Chapter 1

Sustainable Urbanization in the China-Indochinese Peninsula Economic Corridor

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Additional information is available at the end of the chapter

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Abstract

Countries in the China-Indochinese Peninsula are home to rich human and natural resource endowments and have the potential to be one of the world's fastest growing areas. Sustainable urbanization in the China-Indochinese Peninsula Economic Corridor is important for the regional economic development and prosperity. Taking the advantages of the remote sensing and Geographic Information System (GIS) technologies, this chapter is first presents a general overview of urbanization procession in this region and monitors the spatiotemporal dynamics of the urban environment; the second objective is to present the multiple driving force factor analysis for urban development in countries of the China-Indochinese Peninsula Economic Corridor using statistical models. The results indicated that the China-Indochinese Peninsula Economic Corridor has experienced a rapid urbanization process during the past 15 years both in terms of urban areas and urban population (UP). In addition to socioeconomic factors, there is also a noticeable correlation between foreign direct investment (FDI) and international trade and urban development in the China-Indochinese Peninsula Economic Corridor. Active participation in international trade and attracting foreign investment are helpful for the regional urbanization. As a neighboring country, China's economic and trade activity also has a significant impact on the urbanization in countries of the China-Indochinese Peninsula Economic Corridor. Furthermore, as the launch of the Silk Road Economic Belt and the 21st Century Maritime Silk Road and the Asian Infrastructure Investment Bank (AIIB), the China-Indochinese Peninsula Economic Corridor will witness a more rapid urbanization progress in the next decade. This study has its characteristics in focusing on the region of the Indochinese Peninsula in which the most rapid urbanization is occurring, presenting the state-of-the-art techniques for monitoring urban expansion and probing into the driving factors of the urban expansion in the China-Indochinese Peninsula Economic Corridor by multiple principles and multiple-level data. It is expected to benefit policymakers in urban development and also provide a basis for further studies of sustainable urbanization in the China-Indochinese Peninsula Economic Corridor.

Keywords: sustainable urbanization, China-Indochinese Peninsula Economic Corridor, remote sensing, GIS, driving force analysis

1. Introduction

Urbanization is one of the most powerful and visible anthropogenic forces on Earth. Although urban areas only occupy a relatively small part of the Earth's land area, they represent 54% of the global population (and even more in the following decades) [1]. With rapid economic globalization, urbanization is now having a huge impact on the political, socioeconomic, and environmental landscape of countries across the world. In recent years, taking advantage of remote sensing, many studies have been performed by scholars from universities, academic institutions, and international organizations on different subjects related to urbanization. Funded by the National Aeronautics and Space Administration (NASA), the 100 Cities Project was implemented in 2010 by Arizona State University (ASU) to supply remote sensing images of 100 international cities as a tool for creating urban models and formulating an effective policy for policymakers and researchers from around the world. The data set generated by this project could be used to create sustainable urban planning practices in various climatic, ecological, and social regions [2]. In 2012, using the urban and rural information derived from satellite data and other sources, NASA's Socioeconomic Data and Applications Center (SEDAC) launched the Global Rural-Urban Mapping Project to respond to the challenges of sustainable development and environmental management presented by world urbanization. That project presented a series of spatial distribution data of human populations to study urban ecology and address critical environmental and societal issues in urban areas [3]. Recently, the World Bank (WB), in collaboration with the University of Wisconsin and the WorldPop project, has developed a map of built-up areas, urban expansion, and urban population (UP) changes across the East Asian region (stretching from Mongolia to the Pacific Islands) for the years 2000 and 2010. These data sets include data on all 869 urban areas in the region with populations of more than 100,000 and serve as a valuable reference for urban geography studies on changing patterns of urbanization [4]. Meanwhile, many scholars also devote urban development studies using remote sensing technology [5, 6], and studies on sustainable urbanization are ongoing. To leave extreme poverty behind and prosper, East-Southeast Asia is currently experiencing rapid urbanization, and cities play a transformative role in this economic growth. Sustainable urban development in the cities of East-Southeast Asia draws an increasing amount of global attention to the region's stability and development.

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Figure 1. Location of the Indochinese Peninsula.

The Indochinese Peninsula is located between China and the South Asian Subcontinent. It is bordered by the Bay of Bengal, the Andaman Sea and Malacca in the west and the South China Sea in the east (**Figure 1**). In the Indochinese Peninsula, a peninsula in southeastern Asia that contains Myanmar, Cambodia, Laos, Thailand, and Vietnam, the rapid urbanization of recent years exerted strong influences on regional development. In 1992, with assistance from the Asian Development Bank (ADB), those five countries and China established a program of subregional economic cooperation in the Greater Mekong Subregion (GMS) that aimed to enhance economic relations among them. The GMS program helps the five countries implement many high-priority subregional projects in transportation, energy, telecommunications, the environment, human resource development, tourism, trade, private sector investment, and agriculture, all of which were strong drivers of the economy and urbanization process in the Indochinese Peninsula. **Table 1** shows the number of cites in the Indochinese Peninsula in 2015 classified by country-size class; that information was obtained from the World Urbanization Prospects reported by the United Nations (UN) [1]. In the five countries of the Indochinese Peninsula, there are 26 cities with populations of more than 300,000 and 16 cities with populations of more than 500,000. From the table, we conclude that Thailand and Vietnam contain many more big urban agglomerations than the other countries, thus showing their high level of urbanization. Second, despite the presence of some metropolitan cities, urbanization in countries of the Indochinese Peninsula is broad-based. Only 1 city with a population of more than 300,000 can be found in Cambodia and Laos; Thailand and Vietnam have only 1 supercity (5 million or more inhabitants) each. Increasingly, after a process of transition and transformation, modernization and industrialization are emerging in Myanmar, Cambodia, Laos, Thailand, and Vietnam. These countries are gradually shifting from traditional farming to more diversified economies and to more open market-based systems [7]. Parallel with this development are the growing economy links between the five countries and their neighbors, notably in terms of cross-border trade, investment, and labor mobility [8]. Moreover, natural resources, particularly hydropower, are beginning to be developed and used in the region [9]. The Silk Road Economic Belt and the 21st Century Maritime Silk Road [One Belt and One Road (B&R)], which was proposed by China in 2014, comprise a development strategy and framework that aims to enhance the economic relationship among countries in Asia and Europe [10]. The China-Indochinese Peninsula Economic Corridor, as an important international gateway of B&R, is supposed to develop a regional economic entity with common development that uses the railways and roads as a medium. The rich human and natural resource endowments of the Indochinese Peninsula region have made it a new frontier of Asian economic growth. The Indochinese Peninsula has tremendous potential to promote both regional economic growth and urban development. Thus, following the 2014 launch of B&R, the China-Indochinese Peninsula Economic Corridor will witness a more rapid urbanization progress in the next decade.

Size class	Cambodia	Laos	Myanmar	Thailand	Vietnam
5 million or more	–	–	–	1	1
1–5 million	1	–	3	1	3
500,000–1 million	–	1	1	2	2
300,000–500,000	–	–	2	5	3

Sources: World Urbanization Prospects: The 2014 Revision, UN.

Table 1. Number of agglomerations classified by country-size class in the Indochinese Peninsula, 2015.

This chapter gives a general overview of the urbanization procession in countries in the Indochinese Peninsula region and presents the state-of-the-art techniques for monitoring the spatiotemporal dynamics of the urban environment. An analysis of the forces driving urban expansion was also performed based on an integrated analysis of both natural and social economic factors.

