Modelling and assessing linkages between urban growth and road network for Southeast Asian cities

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**MODELLING AND ASSESSING LINKAGES BETWEEN
URBAN GROWTH AND ROAD NETWORK FOR
SOUTHEAST ASIAN CITIES**

KAMARAJUGEDDA SHANKAR ACHARYA

**INTERDISCIPLINARY GRADUATE PROGRAMME
INSTITUTE OF CATASTROPHE RISK MANAGEMENT**

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INSTITUTE OF CATASTROPHE RISK MANAGEMENT**

A thesis submitted to the Nanyang Technological University in partial
fulfillment of the requirement for the degree of
Doctor of Philosophy

2020

Statement of Originality

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LO YAT-MAN EDMOND

Authorship Attribution Statement

This thesis contains material from 3 paper(s), published or under preparation, in the following peer-reviewed journal(s) where I was the first and corresponding author.

Chapter 4 is published as Kamarajugedda, Shankar Acharya, Pradeep V. Mandapaka, and Edmond Y. M. Lo. 2017. “Assessing Urban Growth Dynamics of Major Southeast Asian Cities Using Night-Time Light Data.” *International Journal of Remote Sensing* 38 (21): 6073–6093. doi:10.1080/01431161.2017.1346846.

The contributions of the co-authors are as follows:

- A/Prof Edmond Y.M. Lo, Dr. Pradeep V. Mandapaka and myself discussed on the methodology and the analysis.
- Dr. Pradeep V. Mandapaka assisted on generation of NTL derived urban extents using Matlab software.
- I analyzed the spatial and temporal NTL data results using GIS and also validated using Landsat derived urban extent.
- I analyzed and mapped the NTL urban categorical spatio-temporal transitions.
- Myself and Dr. Pradeep V. Mandapaka together assessed NTL results w.r.t. population datasets.
- I wrote the draft of the manuscript. The manuscript was revised together with A/Prof Edmond Y.M. Lo and Dr. Pradeep V. Mandapaka.

Chapter 5 was submitted to journal as Kamarajugedda, Shankar Acharya, Pradeep V. Mandapaka, and Edmond Y. M. Lo. “Identifying linkages between urban growth, road network and socio-economic indicators for sustainable development in S.E. Asian cities” *International Journal of Remote Sensing*. The paper was rejected and we have since resubmitted to another journal *Environment and Planning B*.

The contributions of the co-authors are as follows:

- A/Prof Edmond Y.M. Lo, Dr. Pradeep V. Mandapaka and myself discussed on the methodology and the analysis.
- I derived the urban extent maps from Landsat data for the analysis using supervised maximum likelihood classification algorithm in ArcGIS platform.
- Statistical linkages and correlations were assessed by me using data analytics softwares.
- Dr. Pradeep V. Mandapaka assisted on generation of regression plots using Matlab software.
- I derived the zoning maps using ArcGIS platform.
- I wrote the draft of the manuscript. The manuscript was revised together with A/Prof Edmond Y.M. Lo and Dr. Pradeep V. Mandapaka.

Chapter 6 is published in the International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences (ISPRS Archives) as Kamarajuggedda, Shankar Acharya and Edmond Y. M. Lo. “Modelling urban growth for Bangkok and assessing linkages with road density and socio-economic indicators”.

The contributions of the co-authors are as follows:

- A/Prof Edmond Y.M. Lo and myself discussed on the methodology and the analysis.
- The SLEUTH urban growth prediction platform setup and the relevant data was prepared and modelled by myself.
- Statistical results were derived and plotted by myself.
- I wrote the draft of the manuscript. The manuscript was revised together with A/Prof Edmond Y.M. Lo.

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Abstract

The key objectives in this PhD research are to analyze and quantify the spatio-temporal urban growth dynamics, specifically growth in urban area for major Southeast Asian (SEA) cities and also to develop quantitative relationships amongst urban growth, city infrastructure and socio-economic indicators. To meet the objectives, a multi-stage approach was used to model and analyze urban growth in SEA cities.

Firstly, a macro-scale analysis was used to assess spatio-temporal urban growth using remotely sensed night-time light (NTL) data. This analysis using yearly NTL data from 1992 to 2012 resulted in identification and assessment of urban growth patterns for 15 SEA cities and also the extraction of three urban categories (specifically, countryside (CS), peri-urban and (PU) core-urban (CU)) using a brightness gradient (BG) approach for each city. The PU and CU urban categories were generally found to increase over time whereas CS urban category decreased implying significant spatial and temporal trends in urbanization. Significant CS to PU transitions were evident in all the studied cities. Most cities have negligible CS-CU transition. The urbanization trends showed strong correlation with the population growth for the SEA cities with inland cities showing an unrestrained spatial growth with population. The studied SEA cities also expanded spatially into the surrounding countryside generally following a linear trend with population increase.

A further multi-scale analysis was performed to assess correlations between urban expansion, road infrastructure and socioeconomic indicators such as GDP and population at inter-city and intra-city scales. This analysis was performed at a higher spatial resolution using remotely sensed Landsat data over a 30-year time change period using two years of 1987 and 2017 in extracting the urban expansion patterns for 9 major SEA

cities. Strong correlations were identified amongst urban growth, road infrastructure, population and GDP between cities at inter-city scale. Furthermore, the intra-city analysis results showed that the logarithmic of the intra-urban expansion rate follows an inverted concave pattern with road density, with the rising/falling limbs indicating gradual increase/decrease of the expansion rate. A “turning point” where the curve starts dipping is shown to differentiate amongst different grades of urban expansion. These turning point thresholds were further used to develop zoning maps within each city highlighting different intra-city urban expansion processes. Similar trends were also identified between the logarithmic population growth rates with road density.

Lastly, considering Bangkok as a case study, an urban growth prediction model (SLEUTH – Cellular Automata) was applied using the same 30 year temporal datasets to identify the future urban scenarios and to correlate the projected urban expansion patterns (future year of 2027) w.r.t. the linkages identified. The results show that Bangkok has a radially outward growing trend with around 287.6 km² expanded area over a historical 30-year (1987-2017) period, and with a SLEUTH predicted expanded area of 129.9 km² over 2017 to 2027. This case study led to better understanding of the future infrastructure demand and expansion zones.

Overall, the linkages amongst urban expansion, road infrastructure and socio-economic indicators such as these developed in the PhD research shed light on the developmental processes for SEA cities which, in turn can inform on the planning for sustainable and resilient developmental activities. This is especially relevant for developing economies, such as in improving their land use efficiency and infrastructure planning.

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Abbreviations

BG	Brightness Gradient
CA	Cellular Automata
CGER	Center for Global Environmental Research
CORINE	Coordination of Information on the Environment
CS	Countryside
CU	Core-Urban
DEM	Digital Elevation Model
DMSP	Defense Meteorological Satellite Program
DN	Digital Number
DNB	Day-Night Band
ESRI	Environmental Systems Research Institute
GDP	Gross Domestic Product
GIF	Graphic Interchange Format
GIS	Geographic Information Systems
GPW	Gridded Population of the World
IPCC	Intergovernmental Panel on Climate Change
LULC	Land-Use Land-Cover
MODIS	Moderate Resolution Imaging Spectroradiometer
NDI	Normalized Difference Index
NOAA	National Oceanic and Atmospheric Administration
NPP	National Polar-orbiting Partnership
NTL	Night-Time Light
OLS	Operational Linescan System
OSM	Open Street Map
PU	Peri-Urban
RS	Remote Sensing
RSR	Ridgeline Sampling Regression
SD	System Dynamics
SEA	Southeast Asia

SEDAC	SocioEconomic Data and Applications Center
SLEUTH	Slope, Landuse, Exclusion, Urban Extent, Transportation and Hillshade
SNDI	Sum of Normalized Difference Index
SPOT	Satellite Pour l'Observation de la Terre
SRTM	Shuttle Radar Topographic Mission
SSP	Shared Socio-economic Pathways
TLI	Total Light Index
TM	Thematic Mapper
UGPM	Urban Growth Prediction Model
UN	The United Nations
UNESCAP	United Nations Economic and Social Commission for Asia and the Pacific
UNPD	United Nations Population Division
US	United States of America
USGS	The United States Geological Survey
VIIRS	Visible Infrared Imaging Radiometer Suite
WEF	World Economic Forum

List of Publications

- Kamarajuggedda, Shankar Acharya, Pradeep V. Mandapaka, and Edmond Y. M. Lo. 2017. “Assessing Urban Growth Dynamics of Major Southeast Asian Cities Using Night-Time Light Data.” *International Journal of Remote Sensing* 38 (21): 6073–6093. doi:10.1080/01431161.2017.1346846.
- Kamarajuggedda, Shankar Acharya and Edmond Y. M. Lo. “Modelling urban growth for Bangkok and assessing linkages with road density and socio-economic indicators”. Published in the *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences (ISPRS Archives)* <https://doi.org/10.5194/isprs-archives-XLII-4-W19-255-2019>, 2019.
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- “Modelling urban growth for Bangkok and assessing linkages with road density and Socio-economic indicators” presented (oral) in *PhilGEOS X Geoadvances 2019* conference during November 14th and 15th held at Manila, Philippines.
- “Assessing and modelling urban growth coupled with road infrastructure for Southeast Asian cities: Towards a resilient framework” presented (oral) at *International Conference on Infrastructure Resilience* during February 14-16th, 2018 at ETH Zurich, Switzerland.
- “Assessing the dynamics of urban growth in major Southeast Asian cities using night-time lights data” presented (poster) in *Urban Transitions 2016* conference held at Shanghai, China during September 5th to 9th, 2016.

1. Introduction

It is well-recognized that the effects of urbanization on the environment are manifold, including the loss of agricultural land, urban heat island effect and associated increase in near-surface temperature, increases in carbon emissions and air pollution, and the depletion of natural resources (Seto et al. 2010; Schneider et al. 2010). The rapid rate of urbanization also poses numerous challenges including infrastructure design, water resource management, and public health. The last century has witnessed an increasing concentration of people in urban regions. For example, the worldwide urban population in the last 25 years has grown by 73% as compared to 38% for total population (UNESCAP 2014). Similarly, the urban population as a percentage of the total has increased from 43% in 1990 to 54% in 2015, and is expected to reach 66% by 2050 (UNPD 2014). These urbanization rates depend on various factors such as the geography, socio-economic conditions, and the political environment. For instance, the urban population percentage in developed and high-income countries is projected to increase at a lower rate compared to less developed and low-income countries. Understanding and modelling the spatio-temporal dynamics of urbanization as conditioned on multiple factors (e.g., economic, geographic, and political) are essential for developing appropriate planning and management strategies with a long-term objective towards sustainable and resilient urban centers and cities.

Cities are complex systems. As cities evolve over time so does its infrastructure. Infrastructures are a vital component which are essential for the socio-economic development of a nation (Peralta et al. 2009). The major components of a city's critical infrastructure system include roads, electricity (power), telecom, water and sanitation. In general, for all the cities, electricity and roads represent the bulk of the infrastructure

value accounting for 75 to 85 percent (Fay and Yepes 2003). Past data has shown that between 1960 and 2010, the electricity infrastructure stock for all countries has doubled unlike roads and other infrastructures (Fay and Yepes 2003). This clearly shows the importance of power infrastructure towards meeting energy demand in the process of urbanization. Further, a city's infrastructure systems tend to become more complex with growth of the city which also increases the vulnerability to various disturbances (Peralta et al. 2009). In most countries, infrastructure systems are mainly vulnerable to natural disasters or non-physical interventions such as government decisions. However, in most developing countries, rapid urban growth also impacts on the performance of infrastructure systems. Large increases in population and population density as accompanying urbanization affect the performance of infrastructure systems due to rapid increases in demand for energy, road infrastructure and water (Peralta et al. 2009).

The major objectives in this PhD research are to (i) analyze and quantify the spatio-temporal urban growth dynamics, specifically urban area for major Southeast Asian (SEA) cities, (ii) to develop quantitative relationships between urban area growth and city infrastructure growth at city level and down to intra-city level and (iii) to assess linkages between urban area growth and population growth at intra-city level with a further projection for future urban area growth using Bangkok as a typical case.

To fulfil the proposed objectives, a multi-stage approach was used to model and analyze urban growth for the SEA cities. SEA is chosen because most Southeast Asian cities are developing and fast-growing economies with a need for proper urban planning strategies that enable sustainable and resilient development. Initially, a macro-scale analysis was applied to assess spatio-temporal urban growth using night-time light (NTL) remotely sensed data. These obtained spatio-temporal trends were next analyzed to

establish linkages between urban growth and population. Further, a micro-scale analysis was performed at city level and at intra-city level, and linkages between urban growth, socio-economic indicators of population and gross domestic product (GDP) and road infrastructure established. The urban growth prediction model (UGPM) using Cellular Automata (CA) algorithm was lastly applied to Bangkok city as a case study to further predict future urban expansion patterns and to assess w.r.t. socio-economic indicators via the linkages developed.

1.1. Objectives of the Research

The specific objectives of the PhD work covering major SEA cities are to:

- Analyze and quantify spatio-temporal urban growth dynamics at city level (macro) and down to intra-city level (micro).
- Identify and deduce linkages between urban area growth and socio-economic indicators.
- Develop quantitative relationships between urban area growth at intra-city level and road infrastructure.
- Develop an urban area growth prediction model for Bangkok city as a case study and assess future urban expansion patterns and linkages with road infrastructure.

1.2. Overview of the Thesis

Chapter 1 is an introduction which gives an overview of the PhD work. Chapter 2 provides a detailed literature review on prior urbanization studies, urban growth modelling and predictions using Cellular Automata (CA) techniques. Chapter 3 discusses

the datasets used in this research and overview of the methodology adopted. Chapter 4 describes the macro-level analysis and results as performed for 15 major SEA cities. Chapter 5 details the micro-level methodology on the linkages amongst urban growth, socio-economic indicators and road infrastructure at intra-city level. Chapter 6 discusses the CA model applied for Bangkok city, the future urban patterns and their assessment w.r.t. road infrastructure and city development plan strategies. Chapter 7 concludes this PhD research with recommendations.

2. Literature review

2.1. Overview of urban growth

2.1.1. Urbanization

Urban growth or urbanization refers to the increase in the proportion of people living in urban areas. The world urban population is expected to rise by 2.5 billion between 2014 and 2050, with nearly 90 percent of the increase concentrated in Asia and Africa (UNPD 2014). By 2030, global land use is estimated to increase by at least 430,000 sq.km from the existing 2000 value of approximately 308,000 sq.km (Seto et al. 2011). The coming decades are also expected to have a drastic change in the distribution of global population with the projected urban population rising to comprise around 66 percent of the world's total population by 2050 as shown in Figure 2-1 (UNPD 2014). This implies that there will be a huge demand for increase in residential, commercial and industrial areas along with infrastructures to satisfy the needs of increasing population worldwide.

Figure 2-1 Global urban population growth (Source: UNPD 2014)

Urbanization is a complex phenomenon with a multitude of scientific disciplines been applied towards developing an understanding of it. There is even no international consensus on a standard definition of “urban” as indicated in the United Nations

Population Division report (UNPD 2014). It can be attributed as being based on population size, density criteria, administrative boundary, continuous built-up areas or other socio-economic factors (Henderson 2005). Alternatively, it can also be attributed to an economic criteria placing emphasis on relations between places of work and residence (Roca et al. 2004). McGranahan (2015) highlights five major macro factors contributing to urbanization mainly, agricultural revolution, technological revolution, commercial revolution, evolution of transportation systems and demographic revolution. Observing such factors at city to country scales can lead to insights of the cause-effect relationships among various underlying processes contributing to urbanization. Owing to the complex nature of this phenomenon, the study of urbanization is being pursued by different disciplines. The shape and metabolism of the urbanization process is also tightly coupled with governing social, economic and political factors (Farrell 2017). These factors mainly contribute both directly and indirectly to shaping the urban growth e.g., demographic factors such as population growth in terms of fertility and mortality, economic factors such as urban pull and rural push, and political factors which build on the various scale of investments in community, infrastructure and educational opportunities.

A study by Ge and Wu (2019) suggests that one of the fundamental driving force for urban expansion is the social aspect, especially understanding people's needs and further indicated that few such quantitative studies are reported. Urbanization studies can provide a critical understanding of the direct or indirect influence of human built environments on societies, policy, and environmental practices (Frank 2017). Nevertheless, studies on urban growth process have been unable to capture all such coupled socio- ecological nature of cities. With the increasing adoption of the urban sustainability paradigm, researchers have realized the need for an approach that considers landscape perspectives,

interdisciplinary approaches, ecosystem services impact on human wellbeing, socio-ecological frameworks, and adaptive planning (Wu 2014). Towards such an understanding is motivating researchers to develop more comprehensive approaches for studying complex urban systems which also captures society's influence on urban areas as reported by Frank (2017) in a review paper. In particular, Frank noted that socio-ecological studies have adopted an interdisciplinary approach to provide insights to the multidimensional perspectives and processes characterizing cities.

To better understand the role played by human built socio-ecological-political systems in shaping environmental changes and long-term sustainability, Frank (2017) noted the need to integrate between natural and social science research, and to bridge the mismatch in spatiotemporal scales and even the vocabulary used. Often, challenges arise as the timeline and geographical scale over which urban areas are explored diverge between the disciplines. The scale at which spatio-temporal urban systems evolve might not be aligned with that of decision-making processes and policies. However there are recent reported works on the use of Agent-based modelling and System Dynamics (SD) coupled with Cellular Automata (CA) to analyze such complex urban systems (Tian et al. 2011; Han et al. 2009). These works could provide a for coupling of such socio-economic and political factors. Tian et al. (2011) developed an agent-based model of urban growth for the Phoenix metropolitan region of the United States, which simulates the behavior of regional authorities, real estate developers, residents, and environmentalists. The heterogeneity of agents is reflected by adjusting parameters according to the agents' beliefs, desires and preferences. The combination of multi-agent system and spatial regression model is employed to predict the future urban development of Phoenix's metropolitan region. Han et al. (2009) developed an integrated SD and CA model to

mainly integrate two aspects: (1) areal change of urban land driven by socio-economic variables, and (2) spatial pattern of urban expansion affected by physical factors. A study by Maparu and Mazumder (2017) looks into different sub-sectors of transport infrastructure to find its long-run relationship and direction of causality with economic development and urbanization. Results showed existence of long-run relationship between transport infrastructure and economic development in Indian cities, with the direction of causality mainly from economic development to transport infrastructure. However there is current debate on the direction of causality, whether road network drives urban expansion (Baum-Snow, 2007) or is driven by the expansion (Zhao et al. 2017). Such papers also highlighted that few studies have explored on such cause-effect relationship between transportation, economic development and urbanization.

