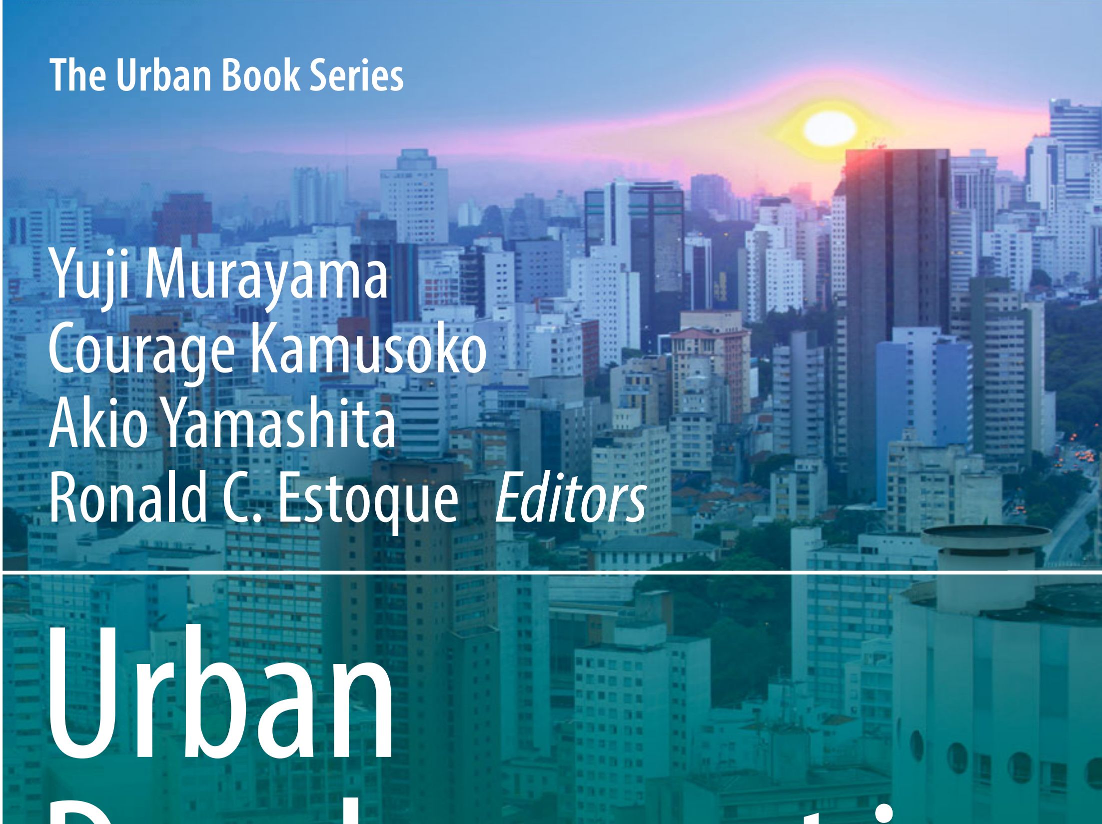

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Urban Development in Asia and Africa

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Preface

This book examines the urban growth trends and patterns of various metropolitan regions in Asia and Africa from a geographical perspective. State-of-the-art geospatial tools and techniques from the geographic information systems (GIS) and science, remote sensing, and machine learning disciplines were used for the land change analysis. In addition to the empirical results, the methodological approaches employed and discussed in this book showcase the potential of geospatial analysis (e.g., land change modeling) for improving our understanding of the trends and patterns of urban growth in Asia and Africa. Furthermore, given the complexity of the urban growth process across the world, issues raised in this book will contribute to the improvement of future geospatial analysis of urban growth in the developing regions. This book is written for researchers, academics, practitioners, and graduate students. The inclusion of the origin and brief history of each of the selected metropolitan regions, including the analysis of their urban primacy, spatiotemporal patterns of urban land use/cover changes, driving forces of urban development, and implications for future sustainable development, makes the book an important reference for various related studies.

Most of the contributors to this book are affiliated with the Division of Spatial Information Science, University of Tsukuba, Japan. The division, which was established in 2000 to include geographical information science within the doctoral program in geoenvironmental sciences, provides an enabling research environment where faculty members, staff, and students work together to advance knowledge in GIS and remote sensing techniques in different areas of interest.

Our sincere thanks go to the staff members of the Division of Spatial Information Science, University of Tsukuba, especially to Mr. Hao Hou, Mr. Hao Gong, Mr. Matamyo Simwanda, Mr. Shyamantha Subasinghe, and Mr. Xinmin Zhang.

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Tsukuba, Japan
September 2016

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Part I
Introduction

Chapter 1
Importance of Remote Sensing and Land Change Modeling for Urbanization Studies

Courage Kamusoko

Abstract Remote sensing analysis and land change modeling provide valuable insights into urban land use/cover changes and growth processes at multiple spatial and temporal scales. This chapter briefly outlines the importance of remote sensing, and land change modeling for urbanization studies in selected countries in Africa and Asia. The methodological approaches discussed in this book showcase the potential of remote sensing and land change modeling analysis in order to improve understanding of urban growth in Africa and Asia. Given the complexity of urban growth processes globally, issues raised in this book will contribute to the improvement of future land use/cover change analysis and modeling, particularly in the developing country context. The geospatial analysis approach based on remote sensing and land change modeling provides a synoptic view of urbanization in Africa and Asia.