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2. Methodology

2.1. Monitoring urban expansion in the Indochinese Peninsula

Urban sprawl monitoring constitutes basic information for urban studies, and accurate information about the extent of urban growth is of great interest to researchers investigating urbanization progress. Long ago, conventional surveying and mapping techniques were primarily used to estimate urban sprawl. These methods were usually expensive and time-consuming, and some key information was unavailable for most cities, especially in developing countries [11]. Fortunately, because remote sensing enjoys the advantages of being both cost-effective and technologically sound, it is increasingly used in the analysis of spatiography and urban geography. Since the 1970s, a variety of studies have been conducted using remote sensing and Geographic Information System (GIS) technologies to examine land-use change, to analyze large landscapes, to analyze farmland change and classification, and to analyze urban space structure and fractal shapes [12–15]. In recent years, with rapid economic development and population increases, rapid urbanization occurs and the city quickly expands; the strained relationship between the population and urban land-use is attracting increasingly broad scholarly attention. Thus, extensive research studies have been performed to monitor urban sprawl using remotely sensed images through either an image-to-image comparison or a postclassification comparison [16–19]. In the countries of the Indochinese Peninsula, there has also been a great deal of research effort devoted to land-use changes using remote sensing and GIS technologies. Kong et al. [20] investigated forestland changes attributed to urbanization and agricultural land expansion in Naypyidaw (Myanmar's capital) using Landsat images. Similarly, based on an analysis of the pattern of urban growth from 1993 to 2011 in Siem Reap, Cambodia, Ourng and Rodrigues [21] reported that urban growth always came accompanied primary roads and the river. Using remote sensing images, Okamoto et al. [22] studied the urbanization of Vientiane (capital of Laos). Kimijiama and Nagai [23] also presented the relationship between urbanization and socioeconomic activities in Savannaket, Laos. Nevertheless, because of the limited availability of regional spatial data, those previous studies rarely focused on urban sprawl at the national level; moreover, there is no systematic study available on the multiple temporal phases and long time series of urban sprawl monitoring by multiple-sourced remote sensing data in the countries of the Indochinese Peninsula. Remote sensing and GIS technologies have broad application space in the estimation of urban sprawl in this region.

2.1.1. Methods for extracting urban land with remote sensing

Remote sensing image classification is a primary method of extracting land surface information at large scale. Different ground objects have different spectral characteristics, which are recorded in satellite remote sensing images, and pixels with similar spectral characters would be considered as one landscape class.

The process of landscape classification is complex. Its accuracy is always influenced by many factors such as the sources of the data, the image quality in remotely sensed images, and the method selected for the classification [24]. The classification method is important for landscape classification. Typically, the classification can be divided into two types: (1) pixels compared one by one, which involves monitoring the changes to each pixel by comparing the various temporal phases, and (2) first classifying and then comparing, which involves classifying the remote sensing images in different temporal phases separately and then comparing the classification results to monitor the land-use change [25, 26]. The various methods all have their own advantages and disadvantages; therefore, there may be no single method that is suitable for all situations. For example, although the previous method is simple and easy to achieve, it only monitors the changes of the pixel rather than obtaining the changes of the objects; the second method is limited by classification accuracy in different temporal phases and accumulates calculated errors, thus making its accuracy dependent on the accuracy of the previous classification result. In reality, we should select a landscape classification method based on our needs. The common methods for extracting urban information are as follows:

2.1.1.1. Supervised classification

Supervised classification is also known as the training classification method. In this method, we select training samples of different land-use types in the image and analyze the sample information for each training area by the computer. Next, each pixel can be classified into the similar sample area based on the comparative result of the pixel and the training samples [27–29]. The common methods for supervised classification are the single linkage method [30], the Fisher discriminant method [31, 32], the Bayes linear discriminant analysis [33], and the maximum likelihood method [34]. Supervised classification has the advantage of selectively determining the quantitative and categorical classification based on the study object and area while eliminating needless classifications. Additionally, supervised classification can control the selection of the training samples. Supervised classification is limited, however, by the subjective factors of humans to select the training samples and determine the classification system [35].

2.1.1.2. Unsupervised classification

Unsupervised classification primarily relies on the structural features of the image data and natural points for the object classification without the known training data and the number of the classification. Based on similar levels of the luminance value of the samples in the multi-dimensional spectrum space, the computer can automatically analyze the classifying parameters and then classify the pixels accordingly [36–38].

Unsupervised classification depends on similar levels of the pixels' luminance value for object classification instead of relying on prior knowledge. The dependency on spectra quality replicates the biggest flaw of unsupervised classification; because of differences in location, shape, and character, the same ground objects may have different manifestations in the spectra image, inducing errors in classification. Compared with the method of supervised classification, the unsupervised classification is neither fast nor precise but does have the advantage of being highly objective [39]. According to the study by Xue and Ni [40], although unsupervised classification is unsuitable for the extraction of residential areas compared to the supervised classification, the selection of the training areas has a greater impact on classification accuracy determined by the supervised classification method. Moreover, Hu et al. [41] also extracted urban land-use information using the two methods.

2.1.1.3. Visual interpretation

Visual interpretation relates to extracting information about specified ground objects from the remote sensing image using either direct observations or assisted instruments [42]. Visual interpretation, which enjoys the advantages of easy operation and less equipment, is popular with geographers. The interpretation marks of visual interpretation can be categorized as direct and indirect. The ground object directly interpreted by the characteristic of the image is defined as the interpretation mark. The basic elements of the direct interpretation mark are the tone and the diagram: the tone reflects the image's physical property, whereas the diagram reflects its geometric properties. The tone is the analog recording of the grayscale, which shows the color code and chroma in the color image. In visual interpretation, although the tone of the recognized ground object is a quick mark, it is an uncertainty criterion because it suffers from various influence factors. Thus, the tone could merely be a relative reference for interpretation, and we cannot identify the ground object by relying exclusively on it [43]. The diagram can reflect the shape, size, location, and plane relation among the ground objects. In general, geomorphologic shape, vegetation distribution, water bodies, and bare land are all interpreted by the tone and diagram. Moreover, clouds, snow, urban land, open-pit mines, and airports can be identified by the image [44]. Based on the studies of the phenomenon close to the interpreted objects, indirect interpretation is defined as inferring and distinguishing among the ground objects. Location, relative positions, and other things close to the interpreted objects can all be regarded as indirect marks. Location is both the reflection of the environment of the objects in the image and the relationship between the objects and the environment. Relative positions relate to the plane layout of the dependence relationship among the landscape elements and the objects in the image [43]. The common methods of visual interpretation include the direct identification method, the comparison method, and logical reasoning. The direct identification method can quickly interpret ground objects by their marks, whereas logical reasoning needs to identify objects' existence and properties by the appearance of the internal relations of the objects or natural phenomena. The comparison method first compares the ground objects and natural phenomenon in the image with a known remote sensing image and then identifies the properties of the objects. In any event, it is very important to analyze the comprehensive feature of interpretation objects for each visual interpretation method. To improve the precision of the interpretation, direct and indirect interpretation marks should be used conjunctively, and the image should be taken as a contrastive analysis of various bands and temporal phases [45].

2.1.1.4. Automatic classification and change detection

On a regional scale, moderate spatial resolution remote sensing images such as land resource satellite data are usually used for the data used in landscape classification and change detection. To rapidly achieve an accurate classification rapidly and to minimize human intervention, Jiang et al. propose an efficient, automatic landscape classification approach taking prior accurate land-cover data as the background experience [46, 47]. By adopting the prior knowledge, this approach is distinguished from the previous semisupervised findings of landscape classifiers. This approach involves two steps. First, based on the historical image data, one detects changed landscape pixels from satellite images. Second, one classifies the changed pixels in the landscape based on pattern recognition and changed rules. This approach enjoys the advantages of multimethods in landscape classification, primarily described as follows: (1) the historical data for land-use cover is high precision and can be better matched with the remote sensing data, and (2) based on the ecology view, this approach assumes that the junction of different land types is the fragile area, which is the main changed areas and the inner area is the relatively stable region. Furthermore, the big plaque will be more stable than the small one. This approach can be applied not only to microsatellite data but also to landscape classification for other spectral remote sensing images.