An equally significant factor in urbanization is that of economic effects. Chen et al. (2014) noted that while there are significant correlations of urbanization level with economic development globally, no significant correlation is found between urbanization speed and growth rate of such economic indicators over 1980 to 2011. They concluded that government-led urbanization, as presenting a form of control may thus have a lesser positive impact than organically developed urbanization. A review paper by Turok and McGranahan (2013) envisages that the urban development effects and economic growth are both variable, with no simple relationship between urbanization and economic growth, or between city size and productivity. The potential of urbanization to promote growth is likely to depend on how conducive the infrastructure and institutional settings are. One way of investigating this is to compare urbanization levels of individual countries with measures of national economic output, average income or social development, in order to test for a statistical association between urbanization and

development (Henderson 2010; Martin 2008). Henderson (2010) reported some level of correlation ($R^2 \sim 0.57$) between the proportion urbanized and Gross National Income per capita in 2004 for countries worldwide. He noted that the correlation would be stronger if there were fewer international differences in how “urban” is defined. Economic policies to encourage or discourage urbanization can have a large effect on the character of urbanization, and influencing the urbanization rate (Feler and Henderson 2011).

Due to the complex factors contributing to urban growth process, there is a need to develop new and/or improved insights towards assessing relationships in order to promote efficient and sustainable urban growth process. For Southeast Asia (SEA), in particular the major risk as reported in Global risks perception survey 2014, World Economic Forum is the failure of urban planning as arising from inadequate or poorly planned national infrastructure. Also, quantitative relationships between urban growth and factors contributing to it are less studied for SEA region.

2.1.2. Impact of urbanization

Currently, there is a strong global transition of population migrating from predominantly rural to urban globally. As shown in Figure 2-2, the rapid rise of urban population is projected to take place predominantly in the developing nations of Africa and Asia. The urban population in Asia and Africa is expected to reach 64% and 56%, respectively by 2050. Planned and organized cities, in particular play a vital role in improving the lives of people and also enable the generation of increased economic activity for the benefit of the nation (McGranahan 2013). The linkages between cities is also the backbone of world trade and are major generators of world GDP (UNPD 2014). Urbanization and sustainable development have mutual relationship. Cities being hubs for government, commercial,

technological, transportation and industrial activities are also reported to account for approximately 80% of the world's GDP generated. With proper planning, urbanization could lead to positive economic and social development of the city and nation, while rapid and unplanned urban growth would threaten the sustainable development process and could further lead to chaotic socio-economic development, a view from Global risks perception survey of the 2014 World Economic Forum (WEF). Urbanization also results in change of land cover, land imperviousness, hydrological systems, and also biodiversity. As urbanization increases, so do the risks associated with such changes. Urban expansion into vegetated lands could alter the carbon flux and threaten biodiversity (Seto et al. 2012; Zhou et al. 2013). The increase in urban areas would also lead to the increase in waste water, gas emissions, solid waste, and dust particles and aerosols which in turn create environmental and health issues. All these potential negative impacts could be mitigated with the proper planning of urban infrastructure.

Figure 2-2 Urban population growth forecast between 2010 and 2050 (Source : UNPD 2014)

The main factor driving rapid urbanization in developing economies is the migration of people from rural areas to urban centers in search of employment opportunities. Greater population would indeed yield economic benefits such as from infrastructure projects (e.g. housing and transportation) that would be generated. Conversely, a higher population density could also trigger negative impacts when rapid urbanization is poorly planned and which could lead to the economic and social downfall of cities (Global risks perception survey 2014; WEF). Figure 2-3 as reproduced from Global risks perception survey 2014, WEF shows that failure of urban planning is the major risk in SEA regions as arising from inadequate or poorly planned national infrastructure. Such negative impacts of urbanization on emerging cities could be further amplified since cities are often the focal points of trade and commerce. Hence, it is key to better understand and if possible to predict such risks at the city level and so further plan for appropriate policies that promotes resilience.

Figure 2-3 Global risk perception (Reproduced from Global risks perception survey 2014, World Economic Forum)

2.1.3. Urbanization and infrastructure systems

Any nation's well-being, national security and economic prosperity depends highly on its critical infrastructure systems (Rinaldi 2004). The quality of city's infrastructure would contribute significantly to the quality of people's life and economic opportunities. These infrastructures include national electric grid, telecommunication, road network, rail network, oil and natural gas systems, water systems, and even banking and health sector. They play an important role in the national economic development and hence need to be resilient to potential risks and catastrophic failures (intentional or unintentional). An example was in the northeastern U.S., Ontario and Canada which had a complete blackout in August 2003. That led to loss of power for millions of homes and business and the power interruption and further led to the loss of water supply in many communities since the water pump stations relied on power to operate (Tolone et al. 2004). Even electric power systems that depend on transportation systems for the transport of fuel were affected. Hence it is evident that these infrastructures are highly interdependent and with their well-being being critical for the smooth running and development of a city. Since population density increases over time will lead to demand increases in energy, travel and water supply and sanitation needs, the urbanization process should be well-planned to reduce potential negative impacts and to make cities more resilient. However most developing nations with their lack of infrastructure facilities and proper planning thereof, often suffer from negative impacts of urbanization resulting in an unbalanced growth of the nation (Bihamta et al. 2015; Zhou et al. 2015).

Currently there is much reported work on the use of data and technologies such as remote sensing (RS) and Geographic Information Systems (GIS) to increase the efficiency of infrastructure management (Clarke and Gaydos 1998; Li and Yeh 2000;

Bhatta 2009; Al-shalabi et al. 2013; Feng et al. 2015). Clarke and Gaydos (1998) demonstrated the importance of RS and GIS technologies in modelling the complexity of urban systems and urban infrastructure. The major advantage of RS and GIS is that RS gives us a spatial snapshot or “bird’s eye view” while GIS has the capability to integrate various layers of urban growth indicators to identify and assess the linkages amongst them. Bhatta (2009) in his case study for Kolkata, India, has shown the necessity for use of RS and GIS tools and technologies to model the urban complexity within cities by studying the past and the present. These models should then be useful to prepare for the future, especially in planning and management of city infrastructure. There is also reported works on assessment of critical infrastructure interdependencies towards developing a resilient framework for emerging cities (Bishop et al. 2000; Fay and Yepes 2003; Rinaldi 2004; Peralta et al. 2009). In particular, Bishop et al. (2000) developed the Bangkok Land Information System project as an example to highlight the infrastructure dependencies and to suggest various generic strategies for efficient planning. Fay and Yepes (2003) estimated the demand for infrastructure demand over the first decade of the new millennium as following the Millennium Development goals. Rinaldi (2004) examined the complexity of existing infrastructure interdependency problem and also reviewed several models and simulations that can be applied to understand such interdependencies. Peralta et al. (2009) demonstrated the use of a SD model to evaluate the effect of urban growth on the electric system.

Road networks act as a skeleton for urban development and as such are also closely linked with urban expansion (Lämmer et al. 2006). Researchers have deeply discussed and shaped various relationships between urban land-use and road network systems from varying perspectives (Ding 2019; Silva and Wu 2012). This include developing urban

growth models to identify the demand in urban traffic networks, with the road network structure and form converted into a relationship between the road network and population density. Land use and transportation systems are considered as two most important subsystems in determining urban form and structure (Rui and Ban 2014), and are further assumed to mutually influence each other over time. Rui and Ban (2014) explored the relationship between different street centralities and land-use types in Stockholm to capture land development patterns based on anthropogenic activities. Urban land-use is considered the root source of urban traffic demand, which not only determines the source of urban traffic and transportation but also regulates the urban traffic structure (Ding 2019). This implies different land-use require different urban traffic patterns and transportation infrastructure. To better understand the interactions between urban land use and transportation networks, two major underlying processes have been proposed (Strano et al. 2012), namely “densification” and “exploration”. Densification is the process of “increase in the local density of roads around existing urban centres”, and exploration refers to the fact that “new roads trigger the spatial evolution of the urbanization front”. On this basis, Mohajeri and Gudmundsson (2014) quantified the characteristics of Sheffield, England and Khorramabad and Kerman for Iran. They further examined the urban traffic network growth process using three methods: orientation, length, and via the Shannon–Gibbs entropy analyses. Human activity is also a factor driving land-use change, hence traffic flow or volume as driven by human activity is also examined via integrated models for determining land-use changes (Lambin et al. 2003). Such integrated models incorporate land-use, employment, population and travel subsystems. However, these models need high resolution data (capturing e.g., traffic volume, transportation costs, means of transport, labour costs and also human social and

economic activities) for identifying linkages and interactions between the various urban sub-systems (Bertolini et al. 2005; Hensher and Ton 2002). Multiple centrality assessment and kernel density estimation approaches are also used to represent the mutual connections of urban traffic networks and surrounding land-uses (Ding 2019). However, research is still needed in terms of assessing quantitative relationships between urban road networks and urbanization factors at an intra – city scale, such as proposed here for urban area growth, to help guide city planners for efficient development. Considering the fact that major SEA cities are in developing economies, there is a lack in availability of high-resolution including temporal, dynamic data for a comprehensive integrated analysis between various urban sub-systems. Even for advanced economies in SEA, e.g. Singapore, there is less publicly available information on dynamic data such as traffic volume or density and traffic flow, as well as data on sub-systems (for e.g., network nodes and links) that potentially impact on the urbanization process.

In the process of rapid urbanization occurring in many cities, there is a high probability that the infrastructure may not be able to cope up with the pace of city growth nor people's expectations. Hence, it is essential to monitor and assess urban growth and with respect to road infrastructure, population or population density and GDP in order to better understand the urban growth patterns especially for developing economies for sustainable and resilient development. In the Chapter 2.2, literature referring to various methods and tools to monitor and assess urban growth dynamics are reviewed.

2.2. Assessing urban growth dynamics

2.2.1. Defining urban extent and urban growth

One of the key parameters to track in urbanization is the extent of urban areas. An urban environment consists of an amalgam of municipalities along with political and administrative boundaries but an urban extent could not be just defined by these boundaries alone (McGranahan 2015). An urban extent or area in the remote sensing perspective is defined as a land cover class meaning e.g. whether the surface is impervious or not (Bhatta 2010). In terms of land use, an urban area can be defined as e.g. residential, commercial, industrial, public, and urban parks and water bodies (Bhatta 2010). However, in a broader perspective, an urban area can refer to urban landscapes such as towns and cities. Therefore, there are many ways to define an urban extent. One approach is to define it as a continuous built-up area while alternatively, it can be defined based on an economic criteria placing emphasis on relations between places of work and residence (Roca et al. 2004). However, the former definition is generally practiced when used with RS tools. Population density is yet another way to define an urban extent (Bhatta 2010). An urban growth rate can also be generally defined as the total increase in developed land with time. Urban growth can also be defined as the change in the spatial structure of the city over time (Bhatta 2010). In this thesis, I am adopting the definition of urban as the “impervious area/built-up area” land cover category (Bhatta 2010). Further, urban growth dynamics then refers to the spatial and temporal changes of urban built-up areas.

2.2.2. Data and tools for assessing urban growth dynamics

Socio-economic and census data are good data sources in urbanization studies (Henderson 2003; Pumain 2004; Chen et al. 2014). Population is often the main parameter used as a proxy to measure urban growth with urban growth assessed by the population change and/or population density change over time. However in many less-developed and developing nations, such data is frequently unavailable at the required spatial and temporal resolutions for modelling urban growth patterns (e.g. Masek et al. 2000). In such situations, RS data can be a dependable alternative, providing data at multiple spatial and temporal scales. Satellite data is more suited for extracting urban areas because of its high visit rates and also the wealth of archived data. RS can readily provide spatio-temporal information for urbanization processes when compared to e.g. census data. Satellite-based RS data with various spatio-temporal resolutions have been applied to investigate urban growth patterns and urbanization impact on natural systems (Ma et al. 2012). Of particular note is the Landsat satellite data which has been extensively used to analyze urban growth and patterns across the globe, and also for urban land-use and land-cover change analysis (Masek et al. 2000; Seto et al. 2002; Bhatta 2010). Land-use and land-cover (LULC) information as delineated from satellite data has proven to be extremely useful for planning and in devising strategies for sustainable urban growth and environment (Seto et al. 2002). One such comprehensive LULC dataset is CORINE (Co-ordination of Information on the Environment) developed using RS satellite products and aerial photographs for specific years (1990, 2000, 2006, 2012 and 2018) and which cover around 44 land cover categories (Manakos and Braun 2014; Pacheco and Gutiérrez 2013). The coverage is for the European territory with the data being available in terms of land use polygons. The spatial resolution is referred to terms of a minimum mapping unit of

25 ha, i.e. LULC categories having an area of minimum 25 ha will be mapped. Spatial patterns of land cover changes for metropolitan cities worldwide have also been assessed using fine and medium resolution (spatial) RS data, e.g. the Moderate Resolution Imaging Spectroradiometer (MODIS) with a resolution of 500 m (i.e. similar to CORINE) and which were used to produce maps of urban regions at global scale (Schneider et al. 2009; 2010). These global urban footprint maps are used to refine land surface characteristics for urban areas by identifying the core downtown urban areas and differentiating them from the low density residential areas. Further, these developed maps were used to identify “hotspots” in rapidly developing metropolitan areas based on temporal land cover changes. Yet another reported approach by Deng et al. (2009) is to integrate historical high spatial-resolution SPOT images (10 m spatial resolution) and spatial metrics (e.g., number of patches, patch density, edge density and Shannon’s diversity index). The spatio-temporal dynamics and evolution of land use change and landscape pattern in response to the rapid urbanization process in Hangzhou city, China from 1996 to 2006 were explored.

A widely used source of RS data is the Defense Meteorological Satellite Program (DMSP) OLS Night-Time Light (NTL) data. The NTL data (e.g. Figure 2-4 for U.S) has been widely used to monitor urbanization at global and regional level (Liu et al. 2012; Elvidge et al. 2014; Ma et al. 2015; Small et al. 2005; Ma et al. 2012; Zhang and Seto 2013). The major advantage of using NTL data is that it captures information directly related to anthropogenic activity and the data is available yearly from 1992 to 2013. Thus urban growth patterns extracted from NTL data analysis are shown to be strongly correlated with socio-economic attributes such as GDP, population and power consumption (Ma et al. 2012; Chand et al. 2009; Sutton et al. 2001; Xie and Weng 2016;

Wu et al. 2013), making it a good proxy to model urbanization. A recent development is the launch of the Suomi National Polar-orbiting Partnership (Suomi-NPP) satellite in October 2011 with its Visible Infrared Imaging Radiometer Suite (VIIRS) sensor that has a day-night band (DNB). This provided a better spatial and spectral resolution compared to NTL data. A study by Jing et al. (2015) compared the results of total night light derived from NTL data and DNB data and concluded that the parameters from DNB data had better correlation with socio-economic indicators than that of NTL data. However temporal analysis cannot be performed for long time scales (e.g. decadal) since the Suomi-NPP satellite was launched much more recently when compared to DMSP satellites.

Figure 2-4 Night-time lights of the U.S.A; year 2012 (Source: NOAA)

The extraction and mapping of urban extent from the NTL raw imagery is also a key processing step. Here, researchers have developed threshold techniques to generate urban extent maps from NTL imagery at different spatial levels (Imhoff et al. 1997; Sutton et al. 2001; Henderson et al. 2003). However, a major issue of under or over estimation in extent mapping arises when using a single calibrated threshold. Due to this, it is now accepted that no single empirical brightness threshold is universally applicable for

mapping urban boundaries from NTL imagery (Small et al. 2005; Small et al. 2011). A cluster based approach was recently developed by Zhou et al. (2015) in order to reduce the constraints from general thresholding approaches. In this approach, an optimal threshold for each cluster is derived based on the cluster size and overall-night-light magnitude in each cluster. A global urban map was then generated using this cluster-based method. However, even these single optimal threshold techniques at cluster level have some drawbacks, e.g. they fail to capture different degrees of anthropogenic activity at a local or regional scale. Machine learning approaches were also applied to delineate the urban extent from NTL data. One such approach by Jing et al. (2015) compared four classification algorithms mainly: the classification and regression tree (CART), k-nearest-neighbors (k-NN), support vector machine (SVM), and random forests (RF) for extracting urban extents from NTL data. Among the four classifiers, RF achieved the most stable results. One critical aspect of using such machine learning methods is the selection of training samples. In Jing et al. (2015), training samples for potential urban pixels were defined with NTL DN greater than 40, i.e. the less-bright areas around the urban cores were ignored which led to the underestimation of urban areas. Another recent study by Goldblatt et al. (2018) also incorporated this idea of “highly lit” NTL pixels derived based on thresholds expressed as a percentile value to successfully train a RF classifier for regions in India, Mexico and the U.S. Hence such machine learning classification methods might not use the full radiometric range of NTL from 0 to 63 but rather depended on setting a threshold to quantify the urban extent. To overcome this, Ma et al. (2015) proposed a brightness gradient approach to better understand the spatio-temporal dynamics of urban growth process from NTL brightness at local scale. This approach utilizes the full NTL radiometric range, partitioning the NTL imagery into different urban categories which are

potentially linked with anthropogenic activity and urbanization level at local scale. The major limitations of using NTL data are - firstly, it is available at a very coarse geospatial resolution (1 km²). Secondly, due to the low radiometric resolution, there is saturation effect observed at core city centers. Thirdly, they tend to extend into neighboring areas called the blooming effect. (Small et al., 2005; Elvidge et al. 2014).

It is also accepted that there is no globally accepted single method to extract urban areas from RS data though with improvements in technologies, the process of urban area extraction is becoming more robust. Since cities are complex systems, analyzing urban growth dynamics from a RS and GIS perspective alone would likely be insufficient to understand the interdependencies within the urban systems. This would then only provide a partial picture of the spatio-temporal patterns of the urban growth. However, urban growth is also associated with socio-economic indicators which also drive the process of urbanization. In the Chapter 2.3, past studies on these linkages or interdependencies between urban growth and socio-economic indicators are reviewed.

2.3. Linkages between urban growth and socio-economic indicators

The urbanization process is directly linked to the shift in population from rural areas to cities. Hence over time, urban growth or transition is also correlated to economic development and as such measures of economic development can be used as indicator to assess urbanization.

It is widely observed that developed nations have higher urbanization levels along with higher GDP per capita as based on historical statistics. Studies have shown that urbanization level is correlated with population and GDP (Henderson 2003; Chen et al. 2014; Bettencourt and Lobo 2016). Over the past few decades, urbanization is rapidly

increasing globally, especially in the developing world. Economic growth tends to boost industrialization and urban population increase, which implies that to some significant extent, urbanization also boosts the economy (Chen et al. 2014).

Studies have been reported at global and regional scales to assess the linkages between urban growth and various socio-economic indicators such as population, GDP and electric power consumption. Pumain (2004) has shown that interdependencies could be examined through co-relationships amongst cities' population size, imperviousness surface extents, economic activity level, income level and transportation. However it is also observed that the form urbanization takes strongly affects the productivity growth (Henderson 2003). Bettencourt (2013) proposed a theoretical framework to predict the social, spatial and infrastructure properties of cities via scaling relationships that can be applied across urban systems. Figure 2-5(a) shows such a scaling relationship between total volume of roads (road-miles) in 415 U.S metropolitan areas and population while Figure 2-5(b) shows a scaling relationship between GDP and population. This study has further shown that urban infrastructure volume scales faster with population for most cities, i.e. the scaling laws indicate a positive super-linear effect.

