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IMPACT OF RAPID URBAN EXPANSION ON STRUCTURE, FUNCTION AND CONNECTIVITY OF GREEN SPACE

SCHOOL OF WATER, ENERGY AND ENVIRONMENT

PhD
Academic Year: 2014 - 2017

Supervisors: Dr. Ron Corstanje
Prof. Jim Harris

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ABSTRACT

Globally, rapid urban expansion has caused a significant decline in green spaces in urban areas. It affects the form and structural patterns of green space. As a result, green space area becomes reduced in size, spatial structure, connectivity and function in urban areas. These gaps extend beyond uncoordinated master planning, which lacks required information regarding the past, present and future structural changes in urban expansion and green space. However, the existing methods and adaptive tools designed to respond to such needs are uncertain. This research aims to understand the impact of rapid urban expansions on the structure, connectivity and function of green spaces and to develop models as diagnostic and decision support tools in three Southeast Asian cities which are all areas of rapid expansion: Kuala Lumpur, Malaysia; Jakarta, Indonesia; and Metro Manila, Philippines. This study has evaluated the changes in the spatial structures and patterns of green space in urban areas of the three cities over the last two decades. The performance of the integrated Land Change Modeler (LCM) and the Markov chain modelling were verified to simulate future urban expansion by 2030. To reveal the priority corridors on maps, a novel integrated model which combines circuit theory, connectivity analysis and the least-cost path modelling, was used based on the target species of the Eurasian tree sparrow (*Passer montanus)* and the Yellow-vented bulbul *(Pycnonotus goiavier*). Overall, this study found that the percentage of green spaces in all three cities had reduced in size as the function of rapid urban expansions over the 25-year period. Key findings clearly indicated that important differences exist in spatial distributions of green space in different cities. LCM-Markov chain models proved to be suitable for the simulation of future land use/land cover (LULC). There were also important differences in the predicted spatial structure for 2030 when compared to the planned development in each city; substantive differences in the size, density, distance, shape and spatial pattern. The increased fragmentation of the landscape will continue in 2030, more shape complexity will be observed and less connectivity between green space patches will be present. Evidence suggests that these spatial patterns are influenced by the rapid urban expansion and respective master planning policies of the municipalities in the cities. This

study identified that, the emergence of potential corridors by integrating structure and functional connectivity of green space could increase the connectivity of green space for conservational significant areas. Therefore, the use of integrated remote sensing, Geographical Information Systems (GIS), landscape ecology analytics, simulation modelling and connectivity modelling tools provide significant insights into understanding the impact of rapid urban expansion on green space structure, identifies constraints and informs intervention for spatial planning and policies in cities, and contributes to the improvement of ecological networks in rapidly expanding cities.

Keywords:

Rapid Urban Expansion, Green Space Structure, Spatial Metrics, Land Change Modeler-Markov Chain, Urban Planning, Landscape Connectivity, Circuit Theory, Ecological Networks

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ANN	Artificial Neural Networks
GIS	Geographical Information Systems
LCM	Land Change Modeler
LCP	Least-cost Path
LPI	Largest Patch Index
LSI	Landscape Shape Index
LULC	Land Use/Land Cover
MLP	Multi-Layer Perceptron
MNN	Euclidean Nearest Neighbour
MPA	Mean Patch Area
NDVI	Normalised Difference Vegetation Index
PD	Patch Density

1 INTRODUCTION

This chapter presents the background, gaps, aims, research questions, objectives and hypotheses of the study. A review of the rapid urban expansion phenomena is provided along with the aspects of spatial structure, function and connectivity of urban green spaces, and the updated research methods. Subsequently, the theories and methods of remote sensing, Geographical Information Systems (GIS), landscape ecology, land change modelling and connectivity modelling tools are captured. This chapter ends by outlining the thesis structure, describes the study areas, lists the outputs utilised in the thesis for publications and list of references for Chapter 1.

1.1 Background

At present, urban areas are expanding and undergoing rapid development. The rapid growth of urban populations has triggered speedy urban expansion and profound changes in the usage of land at both local and global scales. In many developing countries, the cities are now expanding at a rate of twice their population growth rates. For instance, in Accra, Ghana and Bangkok, Thailand, the urbanised area increased by 150% whilst their population increased by only 50% between 1985 and 2002 (Angel et al., 2011). Rapid urban expansion causes significant conversion of green space to urban development (Goddard et al., 2010). Changes in land use have altered green space patterns and influenced the urban landscape structure (Ahern et al., 2014). A number of studies have focused on the temporal dynamics of spatial patterns of urban expansion (Li et al., 2013; Linard et al., 2013; Tv et al., 2012). These studies found that urban expansion constitutes one of the major causes of many ecological and environmental problems in urban areas. Nevertheless, few studies have focused on the spatiotemporal changes of green space in cities with rapid expansion. The influence that built-up area has on the location, size, proportions, spatial distribution and spatiotemporal dynamics of green space pattern is not fully understood. Most studies have focused on social, cultural and economic benefits of green spaces alone, disregarding the structure and pattern of green spaces

(Haq, 2011). In order to understand the spatial structure and pattern of green space, land change modelling is urgently needed to quantify changes in the expansion of urban structures and its effects on green space (Su et al., 2012).

Land change modelling provides an essential tool in understanding the spatial structure of rapid urban expansion and green space (Poelmans & Van Rompaey, 2010). Nonetheless, the spatial structure and pattern of historical, current and future changes of urban land use, and the effectiveness of land change models and simulation of rapid urban expansion remains unexplored. These gaps need to be addressed by means of the integration of multiple approaches such as landscape ecology methods and land change modelling, which can evaluate and validate the potential urban land change model (Teresa et al., 2015). Land change models that are incorporated with landscape metrics provide comparative analysis of landscape structure and pattern. Consequently, improved connectivity among green space patches is achieved (Zorrilla-Miras et al., 2014).

Landscape connectivity constitutes an important measure in mitigating the effects of development, fragmentation and habitat loss (Muratet et al., 2013; Rayfield et al., 2011; Szabó et al., 2012). The development of suitable landscape connectivity is crucial to improving the structural and functional connectivity of green space (Imam et al., 2010; Moseley et al., 2013). Therefore, this study integrates the structure and functions of green spaces into the landscape ecological connectivity networks using combined approaches of (i) remote sensing (ii) GIS (iii) landscape ecological analytics (iv) land change modelling and (v) connectivity modelling. The research highlights an urban ecological landscape connectivity networks as a key planning approach and decision support tool in maintaining the ecological functioning of the urban landscape.

1.2 Literature Review

1.2.1 Rapid Urban Expansion

In recent years, rapid urban expansion has become a central global issue as demonstrated by the increasing number of studies focusing on the phenomenon (Gao et al., 2011; Kantakumar et al., 2016). The total global urban area has been reported as quadrupling in the period from 1970 to 2000 (Seto et al., 2011). More than half of the world's population now resides in cities, a figure which is predicted to reach 67% in 2050 (UNDESA, 2012). The fastest urban growth correlates with the fastest growing economies and human populations in developing countries, especially in Asia. This has been recognized as an important issue, which complicates the management of urban ecosystems and potentially poses threats to the environment (Sharifi et al., 2014). Nearly half of the increase in high-probability urban expansion globally is forecasted to occur in Asia (Seto et al., 2012). Over the last 60 years, the urban population in Asia has grown from 16% (of the total population) in 1950 to 42% in 2010. The urban population in the region is estimated to reach 49% in 2025 and 64% in 2050 (UNDESA, 2012). In particular, the urban population of Southeast Asia is projected to increase by more than 70% over the next 35 years, to surpass 500 million people by 2050 (United Nations, 2014). Consequently, population increases have triggered the rapid growth of urban centers (Kong & Nakagoshi, 2006), and created the human-dominated landscapes and a mixture of dense urban-built structures (Montis et al., 2016). According to United Nations (2014), the percentage of the total urban area exceeds 70% in the cities of Southeast Asia.

Increasing human activity in urban areas has brought about profound changes in land use/land cover (LULC) and landscape pattern at both local and global scales, and is having a marked effect on ecosystem structure, function and dynamics (Yin et al., 2011). Although urban expansion promotes socioeconomic development and can improve the quality of life, urban expansion inevitably converts green space into built-up area (Li et al., 2013). Urban expansion has had and continues to have a negative impact on green space within cities. Recent evidence suggests that rapid urban expansion has caused many ecological and environmental problems (Thapa & Murayama, 2011; Yang et al., 2014) such as local and regional climate change (Kaufmann et al., 2007), hydrological alteration (Yang et al., 2011), biotic homogenisation (McKinney, 2006), pollution and habitat degradation, particularly the loss of green space and fragmentation (Miller, 2012).

Consequently, many studies have been conducted worldwide with the aim of understanding the driving factors of the observed spatial patterns in urban expansion and the related consequences (Jokar et al., 2013a; Pickett et al., 2011; Shu et al., 2014). In particular, an increasing interest in urban land changes is vital in developing the understanding of these driving factors and the impacts of urban expansion (Li et al., 2013; Thapa & Murayama, 2010). Furthermore, Wu et al. (2015) claim that only a few comparative studies have been conducted regarding the spatiotemporal pattern of urban expansion over a relatively long time frame. These studies have mostly focused on the large, developed cities in Asia, especially China (Kong & Nakagoshi, 2006; Liu & Zhou, 2005). Notably, comparative research on developing countries, particularly in the Southeast Asian cities, is relatively limited.

The main driver of rapid urban expansion is the increase in urban population. Cities in Southeast Asia are rapidly changing due to the accommodation of larger populations. The urban population of Southeast Asia is projected to increase by more than 70% over the next 35 years, to surpass 500 million by 2050 (United Nations, 2014). This huge growth in urban population may cause uncontrolled urban growth, with resulting urban land changes, i.e., changes from non-built-up to built-up areas. For example in Metro Manila, its relatively small land area, specific geographical characteristics, high population and economic development are the key factors influencing the spatiotemporal patterns of urban land changes and the overall urban development of the city (Estoque, 2017). These changes are likely to impact upon the composition and configuration of urban green space available in the region. Such changes may have impact on urban green spaces and the ecosystem services that they provide. The rapid growth in cities strains their capacity to provide these services

(Bhatta et al., 2010). Given that contact with the natural environment is a fundamental component of well-being (Standish et al., 2012), such changes may thus have consequences for human well-being. This consistent loss of green space is not only making the city vulnerable to natural hazards such as flooding, but is also reducing the quality of life (Byomkesh et al., 2012). In particular, the loss of urban green spaces is leading to the loss of biodiversity and important species contributing to the emergence of infectious diseases and increasing atmospheric pollution (Yang et al., 2014). These environmental disturbances may not only lead to degraded functioning of the ecosystem, but they can also have serious effects on the climate of the cities, which can have severe impact upon urban ecology and urban dwellers (Byomkesh et al., 2012).

Different cities demonstrate different urban expansion patterns and varied landscape change between spatial scales (Wu et al., 2015). For example, urban areas across Southeast Asia vary in their size and density, from relatively small, dispersed cities such as Kuala Lumpur in Malaysia to the densely packed megacity of Jakarta in Indonesia (Richards et al., 2017). Previous studies into urban expansion have focused on cities in North America and Europe (Arribas-Bel et al., 2011; Nazarnia et al., 2016), and most highly developed regions (United Nations, 2014). A lack of research exists into urban expansion in tropical areas exhibiting rapid population growth, and rapidly developing regions such as Southeast Asia (Seto et al., 2011). In contrast to relatively developed Europe and North America, Southeast Asia provides an opportunity to compare urban expansion between cities that vary considerably in their structure and form. There is considerable variation between cities in the urban form of rapid expansion, allowing comparisons to be made between cities. Therefore, this research suggests comparative studies to examine the changes of urban expansion in different cities in Southeast Asia. This study will provide empirical information for effective urban planning in rapidly expanding cities.

Rapid urban expansion could be either planned or unplanned. Many planned city developments especially in the developed cities (e.g. in Europe and North America) are now influencing large scale models of sustainable development due to the effective planning and policies (UN-Habitat, 2009). However, unplanned growth, coupled with the lack of comprehensive approaches, has caused changes to the structure, shape and functions of built and non-built areas (Madureira et al., 2011). This phenomenon is also defined as an uncontrolled, scattered urban development that depletes natural resources due to land use changes (Tv et al., 2012). The process of unplanned growth involves the conversion of green spaces and the loss of habitats, whilst increasing built-up areas through anthropogenic activities and congestion (Tv et al., 2012). For example, in the developing city of Greater Dhaka in Bangladesh, no official statistics exist regarding land use patterns; even the master plans are missing maps or quantitative statements regarding existing, historical and future land use patterns (Byomkesh et al., 2012). The relatively weak structure of urban planning and policy poses challenges to the adoption of appropriate urban management strategies. Current understanding of unplanned development remains unclear and poorly understood. In the context of rapid urban expansion, development should be planned and properly monitored to aid the management of urban changes.

1.2.1.1 Urban planning in rapidly expanding cities

Much of the current literature regarding rapid urban expansion pays particular attention to improving urban planning, policies and management of the urban landscape (Shu et al., 2014). Previous research has tended to focus mainly on the historical changes and policies affecting urban development and management in developing countries (Seto et al., 2012). Although rapid urban expansion in developing countries has been examined extensively in the literature, very few researchers appear to have focused on the effectiveness of utilising the master plan as a management tool to regulate future urban growth especially in Southeast Asian cities.

Master planning is the process of developing a land use map that determines future urban growth (Sharifi et al., 2014). The master plan should enable decision makers to make more informed decisions regarding urban development, helping to control urbanisation and avoid an uncontrolled mixture. However, poorly planned urban development contributes to unsustainable landscape change and can lead to various socio-economic and environmental problems, such as poor quality of living and degraded urban ecosystems (Dahiya, 2012). They also generate unmanageable land use which negatively impacts on natural capital as well as on green space.

Rapid urban expansion is likely to impact the available green space in the Southeast Asian region. Cities in Southeast Asia are rapidly changing as they accommodate larger populations, causing encroachments into green space in order to support the growth in population (Richards et al., 2017). Sustaining a healthy environment and providing proper landscape and urban planning in the urbanized world of 21st century represents a major challenge, especially in these expansion cities (Estoque & Murayama, 2016).

Master plans in rapidly expanding cities have paid little attention to the green areas beyond the city boundaries (Qian & Wong, 2012). This lack of integrated land use planning and also regional planning in the developing world, constitutes one of the main reasons for the loss of green space (Seto et al., 2010). The relatively weak structure of urban policy and absence of effective tools for controlling land development poses challenges for the appropriate urban planning (Sharifi et al., 2014). Master plans prepared to guide urban development have rarely been successful (Todes, 2012). These plans are often created by international planning consultants who are not necessarily fully aware of the local conditions (Seto et al., 2010; Sharifi et al., 2014). In addition, the timing of the master plan is not compatible with the high rates of urban expansion in the developing world (Balbo, 1993). Balbo (1993) argues that integrating a master plan originally designed in western cities for use in the developing world is not possible as they are incompatible, which makes the utilisation of a master plan difficult. For example, previous studies of trends in urbanisation in Asian mega-cities indicate that in the period between 1970 and 1998, Jakarta had entered the suburbanisation stage whilst Metro Manila remained at an early stage of urbanisation (Mukarami et al., 2005). In order to understand the local situation, land change models of present, past and future urban patterns are needed. The empirical model can provide information concerning the existing situation and the future of rapid urban expansion.

As case studies in this research, a) Kuala Lumpur, Malaysia, b) Jakarta, Indonesia and c) Metro Manila, Philippines (which are located in a densely tropical region) have been experiencing rapid urban expansion during recent decades. This trend of urban expansion is associated with emerging environmental issues such as reduction of green space, increasing health concerns, pollution and urban heat effects (Aflaki et al., 2017). Correspondingly, various plans and policies have been launched in order to regulate the negative effects of urban expansion (Table 1.1).

a) Kuala Lumpur, Malaysia

In Kuala Lumpur, the emergence of cities with residential, industrial and commercial centres proves that development is growing very fast (Aflaki et al., 2017). Urban problems in Kuala Lumpur include growth of squatters, congestion and poverty, which in turn are fuelled by rural migration and resource exhaustion. In addition, the loss of urban green, water and air pollution, erosion, floods, haze and unpleasant odour occurred due to ineffective physical planning. Hence, planning and managing the urban areas has become a significant task in dealing with issues and problems due to the tremendous development growth. Therefore, effective urban planning and management practice is vital in order to delineate the limit of urban expansion in certain areas (Kuala Lumpur City Hall, 2005).

Historically, the process of urban expansion in Kuala Lumpur began in the 1980s. Kuala Lumpur's structural plan was established in 1984, formulating general policies relating to landscape and conservation. This was followed by the Kuala Lumpur Structural Plan 2000 and the current Kuala Lumpur Structural Plan 2020. The urban master plan (Kuala Lumpur Structure Plan 2020) has been applied in the City Hall of Kuala Lumpur (CHKL) through the development of an integrated system that can be seen as an innovative approach to urban planning (Kuala Lumpur City Hall, 2005). The preparation of the Kuala Lumpur Structure

Plan 2020 is undertaken in the conviction that most of the policies of the 1984 Kuala Lumpur Structure Plan (KLSP 1984) need to be revised due to rapid changes over the last 20 years. Some of the major developments that have taken place were not anticipated in the structure plan. Developments such as the Multimedia Super Corridor (MSC), the Kuala Lumpur International Airport (KLIA) at Sepang and the transfer of federal government administrative functions to Putrajaya are expected to stimulate and influence future changes and growth. The Kuala Lumpur Structure Plan 2020 (the Plan) contains the vision, goals, policies and proposals to guide the development of Kuala Lumpur over the next 20 years (Kuala Lumpur City Hall, 2005). It does not contain proposals for detailed physical planning for any specific area.

b) Jakarta, Indonesia

One of Jakarta's current problems is diminishing green areas as population grows. In 1965, 35 percent of Jakarta's land area was green area. Currently, green areas make up only 9.3 percent, far below the target of 30 percent as set by Spatial Planning Law No 26/2007 (Rukmana, 2015). Most of the green areas have been turned into luxury houses, shopping centres, hotels, offices, commercial buildings and malls, which have been growing rapidly for the last 30 years and have contributed to making Jakarta prone to flood (Government of Jakarta Region, 2011). In Jakarta, a new town development was initiated by the early 1990s (Firman, 2014). Policies for the integrated metropolitan-level development were established in the mid-1970s and early 1980s by the Local Preparation Bureau for Development in Jabodetabek Metropolitan Area and the Presidential Decree on Development of the Jabodetabek Area (Hudalah & Firman, 2012). In 2008, a new green space policy was developed but which focused more strongly on natural areas than urban green space (Pribadi & Pauleit, 2015). The development of spatial planning laws 26/2007 and 174/2007 included the maintenance of urban forests, interactive parks, agricultural areas and green belt areas (Mutiara & Isami, 2012). Subsequently, the Jakarta spatial plan (2008-2027) has been established in order to satisfy both economic development and environmental preservation (i.e. water source preservation of Bogor Regency in the metropolitan area) (Government of Jakarta Region, 2011).

Since February 2008, the government of Jakarta city has been preparing the 2030 Jakarta Spatial Plan (Government of Jakarta Region, 2011). It is an important and comprehensive plan for shaping the future of Jakarta. In broad terms, city planning can be defined as systematic effort and action to structure the public domain for the future of urban areas (Herman, 2011). Development planning of urban areas mostly focuses on aspects such as economics, business, community, housing, infrastructure, transportation, environment, water, waste management, natural resources, energy consumption and historic preservation (Government of Jakarta Region, 2011). The planning process normally requires city planners to obtain data and analysis then, working with stakeholders, to decide the plans for the city. However, in this plan most of these organisations emphasise the poor data analysis, less attention on environmental sustainability and lack of participation process during its process. Furthermore, the spatial plan draft is very technical and difficult for lay people to understand and was based more on consultation and data-review (Herman, 2011). Therefore, the 2030 Jakarta spatial plan is inadequate to predict and plan the city's growth over the next 20 years. Twenty-five, or even ten years ago, when the Jakarta government formulated the 1985-2005 and 2005-2010 Jakarta Spatial plan, the urban development does not match the plan (Herman, 2011).

c) Metro Manila, Philippines

In Metro Manila, over the past 21 years (1993 to 2014), the area of built-up lands has increased almost two-fold, transforming the landscape of Metro Manila and its surrounding areas. The intensifying pressure of urban expansion due to rapid population growth and urban land changes poses many challenges that need to be considered in sustainable urban development and landscape planning (Estoque, 2017). In particular, in the zoning plan conflicting decisions exist with regard to land conversion. This would convert areas along subdivision main roads into commercial zones and some parts into industrial zones. These land uses would aggravate the problem of water shortage, poor garbage collection and traffic congestion (Magno-ballesteros, 2000).

In Metro Manila, the development of residential sub-division lots and agricultural lands began in the 1990s (Malaque & Yokohari, 2007). The planning policy began in 1996, for example the Physical Development Framework Plan for Metropolitan Manila (1996 to 2016). Following that, Metro Manila Green Print 2030 has been established to provide a framework and recommendations for the use of land and other resources and the development of green infrastructure systems (MMDA, 2012). The Metro Manila Development Authority (MMDA) working with other government agencies, local government units and supported by the World Bank, Australian Agency for International Development, and the Japanese Government has launched the formulation of a 20-year strategy to transform Metro Manila into a highly competitive East Asian city that promotes a higher standard of living for its residents (MMDA, 2012). Metro Manila Greenprint 2030 will develop a common vision for Metro Manila's future, propose institutional reforms to improve coordination among key players, and provide a spatial strategy that will guide the urban form, primary infrastructure, green systems and the clustering of economic activities to improve liveability (MMDA, 2012). Greenprint 2030 is a broad-stroke document, which aims to look strategically into the future, and provide a long-term direction to guide actions of both the public and private sectors to help Metro Manila achieve greater ecological and economic sustainability. Of special consideration are factors including climate change, the increasing vulnerability of the city to natural disasters, rising demand for affordable housing close to places of work and livelihood (MMDA, 2012).

Table 1. 1 Master plan establishment of the three cities

Cities	Master Plan	Date	Purpose
Kuala Lumpur	Kuala Lumpur Structural plan 1984	1984	The Structure Plan system puts more emphasis on social, economic, physical, traffic, environmental and other issues with a view to achieving the broader goals and objectives
	Kuala Lumpur Structure Plan 2020 (2000-2020)	2000	An interconnected network of green spaces is envisaged, linking major parks and forest reserves with rivers, roads and utility reserves (Kuala Lumpur City Hall, 2005)
Jakarta	Local Preparation Bureau for Development in Jabodetabek Metropolitan Area (1975) and Presidential Decree on Development of Jabodetabek Area (1976)	1975	Purpose for integrated metropolitan-level development
	Jakarta spatial plan (2008- 2027)	2008	The goal is to satisfy both economic development and environmental preservation (water source preservation of Bogor Regency in metropolitan area) (Government of Jakarta Region, 2011)
Metro Manila	Physical Development Framework Plan for Metropolitan Manila (1996-2016) (PDFPFMM)	2016	Designated for industrial and manufacturing development, transportation, communication system,

		city's environment and liveability (MMDA, 2012)
	Metro Manila Green 2030 Print (2030)	A development plan aimed to provide leverage to the metropolitan region towards an investment programming and land use with trunk infrastructure and green systems (MMDA, 2012)

Note: Example of Master plan of Metro Manila
http://documents.worldbank.org/curated/en/286861468189547797/The-Metro-Manila-greenprint-2030-building-a-vision

It can be observed that the development pattern is different from that recommended by the master plan (Sharifi et al., 2014). Research (Sharifi et al., 2014) has identified the major discrepancies between the land use proposed in the master plan and the actual land use in Vientiane, Laos. The conversion of 7% natural land to built-up area in the period between 1995 and 2011 indicates that the actual land use deviates significantly from that proposed in the master plan. Zhao (2010) compared urban land use planning and actual land use during the same period in Beijing, China. The study found that the actual green space land had decreased by 12% compared to green spaces indicated in the land use plans. As a result, urban development has reduced the degree of local balance in land use between built-up area and green spaces. This result indicates that the urban expansion pace of the city has surpassed urban planning and may negatively impact on the green spaces. Collectively, these studies outline a critical role for new methods that determine the effectiveness of planning efforts, so to guide sustainable urban development and highlight the problems that need to be addressed.

It is necessary to provide the current status of urban expansion and its relationship with master planning in the case study cities. Understanding the influence of local planning systems on landscape changes will be crucial for the establishment of regional policy, and has practical planning implications for the management and planning of green space in rapidly developing expansion cities.

1.2.2 Human and Ecological Consideration of Urban Green Space

Natural capital such as urban green spaces play an important role in complex urban ecosystems and provide social, cultural, economic and environmental benefit for biodiversity and well-being of urban dwellers (Niemelä, 2014). Green space definitions are varied in different recognition phases and their own context. At the early stages, the most popular concept was open space, which emphasised the natural and public characteristics of a space (Turner, 1992). The definitions of green space system has evolved with the development of city theory. Referring to some definitions from other countries such as Britain, America, Europe and China, some studies have proposed the definitions of green space from the angle of landscape planning and urban design. In the United Kingdom, Dunnett et al., (2002) refer to green space as those land uses that are covered with natural or man-made vegetation in the built-up area and planning areas. In America, Bonsignore (2003) defines green space as outdoor settings that contain significant amounts of vegetation. In Europe, Van Herzele & Wiedemann (2003) describe green space as all areas within the city and its surrounding regions, enabling people to be in contact with nature. In China, Li et al., (2005) refer to green space as a green network ecosystem in large areas, especially in urban or suburban areas, whether natural or maintained, public or private, including those areas that are not paved or do not have buildings on them. In recent years, the concept of green space has extended to consider the urban green that includes all natural, semi-natural and artificial ecological systems within, around and between urban areas at all spatial scales (Cilliers et al., 2013). This study proposes its own definition of green space by referring to some published literature within the context of rapid urban expansion (Jim & Chen, 2006; M'Ikiugu et al., 2012). Green space is defined as any piece of land covered by vegetation within the built-up matrix of urban areas.

As a critical constituent of urban landscape, it has been increasingly acknowledged and widely documented in the literature that green spaces could effectively counteract various negative environmental impacts associated with urbanisation (Kabisch & Haase, 2013) while providing social and ecological functioning to human well-being (Tzoulas et al., 2007). Notably, green spaces provide vital services such as provisioning (Ortacesme, 2010), regulating and supporting cultural services that aid facing ongoing challenges and threats of urban development (Lehmann et al., 2014). Green spaces also perform important roles in ecosystems such as preventing soil erosion (Jim, 2001), reducing urban heat (Choi & Lee, 2011) and noise effects (Bolund & Hunhammar, 1999), conserving the habitats of rare species, aiding carbon sequestration, flood control, pollution treatment, water supply and storm protection (Cilliers et al., 2013; Standish et al., 2012). On the whole, green spaces are a necessity in ensuring the quality of life in cities due to their extensive contribution to public health and a healthy environment (Breuste et al., 2013).

In addition, they serve to regulate microclimates and provide habitats to maintain biodiversity whilst simultaneously accommodating corridors and gateways to link those habitats (Kong et al., 2010). Even though urban environments are not considered areas of conservation importance, green spaces in cities have been previously identified as areas with significant avian biodiversity (Vallejo et al., 2009). The reduction of green areas in rapidly expanding cities may result in localised extinctions (Alvey, 2006). For instance, bird surveys in cities in Brazil such as conducted by Manhães & Loures-Ribeiro (2005) have shown that loss of green space resulted in a failure to sustain avian biodiversity. Urban ecological studies of birds typically observed a decline in species' richness with increasing urbanisation (Sandström et al., 2006). Similarly in Metro Manila, a study of the distribution and diversity of birds has revealed that green spaces are distinct habitats that preserve faunal uniqueness whereas urbanisation tends to decrease diversity (Vallejo et al., 2009). These observations suggest that green spaces accommodate significant avian biodiversity as well as the presence of endemic and threatened species. Therefore, green space should be preserved and maintained by ensuring that these habitats are incorporated in any urban development plan.

The literature concerning human experience in green environments has widely shown the positive outcomes of getting in contact with nature (Carrus et al., 2015). Urban green space characteristics such as size, shape, distance, distribution, vegetation density and high species richness play a vital role in defining their ecological, social and landscape function (Tian et al., 2014). Several functions of green spaces such as physical attributes (attraction, utility, amenity and recreational opportunities), social attributes (security and community), and ecological quality (ecosystem services, physical and mental health) could demonstrate differences in attitude, visiting pattern, preference and perception towards green spaces in the various regions (Lee & Maheswaran, 2011; Stigsdotter & Grahn, 2011). For example, vegetation density of urban green spaces could enhance the recreational attractiveness and visit frequency in Europe (Kabisch & Haase, 2013). However, in Hong Kong and China, the particularly small size of most green spaces limits the variety of leisure opportunities and ecological services, and the fulfillment of multiple roles (Lo & Jim, 2012; Zhang et al., 2013).

Previous studies have found that the diversity or variety of green space structure such as size, distance and shape of green space contribute to its perception and use (Jim & Chen, 2006; Lo & Jim, 2012; Tian et al., 2014). Cities with more aggregated green spaces provide larger contiguous patches, which have a greater cooling effect than smaller fragments of similar areal coverage (Bowler et al., 2010). In the compact city of Hong Kong, it was found that limited green space areas are often too small, are surrounded by incompatible activities and fail to meet user demands and expectations (Tian et al., 2011). However, the increase of shape variation and patch size in green space would attract more people to use green space. This is because they prefer large parks and attractive designs of green space (Grahn & Stigsdotter, 2010; Peters et al., 2010). Green space with a complicated shape could bring people closer to nature, improve their physical and mental health, and provide diverse visual and amenity resources

(Davies et al., 2008; Tian et al., 2014). The decrease in distance between green space patches suggests high potential of accessibility to green space for leisure and recreation. For example, a study in Taiping, Malaysia has shown that the characteristics and experience of the green network resulted in progressive physical, cognitive and social functioning of urban residents, hence offering enhanced well-being (Mansor et al., 2012). It is important to provide residents with more desirable and safer public spaces for leisure and recreation (Sreetheran & van den Bosch, 2014) and access to green space close to their homes and localised patterns of use in (municipal) urban parks and neighbourhood parks (Wright Wendel et al., 2012). Shading is perceived as quite important for people in Southeast Asia, possibly due to the strong tropical sunshine in summer (Lo & Jim, 2012). Therefore, the size, shape and spatial configuration of green spaces help determine their resulting ecosystem service delivery (Lehmann et al., 2014) as well as public perceptions, visiting patterns and use of that space (Kroll et al., 2012; Le Roux et al., 2014).

Despite the importance of green space for humans and urban ecosystems, there is insufficient understanding in rapidly expanding cities. Therefore, understanding green space functions is important when considering human and ecological benefits, and biodiversity of green space. This research does not measure the green space functions directly but discusses them as implications of the research findings.

1.2.3 Theory and Method of Landscape Ecology

Landscape ecology has become one of the most rapidly developing ecological fields worldwide since the mid-1980s, because it brought spatial analysis and modelling to the forefront of ecological research (Forman & Godron, 1986). Landscape ecology studies are characterised by spatially explicit methods in which spatial attributes and arrangements of landscape elements are analysed and related to ecological processes (Wu, 2013).

Landscape ecology continues to diversify in ideas and perspectives, constituting an effective approach in urban ecology that emphasises the interactions between spatial pattern, ecological processes and scale (Li & Wu, 2004). Landscape ecology theory has been used to study urban landscape patterns (Lv et al., 2012) in the investigation of the spatial arrangement of habitats to conserve landscape structure (Mahmoud & El-Sayed, 2011). Analysing and understanding landscape structures as well as modelling and forecasting changes thereof have long been the primary concerns of quantitative landscape ecology (Lausch et al., 2015).

The spatial structure of the landscape has been studied extensively in a rural context, and its principle may be applied to the field of urban ecology at local and regional levels (Lv et al., 2012). Nonetheless, the structure and functioning of green space in urban areas, especially those experiencing rapid expansion, is not fully understood. Despite the considerable changes in the rapid urban expansion, the loss of green space is expected to occur in Southeast Asian cities in the near future, and it is not clear how these changes will impact the green space structure and function. For instance, the amount of green space in cities varies within regions, e.g. 10 to 36 % across 30 Chinese cities (Yang et al., 2014); and 2 to 46 % across 386 European cities (Fuller & Gaston, 2009). Richards et al. (2017) found that larger cities, and cities with higher population densities such as Jakarta and Metro Manila, had significantly lower green space with less than 20% of green space coverage. This variation in the composition of green space has high potential to influence the configuration of green space (Norton et al., 2016). Such changes may have impacts on green space structure, connectivity and functions that they provide.

An increasing array of tools is available to meet this challenge and increasingly requires ecologists to address rapid urban expansion challenges. An effective model to improve green space structure and function is required in rapidly evolving urban systems, using recent technology and landscape ecological principles (Leita & Ahern, 2002; Mahmoud & El-Sayed, 2011). In general, landscape ecology studies the effect of changes in landscape structure (composition and configuration) and landscape elements e.g. land use/land cover (LULC) on the ecological processes within the spatial and temporal scales (Turner et al., 2001). In the context of landscape ecology of urban green space, three important aspects are emphasised in this study, namely structure, connectivity and function. Green space structure refers to the arrangement of green spaces in terms of their composition and configuration (Uy & Nakagoshi, 2008). The composition of green spaces expresses their proportion, whereas the configuration encompasses their size, shape, density, distance and distribution. Previous studies on composition and configuration of green space suggest that understanding the present situation of green spaces is essential in order to set goals for future land use (Muthulingam & Thangavel, 2012).

In order to overcome the rapid urban challenges and address the complex phenomenon of green space in the urban expansion context, this study employs three types of landscape ecology diagnostic tools, namely i) landscape metrics, ii) land change modelling and iii) connectivity modelling. Landscape metrics were utilised to evaluate the changes in spatial and structural patterns (Lausch et al., 2015) of green space in rapidly developing cities over the last two decades. Land change models were developed to model and predict urban expansion and identify the main drivers including spatial planning in the resulting spatial patterns. Connectivity modelling tools were used to understand the structural and functional connectivity of green space by identifying the potential priority corridors and develop an ecological landscape connectivity model of green spaces. These combined tools provide new insights regarding understanding of the structure, connectivity and function of green space in the cities experiencing rapid expansion.

1.2.3.1 Spatial Landscape Metrics

The theory and concept of landscape ecology can provide rich quantitative information regarding the structure and pattern of green spaces at the landscape level. It shows a better link between different land uses and it can effectively quantify the landscape over the entire study area with metrics (Kong &

Nakagoshi, 2006). Landscape structure is quantified using landscape metrics where three basic attributes exist to characterise landscape structure, these being size, shape, and distance. They are important attributes that contribute to the characterisation of landscape structure and ecological processes (McGarigal et al., 2002). Landscape metrics are quantitative indices that describe the compositional and spatial aspects of the landscape based on data from maps, remotely sensed images and GIS coverage (McGarigal et al., 2002). They quantify the spatial patterns of land changes (Pham et al., 2011; Plexida et al., 2014) and are likely to characterise the landscape structure in landscape monitoring for the foreseeable future. Furthermore, they are simple, intuitive tools for assessing and monitoring changes in landscape pattern and the effects on underlying ecological processes (Kupfer, 2012).

Nevertheless, most studies have focused on metrics at the landscape and class level, particularly on the composition of land use cover (Peng et al., 2010). Lausch et al. (2015) claim that most studies on relationships between landscape structures and ecological processes such as isolation, fragmentation and aggregation (Kupfer, 2012) have little statistical significance, very limited explanatory value and do not translate into a understanding of the underlying mechanisms. The present research fills this gap by quantifying significant changes of spatial pattern at all different levels (landscape, class and patch).

Moreover, previous studies indicate that the usage of a set of metrics comprised of mean patch area (MPA), landscape shape index (LSI), patch density (PD) and Euclidean nearest neighbour (MNN) is usually the most ideal for representing the landscape characteristics to identify landscape fragmentation (Jaeger, 2000; Li et al., 2011) and consecutively, avoid yielding redundant results (Li & Wu, 2004). Fragmentation has three ecological components (Andren, 1994), namely (i) loss of green space (attrition); (ii) reduction in size of green space (shrinkage); and (iii) increasing isolation of green space patches due to the landscape resistance exerted on remnant green space by the surrounding matrix of built-up area (Fry et al., 2009; Leita & Ahern, 2002).

The fragmentation theory states that the ecological factors such as biological diversity and dispersal are closely related to patch attributes such as size, shape, patch isolation and connectivity to other remnants (Tian et al., 2011). From a landscape ecological perspective, understanding of landscape fragmentation is important in green space planning in order to increase the connectivity and green space network (Jaeger et al., 2008). For example, research by Tian et al (2011) found that green space in Hong Kong experiences high fragmentation in the landscape. Consequently, the landscape structure and fragmentation affect connectivity of patches as well as ecological and social functioning of green space in the urban landscape. For instance, the large sizes of green space provide variations in biodiversity and contribute more to the conservation of green space than small ones (Arifin & Nakagoshi, 2011).

These studies highlight that landscape ecology constitutes an effective approach to quantifying the landscape structure in rapidly expanding cities. The concept of landscape ecology provides an integrated approach opportunity to understanding the relationships between landscape pattern and changes in environmental conditions due to rapid urban expansion (Tian et al., 2011). Landscape ecology provides a comprehensive approach to understanding the relationships between landscape structure of particular elements (e.g green space) and environmental changes in the landscape (Jim & Chen, 2003). With the empirical information of landscape structure changes, future rapid urban expansion and land change models can be developed effectively to help planning, management and monitoring of green space.

1.2.3.2 Land Change Models

Nowadays, it is considered very important to analyse the pattern of LULC changes over time to assess probable urban changes in the near future and their consequent impact on green space (Kong et al., 2012). Seto et al. (2011) indicate that between 1970 and 2000 urban areas grew by 58,000 km^2 worldwide, and that by 2030 cities are expected to grow and global urban land cover will increase with an estimate of 1,527,000 km^2. The developed world is now about 80% urban and is expected to grow further by 2050, with some 2 billion people moving to cities, especially in China, India, Southeast Asia and Africa (UNDESA, 2012). India, China and Africa have experienced the highest rates of urban land expansion (2.3 to 3.3%), and Southeast Asia will experience both high rates of urban expansion and population growth by 2030, suggesting that urban growth is becoming more expansive (Seto et al., 2011).

These urban changes are likely to impact on the quantity and structure of green space in the region. Previous studies from outside Southeast Asia indicate that the loss or degradation of green space may impact the structure, pattern and process of the urban landscape (Fuller & Gaston, 2009; Zhou & Wang, 2011). If historical urban expansion patterns are followed, future urbanisation will be concentrated in the existing towns and cities, and develop a major threat to green space. Although the evidence from developed Singapore suggests a similar pattern of urban areal expansion and increased urban density (Sodhi et al., 2004), it is possible that other cities in Southeast Asia will follow fundamentally different trajectories of urban development than the western cities in which urbanisation has mainly been studied previously (Richards et al., 2017). Furthermore, western concepts constitute a substantial influence in shaping urban change around the world, due to the globalised nature of modern urban development (Shatkin, 2008). Local organisations in Bangkok, Thailand have tried to improve the management to keep up with the changes; however, it has failed to stop the growth. This results in the expansion of the built-up area in the cities and may be continuing in the future of urban expansion (Losiri et al., 2016).

The prediction of urban growth in rapidly expanding cities is therefore very important in providing effective land change models, estimates and projections of urban land cover in the regions. The availability of land change models will make it possible to study the effects of present and future urban land cover on green space (Debnath & Amin, 2016). In order to assess the impact of urban growth, land change models have been proposed to simulate the urban dynamics and often require data specifically concerning the locality. However, data collection requires considerable cost, and may not available for developing areas (Losiri et al., 2016).

Currently, LULC analysis has been used extensively to monitor urban expansion forms in specific spaces and times. Remotely sensed data are suitable to provide information on the characteristics of urban land cover and their change over time that represent the actual physical extent of a city (Friehat et al., 2015; Herold et al., 2005). Satellite data are commonly used for the production of land cover maps that indicate the landscape pattern and process, including habitat fragmentation (Griffiths & Lee, 2000; Turner, 1990: Wang & Moskovits, 2001). When used in conjunction with GIS, an efficient and cost-effective approach to monitoring and understanding urban expansion is formed (Seto et al., 2011; Wakode et al., 2013). This also creates opportunities to develop models.

The combination of remote sensing and GIS provides both spatially and temporally consistent data to map and monitor urban expansion (Kantakumar et al., 2016), and to assist in managing land uses (Park et al., 2011). Analysing historical urban expansion can reveal the spatiotemporal dynamics and processes of urban expansion and help to manage complex urban development effectively (Thapa & Murayama, 2011). However, as urban expansion results in green space change, a detailed land change model is necessary to study and understand urban expansion patterns for prediction of future urban expansion. These models are powerful techniques that can support the future land demand evaluation and simulate the spatial pattern of land use based on the driving factors (Haase et al., 2012).

The LULC simulation models in an urban study are developed from the theories of urban morphology and dynamic process of LULC to forecast urban expansion in different patterns and scales (Han et al., 2015; Triantakonstantis & Mountrakis, 2012). Those models can be categorised into (i) empirical and statistical models such as Markov chain (Shafizadeh Moghadam & Helbich, 2013) and logistic regression (Shu et al., 2014; Jokar Arsanjani, 2013b); (ii) dynamic models such as cellular automata and agent-based models (Luo et al., 2010; Mitsova et al., 2011; Sante et al., 2010); and (iii) integrated models such as IDRISI Land Change Modeler and Artificial Neural Networks (ANN) (Thapa & Murayama, 2012; Triantakonstantis et al., 2015). They are composed of the affirmation models, which consider the past changes in the calibration step, and a sigmoidal pattern of the goodness of fit in the change potential function (Losiri et al., 2016; Mas et al., 2014).

Most existing models that predict rapid urban expansion tend to apply the models without validation. Although the models are capable of predicting future land use, their implementation is also associated with several difficulties such as complex data requirement, the absence of a standard method for the definition of transition rules, and lack of easily configurable and usable software (Santé et al., 2010). Teresa et al. (2015) proposed to validate the output of a land change model in order to assess the quantity of each transition and the size of areas for transition changes. In particular, land change modelling is concerned with the comparison between the result validation map and the observed map to predict future urban expansion. In Land Change Modeler (LCM) (Eastman, 2006; available as ArcGIS 10.2 extension, http://www.clarklabs.org), the various parameters will be tested by Cramer V (test of the potential explanatory power of each driving force) before they are chosen as parameters into a spatially-explicit model (Eastman, 2012). The incorporation of LCM with Markov chain models and GIS data is claimed to constitute a suitable approach to model the temporal and spatial change of green spaces (Myint & Wang, 2006). The change prediction process relies on the historical transitions and models forward to a specified future date. The quantity of change is modelled through a Markov chain analysis which controls the temporal change among the different types of land use, providing a transition probability matrix (Guan et al., 2011; Mukhopadhyay et al., 2015). Furthermore, LCM allows for the specification of the number of reassessment stages during which the dynamic variables are updated. At each stage, the system also checks for the presence of planning interventions. Interventions refer to constraints and incentives including proposed green areas and infrastructural changes including road development. Uniquely, this method reveals the best-fitting element and hence, it is most suitable for modelling the complex relationships among factors involved in land changes (Eastman, 2012).

This study has aimed to develop a validation model to predict urban expansion by 2030 for the study area. This study also employs multilayer perception to determine the driver factors from LCM-Markov chain. Moreover, the master plans are applied to compute the transition probability by Markov chain to simulate the urban LULC in 2030. To understand the urban expansion phenomena and green space in Southeast Asian cities, this current study tries to address the complex phenomenon of the urban context by integrating natural and physical data into the LULC model to calibrate and simulate the future land use change from the base year 2014.

1.2.3.3 Connectivity Modelling Tools

Various methods and principles of landscape ecology have been used for conservation of green space since 20th century, such as urban greening, green infrastructure and green network (Jim & Chen, 2003; Li et al., 2005). It highlights the need to adopt relevant attributes in order to understand the changes of green space pattern, structure, function and connectivity in urban landscape (Forman & Gordan, 1986; Ahern et al., 2014). Patch size and patch distance are two of the attributes that vary markedly across urban areas and that have considerable potential to influence the connectivity of green space. Accordingly, Forman & Godron (1986) suggest the model of patch and corridor in an ecological connectivity network. The patches are relatively homogeneous non-linear areas while the corridor is a continuous link between patches that construct a prominent connectivity network of green areas (Mahmoud & El-Sayed, 2011). Wu & Hobbs (2002) add that a network of patches and corridors can provide connectivity of natural elements and aid the preservation of linkage between the different patches. Landscape-level connectivity or urban linkages regulate (i) species-level biodiversity, (ii) wildlife movement, (iii) seed dispersal and (iv) ecological factors (Shanthala et al., 2013). Furthermore, landscape ecologists use connectivity (corridors) to describe a landscape's structural and functional continuity in space and time (Forman & Godron, 1986). The spatial pattern and functional analysis of the patch and corridor need to be applied to the green spaces in rapidly expanding cities by integrating related models in the assessment and development of ecological networks (Kong et al., 2010). The ecological network is required in order to preserve and conserve the structural and functional of green spaces.

