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Impact of rapid urban expansion on green space structure

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ABSTRACT

Rapid urban expansion has had a significant impact on green space structure. A wide variety of modelling approaches have been tested to simulate urban expansion; however, the effectiveness of simulations of the spatial structure of urban expansion remains unexplored. This study aims to model and predict urban expansion in three cities (Kuala Lumpur, Metro Manila and Jakarta), all experiencing rapid urban expansion, and to identify which are the main drivers, including spatial planning, in the resulting spatial patterns. Land Change Modeller (LCM)-Markov Chain models were used, parameterised on changes observed between 1988/1989 and 1999 and verified with the urban form observed for 2014. These models were then used to simulate urban expansion for the year 2030. The spatial structure of the simulated 2030 land use was then compared with the 2030 master plan for each city using spatial metrics. LCM-Markov Chain models proved to be a suitable method for simulating the development of future land use. There were also important differences in the projected spatial structure for 2030 when compared to the planned development in each city; substantive differences in the size, density, distance, shape and spatial pattern. Evidence suggests that these spatial patterns are influenced by the forms of rapid urban expansion experienced in these cities and respective master planning policies of the municipalities of the cities. The use of integrated simulation modelling and landscape ecology analytics supplies significant insights into the evolution of the spatial structure of urban expansion and identifies constraints and informs intervention for spatial planning and policies in cities.

1. Introduction

Globally, urban expansion has increased over recent decades (Cohen, 2006). This is expected to continue as urban areas are expected to absorb most of the global population growth in the upcoming decades (United Nations Department of Economic and Social Affairs UNDESA, 2012). Cities have grown rapidly in size and density (Turrini and Knop, 2015) and in some developing countries, cities have tripled in size (Seto et al., 2012), often denominated rapid urban expansion. In Southeast Asia, the urban expansion rate is 2.8% higher when compared to many urbanised regions of the world (Cohen, 2006; United Nations Department of Economic and Social Affairs UNDESA, 2012). As a consequence, urban green space has come under increasing pressure during the urbanization process and this negatively affects ecosystem services, cultural associations, psychological well-being and the health of urban dwellers (Tian et al., 2011). The conversion of green spaces into the built-up areas has become one of the major reasons for habitat destruction worldwide (Turrini and Knop, 2015) and therefore, if some of this green space can be retained, protected or reclaimed, then it becomes important to monitor and understand the changes in spatial complexity of an urban ecosystem as rapid urban expansion occurs.

Urban dynamics, planned or unplanned, can cause changes to the structure, shape and functions of built and non-built areas (Madureira et al., 2011). In Southeast Asia, the relatively weak structure of urban policy poses challenges for the adoption of appropriate urban management strategies. Uncoordinated master planning strategies often lack information on the past, present and future changes to the urban and green space structure. In this study, we define the master plan as a land use map that determines future urban growth. However, master plans prepared to guide urban development have rarely been successful (Sharifi et al., 2014; Todes, 2012). This is because these plans are often created by international planning consultants who are not aware of the local conditions (Seto et al., 2012; Sharifi et al., 2014). Subsequently, the present understanding of the spatial effects of urban planning arising from rapid urban expansion remains unclear and poorly understood.

The planners often employ simulation modelling to forecast future urban expansion with a view to improve land management policies and

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practices (Bhatti et al., 2015). The integration of remote sensing, geographic information systems (GIS) and urban simulation modelling has been successfully applied to create better understanding of urban development dynamics and to anticipate urban planning activities (Zhang et al., 2011). Numerous simulation modelling techniques have been developed to simulate urban changes, for example; Artificial Neural Networks (ANN), Markov Chain models, Land Change Models (LCM) and cellular automata models (Losiri et al., 2016; Roy, 2016; Triantakonstantis et al., 2015). While these models have potential to inform urban planning, this is difficult to reach in practice as there is a lack of empirical evidence on the relative effectiveness of urban planning in cities under rapid urban expansion (Zhou and Wang, 2011).

Here we seek to understand the effectiveness of these spatial models to identify the effects of master planning strategies in cities experiencing rapid urban expansion. We use a combination of Land Change Modeller (LCM) and Markov Chain modelling, incorporating GIS data and remote sensing satellite imagery. The LCM is less complex, faster and a more understandable process when compared to most modelling techniques (Eastman, 2006; Triantakonstantis et al., 2015). The quantity of change is modelled through a Markov Chain temporal analysis for the LULC types, and the process relies on the historical transitions and past changes (Sinha and Kumar, 2013), as there is evidence that urban land use depends on the historical development process of each city (Niemelä, 2014).

We then combine this with spatial metrics (indicators) associated to the shape, form and spatial distribution of the urban green space. As the landscape becomes urbanised, the resulting fragmentation affects landscape structure and decreases the landscape connectivity (Vergnes et al., 2012). Consequently, green spaces become isolated by a matrix composed of buildings and streets, limiting the distribution and the connectivity of green space patches. Spatial metrics quantify and interpret the changing spatial urban characteristics and patterns based on the characterisation of spatial pattern (size, density, shape, distance of patches) due to the fragmentation of the green space. They are effectively indicators (Uuemaa et al., 2013), describing the changes in shape complexity and variety due processes of urban compaction, aggregation, dispersion and isolation (Aguilera et al., 2011). The quantification of landscape structures using spatial metrics in a simulated model (Kong et al., 2012) is important in assessing and monitoring the effectiveness of master planning when rapid urban expansion occurs.

This paper aims to: (1) test the applicability of integrated LCM-Markov Chain models for three cities undergoing rapid expansion (Kuala Lumpur, Malaysia; Jakarta, Indonesia and Metro Manila, Philippines) to model and simulate the observed spatial patterns of urban expansion and changes to green space structure and (2) use the developed LCM-Markov Chain model to describe, using spatial metrics, the simulated rapid urban expansion potential with proposed master plan 2030. We also identify which are the main drivers, including spatial planning, in the resulting spatial patterns. We hypothesised that the spatial effect of rapid urban expansion and green space are influenced by the historical spatial changes, implementation of the previous master planning efforts and uncontrolled urban expansion.

2. Methods

2.1. Study area

The study focusses on three cities in Southeast Asia: Kuala Lumpur, Malaysia; Jakarta, Indonesia and Metro Manila, Philippines (Fig. 1). Kuala Lumpur, the capital of Malaysia, is located at the confluence of the Klang and Gombak rivers and its total area is approximately 23 934 ha (239 km^2). Jakarta, the capital city of Indonesia, consists of five municipalities within a lowland context on the North Coast of Java Island. The city occupies an area of 64 000 ha (640 km^2). Jakarta has a flat terrain, and the land gradually rises across the city from 5 to 50 m above mean sea level (Murakami et al., 2005). Metro Manila, the capital of the Philippines consists of eight contiguous cities, including Manila, and nine other municipalities, covering an area of approximately 63 800 ha (638 km^2). The capital is located in the lowlands of south-western Luzon Island and is situated on the eastern coast of Manila Bay at the mouth of the Pasig River (Murakami et al., 2005).