Figure 2-5 (a) Scaling of urban infrastructure (road miles) and population (b) Scaling of socio-economic output (GDP) and population (Source: Bettencourt 2013)

A study for China on the long term spatial, temporal and causal relationships amongst urban growth, economic growth and electric power consumption between 1980 and 2012 is reported by Zhao and Wang (2015). Urbanization level in this study was defined as the ratio of urban population w.r.t. total population. Annual socio-economic data was collected from China Statistical Yearbooks. As shown in Figure 2-6, urbanization, GDP and energy consumption were found to have strong correlations amongst each other for China between 1980 and 2012. Other studies have quantified urbanization dynamics not only as a change in urban population relative to total population, but also through other sources of data. For example, Masek et al. (2000) used Landsat data to generate urban growth maps for Washington D.C area between 1973 and 1996. This study indicated that Washington metropolitan area has increased by ~500 sq.km between 1973 and 1996. A correlation analysis between the change in population and urban growth was performed, finding a strong correlation for Washington D.C during those 23 years. Other researchers have used remotely sensed NTL data to extract urbanization dynamics at global and regional scales and also assessed correlations between the urban growth w.r.t socio-economic indicators (see e.g. Zhang and Seto 2011; Liu et al. 2012; Ma et al. 2012; Pandey et al. 2013; Wu et al. 2013; Elvidge et al. 2014).

Zhang and Seto (2011) conducted a global analysis covering 195 countries and compared the normalized difference between NTL sum of lights and population between 1992 and 2008. Their study showed a strong positive linear relationship between urban population change and NTL derived urban growth. However, this study also suggested that NTL derived urban growth dynamics cannot be based on a single variable i.e., population. Rather it can be a proxy for a combination of urban population, economy and also urban land use and land cover (Zhang and Seto 2011). Elvidge et al. (2014)

performed similar analysis using NTL data at country level to assess relationships amongst NTL and population and GDP at national scales for all countries globally over 1992 to 2012. They concluded that increase in population and economy were the major factors that contributed to expansion of night-time lights. The study also indicated that the expansion of lighting within the two decades is a sign of the expansion of built-up infrastructure as caused by the expansion of population growth and economic activity.

Another global study by Chen et al. (2014) was aimed at understanding the relationship between urbanization and economic growth for about a 30 year span over 1980 to 2011. This study primarily used urbanization level data and per capita GDP data from the World Bank online database for about 226 nations and regions globally (annual data from 1960).

Figure 2-6 Fitted curves of urbanization, GDP and energy consumption (Source: Zhao and Wang 2015)

Figure 2-7 as reproduced from Chen et al. (2014) shows that most developed nations such as in North America, Europe and Australia have remained at a relatively high

urbanization level over the 30 years while the developing nations are at lower levels. It also shows that the mainly developing nations located in Africa and Southeast Asia have major urban growth within that time span. Figure 2-8 also from Chen et al. (2014) shows that for both years 1980 and 2011, urbanization level and per capita GDP show positive correlation. This study emphasized that urbanization process in developing nations is increasing much more rapidly as compared to developed nations and related to GDP.

Figure 2-7 Global patterns of urbanization level changes between 1980 and 2011
(Source: Chen et al. 2014)

Apart from the major studies performed at global and national scales, some studies though more limited were also performed at regional scales on the relationships between NTL derived urban growth and socio-economic indicators (e.g. Liu et al. 2012; Ma et al.

2012; Pandey et al. 2013). The study by Ma et al. (2012) used 287 cities in China to analyze for relationships between temporal NTL brightness values and urbanization variables consisting primarily of built-up area, population, per capita GDP and electric power over 1994 - 2009. As shown in Figure 2-9, for results between 1994 and 2008, these socio-economic variables show various temporal patterns for all the 287 cities collectively. The study also reported that urban population and built-up area show a significant linear correlation via an NTL derived weighted urban light area, while urban GDP and electric power consumption show a significant exponential relationship. The authors have further tested these relationships at individual city level and found that about 93% of the studied cities show positive correlation between urban population and the weighted night-time light area. Whilst 96% of the cities show strong positive correlation for the GDP, and 87% show strong positive correlation for electric power consumption. This study by Ma et al. (2012) verified the usage of NTL data for estimating strong trends in urbanization indicators mainly population, GDP, built-up area and electric power consumption for most cities in China during 1994–2009.

Figure 2-8 Correlation plot between Urbanization level and per capita GDP (a) 1980 (b) 2011 (Source: Chen et al. 2014)

Figure 2-9 Statistical relationships between weighted NTL area and four urbanization variables: GDP, built-up area, population and electric power consumption (Source: Ma et al. 2012)

Chand et al. (2009) analyzed the spatial characteristics of electric power consumption patterns in India using NTL data. The extracted information on the changes of light scenarios across India were integrated with demographic data to study the urban growth dynamics for major Indian cities and states during 1993 and 2002. This analysis showed a positive correlation (coefficient of determination R^2 of 0.59 and 0.56) between increase in night-time lights with that in population and in electric power consumption. The study also envisaged that major cities have shown a rise in night-time light intensities along the city peripheries which were an indication of increasing electric power consumption patterns. However, a reduction in night-time lights were also observed in certain provinces in India which were attributed to poverty and reduced economic growth.

Most studies that reported to the dynamics of urbanization are for the regions of U.S, Europe, China and India (e.g. Herold et al. 2003; Batty 2007; Catalán et al. 2008; Luo and Wei 2009; Chand et al. 2009; Liu et al. 2012; Pandey et al. 2013; Cauwels et al. 2014) with very few studies for SEA. However the cause-effect relationship with various socio-

economics and infrastructure factors is much less reported (e.g. with transport as noted in Baum-Snow (2007) or Maparu and Mazumder (2017)). Also, most of the studies were carried out at global or national scales with one possible reason being the lack of availability of high resolution (e.g. at city scale) socio-economic data. Hence many researchers have used NTL data as a proxy for socio-economic data to understand the urban growth dynamics. However, there are very few such studies reported for SEA. As SEA is rapidly urbanizing over the past 30 years, it would be important to analyze major SEA cities and understand these urbanization patterns.

2.4. Urban growth predication models

Urban growth prediction can be performed either at global or regional scales, as partially dependent on the level of data availability. However, growth prediction at national scales (covering large areas or even for whole country) always have higher band of uncertainty. This because cities as contained within national boundaries are complex systems and the accuracy of growth prediction can only be achieved when the intra-urban growth indicators are analyzed.

Urban growth predication models (UGPM) are mainly applied to understand the complex, intrinsic growth relationships in space and time such as that for cities. The first growth models for urban land use and transportation were developed in 1960's and based on the assumption that urban patterns are the result of the changes in equilibrium within the city system (Batty 2007). However, UGPMs also need to consider the spatial and temporal dependence. The spatial complexity reflects the impact of varied bio-physical and socio-economic indicators which make the urban system complex and the temporal complexity further reflects that for a rapidly transforming urban environment, only short

term predictions can be made (Cheng 2003). Thus the most general algorithm for urban growth prediction need to take into account two main processes i.e., spatial autocorrelation and spatial heterogeneity (Triantakostas and Mountrakis 2012). Spatial autocorrelation refers to the interrelationship between variables that follow the rule that objects near to each other are more related than to distant. Spatial heterogeneity in urban environment refers to the varied spatial distribution of urban growth as driven by underlying socio-economic and bio-physical variables. Temporal modelling process is much more difficult and complex than modelling static patterns as it needs to take in account the dynamic interactions in space and time. It is reported that the methods currently available are capable of only modelling and interpreting parts of spatial and temporal processes on different scales, however many factors especially those dealing with complex dynamics have not been incorporated (Cheng 2003).

The most common UGPMs are linear/logistic regression, agent based models and CA models. Linear/logistic regression analysis assesses the interdependencies among urban areas (land-use) and respective independent parameters. A study by Cheng and Masser (2003) presented an analysis framework to assess and model major factors of urban growth for Wuhan City, China between 1993 and 2000. This framework incorporated a spatial data analysis along with spatial logistic regression. The spatial data analysis allows a visual exploration of the impact (spatial) of each variable while the logistic regression provides an approach to identify and deduce relationships between the variables. This study also postulated that the major factors of urban growth are urban road infrastructure and developed urban core areas (containing high level anthropogenic activity) and concluded that such linkages should be further modelled using CA to explore the dynamic process.

While linear/logistic regression models incorporating socio-economic and other relevant variables (bio-physical and environmental) have been extensively applied in urbanization modelling studies, they may not capture the non-linearity of the linkages across the (in)dependent variables (Triantakoustantis and Mountrakis 2012). In comparison, agent based models can model the interaction between “agents”. In urban growth model context, “agents” represent individual autonomous urban units or variables which share information with other units under an interactive communication. Agents can also be introduced to capture the roles of local authorities and community to reflect socio-economic and political factors (Tian et al. 2011). An agent based approach can be better at explaining what happens within a cell but is very sensitive to the initial conditions and interaction rules of the agents (Triantakoustantis and Mountrakis 2012). However, this limitation is overcome by the use of CA modelling.

CA technique was first introduced in 1940 and has been applied since in numerous studies on UGPM (Santé et al. 2010). A review paper on UGPM by Triantakoustantis and Mountrakis (2012) reported that out of 156 manuscripts on urban growth prediction by different researchers, almost 83% used the CA model. The basis of CA models are cells within a two-dimensional defined neighborhood with every cell interacting with its neighboring cells. The state of each cell depends on its earlier state and also its neighbors’ states, and the state transform according to a defined transition criteria (Santé et al. 2010). CA models for urban growth simulation can be classified into two categories. The first are for theoretical model development while the second are for real data application. The former was introduced in earlier years where artificial prototype examples were considered for developing the theoretical models (Itami 1994; Li and Yeh 2000). Since then many researchers have applied the models along with GIS capabilities to real data at

regional and city levels to better understand and predict urban growth for various applications (e.g. Allen and Lu 2003; Herold et al. 2003; Herold et al. 2005; Almeida et al. 2008; Al-shalabi et al. 2013; Bihamta et al. 2015; Ahmed and Bramley 2015; Feng et al. 2015).

The SLEUTH (slope, landuse, exclusion, urban extent, transportation and hillshade) is an example of a very commonly used UGPM based on CA. The SLEUTH model was first implemented to San Francisco Bay area (Clarke and Gaydos 1998). Many studies since have used SLEUTH to predict urban growth at regional scale (e.g. Clarke and Gaydos 1998; Herold et al. 2003; Herold et al. 2005; Al-shalabi et al. 2013; Bihamta et al. 2015). The growth rules in the SLEUTH model are applied cell by cell uniformly throughout the geographical lattice. The dataset needed is the urban extent at the initial time period along with a set of growth parameters/rules. In SLEUTH, the initial condition is the starting ‘seed’ layer, growth occurs one cell at a time with each cell acting independently of all others, and patterns then emerge during growth as the organism ‘learns’ more about its environment” (Clarke and Gaydos 1998). The general structure of a classical SLEUTH model is shown in Figure 2-10. It requires the following datasets to predict the urban growth: historical urban extent maps, digital elevation model, road networks and an exclusion layer. The exclusion layer indicates where urban growth cannot take place. However, SLEUTH model does not take into consideration various political, social and economic factors that also affect the urban growth prediction (Bihamta et al. 2015). A study by Jantz et al. (2004) used SLEUTH model for the Baltimore - Washington metropolitan area of the U.S to simulate the impacts of future policy scenarios on urban land use dynamics. In this research, SLEUTH model was highlighted and demonstrated as a planning tool where the potential land-use change

results developed from the model has been showcased for raising public awareness and facilitating discussions. Lastly, reports about this research were published in media sources (e.g. the Washington Post newspaper) and also displayed on the Chesapeake Bay Foundation website.

Figure 2-10 General structure of a SLEUTH model (Source: Al-shalabi et al. 2013)

Many CA based UGPM's were applied to U.S cities due to the good availability of high resolution spatial data there. However, due to spatial heterogeneity and complexity, different zones of the cities should ideally be addressed with different transition rules, i.e., the transition rules in CA should not be used globally to the cellular space (Triantakoustantis and Mountrakis 2012). Also, one of the disadvantages of CA is its inability to handle stochastic behavior.

Logistic regression model integrated with CA based transition rules has also been developed. Allen and Lu (2003) developed a GIS based integrated approach to predict urban growth as a proxy for land use change using a binomial logistic framework coupled with CA rule-based suitability module and with focus group input. This model was applied to predict urban growth in the Charleston region of South Carolina, U.S for the year 2030, as simulated using different growth scenarios developed based on population growth estimates. The results of this logistic model are reported to be statistically more reliable for short term predictions.

2.5. Urbanization in Southeast Asia

Currently, the world's fastest growing cities are concentrated in the Global South, i.e. Africa, Latin America, Asia and the Middle East (UNPD 2018). In particular, Asia and SEA are home to sprawling megacities such as Tokyo, Bangkok, Jakarta, and Manila, with population exceeding 10 million (UNPD 2018). Global studies on urbanization have indicated that many regions in SEA have been rapidly urbanizing over the past 30 years. SEA region is steadily urbanizing today with about 245 million people living in urban areas, this being around 42% of the total population. It is also predicted that SEA urban population will increase to 47% of the total population by 2025 (Aritenang 2014). The SEA region further possesses a wide range of urbanization levels where the most economically advanced countries (e.g. Singapore and Malaysia) have urbanization levels above 65%. Whilst the least developed countries (e.g. Cambodia, Myanmar and Vietnam) have less than 34% (Aritenang 2014). Southeast Asian cities are also different than cities in U.S, China, and India as most of them are coastal cities having long coastlines, and some are even island cities. It is also reported that the low elevation urban coastal zones represent around 29.4% of the total urban land area of the SEA region which inhabits

around 36% of the total SEA urban population (Aritenang 2014). Due to this geographic landscape, the urban processes evolving within SEA would likely be different from inland cities of U.S, Europe, China or India.

Most studies on urbanization dynamics are for the regions of U.S, Europe, India and China (e.g. Herold et al. 2003; Batty 2007; Catalán et al. 2008; Luo and Wei 2009; Liu et al. 2012; Pandey et al. 2013; Cauwels et al. 2014) with very few studies reported for SEA. The few global studies that included SEA provide only a snapshot of SEA's urban extent at a particular time (Small et al. 2005; Schneider et al. 2009; Schneider et al. 2010; Zhou et al. 2015). For example, Schneider et al. (2015) characterized the urban change in more than 1000 cities across East Asia which includes SEA by analyzing MODIS data for two years of 2000 and 2010. Small and Elvidge (2013) developed a study on mapping decadal changes in anthropogenic night light in Asia. This study has shown that at a critical brightness threshold, India and China together experienced a ~ 270% increase in night-time lighted area while SEA experienced a ~80% increase between 1992 and 2009. This study also indicated that growth trajectory in SEA was different from that of India and China, because of the greater number of light clusters found in SEA. The reason is because SEA had a large number of smaller isolated light clusters located on the coastlines and islands unlike the more clustered inland light areas in India and China.

The literature to date indicates that a more comprehensive spatiotemporal characterization of urban growth in SEA cities is still lacking. Also, spatio-temporal dynamics as linking to anthropogenic activity and urbanization level at local scale (e.g. intra-city) for major SEA cities is not yet explored. This PhD work therefore explores and assesses the urbanization process of major SEA cities to better understand urban area growth and their relations with socio-economic indicators and infrastructure.

2.6. Summary – Problem identification

Based on the review of reported works in this Chapter, there is a continuing need to assess the spatio-temporal urban area growth and evolution of SEA cities and their linkages with road infrastructure and socio-economic indicators. It is also evident that there is no globally accepted methodology for assessing urban area growth and such linkages. There is also not one clear approach for the quantification of urban extent at city and intra - city levels, and scaling laws between urban area growth and socio-economic indicators at these scales. There is also a research need to understand interdependencies between infrastructures (e.g. road network) and urban area growth and also their patterns with socio-economic indicators such as population and GDP.

Considering that SEA cities have been least explored in assessing urban area growth patterns at local scale, this research study takes a first step in quantifying the spatio-temporal urban area growth patterns for major SEA cities using open-source datasets available. One major limitation for SEA is the non-availability of high resolution spatio-temporal in terms of urban datasets (e.g. land cover datasets similar to CORINE), road infrastructure (traffic volume, capacity and travel cost data) and socio-economic datasets. To overcome this limitation and to address a subset of the major problems for major SEA cities as identified in this Chapter, this work has made use of openly available datasets mainly, specifically Night-time light data (1992-2012), Landsat data (1987, 2017), Open Street Map road network data (2017), GPWv4 population datasets (2000,2015) and global GDP gridded dataset (2000, 2020).

Towards addressing the research gaps as identified above, a multi-scale approach is conducted in this PhD study to model and analyze urban area growth in SEA cities. Specifically:

1. Firstly, a macro scale analysis is developed to assess spatio-temporal urban area growth trends using NTL RS data. These spatio-temporal trends were analyzed to establish linkages between urban area growth and socio-economic indicators such as population.
2. The next level is a micro-scale analysis performed at intra-city level. Here, a grid based approach is developed to identify and deduce linkages between urban area growth and socio-economic indicators of population, GDP and road network.
3. Lastly, the SLEUTH - CA model was used to develop a future urban area growth prediction for Bangkok city where the derived urban footprints were analyzed w.r.t. city's road infrastructure, socio-economic patterns and also Bangkok's comprehensive development plans.

3. Data and methodology

3.1. Data used

The needed data gathered for the PhD research study is described in this Chapter 3.1. Their salient features would indicate on the suitability of the data. All the datasets described here are further elaborated in their respective Chapters where the data is used.

3.1.1. Data for spatio-temporal urban extent characterization and delineation:

Night-time lights (NTL): NTL data is available as annual composite from 1992 to 2012. The spatial resolution of NTL dataset is approximately 1 km by 1 km. As NTL data is directly linked to the anthropogenic activity, it is found useful for urbanization studies. Its long temporal data availability (1992 to 2012) also makes it suitable to analyze the changes and developments at city level over time. However, sometimes, pixel saturation could lead to over or under estimate in the derived urban extents. Generally, it over estimates the urban extents for small island cities and also small coastal cities. Also due to the lack of an on-board sensor calibration, NTL data needs to be calibrated in order to perform temporal analysis of urban extents.

Urban categorical extents were derived from NTL data for 15 major SEA cities as described later in Chapter 4. These NTL datasets for the years 1992-2012 have been acquired by six different satellite missions namely DMSP F10, F12, F14, F15, F16 and F18 as highlighted in Table 3-1. The calibration techniques across sensors are also described in Chapter 4.3.1.