1.1 Introduction

According to the United Nations (2015), approximately 54% of the world's population currently lives in urban areas. It is estimated that continuing urbanization will add 2.5 billion people to the world's urban population by 2050, of which 90% of the increase will be concentrated in Asia and Africa (Masser 2001; United Nations 2006, 2012, 2015). While 40 and 48% of the population in Africa and Asia reside in urban areas, urban population is expected to increase to 56 and 64% in these regions by 2050 (United Nations 2015). In addition, the fastest-growing urban agglomerations, which are medium-sized cities and cities with less than 1 million inhabitants will be located in Asia and Africa (United Nations 2015).

The rapid increase in urban population and urbanization poses a number of challenges to planners and policy makers (Yuan et al. 2005; Pacione 2007).

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For example, most urban areas in developing Africa and Asia are confronted with problems such as failure to provide services to the growing urban population, increasing rural–urban migration, proliferation of informal settlements and epidemics, as well as environmental degradation (Rakodi 1995; Brown 2001). While rapid urbanization is expected to exacerbate these problems, experiences from the developed countries show that urbanization has the potential to boost national economic growth (Collier 2016). Therefore, increasing urbanization presents Africa and Asia with an opportunity to improve the quality of life and social well-being. In order to ensure that urbanization produces optimal economic growth levels, African and Asian countries need to formulate smart and sustainable urban development strategies that can guide socioeconomic development (Collier 2016). This requires accurate, consistent, and timely geospatial information on urbanization trends in order to assess current and future urban growth (Herold et al. 2002). Equally important, geospatial information will be useful for setting policies that promote inclusive and equitable urban, environmental, and socioeconomic development (United Nations 2015).

1.2 Application of Remote Sensing for Urban Land Use/Cover Mapping

The past decades have witnessed the rise of sustainable urban development and smart growth initiatives, particularly in developed countries (Herold et al. 2003, 2005). However, the implementation of sustainable Urban development and smart growth initiatives have been lagging behind in most parts of Africa and Asia due to a number of factors. Chief among these factors is the lack of clear and practical urban planning due to the dearth of geospatial information (International Federation of Surveyors 2010). According to the International Federation of Surveyors (2010), 70% of urban growth in developing countries is not planned. Efforts to produce or update existing urban geospatial information for planning purposes have been hampered by high cost of acquiring geospatial data, especially from conventional land use surveys or aerial photography (Conitz 2000). Nonetheless, increases in the use of remote sensing technology (e.g., high and medium-resolution satellite data) for mapping urban land use/cover have been noted in the past decades (Ward et al. 2000; Guindon et al. 2004; Yuan et al. 2005; Lu and Weng 2007). This is because high and medium-resolution satellite remotely sensed data such as Ikonos, Quickbird, WorldView, Landsat satellite series, Systeme Pour l'Observation de Ia Terre (SPOT), Terra-1 ASTER, RapidEye, and Advanced Land Observing Satellite (ALOS) have relatively good global coverage. It is recognized that some of the high and medium-resolution satellite data have coarse spatial resolution, which limits detailed urban planning. However, the high and medium-resolution satellite data is useful for identifying and mapping land use/cover patterns in urban landscapes at a regional scale.

High and medium-resolution earth observation satellite data have been successfully used to map and monitor urban growth in developed countries (Lo and Choi 2004; Yuan et al. 2005; Bagan and Yamagata 2012). Furthermore, a variety of classification techniques have also been developed and used to classify urban land use/cover. These classification techniques include: the incorporation of structural and textural information (Gong and Howarth 1990; Moller-Jensen 1990); combining satellite images with ancillary data (Harris and Ventura 1995); vegetation—impervious surface—soil models (Ridd 1995); expert systems (Stefanov et al. 2001); hybrid methods that incorporate soft and hard classifications (Lo and Choi 2004); the use of built-up indices (Zha et al. 2003; Xu 2007; Estoque and Murayama 2015); neural networks (Seto and Liu 2003); segmentation and object-based classifications (Guindon et al. 2004); linear spectral mixture analysis (Phinn et al. 2002; Wu and Murray 2003); support vector machines (Ghosh et al. 2014) and random forests (Cao et al. 2009). While significant urban land use/cover classification and urban growth monitoring in the developed countries have been noted, urban landscapes are still poorly quantified in Africa and Asia despite their rapid urbanization. This is attributed to the fact that urban land use/cover classification still poses a number of challenges—such as spectral confusion and mixed pixels—given the heterogeneous nature of the urban landscapes coupled with the relatively small spatial size of surficial materials (Foody 2000; Masser 2001; Stefanov et al. 2001; Alpin 2003; Xian and Crane 2005). For example, in most African urban landscapes, spectral confusion is a problem because gravel (dirt) roads in informal settlements or slums areas have similar spectral responses to those of bare vacant plots and agriculture fields leading to inaccurate land use/cover mapping. In this book, a random forests classification approach is used to classify built-up and non-built-up areas based on Landsat imagery.