2.1.1.5. Normalized Difference Built-up Index (NDBI) method

Based on the deep analysis of the Normalized Difference Vegetation Index (NDVI), the NDBI was first proposed by Yang [48] and later improved by Zha and Ni [39]. For the Landsat TM image, the gray value of the objects will show only small changes, except for the urban land in the bands of TM4 and TM5. Based on the spectral characteristics, NDBI achieves urban land extraction using the following formula:

$$NDBI = \frac{(TM5 - TM4)}{(TM5 + TM4)} \tag{1}$$

where TM4 is band 4 and TM5 is band 5 of the TM image. Obviously, the value of NDBI should be between −1 and 1; after the two binary transform, the interval value of −1 and 0 is assigned as 0 and the others are assigned as 255, then obtaining the binary image for urban land extracting.

Based on the National Oceanic and Atmospheric Administration images, NDVI, which is used for vegetation-information extraction on a regional scale, has tended to be mature. In recent years, this approach, which has been improved for urban land extracting, has been widely used in urban sprawl monitoring [41, 49].

2.1.1.6. Artificial neural network (ANN) classification

ANN is a complicated network system that is composed of abundant and simple processing elements; it contains engineering systems that simulate the operative mechanism and organizational structure of the human brain based on studies of human brain. ANN belongs to the nonparametric classifier. Since it was proposed in 1988, this approach has been attracting increasing attention to landscape classification and change detection. ANN is widely used in landscape classification such as land-use classification, ground object identification in different temporal phases, fuzzy classification, remote sensing image classification, and the extraction of the shape structure of the image. With the development of the theory of ANN and technological improvements, ANN has been an effective means for remote sensing classification. In recent years, numerous studies on ANN have been successfully performed for the geologic application. According to the characteristic of remote sensing, Dong et al. propose a landscape classification model based on the Hopfield ANN; this classifier proved to have better accuracy and higher efficiency than other methods [50]. Chen et al. have developed the Self Organizing Feature Map (SOFM) neural network, which is based on the weight of samples and data, to achieve the direct classification change detection for temporal and multispectral remote sensing data [51]. Common ANN models for landscape classification are the Multilayer Perceptron (MLP) classification model, the radial basis function (RBF) neural network classification model, the SOFM classification model, and the Adaptive Resonance Theory (ART) classification model. Aside from the above models, more other ANN models have been gradually applied to remote sensing classifications. In general, compared to other classification methods, ANN for land-use extraction has the following advantages: (1) it has the properties of self-learning, self-organizing, and self-adapting and can not only make maximum use of prior knowledge of the known samples type but also automatically extract the rules for multiclassification; (2) ANN need not make the assumptions of the probabilistic models; (3) with its capacity for fault tolerance, nonlinear decision boundaries can be developed in feature space in the ANN model; and (4) the ANN model has superior association power [52].

2.1.2. Satellite data for extracting urban land

2.1.2.1. Resource satellite data

Land resource satellites are primarily used for resource exploration and studying the natural ecoenvironment status of land surface; they are widely used for resource investigation, environmental monitoring, hazard monitoring, land-use planning, and regional development. The most common resource satellites are NASA's Landsat, France's SPOT, the China Brazil Earth Resource Satellite, India's Cartosat-1 (IRS-P5), and the Moderate Resolution Imaging Spectroradiometer (MODIS). The following is a detailed introduction to NASA's Landsat.

2.1.2.1.1. Landsat

Landsat-1, which the United States developed in 1972, is the first resource satellite in the world. It orbits at 704 km high and an angle of 98.2°; it circles the Earth in 16 days. Landsat-2 and Landsat-3 were launched in 1975 and 1978, respectively. The three satellites were the first-generation test satellites and carried the same sensors [i.e., the Return Beam Vidicon (RBV) and Multispectral Scanner System (MSS)]. Landsat-4 and Landsat-5 were launched in 1982 and 1984, respectively. They were first-generation practical satellites, carrying the MSS and Thematic Mapper (TM) sensors. Landsat-7, launched in 1999, was the third-generation satellite. The Enhanced TM Plus (ETM+) sensor, which had eight bands, was first carried in Landsat-7, replacing the TM sensor [53]. The new sensor can work for the spectral region of visible light, near infrared, shortwave infrared, and thermal infrared, and it contains the following improvements over the TM: (1) it introduced the panchromatic band with a resolution of 15 m, (2) the resolution of thermal infrared band was improved to 60 m, and (3) the solar calibrators reduced the satellite's radiation-calibration errors to less than 5%, which is five times that of a traditional satellite. Landsat-8, which carried the Operational Land Imager (OLI) sensor and the Thermal Infrared Sensor (TIRS), was launched in 2013 by NASA [54]. OLI includes all of the bands in ETM+, improved to exclude water absorption characteristics. Comparing the previous sensors, OLI excluded the water absorption characteristics in 0.825 μm in band 5; the range of panchromatic band 8 was narrow, which can help in differentiating the vegetation and nonvegetation. Furthermore, two added bands were included in Landsat-8, which were band 1 coastal (0.433–0.453 μm) for coastal zone monitoring and band 9 cirrus (1.360–1.390 μm) for clouds monitoring; the near- and short-infrared bands were closer to the MODIS bands. **Tables 2** and **3** show the Landsat launched by the United States and the bands included in ETM+ and OLI.

Satellite	**Landsat-1**	**Landsat-2**	**Landsat-3**	**Landsat-4**	**Landsat-5**	**Landsat-6**	**Landsat-7**	**Landsat-8**
Height (km)	920	920	920	705	705	–	705	705
Cycle (days)	18	18	18	16	16	16	16	16
Scan width (km)	185	185	185	185	185	185	185*170	170*180
Number of band	4	4	4	7	7	8	8	11
Sensor	MSS	MSS	MSS	MSS, TM	MSS, TM	ETM+	ETM+	OLI, TIRS

Table 2. Landsat launched by the United States for remote sensing monitoring.

Name	**OLI**		**Name**	**ETM+**	
	Band (μm)	**Spatial resolution (m)**		**Band (μm)**	**Spatial resolution (m)**
Band 1 Coastal	0.433–0.453	30			
Band 2 Blue	0.450–0.515	30	Band 1 Blue	0.450–0.515	30
Band 3 Green	0.525–0.600	30	Band 2 Green	0.525–0.605	30
Band 4 Red	0.630–0.680	30	Band 3 Red	0.630–0.690	30
Band 5 NIR	0.845–0.885	30	Band 4 NIR	0.775–0.900	30
Band 6 SWIR 1	1.560–1.660	30	Band 5 SWIR 1	1.550–1.750	30
Band 7 SWIR 2	2.100–2.300	30	Band 6 SWIR 2	2.090–2.350	30
Band 8 Pan	0.500–0.680	15	Band 7 Pan	0.520–0.900	15
Band 9 Cirrus	1.360–1.390	30			

Table 3. Bands included in ETM+ and OLI.

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2.1.2.2. High-resolution satellite data

2.1.2.2.1. High spatial resolution remote sensing satellite

High spatial resolution remote sensing data have been a fundamental and strategic national resource, serving to provide accurate mapping, urban planning, land resource management, environmental monitoring, ground mapping, military mapping, and intelligence gathering. Because of its huge economic and military benefits, high spatial resolution remote sensing satellites are quickly developing all over the world. The IKONOS satellite, which was launched in 1999, marked the beginning of the commercial high-resolution satellite era; in 2001, the QuickBird satellite was developed by Digital Globe Company. **Table 4** shows the high spatial resolution remote sensing satellites that have a resolution of no more than 1 m [55].

Satellite	State	Launch time	Panchromatic resolution	Multispectrum resolution
OrbView 5	USA	2007	0.41	1.64
WorldView	USA	2006	0.5	2
QuickBird	USA	2001	0.6	2.5
EROS-B	Israel	2006	0.7	3.5
EROS-C	Israel	2008	0.7	2.5
Pleiades-1	France	2008	0.7	2.8
Pleiades-2	France	2009	0.7	2.8
IKONOS-2	USA	1999	1.0	4
OrbView 3	USA	2003	1.0	4
Kompsat	Korea	2004	1.0	4
Resurs DK	Russia	2005	1.0	3
IRS Cartosat 2	India	2006	1.0	–

Table 4. Bands included in ETM+ and OLI.

