Urban Process and Future Development of Colombo Metropolitan Area, Sri Lanka: An Application of Geospatial Techniques

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Abstract

The Colombo Metropolitan Area (CMA), which surrounds the well-known port city of Colombo, is the only metropolitan area in Sri Lanka that has experienced rapid urban growth over the last two decades. Due to the urbanization pressure, the CMA has been facing serious socioeconomic and environmental challenges in recent years. In such context, investigating the spatiotemporal pattern of urban process and future potential urban development is essential for introducing sustainable urban planning strategies. This research aims to investigate the spatiotemporal pattern of urban process since the 1990s and future potential urban development. Remote sensing and geographic information system (GIS), land-change intensity analysis, spatial metrics, morphological spatial pattern analysis (MSPA), fieldwork techniques, and land-change modeling were applied mainly in order to characterize the urban process and predict the future urban development potentials.

In this study, urban land use (ULU) mapping method was developed using MSPA through neighborhood interaction rules of the surrounding area. Results indicated that the urban land in the CMA has increased over the last two decades (1992–2014) with a higher area dominance of sparse growth. However, it could be identified the changing percentage of urban dense (275%) is higher than urban sparse (192%) from 1992 to 2014. The produced ULU mapping indicated that the urban dense was 3,968 ha, 7,953 ha, and 14,881 ha in 1992, 2001, and 2014, respectively, while the urban sparse was 7,197 ha, 11,439 ha, and 20,994 ha in 1992, 2001, and 2014, respectively. ULU change intensity analysis indicates that the ULU change was rapid in the 2000s (0.54%) compared to the 1990s (0.39%), which mainly coincided with the trends of population, economic growth, and several underlying socioeconomic factors.

Moreover, the spatial metrics that connect to the diffusion–coalescence urban growth theory revealed that the CMA experiences more diffusion than coalescence in urban growth. Recent migration, motivated by the accessibility to administrative services and socio-economic opportunities, has been the major factor of this sparse urban diffusion. The capturing the non-urban space located outside the urban core and fringe area of the CMA, showing leapfrog (outlay pattern) growth pattern in both time intervals could be significantly identified rather than infill growth and extension growth. Moreover, the annual growth intensity (AGI) of leapfrog pattern increased from 0.17% in the 1990s to 0.25% in the 2000s, AGI of infill increased from 0.16% in the 1990s to 0.19% in the 2000s, and AGI of extension increased from 0.06% in the 1990s to 0.10% in the 2000s. The analysis of the questionnaire survey data indicated that the migrants' history and reason for migration for each thematic zones (core, fringe and outside) are significantly different. Specifically, the recent migration into core area has recently declined, while fringe area and outside area, which are mainly visible in suburban areas are attracting more migrants. This significant level of attraction basically has been dominated by the accessibility to urban facilities and increasing price of the lands in core area rather than by urban planning initiatives in the suburban area.

The ULU change prediction results revealed that the ULU will increase into 53,510 ha in 2030. The major transport corridors and the growth nodes will have a great influence in the future spatial patterns of urban growth, and the urban lands will be dense due to infill development. Prediction results further indicated that there are some limitation in introduced urban planning scenarios of the government's master plan due to its less consideration regarding the spatial pattern of future urban growth pattern. Thus, the consideration of the results of this research will be important in forming future urban planning scenarios.

From a scientific standpoint, this empirical study not only has identified past, present and potential future urban process, but also introduced new methods and techniques that can be applied to detect the urban process in a data-sparse urban environment, which is advantageous for developing countries.

Keywords: Colombo Metropolitan Area; Land-change intensity; Spatial metrics; Driving factors; Land-change modeling; Remote Sensing; GIS

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Abbreviations

CMA	Colombo Metropolitan Area
GIS	Geographic Information Systems
ULU	Urban Land Use
GPS	Global Positioning System
UN	United Nation
GDP	Gross Domestic Product
BC	Before Christ
DCSS	Department of Census and Statistic, Sri Lanka
JICA	Japan International Cooperation Agency
DMSL	Department of Meteorology, Sri Lanka
MMWD	Ministry of Megalopolis and Western Development
LKR	Sri Lanka Rupee
UDA	Urban Development Authority
CEA	Central Environmental Authority
SDSL	Survey Department of Sri Lanka
USGS	United States Geological Survey
MSPA	Morphological Spatial Pattern Analysis
ACI	Annual change intensity
UI	Uniform Intensity
FDI	Foreign Direct Investment
EPZ	Export Processing Zones
PB	Pixel-based
OB	Object-based

CBD	Central Business District
Area_MN	Mean Patch Size
CONTAG	Contagion Index
ENN_MN	Mean Euclidean Nearest Neighbor Distance
Frac_AM	Area-weighted Mean Patch Fractal Dimension
LSI	Landscape Shape Index
PD	Path Density
PLAND	Percentage of Landscape
SHDI	Shannon's Diversity Index
CA	Cellular Automata
MLP	Multi-layer Perceptron
NN	Neural Networks
FoM	Figure of Merits
ROC	Receiver Operating Characteristic
AUC	Area Under the Curve

Chapter One

Introduction

1.1. Background and problem statement

The world is undergoing the largest wave of urban growth in its history (UNFPA, 2007). At the beginning of the 20th century (in 1900), the urban population of the world was 13% (220 million) and within a short period the urban population increased rapidly (UN, 2006). Currently, more than 50% of the world's population resides in cities, and this figure is projected to reach 67.2% in 2050 (UN, 2015). During the initial urban stage of the world, a larger proposition of the urban population was concentrated in advanced industrial countries (Cohen, 2006). However, since the late 20th century, this rapid urban growth clearly has moved from Global North to Global South, and it has been predicted that 80% of the world's population will be concentrated in developing countries by 2030 (UN, 2015). At the same time, there has been significant urbanization in the South Asian region among developing countries over the last two decades (Zhou *et al.,* 2015).

The Colombo Metropolitan Area (CMA), which surrounds the well-known port city of Colombo, is the only metropolitan area in Sri Lanka (located in South Asia) that has experienced rapid urban growth over the last two decades (Bandara and Munasinghe, 2007; Senanayake *et al.,* 2013a). In 2013, the World Bank indicated that Colombo, the core of the CMA, was one of the fastest-changing cities in South Asia. Since Sri Lanka's economy was opened in the early 1980s, the urban primacy of the CMA has undergone various developmental stages (Divigalpitiya *et al.,* 2007). At the conclusion of the 30 years of civil war in 2009, the city of Colombo began a new era of urban development, which has led to higher concentrations of population and industrial activity both in the city and its suburbs (Senanayake *et al.,* 2013b). As a result, the rapid urban concentration in the CMA created massive congestion, poor public transportation, and a noticeable lack of proper sanitation in the area. With this trend, various social, environmental, and resource-related problems have occurred, which stem from extensive urban poverty, recurrent flooding, slum growth, extensive alteration of wetland ecosystems, and mismanagement of limited resources (UN-Habitat, 2003; Hettiarachchi *et al.,* 2014). To mitigate these adverse effects of urbanization and to ensure sustainable urban expansion, an accurate assessment of the urban process in the CMA is crucial.

There is no consistent definition of the urban process. The urban process has been regularly used to explain the development of cities and their suburbs. The urban growth, decline (decay), renewal, consolidation, and gentrification, which resulted from social, cultural, economic, technical, historical, political, and geographical changes, are mainly considered in urban process-related studies (Harvey, 1978; Ambrose, 1994). As the urban process of the study area, the author studied that the spatiotemporal pattern of urban land use (ULU) changes urban growth, driving factors, and future implications of urbanizations. In this study, the term "urban process" has been used as an umbrella term to understand all these interrelated processes in the urban environment.

1.2. Research objectives

The main purpose of this study was to investigate the spatiotemporal pattern of the urban process and the future development in the CMA by incorporating geospatial techniques in order to support urban planning initiatives. Specifically, the study aimed to examine ULU change and its intensity; to identify the spatiotemporal pattern of urban growth and related the factors to the current urban growth patterns; and to discuss future urban growth and its implications with urban planning initiatives in the CMA. The study investigated the period from 1992 to 2014, and predicted the 2030 of the future CMA for its discussion. The CMA, located in the western coastal area, originated as a port city on historical maritime Silk Road is interesting case to study as it is being the Sri Lanka's only metropolitan area, higher level of national urban primacy, and one of the fast-changing urban area in South Asian region.

Since the 1990s, the CMA experiences a rapid urbanization and consequently, the landscape of it has transformed considerably. In such context, characterizing the spatiotemporal attributes of urban process from the 1990s to present are important and it also helps to predict the future of urban development in the CMA.

1.3. Research design

Figure 1-1 presents the design of the research and its four major steps. The dashed lines of the figure separate each step of the study. The study focus three time points (1992, 2001, and 2014) and two time intervals (1992–2001 and 2001–2014). The selection of these specific time points and time intervals were based on representation of the CMA's different level of urbanization and socioeconomic transition of the country. In the 1990s, the CMA showed an initial growth stage with low economic growth and political instability in Sri Lanka. In the CMA during the 2000s, the country slowly reached economic and political stability. In the last decade, a substantial amount of foreign capital was attracted to Sri Lanka and economic growth accelerated (Hogg, 2011). Recently, the government has proposed a national physical plan for 2030; thus, this study will spatially compare the urban growth, detected by the land use change predicted results of 2030 with the government's proposed national structural plan of 2030.

In the first step, the study clearly defines its purpose and objectives, having understood the research background and problems related to the CMA.

In the second step, the ULU map of the CMA is developed based on remote sensing data and other spatial ancillary data, such as available paper maps (e.g. 1: 50,000 topographical maps and protected area maps) and Google Earth™ images. The final output of ULU mapping is contained for three time points, namely 1992, 2001, and 2014. In this step, based on its spatial arrangement of built-up area of the CMA, the urban areas are divided into two major urban area categories: urban dense and urban sparse, using geospatial techniques. Moreover, the urban growth is characterized through three indicators: infill growth, extension growth, and leapfrog growth. The classification of ULU categories and detection of urban growth is a novel approach developed in this study. In the third step, the study analyzes ULU change patterns, urban growth, and predicts the future of urban growth. The ULU changes are analyzed across the two time intervals, namely 1992–2001 and 2001–2014. The change maps are presented spatially. The magnitude and speed of the ULU changes are analyzed. The urban growth patterns and processes are examined based on the acquired knowledge of the ULU changes through the ULU change analysis. The factors related to the thematic urban zones of area (core, fringe and outside), were characterized using the questionnaire survey and previous literatures. The whole third step is the analysis of the study.

In the fourth step, the outcomes of the analysis are connected with the research objectives to explain the urban process and the future development of the CMA. Moreover, the implications of the finding with government planning initiatives were discussed. The suggestions and recommendations were mainly formulated in this section.

Overall, this study is contained of six chapters organized as follows: (1) Introduction; (2) Outline of the Colombo Metropolitan Area; (3) Urban land-use change in the Colombo Metropolitan Area; (4) Spatiotemporal pattern of urban growth pattern; (5) Implications for the future urban development planning; and (6) Conclusions.

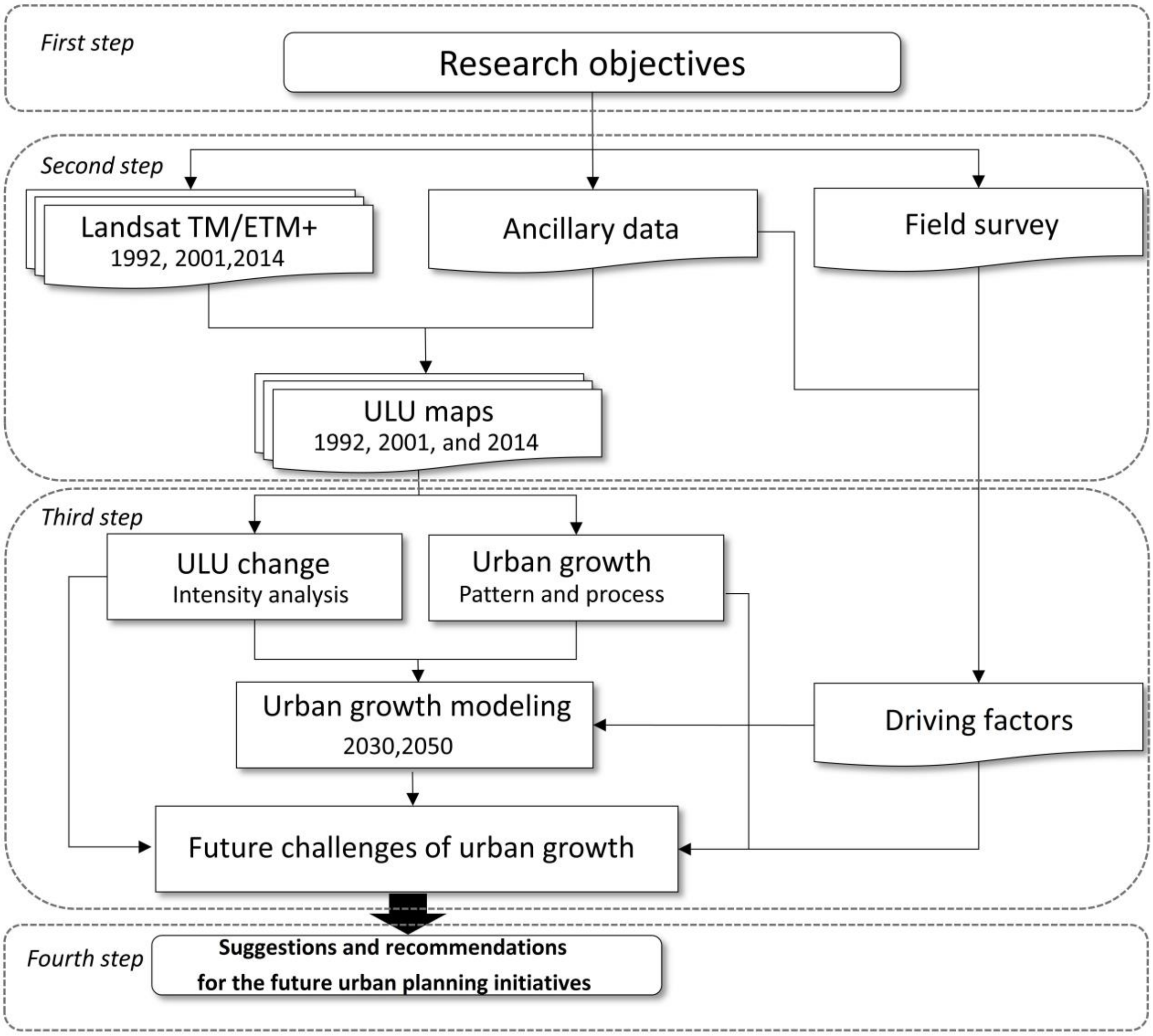

Figure 1-1: Flow chart showing the research design.

1.4. Literature review

This study focuses more on the spatial aspect of urban process than the socioeconomic process in the CMA. The ULU changes, urban growth pattern, and urban growth prediction are heavily examined in this study. The remote sensing and geographic information systems (GIS) were employed as the main techniques. In this section, the related literatures are briefly discussed.

Urban geography and urban process: The geographical study on the urban area mainly deals with the urban geography, which can be considered as part of the larger field of human geography (Pacione, 2009; Russell and Ronald, 2012). The urban geographers seek to understand how factors interact over urban space, what function they serve, and their interrelationship (Pacione, 2009; Russell and Ronald, 2012). There are two major approaches to urban geography: (1) the study of problems relating to the spatial distributions of movement, flows, and linkage that bind them in urban space; and (2) the study of patterns of distribution and interaction within urban areas as a system (Russell and Ronald, 2012). In all the sciences, including urban geography, there is an increasing emphasis being placed upon the development of "process" theory (Forbus, 1984). Recently, borrowing methods from other disciplines, urban geography has used pattern analysis as a technique for analyzing the urban process (David, 2005), including ULU change, urban growth, and future urban development from a local scale to a global urbanization scale (Haregeweyn *et al.*, 2012; Shrestha *et al.*, 2012; Shafizadeh-Moghadam and Helbich 2013; Estoque and Murayama, 2015). The recent development of remote sensing and GIS has created a platform to detect the dynamic urban process more compressively (Yang, 2011).

Urban remote sensing: Remote sensing and GIS are the two major components of geographic information science (GISci) (Goodchild, 1994; Hapner *et al.*, 2005). Although remote sensing and GIS were developed quite independently, the integration between them has become increasingly apparent (Aronoff, 2005). Thus, the application of remote sensing or GIS cannot be discussed separately for urban studies. However, in this subsection, the remote sensing application and its related concepts are discussed. The Canadian Center for Remote Sensing (1999) has defined remote sensing as *"the science (and to some extent, art) of acquiring information about the Earth's surface without actually being in contact with it"*

With the recent innovations in remote sensing data, technologies, and theories in the broad field of Earth observation, the urban application of remote sensing has gained popularity (Yang, 2011). As a result of wide application, a subfield, "urban remote sensing," which merges urban geography and remote sensing, emerged from the scientific studies (Carlson and Arthur, 2000; Miller and Small, 2003; Maktav *et al.*, 2005). However, the application of remote sensing to the urban environment is different, depending on the purpose of application. First, urban and regional planners are increasingly using remote sensing to derive detailed and updated information on planning activities (Sugumaran, *et al*., 2002; Mittelbach and Scheider, 2005; Santana, 2007). Second, urban researchers are using remote sensing to develop urban theories by extracting urban structural information (Batty and Longley., 1994; Longley *et al.*, 2002). Third, environmental scientists are increasingly observing the land cover change driven by the urbanization (Estoque and Murayama, 2013; Salisu *et al.*, 2015; Hegazy and Kaloop, 2015). Lastly, the global change community has recognized remote sensing as a tool to study the spatiotemporal dynamic of global urban changes (Angel *et al.*, 2010; Bagan and Yamagata 2014). The mapping of ULU differs depending on the purpose of the studies.

Recent advances in remote sensing with high-resolution satellite data (0.6–2.5m; QuickBird, IKONOS, SPOT, and ALOS) and medium resolution (15–30m; ASTER, IRS, SPOT, and Landsat) have provided more details for urban area mapping (Guindon *et al.*, 2004; Thapa and Murayama, 2009; Megahed *et al.,* 2015). The high-resolution images have provided a new opportunity to analyze urban structures in more detail both thematically and spatially. Several studies have investigated the application of high-resolution data into urban environment (Chengqi *et al.,* 2003). However, the studies using high-resolution hyperspectral images in an urban environment are still limited due to the lack of data, the cost, and the higher level of data capacity (Fonji and Taff, 2014). The urban application has most widely employed the medium resolution satellite images in urban applications (Xian *et al*., 2015). Specifically, Landsat imagery remains the leading satellite data provider for land-use/cover mapping in general and in urban areas in particular (Schneider 2012; Yuan *et al.,* 2005; Bagan and Yamagata, 2014; Liu and Yang, 2015). Landsat has the ability to provide high-quality, regularly updated information on land surface environments. They have been regularly available since 1972 and have led to the characterization of the historical changes of urban areas from local to global levels (Sohl and Sleeter, 2011).

In general, remote sensing provides several advantages for urban studies. First, the ability of satellite images to provide a synoptic view of a large area at a given time, which is not possible using traditional, conventional surveying techniques (Zhang *et al.,* 2014; Megahed *et al.,* 2015). This synoptic view allows us to understand the pattern of urban feature arrangements and the man–environment relationship (Davis, 2001). This unique perspective helps to characterize the urban processes that operate in a large area. Failure to observe the entire mosaic of an urban phenomenon may hinder our ability to understand the potential process behind the observed pattern (Yong, 2011).

Second, remote sensing can provide detailed data with additional measures for urban studies. Some remote sensing has the ability to collect more detail beyond the human eye (Yong, 2011).The data, collected from the ultraviolet, infrared, and microwave portion of the electromagnetic spectrum, go beyond human visual perception (Yong, 2011). For example, the urban heat island can be measured using thermal remote sensing (Chen *et al.,* 2006; Mallick *et al.,* 2013).

Third, the urban process analysis frequently needs to detect the historical perspective of an urban area. A time-series of remotely sensed data allow the examination of the temporal dynamics of urban attributes or processes that can help to understand significant human or natural process in the urban environment (Liu and Yang, 2015). The ULU change (Aguayo *et al.,* 2007; Wu and Zhang, 2012), urban temperature dynamic (Chen *et al.,* 2006; Mallick *et al.,* 2013; Senanayake *et al.,* 2013a), ecosystem service changes (Polasky *et al.,* 2011; Estoque and Murayama, 2012) have been heavily identified with the time-series of remote sensing data.

Fourth, remote sensing offers the opportunities to create links between urban researchers to develop new urban models and theories (Dietzel *et al.,* 2005; Mesev *et al.,* 1995; Barreira-González *et al.,* 2015).

Finally, remote sensing with different geospatial techniques, such as GIS, spatial analysis, and dynamic modelling, offers crucial opportunities to develop frameworks to monitor and model the urban process (Aguayo *et al.,* 2007; Divigalpitiya *et al.,* 2007; Vliet *et al.,* 2009; Friehat *et al.,* 2015). Also, they can be used to relate different human and natural variables for understanding of indirect and direct driving forces of urban changes and prudential feedback of such changes on the drivers in the urban environment (Aguayo *et al.,* 2007; Long *et al.,* 2007; Wu and Zhang, 2012).

ULU change: Defining the terms "urban area" and "land-use" is very important when we study the urban process and its related ULU changes.

The term "urban area" is widely used in literature and basically refers to the spatial extent of urbanized areas; however, its definition is fuzzy and inconsistent (Taubenböck *et al.,* 2012;

Zhang *et al.,* 2014). Each country has their own national definition for urban area demarcation (Taubenböck *et al.*, 2012). While one country may solely define urbanity based on built infrastructure (e.g. the existence of paved streets or water supply systems), another may define urbanity by population density, livelihoods (e.g. the proportion of agricultural workers), economic characteristics, administrative function (e.g. district or regional capitals) and/or administrative boundaries (Christenson *et al.,* 2014). Several remote sensing studies have identified the extent of the urban area by the extent of the built-up area, and ULU has been defined based on the built-up areas (Shafizadeh-Moghadam and Helbich, 2013; Hegazy and Kaloop, 2015).

The terms "land-cover" and "land-use" are often used interchangeably in literature and in daily practice. In general, the term "land cover" relates to the cover of features prevailing on the surface of the Earth and its immediate subsurface, including biota, soil, topography, surface and ground water, and human structures (Lambin *et al.,* 2001). The term "land-use" explains human employment of the land cover type (Turner and Meyer, 1994). The agriculture, forestry, and building construction that modify land surface processes, including biogeochemistry, hydrology, and biodiversity are included in land use (Turner and Meyer, 1994). Land-use change is the result of socio-economic and biophysical phenomena, and is dependent on spatial location, scale, and existing land use (Lambin *et al.,* 2001). In such a context, ULU identification based on the built-up area is more reasonable and helps to characterize the urban process in a compressive manner (Wu and Zhang, 2012). However, ULU change is considered as one of the most complex processes that link both the natural and human systems (Zhao and Murayama, 2011).

Land-use change is identified with the impacts on soil, water, and atmosphere, which leads to a number of environmental issues (Guo and Gifford, 2001; Chen *et al.,* 2006; Mallick *et al.*, 2013; Zhou *et al.*, 2014). Some land-use/cover change studies have only focused on the urban environment and its related natural environmental changes, such as peri-urban agricultural changes, urban heat islands, and urban green area changes (Adam, 2014; Cobbinah *et al.*, 2015; Samat *et al.*, 2011; Senanayake *et al.*, 2013b). In practice, complex ULU change patterns depend on the socioeconomic, cultural, and biophysical contexts at different spatial scales (Thapa and Murayama, 2012). In fact, ULU change studies aim to quantify the ecological effects of specific land-change processes, while others are concerned with the underlying factors that cause land change in urban areas (Magliocca *et al.*, 2014).

ULU analysis is directly related to land-change science and land-system science (Gutman *et al.*, 2004; Estoque and Murayama, 2015). Land change, consisting of both land use and land-cover change, is broadly conceived of as change in terrestrial ecosystems resulting from human and environmental interactions, and their feedback over time within land systems (Magliocca *et al.*, 2014). The advantages of remote sensing and GIS have recently sharpened land-change science, which deals with observation, monitoring, and modelling (Estoque and Murayama, 2015).

Several methods have been developed to detect complex patterns of land use in the urban environment (Butt *et al.*, 2015). The pixel-based (PB) classification still remains as the basis for thousands of successful applications in ULU classifications (Blaschke, 2010). However, the application of PB classification faces several challenges with its technical and conceptual limitations, such as the "salt and pepper effect" and the limited integration of expert knowledge and feature space optimization (Blaschke, 2010; Platt and Rapoza, 2008). Due to these limitations, the object-based (or segment-based; SB) classification has been receiving more attention than the traditional PB classification (Gamanya *et al.*, 2009). Object-based (OB) classification is mainly driven by the concept of image segmentation (Blaschke, 2010). Image segments are relatively homogeneous and a systematically significant group of pixels that help to classify the land uses (Blaschke, 2010; Hay and Castilla, 2008). On the other hand, the hybrid classification method, integrating both the PB and the OB classifications, is emerging as a new land-use classification, which can maintain a higher level of accuracy over the classification using individual PB or OB classification in the urban environment (Li *et al.*,2013).

Although new, sophisticated methods of remote sensing have been developed to detect the land-use types, a research gap exists in characterizing the conceptual ULU types, which includes urban core, urban fringe, urban density, and urban sparseness. In general, these types of land uses depend on the geographical contexts of their locations rather than on the spectral characteristics of the features (Louw and Sithole, 2011). The spectral responses from remote sensing may not be sufficient to differentiate the conceptual land-use types (Liu and Yang, 2015). Thus, neighborhood interaction rules can be used to characterize these conceptual land uses by incorporating the geographical characteristics of a larger area. Previous studies have used morphological spatial pattern analysis (MSPA) to integrate neighborhood characteristics in defining various conceptual land uses (Vogt *et al.*, 2007; Angel *et al.*, 2010). Vogt *et al.*, (2007) developed a forest-land classification (e.g. core, patch, perforated, and edge) based on forest and non-forest land categories. Angel *et al.* (2010) developed an urban land classification (urban, suburban, rural, fringe open space, exterior open space, and rural open space) based on built and non-built land categories. In developing their conceptual land-use categories, previous researchers have used only binary land use. However, using binary land use to develop conceptual ULU categories may not be sufficient because of the increased complexity in urban areas (Barreira-González *et al.*, 2015). In such contexts, incorporating multiple land uses with MSPA provides a more advanced conceptual ULU classification.

In addition to ULU classification, qualitative and quantitative measurers describing ULU changes and detecting the various patterns of those changes increases the comprehensive understanding of urban processes (Estoque and Murayama, 2015). This knowledge also helps to create sustainable urban development policies to reduce the undesired effects of urbanization. Land-change intensity analysis techniques, proposed by Aldwaik and Pontius (2012), enhance our understanding of the land-change speed across different time intervals. Recently, a significant number of researchers have employed the land-change analysis in their studies (Aldwaik and Pontius, 2012; Zhou *et al.*, 2014; Estoque and Murayama, 2015).

Spatial pattern of urban growth: The physical and functional transformation of rural landscapes into urban forms is recognized as urban growth (Thapa and Murayama, 2010). According to Clark (1982), urban growth is a spatial and demographic process characterized by a change in population distribution from a village to a town or city. The spatial configuration and dynamic process of urban growth is an important topic in contemporary urban studies (Thapa and Murayama, 2010; Thapa and Murayama, 2012; Linard *et al.,* 2013; Kamusoko *et al.,* 2013; Hegazy and Kaloop, 2015). Urban growth pattern recognition, such as infill growth, extension (edge expansion) growth, and leapfrog growth is of great interest to urban geographers (Schneider and Woodcock, 2008; Dewan and Yamaguchi, 2009a; Angel *et al.,* 2012; Dorning *et al.*, 2015; Estoque and Murayama, 2015).