1.3 Developments in Urban Land Change Modeling

The improvements in remote sensing technology during the past 40 years, combined with developments in Geographic Information Systems (GIS) have provided an opportunity to advance urban land change modeling (The State of Land Change Modeling 2014). While many land change models (LCMs) have been developed to examine and simulate urban growth, this book focuses on machine learning and cellular automata-based LCMs. Therefore, this chapter will briefly review some of the major milestones in the development of urban LCMs.

The application of urban models in the context of planning can be traced back to von Thünen's agricultural location model, Weber's industrial location models, and Christaller's central place theory (Liu 2009). Later on, static urban growth and land use pattern models such as Burgess's concentric zone model, Hoyt's sector model, and Harry and Ullmans's multiple nuclei model were developed (Liu 2009). However, interest in modeling in general, and urban growth modeling in particular grew during the "quantitative revolution" of the 1950s and 1960s (Liu 2009).

During this period urban-scale models were generated by heuristic techniques for forecasting (Briassoulis 2000). For example, the Chicago Area Transportation Study (CATS) model used the development capacity concept based on historical information on population densities and vacant land to forecast land use (Hamburg and Creightan 1959). With the emergence of computer simulation techniques in the early 1960s, urban-scale LCMs such as the California Urban Futures Model (CUFM), and the integrated land use/transportation models were further developed (Briassoulis 2000).

The California Urban Futures Model (CUFM) was developed by Landis (1994, 1995). It provided a spatially explicit integrated model of the housing market, which was used to analyze various policies as well as to incorporate the environmental variability of a study area. While the CUFM assumed profit maximizing land developers, it lacked robust theoretical foundations in economics and land development (Briassoulis 2000). Second, the model did not take into account the interaction of land use with the transportation network. Third, the model did not include feedbacks from development or excess demand on housing prices. Fourth, the model did not deal with the allocation of other uses such as industrial and commercial. In essence, the CUFM ignored the important driving influence of the location decisions (Briassoulis 2000).

The integrated land use/transportation models were developed in the 1970s and 1980s. Their purpose was to model land use/cover and transportation interactions. More importantly, they were used to analyze the spatial land use impacts of changes in the transportation system (Briassoulis 2000). For example, the Integrated Transportation and Land Use Package (ITLUP) was implemented to link urban land use and transportation models (Putman 1983). More models such as the transportation and land use (TRANUS) model (de la Barra et al. 1984, 1989), the Integrated Land Use, Transportation, Environment (ILUTE) modelling systems were developed. Although the integration between the urban land use systems and transportation have been achieved, criticism on urban growth modeling intensified in the 1970s and 1980s because the models emphasized modeling techniques and lacked theoretical underpinnings (Liu 2009).

However, innovations in GIS and the availability of GIS data (e.g., remotely sensed-derived land use/cover maps) inspired a new wave of developments in urban growth modeling. This was also supported by rapid advancement in computer technology coupled with the decrease in the cost of computer hardware. In addition, developments in spatial, natural, and social sciences concerning bottom-up, dynamic and flexible self-organizing modeling systems complemented by theories that emphasize locally made decision to give rise to global patterns led to application of cellular automata (CA) models for urban growth modeling (Tobler 1979; Wolfram 1984; Couclelis 1985; Engelen 1988; Batty 1998; Wu and Webster 1998). Cellular automata models were originally conceived by Ulam and Von Neumann in the 1940s to provide a formal framework for investigating the behavior of complex and self-reproducible systems (White and Engelen 1993). Generally, CA models are dynamic and discrete space and time systems. Time progresses in discrete steps and all cells change their state simultaneously as a function of their own state, together with the state of the cells in their neighborhood according to a specified set of transition rules (White and Engelen 1993).

The application of CA models for urban growth modeling offered a flexible platform to integrate GIS data at multiple temporal and spatial scales. This is because CA approaches could easily represent complex patterns using simple rules (White and Engelen 1997). According to Torrens (2003), CA models were suitable to simulate urban systems since land use can be presented as a cell. More importantly, CA models allowed the inclusion of urban theory (e.g., spatial interaction) considering that cities exhibit several characteristics of complexity such as fractal dimensionality and self-similarity across scales, self-organization, and emergence (Torrens 2002). While the past decades have witnessed the development and application of many urban CA land change models (Pijanowski et al. 2005; Mundia and Aniya 2007; Yeh and Li 2009), most of the models have not been adopted by urban planners and policy makers (Sante et al. 2010). Nevertheless, urban CA models have provided deep insights into urban growth dynamics as well as "laboratories" to explore "what if" urban growth scenarios.