2.2. Data acquisition

Landsat satellite imagery was used to obtain LULC (land use land cover) information for each study area. 1988 and 1999 Landsat-5 Thematic Mapper 30 m resolution imagery for Kuala Lumpur was obtained from the Malaysian Remote Sensing Agency (MRSA). The same type of imagery for the years 1989 and 1999 were downloaded from the Global Land Cover Facility (http://glcf.umd.edu/) for Jakarta and Metro Manila. Landsat-8 Enhanced Thematic Mapper 30 m resolution images for 2014 covering the three cities were downloaded from the U.S. Geological Survey (http://www.usgs.gov/). The images were projected to the appropriate Universal Transverse Mercator UTM Zone for each city on the WGS84 datum. The availability of satellite remote sensing data has increased significantly in the last two decades, and it constitutes a useful data source for mapping the composition of urban settings and analysing changes over time (Patino and Duque, 2013). The master plan maps for each city were obtained from the each city authority (Kuala Lumpur City Hall, 2005; Government of Jakarta Special Capital Region, 2011; Metropolitan Manila Development Authority (MMDA, 2012).

2.3. Methodological framework

In this study, LULC categories were modelled using the Land Change Modeller (LCM) software package (Eastman, 2006; available as ArcGIS 10.2 extension, http://www. clarklabs.org) to derive the predicted future LULC maps (Eastman et al., 2005 Pérez-Vega et al., 2012; Shooshtari and Gholamalifard, 2015). The LULC modelling procedures consisted of two stages (Fig. 2). The first stage involved the modelling of potential change using LULC maps of 1988/1989 and 1999 to simulate the year 2014 (15 years interval). The model enabled the comparison of the actual map for 2014 with the results from the simulated model to verify the ability of the model to simulate urban development. We assess the evidence of spatial effects of the urban master plan on the urban expansion pattern by examining the differences between the predicted spatial patterns of urban expansion and the actual expansion observed for 2014. The second stage involved modelling the potential change using actual LULC maps of 1999 and 2014 to generate simulations of the LULC in the year 2030 (15 years interval) and then comparing this with the 2030 master plan map using landscape metrics to detect differences in spatial structure.

2.4. Image processing

Nine satellite images were processed using ERDAS Imagine 2014 (Intergraph Corporation, Madison, AL) and ArcGIS 10.2 (ESRI, Redlands, CA) to produce LULC maps for each city. The geocoded satellite images were subsetted using the boundary of the cities obtained from the Global Administrative Areas database (http://www.gadm.org/) to extract the area of interest from the images. LULC types were classified into three types: built-up area, green space and waterbody, to match the LULC types used on the digitized master plan maps for 2030. The LULC types were classified using maximum likelihood supervised classification (ERDAS Imagine, Hexagon Inc., Jensen, 1996; Fonji and Taff, 2014; Zhou and Wang, 2011) (Table 1). In the classification process, the existing land use maps, topographic maps and visual interpretation of Google Earth imagery were used to provide the training data for the classifier and a separate validation dataset. The accuracy assessment was based on an error matrix that compared the classification results with the validation dataset, expressed as the overall

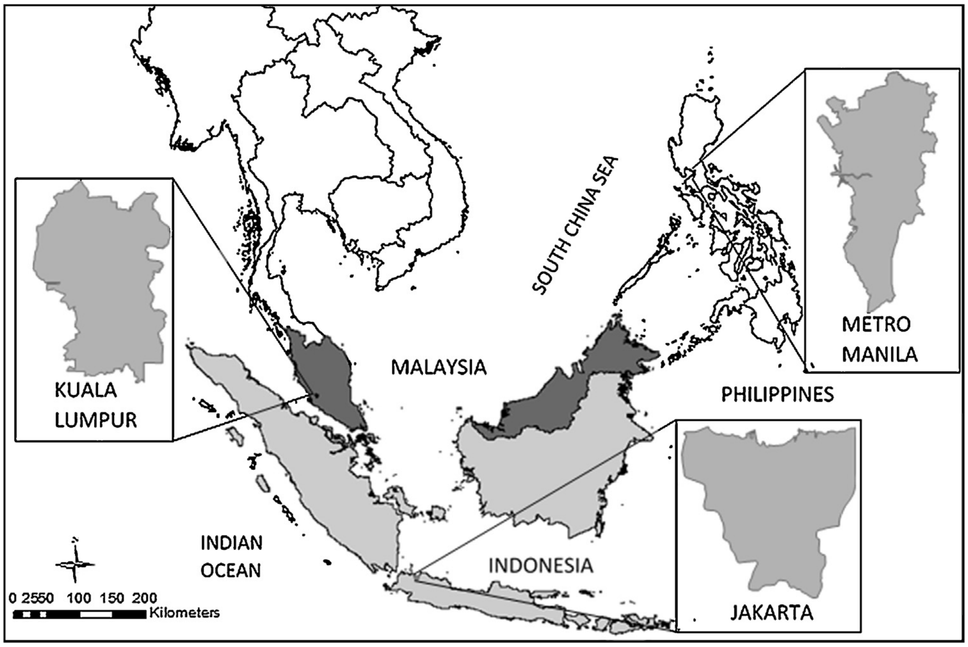

Fig. 1. Location of the three case study cities in Southeast Asia.

accuracy and kappa statistic (Rozenstein and Karnieli, 2011). The validation samples for each class were identified using a stratified random sampling approach (Yang et al., 2014) with 100 points assigned to each LULC. The overall accuracy of the Kuala Lumpur was 88% for all image dates. In Jakarta, the overall accuracies of the images were 87%, 88% and 85%, respectively. In Metro Manila, the image classification accuracies were 88%, 87% and 88%, respectively. The 12–15% inaccuracy was due to misclassified mixed pixels in the waterbodies, for example, pond areas which were spectrally confused with green space because these areas are surrounded by gardens. The spectral confusion occurs when several LULC types share a similar spectral response and this is inherent in medium-spatial resolution images (Estoque and Murayama, 2013; Hansen and Loveland, 2012). However, the levels of accuracy were within the standard range and at an acceptable level, i.e., 85–90%. These datasets were converted to vector and raster grid file formats for simulation and spatial structure analysis.

2.5. Land change modelling

In stage 1, a transition map was generated for all LULC classes to produce the empirical likelihood of change statistic (Eastman, 2009; Shooshtari and Gholamalifard, 2015). The variables used to derive this included: (1) distance from green space edge, (2) distance from roads, (3) slope, (4) terrain height and (5) distance from waterbodies (Figs. A.1–A.3 in supplementary materials). These natural and physical factors in urban systems are used to determine the spatial distribution of potential urban land growth and green space (Mitsova et al., 2011).