There is increased interest in analyzing urban growth patterns using spatial-metric or landscape-metric concepts, which are developed based on information theory measures and fractal geometry (Gustafson, 1998). The ability to quantitatively describe the landscape structure is a prerequisite to studying landscape function and changes (Gustafson, 1998), and spatial metrics have enabled quantifying the three basic concepts used to describe the spatial structure of landscapes: fragmentation, connectivity, and diversity (DiBari, 2007). Several studies have successfully applied spatial metrics to quantifying the spatial structure of urban landscapes and ULU change patterns (Herold, 2005; Plexida *et al.*, 2014; Megahed, 2015; Estoque and Murayama, 2016). The detected patterns of urban growth through spatial metrics can be further characterized using the diffusion and coalescence concept (Dietzel *et al.*, 2005; Estoque and Murayama, 2016). In this concept, the dispersion from the origin point or "seed" location is considered the diffusion process, while the union of individual urban patches is considered the coalescence process (Dietzel *et al.*, 2005; Estoque and Murayama, 2015; Estoque and Murayama, 2016). Moreover, without using the diffusion and the coalescence concepts, the ULU changes also can be used to identify the spatial patterns of urban growth. For example, infill growth, which is characterized by new urban growth, occurs in an already urbanized area; urban extension, which is characterized by new urban growth, occurs in the urban fringe areas; and leapfrog growth, which characterized by new growth, occurs in non-urban areas (Angel *et al.*, 2012; Angel *et al.*, 2010).

Urban growth modeling: The simulation process of urban growth involves the understanding of ULU changes. There are various approaches to simulate land use change (Liu *et al.*, 2016). These approaches can be generally divided into two categories (Tan *et al.*, 2015). First are the top-down models, which are mainly based on traditional macroeconomic theories and are largely derived from gravity-based models (Tan *et al.*, 2015), they cannot deal with micro-level planning or social and environmental problems (Lee Jr., 1973). Second are the bottom-up models, which basically evolved through the development of computer algorithms (Santé *et al.*, 2010; Tan *et al.*, 2015). In the ongoing development of the computer algorithms used in urban geography, the bottom-up models have gradually replaced the top-down models in the field of urban growth modeling (Tan *et al.*, 2015).

The effectiveness of computer-based land-use modeling basically depends upon the calibration process (Herold *et al.*, 2003; Basse *et al.,* 2014). The calibrations of a model should be conducted representing the reality of the influences of driving variables or explanatory variables on ULU changes (Kolb *et al.*, 2013; Estoque and Murayama, 2014). Based on the previous change trends and the probability of change occurring in relation to the driving factors, the models are commonly calibrated (Hersperger *et al.,* 2010; Hosseinali *et al.,* 2013; Sha and Helbich, 2013). The characterizing probability using the driving factors can be conducted through different methods, such as multi-criteria decision analysis (MCA) logistic regression (He *et al.,* 2013; Jokar *et al.,* 2013), and multi-layer perceptron neural network (MLP NN) (Hu and Weng, 2009; Basse *et al.,* 2014; Friehat *et al.*, 2015; Megahed *et al.,* 2015). For competitive change allocation on the created probability map or surface, several researchers have combined cellular automata (CA) spatial rules with Markov chain transition rules (Alsharif and Pradhan, 2014; Sha and Helbich, 2013). The land-change modeler (LCM), which is embedded in the Terrset™ software program, allows us to handle different algorithms for land-use modeling (Mas *et al.,* 2014; Megahed *et al.,* 2015). Among them, the integration of MLP NN with the CA-Markov chain is one of highly recognized modeling algorithms and has been applied in a significant number of successful studies (Camacho-Olmedo *et al.,* 2015).

In general, a model is used to simplify the complex real-world situations, and makes them easier to explain and understand. The occurrence of errors is common in modeling with the simplification of complexity (Tayyebi *et al.*, 2014). However, maintenance of accuracy as much as possible is very important to correctly predict the future in land-use modeling. Various techniques, such as Kappa statistics (Monserud and Leemans, 1992; Barredo and Demicheli, 2003), the figure of merits (FoM) (Sloan and Pelletier, 2012), the receiver/relative operating characteristic (ROC) (Pontius and Schneider 2001; Kolb *et al.,* 2013) and the total operating characteristic (TOC) have been developed and applied to validate land-use models (Pontius and Si, 2014; Estoque and Murayama, 2016).

Urban process of the CMA: According to the Department of Census and Statistic Sri Lanka (DCSS) in 2012, the country's population is concentrated into three sectors: urban, rural, and estate plantation. Approximately 18% of the country's population lives in urban areas. And other two sectors account for approximately 82%: 78% in the rural sectors and 4% in the estate plantation sectors. This provides a clear picture of the spatial distribution on the population, which is predominantly a rural bias distribution (SEVANATHA, 2003). In Sri Lanka, there is no clear definition of what constitutes an urban area; generally, the administrative municipal council areas and urban council areas are considered as urban areas (Biller and Nabi, 2013). One of the significant attributes of the urbanization pattern of Sri Lanka is its slow and low population concentration (below 20%) in urban areas (Groves, 1996). This pattern may be due to several factors, such as the small size of the country, which allows people to reach urban areas within a reasonable time, the low level of economic development, the agricultural economic dominance, and the promotion of urban decentralization (Groves, 1996; Misra, 2013).

The Colombo city where it is located in the CMA is the primate city of Sri Lanka (Bandara and Munasinghe, 2007). The DCSS shows that in 2012, with 3.7 million inhabitants, the CMA accounted for more than 80% of the country's industrial output and about 50% of its GDP. However, the urbanization growth rate of CMA still remains slow compared to other metropolitan areas of the South Asian region. The average annual population growth rate of the CMA is 1.4% (DCSS, 2012), while it is 4.1% in Dhaka (Dewan, 2009b), 4.0% in Kathmandu, and 5% in Karachi (The World Bank, 2013). This reveals that the CMA still retains a lower urban growth rate compared to other metropolitan areas of the South Asian region.

Chapter Two

Outline of Colombo Metropolitan Area

2.1. Geographical setting

The CMA, situated in the western coastal plain of Sri Lanka (Figure 2-1) is the most important administrative, industrial, and commercial center of the country. The CMA enjoys its urban primacy in the national economy and in international relations being the only metropolitan area of the country (Emmanuel, 2005). The growth of the CMA originated based on Colombo City, the commercial capital and largest city in the country (JICA, 2014). The central business district (CBD) of the CMA is located around the Colombo Fort area (6°56"2'N, 79"50"42'E) (Johansson and Emmanuel, 2006). The major transport hubs, such as the main railway station, the central bus terminal, and the harbor are located at the Colombo Fort area. The suburban area of Colombo still remains as a residential area and contains a complex mosaic of land use, including agricultural lands (paddy, rubber), forest, industries, and residential areas.

The topography of the CMA is quite flat and large part area below the 30-meter mean sea level and some areas in east of Colombo are even below the sea level. The climate is classified as "tropical monsoon" under the Köppen climate classification. The average temperature is approximately 27°C and the mean rainfall is approximately 2,300 mm (Johansson and Emmanuel 2006; DMSL, 2016). In the monsoon season (from May to August), Colombo expects heavy rain and frequently experiences the flooding of the Kelaniya River Basin located in the northern area, and the Kalu River Basin located in the southern area. As natural ecosystems, the wetland and lagoon are important in the area (Hettiarachchi *et al.*, 2014).

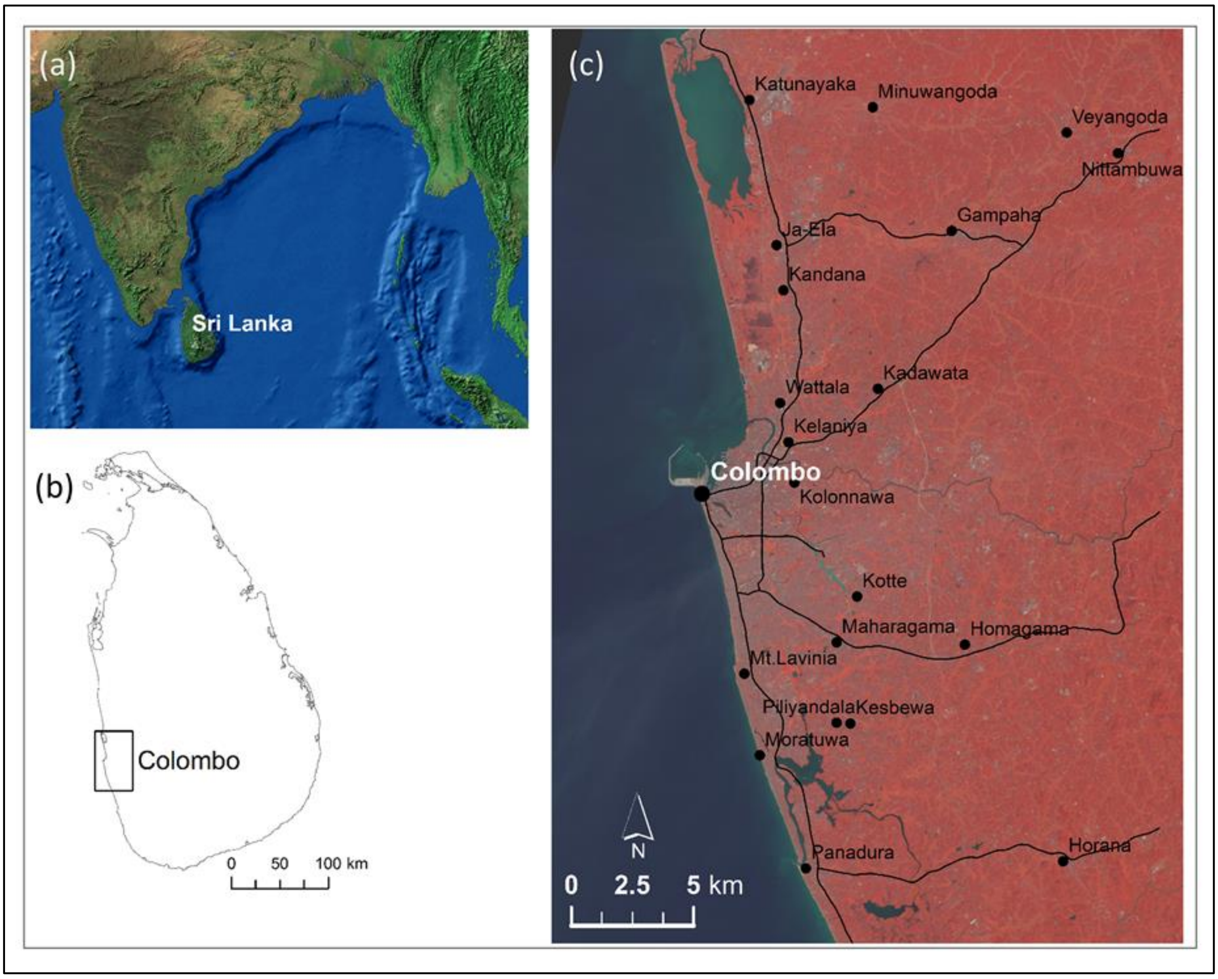

Figure 2-1: Location of the study area: (a) location of Sri Lanka in South Asia (Map Source: ArcGlobe data); (b) areal extent of the study area; and (c) the extent of the study area. Figure 1c shows the roads (lines) and growth nodes (points) in the CMA overlaid over a Landsat ETM+ (2014) displayed in a false color composite. *Note*: Due to the study area mainly covering the metropolitan area of Colombo, the word "Colombo metropolitan area (CMA)" was used in this study. There is not administratively defined boundary to delineate the CMA.

To achieve its objectives, the study analyzed an area of about 237,000 ha encompassing the core of Colombo and the surrounding CMA, which is demarcated by the Colombo Metropolitan Transport Master Plan of 2014 of JICA.

Figure 2-2 shows that the different administrative boundaries related to Colombo and the areal extend of research area boundary in relation to these administrative boundaries. The research area boundary was rationally demarcated based on spatial facts, such as previous research and project boundaries, and other non-spatial facts, such as the percentage of the urban population, the urban facilities and data availability.

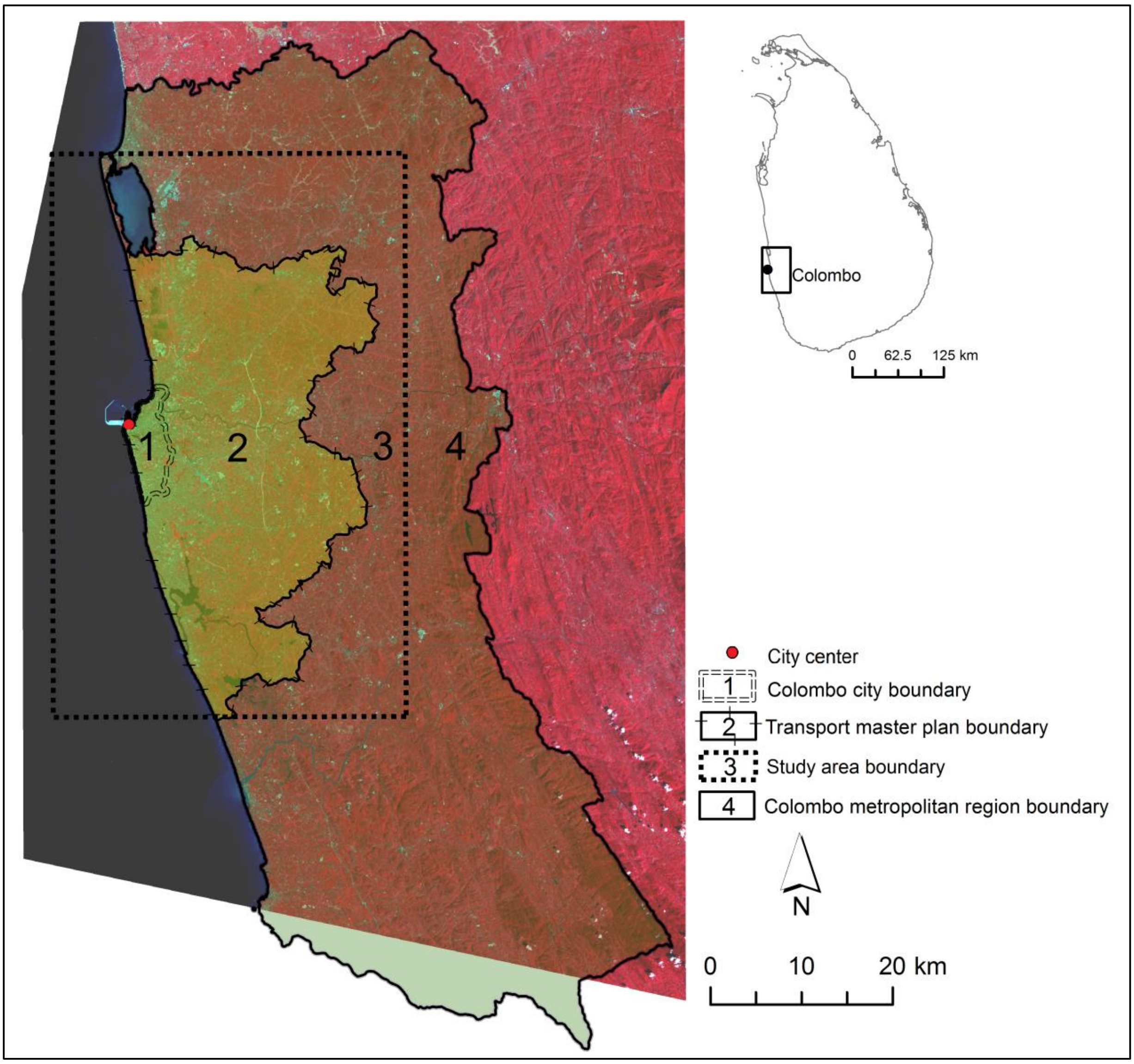

Figure 2-2: The boundary of study area. *Note:* The smallest boundary (indicated by 1) shows the Colombo municipal council area, normally referred as Colombo City; the next boundary (indicated by 2) shows the CMA demarcated by the Colombo transport plan; the rectangular dashed line boundary (indicated by 3) shows the CMA defined in this study; and the largest boundary (indicated by 4) shows the Colombo metropolitan region (CMR).

2.2. Historical background

Sri Lanka has evidence of human settlement dating back approximately 3,000 years. The urban history of the country goes back to the 3rd century BC (Bandaranayake, 1994). Most of the towns and cities were in the dry zone, and depended on tanks and irrigation channels at that time (e.g. Anuradhapura, Polonnaruwa, Sigiriya, Yapahuwa, and Kurunegala) (Bandaranayake, 1994).

With the collapse of the hydraulic civilization in the dry zone of the country, the population concentration emerged in the southwestern quadrant of Sri Lanka in the 13th century (Bandaranayake, 1994.; Manawadu, 2005). During this time, Colombo City slowly emerged as a central place. The location of Colombo Port was the major geographical feature for the development of Colombo as a central place (Bandaranayake, 1994; Hulugalle, 1965). Due to the location of Colombo Port on the maritime Silk Road, several Roman, Arabic, and Chinese traders arrived at Colombo City (Bandaranayake, 1994; Manawadu, 2005).

In 1505, Portuguese explorers fortuitously landed in Colombo port and realized it was a strategic trade and military port in the Indian Ocean (Perera, 2002; Hettiarachchi *et al.,* 2014; Magliocca *et al.,* 2014). They were established fortified with a mosque in 1518 in the Colombo Port area (Figure 2-3). The name "Colombo", firstly introduced by the Portuguese, is believed to be derived from the classical Sinhalese name “Kolon Thota”, meaning "port on the river Kelani." (Hulugalle, 1965). Step by step over time, the Portuguese started the construction of commercial, residential, administrative, military, and religious functions (Perera, 2008; Horen, 2002; Manawadu, 2005). This development gradually segregated agricultural and non-agricultural activities, and transferred Colombo from a small village center to a fine colonial township (Manawadu, 1996; Manawadu, 2005).

In 1756, the Dutch terminated the Portuguese occupation of Colombo after an extensive battle. This battle resulted in severe destruction of the already developed urban forms and infrastructures (Manawadu, 1996). The Dutch used Colombo as the maritime administrative center of Sri Lanka (Horen, 2002; Perera, 2008). The urban forms and infrastructural development were gradually expanded by the Dutch (Schrikker, 2006). A strong fortification was established around the Colombo Port, and residential and commercial functions were located outside the fortification (Manawadu, 1996).

In 1796, the British captured Colombo following the war between the British and the Dutch (Horen, 2002). However, when the power of Colombo transferred from the Dutch to British, the existing built environment was not affected (Manawadu, 1996). Figure 2-4 shows the map of Colombo City in this period.

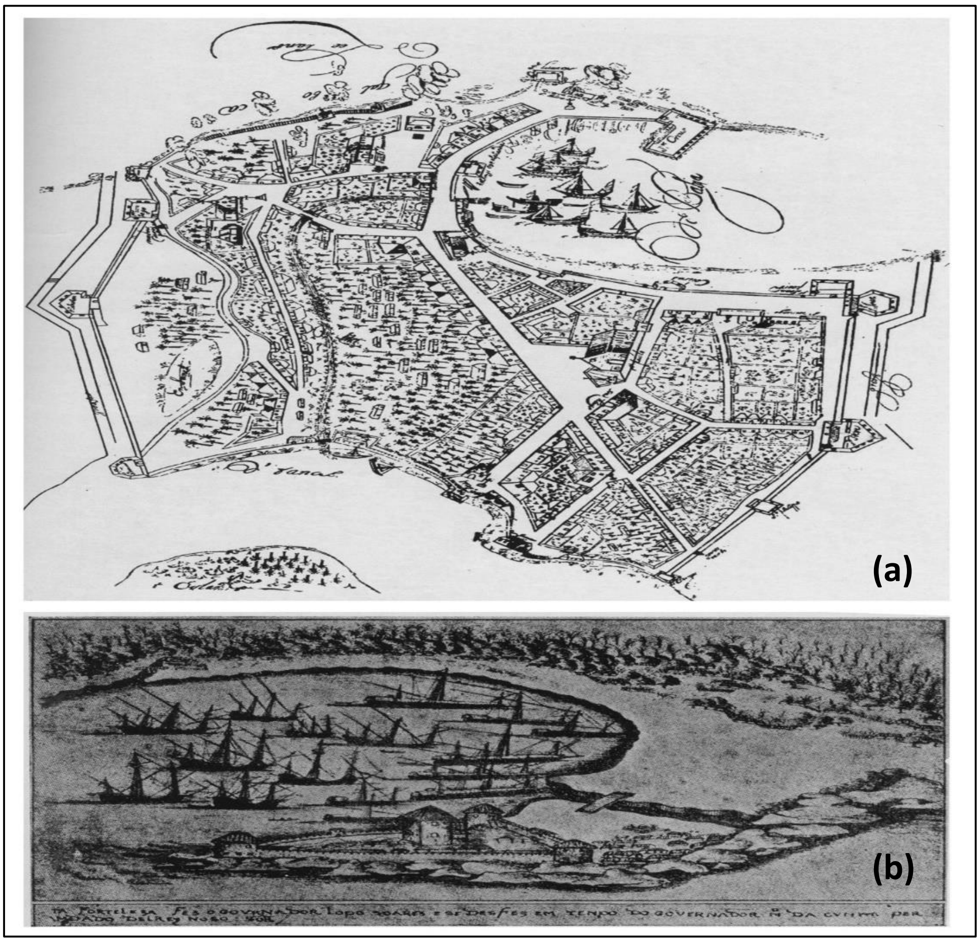

Figure 2-3: Portuguese period Colombo: (a) a map of Colombo city; and (b) the Colombo port area (Source: Hulugalle, 1965).

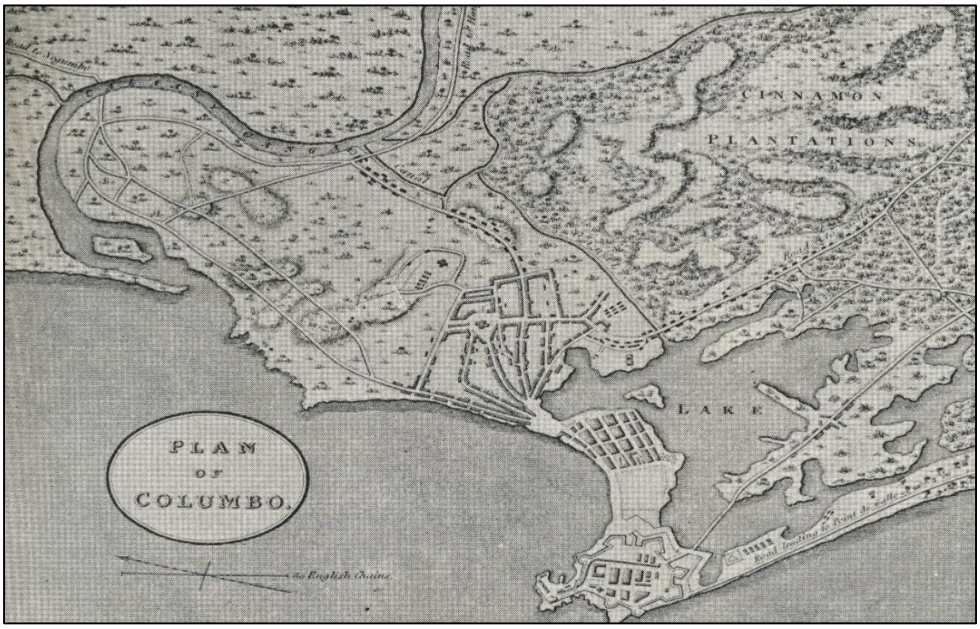

Figure 2-4: The map of Colombo city in 1800 (Source: Hulugalle, 1965).

In 1815, the British seized Sri Lanka with the capturing of the Kandyan Kingdom. With this political change, the British developed Colombo as the administrative and commercial capital for the whole country (Manawadu, 2005; Schrikker, 2006). Until the administrative capital transferred to Sri Jayawardhanapura Kotte in 1982, Colombo enjoyed its privilege as the country's capital of administration and commerce (Manawadu, 2005; Schrikker, 2006). The British mainly developed the plantation industry (e.g. tea, coconut, and rubber), and introduced a railway network connecting the Colombo Port to the rest of the country for the transportation of produce (Manawadu, 1996). Then, Colombo became the main international gateway for British trading activities. With the opening of the Suez Canal in 1869, maritime trading activities with Colombo Port increased (Manawadu, 1996). During the British period, the increased Colombo primacy resulted in several structural changes in the urban areas. The colonial architectural buildings from that time in Colombo City still remain (Figure 2-5) (Horen, 2002; Perera, 2008; Abeysuriya, 2015).

In 1948, the British administration in Sri Lanka formally ended with the granting of independence by the British Empire. The importance of Colombo continued as it remained the administrative capital and commercial center of the country (Manawadu, 2005; Schrikker, 2006). During the post-independence period, the city development underwent many rapid changes. However, with different government policies, the urban and functional changes during the post-independence period were varied (Manawadu, 1996).

Up until the 1960s, the independence government attempted to introduce nationalization to the economic policy and controlled the privately owned industrial development (Hearth, 2010). While the government owned institutions it controlled the economy of the country.

In the 1960s, the government tried to develop agricultural industries and a tourism industry to parallel the European economic boom during this period (Manawadu, 1996). Urban decentralization projects started outside Colombo with new infrastructural development. Although many outside urban centers emerged, the development of Colombo continued (Manawadu, 1996).

Figure 2-5: Colonial influence of building form in Colombo City (Source: (a), (b), and (d) photos by author; (c) photo by https://adventuresinserendipity.wordpress.com/).

In the 1970s, the county's economy was liberalized (after 1977) and foreigners were encouraged to invest in Sri Lanka (Herath, 2010). This policy created a new urban form in Colombo with the establishment of foreign industries and commercial activities (Horen, 2002; Perera, 2008). The short-term urban planning initiatives were mainly introduced during this time than master plan to support foreign investors (Manawadu, 1996).

In the 1980s, many political movements began (e.g. the Liberation Tigers of Tamil Eelam –LTTE and the Janatha Vimukthi Peramuna –JVP) with the rapid social changes that occurred after 1977 with economic liberalization (Hearth, 2010; Dayaratne, 2010; Misra, 2013). The urban development of Colombo was victim to the adverse results of these movements. Until the end of civil war (2009), the country's urban development significantly suffered under the political unrest (Misra, 2013).

In the 2000s, having ended the civil war, the government introduced new urban planning initiatives to convert Colombo into a strategic economic hub (Senanayake *et al.*, 2013b). Among these initiatives, the Colombo beatification project was very important. This project transferred the core area of Colombo from a mere commercial hub to a vibrant city with rich colonial architecture and public recreational facilities by focusing the development of the tourism industry of the country. In 2015, the government introduced a separate ministry to manage and develop the Colombo metropolitan region called "Ministry of Megalopolis and Western Development (MMWD)" (MMWD, 2016).

2.3. Demographic background

According to DCSS (as at 2012), Colombo City had a population of 752,993 people, with an average population density of 17,344 persons/km^2, while the CMA accounted for 3,702,912 of the population with an average population density of 3,699 persons/km$^{2.}$ When compared to those of Ho Chi Minh City (3,900 person /km^2) and Taipei metropolitan areas (2,868.0

persons/km^2), the density is almost in the same range in the CMA (JICA, 2014). However, the central area of CMA, called the Colombo maniple council area (CMC) or Colombo City, shows a recent population decline, while the suburban area population showed a gradual increase (Figure 2-6). This population decline is mainly associated with the decreasing trend of the residential importance in the central area of the CMA.

The spatial pattern of population distribution in the study area by years is shown in Figure 2-7 and reveals that populations are concentrated around Colombo central and the coastal areas. In the suburban regions, high density areas are concentrated along major transport corridors and railway lines. Population concentration around Katunayake, where the international airport is located, is also high.

