SPATIO-TEMPORAL GROWTH PATTERN ANALYSIS AND URBAN SIMULATION IN COLOMBO CITY USING OPEN SOURCE SOFTWARE TOOLS - APPLICATION OF FUTURES SIMULATION MODEL

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ABSTRACT: Cities in South Asia are experiencing a rapid urban expansion with upcoming development activities and high population growth. Urban planning practitioners are facing challenges in understanding complex spatial changing trends associated urban issues with population as well as infrastructure agglomeration. Understanding of complex urban growth process which involves various factors with different patterns of behavior has become an essential requirement which accelerated the need of urban growth analysis and simulation. This study attempts to simulate the urban growth pattern of Colombo city in Sri Lanka which is a dynamic and rapid urbanizing region using FUTURES (FUTure Urban-Regional Environment Simulation) model. FUTURES is a patch-based, multilevel modeling framework for simulating the emergence of landscape spatial structure in urbanizing regions. The spatio-temporal urban growth patterns during 1997 to 2014 were first analyzed by comparing three land cover (LC) maps (1997, 2005 and 2014) that were produced from LANDSAT data using K-Nearest Neighbor (KNN) method. Changes of spatial patterns were analyzed using selected statistical landscape metrices. Major urban expansions were modeled to predict different future scenarios for the year 2030 using FUTURES model embedded in the GRASS GIS open source software. Business as usual, infill growth and urban sprawl scenarios were predicted, and they were compared with the proposed spatial pattern for Colombo city. With certain strengths and weaknesses, the model is competent to predict possible urban scenarios, which could involve in providing suggestions for a better decision making to achieve a sustainable development for emerging urban areas.

1. INTRODUCTION

1.1 Land use Land cover Change (LULCC)

Rapid urbanization has greatly accelerated economic and social development, and global cities are engines of economic growth but urbanization has also created numerous environmental problems ranging from local to the global scale (Kim and Baik, 2005; Zhao et al., 2006), including increased air and water pollution (Liu and Diamond, 2005), local climate alteration and increased energy demands (Zhou et al., 2004; González et al., 2005), insufficient housing and sanitation facilities, traffic congestion (Jago-on et al., 2009), and a major reduction in natural vegetation (Yuan, 2008). To overcome such issues and to achieve a sustainable development of urban areas, monitoring and modeling LULCC associated to urbanization are of great importance. LULCC models are tools to support the analysis of the causes and consequences of LULCC and important for simplifying the complex socioeconomic and biophysical forces that influence the rate and spatial pattern of LULCC.

1.1.1 Land Use/Land Cover (LULC) classification

Prior applying LULCC model, producing accurate LULC maps is of extreme importance in representing current and historical changes of a particular area. Numerous classification methods have been developed and tested for LULC mapping (González, J. et al.,2005), (Jago-on, K., et al., 2009), (Jantz, C. and Goetz, S. 2005) using remote sensing data during recent past. These methods range from unsupervised algorithms to supervised algorithms (i.e., maximum likelihood) and machine learning algorithms such as artificial neural networks (ANN), k-Nearest Neighbors (kNN), decision trees (DT) and random forest (RF). Among these, widely used three methods; maximum likelihood classifier (MLC), RF and kNN were selected to be tested in this study.

1.2 Modelling urban change with FUTURES

Most urban growth models are based on cell-level conversions and have not focused on generating realistic spatial structures across scales (Jantz and Goetz, 2005). In order to bridge the gap between cell and object-based representation, FUTURES (FUTure Urban-Regional Environment Simulation), a patch-based, multilevel modeling framework for simulating the emergence of landscape spatial structure in urbanizing regions was developed (Meentemeyer et al.,2013). The FUTURES model was successfully applied in several cases including a study of land development dynamics in the rapidly expanding metropolitan region of Charlotte, North Carolina (Meentemeyer et al., 2013) and an analysis of the impacts of urbanization on natural resources under different conservation strategies (Dorning et al., 2015).
FUTURES model consists with three sub-models POTENTIAL, DEMAND and PGA (Patch Growing Algorithm). The POTENTIAL sub-model uses site suitability modeling approach to quantify spatial gradients of land development potential or likelihood based on multilevel relationships between observed change and the socioeconomic, infrastructural, and environmental characteristics of a region. DEMAND estimates the rate of per capita land consumption specific to each sub region or level. Forecasts of land consumption are based on relationship between historical changes in population and land conversion. Per capita demand relationship for any level of population aggregation can be constructed, depending on the user’s preferred level of observation or data availability (e.g. population in administrative boundary wise or block wise). PGA constructs conversion event objects by combining cell- and object-based representations of land change.