All input datasets were prepared at a 30 m spatial resolution so that they were consistent with that of the LULC maps. Layers of roads were downloaded from DIVA-GIS (http://www.diva-gis.org/gdata) and were calculated as the distance from the main road to the centre of developed area to produce the road network buffer (Park et al., 2011). Main roads were considered to be those linking major districts, including all national and local roads of autonomous entities in city areas (Bhatti et al., 2015). The change of non-urban to urban land is strongly and negatively related with the distance to roads. Road network development is considered the most important spatial factor affecting urban land expansion (Gao and Li, 2011). Green spaces also become more fragmented where built-up areas are in close proximity to roads. Urban expansion also tends to occur at the edge of green space. Physical characteristics such as slope were also considered as drivers of green space loss in the change analysis. Slopes can affect LULC changes, as green spaces in flatter and more fertile areas are more likely to be cleared for development (Batisani and Yarnal, 2009), as well as the infrastructure development which is related to urban expansion. The pattern of landscape fragmentation is also influenced by the pattern of slope as there tends to be an increase in human activities on the lower slope angles (Gao and Li, 2011). Terrain height (Thapa and Murayama, 2011) and distance from water bodies (Yin et al., 2011) are also considered important factors as urban development tends to occur in areas of relatively higher elevation to avoid the risk of flooding (Perotto-Baldivieso et al., 2011).

Based on these factors, maps of the variables were produced using the 'Euclidean Distance' tool in ArcGIS 10.2. These maps were then imported to raster format and incorporated in the LCM as explanatory driver variables of change for a particular transition. Cramer's V analysis was used to quantify the association between LULC and the previously described drivers of change in a particular land transition (Bhatti et al., 2015; Eastman, 2012; Friehat et al., 2015). Here, the majority of variables had an acceptable associations (Cramer's V value > 0.15) with a particular LULC; for example, the Cramer's V value for distance to roads in Kuala Lumpur was 0.27, 0.18 in Jakarta and 0.15 in Metro Manila.

The probability of LULC change for the period 1988/1989 to 1999 was modelled using an artificial neural network (ANN) approach based on a Multi-Layer Perceptron (MLP). The advantages of using a MLP is that it is a system capable of modelling complex nonlinear relationships between variables (Joshi et al., 2011) and it is a robust method for modelling the potential transitions (Eastman, 2009). Potential transition maps were generated for each LULC (see Supplementary material, Fig. A.4). The probability values vary in the range between 0 to 1, where there was less potential for transition if the value was nearer to 0 and higher if it is nearer to 1 (0: non-incidence and 1: incidence) (Fig. A.4). The root-mean-square-error (RMSE) and the overall accuracy rates of the MLP were used to evaluate the accuracy of the models of potential transition g. In this study, most of the RMSE values were below 0.4 and the overall accuracy rates were more than 80% (see Supplementary Material in Table A.1).

2.6. Model verification

Before the simulation of the future scenarios, it was necessary to

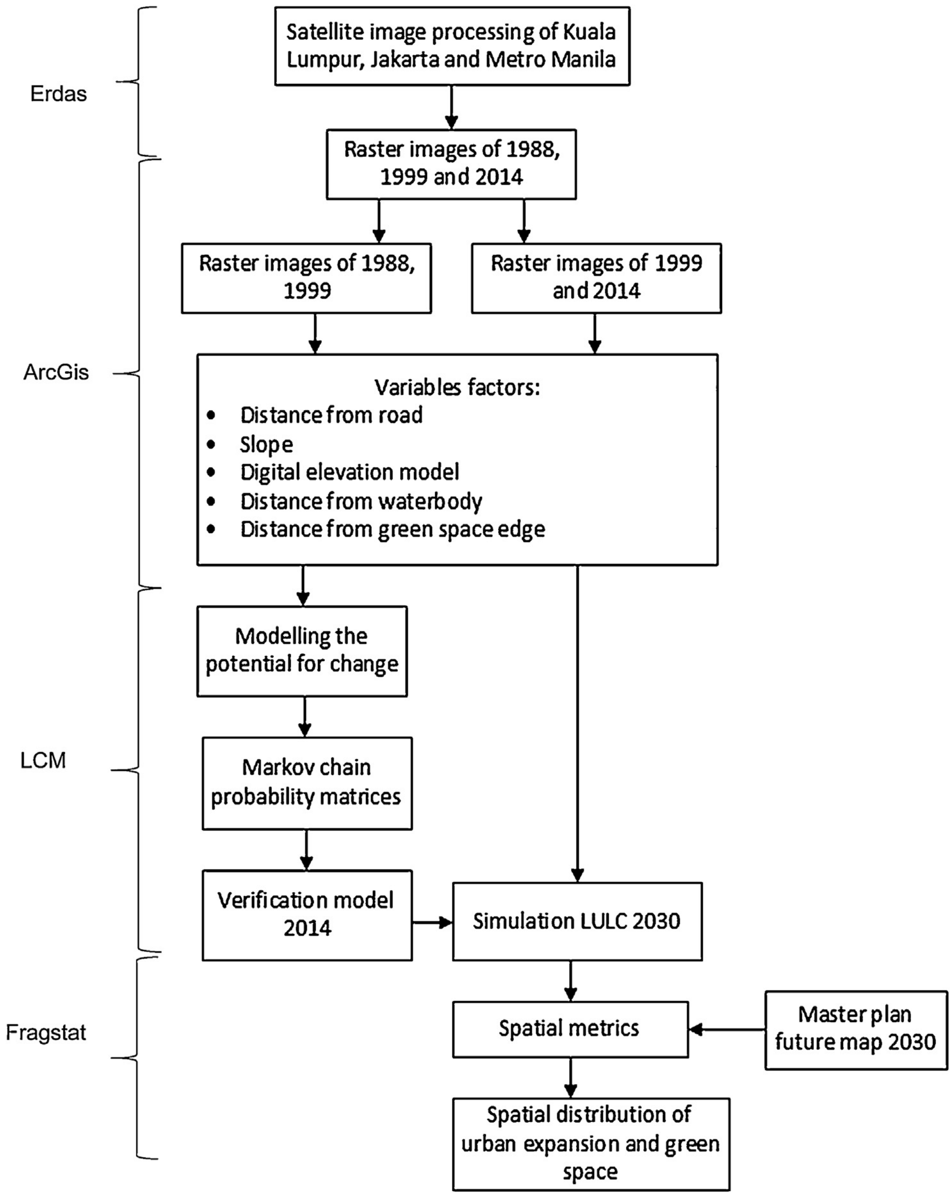

Fig. 2. Methodological framework.

Table 1
LULC classification scheme.

Code	LULC categories	Description
1	Built-up area	The built-up area includes areas with all types of artificial, impervious surfaces and cleared land including residential, commercial and industrial areas as well as transportation infrastructures
2	Green space	All green areas covered with green space, trees, shrubs and grassland
3	Waterbody	River, drain, lakes and pond

Table 2
Interpretation of agreement and disagreement in the validation map.

