LONG-TERM LAND USE LAND COVER CHANGE AND ITS IMPACT ON ECOSYSTEM SERVICES: A COMPREHENSIVE STUDY IN GUANGDONG, HONG KONG, AND MACAU (GHKM) REGION

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Long-term Land Use Land Cover Change and Its Impact on Ecosystem Services: A Comprehensive Study in Guangdong, Hong Kong, and Macau (GHKM) Region

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CERTIFICATE OF ORIGINALITY

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___ __(Signed)

Sarah Hasan ___________(Name of Student)

Dedication

To my parents and husband with love

Abstract

Land use and land cover (LULC) changes is a major global problem cause by intense human activities and socioeconomic development. These are especially more pronounced in fast developing regions such as Guangdong, Hong Kong, and Macau (GHKM), in South China. GHKM has undergone rapid economic development and urbanization over the past three decades (1986–2017) significantly influenced the LULC changes and ecosystem service value (ESV) and expected to continue in future. The alteration in ESV leads to the requirement of a significant tailored analysis of ecosystem services regarding incisive and relevant planning to ensure sustainability at regional level. To understand and assess the outcomes of these changes in the long term, the availability of reliable and adequate information about LULC change over the years is becoming increasingly necessary. It is essential to monitor, manage, and utilize ecosystems accurately to halt the ongoing loss of ecosystem services and maintain or balance the supply of different ecosystem services in the landscape. To date, studies in their quantitative analysis and the spatiotemporal variability at the regional level (in GHKM) are very limited. Therefore, this study aims to investigates the changes in LULC of GHKM based on multi-year Landsat (TM, ETM+ and OLI) and nighttime light (NTL) data, simulate future scenario using Land Change modeler (LCM), and their impact on ecosystem services value (ESV).

A supervised classification technique, i.e., support vector machine (SVM), is used to classify the Landsat images into seven thematic classes: forest, grassland, water, fishponds, built-up, bareland, and farmland. The demographic activities are studied by calculating the light index, using nighttime light data. Several socioeconomic factors, derived from statistical yearbooks, are used to determine the impact on the LULC changes in the study area. The post-classification change detection shows that the increase in the urban area, from 0.76% (1488.35 km^2) in 1986 to 10.31% (20,643.28 km^2) in 2017, caused GHKM to become the largest economic segment in South China. This unprecedented urbanization and industrialization resulted in a substantial reduction in both farmland (from 53.54% (105,123.93 km^2) to 33.07% (64,932.19 km^2)) and fishponds (from 1.25% (2463.35 km^2) to 0.85 % (1674.61 km^2)) during 1986–2017. The most dominant conversion, however, was of farmland to built-up area. The subsequent urban growth is also reflected in the increasing light index trends revealed by NTL data. Of further interest the overall forest cover increased from 33.24% (65,257.55 km^2) to 45.02% (88,384.19 km^2) during the study period, with a significant proportion of farmland transformed into forest as a result of different afforestation programs. An analysis of the socioeconomic indicators shows that the increase in gross domestic product, total investment in real estate, and total sales of consumer goods, combined with the overall industrialization, have led to (1) urbanization on a large scale, (2) an increased light index, and (3) the reduction of farmland.

Using Land Change Modeler (LCM) predict the future scenario of the years 2024 and 2031 based on the past trend 2005—2017. The changes in spatial structural patterns are quantified and analyzed using selected landscape morphological metrics. The results show that the urban area has increased at the rate of 4.72% during 2005—2017 and will continue to rise from 10.31% in 2017 to 16.30% in 2031 at a rate of 3.27%. This increase in urban area will encroach further into farmland and fishponds. However, forest cover will continue to increase from 45.02% in 2017 to 46.88% in 2031. This implies a decrease in the mean Euclidian Nearest Neighbor Distance (ENN) of forest patches (from 217.57m to 206.46m) and urban clusters (from 285.55m to 245.06m) during 2017—2031, indicating an accelerated landscape transformation, if the current patterns of change continue over the next decade.

The most renowned established unit value transfer method has been employed to calculate the ESV. The results show that the total ecosystem service value in GHKM has decreased from 680.23 billion CNY in 1986 to 668.45 billion CNY in 2017, mainly due to the decrease in farmland and fishponds. This overall decrease concealed the more dynamic and complex nature of the individual ESV. The most significant decrease took place in the values of water supply (-22.20 billion CNY, -14.72%), waste treatment (-20.77 billion CNY, −14.63%), and food production (-7.96 billion CNY, −33.18%). On the other hand, the value of fertile soil formation and retention (6.28 billion CNY, +7.26%) and recreation and culture (5.09 billion CNY, +12.91%) increased. Furthermore, total ESV and ESV per capita decreased significantly with the continuous increase in total gross domestic product (GDP) and GDP per capita. A substantial negative correlation exists between farmland ESV and GDP indicating human encroachment into a natural and semi natural ecosystems. The results suggest that in the rapidly urbanizing region, the protection of farmland and to control the intrusion of urban areas has marked an important societal demand and a challenge to the local government.

Thus, the speed of development suggests that opportunistic development has taken place, which requires a pressing need for smart LULC planning and to improve land use policies and regulations for more sustainable urban development, to guarantee ecosystem service sustainability, and protection of natural resources.

Keywords: Land use land cover; Landsat; Land change modeler; ecosystem service value; urbanization; Guangdong, Hong Kong, and Macao.

Publications Arising from the thesis

Journal

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Sarah HASAN

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List of Abbreviations

ANN	Artificial neural network
BFPR	Basic farmland protection regulation
CA	Cellular Automata
CLUE	Conversion of land use and its effects
CS	Coefficient of sensitivity
CVA	Change vector analysis
DEM	Digital elevation model
EVI	Enhanced vegetation index
GHKM	Guangdong, Hong Kong, and Macao
IGBP	International Geosphere-Biosphere Programme
IHDP	International Human Dimensions Programme
GDP	Gross domestic product
ESV	Ecosystem service value
ETM+	Enhanced thematic mapper
LAL	Land administrative law
LULC	Land use land cover
LULCC	Land use land cover changes
LCM	Land Change Modeler
MC	Markov Chain
MCE	Multi criteria evaluation
MLC	Maximum likelihood classifier

MLP	Multi-layer perceptron
MODIS	Moderate resolution imaging spectro-radiometer
MOLA	Multi-objective land allocation
OLI	Operational land imager
PRD	Pearl river delta
RFFP	Returning farmland to forest program
RF	Random forest
SVM	Support vector machine
TM	Thematic mapper
UNCED	United Nation Conference on Environment and Development
UHI	Urban heat island
VC	Value of coefficient