Table 3-1 DMSP-OLS NTL stable lights annual composites data from 1992 to 2012, satellite and respective sensors shown in columns

Average Visible, Stable Lights, & Cloud Free Coverages						
Year\Sat.	F10	F12	F14	F15	F16	F18
1992	F101992	-	-	-	-	-
1993	F101993	-	-	-	-	-
1994	F101994	F121994	-	-	-	-
1995	-	F121995	-	-	-	-
1996	-	F121996	-	-	-	-
1997	-	F121997	F141997	-	-	-
1998	-	F121998	F141998	-	-	-
1999	-	F121999	F141999	-	-	-
2000	-	-	F142000	F152000	-	-
2001	-	-	F142001	F152001	-	-
2002	-	-	F142002	F152002	-	-
2003	-	-	F142003	F152003	-	-
2004	-	-	-	F152004	F162004	-
2005	-	-	-	F152005	F162005	-
2006	-	-	-	F152006	F162006	-
2007	-	-	-	F152007	F162007	-
2008	-	-	-	-	F162008	-
2009	-	-	-	-	F162009	-
2010	-	-	-	-	-	F182010
2011	-	-	-	-	-	F182011
2012	-	-	-	-	-	F182012

Landsat: The Landsat Thematic Mapper (TM) dataset has a spatial resolution of 30 m by 30 m. This optical RS data has 7 bands (6 in visible spectrum and 1 thermal band). Landsat TM 4 and 5 data available from 1982 to 2012 from the USGS earth explorer website (<http://earthexplorer.usgs.gov/>). Cloud cover can hinder the quality of the image by masking the information. Here, selected Landsat datasets had less than 10% cloud cover. In order to extract urban land cover class from this dataset, a supervised classification technique has been applied as described later in Chapter 5.3.1.

Landsat data was used in three phases, initially for comparison with NTL derived urban categories, then for inter and intra-city spatio-temporal urban growth analysis and finally for SLEUTH urban growth prediction model. Landsat data was mainly used to extract land cover categories for built-up area quantification. For comparison with the NTL analysis, Landsat data for two years of 1994 and 2008 were used. For inter and intra-city level analysis temporal Landsat data over two years of 1987 and 2017 (~ 30 year apart) was used. Lastly the SLEUTH model incorporated Landsat data for four years of 1987, 1997, 2007 and 2017 for the respective SEA cities.

3.1.2. Socio-economic data:

Population data: The Socioeconomic Data and Applications Center (SEDAC) at the Columbia University, U.S has in December, 2018 released a gridded population of the world data (GPW) version 4.0, which has a raster grid of 30 arc-second spatial resolution (approximately 1 km by 1 km). This dataset contains gridded population count and population density, as well as the corresponding U.N adjusted values, for years 2000, 2005, 2010, 2015 and 2020. The gridded data was developed by taking population input data (non-spatial tabular global population count data per administrative area and spatial

administrative boundary) from the 2010 census (data between 2005 and 2014). This raw input data was collected from various national statistics offices and organizations. This population data at administrative level resolution was re-distributed to a uniform 1 km by 1 km grid using an areal-weighting method. Population count is allocated to each cell as a function of land area within the cell (Doxsey-Whitfield et al. 2015). Here, we used the UN adjusted GPWv4 population density datasets for two years of 2000 and 2015. For example, Figure 3-1 shows the gridded population count data of Singapore and Johor area (highlighted in red boundary).

Figure 3-1 Gridded population (GPWv4.0) data for the year 2000 for Singapore and Johor area (red boundary)

Gross domestic product (GDP): The gridded global dataset of GDP developed by the Center for Global Environmental Research (CGER), Japan (Murakami and Yamagata, 2016) was used to extract GDP values. This 0.5° (~55 km at the equator) spatial resolution

dataset consists of historical values for the years 1980 – 2010 (at 10-year intervals), and projections for years 2020 – 2100 under three Shared Socio-economic Pathways (SSP1, SSP2 and SSP3) scenarios. Since, the GDP gridded data were available only for every 10 years, we used the GDP values for years 2000 and 2020 under SSP1. The SSP1 scenario was selected as SSP1 represented progress towards sustainability. For example, Figure 3-2 shows the Singapore GDP grid value (1980-2100) extracted from the GDP gridded data under the SSP1 scenario.

Figure 3-2 Singapore grid value of GDP (billion USD/year) graph for IPCC - SSP1 scenario.

All datasets described in this Chapter were converted and projected to the same coordinate system and were extracted for each SEA city w.r.t. to their administrative boundaries. These administrative boundaries were taken from the global administrative areas database (website - www.gadm.org)

3.1.3. Geographic data:

Road infrastructure: Open Street Map (OSM) road network vector data for the year 2017 were obtained from <http://download.geofabrik.de> licensed under www.openstreetmap.org. The road network data covers most of the major cities in SEA and is in GIS vector shapefile format. This data was used in this research to analyze the relationships between road network density, urban growth and population growth. A vector GIS shapefile of the road network of a sub-section of e.g. Kuala Lumpur city is shown in Figure 4-3.

Figure 3-3 Road network map of northeast sub-section of Kuala Lumpur city obtained from OSM data (map not drawn to scale)

Digital Elevation Model (DEM): The Global Shuttle Radar Topographic Mission (SRTM) Digital Elevation Model (DEM) data is available at 30 m by 30 m spatial resolution. This study incorporated the DEM for Bangkok city for SLEUTH model calibration and urban growth prediction. Parameters such as slope and hillshade were also extracted from the DEM.

3.2. Methodology overview

As discussed in Chapter 2 on literature review, urban area growth is not only linked to spatio-temporal extent changes but also to the socio-economic conditions. Thus, urban growth analysis at city scale should also be analyzed in tandem with the socio-economic parameters which form the major factors for the growth of a city and its infrastructure. The major goal of the thesis is to assess the growth and evolution of cities for major SEA cities. A framework is developed as shown in Figure 3-4. The proposed framework has multi-levels of analysis, firstly at a city level (macro), then an intra-city level (micro).

To address the research objective regarding analyzing and quantifying spatio-temporal urban growth dynamics, an urban extent mapping using NTL was performed at city level for 15 major SEA cities from 1992 to 2012 as presented in detail in Chapter 4. In this macro – scale study, the yearly NTL derived urban extent maps for each studied city were further categorized into three intra-urban categories (countryside, peri-urban and core-urban). The spatio-temporal dynamics of the three categories for the cities were analyzed and also compared with Landsat derived urban extent maps. Correlations between NTL derived data and populations at city scale were assessed and inter-city comparisons performed.

At the micro – scale, urban growth dynamics were analyzed in relation with socio-economic data and road infrastructure. A key objective is whether relationships amongst urban area growth, socio-economic indicators and road infrastructure exist for SEA cities. As discussed in Chapter 2, many studies have shown such relationships between urban area growth and socio-economic indicators such as population, GDP and transport infrastructure are not valid globally and can behave differently within an intra-city scale. Further, for the analysis at micro-scale (intra-city), it is expected that information from NTL would not be effective because of its low spatial resolution. Hence, this study used a grid based analysis at intra-city level to identify and deduce linkages between urban area growth, road infrastructure and socio-economic indicators of population and GDP. This analysis was performed over a 30 year time change period using two years of 1987 and 2017. Urban extents at the city level for 9 major SEA cities (population greater than 2 million in 2015) were derived from higher spatial resolution Landsat satellite data (30 m by 30 m resolution) for these two years.

Lastly, considering Bangkok as a case study, an urban growth prediction model (SLEUTH – cellular automata) was developed using the same 30 year temporal datasets to identify the future (till year 2027) urban scenarios and correlate the projected urban expansion patterns w.r.t. the linkages identified.

Figure 3-4 Conceptual urban growth modelling approach covering (I) inter-city level analysis with NTL RS data (Chapter 4); (II) intra-city grid level analysis using Landsat RS data and linkages with population, GDP and road density (Chapter 5); and (III) future urban growth prediction model using Bangkok (Chapter 6)

4. Assessing urban growth dynamics of major Southeast Asian cities using Night-Time Light data

4.1. Introduction and overview

Spatio-temporal dynamics as linking to the anthropogenic activity and urbanization level at macro scale for major SEA cities is not yet explored as discussed in Chapter 2.6. This gap is addressed here by characterizing the growth patterns of major SEA cities at city level using yearly NTL imagery from 1992 to 2012. Urban growth dynamics for 15 major SEA cities were investigated using remotely sensed NTL data from 1992 to 2012. Specifically for each city, NTL data was categorized for each year as countryside (CS), peri-urban (PU) and core-urban (CU) categories, and trends quantified for each category. The thresholds employed for above classification were obtained using a recently proposed Brightness Gradient (BG) approach (Ma et al. 2015). This approach partitions the NTL imagery into different urban categories (CS, PU and CU categories considered here) which are potentially linked with anthropogenic activity and urbanization level. These urban categories would be different for different cities as directly dependent on the urban size and also development level. This could provide insights into the anthropogenic activity level and urban growth. The high urban category derived from the NTL data would generally represent the urban core of the city and the medium would represent the periphery where the city would tend to expand. Lastly, this study further assessed the sensitivity of extracted urban categories to three recently proposed inter-sensor calibration methodologies as the raw NTL data varies significantly with sensor and over time. Chapter 4.2 provides a description of the data, the cities chosen, the BG approach,

and the three calibration techniques. The results are presented in Chapter 4.3 followed by concluding remarks in Chapter 4.4.

4.2. NTL data processing

It is well-known that the non-availability of on-board sensor calibration limits the usage of the raw NTL data for urban growth studies (Elvidge et al. 2009; Zhang and Seto 2011; Elvidge et al. 2014). Sensor degradation, difference in sensor orbits and average annual composites can give different magnitude of lit pixels on the ground even when there is no actual change detected (Zhang and Seto 2011). As shown in Table 3-1, it is seen that for few years (1994, 1997 to 2007), there are two different satellites providing the data for the respective year. These inter-sensor differences then need to be minimized through inter-sensor calibration (Wu et al. 2013; Elvidge et al. 2009; Elvidge et al. 2014; Zhang and Seto 2013). Bridging the inter-sensor gap in NTL data has received more attention in the last few years with the increasing use of NTL for temporal analysis (e.g. in characterizing trends). Three calibration methods have been proposed since 2009 to ensure continuity in NTL data across the sensors (Elvidge et al. 2009; Wu et al. 2013; Zhang et al. 2016). Although, assessment of these approaches has been conducted at global scales, their merits and disadvantages at a regional scale (e.g. SEA region) is not completely analyzed.

The first calibration technique proposed by Elvidge et al. (2009) involves the selection of a reference area (Sicily city in Italy) that has undergone minimal changes in NTL patterns over time. A second-order polynomial is fitted as follows:

$$DN_{cal} = C_0 DN_{raw}^2 + C_1 DN_{raw} + C_2 \quad (4-1)$$

where, DN_{raw} and DN_{cal} are raw and calibrated NTL digital number (DN) data, respectively. This calibration approach has been shown to reduce the discrepancies between raw DN values captured by two different sensors in a single year. We used coefficient values from Elvidge et al. (2014) for years 1992 to 2012 here.

Zhang et al. (2016) proposed a calibration approach which also involves fitting a second-order polynomial, but with coefficients estimated using a technique called ridgeline sampling regression (RSR). In this approach, a reference image is initially selected and then the other images are corrected (as target images) to match the reference image (chosen as year 2000 global NTL image using the F15 sensor). The corresponding coefficients for the second calibration technique used here were taken from Zhang et al. (2016).

Wu et al. (2013) proposed an alternative strategy for inter-sensor calibration, which performs radiometric calibration as well as reducing errors caused by pixel saturation and inter-annual variation. This study also used a reference global night-time light product image with no sensor saturation for the year 2006 for temporal inter-sensor calibration. This approach uses the following power function to calibrate raw DN values.

$$DN_{cal} = a_1(DN_{raw} + 1)^{b_1} - 1 \quad (4-2)$$

Here coefficients a_1 and b_1 for each year from 1992 to 2010 were taken from the third calibration technique by Wu et al. (2013).

NTL data was extracted for 15 major SEA cities based on a bounding box for each city as shown in Figure 4-1. These 15 cities have been selected based on their population size exceeding 1.5 million according to 2014 year census (UNPD 2014). The bounding box coordinates and the population for each city are listed in Table 4-1. The bounding

box for each city was selected as the maximum fitting box encapsulating the 2012 year DN values.

The extracted NTL data for each city and year were calibrated separately using the three techniques mentioned above. It is noted that for Wu et al. (2013)'s approach, calibration coefficients were available over 1992-2010 (i.e., 2 years less than the NTL data used of 1992-2012), while coefficients were available over 1992-2012 for the other two approaches. Also, for years having annual composites collected by two different satellite sensors, the latest sensor data was selected in order to reduce effects of sensor degradation. For compactness of presentation, the results from the three calibration approaches is referred to as WU2013, EL2014, and ZH2016 below.

Figure 4-1 2012 year Night-Time Light (NTL) image for 15 selected SEA cities with population exceeding 1.5 million

Table 4-1 Coordinates (lat-long) of the bounding box and 2014 population for each city

City	NW corner	SE corner	Population (× 10³ people)
Bandung (BDO)	-6.76° 107.41°	-7.11° 107.88°	2,544
Bangkok (BKK)	14.26° 100.19°	13.53° 100.89°	9,270
Batam (BTH)	1.18° 103.88°	1.01° 104.14°	1,391
Davao (DVO)	7.34° 125.46°	7.00° 125.70°	1,630
Ho Chi Minh (HCM)	11.16° 106.35°	10.61° 106.96°	7,298
Hanoi (HAN)	21.36° 105.53°	20.85° 106.12°	3,629
Jakarta (JKT)	-5.92° 106.34°	-6.78° 107.28°	10,323
Kuala Lumpur (KUL)	3.42° 101.25°	2.74° 101.87°	6,837
Medan (MDN)	3.81° 98.44°	3.45° 98.88°	2,204
Makassar (MKS)	-5.00° 119.38°	-5.20° 119.56°	1,489
Manila (MNL)	14.86° 120.84°	13.91° 121.24°	12,946
Phnom Penh (PNH)	11.66° 104.75°	11.45° 104.97°	1,731
Singapore (SIN)	1.71° 103.49°	1.23° 104.04°	5,619
Surabaya (SUB)	-7.06° 112.36°	-7.72° 112.84°	2,853
Yangon (RGN)	17.02° 96.01°	16.76° 96.28°	4,802

4.2.1. Extraction of urban categories from calibrated NTL data

Capturing the pixel level fluctuations is key in detecting spatial changes in the NTL data. For this we employed the BG approach, proposed recently by Ma et al. (2015). The BG refers to the spatial gradient in NTL over a pixel w.r.t. its neighbors. By considering the spatial gradient instead of an absolute NTL value, one can delineate urban areas according to different degrees of urbanization. In this approach, a flatter spatial gradient

implies minimal NTL changes in space, which is expected either within core urban regions or in relatively rural regions. Conversely, steeper spatial gradient implies a transition zone between core urban and rural, i.e. medium urban areas.

There are alternate ways in which the spatial gradient can be computed. Here we follow Ma et al. (2015)'s approach and use the maximum gradient technique of Burrough et al. (2015). The relationship between pixel-level DN and corresponding BG is modelled using the quadratic polynomial.

$$BG = aDN^2 + bDN + c \quad (4-3)$$

The fitted polynomial is a downward parabola, which is used later to derive urban categories as shown in Figure 4-2 from Ma et al. (2015), which had five urban categories (low, medium-low, medium, medium-high and high). Here we have chosen to use three categories (low, medium, and high) as some cities in our study are relatively smaller. The midpoint between the lowest and highest BG of the rising limb of equation (4-3) is identified and the corresponding DN is chosen as lower threshold DN_1 . Similarly, DN_2 is the upper threshold that corresponds to the midpoint BG of the falling limb. Then, all pixels with DN values ranging from 3 to DN_1 were categorized as low urban, pixels with $DN_1 < DN < DN_2$ as medium, and pixels with $DN > DN_2$ as high urban. This approach involving DN thresholds which are city-specific avoids setting arbitrary thresholds for heavily urbanized areas that has large DN values. Lastly a minimum threshold of 3 is used because of high interannual variability of very low DN values also being attributed to calibration anomalies and noise (Small et al. 2011). Further, in this study, the pixels corresponding to the low urban category are referred to as countryside (CS), medium as peri-urban (PU) and high as core-urban (CU). In this work, the BG approach was applied

on the calibrated NTL data derived for all the 15 cities using the three calibration approaches.

Figure 4-2 (a) Relationship between NTL (DN) and Brightness Gradient (BG) and (b) urban category delineation (as following Ma et al. 2015)

4.2.2. Comparison of NTL urban extent with Landsat TM urban extent

The supervised maximum likelihood classification technique was applied on the Landsat TM datasets using ArcMap 10 software to extract the urban land use category or artificial surfaces. Training samples for the supervised classification were selected based on visual inspection (e.g., comparing with Google Earth imagery). The classification was validated with 100 separate ground truth points which were selected with the aid of satellite imagery for the respective years. The predicted land-cover classes from the supervised classification were then compared with the respective ground truth data. The overall classification accuracies over the years of 1994 and 2008 were high with values ranging from 76% for Ho Chi Minh to 93% for Bangkok. Later, the three urban categories extracted from BG approach are compared with the urban extent extracted from Landsat TM data.

4.3. Results and discussion

4.3.1. Evaluation of inter-sensor calibration results

The Total Light Index (TLI) is defined as the sum of all grey (i.e., non – zero) values in an NTL image, and is widely used to display and analyze interannual variability and volatility in a NTL time series (e.g. Wu et al. 2013). These TLI results in a single value for a specific year for both uncalibrated and calibrated NTL datasets. The TLI values are then used to compute the Sum of Normalized Difference Index (SNDI) (Zhang et al. (2016)) which measures the level of convergence between the TLI values of a given region over the overlapping years of sensors. In this approach, the SNDI is calculated as the sum of Normalized Difference Index (NDI) for all the overlapping year NTL images. The NDI is calculated as the ratio of the difference of the Total Light Index (TLI) between two overlapping year images w.r.t. the sum of the two corresponding overlapping year images. Thus, the lower the NDI values, the smaller is the relative gap between the two images in the same year. As such the SNDI (and NDI) is used to evaluate the performance of the calibration approaches. Figure 4-3 shows the interannual variability of TLI for the uncalibrated NTL data for the entire SEA region using sensors F10, F12, F14, F15, F16 and F18 of Table 3-1 for the year each sensor was operational. There is a clear gap in TLI where two sensors overlap in the uncalibrated NTL data. The interannual volatility within each sensor is also evident in Figure 4-3 (e.g. TLI from F15 has a sudden dip after 2002), thus illustrating the necessity of inter-sensor calibration before temporal analysis.