LCM validation terminology	Revised terminology	Interpretation
Hits	Agreement	Model simulated change and LULC changed
False alarm	False negative	Model simulated persistence and LULC changed
Misses	False positive	Model simulated change and LULC persisted
None	Persistence	Model simulated persistence and LULC persisted

evaluate the reliability of the LCM-Markov Chain models and the relevant variable settings (Pérez-Vega et al., 2012; Pontius et al., 2011; Pontius and Petrova, 2010). The aim of the verification model was to test "how well do a pair of maps agree regarding the transition in each category?" (Zhang et al., 2011). Based on Pontius and Millones (2008), a comparison of the agreement and disagreement between maps was adopted by using the validation module in LCM comparing the 2014 simulated result to the observed LULC. In this study, we revised the terminology used to describe the outputs from the analysis to aid the interpretation of the results (Table 2). The relatively high levels of agreement achieved allowed the simulation of future scenarios to be carried out with confidence to their reliability (Zhang et al., 2011).

2.7. Comparison of simulated urban expansion 2030 and urban master plans using spatial metrics

After the LCM model was verified, a similar process was conducted for the stage 2 so to generate simulated LULC in 2030 based on the LULC maps in the period from 1999 and 2014 using the probability Markov Chain modelling. The procedure determines how much land of each LULC types would be expected to transition in the period from 2014 to the simulated date, based on a projection of the potential future transition and the probability of change through the creation of transition probability file. This is a matrix that records the probability of each LULC category changing into every other category (Araya and Cabral, 2010). One of the advantages of Markov Chain modelling is the efficiency of using multiple LULC types within the iteration of a cell with the outcome of the prediction dependent upon the LULC types of neighbouring cells (Vaz et al., 2012).

The simulated LULC maps were compared with digitised master plans using landscape metrics to identify the impact of urban expansion on green space structure and pattern. Landscape structure was analysed in the FRAGSTATS software (McGarigal et al., 2002), at the class level for simulated and master plan maps using six landscape metrics: percentage area (PAREA; %), patch density (PD; patches/100 ha), mean patch area (MPA; ha), largest patch index (LPI; %), landscape shape index (LSI; m/ha) and Euclidean nearest neighbour (MNN; m). We use class level metrics to provide more specific information about the spatial patterns on built-up areas and green spaces. Green space fragmentation in response to urban expansion was quantified using PAREA, PD and MPA; high values of PD and low values of MPA indicate a fragmented landscape composed of many small patches (Perotto-Baldivieso et al., 2009). While the low values of PD and high values of MPA indicate the aggregation of patches. Three metrics (LPI, LSI and MNN) were calculated to represent patch structural relationships owing to size, shape and patch distance. The LPI metric provides an indication of dominance for the different LULC classes. The LSI is a standardized descriptor of patch compactness that adjusts for the size of the landscape (Plexida et al., 2014). The MNN metric was selected to quantify the distance between patches and define the connectivity, isolation and dispersion between the patches (Aguilera et al., 2011; Paudel and Yuan, 2012).

3. Results

3.1. Model verification

In the model verification process the actual LULC map for 2014 was compared with the results from the simulated model. In Jakarta, the percentage of combined agreement and persistence was 86%, 4% false negative and 10% false positive (Table 3; Fig. 3). In Metro Manila, the combined agreement and persistence was 87%, and the false negative and false positives were 4% and 9%, respectively. In Kuala Lumpur, the combined agreement and persistence was lower compared to Jakarta and Metro Manila at 70% and the false negative and false positive values were 12% and 18%, respectively (Table 3; Fig. 3). The reason why the Kuala Lumpur results showed less agreement may be due to the earlier initiation of the Kuala Lumpur Structural Plan 1984 when compared to the other two cities. It is an integrated plan formulating general policies related to landscape, townscape and conservation with the implementation of a green planting programme along road in the year 2000 and highway infrastructure (Kuala Lumpur City Hall, 2005). Many of the false negative results in Fig. 3a can be seen following linear features. Across the three cities, the low level of disagreement (false negative and false positive) would indicate that the model and the relevant variable settings are appropriate. Given the observed level of accuracy of the simulated LULC results given the observed changes, there was sufficient confidence in the model for it to be used to simulate LULC in the future urban expansion.

3.2. Comparison of simulated urban expansion 2030 and urban master plans using spatial metrics

In 1989, the highest percentages of built-up areas were in Metro Manila (63%) followed by Kuala Lumpur (50%) and Jakarta (42%) (Figs. 4 and 5). Conversely, Metro Manila had the smallest area of green space (31%). The percentages of green space were similar for Jakarta (46%) and Kuala Lumpur (45%). By 2014, Jakarta and Metro Manila had substantial built-up areas of 90% and 89% respectively, compared to Kuala Lumpur with 78%. By 2014, the urbanised areas were almost doubled in Kuala Lumpur and Metro Manila, while the green areas in Jakarta had more than doubled compared to the extent in 1989 (Figs. 4 and 5).

The built-up areas were also the dominant LULC in the 2030 simulated model: 96% in Jakarta, Metro Manila (91%) and Kuala Lumpur (81%) (Fig. 4). In contrast, the city with the smallest area of green space was in Jakarta (3%), followed by Metro Manila (8%) and Kuala Lumpur (17%) (Fig. 4). However, compared to the master plan, urban expansion was predicted to be highest in Kuala Lumpur (86%), followed by Metro Manila (81%) and Jakarta (74%) (Figs. 4 and 6). The area of green spaces was predicted to double in Jakarta (24%) and Metro Manila (16%), compared to a decline in Kuala Lumpur (12%) (Figs. 4 and 6).

In the 2014 to 2030 time period, a major change is predicted from green space to built-up areas in Jakarta, Metro Manila and Kuala Lumpur with the Markov Chain values of 0.79 (4115 ha), 0.76 (3898 ha) and 0.47 (2617 ha), respectively (Tables 4 and 5). The Markov Chain value for the transition from built-up areas to green space was the highest in Kuala Lumpur (0.09) compared with Jakarta and Metro Manila (0.01) (Tables 4 and 5).

However, the distribution of urban expansion and green space structure in the simulated 2030 data showed a different spatial pattern compared to the master plan in all three cities (Fig. 7). In Kuala Lumpur, the landscape metric values of the built-up areas showed that the largest patch index (LPI) and Euclidean nearest neighbour (MNN) were higher in the master plan compared with the simulated 2030 data. Meanwhile, the landscape shape index (LSI) and the mean patch area (MPA) were lower in the master plan compared with the simulated 2030 data (Fig. 7). This indicates that the patch size and distance between patches of the built-up area is greater and there is less variety of shape in the master plan compared with the simulated 2030 data. Jakarta and Metro Manila indicate a different spatial pattern with compacted and dispersed built-up areas exhibiting a variety of shapes but with decreased size and distance between patches in the master plan compared with the simulated 2030 data as indicated by the higher patch density (PD) and landscape shape index (LSI) while there are lower mean patch area (MPA), largest patch index (LPI) and Euclidean nearest neighbour (MNN) values.

Table 3
Percentage and area (ha) of agreement.