Chapter 1

1 Introduction

1.1 Background

Land use land cover (LULC), a complex system involving both the socioeconomic and natural ecosystem, is a foremost global issue instigated by intense socioeconomic development over the last few decades (Ayele, Hayicho, and Alemu 2019; Batunacun et al. 2018; J. Liu et al. 2014; Wu et al. 2013; Yu and Ng 2007). Socioeconomic development, industrilization, urban sprawl, and land use policies are the major driving forces of LULC changes; however, urbanization has been the most direct expression of said changes (Dou and Chen 2017; Ma and Xu 2010). These variations have a profound impact on the earth's ecosystems (Chen et al. 2013b; Dewan and Yamaguchi 2009a), biodiversity, atmospheric environment, climate change, carbon cycle, soil environment, energy balance, sustainability, and hydrological cycle both at a local and global scale (Liping, Yujun, and Saeed 2018; K. Yang et al. 2018; Zhu and Woodcock 2014). They have also influenced the physical characteristics of albedo, emissivity, photosynthetic capacity, transpiration, and roughness (Zhu and Woodcock 2014). Therefore, monitoring and mapping LULC changes have been widely acknowledged as an essential scientific objective and research theme.

Increased urbanization, industrialization, and economic development have resulted in increased population pressure (Liping et al. 2018), which is accommodated by the urban growth pattern being towards the peripheral of rural areas (Araya and Cabral 2010), causing the conversion of natural and semi-natural resources at an unprecedented rate (Li and Liu 2017; Wu et al. 2013). This indicates that demand for natural resources is increasing day by day, and urbanization is proceeding at a staggering rate (Haas and Ban 2014; Karakuş 2019; Wu et al. 2013). Over half of the world populace currently lives in a metropolitan region (Jiang and Wu 2015; Karakuş 2019; Maimaitijiang et al. 2015), though they account for only 2-3% of the Earth's land surface (Dewan and Yamaguchi 2009a; Dou and Chen 2017; Sexton et al. 2013; Yu and Ng 2007). From 1970 to 2000, the global urban area increased by approximately 58,000 km^2 and is estimated to increased to 1,527,000 km^2 by 2030 (Wang and Murayama 2017). In developing countries, urban areas are predicted to surge from 300,000 km^2 in 2000 to 770,000 km^2 in 2030 and 1,200,000 km^2 in 2050, respectively (Angel et al. 2011; Wu et al. 2017). Moreover, in Asia and Africa, 90% of the development is set to happen in the urban populace (Wang et al. 2019). In 2017, the world population has reached to 7.5 billion (Wang and Murayama 2017).

Thus, the unparalleled increase in urbanization and pervasive LULC changes have exacerbated the (Wu et al. 2013) loss of arable land (Lopez et al. 2001), residential crowding, traffic congestion, and irreversible damage to ecosystem services and biodiversity (Dou and Chen 2017; Ma and Xu 2010). Ecosystem service (ES) is defined as the merchandise and services given by the ecosystem add to the prosperity of both directly or indirectly. It may also affect the health of the next generation of land users both at a local and regional scale (Kityuttachai et al. 2013; Liu et al. 2017). These significant changes are more pronounced in fast developing countries (such as China), given that, compared to the developed countries, their urbanization is often unplanned, improvised, and even chaotic (Rimal et al. 2020).

China total urban population has increased from 172.45 million (17.92%) in 1978 to 831.37 million (59.58%) in 2018 (China National Bureau of Statistics 2019; Wu et al. 2013) and is expected to reach 68.38% and 81.63% by 2030 and 2050, respectively, with an average annual growth rate of 0.793% (S. Liu, Yu, and Wei 2019; Wu et al. 2017). This is mainly because Chinese cities are receiving more migrants from rural areas, catching up or shrinking the gap with developed countries, its economic position in the world (Yue, Liu, and Fan 2013), different developmental strategies across China were employed, such as "Western development", "Rising of central China" and "North East Revitalization" (Jiyuan et al. 2010). Moreover, China bestows great significance to information application and turns external information into its resources by fortifying digestion, absorption, and re-innovation information (Zhao 2010). All these factors together with an unreasonable mode of growth, have led to severe deterioration of LULC, strengthened land use conflicts, urbanization, and a substantial reduction in agricultural land resources in many fast-developing regions such as Guangdong, Hong Kong, and Macao (GHKM) (Li and A. G. Yeh 2004; K. Zhang et al. 2016).

After the opening of economic reform in 1978, GHKM, the south east region of China, have practiced the highest rates of LULC changes, especially urban growth and reduction of farmland, socioeconomic development, and industrialization. This is due to decentralizing decision making and fiscal powers, permitting a more market-oriented economy, privatizing urban enterprises and housing, transition from the gross domestic product (GDP) to fanatical development evaluation (Li and A. G. Yeh 2004), opening to foreign direct investment (FDI) (Schneider and Mertes 2014), promotion of new industrial and technology parks on the fringe of an urban area and pushing of industrial/urban development further into sub-urban/rural areas (Y. N. Zhang et al. 2011). The unprecedented increase of industrialization and urbanization has turned the GHKM from a predominate farmland region into a ''world's manufacturing workshop'' (Shi and Shaker 2014). This region has become one of the most active, strong economic and flourishing regions across China (Chokkalingam, Zhou, and Toma 2006; World Bank 2011).

Different periods of politics, socioeconomic development, and urbanization such as "opening up and economic reform 1978–1991", "Initial period of the socialist market-oriented economy 1992–2002", "Mid-term of the socialist market-oriented economy 2003–2008", and "Socialist market-oriented economy 2009–now" has a profound impact on GHKM LULC changes and urbanization (Wang et al. 2018) and moved the accentuation from one-way land development to both development and conservation (Jiyuan et al. 2010). These significant changes have attracted increasing attention from planners and policy makers, resulting in heated discussions on its definition, measurement, causes, and negative consequences (Yue et al. 2013).

In this region, the land cover being used by enterprises for speculative activities and the development of real estate (World Bank 2011), given that it is a preferred destination region for millions of domestic immigrants and foreign investors; as such, the GHKM have spearheaded much of China's socioeconomic development (Chen, Zeng, and Xie 2000; Wu et al. 2013; Ye and Xie 2012). With fiscal restructuring in China, GHKM started to take care of a large portion of their local fiscal revenue; local governments are under more pressure to increase local revenue, enabling infrastructure development to attract more investment (Yue et al. 2013). Instead of retaining farmland resources, local governments have given priority to the conversions of collective land for commercial and residential purposes (Han, Yang, and Song 2015; Wang et al. 2018). 'Low-cost' lands for urban development and industrialization gave significant motivations to promote the anomaly of 'financing through land' and to modify assigned land uses, such as a reduction in farmland and an increase in urban land (Wang et al. 2018; K. Zhang et al. 2016). Thus, the urbanization process followed by increased energy utilization power, and LULC changes (Wu et al. 2017; Zhao 2010).

