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Comparative Evaluation of Urban Growth Models

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１．Introduction

Models are useful tools for simplifying complex socioeconomic and biophysical forces that influence the rate and spatial pattern of landuse change and for anticipating future evolutions. The landuse change driven urban expansion is one of the most influential transformation that can affect the natural and social cohesion (Kantakumar *et al.*, 2020). This may be reasoning the use of urban growth models to predict urban expansion and its forms increasing gradually in the scientific literature. However, several open source urban growth models are available and comparative analysis of these models is still missing. The attempt of this study is to evaluate the outputs of three urban growth models namely, FUTURES (FUTure Urban-Regional Environment Simulation), MOLUSCE (Modules for Land Use Change Simulations) and SLEUTH to construct quantitative, spatially explicit urban simulation using Colombo as study area with identical inputs.

２．Data and Methodology

This study uses the urban area maps derived from 30m spatial resolution Landsat data as input for model calibration and validation. The data used along with the data sources are shown in Table 1. FUTURES and MOLUSCE models require a site suitability surface and an estimate of the quantity of future urban growth. SLEUTH model requires urban extents, roads and a user-defined exclusion layer that denotes the site suitability. FUTURES model uses past population trends and projected population to estimate per capita land demand when estimating the amount of future urban growth.

Table 1: Input data used in this study

Data	year	Data source
Landsat 5 TM	1997,2005,2008	USGS
Landsat 8 OLI	2019	USGS
Population	1991,2001,2012	Dept of Census and Statistics
Road network	2013	JICA
Water bodies	2013	JICA
DEM	2000	SRTM 30m
Social infrastructure (Hospitals, schools)	2004	Survey Dept
Growth centers	2010	Survey Dept
Administrative boundary	2010	Survey Dept

FUTURES model is a multilevel modelling framework consists of three sub models namely, POTENTIAL, DEMAND and PGA (Meentmayer *et al.*, 2013). POTENTIAL sub-model quantifies the site suitability based on hypothesized environmental, infrastructural, and socioeconomic factors. FUTURES model uses logistic regression to estimate transition potential. DEMAND sub-model quantifies per capita land demand. PGA is a stochastic patch-growing algorithm that determines the shape, size and distribution of urban patches.

SLEUTH is a cellular automata (CA) based urban growth model (Clarke *et al.*, 1997). The name of the model is an acronym of inputs used namely, Slope, Land use, Exclusion, Urban, Transport and Hillshade. SLEUTH uses four growth rules namely, spontaneous, new spreading center, edge and road-influenced growths. These four urban growth rules are performed sequentially in each growth cycle and are controlled by five-growth coefficients dispersion, breed, spread, road gravity, and slope resistance coefficients. These growth coefficients need to determine by using model calibration with historical urban growth. Brute force calibration method using Monte Carlo simulations with POP metric has been used to determine these five coefficients in this study.

MOLUSCE is a CA based model developed as a plugin for QGIS. MOLUSCE uses historical urban maps to calculate area of change as a first step. One method can be selected among four available methods; Artificial Neural Network (ANN), Weight of Evidence, Logistic Regression or Multi Criteria Evaluation to estimate the transition potential in second step. We have applied ANN for estimating the transition potential using distance to roads, growth centers, water bodies, schools, hospitals and slope as explanatory variable. CA use the area of change and transition potentials derived in first and second step to simulate the urban growth.

In order to facilitate a fair comparison of simulation capability of three models under study, the urban area maps of 1995, 2005, 2014 and 2019 were used for calibration/training. After calibration, we used 2008 urban area map to initiate the simulation to predict urban extent of 2019. The simulation maps of three models were validated by comparing it remote sensing derived urban area map of 2019 using a confusion matrix.