2.1.2.2.2. Hyperspectral remote sensing satellite

Hyperspectral resolution remote sensing is performed to obtain many narrow- and continuous-spectrum remote sensing images in the visible light, near infrared, intermediate infrared, and thermal infrared of the electromagnetic spectrum [56]. Hyperspectral resolution remote sensing technology contains the special properties of a fine structure of spectra and abundant date information; moreover, it has incomparable application advantages with respect to the identification, assortment, and information extraction of ground objects, which give it great potential for application to ecological environment monitoring [57].

On August 23, 1997, the first hyperspectral remote sensing satellite (LEWIS) was launched in the United States. After years of development, many hyperspectral remote sensing satellites have been developed and successfully operated. **Table 5** shows some of the hyperspectral resolution remote sensing satellites [57].

Satellites	Launch time	State	Band (nm)	Number of bands	Spatial resolution (m)
MODIS	1999	USA	400–1400	36	250, 500, 1000
ASTER	1999	USA–Japanese	520–860	3	15
			1600–2430	6	30
			8125–11,650	5	90
MightySat	2000	USA	500–1050	256 or 512	30
HYPERION	2000	USA	400–1100	60	30
			900–2500	160	
CHRIS	2001	European Space Agency (ESA)	400–1050	18–62	17
ARIES	2004	Australian	400–1100	60	30
			900–2500	160	
HSI	2008	Chian	450–950	115	100

Table 5. Common hyperspectral resolution remote sensing satellites.

2.1.3. Extracting urban land areas using remote sensing in the Indochinese Peninsula

2.1.3.1. Remote sensing data sources

In this chapter, for the study of urban expansion of the primary cities in the Indochinese Peninsula, Landsat TM/ETM+ and Landsat-8 images from 2000 to 2015 were primarily selected for urban area identification. Dynamic changes were analyzed using results from multiple years. In the process of interpreting the remote sensing data, Google Maps is an important reference for this region. **Table 6** shows the various types of high-quality satellite remote sensing data used in this study. To study urban expansion at the national level, spatial data on built-up areas in the East Asia region for the period from 2001 to 2010 were also used in this chapter.

2.1.3.2. Image processing of remote sensing

To study urban development in the Indochinese Peninsula, eight primary cities with populations of more than 500,000 were selected in this chapter: Naypyidaw and Yangon (Myanmar), Hanoi and Bien Hoa (Vietnam), and Bangkok and Chon Bury (Thailand) for the period from 2000 to 2015 and Vientiane (Laos) and Phnom Penh (Cambodia) for the period from 2000 to 2010 because the remote sensing data for Vientiane and Phnom Penh were deficient in 2015 (**Figure 1**). In this study, we extracted the urban land information from the remote sensing

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Type of data	Years	Sources	Band
Landsat TM/ETM+	2000 and 2010	Global Land Cover Facility Earth Science Data Interface (URL: http://glcfapp.glcf.umd.edu:8080/esdi/index.jsp)	7, 4, 3
Landsat-8	2015	Download system for Landsat-8 (Chinese Academy of Sciences; URL: http://ids.ceode.ac.cn/query.html) China Centre For Resources Satellite Data and Application (URL: http://218.247.138.121/DSSPlatform/index.html)	7, 4, 3

Table 6. Types of high-quality satellite remote sensing data used in this study.

image by visual interpretation. This approach was used because of its advantages of simplicity and accuracy, although it is also time-consuming and costly. According to the shape and image features of the ground objects, most of the study area can be identified using this approach. For example, farmlands, water bodies, residential blocks, etc., can be easily recognized. Remote sensing TM7 is a medium-infrared waveband in which the rock shows a strong reflection, TM4 is a near-infrared waveband in which vegetation can be strongly reflected, and TM3 is the red waveband that shows the primary absorption of vegetation chlorophyll. Thus, we selected band combinations 7, 4, and 3, which can be used to identify the urban area with the characteristic of the built-up areas on less vegetation biota, whereas the suburban area shows abundant vegetation biota. **Figure 2** shows the technical route for the built-up area extraction, and **Figure 3a–d** shows the distribution of built-up areas in the representative cities of Yangon, Chon Bury, Bangkok, and Hanoi during various periods.

Figure 2. Map showing the technical route for the built-up area extraction.

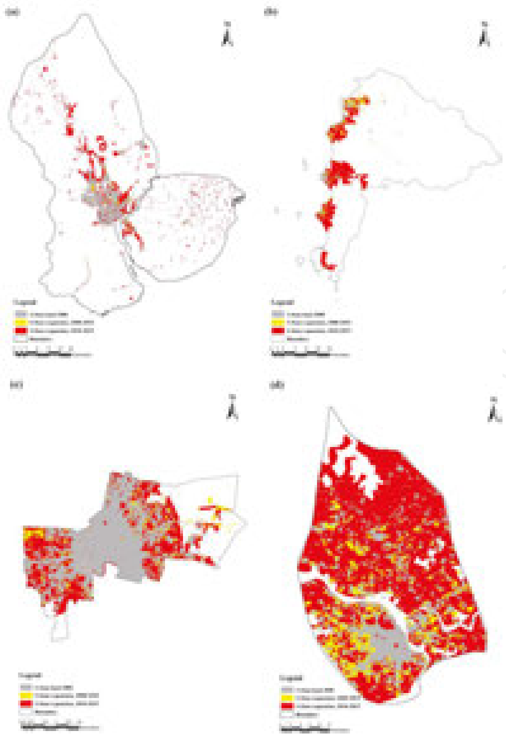

Figure 3. Maps showing the distribution of built-up areas in the cities of Yangon **(a)**, Chon Bury **(b)**, Hanoi **(c)**, and Bangkok **(d)** in the Indochinese Peninsula in different periods.

2.1.4. Urban expansion rate

In some of those previous studies [58, 59], the built-up area is considered an indicator for urban sprawl monitoring, and these areas always represent the status of a city's construction and development from the perspective of space in urban geography. Thus, in this study, the urban expansion rate was adopted to evaluate the spatial distribution and rate of urban sprawl in the Indochinese Peninsula for the period 2000 to 2015. The urban expansion rate that can be defined in Equation (2) shows changes in the quantity of the urban area per unit time and is a key parameter for evaluating spatial changes in urban sprawl [59, 60].

$$R_{UL} = \frac{UL_{n+i} - UL_i}{UL_i} \times \frac{1}{n} \times 100\% \qquad (2)$$

where R_{UL} stands for the expansion rate of urban land; UL_{n+i} and UL_n stand for the built-up area in the target unit at times $n+i$ and i, respectively; and n is the interval of the calculation period (in years).

2.2. Methodology for driving force analysis for urban expansion

The dynamic changes of urban areas meet socioeconomic development, along with land use in the urban fringe area and the interior region, after continuous adjustment and configuration

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result in a transformation into urban land. With increased population, an increasing amount of the rural population is changed into an UP [61]. The dynamic changes of urban areas express urbanization in space and are an inevitable consequence of urbanization. Pattern-process-mechanism always guides the geographical study, and pattern is the distribution of the geographical objects and phenomena; process stands for the analysis of changes in the geographical objects and phenomena in time and space; and mechanism finds the reasons for these changes. Thus, driving force analysis for urban expansion can enable a better understanding of urban development and policy decisions [62]. This chapter presents a multiple-factor model (geographic position, regional economic development, population, infrastructure, and foreign economic and trade relations) to explore the driving forces of urban expansion in countries of the Indochinese Peninsula using multiple principles and multiple-level data.