GHKM degraded land cover and environments represent a new normal. The new social conditions are currently combined to significantly transform ecological conditions and the conversion of farmland (K. Zhang et al. 2016). These audacious changes are promising. Burgeoning urban growth, insufficient housing and infrastructure, slum proliferation, and uncoordinated land development represent a significant challenge for accomplishing sustainable development objectives that require urban planners and decision-makers to intervene (Wang and Maduako 2018; Zhao 2010). In short, as land/natural resources continue to decline for regional development, sustainable LULC is an inescapable decision. Therefore, monitoring LULC changes is a prerequisite for a deeper understanding of LULC changes and to determine the major land use conversion. The comprehensive study regarding LULC can give scientific guidance to the land development department and help policy decision-makers to set/formulate and adopt appropriate practices for sustainability.

Industrialization and urbanization are firmly interrelated with socioeconomic variation, significantly affecting the changes and distribution of developed land and farmland. The conversion of farmland to other land use types primarily increased due to high economic yield, urban expansion, immense development, industrialization, and the ecological effect of different policies. These include industrial, regional development, urbanization, ecological/environmental conservation, and land conservation policies (S. Du, Shi, and Van Rompaey 2014; Song and Deng 2017a; Wang et al. 2018) Urban land owned by the state; its utilization is under the control of local officials acting as agents of the state, subject to oversight by senior officials at the higher levels of government (Feng, Lichtenberg, and Ding 2015). The process of urbanization, rural-urban migration, land transaction practices (state and collective ownership of land), and landscape transformation from farming to non-agricultural use have become land-centered. Consequently, strengthen economic localism as it generates more revenue/financial incentives to the government than traditional farming activities (Chen et al. 2018; Ding 2003). Urban land produces profits as taxes, surcharges, and transaction fees. In China as a whole, land-related revenue grew from less than 10% in 1999 to 55% of tax revenue in 2003-2004 and 67% in 2010 (Feng et al. 2015; P. Zhang et al. 2015). Hence, in local government, the relevant administrative departments (such as the land and resources bureaus) have played a vital role in the provision of urban land and its development (Chen et al. 2018; Long 2014). Thus, urbanization has created a mixed pattern of LULC where villages are merged with urban communities, and villages are placed on urban areas (J. Wang et al. 2012), thus moving GHKM away from an agrarian society.

Similarly, changes in LULC due to anthropogenic activities are responsible for the degradation and loss of essential ecosystem services (Song and Deng 2017a). These include nutrient cycling, carbon absorbent, the provision of ecological barriers against extreme weather events (control environmental pollution), and tourism and recreation value (K. Zhang et al. 2016). They have been transformed into an urban ecosystem. Ecosystem services, their function, and process are lifesaving products. The changes in their structure, functions, various type, area, and spatial distribution respond according to the structural changes in LULC (Feng et al. 2012; Ye, Zhang, et al. 2018; Zhu et al. 2017). There is growing proof that they might be moving or have moved into a new framework or states that are hard to recover (Zhao 2010). These new states have severe and long-term ramification for human well-being. Furthermore, growing system moves within neighboring ecosystems can interfere with one another and cause falling impacts, which can prompt synchronous breakdown on a large scales (K. Zhang et al. 2016).

Assessing ecosystem services provides a promising way to stimulate ecological construction and regional sustainable development (Dewan and Yamaguchi 2009a; Yeh and Li 1999; Zhu et al. 2017). For sustainable planning, by underlining the whole human-induced structure, planners have to think beyond the city boundaries greatly relies on the natural environs that provide the advantages and benefits that trigger the establishment of human society (Wu et al. 2013; Zhu et al. 2017). Therefore, it is necessary to determine the influences of LULC changes on ecosystem service values, which could provide useful information to urban planners and policy decision-makers for sustainable socioeconomic, environmental, and urban development and a safe ecological environment (Feng et al. 2012; Ye, Zhang, et al. 2018).

Enormous socioeconomic development, industrialization, and population growth have exceeded the coping capacities, leading to squatter settlements and shanty townscapes. These trends are expected to project in the coming decades with the consumption of more resources. Consequently, more significant variations in LULC occur and have encourage the Chinese government to fortify urban growth surveillance, whereas scientific supervision needs the help of accurate prediction of sprawl. Thus, examining and summarizing the characteristics of urban growth, including the future potential of sprawl, is essential. The precise prediction of future LULC and comprehensive understanding of their trends are important and put forward proposals about improving environmental quality, gaining much attention from researchers and help policy decision-makers for land use planning (Megahed et al. 2015; Mishra, Rai, and Mohan 2014; Rimal, Zhang, Keshtkar, B. N. Haack, et al. 2018; Zhang, Zhou, and Song 2020).

In summary, land use planning, the process of economic development, extensive urban sprawl, and an enormous reduction of farmland resulted in significant LULC changes. Although land planning have been made or updated every 5 to 10 years but these planning lagged behind the unprecedent mode of socioeconomic development, industrialization, and urbanization that led to loss of farmland, ecosystem, widen urban rural gay, and social inequality gap. Some ecological systems have permanently transformed into a different regime, such as, shift of farmland to human benefit. All such changes have subverted the long-term relationship between man and nature. The route of sustainable urbanization and to control the reduction of farmland has not been well entrenched. Though detailed nation-wide land use has been made in china three times, these investigations have underpin loss of natural resources, essential ecosystem services, and unsustainable development. Decisions, long term planning and strict policies have been made but they lagged behind the socioeconomic development and industrialization. As country in more concerned towards its economic position and shrinking the gap with the developed countries. Therefore, a market-oriented allocation and a control mechanism employing financial levers should be required. It is necessary to draw up ‘basic’ land legislation and sustainable development (Li and A. G. Yeh 2004; J. Liu et al. 2014; Ma and Xu 2010; Yansui, Lijuan, and Hualou 2008). The main challenge is to maintain a framework in a way that evades the new regime from deteriorating to an even worse and more robust system (Fang et al. 2005; K. Zhang et al. 2016).