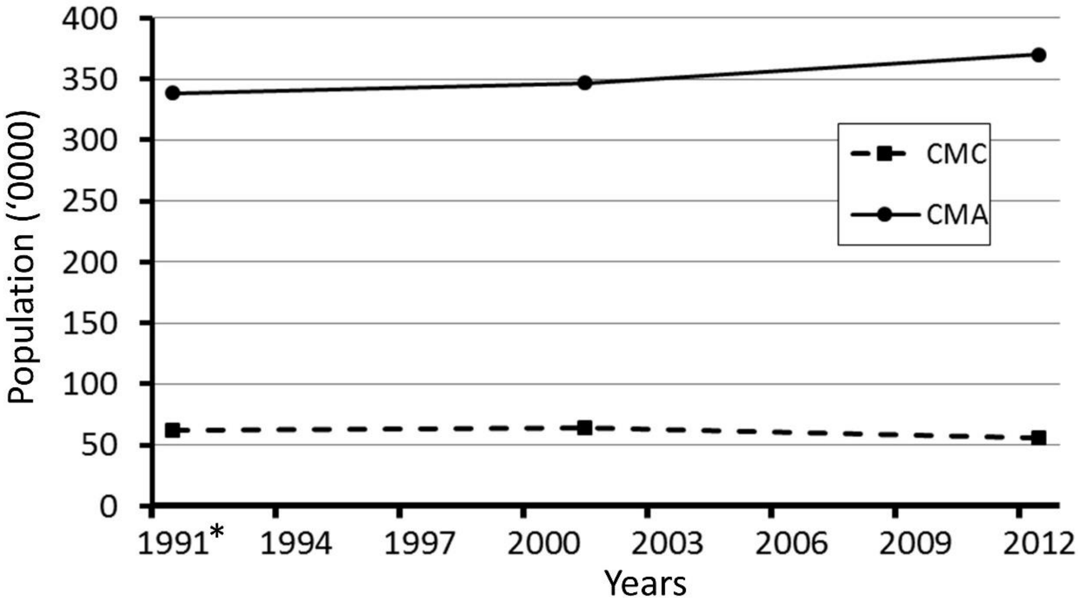

Figure 2-6: Population change differences in CMA and the Colombo City urban population in CMC and CMA (Source: Census and statistic department, http://www.statistics.gov.lk/) Note: * = estimated population.

Due to the economic opportunities, administrative services, and other urban facilities, migration from rural areas to Colombo district has increased, but still remains at a low level (in 2012 it was 641,922 people; 16.2% of the total in-migration). This may be due to several factors, such as the smaller size of the country, which allows people to reach towns and cities within a reasonable time, and to move back to their place of residence; low transport costs; and the reasonable level of infrastructure development that has taken place in the rural areas of the country. However, this migration level is higher than the 1981 statistics, which were reported as 274,201 people. DCSS reported that, the reason for the migration to Colombo that related to employment was more than half of the total migration (55%), while education was responsible for 34%, and marriage for 11% (in 2012).

The population structure by age and housing characteristics are shown in Figure 2-8. It shows the higher percentage of that the labor force (15–65), while the area having permanent housing characteristics than other housing types in the CMA.

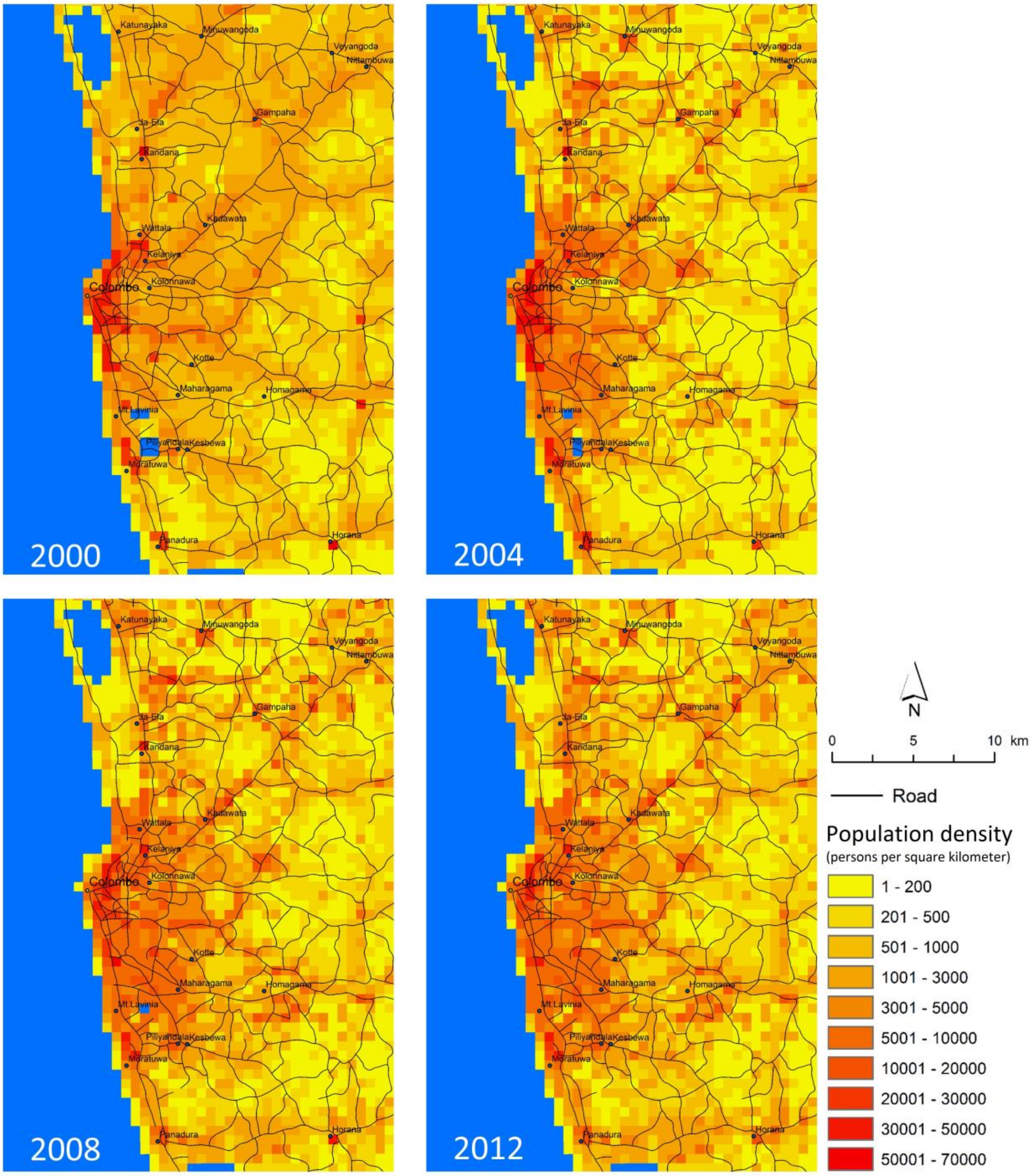

Figure 2-7: Spatial pattern of population distribution (Source: Landscan, 2000, 2004, 2008, and 2012).

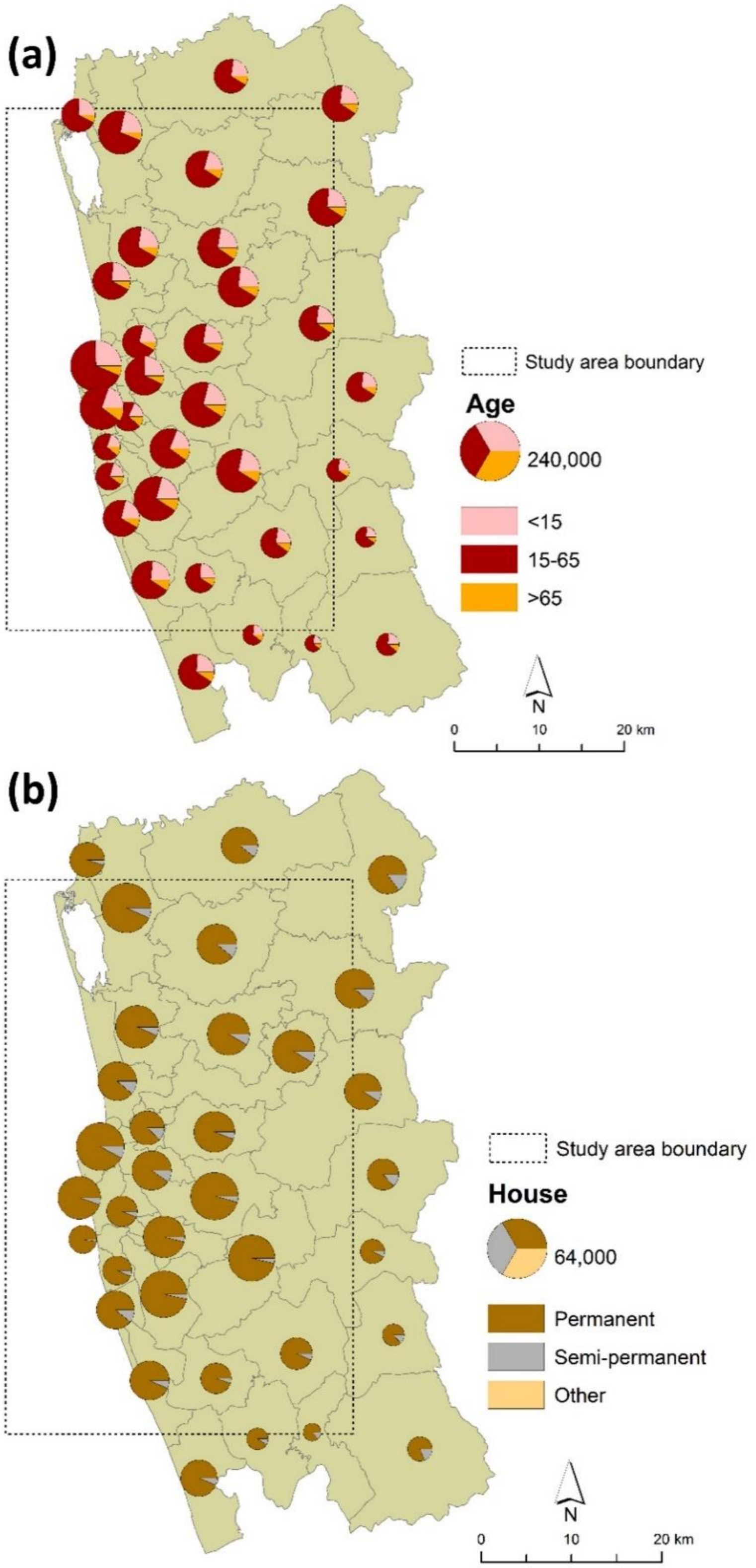

Figure 2-8: Population and housing structure of the CMA: (a) population distribution by age; and (b) housing distribution by housing types (Source: DCSS, 2012).

2.4. Socioeconomic background

The Colombo metropolitan region had a GDP of LKR.3, 292 billion (US$23 billion) in 2012, making it the economic hub of Sri Lanka. It contributed 43% of the national GDP (Figure 2-9) (Central Bank, 2013). The economy of the area was mainly driven by the manufacturing, construction, transportation, and trade sectors.

According to the DCSS of 2012, 52% of the total population of the area was economically active, while the reminder was economically inactive. The majority of the population were involved in the service and industrial sectors rather than the agricultural sector. Of the employed population, 57% were in the service sector, while 33% were in the industrial sector, and 10% were in the agricultural sector in the CMR. These values show whole region, but Colombo city area, highly urbanized area, the agricultural sector employment is lower than this value. However, there is a significant difference between male and female involvement in economic activities. The economically active male population is approximately 66%, while the female population is approximately 34%. The major reason for lower level female percentage is because they are often engaged in housework (57%) and in studies (25%). Figure 2-10 shows the distribution of the employed, unemployed, and economically inactive population distribution of the area.

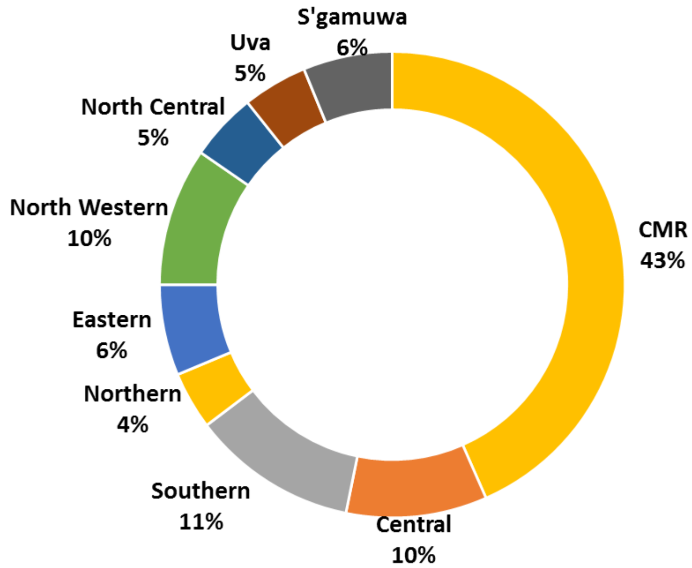

Figure 2-9: Contribution for GDP of Sri Lanka by regions, in 2012 (Source: Central Bank, 2013).

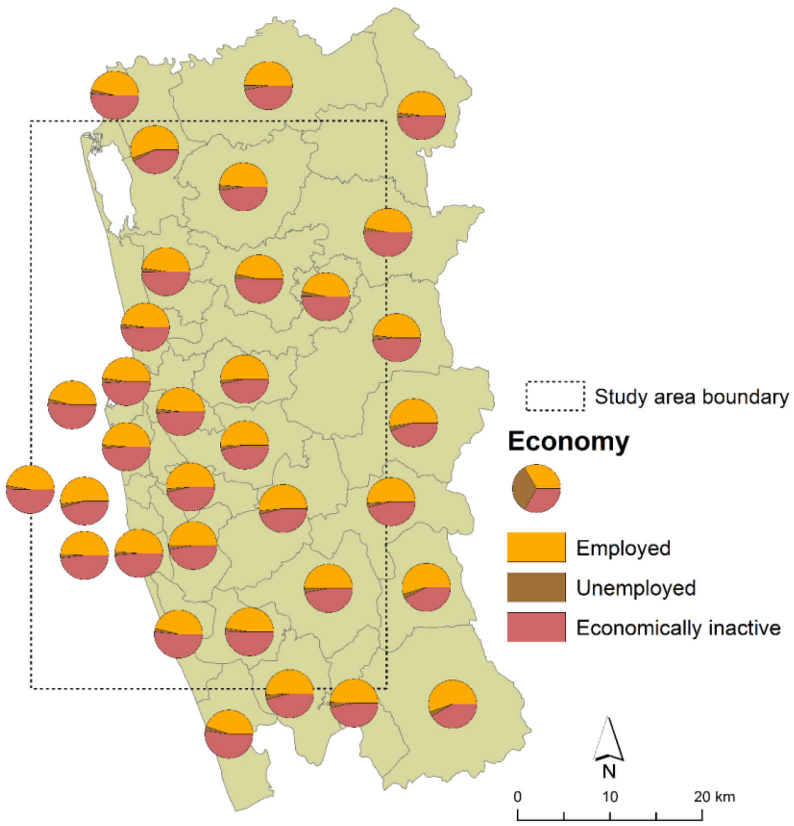

Figure 2-10: Economic characteristics in the CMA (Source: DCSS, 2012).

2.5. Urban planning initiatives

Although the city has recently grown in an unplanned shape, several attempts have been made to plan the city science from the colonial period of the country. The first city plan for Colombo was prepared by an eminent British town planner, Sir Patrick Geddes, in 1921 (Horen, 2002; Perera 2008). The aim of the plan was to make Colombo the "Garden City of the East" by preserving the rural spirit (Horen, 2002). The tree-lined streets and grid system of roads in the higher income area of Cinnamon Gardens are among the legacies of the Geddes Plan (Horen 2002). However, that plan was not operated successfully, and the next planning exercise was introduced by another British town planner, Sir Patrick Abercrombie, in 1949. Abercrombie's plan proposed to decentralize the city's economic activities and create satellite towns around Colombo (Horen 2002; Perera, 2008). This plan also was not successfully implemented.

Due to the rapid increase of functional concentrations in Colombo and its suburban regions, the government initiated the Colombo Master Plan project in 1978 (Horen, 2002). The master plan covered the entire metropolitan region, and consisted of three administrative districts: Colombo, Gampaha, and part of Kalutara. The major objective of this master plan project was the promotion of balanced regional development, and for Colombo to play a central role in stimulating economic development in the country (Horen, 2002). However, this master plan also was not successful due to three unrealistic projections: (1) population growth; (2) job opportunities; and (3) income levels. The Urban Development Authority (UDA)—the key government authority for urban planning in Sri Lanka—was introduced by this master plan project (Abeysuriya, 2015).

In 1985, the UDA initiated the "Colombo Development Plan" and mainly introduced the zoning system to Colombo. Under this plan, Colombo City was developed as the financial capital, and Sri Jayawardhanapura Kotte was developed as the administrative capital (Horen

2002; Abeysuriya, 2015). Other than these two major zones, there were two economic zones that were established by this plan; namely, Biyagama and Katunayaka. Basically, the structural plan that was implemented during this period brought positive changes, such as economic diversification, new employment opportunities, and better infrastructure facilities (Horen 2002; Abeysuriya, 2015).

In 1996, the government directed the UDA to revise the Colombo Master Plan of 1978. But the UDA's planning team decided to prepare a new structural plan because the urban fabric of Colombo had changed significantly since 1978 (Horen 2002; Abeysuriya, 2015). In 1998, UDA introduced the Colombo Metropolitan Regional Structure Plan. This plan focused on the Western Province as a whole, while strengthening Colombo's role as the financial and banking center and developing links with international centers, and strengthening Kotte as the administrative capital (Horen 2002; Perera 2008; SEVANTHA, 2003).

In 1999, the government realized that there were emerging significant social and environmental issues in Colombo City. As a result, the Colombo Development Plan 1999 was prepared to address these issues (Horen 2002; Abeysuriya, 2015). A land-use zone plan was introduced, which decided where different development activities should take place under this planning project. In 2008, the government introduced an amendment to the Colombo Development Plan: the Public Open Spaces green development concept allowed a zoning plan for all development zones (Horen 2002; Perera 2008; SEVANTHA, 2003).

In 2011, the Colombo Port City project was initiated as a major project (MMWD, 2016). After several discussions, the government approved its implementation in 2014. This project has influenced the urbanization of Colombo City and its suburbs.

Chapter Three

Urban Land Use Change in the Colombo Metropolitan Area

3.1. Introduction

The ULU change analysis is an important part of the urban process studies. The monitoring of ULU changes spatiotemporally is crucial in initiating sound landscape and urban planning (Tan *et al.,* 2015; Haregeweyn *et al.,* 2012; Ahmed and Bramley, 2015). The multi-temporal and spatially consistent maps are necessary for monitoring the ULU change over time. However, multi-temporal and spatially consistent land-use data are not available in most developing countries, such as Sri Lanka. This is one of the obstacles for researchers and urban landscape planners for detecting the spatiotemporal pattern of ULU changes. In such a context, remote sensing data provide several advantages to create multi-temporal and spatially consistent land-use maps in a sophisticated manner (Thapa and Murayama, 2012; Bagan and Yamagata, 2014).

The incorporation of different techniques, such as PB classification, SB classification, and hybrid classification with remotely sensed data, allow us to detect ULU more accurately (Li *et al.*,, 2013), and further classification can be improved or classified into subcategories based on neighborhood characteristics.

In this chapter, the ULU mapping adopted in the study and the detected ULU changes are presented. The methodology section describes the data collection, the ULU mapping, the categorization of ULU, and the quantification of changes. The results of the output areas are discussed quantitatively and qualitatively.

3.2. Material and methods

3.2.1. Data collection

Due to the lack of temporally and spatially consistent datasets for the whole metropolitan area, Landsat imageries were employed as the major data source for ULU mapping of three selected time points, namely 1992, 2001, and 2014. In addition to Landsat imageries, the Google Earth imageries, topographical maps, and paper maps were employed to develop ULU maps. As the primary data, the data collected through GPS and field-based observation in the fieldwork sessions (August–September 2015, February–March 2016) were also used to improve the accuracy of ULU mapping (Appendix I). Table 3-1 gives the description of used data to develop multi-temporal maps of the study area.

Table 3-1: Data used to create urban land-use mapping.

Data	Year	Resolution	Sources
Satellite imageries			
• Landsat-5 TM	1992.01.13	30m	USGS
• Landsat-7 ETM+	2001.12.27	30m	USGS
• Landsat-8 OLI/TIRS	2014.01.21	30m	USGS
• IKONOS/QuickBird	Various	Various	Google Earth
Topographical map	2001, 2012	1:50000 1:10000	SDSL
Paper maps			
• Protected area map	Various	Various	CEA
• Urban zoning map	Various	Various	UDA
Field survey	2015.8/ 2016.2	Various	GPS data Photography

CEA = Central Environment Authority; GPS = global positioning satellite; SDSL = Survey Department, Sri Lanka; UDA = Urban Development Authority; USGS = United States Geological Survey.

3.2.2. Urban land-use (ULU) mapping

Data acquisition and preparation: Landsat TM/ETM+ imageries from the United States Geological Survey (USGS) website were acquired. These imageries, with a spatial resolution of 30-m, included a Landsat-5 TM acquired on January 13, 1992; a Landsat-7 ETM+ acquired on December 27, 2001; and a Landsat-8 OLI/TIRS acquired on January 21, 2014. For each time point, one scene (path 141, raw 55) was enough to cover the entire study area. The 2001 and 2014 images were L1T (Standard Terrain Correction) data (Taubenböck *et al.*,, 2012). Therefore, geometric correction and resampling were needed only for Landsat-5 TM for 1992. All images were cloud free, and no atmospheric correction was required.

In addition to the satellite images, ancillary data were collected to develop a land-use classification of the study area. These data included topographical maps created by the Survey Department of Sri Lanka (SDSL), maps of environmentally sensitive areas created by Central Environment Authority (CEA), and urban zoning maps created by Urban Development Authority (UDA). In addition, satellite images provided by Google Earth™ were used at several stages during the data processing, including classifying the land-use and assessing the accuracy.

Classification of Landsat imageries: The ULU classification was involved with several steps (Figure 3-1). Briefly, the approach involved generating independent classifications of Landsat scenes, one at the PB classification and the other at the SB classification. Subsequently, these two classifications were merged (referred hereto as the hybrid classification). The hybrid (PB and SB) land-use product contained six broad classes; namely, built, non-built, protected area, urban open spaces (parks, playgrounds, and runways), and water. Having classified the land-use categories, the neighborhood interaction rules were processed with the MSPA method.

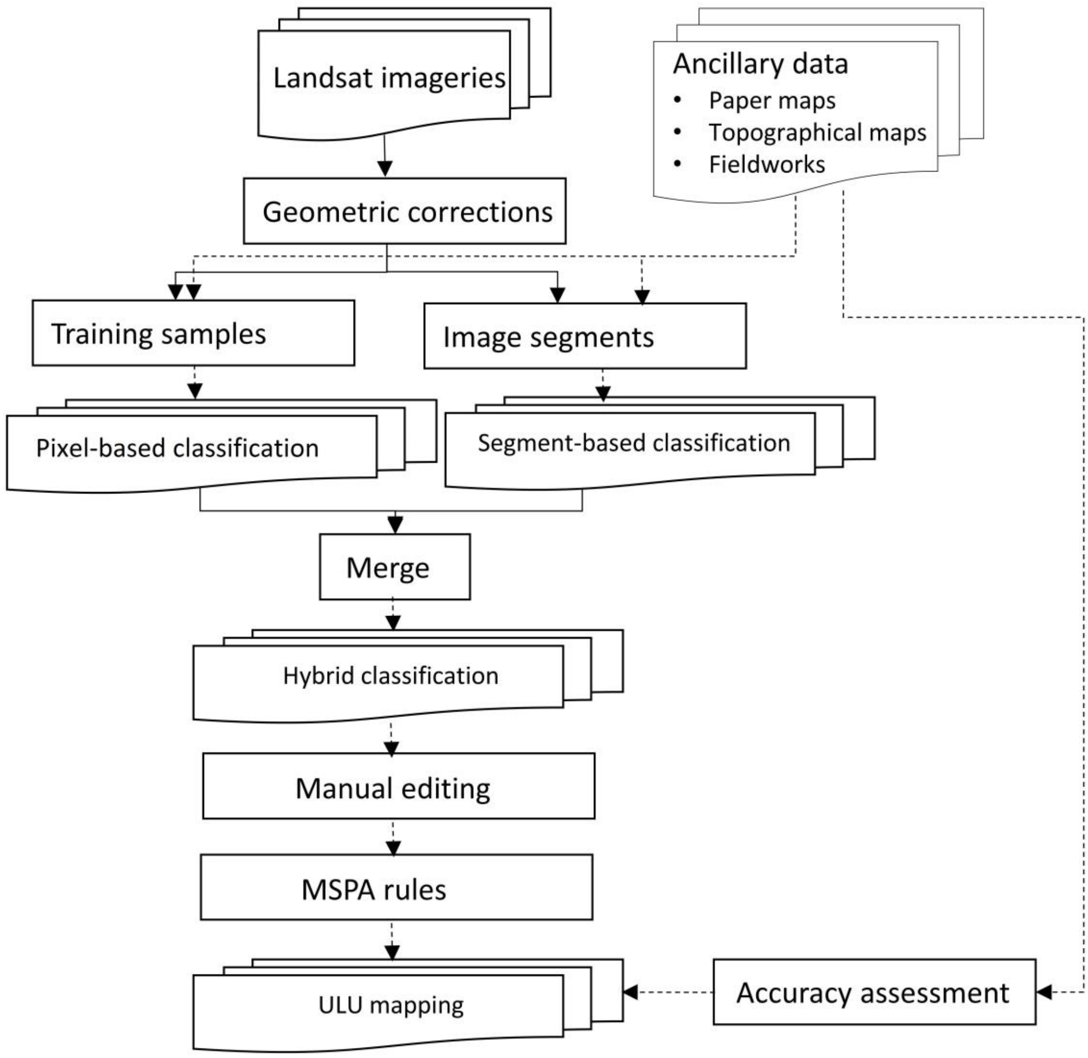

Figure 3-1: ULU mapping approach adopted in the study.

PB classification: The supervised classification with the aid of the maximum likelihood classification algorithm in ENVI 5.2™ software package was used for PB. The PB classification produced three main classes; namely, built, non-built, and water. Built includes human-constructed structures, such as buildings, roads, and other impervious surfaces. Non-built includes previous surfaces, such as agricultural lands, forests, grasslands, and bare lands. Water includes the sea, rivers, ponds, and other waterbodies. At least 150 training samples were carefully collected for each of the classes through an iterative procedure based on our examination of their representativeness. The collected topographical maps and Google Earth™ images were used as the reference data to collect these training samples. Figure 3-2 (a) illustrates an example of the PB classification output.

SB classification: The segment of each the imageries was accomplished using the ENVI 5.2 software package. At the end of PB classification, the ENVI creates the image segments based on the spectral values of satellite imageries. With the aid of ancillary data, region merging segmentation techniques were processed and merged the similar adjacent image segments while minimizing object heterogeneity. SB finally produced the classification with the protected area and urban open spaces (parks, playground, and runaway). Figure 3-2(b) illustrates an example of SB classification output.

Hybrid classification: The results of PB and SB classification were merged using the raster algebra tool in the ArcGIS™ software package to generate the final land-use classification of the study area. The hybrid classification accomplished the classification with five classes; namely, built, non-built, protected areas, urban open spaces, and water. Some places were manually edited through visual inspections. Figure 3-2 (c) illustrates an example of hybrid classification output.

MSPA rules: Before utilizing the MSPA, the active and inactive land-use categories were defined. The active land-use categories were those that influenced ULU classification as a neighborhood, and inactive land-use categories were those that did not. Built and non-built land-use categories of the land-use map were considered active land-use categories, while protected areas, urban open spaces, and water were considered inactive land-use categories because the author assumed that the influence of those inactive land uses to define ULU was not significant. After the active and inactive land-use categories were identified, neighborhood rules were processed, and built land uses were classified into two ULU categories (Figure 3-3): (1) urban dense, meaning dense urban land, which was the built area that contained greater than or equal to 50% of the surrounding built area; and (2) urban sparse, meaning sparse urban land, which was the built area containing less than 50% of the surrounding built area. After these three ULU categories were delineated, the non-built area, the protected area, and the urban open space were merged and renamed as non-urban, which resulted in final ULU maps for each time point (1992, 2001, and 2014) containing four categories: urban dense, urban sparse, non-urban, and water.