Figure 4. Map showing GDP in the countries of the Indochinese Peninsula.

2.2.1. Data sources for driving force analysis

2.2.1.1. Regional economic development

Urban development primarily rests on financial strength, and economic development accelerates city changes and urban expansion. To an extent, urban land-use can be viewed as an economic issue, which is also noted in prior studies [63, 64]. Thus, Gross Domestic Product (GDP) can be regarded both as an integrated index reflecting regional economic development and as a predictive factor for urban development. **Figure 4** shows GDP in the countries of the Indochinese Peninsula. These data were obtained from the GMS Statistics data set on the ADB Website, and the data set provided the latest state and trend of key GMS economic data according to the International Monetary Fund (IMF) World Economic Outlook [65, 66]. From

2000 to 2014, the economies of the countries of the Indochinese Peninsula have experienced rapid growth. Except for Thailand, the peninsula's economy has grown almost 7-fold over the last 15 years in Myanmar, Laos, Cambodia, and Vietnam.

2.2.1.2. Population data

To analyze the driving force of urban expansion, data on the UP (% of total) were used in this study. The number of people living in the urban land area is generally defined as UP, and the ratio of UP to total population relates to the percentage of the total population living in cities; UP (% of total) is usually regarded as an indicator of urbanization additional to built-up areas [67, 68]. The UP (% of total) data set for countries in the Indochinese Peninsula for the period from 2001 to 2014 used in this chapter were obtained from the WB's World Development Indicators (WDI), and these data show the numbers of urban residents per 100 total population [69]. The UN Department of Economic and Social Affairs, using the cohort component method, has developed population estimates for developing countries that lack census data. The Department calculated this data set and provided information that is convenient for population studies. These data are considered a valuable scientific reference for population studies, although there is some uncertainty caused by data limitations. **Figure 5** shows the UP (% of total) for countries in the Indochinese Peninsula for the period from 2001 to 2014. According to that figure, the UP proportion increased during the 14 years and the region appeared to experience rapid urbanization, especially in Thailand.

Figure 5. Map showing the UP (% of total) for countries in the Indochinese Peninsula for the period from 2001 to 2014.

To explore the relationship between urban expansion and UP, the UN's population statistics for urban agglomerations with 300,000 inhabitants or more in 2014 by country were used in this chapter to perform an urban expansion analysis of the eight cities in the Indochinese Peninsula [1]. Based on national statistics data (population censuses are the most commonly used sources), the UN developed the UP estimation to respond to the sustainable development

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challenges of urbanization. **Figure 6** shows the UP in Naypyidaw, Yangon, Hanoi, Bien Hoa, Bangkok, Chon Bury, Vientiane, and Phnom Penh in 2000, 2010, and 2015.

Figure 6. Map showing the UP in Naypyidaw, Yangon, Hanoi, Bien Hoa, Bangkok, Chon Bury, Vientiane, and Phnom Penh in 2000, 2010, and 2015.

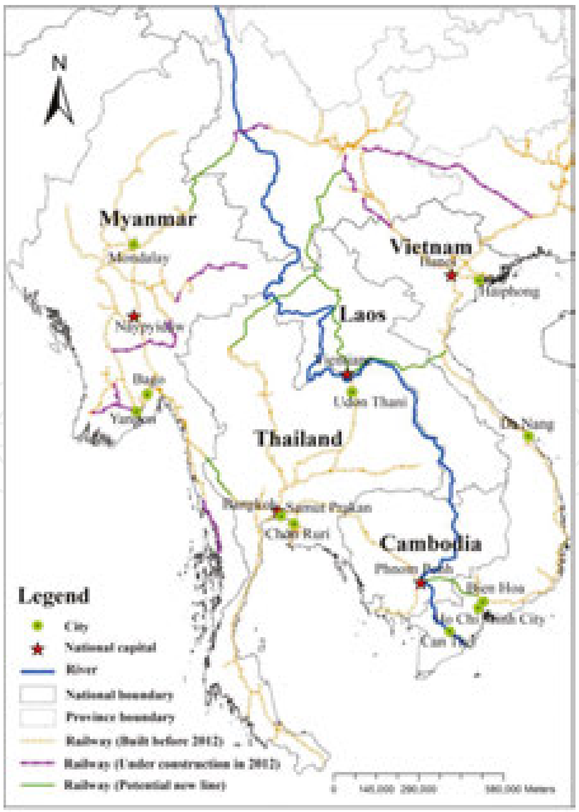

Figure 7. Map showing the existing, under construction, and planned/potential railways in GMS countries in 2012.

2.2.1.3. Infrastructure

As seen from the development of urban areas, transport infrastructure will necessarily accelerate the expansion of urban land-use and is one of the primary driving forces of urban expansion [70]. Chen and Xia [71] also reported that a cross-regional high-speed rail network had greatly advanced China's urban development. In this study, we therefore presented a qualitative analysis of the impact of railways in the Indochinese Peninsula on urbanization during the period from 2000 to 2015. **Figure 7** shows existing, under construction, and planned/potential railways in countries of the Indochinese Peninsula in 2012. These data were obtained from the GMS Core Environment Program of ADB and were developed based on the International Vector Data and ADB maps [72]. These data provided the state of the railways in the Indochinese Peninsula around 2012 for academic research.

2.2.1.4. Foreign economic and trade relations

According to the econometric analysis by Huff and Angeles [73], in some Southeast Asian countries, the measures of globalization are more predictive of urbanization than domestic factors. Increasingly, the five countries in the Indochinese Peninsula are linked with the global economy through both trade and foreign direct investment (FDI) [74], and their increased outward orientation toward regional and global markets was regarded as a key contributing factor to the rapid growth during the 2000s [75]. To present a comprehensive analysis of the driving forces for urban expansion in this region, the FDI inward data and Total Merchandise Exports (TME) data were used in this chapter; they were designed to investigate the impact of foreign economic and trade relations on the region's urbanization. These two data sets were obtained from the GMS Statistics data set on the ADB Website [66], and the source of their data was the UN Conference on Trade and Development (UNCTD) [76]. **Figure 8** shows the FDI inward (a) and TME (b) for the five countries in the region.

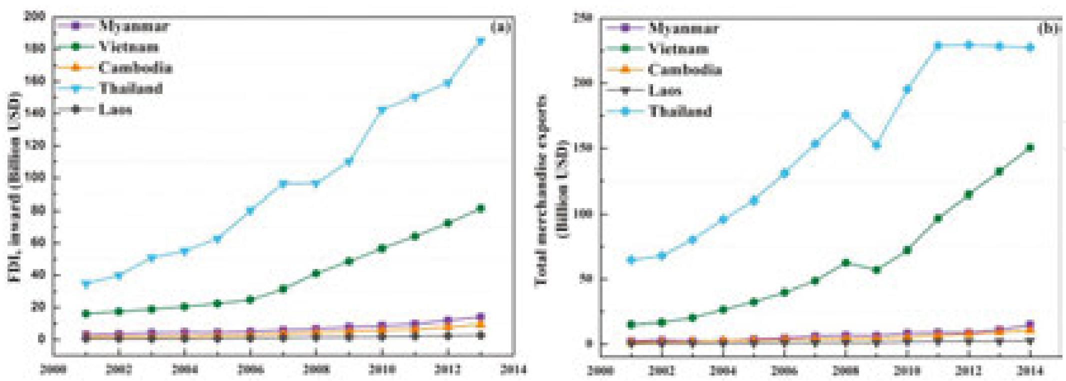

Figure 8. Map showing the FDI inward to Myanmar, Vietnam, Cambodia, Thailand, and Laos for the period from 2001 to 2013 **(a)** and TME of the five countries for the period from 2001 to 2014 **(b)**.