Acknowledging these realities are urgently needed new approaches, paradigms, and more flexible policies, as well as scientific and technological service for the management and optimized allocation of natural resources and regional sustainable development (Dewan and Yamaguchi 2009a; Long et al. 2007). Therefore, there is a need to study non-linear LULC dynamics comprehensively at the regional level within a holistic and integrated system for the long term. This study aims to understand the above underlying system dynamics and monitor the spatio-temporal LULC magnitude, pattern, and changes, the factors affecting these changes, and project them for future land development.

1.2 Objectives

This study aims to use remotely sensed images to monitor and investigate the patterns and processes of LULC changes in GHKM, their impact on ecosystem service value, and simulate future scenario. The specific objectives of the research are as follows:

- Investigate spatio-temporal LULC change detection and patterns (urbanization, farmland, and forest) by sequential analysis of remote sensing and determine its socioeconomic determinants over the past three decades (1986-2017).
- Predict the spatial explicit future LULC for the next 14 years using the LCM embedded with the Markov model.
- Evaluate the influence of LULC changes on the ecosystem service value (ESV) and their function, its spatial distribution and examine the relationship between them.

Chapter 2

2 Literature Review

Monitoring and effective analysis of LULC changes require a significant amount of information about the surface of the earth (Araya and Cabral 2010). Since the launch of a first satellite, satellite remote sensing (RS) has been widely used in detecting the historical LULC changes both qualitatively (landscape changes either natural or human-induced) quantitatively (categorical transformation of the land) and its spatial distribution (Falahatkar and Soffianian 2011; Weng 2002). Remote sensing has proven effective in explaining human interactions with urban environments in which they live (Dewan and Yamaguchi 2009a; Gatrell and Jensen 2008). It provides cost-effective, multi-spectral, and multi-temporal data and has the characteristics of extensive area coverage and high precision (Nath, Niu, and Singh 2018). This has enable us to determine and analyze LULC changes (Al-Bakri, Duqqah, and Brewer 2013; Yang et al. 2003), urban expansion (Li and A. G. Yeh 2004), urban growth modeling (Dewan and Corner 2014; Dewan and Yamaguchi 2009a; Poelmans and Van Rompaey 2009), and their development, patterns, trends, and processes (Falahatkar and Soffianian 2011; Weng 2002). The information derived from remote sensing can be used to avoid irreversible and aggregative impacts of urban development (Yuan 2008) and are imperative in optimizing the provision of urban facilities and LULC changes (Barnsley and Barr 1996; Dewan and Yamaguchi 2009a, 2009b).

Moreover, approaches related to landscape ecology, for example, landscape metrics, also help to describe the details and structures of spatiotemporal trends and changes of LULC at multiple scales. Combining remote sensing data with landscape metrics has quantified the urban growth and LULC change pattern in different cities and urban agglomeration around the globe (Araya and Cabral 2010; Geri, Rocchini, and Chiarucci 2010; Hamad, Balzter, and Kolo 2018; Jia et al. 2019; Jiao, Hu, and Xia 2019; Shi and Shaker 2014; Weng 2007; Wu, Li, and Yu 2016). Therefore, studying LULC is one of the most prevalent research focuses today, as China still need innovative mode to establish a balance between economic development and natural resources' preservation at the provincial level with sustaining its international image of a capable power. Although new development mode and strategy have been introduced recently which have changed the previous mode of extensive land utilization to some extend and trend towards the more efficient and effective use but they are in initial stages. The overall aim of this study is to scrutinize the socioeconomic, spatial/contextual causes of changes, the process and trajectory of LULC changes, and their effects on ecosystem services by remotely sensed data in the form of multi-temporal optical Landsat image analysis.

This would enable policy and decision makers to make proposals for sustainable development and land use management.

2.1 Land use land cover change detection

Change detection is defined as "the process of detecting differences of state of an object or phenomenon between two different dates of the same geographical region" (Arastoo and Ghazaryan 2013; Özyavuz, Onur, and Bilgili 2011). It is split into (a) pre-processing, (b) appropriate selection of change detection algorithm, and (c) accuracy assessment. In the language of remote sensing, the changes occur due to spectral, spatial, thematic, and temporal constraints, soil moisture, and atmospheric conditions (Hussain et al. 2013). Generally, there are two change detection approaches: (1) change detection without classification and (2) post-classification comparison. Change detection without classification automatically identifies changes from the multi-temporal remote sensing images without requiring any previous knowledge based on the difference feature map. These include change vector analysis (CVA), bands stacking of different time, time series modeling (trajectory-based), and so on. In the post-classification comparison, multi-temporal images are compared for change analysis. These include image differencing, aerial difference calculation, image rationing, image regression, and composite analysis (Falahatkar and Soffianian 2011; Haque and Basak 2017; Weng 2002; Zhang et al. 2019). The most commonly used approach is post-classification, as it is relatively easy to use, gives 'from-to' change information, and reduces the environmental differences and sensor effect (MAS 1999), however being sensitive to the prior classification accuracies (Hu and Zhang 2013). All these approaches are successively used in the monitoring of a variety of LULC changes (Dai and Khorram 1999; Dewan and Yamaguchi 2009a; Fan, Weng, and Wang 2007; Gopal and Woodcock 1996; Jaafari et al. 2016; Kaufmann and Seto 2001; Lambin 1997; Li and Liu 2017; Woodcock and Collins 1996). For example, vegetation, deforestation, disaster monitoring, (Hussain et al. 2013), landscape fragmentation (Nagendra, Munroe, and Southworth 2004), variations in ecosystems (Sharma et al. 2019), climate change (Tasser, Leitinger, and Tappeiner 2017), and urbanization (Rimal 2011). They provide the basis for understanding the interactions and relationships between natural phenomena and human activities (Yu et al. 2016).

For monitoring LULC changes and urban growth, multi-spectral imagery such as Moderate Resolution Imaging Spectroradiometer (MODIS), Landsat thematic mapper (TM)/ enhanced thematic mapper (ETM+)/ operational land imager (OLI), and Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) data used. To map urban growth based on nighttime light data Defense Meteorological Satellite Program's Operational Linescan System (DMSP OLS) images have been used (Shi et al. 2017). Amongst all different remote sensing data, in high resolution satellite data, temporal resolution and geographic coverage is a limiting factor, whereas conventional satellite data constrained by spatial resolution cannot comprehensively reflect LULC changes and urban sprawl (Zhang and Seto 2013). In developing regions, the pace of urban growth and LULC changes is highly policy or event manipulated, which is temporally uneven and hard to capture using coarse temporal resolution satellite data (Li et al. 2018). For monitoring small changes, regional and local scale studies, and to meet the demands of land management medium to high resolution/ finer resolution satellite data needed (such as Landsat) to identify the changes more accurately (Li et al. 2018; Zhu and Woodcock 2014).