Quantitative methods in landscape ecology for measuring connectivity have stimulated the development of extensive connectivity-related indices (Pascual-Hortal & Saura, 2007). Simple spatial metrics and software such as FRAGSTATS (Version 4.2; McGarigal et al., 2002), connectance index, patch cohesion and buffer metrics are used for descriptive analysis (Shanthala et al., 2013). Nevertheless, they have limitations with reference to visual mapping. Most connectivity models function in a point-to-point or patch-to-patch fashion (Pelletier et al., 2014), limiting their usage in the assessment of connectivity over very large areas.

In this research, these gaps are addressed using connectivity network models including circuit theory to allow the creation of connectivity maps that illustrate the flow paths and movement across a large study area. Circuit theory provides a simple solution to identifying the potential corridors of connectivity networks and it can be applied at the patch and landscape levels to quantify either structural or functional connectivity (McRae et al., 2008; Yu et al., 2012). Using modest computational resources, empirical evidence indicates that these continuous, fine-scale maps of nearly unlimited size allow the identification of movement paths and barriers that affect connectivity (Pelletier et al., 2014). This effort has developed a powerful new application of circuit models by pinpointing areas of importance for conservation, animal distribution and movement.

Nonetheless, circuit modelling runs are constrained to limited raster sizes (relatively small areas or large areas at coarsened spatial resolutions) and calculate the distance between linked patches of intrapatch connectivity (within the patch itself) and interpatch connectivity (the connections between different patches) (Luque et al., 2012). These limitations inhibit the potential application of circuit theory in identifying potential movement corridors at a fine level of detail spanning a very large area (Pelletier et al., 2014). Nevertheless, the applicability of circuit theory to develop the expansion of potential corridor at regional scales may be broadened by combining it with connectivity analysis (Xun et al., 2014) and least-cost path analysis (Teng et al., 2011). This combination produces a potential corridor map for the specific target species studied. The method is intended to allow users to identify hypothesised movement paths, especially to view areas where movement options are constricted.

The primary rationales for increasing connectivity is to mitigate the effects of land cover fragmentation as well as to enhance the ability of species to move into new regions and consequently, decreasing the probability of extirpation or extinction (Auffret et al., 2015; Krosby et al., 2010). Managing connectivity to facilitate dispersal of organisms among green spaces is possible through the connection of ecological corridors with habitats or through actions that increase matrix traversability or permeability (Yu et al., 2012; Xun et al., 2014). These studies highlight that landscape ecology constitutes an effective approach to developing ecological networks in rapidly expanding cities. Moreover, the development of a green space connectivity model in an urban area based on a combined approach is regarded as one of the important frameworks in prioritising the urban biodiversity conservation strategies.

1.3 Aim, Research Questions, Objectives and Hypotheses

This research aims to understand the impact of rapid urban expansion on structure, function and connectivity of green space. It targets to develop models as diagnostic and decision support tools to help maintain the ecological functioning of the urban landscape. Accordingly, the following questions are addressed in this research:

a) How did green space change during a period of rapid urban expansion for the three cities in the last 25 years?

b) Is it possible to model and predict urban expansion in three cities (Kuala Lumpur, Jakarta and Metro Manila), and what are the main drivers in the resulting spatial patterns?

c) What decision support tools might help the urban environmental planning process to optimise the structure, connectivity and function of green spaces?

The objectives of this research are:

a) To evaluate the changes in spatial and structural patterns of green space in rapidly developing cities over the last two decades.

b) To model and predict urban expansion in three cities experiencing rapid expansion and to identify the main drivers including spatial planning in the resulting spatial patterns.

c) To identify potential priority corridors and to develop an ecological landscape connectivity model of green spaces.

With the above questions and objectives, three hypotheses are tested:

a) Rapid urban expansion negatively impacts the landscape structure of green space changes. Urban expansion results in increasing fragmentation and less connectivity between green spaces.

b) An integration of LCM-Markov chain modelling and spatial metrics is proposed as an effective model for simulating urban expansion. Historic and current master planning and future urban expansion have negative implications on green space structure.

c) Priority corridors are identified to have the potential for ecological landscape connectivity networks that can optimise structure, connectivity and ecological functioning of urban landscape.

1.4 Brief Description of Approach and PhD Thesis Structure

Overall, this study developed multiple combined approaches to assess the impact of rapid urban expansion on structure, function and connectivity of green spaces. The integrated approach of remote sensing, GIS, landscape ecology analytics, land change models and connectivity modelling was utilised to develop models as diagnostic and decision support tools for green spaces under rapid urban expansion. Furthermore, a comparative analysis was conducted on three cities generated by the models. This research is significant because it provides quantitative empirical information for urban planning and it contributes to the knowledge of landscape ecology science in urban systems.

The thesis consists of six chapters; three chapters were written as a collection of papers to achieve the objectives of the project. The chapters are continuous and are interlinked. The structure of this thesis clarifies its area of application and its potential benefits (Fig. 1.1 and 1.2).

Chapter 1 covers the background of the thesis and presents the updated literature review which captures the theory, concept and application of the research methods. This chapter provides aims, questions, research objectives and hypotheses of the study. The chapter also describes the location and geographical area of Kuala Lumpur, Malaysia; Jakarta, Indonesia; and Metro Manila, Philippines.

Subsequently, the land use/land cover maps of the study areas are utilised in Chapter 2 to address the first objective. The chapter examines the structure and pattern changes of green spaces using remote sensing, GIS and landscape ecology analytics. In this chapter, problems are identified, and the landscape structure changes are analysed and evaluated.

Chapter 3 uses the data analysis from Chapter 2 to address the second objective. This chapter verifies the model and simulates urban expansion using integrated LCM-Markov chain modelling incorporated with spatial metrics. This objective provides the potential drivers and an effective model for simulating urban expansion. The chapter addresses the important topic of rapid urban expansion and master planning in complex urban landscapes. It also aids the understanding on how models can be appropriately used as a valuable tool for this topic.

Consecutively, Chapter 4 develops the ecological landscape connectivity networks using the circuit theory, connectivity analysis and least-cost path models. The consideration of the spatial structure and ecological function of green spaces using the behaviour of target species in the connectivity models for landscape planning and design generates new patterns of evidence and hypotheses for further research. It also provides linkage for the supportive outcomes of biodiversity and green space. Consequently, the findings of this objective will influence the development of the decision support framework.

In Chapter 5, the key findings of each chapter objective are discussed. The chapter also explains the research limitations, the implication of the findings, and a perspective on future work required in this area. It highlights how the thesis has made an original contribution to the knowledge in the literature. It will guide the effective implementation of sustainable policies, planning and management of green spaces.

Finally, Chapter 6 states the overall conclusions of the thesis while summarising the achievements of each objective. It also delivers the key messages of this research and outlines the recommendations made in this study. Moreover, a discussion on the implementation of the model in Southeast Asian cities and other regions is presented.

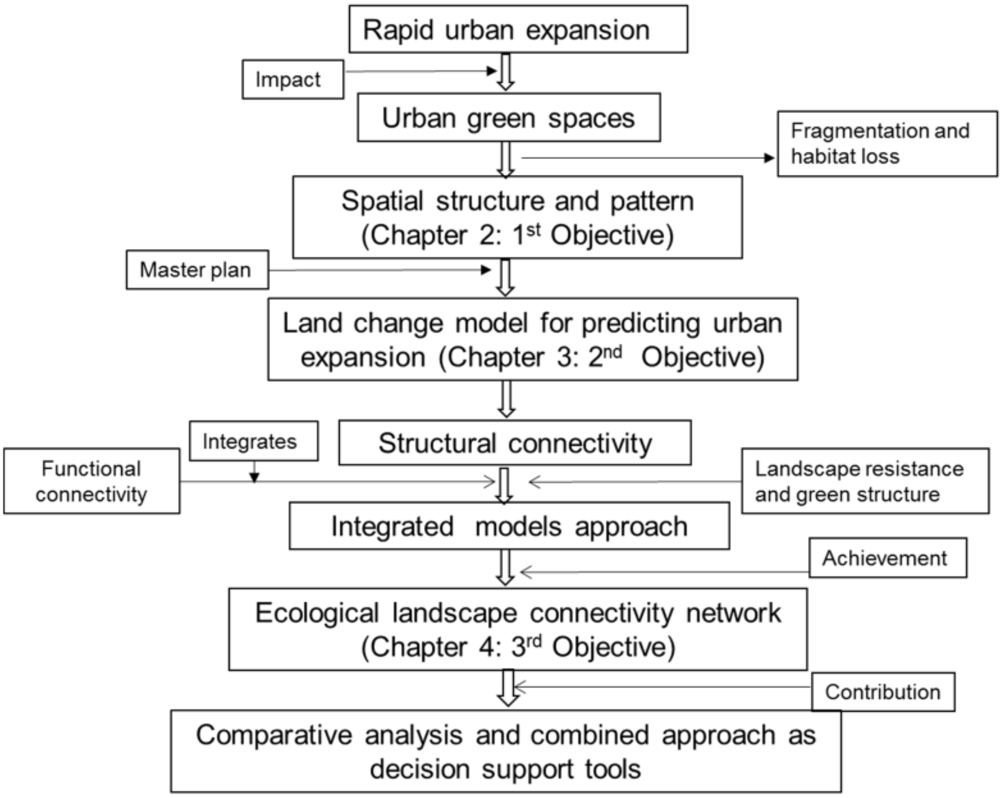

Figure 1. 1 Thesis framework

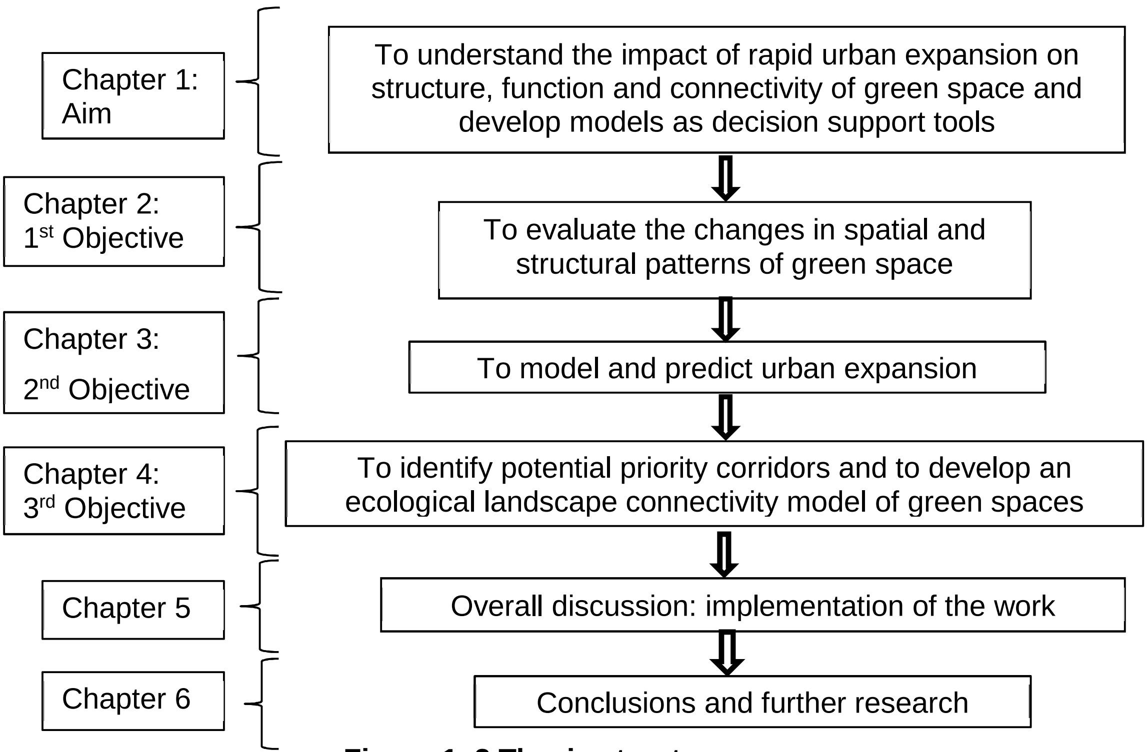

Figure 1. 2 Thesis structure

1.5 Study Area

This study focussed on three megacities in Southeast Asia; Kuala Lumpur City, Malaysia; Jakarta, Indonesia and Metro Manila, Philippines (Fig. 1.3). These cities were selected due to their rapid expansion, the emergence of urban regions, and the challenges posed by their economic growth, environmental degradation and their large social and environmental future challenges (Dahiya, 2012; McGee, 1995).

Kuala Lumpur City, the capital of Malaysia, is located at the confluence of the Klang and Gombak rivers, its total area measuring 23934 ha (239 km^2). The population of Kuala Lumpur in 2010 was estimated at 1.6 million (Department of Statistics Malaysia), and the Kuala Lumpur Structural Plan 2020 projects a population of 2.2 million inhabitants by 2020 (Kuala Lumpur City Hall, 2005). Jakarta, the capital of Indonesia, consists of five municipalities and lies in the lowland on the northwest coast of Java Island. The city occupies an area of 64000 ha (640 km^2). Jakarta has a flat terrain and the land gradually rises from 5 to 50 m above mean sea level (Murakami et al., 2005). The population was estimated at 9.7 million in 2012 (BPS DKI Jakarta Provinces, Indonesia). Metro Manila, the capital of the Philippines consists of eight contiguous cities, including Manila city and nine other municipalities, covering an area of approximately 63800 ha (638 km^2). The capital is located in the lowlands of Southwestern Luzon Island on the eastern coast of Manila Bay (Murakami et al., 2005). It has a population of 11.8 million according to the 2010 census of the Philippine National Statistical Coordination Board. Multi-year population data of Kuala Lumpur, Jakarta and Metro Manila were taken from the Department of Statistics (Department of Statistics Malaysia), the Bureau of Statistics (BPS DKI Jakarta Provinces, Indonesia) and the Philippine National Statistical Coordination Board, respectively. The administration of each of the three metropolitan areas were defined by the Global Administrative Areas (http://www.gadm.org/). The establishment date for the administrative definition of Kuala Lumpur, Jakarta and Metro Manila was on 1 February 1974 (Kuala Lumpur City Hall, 2005), 1974

(Government of Jakarta Region, 2011) and 2 June 1978 (MMDA, 2012) respectively.

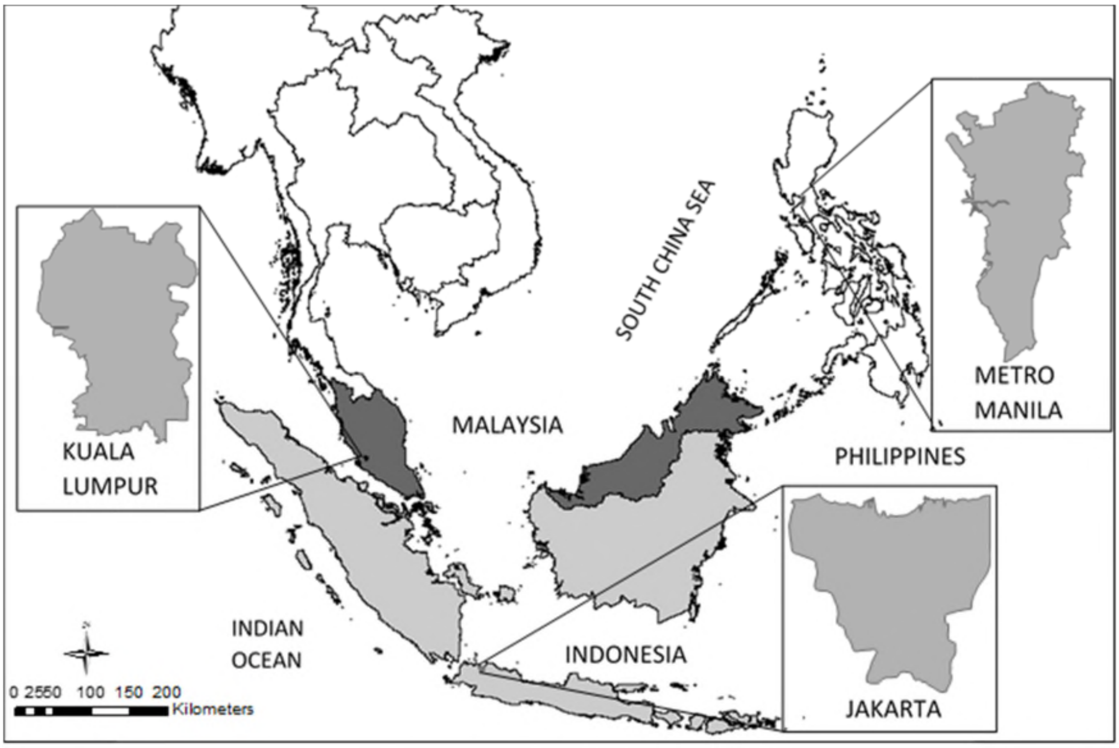

Figure 1. 3 Location map of the three cities in Southeast Asia

1.6 List of Outputs from Thesis

a) Authors: Nor, A. N. M., Harris, J., Perroto-Baldievieso, H., Grafius, D. R., & Corstanje, R.
Title: Evolution of green space under rapid urban expansion in Southeast Asia cities
Status: In preparation
Journal: *Landscape and Urban Planning*

b) Nor, A. N. M., Corstanje, R., Harris, J., & Brewer, T. (2017) Impact of rapid urban expansion on green space structure. In press. *Ecological Indicators*. 10.1016/j.ecolind.2017.05.031

c) Author: Nor, A. N. M., Corstanje, R., Harris, J., Grafius, D. R., & Siriwardena, G.
Title: Ecological connectivity networks in rapidly expanding cities.
Status: Accepted (8th June 2017)
Journal: *Heliyon*

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2 EVOLUTION OF GREEN SPACE UNDER RAPID URBAN EXPANSION IN SOUTHEAST ASIAN CITIES

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Abstract

Globally, rapid urban expansion has caused a significant decline of green space in urban areas. Rapid urban expansion affects the form and structural patterns of green space, however, how this occurs, and its contextual dependency are not well understood. This study evaluates the changes in spatial and structural patterns of green space in urban areas of Kuala Lumpur, Malaysia; Jakarta, Indonesia and Metro Manila, Philippines over the last two decades. The effect of rapid urban expansion on green space structure over three periods was analysed by determining the changes in landscape metrics at landscape, class and patch level based on land use/land cover maps. The percentage of green space in all three cities reduced in size as a function of rapid urban expansion over the 25 year period. Significant changes in green space structure were also observed particularly for Jakarta and Metro Manila. Here, green space gradually fragmented, became less connected and more unevenly distributed. These changes were not seen in Kuala Lumpur City. Overall, the impact of rapid urban expansion on green space was more significant in Jakarta and Metro Manila when compared to Kuala Lumpur. There are important differences in spatial distribution of green space in different cities, and there is evidence that this is at least partially due to management and planning policies. The use of integrated remote sensing, Geographical Information Systems (GIS) and landscape ecology

analytics provides significant insights into understanding the impact of rapid urban expansion on green space structure, and therefore, its functioning in Southeast Asian cities.

Keywords: change detection; urban green space; landscape, class and patch level metrics; planning, spatial patterns

2.1 Introduction

Globally, urban areas are expanding, undergoing rapid development with 65% of the world's population expected to be urban by the year 2025 (Angel et al., 2011). This development is predominant in the fastest growing economies and human populations, particularly in developing countries (Cohen, 2006). According to the United Nations Population Fund [UNFPA] (2007), 90% of urban population growth will be in Asia, Africa and Latin America with 80% of the world's largest cities being in these areas. In Southeast Asia, urbanisation has increased significantly in the last two decades as industry has become the focus for economic development (Sharifi et al., 2014). In this region the urban growth rate is 2.8% per year; relatively high versus developed regions of the world (UNDESA, 2012) and exhibiting different patterns of growth to well-studied developed cities (Cohen, 2006). This situation complicates the management of urban ecosystems and green spaces and potentially poses threats to the environment (Sharifi et al., 2014).

Urban green spaces support valuable functions and provide many different ecosystem services, offsetting the negative environmental and health effects of urbanisation while providing benefits to human well-being (Carrus et al., 2015). Rapid urban expansion profoundly transforms these spaces and can result in significant decline of green spaces (Ward et al., 2010). For example, cities in China have lost an estimated 47.1 km^2 of green space annually (1992 to 2004; Xu et al., 2011). As green spaces shrink and become fragmented within the built-up matrix, they suffer degradation in connectivity, biodiversity and ecosystem function (Tian et al., 2011). This degradation may reduce the quality of life of urban dwellers (Konijnendijk et al., 2004).

Changes in landscape structure are associated with patterns and processes at various spatial scales, so quantifying these changes is important for assessing the impact of rapid urban expansion on green space (Seburanga et al., 2014). However, it is not clear how interactions between rapid urban expansion patterns affect the amount and spatial distribution of green space. The examination of spatial information over time is one way to determine these relationships (Li et al., 2014). The size, shape and spatial configuration of green spaces help determine their resulting ecosystem service delivery as well as public perceptions, visiting patterns and their use (Lo & Jim, 2012).

Limited studies exist for Southeast Asian cities on the importance of green space structure. Previous studies in Asian countries and on large cities in China have focused primarily on urban expansion and social benefits of green space rather than understanding landscape structure (Lo & Jim, 2012; Yang et al., 2014). Less attention has been paid to middle-sized Southeast Asian cities, such as Kuala Lumpur, Jakarta and Metro Manila. These three cities are the capitals of their respective countries and their most important economic and political centres, and have developed rapidly in recent decades (Cohen, 2006). Mixing of land use and uncontrolled rapid growth are major features of Southeast Asian urban expansion (Estoque & Murayama, 2015), which is further typified by increasing populations and rural to urban migration (Sharifi et al., 2014). Sodhi et al. (2010) reported that among tropical regions, Southeast Asia has one of the highest rates of green space loss and deforestation. This loss is due largely to a lack of integrated land use and regional planning, the relatively weak structure of urban policy and the absence of a legal basis for controlling urban expansion (Zhou & Wang, 2011). The pace of development has largely surpassed the ability of policy to keep pace (Chen & Hu, 2015). While integrated city planning is available, it has generally been designed for developed Western cities and is not readily compatible with the considerations of rapidly growing cities (Sharifi et al., 2014). As such, studies of urban development in this region should consider the impacts of local planning policy in order to understand its effects on green space condition, extent and form (Estoque & Murayama, 2015). This is not only key to understanding the dynamics of the landscape, but can inform future urban planning enabling maintenance and expansion of ecosystem services and human well-being (Kowarik, 2011). Comparing changes in green space and urban development between similar but distinct cities is important to gaining a better understanding of how these changes are affected by different driving forces and framing conditions. Moreover, comparative analysis may lead to identifying policies that effectively protect and promote urban green space. Not least, it is hoped that comparative analysis will lead to results and conclusions that can be generalised and applied to different cities.

In order to understand the impact of urban expansion on green space in Southeast Asia, and to support local urban planning, this study used landscape structure analysis to address three objectives: i) to quantify changes in urban areas and green space spatial distribution in three rapidly growing cities in Southeast Asia; ii) to evaluate the impact of these changes to the structure of green space; and iii) to explore the impact of different types of urban expansion and planning policies on changes to green space structure. The results from this study may lead to new insights into the effects of rapid urban expansion on green space in the developing urban landscapes of Southeast Asia, and provide empirical support for more effective green space design and planning.

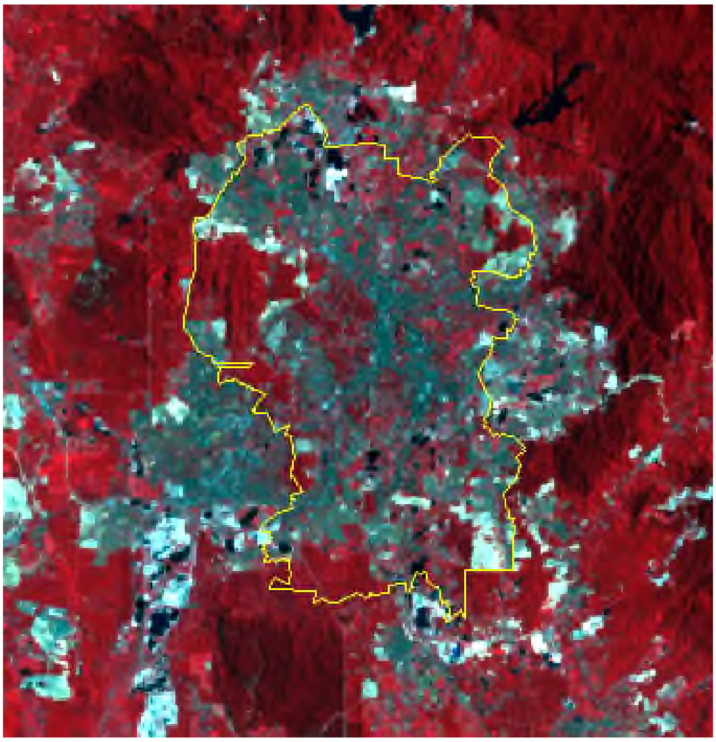
2.2 Data and Methods

2.2.1 Data Acquisition and Processing

Satellite imagery was used to obtain land use/land cover (LULC) information for the study areas. Landsat-5 Thematic Mapper 30 m imagery in 1988 and 1999 for Kuala Lumpur was obtained from the Malaysian Remote Sensing Agency (MRSA), and for Jakarta and Metro Manila in 1989 and 1999 were downloaded from the Global Land Cover Facility (http://glcf.umd.edu/). Landsat-8 Enhanced Thematic Mapper 30 meter images in 2014 for all three cities were downloaded from the U.S. Geological Survey (http://www.usgs.gov/).

Nine geocoded satellite images were processed using ERDAS Imagine 2014 (Intergraph Corporation, Madison, AL) and ArcGIS 10.2 (ESRI, Redlands, CA) to produce LULC maps for Kuala Lumpur, Jakarta and Metro Manila. This study used boundaries of the cities obtained from Global Administrative Areas (http://www.gadm.org/) to extract the area of interest from the images (Fig. 2.1). Multi-temporal satellite images were used to analyse the dynamics of urban landscapes, green space pattern and to monitor LULC changes. However, the selection bias of satellite images is a potential concern in this approach. The different selections of Landsat-5 Thematic Mapper year 1988 for Kuala Lumpur and 1989 for Jakarta and Metro Manila were chosen based on the availability of images according to cloud cover and image quality. Where available, high resolution imagery may produce more accurate results when conducting landscape analysis on urban green spaces (Myeong et al., 2003). Although high resolution images are available for 2014, 30 m Landsat images were chosen to standardise across the three periods as suitable high-resolution imagery was not available for all periods and areas of interest. The research demonstrates the potential applicability of Landsat Thematic Mapper data to urban studies and the value of 30 m imagery for the analysis of green space at the regional scale.

a)



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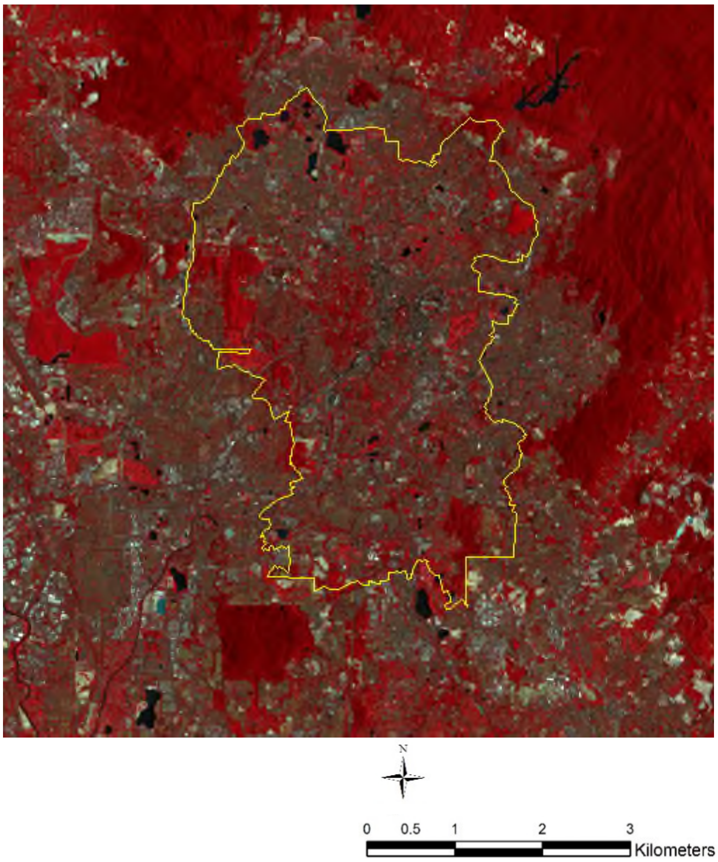

Figure 2. 1 Landsat images of Kuala Lumpur (the yellow line denotes the boundary of the city defined by Global Administrative Area-www.gadm.org); a) Landsat 5 (17.4.1988) shows the false colour composite image (Bands 4, 3 and 2) and b) Landsat 8 (7.6. 2014) shows the false colour composite images (Bands 5, 4 and 3).

The LULC classes (built-up area, green space, cleared land and waterbody) for each year were classified using maximum likelihood supervised classification (ERDAS Imagine, Hexagon Inc., Jensen, 1996). For this study, level 1 of the Anderson classification system was used (Anderson, 1976). This classification system is designed to rely mainly on remote sensing; therefore only land use/land cover types identifiable by remote sensing are used as the basis for organising this classification. Level 1 of the Anderson classification system is recommended for use with Landsat resolution data. The description of LULC in this study was modified from Rozenstein & Karnieli (2011) (Table 2.1).

Table 2. 1 Land use/land cover classification scheme (modified from Rozenstein & Karnieli, 2011).

Code	LULC Categories	Description
1	Built-up area	Areas with all types of artificial and impervious surfaces, including residential, commercial and industrial areas as well as transportation infrastructure.
2	Green space	All green area covered with forest tree, shrubs and grassland.
3	Water body	River, drain, reservoirs, lakes and pond.
4	Cleared land	Land with bare soil, bare exposed rock, quarries and disturbed ground at building sites and dirt roads (cleared but not developed or colonised by vegetation).

Here, green space is defined as any piece of land covered by vegetation within the built-up matrix of urban areas and large enough to be captured by the 30 m resolution of the sensor. Systematic sampling was used to collect training points from sample grids (1 km^2) created in ArcGIS (Fig. 2.2), ensuring an even distribution across the study area (Bodart et al., 2011).

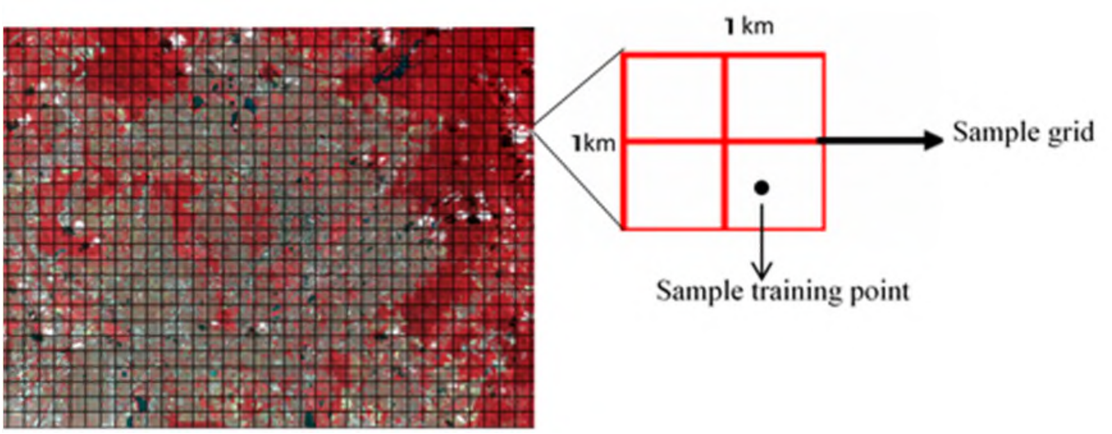

Figure 2. 2 Area frame sampling with systematic sampling (sample grid is the area sampling frame of 1 km x 1 km; sample training point is the point used for training signatures in supervised classification).

In the classification process Google Earth was used for reference. Ground-truth verification was performed using a stratified sampling method based on assistant datasets such as the Google Map to assess the accuracy of the generated land use maps. This is an effective way to ensure the accuracy assessment of a very large area and the cost limited (Li, 2014). Accuracy assessment produced statistical outputs to check the quality of the classification results (Tewolde & Cabral, 2011). These are based on an error matrix which compares class-by-class, based on the training samples and classification results. Validation samples for each class were identified in a stratified random sampling approach (Yang et al., 2014) in which 100 points were assigned to each LULC to avoid uneven distribution. The overall accuracy and kappa statistic were calculated to explain differences and improvements in the classification of images (Rozenstein & Karnieli, 2011). The overall classification accuracy was above 85% in the three years in the three cities. The accuracy of images in Kuala Lumpur was 88% in all three years. In Jakarta, the accuracy of the images in 1989, 1999 and 2014 was 87%, 88% and 85% respectively. In Metro Manila, the accuracy for 1989, 1999 and 2014 was 88%, 87% and 88% respectively. The 15% of inaccuracy resulted from misclassified pixels, which are inherent in medium-spatial resolution images (Estoque & Murayama, 2013). The spectral confusion occurs when several land use land cover classes share a similar spectral response (Hansen & Loveland, 2012). However, the levels of accuracy were within the standard range and at an acceptable level i.e., 85 to 90%. They therefore, enabled a certain degree of confidence in change detection analysis that involved the spatiotemporal changes of land use/land cover across the two time periods (Appendix B.4). Raster data was converted to vector format using ArcGIS. Finally, the LULC maps were analysed in order to study the spatial pattern evolution of green space.

2.2.2 Landscape Change Analysis

Change detection analysis was used to determine the amount of green space converted to urban areas and other land uses between 1988/1989 and 1999, and between 1999 and 2014 for each city. In this analysis, maps from two different years were overlaid, and a table containing the conversion of LULC was produced. This study used the following formula to calculate the proportional rate of change for each LULC (Li et al., 2014):

$$\boldsymbol{C} = \frac{\boldsymbol{A_j - A_i}}{\boldsymbol{A_i}} \qquad \textbf{(2. 1)}$$

where C represents the proportional change in LULC, and A_i and A_j represent the area of the land type in years *i* and *j*, respectively. This study used the following formula to calculate the changes per year in each LULC:

$$\boldsymbol{D} = \frac{\boldsymbol{1}}{\boldsymbol{n_j - n_i}} \times \frac{\boldsymbol{A_j - A_i}}{\boldsymbol{A_i}} \qquad \textbf{(2. 2)}$$

where D represents the change in each LULC per unit time, and n_i and n_j represent years *i* and *j*, respectively.

2.2.3 Landscape Structure Analysis

Landscape structure of the cities over the three periods (1988/1989, 1999 and 2014) was analysed at landscape, class and patch levels to quantify changes in the spatial structure of green space (McGarigal et al., 2002). Landscape level metrics are effective for quantifying the entire landscape while class level metrics analyse landscape patterns of each LULC individually (Su et al., 2012). Class level metrics provide more specific information about landscape spatial patterns, variations at the local level and the distribution of LULC (Abdullah & Nakagoshi, 2008). Patch level metrics are critical in understanding the mechanisms of landscape change (Perotto-Baldivieso et al., 2011) and important in determining significant changes between patches within a LULC class. Choices for appropriate landscape metrics are dependent upon the scale of analysis and objectives of the study (Abdullah & Nakagoshi, 2008). In this study, six metrics for landscape structure analysis were selected; percentage of area (PAREA; %), patch density (PD; no. of patches/100 ha), mean patch area (MPA; ha), largest patch index (LPI; %), landscape shape index (LSI; m/ha) and Euclidean nearest neighbour distance (MNN; m) (Table 2.2). The metrics were calculated using FRAGSTATS (Version 4.2; McGarigal et al., 2002). 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). Three metrics (MPA, LSI and MNN) were calculated at the patch level to represent patch structural relationships owing to size, shape and inter-patch distance (Table 2.2). These landscape metrics were used by Tian et al. (2014) to characterise changes in green space landscape characteristics such as size, shape and patch isolation. For statistical analysis, data was log-transformed due to non-normal distributions. Based on the landscape metrics, this study compared significant changes at the landscape level for each city in between 1988/1989 and 1999, and between 1999 and 2014 using a Kruskal-Wallis test (significance level 0.05). This study also compared the significant changes in LULC pattern at class level between 1988/1989 and 1999, and between 1999 and 2014 for each city. Furthermore, associations between population density (calculated by dividing the population by the size of the urban area), urban expansion, and changes in built-up area and green space were illustrated using a correlation graph (Fig. 2.8).

Table 2. 2 Landscape metrics used for landscape structure analysis (modified from McGarigal et al., 2002).

Metrics	Abbre-Viation	Description of Metric Level (Units)		
		Landscape Level Metrics (The landscape as a whole)	**Class Level Metrics (Each patch type (class) in the landscape)**	**Patch Level Metrics (Individual patch in the given class, where applicable)**
Percentage of area	PAREA (%)	n/a	The percentage of each patch type in the landscape. Proportional abundance of class	n/a

			types in the landscape.	
Patch density	PD	Number of patches per 100 ha.	Number of patches per 100 ha in that class.	n/a
Mean patch area	MPA (ha)	The area occupied by a particular patch type divided by the number of patches of that type. A function of the number of patches in the total area.	A function of the number of patches in the class and total class area.	A function of the difference in patch sizes among patches.
Largest patch index	LPI (%)	Area (m^2) of the largest patch of that type divided by total landscape area (m^2), multiplied by 100.	An indication of the dominance of the different land cover classes.	n/a
Landscape shape index	LSI (m/ha)	SHAPE equals patch perimeter (m) divided by the minimum perimeter of the corresponding patch area in a landscape. A measure of the overall geometric complexity of the landscape.	A measure of the overall geometric complexity of a focal class. It can also be interpreted as a measure of landscape disaggregation. The greater the value of LSI, the more dispersed the patch types.	LSI is one patch and any patch edges (or class edges) measured by the perimeter.
Euclidean Nearest-Neighbor Distance	MNN (m)	Distance (m) from a patch to nearest neighboring patch in a landscape.	The distance between a patch and its nearest neighbor of the same class, based on the distance between cell centers of the two closest cells from the respective patches.	MNN deals explicitly with the degree to which patches are spatially isolated from each other. The context of a patch is defined by the proximity and area of neighboring habitat patches; variation in nearest-neighbor distance among patches.

2.3 Results

2.3.1 Landscape Change Analysis

In 1989, the highest percentage of built-up area was in Metro Manila (56%) followed by Jakarta (41%) and Kuala Lumpur (35%; Figs. 2.3 and 2.5). Metro Manila had the smallest percentage of green space (31%), with similar values for Jakarta (46%) and Kuala Lumpur (45%). By 2014, the total urbanised area was almost doubled that of 1989 and the built-up area in Jakarta and Metro Manila (86% and 84% respectively) exceeded Kuala Lumpur (76%). Green space in Jakarta and Metro Manila was < 10%, and 20% for Kuala Lumpur (Fig. 2.5).

The total urbanised area increased by 31 to 73% in the period from 1988 to 1999 in all three cities; a higher rate of expansion than the latter 1999 to 2014 period (15 to 41%; Figs. 2.4 and 2.5). Over the same period, green space area was reduced by more than 30% in all three cities. The change rate of green space in Kuala Lumpur was smaller than Jakarta and Metro Manila. In Kuala Lumpur, decrease of green space was greater in 1988 to 1999 (36%) compared to 1999 to 2014 (30%). In Metro Manila and Jakarta, green space decreased by 62% and 54% respectively between 1999 and 2014 (Figs. 2.4 and 2.5). In the period from 1988 to 2014, cleared land in Kuala Lumpur and Metro Manila decreased by 72% and 38% respectively. However in Jakarta, cleared land increased by 70% between 1989 and 1999 and decreased by 7% in the period from 1999 to 2014. Waterbody in Kuala Lumpur, Jakarta and Metro Manila decreased by 31%, 42% and 59% respectively between 1988 and 2014.

In the period from 1988 to 1999, more than 10% of green space was converted to built-up areas in the three cities (Table 2.3). The highest conversion of green space to built-up areas was in Jakarta (25%) compared with Kuala Lumpur (17%) and Metro Manila (12%) (Table 2.3). Built-up areas converted to green space were highest in Kuala Lumpur (4%), followed by Metro Manila (1.8%) and Jakarta (0.8%) (Table 2.3). Built-up areas showed great persistence (i.e. no conversion or changes to another LULC over time) of 26% to 53%, and were only approached by green space, with a persistence of 15% to 22% in the cities (Table 2.3).

In the period from 1999 to 2014, the conversion of green space to built-up areas were smaller in Jakarta (12%) and Metro Manila (10%) when compared with Kuala Lumpur (19%) (Table 2.3). Despite this, the remaining green space in Kuala Lumpur was still highest (11%) compared to Jakarta (5.7%) and Metro Manila (6.6%). However, the conversion of built-up areas to green space showed a different transformation pattern in Kuala Lumpur as the percentage of this change is substantially larger (6%) when compared to Jakarta (0.7%) and Metro Manila (1.3%; Table 2.3). This conversion was the main contribution to the remaining green space in Kuala Lumpur.

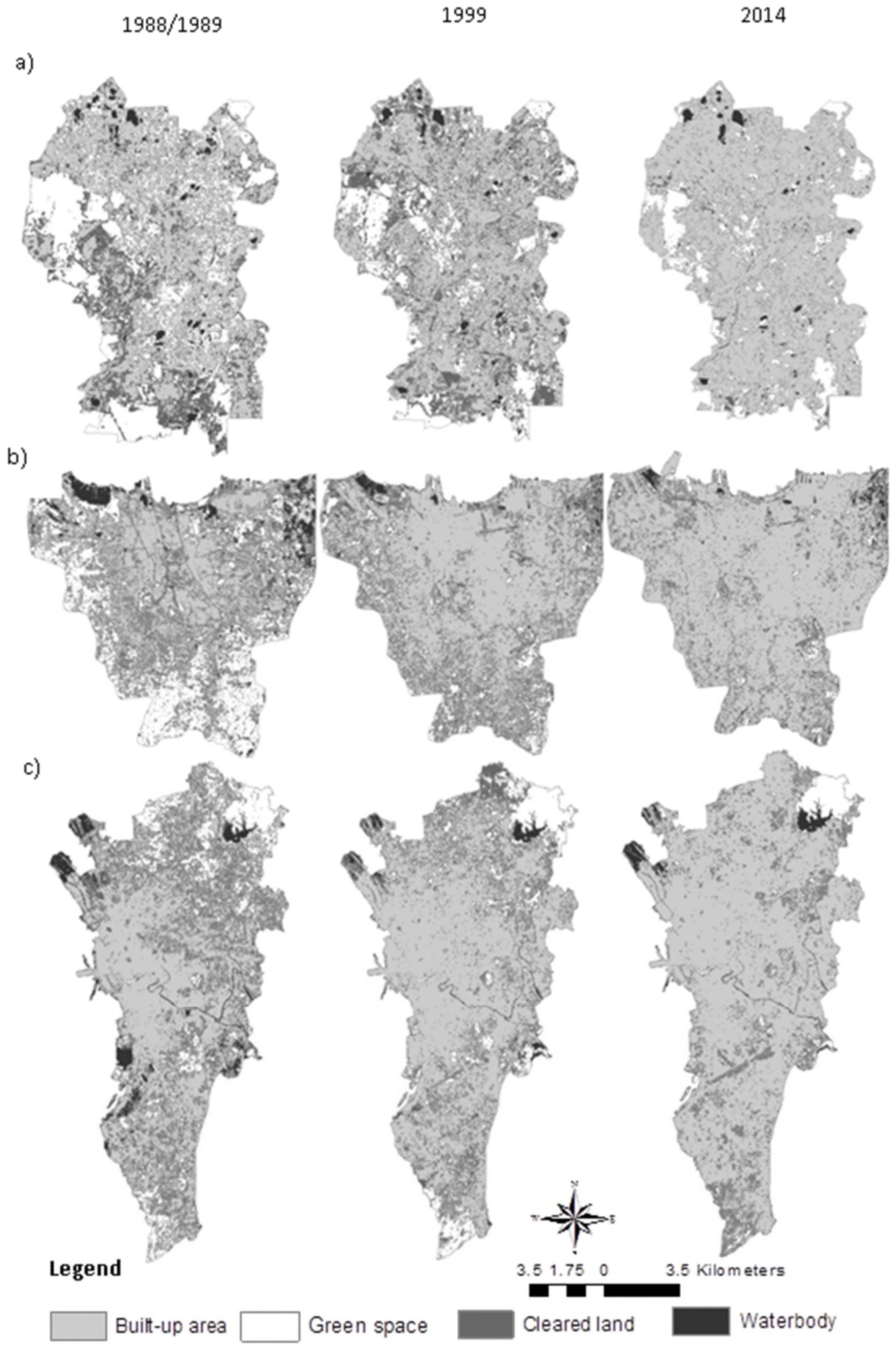

Figure 2. 3 Land use/land cover maps in three year periods in a) Kuala Lumpur b) Jakarta and c) Metro Manila.