Study area	Agreement		Persistence		False negative		False positive	
	Area ha	%	ha	%	ha	%	ha	%
Kuala Lumpur	3977	16	12925	54	3235	12	4515	18
Jakarta	8038	12	48 249	74	2350	4	6495	10
Metro Manila	6012	10	43383	77	2133	4	4977	9

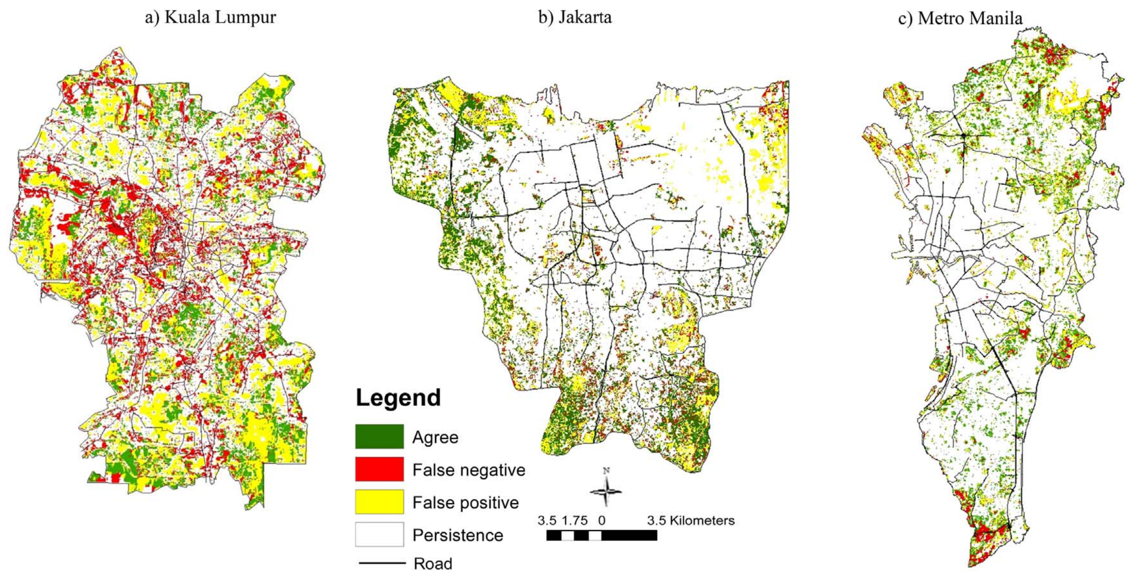

Fig. 3. Verification of LCM-Markov Chain potential change of 2014 in (a) Kuala Lumpur, (b) Jakarta, (c) Metro Manila.

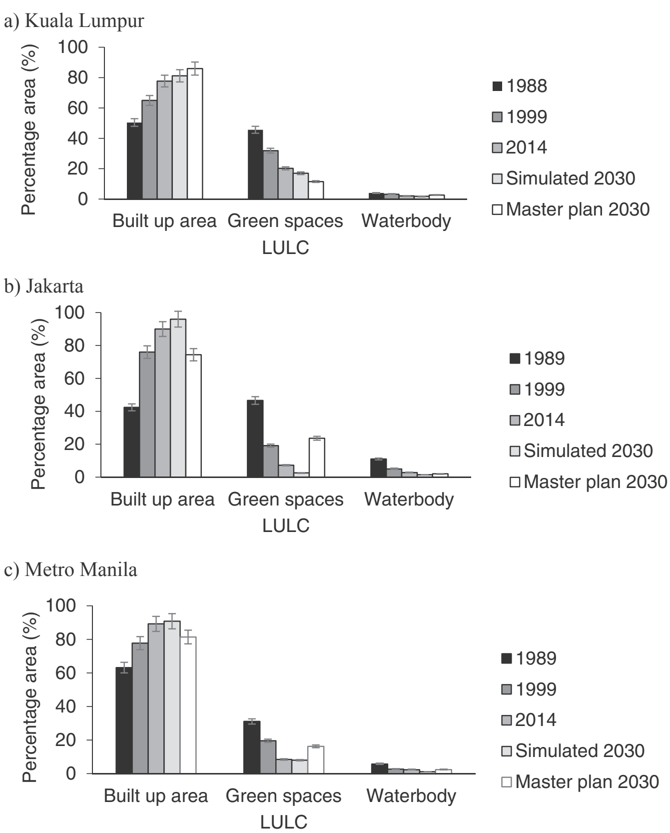

Fig. 4. The percentage area of LULC in 1988/1989, 1999, 2014, simulated 2030 and master plan 2030 for (a) Kuala Lumpur, (b) Jakarta and (c) Metro Manila.

In contrast, the green space in Kuala Lumpur exhibits higher landscape shape index (LSI) and Euclidean nearest neighbour (MNN) values in the master plan, compared to the simulated 2030 data. This indicates that the variety of the shape and the distance between patches had increased. In Jakarta, the fragmentation metrics (PD, MPA, LPI) and landscape shape index (LSI) are higher but Euclidean nearest neighbour (MNN) is lower in the master plan, compared to the simulated 2030 data (Fig. 7). This indicates that green space is fragmented with larger mean patch areas, exhibiting a greater variety of shapes and with shorter distances between patches. However, green space in the Metro Manila's master plan is aggregated, larger in size, with greater variety of shape and smaller distances between patches in the master plan compared with simulated 2030 data (Fig. 7), as illustrated by lower patch density (PD) and Euclidean nearest neighbour (MNN) values; while the mean patch area (MPA), largest patch index (LPI) and landscape shape index (LSI) values were higher.

4. Discussion

For these cities, the training of the LCM model on 1988/1989 to 1999 interval was generally satisfactory and therefore there is some confidence in using these models for proposing future transitions (Fig. 3). Previous research shows that the data generated using LCM is more accurate when the per transition susceptibilities are combined to compose an overall potential change map (Pérez-Vega et al., 2012). It is because the neural network outputs can express the simultaneous potential change for various LULC types more adequately, than the individual probabilities obtained (Mas and Flores, 2008). These predictive capacities allow models to be useful tools for impact assessment of urban change in the landscape. The overall verification results showed that the proportion of agreement and persistence in three cities is more than 70%, however, it should be noted that Kuala Lumpur showed highest level of disagreement (30%) compared to the other two cities. Many of the false negative results in Fig. 3a can be seen following linear features describing the transition of built-up areas into green space. This may be due to a green planting programme along roads and highway infrastructure in 2000 (Kuala Lumpur City Hall, 2005). The probability transition from built-up areas to green space were significantly improved in Kuala Lumpur compared with Jakarta and Metro Manila (Tables 4 and 5) when interventions that supported green space conservation in Kuala Lumpur were included in the model.