Landsat with 30 m spatial resolution data, 16 days temporal resolution, near nadir observation, relatively wide geographic coverage, continuous, and longest record of measurement is one of the most significant sources of data for studying LULC change detection at a moderate scale (Shi et al. 2017; Tan et al. 2010; Yang et al. 2014; Yang, Li, et al. 2019; Zhang and Seto 2013). Human-induced activities, socioeconomic development, and other environmental factors are responsible for significant changes in the landscape both at global and regional scales (Zhu et al. 2016; Zhu and Woodcock 2014). With the help of Landsat data, one can easily extract regional scale quantitative estimations and monitor and analyze the information of LULC changes, such as impervious surface change, changes in vegetation cover, inter-annual climatic variability, and urban growth (Bhandari, Phinn, and Gill 2012; Coppin and Bauer 1996; Galford et al. 2008; Jensen et al. 1995; Seto et al. 2002; Woodcock et al. 2001; Zhang and Weng 2016; Zhu and Woodcock 2014).

Several studies have been conducted addressing LULC change detection at different spatial and temporal resolution in China (Dou and Chen 2017; Fan, Wang, and Wang 2008; Feng and Fan 2018; Y. Hu et al. 2019; Hu and Zhang 2013; X. Li et al. 2016; Li et al. 2017; Li and Wang 2015; Mertes et al. 2015; Seto et al. 2002; Shen et al. 2019; Su et al. 2010; Xiaopei, Jiangxing, and Jun 2006; XU, Wang, and Xiao 2000; Yang, Li, et al. 2019; Yongming et al. 2007) and around the world (Al-Bakri et al. 2013; Dewan and Yamaguchi 2009a; Dewan, Yamaguchi, and Rahman 2012; Falahatkar and Soffianian 2011; Karakuş 2019; Latifovic, Pouliot, and Olthof 2017; Mallupattu and Sreenivasula Reddy 2013; Mertes et al. 2015; Sleeter et al. 2018), human geography, urban geography, and economic geography, particularly their concept, processes, and driving forces (Braimoh and Onishi 2007; Dewan and Corner 2014; J. Du et al. 2014; Sun et al. 2012; Wu and Zhang 2012). In the Pearl River Delta (PRD) cities, the LULC accompanied by urban sprawl has endured severe changes (Hu and Zhang 2013). They examined the seasonal changes from March 2008 to December 2009 using MODIS data. Their result demonstrates continuous increase in urban area while other LULC classes had different increasing or decreasing trend at the same period. Y. Wu, Li, and Yu (2016) examined urbanization and LULC changes in Guangzhou from 1979 to 2013 using multi-date Landsat images. They concluded that during the studied period, urbanization increased by 1,512.24 km^2 with an annual rate of change of 11.25% (Wu et al. 2016). Zhang, Chen, and Zhou (2015) assessed the long-term LULC changes of Dongguan, and their results exhibited that during 1979-2013, the urban area grew by more than 52% (H. Zhang, Chen, and Zhou 2015). Jiyuan et al. (2014) has explored the spatio-temporal LULC changes, patterns, and causes from 1980 to 2010 for China using Landsat images (TM/ETM+) (J. Liu et al. 2014). Yansui et al. (2008) analyze the spatio-temporal LULC transformation in the eastern coastal region of China from 1996 to 2005. Their results show that an increase in populace and socioeconomic development were the primary driving forces of urbanization and LULC changes (Yansui et al. 2008). Karen C Seto and Fragkias (2005) quantify the physical process of urban growth, LULC change, and the underlying socioeconomic process in a special economic zone of PRD (Seto and Fragkias 2005). Lambin et al. (2001); Wang et al. (2012); and Sodango et al. (2017) concluded that not only economic fluctuation but also development policies, strategies, and competition with other parts of the world were responsible for significant LULC change (Lambin et al. 2001; Sodango, Sha, and Li 2017; J. Wang et al. 2012).

Existing studies, however, have thoroughly investigated LULC change and urban expansion using remote sensing technology. These studies distinguished the accompanying characteristics Research objectives ranging from a solitary city (i.e., Beijing (Y. Yang et al. 2018), Shanghai (Zhao et al. 2006), Guangzhou (Gong et al. 2018; S. Liu et al. 2019), Shenzhen (Dou and Chen 2017), Hangzhou (Yue et al. 2013)) to urban aggregations (i.e., Beijing–Tianjin–Hebei (Sun and Zhao 2018), Pearl River Delta (Fan et al. 2008; Feng and Fan 2018; K. Yang et al. 2018; Yang, Li, et al. 2019), Yangtze River Delta (Lu et al. 2018; Luo et al. 2018))(Yu et al. 2019). These studies lack in explaining the aggravating complex structure of the land, intensive urbanization and development, and the relationship between them at a provincial scale using a medium to high-resolution data over a long period. There are still challenges in deriving the change information of LULC and urbanization in timing and location over a long period. Therefore, to mitigate the effects of significant LULC changes and provide effective policy alternatives, it is critical to understand the evolving nature of the GHKM region. Also, to provide a time series consistent LULC map for this significantly urbanizing region of the world, as a precursor to a quantitative assessment of regional LULC change and urbanization.

Recent studies are more concerned and focused on the protection of farmland, reforestation, and sustainable development (Cortina et al. 2011; Li et al. 2013; Nagendra 2010; Plieninger et al. 2012; Rudel 1998). Urbanization, socioeconomic, and political development does not always mean destruction in the forest cover. However, they can endorse increasing forest cover and afforestation. In many parts of the world, especially in Europe, Asia, and North America, an increasing trend of forest cover has been seen after having massive deforestation. Kauppi et al. (2006) revealed that in France, although urbanization has increased from 42 million to 61 million during 1960-2006, at the same time, an increasing trend in forest cover was observed, almost more than a quarter (Kauppi et al. 2006). Similarly, southern China accounts for 65% of the forest in China, especially for the fast-growing tree species (Shen et al. 2019). Forest succession in GHKM started after the establishment of the Forest Law of China. To make GHKM greener and mitigate the loss of forest due to massive urbanization, the government initiated different programs such as "to rehabilitate all degraded forest," "National afforestation project," "to strengthen the afforestation achievements and modernize forestry practices," and "decision on speeding up forestry development". These programs have also increased people's incentives and guarantee people's ownership rights of forests. Thus, urbanization and economic activity have endorsed forestry development and different afforestation programs in the Guangdong, Hong Kong, and Macao (Chokkalingam et al. 2006).