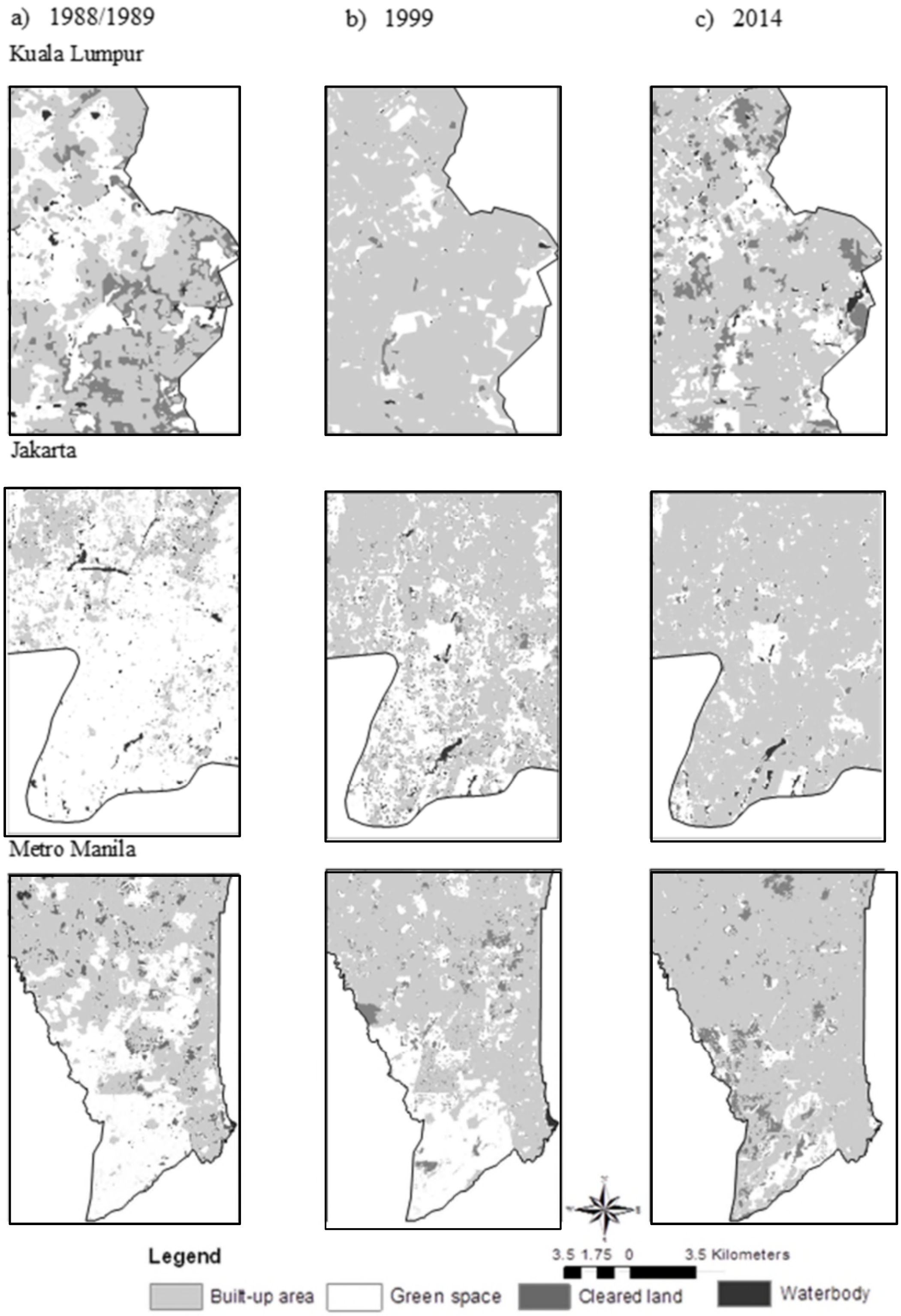

Figure 2. 4 Detailed map of changes in green space patches in a) 1988/1989 b) 1999 and c) 2014 in Kuala Lumpur, Jakarta and Metro Manila.

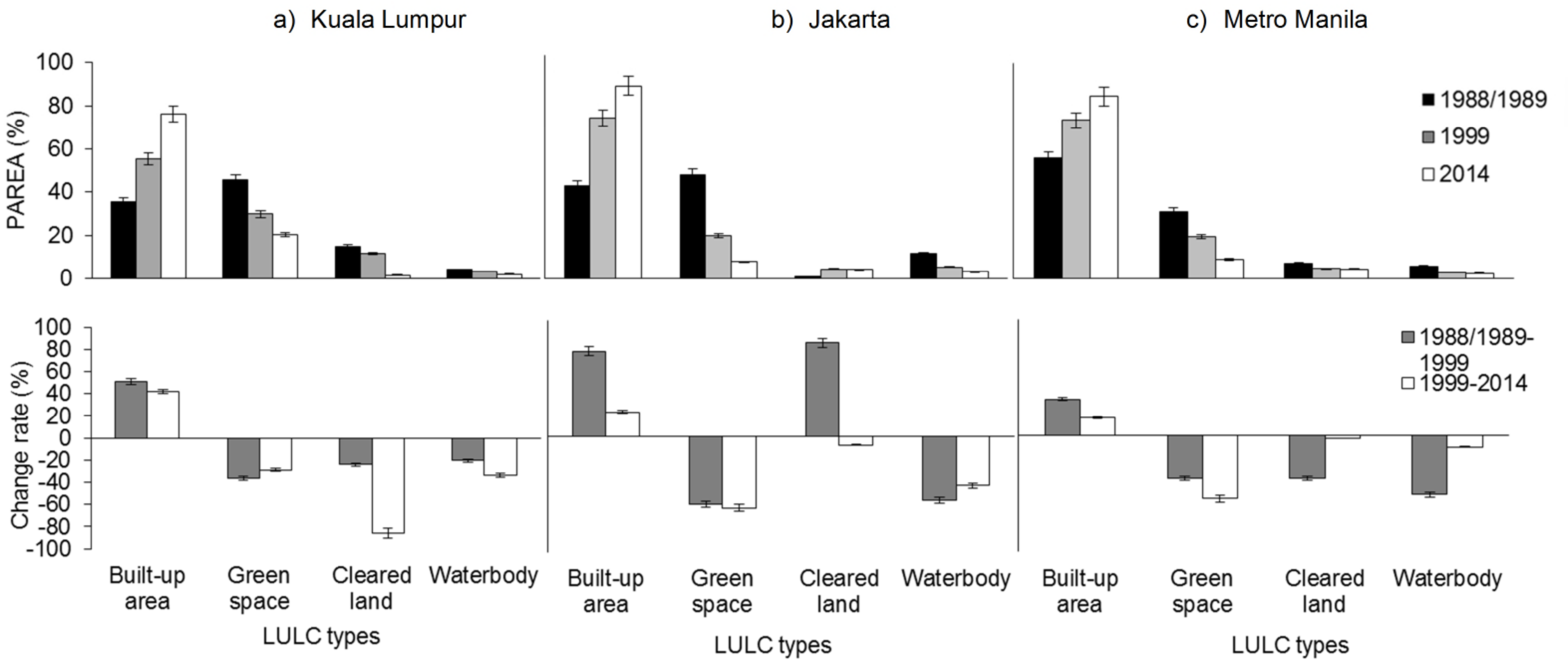

Figure 2. 5 Percentage of area and change rate of land use/land cover types (using formula *C* and *D* in landscape change analysis) in three cities in 1988/1989, 1999 and 2014.

Table 2. 3 Comparison of change detection in three cities.

Landscape Changes	Kuala Lumpur	Jakarta	Metro Manila
1988-1999			
Green space to built-up area	17%	25%	12%
Built-up area to green space	4%	0.8%	1.8%
Green space persistence	22%	16%	15%
1999-2014			
Green space to built-up area	19%	12%	10%
Built-up area to green space	6.0%	0.7%	1.3%
Green space persistence	11%	5.7%	6.6%

2.3.2 Landscape Structure Analysis

At the landscape level, PD ($p<0.05$) increased from 11 to 14 patches/100 ha and MPA significantly ($p<0.05$) decreased from 9 to 6 ha in Kuala Lumpur between 1988 and 1999. However, between 1999 and 2014, PD decreased (14 to 13 patches/100 ha) and MPA increased (6 to 7 ha) significantly ($p<0.05$; Fig. 2.6). The pattern was similar in Jakarta, PD increased (3 to 4 patches/100 ha) and MPA decreased (26 to 25 ha) significantly ($p<0.05$) between 1989 and 1999. However, between 1999 and 2014, PD decreased (14 to 13 patches/100 ha) and MPA increased (6 to 7 ha) significantly ($p<0.05$; Fig. 2.6). By contrast, PD decreased and no significant changes (p>0.05) in MPA were observed in Metro Manila over the study period. LPI increased over the study period in all three cities. Similar significant changes in MNN were seen in Jakarta (102 to 221 m), Kuala Lumpur (102 to 223 m) and Metro Manila (124 to 269 m) in the period from 1988 to 1999. The MNN continues to increase in Jakarta (221 to 225 m) between 1999 and 2014. Conversely, values decreased significantly between 1999 and 2014 in Kuala Lumpur (223 to 188 m) and Metro Manila (296 to 240 m). LSI decreased in Jakarta and Metro Manila, but increased significantly (p<0.05) in Kuala Lumpur over the study period (Fig. 2.6).

At the class level, changes in green space structure were similar for Metro Manila and Jakarta, but different for Kuala Lumpur. In all three cities, PD increased (Kuala Lumpur, 1 to 6 patches/100 ha; Jakarta, 1 to 2 patches/100 ha; Metro Manila, 1 to 3 patches/100 ha) and MPA decreased (Kuala Lumpur, 38 to 5 ha; Jakarta, 48 to 13 ha; Metro Manila, 26 to 8 ha) in the period from 1988 to 1999, indicating that the green space was fragmented (Fig. 2.7). The decline in MPA has been significant in all three cities in the period from 1988 to 1999. However, PD decreased (6 to 5 patches/100 ha) and MPA increased (5 to 6 ha) in Kuala Lumpur in the period from 1999 to 2014 were not statistically significant (p>0.05; Fig. 2.7). The value of PD and MPA values decreased in Jakarta (1.3 to 1.2 patches/100 ha) (2 to 1 ha) and Metro Manila (13 to 5 patches/100 ha) (8 to 4 ha) in the period from 1999 to 2014 respectively indicating the disappearance of green spaces. LSI increased (p>0.05) in the period from 1988 to 2014 in Kuala Lumpur. Compared to Jakarta and Metro Manila, LSI increased significantly (p<0.05) in the period from 1989 to 1999 and decreased in the period from 1999 to 2014 (Fig. 2.7). The patch size was smaller (LPI decreased) in the period from 1988 to 1999 but slightly increased in the period from 1999 to 2014 in Kuala Lumpur. However in Jakarta and Metro Manila, the patch size also became smaller (LPI decreased) in the period from 1989 to 2014. In Jakarta, the increase of MNN (306 to 393 m) between 1989 and 2014 indicated that green space inter-patch distance increased. By contrast, MNN decreased in Kuala Lumpur (81 to 39 m) and Metro Manila (161 to 135 m) (p<0.05) in the period from 1988/1989 to

1999. Conversely, MNN increased ($p<0.05$) in Kuala Lumpur (39 to 67 m) and Metro Manila (135 to 179 m) in the period from 1999 to 2014 (Fig. 2.7).

In Kuala Lumpur and Metro Manila, built-up PD values decreased and MPA values increased significantly ($p<0.05$) in the period from 1988/1989 to 2014, indicating a coalescence of built-up patches due to increase in built-up area cover (Fig. 2.7). In Jakarta, built-up areas were expanded more in the period 1989 to 1999 than 1999 to 2014. In all three cities, the increase of LPI and MPA showed that built-up patches coalesced owing to gains made from adjacent green space areas. In Kuala Lumpur, LSI increased significantly ($p<0.05$) in the period from 1988 to 2014 indicating greater variation among shapes at the edges of built-up areas. Compared to Jakarta and Metro Manila, LSI decreased for the same period (Fig. 2.7). In Kuala Lumpur, distance between built-up patches to the nearest patch (MNN) decreased in the period from 1988 to 2014. In Jakarta, MNN decreased ($p>0.05$) in the period from 1989 to 1999 but increased in the period from 1999 to 2014. In contrast to Metro Manila, MNN increased in the period from 1989 to 1999 and then decreased in the period from 1999 to 2014. Concurrently, the population in Jakarta and Metro Manila increased substantially along with the corresponding spatial urban extension trends (Fig. 2.8). The results showed that connections exist between population and urban expansion, due to the similarity in trends of population density and the spatial structure of built-up areas in Jakarta and Metro Manila.

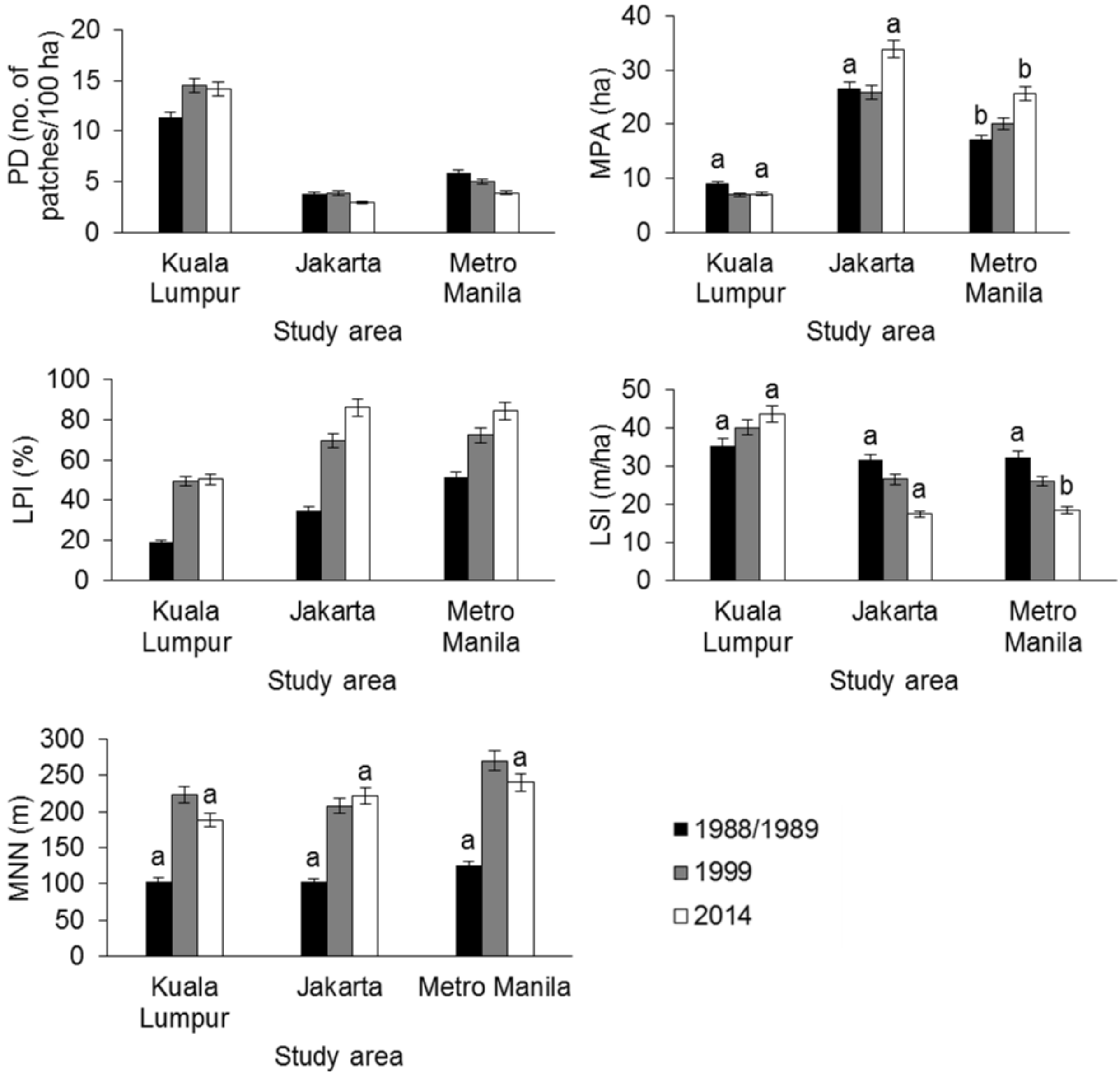

Figure 2. 6 Comparison of metrics at landscape level for each city (letters; a, b) indicate statistical differences with a significance level of 0.05 for MPA, LSI and MNN; the letters 'a' above bars indicate the significant changes (p<0.05); the letters 'b' above bars indicate no significant changes (p>0.05) between patches in the period from 1988 to 1999, and 1999 to 2014) [Patch density (PD); Mean patch area (MPA); Landscape shape index (LSI); Largest patch index (LPI); Euclidean nearest neighbour (MNN)].

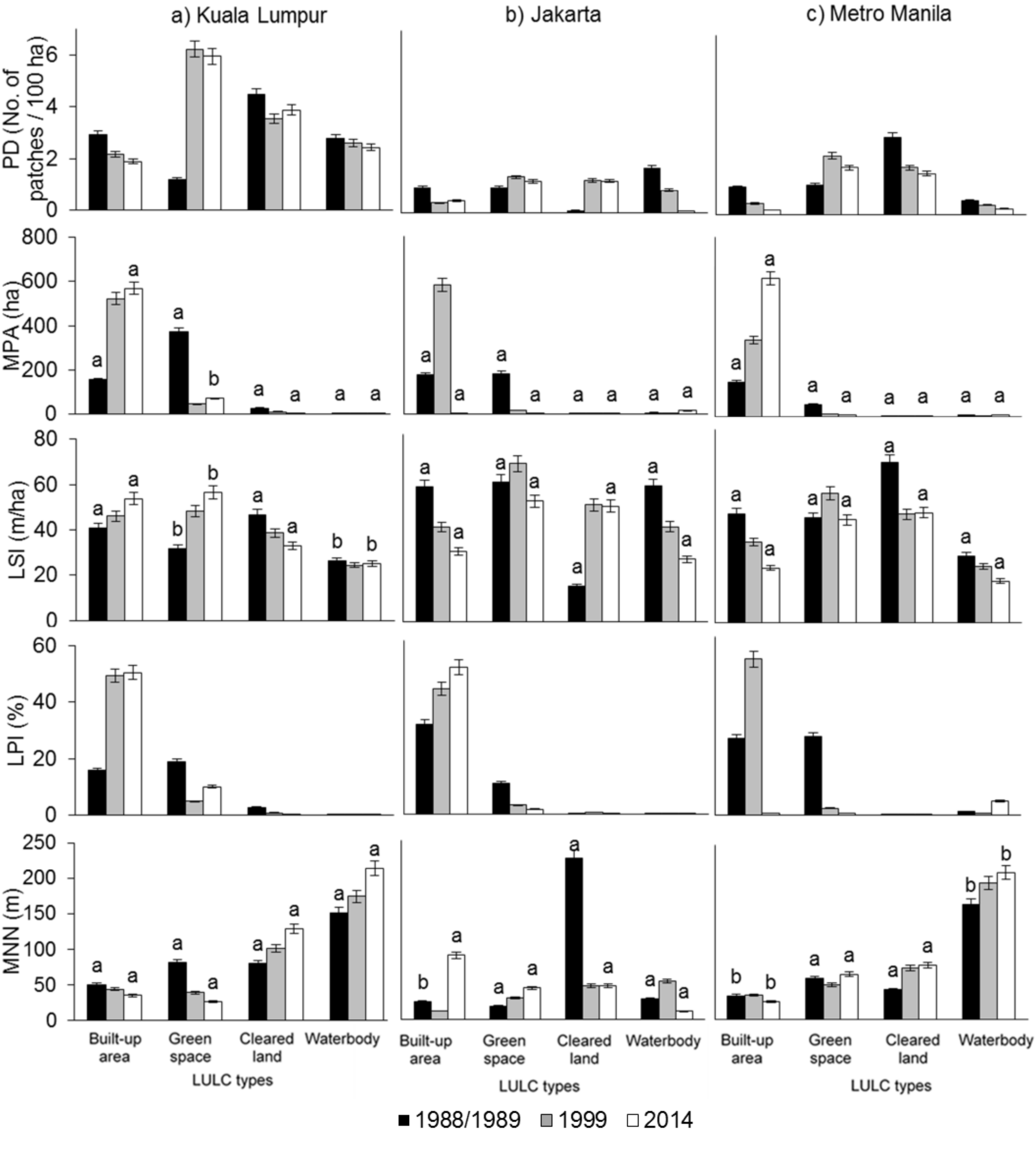

Figure 2. 7 Comparison of metrics at class level for each city (letters; a, b) indicate statistical differences with a significance level of 0.05 for MPA, LSI and MNN; the letters 'a' above bars indicate the significant changes (p<0.05); the letters 'b' above bars indicate no significant changes (p>0.05) between patches in landscape

structure in the period from 1988 to 1999, and 1999 to 2014 [Patch density (PD); Mean patch area (MPA); Landscape shape index (LSI); Largest patch index (LPI); Euclidean nearest neighbour (MNN)].

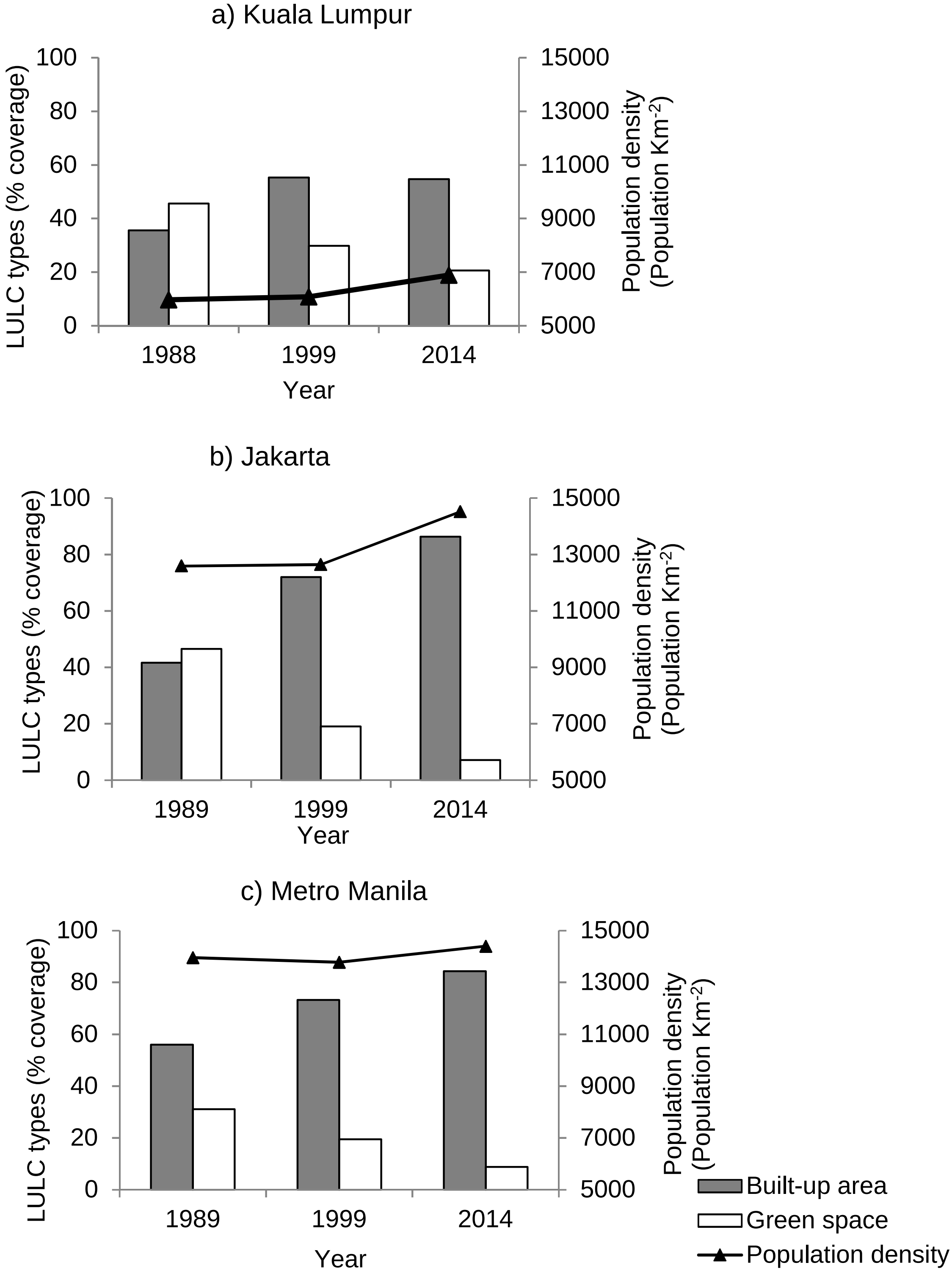

Figure 2. 8 Correlation between built-up area, population density and green space in three periods in a) Kuala Lumpur b) Jakarta and c) Metro Manila.

2.4 Discussion

In three cities of Kuala Lumpur, Jakarta and Metro Manila, the built-up areas expanded and encroached on green space, reducing green space by more than 30% over the 25-year period. Metro Manila saw the greatest reduction in green space over the study period, followed by Jakarta and Kuala Lumpur (Figs. 2.3, 2.4 and 2.5). This is comparable to other Asian countries: for example the trends of green space between 1990 and 2010 in 30 major Chinese cities showed that 46.9% of original vegetation cover was converted to other land cover types (Yang et al., 2014). Similar results occurred in Greater Dhaka, Bangladesh (Byomkesh et al., 2012); Sapporo, Japan (Rupprecht & Byrne, 2014); Mumbai, India (Shafizadeh Moghadam & Helbich, 2013) and Hong Kong (Tian et al., 2011) with green space losses ranging from 10% to 50%. The results from these studies suggest that economic growth, population increases, urbanisation and weakness in planning, controlling and managing urban development are factors in green space loss (Byomkesh et al., 2012; Uy & Nakagoshi, 2007). While exact definitions of 'green space' varied between studies, they are largely comparable in the above examples in referring to vegetated areas within the urban matrix (Jim & Chen, 2006; M'Ikiugu et al., 2012). Despite the importance of green space, urban growth and urban densification are contributing to the reduction and isolation of green space structure in these study areas. Although green spaces are considered important in Asian cities, there is a potential that green spaces may become encroached and therefore too small and isolated to maintain their environmental and social effectiveness (Lo & Jim, 2012; Tian et al., 2011).

This research interprets various patterns of green space change and sequences of changes in rapidly expanding cities. These observations can lead to an increased understanding of green space dynamics and their relation to ecological processes. In all three cities, green spaces have fragmented, shrunk, complicated and dissected as indicated by increased patch density (due to the presence of many smaller patches) and landscape shape index, but reduced mean patch area and largest patch index between patches in the period 1988 to 1999. The distance between green patches increased in Jakarta but decreased in Kuala Lumpur and Metro Manila. Small patches then disappeared in Jakarta and Metro Manila but not in Kuala Lumpur. In contrast, the distance between patches increased and patch density declined in all three cities in the later period from 1999 to 2014. These results demonstrate the ecological processes of attrition (loss of habitat patch) and isolation (Forman, 1995) of green space in the cities.

Spatially, green space loss was not random and appeared to take place primarily on the urban fringes in Jakarta and Metro Manila (Figs. 2.3 and 2.4). Sharifi et al. (2014) found that migration of people from rural to urban areas increased the population density in the urban fringe and caused rapid development there. Based on visual observation (Fig. 2.3) in Kuala Lumpur and Jakarta, the changes in green space spatial pattern mostly occur at the west and south of boundaries of the cities. According to Kuala Lumpur City Hall (2005), industrial and economic development took place in the west of Kuala Lumpur as it is a conurbation with the growing state of Selangor, and the new administration centre of Putrajaya was developed at the South of Kuala Lumpur. A new town development initiated by the early 1990s called Bukit Jonggol Asri (Beautiful Jonggol Hills) has reinforced spatial segregation in the south of Jakarta (Firman, 2014) and might influence spatial pattern changes. In Metro Manila, rapid land use conversions took place in the urban fringe particularly in the north, which started in the 1990s, because of the development of residential sub-division lots and agricultural lands (Malaque & Yokohari, 2007) resulting in green space loss.

The observed changes in the cities correspond to increasing population density, indicating the relationships between urban expansion, population density and green space change (Fig. 2.8). Population increased more than 20% in Jakarta and Metro Manila in the period from 1989 to 2014 which is the main driving force of the urbanisation process (Murakami et al., 2005). These observations would therefore suggest that both rapid urban development and increasing population density accounted for the process of green space change in the urban boundaries similar to the results observed by Zhou & Wang (2011). In these types of cities urban planning therefore needs to pay particular attention to the urban fringe where the impact of increasing population density on land cover change may be the most drastic.

When comparing the three cities, different patterns of changes in overall landscape structure were found at different scales, cities and years in response to rapid urban expansion, policies and population density. Fragmentation in Jakarta was evidenced by larger patch density and smaller mean patch area values in 1988 than in 1999 suggesting rapid expansion during this period (Fig. 2.6). This coincides with policies for the integrated metropolitan-level development initiated in the mid-1970s and early 1980s by the Local Preparation Bureau for Development in Jabodetabek Metropolitan Area, the Presidential Decree on Development of the Jabodetabek Area, and the construction of new road infrastructure (Hudalah & Firman, 2012). In 2008, new green open spaces policies were developed but with a stronger focus on natural areas than urban green space (Pribadi & Pauleit, 2015). The Kuala Lumpur Structure Plan 1984 resulted in a similar transformation of landscape structure: green space was highly fragmented between 1988 and 1999; however between 1999 and 2014 the patches were aggregated, coinciding with an increase in population density in the period from 1988 to 1999 and stabilised in the period from 1999 to 2014. These trends in population change are theorised to have driven rapid urban expansion and development in the city during the earlier period (Fig. 2.8). By contrast, lower fragmentation and increasing inter-patch distance in Metro Manila over the study period suggests that patches were aggregated or eliminated due to the later establishment of development plans (Development Framework Plan for Metropolitan Manila; 1996 to 2016). These would suggest that the different sizes, fragmentation degree, and densities of landscape features found in the three cities are related to the establishment of master planning and policies in the cities.

The changes in green space structure were observed differently in each city at the class level as well. Generally, green space structure has gradually fragmented, and become more unevenly distributed. Recent conversions to green space from other LULC in Jakarta may result from planning regulations enacted in 2007. Spatial planning laws 26/2007 and 174/2007 relate to the planting and maintaining trees for 2010 to 2030 (Rukmana, 2015) and involve the development and maintenance of urban forests, parks and agricultural areas (Mutiara & Isami, 2012). Metro Manila also saw slower conversion of green space to built-up areas in the recent period. There, planning policies started in 1996, such as the Physical Development Framework Plan for Metropolitan Manila (1996 to 2016) and Metro Manila Green Print 2030, were established to provide a framework and recommendations for the use of land and other resources (MMDA, 2012). However, the continued green space decline, which almost doubled in the period from 1999 to 2014 (Fig. 2.5) suggests that the policies are currently inadequate; despite these planning efforts, urban expansion continues at the expense of green space (Estoque & Murayama, 2015). In contrast, the Kuala Lumpur Structural Plan 1984 began earlier in Kuala Lumpur than the other cities and with a greater emphasis on providing green space (Kuala Lumpur City Hall, 2005). As a result, some of the area and distribution of green space structure in this city has increased between 1999 and 2014 (Fig. 2.7). In 2000, Kuala Lumpur City Hall launched a programme to plant trees along major roads and develop more parks and play areas, to further increase the amount of green space (Fig. 2.4) (Kuala Lumpur City Hall, 2005). Nevertheless, built-up areas in Kuala Lumpur have expanded at greater rates than green space structure resulting in the dislocation and continued isolation of green space (Fig. 2.7). According to Haq (2011), the municipalities in Kuala Lumpur tend to focus on the beautification of green spaces and landscaping that increase property values and financial returns for land developers and thereby attract foreign investments that have contributed to the rapid economic growth.

A wider recognition of the environmental and social value of connected green space is needed by policy makers to maintain biodiversity and secure ecological and cultural benefits (de la Barrera et al., 2016). The correlations between the observed landscape trends and the policy history of each city suggest that differentiated policies should be formulated to guide reasonable expansion of urban land. This study therefore has regional policy relevance and practical planning implications for the current management of green space structures in urban landscapes. Such research can help us better understand the driving mechanisms of urban land expansion in compact cities, thus having important implications for policy, urban planning and management of green space in Southeast Asia and similar countries. Studying these relationships from a dedicated policy perspective could prove valuable for better understanding the realised and detailed effects of planning policies on the development of green space patterns in rapidly developing expansion cities (Shu et al., 2014).

The drastic changes faced by green space structures in the three cities have powerful implications for the ecological and social functioning of the cities. The increased size of built-up area affects the ecological function of individual patches of green space through its effects on edge and core habitat (Fry et al., 2009), producing a poor quality landscape with irregular patches and an uneven distribution of green space in the cities (Byomkesh et al., 2012). A significant increase of landscape shape index of built-up area and green space was observed in the period from 1988 to 2014, creating a more complicated landscape in Kuala Lumpur relative to Jakarta and Metro Manila (Fig. 2.7). Landscape shape index is an important metric to characterise landscape change, being a standardised measure of total edge which increases without limit as patches become more disaggregated and is essentially a descriptor of connectivity and spatial heterogeneity in the landscape (McGarigal et al., 2002). The complexity of shapes is a dimension for both ecological function and visual character (Fry et al., 2009). For example, boundary shape influences ecological processes, and hence species composition and relative abundances (Turner et al., 2001) and also affects the spatial distribution of edge species and interior species (Forman & Godron, 1986). Pattern complexity describes the spatial relationships between patches and is important to ecological functions with regards to the movement of species across landscapes (Forman, 1995; Fry et al., 2009). Growing evidence from previous research suggests that these changes are making the cities vulnerable to natural hazards such as flooding (Perotto-Baldivieso et al., 2011), loss of biodiversity and important species (Sodhi et al., 2010), degraded functioning of the ecosystem, effects on the climate of the cities, as well as contributing to atmospheric pollution and degrading the provision of ecosystem services (e.g. climate regulation and cooling effect) (Su et al., 2012). This would intensify the urban heat island effect, pose a major public health threat and reduce the quality of environmental health and life of urban residents (Lee & Maheswaran, 2011).

Conversely, the increases in shape variation and patch size of green space in Kuala Lumpur may attract more people to use those spaces, as residents have been found to prefer large parks and attractive design (Peters et al., 2010). Green spaces with complicated shapes could bring people closer to nature, improve their physical and mental health and provide diverse visual and amenity resources (Tian et al., 2014). Previous studies in Asia found that the characteristics, diversity and variety of structures in the green networks such as size, distance and shape contribute to its perception and use resulting in progressive physical, cognitive and social functioning of urban residents, hence offering improved well-being (Jim & Chen, 2006; Lo & Jim, 2012; Tian et al., 2014). The increase in distance between green space patches in all three cities in the later period of 1999 to 2014, however, suggests an isolation of green space patches. If these trends continue, Metro Manila and Jakarta may both be at risk of losing green space function through decreased accessibility to green space for amenity, leisure and recreation as demonstrated by Tian et al., (2011) in Hong Kong. It is important to provide residents with more access to green space near their homes and localised patterns of use in municipal and neighborhood parks (Wright Wendel et al., 2012) for leisure and recreation (Sreetheran & van den Bosch, 2014). Thus, it is clear that the structure, form and shape of green space patches are fundamental components of the urban green networks and important indicators to characterise the need for green space. This study illustrates the usefulness of spatial structure and pattern metrics of city development for green space planning and design to the use and value placed on green space, especially for Southeast Asian people and other related developing countries.

Strategies for future studies should focus on optimising the configuration of green space structure (shape, density and connectivity) in ways which increase their amount and can improve their spatial distribution for conservation and rehabilitation of ecological functions and networks in urban areas. Additionally, the impacts of planning policies on green space development patterns could be valuable to explore from a dedicated policy perspective as discussed above. Planning policies may have had mixed influences on the development of green space structure, and understanding their dynamics at regional or city-wide scales in the different time periods is important to the improvement of green space policies. A more developed understanding of linkages between policy drivers and landscape change could potentially enable the use of these metrics as an early warning system for the degradation of urban ecosystems.

2.5 Conclusions

This study sought to i) quantify changes in the spatial distribution of urban green space in three Southeast Asian cities over the past two decades, ii) evaluate the impact of changes to green space structure, and iii) explore the impact of urban expansion, population density and planning policy on changes to green space structure. This work has shown that built-up areas expanded and encroached on green space in all three cities studied here, reducing green space by more than 30% over the past 25 years. These changes have affected green space structure differently in each city. Jakarta and Metro Manila exhibited the highest percent coverage of built-up areas and a greater impact of urban expansion on green space structure than Kuala Lumpur, with green space structure gradually fragmenting to become less connected and more unevenly distributed. Relationships between urban development and spatial structure in Southeast Asian cities are believed to be heavily driven by population density, planning and policy. This work has shown how landscape metrics that have been widely applied in landscape ecology, but hitherto not widely applied to urban areas in Southeast Asia, have a significant capability to quantify green space dynamics and assess its spatial and temporal changes. This new information could be potentially used to assess current policies and inform new policies for the development and maintenance of green space structure and its network in urban areas. This could contribute to maintaining or improving current ecological functions and networks for the provision of ecosystem services in rapidly developing cities such as the ones in this study. Additional drivers of change such as socioeconomic factors should be emphasised in future studies to solidify the understanding of the driving relationships between society, policy and landscape change. Similar studies in other cities, regions and cultural realms would also be valuable for exploring the diversity of urban landscape dynamics and relationships around the world and informing sustainable policy and planning.

An understanding of historical green space changes, and the policy contexts surrounding them, can inform future policy and thus serve as early warning systems for ecological degradation in urban areas. Temporal patterns of change, in turn provide empirical support for urban design for human and ecological well-being. However, it is clear from the results that, in the absence of sustainable planning and without adequate regulatory control, green space have been encroached upon by urban development and sprawl, decreased in size, and become increasingly fragmented. Southeast Asia’s urban green areas require more attention, especially near the urban boundaries, and are critically important for improving ecosystem function and residential quality of life within the urban landscape.

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3 IMPACT OF RAPID URBAN EXPANSION ON GREEN SPACE STRUCTURE

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Abstract

Rapid urban expansion has had an impact on green space structure. A wide variety of modelling approaches have been tested to simulate urban expansion; however, the effectiveness of model validation and simulation of the spatial structure and pattern of urban expansion remains unexplored. This study aims to model and predict urban expansion in three cities (Kuala Lumpur, Metro Manila and Jakarta) experiencing rapid expansion using the integration of Land Change Modeler (LCM) with Markov chain models and identify which are the main drivers, including spatial planning, in the resulting spatial patterns. LCM-Markov chain models were used, parameterised on changes observed between 1988/1989 and 1999 and verified with the urban form observed for 2014 to simulate urban expansion for the year 2030. The spatial structure of the simulated 2030 land use was compared with the 2030 master plan for each city using spatial metrics. LCM-Markov chain models proved to be suitable for the simulation of future land use. There were also important differences in the predicted 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 rapid urban expansion and respective master planning policies of the municipalities in 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.

Keywords: Land Change Modeler, Markov chain, landscape metrics, spatial structure and pattern, simulated model, master planning and policies

3.1 Introduction

Globally, rapid 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 (UNDESA, 2012). Cities have grown rapidly in size and density (Turrini & Knop, 2015) and in some developing countries, cities have tripled in size (Seto et al., 2012). Specifically, in Southeast Asia, the urban expansion rate is 2.8% and highly comparable to many urbanised regions of the world (Cohen, 2006; UNDESA, 2012). Consequently, green space has come under pressure during the urbanisation process and this negatively affects ecosystem services, cultural associations, psychological well-being and the public health of urban dwellers (Tian et al., 2011). The conversion of green spaces into built-up areas has become one of the major reasons for habitat destruction worldwide (Turrini & Knop, 2015) and therefore, it is important to monitor and understand the spatial complexity of an urban ecosystem under rapid urban expansion (Li et al., 2013).

Urban dynamics, planned or unplanned have caused changes to the structure, shape and functions of built and non-built areas (Madureira et al., 2011). The relatively weak structure of urban policy poses challenges for the adoption of appropriate urban management strategies. Uncoordinated master planning strategies often contain a lack of information on the past, present and future changes to the urban and green space structure. 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. Therefore, monitoring and managing of changes are important and master planning should be revised to provide a more realistic account of the existing situation and the future of rapid urban expansion.

The planners often employ simulation modelling to forecast the future of urban expansion for improving land management policies and practices (Bhatti et al., 2015). Many modelling techniques have been applied to simulate urban changes, for example, Artificial Neural Networks (ANN), Markov chain models, Multi-Layer Perceptron (MLP), Land Change Modeler (LCM) and cellular automata models (Losiri et al., 2016; Roy, 2016; Triantakonstantis et al., 2015). While these models have potential for urban planning, it is difficult to reach this potential in practice because there is a lack of empirical evidence to determine the impacts of planning scenarios in rapidly expanding cities. Accordingly, although these different techniques have been employed to quantify the impact of urban expansion on green spaces, the effect of urban planning as one of the key controls of rapid urban expansion are less understood (Zhou & Wang, 2011).

The integration of remote sensing, Geographical Information System (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). Here, this study developed a spatial tool to distinguish the effects of master planning strategies under a rapid urban expansion scenario. This study used Land Change Modeler (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 land use/land cover (LULC) types, and the process relies on the historical transitions and past changes (Renslow, 2013), as there is evidence that urban land use depends on the historical development process of each city (Madureira et al., 2011; Niemelä, 2014).

As a landscape becomes urbanised, 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 spatial urban characteristics and patterns in the rapidly expanding cities based on the characterisation of spatial patterns (size, density, shape and distance of patches), such as fragmentation of the adjacent green space, shape complexity and variety, urban compaction, aggregation, dispersion and isolation (Aguilera et al., 2011). The quantification of landscape structures using the spatial metrics in a simulated model (Kong et al., 2012) is an important aspects in assessing, understanding and monitoring the spatial effect of master planning on rapid urban expansion.

In this regard, this study aims to: (1) test the applicability of integrated LCM-Markov chain models for three cities (Kuala Lumpur, Malaysia; Jakarta, Indonesia; and Metro Manila, Philippines) undergoing rapid expansion 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 compare the simulated rapid urban expansion potential with proposed master plan 2030 based on spatial metrics. This study also identifies the main drivers, including spatial planning, in the resulting spatial patterns.

3.2 Methods

3.2.1 Methodological Framework

In this study, LULC were modelled using the Land Change Modeler (LCM) software package (Eastman, 2006; available as ArcGIS 10.2 extension, http://www. clarklabs.org) to derive the simulation maps (Eastman et al., 2005; Pérez-Vega et al., 2012; Shooshtari & Gholamalifard, 2015). The LULC modelling procedures consisted of two stages (Fig. 3.1). 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 models enable the comparison of the actual map for 2014 with the results from the simulated model to verify future simulations. This study assessed the evidence of spatial effects of the master plan on rapid urban expansion patterns by examining the differences between the predicted spatial patterns of urban expansion and the actual expansion observed for 2014 based on physical and geographical features (e.g. distance from roads). Next, the second stage involved the modelling of potential change using actual LULC maps of 1999 and 2014 to simulate the LULC in the year 2030 (15 years interval) and comparing this with the 2030 master plan map using landscape metrics to detect differences in spatial structure.