In addition, as a neighboring country, China has played an important role in the economic development for the five countries of the Indochinese Peninsula; in GMS, according to Poncet [77], there has been a high degree of trade linkage between China's Yunnan Province and its neighboring countries (Laos, Myanmar, and Vietnam) based on the development of a gravity model of trade. In recent years, China's outward investments in the Association of Southeast Asian Nations (ASEAN) have increased in spite of an overall global decline in FDI because of the 2008 financial crisis [78]. For this reason, China is to believed to have immense influence on the economic development in the Indochinese Peninsula. Therefore, a statistical analysis of UP (% of total), FDI from China to the five countries, and foreign trade with China was also performed in this study. FDI from China to the five countries for the period from 2003 to 2013 was used in this chapter; the data were extracted from China's Outward FDI of 2010 and 2013 [79, 80]. Data for gross imports and exports (GIE) with China for the period from 2000 to 2010 were obtained from World Integrated Trade Solution (WITS) because data from 2011 to 2015 were not obtained in China. **Figure 9** shows the FDI flowing to the five countries from China (a) for the period from 2003 to 2013 and GIE between China and the five countries (b) for the period from 2000 to 2010.

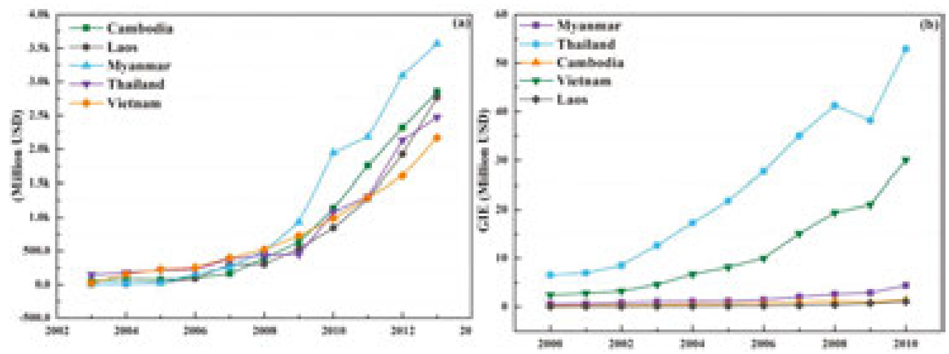

Figure 9. Map showing the FDI from China to Myanmar, Vietnam, Cambodia, Thailand, and Laos for the period from 2003 to 2013 **(a)** and GIE between China and those countries for the period from 2000 to 2010 **(b)**.

3. Result and analysis

3.1. Analysis of urban expansion in the Indochinese Peninsula

For clear information about urban expansion at the national level, the spatial data on built-up areas for the East Asian region for the period from 2000 to 2010 developed by WB were used first (data source: Platform for Urban Management and Analysis (PUMA) of WB [4]). **Figure 10** shows the built-up area in the countries of the Indochinese Peninsula in 2000 and 2010. Generally, as shown in the figure, regionwide from 2000 to 2010, the built-up area increased approximately 1963.2 km^2, expanding from 11,022.21 to 12,985 km^2. In addition, Thailand and Vietnam had much larger urban land areas in both 2000 and 2010 than the other three countries. **Table 7** shows the expansion area, expansion rate, and annual change rate for urban sprawl of the five countries for the period from 2000 to 2010. The expansion rate shows a clear heterogeneity in the region and that Thailand and Vietnam's expansion rates were higher than those of the other countries.

Figure 10. Built-up area (km²) in countries of the Indochinese Peninsula in 2000 and 2010.

Item	Myanmar	Thailand	Vietnam	Laos	Cambodia
Expansion area (km²)	182.54	749.88	897.63	60.59	72.58
Expansion rate (km²/year)	20.28	83.32	99.74	6.73	8.06
Annual change rate (%)	1.11	1.80	2.37	4.15	3.69

Table 7. Expansion area, rate, and annual change rate for urban sprawl in countries of the Indochinese Peninsula for the period from 2000 to 2010.

Table 8 shows the built-up areas of Bangkok, Chonburi, Yangon, Naypyidaw, Hanoi, Bien Hoa, Phnom Penh, and Vientiane in 2000, 2010, and 2015 (Vientiane in 2000 and 2010), and **Table 9** shows the expansion rate and annual change rate for urban sprawl in those eight cities for the period from 2000 to 2015 (Vientiane for the period from 2000 to 2010). As shown in the tables, the built-up area of the cities in the Indochinese Peninsula, except for Phnom Penh and Vientiane, increased quickly with increased urbanization from the period from 2000 to 2015. In 2015, the built-up area of Bangkok reached 1211.55 km², increasing 397.19 km² compared to the year 2000, which shows that Bangkok has experienced a rapid urban expansion in terms of space during the past 15 years. The high annual change rate also indicates Bangkok's rapid urbanization from 2000 to 2015, especially in the past 5 years. Chonburi, Thailand, also experienced rapid urban development in the past 15 years, and the built-up area of Chonburi was approximately 94.51 km² in 2000 but reached 466.56 km² in 2015, which appears approximately five times larger than in 2000; moreover, Chonbur's annual change rate is 37.7%, the largest among the cities studied, from 2010 to 2015, which indicates a much more rapid urban development than Bangkok and the other cities in that period. In Myanmar, the built-up areas of Yangon in 2000, 2010, and 2015 are all larger than those of Naypyidaw, which indicates a high urbanization level in Yangon. Nevertheless, the expansion rate and the annual change rate of Naypyidaw are much larger than those of Yangon during the period because Myanmar's capital was moved to Naypyidaw from Yangon in 2006, thus greatly promoted urban development in the latter city. Hanoi, the capital of Vietnam, has the biggest built-up areas among the eight cities. The built-up areas of Hanoi expanded immensely in the past 15 years, increasing from 284.4 to 1164.1 km². The annual change rate in Hanoi from 2010 to 2015 is 36.6%,

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whereas it was 4.5% in the period from 2000 to 2010, which shows that Hanoi has experienced more rapid urban development in the past 5 years. Bien Hoa, as an industrial city in Vietnam, also rapidly expanded its built-up area from 2000 to 2015, with its area increasing from 58.38 to 121.54 km^2. Bien Hoa's proximity to Ho Chi Minh City and its convenient transportation are considered two important contributions to its rapid urban development. Similar to the situation in the national level, the built-up area in Phnom Penh and Vientiane are both small and the urban development levels of the two cities are relatively low. The lower expansion rate and the annual change rate also prove that the urbanization of Phnom Penh and Vientiane is slower than in other cities, and there is room for growth in their urban development.

City	2000	2010	2015
Bangkok	724.36	795.50	1121.55
Chonburi	94.51	161.60	466.56
Yangon	419.00	440.00	710.50
Naypyidaw	8.88	34.48	71.57
Hanoi	284.40	411.00	1,164.10
Bien Hoa	58.38	84.88	121.54
Phnom Penh	23.53	24.57	25.29
Vientiane	42.34	44.33	–

Table 8. Built-up area (km^2) of the eight cities selected in this study for the years 2000, 2010, and 2015.

City	2000–2010			2010–2015
	Expansion rate (km^2/year)	Annual change rate (%)	Expansion rate (km^2/year)	Annual change rate (%)
Bangkok	7.114	1.8	65.21	8.2
Chonburi	6.709	7.1	60.992	37.7
Yangon	2.1	0.5	54.1	12.3
Naypyidaw	2.56	28.8	7.418	21.5
Hanoi	12.66	4.5	150.62	36.6
Bien Hoa	2.65	4.5	7.332	8.6
Phnom Penh	0.104	0.4	0.144	0.6
Vientiane	0.199	0.5	–	–

Table 9. Expansion rate and annual change rate for urban sprawl in the eight cities for the period from 2000 to 2015.