Table 2: Validation matrices for three models

Models	Producer Accuracy	User Accuracy	Overall Accuracy	Specificity	Matthews correlation coefficient (MCC)	Figure of Merit	Kappa
MOLUSCE	0.27	0.44	0.98	0.98	0.31	0.2	0.75
SLEUTH	0.61	0.31	0.93	0.93	0.39	0.26	0.66
FUTURES	0.36	0.31	0.96	0.96	0.29	0.2	0.69

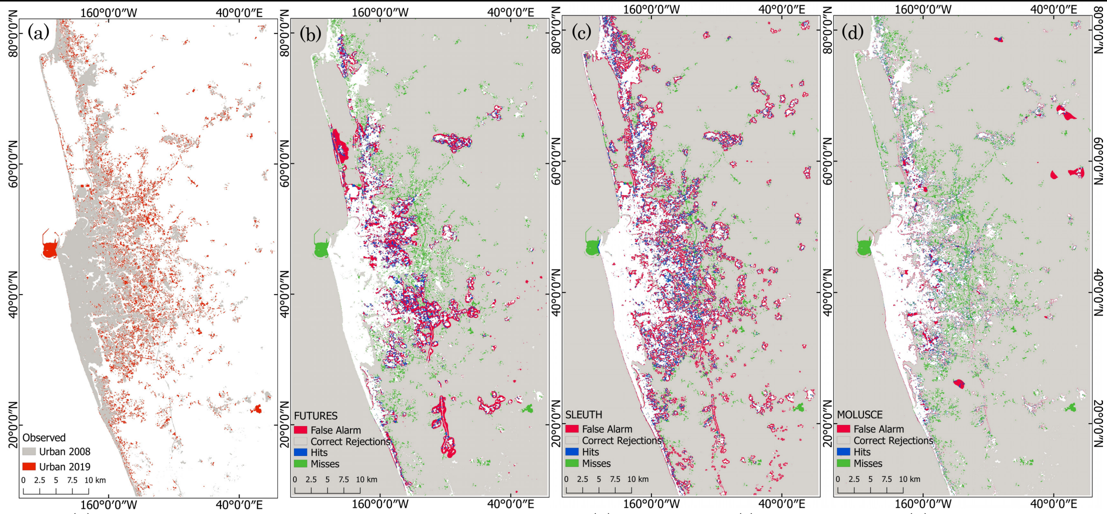

Figure 1: (a)Observed urban area map and validation maps of (b)FUTURES, (c) SLEUTH and (d) MOLUSCE models

3. Results and Discussion

The urban growth models are approximation of complex urban system. Thus, the validation of an urban growth model is essentials to determine whether the model is capable of representing city growth with sufficient accuracy (Kantakumar *et al.*, 2019). The results of validation are presented in form of hits, misses, false alarms and correct rejections are presented in Figure 1 and the validation metrics in Table 2.

The results show that the, overall accuracies of all three models are over 90% indicates the higher agreement of simulated pixels both urban and nonurban at correct locations. The overall accuracy of MOLUSCE model is the highest compared to SLEUTH and FUTURES. It is important to note, the use of overall accuracy cannot be interpreted as a direct method of model capability, due to persistence of non-urban area is higher in the study area in comparison to urbanized area (Kantakumar et al., 2019). Therefore, Matthews correlation coefficient (MCC) was used to avoid unbalanced effect of persistence and change. The MCC is higher for SLEUTH (0.26) compared to FUTURES and MOLUSCE. The Producers accuracy of SLEUTH model is comparatively higher than other models which explicit a higher capability of the model to simulate urban pixels at the correct locations. Compared to urban area growth 127.37sq.km during 2008-2019, FUTURES, SLEUTH and MOLUSCE models simulated 148.91, 250.55, 77.10sqkm respectively. Among simulated quantities, SLEUTH model showed over estimation and MOLUSCE model showed an under estimation while FUTURE model simulated closely correct quantity of urban growth. As FUTURES uses sub region wise urban change and population growth to determine per capita land demand which could be the reason for better estimation of urban growth. The over estimation of SLEUTH model simulations might be due to the reason of only excluding water bodies from the development and allowing unrestricted growth at all locations without considering site suitability. The underestimation of urban growth by MOLUSCE model might be the reason for higher accuracy in contrast with other two models.

4. Conclusion

Considering easy implementation with limited data requirement, MOLUSCE could be identified as a model with an acceptable accuracy. FUTURES is a robust, easily customizable model with flexibility in incorporation of complex policy scenarios. As SLEUTH model is extensively used for urban growth studies, continuous development of new extensions and usability has widely explored. The aim of the study was to use identical inputs to evaluate the performance of FUTURES, SLEUTH and MOLUSCE models in their simplest status. The present results reveals that keeping the variations of implementation techniques and procedures involved in these models, it is not fair to conclude which model is performed better than other based on the current stage of study. Thus, we are interested to carryout the study further by customizing the models by using the same method for estimating the transition potential modelling.

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