2. STUDY AREA AND MATERIAL

Colombo (Figure 1), western coastal city in Sri Lanka is selected as the study area considering its rapid urban expansion within past few decades.

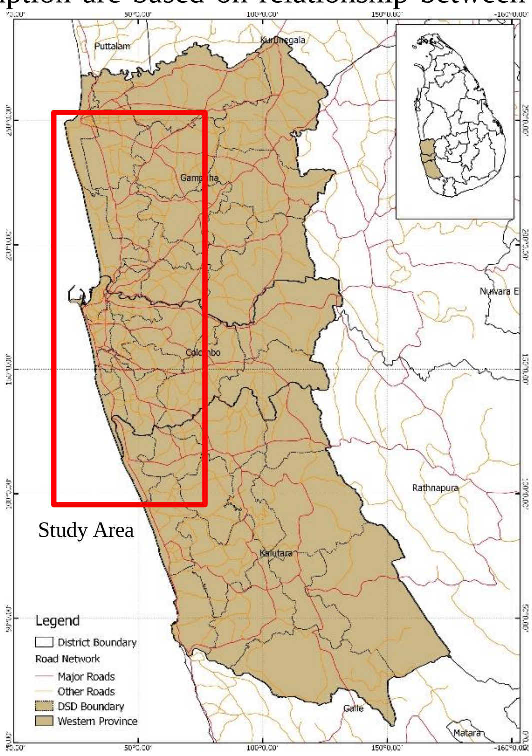

Figure 1: Location of the study area

Expanded urban areas of Colombo city core and its suburbs during 1997 to 2014 were the key concern in this study. Temporal satellite imageries from Landsat 5 TM in 1997, 2005 and Landsat 8 OLI in 2014 were used to detect land cover classes of the area. Other than freely available satellite images, environmentally sensitive areas, water bodies, road network and population data were used for urban change modeling approach. Table 1 shows the description of used data.

Table 1: Used data

Data	Updated year	Data source
Landsat 5 TM	1997,2005	Earthexplorer (USGS)
Landsat 8 OLI	2014	Earthexplorer (USGS)
Population	1991,2001,2012	Dpt of census and statistics, Sri Lanka
Road network	2013	JICA (ComTrans Project)
Water bodies	2013	JICA (ComTrans Project)
Colombo wetland zoning	2008	Urban Development Authority (UDA)
Elevation	-	Survey department Sri Lnaka
Administrative boundary map	-	Survey department Sri Lnaka

3. METHODOLOGY

3.1 LULCC detection

LC maps for 1997, 2005, 2014 were derived from remotely sensed imageries. Image preprocessing routine including radiometric, atmospheric, and geometric corrections was performed. Three preprocessed images were then classified using supervised pixel-based approach into four major classes: water, built-up, wetland/paddy and other vegetation which are prominent land cover categories in the study area. Classification was performed using three different methods; Maximum likelihood (MLK), Random Forest (RF) and K-Nearest Neighbor (KNN) to derive LC map for 2014. r.learn.ml module which uses machine learning in GRASS GIS was used to execute three classification methods. It enables scikit-learn classification and regression models to be applied to GRASS GIS rasters. To evaluate the performance of each method, accuracy was assessed using Kappa statistics. With the assumption of similar performance, remaining two LC maps of 1997, 2005 were generated using the selected classification method. As major concern is expansion of urban lands, wetland/paddy, vegetation and other classes were combined as non-urban class in further analysis steps. Accordingly, final LC maps (Figure 2) which were generated to use in urban simulation step consist with three classes namely, Water, Non-urban and Urban. Criteria to extract Urban category is explained in the next section. Dynamics of urban class was analyzed during past two decades using statistical comparison and landscape matrices.

3.2 FUTURES model implementation

3.2.1 Data and model application: In order to simulate urban change, extracted built-up areas were further categorized into urban areas based on urbanness. For urban category, 1km^2 area was considered as a neighborhood and ratio of built up areas into total area was calculated as urbanness.

- **urban built-up area**: built-up pixels with urbanness values greater than 50%
- **suburban built-up area**: built-up pixels with urbanness values between 10-50%

Urban built-up and sub urban built-up categories together was taken into account as Urban category in in final LC map.