2.1.1 Land use land cover classification

Classification is one of the significant approaches to acquiring LULC information from remote sensing images (Q. Liu et al. 2014). Various classification techniques have been developed and employed in multiple perspectives (such as in the studies of environmental change, land resource and town planning, geological mapping, spatio-temporal modeling, LULC, and change detection) (Bahari, Ahmad, and Aboobaider 2014; Jung et al. 2006; Rogan et al. 2010; Zhu and Woodcock 2014). These techniques include: (1) both parametric (such as maximum likelihood classifier (MLC), minimum distance to means and the box classifier, ISODATA, and K-Means) and non-parametric (e.g., supervised classifier, support vector machine (SVM), decision tree, and artificial neural network (ANN)), (2) convolution neural network (CNN), (3) automated and semi-automated, (4) pixel and object based, and (5) spectral indices (Ayele et al. 2018; Mountrakis, Im, and Ogole 2011).

Factors such as accuracy, speed, and practicality were considered when selecting a classification method (Bahari et al. 2014). MLC works with the assumption of the assignment of each pixel to the LULC class for which they have the highest probability (Ayele et al. 2018), whereas ANN estimate data properties based on training data (Hussain et al. 2013). In the decision tree, no assumption on data distribution and can provide a rule set for change and no-change classes. The drawback of a decision tree is that it (1) can be overtrained as it is responsive to both quality and quantity of training data each class; (2) do not aim for an optimal match; and (3) may grow much larger making it harder to analyze. A review of classification methods of remotely sensed can be found in (Hussain et al. 2013; Längkvist et al. 2016; Mather and Tso 2010; Rai et al. 2020; Talukdar et al. 2020) and Table 1. However, MLC and ANN are among the most frequently used methods, but they have some drawbacks. ANN has been related to the problems of over-fitting and local minima (Candade and Dixon 2004), whereas MLC requires a large training area (Bahari et al. 2014) and is unable to resolve the interclass confusion. These limitations are overcome by the support vector machine, which does not rely on any presumptions for the class distribution data (Mountrakis et al.

2011). According to Rimal et al. (2018) (Rimal, Zhang, Keshtkar, B. N. Haack, et al. 2018) and Waske and Benediktsson (Waske and Benediktsson 2007) when classifying the multispectral data, SVMs have achieved the highest overall accuracies among all approaches.

The support vector machine is an advanced machine learning algorithm, relatively new supervised classification, and binary classifier actively used for the classification of satellite data. It has gained importance because of its robustness, high precision, and potent output results, even though using a small training sample. It works on the principle of Structure Risk Minimization (SRM) (Ustuner, Sanli, and Dixon 2015), which separates the classes with a decision surface, called optimal hyper-plane, increases the margin between the classes using minimal training area. The data points closest to the hyper-plane are called support vectors (training areas) (Bahari et al. 2014; J. Liu et al. 2014). The complexity of the resulting classifier is represented by several support vectors instead of the dimensionality of the changing space. Consequently, SVMs tend to be less liable to over-fitting problems compared to other methods (Bahari et al. 2014; Candade and Dixon 2004; Duda et al. 2002).

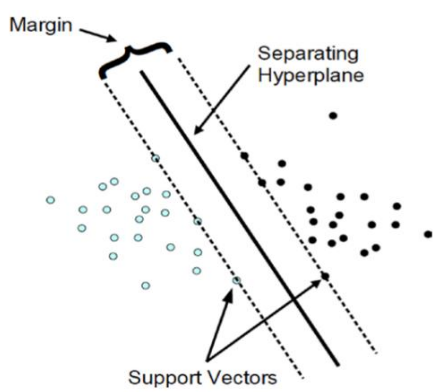

Figure 1. Schematic diagram of the Support Vector Machine (SVM).

The classification based on SVM has been known to strike the right balance between accuracy achieved through a given finite amount of training patterns and the ability to generalize to unseen data (Candade and Dixon 2004; Mountrakis et al. 2011). It classifies the data both linearly and nonlinearly. For nonlinear data, the kernel function is used. The SVM kernel includes polynomial, linear, radial bias function, and sigmoid. The following parameters were used for SVM classification: (1) error penalty or cost (C) for all kernels, (2) gamma (γ) for all kernel types except linear, (3) bias term (r) for polynomial and sigmoid kernel, and (4) polynomial degree for the polynomial kernel. The optimum selection of the above-mentioned parameters increased classification accuracy. Despite its many advantages, SVM also has some limitations

(Bahari et al. 2014; Devadas, Denham, and Pringle 2012; Mohammadimanesh et al. 2018). The major drawback is the selection of an appropriate kernel function. Despite this constraint, this supervised technique remains most popular and produces more accurate classification results compared to conventional classification methods (Rimal, 2018).

Table 1. Summary of different classification techniques (Hussain et al. 2013; Mondal, Kundu, and Chandniha 2012; Nitze, Schulthess, and Asche 2012; Shao and Lunetta 2009; Talukdar et al. 2020).

Maximum likelihood classifier (MLC)	• Parametric approach • Involves the assumption of the selected classes of signature in a normal distribution • No parameters • Less computational complexity • Exhibited inferior accuracies and higher variability • Disadvantage: requires a large training area and unable to resolve the interclass confusion
Artificial neural network (ANN)	• Non-parametric technique • Do not make assumptions about the nature of data distribution • Estimate data properties based on training data • Computational complexity is higher compared to traditional supervised methods (such as MLC) • Disadvantages: (1) complex architecture optimization; (2) low computational robustness; (3) exceed the good mean classification accuracy due to tremendous training time; (4) the hidden layer is not well-known; (5) for network teaching the amount of training data is essential
Convolutional neural network, (CNN)	• A standard feed-forward neural network consists of one input layer, multiple hidden layers, and an output layer. • Hidden layer includes convolutional layers, ReLU (activation function) layers, Kernels/filter, stride, padding, pooling layers, fully connected layers, and normalization layers. • Computationally expensive as it is far more data hungry because of its millions of learnable parameters to estimate • capture the remarkable features from raw images directly • do not require prior feature extraction, resulting in higher generalization capabilities • Uses stacked convolutional kernel to learn the features of images, so not only the spectral but also the texture information in spatial space is learned. • mainly used in high resolution remote sensing images which have fine texture features and fixed shapes as natural images employed in computer vision. • While texture features of Landsat images are not as fine as high resolution remote sensing images and objects captured with 30m resolution generally do not have fixed shapes • Disadvantage: (1) requires a large Dataset to process and train the neural network; (2) requiring graphical processing units (GPUs) for model training; (3) slower due to an operation such as maxpool; (4) Data requirements leading to overfitting & underfitting; (5) Classification of Images with different Positions; (6) adversarial examples; (7) Coordinate Frame
Fully Convolutional Networks (FCN)	• Consists of input layer, fully connected neurons, and output layer • can perform sematic segmentation and fits well to the pixel-wise classification of remote sensing data • If properly trained with a small number of labeled samples, the FCN based method can also significantly outperform the traditional method capability of the FCN model to exploit the spatial context