Figure 4-4 shows the interannual variability of TLI for the NTL data after application of the three calibration approaches described in Chapter 4.2. The gap in TLI for overlapping years has reduced considerably after calibration in all three approaches. For example, the NDI value for the year 1997 between sensors F12 and F14 (Figure 4-3) was

0.16, after inter-sensor calibration (ZH2016) the NDI value for the same year between sensors F12 and F14 (Figure 4-4) obtained was 0.01 which was reduced significantly. Even the interannual volatility for the same sensor has reduced significantly (e.g. sensor F15). It is noted that the overall TLI for each sensor derived from WU2013 are significantly larger compared to the other two approaches. This pattern is partly because of the power law used (equation (4-2)) in the calibration which can over-correct high raw DN values unlike the other two approaches involving second order polynomials. This is consistent with Wu et al. (2013) reporting that the higher TLI values might be due to the use of a non-saturated radiance-calibrated image for calibration. The results derived using EL2014 and ZH2016 follow a similar pattern for most of the sensors except F18 sensor, in which the TLI for the years 2010 and 2012 have contradictory patterns. Such patterns were reported by Zhang et al. (2016) as being attributed to sensor bias for these two years. This artefact is also reflected later during SEA urban growth analysis of Chapter 4.3.2. ZH2016 approach gives the lowest SNDI value (0.225) compared to WU2013 (0.258) and EL2014 (0.379). Hence, ZH2016 calibration approach was selected for the subsequent analysis here. Further, if data from more than one sensor is available for a particular year, data from the latest sensor was used. This reduces the discrepancy caused by sensor degradation.

Figure 4-3 TLI value calculated for 15 SEA cities using uncalibrated NTL images

Figure 4-4 Comparison of inter-calibration results for 15 SEA cities based on three different calibration approaches

4.3.2. Spatio-temporal analysis of urban categories

CS, PU and CU categories were delineated using the BG approach from the calibrated NTL annual composites for all 15 SEA cities. For illustration, the BG-DN scatterplot and corresponding fitted quadratic relationships are shown in Figure 4-5 for Bangkok and Singapore for the year 2012. The fitted polynomials are then used to obtain the DN

thresholds for defining the three urban categories of CS, PU and CU. Figure 4-6 shows the interannual variability of CS, PU and CU categories for the 15 SEA cities studied. Here the CS, PU and CU values for each city are normalized with the total areas (i.e. sum of CS, PU and CU). The CS (CU) category for all cities showed a decreasing (increasing) trend with time. In addition, the decreasing (increasing) trends in CS (CU) urban categories are stronger compared to the PU category, which is an indication of increasing urbanization, and can lead to a flattening in the PU category (e.g. seen for Bangkok, Kuala Lumpur and Singapore). Generally, all the 15 SEA cities have undergone increase in urbanization (CU and PU) over time. Bangkok, Singapore and Kuala Lumpur further have a stronger urbanization trend compared to other cities since the CU category crosses the PU and CS, i.e. forming the largest category. This rapid urbanization trend can be associated with the nature of these cities having developed larger metropolitans associated with rapid development when compared to the other SEA cities.

Figure 4-5 BG and quadratic polynomial fit vs DN values for Bangkok and Singapore, and for year 2002. The black and red vertical lines indicate the DN thresholds for CS and CU categories

Figure 4-6 Temporal change of urban categories (CS, PU and CU) for 15 SEA cities studied

4.3.3. Comparison of NTL urban extent with Landsat-TM urban extent

The urban categories extracted from the NTL data were compared with the urban land use map generated from Landsat TM data for two specific years 1994 and 2008. Landsat TM data with minimal cloud cover (<5% within the bounding box) were extracted for 11 cities and the two selected years, and supervised classification applied to extract the urban extent. Landsat TM data for Surabaya and Davao was not available for the year 2008 and for Manila and Medan, had more than 20% cloud cover for 2008. Hence these four cities were not included in this analysis reducing the number of studied cities to 11.

Figure 4-7 shows spatiotemporal comparison of Landsat TM derived urban extent with NTL derived urban categories for Bangkok and Kuala Lumpur. The NTL derived CU category is in good agreement with the Landsat TM derived urban land use map with the NTL CU region consistently enveloping the Landsat TM urban extent. The difference in area between NTL and Landsat TM is expected given the different spatial resolutions (1 km for NTL vs 30 m for Landsat TM) and that the Landsat map shows the impervious surfaces (i.e. built-up areas) as opposed to lit pixels in the NTL maps. Nevertheless, both maps clearly show the spatial evolution of the urban extent (NTL CU and PU categories) from 1994 to 2008. The decrease in CS and the increase in CU categories in the NTL maps are particularly evident as is the impervious surface from the Landsat map.

Figure 4-8 shows similar results as Figure 4-7 for two cities Singapore and Ho Chi Minh while Figures A-1, A-2 and A-3 (Appendix) show results for Bandung, Batam, Hanoi, Jakarta, Makassar, Phnom Penh and Yangon. As expected, urban extent maps from NTL images are unable to accurately capture inland water bodies such as lakes and rivers, and land–sea boundaries, especially when such feature sizes are comparable to the spatial resolution. To further examine the effect of land-sea boundaries, Figure 4-9 provides a closer view between NTL derived urban categories and Landsat TM derived land-use land-cover (LULC) classes for Singapore for year 1994. Note that the bounding box for Singapore also includes a part of southern Johor, Malaysia. As seen the urban areas of Singapore and southern Johor merges, this is because Singapore is small (approx. 700 sq.km), and the southern Johor region is influenced by Singapore’s urban growth. As such the water body, primarily the narrow Johor Straits that separates Singapore from southern Johor seen in the Landsat TM LULC map is not captured in the NTL urban categorization. While spatial resolution difference is one reason (the Johor Straits is 1.3

km at its narrowest point), another reason is saturation in the NTL imagery in the highly developed areas on both sides of the Johor Straits. This indicates that NTL derived urban extents for island cities could be affected with pixel saturation and unresolved water bodies. A similar phenomenon is also observed in Batam which is also an island city where saturation effects are seen along its coastline.

Figure 4-7 Comparison of Landsat TM urban extent with NTL derived urban categories for Bangkok and Kuala Lumpur

Figure 4-8 Comparison of Landsat TM urban extent with NTL derived urban categories for Singapore and Ho Chi Minh City

Figures 4-7 and 4-8 and Appendix Figures A-1, A-2 and A-3 readily show that NTL derived core-urban (CU) extent is in overall good agreement with the Landsat derived impervious area. Figure 4-10 further compares each city's percentage of Landsat derived impervious area (expressed as a percentage of the NTL CU area) for each city with the NTL CU extent (expressed as a percentage of the total extent CS+PU+CU) for years 1994 and 2008. It is noted that the area comprising the NTL derived CU category for cities is

larger compared to the Landsat derived urban pixels (e.g. see Figure 4-9 for Singapore), hence this influences the slope of the curves in Figure 4-10. There is a very good correlation between the Landsat derived impervious area with NTL derived CU area. Cities such as Singapore and Bangkok which have large percentages of CU area also have large percentages in their built-up impervious surfaces. Kuala Lumpur and Ho Chi Minh also significantly expanded (both in NTL and Landsat) between 1994 and 2008 when compared to other cities, an indication of their rapid development. Phnom Penh, Batam, Bandung, Makassar, Hanoi and Jakarta (except Yangon) also have expanded though to a lesser degree.

Figure 4-9 Map of NTL urban categories using calibration of Zhang et al. (2016) (left) and Landsat TM LULC classes (right) for Singapore for the year 1994

Figure 4-10 Comparison of Landsat-derived impervious area percentage for (a) 1994 and (b) 2008 with NTL derived core urban extent percentage. City abbreviations are listed in Table 4-1

4.3.4. Analysis of NTL derived urban transitions

Transition maps for each of the 11 SEA cities were constructed to assess the spatiotemporal transitions of NTL urban categories over 1994 to 2008 and shown in Figures 4-11 and 4-12. Years 1994 and 2008 were chosen to coincide with the Landsat images processed. Pixels which changed from CS in 1994 to PU in 2008 (i.e. increasing

urbanization) are denoted as “CS-PU”, and similarly for the other five transitions seen (CS-CU, PU-PU, PU-CU, CU-CU and CU-PU). There was a low number of pixels (<1% in all cities except for Jakarta and Yangon which had <5%) showing the reverse trend of going from a higher urbanization category to a lower (specifically CU-PU). These were neglected below. The NTL TLI data for Yangon in year 2008 also has an unexpected dip and this would be a reason for such a reverse trend as also seen in Figure 4-6 for Yangon where the CU shows a broad dip.

As expected, cities which already had a larger percentage CU category in 1994 (e.g., Bangkok and Singapore shown in Figure 4-11, and Jakarta shown in Figure 4-12) show large amounts of CU-CU pixels. Transition percentages calculated by normalizing the areas under a particular transition type with the total NTL derived urban area (i.e. sum of CU, PU and CU) in 1994 is tabulated in Table 4-2 for all 15 cities. It is seen that all cities have experienced significant CS-PU transitions, with values ranging from 5% for Manila to 50% for Ho Chi Minh, while Phnom Penh, Kuala Lumpur, Hanoi, Batam and Davao also having >20% transitions. Most cities have negligible CS-CU transition with the exception of Kuala Lumpur having 9.5% and Ho Chi Minh with 5.9%. The Indonesian cities of Batam, Medan and Makassar have large PU area in 1994 and remained so in 2008. This behavior could be attributed to them being smaller island/coastal cities having geographical constraints (e.g., sea and/or surrounding high terrain) for expansion. The PU-CU transition was found to be highest for Ho Chi Minh followed by Kuala Lumpur and then Bangkok.

Figure 4-11 NTL derived urban class transition map between 1994 and 2008 for Bangkok, Kuala Lumpur, Singapore, Ho Chi Minh, Makassar and Yangon

Figure 4-12 NTL derived urban class transition map between 1994 and 2008 for Bandung, Batam, Hanoi, Jakarta and Phnom Penh

Table 4-2 Transition percentages between 1994 and 2008 calculated as the area of a transition region normalized by the sum of CS, PU and CU (year 1994) for each city.

City	Transition as proportion of total area (%)				
	CS-PU	CS-CU	PU-PU	PU-CU	CU-CU
BDO	6.92	0.00	26.57	0.80	7.06
BKK	11.45	0.00	22.37	10.88	28.26
BTH	32.52	0.81	28.62	4.72	2.60
DVO	31.99	0.00	23.02	5.10	2.11
HCM	50.49	5.93	4.51	20.37	5.16
HAN	24.42	0.00	7.32	2.24	1.75
JKT	5.94	0.49	24.97	3.13	15.58
KUL	32.59	9.46	9.46	19.11	16.79
MDN	5.97	0.00	27.14	1.74	6.18
MKS	18.98	0.00	39.04	4.01	9.09
MNL	4.97	0.00	28.36	1.48	13.85
PNH	40.52	1.31	16.01	7.52	4.25
SIN	17.21	0.85	15.82	10.26	30.64
SUB	11.95	0.00	23.34	3.64	6.20
RGN	10.30	0.00	34.37	0.12	11.79

4.3.5. Comparison with population

The urban extents extracted from NTL were compared with population data to explore linkages with population growth. Population data from UNPD (2014) as available for four years of 1995, 2000, 2005 and 2010 and for all 15 SEA cities were used. Here it is noted that only NTL derived PU and CU categories were considered for this comparison as the CS is expected be sparsely populated. Figure 4-13 shows the comparison between the TLI

(computed using PU and CU pixels) and population for all 15 cities in the 4 years of 1995, 2000, 2005 and 2010. It is observed that TLI generally increases with population except for Yangon, Manila, Kuala Lumpur and Bangkok. Yangon and Manila have their TLI not increasing proportionately with population while Kuala Lumpur and Bangkok show stronger increases above linear. Figure 4-14 further shows the comparison between population and urban extent (PU and CU only) for all 15 cities for the same four years. Similar results as in Figure 4-13 were observed. Bangkok and Kuala Lumpur have significantly increased in terms of urban extent but the population has not proportionally increased.

Figure 4-13 NTL Total Light Index (PU and CU pixels) versus population for (a) 1995, (b) 2000, (c) 2005 and (d) 2010

Figure 4-14 NTL derived urban extent (PU and CU) versus population for (a) 1995, (b) 2000, (c) 2005 and (d) 2010

Confidence ellipses are further used to assess the correlation between the NTL derived TLI and urban extent w.r.t. population shown in Figures 4-13 and 4-14. Confidence ellipses serve as visual indicators of correlations. The confidence ellipse collapses diagonally as the correlation coefficient R approaches 1 or -1 (perfect correlation). The ellipse is more circular when the two variables are uncorrelated. Confidence ellipses at 95% and 90% confidence levels using the Past v4.02 statistical software (<https://folk.uio.no/ohammer/past/>) are plotted for Figures 4-13 as Appendix Figures A-12 and A-13, and for Figure 4.14 as Figures A-14 and A-15. A 95% confidence ellipse defines the region that contains 95% of all samples that can be drawn from the underlying (albeit assumed) Gaussian distribution. Figures A-12 and A-13 shows that the

confidence ellipse plot between NTL derived TLI vs population are well elongated and elliptical indicating good correlation between NTL TLI and population for 15 SEA cities. The similar plots at 95% and 90% confidence levels for NTL derived urban extents versus population (Figures A-14 and A-15) also exhibit good, diagonally elongated ellipses indicating good correlations. 14 of the 15 city results lie inside the 95% confidence ellipse (Figures A-12 and A-14 corresponding to Figure 4-13 and 4-14). Also 13 to 14 city results (13 cities for year 1995 and 14 cities for years 2000, 2005 and 2010 in the sub-plots) lie inside the 90% confidence ellipse (Figures A-13 and A-15 corresponding to Figures 4-13 and 4-14).

Figure 4-15 shows the rate of change of NTL derived urban extent (PU+CU) versus rate of change of population over 1995-2010, normalized w.r.t. 1995. Specifically, the percentage change in urbanized land was obtained as $[(PU+CU)_{2010} - (PU+CU)_{1995}]$ divided by $(PU+CU)_{1995}$, where $(PU+CU)_{1995}$ and $(PU+CU)_{2010}$ represent the combined peri-urban and core-urban areas for years 1995 and 2010, respectively. The percentage change in urbanized land ranges from 8% to >300%, with lower values for Manila and Yangon and higher values for Hanoi and Ho Chi Minh, and with an overall correlation R of 0.78. Inland cities such as Hanoi, Ho Chi Minh and Phnom Penh have their rapid increase in populations accompanied by a corresponding increase in urbanized land. Conversely, increase in urbanized land is not as strongly linked to increase in population for Kuala Lumpur, Singapore and Davao, as these cities are geographically constrained. It is interesting to note that the Vietnamese cities of Hanoi and Ho Chi Minh have dramatic increases in population and urbanized land over 1995-2010 which could be possibly linked to the extensive developmental activities following the post-Vietnam war era. Batam showed an even larger (416%) increase in population, this arising because

it only started growing from 1995 when its population was < 200,000, and as such is not shown in Figure 4-15. Corresponding to Figure 4-15, 95% and 90% confidence ellipse plots were plotted for rate of change of NTL derived urban extent (PU+CU) versus rate of change of population over 1995-2010, normalized w.r.t. 1995. These plots are depicted as Appendix Figures A-16 and A17. Both figures exhibit good correlation between the parameters via elongated elliptical curves. All 15 cities lie within the 95% confidence ellipse (Figure A-16 corresponding to Figure 4-15) with 13 cities inside the 90% confidence region (Figure A-17 corresponding to Figure 4-15).

Figure 4-15 Rate of change in urban extent from 1995 to 2010 (normalized w.r.t. 1995 urban extent) with rate of change in population (Note: Batam (BTH) has an exceptional 416% increase in population and not included)

4.4. Summary

The major works and outcomes from this chapter are as follows:

1. 15 SEA cities were analyzed with RS NTL yearly data from 1992 to 2012.
2. The BG approach was used to extract three major urban categories of CS, PU and CU within each studied city.
3. The results show strong spatio-temporal trends in urbanization for all 15 SEA cities analyzed.
4. The PU and CU categories were generally found to increase over time whereas the CS category decreased with time.
5. The urbanization trends showed strong correlation with the population growth.

The analysis provided insights into the spatio-temporal urban growth trends at city level as well as illustrating inter-city patterns for major SEA cities. This work covers the inter-city analysis level referred in Figure 3-4 work flow; which is the initial approach to assess the urban growth dynamics at city level. However, a much deeper understanding is necessary to identify linkages between urban growth, socio-economic indicators (e.g. population and GDP) and infrastructure (e.g. roads) at intra-city scale to enable better assessments of the urban growth dynamics. Hence the next chapter focused on a higher spatial resolution (30 m) grid to extract and quantify information such as built-up area, population and road density to assess the intra-city urban growth spatio-temporal dynamics for major SEA cities. This represents the micro-scale analysis of major SEA cities.

5. Linkages amongst urban growth, road network and socio-economic indicators in S.E. Asian cities

5.1. Introduction and overview

Studies on the urban growth dynamics and their linkages to population, GDP and power consumption patterns are typically performed at national and regional scales (Bettencourt 2013; Bettencourt and Lobo 2016; Chen et al. 2014; Pandey et al. 2013; Zhao and Wang 2015). Infrastructure systems, specifically road networks are key elements in urbanization and evolution processes of a city (Angel et al. 2011). Road networks integrate various functional elements of a complex city system playing a pivotal role in spatial development of urban areas as well as for the evolution of urban forms (Bettencourt and West 2010; Lämmer et al. 2006). However, there has always been a debate whether road network is the driver of urban expansion (Baum-Snow, 2007) or is driven by the expansion (Zhao et al. 2017). The previous Chapter 4 mainly assessed the spatio-temporal urban growth patterns for major SEA cities using RS NTL data at city level. However, as infrastructure plays a key role in the growth and evolution of the cities, road infrastructure (road density) is considered here as a key parameter to identify and assess linkages w.r.t. urban growth for major SEA cities.

Road density has also been reported to be an important index in understanding urban developmental scenarios, e.g. Borruso (2003) and Zhang et al. (2015) have used this index to analyze the developed urban patterns. Rui and Ban (2014) explored the relationship between different street centralities and land-use types in Stockholm to capture land development patterns based on anthropogenic activities. Strano et al. (2012) studied road network data over a long time period of 200 years for an area near Milan, Italy and

reported that the evolution of the road network is governed by two processes; namely densification (i.e. increase in the density of roads in existing urban centers) and exploration (i.e. expansion of the network into non-urban areas), while the high-centrality streets remained relatively stable over time. The study further showed that the evolution of road network was strongly correlated with population. A recent study by Zhao et al. (2017) explored the correlation between urban expansion and road networks proposing predictive capabilities for future urban expansion and sustainable development. Another recent study by Shi et al. (2019) quantified the spatial evolution of road networks in Nanjing city, China using road densities developed from road networks using the kernel density algorithm. Such studies highlight the need for understanding of intra-urban developmental activities towards planning for sustainable future especially for developing and under-developed economies.

The fastest wave of urbanization over the last few decades, is happening in the Global South, i.e. in the developing nations of Africa, Asia, Middle East and Latin America (UNPD 2014). Asia and Southeast Asia (SEA) have given rise to major megacities (population over 10 million), such as Tokyo, Bangkok, Jakarta, and Manila. Also, the SEA region holds an amalgam of countries with differing geographical characteristics and varying urbanization levels in terms of percentage being urban, ranging from 22% in less developed nations such as Cambodia, to 74% in Malaysia and 100% in Singapore (UNPD 2018). According to the 2014 Global Risks perception survey of the World Economic Forum, failure of urban planning (e.g. inadequate or poorly planned national infrastructure) is a major risk in many regions of SEA. Considering the widespread economic dynamism and high urbanization rates in SEA, it is critical to understand the

local scale urban growth processes in order to promote sustainable and resilient development.

