 0.97 | 0.98 | 0.40 | 0.68 | 0.98 | 0.99 | 0.18 | 0.98 | 1 | 50 | 50 | 100 | 1 |
| 220 | 0.01 | 0.71 | 0.98 | 0.99 | 1.00 | 0.81 | 0.40 | 0.59 | 0.98 | 0.99 | 0.09 | 0.98 | 1 | 25 | 75 | 100 | 1 |

Notes: The Lee-Salle metric is used to sort the simulations of Model runs to identify the best runs. Percentage Urban means the percent of available pixels urbanized during simulation compared to the actual urbanized pixels for each control year.

**Table 7** Results of calibration and best fit values for prediction

| | Diffusion | Spread | Breed | Slope resistance | Road gravity |
|---|---|---|---|---|---|
| Calibration | 1 | 90 | 30 | 75 | 1 |
| Prediction best fit | 1 | 100 | 40 | 1 | 9 |

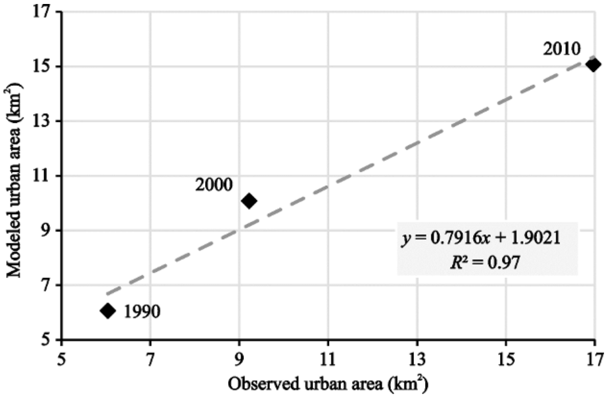


**Fig. 4** Modeled urban area by SLEUTH model and observed urban area from remote sensing

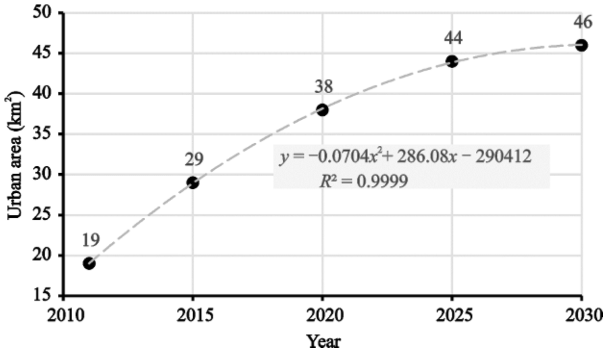


**Fig. 5** Graph showing the area of urban land in Matara from 2011 to 2030

sidering the pixels having more than 50% urban growth probability as urban pixel to calculate the urban extent in each GND by 2030. The percentage urban area with respect to the total area of GND calculated was used to summarize the level of urbanization by 2030. The results showed 29 GNDs out of 66 GNDs will be totally converted into urban land by 2030, 28 GNDs will have urban land cover from 75% to 99%, 3 GNDs will have urban land cover from 50% to 75% and 6 GNDs will have urban land below 50%.

## 4 Discussion

The urban area of the city of Matara has increased its share from 5% of the study area (2.88 km$^2$) in 1980 to 31% (16.97 km$^2$) by 2010. The widespread urbanization in Matara took place after the announcement of Matara as municipality by UDA in 2002. This speedy urbanization within a span of thirty years took place by conversion of most of the garden/ homestead areas followed by paddy fields. The conversion of paddy fields into urban areas is a notable transformation in developing countries (Li and Yeh, 2000). The share of the forest land in Matara reduced to 4% of the study area in 2010 from 18% in 1990. The forest land lost its major share to the homestead/garden land use and further homestead/ garden land use lost its major share to the urban land use. Thus, agricultural intensification and urbanization are the two major factors of deforestation in developing countries (Goers et al., 2012; Sacchi and Gasparri, 2016). The conversion of forest and agricultural lands should be restricted by devising effective town planning measures. The calibration results of the SLEUTH model show that the historic urban growth mainly took place because of organic growth (Clarke and Gaydos, 1998) of old urban areas in the city, since the spread coefficient value reached its maximum value of 100 in prediction 'best fit values' (Table 7). From the historic urban growth maps from 1980 to 2010 of Matara City (Fig. 3), one can notice that the city mainly expanded around the old urban area.