	• Disadvantage: (1) computationally expensive; (2) significantly slower operation than, say maxpool, both forward and backward. If the network is pretty deep, each training step is going to take much longer; (3) loss of spatial information - because its "fully connected"
Decision Tree (DT)	• Non-Parametric technique • Do not make assumptions about the distribution of data • For change and no-change classes can give a set of rules • Disadvantages: (1) Sensitive to both quality and quantity of training data; (2) can be over-trained; (3) do not aim for an optimum match; (4) may increase much larger in sizes making it harder to analyze
Support Vector Machine (SVM)	• Non-parametric technique • Do not make assumptions about the distribution of data • Capable of managing small training data sets • As compared to traditional methods produces high classification accuracy • A theoretically bigger data set can be dealt with higher dimensionality • Outperformed RF and ANN. • Using radial basis function or polynomial kernels exhibited superior results to ANN and RF in terms of overall accuracy and robustness • Computational complexity is higher compared to traditional supervised methods (such as MLC) • Relatively high classification accuracy • Disadvantages: (1) Difficulty in choosing the best kernel function; (2) The computational time for classification and achieving optimization during the learning phase increases polynomially with the increase of data dimensionality
Random Forest (RF)	• Bagging and random algorithm based on a decision tree • Based on two parameters: (1) the number of trees, described by 'n-tree' and (2) in each break numerous features described by 'm-try' • Much more computationally expensive than SVM classifiers • Classification trees give an individual choice of vote • Give precise classification in directing the majority vote from trees in the entire forest • Stable and robust • Disadvantages: (1) complexity; (2) much laborious and time-consuming to construct a number of trees; (3) overfitting; (4) no interpretability

2.2 Future prediction modelling

In the environment of remote sensing and GIS, studies on change detection have mainly engrossed to provide information related to how much, where, and what type of LULC changes have occurred. After assessing how the land is currently being used, an evaluation of future predictions is required to ensure the adequacy of the future supply and for sustainable development. In short, the changes in LULC encourages the government to fortify the land cover management, whereas scientific management requires help in precisely foreseeing the LULC changes. Therefore, to answer the question of how LULC may change in the future, a modeling approach is deemed to be a valuable tool (Liping et al. 2018; Yirsaw et al. 2017). LULC models comprise various methods and approaches, can be static and spatial, and investigate change vs. change rates (Mas et al. 2014). These models commonly encompass the following steps: (1) a change demand sub-model, (2) transition potential sub-model, and (3) change allocation sub-model. These steps specify the amount and spatio-temporal location of LULC changes and the conversion of the LULC class from one to another (Rimal, Zhang, Keshtkar, B. N. Haack, et al. 2018).

LULC models are classified into two groups: (1) regression-based model and (2) spatial transition-based models. In a regression-based model, such as a logistic model (Landis 1994; Turner, Wear, and Flamm 1996; Wear, Turner, and Naiman 1998), LULC changes are defined through a set of spatially explicit factors (Weng 2002). In spatial transition-based models, such as cellular automation, future prediction of the land cover is made based on a probabilistic assessment with Monte Carlo or other methods (Clarke and Gaydos 1998; Clarke, Hoppen, and Gaydos 1997; Weng 2002). The models involve the simulation or prediction of the environment as well as social systems' behavior in the study area during the studied period so that it contributes to the measured land changes (Gibson et al. 2018). Thus, they are needed to integrate spatial scales, to project future regimes, and their explanatory variables to simulate changes in LULC in response to biophysical and economic/human drivers (Shi and Shaker 2014). They are helpful in the selection of suitable development strategies.

In recent decades, modeling of land use has been of increasing importance as urbanization, and LULC change has increased apprehension among planners and decision-makers about the future effects on the ecosystem and natural resources (Aburas et al. 2016; Bihamta et al. 2015; Dzieszko 2014; Liu and Phinn 2004). The increasing trend of urbanization depends on various factors, such as socioeconomic development, demography, environment, geography, and culture. This specifies the increased importance of urban areas as the focal point of the populace and commercial concentration within a particular society (Aburas et al. 2017). The modeling of such dynamic systems is not an easy job (Ahmed et al. 2013). To date, many models have been developed which are classified as (1) mathematical equation based (e.g., logistic regression and Markov chain model), (2) system dynamic, (3) statistical, (4) expert system, (5) evolutionary, (6) models cellular, (7) hybrid or agent-based, and (8) integrated models (Aburas et al. 2017; Al-sharif and Pradhan 2014; Falahatkar and Soffianian 2011; Hyandye and Martz 2017). The most commonly used models are: (1) Land Change Modeler (LCM); (2) Cellular Automata (CA); (3) Markov Chain, (4) CA-Markov, (5) Geometric modeler (GEOMOD), (5) Conversion of land use and its effects (CLUE), and (6) STCHOICE (Mishra et al. 2014). However, it is difficult to compare which model gives a more accurate demonstration (Mishra et al. 2014). According to Deng et al. (2008), Li & Yeh (2002), Dimitropoulos (2011), Yang et al. (2012), and Al-Sharif and Pradhan (2014), models are tremendously helpful for the assessment of the effect of urban sprawl, in the planning and management of LULC, and identify best land use change patterns and trends (Al-sharif and Pradhan 2014; Deng, Su, and Zhan 2008; Li and Yeh 2002; Sun 2008; Xin, Xin-Qi, and Li-Na 2012).

2.2.1 CLUE and GEOMOD

The CLUE dynamic model was developed by Veldkamp and Fresco (1996). This model depends on the analysis of location suitability using logistics regression. The main purpose of this model is to study LULC changes by incorporating driving factors such as biophysical and human. This model consists of three components: (1) regional biophysical component, (2) regional land use objective component, and (3) local land use allocation component. They used this model to simulate the LULC changes at local, regional, and national scales, a case study of Costa Rica and represents how biophysical and population factors have affected LULC (Sun 2008). With the increase in polulation and different biopysical factors (such as food, technology level, and socioeconomic condition) a land use conversion takes place only when the new land use gives a clear yiled or value improvement (Veldkamp and Fresco 1996). The drawback of this model is that it requires another mathematical model to predict future LULC (Han et al. 2015; Mas et al. 2014).