Over the 25 year period, each of the three cities would experience a decrease in green space and an increase in built-up area (Fig. 4). In all three cities, the predictions indicate a further increase in built-up area and a decrease in green space by 2030 (Fig. 4). The results further suggest that built-up area expansion and the location of the variables affecting the model outputs are the major drivers of green space change and fragmentation. The projected Markov Chain conditional probability matrices for 2030 revealed that the growth of built-up areas in all three cities showed a multidirectional urban expansion growth pattern which tend to occur in areas of better road accessibility, near the green space edge, on higher elevations and steep slopes where there is a low risk of flooding (Figs. A.1–A.3 and A.5). These results agree with the findings

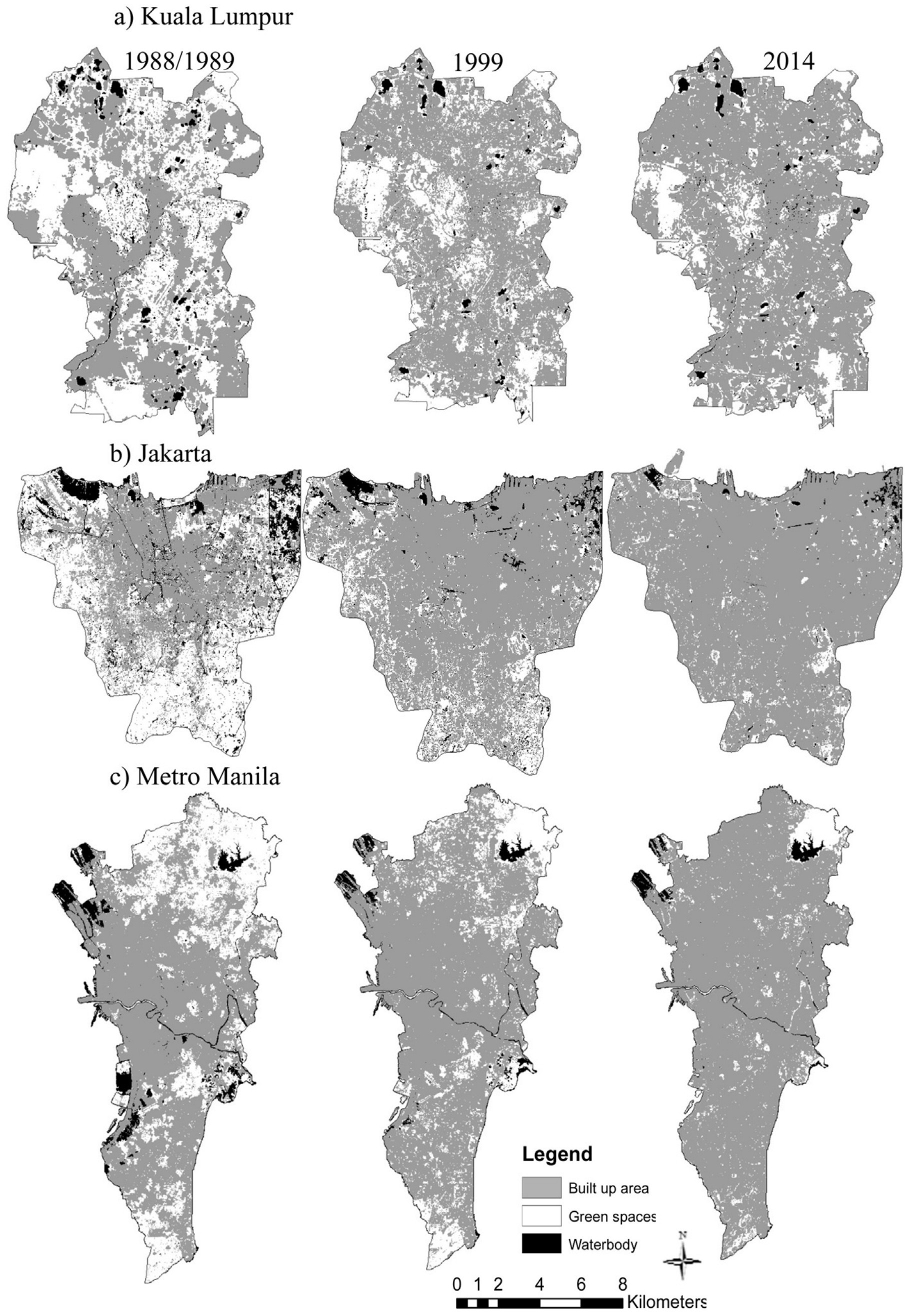

Fig. 5. Land use maps of 1988/1989, 1999 and 2014 for (a) Kuala Lumpur, (b) Jakarta and (c) Metro Manila.

of other studies, where the distance from main roads is linked to the degree of landscape fragmentation (Gao and Li, 2011; Wu et al., 2014). The combined fragmentation and barrier effects of road networks considerably degrade landscape connectivity and ecological processes in the landscape (Fu et al., 2010). Inherently, green space edge has a high probability of being fragmented and the results from Kuala Lumpur show that development changes tend to start from the edge of existing green space (Fig. A.1a).

The land change model described the influence of the spatial transformation of urban expansion on green space structure. For instance, for the period 2014 to 2030, the model predicts that there will be a major change that will alter the green spaces to built-up areas in all the three cities (Tables 4 and 5). The increase of the proportion of built-up areas over the past period (Figs. 4 and 5) leads to a projected decrease in green spaces in 2030. This is comparable to other observational studies, such as the studies conducted in Bangladesh (Roy, 2016), Vijayawada City India (Kumar et al., 2015); Pearl River Delta, China (Feng et al., 2012) and Nepal (Uddin et al., 2015), which predicted an increase of urban expansion ranging from 30% to 50% in the next 20 years and causing decline of green space ranging from 10% to 30%. The built-up patches become bigger, their forms more compact and contiguous. The green space patches decrease in size and become more heterogeneous (Li et al., 2012).

The observed effects of an increase in the proportion of built-up area in this study can therefore be explained by the historical change trajectories and through intensification of human activities (Peres et al., 2010). The results from the various studies (Feng et al., 2012; Kumar et al., 2015; Roy et al., 2016; Uddin et al., 2015) suggest that urban expansion and a weakness in planning, controlling and managing urban development are key factors in green space loss (Byomkesh et al., 2012). In this study, the built-up areas were the dominant LULC in the 2030 simulated model resulting in the smallest area of green space in Jakarta compared with Metro Manila and Kuala Lumpur (Fig. 4). However, compared to the master plan, the area of green spaces was