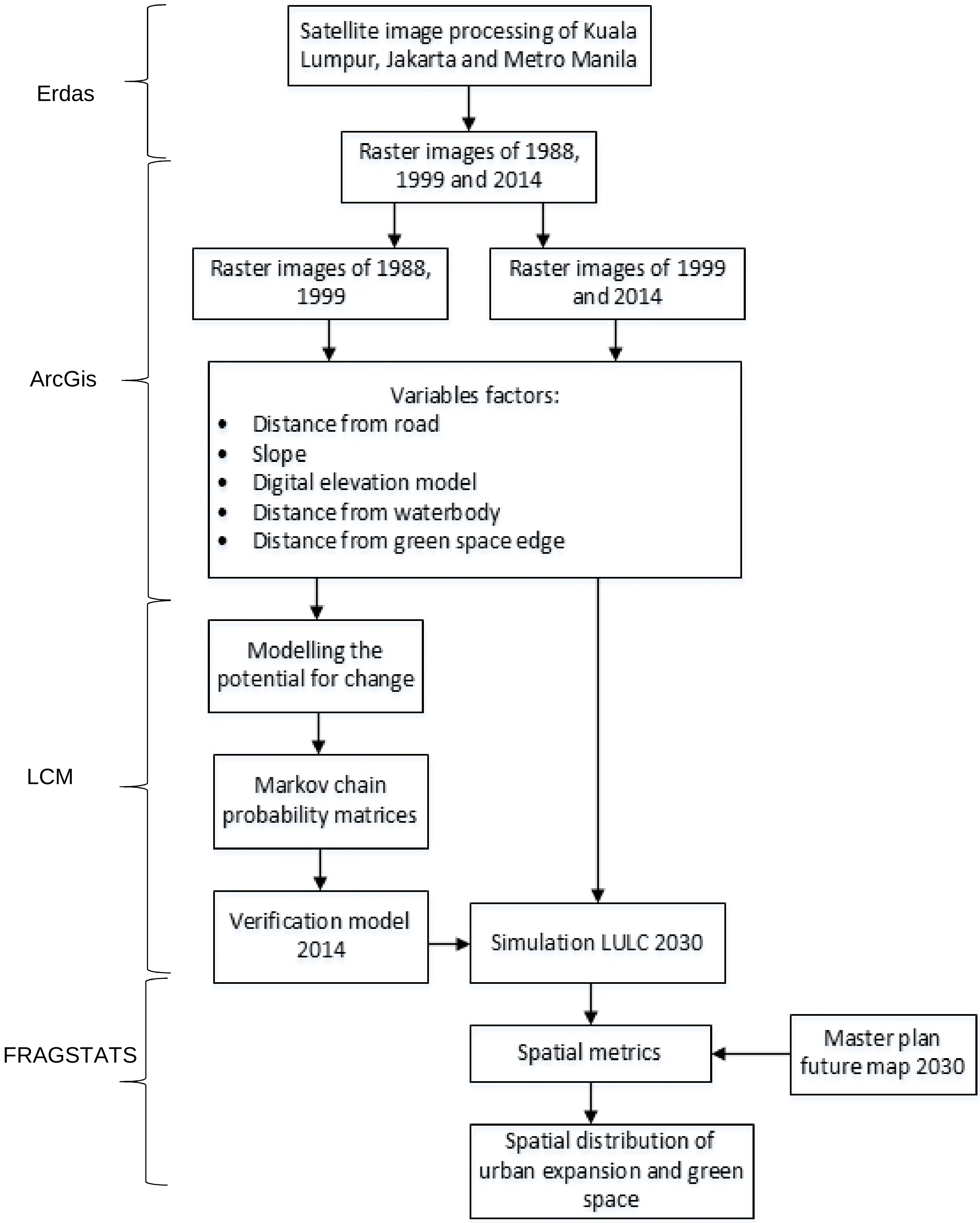


Figure 3. 1 Methodological framework

3.2.2 Data Acquisition and Processing

Land use/land cover maps of 1988/1989, 1999 and 2014 (obtained from chapter 2) were used to predict future LULC of 2030 for each study area. The master plan maps for each city were obtained from the each city authority (Kuala Lumpur City Hall, 2005; MMDA, 2012; Government Jakarta Region, 2011). The LULC were reclassified into three types: built-up area, green space and waterbody (Table 3.1), to match the LULC types used on the digitised master plan maps for 2030. These data sets were converted to vector and raster grid file formats for simulation and spatial structure analysis.

Table 3. 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.

3.2.3 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 & Gholamalifard, 2015). The variables used to derive this include: 1) distance from green space edge, 2) distance from roads, 3) slope, 4) terrain height and 5) distance from waterbodies (Appendices B.1, B.2 and B.3). These physical factors in urban systems are used to determine the potential spatial distribution of urban land growth and green space because they are static compared to the other variables such as socio-economic (Mitsova et al., 2011). The evidence of spatial effects of the urban master plan was assessed on rapid urban expansion pattern by examining the differences between the predicted spatial patterns of urban expansion and the actual expansion observed for 2014, based on physical and geographical features (e.g. distance from roads). The physical drivers were incorporated in the LCM which is less complex, faster and a more understandable process when compared to most modelling techniques (Eastman, 2006; Triantakonstantis et al., 2015).

All input datasets were prepared at 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 the developed area to produce and analyse 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 to the distance to roads. Road network development is the most important spatial factor affecting urban land expansion (Gao & Li, 2011; Han et al., 2009). The green spaces are also more fragmented where built-up areas are in close proximity to roads. This implies that the changes in LULC are mainly related to the physical accessibility factor (transportation through roads). The urban expansion also tends to occur at the edge of the green spaces. Slopes 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 & Yarnal, 2009), as well as infrastructure development which is related to urban expansion and an increase in the built-up areas. The pattern of landscape fragmentation is also influenced by the pattern of slopes where there is an increase in human activities on the lower slope angles (Gao & Li, 2011). Terrain height (Thapa & Murayama, 2011) and distance from waterbodies (Yin et al., 2011) are also considered as important factors as development tends to occur in areas of high elevation to avoid the risks of flooding (Perotto-Baldivieso et al., 2011).

Based on this concept, maps of variables were produced using the 'Euclidean Distance' tool in ArcGIS 10.2. These maps were imported to raster format and the drivers were incorporated in the LCM as explanatory driver variables of change for a particular transition (Uddin et al., 2015). Cramer's V analysis was used to measure the association between LULC and the previously described drivers of change quantitatively in a particular land transition (Bhatti et al., 2015; Eastman, 2012; Friehat et al., 2015). The majority of variables had acceptable associations (Cramer's V value > 0.15) with 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, showing a strong association with land cover change.

The probability of LULC change for the period 1988/1989 to 1999 was modelled using an Artificial Neural Networks (ANN) approach based on the Multi-Layer Perceptron (MLP). The advantages of using a MLP are that it is a system capable of modelling complex relationships between the variables, nonlinear relationships among variables can be modelled (Joshi et al., 2011) and it is the most robust for potential transition modelling (Eastman, 2009). As a result, potential transition modelling maps were generated for each LULC (see Appendix B.4). The probability values vary in the range between 0 to 1, where there was less potential for transition if the value was near 0 or the potential for the transition was higher if it is near 1 (0: non-incidence and 1: incidence) (Appendices B.4 and B.6). The root-mean-square-error (RMSE) and the overall accuracy rates of the MLP were used as statistical measures to evaluate the accuracy of the potential transition modelling. In this study, most of the RMSE values were below 0.4 and the overall accuracy rates were more than 80% (see Appendix B.5).

3.2.4 Model Verification

Before the simulation and assessment of the future scenarios, it was necessary to evaluate the reliability of the LCM-Markov chain models and the relevant variable settings (Pérez-Vega et al., 2012; Pontius et al., 2011; Pontius & 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 & Millones (2008), a comparison of the agreement and disagreement between maps was adopted by using the validation module in LCM to evaluate the 2014 simulated result compared to the actual LULC. This study revised the terminology used to describe the outputs from the analysis to aid the interpretation of the results (Table 3.2). The high levels of agreement achieved allowed the simulation of future scenarios to be carried out with considerable confidence to their reliability (Zhang et al., 2011).

Table 3. 2 Interpretation of agreement and disagreement in the validation map

LCM Validation Module Terminology	Revised Terminology	Interpretation
Hits	Agreement	Model simulated change and it changed
False alarm	False negative	Model simulated persistence and it changed
Misses	False positive	Model simulated change and it persisted
None	Persistence	Model simulated persistence and it persisted

3.2.5 Comparison of Simulated Urban Expansion 2030 and Master Plans Using Spatial Metrics

After the LCM model was verified, a similar process was conducted for the stage 2 to simulate 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 for transition in the period from 2014 to the simulated date, based on the projection of the potential future transition and the probability of change through the creation of the transition probability file. This is a matrix that records the probability of each LULC category changing into every other category (Araya & 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 both 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). This study used class level metrics to provide more specific information about landscape spatial patterns on built-up area and green space. 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 standardised 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 defines the connectivity, isolation and dispersion between the patches (Aguilera et al., 2011; Paudel & Yuan, 2012).

3.3 Results

3.3.1 Model Verification

In this 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%, with 4% false negative, and 10% false positive (Table 3.3; Fig. 3.2). In Metro Manila, the combined agreement and persistence was 87%, and the false negative and false positive were 4% and 9%, respectively.

Meanwhile 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 3.3; Fig. 3.2). The Kuala Lumpur results showed less agreement because the changes may influenced by the Kuala Lumpur Structural Plan 1984, which had started earlier than the plans in 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 the road in the year 2000 and highway infrastructure (Kuala Lumpur City Hall, 2005). Many of the false negative results as shown in Figure 3.2a can be seen following linear features. Overall, the low level of disagreement (false negative and false positive) indicated that the model and the relevant variable settings were appropriate. The accuracy of the simulated LULC results was deemed to be acceptable allowing the model to be used to simulate LULC in the future of urban expansion.

Table 3. 3 Percentage and area (ha) of agreement

Study Area	Agreement		Persistence		False Negative		False Positive	
	Area (ha)	**%**	**Area (ha)**	**%**	**Area (ha)**	**%**	**Area (ha)**	**%**
Kuala Lumpur	3977	16	12925	54	3235	12	4515	18
Jakarta	8 038	12	48 249	74	2350	4	6495	10
Metro Manila	6012	10	43383	77	2133	4	4977	9

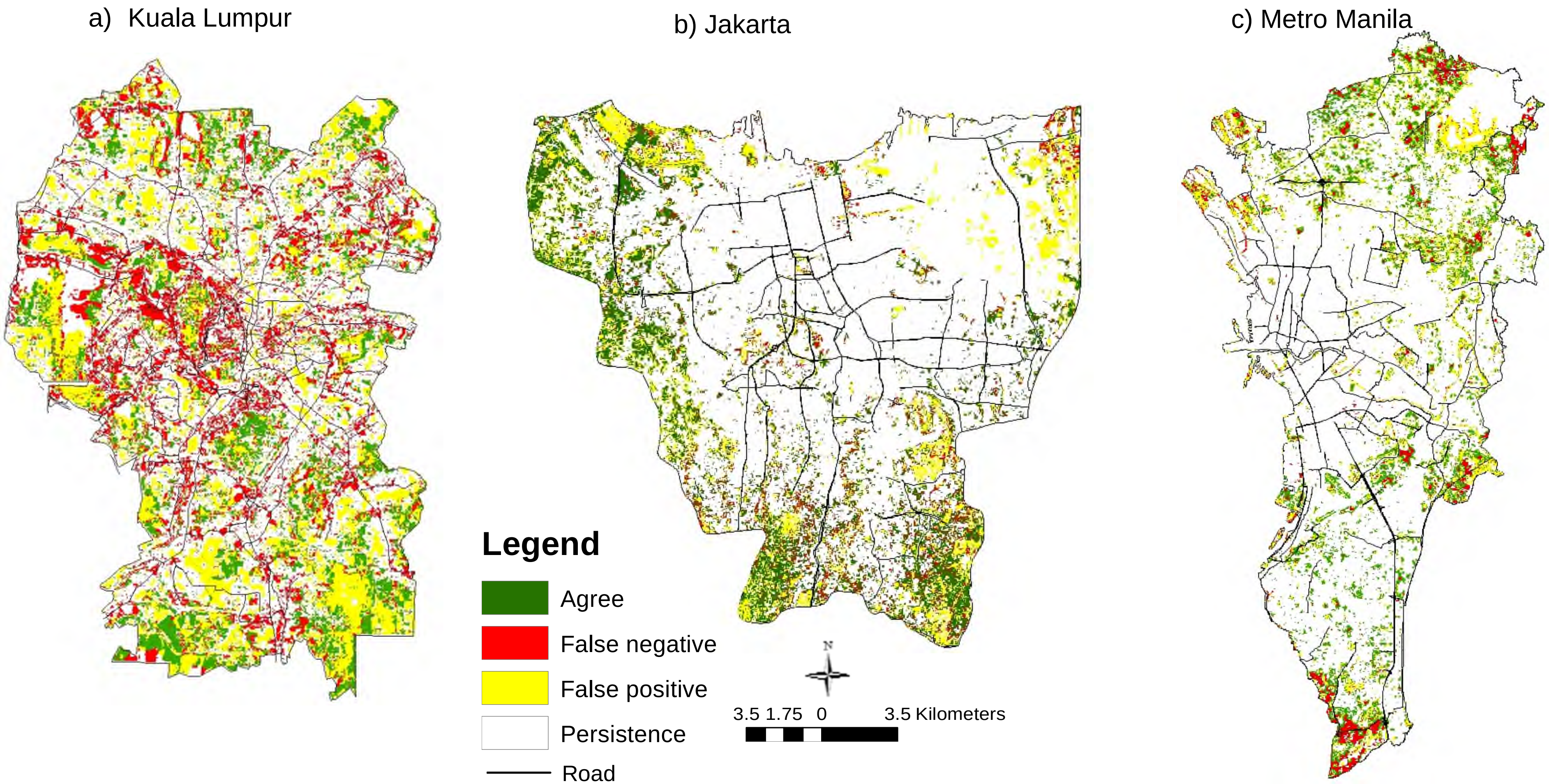


Figure 3. 2 Verification of LCM-Markov chain potential change of 2014 in a) Kuala Lumpur, b) Jakarta and c) Metro Manila.

3.3.2 Comparison of Simulated Urban Expansion 2030 and Master Plans Using Spatial Metrics

In 1989, the highest percentage of built-up areas was in Metro Manila (63%) followed by Kuala Lumpur (50%) and Jakarta (42%) (Figs. 3.3 and 3.4). Conversely, Metro Manila had the smallest areas 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 area was almost doubled in Kuala Lumpur, while the green space decline in Jakarta had more than doubled compared to the extent in 1989 (Figs. 3.3 and 3.4).

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. 3.3). 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. 3.3). 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. 3.3 and 3.5). 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. 3.3 and 3.5).

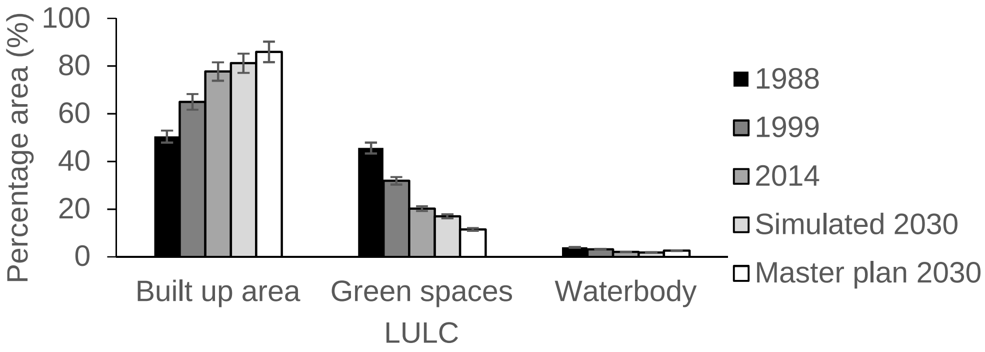
In the 2014 to 2030 time period, a major change is predicted from green space to built-up areas in Jakarta, Metro Manila and Kuala Lumpur with the Markov chain values of 0.79 (4115 ha), 0.76 (3898 ha) and 0.47 (2617 ha), respectively (Tables 3.4 and 3.5). The Markov chain value for the transition from built-up areas to green space was the highest in Kuala Lumpur (0.09) compared with Jakarta and Metro Manila (0.01) (Tables 3.4 and 3.5).

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. 3.6). In Kuala Lumpur, the landscape metric values of the built-up areas showed that the largest patch index (LPI) and the

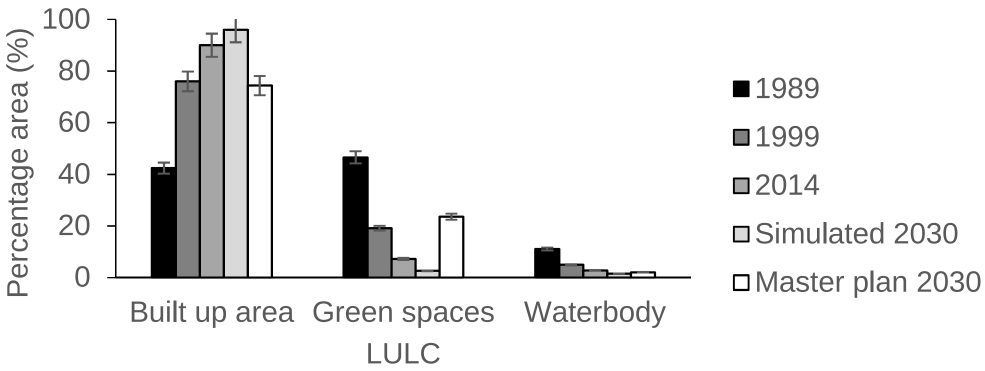
Euclidean nearest neighbour (MNN) were higher in the master plan compared with the simulated 2030 data. Meanwhile, the landscape shape index (LSI) and the mean patch area (MPA) were lower in the master plan compared with the simulated 2030 data (Fig. 3.6). This indicates that the patch size and distance 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 less dispersed and compacted built-up areas exhibiting a variety of shapes, 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.

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 shapes 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. 3.6). 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, the 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. 3.6), 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.

a) Kuala Lumpur



b) Jakarta



c) Metro Manila

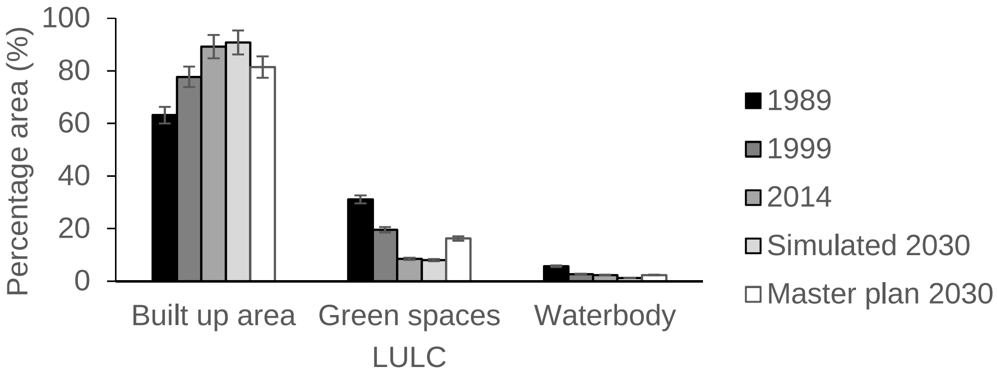


Figure 3. 3 The percentage area of LULC in 1988/1989, 1999, 2014, simulated 2030 and master plan 2030 for a) Kuala Lumpur, b) Jakarta and c) Metro Manila.

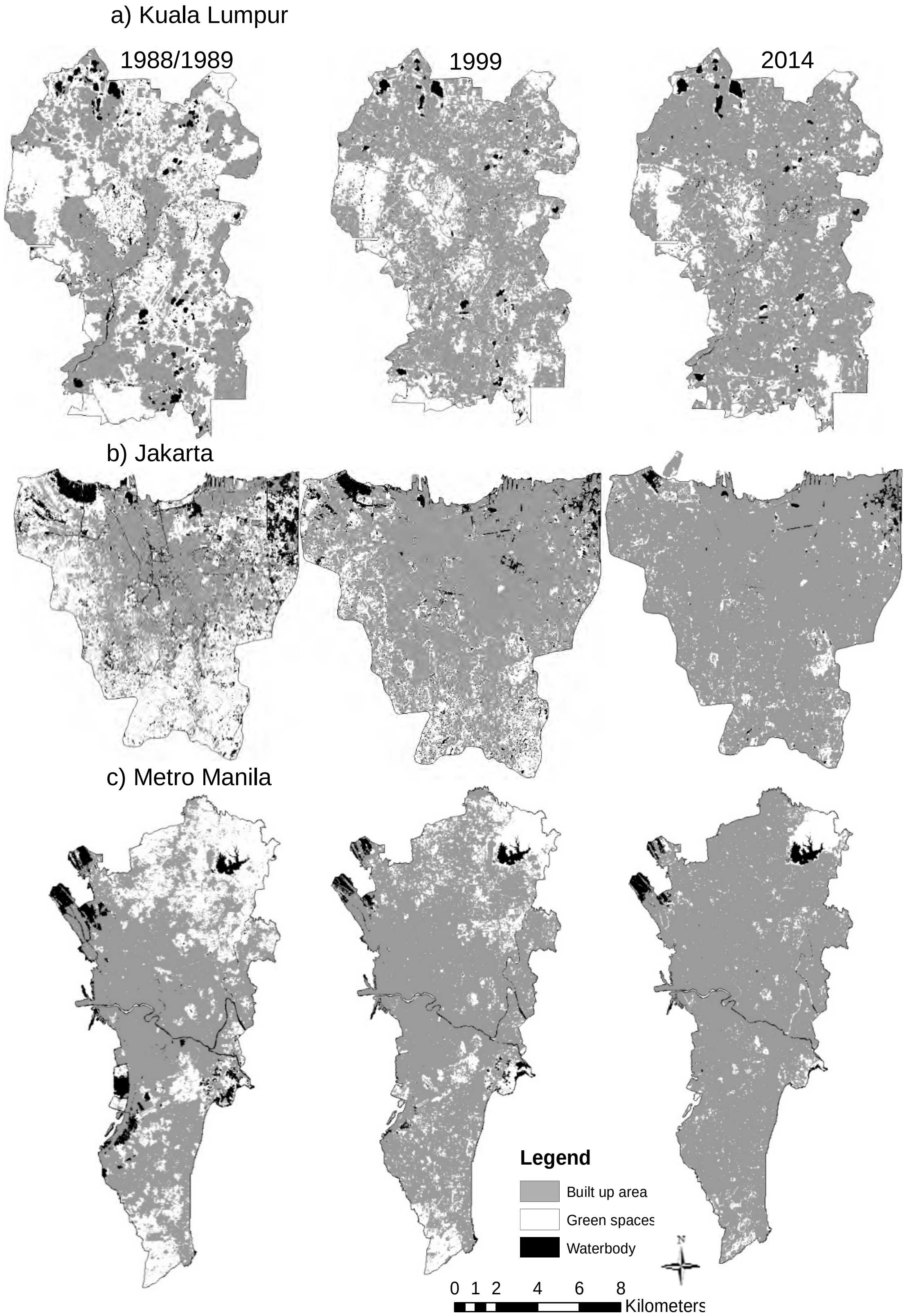


Figure 3. 4 Land use/land cover maps of 1988/1989, 1999 and 2014 for a) Kuala Lumpur, b) Jakarta and c) Metro Manila.

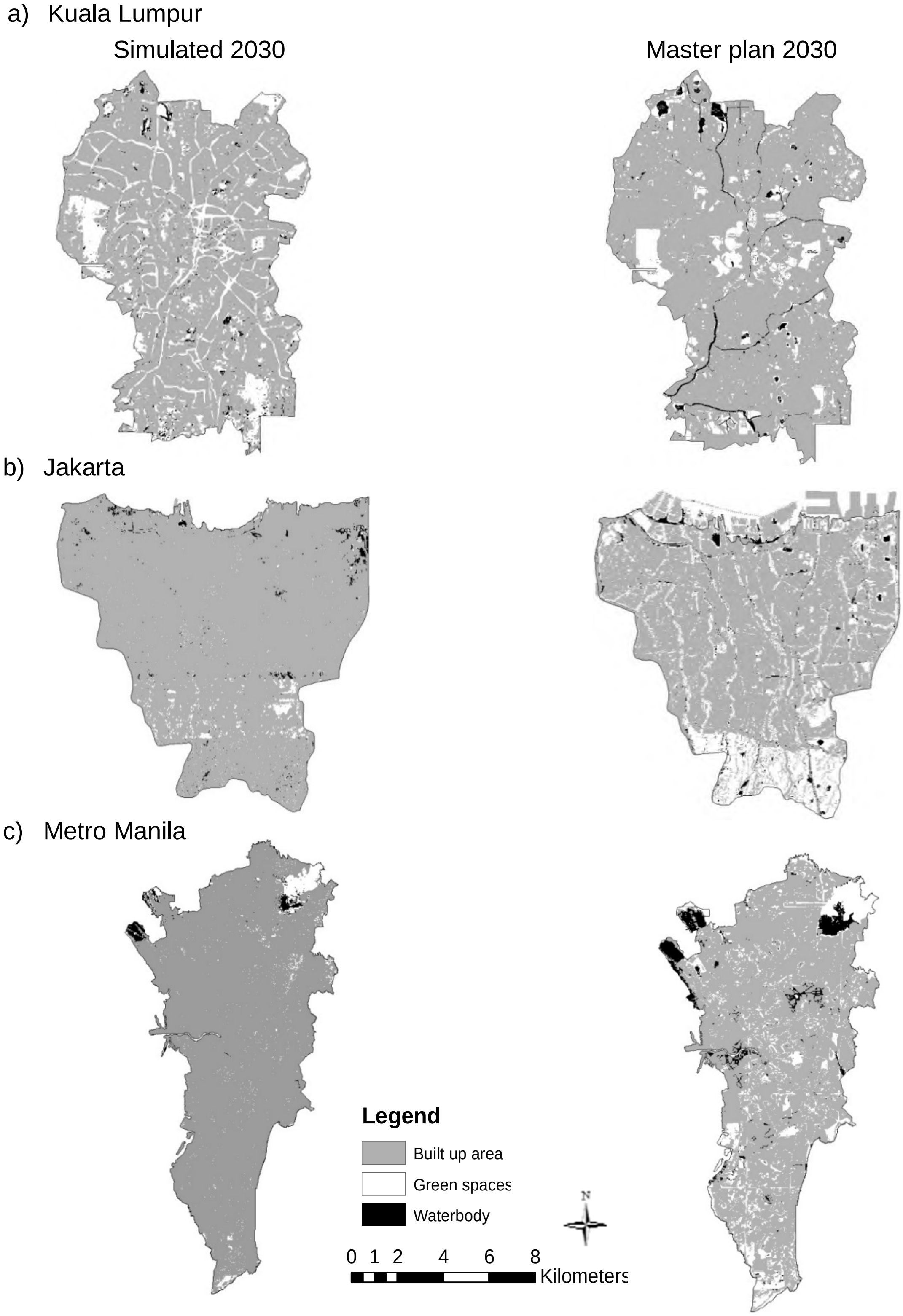


Figure 3. 5 Land use/land cover maps of simulated and master plan 2030 for a) Kuala Lumpur, b) Jakarta and c) Metro Manila.

Table 3. 4 Markov chain modelling values of expected transition of LULC to other LULC from 2014 to 2030 (low:0 – high:1) (bold figures indicate no change)

2014	2030		
	Built-up Area	Waterbody	Green Space
a) 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**
B) 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**
C) 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 3. 5 Area (ha) and percentage area (%) of expected transition of LULC to other LULC from 2014 to 2030 (bold figures indicate no change).

2014	2030		
	Built-up Area	Waterbody	Green Space
a) Kuala Lumpur			
Built-up Area	**18616 (77.0)**	207 (0.9)	1932 (8.0)
Waterbody	162 (0.7)	**229 (0.9)**	181 (0.7)
Green Space	2617 (10.8)	82 (0.3)	**2847 (11.8)**
b) Jakarta			
Built-up Area	**65060 (97.5)**	424 (0.6)	916 (1.4)
Waterbody	1126 (1.7)	**643 (1.0)**	253 (0.4)
Green Space	4115 (6.2)	117 (0.2)	**959 (1.4)**
c) Metro Manila			
Built-up Area	**54068 (96.9)**	332 (0.6)	1025 (1.8)
Waterbody	256 (0.5)	**878 (1.6)**	296 (0.5)
Green Space	3898 (7.0)	35 (0.1)	**1171 (2.1)**

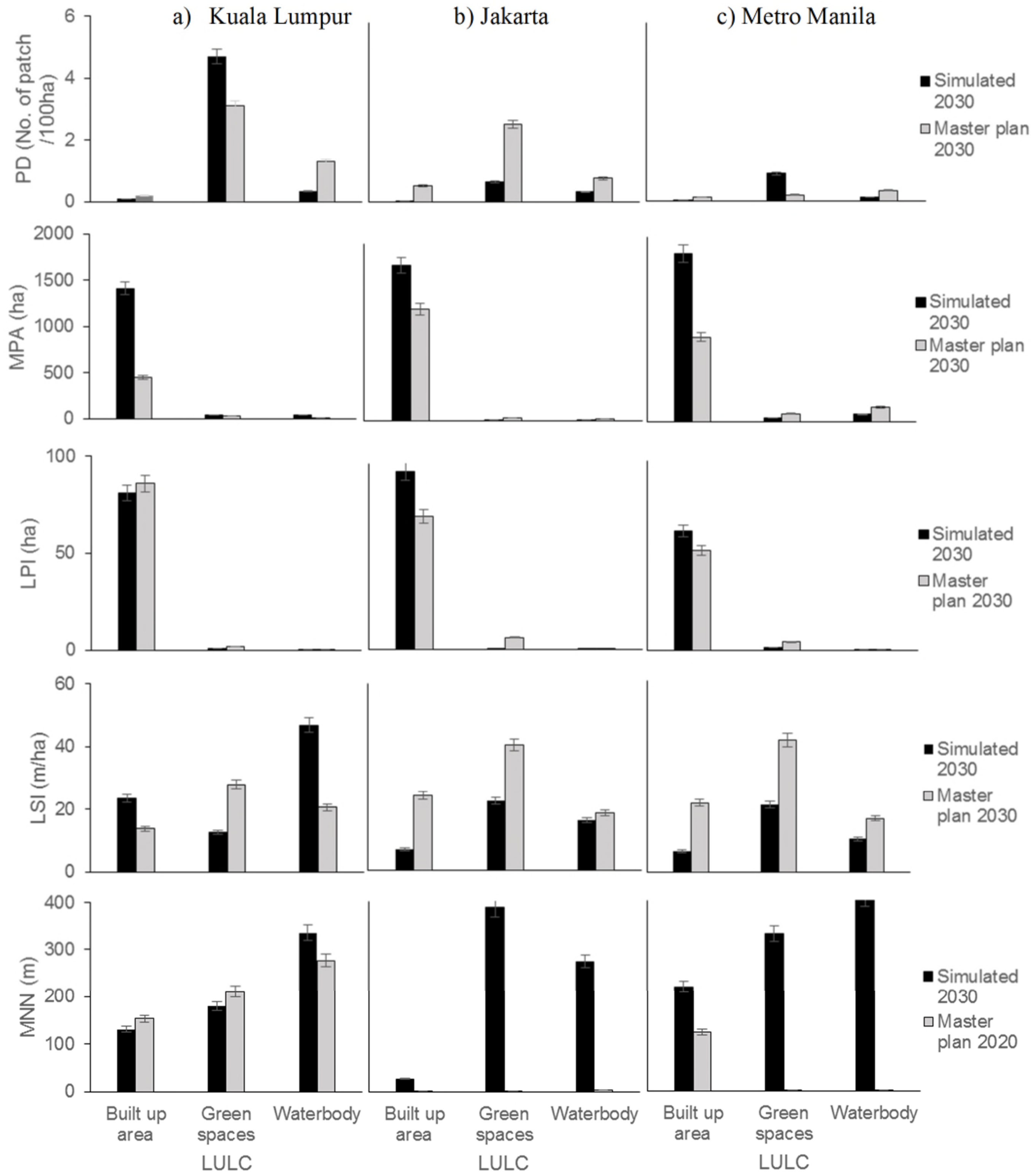


Figure 3. 6 Comparison of simulated and master plan map spatial structure of LULC in 2030 [Patch density (PD); Mean patch area (MPA); Largest patch index (LPI); Landscape shape index (LSI); Euclidean nearest neighbour (MNN)].

3.4 Discussion

In this study, the LCM model verification for 2014 was satisfactory with a good agreement, and therefore, the model is appropriate for predicting future transitions (Fig. 3.2). The differences between the modelled spatial structure and what was observed in 2014 supplied evidence of successful planning interventions. 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 & Flores, 2008). These predictive capacities allow models to be useful tools for impact assessment of urban change in the landscape. The results from these models obtained in this study suggest that a verified LCM-Markov chain model is an effective tool to simulate future urban expansion.

Over the 25-year period, each of the three cities would experience a decrease in green space and an increase in the built-up area (Fig. 3.3). In all three cities, the predictions indicate a further increase in built-up area and a decrease in green spaces by 2030 (Fig. 3.3). 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 (Appendices B.1, B.2 and B.3). These results agree with the findings of other studies, where the distance from main roads is linked to the degree of landscape fragmentation (Gao & 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 (Appendix B.1a).

The land change model described the influence of the spatial transformation of urban expansion on green space structure. For instance, in the 2014 to 2030 time period, a major change (10%) is predicted from green space to built-up areas in all three cities (Tables 3.4 and 3.5). The increase of the proportion of built-up areas over the past period leads to a projected decrease in the green spaces in 2030 (Fig. 3.3). 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 at 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 spaces 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 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 transition from built-up areas to green space was the highest in Kuala Lumpur compared with Jakarta and Metro Manila (Tables 3.4 and 3.5) when interventions that supported green space conservation in Kuala Lumpur were included in the model. 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 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 patterns such as fragmentation, aggregation, compaction, dispersion and isolation (Aguilera et al., 2011), this study was 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. The development of this spatial pattern is influenced by the rapid urban expansion and regulatory history of their respective regions and municipalities. Therefore, the pattern and processes describe here can be used to inform planning and policies in other cities.

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 urban growth 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. 3.5 and 3.6). The aggregation and compaction of built-up areas results in the dislocation, dispersion and isolation of green space (Fig. 3.6), where the green space area will be smaller, with less connectivity and shape complexity. This is because the Kuala Lumpur Structure Plan 2020 (2000-2020) that supported green space conservation seems uncoordinated and lacked follow-up (Kuala Lumpur City Hall, 2005). The continued green space decline in the master plan (Fig. 3.3), suggests that the current policies are currently inadequate, which caused urban expansion to continue at the expense of green space (Estoque & Murayama, 2013).

In contrast, urban development based on the master plan in Jakarta and Metro Manila would result in more fragmented built-up areas with a larger variety of shape, smaller patch sizes and shorter distances between patches when compared to the simulated for 2030. Inherently, the development of the master plans in Jakarta and Metro Manila are under-controlled compared to Kuala Lumpur. This is demonstrated by the increased green space area in Jakarta, variety of shape and greater connectivity between patches in the master plan compared with the simulated 2030 map suggesting that there is an initiative to develop and optimise the green space structure. 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 Jakarta Region, 2011). Similarly, in Metro Manila, the master plan is also under-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 (MMDA, 2012).

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

3.5 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. This study is important and timely as it highlights the planning problems faced by rapidly expanding cities, distinguishes the best master planning strategies under a rapid urban expansion scenario and proposes a new integrated methodology for simulating urban expansion. The LCM-Markov chain model proved to be suitable for simulation of the future LULC to improve the information base at regional scales, and contribute to the understanding of the dynamics of current changes in LULC structure. In all three cities, the predictions indicate a further increase in built-up areas and a decrease in green space by 2030. 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 strategies and uncontrolled planning policies. This work has shown how an integrated landscape ecology approach in LULC simulation modelling has the capability to quantify the spatial effects of successful planning interventions under rapid urban expansion and their effect on green space dynamics. The models allow for a set of diagnostic tools to assess failure and successes in planning strategies, illustrating possible improvements to the master planning process and informing effective planning in the future. The models can be used by administrative planners and decision makers to assess, understand and monitor the effectiveness of master planning. This study illustrates a novel approach through the application of LCM-Markov chain models as a diagnostic tool to identify evidence of past or current planning interventions. This is particularly critical in cities undergoing rapid expansion, where assessing the relative impact and degree of success that planning can have is often difficult.

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4 ECOLOGICAL CONNECTIVITY NETWORKS IN RAPIDLY EXPANDING CITIES

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Abstract

Urban expansion increases fragmentation of the landscape. In effect, fragmentation decreases connectivity, causes green space loss and impacts upon the ecology and function of green space. Restoration of the functionality of green space often requires restoring the ecological connectivity of this green space within the city matrix. However, identifying ecological corridors that integrate different structural and functional connectivity of green space remains vague. Assessing connectivity for developing an ecological network by using efficient models is essential to improve these networks under rapid urban expansion. This paper presents a novel methodological approach to assess and model connectivity for the Eurasian tree sparrow (*Passer montanus*) and Yellow-vented bulbul (*Pycnonotus goiavier*) in three cities (Kuala Lumpur, Malaysia; Jakarta, Indonesia and Metro Manila, Philippines). The approach identifies potential priority corridors for ecological connectivity networks. The study combined circuit models, connectivity analysis and least-cost models to identify potential corridors by integrating structure and function of green space patches to provide reliable ecological connectivity network models in the cities. Relevant parameters such as landscape resistance and green space structure (vegetation density, patch size and patch distance) were derived from an expert and literature-based approach based on the preference of bird behaviour. The integrated models allowed the assessment of connectivity for both species using different measures of green space structure revealing the potential corridors and least cost pathways for both bird species at the patch sites. The implementation of improvements to the identified corridors could increase the connectivity of green space. This study provides examples of how combining models can contribute to the improvement of ecological networks in rapidly expanding cities and demonstrates the usefulness of such models for biodiversity conservation and urban planning.

Keywords: connectivity; landscape resistance; circuit theory; least-cost path; bird species; green space; biodiversity conservation

4.1 Introduction

In urban systems, green spaces play a key role in conserving biodiversity in a sustainable landscape by providing habitat, food sources and connectivity between groups which otherwise would be isolated by the urban matrix (Tzoulas et al., 2007; Yu et al., 2012). However, green space is increasingly encroached upon and fragmented as cities' population density increases (Jongman, 2008). The proportion of the world's population living in cities is expected to surpass 65% by 2025 (Schell & Ulijaszek, 1999), and population increases are accompanied by intensified urban development. As a result, urban expansion has increased the fragmentation in the landscape and has eliminated green space, particularly the dispersal corridors (Harris & Scheck, 1991). In this regard, fragmentation decreases connectivity, increasing isolation of habitats and green space loss (Kong et al., 2010). Therefore, conservation of green space connectivity through ecological networks in rapidly expanding cities is needed to protect the habitat for biodiversity.

The term 'ecological network' is defined as a network composed of ecological components such as core areas, ecological corridors and buffer zones (McHugh & Thompson, 2011). These components contain natural, semi-natural or restored vegetation and are configured and managed to allow the sustainable use of natural resources and to conserve biodiversity (Fumagalli & Toccolini, 2012). Such networks play the role of corridors for wildlife species to sustain healthy populations. Ecological networks can provide a solution to the problems of intensified land use and fragmentation, enabling natural populations of species and threatened habitats to survive (Jongman, 2008). Despite the increased research in landscape connectivity in conservation planning in rural areas, there are limited number of such studies in urban areas. Therefore, the development of ecological networks is increasingly considered a suitable approach to improve the ecological function of green space in the urban landscape (Hepcan et al., 2009; Kong et al., 2010).

In landscape ecology, connectivity (corridors) is used to describe a landscape’s structural and functional continuity in space and time (Forman & Godron, 1986). Landscape-level habitat connectivity plays an important role in population viability by maintaining the gene flow and facilitating movement, migration, dispersal, distribution and recolonisation (Saura & Pascual-Hortal, 2007; Wade & McLean, 2014). In particular, the landscape-scale spatial configuration and distribution of habitats determine species survival and persistence (Xun et al., 2014). Therefore, establishing and maintaining connectivity among patches is essential in facilitating biodiversity conservation.

Furthermore, while urban greening is a key element in sustainable urban development, biodiversity must be an integral component of this greening. Consequently, preserving habitat and dispersal routes and developing a comprehensive ecological network that can maintain landscape-scale connectivity have become crucial factors in urban biodiversity conservation (Kong et al., 2010; Parker et al., 2008). The development of ecological networks includes protection of existing green spaces, the creation of new spatial forms, restoration and maintenance of connectivity among diverse green spaces. However, only few current analytical tools comprehensively identify potential corridors in regional landscapes under rapid urban expansion. Connectivity models that offer an understanding of the different patterns of functional connectivity under rapid urban expansion are less studied. Planners generally consider only distances between habitat patches (Hargrove et al., 2005), not the spatial, ecological or other landscape factors to model the integrated structural and functional connectivity of the landscape. To maintain or restore connectivity, planners must identify the best habitat and potential corridors by quantifying the landscape characteristics such as distances, size and density and consider landscape resistance and the barriers between habitats posed by the landscape and land use (Opdam, 1991).

Current models use Euclidean distance, connectivity indices, least-cost path, least-cost distance and landscape resistance using circuit theory to model connectivity (McGarigal et al., 2002; Mcrae & Beier, 2007; Pascual-Hortal & Saura, 2007) in a very complex urban landscape. Notably, this study considers landscape resistance and green space structure linked to the behaviour of species as parameters and indicators for movement along corridors. Developing landscape connectivity models using circuit theory parameterised with green space structure characteristics such as size and density allows the modelling of multiple paths between nodes (McRae et al., 2008). Moreover, the use of circuit theory to depict spatial patterns of landscape resistance or conductance provides an easily interpretable method for calculating metric values and modelled linkages (Kupfer, 2012). Apart from that, least-cost path analysis represents a valuable method for conservation planning by analysing and designing habitat corridors. It allows quantitative comparisons of potential movement routes over large study areas, can incorporate simple or complex models of habitat effects on movement and influences functional connectivity for species movement (Sawyer et al., 2011).

This study proposes the identification of potential corridors in the cities using circuit theory, connectivity analysis and least-cost path models to develop potential corridors and can improve ecological networks, so planners can identify the relative high-quality habitats and choose the best opportunities to maintain and restore connectivity. The ecological networks developed based on these integrated models simplified and systematised the complex landscape, helping to identify the significance of each green space and guiding urban planning for biodiversity conservation (Kong et al., 2010).

The aims of this study were to develop an ecological landscape connectivity network in three cities under rapid expansion in Southeast Asia to conserve critical green space patches. This study presents a novel integrated approach to assess and model connectivity for two bird species: the Eurasian tree sparrow (*Passer montanus*) and the Yellow-vented bulbul (*Pycnonotus goiavier)* in the cities. This study chose these species because they represent different functions of green space and help to link the structure and functional connectivity of green space to identify potential corridors and to provide an initial guideline for urban planning.

4.2 Materials and Methods

4.2.1 Connectivity Modelling

The methodological framework for modelling of potential corridors involved: (1) modelling a resistance surface for Eurasian tree sparrow *(Passer montanus)* and Yellow-vented bulbul (*Pycnonotus goiavier)* based on the selected parameters; (2) modelling hypothetical dispersal corridors from the resistance surface models using circuit theory analyses with patch sites for both species; and (3) identifying the priority corridors and assessing their connectivity by combining circuit models, connectivity analysis and least-cost modelling (Fig. 4.1). In this study, circuits are defined as networks of nodes connected by resistors (electrical components that conduct current, voltage and resistance) (McRae et al., 2008) and were used to represent potential corridor maps. Connectivity analysis was conducted to calculate linear distance metrics between nodes to be used in the least-cost path models. The least-cost paths were calculated to represent the route of maximum efficiency between two locations (McRae & Kavanagh, 2011) as a function of the distance travelled and the costs traversed. These analyses were chosen for their simple, easy-to-apply approach, computable, and capable of handling various data while avoiding excessive and unnecessary complexity.