Futures model was then applied in two stages, first stage to validate the accuracy of the model Sri Lankan context comparing observed urban change in 2014 and predicted urban change in 2014. Second stage to simulate expected future urban change of Colombo in 2030.
In addition to LC maps, the calibration of FUTURES requires inputting other types of data which particularly consist of explanatory variables (road density, distance to roads, distance to waterbodies, distance to protected areas, slope). These factors were determined considering prominent factors that could influence the urban change of Colombo city. POTENTIAL sub-model determines the suitable locations for potential development using explanatory variables. DEMAND sub-model used population trend and calculates the per-capita land consumption at DSD level. Input files are population trend, population projection and development raster maps belong to each considered year to determine population trend. Based on data availability, DSD wise census population data (census years 1991,2001,2012) were used and population for analysis time periods (1997,2005,2014) were calculated based on population growth rate.
Final step is calibrating the model to predict new development as patches in each time step within the prediction time period. The calibration process is conducted to match observed urban growth patterns to those simulated by the model, including the sizes and shapes of new development.
Calibration requires the development binary raster in the beginning and end of the reference period to derive the patch sizes and compactness. Other than development binary raster, POTENTIAL and DEMAND output files are required as inputs in this step. Apart from business as usual scenario, different other scenarios such as infill versus sprawl can also be explored using FUTURES model.

3.2.2. Model validation: Extracted Urban category in 1997 and 2005 was used to simulate the urban change for 2014. Simulated urban change was compared with the observed urban areas in 2014. Result was evaluated using kappa statistics.

4. RESULT AND DISCUSSION

4.1 LULC Mapping LCC detection

The accuracy assessment resulted in an overall accuracy of 80.9%, 83.3%, and 84.5%, for 1997, 2005, and 2014 LULC maps. Considering final LC maps (Figure 2) the most significant changes in both periods (1997–2005 and 2005–2014) are the expansion of urban areas. Over 8 years urban, expansion is represented in Table 2.

Table 2: Urban area expansion

Year	Urban area (sqkm)	Area increase	% Increase
	120.62		
2005	257.72	137.10	53%
2014	342.99	85.27	25%