1.4 Summary of Book Chapters

As we will see from the various examples provided in this book, urbanization in Africa and Asia is creating metropolitan areas whose boundaries are constantly changing beyond the defined administrative boundaries. Therefore, it is critical to map land use/cover in an accurate, consistent and timely manner in order to understand the constantly evolving urban spatial developments beyond the defined formal city administrative boundaries. The combined methodological approach—based on remote sensing, spatial metrics and LCMs—adopted in this book has great potential to improve urban land use/cover mapping and modeling, particularly in complex urban areas in Africa and Asia.

This book is organized into four main parts. Part I presents the introduction, which is covered in Chaps. 1–3. This chapter outlines the importance of remote sensing and LCMs for urbanization studies, while Chap. 2 describes the overall methodological framework used to map, analyze and model land use/cover changes. Chapter 3 provides an overview of the rapid urbanization in Africa and Asia.

Part II covers Chaps. 4–12 and focuses on the major cities in Asia, including Beijing, Manila, Jakarta, Hanoi, Bangkok, Yangon, Dhaka, Kathmandu, and Tehran metropolitan areas. Part III covers Chaps. 13–18 and focuses on the major cities in Africa, including Dakar, Bamako, Nairobi, Lilongwe, Harare, and Johannesburg metropolitan areas. These chapters trace the origin and brief history of each of the metropolitan areas. The urban primacy of these cities and the spatiotemporal patterns and changes of their urban land use/cover are examined. The factors driving their urban development, as well as the implications of the observed and projected urban land use/cover changes for future sustainable urban development, are discussed.

Finally, Part IV provides the overall book summary and conclusions. More specifically, Chap. 19 focuses on the comparative analysis of the trends and spatial patterns of urbanization in Africa and Asia. Chapter 20 discusses the future of metropolitan areas in developing Africa and Asia.

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Chapter 2
Methodology

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Abstract Remote sensing, GIS, and land change models (LCMs) are critical for mapping urban land use/cover and simulating "what if" urban growth scenarios, particularly in developing countries experiencing rapid urbanization. The purpose of this chapter is to describe briefly the methodology used to produce land use/cover maps, and simulate land use/cover changes for selected metropolitan areas in Asia and Africa. Land use/cover maps were classified from Landsat imagery for 1990, 2000, 2010, and 2014 using the random forest (RF) classifier. Quantitative accuracy assessment was not conducted for the 1990 land use/cover maps due to lack of reference data. However, qualitative and quantitative accuracy assessment was performed for the 2000, 2010, and 2014 land use/cover maps based on Google Earth imagery. Overall land use/cover classification accuracy for all land use/cover maps ranged from 70 to 90%. Land use/cover changes were simulated based on the boosted regression trees-cellular automata (BRT-CA) and RF-CA LCMs. We evaluated the goodness-of-fit of transition potential maps, and validated the simulated land use/cover changes based on robust statistical measures. Generally, the BRT-CA and RF-CA LCMs for all metropolitan areas in Asia and Africa performed relatively well. In particular, the BRT-CA and RF-CA LCMs for metropolitan areas in Africa had the best performance. The modeling and simulation results presented in this chapter provide an initial exploration of BRT-CA and RF-CA LCMs in Asia and Africa. This chapter demonstrates the significance of robust calibration, validation, and simulation of spatial LCMs for all metropolitan areas in Asia and Africa.

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2.1 Introduction

The past decades have witnessed tremendous development of land change models (LCMs) due to availability of remote sensing data, advances in geographical information and social sciences as well as theoretical developments of complexity and self-organizing systems (Tobler 1979; Wolfram 1984; Couclelis 1985; Engelen 1988; Batty 1998, 2005; Wu and Webster 1998; Torrens 2008; The Sate of Land Change Modeling 2014). To date, numerous LCMs have been developed to model and simulate land use/cover changes (Wu and Webster 1998; Verburg et al. 1999; Messina and Walsh 2001; Soares-Filho et al. 2002), deforestation (Lambin 1997; Geoghegan et al. 2001; Mas et al. 2004), urban growth (Couclelis 1989; Clarke et al. 1997; Cheng and Masser 2004; Yeh and Li 2009), climate change (Dale 1997), and hydrology (Matheussen et al. 2000).

While LCMs have highlighted significant insights into landscape change processes, most of these models have been criticized for lacking robust calibration and validation procedures (Pontius and Malanson 2005; Vliet et al. 2011). For example, previous studies show that transition potential maps—which are key inputs of LCM—have been validated using the relative operating characteristic (ROC) area under the curve (AUC) statistic (Eastman et al. 2005). However, the AUC statistic has limitations, especially for validating transition potential maps (Mas et al. 2013; Pontius and Parmentier 2014; Pontius and Si 2014) since it includes persistence areas (Eastman et al. 2005). For example, Kamusoko and Gamba (2015) demonstrated that the AUC can be large due to correctly predicted persistence not correctly predicted change (The Sate of Land Change Modeling 2014). Furthermore, percent correct and the standard Kappa statistics have been widely used to validate LCM (Verbug et al. 2004, Pontius and Malanson 2005; Vliet et al. 2011). However, the use of standard Kappa statistic for validating LCM has been criticized given its tendency to overestimate the agreement between the simulated and observed (reference) maps (Hagen 2002; Pontius et al. 2002). It has also been noted that the standard Kappa statistic neither reveals the components of agreement and disagreement between the simulated and observed (reference) maps nor accounts for persistence (that is, land use/cover classes that do not change during the simulation) (Pontius et al. 2007, 2008).