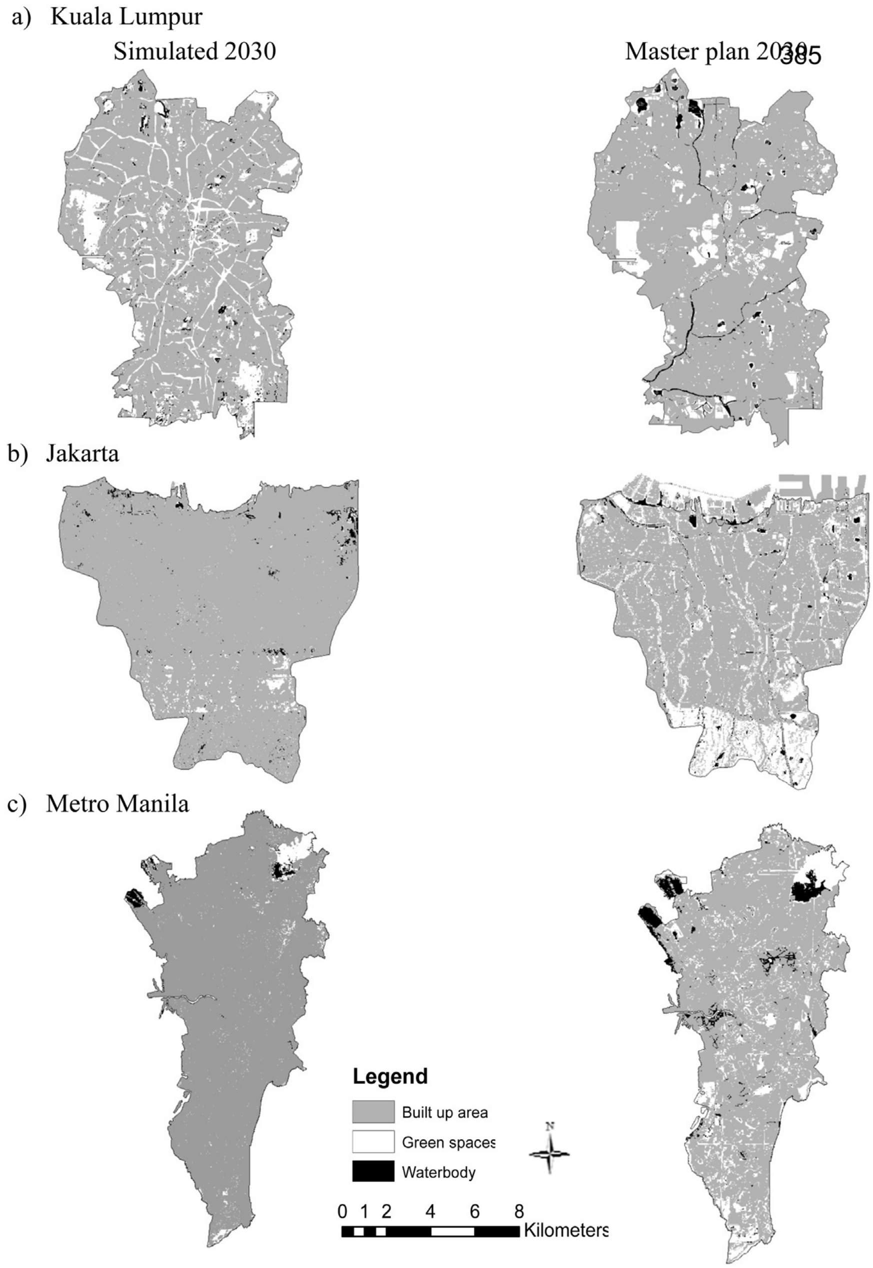

Fig. 6. Simulated and master plan 2030 LULC for (a) Kuala Lumpur, (b) Jakarta and (c) Metro Manila.

Table 4
Markov Chain modelling values for 2030 based on the LULC maps of 1999 and 2014 (low: 0 – high: 1) (bold figures indicate no change).

LULC	Built-up area	Waterbody	Green space
Kuala Lumpur			
Built-up area	**0.89**	0.01	0.09
Waterbody	0.28	**0.40**	0.31
Green space	0.47	0.01	**0.51**
Jakarta			
Built-up area	**0.97**	0.006	0.01
Waterbody	0.55	**0.31**	0.12
Green space	0.79	0.02	**0.18**
Metro Manila			
Built-up area	**0.97**	0.006	0.01
Waterbody	0.17	**0.61**	0.2
Green space	0.76	0.006	**0.22**

Table 5
Area (ha) of expected transition of LULC to other LULC for 2030 (bold figures indicate no change).

LULC	Built-up area	Waterbody	Green space
Kuala Lumpur			
Built-up area	**18616**	207	1932
Waterbody	162	**229**	181
Green space	2617	82	**2847**
Jakarta			
Built-up area	**65060**	424	916
Waterbody	1126	**643**	253
Green space	4115	117	**959**
Metro Manila			
Built-up area	**54068**	332	1025
Waterbody	256	**878**	296
Green space	3898	35	**1171**

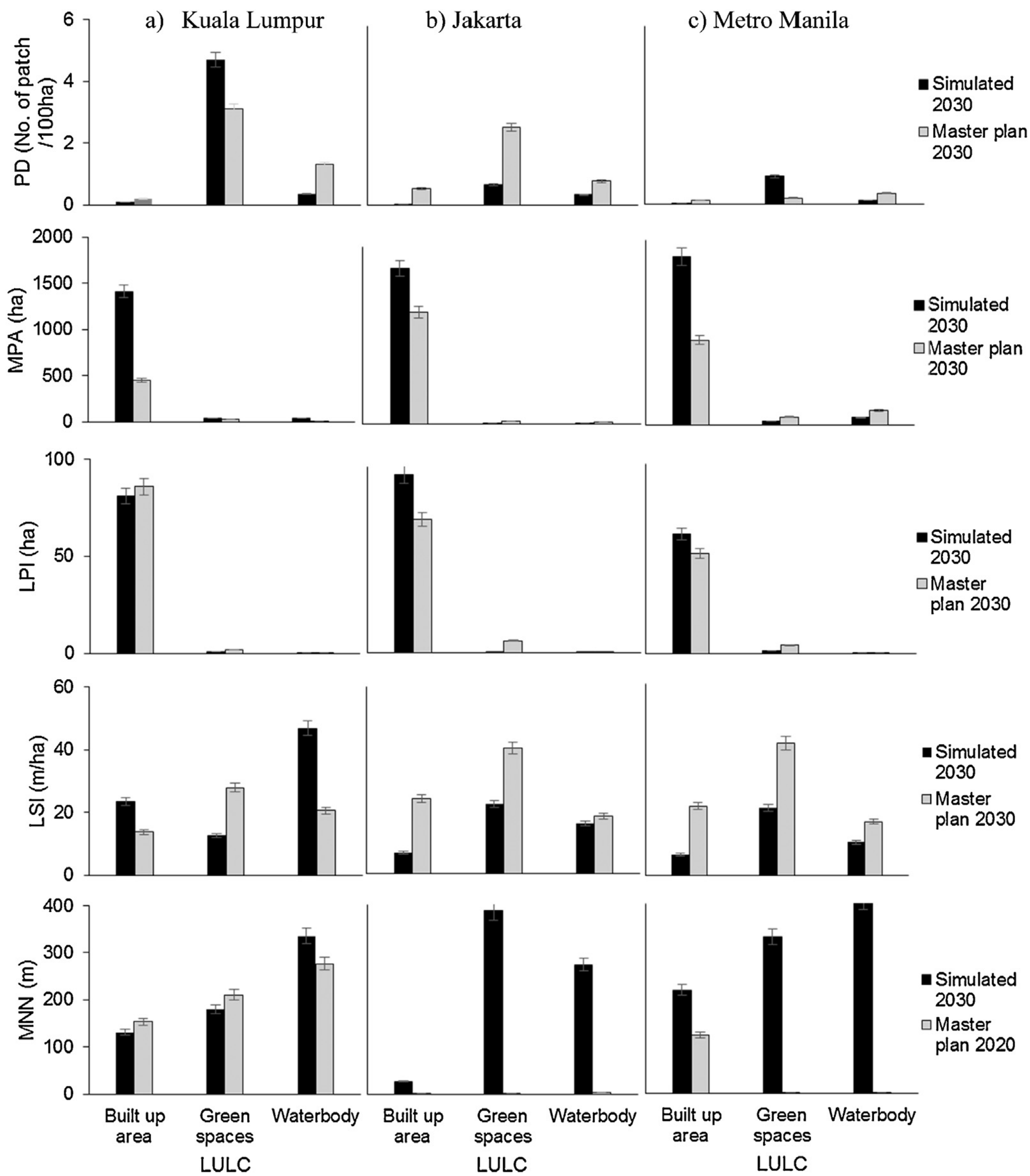

Fig. 7. Comparison of simulated and master plan map spatial structure of LULC in 2030 (patch density (PD); mean patch area (MPA); largest patch index (LPI); landscape shape index (LSI); Euclidean nearest neighbour (MNN)).