According to the population and housing statistic reports of Department of Census & Statistics of Sri Lanka (2001 and 2009) of Matara, the rural population in Matara will gradually reduce to 31% by 2030 from 60% in 2009. And, the simulations based on the SLEUTH urban growth model shows that Matara urban land extent will reach near to 82% of the study area by 2030. Thus, the results from the SLEUTH model match with the projections of Sri Lankan population and housing statistic reports. These results indicates that the SLEUTH urban growth model is successful in capturing the urban growth characteristics of the city of Matara. However, these results are in contrast to the findings of other South Asian cities Pune (Kantakumar et al., 2011), Hyderabad (Gandhi and Suresh, 2012) and Ajmer (Jat et al., 2017), which have been reported the underestimation of urban growth by the SLEUTH model. The underestimation of urban growth by the SLEUTH in the previous studies of South Asian cities might be either due to the approach of increasing spatial resolution of inputs while calibration of SLEUTH model to reduce the calibration time or due to the use of different statistical fit metric, i.e., Optimum SLEUTH Metric (OSM) (Dietzel and Clarke, 2007) to narrow down the coefficient space in calibration. It was noticed in this study that urban areas in Matara will increase their share from 31% in 2010 to near to 82% of the study area by 2030, with increasing urban population from 40% to 69% by