More recently, numerous statistical measures for calibrating and validating LCMs have been developed to overcome limitations of the ROC statistic and standard Kappa. For example, Pontius and Si (2014) developed the total operating characteristic (TOC) statistic to validate transition potential maps. The TOC statistic provides information such as misses and correct rejections in addition to ROC statistic such as hits (hits plus misses) and false alarms (false alarms plus correct rejections) (Pontius and Si 2014).

More importantly, the TOC statistic shows the actual units in the contingency table (e.g., square kilometers) instead of a unitless statistic such as AUC (Pontius and Si 2014). Furthermore, Visser and de Njis (2006) and Vliet et al. (2011) developed additional accuracy assessment statistics, which take into account information contained in the initial land use/cover map and the proportion of persistent land use/cover classes during the simulation period. The KSimulation expresses the agreement between the simulated land use/cover transitions and reference land use/cover transitions, while KTranslocation measures the degree to which the transitions agree in terms of allocations (Vliet et al. 2011). The KTransition captures the agreement in terms of quantity of built-up and non-built-up transitions (Vliet et al. 2011). The KSimulation, KTransition, and KTranslocation statistics are available in the Map Comparison Kit software by Visser and de Njis (2006). Pontius et al. (2007, 2008) also introduced the Figure of Merit (FoM), which expresses agreement between the observed and simulated changes for validating simulated land use/cover changes.

While these novel statistics have provided a new paradigm for validation, to date, few studies (Kamusoko and Gamba 2015) have applied these robust statistical measures for validating LCMs. Therefore, more research is needed to better understand uncertainty of LCMs based on the above-mentioned validation statistics. This is critical since LCMs are being considered as useful procedures or tools to establish business-as-usual baselines for urban growth and other land use/cover change studies (The Sate of Land Change Modeling 2014; Kamusoko and Gamba 2015). The purpose of this chapter is to describe briefly the methodology used to produce the land use/cover maps, calibrate and validate LCMs (in this case, both transition potential and simulated land use/cover maps). The specific objectives of this chapter are to evaluate the goodness-of-fit of transition potential maps, validate the simulated land use/cover maps, and elucidate components of agreement and disagreement. Validation statistics developed by Pontius and Si (2014), Pontius and Malanson (2005), Visser and de Njis (2006), and Vliet et al. (2011) as well as simple GIS overlay analysis are used in this chapter.

This chapter is organized as follows: Sect. 2.2 provides an overview of the image processing and change analysis; Sect. 2.3 describes land change modeling implementation procedures for all the metropolitan areas in Asia and Africa; Sect. 2.4 presents the results and discussions; while Sect. 2.5 provides the summary and conclusion of the chapter.

2.2 Image Processing and Change Analysis

2.2.1 Satellite Imagery and Reference Data

Landsat 4 and 5 Thematic Mapper (TM), Landsat 7 Enhanced Thematic Mapper Plus (ETM+), and Landsat 8 datasets were used for land use/cover classification

(Tables 2.1 and 2.2). All the Landsat datasets were acquired between 1988 and 2014 (Tables 2.1 and 2.2). The selection of the image data was based on the availability of high-quality satellite imagery with minimal cloud cover. Landsat 8 (originally called Landsat Data Continuity Mission) was launched on February 11, 2013, as the eighth

Table 2.1 Summary of Landsat imagery used for Metropolitan Areas in Asia

Metropolitan area	Landsat sensor	Path/row	Acquisition date
Bangkok	L4 TM	129/50	30/03/1988
		129/51	30/03/1988
	L7 ETM+	129/50	20/12/1999
		129/51	20/12/1999
	L5 TM	129/50	19/01/2009
		129/51	19/01/2009
	L8	129/50	17/01/2014
		129/51	17/01/2014
Beijing	L4 TM	123/32	25/12/1988
		123/33	25/12/1988
	L7 ETM+	123/32	30/04/2000
		123/33	30/04/2000
	L5 TM	123/32	14/03/2009
		123/33	14/03/2009
	L8	123/32	29/04/2014
		123/33	29/04/2014
Dhaka	L4 TM	137/44	13/02/1989
	L7 ETM+	137/44	28/02/2000
	L5 TM	137/44	15/03/2010
	L8	137/44	30/03/2014
Hanoi	L5 TM	127/45	11/09/1988
	L7 ETM+	127/45	20/12/1999
	L5 TM	127/45	05/11/2009
	L8	127/45	19/01/2014
Jakarta	L5 TM	122/64	03/05/1989
	L7 ETM+	122/64	16/08/2001
	L5 TM	122/64	21/05/2010
	L8	122/64	25/08/2013
Kathmandu	L5 TM	141/41	24/01/1989
	L7 ETM+	141/41	04/11/1999
	L5 TM	141/41	11/02/2010
	L8	141/41	26/03/2014
Manila	L5 TM	116/50	02/04/1993
	L7 ETM+	116/50	26/11/2001
	L5 TM	116/50	05/03/2009
	L8	116/50	07/02/2014