predicted to double in Jakarta and Metro Manila compared to a decline in Kuala Lumpur (Figs. 4 and 6). This indicates that land cover change studies are a very useful tool in projecting and planning for rapid urban expansion, indicating where interventions are likely to be effective for conservation planning of urban green space.

The evidence of effective spatial planning on rapid urban expansion and green space is reflected in the difference in size, density, distance, shape and spatial configuration of landscape features between the modelled and observed urban development in the period between 1999 and 2014. Based on the interpretation of spatial pattern such as fragmentation, aggregation, compaction, dispersion and isolation (Aguilera et al., 2011), we were able to use spatial metrics to compare and identify the land use patterns resulting from effective planning interventions. The several studies which used models to detect urban future change were not able to quantify the developed urban pattern and morphology (He et al., 2008; Kong et al., 2012; Weber, 2003). However, in this research, the use of spatial metrics allowed for quantifying and categorising complex rapid urban expansion dynamics into simple, quantifiable and identifiable patterns.

The present study is among the first quantitative studies to assess the effect of master planning on rapid urban expansion patterns. The various landscape metrics such as built-up area density, aggregation and compaction as defined by patch density (PD), mean patch area (MPA), largest patch index (LPI) and landscape shape index (LSI) provide a measure of rapid urban expansion and help link pattern and processes. Incorporating Euclidean nearest neighbour (MNN) into the comparison between the simulated models and master plans identifies the pattern of dispersion and isolation of connectivity patches. Ecological factors such as biological diversity and dispersal are known to be closely related to patch attributes such as size, shape, patch isolation and connectivity to other remnants (Tian et al., 2011), the larger sizes of green space provide a wider variety in biodiversity and contribute more to the conservation of green space than small ones (Arifin and Nakagoshi, 2011). Urban ecological studies of birds typically observe a decline in species' richness with increasing urbanisation (Sandström et al., 2006). For instance, studies in Metro Manila (Vallejo et al., 2009) and cities in Brazil (Manhães and Loures-Ribeiro, 2005) showed significant declines in avian species abundancies and biodiversity with increasing fragmentation of green space due to urbanisation. In terms of ecosystem services, the process of green space fragmentation due to urban expansion results in similar decreases as observed in a study in Baquio City, Philippines, where the overall annual ecosystem service value (ESV) dropped approximately by 60%. The human-to-ESV ration in the city has also decreased from 1:31 (US

$/year) in 1988 to just 1:7 in 2009 (Estoque and Murayama, 2013).

There are important differences in the spatial patterns of built-up areas and green space structure between the 2030 simulations and the planned development under the 2030 urban master plans in all three cities. The evidence suggests that these spatial patterns are influenced by the rapid urban expansion and respective master planning policies of the municipalities in the cities. Uncontrolled urban growth in a city influences the structure and pattern of urban expansion and consequently affects the fragmentation of green space. For instance, in Kuala Lumpur, the master plan would result in built-up areas increasing in size and distance between patches and will exhibit less variety of shape (indicating the aggregation and compaction of built-up areas) when this is compared to the simulation of 2030 (Figs. 6 and 7). The aggregation and compaction of built-up areas results in the dislocation, dispersion and isolation of green space (Fig. 7), where the green space area will be smaller, with less connectivity and shape complexity. This is because in the Kuala Lumpur Structure Plan 2020 (2000–2020), green space conservation seems uncoordinated and lacks persistent monitoring (Kuala Lumpur City Hall, 2005). The continued green space decline in the master plan (Fig. 4), suggests that the policies are currently inadequate, which caused urban expansion to continue at the expense of green space (Estoque and Murayama, 2013).

In contrast, the planned urban development based on the master plan in Jakarta and Metro Manila would result in more compacted built-up areas with a larger variety of shape, smaller patch sizes and shorter distances between patches when this is compared to the simulated patterns for 2030. The development of the master plans in Jakarta and Metro Manila are controlled and there is a better master plan strategy compared to Kuala Lumpur. This is illustrated by the proposed increase in green space area in Jakarta, variety of shape and greater connectivity between patches in the master plan when compared with the 2030 simulation map. The Jakarta spatial plan (2008–2027) was established to satisfy both economic development and environmental preservation (water source preservation of Bogor Regency in the metropolitan area; Government of Jakarta Special Capital Region, 2011). Similarly, in Metro Manila, the master plan is also controlled as illustrated by the aggregation of green space indicated by the decreased of patch density (PD) and increased mean patch area (MPA) values. The latest development plan is the Metro Manila Green Print (2030) to lever the metropolitan region towards the development of green infrastructure systems (Metropolitan Manila Development Authority (MMDA), 2012).

Given the observed importance of master planning on maintaining green space structure and the potential for encroached green spaces to become too small and isolated to meet user's demands (Tian et al., 2011), it is clear from this study that Kuala Lumpur is at risk of losing its green space functions in the future. There is evidence that planning policies have influenced the development of green space structure, and their implementation success (or lack thereof) at regional or city-wide scales in the different time periods can function as an important guide to policy improvement in planning, monitoring the effectiveness of plans and the management of green space. Based on results from these models, the planning authorities could design interventions which support planning at the landscape level with a better understanding of the future spatial configurations of urban landscapes.

5. Conclusions

This study sought (i) to simulate rapid urban expansion and green space using an integrated LCM-Markov Chain model; and (ii) to understand the spatial effect of master planning on rapid urban expansion and green space. Overall, the result from this study suggests that the master planning and future urban expansion has negative implications on green space structure in Kuala Lumpur, but not in Jakarta and Metro Manila. Notably, the spatial effect of master planning on rapid urban expansion and green space are influenced by the historical spatial changes, implementation of the previous master planning efforts and uncontrolled planning policies. An integrated LCM-Markov chain model and spatial metrics might be an efficient model for simulating urban expansion. The models allow for a set of diagnostic tools to assess failure and successes in planning strategies. An analysis of future land use changes in the longer term is recommended to compare potential green space changes influenced by rapid urban expansion beyond the year 2030.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.ecolind.2017.05.031.

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