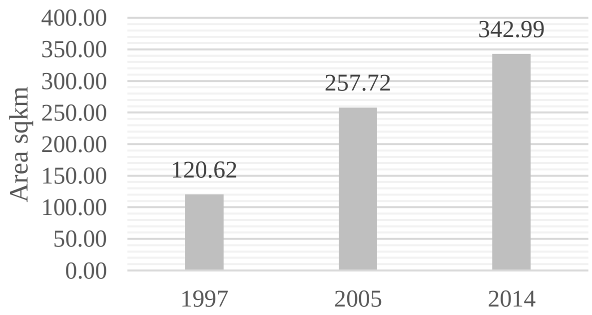

Figure 2: Urban area increase

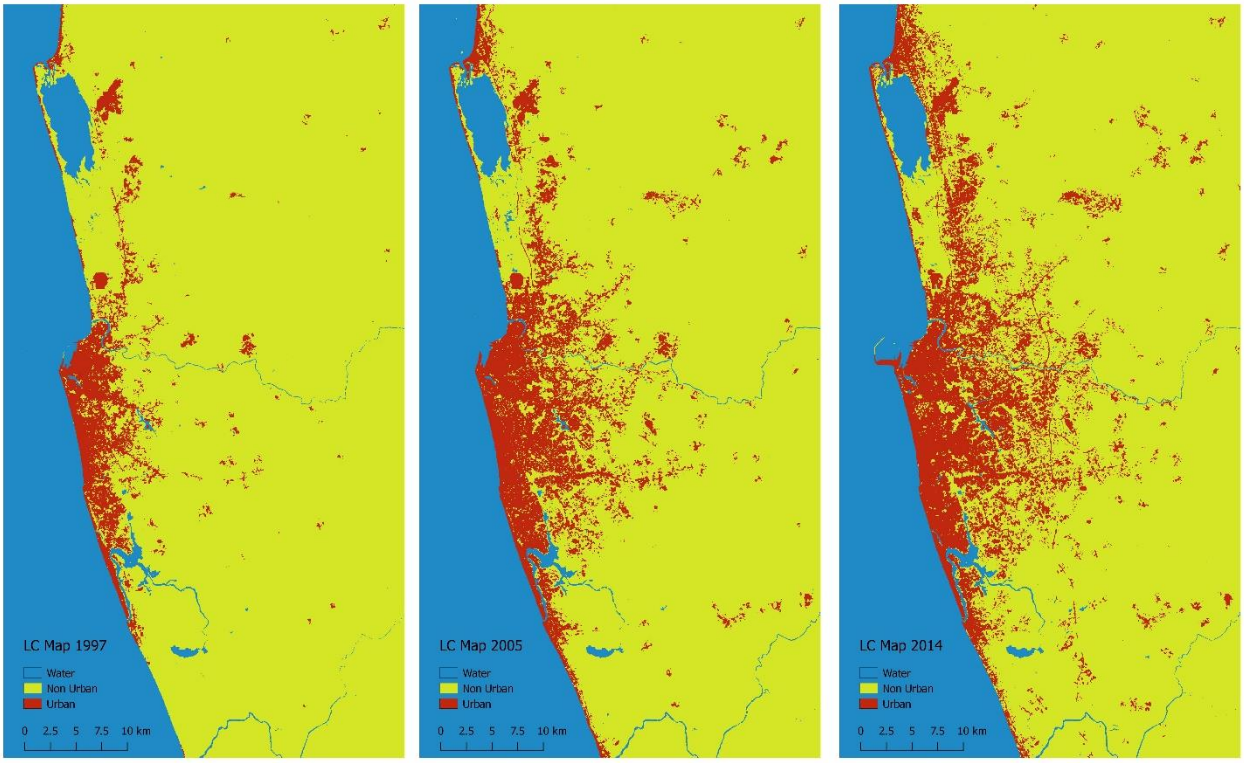

Figure 3: LC maps

During first 8 years urban areas in 1997 has almost doubled and from 2005 to 2014 the percentage of increase 25% representing 85.27sq km. Urbanized lands has increased by nearly three times during past 17 years which indicates a massive loss of vegetated and other lands for urbanization purposes due to massive development projects taken place in past two decades.

4.2 Urban Landscape Dynamics

During first 8 years urban areas in 1997 has almost doubled and from 2005 to 2014 the percentage of increase 25% representing 85.27sq km. Urbanized lands has increased by nearly three times during past 17 years which indicates a massive loss of vegetated and other lands for urbanization purposes due to massive development projects taken place in past two decades.

As a result of the continuous urban expansion over the study period, Number of Patches indicates a rapid increase between 1997 and 2005 and a dramatic increase in 2005 to 2014, representing a higher urbanization rate in first time span. Mean patch size clearly explicit the decrease in patch sizes which means although number of patches increases, the fragmentation of urban patches has taken place.

Patch density has a gradual increase which altogether three metrices indicating emergence of fragmented urban patches in an accelerated rate. Shape index is an indicator showing that the complexity and irregularity of the patches has increased over the time. Edge Density has also increased over the time, thus, indicating an increase in the total length of the edge of the urban patches due to land use fragmentation. Moreover, for the considered period, Shannon's Diversity Index also increased showing that the diversity of the patches have increased over the time.

The temporal urban growth signatures of the spatial metrics are illustrated in Figure 4.