(continued)

Table 2.1 (continued)

Metropolitan area	Landsat sensor	Path/row	Acquisition date
Tehran	L5 TM L4 TM	164/35 165/35	19/09/1988 16/09/1987
	L7 ETM+	164/35	18/07/2000
		165/35	25/07/2000
	L5 TM	164/35	22/07/2010
	L8	164/35	08/12/2014
		165/35	13/11/2014
Yangon	L5 TM	132/48	26/02/1989
	L7 ETM+	132/48	21/11/1999
	L5 TM	132/48	24/01/2009
	L8	132/48	23/02/2014

Table 2.2 Summary of Landsat imagery used for Metropolitan Areas in Africa

Metropolitan area	Sensor	Path/row	Acquisition date
Bamako	L4 TM	199/51	22/03/1990
	L7 ETM+	199/51	30/12/2000
	L5 TM	199/51	16/01/2010
	L8	199/51	16/03/2014
Dakar	L4 TM	205/50	15/10/1989
	L7 ETM+	205/50	04/11/1999
	L5 TM	205/50	25/10/2010
	L8	205/50	17/03/2013
Harare	L5 TM	170/72	23/06/1990
	L7 ETM+	170/72	30/09/2000
	L5 TM	170/72	26/05/2009
	L8	170/72	24/05/2014
Johannesburg	L5 TM	170/78	25/07/1990
	L7 ETM+	170/78	28/07/2000
	L5 TM	170/78	26/05/2009
	L8	170/78	25/06/2014
Lilongwe	L5 TM	168/70	11/07/1990
	L5 TM	168/70	02/06/1999
	L5 TM	168/70	22/08/2011
	L8	168/70	26/07/2013
Nairobi	L5 TM	168/61	17/10/1988
	L7 ETM+	168/61	21/02/2000
	L5 TM	168/61	19/08/2010
	L8	168/61	03/02/2014

satellite in the Landsat program (NASA 2013; USGS 2013). Landsat 8 consists of the Operational Land Imager (OLI) and the Thermal Infrared Sensor (TIRS), which provide images at a spatial resolution of 15 m (panchromatic), 30 m (visible, NIR, SWIR), and 100 m (thermal) (NASA 2013; USGS 2013).

2.2.2 Random Forest Classification

A modified land cover classification scheme was used for image classification. Three land use/cover classes were considered in this study: (1) built-up; (2) non-built-up; and (3) water. Detailed descriptions of the land use/cover classes are provided in Table 2.3. Land use/cover maps were produced from the classification of Landsat imagery for 1990, 2000, 2010, and 2014 using the (RF) classifier, an ensemble decision tree machine learning method (Breiman 2001). The RF classifier combines bootstrap sampling to construct many individual decision trees, from which a final class assignment is produced (Breiman 2001). This machine learning classifier can be used to learn nonlinear relationships, particularly in heterogeneous urban landscapes. The RF classifier has been demonstrated to be effective for accurate land cover mapping across complex and heterogeneous landscapes (Rodriguez et al. 2012). All the Landsat imagery for all metropolitan areas were classified using the "randomForest" package (Liaw and Wiener 2002), which is available in R (R Development Core Team 2005).

Quantitative accuracy assessment for the 1990 land use/cover maps was not conducted because of the unavailability of reference data such as aerial photographs and high-resolution satellite imagery. However, the Atlas of Urban Expansion developed by the Lincoln Institute of Land Policy (Angel et al. 2010) was used to visually check the quality of land use/cover maps for the 1990 epoch (that is, Landsat imagery acquired between 1988 and 1993). Qualitative and quantitative accuracy assessment was conducted for land use/cover maps from 2000, 2010, and 2014 epochs. The primary reference data for accuracy assessment was obtained from very high-resolution images (e.g., QuickBird image) in Google Earth™

Table 2.3 Land use/cover classes

Class	Description
Built-up	Residential, commercial and services, industrial, transportation, communication and utilities, construction sites, and landfills
Non-built-up	All wooded areas, riverine vegetation, shrubs and bushes, grass cover, golf courses, parks, cultivated land, fallow land, land under irrigation, bare exposed areas and transitional areas
Water	Rivers, reservoirs, and other water bodies

(Google Earth 2015). Overall land use/cover classification accuracy for all land use/cover maps (from 2000 to 2014) ranged from 70 to 90% for all the metropolitan areas.

2.3 Land Change Modeling

2.3.1 Data

We used land use/cover maps and driving factors to develop spatial LCMs for all metropolitan areas (Table 2.4). Major roads were obtained from OpenStreetMap data, while city center was digitized from Google Earth. Elevation was derived from ASTERGDEM, while population density data were acquired from the LandScan data (Bhaduri et al. 2007). We used built-up areas (extracted from the 1990 and 2010 land cover maps), major roads, and city center data to compute "distance to built-up areas", "distance to major roads", and "distance to city center" using the Euclidean distance procedures available in ArcGIS 10.2. We computed "distance to built-up areas" for 1990 and 2010, and "distance to major roads" because built-up areas and roads are dynamic driving factors that change over time. Furthermore, we used "distance to built-up areas" as the driving factor because previous urban form influences future urban patterns (Liu 2009). Finally, all driving factors were resampled to 30 m × 30 m spatial resolution in order to match the spatial resolution of the Landsat-derived land use/cover maps.