As noted earlier, the various reported studies on the relationships amongst urban growth, landscape and infrastructure metrics, and socio-economic indicators are for city to continental scales. In addition, few such studies have been performed for the SEA region. Notable examples are by Kamarajuggedda et al. (2017) and Zhao et al. (2018) on assessing spatio-temporal dynamics using NTL data, and Schneider et al. (2015) on quantifying change in urban land agglomerations using RS and population density datasets. In addition, even fewer studies have been performed at intra-city scales such as that by Zhao et al. (2017) for Beijing, New York, London and Chicago. Therefore, the focus of this chapter is to present a more comprehensive exploration of such linkages at intra-city scales, focusing on major SEA cities. Specifically, we explored and identified linkages between urban expansion, road network and socio-economic indicators, covering population and GDP at intra-city scales. The key objectives of the work in this chapter are to: 1) Quantify the spatial urban expansion over decadal time scales (specifically over a ~30 year temporal domain using time stamps of 1987 and 2017) using remotely sensed satellite data (Landsat Thematic Mapper); 2) Identify and quantify the relationship between spatially expanded urban areas and road density; 3) Assess correlations between urban expansion, road density and socio-economic indicators comprising of GDP and population at inter-city and intra-city scales. These presented results would guide understanding of the urbanization processes across major SEA cities, which are largely in developing economies, with regard to urban planning strategies for sustainable development.

5.2. Studied cities

Major cities in SEA were selected based on population being greater than 2 million in year 2015. This yielded 11 cities but Hanoi was excluded considering the incompleteness of Open Street Map (OSM) road network data there. Similarly, Surabaya was excluded for non-availability of Landsat datasets for the respective time stamps. The nine remaining cities are Jakarta, Bangkok, Manila, Singapore, Kuala Lumpur, Ho Chi Minh, Yangon, Bandung and Medan as highlighted in Figure 5-1. The administrative boundaries for these cities as used for extracting Landsat data and road network vector shapefiles were obtained from <https://gadm.org/>.

Figure 5-1 SEA cities (in red boxes) used in the analysis overlaid on a background ESRI basemap

These nine selected cities span a range of geographical and social economic characteristics. Geographically, the administrative regions for the cities are connected to coastlines except for Bandung and Kuala Lumpur. Singapore, in particular is an island city. The megacities of Jakarta and Manila have population greater than 10 million. Bangkok, Singapore, Kuala Lumpur and Ho Chi Minh have population between 5 and 10 million, while Medan, Bandung and Yangon have less than 5 million population.

Economically, the output of major SEA cities has been categorized into four tiers along with other major global cities according to an economic output per capital index (Florida and Fasche 2017), as based on the 2014 Global Metro Monitor Statistics (The Brookings Institution 2015). Singapore is in tier one with per capita economic output of 66,854 USD, a value comparable to cities such as New York and Tokyo. Kuala Lumpur is in the second tier with 28,076 USD per capita economic output, Bangkok and Manila are in the third tier with 19,705 and 14,222 USD per capita, respectively, while Jakarta and Ho Chi Minh are in the fourth tier with 9,984 and 8,660 USD per capita, respectively.

5.3. Methodology

The research methodology is outlined in the flowchart of Figure 5-2. It is delineated into two main parts namely:

(1) Data processing – this includes Landsat data classification, urban area extraction, and generation of urban expansion maps, population growth maps, road density maps and GDP growth data. It is noted that urban expansion, population growth, and GDP growth maps were obtained using time intervals of 30 years (1987-2017), 15 years (2000-2015), and 20 years (2000-2020), respectively with the assumption that the growth rates obtained from shorter spans hold for the longer 30-year period. This is because the population

dataset is available from year 2000 at every 5-year interval while the GDP dataset is available from 1980 at 10-year interval. Hence, shorter periods are used for the growth rates for population and GDP versus that used for the urban expansion rate.

(2) Spatial analysis and modelling – this includes spatial overlay analysis for extracting urban expansion areas and their respective road network densities and population growth values to enable identification and modelling of linkages amongst urban expansion, road network and population growth.

Figure 5-2 Flowchart showing the methodology applied

5.3.1. Data processing

Landsat imagery for years 1987 and 2017, and for each studied SEA city were used to perform supervised image classification (in ArcGIS 10.0 software) into four land cover classes, namely urban, vegetation, water body and barren land. Training samples for the supervised classification were derived based on visual inspection. The classification was validated using 200 separate ground truth points (i.e. no overlap with training sample) and which contained at least 100 urban points. These ground truth points were selected with the aid of satellite imagery, topographic maps and Google Earth. The land-cover classes from the supervised classification were grouped into urban and non-urban

(vegetation, water body and barren land) categories and compared with the corresponding ground truth data. Table 5-1 shows the classification accuracy over the verification samples for urban and non-urban pixels for 1987 and 2017 for all 9 cities. The overall classification accuracies over the years of 1987 and 2017 were high with values for urban pixels ranging from 75.4% for Yangon to 95.3% for Jakarta. The corresponding accuracies on non-urban pixel classification ranged from 79.6% for Bandung to 94.7% for Bangkok. These extracted urban land covers for years 1987 and 2017 were further overlaid and spatial difference performed in GIS to obtain urban expansion layer occurring over the 30-year period.

Table 5-1 Landsat imagery classification accuracy percentages (over verification samples) for urban and non-urban pixels

City		Land-use category	Bandung	Bangkok	Ho Chi Minh	Jakarta	Kuala Lumpur	Manila	Medan	Singapore	Yangon
Year	1987	Urban	90.8	78.4	92.8	89.5	81.9	90.0	78.9	83.5	75.4
	2017		87.4	87.2	91.0	95.3	93.9	90.4	94.7	83.3	75.7
	1987	Non-urban	79.6	87.9	91.9	93.7	88.7	85.5	90.7	84.3	81.5
	2017		87.7	94.7	80.3	86.5	83.3	93.0	91.9	89.2	89.2

The methodology for Landsat and road network data processing is illustrated in Figure 5-3 for the city of Jakarta. Figure 5-3(a) represents the Landsat imagery (false color composite) for the year 1987. Cyan color represents urban land or artificial surfaces, red represents vegetation, and dark blue and black colors represent water bodies. Figure 5-3(b) shows the classified land cover for years 1987 and 2017. It is readily observed that urban areas (i.e. red pixels) have increased significantly over 1987 to 2017. In particular, vegetated areas (green) in the south, east and west of Jakarta have been transformed to urban areas. Figure 5-3(c) shows the urban expansion areas over the three decades showing a radial expansion pattern.

Figure 5-3 Illustration of methodology for the city of Jakarta

Road network vector shapefiles were extracted from OSM data for the studied SEA cities. Kernel density analysis was performed to generate road density maps using ArcGIS 10.0 software. Here road density refers to the ratio of the total length of the centerline of the roads to the land area (i.e. units of km/km^2). The road density maps were generated at 30 m spatial resolution similar to the Landsat data. Figure 5-3(d) represents Jakarta's roads vector data (left, in black lines) and road density map (right) for the year 2017. The road density map was further categorized into five grades using Jenks natural breaks algorithm. The purpose of using this algorithm is to maximize the variation between the road density grades while minimizing the variation within each grade. Similar plots for the other 8 cities are shown in Figures A-4 to A-11 in the Appendix.

The gridded UN adjusted GPWv4 population density values for years 2000 and 2015 were used to derive a population density change map over the 15 years, which was then resampled to Landsat data spatial resolution for maintaining spatial uniformity in the

intra-city analysis. GDP datasets were available at 0.5-degree spatial resolution (approximately 55 km resolution), which is much coarser for a city-level determination of GDP. We incorporated a spatial downscaling approach to derive the GDP for each city using population count gridded datasets from the UN adjusted GPW v4 population count dataset. First population weights over 1 km² grids were derived as the population value per grid w.r.t. the total population count for all grids within the city administrative boundary. To obtain the city-level GDP, we downscaled the gridded GDP values to 1 km² spatial resolution based on weights derived, thus distributing the 0.5 degree gridded GDP value into 1 km² grids. Since, we are using years 2000 and 2015 population count dataset to downscale the GDP gridded dataset, the GDP datasets for this analysis were selected in order to coincide closely with the population dataset availability. The GDP values of all pixels within the administrative boundary of each city were then accumulated to obtain the city-level GDP and the average annual GDP growth rate (in billion US dollars/year) calculated using the values from years 2000 and 2020.

5.3.2. Spatial analysis and modelling

For an inter-city comparison, Landsat derived urban expansion maps were quantitatively analyzed in terms of overall expanded area and intensity (i.e., time rate) for each city, with the urban expansion rates compared with GDP growth rates. Next, the generated maps covering urban expansion, road density and population growth were used in spatial overlay analysis at intra-city level. Specifically, all the urban expanded pixels over 1987 to 2017 were converted to vector shapefile (points), with the corresponding road density and population growth values extracted. This resulting data was employed to perform regression analysis for each city. Via this, the linkage between urban

expansion rate, specifically the logarithm of urban expansion rate, and road density values as following Zhao et al. (2017) at intra-city scales was examined (see detailed description in Chapter 5.4.4). An inverted (downward) concave pattern was observed, which was then modelled using a third-order polynomial where the road density value at which the slope is zero or the “Turning Point” as coined by Zhao et al. (2017) was identified. Based on the turning points, zoning maps were developed for each city for identifying the different developmental zones within each city. Linkages between population growth and road density were also assessed. Considering again the urban expanded pixels, a log-linear relationship for population growth rate with road density was analyzed similar to that used for the urban expansion rate.

5.4. Results and discussion

5.4.1. Landsat data derived urban expansion

The Landsat data derived urban expansion revealed that all nine studied SEA cities experienced significant spatial urban expansion over the period 1987 to 2017 (Figure 5-4). Strong radial urban expansion from the city centers is observed for Bandung, Bangkok, Ho Chi Minh, Jakarta, Manila and Medan, whereas the expansion is in the form of scattered patches for Kuala Lumpur and Singapore. Particularly for Singapore, pronounced urban expansion has occurred in the southwestern islands, which is attributed mainly to land reclamation (Koninck 2017; Lai et al. 2015).

Figure 5-4 Urban expansion (red pixels) during 30 years (1987 – 2017) for nine SEA cities

Table 5-2 City administrative boundaries and urban expanded areas for SEA cities

City	Administrative boundary area (km²)	1987 Urban area (km²)	2017 Urban area (km²)	Urban expansion area (km²)	Urban expansion intensity (%)
Bandung	150.7	52.7	115.6	62.9	119.4
Bangkok	1564.5	435.2	722.8	287.6	66.1
Ho Chi Minh	1746.6	71.2	463.3	392.1	550.8
Jakarta	662.1	336.9	531.5	194.6	57.8
Kuala Lumpur	272.3	133.3	192.4	59.1	44.3
Manila	557.7	293.5	447.5	154	52.5
Medan	292.9	114.0	174.6	60.6	53.2
Singapore	696.8	293.6	476.0	182.4	62.1
Yangon	268.4	98.3	177.1	78.8	80.2

The urban expansion intensity is highest for Ho Chi Minh (550.8%) followed by Bandung (119.4%). A similar large increase in urban land area was also observed for Ho Chi Minh based on NTL data over 1995 to 2010 (see Chapter 4.3.5) and which was attributed to extensive developmental activities following the post-Vietnam war era in Chapter 4. It is noted that although Bandung showed a small urban expansion of about 63 km² within three decades, it showed a higher urban expansion intensity of 119.4%. Yangon is similar with a small expansion area of around 79 km² but high urban expansion intensity of 80.2%. Bangkok and Singapore have close urban expansion intensities i.e. 66.1% and 62.1%, respectively with similar urban expansion areas of 287.6 km² and 182.4 km². Jakarta, Manila and Medan have similar urban expansion intensities in the range of 52 – 58%. However, Medan being a smaller city only has 60.6 km² of urban expansion area when compared to Jakarta and Manila, which have 194.6 km² and 154 km², respectively. Finally, Kuala Lumpur exhibited the lowest urban expansion intensity of 44.3% along with a lower urban expansion area of 59.1 km².

5.4.2. Urban expansion versus GDP growth rates

The GDP growth rates were assessed w.r.t. urban expansion rates for all nine cities as plotted in Figure 5-5. It is observed that the GDP growth rate tends to increase with increasing urbanization rate. Singapore exhibits the highest GDP growth rate at around 11.5 billion USD/yr followed by Bangkok at 5.5 billion USD/yr. Following the economic tiers of Florida and Fasche (2017) mentioned in Chapter 2.1, Singapore is in tier one with the highest economic output per capita which is also being reflected here. However, its urban expansion rate is not as high as its GDP growth rate with one key geographical constraint being that of a small island city of area 696.8 km² (Table 5-2). Thus, Bangkok and Ho Chi Minh, the next two highest in GDP growth rate and which are not so geographically constrained (areas of 1,564 and 1,746 km², respectively) show higher urban expansion rates than Singapore. Ho Chi Minh and Jakarta at similar GDP growth rates fall under the same tier 4 of economic output per person but the urban expansion rate of Jakarta, being an urbanized coastal city with 662 km² is more constrained. Four cities namely Kuala Lumpur, Bandung, Yangon and Medan display comparatively similar GDP growth rates varying between 0.72 and 1.22 billion USD/yr. All these four cities also exhibit similar urban expansion rates. However, Kuala Lumpur is reported as tier 2 in its economic output per capita, which is not being reflected in its lower GDP growth rate value (0.72 billion USD/yr). This is attributed to Kuala Lumpur's significantly smaller administrative (272 km²), while the economic growth and output has occurred in the surrounding areas outside the city limits.

Figure 5-5 GDP growth rate versus urban expansion rate

5.4.3. Road density gradation and urban expansion

The road density ranges were expectedly different for each city with maximum values ranging from about 25 km/km² in Ho Chi Minh and Bangkok to about 50 km/km² in Kuala Lumpur. We partitioned the road density maps, as first normalized based on each cities' maximum road density value, into 5 grades using the Jenks natural breaks algorithm to allow for an inter-city assessment for each city. The urban expansion layers from Chapter 5.4.1 were then overlaid on road density layers to extract expanded areas within each road network grade. This overlay analysis thus identifies the road density grades where most urban expansion occurred. The normalized road density grades, the corresponding urban expansion areas, both absolute (in km²) and relative (%) w.r.t. total expanded area, and expansion rates are listed in Table 5-3.

Table 5-3 shows that most cities show the largest urban expansion area within the road density grades of 2 to 4. The relative expanded areas as summed over road density grades of 2 to 4, range from 71.1% (Singapore) to 90.2% (Kuala Lumpur). The sole exception is Yangon, which shows high urban expansion over road density grades of 3 to 5. In general, Ho Chi Minh, Bangkok and Jakarta have shown higher urban expansion rates followed by Manila, Singapore and the rest.

Table 5-3 Urban expansion areas and rates with respective to their normalized road density grades

City	Road density grade	Road density ranges (normalized)	Urban expansion area (km ²) and relative percentage (%)	Urban expansion rate (km ² /yr)
Bandung	1	0.00 - 0.11	5.7 (9.1%)	0.2
	2	0.12 - 0.29	15.4 (24.4%)	0.5
	3	0.30 - 0.45	18.6 (29.6%)	0.6
	4	0.46 - 0.63	16.9 (26.9%)	0.6
	5	0.64 – 1.00	6.3 (10.0%)	0.2
Bangkok	1	0.00 - 0.09	16.7 (5.8%)	0.6
	2	0.10 - 0.27	69.7 (24.2%)	2.3
	3	0.28 - 0.47	88.2 (30.7%)	2.9
	4	0.48 - 0.67	79.6 (27.7%)	2.7
	5	0.68 – 1.00	33.4 (11.6%)	1.1
Ho Chi Minh	1	0.00 - 0.04	21.6 (5.5%)	0.7
	2	0.05 - 0.16	110.3 (28.1%)	3.7
	3	0.17 - 0.33	121.8 (31.1%)	4.1
	4	0.34 - 0.55	114.6 (29.2%)	3.8
	5	0.56 – 1.00	23.9 (6.1%)	0.8
Jakarta	1	0.00 - 0.09	8.5 (4.4%)	0.3
	2	0.10 - 0.24	64.6 (33.2%)	2.2
	3	0.25 - 0.39	60.4 (31.0%)	2.0
	4	0.40 - 0.55	40.8 (21.0%)	1.4
	5	0.56 – 1.00	20.2 (10.4%)	0.7
Kuala Lumpur	1	0.00 - 0.10	0.6 (1.0%)	0.0
	2	0.11 - 0.26	10.9 (18.4%)	0.4
	3	0.27 - 0.40	22.9 (38.7%)	0.8
	4	0.41 - 0.55	19.6 (33.1%)	0.7
	5	0.56 – 1.00	5.2 (8.8%)	0.2
Manila	1	0.00 - 0.10	4.3 (2.8%)	0.1
	2	0.11 - 0.28	26.9 (17.5%)	0.9
	3	0.29 - 0.42	48.7 (31.6%)	1.6
	4	0.43 - 0.56	57.5 (37.4%)	1.9
	5	0.57 – 1.00	16.6 (10.7%)	0.6
Medan	1	0.00 - 0.08	12.2 (20.1%)	0.4
	2	0.09 - 0.24	20.1 (33.1%)	0.7
	3	0.25 - 0.40	17.6 (29.1%)	0.6
	4	0.41 - 0.58	8.4 (13.9%)	0.3
	5	0.59 – 1.00	2.3 (3.8%)	0.1
Singapore	1	0.00 - 0.06	19.1 (10.4%)	0.6
	2	0.07 - 0.20	42.7 (23.4%)	1.4
	3	0.21 - 0.37	42.8 (23.5%)	1.4
	4	0.38 - 0.54	44.3 (24.3%)	1.5
	5	0.55 – 1.00	33.6 (18.4%)	1.1
Yangon	1	0.00 - 0.11	3.8 (4.8%)	0.1
	2	0.12 - 0.30	12.1 (15.4%)	0.4
	3	0.31 - 0.47	19.1 (24.3%)	0.6
	4	0.48 - 0.65	21.3 (27.1%)	0.7
	5	0.66 – 1.00	22.4 (28.4%)	0.7

5.4.4. Linkages between intra-urban expansion rate and road density

To assess the linkage between intra-urban expansion rate and road density, we aggregated the urban expansion areas at 0.1 km/km² road density bins and obtained the urban expansion rate at each road density bin for each city. The relationship between the logarithm of the urban expansion rate and road density exhibited an inverted concave pattern (Figure 5-6) as also reported by Zhao et al. (2017) for Beijing, New York, Chicago and London. The urban expansion rate initially increases with road density but subsequently drops forming an inverted concave pattern, which was modelled using a third-order polynomial as:

$$\log_{10} y = B_0 + B_1 \times x + B_2 \times x^2 + B_3 \times x^3 \quad (5-1)$$

where

y denotes the urban expansion rate;

x denotes the road density; and

B_0, B_1, B_2 and B_3 denote the coefficients of the fitted polynomial equation;

Figure 5-6 also shows the fitted polynomials for the nine cities from which the turning points (as also showed by Zhao et al. (2017)) were calculated as:

$$\text{Turning point } x_t = \frac{-B_2 - \sqrt{B_2^2 - 3 \times B_1 \times B_3}}{3 \times B_3} \quad (5-2)$$

where

x_t denotes the road density turning point value;

This turning point is interpreted as the threshold at which the effect of road network density on promoting (i.e. increasing the rate of) urban expansion changes to one which decreases the rate (Zhao et al. 2017). It is attributed to the likely effects of urban saturation

w.r.t it's high road density areas. The turning point values range from about 5.11 km/km² for Medan to about 17.03 km/km² for Kuala Lumpur (Figure 5-6). Bandung, Bangkok, Jakarta and Singapore have close turning point values of 11 to 12 km/km². Manila and Yangon show slightly higher turning point values of about 16 km/km². Figure 5-6 also shows Ho Chi Minh having a sharp rise over the smaller road densities followed by a rapid downward curve leading to a smaller turning point value (5.96 km/km²). Such a trend is also observed for Medan.