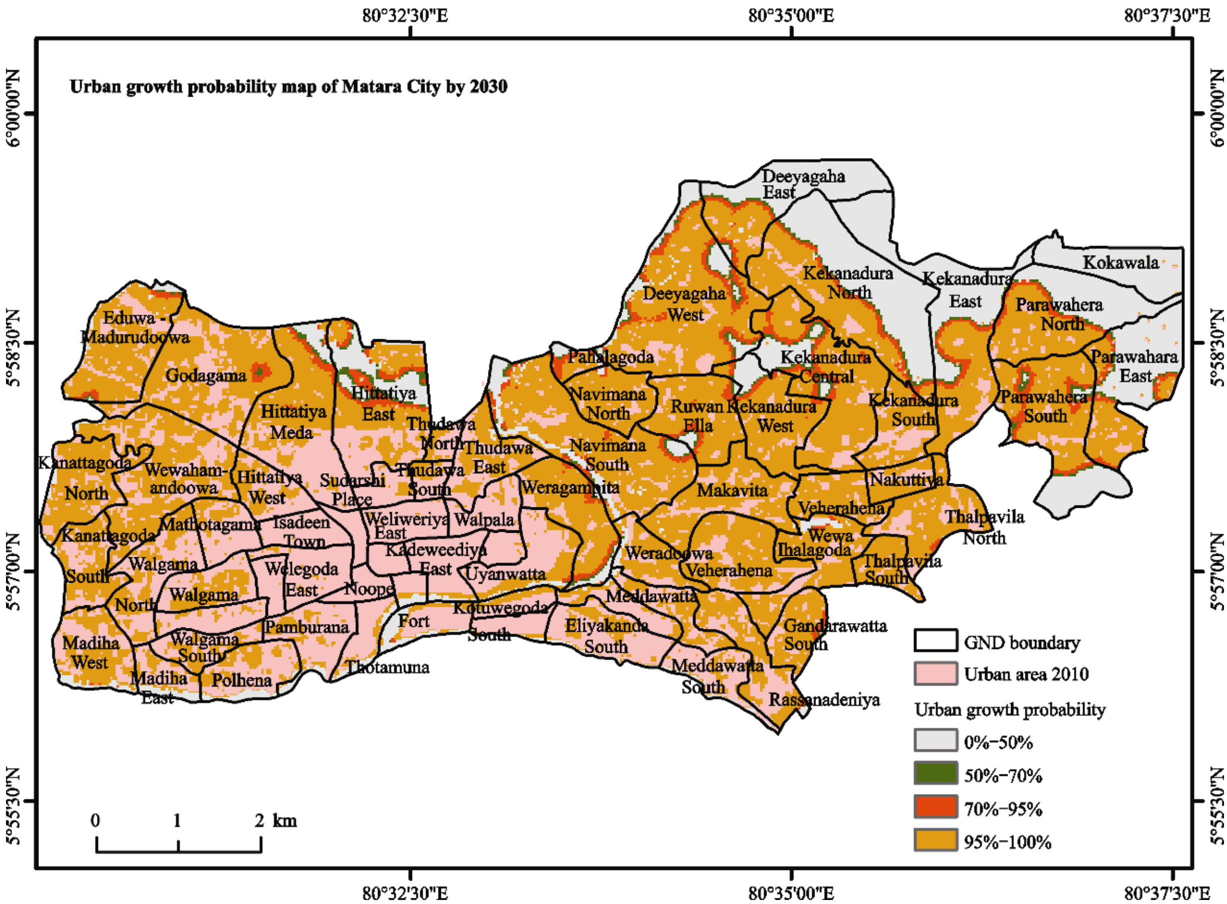


**Fig. 6** Urban growth probability map of Matara City by 2030 (Superimposed on GND Map)

2030. This huge rural to urban transformation needs to be managed properly to achieve suitable and vibrant urbanization in the city of Matara.

The rapid urbanization of cities in developing countries is posing a challenge to urban planners, as the development often outpaces the planning process (Kantakumar et al., 2016). This is particularly true in the context of Matara, because when we superimposed the urban simulations over Urban Development Authority (UDA)'s development proposal (Fig. 7), it was noticed that the proposed urban area in the development plan is far less than the urban land demand simulated by the SLEUTH model based on historic development trend. In addition, the urban growth simulations shows that the protected areas in Matara City will be encroached by urbanization by 2030. Specially, the proposed southern express highway extension project form Godagama to Hambantota will spur the urban growth in the vicinity of Kiralakale wildlife reserve by 2030 (Fig. 7) and endanger the flora and fauna in the wildlife reserve. The western edge of Kekanadura forest reserve may also likely to be encroached by urbanization by 2030. This information from the simulation of urban growth model is vital to the policy makers and urban planners to devise polices and plans to control the urban expansion in the protected areas.

The model simulations shows that the western part of Matara City has good potential for urbanization. It agrees with the UDA's proposal to extend the urban area towards the west part of the study area; from Matara DSD to part of Weligama DSD (Fig. 7). The UDA has proposed to extend the urban area towards west part of the study area; from Matara DSD to part of Weligama DSD (Fig. 7). The other major proposed development projects such as, expansion of railway track from Matara to Kataragama and southern highways will increase the potential of urban expansion in the eastern part of Matara City. However, The GNDs in northeast region of Matara City, that is, Parawahera East, Parawahera North, Kakenadura East, Kakenadura North and Deeyagaha East (Fig. 6) will experience less urban expansion as compared to the other GNDs, because of their location on steep slopes of hills. This proves urbanization