Table 10 shows the increased and annual change rate of population growth in cities with populations of more than 300,000 in the Indochinese Peninsula. In general, the total increased population in Thailand is approximately 3,419,230 persons for the period from 2000 to 2010

Cities	Country	Population growth from 2000 to 2010	Annual change rate from 2000 to 2010	Population growth from 2010 to 2015	Annual change rate from 2010 to 2015
Bangkok		1852.88	2.9	1056.46	1.3
Chonburi		184.14	9.9	147.49	4.0
Hat Yai		79.16	4.2	48.97	1.8
Lampang		131.20	8.7	100.55	3.6
Nakon Patchasima	**Thailand**	98.40	4.8	62.90	2.1
Nonthaburi		74.57	2.5	41.40	1.1
Rayong		121.53	11.2	101.92	4.4
Samut Prakan		703.96	18.1	721.48	6.6
Udon Thani		173.39	7.7	127.41	3.2
Bien Hao		228.45	5.0	147.83	2.2
Can Tho		412.09	9.4	324.05	3.8
Da Nang		237.35	4.2	146.88	1.8
Hanoi		1151.28	6.9	818.47	2.9
Haiphong	**Vietnam**	290.34	4.8	186.50	2.1
Hue		71.47	3.0	40.97	1.3
Nha Trang		32.09	1.2	15.61	0.5
Ho Chi Minh City		1800.00	4.1	1108.41	1.8
Vung Tau		89.59	4.4	56.01	1.9
Bago		136.10	4.7	90.13	2.1
Mandalay		222.81	2.7	133.67	1.3
Mawlamyine	**Myanmar**	93.82	2.8	56.43	1.3
Monywa		140.95	5.9	98.89	2.6
Naypyidaw		908.04	162	65.68	0.7
Yangon		789.40	2.5	459.79	1.2
Vientiane	**Laos**	318.99	7.2	235.45	3.1
Phnom Penh	**Cambodia**	361.01	2.2	221.57	1.1

Table 10. Increased (1000 persons) and annual change rate (%) for population growth in cities of the Indochinese Peninsula with populations of more than 300,000.

and 2,408,580 persons from 2010 to 2015. The mean of the annual change rate is approximately 7.78% from 2000 to 2010 and approximately 3.12% from 2010 to 2015, which shows that the UP increased much more slowly in the past 5 years than in the past. It is particularly necessary to note that Samut Prakan, Rayong, and Lampang's UPs grew faster than in the other cities from 2000 to 2010, and this is also the case during the most recent 5 years. The high annual change rate indicates that the three cities have higher urbanization levels than other cities. For cities with populations of more than 300,000 in Vietnam, the UP is also increasing rapidly, with the number growing by 4,312,660 for the period from 2000 to 2010 and 2,844,730 from 2010 to 2015. The mean of the annual change rate is approximately 4.78% and 2.03% for the period from 2000 to 2010 and from 2010 to 2015, respectively, and UP growth also slowed in recent years. In Thailand, no city showed an obvious population increase for the past 15 years, except for Can Tho. There are six cities with populations of more than 300,000 in Myanmar, and the increased population in those cities is 2,291,120 for the period from 2000 to 2010 and 904,590 for the period from 2010 to 2015. The mean of the annual change rate is 30.1% for the period from 2000 to 2010 but only 1.53% from 2010 to 2015. It should be noted that the annual change rate in Naypyidaw for the period from 2000 to 2010 is far greater than in other cities, which proves once again that moving the capital significantly contributed to population growth in Naypyidaw. Unlike the situation of urban expansion, the population of Vientiane, Laos, grew rapidly during the past 15 years; this growth was more obvious in the previous decade. Phnom Penh's population only increased by approximately 582,580 persons over the past 15 years and its population growth rate remains lower compared to other cities during that period.

3.2. Analysis of driving forces for urban expansion in the Indochinese Peninsula

3.2.1. Geographical elements

Geographical location, including absolute and relative location, plays an important role in the formation and development of the city, and the correlation between urban growth and geographical location is primarily reflected in the interaction between urban and geographic elements. A city's location is the characteristic of the combination of the city, nature, politics, and economics in space, and a favorable geographic location will promote urban development. In addition, the urban area's geographical location can also decide the specificity of the city's function and size. The urban development in the countries of the Indochinese Peninsula is generally affected by their relative geographical location, and cities with populations of more than 500,000 are primarily distributed around the coastal areas of the Peninsula (see **Figure 1**). Ho Chi Minh City, the largest city in Vietnam, is one of the world's largest seaports, and its urban development is primarily credited to its favorable geographical location, which is close to the rivers. Haiphong, Vietnam's urban development is largely influenced by the international maritime services. In addition, a favorable geographical location is also considered as one of the key factors in the urban development of Yangon, Myanmar. In any event, geographical location has determined the development of cities in the Indochinese Peninsula, at least to some extent.

3.2.2. Transport infrastructure elements

There is a complicated relationship between urban development and the transport infrastructure, and urban development creates many advanced vehicles to improve the urbanization process. The influence of the transport infrastructure on urban development primarily emanates from two important aspects. First, we consider metropolitan transportation and exterior traffic conditions. Very convenient transportation conditions can optimize the industrial layout of the city, and its changes can directly affect the city's structure and industrial layout. Second, convenient transportation conditions also have a substantial impact on economic development, thus accelerating urbanization. Moreover, the direction of emigration is decided by the transport infrastructure, and convenient transportation conditions provide opportunities for labor-force exchanges. In the cities of the Indochinese Peninsula, in addition to the influence of seaway transportation, regional railways' transportation conditions determine urban development. **Figure 7** shows that the big cities in the region all follow convenient railway transportation. This phenomenon can be better illustrated by the urban development differentials among the five countries. As mentioned above, the level of urban development in the five countries reveals heterogeneity, and the urbanization process for the period from 2000 to 2015 varies by country. Thailand, Vietnam, and Myanmar, which have more developed railway networks, show much stronger capabilities in their urban development than do Laos and Cambodia. To improve the railways, basic facilities construction is essential for urbanization in Laos and Cambodia. Furthermore, with the development of high-speed rail, the cities in the Indochinese Peninsula will obtain a new development opportunity.

3.2.3. Economic growth elements

Most empirical studies report that economic growth promoted the increase of both the built-up areas and UP growth, and there is a strong correlation between economic growth and urbanization [81, 82]. **Table 11** shows the summary statistical results from the linear regression model examining the relationship between urbanization and GDP in the countries of the Indochinese Peninsula during the period from 2001 to 2014. In general, we learn that there is an obvious correlation between UP (% of total) and GDP in each country, with an average value of 0.981. Additionally, there are no significant differences in the *R* values among the countries. Furthermore, the functions of the linear regression model indicate that UP grows with the increase of GDP, demonstrating the most direct influence on UP growth by economic growth in the cities.

Country	**Dependent variable (y)**	**Independent variable (x)**	***R***	**Function**[a]
Myanmar	UP (% of total)	GDP (billion USD)	0.982	$y = 0.09x + 27.23$
Thailand			0.983	$y = 0.05x + 27.67$
Vietnam			0.986	$y = 0.05x + 24.23$
Laos			0.970	$y = 1.42x + 22.67$
Cambodia			0.985	$y = 0.13x + 18.3$

[a]The functions were valid because they all passed the F-test, and all of the regression coefficients passed the t-test (at the level of 0.05).

Table 11. Relationship between urbanization in the countries of the Indochinese Peninsula and GDP during the period from 2001 to 2014 ($n = 14$).

3.2.4. Foreign economic and trade relations

Table 12 shows the summary statistical results from the linear regression model examining the relationship between UP (% of total) and FDI in the five countries. High *R* values appear in the five countries, thus indicating that the two items are highly correlated. The functions also illustrate that increased FDI could drive urban development in the countries of the Indochinese Peninsula. Much like the situation in the previous model, high *R* values between UP (% of total) and TME are obtained in all countries (**Table 13**), denoting that there is a positive correlation between them. From the results of the functions, we further find that boosting the export value can promote urban development in the five countries. Moreover, from the summary statistical results for both scenarios, we learn that the influences from FDI and TME on UP growth are at almost the same level because there is little difference in the values of the Pearson correlation coefficient. FDI and foreign trade have played an almost equally important role in the urban development of the five countries for the period from 2000 to 2015. Furthermore, there is little difference among the various nations in the *R* values in both scenarios, which indicates that the continued outward orientation towards the global market and the absorption of foreign investment are considered key contributing factors to the rapid urbanization of each country of the Indochinese Peninsula during the studied period.