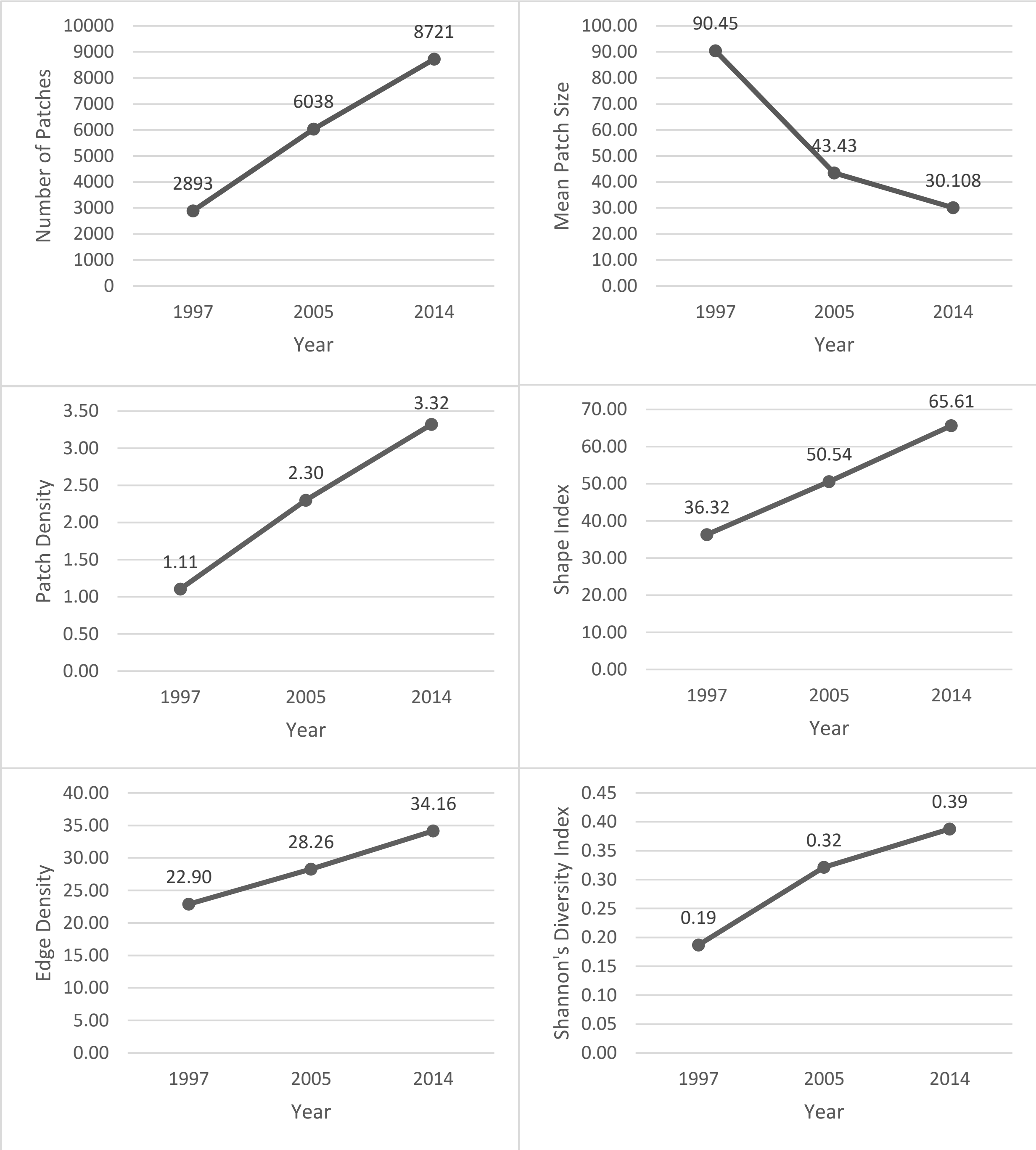

Figure 4: Spatial matrices to assess LC dynamics

4.3 Urban Simulation

Urban simulation using FUTURES model was first done for a known period to determine best model parameters suitable for Colombo and to validate the model. Prediction and observed urban area maps in 2014 are shown in Figure 5. Predicted urban areas shows a little more (predicted total urban = 470.86km^2, observed urban =342.99km^2) in contrast to observed/extracted built-up areas although distribution is different. According to previous studies used FUTURES model indicate that the model underestimated in urban contexts and overestimated in sub-urban and rural contexts which is identical with this particular application. Model was validated using 3 different methods. Overall Kappa value for observed and simulation maps is 0.629 which falls in the substantial agreement range according to kappa value interpretation.