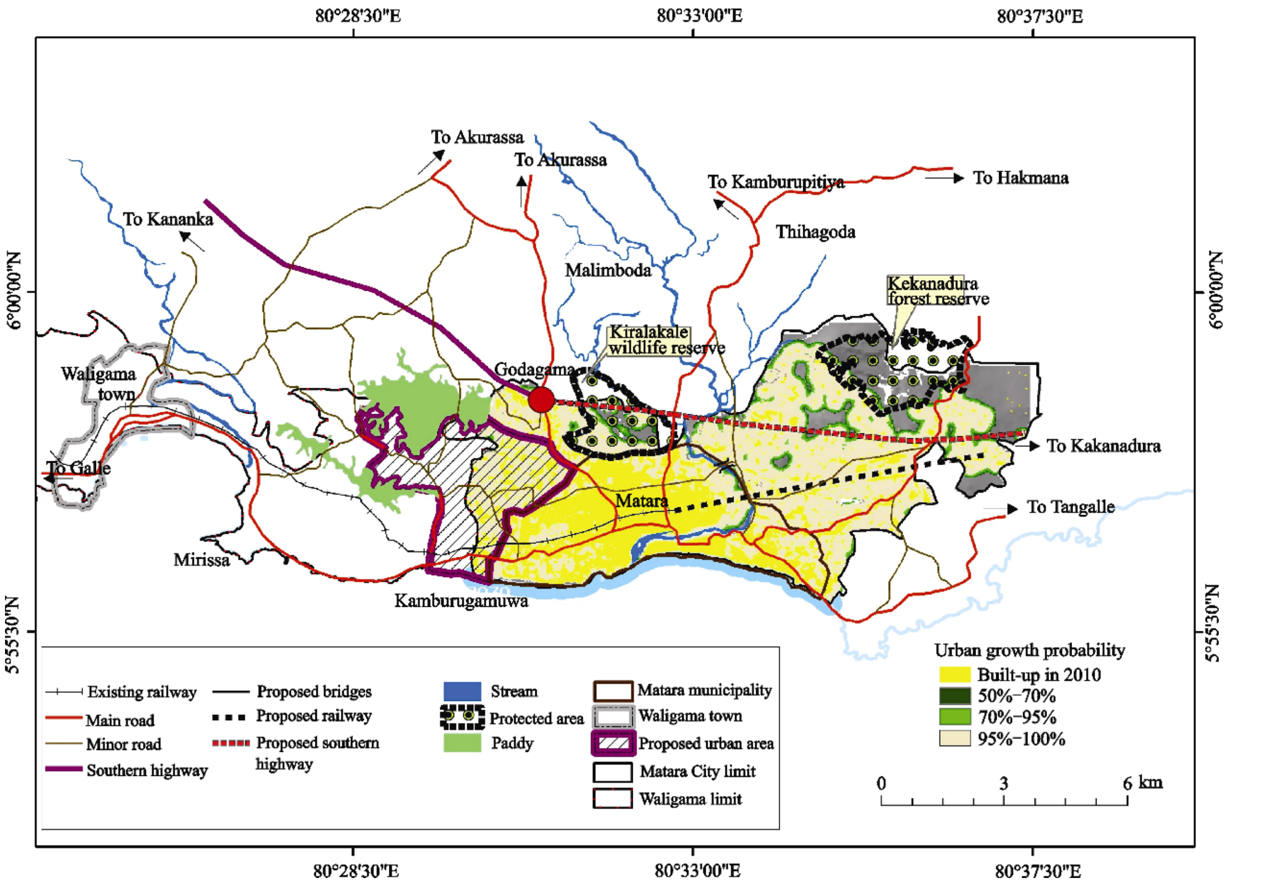


**Fig. 7** Comparing SLEUTH urban growth simulation by 2030 with the development proposal of Urban Development Authority (UDA), Sri Lanka. Source: UDA and SLEUTH model simulation 2030

mostly occurs in relatively flat areas (Li et al., 2013).

## 5 Conclusions

In this study, the SLEUTH urban growth model is calibrated and tested for the first time to a Sri Lankan city. The urban growth simulation form any urban growth modeling exercise should provide relevant information to the planners to device sustainable development strategies. Thus, this study investigated the appropriateness of loose-coupling approach to understand the urban growth dynamics and effectiveness of urban development plans using SLEUTH urban growth model, remote sensing data and GIS. The results of this study identified unsustainable urban land transitions processes such as conversion of paddy land into urban and the loss of forest land in Matara City and suggesting the need for strict implementation of development control rules to protect the forest and paddy lands from encroachment. The results of SLEUTH model simulation show, the urban growth of Matara will pose a serious threat to the wild life in Kiralakele wildlife reserve and Kekanadura forest reserve by 2030. The proposed southern highway extension project form Godagama to Hambantota and railway track from Matara to Kataragama may offer better and reduced transportation costs, and enough infrastructure facilities, which are not available presently in countryside. However, it will intensify the negative effects of urbanization such as increasing anthropogenic land use conversion, dense built-up areas, air pollution and urban heat island, etc., upon the local climate of the city. Since, the SLEUTH model effectively captured the dynamics of Matara City, it may be used as an urban planning decision support tool by the Sri Lankan planners to understand the urban growth dynamics to plan sustainable urban Sri Lanka.

The SLEUTH model simulation results suggests that the existing development plan of Matara is likely to be outpaced by rapid urbanization in the near future. Thus, the UDA, local authorities and provincial council have planning responsibilities to mitigate the escalating environmental issues and urban sprawl to provide superlative facilities for the people living in the area. But the major problem in planning, city management, land and housing development is investment. Therefore, to avoid the above circumstances and to achieve sustainable urbanism by 2030, proper policy reforms and strategies are needed, based on integrated national, regional, and local level planning to make sure of viable funding to improve social and physical infrastructure, as well as housing development which includes encouraging more efficient land use in urban areas enabling environment for better and more affordable shelter options for all.

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