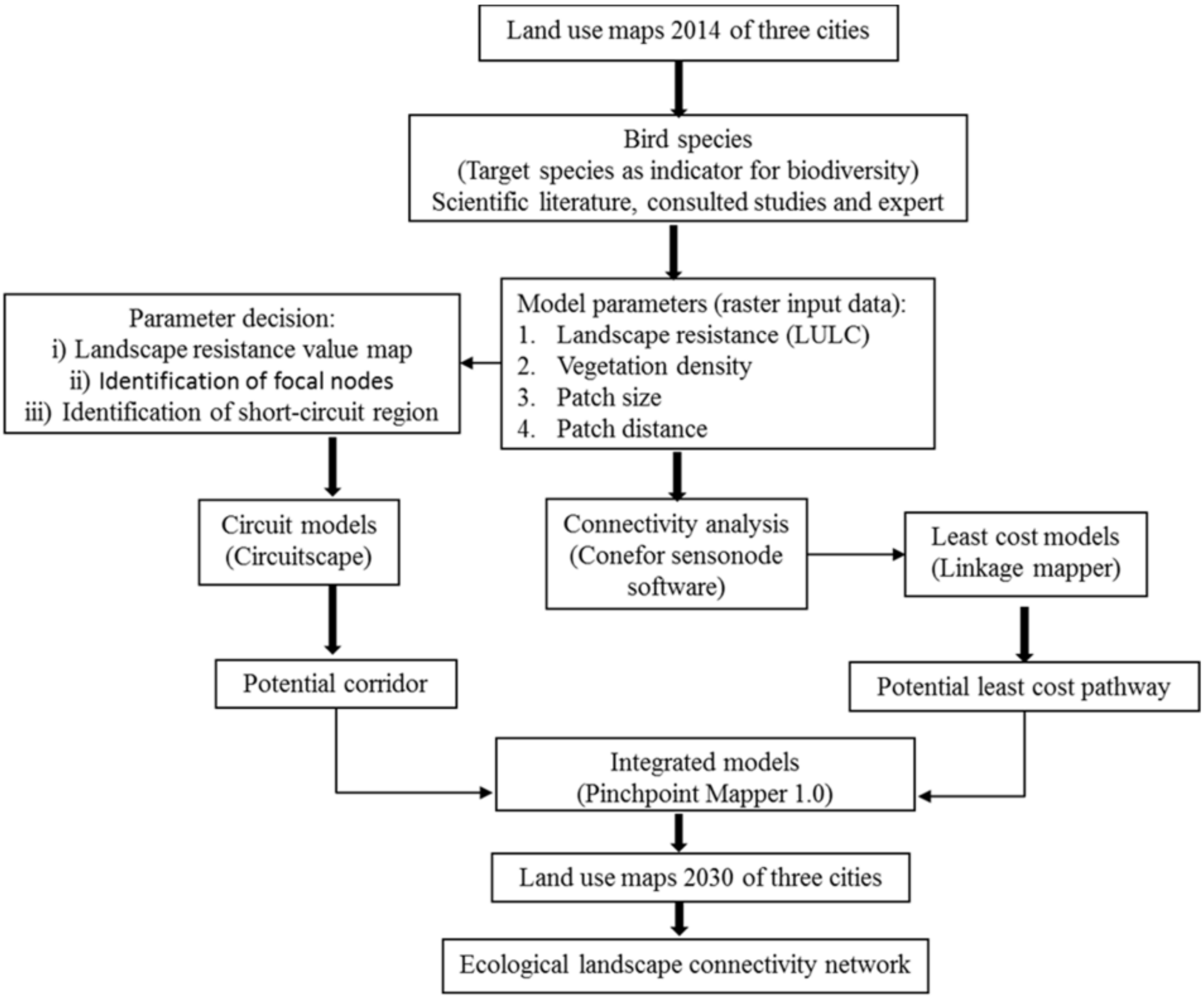


Figure 4. 1 Methodological framework

4.2.2 Target Species

The level of connectivity in a landscape varies not only among environments, but also among most species. Thus, depending on the species, a landscape will be perceived differently (Neumann et al., 2016a) and may provide different levels of connectivity (Bennett, 2003). This study chose birds as target species because they are visible and provide an indicator for ecological functions such as seed dispersal. This approach was adopted from the study by Montis et al. (2016). Seed dispersal is deemed as important in increasing the vegetation cover in the landscape. In this regard, the Eurasian tree sparrow *(Passer montanus)* is an adapted urban bird which is found most abundantly in the cities and also in various urban land use types such as built-up area and green space (Soh et al., 2006). Yellow-vented bulbul (*Pycnonotus goiavier)* is also an adapted urban bird, but it prefers habitat covered by vegetation (Sodhi et al., 1999). Parameterisation of models obtained highlights the characteristics and behaviours of the focal species involved in the study.

4.2.2.1 Eurasian Tree Sparrow (*Passer Montanus*)

The Eurasian tree sparrow *(Passer montanus)*, is a dominant species in the urban areas and one of the most abundant species in Southeast Asia. These birds are opportunistic feeders that typically search for handouts or food scraps on the ground. They are ground nesters, secondary cavity nesters, exotic species and carnivores (Lim & Sodhi, 2004). The populations of the Eurasian tree sparrows have rapidly declined in various breeding habitats within urban environments; hence, the sparrows were found in rural as well as urban areas (Karuppannan et al., 2014). Species richness estimates in mildly disturbed urban forested sites implies that Eurasian tree sparrows can still thrive when there are slight disturbances to their natural habitats (Jasmani et al., 2016). As shown in one study, although the studied fragment was small, the road separating it from a larger forest tract was narrow and this may encourage birds to move more freely across the area (Develey & Stouffer, 2001). Alternatively, the birds may still use slightly disturbed sites to move between adjacent undisturbed habitats (Soh et al., 2006). In some cases, birds were more vulnerable probably due to the lack of higher vegetative cover in concurrence with other studies (Castelletta et al., 2000). For nesting sites, the habitat occupancy of the Eurasian tree sparrow is frequent in urban areas where it chooses trees and buildings for nesting (Rolando et al., 1997). From this information, the key parameters included in the models for Eurasian tree sparrow are habitat patch size and patch distance. The current functions of the patches usually determine the behaviour of nesting, foraging and seed dispersal.

4.2.2.2 Yellow-Vented Bulbul (*Pycnonotus Goiavier*)

The Yellow-vented bulbul (*Pycnonotus goiavier)* is a song bird species and the second most abundant bird species in Southeast Asia. These birds are found predominantly in lowland disturbed habitats such as the scrub forest edge, other plantations and garden habitats (Soh et al., 2006). There are 130 species of Yellow-vented bulbuls, family *Pycnonotidae*, and they are mainly found in Asia and Africa. The population occurs in mixed-species flocks and small flocks, comprising 6 to 8 individuals and can be identified through their high-pitched calls. Individuals are likely to disperse into plantations as a consequence of upland directed urban or agricultural sprawl. They are shrub nesters and omnivores (Lim & Sodhi, 2004). The Yellow-vented bulbuls are an urban-adapted species that searches for food predominantly on the ground or in low-lying vegetation (Jeyarajasingam & Pearson, 1999). They are frugivorous (fruit eaters) and insectivore–frugivores which typically take fruits from a perch and swallow them whole. The seeds defecated or regurgitated at open sites are limited by perch availability, in terms of height, diameter and branching (Slocum & Horvitz, 2000). They forage within the tree foliage and adjust their breeding activities and foraging areas by tracking food resources. During the breeding seasons, foraging is the most intensive within 500 m of their nesting sites, as they provide for their nestlings. They rely on invertebrates for food (Smith & Bruun, 2002) and the availability of soft grounds to provide feasible hunting. This species is the second most important feeder on the fruits in the tree canopy, moving in the range of 1 to 1250 m and dispersing seeds 50 to 100 m from their parent tree (Morneau et al., 1999). From these facts, it can be argued that the key parameters to be included in resistance models for Yellow-vented bulbul are vegetation density and patch distance.

4.2.3 Model Parameters

Four parameters representing the behaviour of the two focal species were identified: i) landscape resistance (based on land use/land cover types), ii) vegetation density (foraging and nesting), iii) patch size (nesting sites and breeding) and iv) patch distance (seed dispersal).

4.2.3.1 Landscape Resistance Values

The resistance surface models were used in circuit analysis to generate maps of movement resistance for both bird species using land use/land cover (LULC) maps 2014 of three cities in Southeast Asia (derived from Chapter 3). The resistance values ranged from 1 to 100 with the highest resistances mainly related to the presence of built-up area. However, both species have different habitat preferences (Tables 4.1 and 4.2), hence, highly suitable areas are located on the borders of the resistance surface, due to the presence of nesting sites, green space and breeding sites surrounding the cities (Figs. 4.2 and 4.3).

Table 4. 1 Landscape resistance value for Eurasian tree sparrow (*Passer montanus*)

LULC	Resistance Value	Justification
Green space	1	Usually forages on the ground and on trees. Breeding sites are on trees and area with low urbanisation (low density building residential roads area) (Sodhi et al., 1999).
Built-up area	60	Most abundant in development areas (Zhou & Chu, 2012), less found in new growth areas and not found in forest reserves. According to (Sodhi et al., 1999) the abundance of human-associated species increase as the amount of building cover increased. Feeding guild, granivores, was higher in developed areas and sometimes found areas with greater intensity of land use (Zhou & Chu, 2012).
Road	70	Along with all routes, most birds were observed in trees and appeared to be either foraging, nesting or singing, with little evidence of the routes being used as flyways (Nichol et al., 2010).
Waterbody	20	Marked preference for breeding sites adjacent to aquatic habitats over sites on farmland associated with wetland habitats, breeding season preference for areas containing water bodies (Field & Anderson, 2004).

Table 4. 2 Landscape resistance value for Yellow-vented bulbul (*Pycnonotus goiavier)*

LULC	Resistance Value	Justification
Green space	1	Species abundance increased when vegetation cover increased. Nest in urban gardens; arboreal and make untidy, cup-shaped nests in trees (Sodhi et al., 1999).
Built-up area	90	Rarely found in non-vegetation areas (Sodhi et al., 1999)
Road	80	Recognises only dense trees, lower tree fractions equal to no trees (Nichol et al., 2010). Prefer denser trees but can traverse non-tree as last resort (Nichol et al., 2010).
Waterbody	10	Yellow-vented bulbul (*Pycnonotus goiavier)* recorded the highest densities in the open water body habitat (Rajpar & Zakaria, 2013).

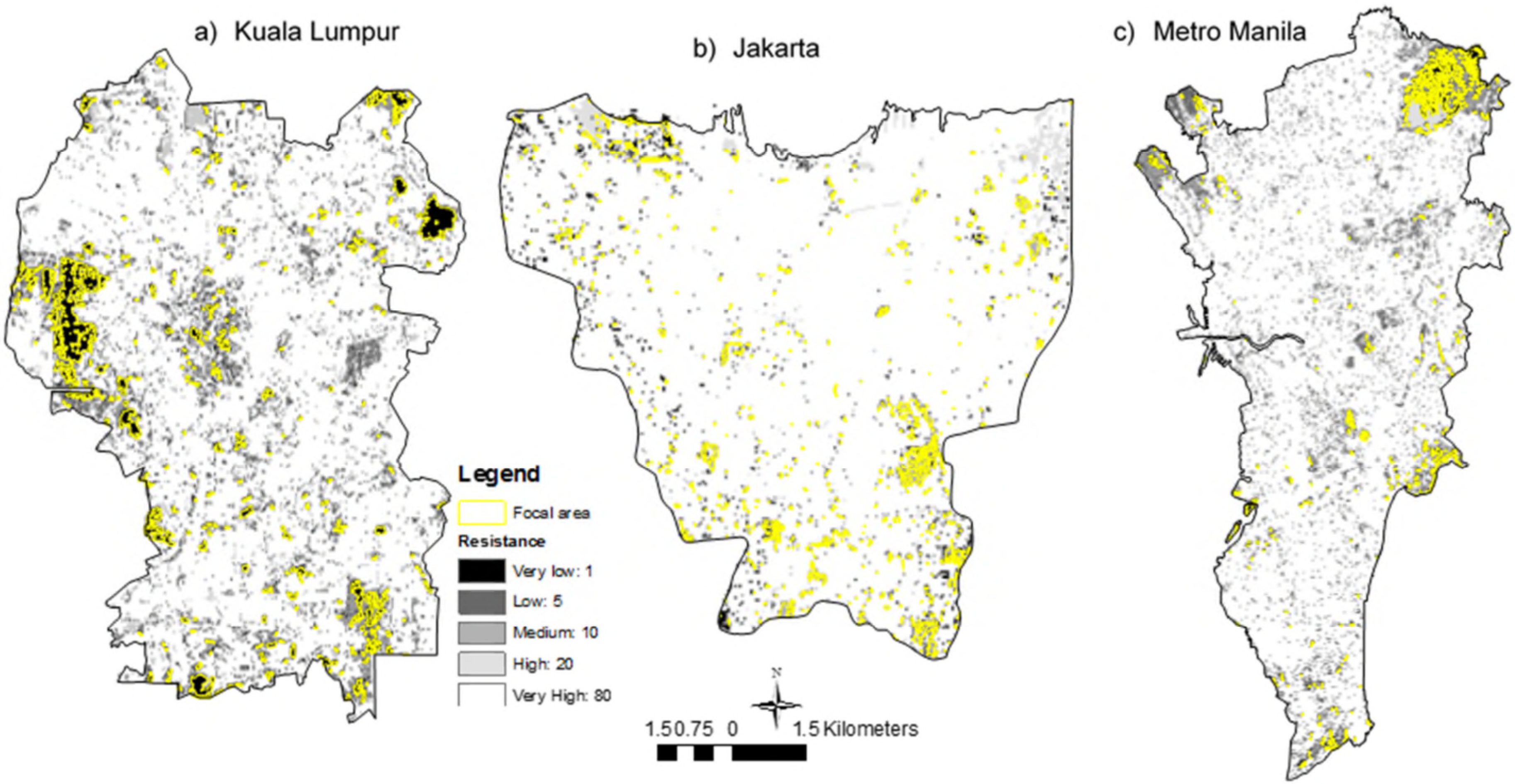


Figure 4. 2 Landscape resistance for Eurasian tree sparrow (*Passer montanus*) within the focal area. Resistance values range from 1 (black) to 100 (white) in a) Kuala Lumpur, b) Jakarta and c) Metro Manila.

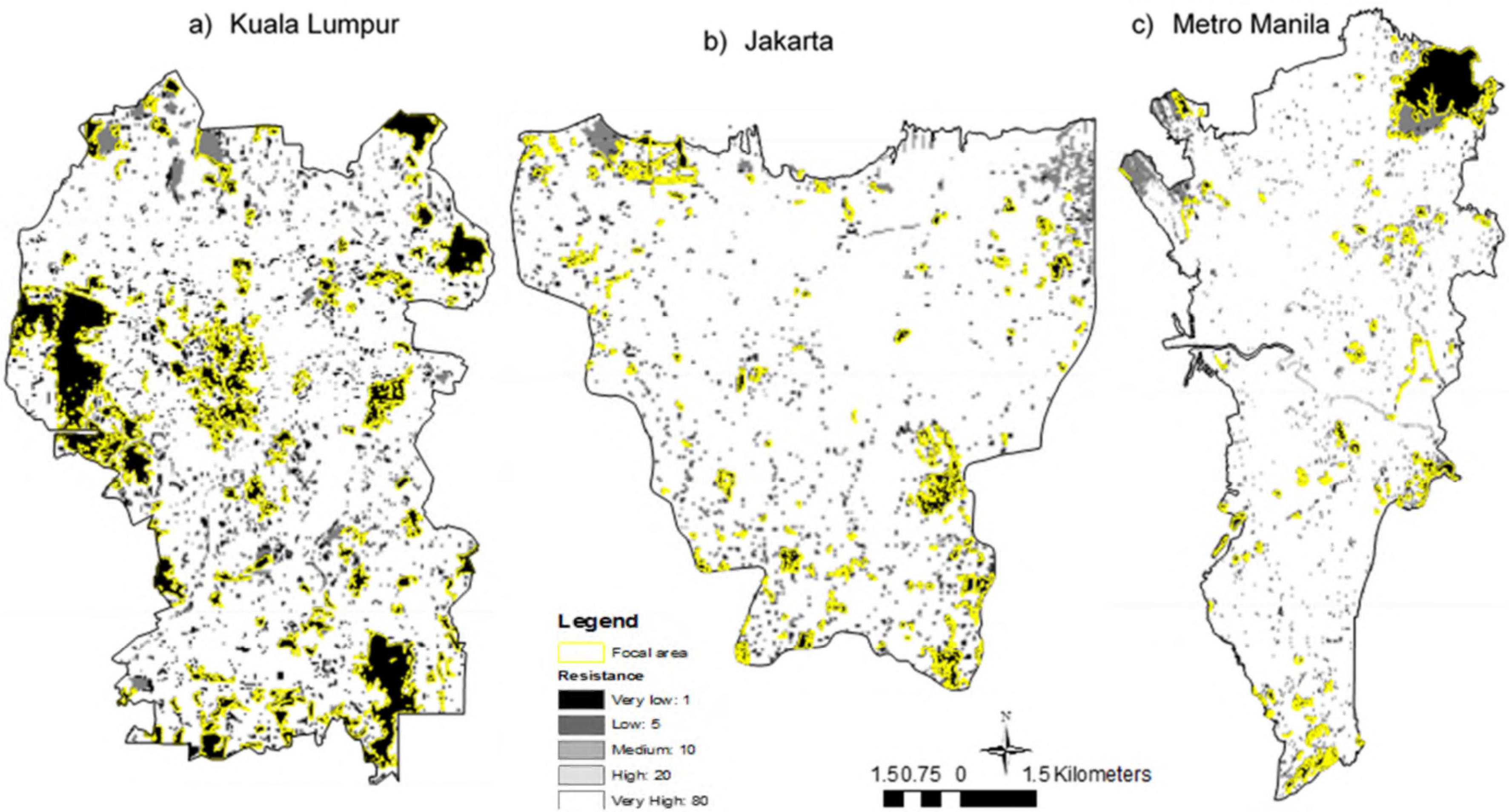


Figure 4. 3 Landscape resistance for Yellow-vented bulbul (*Pycnonotus goiavier)* within the focal area. Resistance values range from 1 (black) to 100 (white) in a) Kuala Lumpur, b) Jakarta and c) Metro Manila.

4.2.3.2 Identification of Focal Nodes

Focal nodes represent the key habitat patches of interest on the landscape between which flows were modelled in circuit analysis (McRae et al., 2008). In the interest of computational feasibility, it is advisable to not treat every occurrence of suitable habitat on the landscape as a focal node (McRae & Shah, 2011). For example, green space structure is the important aspect of habitat heterogeneity; it affects bird community structure and enhances bird species diversity (Evans et al., 2009; Neumann et al., 2016; Yamaura et al., 2009). There are different focal areas used for both species. For the Eurasian tree sparrow (*Passer montanus*) the focal nodes are based on patch size, while for Yellow-vented bulbul (*Pycnonotus goiavier*), the focal node used is vegetation density. In this study, patch size refers to green space patch size in unit ha (Zhou & Chu, 2012), while the vegetation density describes the greenness of the vegetation based on the vegetation index NDVI (Gupta et al., 2012). The reasoning of focal node selection is presented below and also in Table 4.3 and 4.4. The parameters for focal areas used in this study include:

a) Patch size

Here, focal nodes were arbitrarily selected as all green space patches greater than 5 ha in size, producing more than 200 focal nodes for the study areas (Table 4.3). Green patch size has been demonstrated to be important for urban birds (Zhou & Chu, 2012). For example, in the breeding season the number of species of Eurasian tree sparrows (*Passer montanus*) was affected mainly by park size, with the highest relative importance of 1.00 (Zhou & Chu, 2012). Larger parks are easier to move within and have more diverse tree species which could provide various foods (Zhou & Chu, 2012). Green patch size was not chosen for the Yellow-vented bulbul (*Pycnonotus goiavier*) as Weir and Corlett (2007) suggest that patch size has little impact on seed dispersal by these birds and they disperse seeds between a wide range of green patch sizes.

b) Vegetation density

Most of the Yellow-vented bulbuls (*Pycnonotus goiavier*) are found in the green space area particularly in high vegetation density (Jasmani et al., 2016). For example, Yellow-vented bulbuls (*Pycnonotus goiavier*) were mostly seen in short or medium height trees (Jasmani et al., 2016). Therefore, vegetation density was chosen for the focal node selection in the circuit analysis. Normalized Difference Vegetation Index (NDVI) derived from remotely sensed images has been used in various studies to distinguish between vegetated and non-vegetated areas (Gupta et al., 2012).Therefore, NVDI analysis was chosen to detect density in the vegetation cover (Table 4.4). The NDVI is a graphical indicator that indicates the amount of green biomass in the area (Conway & Hackworth, 2007). The NDVI was calculated using the ERDAS Imagine software 10.1. Highly vegetated areas have a NDVI value closer to 1, while locations dominated by water, cleared land or bare soil and built up area have values closer to 0. Based on the percentage, each cell was classified based on three vegetation density classes, i.e. high, medium and low vegetation density (see Table 4.4) on the scale of 0.25 to 1, where less than 50% of the green in a cell was categorised as low vegetation density, and given a value of 0.25. In the same manner, 0.5 (medium vegetation density) and 0.75 to 1 (high vegetation density) values were given to cells where the percentage of green is 25 to 50%, 50 to 75% and more than 75%, respectively. Sandström et al. (2006) found that species richness of hole-nesters partially adapted to urban environment (e.g. the Yellow-vented bulbul) was positively correlated with vegetation density while well-adapted urban birds (e.g. the Eurasian tree sparrow) showed an inverse correlation. Therefore, the parameter of vegetation density was not used in focal node selection for the Eurasian tree sparrow (*Passer montanus*) because it showed no preference for vegetation density (Sandström et al., 2006). These birds usually forage on the ground and on trees and have adapted to foraging in garbage. Their breeding site can also be in trees and in low urbanisation areas (low density of building, residential and road areas) (Sodhi et al., 1999).

4.2.3.3 Patch Distance for Connectivity Analysis

A parameter of patch distance was used in the connectivity analysis for both species. Distance factor relates to the behaviour of seed dispersal. Frugivorous birds are the most important seed dispersal agents for urban tropical forest into grasslands and early successional vegetation because the simple structure of these habitats poses less of a barrier to them. The inputs of bird-dispersed seeds increases with distance from forest edge more than bat-dispersed seed (Gorchov et al., 1993), presumably because birds are more likely to perch and defecate rather than doing so in flight. Dispersal of seeds between habitats may also be influenced by vegetation density. Small-seeded species predominate in the seed rain of forest plants in successional areas adjacent to forest (Duncan & Chapman, 1999), and large-seeded forest trees are thought to have limited dispersal in the colonisation of successional habitats (Wunderlee, 1997). For input of forest seeds into the successional area, both seed density and number of species were significantly affected by the distance from vegetation area (0 to 40 m) (Ingle, 2003) (Tables 4.3 and 4.4).

Table 4. 3 Weight for each parameter and related input layers for the Eurasian tree sparrow (*Passer montanus*)

Parameter (Green space structure)	Weight	Eurasian tree sparrow (*Passer montanus*)			
		Bird nesting site	**Seed dispersal**	**Diet/Feeding/Foraging**	**Breeding**
Habitat patch size	1: < 1 ha 2: 1 to 2 ha 3: 2 to 3 ha 4: 3 to 4 ha 5: 4 to 5 ha 6: > 5 ha	Most species successfully colonised large patches more than smaller ones (Moller, 1987). Population density decreased with smaller habitat patch area (Moller, 1987).	Larger parks tend to support more diverse habitats and tree species, and have reduced edge effects, which help birds to establish larger, and thus more stable populations (Evans et al., 2009).	Non-random preferences for foraging habitats (Field & Anderson, 2004). Lower found in larger areas of lawns under the canopy because of more intensive human management and disturbance.	The area covered with bush layer, tree layer and pond, >0.05 ha (Moller, 1987). Larger parks with more visitors could support more omnivores in the breeding Season (Zhou & Chu, 2012). Increasing random extinction with decreasing habitat size (Corlett, 2005).

Patch distance	Maximum distance 1000 m	Seed food within 1 km of the nest-site influenced nest-site choice or affected productivity (Field & Anderson, 2004).	All tree fractions are equally suitable; avoids gaps (Nichol et al., 2010).	Birds choose the least-cost (optimum) path, encounter fewer hazards, would spend less time in traveling, and travel through habitat with higher probability of containing food and cover (Nichol et al., 2010).	The importance of seed food resources to the persistence of Tree Sparrow *(Passer montanus)* populations operates on a larger spatial scale due to the greater mobility in the non-breeding season (Field & Anderson, 2004).

Table 4. 4 Weight for each parameter and related input layers for Yellow-vented bulbul (Song bird) *Pycnonotus goiavier*

Parameter (Green space structure)	Weight	Yellow-vented bulbul (Song bird) *Pycnonotus goiavier*			
		Bird nesting site	**Seed dispersal**	**Diet/Feeding/Foraging**	**Breeding**
Vegetation density	1: High density (Trees) 2: Medium density (Shrub) 3: Less density (Grassland)	Nest in urban gardens; arboreal and make untidy, cup-shaped nests in trees. Hole nester (versatile). Strong preference for nest-sites adjacent to wetland habitats, woody vegetation and farmland sites.	Fruit 8–10 mm, seed deposition, seeds defecated or regurgitated at open sites is limited by perch availability in terms of height, diameter, branching (Slocum & Horvitz, 2000).	Forages within tree foliage Berries and fruits; which typically take fruits from a perch and swallow them whole, defecating viable seed. High abundance in high vegetation density (woodland) (Field & Anderson, 2004).	Adjusting their breeding activities and/or foraging areas by tracking food resources.

Patch distance	Maximum distance 1000 m	Nesting site on the tress.	All tree fractions are equally suitable; avoids gaps within 500-m intervals (Nichol et al., 2010) at distances 10, 20 and 40 m from the border with urban forest to the fringe and 10, 20, 40 and 65 m from urban forest (Ingle, 2003).	Birds are assumed to choose the least-cost (optimum) path, encounter fewer hazards, would spend less time in traveling, and travel through habitat with a higher probability of containing food and cover (Nichol et al., 2010).	Small highly isolated patches of forest adversely affect some bird. Nearest distance to waterbody, grassland and trees (Helzer & Jelinski, 1999).

4.2.3.4 Identification of Short-Circuit Regions

Short-circuit regions were used in circuit analysis to represent areas that the organisms under study can traverse freely with no cost. It must be determined if this should be represented by all favourable habitats on the landscape (e.g. all green space cells), only the same areas as the focal nodes (thus treating smaller green space patches as having low resistance but not quite as favourable as focal habitat patches), or if some other criteria would be most appropriate. Here, the same file (patch size and vegetation density) was used for both short-circuit regions for their focal nodes. This was based on the literature that large habitats would act as sources and destinations for the movement of Eurasian tree sparrows *(Passer montanus)*, but smaller patches may act as low-cost corridors for movement between larger habitats rather than sources and destinations in their own right (Zhou & Chu, 2012). Meanwhile, for Yellow-vented bulbul (*Pycnonotus goiavier)*, habitats with more vegetation cover provide more food sources, movement and breeding compared to low vegetation cover (Field & Anderson, 2004).

4.2.4 Circuit Models

Circuit models were created using the Circuitscape software (McRae & Shah, 2011). Circuitscape enables the consideration of least-cost flow pathways and variable maps of 'resistance'. Circuitscape is used in the field of landscape ecology to model an organism's tendency or reluctance to move through certain land cover types that can be mapped in a Geographical Information Systems (GIS). Landscape resistance and patch sites had to be converted into ASCII rasters via the 'Export to Circuitscape' extension for ArcGIS for use in the software. Circuit models for both species were generated using the pairwise mode in order to model the connectivity between all pairs of patch sites. The pairwise operation runs by iteratively testing the 'current flow' (i.e. connectivity) between all identified pairs of 'focal nodes' (i.e. key habitat patches) in the landscape. When it is run in this way, Circuitscape requires three input datasets: i) input resistance data ii) focal node location files and iii) short-circuit region file.

Apart from that, parameter decisions were made based on: i) landscape resistance values: ii) identification of focal nodes and iii) identification of short-circuit regions. A cumulative current density map was produced that combined the results of all pairwise current density maps.

4.2.5 Connectivity Analysis

This study calculated patch distance using the Conefor Inputs extension runs in ArcGIS. The Sensonode Software (Saura & Torné, 2009), which was embedded in ArcGIS 10.2 was used to generate link ID for both species. The maximum distance value for both species was set to 1000 m distance according to the behavioural factor of maximum dispersal distance (Tables 4.3 and 4.4; Field & Anderson, 2004). The extension generates the node and connection files required by Conefor from a vector layer in ArcGIS. Before using this extension, the vector layer must have two fields containing the IDs of the nodes or patches (spatial features, typically polygons) and the attributes of the nodes (e.g. habitat areas, or any other attributes of interests that could be used). The extension generates the nodes and connection files, with the connections characterised by the Euclidean (straight-line) distance between patches. These distances are calculated either from the edges of the patches (the most typical and generally recommended option) or from the centroids of the patches.

4.2.6 Least-cost Models

The tool Linkage Mapper 1.0 (McRae & Kavanagh, 2011) generated the least-cost models for both species. Landscape resistance was used as cost surfaces together with the patch site polygons and a file comprising calculated distances between patch sites.

4.2.7 Integrated Models

The Pinchpoint Mapper 1.0 (McRae, 2012), which is part of the Linkage Mapper toolkit, was used to create models combining the least-cost and circuit methods. By constraining the current flow to the least-cost corridors identified, the combined method was able to highlight least-cost corridors and to assess the connectivity via the least-cost distance and least-cost path length metrics. Then, by running the Circuitscape software within the least-cost corridors, the tool assessed the connectivity via the effective resistance metric and mapped existing pinchpoints (critical connections) within least-cost corridors.

4.2.8 Ecological Connectivity Model 2030

To provide an idea of how the connectivity models could be used to improve connectivity for future planning, the combined model was overlaid to the predicted land use/land cover map for 2030 (derived from Chapter 3) for the ecological connectivity model in 2030.

4.3 Results

4.3.1 Circuit Models

Cells with high current density (black) indicate higher probabilities for Eurasian tree sparrow *(Passer montanus)* and Yellow-vented bulbul (*Pycnonotus goiavier)* movement between patch sites. Cells with low current density (white) show portions of the landscape contributing the least to connectivity. The red lines represent the least-cost path while the yellow lines represent the input parameters of landscape resistance and focal node areas (vegetation density and patch size) (Figs. 4.4 and 4.5).

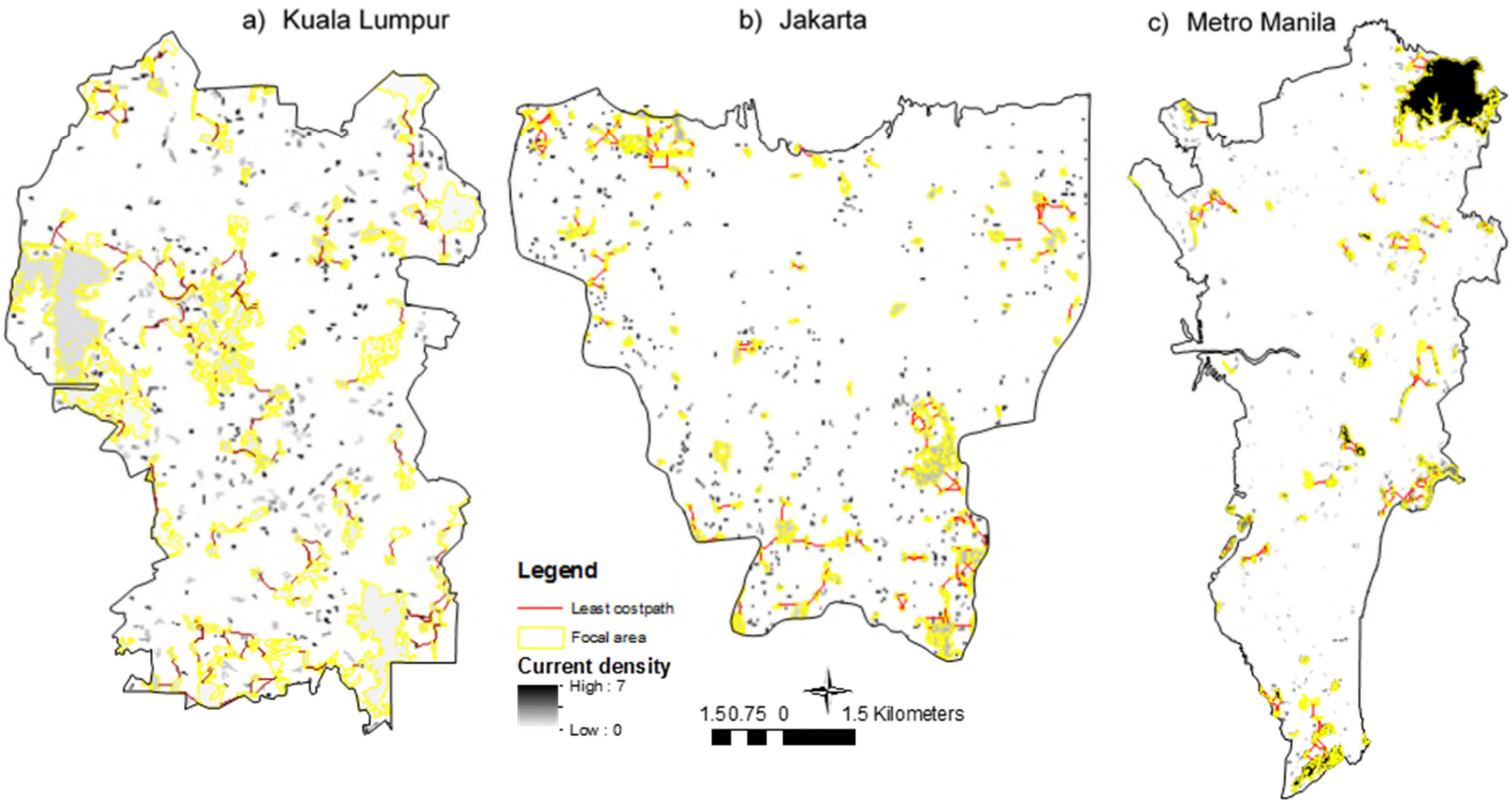


Figure 4. 4 Current density for Eurasian tree sparrow *(Passer montanus)* within focal area in a) Kuala Lumpur, b) Jakarta and c) Metro Manila.

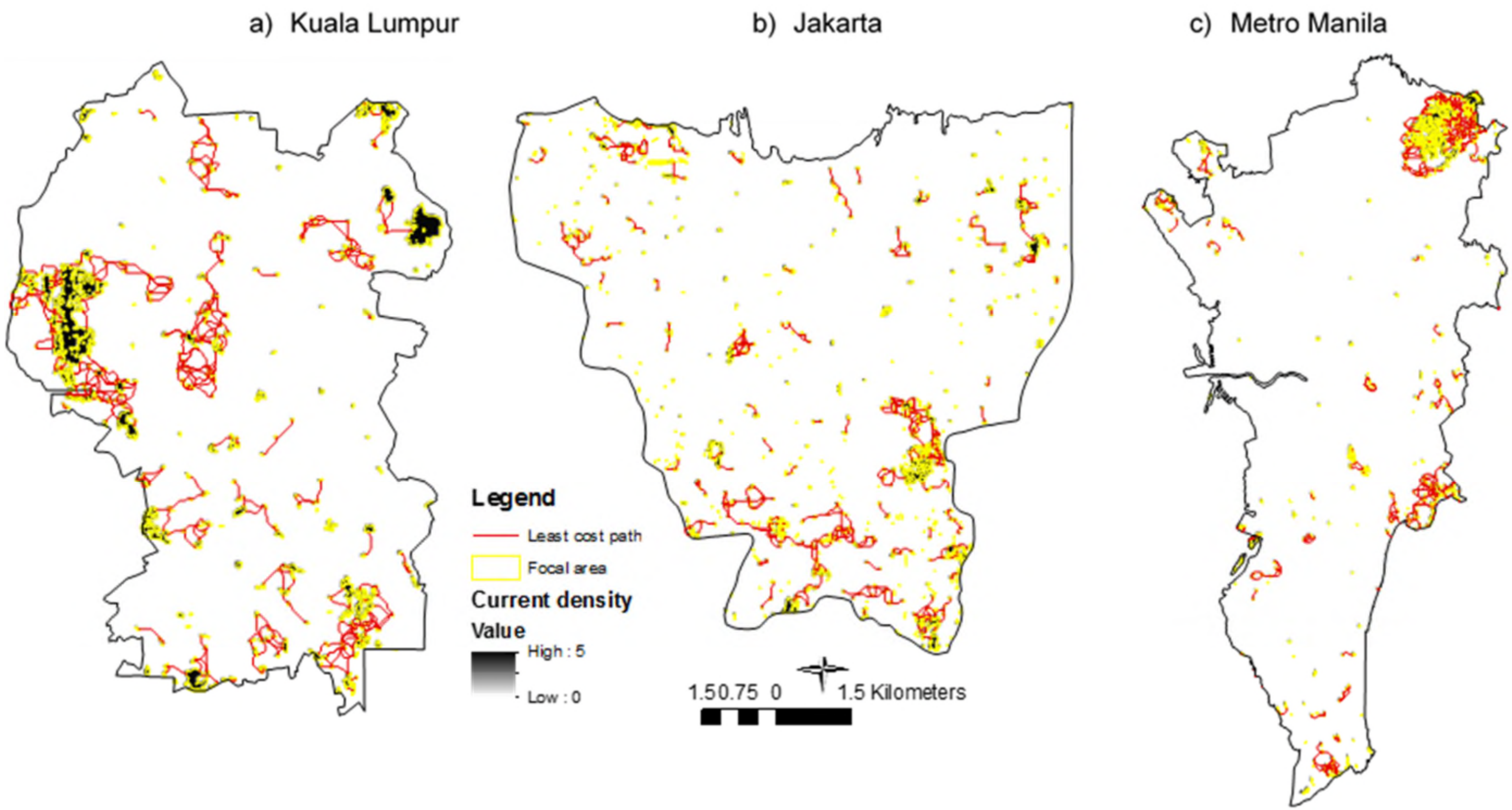


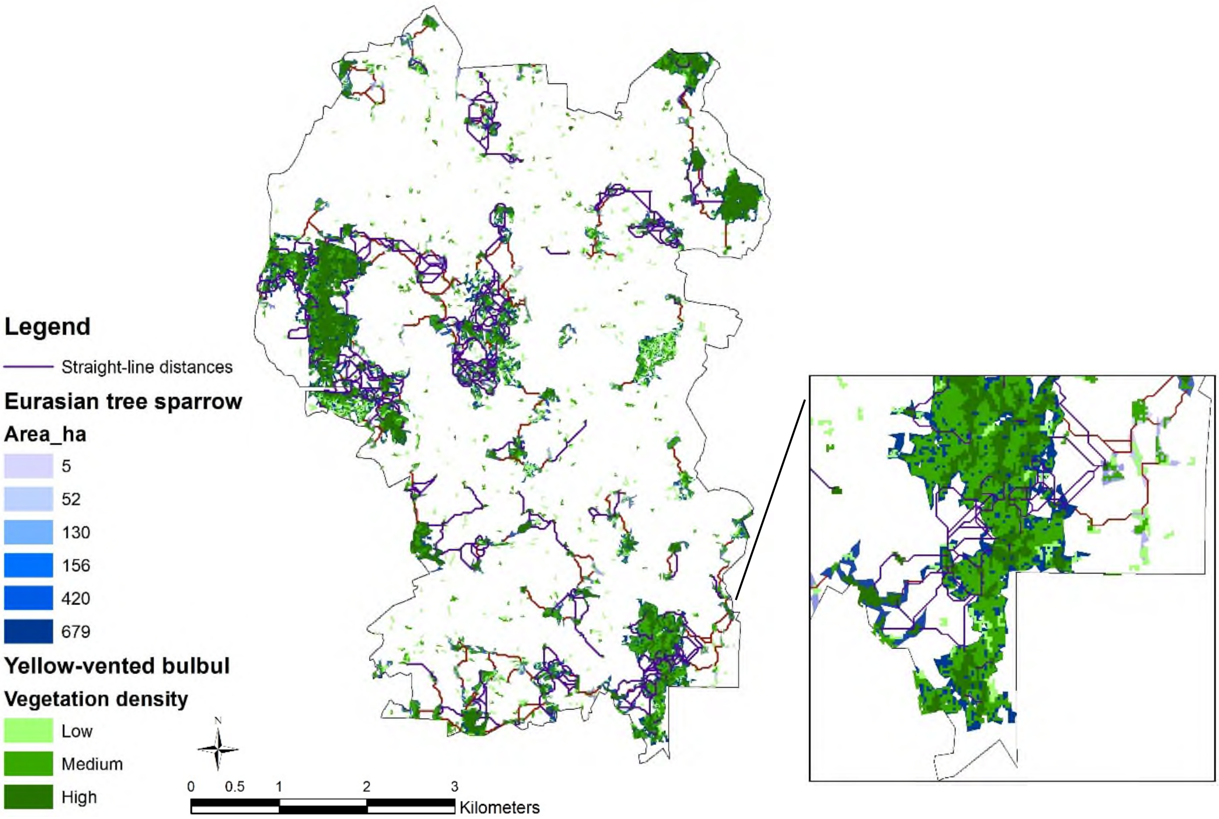
Figure 4. 5 Current density for Yellow-vented bulbul (*Pycnonotus goiavier)* within the focal area in a) Kuala Lumpur, b) Jakarta and c) Metro Manila.

4.3.2 Connectivity Analysis

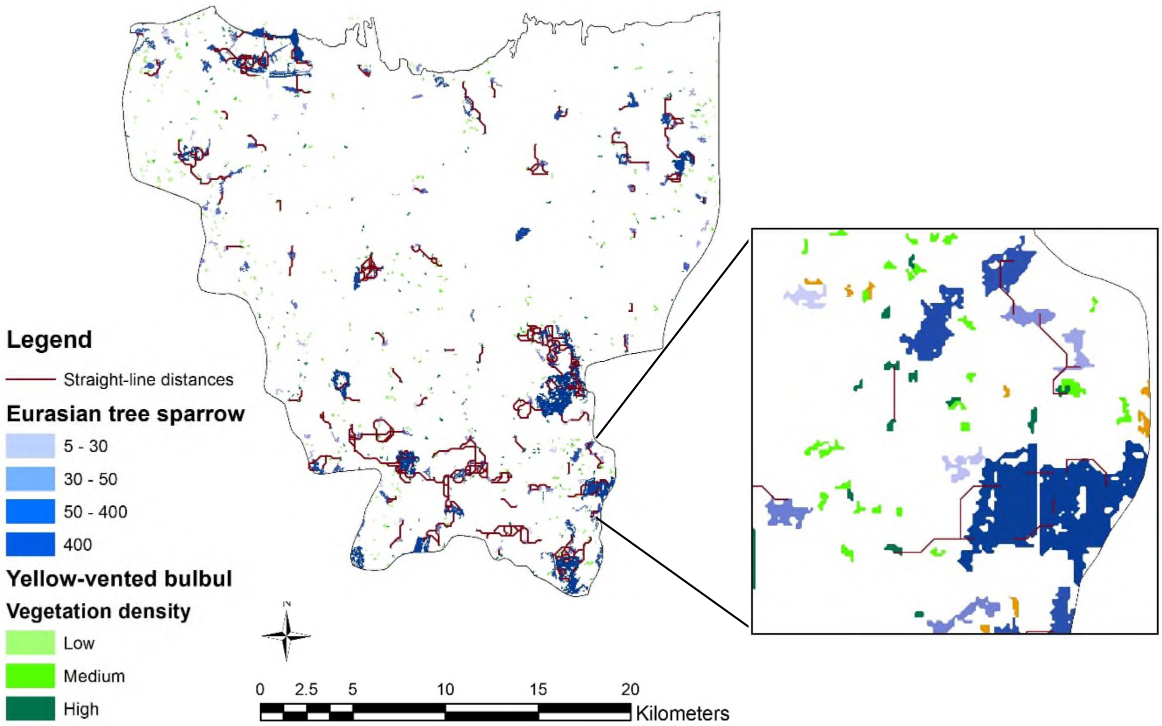
There were 251 focal nodes calculated for connectivity analysis for the Eurasian tree sparrow *(Passer montanus)* in Kuala Lumpur. The minimum distance is between site edge 81 and 82 (17 m) while the maximum distance is between 62 and 67 (997 m). In Jakarta, 160 focal nodes were calculated for connectivity analysis. The minimum distance is between site edge 1 and 2 (30 m) while the maximum distance is between 30 and 39 (999 m). In Metro Manila, 105 focal nodes were calculated. The minimum is between site edge 18 and 59 (30 m) while the maximum distance is between 15 and 86 (997 m) (Fig. 4.6 and Table 4.5).