Figure 5-6 Urban expansion rate vs road density (blue color) modelled using a third-order polynomial (upper and lower bounds for the fitted polynomials indicate 90% confidence intervals). Turning point values (km/km²) are listed in parenthesis

City zoning maps were next generated based on the turning point values to identify regions that are before the turning point, i.e. before the peak urban expansion rate, and regions after. These zoning maps shown in Figure 5-7 have orange (yellow) color indicating areas before (after) the turning point threshold. The urban expanded pixels (black) are overlaid for reference. It is noted that while the turning point values computed here are based on expanded areas occurring within the three decadal timeframe, such maps as generated using different timeframes would be helpful in identifying the pre- and post-turning point regions within each city and so can steer future intra-urban growth planning towards a more sustainable path. Cities such as Bangkok and Ho Chi Minh having comparatively larger administrative boundaries ($> 1,500 \text{ km}^2$) show large areas before the turning point (orange areas) outwards of the core (Figure 5-7). These areas indicate lower values of road densities and correspond to the rising limb of the fitted urban expansion curves (Figure 5-6), and so indicate a larger scope for providing urban expansion. This can guide sustainable urban planning, such as for new infrastructure, and identification of new business districts/development hubs.

Figure 5-7 Zoning maps derived from turning point thresholds. Black pixels indicate urban expanded areas

5.4.5. Assessing linkages between population growth rate and road density

Similar to the analysis in Chapter 5.4.4, linkages between population growth rate and road density were assessed. The results, shown in Figure 5-8, indicate that the logarithm of

population growth rate also has a similar inverted concave pattern with road density, as for the case of urban expansion rate, for all the nine studied cities. This can be expected as urban expansion rates are tightly coupled with population growth patterns. These population trends are again modelled using the third-order polynomial of Eq. (5-1) for turning point analysis.

Figure 5-8 Population growth rate vs road density (blue color) modelled using a third-order polynomial (upper and lower bounds for the fitted polynomials indicate 90% confidence intervals). Turning point values (km/km²) are listed in parenthesis

A comparison of the two sets of curves in Figures 5-6 and 5-8 shows that the road density turning point values from population growth rates were close to those from urban expansion rates for seven of the nine studied cities, specifically Bandung, Bangkok, Jakarta, Kuala Lumpur, Manila, Medan and Yangon. It is noted that this comparison made between Figure 5-6 and 5-8 is between same cities (e.g., Kuala Lumpur shows similar trends in Figure 5-6 and 5-8 resulting in close turning point values w.r.t. road density, both for urban expansion rate vs road density and for population growth rate vs road density). The population growth rate turning points for Singapore and Ho Chi Minh were doubled even though their respective curves have similar shapes, suggesting that the population growth and urban expansion processes for these cities are less correlated. Considering that Singapore is an island nation, the spatial growth over years would likely be constrained when compared to its population growth. This is consistent with the flatter rising limb of the fitted polynomial for Singapore's urban expansion rate plot (Figure 5-6) as compared to that of population growth rate (Figure 5-8). Consequently, the turning point is lower for urban expansion rate (at 12.43 km/km²) than that for population growth rate (at 21.22 km/km²). Ho Chi Minh also has a significant difference in the turning point values derived from urban expansion rate (5.96 km/km²) and that from population growth rate (10.55 km/km²). Unlike Singapore, the administrative region of Ho Chi Minh is very large. The urban expansion has occurred predominantly in the central part, with very little expansion in the outer fringes as seen in Figure 5-4. Therefore, the rising limb of the urban expansion rate for Ho Chi Minh is flatter near lower values of road density compared to that of population growth in Figure 5-6, resulting in a lower turning point.

5.5. Summary

The key outcomes of this chapter are addressed as below:

1. Urban expansion for nine major SEA cities over a 30 year time period using Landsat data (30 m spatial resolution) was analyzed.
2. Linkages amongst urban area growth, road density and population growth have been established.
3. The intra-city urban expansion patterns w.r.t. road density grades revealed that for most of the studied cities, significant urban expansion has occurred in medium road density grades of 2 to 4.
4. The relationship between each cities' intra-urban expansion rate and road density exhibited an inverted concave pattern, which was modelled using a third-order polynomial with turning points
5. City level zoning maps were generated from these turning point results to identify the intra-city urban expansion variations.
6. The analysis of population growth rate conditioned on road density also revealed a similar inverted concave relationship, with turning points similar to those in urban expansion analysis, suggesting strong linkages between urban expansion and population growth rates.

This comprehensive intra-city analysis amongst urban growth, road density and population growth was useful in identifying the urban growth dynamics at local scale. As seen from the work flow of Figure 3-4, this analysis helps us in understanding urban growth dynamics at intra-city scale which further provides an insight into exploring the last phase of urban growth which is for a future prediction. This is addressed in the next chapter 6.

6. Modelling future urban growth for Bangkok and assessing its linkages with road density and socio-economic indicators

6.1. Introduction and overview

Urban growth prediction can be performed at scales spanning global, regional or city as depending on the level of data availability. However, growth predication at city scale have inherent higher uncertainty as cities are complex systems with intra-city growth dynamics. Various urban growth prediction models (UGPM) are developed with the most common being linear/logistic regression, agent-based, and Cellular Automata (CA) models, and with CA models being increasingly used (Santé et al., 2010). A UGPM review paper by Triantakostas and Mountrakis (2012) reported that 83% of 156 manuscripts on urban growth prediction used the CA approach. The SLEUTH (Slope, Landuse, Exclusion, Urban extent, Transportation and Hillshade) is one commonly used CA-based UGPM with many reported studies (Al-shalabi et al. 2013; Bihamta et al. 2015; Clarke and Gaydos 1998; Herold et al. 2003; Mallouk et al. 2019; Saxena and Jat 2019). In the SLEUTH model, urban growth rules are applied on a cell-by-cell basis within a uniform geographical lattice thus making it highly ideal for spatial growth predictions. The dataset used by SLEUTH has at its initial time period a set of growth parameters and probabilities, as determined via calibration using historical urban growth data. This initial, or starting ‘seed’ layer is then used to generate growth over time with each cell acting independently, and growth patterns emerging (Clarke and Gaydos 1998).

The previous Chapters 4 and 5 examined the spatio-temporal interdependencies amongst urban area growth, infrastructure and socio-economic indicators for fifteen (Chapter 4) and nine (Chapter 5) SEA cities. Here, Bangkok is used as a demonstration

megacity to predict the future urban expansion pattern during the next decade using SLEUTH and to examine these interdependencies. Specifically, Bangkok's historical urban areal and population expansion rates were quantified over decadal time scales (year 1987 to 2017) with the intra-city expansion trend delineated based on deduced road density grades, and also via a turning point between the urban expansion rate and road density. Via SLEUTH, we further projected the urban expanded areas to year 2027 and assessed the predicted urban expansion trends with road density. This study thus represents one of the few very reported at intra-city scales and especially for SEA cities with future projections (e.g. Zhao et al. (2017) reported on a historical study but for Beijing, New York, London and Chicago). As such our results and similar results from other studies should find use in guiding urban development planning, particularly for the rapidly expanding regions of Asia and SEA.

6.2. Study area

Bangkok metropolis is one of the largest cities in Southeast Asia with population of over 5 million. More than half of the population in the larger Bangkok metropolitan region, which comprises of Bangkok metropolis and 5 adjacent provinces, lives in Bangkok metropolis, resulting in a high population density of around 5258 people/km² (Losiri et al. 2016). About 97 % of the Gross Regional Product (GRP) of the Bangkok metropolitan region is further generated by Bangkok metropolis (Losiri et al. 2016) and Bangkok is reported to have around 19,705 USD per capita economic output (Florida and Fasche 2017). Figure 6-1 shows the Bangkok metropolis region used in our study with its administrative boundary as downloaded from www.gadm.org. The general urbanization pattern in the Bangkok metropolis or city (the term city is used hereafter to denote

metropolis) is concentrated along the Chao Phraya River, and then expanded along the transportation network with centers of smaller urban clusters.

Figure 6-1 Bangkok metropolis area (boundary highlighted in black)

6.3. Methodology

The methodology comprises mainly the development of urban growth prediction model using SLEUTH for future urban expansion for Bangkok metropolis. Turning point maps and results as described in detail in Chapter 5 are also used in this current chapter to support the further analysis.

6.3.1. SLEUTH model development for Bangkok

The SLEUTH model requires the following datasets to predict future urban growth scenarios: historical urban extent maps (at least four urban layers at different years for model calibration), digital elevation model (DEM), road networks (at least two years) and

an exclusion layer. Chapter 5 has already incorporated Landsat data for years 1987 and 2017, which were processed with urban land-cover extracted using supervised classification approach. Two Landsat imagery for years 1997 and 2007 were similarly selected and processed to provide the additional two urban layers needed. The exclusion layer indicates where urban growth cannot take place. We generated this exclusion layer to include the Chao Phraya River and major water bodies within the selected administrative boundary area. Hillshade layer and slope layers were derived from the SRTM DEM. While the slope layer is used in SLEUTH's lattice prediction probability computation, the hillshade layer is mainly used as a background layer to add lustre to the mapped results. SLEUTH needs at least two timestamps of road network layers for calibration. The two road layers selected were for years 1987 and 2017. The 2017 road network layer was obtained from OSM (readily available and used in Chapter 5). Due to the non-availability of an OSM road network layer for 1987, this road layer was derived from a Landsat image by visual digitization and thus is at a lower accuracy than the 2017 OSM layer. Lastly, it is noted that SLEUTH does not take into consideration the socio-economic and political factors in its urban growth prediction. The general SLEUTH model structure is shown in Figure 6-2. It comprises of three modules mainly: test, calibration and prediction.

Figure 6-2 General structure of a SLEUTH model (Source: Al-shalabi et al. 2013)

SLEUTH's dynamic urban growth is described by four rules: spreading center, edge growth, and road influenced growth. The growth rules correspond to a set of coefficients with values ranging from 0 to 100, and which indicate how much influence the different growth rules have across the study area. There are five factors which control the behavior of the urban growth model: diffusion factor, breed coefficient, spread coefficient, slope coefficient, and road-gravity factor. The relationship between these five coefficients and growth rules is represented in Table 6-1.

SLEUTH model calibration is run over three phases of increasing spatial resolution, i.e., coarse, fine and final. The input layers were prepared according to respective spatial resolutions in GIF format, specifically 120 m, 60 m and 30 m for coarse, fine and final resolutions, respectively. Calibration of SLEUTH is the most important step for capturing

the historical urban growth pattern trends and rules; and so, allow a forecasting. During calibration, values for the five growth control parameters (Table 6-1) are chosen as best fitting the historical urban extent data based on statistical measures.

Table 6-1 SLEUTH model growth types and respective coefficients

<i>Growth cycle order</i>	<i>Growth type</i>	<i>Controlling coefficients</i>	<i>Summary description</i>
1	spontaneous	dispersion	Randomly selects potential new growth cells.
2	new spreading centre (diffusive)	breed	Growing urban centres from spontaneous growth.
3	edge (organic)	spread	Old or new urban centres spawn additional growth.
4	road-influenced	Road-gravity dispersion, breed	Newly urbanized cell spawns growth along transportation network.
Throughout	slope resistance	slope	Effect of slope on reducing probability of urbanization.
Throughout	excluded layer	User-defined	User specifies areas resistant or excluded to development.

The calibration was performed progressively at the three spatial resolutions with regression metrics obtained at the end of each phase representing the goodness-of-fit between the simulated growth and actual growth. The final step of the SLEUTH modelling is prediction wherein the calibrated growth coefficients together with the historical trends are used to generate a future scenario, this representing a “continuation of historical urban growth without changing current conditions” (Clarke and Gaydos 1998), i.e. a “business as usual” approach.

6.4. Results and discussion

6.4.1. Urban expansion and linkages with road density and population

The Landsat derived urban expansion map (Figure 6-3 black pixels as extracted from Figure 5-7 in Chapter 5) showed significant expansion of Bangkok’s built up area over the 30 years from 1987 to 2017. It is readily seen that the expansion pattern is radially

outwards, and towards inland from the city core which borders the coastline. The urban expanded area over the 30 years was 287.6 km² out of Bangkok city's administrative area of 1564.5 km².

The 30-year urban expansion map was assessed w.r.t. the 2017 road density map to analyze the intra-urban expansion patterns with road density in Chapter 5.4.3. The road density map was partitioned into 5 grades using the Jenks natural breaks and the corresponding urban expanded areas within each grade were extracted. The road density grading and urban expansions area and rates are shown in Table 6-2 (as extracted for Bangkok from the earlier Table 5-3).

Table 6-2 Urban expansion areas and rates versus the road density grades for Bangkok

Road density grade	Road density ranges (km/km ²)	Urban expansion area (km ²) and relative percentage (%)	Urban area expansion rate (km ² /yr)
1	0-2.42	16.7 (5.8%)	0.6
2	2.43-7.05	69.7 (24.2%)	2.3
3	7.06-12.09	88.2 (30.7%)	2.9
4	12.10-17.23	79.6 (27.7%)	2.7
5	17.24-25.70	33.4 (11.6%)	1.1

As seen from Table 6-2, 83% of the total intra-city expansion area of 287.6 km² occurred over the road density grades of 2 to 4, with grades of 1 and 5 having much small expanded areas. The urban expansion areas were aggregated over road density bins of 0.1 km/km² to obtain an urban expansion rate versus road density plot shown in Figure 6-4(a) (extracted from Figure 5-6) and represented here again for clarity and discussion. The turning point value for Bangkok is 12.08 km/km², a value between road density grades of 3 and 4 (Table 6-2). This is shown in the zoning map of Figure 6-3 wherein orange and yellow colors denote areas before and after the turning point, respectively, and with the

urban expanded pixels (black) overlaid for reference. The population growth rate with road density has a similar dependence with results shown in Figure 6-4(b) (extracted from Figure 5-6).

Figure 6-3 Zoning map for Bangkok based on turning point threshold. Overlaid black pixels indicate urban expanded areas

Figure 6-4 (a) Urban expansion rate and road density values for Bangkok and fitted using a third-order polynomial (upper/lower bounds in the fit indicate 90% confidence intervals). (b) As (a) but for population growth rate. Turning point values (km/km^2) are listed within parenthesis

6.4.2. SLEUTH model results

The SLEUTH model was calibrated with input datasets as described earlier in Chapter 6.3.1 with the final growth coefficients obtained after the final calibration run. These coefficient values were: Diffusion - 2; Breed - 20; Spread - 22; Slope - 90; Road gravity – 20 as selected based on the Lee-Salee metric. The Lee-Salee metric measures the degree of spatial match between the modelled extent and input extent for each combination of variables. A metric value of 0.56 obtained during the final calibration indicated a successful calibration as consistent with reported studies (Clarke and Gaydos 1998; Hua et al. 2014) using SLEUTH. These derived coefficient values were used in the predict function of SLEUTH with the final 2017 urban layer as the seed layer from which the growth was propagated. Here, the growth prediction was run for 10 years, i.e. till 2027, i.e. a total of 10 predicted urban layers spaced yearly apart, where the urban expanded pixels can be analyzed. Figure 6-5 shows the predicted Bangkok growth at 3 years, namely 2018, 2022 and 2027.

Figure 6-5 Urban growth prediction maps for Bangkok. Black colored pixels represent seed (2017) urban layer; green represent urbanized pixels at 80-94% probability. A small area is expanded for clarity showing the expanded (green) pixels (Note: Map not drawn to scale)

Figure 6-5 shows that the predicted growth pattern follows a radially outward/edge-based transition from the seed (year 2017) layer pixels as was also observed for the historical (Figure 6-4 black pixels). This growth being more representative of edge growth/spreading outwards is attributed mainly to the spread coefficient value being larger than the breed, diffusion and road gravity coefficients. From the topography/hillshade data, it is evident that most of the Bangkok metropolis region is low-lying without significant topographic undulations, which would augment the spreading pattern observed. Such behavior in urban land expansion is also consistent with Losiri et al. (2016) who reported that most of the historical expansion is from conversion of agricultural lands in Bangkok's plains into urban areas.

The future urban expanded pixels were accumulated and plotted temporally in Figure 6-6 (a) where a linear trend is seen. The 10-year projected expanded area of 129.9 km² when compared with the historical 30-year value of 287.6 km² indicates a faster expansion rate going forward. Trend lines are plotted for the predicted urban growth from 2018 to 2027 (Figure 6-6(a)) and for the historical urban growth for years 1987, 1997, 2007 and 2017 (Figure 6-6(b)). In Figure 6-6 (b), the predicted urban growth (2018-2027) is also plotted with the historical urban growth (1987 – 2017) to compare the trends. This near-future predicted linear trend to year 2027 represents a result of “continuation of historical urban growth without changing current conditions” (Clarke and Gaydos 1998). For Bangkok city which is flatter and less topographically undulated, this growth stems from “edge growth” that results in a spatially outward expansion and which increases fairly linearly with time. This followed the historical (Figure 6-6 (b)) though with an increased slope.

Figure 6-6 (a) Predicted urban growth (in km^2) from 2018 to 2027 for Bangkok
 (b) (Inset) Change in historical urban growth (in km^2) for Bangkok for years 1987,1997,2007 and 2017 w.r.t. year 1987 (shown in blue dots) along with future urban growth (in km^2) from 2018 to 2027 (red dots)

The SLEUTH model prediction results were further analyzed w.r.t the road density turning point map developed earlier. This turning point highlighted the intra-city zones where the urban expansion with road density had rate behavior changing from increasing to decreasing. The urban expanded pixels were divided into these two zones for all the 10 predicted years as based on Bangkok's turning point threshold of 12.08 km/km^2 from Figure 6-3. The accumulated urban expanded areas within these two zones for the 10 predicted years is shown in Figure 6-7.