2.3.2 Model Calibration and Simulation

We used the following procedures to implement the LCMs for all metropolitan areas: (I) computing transition rates, (II) transition potential modeling, and (III) CA simulation. Machine learning and statistical algorithms available in R were used to model transition potential, while functions available in Dinamica Environment for Geoprocessing Objects (EGO) were used to compute transition rates and simulate land use/cover changes. R is a free and open-source statistical and computer graphic

Table 2.4 Input data for calibrating and simulating land use/cover change

Variable	Source
Land use/cover maps (1990, 2000, and 2010)	Classified from landsat data
Distance to built-up areas (1990, 2000, 2010)	Derived from land use/cover
Distance to major roads (1990–2000, 2000–2010)	Open street map
Distance to city center	Digitized from Google Earth
Elevation	ASTER GDEM
Population density (2000, 2010)	LandScan data

software (R Core Development Team 2005), while **Dinamica EGO** is a freeware that was developed by Soares-Filho et al. (2009). **Dinamica EGO** consists of a sophisticated platform for developing dynamic spatial models, which involve nested iterations, multiple-step transitions, dynamic feedbacks, and multiscale approaches (Soares-Filho et al. 2009).

(I) Computation of transition rates

We used land use/cover maps for 1990, 2000, and 2010 to compute multiple-step transition rates in Dinamica EGO. Multiple-step transition rates refer to transition rates that are computed at annual time step. Therefore, the "1990–2000", "2000–2010", and "1990–2010" multiple-step transition rates for all the metropolitan areas were used as input for the final CA simulation run following the methodology described in Kamusoko and Gamba (2015).

(II) Computation of transition potential maps

In order to compute the "non-built-up to built-up" transition potential maps, "non-built to built-up" change map from 1990 to 2010, biophysical and socioeconomic driving factors were combined based on two machine learning procedures. First, the RF model (Breiman 2001) was used to compute transition potential maps for all metropolitan areas. RF is a machine learning approach, which builds regression trees to describe the relationship between the response and predictor variables (Breiman 2001). In general, multiple trees are built, each based on a bootstrap sample of the data and a random subset of the predictors. The final model predictions are an average prediction across component trees. Previous studies have shown that the RF model is effective for modeling transition potential maps (Kamusoko and Gamba 2015). However, preliminary transition potential calibration results indicated overfitting problems for some metropolitan areas such as Beijing, Bamako, Dhaka, Hanoi, Johannesburg, Kathmandu, and Nairobi. Therefore, an alternative method based on boosted regression trees (BRT) (Friedman 2002; Elith et al. 2008) was employed. BRT is also a machine learning approach, which forms a relationship between a response variable and its predictors without a priori specification of a data model (Friedman 2002; Elith et al. 2008). Generally, a large number of simple models are combined to form a final model (Elith et al. 2008). The main advantage of the BRT model is that it uses a sequential model-fitting algorithm, which reduces both bias and variance and therefore improves model accuracy.

In this study, approximately 2000 training points randomly sampled from "non-built-up to built-up" and "no change" (that is, built-up and non-built-up persistence) areas between 1990 and 2010 were used to fit the BRT and RF models. Generally, 70% of the training areas were used for model development, while 30% were used for cross-validation. The gbm and dismo packages (Ridgeway 2006; Elith et al. 2008) available in R were used to fit the BRT model. The BRT model was optimized by changing the learning rate, tree complexity, and number of trees parameters. The learning rate controls the weight that is given to each component tree, while the complexity controls the number of nodes within each tree (Ridgeway 2006; Elith et al. 2008). We set the initial number of trees to five, learning rate to a maximum of 0.001, and bagging fraction to 0.5 (that is, at each iteration 50% of the data is drawn at random, without replacement from the full training set) for each metropolitan area. After many iterations, the best model was selected to compute a "non-built-up to built-up" transition potential map for each metropolitan area.

The RF model was used to compute "non-built-up to built-up" transition potential maps for Bangkok, Jakarta, Manila, Tehran, Yangon, Dakar, Harare, and Lilongwe. The "randomForest" (Liaw and Wiener 2002) package available in R was used to fit the RF model. The RF model parameters were adjusted by changing the number of input variables selected at each node split and the total number of trees included in the model (25, 50, 100, and 500) in order to achieve optimum model performance. After calibration, between 100 and 500 trees were used to construct the final RF model and then compute the "non-built-up to built-up" transition potential maps.