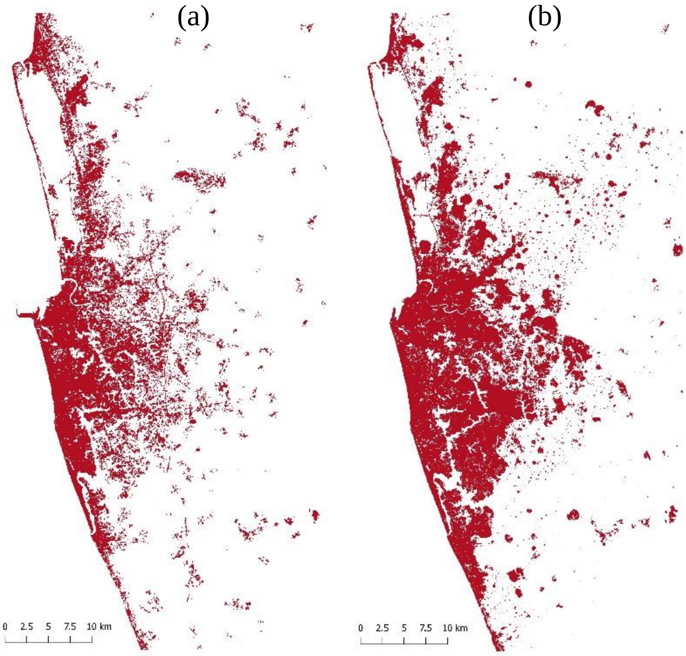

Figure 5: (a).Observed urban areas (b).Predicted urban areas

So, the model was selected to predict for 2030 development using identified parameters in model validation step carried out before for a known time period. In 2030 prediction, same values for each parameter were used and in the last step of patch calibration, the model resulted an extensive number of urban patches for the generated map of 2030 development. It emphasizes that if the current trend will continue, the expansion of built areas will adversely influence for haphazard development in the future.

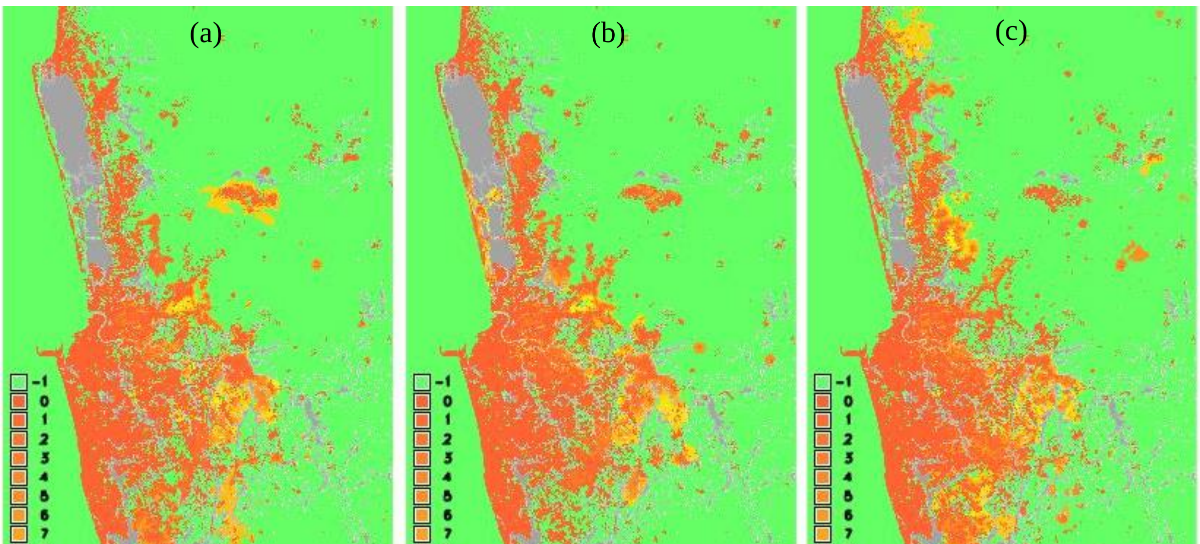

Figure 6: (a). Business as usual (b). Infill growth (c). Urban sprawl scenarios

The model allows to predict different scenarios such as infill and sprawl. So, for 2030 prediction, business as usual, infill and sprawl scenarios were tested. Figure 6 illustrates the different predicted scenarios for Colombo in 2030. It results the urban areas in each time step.

5. CONCLUSION REMARKS

Based on findings of the study, it is clear that Colombo is experiencing a rapid expansion of built-up areas within the time span considered. By analyzing the spatial pattern and quantifying the change of built-up areas demonstrated the spatial direction of the spread is happening from coastal areas towards inland in an accelerated rate.

As Colombo has a network of wetlands and paddy areas close proximity to the areas where urban development takes place, the influence on those sensitive areas should also need to be considered. According to the predictions in 2030, due to massive urban growth there will be a conversion of such lands into urban areas. Such thing need to be addressed by policy initiatives to prevent adverse environmental impacts due to urbanization.

Considering model performances, in validation step it resulted an over estimation. As a possible reason, percentage increase of urban areas during 1997 to 2005 (53%) is two times greater than it is during 2005 to 2014 (25%). Consequently, accuracy could be improved by considering one more time step in between. Urban areas used in this study was extracted using best possible freely available satellite data. So, a further study is expected to carryout to validate the FUTURES model application.

Although urbanization is a complex phenomenon that is difficult to predict precisely, understanding the natural pattern of urban growth/expansion will help to introduce practical urban development scenarios.

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