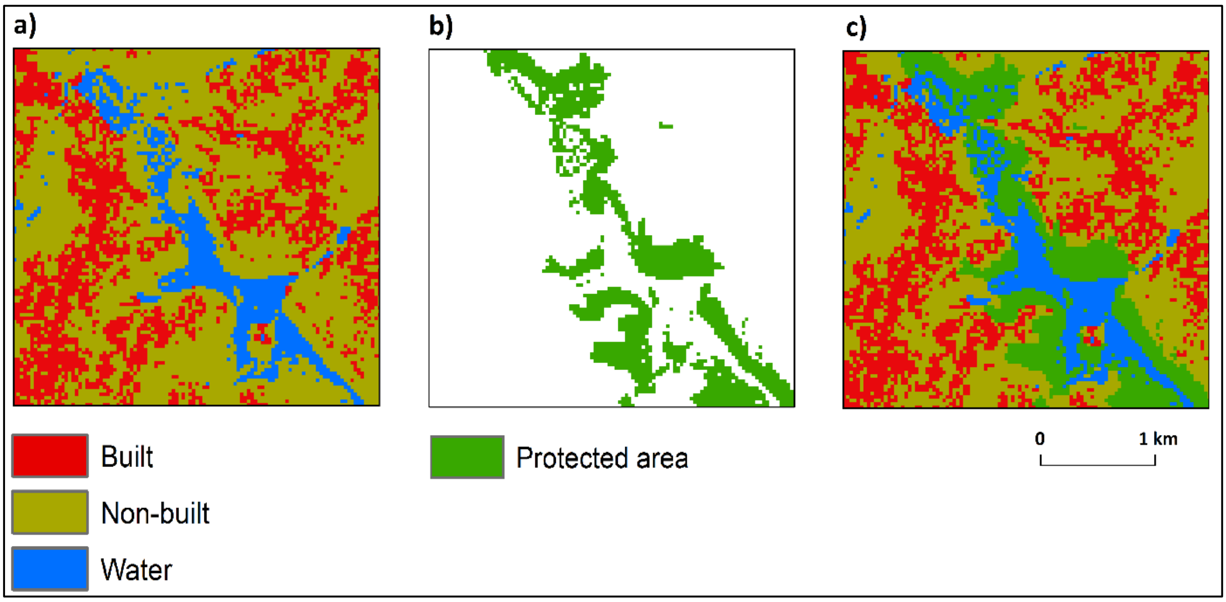

Figure 3-2: Examples for ULU mapping (a) PB classification; (b) SB classification; and (c) hybrid classification.

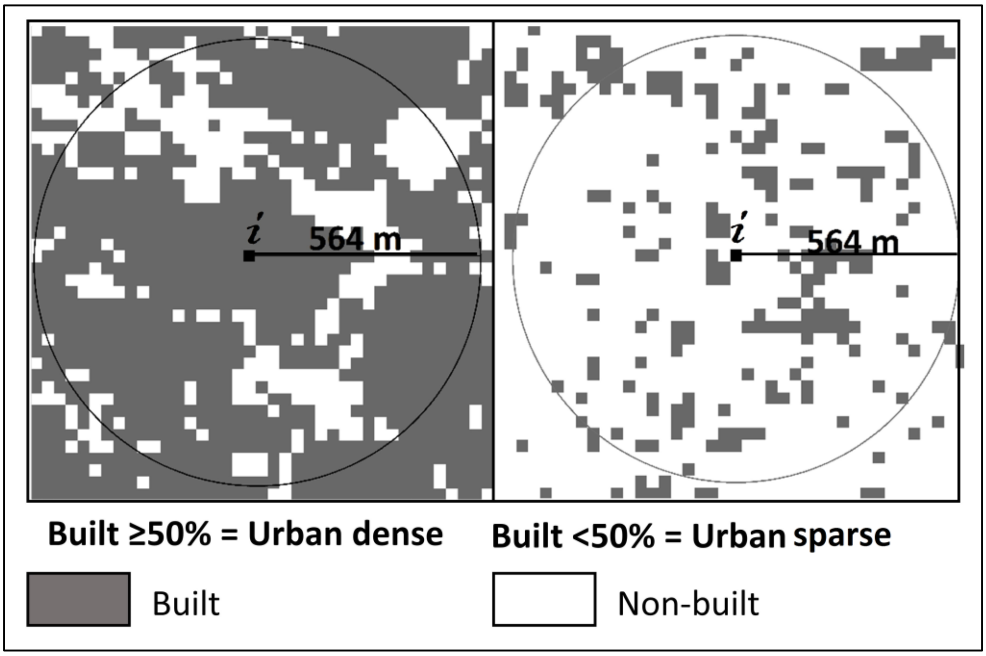

Figure 3-3. Determination of built-pixel percentage as a percentage of the total pixels in the neighborhood area. i = processing pixel and processed with 30 m × 30 m pixels.

3.2.3. Assessing the accuracy of ULU maps

Two levels of accuracy assessment were conducted. The first involved assessing the accuracy of the land-use classification, and the second involved assessing the accuracy of the ULU mapping.

The accuracy of the land-use classification was checked with 300 random sample points for built, non-built, and water (1992, 2001, and 2014) through careful, rigorous visual inspection using the stratified random sampling method (Appendix II). For the 1992 and 2001 classification results, the topographical maps and Landsat images were used as reference data. For the 2014 classification results, Google Earth™ images were used. The overall accuracy was calculated separately for each time point (Congalton, 1991).

Initially, to assess the accuracy of the ULU mapping (urban dense and urban sparse), 200 random sample buffers—each with a 564-m buffer distance—were created in shape file format separately for urban dense and urban sparse categories. Subsequently, these buffer shape files were converted to KML file format and uploaded to Google Earth™ for visual assessment. Agreement was checked visually through careful rigorous inspection using Google Earth™ images as reference data (Figure 3-4). Because of the lack of reference data from earlier years, this assessment was conducted only for the 2014 ULU category results. Finally, the percentage of conceptual agreement with ground truth was calculated separately for each year.

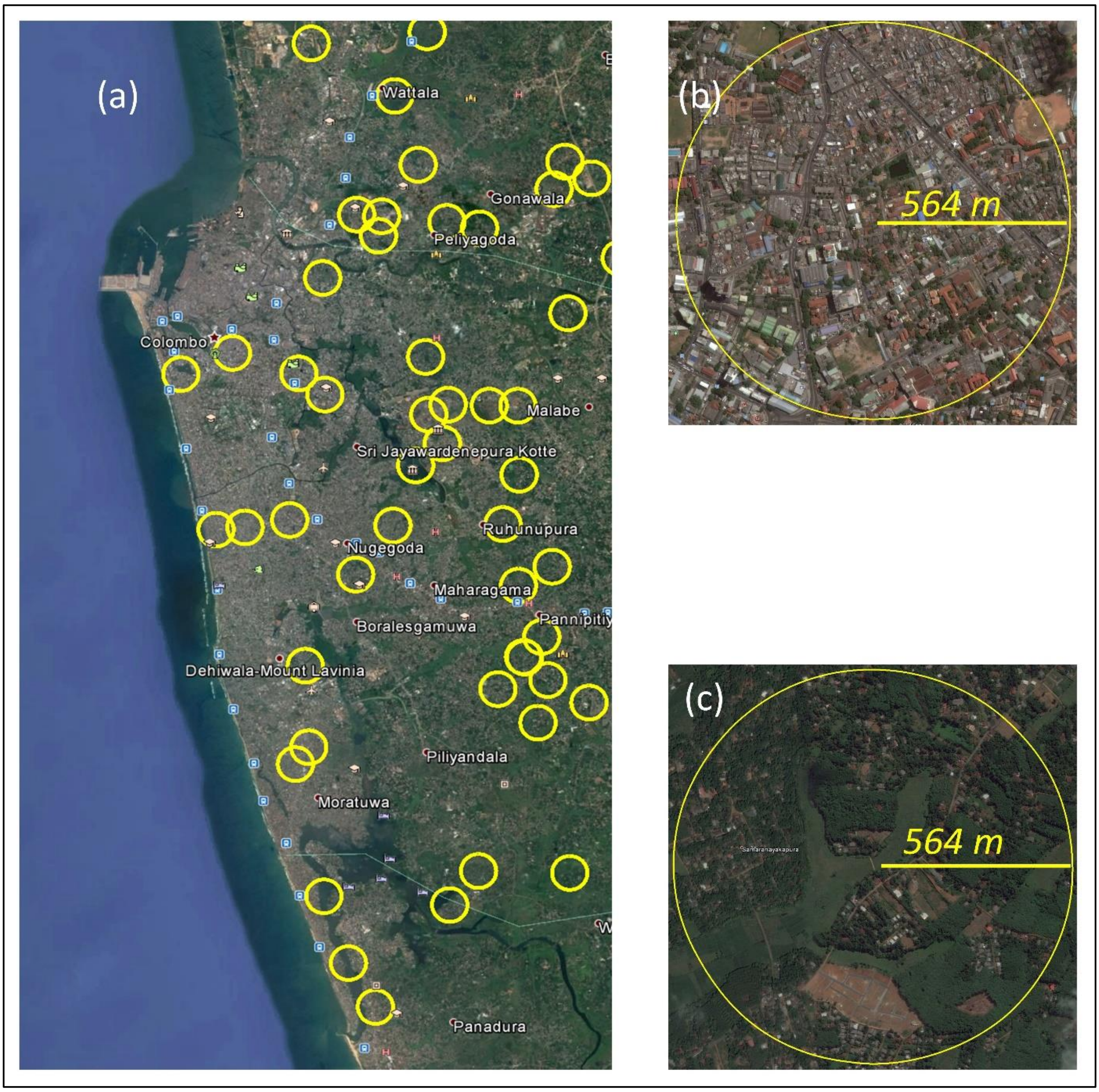

Figure 3-4: Examples for sample buffers in accuracy assessment: (a) Overlaid sample buffers; (b) spatial structure of urban dense; and (c) spatial structure of urban spares.

3.2.4. ULU change intensity analysis

Land-change intensity analysis (Aldwaik and Pontius 2012; Estoque and Murayama, 2015) was used to examine the extent and rate of urban land change in the CMA (ULU change; i.e. a change from non-built to built) across the two time intervals (i.e. 1992–2001 and 2001–2014). The annual change intensity (ACI) for each time interval (1992–2001 and 2001–2014) (Equation 3-1) was calculated (Aldwaik and Pontius 2012; Estoque and Murayama, 2015). Then, each ACI was compared to the uniform intensity (UI), which is the rate of change relative to the entire time extent of the land-change analysis (Equation 3-2). If the ACI in a particular time interval (e.g. t1–t2) was less than the UI, then the ACI intensity of that particular time interval was considered slow; however, if it was greater than the UI, it was considered fast (Estoque and Murayama, 2015; Aldwaik and Pontius 2012).

$$\mathrm{ACI}\ (\%) = \frac{(\mathrm{LC}/\mathrm{LA})}{\mathrm{TE}} \times 100 \tag{3-1}$$

where ACI is the annual change intensity for a given time interval (e.g. t1–t2), LC is the area of land change from non-built to built for a given time interval, LA is the area of the entire landscape, and TE is the duration of a given time interval.

$$\mathrm{UI}\ (\%) = \frac{[(\mathrm{LC_{TI1}} + \mathrm{LC_{TI2}})]/\mathrm{LA}}{\mathrm{TE_{TI1}} + \mathrm{TE_{TI2}}} \times 100 \tag{3-2}$$

where $\mathrm{LC_{TI1}}$ and $\mathrm{LC_{TI2}}$ are, the land change from non-built to built during time interval 1 and time interval 2, respectively. $\mathrm{TE_{TI1}}$ and $\mathrm{TE_{TI2}}$ are the time extent of time interval 1 and time interval 2, respectively,

3.3. Results and discussions

3.3.1. Defining the ULU with neighborhood interaction rules

Neighborhood interactions are an important component of many land-use models connecting to Tobler's (1970) first law of geography: "Everything is related to everything else but near things are more related than distance things." CA is commonly used to implement neighborhood interactions in land-use models through Vin Neumann's adjacent four cells rule (Figure 3-5(a)) or Moor's adjacent eight cells rule (Figure 3-5(b)). In reality, a cell not only influences the state of adjacent cells, but also those located at a certain distance, although with less effect (Barreira-González *et al.,* 2015). In this respect, a distance decay function can be used to integrate neighborhood interaction to the cells (Figure 3-5(c)) (Zhao and Murayama, 2011).

The study employed the neighborhood concept with distance to characterize the ULU of the study area, and it successfully classified it. The percentage of the built environment was considered to classify the ULU categories. This novel method, introduced in this study, was based on the MOLAND (2011) project land-use classification approach, which cannot be performed in traditional land-use classification methods. MOLAND has developed five basic ULU: continuous urban fabric, consisting of built features surrounded by more than 80% built features; discontinuous dense urban fabric, consisting of built features surrounded by 50–80% built features; discontinuous medium-dense urban fabric, consisting of built features surrounded by 30–50% built features; discontinuous low-dense urban fabric, consisting of built features surrounded by 10–30% built features; and discontinuous very low-dense urban fabric, consisting of built features surrounded by less than 10% built features. Angel *et al.,* (2010) used a very similar approach (with a 1-km^2 area) to characterize ULUs using neighborhood attributes and binary land-use types.

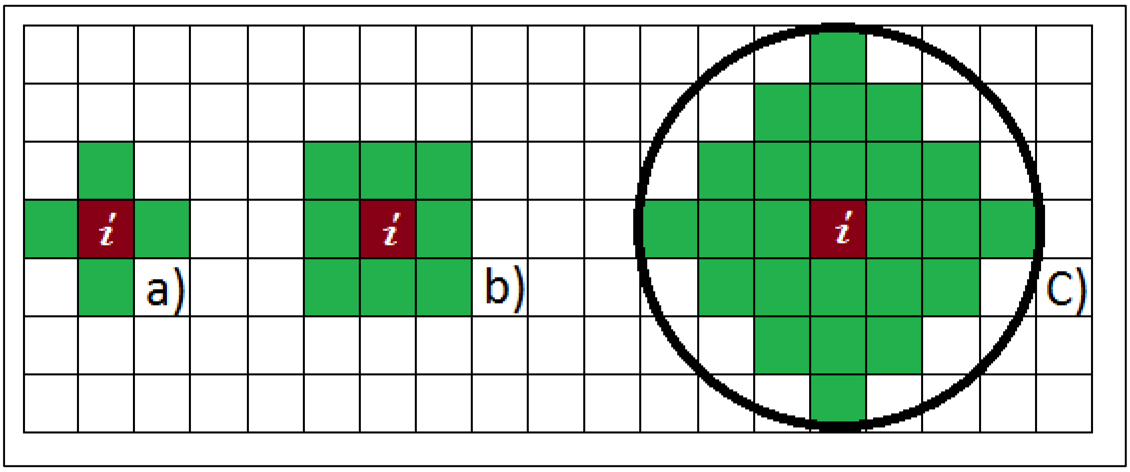

Figure 3-5**:** Neighborhood concepts (a) Van Neumann's concept (4 cells); (b) Moore's concept (8 cells); and (c) processing the neighborhood concept with distance (*i* = processing cell).

3.3.2. ULU mapping

Figure 3-6 shows the results of ULU mapping. An accuracy assessment of the land-use classification found overall accuracies of 88.66%, 90.33%, and 93.66% for 1992, 2001, and 2014, respectively. Based on the ULU classification results for 2014, the conceptual agreement of the urban dense area was 97.00%, while the conceptual agreement of the urban sparse area was 87.00%. The classification accuracy was satisfactory for monitoring urban areas and clearly shows the continuous urban growth of the area**.**

The results show that urban dense was 3,968 ha, 7,953 ha, and 14,881 ha in 1992, 2001, and 2014, respectively, while the urban sparse was 7,197 ha, 11,439 ha, and 20,994 ha in 1992, 2001, and 2014, respectively (Figure 3-7). The spatial extent of the sparse urban area compared to the dense urban area was higher in all the time points. This revealed that the dominance of sparse growth in the area rather than dense urban growth. However, the change percentage indicates that the higher level of changes (275%) occurs on dense urban area compare to the sparse urban (192%).

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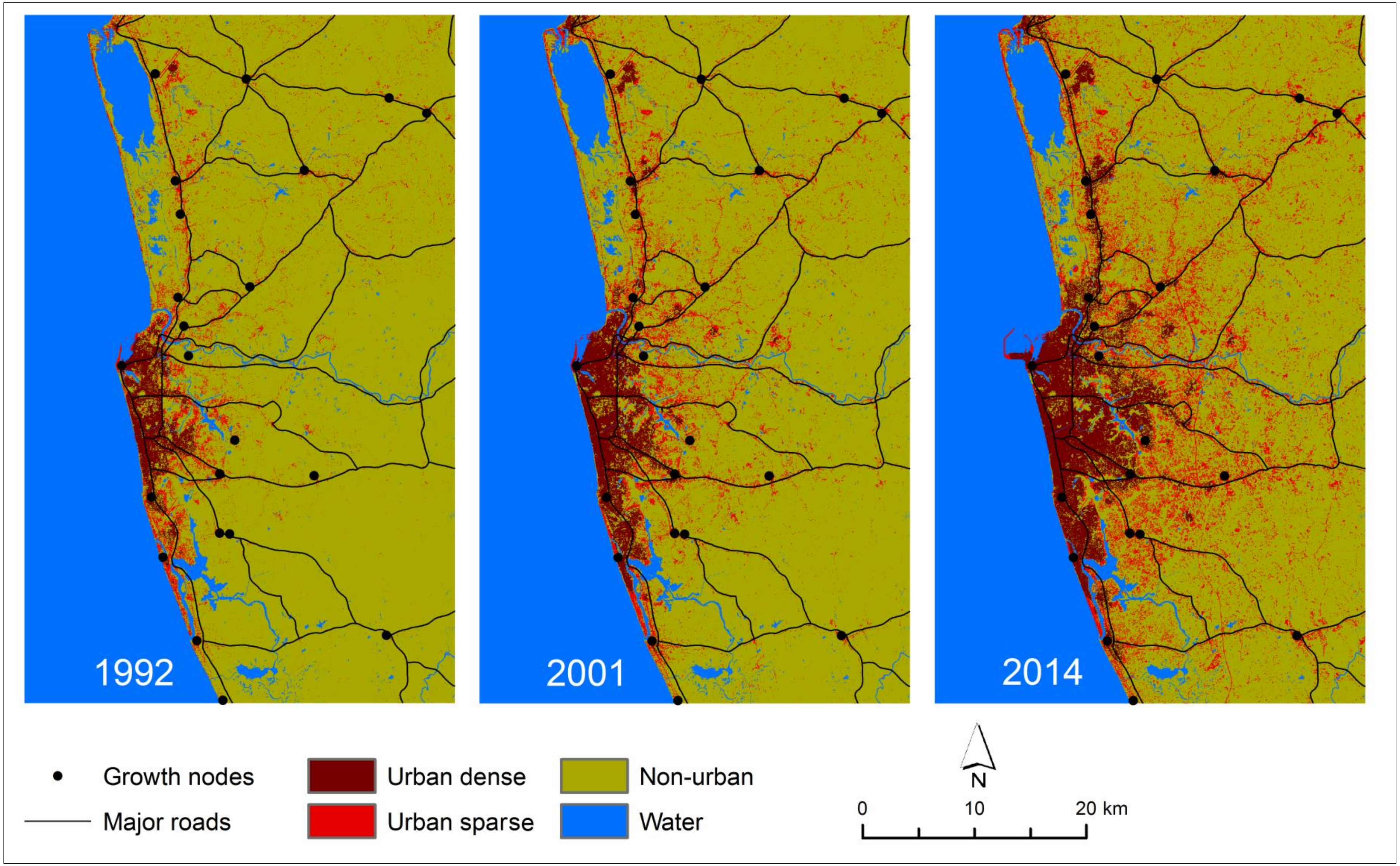

Figure 3-6: Spatial pattern of ULU distribution.

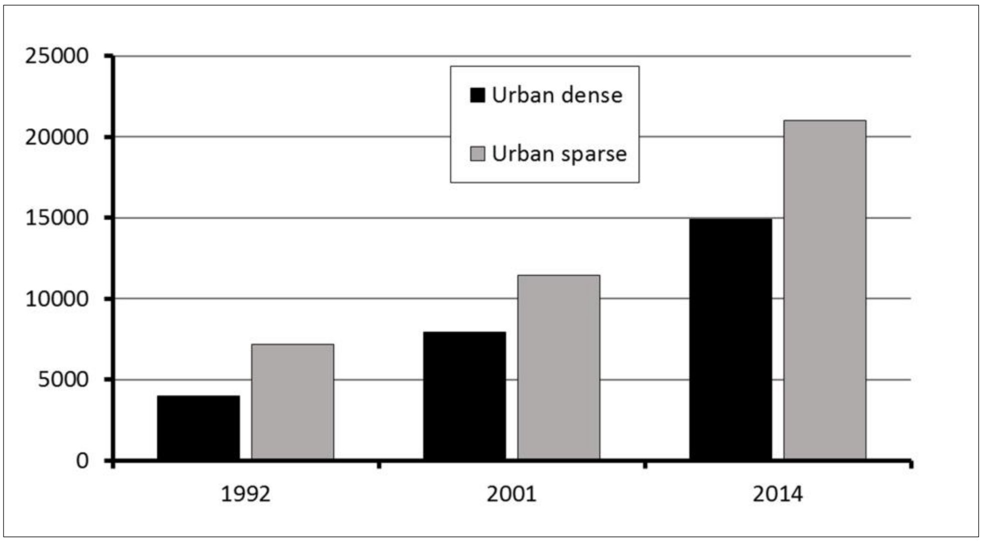

Figure 3-7: The changes of spatial extent in urban dense and urban sparse categories in CMA.

Table 3-2 and Table 3-3 show ULU transition matrices. The underlined values indicate the persistence of each land-use category, while the other values indicate the exchange among land-use categories. According to the statistics obtained as a percentage of the total landscape, urban dense gained 1.69% and urban sparse gained 2.64% in the first time interval, while urban dense gained 2.93% and urban sparse gained 5.53% in the second time interval. However, it should also be noted that the time extent during the 2000s is longer than during the 1990s. Thus, examining the annual ULU change was very important in characterizing the ULU. These ULU transition statistics show that during both time intervals, more transitions occurred from non-urban to urban sparse areas (1990s = 2.58%; 2000s = 5.46%). The second important transition is from urban sparse to urban dense (1990s = 0.84%; 2000s = 1.47%). The third important transition was non-urban to urban dense (1990s = 0.80%; 2000s = 1.40%). These land-use transitions clearly revealed that there were gradual changes of non-urban areas into urban areas and an increased density of ULU from 1992 to 2014. Especially, the change of the rural landscape in to an urban landscape can be predominantly identified with this ULU transition in the CMA. The major transformation of the landscape could be identified in relation to the development of transportation networks of the area in recent years. The diffusion of the urban area covering mainly green space, including agriculture and forest areas, can be identified very clearly. The images visually show how the road emerged over the last few years and the association of build-up (Figure 3-8). Suburban growth in the CMA was mainly dominated by an increase in industrial development and a decline in the agricultural-based economy in recent decades.

Table 3-2: ULU transition matrix in the percentage of landscape for 1992–2001.

		2001					
	Category	Urban dense	Urban sparse	Non-urban	Water	Total	Gross loss
1992	Urban dense	1.67	0.00	0.00	0.00	1.67	0.00
	Urban sparse	0.84	2.19	0.01	0.00	3.04	0.85
	Non-urban	0.80	2.58	61.42	0.04	64.84	3.42
	Water	0.05	0.06	0.22	30.12	30.45	0.33
	Total	3.36	4.83	61.65	30.16	100.00	
	Gross gain	1.69	2.64	0.23	0.04		4.60

Table 3-3: ULU transition matrix in the percentage of landscape for 2001–2014.

		2014					
	Category	Urban dense	Urban sparse	Non-urban	Water	Total	Gross loss
2001	Urban dense	3.35	0.00	0.01	0.00	3.36	0.01
	Urban sparse	1.47	3.33	0.03	0.00	4.83	1.50
	Non-urban	1.40	5.46	54.72	0.08	61.66	6.94
	Water	0.06	0.07	0.02	30.00	30.15	0.15
	Total	6.28	8.86	54.78	30.08	100.00	
	Gross gain	2.93	5.53	0.06	0.08		8.60

Figure 3-8: Recent urban transformation in CMA—Homagama area (Source: Google Earth).

The movement of sparse growth from the central city area outward, which can be identified in the ULU transition map (Figure 3-9), was spurred on mainly by the increasing residential and commercial value of land in the central area, while areas surrounding the city center area declined in importance as residential areas. This trend has increased the number of real estate agents, and both agricultural and forestland has been illegally converted to residential land in the CMA. However, these growth patterns should be identified quantitatively to support the urban planning initiatives. In Chapter Four, the urban growth pattern is discussed in relation to this land-use transformation.

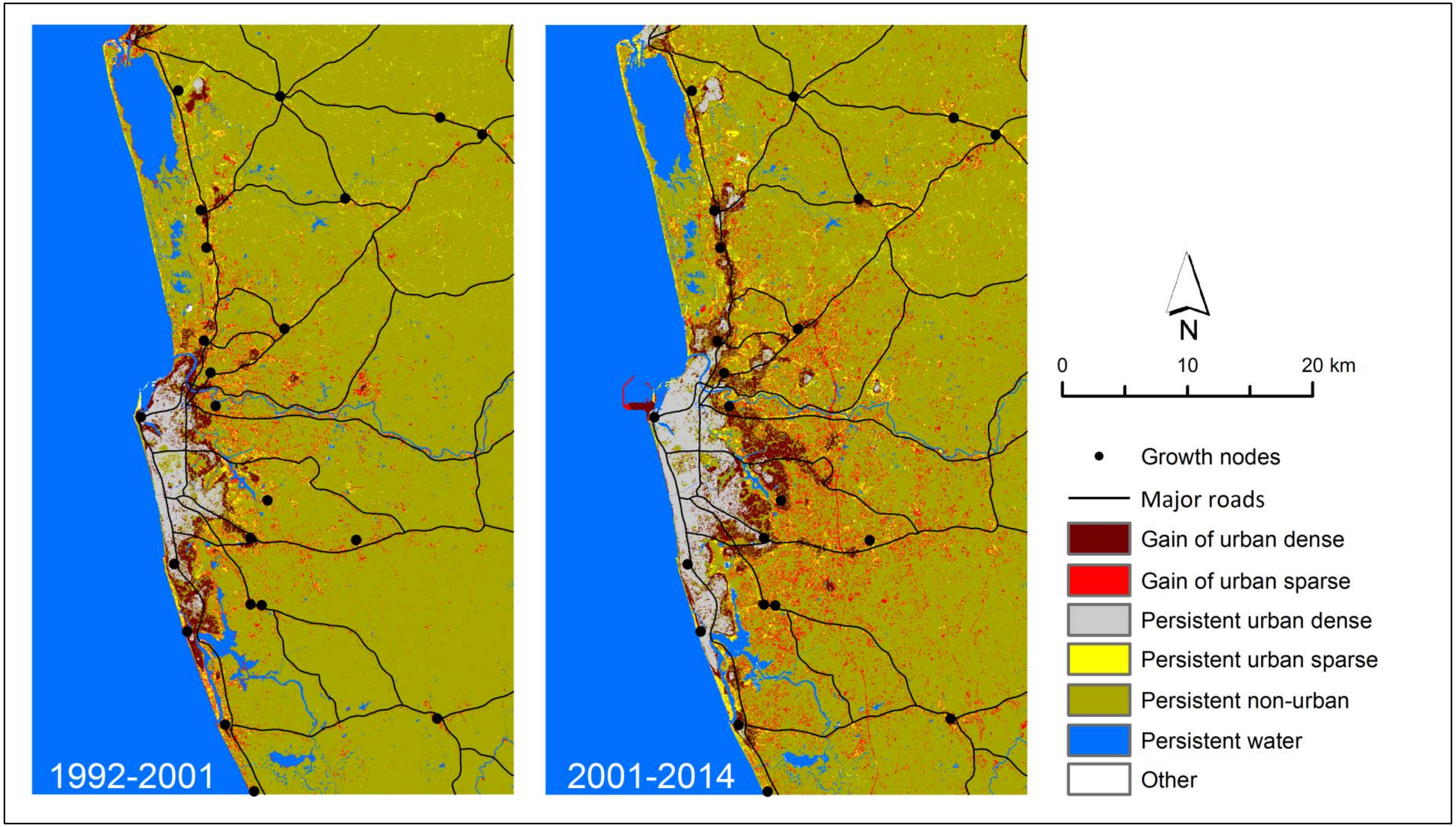

Figure 3-9: ULU change mapping.