Meanwhile, there were 295 focal nodes calculated for connectivity analysis for Yellow-vented bulbul (*Pycnonotus goiavier)* in Kuala Lumpur. The minimum distance is between site edge 295 and 71 (28 m) while the maximum distance is between 35 and 132 (999 m). On the other hand, in Jakarta, 611 focal nodes were calculated for connectivity analysis. The minimum distance is between site edge 45 and 46 (13 m) while the maximum distance is between 230 and 239 (1000 m). In Metro Manila, 340 focal nodes were calculated for connectivity analysis. The minimum distance is between site edge 75 and 76 (12 m) while the maximum distance is between 71 and 207 (120 m) (Fig. 4.6 and Table 4.5).

a) Kuala Lumpur



b) Jakarta



c) Metro Manila

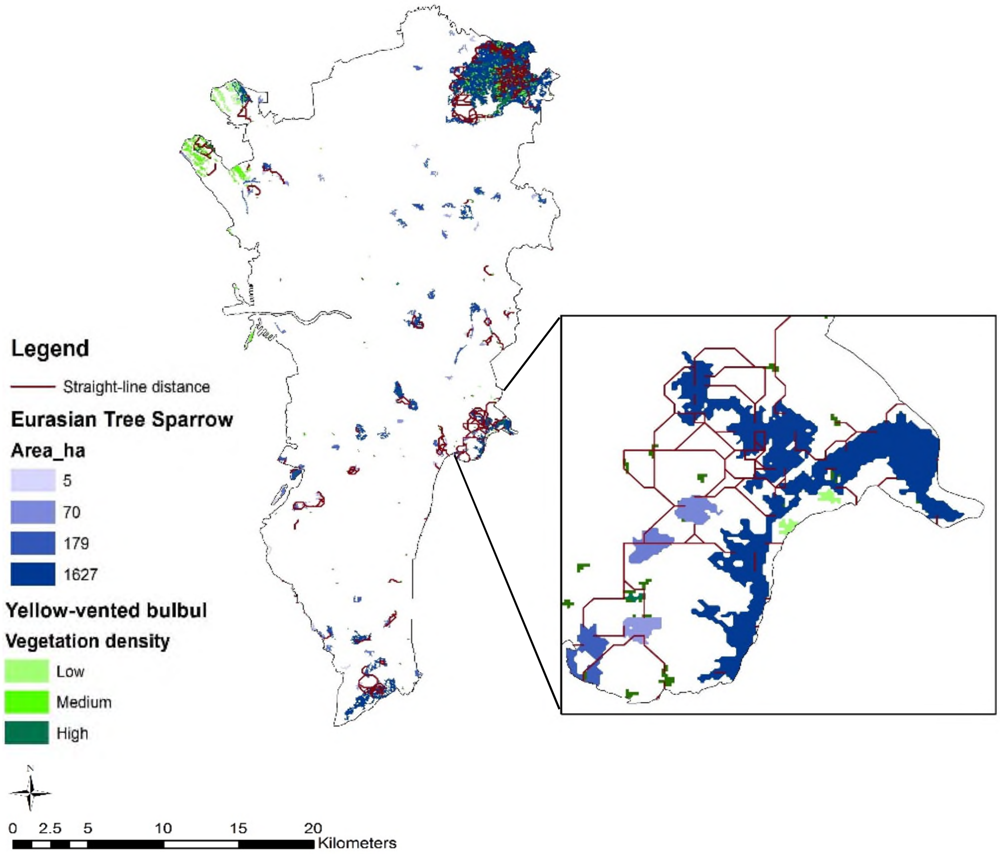


Figure 4. 6 Straight line distance and focal node in a) Kuala Lumpur b) Jakarta c) Metro Manila (link viewer of 10x10 cm box).

Table 4. 5 Calculated straight-line distances between sources site edges for each species in Kuala Lumpur, Jakarta and Metro Manila.

Study area	**Kuala Lumpur**				**Jakarta**				**Metro Manila**			
Conefor input	**Eurasian tree sparrow *(Passer montanus)***		**Yellow-vented bulbul (*Pycnonotus goiavier*)**		**Eurasian tree sparrow *(Passer montanus)***		**Yellow-vented bulbul (*Pycnonotus goiavier*)**		**Eurasian tree sparrow *(Passer montanus)***		**Yellow-vented bulbul (*Pycnonotus goiavier*)**	
	Min	Max	Min	Max	Min	Max	Min	Max	Min	Max	Min	Max
Patch site IDs	81, 82	62, 67	295, 71	35, 132	1, 2	30, 39	45, 46	230, 239	18, 59	15, 86	75, 76	71, 207
Straight-line distances (m)	17	997	28	999	30	999	13	1000	30	997	12	120

Note: Patch site IDs is a name of focal nodes. Link ID is the identification of a single label which returns the numerical ID of the link between focal nodes

4.3.3 Least-cost Models

The least-cost models generate maps of the cumulative cost that highlight least-cost corridors and least-cost paths between patch sites. Cells with the lowest cumulative cost (white) define the least-cost paths (LCPs), represented in red line (Figs. 4.7 and 4.8). As for circuit model outputs, the cells with low cumulative cost which are highlighted in white show where species are more likely to move, and cells with high cumulative cost (black) show portions of the least-cost corridors that contribute less to connectivity (Figs. 4.7 and 4.8).

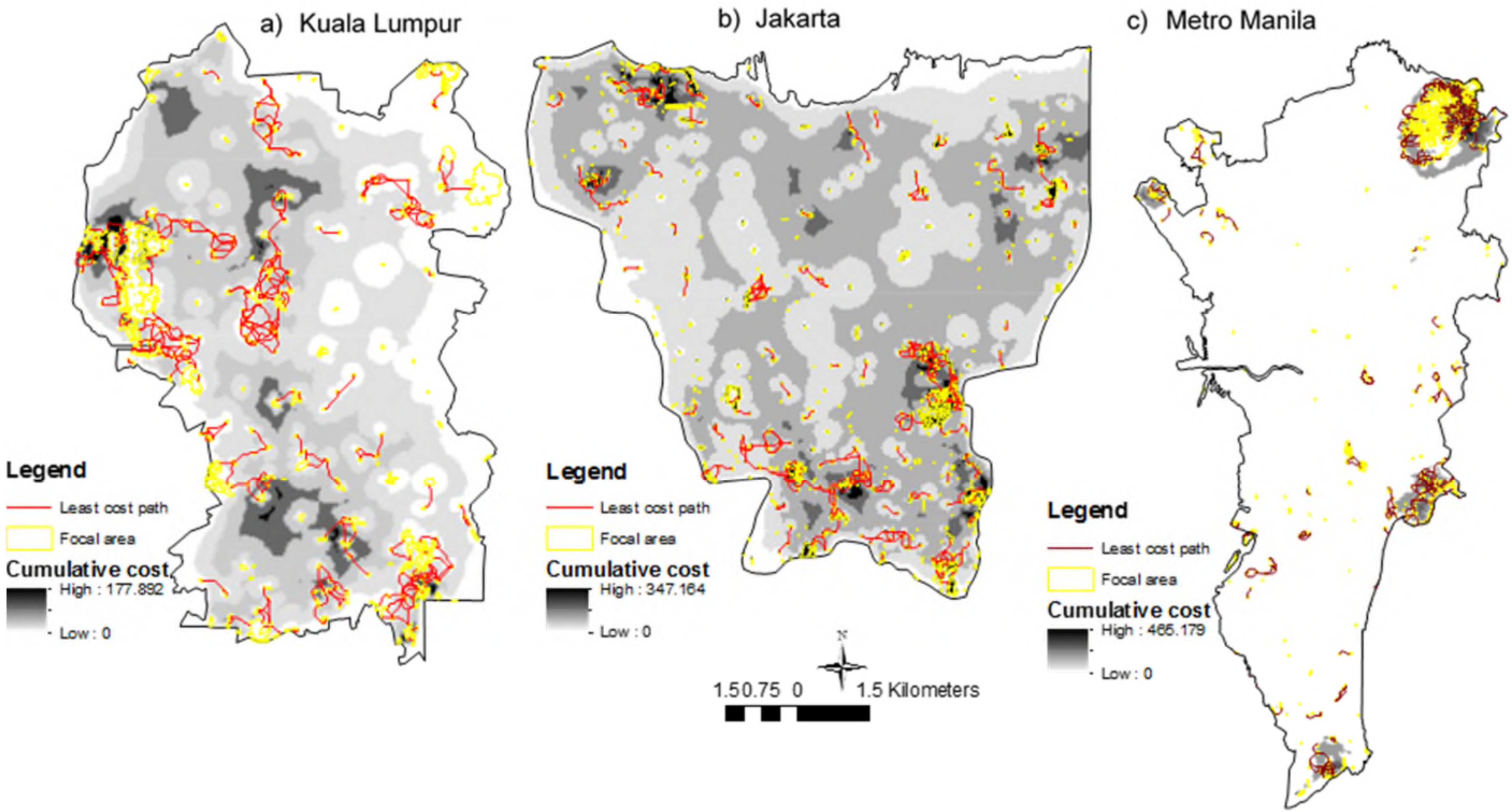


Figure 4. 7 Cumulative cost and identified LCPs between patch sites for Eurasian tree sparrow *(Passer montanus)* within the focal area in a) Kuala Lumpur, b) Jakarta and c) Metro Manila.

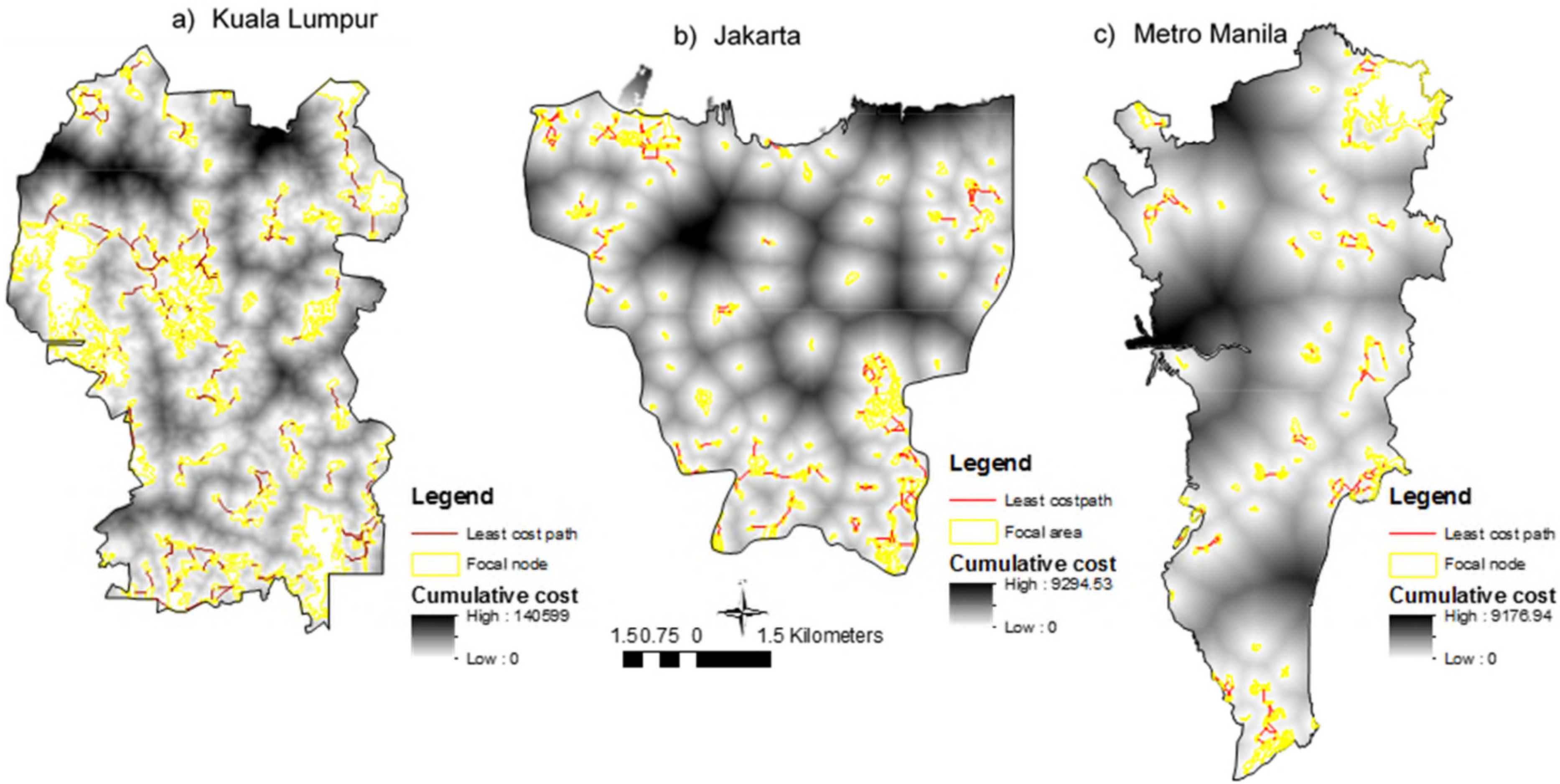
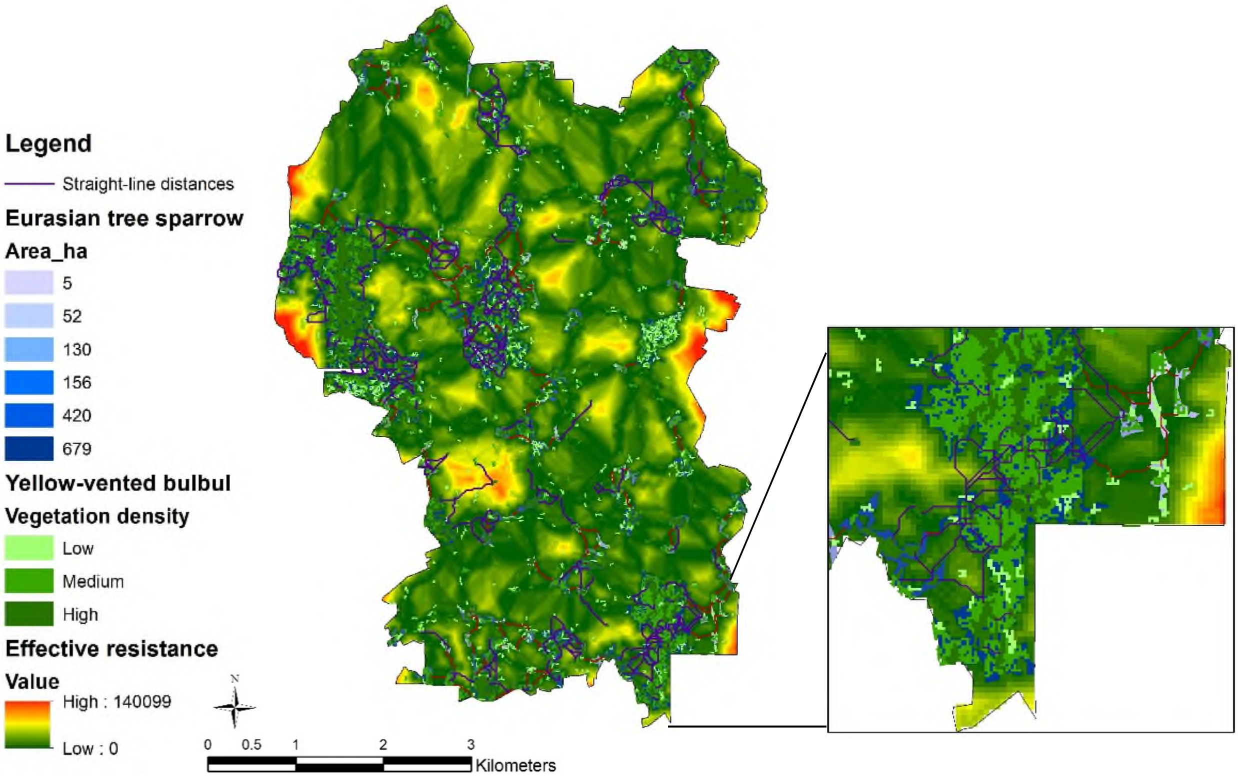


Figure 4. 8 Cumulative cost and identified LCPs between patch sites for Yellow-vented bulbul (*Pycnonotus goiavier*) within the focal area in a) Kuala Lumpur, b) Jakarta and c) Metro Manila.

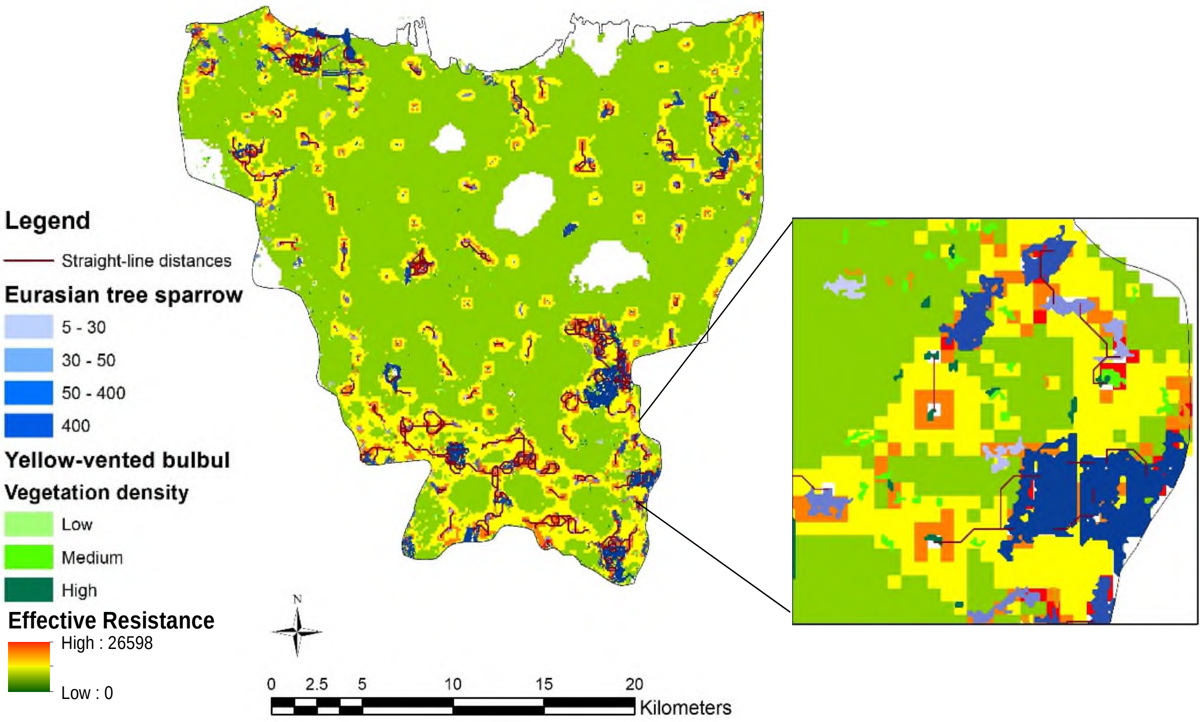
4.3.4 Integrated Models

The combined models show the current density within the corridors identified in the least-cost models and provide values of effective resistance, a connectivity measure complementing LCP lengths (Fig. 4.9 and Table 4.6). Only the current density values within least-cost corridors are taken into account in combined models. In general, this means that smaller ranges of values have to be displayed, allowing critical connections on the map to be highlighted more accurately (Fig. 4.9 and Table 4.6).

a) Kuala Lumpur



b) Jakarta



c) Metro Manila

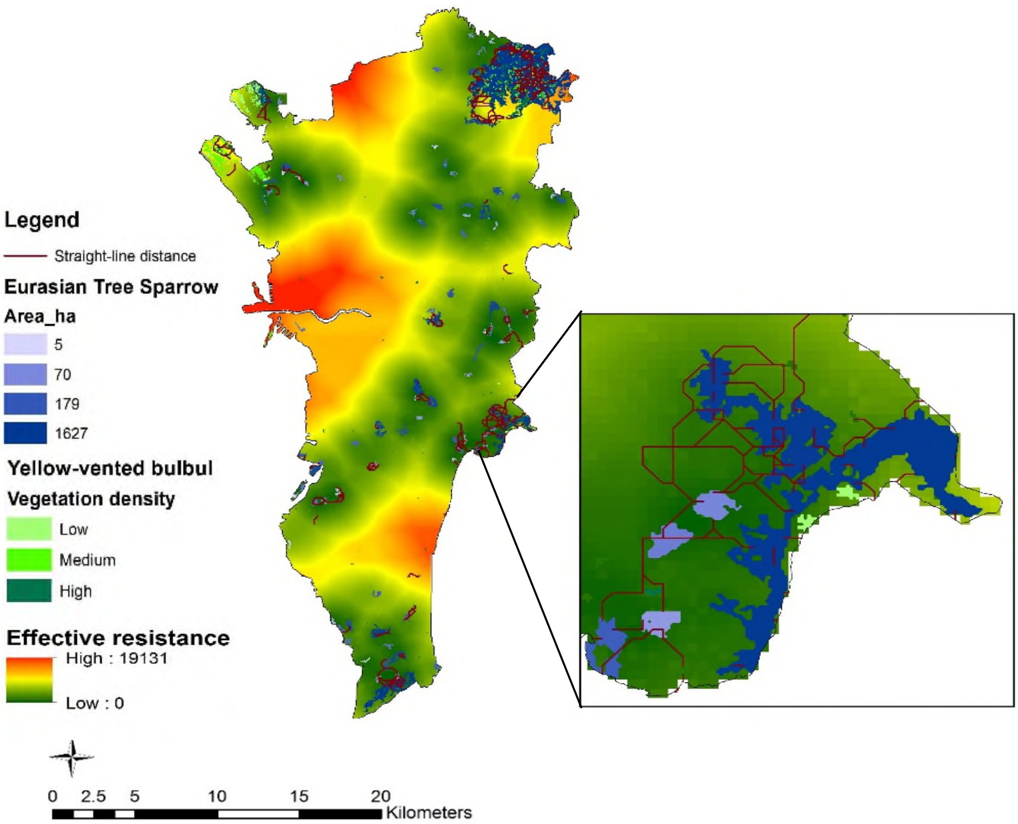


Figure 4. 9 Effective resistances of both species in Jakarta in a) Kuala Lumpur b) Jakarta c) Metro Manila (link viewer of 10x10 cm box).

Table 4. 6 Comparative table of the straight line distance (SLDis), least-cost path lengths (LCP length) and effective resistances (EffResist) resulting from the combined models for Eurasian tree sparrow *(Passer montanus)* and Yellow-vented bulbul (*Pycnonotus goiavier*) in Kuala Lumpur, Jakarta and Metro Manila.

Study area	Link ID	Patch site ID 1	Patch site ID2	SLDis (m)	LCP length (m)	EffResist
Kuala	Min	131	132	13	121	351
Lumpur	Max	45	61	453	999	1053
Jakarta	Min	52	358	28	130	551
	Max	50	51	740	995	1833
Metro	Min	101	121	40	106	402
Manila	Max	60	61	860	998	1935

Note: Patch site IDs is a name of focal nodes. Link ID is the identification of a single label which returns the numerical ID of the link between focal nodes

4.3.5 Ecological Connectivity Model 2030

The ecological connectivity model for 2030 shows the combined least-cost paths of both species in three cities. This model can be used as guidance for future urban planning (Fig. 4.10).

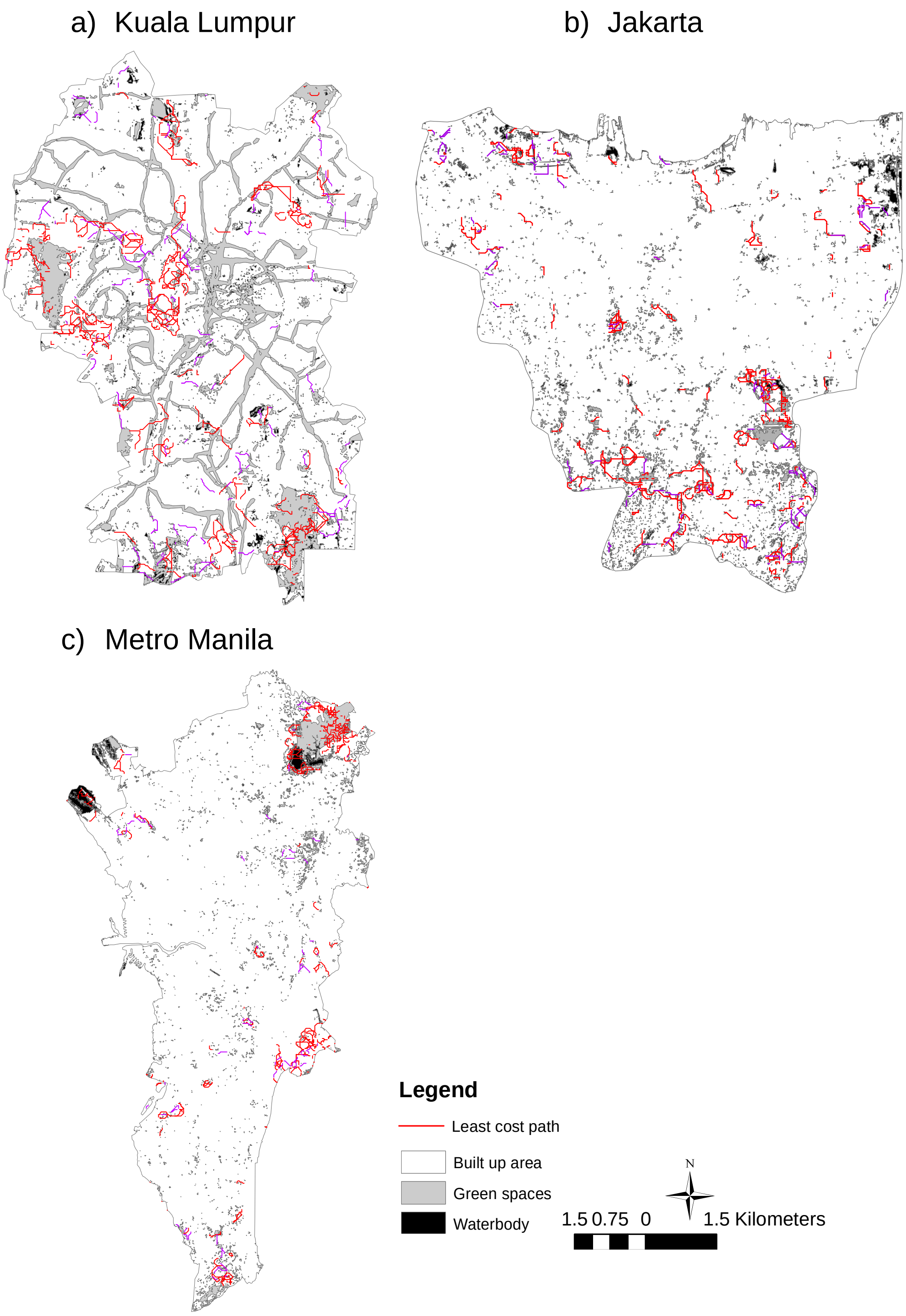


Figure 4. 10 Ecological connectivity networks 2030 in a) Kuala Lumpur, b) Jakarta and c) Metro Manila.

4.4 Discussion

A novel integrated modelling approach combining circuit theory, connectivity and least-cost path analysis was used to identify the potential corridors to connect green space patches for ecological connectivity networks. The present study is among the first to present a novel integrated approach to identify and assess optimal corridors in urban environments under current and future development scenarios. In such a rapidly evolving, heterogeneous and highly fragmented landscapes, the identification of corridors which should be prioritised is important to better design, preserve and can improve ecological networks. These networks of multifunctional ecosystems are undoubtedly crucial for nature conservation and human well-being as well, since they support biodiversity, ecological processes and services in urbanised landscapes (Teng et al., 2011; Tzoulas et al., 2007).

This study used circuit theory, which was parameterised with green space structures such as patch size and vegetation density to optimise corridor effectiveness for two bird species (Eurasian tree sparrow *(Passer montanus)* and Yellow-vented bulbul (*Pycnonotus goiavier*). Similar to the surrogate species approach adopted by earlier studies (Fleury & Brown, 1997; Parker et al., 2008), the present study employed two target species with different uses of landscape structure. This approach aims to optimise the continuity and conditions of green spaces within the study area so that opportunities for individual passage may be maximised for a wide range of species. The present study was based on the literature (Tables 4.3 and 4.4) which advocated that species that are present within the identified habitat patches may benefit from the establishment of connective landscape features between them, if the composition of vegetation within such patches is sufficiently similar. As similar species may benefit to a greater extent from particular landscape attributes than others, the approach used here effectively aims to restore the condition of habitat and thus most likely to suit the individual requirements of the species present.

The model (Figs. 4.6 and 4.7) is significant in predicting bird density from ecological and structural connectivity, through the use of foraging and nesting (vegetation density and patch size), as well as seed dispersal (patch distance) as indicative measuring variables. It extended the use of circuit theory and connectivity to build a spatially explicit model to understand habitat factors on biodiversity. The landscape structure factors can give an indication of the conditions of the surrounding matrix and possible future change surrounding green spaces. Uezu et al. (2005) demonstrate that species differ in their responses to fragmentation, and bird diversity and abundance are related to the structural and functional connectivity and patch size factors (Fontana et al., 2011). For the Eurasian tree sparrow *(Passer montanus)*, patch size was the main factor determining cumulative cost current density, while the least-cost path was more affected by the degree of patch connectivity; the former by the presence of corridors and the latter by the distance between patches. On the contrary, vegetation density had no effect on the priority corridors of Eurasian tree sparrow *(Passer montanus)* and had a positive effect on Yellow-vented bulbul (*Pycnonotus goiavier)*. This study emphasises the importance of considering species perceptions of landscape, especially functional connectivity, in developing priority corridors of ecological connectivity networks.

Circuit theory was selected because of its ability to provide rapid, repeatable results using the simple connectivity measure of resistance distance (distance metric) as the effective resistance between a pair of nodes (McRae et al., 2008). A convenient property of the resistance distance is that it incorporates multiple pathways connecting nodes, with resistance distances measured between node pairs decreasing as more connections are added. The use of the model was also favoured as it evaluates sites on the basis of their ability to support a wide range of species, not only in areas containing significant habitat, but also in sites currently lacking vegetation. However, it must be noted that this methodology may not be as easily applied in less densely populated urban settings where differences in habitat condition are more subtle. However, many urban centres have already experienced comparable levels of modification, and as such, this methodology will be readily applicable to landscape planners in many regions (Parker et al., 2008).

In this study, the model has proven that the circuit theoretic model was able to overcome the limitation of the least-cost model by simultaneously considering different suitable routes. This major advantage over the least-cost model was mentioned by other studies (e.g. McRae & Beier, 2007; McRae et al. 2008). The circuit model was also able to spot the critical connections that contribute the most to network connectivity and to identify corridors with optimal connectivity. These latter findings were similar to the one highlighted by the least-cost model but were more difficult to spot on maps, as observed in Rainey (2009), which compared the least-cost and circuit analyses. In addition, this study highlighted an additional limitation of circuit theory approach. The approach is only effective in urban heterogeneous landscapes, as illustrated in the results for the Eurasian tree sparrow *(Passer montanus)* and Yellow-vented bulbul (*Pycnonotus goiavier)* in Metro Manila, where a few optimal corridors were identified by the circuit model due to the presence of homogeneous areas (built-up area) around the city (Figs. 4.4c and 4.5c).

The least-cost model was the first and most popular method studied. Throughout the study, this has proven to be an effective way to calculate distances and to identify the most optimal routes between source sites (Fig. 4.6 and Table 4.5). This method also provides an easily understandable assessment of connectivity via the least-cost path length metric, which is a much easier way to interpret than accumulated-cost in terms of dispersal distance (Etherington & Penelope Holland, 2013). Nevertheless, the study has demonstrated that the least-cost model has also some constraints such as not considering all possible routes that could contribute to connectivity or providing connectivity assessments that are only related to a single, most cost-efficient route identified in a given landscape. These same limitations were pointed out previously by Mcrae & Beier (2007).

The combined model benefits from the advantages of both least-cost and circuit models. In this study, the outputs generated via the combined model showed the outlines of the optimal corridors identified by the least-cost models and highlighted the critical connections within them with more precision (Figs. 4.6 and 4.7). It also provided an assessment of connectivity for each corridor via the least-cost path length metric. In addition, the combined model was able to compute the effective resistance for each least-cost corridor identified (Fig. 4.9 and Table 4.6). This second connectivity metric complements the least-cost path length metric and reflects the contribution of alternative suitable corridors. The results suggest that planning for priority corridors should be developed at the link between patches which have low values of least-cost path lengths (LCP length) and effective resistances (EffResist), for example in Kuala Lumpur which showed the lowest effective resistance value followed by Jakarta and Metro Manila (Fig. 4.9 and Table 4.6). Even though the combined model appears to be the ideal combination between least-cost and circuit models, it must be emphasised that the circuit models have to be processed in the first place in order to generate the combined model outputs, as well as to interpret them adequately.

The models generated for this study present a first approximation of connectivity for both species of ecological significance, an integrative approach towards structure and function of green spaces. The results indicate some of the challenges currently confronting both bird species, particularly at the source sites selected (Fig. 4.9 and Table 4.6). This study provides scientific implications and solutions to optimise the green space structures under rapid urban expansion, and to ensure species' persistence and connectivity of green space. As practical implications, ecological connectivity networks introduce a novel integrated methodological approach that can help planners and decision makers to design proper policy and urban planning for the cities and predict changes in avian biodiversity (Fig. 4.10). Ecological connectivity networks can inform conservation planning for biodiversity and it can then indicate how urban planning can minimise ecological damage (Fontana et al., 2011). For social implications, green planning is known to have various psychological benefits. The ecological network is a decision support tool and thus incorporates public opinions, enhances social responsibility and enhances awareness of the broader benefits of green spaces.

This study provides recommendations to improve landscape connectivity for both species. This study was based on bird species but the method can be repeated on a range of animals from amphibians to mammals. It will improve the understanding of the use of integrated circuit theory and least-cost path models in connectivity assessment by using various target species with different dispersal distances and habitat requirement. It may promote the use of circuit theory among stakeholders from different backgrounds. The selection of appropriate landscape structure in this model will allow many applications, ease of calculation, functional basis and simplicity of interpretation by a range of specialist and non-specialist stakeholders. Regardless, there continues to be a need for landscape metrics to calculate landscape structure because they are seen by many land managers and stakeholders as simple, intuitive tools for assessing and monitoring changes in landscape pattern and, by extension, the effects on underlying ecological processes. Future needs include: (1) the development of more user-friendly landscape analysis software that can simplify analyses and visualisation; and (2) studies that clarify the strengths and weaknesses of different approaches, including the potential limitations and biases in modelling connectivity. In the future, they could be related to other datasets to provide a complete interpretation of ecological processes and phenomena. By replicating the methodological approach presented in this study, these results could also be used as initial data to predict how urban developments might affect the urban connectivity in rapidly expanding cities, either for birds or other animals.

4.5 Conclusions

This study sought to present a novel integrated approach to assess and model connectivity for two species in the studied cities in order to provide priority corridors for an ecological connectivity network. This study has: first, developed predictive connectivity models for two focal species based on least-cost and circuit models; second, identified priority corridors and assessed their connectivity and highlighted critical connections within them; and third, provided recommendations to improve landscape connectivity for both species. The models used in this study have complementary approaches that can contribute to a more concrete assessment of the connectivity for biodiversity conservation and urban planning. This model also could be applied for human recreation using factors such as social, cultural and economic variables. This study has important implications for the design and management of landscape connectivity in Southeast Asian cities and possibly other similar tropical areas which experience rapid urban expansion. This study can conclude that the popular least-cost model is an efficient and reliable method to identify corridors where maintenance and improvement have to be prioritised to establish and implement ecological networks. Meanwhile, the least-cost path lengths calculated by the least-cost models provide a convenient connectivity assessment that could explain the potential corridors for bird’s movement at one of the source sites. The circuit model, despite the fact that it has not been widely used yet in connectivity studies, has proved to be a valuable method complementing the least-cost model by highlighting alternative corridors and critical connections playing an important role in landscape connectivity. The circuit model has also shown its ability to highlight priority corridors similar to the ones identified by the least-cost model under rapid urban expansion. Consequently, the combined model is an effective way of highlighting critical connections within the priority corridors identified by the least-cost model. It allows for the maintenance and improvement of existing corridors or for the creation of ecological networks in future planning. This study can help nature conservation and urban planning decisions to maintain or design appropriate ecological networks. The multistep framework of this study will allow other researchers to identify priority corridors in urban environments and quantify their connectivity.

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5 OVERALL DISCUSSION: IMPLEMENTATION OF THE WORK

This chapter contains a synthesis of the main findings, research limitations and suggestions for future work are summarised according to the research objectives. Subsequently, the general contribution and the implications of the research are presented.

5.1 Objective 1: Evolution of Green Space under Rapid Urban Expansion

The first objective addresses the first question, “how did green space change during a period of rapid urban expansion for the three cities in the last 25 years?” The built-up areas in these cities expanded and encroached on green space, reducing the green space by more than 30% over the 25-year period but at different growth rates and changes as explained in Chapter 2. By 2014, the total urbanised area was almost doubled that of 1989 and the built-up area in Jakarta and Metro Manila (86% and 84% respectively) exceeded Kuala Lumpur (76%) (Figs. 2.3 and 2.5). Similarly, the highest population density was in Metro Manila followed by Jakarta and Kuala Lumpur (Fig. 2.8). In contrast, Metro Manila and Jakarta had the smallest percentage of green space (<10%), compared with 20% for Kuala Lumpur (Fig. 2.5): a finding that is consistent with the previous study of Richards et al. (2017). Built-up area and population density show significant relationships with the proportion of green space in the cities because these factors influence the urban development and the policies that city governments put in place (Richards et al., 2017).

Southeast Asian cities (Jakarta and Metro Manila) with increased of built-up area had decreased green space, a pattern which has been observed in other developing cities (Fuller & Gaston, 2009). However, the negative relationships between built-up areas and the green space could potentially be mitigated to some extent, if green space can increase in dense cities as an example in Kuala Lumpur (Table 2.3). In the period from 1999 to 2014, the conversion of 6% built-up areas to green space was the main contribution to the remaining 11% of green space in Kuala Lumpur. The results help to better understand the changes of green space proportion and its relationship with the expansion of built-up area.

This study also illustrates that quantification of spatial characteristics using landscape metrics (McGarigal et al., 2002) is useful in understanding green space fragmentation under rapid urban expansion. It also extends the research of Peng et al. (2010) by quantifying significant changes of the spatial pattern at all different levels of landscape, class and patch. While landscape and class level metrics are effective for quantifying the entire landscape and each land use/land cover (LULC), the results of patch level metrics shown in this study determined significant changes between built-up area and green space patches. For instance, green space was significantly fragmented in all three cities as indicated by increased patch density (PD) and decreased mean patch area (MPA) in the period from 1988 to 1999. However, in all three cities, built-up patch density (PD) decreased and mean patch area (MPA) increased significantly in the period from 1988 to 2014, indicating a coalescence of built-up patches due to increases in built-up area (Fig. 2.7). These findings support the previous studies in establishing landscape ecology theory to quantify landscape patterns of rapid urban expansion (Lv et al., 2012; Mahmoud & El-Sayed, 2011). This research considers the spatial arrangement of habitats, namely the (i) patch size, (ii) density, (iii) shape and (iv) distance. This empirical evidence helps us to understand the relationships between them and mechanisms of landscape change.

This study is significant as it interprets all multi-pattern green space changes and their sequences that can be observed in cities undergoing rapid expansion. The changes of green space spatial pattern were observed differently in the three cities during the study period. The theories of structural patterns and ecological processes are also explained. Green space in the three cities reduced in size, became less connected and more unevenly distributed in response to the rapid expansion of urban areas. The multi-pattern changes and process of fragmentation in the study areas were identified; in the early period of 1988 to

1999, the green space of the three cities experienced loss (attrition), reduction in size (shrinkage) and increasing distance of patches (isolation) due to the expanding built-up area. Green spaces are rapidly disappearing and becoming highly fragmented over the periods of study. This is assumed to be mainly driven by rural-urban migration (Byomkesh et al., 2012), leading to the deterioration of the ecological condition of the landscape (Zhou & Wang, 2011). In addition, rapid urban expansion accounted for the process of green space change, particularly in the outer belts of the city. This study understands the influence of built-up area on the location, size, proportions, spatial distribution and spatiotemporal of green space dynamics in rapidly expanding cities. Therefore, the quantification of landscape metrics give us the ability to examine the relationships between landscape structures and ecological processes such as fragmentation, shrinkage, attrition and isolation (Kupfer, 2012).

Conversely, the fragmentation of green spaces in Kuala Lumpur was not statistically significant compared to Jakarta and Metro Manila in the period of 1999 to 2014. The evidence supports the hypothesis that the impact of urban expansion on green space structure is higher in Jakarta and Metro Manila compared to Kuala Lumpur. This is anticipated to be due to greening policies contributing to the recovery of green area in Kuala Lumpur in the latter period of 1999 to 2014 (Kuala Lumpur City Hall, 2005). Using the observations, this study is able to predict the ecological consequence of the changes in spatial pattern and consecutively, provides a proper model for landscape change which differs among the three cities and time periods. The spatial patterns also explain the relationships between patch attributes and ecological factors such as patch isolation and connectivity which are closely related to biological diversity, dispersal, social and cultural of green space (Tian et al., 2011). This study helps to understand the structure and functioning of green space in rapidly expanding cities. Therefore, this research shows the different patterns and provides the broader picture of green space dynamics in the three cities, to establish the differences between the three cities.

Overall, the findings confirm the hypothesis that rapid urban expansion negatively impacts the landscape structure of green space. Different patterns of landscape structural changes were found at different scales, cities and years in response to rapid urban expansion, policies and population density. Integrated Geographical Information Systems (GIS) and landscape ecology analytics is an effective monitoring tool in evaluating the changes in spatial and structural patterns of green space in rapidly developing cities over the last two decades. This approach provides an understanding of the importance of spatial structure analysis such as size, density, shape and distance in the landscape of rapidly expanding cities. Apart from that, historical green space changes can inform future predictions and thus serve as an early warning system for ecological degradation. Therefore, this study will help for future research on urban studies in comparative to the other regions.

5.2 Objective 2: Impact of Rapid Urban Expansion on Green Space Structure

In the second objective that is presented in Chapter 3, the question addressed is, "is it possible to model and predict urban expansion in three cities (Kuala Lumpur, Jakarta and Metro Manila), and what are the main drivers in the resulting spatial patterns?" This study shows that the simulation of future urban expansion is performed well using a combination of Land Change Modeler (LCM), Artificial Neural Networks (ANN) and Markov chain modelling. The LCM-Markov chain model proved to be suitable for simulation of the future land use. The present research improves on the study of Renslow (2013) by incorporating physical variables (slope, terrain height, edge of green space, distance from waterbody and distance from roads) and highlighting their relative importance in landscape factors to improve the understanding of the causes, drivers and locations of land cover change. Limited spatial variables are available for predictive modelling due to the difficulties in obtaining the data sets such as socioeconomic data (Guan et al., 2011), climate change, and water and air quality. However, the variables that have been used in this study (i.e. physical variables and landscape structure) provide an indication of the conditions of the surrounding matrix and any possible future change in the surrounding green spaces.

This study further advances the LCM-Markov chain modelling approach to reveal transitions of land use as proposed by Liu et al. (2008). The gap of previous studies on cities experiencing rapid expansion (Jokar et al., 2013; Shafizadeh Moghadam & Helbich, 2013) is filled using historical data to empirically derive transition matrices across landscapes. Data from the earlier period of 1988/1989 and recent data from 2014 were utilised to compare transition probabilities between the change intervals as illustrated in Table 3.4 and Table 3.5. Consequently, this explains the likely future progress of land cover change process and the possibility to infer future changes by observing the recent changes in a single land cover map.