Figure 6-7 shows the two trend lines of predicted urban expansion areas as occurring where the urban expansion rate was increasing with the increasing road density (i.e. below

the turning point denoted by the red-dotted line) and where the rate was decreasing (i.e. after the turning point denoted by the yellow-dotted line). The trend line over areas after the turning point is consistently lower than areas before. It further flattens as the urban expansion within these areas become saturated over time with such areas mainly representing city core regions with new space for built up areas becoming increasingly limited. Conversely the (red-dotted) trend line for areas below the turning point has its urban expansion rate increase initially with time before slightly levelling off, but still maintaining a higher rate than the (yellow-dotted) trend line for areas after the turning point. These represent areas which are getting urbanized at a higher rate resulting from spreading outward of the core city, and would also indicate areas with an increased future infrastructure demand. Such areas should then be prioritized in terms of urban planning.

Figure 6-7 Predicted urban growth categorized and quantified w.r.t. road density turning point value

Figure 6-8 Predicted urban growth categorized and quantified w.r.t. the five road density grades

Figure 6-8 shows the predicted urban expansion trend lines categorized and quantified using the five road density grades presented in Table 6-2. As seen, the increasing trend of urban expansion is highest in road density grades 3 and 4, followed by grade 2, and then grades 5 and 1. The slope of the future urban expansion pattern increases initially before flattening for road density grades 2, 3 and 4. This is consistent with the historical trend of Table 6-2. Whereas it flattens much earlier for grades 1 and 5. It is also observed that about 82% of the total predicted expansion area of 129.9 km² (i.e., for year 2027) have occurred over the current road density grades of 2 to 4 which correlates well with the historical trend (1987-2017) of urban growth over these road density grades. Hence, the SLEUTH modelling is shown to not only help identify probable new urbanization areas but together with road density turning point map and road density grades, able to inform on the expansion rates as well as indicating areas needing additional infrastructure to support the expansion.

Figure 6-9 Urban expansion rate (2017 to 2027) vs road density modelled using a third-order polynomial. Turning point value obtained is 11.42 km/km²

A turning point analysis as in Chapter 5.4.4 was performed using the predicted urban expansion between 2017 and 2027; i.e., for the expanded pixels over the 10 future years. In this we assumed the current 2017 road density map also holds over the 10 future years. A turning point plot was generated (Figure 6-9), which shows that the relationship between the logarithm of urban expansion rate and road density also exhibited an inverted concave pattern as historical. The turning point value obtained was 11.42 km/km², similar to the current condition turning point of 12.08 km/km² (Figure 6-4). However, considering that the predicted expansion for the next decade (2017 - 2027) showed a slight reduction in the turning point value (11.42 km/km² versus 12.08 km/km²), this suggests that as the city expands (i.e. accumulates new built up area), the turning point value also changes accordingly. The reduction in the new turning point value could be attributed to the accumulation of new built up areas in the zones where urban expansion was progressively increasing (i.e. orange zone as in Figure 6-4). However, the predicted

expansion here is only for a decade time scale. As such analysis over longer prediction time scales would provide better insights in the turning point dynamics.

The latest Bangkok city development master plan, as prepared once every 5 years cycle, was last released in 2013. Figure 6-10 shows this plan as available through the Bangkok Department of City Planning. Assuming that the current Bangkok city is still based on the current land-use plan of Figure 6-10 and also assuming that it holds for the next 10 years, we examined the SLEUTH predicted built up area for 2027 based on the planning zones. This is to identify the future built up area demand patterns within the city.

Figure 6-10 The Bangkok Comprehensive Plan 2013 (3rd revision) (Source: Department of city planning – Bangkok Metropolitan Administration <http://cpd.bangkok.go.th/eng-compre-map.html>)

Table 6-3, shows the percentage values of 2027 built-up area within Bangkok's existing land-use zones. It is clearly seen that around 60% of future built-up area demand are in the residential zones, low, medium and high-density residential zones. However, of this 60%, 37.5% (i.e., half) is in the low-density residential zone. The next highest

demand in built-up area is in the rural and agricultural zones (including conservation zones) which summed to around 34.1%. These zones are mainly located towards the easternmost and westernmost corridors of Bangkok city administrative area.

A recent paper by Cao et al. (2019) suggested that over the past decades, more than 75% of the newly grown built up areas in Bangkok were transformed from paddy and orchard fields. Urban expansion in the east occurred mostly before 2000, as also through converting paddy fields around the urban areas. Unlike the east, urban expansion in the west was mainly along the transportation infrastructures. Our results here indicated a similar pattern where the future expansion also depends on the conversion of rural lands in the westernmost and easternmost corners of the Bangkok administrative boundary into built up areas. The majority of the predicted built-up area demand (about 87.5%) till year 2027 falls mainly under the residential, rural and agricultural zones. This is predicted to drive the pattern of development for the coming decade in Bangkok city.

Table 6-3 Predicted built up area (in percentage) characterized w.r.t land-use zones

Land use zones (The Bangkok Comprehensive Plan 2013)	2027 predicted built-up area %
National identity cultural conservation zone	0.2
Commercial zone	2.0
Government institutes public utility and amenity	4.1
Industrial zone	0.8
Low density residential	37.5
Medium density residential	18.4
High density residential	2.8
Rural agricultural conservation zone	19.7
Rural agricultural zone	14.4
Warehouse	0.2

6.5. Summary

The key outcomes and findings of this chapter are:

1. Bangkok city showed a radially outward growing pattern with around 287.6 km² expanded area over a 30 year (1987-2017) period.
2. The SLEUTH model predicted about 129.9 km² of future urban expansion over 2017 to 2027.
3. The developed trends of urban expansion with turning point and with road density grades also hold for Bangkok under the SLEUTH predicted future (to 2027) urban growth.

The results in this chapter fulfill on the last part of Figure 3-4 workflow on urban growth. The SLEUTH growth prediction model allows an assessment of the predicted growth w.r.t. road density and population growth for Bangkok city. It is shown that SLEUTH can be a highly useful tool for urban planners for investigating likely outcomes of city developmental plans, thereby supporting the development of actions for sustainable and resilient urban planning. Despite these findings, there are two major constraints with SLEUTH can be summarized as follows: (1) there is only one set of parameters for a whole urban area, which is insufficient for multicore cities; and (2) the model predicts urban area growth based on a simple extrapolation of historic growth trends calibrated by at least four time control points (or time stamps), without taking into account explicit influences exerted by macro driving forces, such as political, social and economic factors. In this, only an indirect influence is introduced, at best, via the calibration using the urban pattern at the control time stamps.

7. Discussion and conclusions

7.1. Study objectives

This PhD research study focusses on identifying and assessing urban area growth for major SEA cities w.r.t. road network, population and GDP from an inter-city to intra-city scale. This study thus analyzes a sub-set of issues within the larger urbanization phenomenon. Urbanization dynamics is multi-faceted, requiring a multi-disciplinary approach to address issues such as related to urban and infrastructure planning, and for sustainable and efficient development. Considering that most SEA cities are in developing economies and therefore a potential risk of failure in infrastructure planning, this study focusses on quantifying urban area growth for major SEA cities at macro-scale, and further assessing linkages amongst urban area growth, road network and population at micro-scale. An urban area growth prediction is also predicted for Bangkok city using SLEUTH and the developed linkages are assessed under the predicted urban growth scenario. Specially, the research objective addressed in Chapter 4 to derive a spatio-temporal urban area growth pattern at inter-city level using NTL data for 15 major SEA cities. The chapter also demonstrated linkages between urban growth and population. In chapter 5, quantitative relationships between urban area growth at intra-city level, road infrastructure and population are developed. Lastly in Chapter 6, SLEUTH is applied to develop an urban area growth prediction for Bangkok city as a case study for an assessment of the future urban expanded area patterns and linkages with road infrastructure. These key findings are further elaborated below.

7.2. Key findings of this research

7.2.1. Assessing urban growth patterns at city level using NTL data

SEA has been going through rapid urbanization over the last few decades. In this thesis, we analyzed urban area growth patterns for 15 SEA cities over 1992 to 2012 using remotely sensed NTL yearly data. In contrast to most prior studies on urban growth patterns that used a single arbitrary and city-specific NTL threshold, this analysis here extracted three urban categories (CS, PU and CU) for all 15 SEA cities following a BG approach. The derived CU and PU categories compared favorably with Landsat derived impervious areas, with the NTL spatial extents enveloping the impervious cover. The combined PU and CU categories were found to increase over time for all 15 SEA cities studied. It is evident that all cities have experienced significant CS-PU transitions, with values as high as 50% for Ho Chi Minh. Most cities have negligible CS-CU transition with the exception of Kuala Lumpur and Ho Chi Minh. The Indonesian cities of Batam, Medan and Makassar have large PU areas in 1994 and remained so in 2008, which can be attributed to them being smaller island/coastal cities having geographical constraints for expansion. Ho Chi Minh shows the highest PU-CU transition followed by Kuala Lumpur and Bangkok. The complex land-sea structure of SEA region also presented accuracy issues in extracting urban categories for smaller island cities such as Singapore, which is affected by narrow water bodies with size comparable to the NTL 1 km resolution.

The urbanization trends showed strong correlation with the population growth for the SEA cities with inland cities showing an unrestrained spatial growth with population. The

SEA cities also expanded spatially into the surrounding countryside generally following a linear trend with population increase.

7.2.2. Linkages amongst urban growth, road network and socio-economic indicators at inter and intra-city scale

The urban area expansion for nine major SEA cities over a 30-year time period, specifically using years 1987 and 2017 was analyzed using higher resolution Landsat data. This allowed for an assessment of linkages with road density, population growth, and GDP growth at an intra-city level. Results from Landsat data analysis as similarly done using coarser NTL data, showed that all nine cities have undergone significant spatial urban expansion over 1987 to 2017. The expansion was observed to be radially outward in most cities, whereas it was only seen in the form of scattered patches in other cities (e.g. Kuala Lumpur and Singapore). The urban expansion areas varied among SEA cities, with highest observed in Ho Chi Minh and lowest in Kuala Lumpur. The expansion rates were found to depend on the geography as well as the city's administrative boundary. For example, geographically unconstrained cities show higher urban expansion rates compared to island and coastal cities. It was observed that the GDP growth rates tend to increase with increasing urbanized area. Singapore showed the highest GDP growth, while Bandung showed the lowest GDP growth rate.

The intra-city urban area expansion w.r.t. the road density grades revealed that for most of the studied cities, significant urban expansion has occurred in medium road density grades of 2 to 4. The relationship between each cities' intra-urban expansion rate and road density exhibited an inverted concave pattern, which was modelled using a third-order polynomial with a turning point. Turning point values ranged from about 5.11

km/km² for Medan to about 17.03 km/km² for Kuala Lumpur. City level zoning maps were generated from these turning point results to identify the intra-city urban area expansion variations. The analysis of population growth rate conditioned on road density also revealed a similar inverted concave relationship, with turning points similar to those in urban expansion analysis. This indicates strong linkages between urban area expansion and population growth rates between same cities.

7.2.3. Urban growth prediction – Bangkok case study

Bangkok is continually growing as a major global metropolis in terms of population, economy and urbanized area, as typical of many SEA cities. It is thus important to identify and assess the spatial urban growth, infrastructure and socio-economic patterns over time into the future and also their linkages in order to better plan for sustainable development. Towards this, the results as based on detailed spatial-temporal analysis of urban area extents and road density at current conditions is projected to future urban conditions using SLEUTH.

The results show that Bangkok has a radially outward growing trend with around 287.6 km² area expanded over a historical 30-year (1987-2017) period, and with a SLEUTH predicted expanded area of 129.9 km² over 2017 to 2027. This urban expansion was found to depend on derived road density grades with a predominant 83% of the urban expanded areas historically (1987-2017) and 82% projected (2017-2027) occurring over road density grades of 2 to 4. The current condition relationship between the intra-city expansion rate and road density exhibited an inverted concave pattern as modelled using a third-order polynomial with a turning point. Areas with read density before the turning point shows an increasing expansion rate with road density and vise-versa. These trends

of urban expansion with turning point and with road density grades also hold under the SLEUTH predicted future (to year 2027) urban growth.

7.3. Implications of the key finding

The NTL data analysis for major SEA cities in Chapter 4 is the first study of its kind across major SEA cities, to identify suitable spatio-temporal urban area categories and their transitions. Our study highlighted the suitability of brightness gradient approach to explicitly identify spatial extents as typically connected to different population and socio-economic levels in a given city. This was achieved by the urban area growth patterns derived by NTL data w.r.t population datasets. The results also demonstrate the successful application of the NTL-based approach to SEA cities, as complementing those reported for regions of U.S, Europe and China.

Road networks are an important foundation for urban development, and their features affect urban expansion. Firstly, urban development requires efficient road networks for support, whereas improving road networks plays a key role in affecting urban land use and guiding changes to the urban landscape. The research results presented in Chapter 5 demonstrate that an urban area expansion-road network relationship exist and with a turning point analysis to identify the direction and scale of urban expansion. The led to the generation of road density turning point values for nine major SEA cities which enabled generation of zoning maps to identify regions with different urban growth and population growth. Such turning points were reported by others for four global cities, are now extended here to nine major SEA cities. This work also demonstrated a new, though quantitatively similar relationship between population growth and road density. The linkages between urban area expansion, road density and socio-economic indicators such

as developed here could guide understanding of the urbanization and developmental processes for SEA cities which, in turn could inform on urban planning. The turning point provides one such indicator that could assess the direction of urban area expansion and population growth processes w.r.t. the road density. The derived intra-city zoning maps could help improve on urban planning, thereby promoting more sustainable development. This is especially relevant for developing economies towards improving their land use efficiency and infrastructure planning.

Cellular Automata (CA) is a modeling procedure which is widely used in urban growth studies for predicting future urban extents. The research presented in Chapter 6 used a CA-based SLEUTH model to simulate and predict the urban area growth in Bangkok city, as a typical SEA city that underwent recent rapid urban growth. The results highlight that spatial-temporal analysis of urban extents together with SLEUTH can provide useful information towards identifying near-future built-up area demand and therefore also supports sustainable development planning. The intra-city zoning map could help improve on urban planning as well as identify areas likely to require additional infrastructure.

7.4. Limitations of this research

Modelling urban growth within cities is a challenging task as cities are complex systems with a large number of factors influencing each other while shaping a city. Modelling linkages between urban extent, road infrastructure and socio-economic indicators at intra-urban scale is inherently data-driven and data-intensive, and made more so due to newer IT-based systems (e.g. cyber-physical) being progressively introduced to enable high level synergistic interactions among the various urban sub-systems. This study had made

use of openly available datasets for major SEA cities to establish quantitative linkages spanning between 1987 and 2017. This is in light of the fact that most cities in SEA being in developing economies lack adequate publicly available, high resolution, time-varying flow (e.g. traffic flow) data that would be needed to improve on the spatio-temporal trend analysis presented here.

Infrastructure is an important backbone for a city's development. While roads primarily act as a skeleton for the city's spatial form, other infrastructure components such as power, telecommunication and water are also equally vital in shaping a city. The incorporation of such infrastructure systems would also improve on the urban area expansion analysis presented. Temporal datasets on transport networks and traffic flow, power networks, and water networks could therefore improve on intra-urban growth analysis. The quantitative relationships developed here amongst built-up areas, road infrastructure and population could be augmented with similar studies using relevant data from other infrastructure as such data become available.

Cellular Automata based SLEUTH model has been widely adopted in urban growth analysis globally. This research also adopted the SLEUTH model in Chapter 6 to predict urban growth patterns for Bangkok city from 2018 to 2027. However, the SLEUTH model incorporates only one set of parameters for a whole urban area, which is insufficient for multicore cities. The model predicts urban growth based on a straightforward extrapolation of historic growth trends calibrated by at least four urban time stamps and two road networks time stamps. There is no explicit account of influences caused by other macro driving forces, such as political, social and economic which is an inherent limitation. At best only an indirect influence as is reflected through the pattern of urbanization over these calibration time stamps.

7.5. Recommendations and future work

Taken together, the obtained results on SEA cities' spatio-temporal growth (Chapter 4), the cities' historical intra-city growth w.r.t. road density (Chapter 5) and Bangkok future growth (Chapter 6) represent a comprehensive study on the urban area growth dynamics of SEA cities. Follow-on studies should expand on the scope to include other SEA cities, analyze infrastructure beyond road networks, explore the use of temporally varying flow data, as well as using different urban growth models that captures macro socio-economic factors to confirm on the conclusions reached. The present results, particularly on the role turning point thresholds can be reassessed with respect to patterns of power infrastructure, telecommunication and traffic flow as data layers on these become increasingly available. This could then contribute to the debate on the cause-effect relationship between urban growth and infrastructure. Quantitative relationships such as turning points could also seed similar research regarding the impact of economic activity and income distributions w.r.t. urbanization scenarios. Identifying and developing a capability to model infrastructure growth patterns in tandem with urban area growth would represent a major breakthrough towards the understanding of urbanization.

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Appendix

Additional figures:

Figure A-1 Comparison of Landsat TM urban extent with NTL derived urban categories for Bandung, Batam and Hanoi

Figure A-2 Comparison of Landsat TM urban extent with NTL derived urban categories for Jakarta and Makassar

Figure A-3 Comparison of Landsat TM urban extent with NTL derived urban categories for Phnom Penh and Yangon

Figure A-4 Illustration of methodology for the city of Bandung

Figure A-5 Illustration of methodology for the city of Bangkok

Figure A-6 Illustration of methodology for the city of Ho Chi Minh

Figure A-7 Illustration of methodology for the city of Kuala Lumpur

Figure A-8 Illustration of methodology for the city of Manila

Figure A-9 Illustration of methodology for the city of Medan

Figure A-10 Illustration of methodology for the city of Singapore

Figure A-11 Illustration of methodology for the city of Yangon

Figure A-12 Confidence ellipse (95%) plots for NTL Total Light Index (PU and CU pixels) versus population for (a) 1995, (b) 2000, (c) 2005 and (d) 2010

Figure A-13 Confidence ellipse (90%) plots for NTL Total Light Index (PU and CU pixels) versus population for (a) 1995, (b) 2000, (c) 2005 and (d) 2010

Figure A-14 Confidence ellipse (95%) plot for NTL derived urban extent (PU and CU) versus population for (a) 1995, (b) 2000, (c) 2005 and (d) 2010

Figure A-15 Confidence ellipse (90%) NTL derived urban extent (PU and CU) versus population for (a) 1995, (b) 2000, (c) 2005 and (d) 2010

Figure A-16 Confidence ellipse (95%) plot for the rate of change in urban extent from 1995 to 2010 (normalized w.r.t. 1995 urban extent) with rate of change in population (Note: Batam (BTH) has an exceptional 416% increase in population and not included)

Figure A-17 Confidence ellipse (90%) plot for the rate of change in urban extent from 1995 to 2010 (normalized w.r.t. 1995 urban extent) with rate of change in population (Note: Batam (BTH) has an exceptional 416% increase in population and not included)