3.3.3. ULU change intensity

Land-change intensity analysis was employed to capture the speed of ULU change. The land-change intensity analysis revealed that ACI during the first time interval (1992–2001) was 0.39%, while the second interval (2001–2014) had an ACI of 0.54% (Figure 3-10). With a uniform intensity (UI) of 0.48%, the ACI during the 2000s is considered fast, while the ACI during the 1990s is considered slow. It other words, the intensity of ULU change during the 2000s was faster than during the 1990s. Overall, these results show that ULU change in CMA was not stationary across the two time intervals.

Several socioeconomic and political factors can be traced, which are associated with the difference in annual ULU change intensity across the 1990s and 2000s. Census data show that the population growth rate in the CMA was higher during the 2000s than the 1990s (Figure 3-11). The higher population growth rate during the 2000s was influenced by rural-to-urban migration. After the mid-2000s, the decrease in the productivity of agricultural lands in the dry zone of the country prompted the government to promote rural-to-urban migration as a poverty-reducing initiative (Hewavitharana, 2004). Employment in urban, industrialized areas was seen as providing better living conditions for struggling farmers. This policy change motivated the generation of young migrants to settle in the CMA. As at 2012, there were 641,922 people who had migrated to Colombo, accounting for 16.2% of the country's total in-migration (DCSS, 2012).

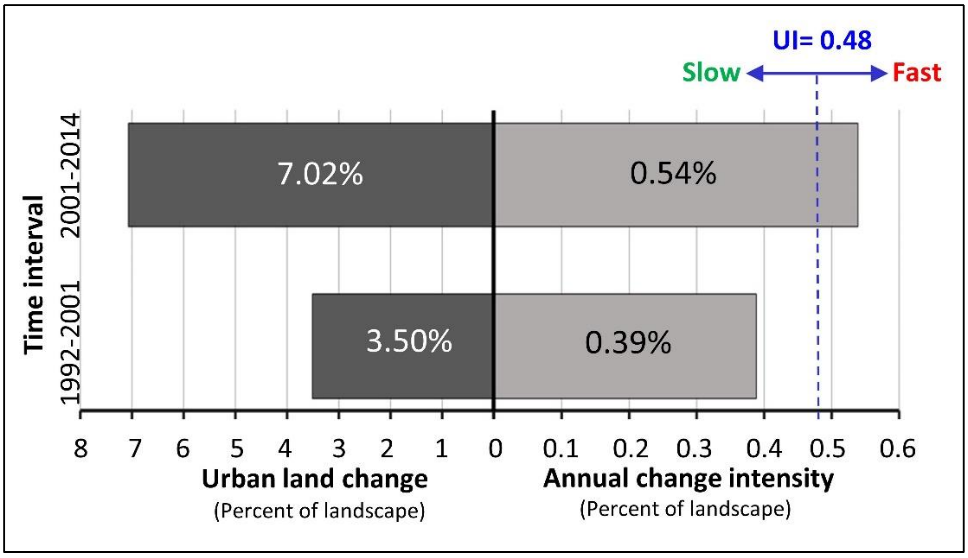

Figure 3-10: Annual ULU change intensity.

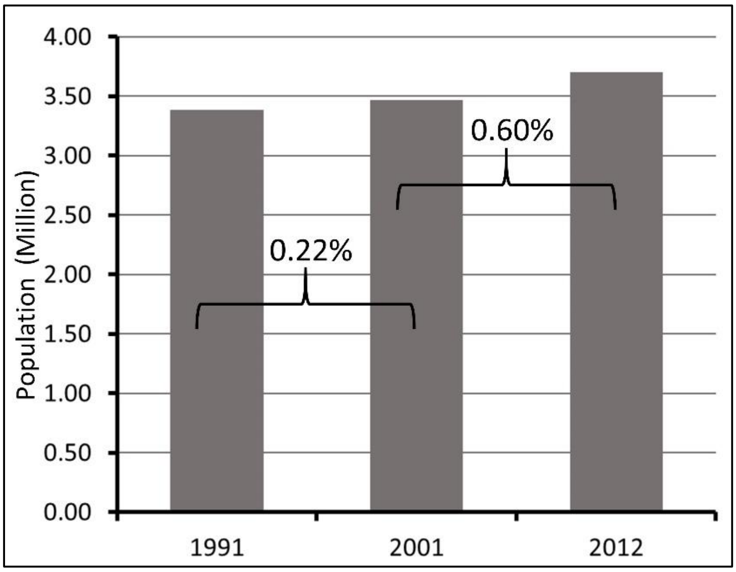

Figure 3-11: Population growth of the CMA (Data Source: Census data, 1991, 2001, and 2012). The numbers in percent represent the annual population growth rate (APGR), calculated as: APGR (%) $= \left(\sqrt[n]{P_{t2}/P_{t1}} - 1\right) \times 100$, where P is the population for a particular census date (e.g. t1 or t2); and n is the time interval in years between two census dates (e.g. t1-t2).

In the 1990s, Sri Lanka's economy faced several challenges due to the JVP insurrections (1987–1989) and a civil war (1983–2009) (Hogg, 2011). The combined influence of these two political movements slowed economic development in general and urbanization in particular. However, after the end of the JVP insurrections in 1989 and the civil war in 2009, development in Colombo accelerated. Specifically, after 2009, post-war policies attracted substantial foreign capital to Sri Lanka as a whole, and development projects in Colombo made it the country's industrial capital (Hogg, 2011). Furthermore, the slow urban growth of the CMA during the 1990s was due to the country's urban development policy at that time. In the 1980s and 1990s, government policy focused more on the promotion of urban decentralization into north-central and eastern Sri Lanka rather than on the development of Colombo and its suburbs (Groves, 1996). This policy slowed down the growth of the CMA. However, from the 2000s up to the present, Colombo has developed to become the apex of Sri Lanka's urban system, providing the highest level of urban functions and services, which have also contributed to the much improved GDP per capita in the country as a whole (Figure 3-12). Moreover, with its central location in the region and it being one of the important nodes in the proposed "new silk road economic belt" (Zimmerman, 2015), the CMA recently attracted large amounts of foreign direct investment (FDI). The FDI net inflow as a percentage of GDP of the country was 0.28% in the 1990, 1.09% in 2001, and 1.46% in 2011 (Figure 3-13). Most of these foreign investments are industries, which were established in export processing zones (EPZs), such as in Katunayake, Biyagama, and Horana, which are located in the CMA. The location of the administrative capital city, Sir Jawardhanapura Kotte, in the CMA has attracted most of the national government's administrative headquarters and several government institutions into the CMA. These factors, together with population growth, are among the underlying factors driving the rapid ULCs in the CMA.

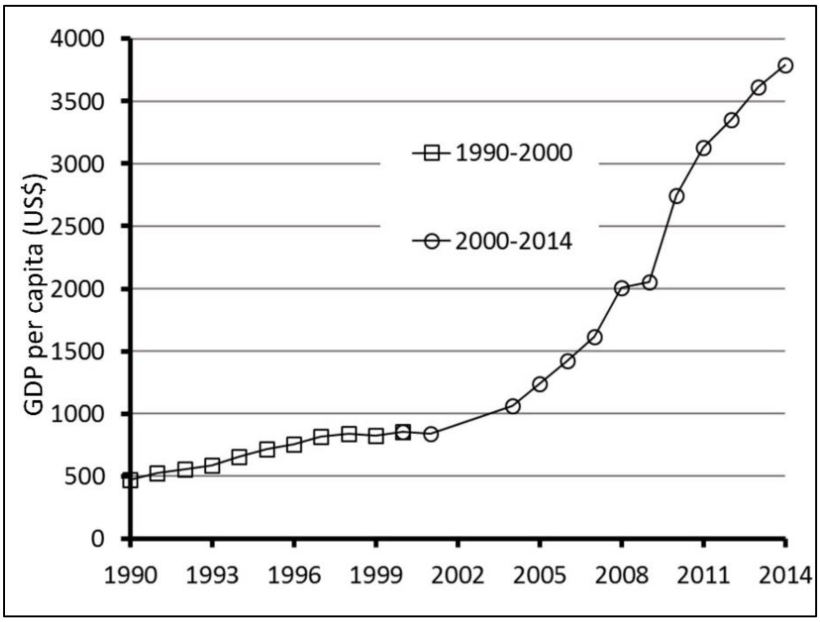

Figure 3-12: The GDP of Sri Lanka for various years (Data Source: World Bank open data, 2016).

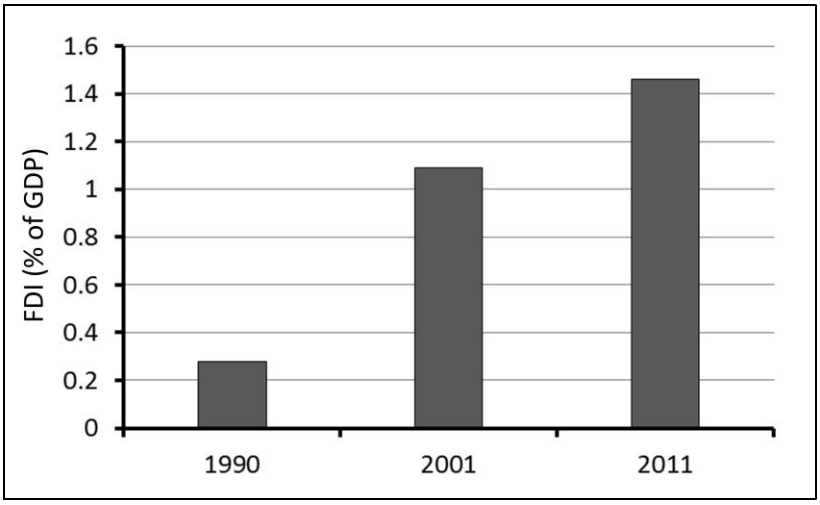

Figure 3-13: The FDI net inflow as a percentage of GDP of Sri Lanka (Data Source: World Bank open data, 2016).

Chapter Four

Spatiotemporal Pattern of Urban Growth

4.1. Introduction

The physical and functional transformation of rural landscapes into urban forms is recognized as urban growth. According to Clark (1982), urban growth is a spatial and demographic process characterized by a change in population distribution from a village to a town or city. A remarkable dynamic urban growth process can be identified globally. Understanding both the pattern of urban growth and the process undergone, helps to introduce sustainable urban landscape planning.

However, Batty and Longley (1994) identified two classes of urban growth: organic (or natural) and planned (or artificial). Clark and Gydos (1998) classified urban growth patterns into five types: spontaneous, organic, spread, road-influenced, and diffusive. Wu (2000) generally classified urban growth as spontaneous and self-organizing. Dietzel *et al.,* (2005) employed the diffusion and coalescence urban theory to identify urban growth patterns. Most of these classifications primarily focused on the spatial patterns (form, density, and distribution) of physical growth and spatial impacts (planned or self-organized) of human activities. The advantages of all these urban growth classifications is the close linkage with spatial pattern, which is one of the major concerns in GIS and remote sensing approaches.

In this chapter, the urban growth pattern is mainly characterized using landscape metrics and three indicators: infill, extension, and leapfrog (Dewan and Yamaguchi 2009; Schneider and Woodcock, 2008; Angel *et al.,* 2012; Dorning *et al.,* 2015; Schneider and Woodcock, 2008; Estoque and Murayama, 2015). The built-up area was considered the urban area, and the ULU changes and diffusion-coalescence urban growth theory was used to understand urban growth patterns (Dietzel *et al.*, 2005; Estoque and Murayama, 2016). Moreover, the underlying factors associated to the urban growth was characterized using the field-based questionnaire survey.

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4.2. Materials and methods

4.2.1. Landscape metrics

For the landscape fragmentation and connectivity analysis, three landscape-level metrics and five class-level metrics were used to analyze and describe the characterization of the geometric and spatial properties of the categorical map patterns. Landscape metrics can be a very valuable tool to better understand and more accurately characterize urban growth and their consequences (Herold, 2005; Plexida, 2014; Megahed, 2015; Estoque and Murayama, 2016). Moreover, Herold *et al.,* (2005) explained that the combined application of remote sensing and landscape metrics can provide more spatially consistent and detailed information on urban structure and change than either of these approaches used independently. The landscape-level metrics included the contagion index (CONTAG), the landscape shape index (LSI), and Shannon's diversity index (SHDI). The class-level metrics included the percentage of landscape (PLAND), path density (PD), mean patch size (Area_MN), area-weighted mean patch fractal dimension (Frac_AM), and mean Euclidean nearest neighbor distance (ENN_MN). All these metrics were calculated using the FRAGSTATS 4.1 software, employing the 8-cell neighbor rule (McGarigal, 2012). The description of each metric used in this study is given in Table 4-1.

Table 4-1: Description of landscape metrics used in this study.

Metrics	Description	Units and range	Explanation
Landscape-level			
CONTAG	The contagion index describes the degree of clumpiness or aggregation of patches with regard to configurational and compositional features of landscape pattern.	Percent 0<CONTAG ≤100	The degree of fragmentation and aggregation
LSI	The landscape shape index describes the degree of landscape disaggregation or dispersion.	None LSI ≥ 1, without limit	The overall complexity of the landscape
SHDI	Shannon's diversity index describes the diversity of the landscape based on two components: the number of different patch types and the proportional area distribution among patch types.	Information SHDI ≥ 0, without limit	The patch diversity
Class-level			
PLAND	The percentage of landscape quantifies the proportional abundance of each patch type in the landscape.	Percent 0 < PLAND ≤ 100	A measure of landscape composition (class)
PD	PD equals the number of patches of the corresponding patch type divided by total landscape area.	No. /100 ha. PD > 0	A measure of fragmentation

Area_MN	Area mean equals the sum of the corresponding patch metric values across all patches of the corresponding patch type, divided by the number of patches of the same type.	ha. Area_MN>0	The average mean surface of patches
Frac_AM	The area-weighted mean patch fractal dimension equals the average patch fractal dimension of patches in the landscape, weighted by patch area.	1≥ Frac_AM ≤ 2	The shape complexity (increases as patches become more irregular)
ENN_MN	The mean Euclidean nearest neighbor distance is defined using average Euclidean distance between the focal patch and its nearest neighbor of the same class.	Meter 0≤ ENN_MN	The average distance between two patches in a landscape

Source: McGarigal *et al.,* (2012); Estoque and Murayama, 2016.

Note: Area_MN = mean patch size; CONTAG = contagion index; ENN_MN = mean Euclidean nearest neighbor distance; Frac_AM = area-weighted mean patch fractal dimension; LSI = landscape shape index; PD = path density; PLAND = percentage of landscape; SHDI = Shannon's diversity index.

4.2.2. Characterizing urban growth using ULU mapping

The ULU transition from the initial time point and the final time point were used to detect these growth patterns—infill, extension, and leapfrog.

As the first step in detecting urban growth patterns, new ULU sub-categories were defined based on the relative location from the built area (the same methods used in Chapter Three). In general, the measure of geographical phenomena involves two perspectives of space: relative and absolute. The relative view of space focuses on objects as the subject matter, and space is measured as the relationships between objects. The absolute view of space focuses on object based on their latitudinal and longitudinal location. Here, the main argument is that the patterns of urban growth should be identified in a relative space; that is, if the new urban growth happens in a closed area of already urbanized area and far from the already urbanized area shows the different patterns.

This idea results in a new methodology to capture the urban growth pattern visually through infill, extension, and leapfrog, as illustrated in Figure 4-3.

Temporal mapping: The temporal mapping here includes the land-use maps used in ULU change analysis in Chapter Three. The ULU maps of three time points (1992, 2001, and 2014) include only three land-use categories: built, non-built, and water.

MSPA: Using the neighborhood interaction rules, new sublevels of ULU were defined as shown in Table 4-2. The image processing procedure is shown in Figure 4-3.

Table 4-2: Neighborhood interaction rules of ULU sub-categories.

ULU categories	Description of neighborhood interaction rule
Urban dense	50–100% built-up pixels in a 1-km^2 area of neighborhood: buffer with 564 meters map unit (18 pixels) distance from built pixel was employed to determine a 1-km^2 area.
Urban sparse	0–50% built-up pixels in a 1-km^2 area of neighborhood: buffer with 564 meters map unit (18 pixels) distance from built pixel was employed to determine a 1-km^2 area.
Urban open space	Non-built land within a 100 m distance from urban area: buffer with 100 meters map units (3 pixels) distance from urban built was employed to determine a 1-km^2 area.
Captured urban open space	Patches of non-built, less than 2 km^2, completely surrounded by urbanized area (included urban dense, urban sparse, and urban open space).
Urban fringe	100 m (3 pixels) distance edge in between urbanized (urban dense, urban sparse, and urban open space) and non-urban area (non-urban built and non-urban open space).
Non-urban	All other land-use except water.
Water	Water bodies which classified in the initial classification.

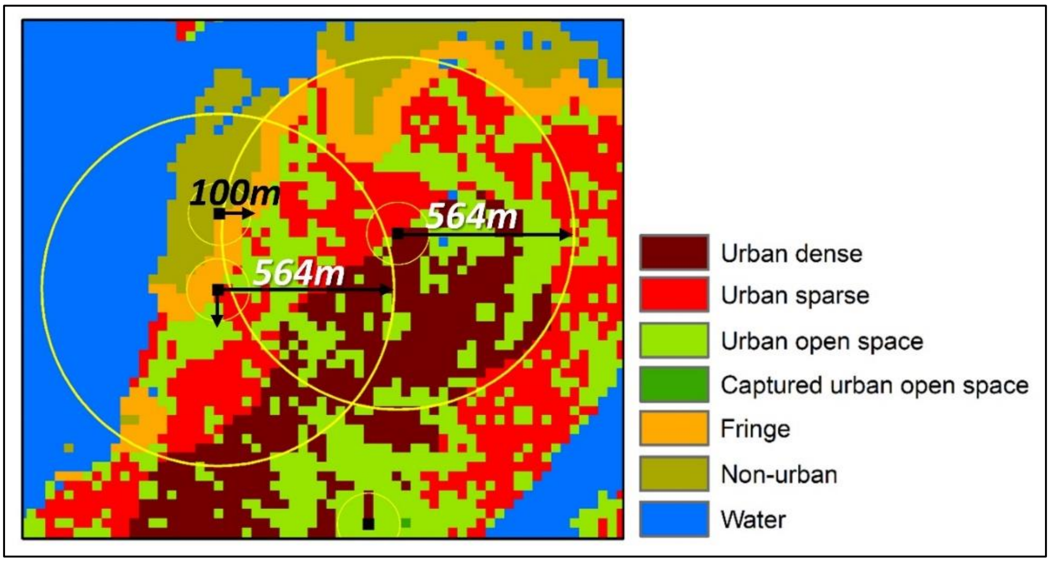

Figure 4-1: MSPA for ULU sub-category classification.

Urban growth patterns: To spatially distinguish three urban growth patterns—infill, extension, and leapfrog—ULU changes (based on newly defined sub-categories) were analyzed. Briefly, each urban growth pattern contained the following characteristics: (1) infill, characterized by new urban growth that occurs in an already urbanized area (Figure 4-2(a)); (2) extension, characterized by new urban growth, which occurs in the urban fringe area and connects it to new growth, (Figure 4-2(b)); (3) leapfrog, characterized by new growth that occurs in a non-urban area (Figure 4-2(c)) (Angel *et al.*, 2012). The ULU sub-category changes in relation to the growth patterns are summarized in Table 4-3.

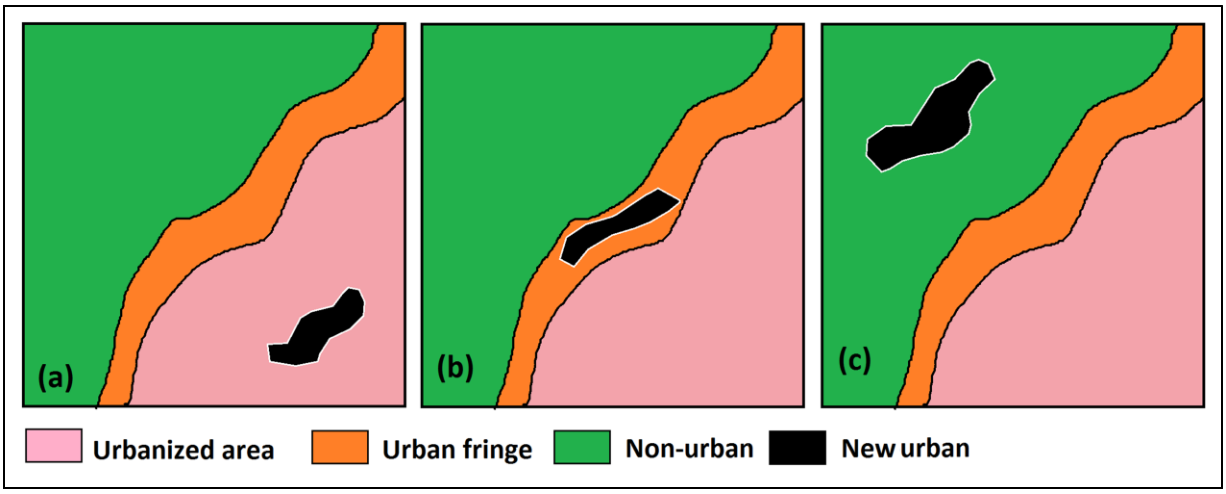

Figure 4-2: Locational characteristics of each growth pattern: (a) infill; (b) extension; and (c) leapfrog (The urbanized area contains urban dense, urban sparse, urban open space, and urban open space).

Table 4-3: ULU change to develop urban growth patterns.

Urban growth pattern	Change from	Change to
Infill	Urban open space	Urban dense
	Urban open space	Urban sparse
	Captured urban open space	Urban dense
	Captured urban open space	Urban sparse
Leapfrog	Non-urban	Urban dense
	Non-urban	Urban sparse
Extension	Any above transition occurs in the urban fringe area and connects the new growth to the extension	

Urban growth intensity analysis: To quantify the urban growth, Equation 4-1 was used. The annual urban growth intensity (AUGI) was separately calculated for each indicator, and this can be used to compare the urban growth patterns. This equation was derived from the annual land-change intensity analysis formula, which was introduced by Aldwaik and Pontius (2012).

$$AUGI = \left[\frac{\left(\frac{GG_i}{TL_c} \right)}{TE} \right] \times 100 \qquad (4\text{-}1)$$

where $AUGI$ is the annual urban growth intensity rate, GG_i is gross growth by indicator, TL_c is the total landscape, and TE is duration of given time interval.

4.2.3. Field-based questionnaire survey

A survey questionnaire (Appendix III) was conducted during the fieldwork session (February–March 2016) to understand the factors that possibly encourage urban growth in the CMA. The clustered random sampling method was employed to collect data using a survey questionnaire. The clusters were demarcated to represent the core area, fringe area and the outside area of the CMA (Figure 4-3). 150 questioners were employed for each thematic zones and all the respondents were older than 20 years of age.

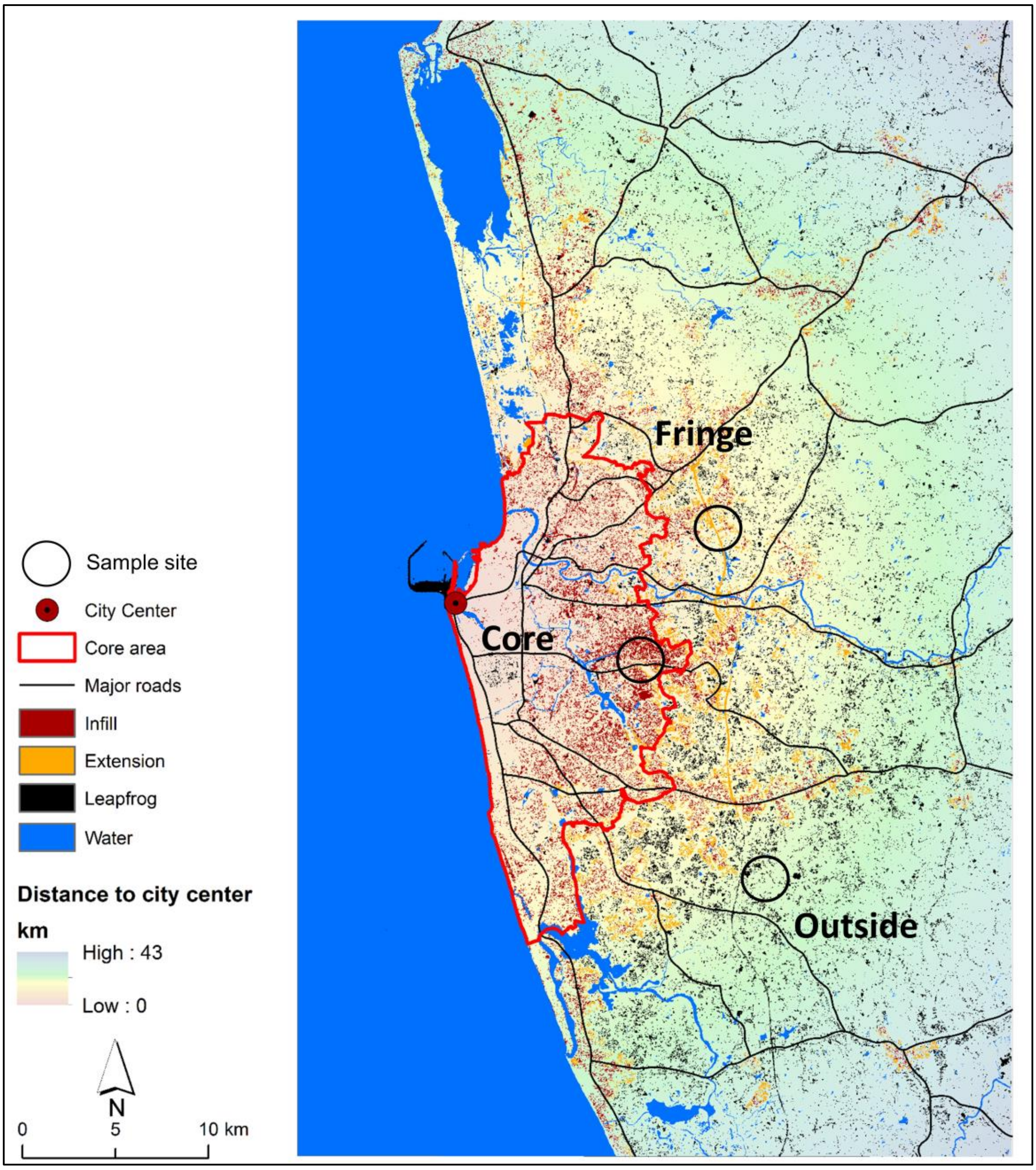

Figure 4-3: The location of sample sites of questionnaire survey by thematic zones.

4.3. Results and discussion

4.3.1. Landscape fragmentation and connectivity

The results obtained from the landscape fragmentation and connectivity analysis are shown in Figure 4-4, which show that, from 1992 to 2014, the value of CONTAG decreased, while the value of LSI and SHDI increased. This indicates that the landscape of the CMA has become more fragmented and dispersed, and its patch richness has increased.

The landscape connectivity and fragmentation analysis also revealed that the CMA's urban areas have become more fragmented. At the class level (urban), the results show that the values of PLAND, PD, AREA_MN, and Frac_AM increased from 1992 to 2014; whereas the value of ENN_MN decreased. The increase in the values of PLAND and PD indicates that CMA's urban lands have become more fragmented. The size and shape of CMA's patches of urban lands also have become larger and more complex, as indicated by the increase in the values of AREA_MN and Frac_MN, respectively. The decrease in the value of ENN_MN was due to the increase in the size of urban patches (i.e. AREA_MN) and the development of urban patches near or between existing urban patches (i.e. PD).