Compared to the cellular automata-Markov chain prediction model (Acevedo et al., 2010), the LCM-Markov chain model offers alternative possibilities regarding change as the accuracy of the simulated scenarios is easy to assess. The interpretation of the validation results in Table 3.3 and Figure 3.2 was carried out using the component of disagreements (quantity and location) as recommended by Pontius et al. (2011). The patterns of the proportions of the disagreements (quantity and location) were also different among cities. This was probably influenced by the changes in land cover area and spatial pattern. In addition, LCM-Markov chain modelling is a suitable procedure for the context of the spatial resolution adopted in this study. This procedure converts pixels into new land use categories within areas with the highest probability of change. It is able to describe the change rate in land use, and define the specific localities for the occurrences of change (Acevedo et al., 2010). Therefore, this study shows the effectiveness of land change modelling to regulate future urban expansion especially in Southeast Asian cities.

Moreover, this study strengthens the research by Friehat et al. (2015) by combining landscape metrics (size, shape and distance) with simulation modelling to characterise and assess the differentiation of landscape structure between the master plan and future scenarios. The green space structure in Kuala Lumpur is foreseen to be impacted at a higher rate by future expansion resulting in decreasing patch size when this is compared to Jakarta and Metro Manila (Fig. 3.6). Although it is difficult to prescribe land use configuration that can mitigate green space changes in the future, this modelling result suggests that increased green space area in the master plan of Jakarta and Metro Manila at the expense of built-up areas could serve as empirical information for land use planning in the cities to some extent. This model is a useful tool in simulating and projecting for rapid urban expansion as strategies for interventions for conservation planning of green space. The models help to understand the spatial structure and pattern of historical, current and future changes of urban land use. This study shows that an integration of land change modelling approach, remote sensing data, and spatial structure data can be used to simulate the future green space change and, hence, the urban expansion phenomena in spatial distribution, direction and time can be monitored.

Overall, the result from this study suggests that the master planning and future urban expansion have 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.

5.3 Objective 3: Ecological Connectivity Networks in Rapidly Expanding Cities

Chapter 4 explains the third objective while addressing the question, “what decision support tools might help the urban environmental planning process to optimise the structure, connectivity and function of green spaces?" This research adopts connectivity (corridors) (Forman & Godron, 1986) to describe a landscape's structural and functional continuity in space and time. The spatial pattern and functional analysis of the patch and corridor (Zhang & Wang, 2006) were applied to the green spaces in three cities by integrating models (circuit models, connectivity analysis and least cost patch models) in the assessment and development of ecological networks.

In this research, land use types were used as landscape resistance in circuit theory (Figs. 4.2 and 4.3). The value of landscape resistance reflects the contribution of the particular green space in maintaining an overall connectivity of the study area. This extends the application of circuit theory by Mcrae & Beier (2007) to build a spatially-explicit connectivity model in effort to understand habitat factors on biodiversity. Accordingly, this research applied spatially-explicit variables such as behavioural factors (foraging, nesting, breeding and seed dispersal) and green space structure (vegetation density, patch size and patch distance) in the circuit theory framework to develop a connectivity model (Tables 4.3 and 4.4). The findings demonstrate that patch size and distance are the main factors determining cumulative cost and current density for the Eurasian tree sparrows (Fig. 4.7). In addition, the least-cost path was more affected by the degree of patch connectivity; the former was influenced by the presence of corridors, whereas the latter was influenced by the distance between patches.

On the contrary, vegetation density had no effect on the priority corridors of Eurasian tree sparrows but it had a positive effect on the Yellow-vented bulbuls. Size plays an important role in the connectivity model because large suitable habitats can support large populations and are prone to maintaining species persistence (Xun et al., 2014). Bird diversity, abundance and their responses to fragmentation differ among species. This is related to the size and distance of patches (Uezu et al., 2005) that influence the structural and functional connectivity of green spaces (Art, 2010).

This study emphasises the importance of functional and structural connectivity of green space in the landscape. In particular, functional connectivity (e.g dispersal distance) is incorporated into the green space structure as an indicator in developing priority corridors and minimum cost for movement of ecological connectivity networks in cities with rapid expansion. With the connectivity and least-cost path analysis, the patches or links are acting as the connecting elements and provides the least-cost path for both species (Figs. 4.6 and 4.7). Conversely, organisms that could move in a long distance across the hostile matrix may not be sensitive to heterogeneous landscape mosaics (Laita et al., 2010). For instance, a research by Xun et al. (2014) reported that the efficiency of habitat conservation is decreased when the dispersal distance is over 5 km. The key threshold range is 1.5 to 5 km where a small change of dispersal distance brings about a great change of connectivity. In this research, both species have a dispersal capability of about 1 km (Fig. 4.6 and table 4.5). The green space patches are likely to constitute an optimal way of providing habitat availability to these species. This study considers that both species with dispersal ability in this threshold range gain the most benefit from the green space patches. The results identified the minimum least-cost path for the persistence of a species in a landscape and the key locations where conservation efforts can be made directly on those critical patches and links (Fig. 4.9 and table 4.6).

Although the selection of behavioural factors and data such as bird distribution, abundance and density on the ground to measure structural connectivity may be difficult, this study contributes to the effective visual mapping of priority corridors for the conservation of biodiversity and green space. In addition, the model approach can be used in the assessment of connectivity over very large areas, especially urbanised regions of Southeast Asia. Therefore, the developed ecological landscape connectivity network supports the assertion that the models have potential to identify priority corridors and thus act as decision support tools that can help to optimise the structure, function and connectivity of green spaces.

5.4 Contribution to Landscape Ecology Science in Urban Systems

This research is among the first comparative studies (e.g. Estoque & Murayama, 2015; Estoque & Murayama, 2016; Murakami et al., 2005; Richards et al., 2017) to evaluate the changes in spatial and structural patterns of green space in urban areas of three rapidly growing cities in Southeast Asia over the last two decades. The differences in the spatial pattern of green space dynamics and urban expansion explain the new land change model of rapidly expanding cities. This empirical information contributes to further advancement of theory and method in the study of urban expansion and green space dynamics. This study helps us to understand the evolution of green space under rapidly expanding cities, the future of urban expansion and the effectiveness of master planning. Subsequently, this study provides ecological connectivity networks as guidance for green space conservation. Together, the evidence presented supports the application of theory and methods in landscape ecology, a novel integrated approach and modelling tools to analyse, predict and develop tools for green space under rapid urban expansion. This work has contributed to the development of land change modelling, prediction and ecological connectivity network models for rapidly expanding cities as decision support tools for the use of urban planning and green space conservation. These models have wider global implications and hence, allow many applications, ease of calculation, functional basis and simplicity of interpretation by a range of specialist and non-specialist stakeholders. This is particularly important in order to understand a complex land use system where the ability to conduct field site visits is limited.

5.5 Implications

The findings of this study have a number of important implications for future practice as follows:

5.5.1 Social

The different landscape structures and their respective dynamics in the three cities may have implications for social value and ecological functioning of green space to the urban environment. The reduction of green space, results in a poor quality of landscape with irregular patches and an uneven distribution (Figs. 2.5 and 2.7; Chapter 2). It is important to provide residents with more desirable and attractive designs of public spaces by including large parks with high density and shape variation for leisure and recreation. They must also have access to green spaces near residential areas such as local urban parks and neighbourhood parks (Wright Wendel et al., 2012). These could bring people closer to nature, improve their physical and mental health, and provide diverse visual and amenity resources (Tian et al., 2014).

The size, structure, form and shape of green space patches are fundamental components in designing green space and are important indicators that characterise the need for green space (Fig. 2.7). The findings of this research may assist green space planning and management (Madureira et al., 2011). They also suggest the need to consider spatiotemporal structure and pattern in relevant public policies and decision-making for human preference, society and culture, especially for the Southeast Asian people and other relevant developing countries.

5.5.2 Urban Planning and Policies

The findings of this study demonstrate how remote sensing and GIS can be used to assess, monitor and quantify LULC changes in large areas (Figs. 2.3 and 3.5) where traditional methods including field observations may not be adequate. The spatial information and historical changes of green space pattern can serve as an early warning system for understanding the effects of green space change (Thapa & Murayama, 2011). This study emphasises the capability of GIS methods in (i) processing and managing spatial data, (ii) classifying the LULC into categories, (iii) understanding the changing landscape and transitions, and

(iv) discovering the relations and differences in LULC (Chapter 2). These capabilities can guide urban planning, particularly the master plans such as the Kuala Lumpur Structure Plan 2020, the Master Plan of Greater Jakarta for 2010-2030, and Metro Manila Green Print (2030) (Fig. 3.5; Chapter 3). They are also important in evaluating long-term changes (Kantakumar et al., 2016).

This study also indicates the importance of a landscape ecological approach in the land change model (Fig. 3.6; Chapter 3) to understand the mechanisms shaping urban expansion and to underline the potential of proper urban planning for mitigating green space losses (Madureira et al., 2011). Regardless, landscape metrics are simple, intuitive tools for assessing and monitoring changes in landscape pattern and the effects on underlying ecological processes (Kupfer, 2012). This study provides effective and practical applications of landscape metrics and the results characterise synoptically the evolution of green space structure in these three cities (Figs. 2.6 and 2.7; Chapter 2). It provides empirical information to predict the changing dynamics for future urban expansion.

Practically, modelling the effects of past and current land use compositions and patterns on green space structure is a fundamental step to simulate future land use (Figs. 3.3 and 3.4; Chapter 3). The model overcomes the defects of previous research (Byomkesh et al., 2012) that was unable to describe the spatial transformation, which is very important for cities like those in Southeast Asia with a fast-paced urban growth. The integrated approach of remote sensing, GIS and landscape ecology analytics supports the land change model in understanding the differences of green space change in response to rapid urban expansion. This study demonstrates the usefulness of spatial time series data for long-term land cover change modelling using Markov chain transition matrices (Tables 3.4 and 3.5) as an indicator of the direction and magnitude of future changes, and as a description of past changes. This method can improve the creation of the comparison map, producing a map that relates closer to the reference map (Fig. 3.2). These components are simpler and more helpful for the vast majority of applications. Plus, they are also useful in explaining the reasons for the disagreement based on the matrix information (Zhang et al., 2011). Consecutively, this study suggests a cost-effective and automated simple, flexible and intuitive model with the ability to incorporate spatiotemporal changes.

This work has shown how an integrated landscape ecology approach in LULC simulation modelling has the capability to drive understanding of the urban landscape dynamics and pattern (Fig. 3.1; Chapter 3). This study allows for a set of diagnostic tools to assess failure and successes in planning strategies, illustrating possible improvements to master planning process and informing effective planning in the future. The planning authorities could design interventions which support planning at the landscape level and a better understanding of the future spatial configuration of urban expansion to a sustainable urban development and planning scenario (Sharifi et al., 2014).

This study addresses the important topic of rapid urban expansion and master planning in complex urban landscapes, as well as furthering an understanding of how models can be effectively used as valuable tools for monitoring the effectiveness of master planning (Fig. 3.2). It also illustrates a novel approach and application to LCM-Markov chain models, namely as diagnostic tools to identify evidence of past or current planning interventions. This is particularly critical in cities undergoing rapid expansion, where assessing the relative impact and degree of success that planning can have is often difficult.

This study provides the relationships between spatial patterns and the planning and policies of the environment in each city (Fig. 3.6). These can be used by researchers, administrative planners and decision makers to assess and monitor green space structure and to develop effective master planning for rapidly expanding cities. This study draws attention to sensitive areas in the landscape based on explanatory variables (road, green space edge and slope) (Appendices B.1, B.2 and B.3) and green space structure changes (patch size, shape, density and distance) (Fig. 3.6) to manage urban development. Subsequently, differentiated policies for the areas should be formulated to guide reasonable expansion of urban land (Sharifi et al., 2014). Therefore, understanding the impact of structural patterns of urban expansion on green space structure will help policymakers to reassess the previous policies in the area of research such as (i) Physical Development Framework Plan for Metropolitan Manila (1996-2016) (PDFPFMM), (ii) Local Preparation Bureau for Development in Jabodetabek Metropolitan Area (1975), (iii) Presidential Decree on Development of Jabodetabek Area (1976): Spatial Planning Law 26/2007 and 174/2007, and (iv) Kuala Lumpur Structural Plan (1984).

In contrast, greening policies such as Metro Manila Green Print (2030) and the Master Plan of Greater Jakarta for 2010-2030 may be implemented to reverse the decline and to enable the increase of green space cover (Fig. 3.5b and 3.5c). This research recommends the master plan of Kuala Lumpur Structure Plan 2020 (2000-2020) to be coordinated properly and to be monitored effectively in order to support green space conservation (Fig. 3.5a). This is significant to the authorities as they are prompted to design interventions at the landscape and regional levels for the improvement of master planning. Additionally, this research also facilitates the effective planning of future urban expansion and green space conservation. Future land change is crucial information for planners and organisations to allocate important green space and manage sustainable land use in response to the diverse requirements of the people in this region (Losiri et al., 2016). Furthermore, the spatial comparison analysis reveals that this combined method can be adopted to choose the best urban master plan that can mitigate potential future rapid urban expansion. Application of integrated simulation modelling and landscape ecology analytics provides significant insights into the evolutionary structure of spatial urban expansion, identifies associated constraints, and prompts intervention for spatial planning and policies in cities.

5.5.3 Green Space Conservation

Apart from quantitatively assessing the present situation and the rationality of recent and future urban expansion, this research can also facilitate the design of urban ecological networks using combined modelling tools of circuit theory, connectivity and least-cost path analysis for green space conservation (Fig. 4.1; Chapter 4). This study highlights the importance of connectivity in an urban area to optimise the green space structure and maximise the effectiveness of dispersal and movement for urban wildlife (Fig. 4.9 and table 4.6). This approach can provide practical guidelines for habitat network protection in urban areas by ranking the contributions of landscape patches and linking the overall connectivity (Fumagalli & Toccolini, 2012). Accordingly, it is recommended that different species be parameterised with their own corresponding threshold distances to ensure that species-specific behaviours relating to connectivity, dispersal distance and habitat requirements are preserved in the model framework (Tables 4.3 and 4.4). This method is generally applicable to most relevant species.

This study provides guidance for the restoration of green space using ecological connectivity networks to supplement the environmental and ecological functions for social and psychological benefits (Coombes et al., 2010; Ernst, 2014). Enhanced connectivity between green space patches means high potential accessibility to green space for leisure and recreation by urban residents. It also facilitates biodiversity, movement, survival and persistence (Lo & Jim, 2010). The present research adapted the eco-profile method (Parker et al., 2008) as a multispecies approach and connectivity modelling tool to facilitate a number of stakeholders in setting the goals of biodiversity. This study is important and timely as it highlights the conservation problems faced by rapidly expanding cities, and proposes a new integrated methodology for developing ecological connectivity networks that can be used by administrative planners and decision makers for biodiversity conservation. This study addresses the important topic of structural and functional connectivity of green space under rapid urban expansion as well as furthering an understanding of how models can be appropriately used as valuable tools for this topic. It also illustrates a novel approach and application to integrated models, namely as a diagnostic tool to identify priority corridors for bird species (Fig. 4.10). These models could potentially solve practical planning issues. The planning of landscape connectivity and potential corridors will also help governments, nongovernmental organisations and other stakeholders to make decisions and take proactive actions, particularly in areas marked as a least-cost path. In this way, green spaces can be protected and managed adequately as natural capital (Kong et al., 2010). Therefore, an ecological connectivity network is needed as a guideline for green space planning to conserve the natural habitat of the urban ecosystem.

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6 CONCLUSIONS AND FURTHER RESEARCH

This chapter summarises the project as a whole. Additionally, investigations for future understanding of green space dynamics and the impacts of rapid urban expansion are presented in the Further Research section. The aims of this research are to i) understand the changes in urban areas and green space dynamics of rapidly developing cities over the last two decades, ii) verify land change models for simulation of urban expansion and identify the main drivers, including spatial planning, in the resulting spatial patterns, and iii) develop an ecological landscape connectivity network model of green spaces.

Firstly, this study highlights the significant use of remote sensing, Geographical Information Systems (GIS) and landscape ecological analytics in evaluating the spatial structure of rapid urban expansion and green space dynamics. The research results contribute to the understanding of different urban forms which give different impacts on the green space structure. Previously, limited studies on this topic had been developed for Southeast Asia and other developing countries. The differences in spatial structure can also have implication on the policy, use, function and value of green space. This research demonstrates the application of the theory and method of an integrated landscape ecology approach on land use/land cover (LULC) modelling. Consequently, this facilitates the understanding on the urban landscape dynamics and the pattern, structure, connectivity and function of green space.

Secondly, integrated of Land Change Modeler (LCM), Markov chain and landscape ecological analytics has proved to be an effective method for the simulation of future land use and the assessment of master plan. This study proposes an effective master plan as the intervention to limit urban expansion. Key findings clearly indicated essential differences in the predicted spatial structure for 2030 when compared to the planned development in each city. The substantial differences were evident in the size, density, distance, shape and spatial pattern of green spaces. Increased fragmentation of the landscape will continue in 2030, more complexity in shapes will be observed and less connectivity between green space patches will be present. Evidence suggests that these spatial patterns are influenced by the rapid urban expansion and the respective master planning policies of the cities. The development of land change models provides a set of diagnostic tools to assess failure and successes in planning strategies. Consequently, this demonstrates possible improvements to master planning and facilitates effective planning of future land use.

Thirdly, circuit theory, least-cost path modelling and connectivity analysis could potentially act as a connectivity modelling tool to develop priority corridors of green spaces. This research introduces a different perspective to the structural and functional connectivity of green spaces. Birds were adopted as the target species to determine the driving behavioural factors and green space structural characteristics. Particularly, ecological connectivity networks could identify significant areas for biodiversity conservation.

Land change models, prediction models and ecological connectivity networks contribute to the understanding of complex urban landscape. This study is important and timely as it highlights the planning problems faced by rapidly expanding cities and distinguishes the best master planning strategies under a rapid urban expansion scenario. Furthermore, this research proposes a new integrated method for simulating urban expansion and provides connectivity network models. These models have potential as a key planning approach and decision support tools to help in maintaining ecological functioning of the urban landscape.

Recommendations for Future Research

The concept, framework, methods and practical demonstration of the integrated models in this research are documented for cities experiencing rapid expansion. Nevertheless, several recommendations below address the development of the integrated model approach in a global aspect. The recommendations are interrelated, recommending specific actions to researchers and are sequential for future studies on green space under rapid urban expansion:

i. Analyse evolution of green space under rapid urban expansion using different spatiotemporal analyses and scales such as high resolution data, different scales of cities, and the inside and outside boundaries of rapidly expanding cities.

ii. Identify the other driving forces of rapid urban expansion and assess factors such as socioeconomic, cultural, physical, land use activities, population density and urban planning.

iii. Compare LCM-Markov chain with other prediction models such as regression analysis, moving window, cellular automata, SLEUTH and DYNAMICA to assess the limitations of LCM-Markov chain model.

iv. Identify, classify and delineate green space priority areas for green space networks.

v. Expand the theory and factors applied in the integrated structure and functional connectivity of ecological network model to the other relevant target species.

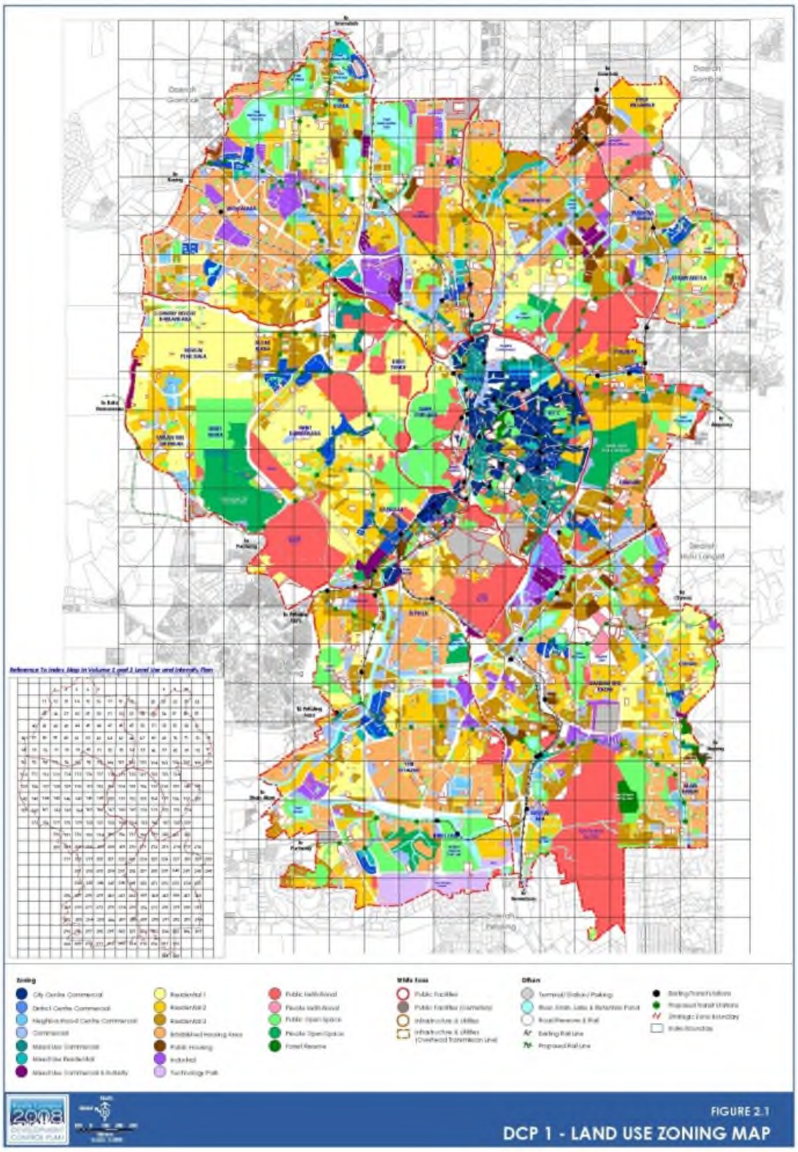
vi. Compare the connectivity models of circuit theory, connectivity and least-cost path analysis with another connectivity model such as graph theory, network analysis and connectivity index. Clarify the strengths and weaknesses of different approaches, including the potential limitations and biases in modelling connectivity.

vii. Explore how this integrated approach could be taken up by planning departments and decision makers of the municipalities in the cities.

APPENDICES

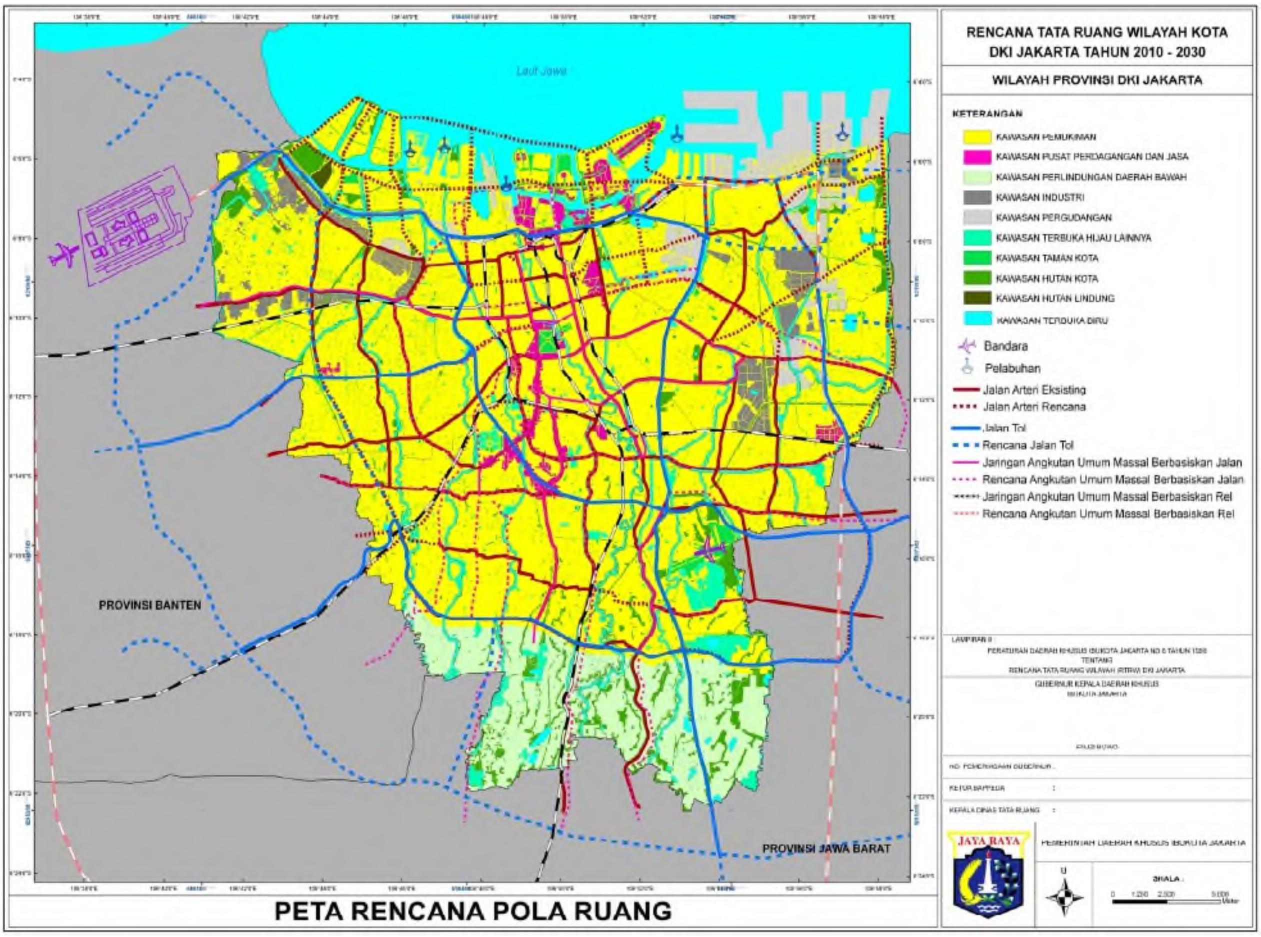
Appendix A Master plan maps

A.1 Master plan 2030 of Kuala Lumpur



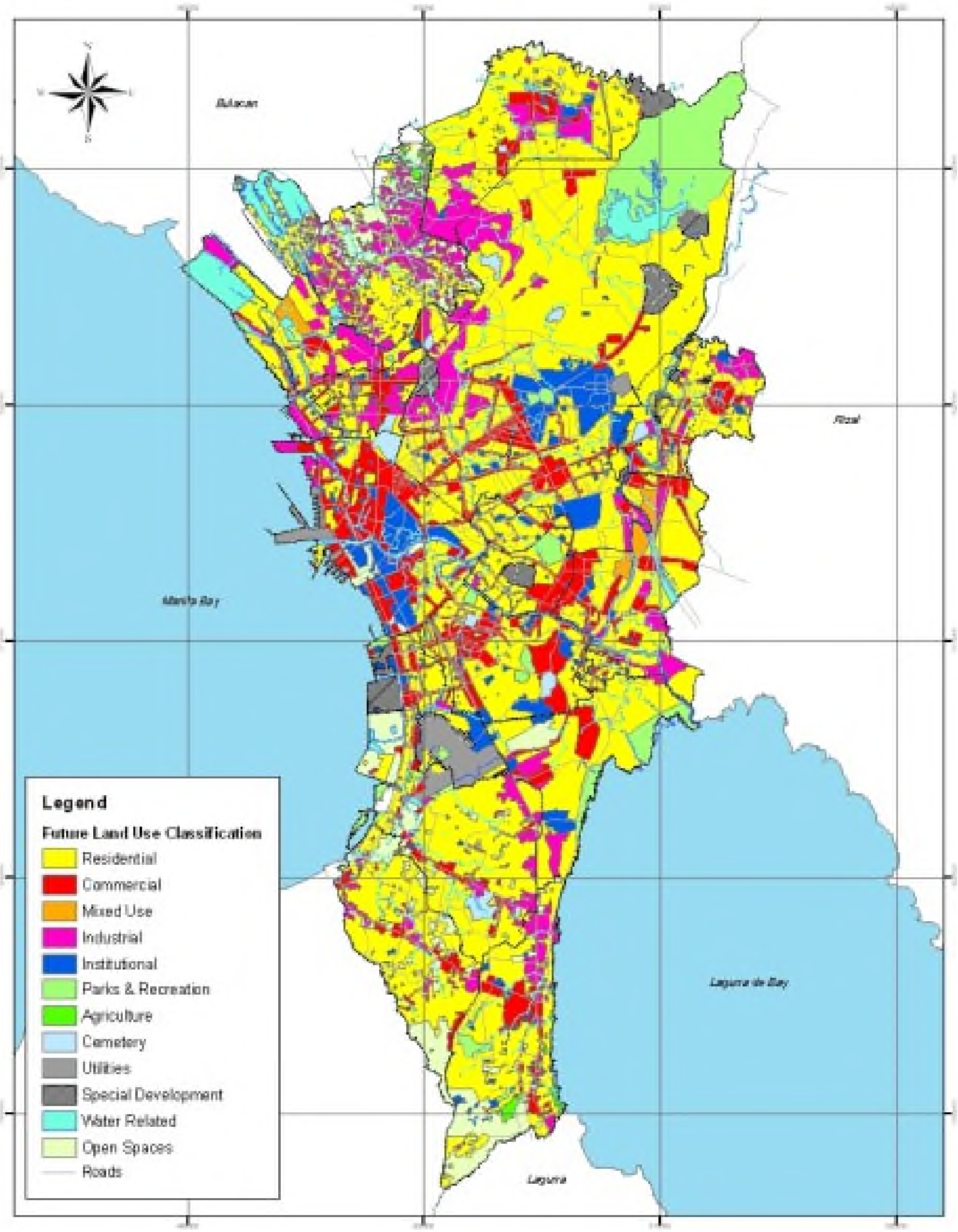
Note: The typology of urban morphology in the city consist of 19 classes (city centre commercial, district centre commercial, neighbourhood centre commercial, commercial, mixed use commercial, mixed used residential, mixed use commercial and industry, residential 1, 2, 3, established housing area, public housing, industrial, technology park, public institutional, private institutional, public open space, private open space, forest reserve) (Kuala Lumpur City Hall, 2005)

A.2 Master plan map 2030 of Jakarta



Note: The typology of urban morphology in the city consist of 10 classes (district area, commercial, local protected area, industrial, warehouse, open green space, park area, forest, forest protected area and waterbody) (Government Jakarta Region, 2011).

A.3 Master plan maps 2030 of Metro Manila

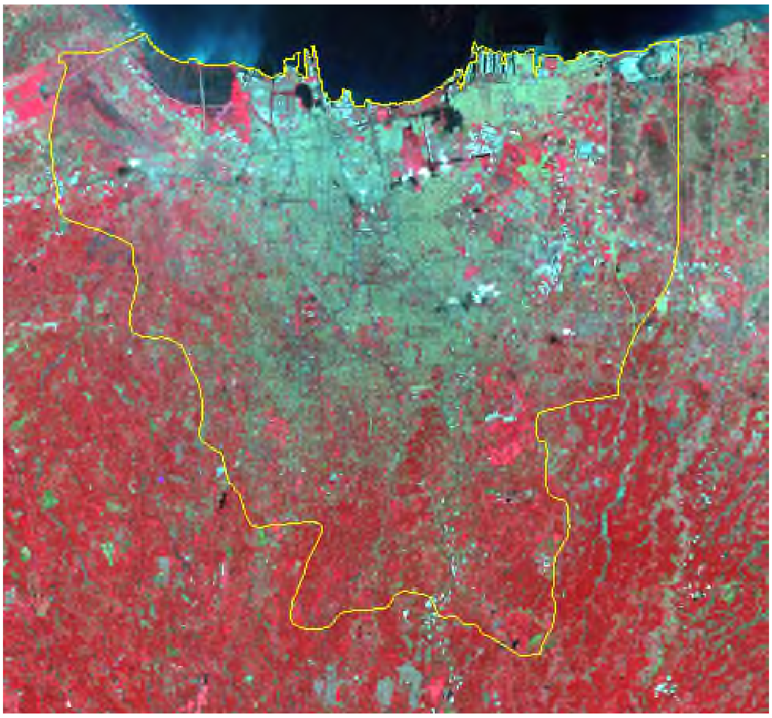


Note: The typology of the urban morphology in the city consist of 12 classes (residential, commercial, mixed use, industrial, institutional, parks and recreation, agriculture, cemetery, utilities, special development, water related, open spaces and road) (MMDA, 2012).

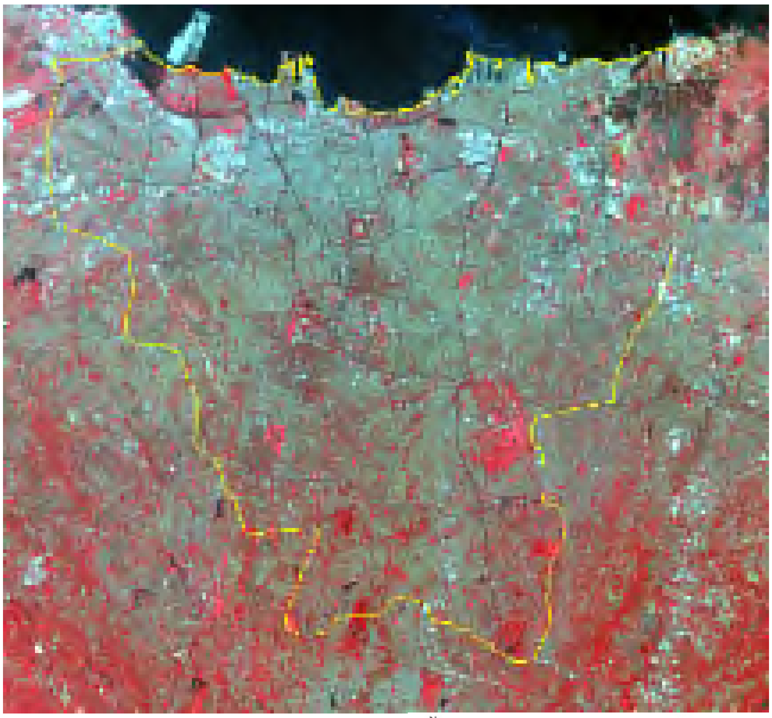
Appendix B Evolution of Green Space under Rapid Urban Expansion

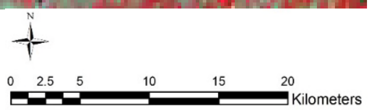
B.1 Landsat images of Jakarta

a)



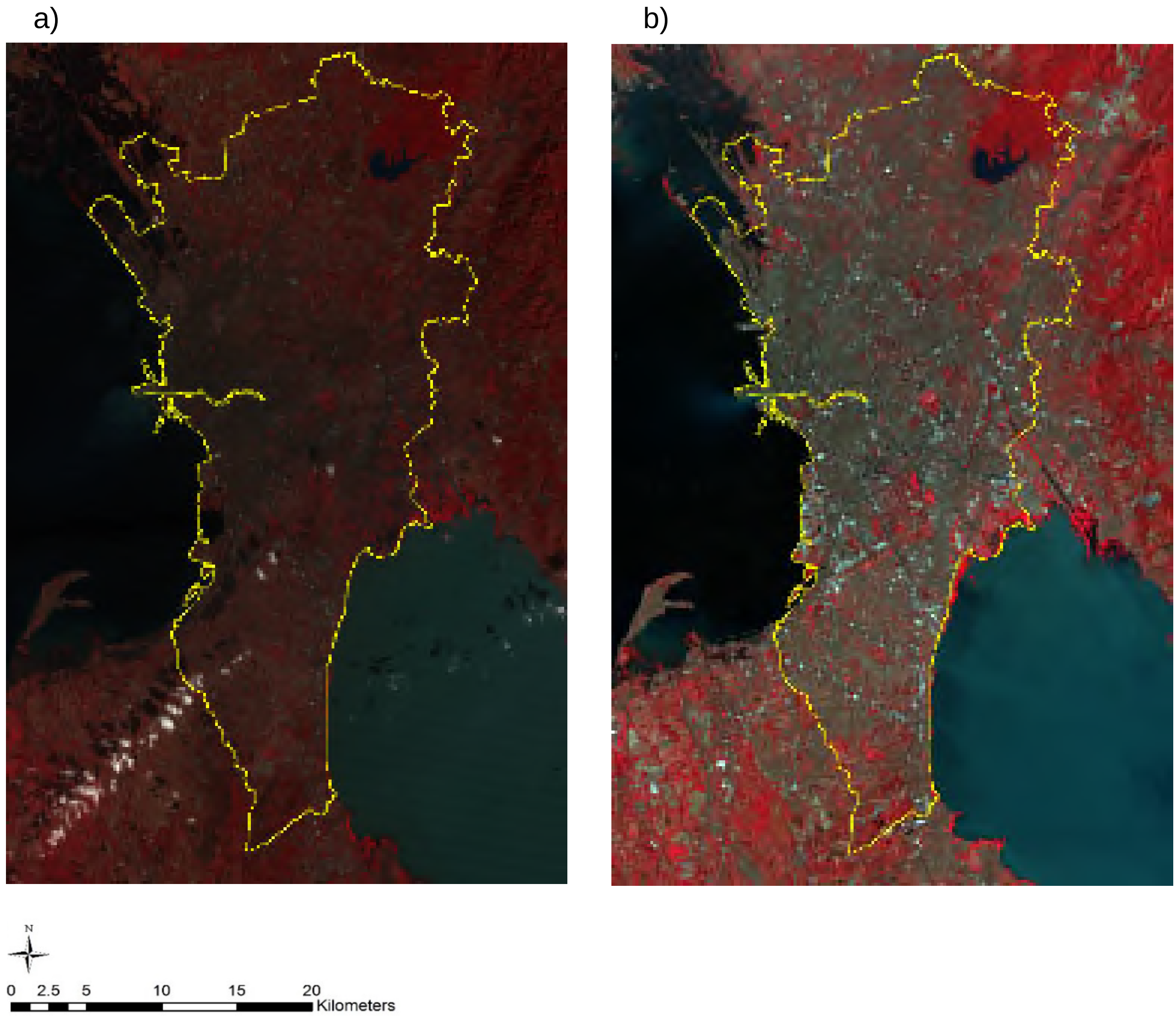
b)





Note: Yellow line is the boundary of the city define by Global Administrative Area-www.gadm.org); a) Landsat 5 (3.5.1989) shows the false color composite image (Bands 4, 3 and 2) and b) Landsat 8 (25.6.2014) shows the false color composite images (Bands 5, 4 and 3).

B.2 Landsat images of Metro Manila



Note: Yellow line is the boundary of the city define by Global Administrative Area-www.gadm.org); a) Landsat 5 (16.9.1989) shows the false color composite image (Bands 4, 3 and 2) and b) Landsat 8 (8.3. 2014) shows the false color composite images (Bands 5, 4 and 3).