Country	Dependent variable (y)	Independent variable (x)	R	Function[a]
Myanmar	UP (% of total)	FDI (billion USD)	0.964	$y = 0.54x + 26.17$
Thailand			0.986	$y = 0.10x + 30.40$
Vietnam			0.968	$y = 0.10x + 24.51$
Laos			0.961	$y = 5.48x + 22.26$
Cambodia			0.979	$y = 0.20x + 18.58$

[a]The functions were valid because they all passed the F-test, and all of the regression coefficients passed the t-test (at the level of 0.05).

Table 12. Relationship between urbanization in the countries of the Indochinese Peninsula and FDI during the period from 2001 to 2013 ($n = 13$).

Country	Dependent variable (y)	Independent variable (x)	R	Function[a]
Myanmar	UP (% of total)	TME (billion USD)	0.962	$y = 0.52x + 26.82$
Thailand			0.979	$y = 0.08x + 27.92$
Vietnam			0.964	$y = 0.06x + 25.31$
Laos			0.964	$y = 5.38x + 23.75$
Cambodia			0.976	$y = 0.20x + 18.58$

[a]The functions were valid because they all passed the F-test, and all of the regression coefficients passed the t-test (at the level of 0.05).

Table 13. Relationship between urbanization in the countries of the Indochinese Peninsula and TME during the period from 2001 to 2014 ($n = 14$).

3.2.5. Trade and investment linkage with China

Tables 14 and **15** show both the results of the linear regression model examining the relationship between urbanization and FDI from China during the period from 2003 to 2013 and the results examining the relationship between urbanization and GIE with China during the period from 2000 to 2010 in the countries of the Indochinese Peninsula. As shown in **Table 14**, the UP is highly correlated with FDI from China in the five countries, and the high R values indicate that urbanization is sensitive to increased investment from China. In addition, the functions derived from the analytical models demonstrate that investment from China is a key driving force for UP growth in the region. According to the analytical results of the relationship between UP (% of total) and GIE with China, we can obtain a similar situation with the aforementioned scenario, and the two items are highly correlated with each other in each country of the Indochinese Peninsula. Moreover, the derived functions show both that trade with China has positive effects on UP growth in the five countries and that increasing bilateral trade will be beneficial to facilitate urbanization in the region. Briefly, trade and investment with China have a substantial effect on the urbanization process in the countries of the Indochinese Peninsula during the study period, and improving the economic cooperation between China and the five countries will contribute to the region's urbanization.

Country	Dependent variable (y)	Independent variable (x)	R	Function[a]
Myanmar	UP (% of total)	FDI from China (million USD)	0.946	$y = 0.001x + 29.07$
Thailand			0.950	$y = 0.005x + 37.60$
Vietnam			0.952	$y = 0.003x + 26.96$
Laos			0.892	$y = 0.004x + 28.08$
Cambodia			0.939	$y = 4.2x + 19.21$

[a]The functions were valid because they all passed the F-test, and all of the regression coefficients passed the t-test (at the level of 0.05).

Table 14. Relationship between urbanization in the countries of the Indochinese Peninsula and FDI from China during the period from 2003 to 2013 ($n = 11$).

Country	Dependent variable (y)	Independent variable (x)	R	Function[a]
Myanmar	UP (% of total)	GIE with China (million USD)	0.934	$y = 1.17x + 27.00$
Thailand			0.979	$y = 0.26x + 31.19$
Vietnam			0.950	$y = 0.21x + 24.97$
Laos			0.854	$y = 9.54x + 24.64$
Cambodia			0.961	$y = 0.95x + 18.55$

[a]The functions were valid because they all passed the F-test, and all of the regression coefficients passed the t-test (at the level of 0.05).

Table 15. Relationship between urbanization in the countries of the Indochinese Peninsula and GIE with China during the period from 2000 to 2010 ($n = 11$).

3.3. Sustainable urbanization in the China-Indochinese Peninsula Economic Corridor

The coordinated development between urban area expansion and UP growth is one important aspect of sustainable urbanization [83]. In this chapter, we use Spearman rank correlation to test the association between the annual change rate of urban expansion and population growth in the Indochinese Peninsula for the period from 2000 to 2015. According to the result of the Spearman model, we determine that the correlation coefficient between the two items is 0.807 (Sig.=0.015) for the period from 2000 to 2010 and 0.536 (Sig.=0.215) for the period from 2010 to 2015. It is obvious that the annual change rates for urban expansion and population growth are highly correlated with each other for the period from 2000 to 2010 among the cities in the Indochinese Peninsula; however, for the period from 2010 to 2015, the statistical analysis result does not pass significance testing, which indicates that there has been disequilibrium developing between urban expansion and population growth in the region since 2010. Thus, in the future, more attention should be paid to sustainable urbanization in the Indochinese Peninsula.

Based on the analysis of driving forces for urban expansion, we conclude that, in addition to socioeconomic factors, FDI and international trade have a noticeable correlation with urban development in the countries of the Indochinese Peninsula. As we have discussed above, railway infrastructure construction is significant to urbanization in countries of the Indochinese Peninsula. However, some previous studies reported that the lack of financial resources was a serious obstacle to infrastructure development in Southeast Asia, and transportation infrastructure in the region could not meet the need for urban development because of fiscal pressures [84]. With assistance from the ADB and the WB, Asian countries receive approximately 20 billion USD in annual fiscal support but still cannot maintain basic transport infrastructure investments in the railways, airports, seaports, roads, and communication facilities needed for urban development [85]. Therefore, new investment has become a key factor, especially in Cambodia and Laos. The Asian Infrastructure Investment Bank (AIIB), proposed by President Jinping Xi of China on October 2, 2013, primarily aims to provide financing for infrastructure projects in the Asia Pacific region [86]. Increased investment by the AIIB will be very helpful for the construction of urban infrastructure and the promotion of urban development. Furthermore, the trade cooperation between the five countries and China is an important contributing factor to the forces driving urbanization at least according to the statistical analysis. With the benefit of the investment and trade opportunity provided by B&R, the China-Indochinese Peninsula Economic Corridor will embrace new and increased opportunities for urban development.

4. Conclusion

This chapter presents a review of the urbanization in countries of the Indochinese Peninsula using advanced remote sensing technology. It also analyzes the driving forces for urban expansion. Our conclusions are as follows:

1. The urbanization progress increased rapidly in the Indochinese Peninsula region both in terms of urban areas and UP; however, the level of urban development in countries of the

Indochinese Peninsula appears to represent a spatial heterogeneity; Thailand and Vietnam have expanded rapidly in urban land compared to the other countries in the study period, whereas Laos remains at a low level of development. Overall, the urbanization of the Mekong countries remains broad.

2. In addition to socioeconomic factors, FDI and international trade also have a noticeable correlation with urban development in the Indochinese Peninsula. Foreign investment plays a significant role in regional urbanization.

3. Investment from China increased quickly in the past 5 years and has close relationship with regional urbanization rate. China, as a neighbor to the Mekong countries, will play an increasingly important role in their urbanization.

4. The China-Indochinese Peninsula Economic Corridor will witness a more rapid urbanization progress in the next decade primarily because of the launch of the Silk Road Economic Belt and the 21st Century Maritime Silk Road and the AIIB.

5. The primary advantages of the manuscript include the following:

    - Its focus on the areas of the Indochinese Peninsula in which the most rapid urbanization is occurring.
    - It adoption of the latest and most precise data set.
    - Its integrated analysis that employed multiple principles and multiple-level data.

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