However, the analysis also revealed that existing urban patches have become larger and the distance between them has become closer. The increase in the size of urban patches was due to the process of extension or expansion, while the decrease in the mean distances between them was due to the combined effect of diffusion, expansion, and the development of new patches near or between patches, which is also a type of infill urban development. In general, these results show evidence for the diffusion–coalescence urban growth theory. Diffusion is a process in which new urban areas are dispersed from the origin point or "seed" location, while coalescence is the union of individual urban patches, or the growing together of the individual urban patches into one form or group. Based on the results, one can say that the CMA is still in the early stage of this oscillating process (i.e. more on diffusion, while still less on coalescence). As a metropolitan region, the CMA is still young with its urban development recovery having just started after the end of the civil war in 2009.

The landscape fragmentation and dispersed growth of the CMA may be caused by several factors. On the one hand, there are no major physical constraints, such as high elevation and steep slopes, in the land side of the CMA, which encourages landscape fragmentation and dispersed growth. On the other hand, a significant extension of road networks has been observed in the CMA during past two decades. This road development reduced the travel time from the suburbs to central areas or the business district (CBD) and has created land fragmentation. Consequently, people moved into the suburbs, influencing landscape fragmentation and dispersed urban growth. More specifically, the non-built-up lands in close proximity to the roads were gradually converted into built-up lands. The government industrialization strategy promoting the export processing zones (EPZs) in the CMA generally enhanced population pressure and, in particular, influenced landscape fragmentation in the area. The influence of EPZs, represented by the growth nodes, on the urban growth of the CMA can be understood through the gradient analysis results (in Chapter five). Moreover, the increase in the residential and commercial utility value of lands in the CMA leads to the proliferation of real estate agents participating in the land market and to the increased fragmentation of non-built-up lands, including agricultural and uncultivated lands in the past two decades (Groves, 1996).

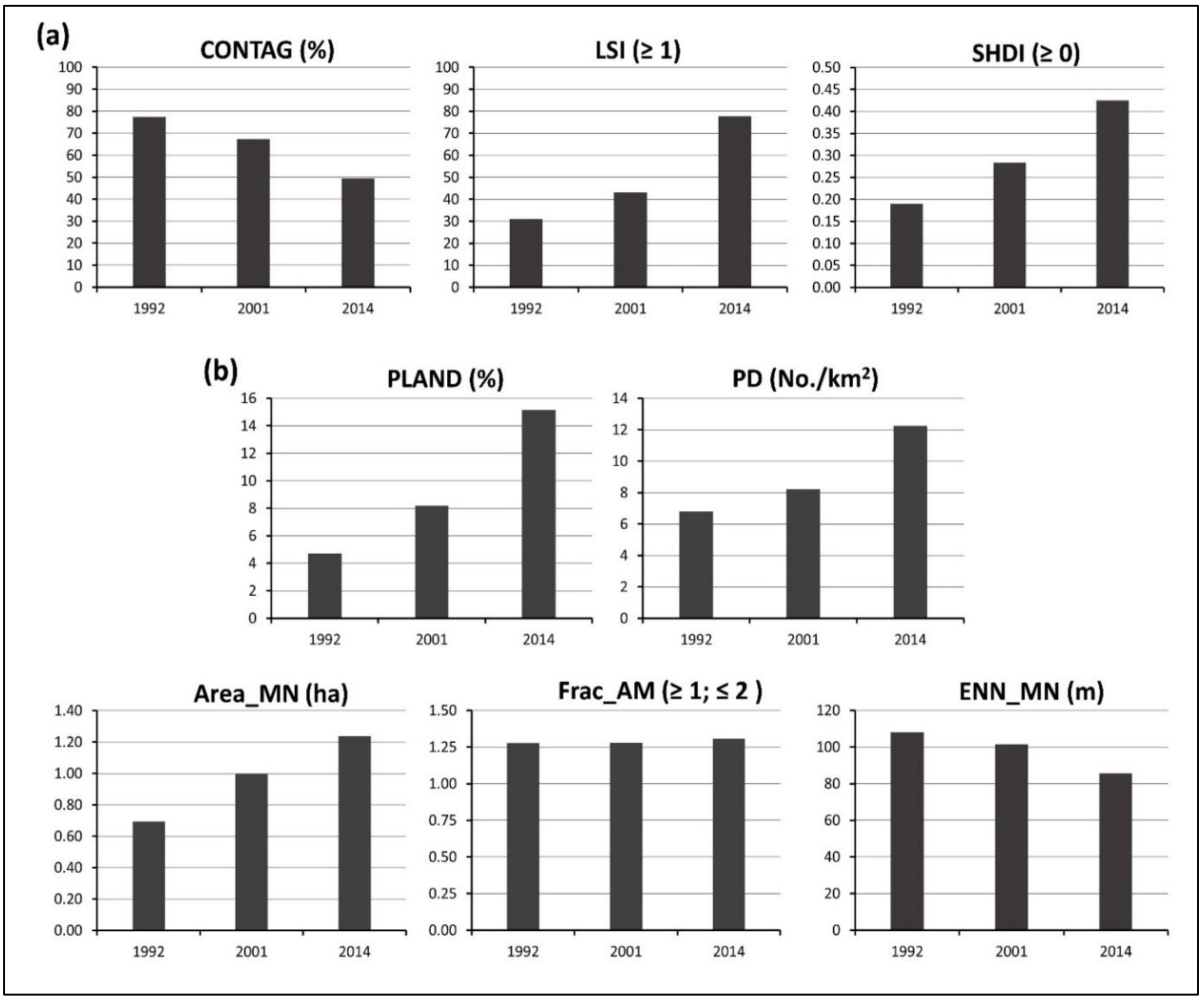

Figure 4-4: Landscape matrices: (a) the landscape level; and (b) the class level.

4.3.2. Mapping the spatial pattern of urban growth

Figure 4-5 presents the newly developed ULU classification with sublevels. It further proved rapid urban growth of the CMA. The ULU mainly captures the northeast direction and along the coastal area and the road networks.

According to the statistics obtained from Figure 4-6, which shows the three types of urban growth patterns (infill, extension, and leapfrog) in the CMA, the leapfrog growth shows a dominant growth pattern in both time intervals (1992–2001 and 2001–2014) (Table 4-4). Leapfrog growth accounts for 3,621ha (1.53%) in the 1990s and 7,670 ha (3.24%) in the 2000s. The infill growth accounts for 3,399 ha (1.43%) in the 1990s and 5,896 (2.49%) in the 2000s, and the extension accounts for 1,283 ha (0.54%) in the 1990s and 3,067 (1.29%) in the 2000s.

However, it should be noted that the time extent covered by the 2000s (13 years) is longer than that covered by the 1990s (9 years). Therefore it is important to consider the AUGI analysis (Figure 4-7). The AUGI analysis revealed that during the first time interval, growth was 0.16% in infill, 0.06 in extension, and 0.17% in leapfrog; and during the second time interval AUGI growth was 0.19% in infill, 0.10 in extension, and 0.25 in leapfrog.

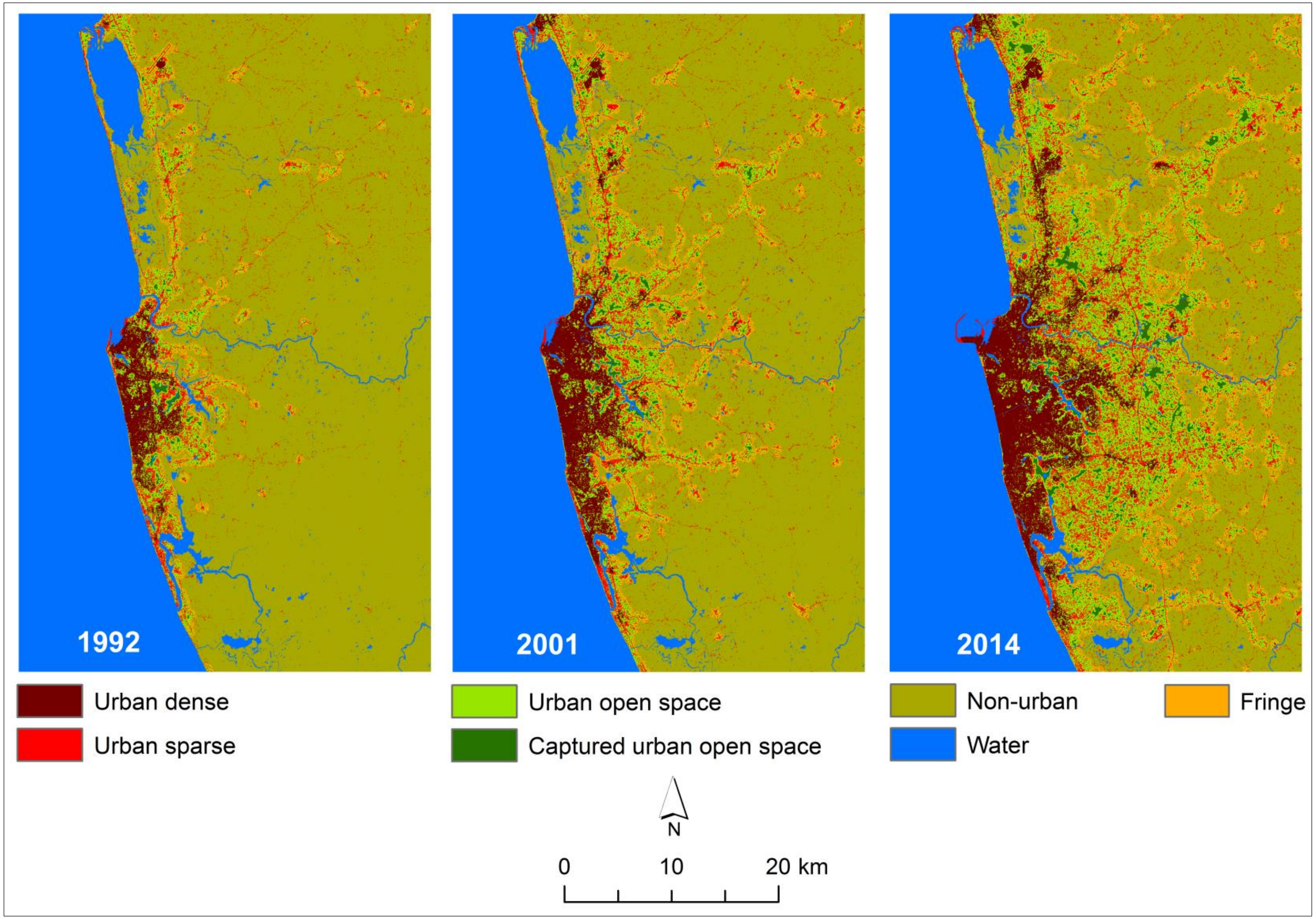

Figure 4-5: Sub-categories of ULU.

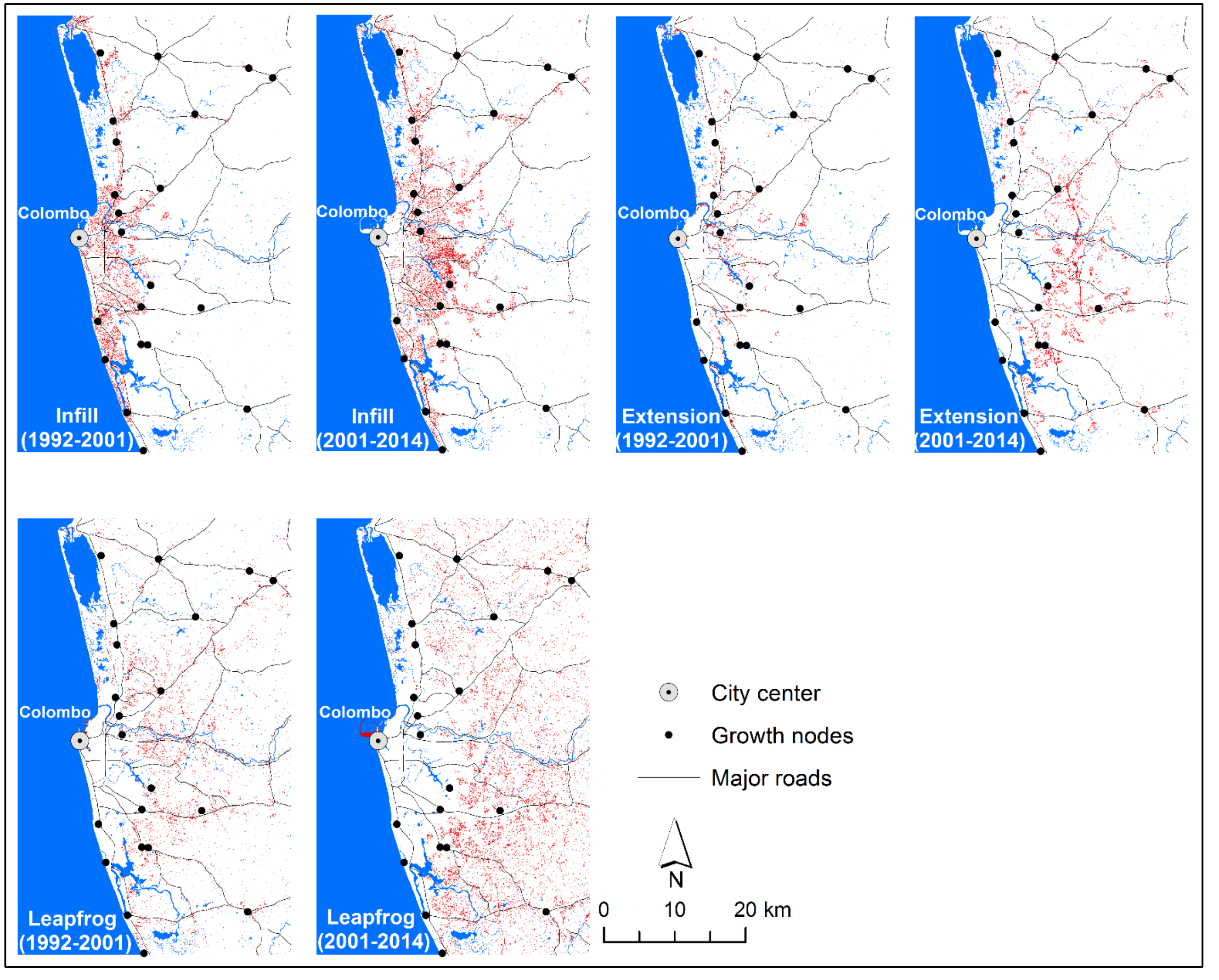

Figure 4-6: Urban growth patterns in CMA. Note: Growth nodes and major roads were extracted from the 2000 topographical data (Source: SDSL, 2000).

Table 4-4: Statistics of urban growth by three indicators.

Growth Pattern	1992–2001		2001–2014	
	Area (ha)	% of landscape	Area (ha)	% of landscape
Persistent	228,596	96.50	220,265	92.98
Infill	3,399	1.43	5,896	2.49
Extension	1,283	0.54	3,067	1.29
Leapfrog	3,621	1.53	7,670	3.24
Total	236,898	100	236,898	100

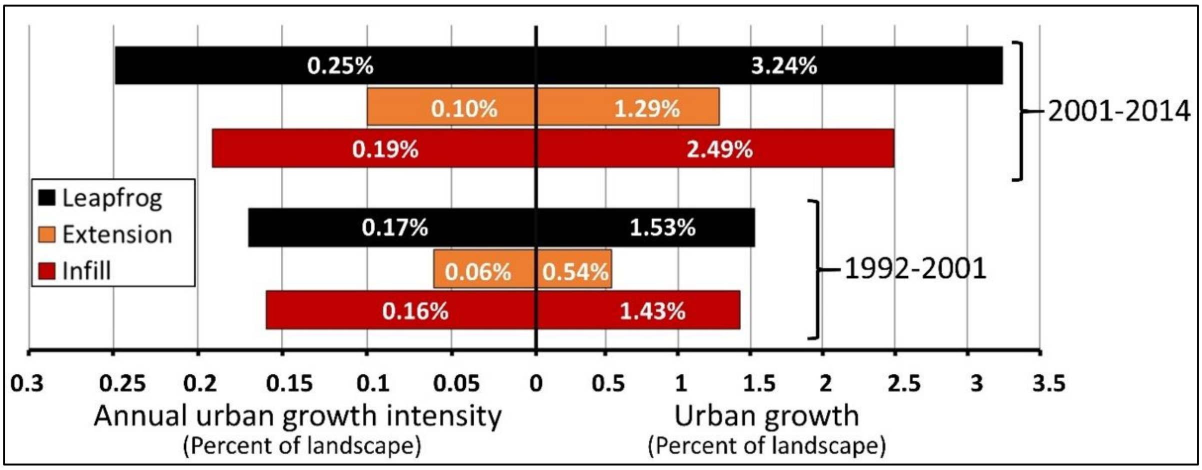

Figure 4-7: AUGI in CMA.

According to the results, all the patterns of urban growth intensively occurred in the second time interval compared to the first time interval. The infill growth has occurred mainly in the surrounding area of the CBD where the city center and Colombo harbor are located. Later, the infill growth moved toward the main suburban centers of the CMA, such as Sri Jayawardhanapura, Maharagama, Kolonnawa, and Kelaniya. This pattern explains that the central area of the CMA has been saturated by the urban land and there is no more space for horizontal urban expansion. Basically, filling the CBD with complex urban structures created the center as an inefficient place with high traffic congestion and pollution, limited open space, and crowded services. However, the efficiently managed infill growth has helped to reduce the environmental deterioration, and strengthen the economical use of existing urban land, because this growth occurred in the area where the urban growth altered the land use (McConnell, 2011; Estoque and Murayama, 2015). Due to less space in the CBD with infill growth, the occurrence of the ribbon-type growth, which now radiates out from the CBD area of the CMA along the major transport corridors (i.e. Colombo-Kandy and Colombo-Galle) and along the western coastal belt, is a very common pattern. This concentration of the urban footprint in a limited area with the transport corridors and coastal belt preserves most of its natural and rural environments and offers ample greenery—even in its denser urban areas, such as central Colombo (UN-Habitat, 2012). However, this growth pattern has created some problems in urban planning due to the spread of the urban footprint across several administrative boundaries (UN-Habitat, 2012). Some highly urbanized areas are located in the administratively defined rural area, and the UDA of Sri Lanka does not have institutional power to introduce urban planning initiatives for these areas. Further, the ribbon-typed growth led to missed economic opportunities. The compact growth of cities, supported by high-density urban transport, increases the opportunities for agglomeration economies to urban form.

As a result of the rapid expansion of the ribbon-type growth, urban extension has taken place also along the transport corridors. This is a widespread form of urban expansion in many cities, including Beijing, Tokyo, Shanghai, and Shenzhen (Wu, *et al*., 2015). This pattern has led to the conversion of CMA from a monocentric urban area to a polycentric urban area with new suburban centers. As the newly emerged sub-cores in the CMA, Negambo, Ja-Ela, Wattala and Kaleniya (in the north), Kesbewa, Biyagama, Mahara, and Sri Jaywardanapura (in the east and southeast), and Maharagama, Dehiwala-Mount Lavenia, Kesbewa, Moratuwa and Panadura (in the south and southeast) can be highlighted. The emergence of the polycentric urban region is a common phenomenon with rapid urban growth (Berry and Kim, 1993). Typically, the transformation of a monocentric urban area into a polycentric urban area requires multiple links between sub-centers. However, a lack of transport between these multiple centers of CMA has created huge traffic congestion in the CMA and has brought with it a huge economic loss (JICA, 2014).

4.3.3. The underlying factors related to the urban growth

The urban growth in developing countries is greatly influenced by population growth due to the in-migration (Taubenböck *et al.*, 2012). The questionnaire results indicate that the migrants' history, the purpose of migration, and the land alteration by the migrant are considerably different by the thematic zones. Moreover, by summering people's perception, author's local knowledge about the study area, and previous literature, the factors, related to the urban growth could be ranked by the thematic areas (Table 4-5).

According to the questionnaire survey results, the migration into the core area has recently declined. Most of the migrants (56%) migrated into this area more than 10 years ago, 23% within 5–10 years, and 21% less than 5 years ago (Figure 4-8 (a)). This implies that the core area where the infill growth highly visible is greatly dominated by non-residential activities. According to the responses, 48% of the migrants selected this area due to industrial and commerce-related reasons, 30% due to service-related reasons, and 22% due to land-ownership-related reasons (Figure 4-8(b)). In the land-use change aspects, 53% of respondents altered the existing built land, 34% the bare land, 8% the agricultural land, and 5% the forest land (Figure 4-8(c)).

The fringe area where urban extension growth occurred show a higher level of recent migration attraction. Most of the migrants (42%) migrated into this area within the last 5–10 years, 30% less than 5 years ago, and 28% more than 10 years ago (Figure 4-9(a)). According to responses, 62% selected these areas due to service-related reasons, 25% due to land-ownership-related reasons, and 13% due to industrial- and commerce-related reasons (Figure 4-9(b)). In land-use change aspects, 42% of respondents have altered the existing built land, 33% the agriculture land, 23% the bare land, and 2% the forest land (Figure 4-9(c)).

A higher percentage of the most recent migrants of less than 5 years (53%) could be identified in the outside areas where the leapfrog urban growth is dominant. Other immigrants migrated within the past 5–10 years (29%) and more than 10 years ago (18%) (Figure 4-10(a)). According to responses, 42% migrated due to land-ownership-related reasons, 31% due to service-related reasons, and 27% due to industrial- and commerce-related reasons (Figure 4-10(b)). In land-use change aspects, 39% of respondents altered the existing built land, 34% the bare land, 15% the agricultural land, and 12% the forest land (Figure 4-10(c)).

Table 4-5: Ranking the factors that drive the current urban growth by thematic zones.

Urban growth pattern	The factors related to urban growth (ranking)
Core	01. natural population growth
	02. population growth by migration
	03. socioeconomic opportunity
	04. accessibility to administrative service
	05. urban planning initiatives
	06. accessibility to education service
Fringe	01. population growth by migration
	02. natural population growth
	03. accessibility to administrative services
	04. socioeconomic opportunities
	05. accessibility to education services
	06. urban planning initiatives
Outside	01. population growth by migration
	02. natural population growth
	03. accessibility to administrative services
	04. socioeconomic opportunities
	05. accessibility to education services
	06. urban planning initiatives

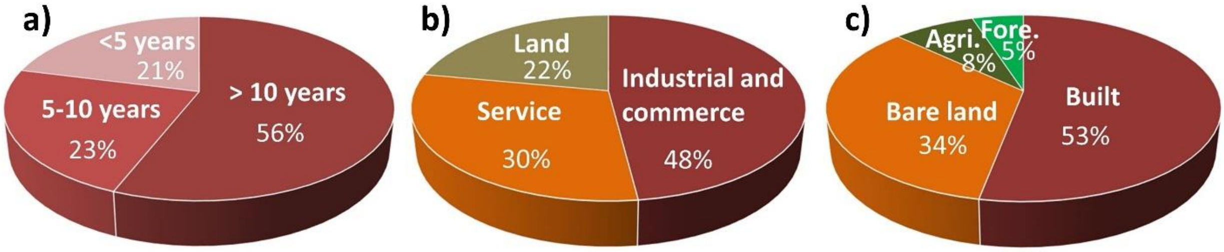

Figure 4-8: Core: (a) Migrants' history; (b) the reasons for migrating; and (c) the land before alteration.

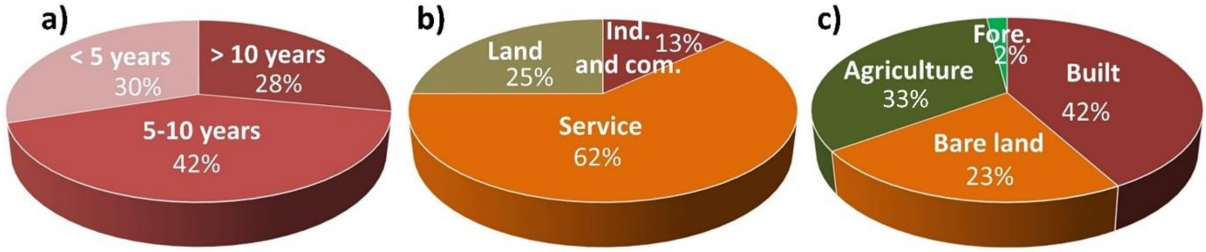

Figure 4-9: Fringe: (a) Migrants' history; (b) the reasons for migrating; and (c) the land before alteration.

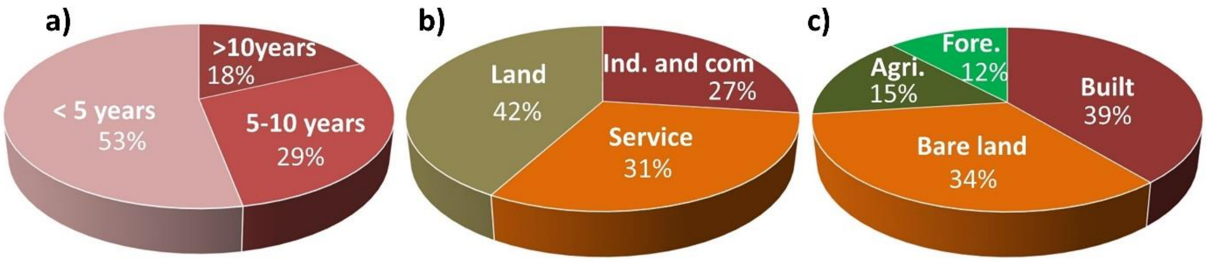

Figure 4-10: Outside: (a) Migrants' history; (b) the reasons for migrating; and (c) the land before alteration.

Chapter Five

Implications for Future Urban Development Planning

5.1. Introduction

Characterizing future urban growth is one of the major components of explaining the urban process and it helps to develop sustainable urban planning and landscape initiatives. The land-change modeling approach is frequently used to predict future urban growth in a spatiotemporal manner. However, many challenges must be faced when attempting to develop models of urban growth process (Mas *et al.*, 2004). These challenges are mainly associated with the higher degree of complication, the large number of conditions, and the complexity of interaction between human and environmental factors in the urban environment.

During the past decades, several land-change models have been developed and successfully implemented, including artificial neural network (ANN) (Thapa and Murayama 2012; Rahimi 2016), weight of evidence (Soares-Filho *et al.*, 2004), Markov chain (Sha and Helbich, 2013), and GEOMOD (Pontius *et al.*, 2001; Estoque and Murayama, 2012), to capture the land change in general and urban growth in particular. Most of these models simulate the land change on both its previous and neighboring land change, and on biophysical and socioeconomic driving forces that affect the land change in a particular region.

This chapter presents the modeling results of future urban growth of the CMA using MLP neural network and the implications of future urban development in the CMA. The selection of this study was based on similar previous successful research (explained in section 1.4).

5.2. Materials and methods

5.2.1. Data preparations

The ULU maps of three time points, namely 1992, 2001, and 2014, used in previous chapters, were employed with five spatial explanatory variables or driving variables. These explanatory variables were identified based on people's perception (identified through the questionnaire survey), author's knowledge about the study area and pervious literature. These five variables were distance to administrative centers, distance to growth nodes, distance to education centers, and distance to major roads and the distance to existing urban areas (built land).

The administrative center locations and growth nodes were produced using the paper maps collected from UDA. Initially, these paper maps were scanned and geo-referenced, and later they were digitized (on-screen). The road maps and education center location maps were collected in vector file format from the SDSL. The built land was extracted from the ULU map, which was produced using the ULU classification.

As a part of the data preparation, the raster files for each explanatory variable containing the Euclidean distance were prepared using ArcGIS™ software with a 30 m × 30 m cell size. These explanatory variables and the ULU maps were used to predict future urban growth with the aid of the multi-layer perceptron neural network (MLP NN) and CA-Markov chain modules using LCM available in TerrSet™. The ULU of 2014, and 2030 were predicted. The 2014 predicted ULU map was used only for validation. The simplified procedure that was followed in urban growth modeling is shown in Figure 5-1.