Figures 2.1 and 2.2 show "non-built-up to built-up" transition potential maps for metropolitan areas in Asia and Africa, respectively. Visual analysis revealed that the BRT and RF models produced relatively accurate transition potential maps. In particular, the BRT and RF models were relatively good at modeling built-up areas near previous built-up areas (from 1990 to 2010). In general, the transition potential maps have identified the areas where a change is likely to occur. As a result, the transition potential maps can be used as a useful input to the CA models.

(III) Cellular automata (CA) simulations

The initial land use/cover map (1990), the transition potential maps (1990–2010), and the three multiple-state transition rates were used to simulate land use/cover up to 2014 based on cellular automata (CA) functions available in Dinamica EGO. The expander transition function expands or contracts previous land use/cover class patches, while the patcher transition function forms new patches (Soares-Filho et al. 2009). The expander and patcher transition functions are composed of an allocation mechanism responsible for identifying cells with the highest transition potential for each transition (Soares-Filho et al. 2009). In order to simulate land use/cover changes, both transition functions use a stochastic selecting mechanism (Soares-Filho et al. 2009). The sizes of new land use/cover patches are set according to a lognormal probability function, whose parameters are defined by the mean patch size (MPS), patch size variance (VAR), and isometry (ISO). The CA model for each metropolitan area was calibrated by changing the parameters of the expander and patcher transition functions using trial and error. The initial simulation year was set to 1990, while the final year was set to 2014.

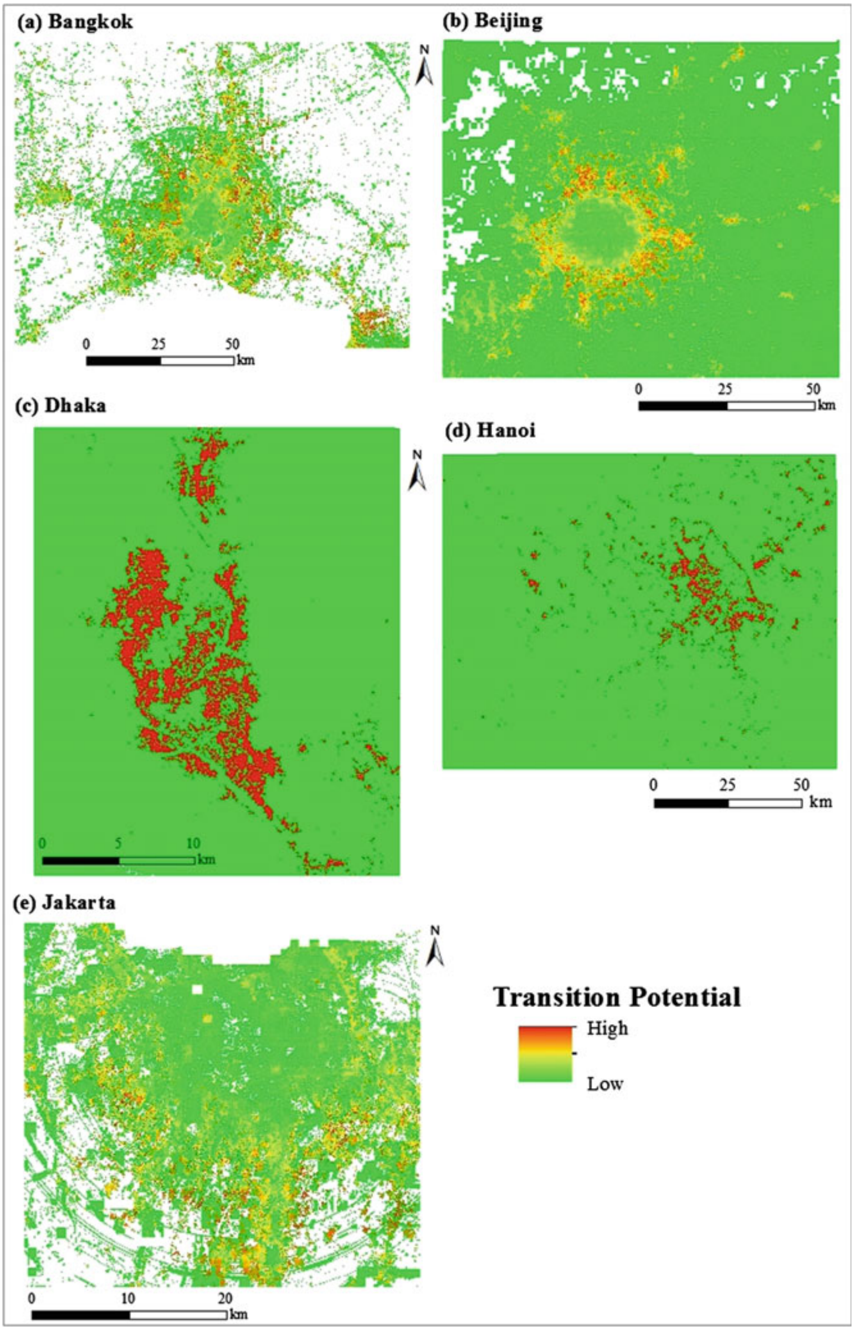

Fig. 2.1 Transition potential maps for Metropolitan Areas in Asia