B.3 Detail of satellite imagery information for three cities

City	Satellite imagery	Path/Row	Resolution	Date
Kuala Lumpur	Landsat 5 Thematic Mapper (TM)	127/58	30m	17/04/1988
	Landsat 5 Thematic Mapper (TM)	127/58	30m	11/02/1999
	Landsat 8 Enhanced Thematic Mapper	127/58	30m	07/06/2014
Jakarta	Landsat 5 Thematic Mapper (TM)	122/64	30m	03/05/1989
	Landsat 5 Thematic Mapper (TM)	122/64	30m	14/09/1999
	Landsat 8 Enhanced Thematic Mapper	122/64	30m	25/06/2014
Metro Manila	Landsat 5 Thematic Mapper (TM)	160/50	30m	16/09/1989
	Landsat 5 Thematic Mapper (TM)	160/50	30m	04/10/1999
	Landsat 8 Enhanced Thematic Mapper	160/50	30m	08/03/2014

B.4 Accuracy assessment

B.4.1: Accuracy assessment of year a) 1988, b) 1999 and c) 2014 of Kuala Lumpur (the bold value indicate the number correct)

a) 1988

Types of land use land cover	Reference data						
Classification	*Built up area*	*Green spaces*	*Cleared land*	*Waterbody*	*Classified Total*	*Producers Accuracy (%)*	*User accuracy (%)*
Built up area	**81**	5	7	7	100	87.10	81.00
Green spaces	1	**95**	2	2	100	86.36	95.00
Cleared land	9	8	**74**	9	100	86.05	74.00
Waterbody	2	2	3	**93**	100	83.78	93.00
Reference Total	93	110	86	111	400		
Overall accuracy (%) = 88.60 Kappa statistic = 0.8575							

b) 1999

Types of land use land cover	Reference data					
Classification	*Built up area*	*Green spaces*	*Cleared land*	*Waterbody*	*Classified Total*	*Producers Accuracy (%)*	*User accuracy (%)*
Built up area	**85**	3	4	8	100	87.63	85.00
Green spaces	4	**76**	12	8	100	88.37	76.00
Cleared land	7	6	**81**	6	100	83.51	81.00
Waterbody	1	1	0	**98**	100	81.67	98.00
Reference Total	97	86	97	120	400		
Overall accuracy (%) =88.00 Kappa statistic = 0.85							

c) 2014

Types of land use land cover	Reference data						
Classification	*Built up area*	*Green spaces*	*Cleared land*	*Waterbody*	*Classified Total*	*Producers Accuracy (%)*	*User accuracy (%)*
Built up area	**77**	4	9	10	100	86.52	77.00
Green spaces	6	**88**	3	3	100	88.00	88.00
Cleared land	2	6	**89**	3	100	83.96	89.00
Waterbody	4	2	5	**89**	100	84.76	89.00
Reference Total	89	100	106	105	400		
Overall accuracy (%) =88.60 Kappa statistic = 0.8575							

B.4.2: Accuracy assessment of year a) 1989, b) 1999 and c) 2014 of Jakarta (the bold value indicate the number correct)

a) 1989

Types of land use land cover	Reference data						
Classification	*Built up area*	*Green spaces*	*Cleared land*	*Waterbody*	*Classified Total*	*Producers Accuracy (%)*	*User accuracy (%)*
Built up area	**90**	3	3	4	100	85.71	90.00
Green spaces	7	**79**	5	9	100	84.04	79.00
Cleared land	7	8	**78**	7	100	85.71	78.00
Waterbody	1	4	5	**90**	100	81.82	90.00
Reference Total	105	94	91	110	400		
Overall accuracy (%) = 87.40 Kappa statistic = 0.8425							

b) 1999

Types of land use land cover	Reference data						
Classification	*Built up area*	*Green spaces*	*Cleared land*	*Waterbody*	*Classified Total*	*Producers Accuracy (%)*	*User accuracy (%)*
Built up area	**89**	2	6	3	100	85.58	89.00
Green spaces	7	**81**	5	7	100	88.04	81.00
Cleared land	5	5	**87**	3	100	82.08	87.00
Waterbody	3	4	8	**85**	100	86.73	85.00
Reference Total	100	98	106	92	400		
Overall accuracy (%) =88.40 Kappa statistic = 0.8550							

c) 2014

Types of land use land cover	Reference data						
Classification	*Built up area*	*Green spaces*	*Cleared land*	*Waterbody*	*Classified Total*	*Producers Accuracy (%)*	*User accuracy (%)*
Built up area	**79**	9	8	4	100	87.78	79.00
Green spaces	7	**83**	7	3	100	82.18	83.00
Cleared land	2	3	**92**	3	100	83.64	92.00
Waterbody	2	6	3	**89**	100	89.90	89.00
Reference Total	90	101	110	99	400		
Overall accuracy (%) =85.75 Kappa statistic = 0.8100							

Table B.4.3: Accuracy assessment of year a) 1989, b) 1999 and c) 2014 of Metro Manila (the bold value indicate the number correct)

a) 1989

Types of land use land cover	Reference data						
Classification	*Built up area*	*Green spaces*	*Cleared land*	*Waterbody*	*Classified Total*	*Producers Accuracy (%)*	*User accuracy (%)*
Built up area	**91**	2	4	3	100	87.50	91.00
Green spaces	6	**74**	11	9	100	84.09	74.00
Cleared land	2	8	**85**	5	100	84.16	85.00
Waterbody	5	4	1	**90**	100	84.11	90.00
Reference Total	104	88	101	107	400		
Overall accuracy (%) = 88.00 Kappa statistic = 0.85							

b) 1999

Types of land use land cover	Reference data						
Classification	*Built up area*	*Green spaces*	*Cleared land*	*Waterbody*	*Classified Total*	*Producers Accuracy (%)*	*User accuracy (%)*
Built up area	**91**	2	3	4	100	85.05	91.00
Green spaces	0	**99**	1	0	100	83.19	99.00
Cleared land	7	8	**77**	8	100	83.70	77.00
Waterbody	9	10	11	**70**	100	85.37	70.00
Reference Total	107	119	92	82	400		
Overall accuracy (%) =87.40 Kappa statistic = 0.8425							

c) 2014

Types of land use land cover	Reference data						
Classification	*Built up area*	*Green spaces*	*Cleared land*	*Waterbody*	*Classified Total*	*Producers Accuracy (%)*	*User accuracy (%)*
Built up area	**89**	2	6	3	100	85.58	89.00
Green spaces	7	**81**	5	7	100	88.04	81.00
Cleared land	5	5	**87**	3	100	82.08	87.00
Waterbody	3	4	8	**85**	100	86.73	85.00
Reference Total	100	98	106	92	400		
Overall accuracy (%) =88.40 Kappa statistic = 0.8550							

B.5 Conversion of land use types in the period from 1988/1989 to 1999 and from 1999 to 2014 in a) Kuala Lumpur, b) Jakarta and c) Metro Manila (bolded values indicate no change)

a) Kuala Lumpur

1988	**1999 (%)**				
	Green Space	**Built-up Area**	**Cleared Land**	**Waterbody**	**Total**
Green space	**22.1**	17.1	5.4	1.0	45.6
Built-up area	4.0	**26.8**	3.8	0.6	35.6
Cleared land	4.2	8.6	**1.7**	0.3	14.8
Waterbody	1.1	1.2	0.4	**1.3**	4
Total	31.4	53.7	11.2	3.2	100.0

1999	**2014 (%)**				
	Green Space	**Built-up Area**	**Cleared Land**	**Waterbody**	**Total**
Green space	**11.7**	19.1	0.7	0.5	31.9
Built-up area	6.1	**46.5**	0.6	0.6	53.8
Cleared land	1.7	9.1	**0.3**	0.2	11.2
Waterbody	0.9	1.5	0.0	**0.8**	3.2
Total	20.2	76.1	1.6	2.04	100.0

b) Jakarta

1989	1999 (%)				
	Green Space	**Built-up Area**	**Cleared Land**	**Waterbody**	**Total**
Green space	**16.5**	25.1	2.8	2.3	46.6
Built-up area	0.9	**40**	0.5	0.3	41.6
Cleared land	0.1	0.6	**0.0**	0.0	0.8
Waterbody	1.7	6.4	0.6	**2.3**	11.0
Total	19.1	72.1	3.9	4.9	100.0

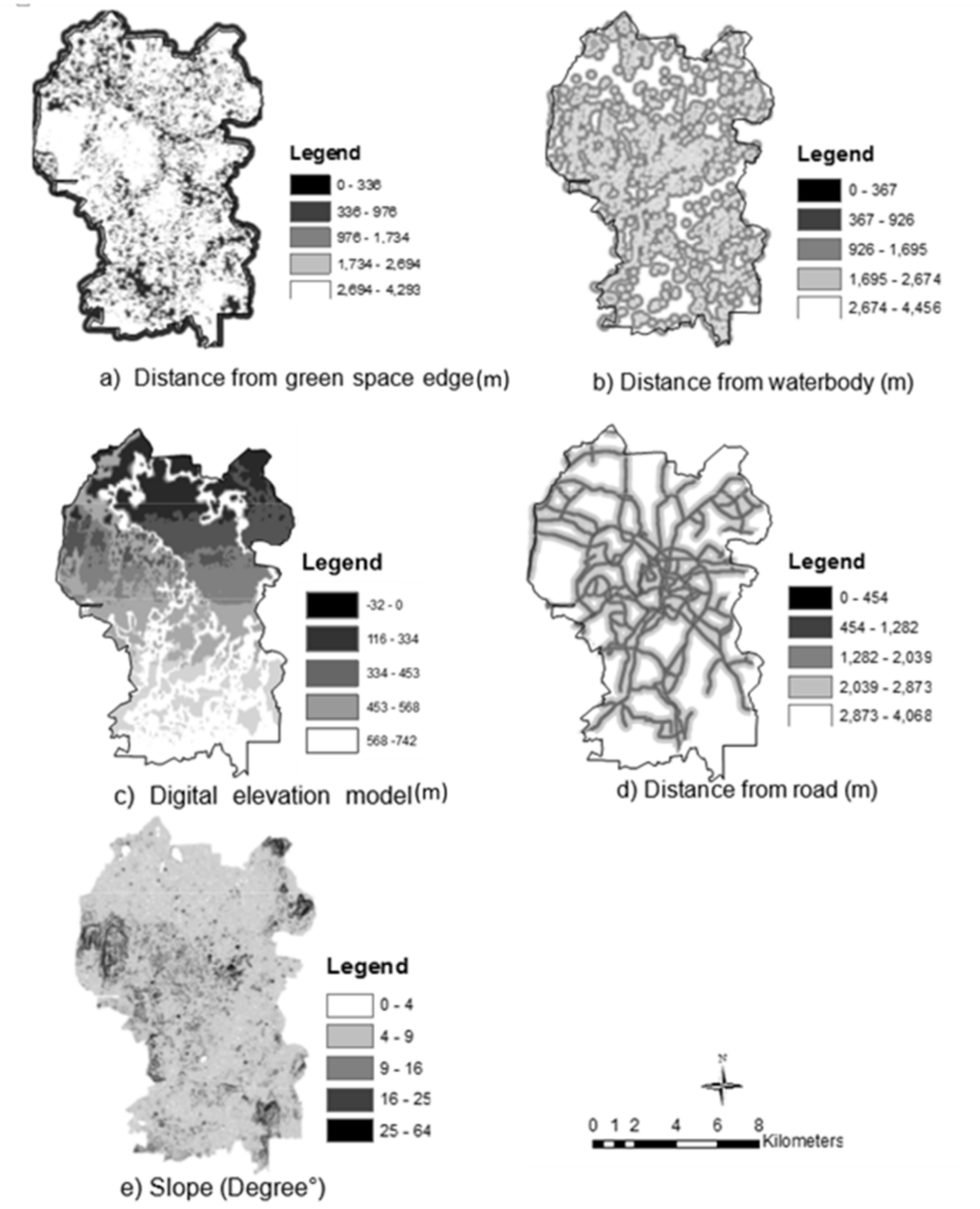
1999	2014 (%)				
	Green Space	**Built-up Area**	**Cleared Land**	**Waterbody**	**Total**
Green space	**5.7**	11.9	1.1	0.4	19.1
Built-up area	0.7	**69.8**	1.3	0.4	72.0
Cleared land	0.3	2.4	**1.1**	0.1	3.9
Waterbody	0.6	2.3	0.1	**2**	4.9
Total	7.2	86.4	3.6	2.8	100.0

c) Metro Manila

1989	1999 (%)				
	Green Space	**Built-up Area**	**Cleared Land**	**Waterbody**	**Total**
Green space	**15.4**	12.9	2.6	0.2	31.1
Built-up area	1.8	**52.7**	1.4	0.1	56.0
Cleared land	1.5	5.1	**0.4**	0.1	7.1
Waterbody	0.8	2.6	0.1	**2.3**	5.7
Total	19.6	73.2	4.5	2.7	100.0
1999	**2014 (%)**				
	Green Space	**Built-up Area**	**Cleared Land**	**Waterbody**	**Total**
Green space	**6.6**	10.0	2.8	0.1	19.5
Built-up area	1.3	**70.4**	1.1	0.4	73.2
Cleared land	0.1	3.9	**0.5**	0.0	4.5
Waterbody	0.5	0.4	0.1	**1.8**	2.8
Total	8.5	84.7	4.5	2.3	100.0

Appendix C Impact of Rapid Urban Expansion on Green Space Structure

C.1 Variables of LCM in Kuala Lumpur



a) Distance from green space edge(m)

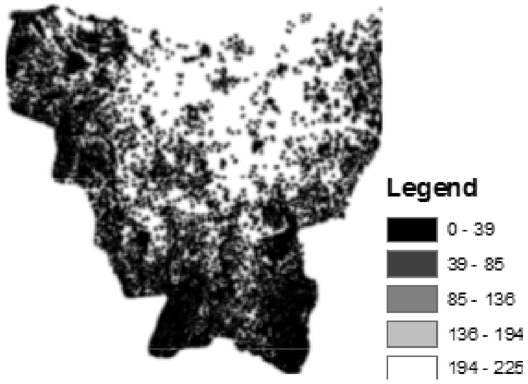
b) Distance from waterbody (m)

c) Digital elevation model(m)

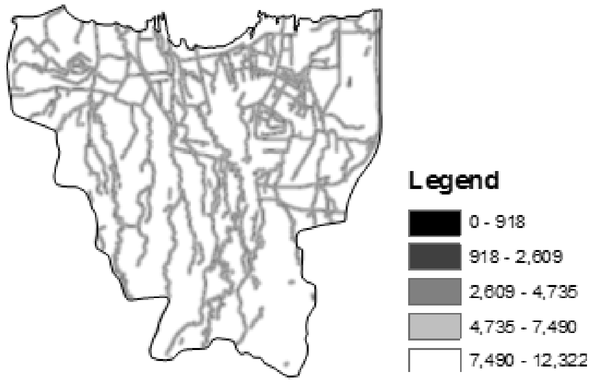
d) Distance from road (m)

e) Slope (Degree°)

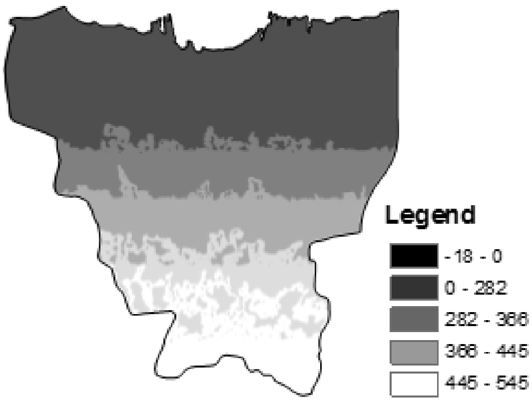
C.2 Variables of LCM in Jakarta



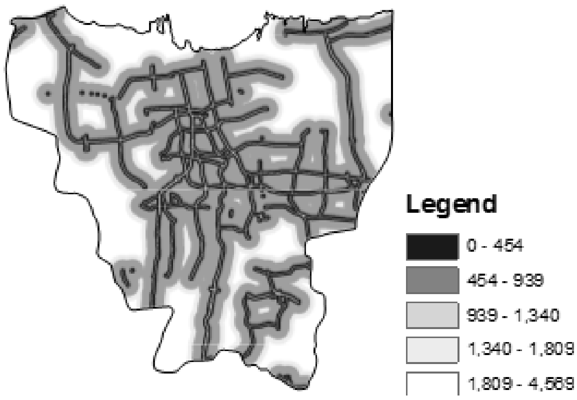
a) Distance from green space edge (m)



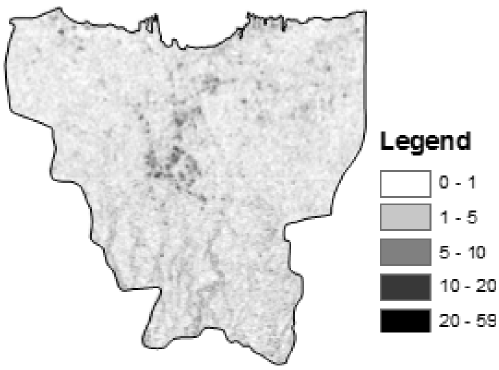
b) Distance from waterbody (m)



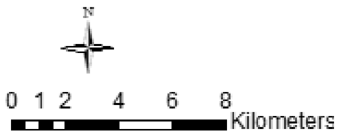
c) Digital elevation model (m)



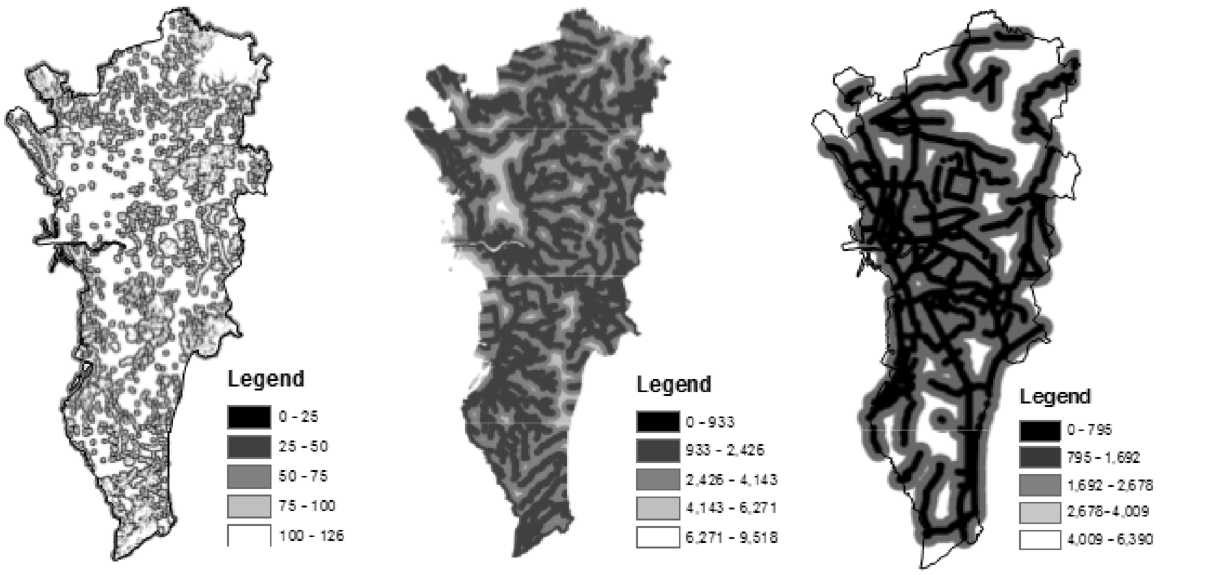
d) Distance from road (m)



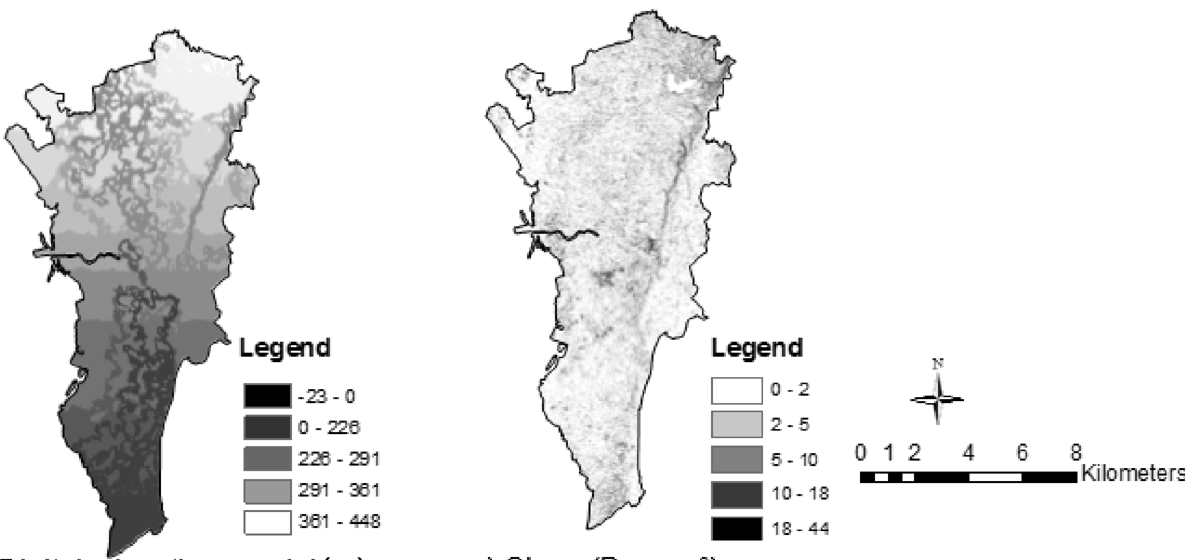
e) Slope (Degree°)



C.3 Variables of LCM in Metro Manila

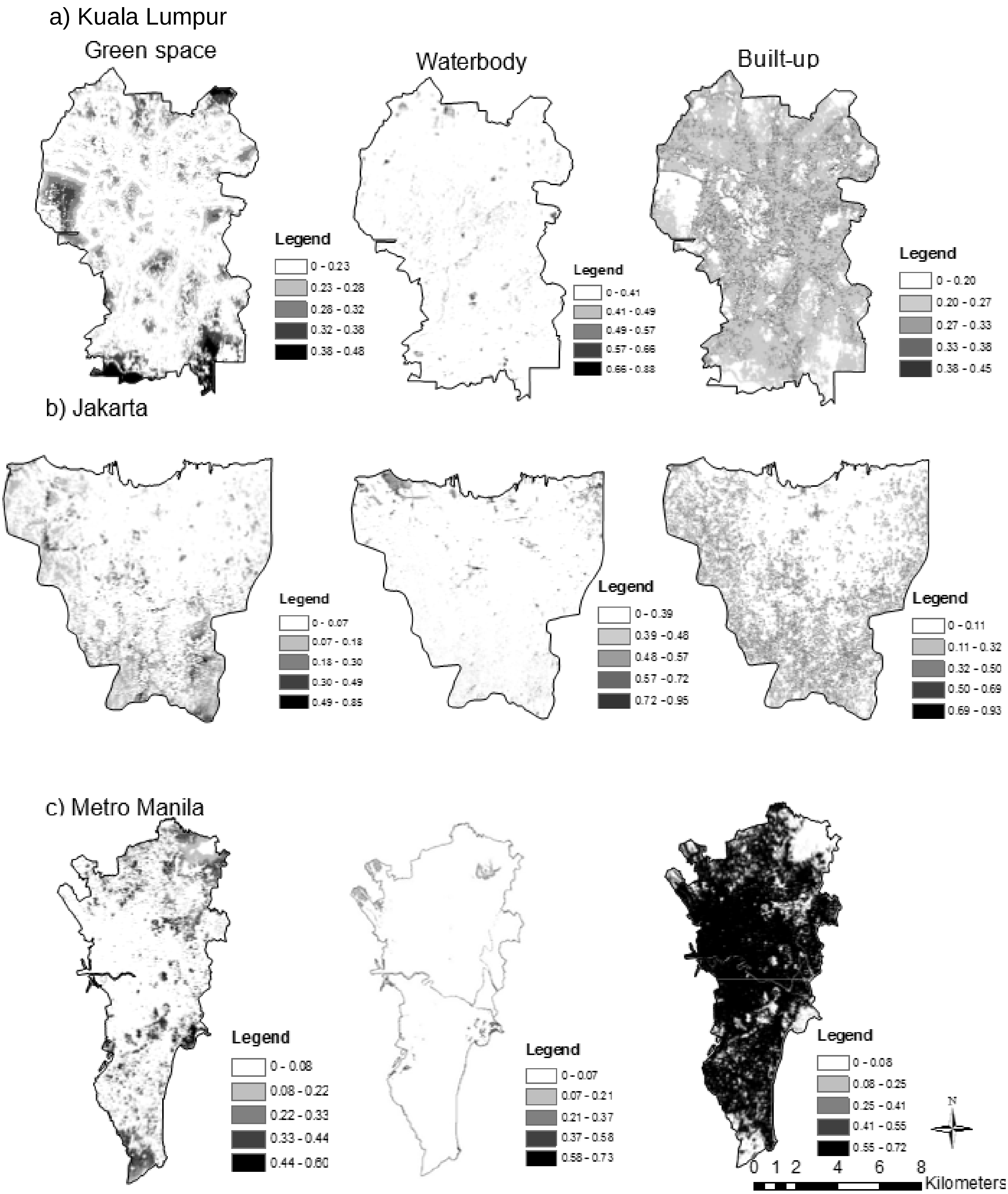


a) Distance from green space edge (m) b) Distance from waterbody (m) c) Distance from road (m)



d) Digital elevation model (m) e) Slope (Degree°)

C.4 Potential transition maps of simulated 2014 showing probability of transition from green space, waterbody and built-up area (low: 0 – high: 1)



C.5 Accuracy assessment of MLP variables (RMS error and accuracy rate %) between 1988 and 1999 of a) Kuala Lumpur, b) Jakarta and c) Metro Manila

a) Kuala Lumpur

LULC	Waterbody	Built-up Area	Green Space
Waterbody		0.49, 100	0.48, 100
Built-up area	0.39, 100		0.5, 100
Green space	0.45, 100	0.47, 100	

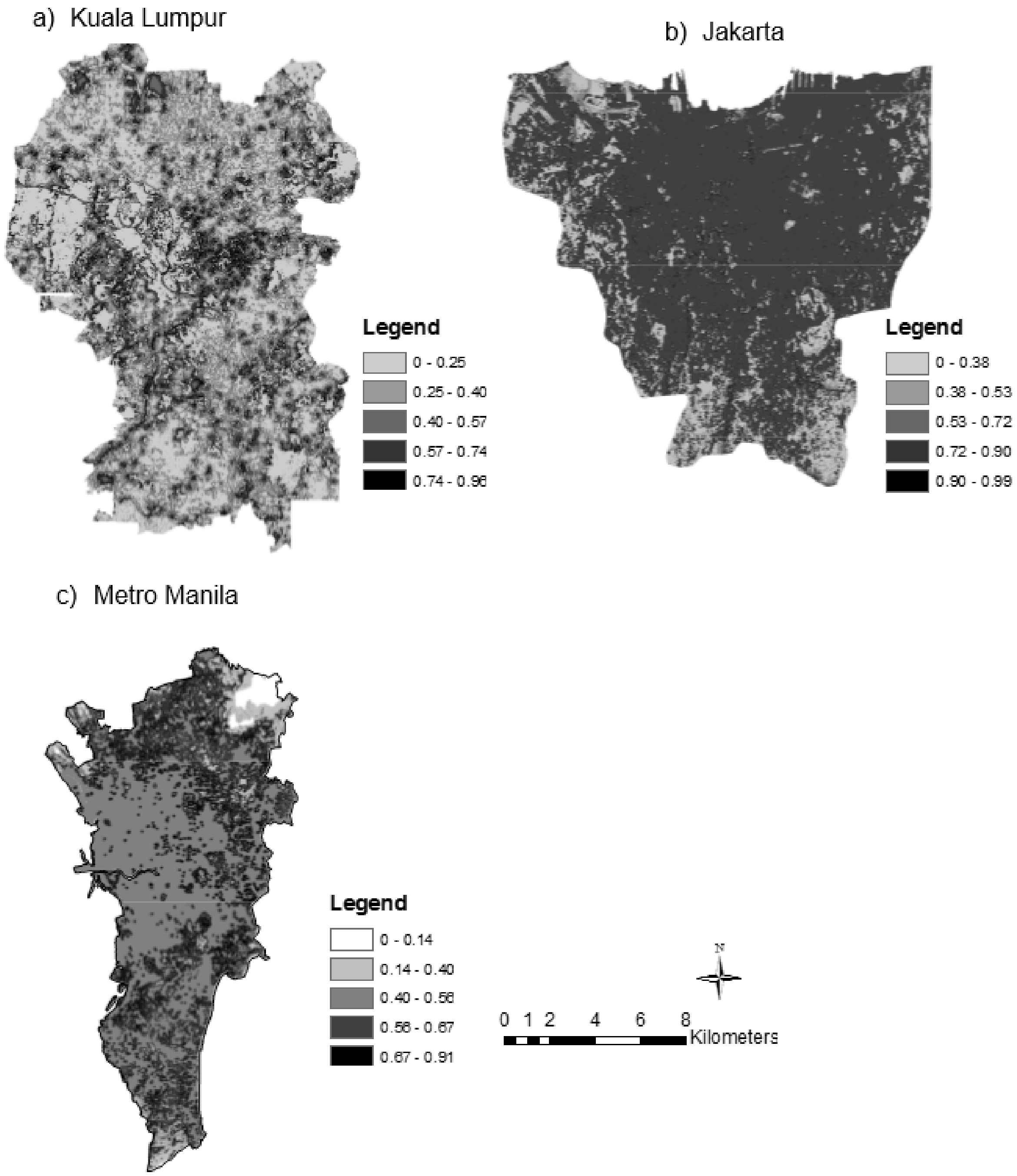
b) Jakarta

LULC	Waterbody	Built-up Area	Green Space
Waterbody		0.47, 62.87	0.15, 99.11
Built-up area	0.45, 69.14		0.13, 98.23
Green space	0.25, 96.58	0.32, 86.97	

c) Metro Manila

LULC	Waterbody	Built-up Area	Green Space
Waterbody		0.37, 80.48	0.49, 100
Built-up area	0.33, 85.59		0.44, 100
Green space	0.48, 100	0.49, 100	

C.6 Projected Markov conditional probability matrices 2014 (Range low: 0 - high: 1)



Appendix D Ecological Connectivity Networks in Rapidly Expanding Cities

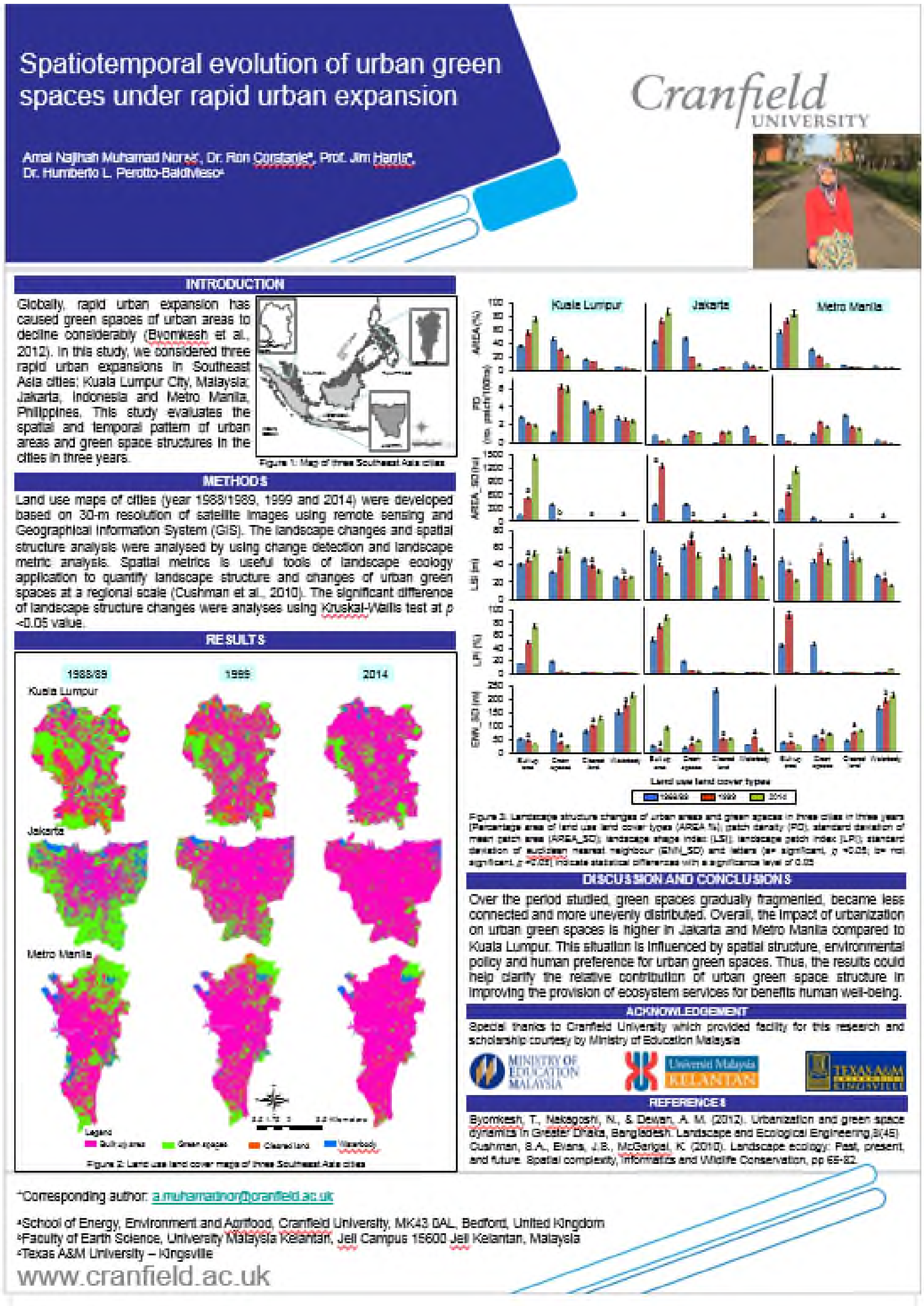
D.1 Pictures of Eurasian Tree Sparrow (*Passer montanus*) and Yellow vented bulbul (*Pycnonotus goiavier*)

Eurasian Tree Sparrow (*Passer montanus*)	Yellow vented bulbul (*Pycnonotus goiavier*)
	

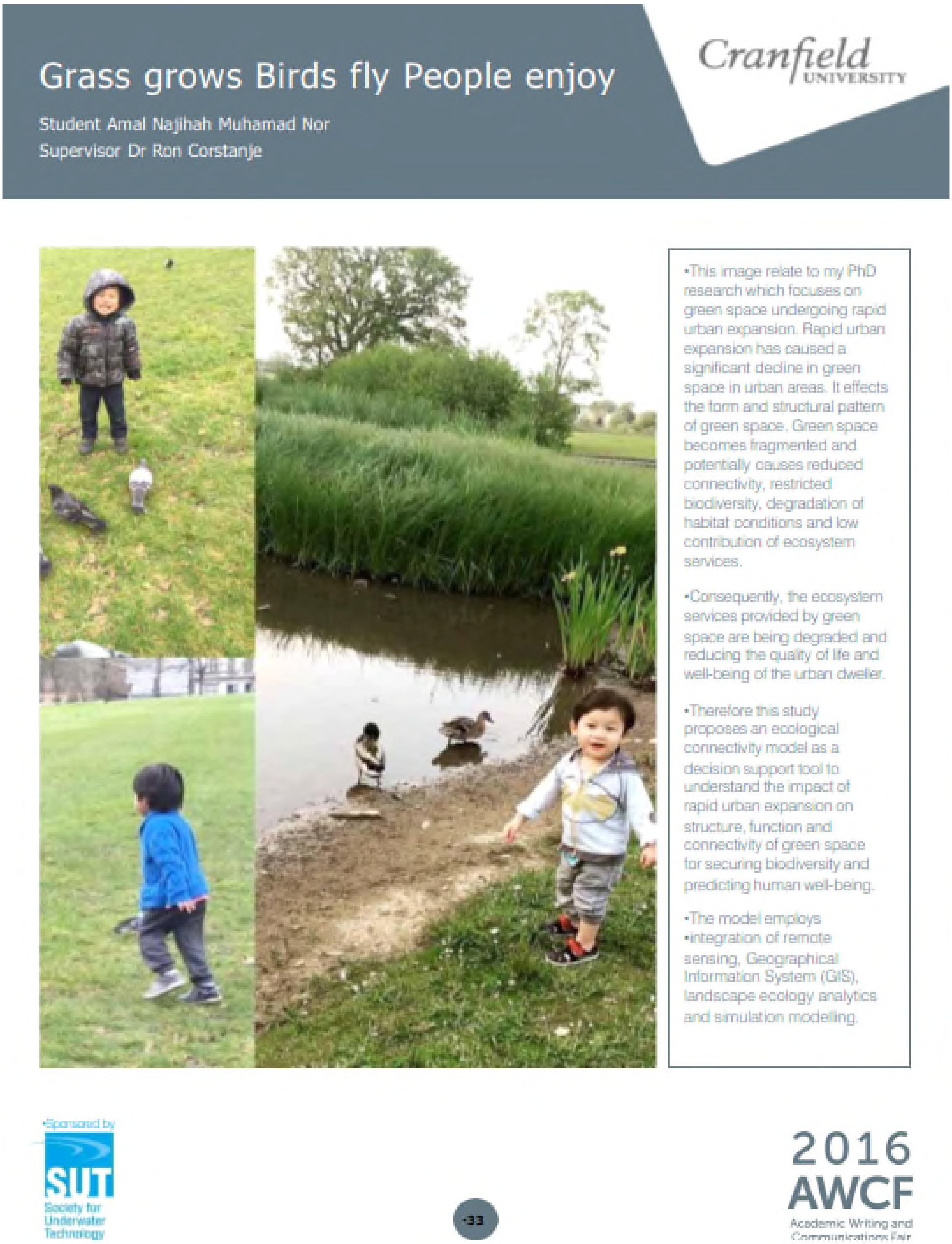
Description: 15 cm (6 in). Brownish upperparts with black streaks, black throat and ear coverts. Dark chestnut cap, white cheek patch, black throat and patch on ear coverts diagnostic. Brownish upperparts and chestnut wings boldly streaked with black. Underparts pale greyish, merging into whitish on belly. **Voice:** A repertoire of harsh chirping notes. **Range:** Europe, temperate Asia and the Himalayas through South-East Asia to Sulawesi and the Lesser Sundas. In Borneo, feral populations have been established from shipborne specimens. Widely introduced in North America, Australia, New Zealand, and the western Pacific. Habitat: Towns, rural settlements, gardens, scrub. **Habits:** Strictly a commensal of man, frequenting buildings and settlements in small groups. Nests under the eaves of buildings. Feeds largely on grass seeds but will also take scraps of leftovers from roadside food stalls and restaurants. Will also forage at rubbish dumps. Tame and confiding.	**Description:** 20 cm (8 in). Whitish throat and broad white supercilium contrasting sharply with black lores and narrow dark brown coronal stripe diagnostic. Upperparts dark brown; underparts whitish; undertail coverts yellow. Upperparts brown, with dark brown crown including a short, erectile crest at rear. Underparts white, except for yellow vent, and some faint brown streaking on the flanks and breast. Broad white eyebrow and inner ear coverts, contrasting with black lores, eye-stripe and narrow eye-ring. **Voice:** A bubbling tud-liu,tud-liu,tud-liu, frequently uttered at dawn. Also a rapid chic-chic-chic with an unmistakable bubbling quality. Cheerful, gurgling "crook crook crook" or “trikutruk-trikutruk-trikutruk” or “key-diddle-diddledoo”, Repeated **Range:** Tenasserim (Myanmar), southern Vietnam to the Malay Peninsula, the Sunda region to the Philippines.. **Habits:** The most commonly seen bulbul. Small parties often gather in fruiting trees and shrubs. A regular visitor to gardens, it is opportunistic, feeding on food scraps and utilizing potted plants to nest in. Although the diet is primarily berries and other fruits, it also eats seeds and drinks nectar, as well as consuming large quantities of invertebrates, gleaned or snatched from foliage, bark or the ground. Active throughout the day.
Reference: Allen Jeyarajasingan & Alan Pearson (2012) A Field Guide to the Birds of Peninsular Malaysia and Singapore, Second Edition, Oxford University Press Inc, New York, Sources: https://en.wikipedia.org/wiki/Eurasian_tree_sparrow	**Reference:** Swiss Winnasis (2011), Birds of Baluran National Park, Baluran National Park, East Java- Indonesia Sources: https://en.wikipedia.org/wiki/Yellow_vented_bulbul

Appendix E Research Presentations

E.1 Poster Presented at Female Researcher Network (FeRN) Annual Lecture Event, Cranfield University (3rd June 2015)



E.2 Digital Image Competition, Cranfield University (3rd Prize Winner) (27 April 2016)



E.3 Paper presented at World Multidisciplinary Civil Engineering-Architecture-Urban Planning Symposium, Prague, Czech Republic (13-17 June 2016)

WWW.WMCAUS.ORG :: WMCAUS@WMCAUS.ORG

World Multidisciplinary Civil Engineering-Architecture-Urban Planning Symposium - WMCAUS

WMCAUS 2016 13-17 June, 2016 - Prague (Czech Republic)

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INVITATION LETTER

Dear Amal Najihah Muhamad Nor

Cranfield University, School of Energy, Environment and Agrifood, MK43 0AL, Bedford, United Kingdom

You are kindly invited by the Organizing Committee of the "World Multidisciplinary Civil Engineering-Architecture-Urban Planning Symposium – WMCAUS 2016" to come to Prague (Czech Republic) in June 2016 and present your paper under the title:

Simulating urban expansion 2030 and its impact on green space structure
(Presentation Type: Oral)

at WMCAUS 2016 which will be held in Duo Hotel Congress Centre, Prague, Czech Republic on June 13-17, 2016.

You are also expected as a representative of the Cranfield University and a Lecturer at WMCAUS 2016.

Sincerely yours,

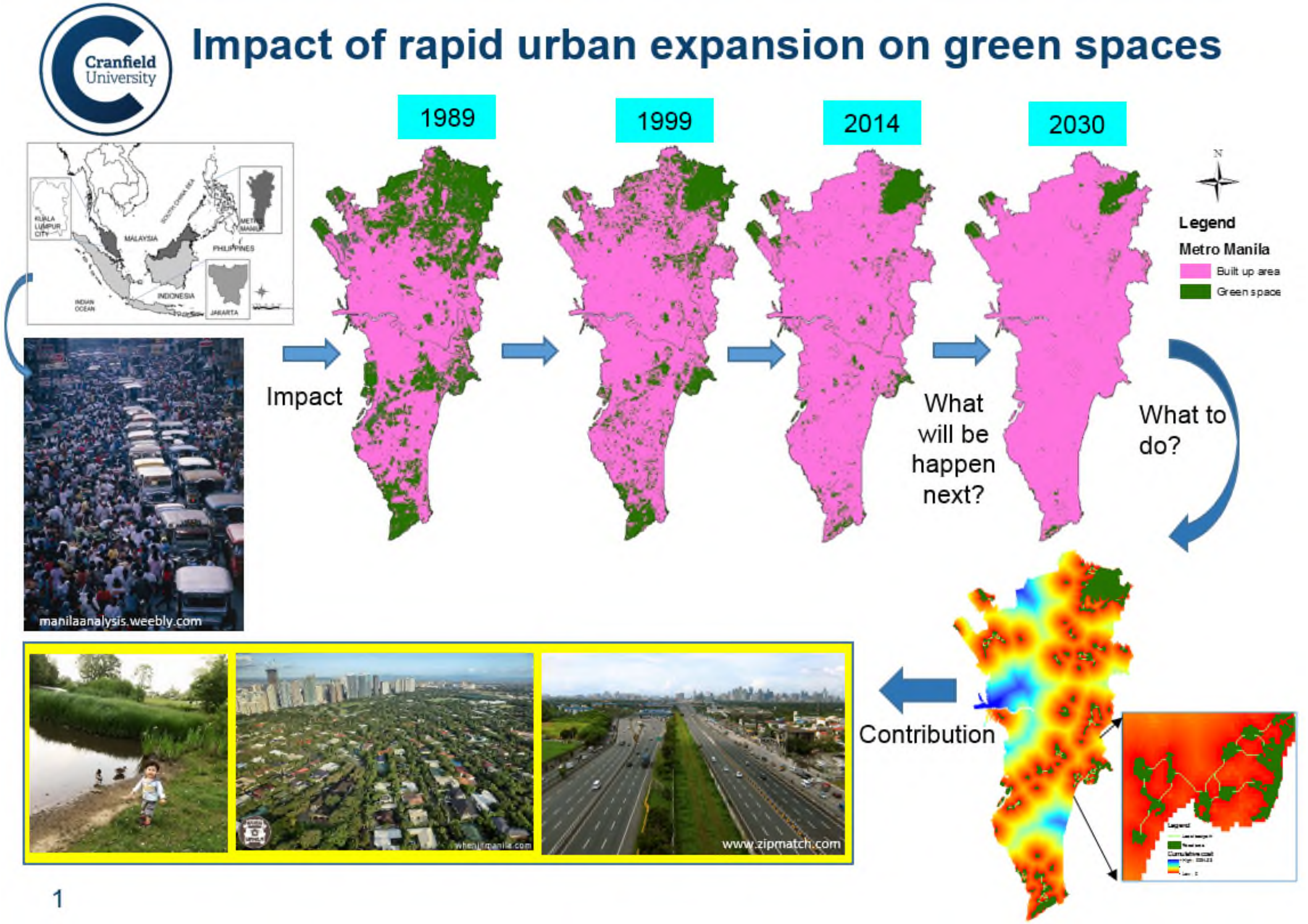
Prof.Dr. ISIK YILMAZ
Symposium Chair of WMCAUS

NOTES:

This Invitation Letter is to be presented to the academic leadership of University/Institute/etc. and also USED for VISA APPLICATION!
All expenses incurred with relation to the conference are the sole responsibility of the attendee.

World Multidisciplinary Civil Engineering-Architecture-Urban Planning Symposium – **WMCAUS 2016**
e-mail: wmcaus@wmcaus.org URL: www.wmcaus.org

E.4 3 Minute Competition, Cranfield University (Final Contestant) (5th August 2016)



E.5 Poster Presented at Student Symposium 2017, Cranfield University (1st February 2017)

Cranfield University

Impact of Rapid Urban Expansion on Green Space Structure

Introduction

Rapid urban expansion has had an impact on green space structure. A wide variety of modelling approaches have been tested to simulate urban expansion, however, the effectiveness of model validation and simulation of the spatial structure and pattern of urban expansion remains unexplored. This study aims to model and predict urban expansion and green space in three Southeast Asian cities (Kuala Lumpur, Jakarta and Metro Manila) experiencing rapid urban expansion using the integration of Land Change Modeler (LCM) with Markov Chain models and identify which are the main drivers, including spatial planning, in the resulting spatial patterns.

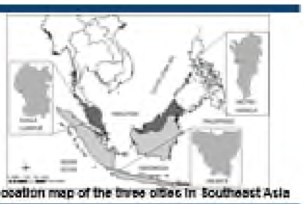


Fig. 1: Location map of the three cities in Southeast Asia

Methods

LCM-Markov Chain models were used, parameterised on changes observed between 1988/1989 and 1999 and verified with the urban form observed for 2014 to simulate land use land cover (LULC) for the year 2030. The spatial structure of the simulated 2030 land use was compared with the 2030 master plan for each city using spatial metrics [percentage area (AREA), patch density (PD); landscape shape index (LSI); Euclidean nearest neighbour (MNN)].

Table 1: Interpretation of agreement and disagreement in the validation map

LCM Validation Module Terminology	Revised Terminology (%)	Interpretation	Kuala Lumpur	Jakarta	Metro Manila
Hits	Agree	Model simulated change and it changed	16	12	10
False alarm	False negative	Model simulated persistence and it changed	12	4	4
Misses	False positive	Model simulated change and it persisted	18	10	5
None	Persistence	Model simulated persistence and it persisted	54	74	77

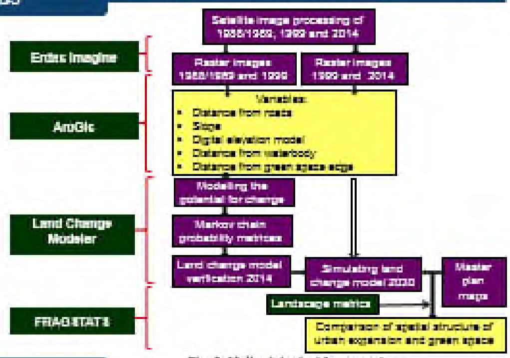


Fig. 2: Methodological framework

Results

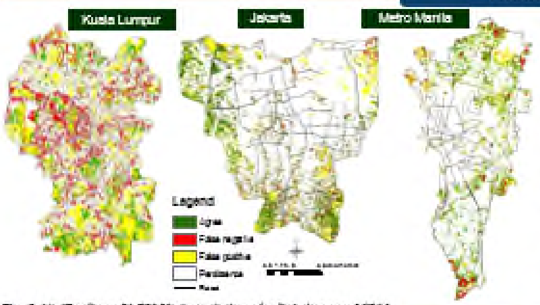


Fig. 3: Verification of LCM-Markov chain potential change of 2014

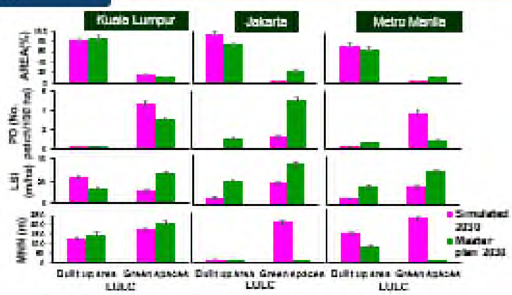


Fig. 4: Comparison of spatial structure in 2030 simulated and master plan

Conclusions

LCM-Markov Chain models proved to be suitable for the simulation of future land use. There were important differences in the predicted 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 pattern influenced by the rapid urban expansion and respective master planning policies of the municipalities in the cities. The use of integrated simulation modelling and landscape ecology analytics supplies significant insights into the evolution spatial structure of urban expansion and identifies constraints and informs intervention for spatial planning and policies in cities.

Amal Najihah M. Nor; Dr. Ron Corstanje; Prof. Jim Harris; Dr. Tim Brewer

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