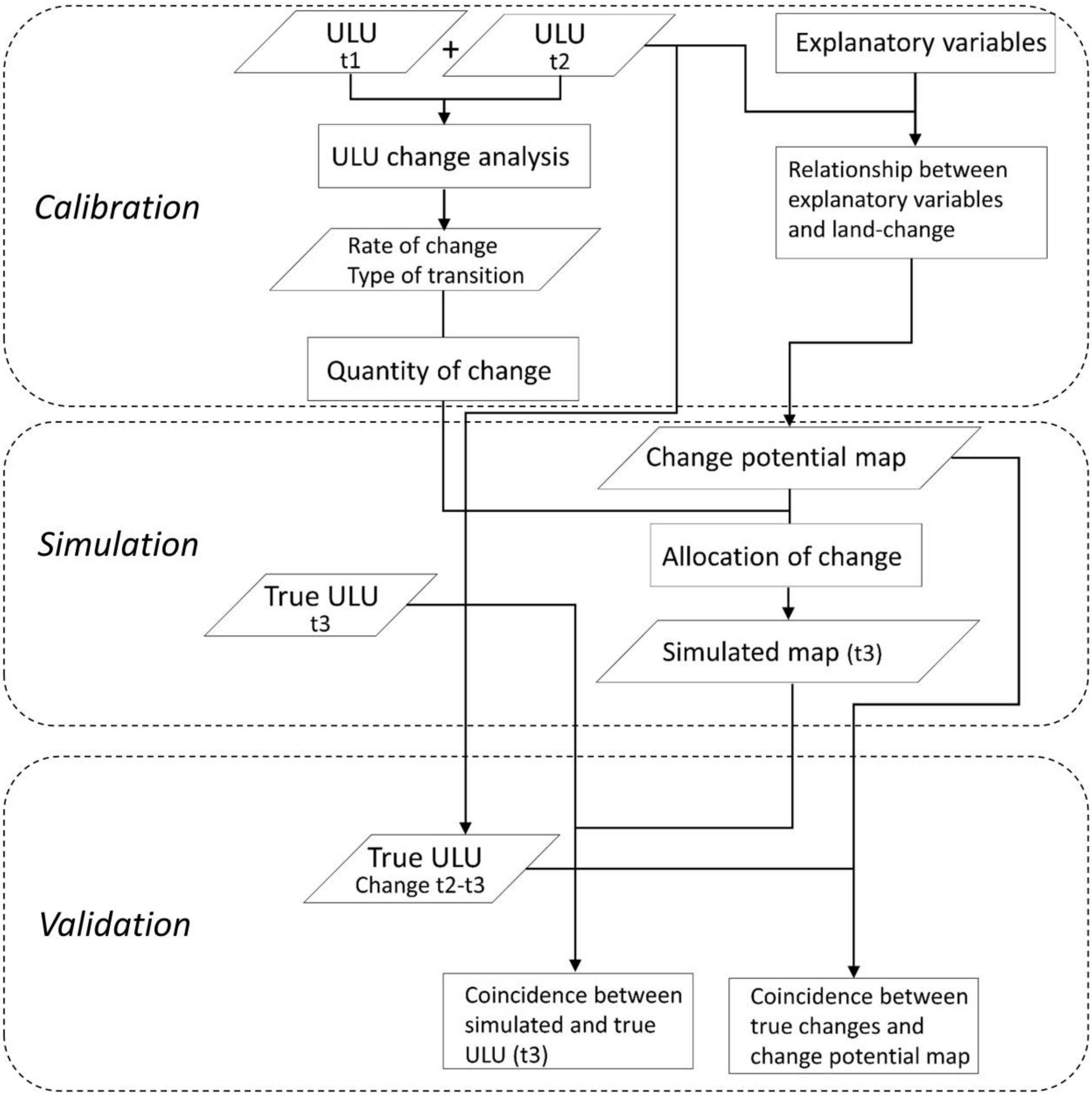

Figure 5-1: Simplified procedure of urban growth modeling.

5.2.2. The multi-layer perceptron neural network (MLP NN)

ANN is a non-parametric technique, which was developed based on the biological neural network concept that can be used to quantify and model complex behavioral patterns. ANN has the following major advantages over other statistical methods (Maithani 2009):

(1) It makes no assumption regarding the data.

(2) Measurement data of different types can be used.

(3) They can solve highly non-linear problems.

Urban growth is a complex phenomenon that dominates a number of non-linearly interacting variables. Thus, ANN can be logically used to model urban growth. A neural network consists of an interconnected group of artificial neurons entrusted with the storage of knowledge acquired with the system, which then are rendered available for further use (Basse *et al.*, 2014). The arrangement of neurons in layers, and the pattern of connection within and in between layers is called "ANN architecture" (Basse *et al.*, 2014; J. F. Mas *et al.*, 2004).

MLP NN is a well-developed ANN, which uses back propagation as a training algorithm (Taravat *et al.*, 2015). It is often capable of modeling complex relationships between variables with remote sensing data. The architecture of MLP NN consists of three types of layers: input, hidden, and output (Megahed *et al.*, 2015). MLP NN allows the prediction of an output object for a given input object or a set of input objects. It has been used in many different applications, including land-use/land cover classification; land-use transition potential modeling; deforestation modeling; and urbanization modeling (Friehat *et al.*, 2015; Mas *et al.*, 2014; Taravat *et al.*, 2015).

In MLP NN, when the network is implemented, the input variable values are placed in the input units, and then the hidden and output layer units are progressively executed (Mas *et al.*, 2004). Each of them calculates its activation value by taking the weighted sum of the outputs of the units in the preceding layer (Mas *et al.*, 2004). The activation value is passed through the activation function to produce the output of the neurons (Mas *et al.,* 2004). When the entire network has been executed, the output of the output layer act as the output of the entire network. The learning procedure of MLP NN is based on a relatively simple concept (Mas *et al.*, 2004): if the network gives the wrong answer, the weights are then corrected so the error is lessened, which means that future responses of the network are more likely to be correct.

5.2.3. Gradient analysis

'Gradient' can be defined as the variation in the values of a given variable; e.g., distance to the growth nodes, across its range of values (Estoque and Murayama, 2016). Although five driving variables are employed in land-change modelling (Table 5-1), the gradient analysis was conducted to four major diving variables of urban growth only. These are: the distance to major roads, distance to schools, distance to growth nodes, and distance to the administrative centers. The distance to built-up area is extracted from the created maps which was used to analysis the urban growth patterns. Basically, each driving variables represent a certain socioeconomic factors that drive the urban growth in the CMA.

In gradient analysis, first, multiple ring buffers around each driver variable were created with a zone size of 300 m. Then, we examined the extent of ULU changes along the gradient of each variable across the two time intervals (1992–2001 and 2001–2014). The analysis basically gives how the urban growth taking place along the gradient distance to each driving factors and their relative influences.

Table 5-1: Driving variables used for land-change modeling and their descriptions.

Representative Factors	**Descriptions**
Distance to major roads	Represents access to transport facilities. The road map (1995) includes only A and B types (major roads).
Distance to schools	Represents access to educational services. The map shows the spatial distribution of primary and secondary schools as of 2000.
Distance to growth nodes	Represents access to urban facilities and locations of export processing zones (EPZ). Includes emerging urban centers identified in 1996 by Sri Lanka's urban development authority (UDA).
Distance to administrative centers	Represents access to administrative services. Includes local and national government administrative-service offices (1999).
Distance to build-up area	Represent the already urbanized area. The data was extracted from the created ULU maps.

5.2.4. MLP NN with the land-change modeler

LCM embedded in TerrSet™ was employed to develop the urban growth model in this study (Figure 5-2). LCM facilitates the evaluation land-cover changes between two different time points, calculates the changes, and displays the results with various graphs and maps. Several studies have proved that MLP NN-Markov in LCM is one of the most accurate modeling approaches, which can be used to predict future land change (Megahed *et al.*, 2015; Mas *et al.*, 2014).

First, two transition potential maps were created: (1) by integrating the five explanatory variables and the ULU maps of 1992 and 2001; and (2) by integrating the five explanatory variables and the ULU maps of 2001 and 2014. The first potential map was used to predict 2014 urban growth, which was used to validate the model. The second potential map was used to predict 2030 urban growth. The five explanatory variables used in modelling is shown in Figure 5-3.

In LCM, the MLP NN first created a random sample of cells from the land transition from non-built to built-up, and automatically started the training process. MLP NN developed a multivariate function that predicts the potential for transition based on the values at any location for the five explanatory variables.

Second, a CA-Markov chain was used to predict the quantity of change expected, and to allocate the possible changes from the non-built to the built categories using the probability map created. The quantity of change from 1992 to 2001 was used to predict the quantity of change in 2014, and the quantity of change from 2001 to 2014 was used to predict the quantity of change of 2030. These quantities of change were distributed based on the probability maps developed through MLP NN.

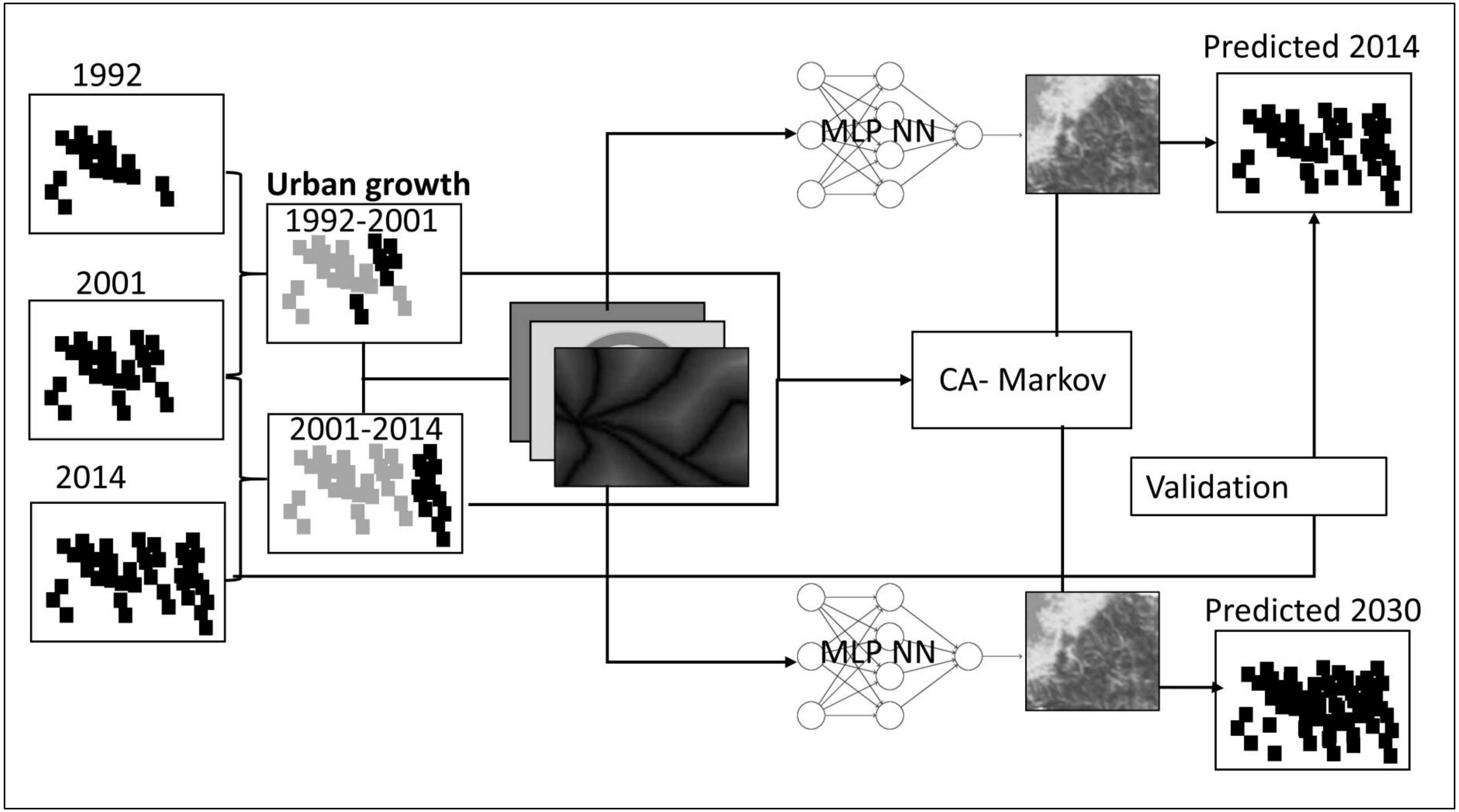

Figure 5-2: The process of land change modeling in LCM.

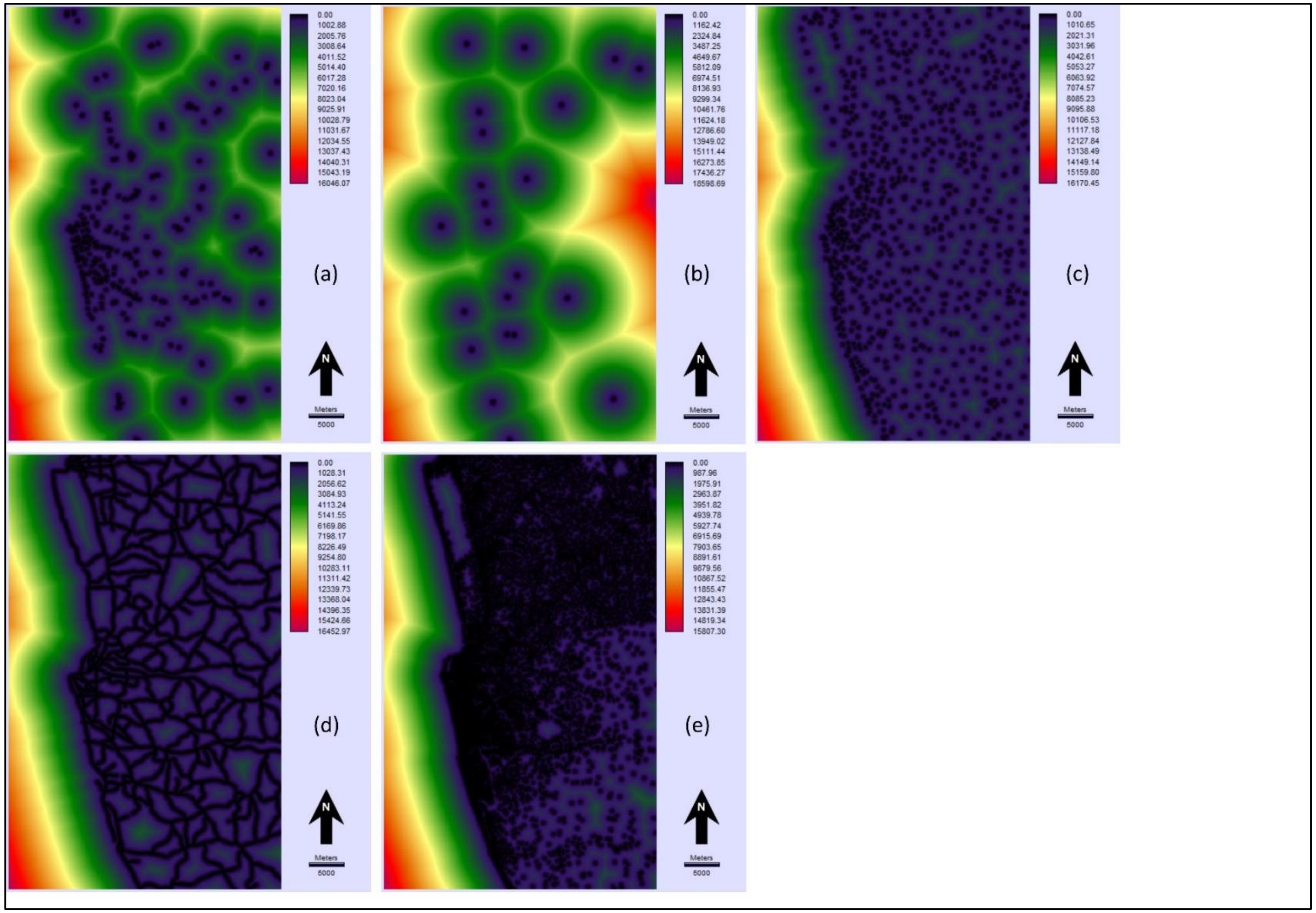

Figure 5-3: Selected explanatory variables used with MLP NN land-change modeling: (a) administrative center; (b) growth nodes; (c) education centers; (d) major roads; and (d) urban area (built).

5.2.5. Model validation

In general, the comparison between the predicted map and the empirical map is usually carried out to validate the land-change model. There is an argument that model validation should be used in different time periods from those used in model calibration. Thus, this study used the maps of 1992 and 2001 to predict 2014 and validate the 2014 actual map. However, there is no universally accepted procedure; nor is there an accepted set of guidelines for validating land-change models. Several map comparison tools have been used for validation; namely, the Kappa statistics and its variants (i.e. fuzzy Kappa). In this study, FoM and ROC were used to validate the model.

The quantitative error was analyzed to calculate the FoM. It enabled the assessment of the cell-to-cell coincidence between simulated and actual maps in a more realistic way than a more common metric, such as the Kappa index, which is usually calculated using the entire area with fixed land use. In FoM, four components of correctness and errors were considered; namely, null success, hits, misses, and false alarms. Equation 6-1 was used to calculate FoM

$$FoM = \left[\frac{H}{H + M + F}\right] \times 100\% \qquad (6\text{-}1)$$

where H = hits: the area of observed change correctly predicted as change; M = misses: the area of observed change incorrectly predicted as persistence; F = false alarms: the area of observed persistence incorrectly predicted as change; and 100% = a perfect predicted of change.

The ROC is widely used for assessing the performance of the classification algorithm. It allows one to assess the performance of binary classification methods with rank order or continuous output values. The area under the time curve (AUC) statistic of the ROC module was used to validate the model, which compared the transition potential map with the Boolean map of the observed ULU from 2001 to 2014. The AUC is a summary statistic with values ranging from 0 to 1, where a value of 0.5 represents no skill, a value of 1 indicates perfect skill, and values between 0 and 0.5 represent the wrong calibration of the model. In this study, ROC evaluated the skill of the land-change model (Eastman, 2005; Estoque and Murayama, 2016)

5.3. Results and discussion

5.3.1. Influence of driving variables on urban growth

Figure 5-4 shows the spatial distribution of ULU changes along the gradients of the driver variables: (a) distance to major roads, (b) distance to schools, (c) distance to growth nodes, and (d) distance to administrative centers.

The results show that at < 1.5-km distance along the gradients of all the driver variables, distance to major roads (1990s: 3.45%; 2000s: 6.89%) and distance to schools (1990s: 3.44%; 2000s: 6.89%) had much higher gains of built for both time intervals (the 1990s and 2000s). Distance to administrative centers (1990s: 2.71%; 2000s: 3.71%) and distance to growth nodes (1990s: 0.94%; 2000s: 0.95%) had much lower gains of built for both time intervals (Figure 4). However, at a 1.5–3.0 km distance, the results show that distance to growth nodes (1990s: 1.14%; 2000s: 1.49%) and administrative centers (1990s: 0.52%; 2000s: 0.52%) had much higher gains of built during the 1990s and 2000s than distance to schools (1990s: 0.01%; 2000s: 0.07%) and major roads (1990s: 0.00%; 2000s: 0.08%; Figure 5-4).

At distances > 3.0 km, the results show that distance to growth nodes (1990s: 1.36%; 2000s: 3.80%) and administrative centers (1990s: 0.22%; 2000s: 0.93%) also had much higher gains of built during the 1990s and 2000s than distance to schools (1990s: 0.00%; 2000s: 0.01%) and major roads (1990s: 0.00%; 2000s: 0.00%; Figure 4).

Overall, these results show that at closer distances (< 1.5 km), the distance to major roads and schools were relatively more influential with regard to ULU changes across the two time intervals. At further distances (≥1.5 km), however, the distances to growth nodes and administrative centers were relatively more influential. This pattern could be due to the limited availability of space for urban development near the growth nodes and administrative centers, as most of the area was built during the early 1990s, unlike the areas in close proximity to major roads and schools.

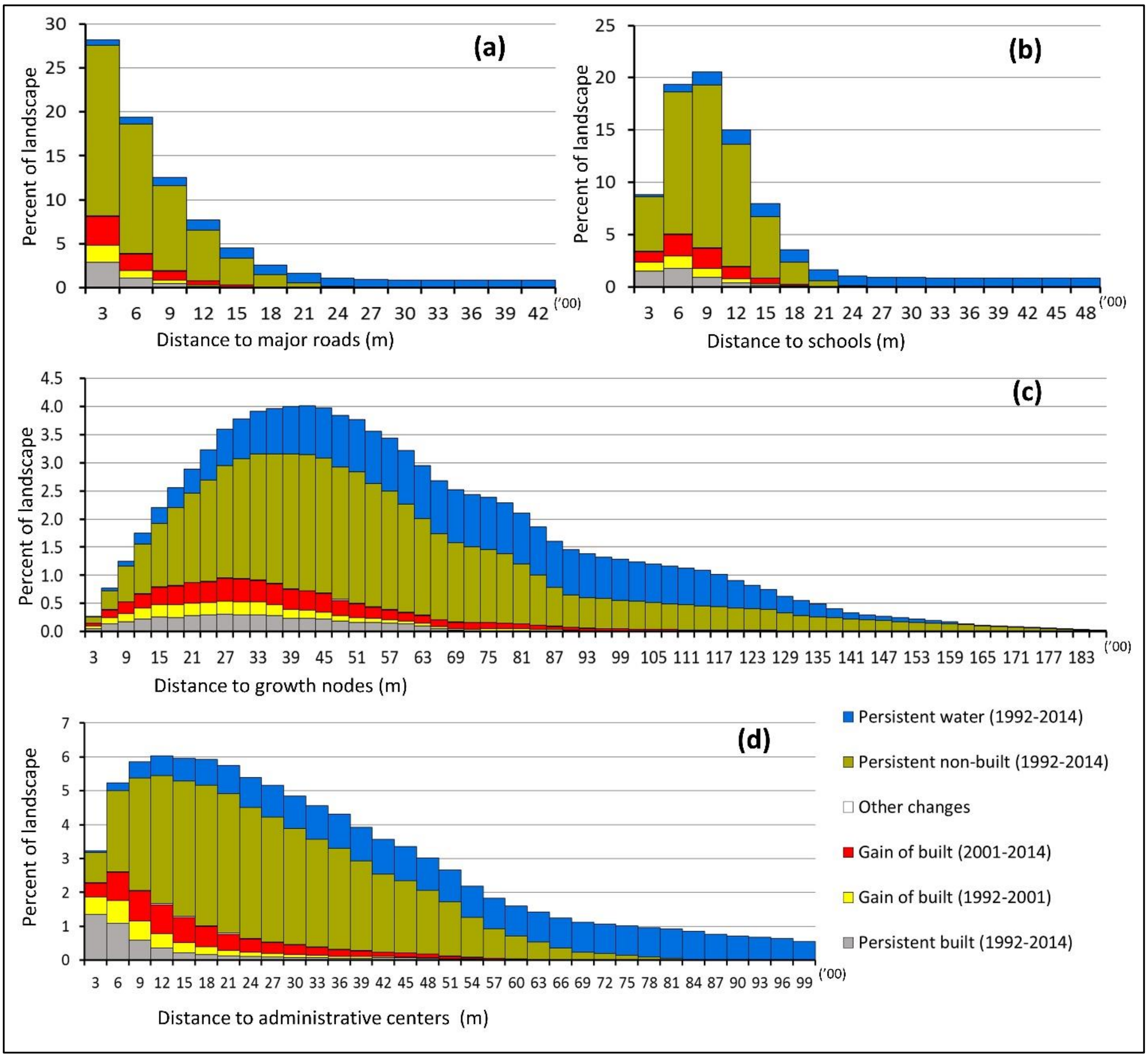

Figure 5-4: Observed ULU changes along the gradients of the driver variables: (a) distance to major roads, (b) distance to schools, (c) distance to growth nodes, and (d) distance to administrative centers.

5.3.2. Simulation and validation of the results

As previously explained, the model validated using the predicted 2014 results and the observed 2014 map. Certain spatial distribution of simulation correctness and errors, namely null successes, hits, omission errors, and commission errors (Figure 5-5) were revealed. The accuracy measures were noted as: hits of 2%; a commission error of 3%; an omission error of 5%; and null successes of 90%. The union of the omission errors and hits was the observed change, which was equal to 7%, while the union of the commission errors and hits was the simulated change, which was equal to 5%. The union of the commission errors and null successes was the observed non-change (93%), while the union of the omission errors and null successes was the simulated non-change (95%).

The model achieved a FoM of 8.36% for a landscape with a change of 11.3%. In a review, it was found that landscape observing change over ~<10% had FoM of less than 15%. Hence, FoM was acceptable considering that it only had 7.25% ULU change relative to the whole landscape during the simulation/validation interval (from 2001 to 2014). Moreover, the AUC value was 0.822, indicating that the transition potential map had a "high skill" in predicting future ULU changes. In such a context, it was proved that the selected explanatory variables were suitable to predict the future urban growth in the CMA.

However, the usage of the same probability map, used to predict 2014 was doubtful due for predicting 2030 due to the recent rapid urban growth, which was identified through the intensity analysis (from 2001 to 2014). Thus, a new probability map was used to predict the 2030 results. In creating this new probability map, the ULU change from 2001 to 2014 was considered, and prediction was implemented based on the ULU intensity of this time interval.

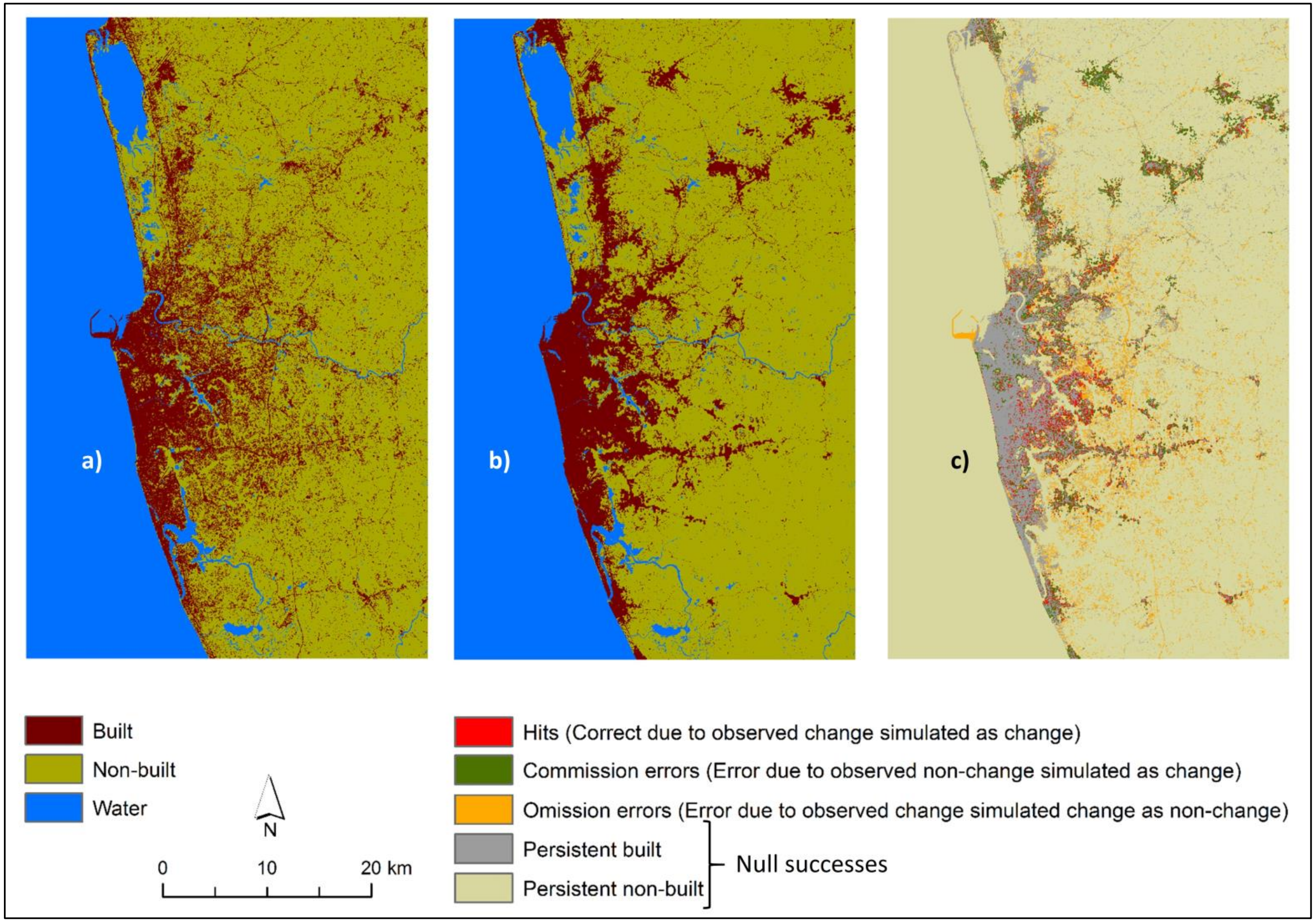

Figure 5-5: Validation of prediction: (a) The observed 2014 map; (b)the predicted 2014 map; and (c) the cross-tabulation of the 2001 and 2014 ULU maps and the predicted 2014.

5.3.3. Predicted 2030 urban growth

Urban growth is a highly complex process, which is a well-recognized fact. Thus, understanding the natural pattern of urban growth will help to introduce the practical urban development scenarios. In such a context, a comparison of the proposed urban development scenarios and the projected urban growth pattern based on ULU change will help to identify the future urban planning implications.

The predicted ULU of 2030 in the model developed in this study, showed that the urban area will increase from 35,875 ha in 2014 to 53,510 ha in 2030 (Figure 5-6). It is clearly visible on the maps how the major roads and growth nodes will have a great influence on the spatial pattern of future built-up expansions. The predictions also showed that the northern and northeastern parts of the CMA will experience great landscape changes in the future associated to the growth nodes and roads. Moreover, most of the growth nodes in this part are influenced by the location of EPZ such as Biyagama, Katunayake. ULU along the coast and in the central area also will become denser. The tourism functions based development such as hotels may dominate the urban growth along the coastal line.

The comparison of current and future spatial pattern using the landscape metrics is shown in Figure 5-7. The results revealed that the landscape fragmentation will continue while the overall complexity is increased due to increase of urban dense. The patch richness and/or the proportional distribution of an area among land-use/cover classes will become more even. The urban area will become larger, and aggregate together and the shape complexity of urban area will decline in future. The land fragmentation will further increase the problems such as the agricultural land fragmentation and forest land fragmentations. The increasing density of ULU will mainly dominate the decline the shape complexity of ULU.

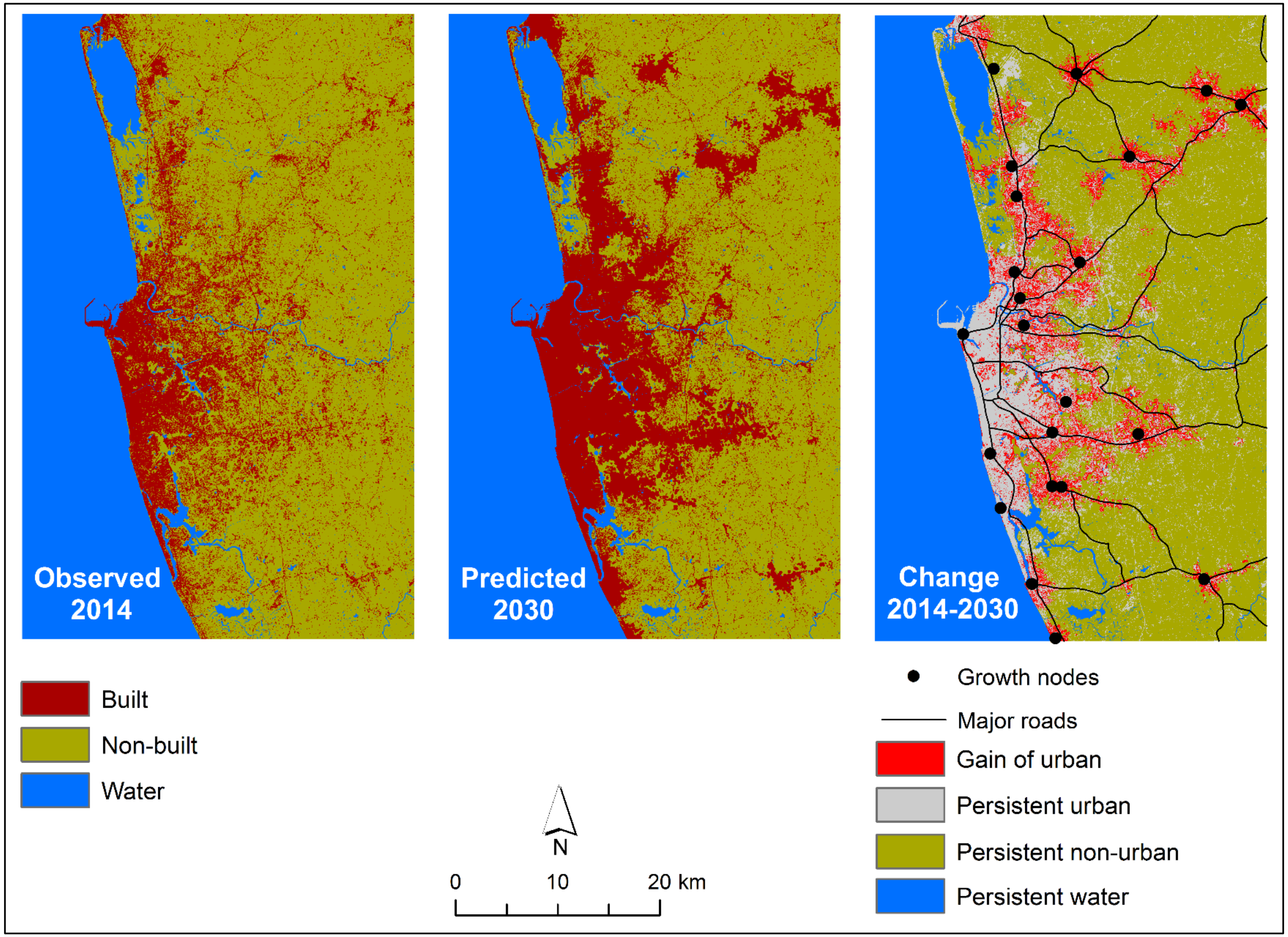

Figure 5-6: Observed 2014, predicted 2030, and detected ULU changes.

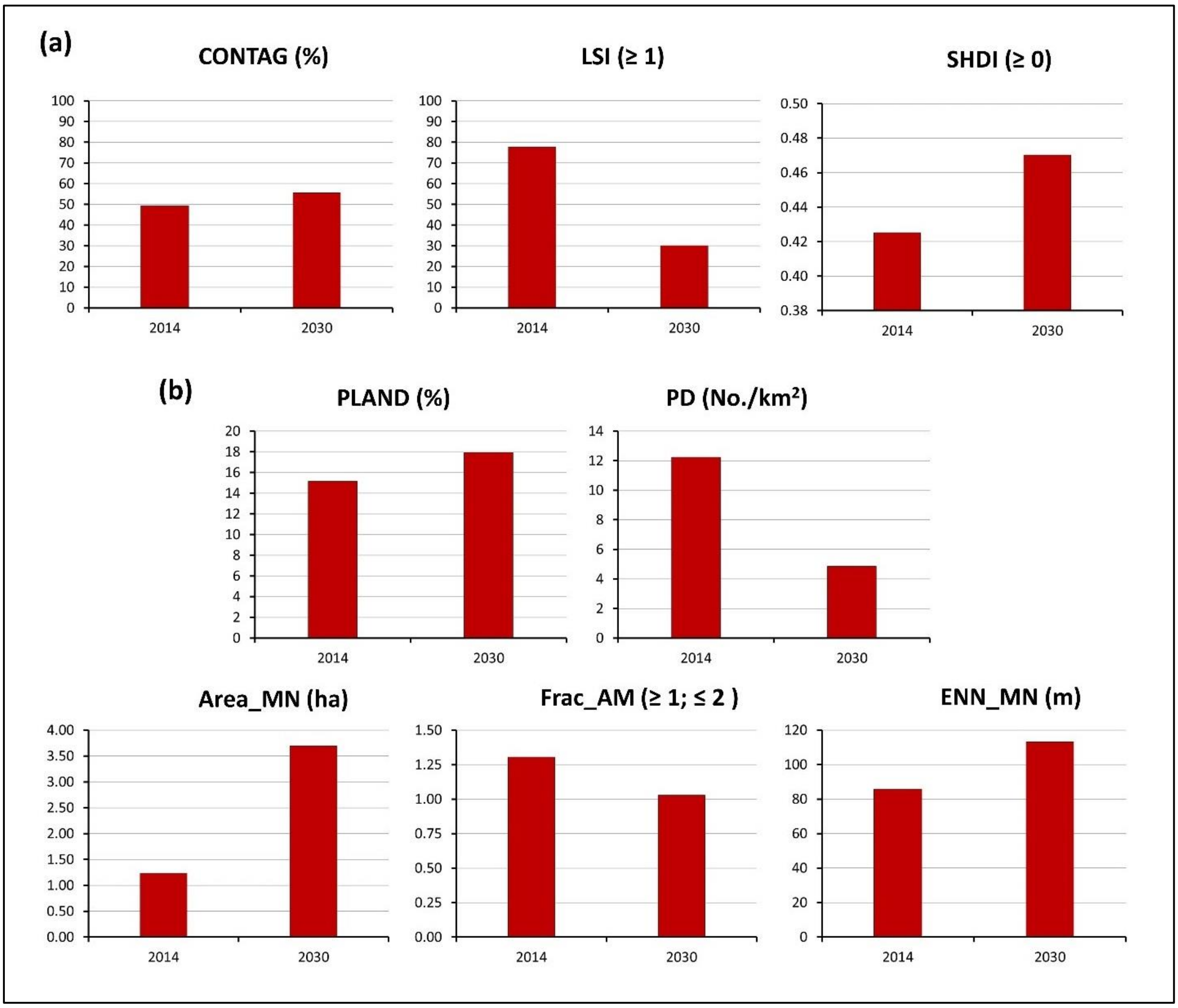

Figure 5-7: Detecting the future spatial pattern of ULU using landscape metric: (a) Landscape level metrics, and (b) class level metrics.

5.3.4. Proposed scenarios of the 2030 masterplan

To manage the urbanization of the western province of Sri Lanka where the CMA is located, the government has introduced the Western Region Megapolis Land-use Structural Plan–2030. This land-use structural plan proposes four potential urban development scenarios: (1) compact polycentric; (2) monocentric; (3) necklace; and (4) urban functional cluster-based.

The compact polycentric development has the target to develop Colombo city as a core area and surrounding selected growth nodes, namely Kiribathgoda, Kaduwela, Maharagama, and Kesbewa as the compact cities. Meanwhile, it proposed other townships as the moderate- and low-density areas in the peripheral area. According to this plan, the southern coastal belt from Colombo city is planned as a tourism development area. The airport and the harbor are used as the key economic drivers of the region with extended development as a port city and an airport city, which are connected through city corridors. The Colombo core area is proposed for development as a business and entertainment center with high-density settlement for work and life with concentrated infrastructure.

The proposed monocentric development scenario mainly plans to develop Colombo city as a high-density and predominantly finance- and commerce-related development. A coastal belt for tourism, fishing, and other marine-related development will be promoted. The peripheral regional centers are linked with the high mobility road corridors. The expected regional centers, such as Mirigama, Nitambuwa, Kirindiwela, Hanwella, Padukka, Horana, and Matugama are far from the core.

The necklace development scenario follows the geometrical form of urban growth. Two ring roads are identified as the inner necklace and outer necklace respective to the geometric form of the urban growth. The peripheral region, which will incorporate the outer necklace townships, is made up of self-contained low density residential townships along the outer ring road on the undulating areas further away from the Colombo city core. There will be a suburban region that will incorporate the inner necklace townships, which are medium density residential townships along the inner ring road and immediately adjacent to the Colombo city core as self-contained townships where most of the population will be accommodated. Regional centers are linked with technology and industrial corridors while sub-centers are linked through business corridors.

The urban functional cluster-based development scenario mainly proposed different development zones, including an aero city zone, and logistics and freight, core, industrial, and tourism zones. The overall development objective of this scenario is to protect environmentally sensitive areas and disperse the development in the outer regions of Colombo. The marine development zone is identified with the purpose of managing marine assets and the wise use of shoreline mineral and biological resources.

5.3.5. Implications for future urban planning

Figure 5-8 shows the overplayed dominant characteristics of each proposed development scenario and predicted 2030 ULU change.

The land-change model revealed that there is higher possibility to increase the compact development that is identified sub-centers by the polycentric development scenario. However, some regional and sub-regional centers will not show centralized urban growth with the present urban growth patterns. This situation is mainly visible in centers where urban growth is located in the central area of the map. The two regional centers, located in the coastal north and south directions from Colombo city, will experience compact urban growth. The north regional center, located in the Negambo area development, is associated with the international airport and with tourism development. The south regional center, located in the Pandura area, acts as a major service center to a large rural hinterland covering the Horana, Mathugama, Keselwatta, and Wadduwa areas. The central regional center, located in the Avissawella area, will not experience urban growth like the coastal area centers in future. Connecting to the urban growth trend identified in this study, two compact centers are suggested: Ja Ela-Kandana, located to the north of Colombo city, and Moratuwa, located to the south. The development of Katunayaka, Minuwangoda, and Homagama will be more successful as sub-regional centers.

The monocentric development scenario has identified the major cluster of a potential future development area as the core and other clusters as the sub-cores. The prediction results indicated that a higher level of urban density increase will be experienced in the Colombo city area. With this trend, central area development as a mono-core with multi-functions will create some urban problems, although it may help to protect the natural environment of the surrounding area. However, the monocentric scenario development may increase traffic congestion and land prices, and create a central area as an inefficient place with a higher level of economic loss. If monocentric growth is implemented, it would be better to establish multiple transport links with other sub-centers.

The necklace development scenario is proposed based on the geometric shape of the CMA. The establishment of the ring-shaped road is the basis of this scenario. Several cities in the world, such as Tokyo, Beijing, Ahmadabad, and Bangalore, have employed this approach as an urban planning strategy. The introduction of transport corridors is important to reduce the higher level of urban concentration into the core area, but the artificially introduced ring roads with necklace shape development may not be enough to manage the urbanization of the CMA. The prediction results indicate that the potential development of the outer ring area is very limited compared to the inner ring. Thus, the planning of urban functions linked to this road pattern is needed. Moreover, the ring road will create greater potential for a linear type of development along these roads, such as the current most visible spatial pattern of urban growth in the CMA.

The urban functional cluster development scenario has been mainly designed based on the locational specification of each zone. The separation of functional zones based on the location of each zone will have more economic advantages and more efficient management. As an example, the Muthurajawela wetland area is to be managed as an eco-tourism zone under the environmental protected area. The core area development should be considered for business and commercial development, which relates to the Colombo harbor. With the emergence of poly-center, it can be identified the sub-cores in the residential zone, these sub-core areas may not be residentially important. Thus, the separation of these zones based on potential development patterns will be useful for urban planning, rather than the separation of these zones based on existing patterns.

Considering the predicted ULU pattern in 2030, it is suggested that urban development planning should anticipate the quantity and spatial patterns of future urban expansions more accurately before introducing different urban planning scenarios. This will minimize the adverse effects on agricultural, forested, and wetland areas, including the remaining urban green spaces in the central area, and increase the economic efficiency of urban planning. Currently, there is also a high population concentration in the wetland areas of the CMA, and unplanned rapid urban growth in the CMA will certainly affect these wetland ecosystems (e.g. Muthurajawela and Aththidiya). Thus, the future urban planning initiatives should consider these matters to diversify these population concentrations into other areas.

The ribbon-type development will further increase the difficulty of introducing urban development planning initiatives because Sri Lanka's UDA has no jurisdiction over administratively defined rural areas—even if these areas contain high concentrations of urban features (UN-Habitat, 2012). Therefore, this type of urban development also needs to be taken into account in the CMA's landscape and urban development planning.

The CMA's landscape and urban development planning should also pay particular attention to the coastal area, which has been projected to experience more intense ULU change in the future. Coastal areas, such as the one in the western CMA, are prone to disasters (e.g. tsunamis and cyclones). Thus, in the CMA's planning, appropriate disaster risk-management plans also should be considered. Consideration of vertical urban space for the future urban development will help to reduce the environmental impacts that is emerging. Specifically, the urban planning initiatives should manage the rapid horizontal growth that is motivated by the residential activities in the suburban areas. Moreover, it is necessary to accommodate the recent fast industrial growth associated to the economic growth into the urban planning strategies of future.

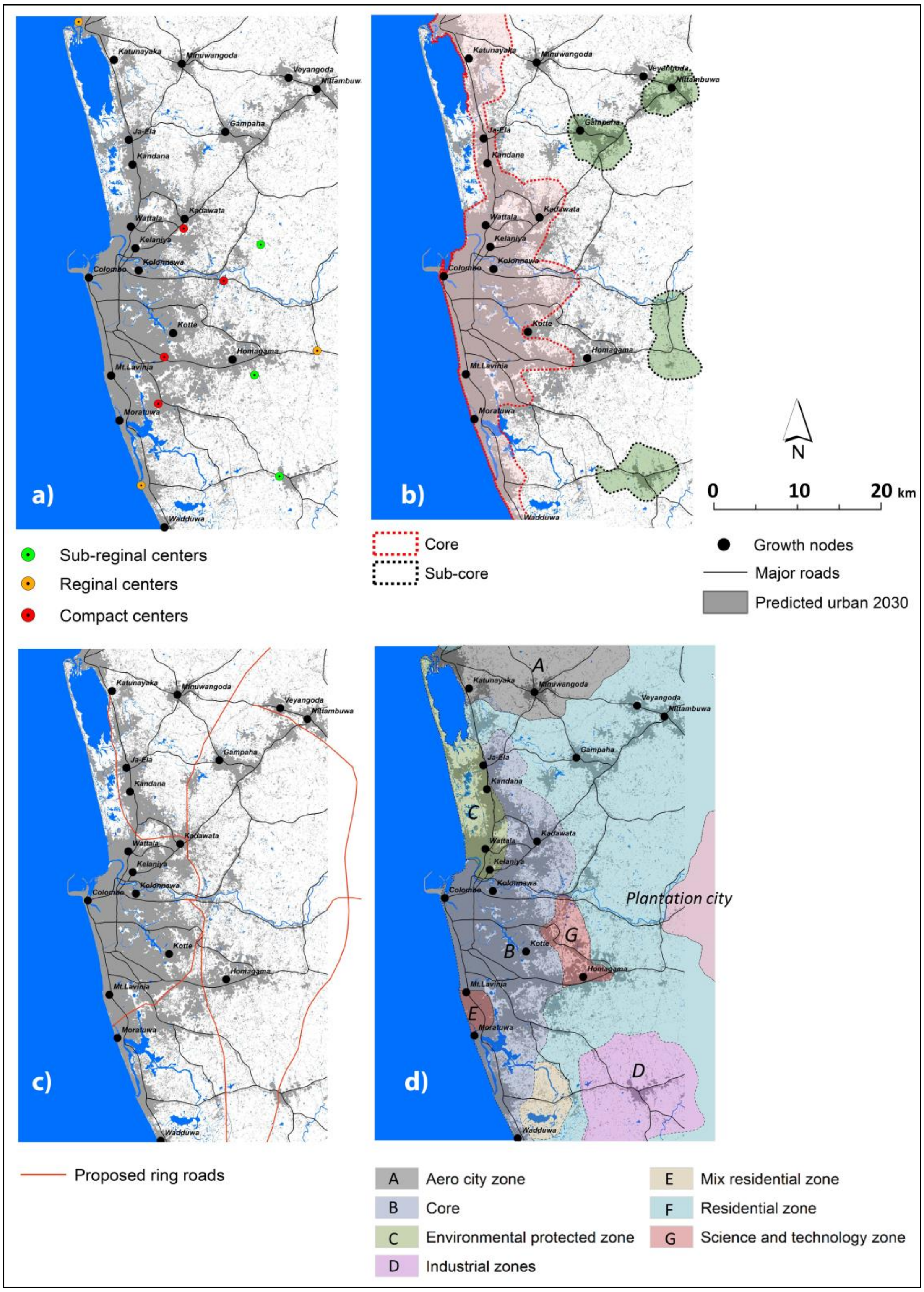

Figure 5-8: Comparison of predicted 2030 ULU and proposed urban planning scenarios: (a) Compact poly-centric development scenario; (b) mono-centric development scenario; (c) the necklace development scenario; and (d) the urban functional cluster development scenario.

Chapter Six

Conclusions

The CMA exhibits urban primacy in the national urban system and serves as a node of the international urban system, being Sri Lanka's only metropolitan area for decades. Recently the CMA is considered as one of the fast-changing urban area in the South Asian region. The rapid urbanization and concentration of increased urbanization in the CMA has created several socioeconomic and environment problems that stem from extensive urban poverty, recurrent flooding, slum, extensive alteration of wetland ecosystem. In such context, this study has examined the spatiotemporal patterns of urban process and future development in the CMA—the country's main socioeconomic "powerhouse".

For the past twenty two years (1992–2014), the CMA has been transformed physically with as indicated by an almost 3-fold increase in its ULU (1992: 11,165 ha, 2001: 19,392 ha, and 2014: 35,875 ha). However, from the analysis of ACI, it could be identified that the ULU change intensity was fast in the 2000s (ACI of 0.54%) than the 1990s (ACI of 0.39%), coinciding with the trends of population, economic growth, and several underlying socioeconomic factors. Moreover, it could be identified that although the areal extent of urban sparse is significant compared to the urban dense in all the selected years, the changing percentage of urban dense (275% as the percentage of landscape) is higher than the changing percentage of urban sparse (192% of the percentage of landscape). Similarly, landscape metrics revealed that the landscape of the area is largely getting fragmented, overall complexity is increasing, and growing new urban land near the existing land. It also indicated more urban diffusion rather than coalescence; in facts, more leapfrog (outlay) growth rather than infill growth and extension growth. This urban growth pattern tendency indicates a complex urban process in the CMA. The study revealed that ongoing urban growth, loss of non-urban land, and higher levels of land fragmentation with dispersed urban growth in the CMA have not been resolved by the urban policies in last two decades. Due to landscape fragmentation, the sustainability of the ecosystem could be affected. Thus, encouraging new development in already altered land can be effective in terms of urban planning. Capturing the vertical urban space in the CMA is very limited except for in the CBD; the promotion of vertical development particularly focused on the urbanized areas may help to reduce the pressure on the sustainability of the ecosystem. The planning initiatives need to address this factor when the new urban planning strategies are introduced. Through a questionnaire survey, the review of previous literature, and the author's local knowledge of the study area, the six factors related to urban growth were selected and ranked by the thematic zones of the CMA (core, fringe, and outside). The finding of questionnaire survey indicated that the causes for the urban growth and history of migration attractions are different depending on the functional diversity and the land price of each zone.

The predicted results of the land-change model of the study indicated that the ULU of the CMA will increase into 53,510 ha in 2030. It could be identified that major roads and growth nodes have greatly influenced on the spatial pattern of future ULU. Moreover, the landscape fragmentation will continue, the overall complexity of landscape will decline due to the increase in urban density; the patch richness and/or the proportional distribution of an area among land-use/cover classes will become more even; the urban area will become larger, and aggregate together; and the shape complexity of urban area will decline in the CMA. It seems that in the context of this study, the proposed masterplan-2030 has not addressed the spatial pattern of future ULU expansion. Proposed future planning scenarios in the masterplan of 2030—compact polycentric urban development, monocentric development, necklace development, and urban functional cluster-based development—show some contradictions with potential future urban growth. Thus, the incorporation of these identified potential urban growth of the study into the masterplan of CMA is curial to achieve the sustainable urban planning targets in future. Moreover, management of suburban growth, accelerated by recent rapid growth of the CMA, should be highly anticipated in urban planning activities. In the urbanization perspective, the coastal area has proven to be a significant region in the CMA. In general, there is greater potential for several natural disasters (e.g. tsunamis and cyclones) in the coastal area; thus, the incorporation of an appropriate disaster risk-management plan into the urban planning initiatives should be considered in developing masterplan.

The empirical observations and the integrated framework developed in this dissertation contribute not only to the understanding of the urban process of the CMA, but also it can be employed to conduct the comparative urban studies in future. The study mainly reveals robust approach to ULU mapping and urban growth pattern analysis. All the results and the discussion from mapping to future prediction can be useful to form urban development policies and scenarios for sustainable land-use planning.

Beside the factors considered in this study, urban process is also strongly affected by political, cultural, and different socioeconomic underlying factors. These factors are difficult to incorporate into geospatial analysis due to their aspatial characteristics and the lack of data in a spatial manner. Thus, the development of methodological approaches to incorporate aspatial aspects, which is associated with the urban process, is essential for future research activities.

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Appendix I: Photography showing the fieldwork sessions and urbanization of the CMA

Appendix II: Accuracy assessment

Producer's accuracy

X_{ii} / X_{+i} *x* 100%

Where,

X_{ii} = total number correct cells in a class, and

X_{+i} = sum of cell values in the column.

User's accuracy

X_{ii} / X_{i+} *x* 100%

Where,

X_{ii} = total number correct cells in a class, and

X_{i+} = sum of cell values in the row.

Overall accuracy

D / N *x* 100%

Where,

D = total number correct cells as summed along the major diagonal, and

N = total number of cells in the error matrix.

Error matrix for the classified 1992 land use/cover map

Classified data	Reference data			Total	User's accuracy
	Built	Non-built	Water		
Built	272	16	12	300	90.67
Non-built	31	258	11	300	86.00
Water	7	25	268	300	89.33
Total	310	299	291	900	
Producer's accuracy (%)	87.74	86.29	92.10		

Overall Accuracy (%) = 86.66%

Error matrix for the classified 2001 land use/cover map

Classified data	Reference data			Total	User's accuracy
	Built	Non-built	Water		
Built	279	7	14	300	93.00
Non-built	14	274	12	300	91.33
Water	17	23	260	300	86.67
Total	310	304	286	900	
Producer's accuracy (%)	90.00	90.13	90.91		

Overall Accuracy (%) = 90.33%

Error matrix for the classified 2014 land use/cover map

Classified data	Reference data			Total	User's accuracy
	Built	Non-built	Water		
Built	286	6	8	300	95.33
Non-built	6	282	12	300	94.00
Water	9	16	275	300	91.67
Total	301	304	295	900	
Producer's accuracy (%)	95.02	92.76	93.22		

Overall Accuracy (%) = 93.66%

Appendix III: Survey Questionnaire

No:	The area:	Type:

Survey Questionnaire: The urban process of Colombo metropolitan area

Basic information	
Age	<15 ☐ 15-30 ☐ 30-50 ☐ >50 ☐
Is the urbanization feels as a threat in your region? ☐ = Yes ☐ = No	
Are there dedicated national/reginal/local measures to limits or plan urbanization? ☐ = Yes ☐ = No	
If yes, describe briefly	
What was the status of the land before your present house was built? Building ☐ Agriculture☐ Park☐ Forest☐ Bare land☐ Other ……………..	
Reasons for urban growth	
Please rank following reasons: 1,2,3….	

Natural population growth		Population growth by migration	
Socioeconomic opportunities		Accessibility to administrative services	
Urban planning initiatives		Accessibility to education services	
Other (…………………….)		Other (…………………….)	

Personal history		
When did you come to this area	Birth area ☐ < 10 years ☐ > 10 years ☐	
If this is not your birth area, where did you live before	**Previous places**	**Reasons for change**
	1. ………………….. 2. ………………….. 3. ………………….. 4. ………………….. 5. ………………….. 6. ………………….. 7. ………………….. 8. ………………….. 9. ………………….. 10. …………………..	
Why did you reside here	1. Business ☐ 2. Accessibility to services ☐ 3. Accessibility to working place☐ 4. Family ☐ 5. Land ownership ☐ 6. Industries ☐	
According to your understanding	People like to come this area Why……………………………………………………… People do not like to come this area Why ………………………………………………………	