The **GEOMOD** simulation model was developed by Pontius, Cornell, and Hall (2001). This model comprises three main decision rules: (1) the nearest neighbors, (2) political regions, and (3) the biophysical patterns. They used this model to study the spatial trend of the LULC and their changes with time, a case study of Costa Rica. They simulate the progressive loss of closed canopy forest for years 1940, 1961, 1983, and also extrapolates the LULC patterns for 2010. Over the several decades this model extrapolates LULC change for two categories with accuracy between 74% and 88%. Conversely, this model only simulates the conversion between the two LULC types (Pontius, Cornell, and Hall 2001; Sun 2008).

2.2.2 Markov chain model

The Markov model is a robust model commonly used in monitoring, ecological modeling, modeling, and simulating changes, trends, and predicting the future scenario at a different spatial scale (Hamad et al. 2018; Verburg and Overmars 2009; Wang and Murayama 2017). This model predicts the future LULC changes from one time period (t=1) to another time (t+1) (Falahatkar and Soffianian 2011) based on the transition probability matrix of each LULC class (Hyandye and Martz 2017). The changes are considered a stochastic process in this model. However, the transition matrix is key to simulating LULC changes in the future (Wang and Murayama 2017; Weng 2002). The major drawback of this model is that it is unable to give the spatial distribution of LULC change activities (Al-sharif and Pradhan 2014).

The future prediction of LULC changes can be calculated using the following equation:

$$S(t+1) = P_{ij} * S(t) \tag{1}$$

$$P_{ij} = \begin{pmatrix} P_{11} & P_{12} & P_{1n} \\ P_{21} & P_{22} & P_{2n} \\ P_{n1} & P_{n2} & P_{nn} \end{pmatrix} \tag{2}$$

$$0 \leq P_{ij} < 1 \; and \; \sum_{j=1}^{n} P_{ij} = 1, (i, j = 1,2, \dots . n) \quad (3)$$

where S(t) is the system state at time t; S(t+1) is the system state at a time (t+1); P_{ij} is the transition probability matrix from the current state i to another state j in the next time (Al-sharif and Pradhan 2014; Hamad et al. 2018; Kumar, Radhakrishnan, and Mathew 2014).

Several studies have been carried out that used the Markov chain model to determine the future LULC scenario (Falahatkar and Soffianian 2011; Y. Hu et al. 2019; R. Zhang et al. 2011). Muller and Middleton (1994) studied the LULC change of the Niagara Region, Ontario, Canada, and analyzed that the transition matrix generated by the markov chain represents the multidirectional process. There result shows that (1) urbanization of agriculture land was the predominant LULC change during 1935 and 1981; (2) a continuing land transformation between wooded and agriculture LULC class has minute effect on the wooded net amount, but which could determine the long haul ecological value of remaining natural areas of the study area. They have also explained the mathematical working of this model (Muller and Middleton 1994). Lopez et al. (2001) determined the relationship between the expansion of urban sprawl and LULC change of Morelia city during 1960—1990, Mexico using markov chain and regression analysis. There result suggests that the highest LULC attractor is the Morelia city, followed by plantation and croplands; on contrary grassland and shrublands are the least stable classes. They also indicate that this model is more effective in determining LULC changes than predicting future LULC changes (Del Mar López, Aide, and Thomlinson 2001). Hathout (2002) examined how increasing urbanization trends affect agricultural land, a case study between West and East St. Paul in Manitoba, Canada, using this model. Their result depicts that East St Paul have higher urbanization rate (from 10.41% to 43.75%) during 1960—1989 than the West St Paul (from 7.36% to 23.57%). The prediction result shows that East St Paul will experience a reduced rate of increase than West St Paul (Hathout 2002). Zhang et al. (2011) predicted the changes and analyzed the factors that were responsible for changes in a wetland in Yinchuan plain China. Their result indicates increasing trend for artificial wetland distribution area while decreasing trend for natural wetland area. This depicts that human activities will remain the major cause of changes in the wetland distribution area of the studied area. They conclude that the markov model provides an effective means to policy and decision makers for wetland management and protecting its resources (R. Zhang et al. 2011). Kumar et al. (2014) examined the change from 1998 to 2006 using Indian Remote Sensing satellite images and simulated future scenarios for years 2014 and 2022 using the markov chain model, a case study of Tiruchirappalli city, India. Their result shows that urban increased from 19.08% to 38.06% during 1996—2006 and will increase to 62.28% in 2022 as a result of increase in population pressure, whereas waste land area decreased by -10.68%. Thus, the Markov model, coupled with the geospatial technology has indicated the descriptive capability of trend projection (Kumar et al. 2014).

2.2.3 Cellular Automata (CA)

Cellular Automata (CA) was first developed by John Von Neumann and Stanislaw Ulam for determining the logical reinforcements of life (Wang and Murayama 2017). In 1970, Tobler, for the very first time, used the CA model for geographical modeling. This first theoretical approach of CA became the base of other models that appeared in the1980s with an objective of simulation and prediction of urban sprawl and LULC changes (Batty and Xie 1994; Couclelis 1985). In the 1990s, growth and advancement in the CA model (i.e., the ability to figure out added to the model), was utilized in the framework of LULC and urban dynamic (Aburas et al. 2017).

CA is a dynamic process capable of modeling and controlling non-linear and complex spatial trends. It provides a clear insight picture of LULC changes from social behavior to global patterns. The major components of the CA model are (1) neighborhood type, (2) neighborhood size, (3) cell size, and (4) transition rules (Aburas et al. 2017; Al-sharif and Pradhan 2014). These parameters give optimum simulation results. The most important parameter in this model is the transition rule, depending on the training data, which controls the model. The transition rule is defined as the condition of each coming step that relies upon the present condition of that cell and its encompassing neighborhood cells (Al-sharif and Pradhan 2014). The transition rule successively demonstrates the complexities of land cover both spatially and temporally (Al-shalabi et al. 2013).

The use of this model has increased in modeling LULC and urban expansion (Clarke et al. 1997; He et al. 2006). It is essential to mention that space and time are discrete units in this model. However, in two dimensions, space is measured as a regular grid. The critical properties of this model are that they demonstrate the spatial and complex dynamicity of the system (Aburas et al. 2017; Al-sharif and Pradhan 2014; S. Q. Wang, Zheng, and Zang 2012). The expression of the CA model can be expressed in the following equation:

$$S(t, t+1) = f(S(t), N) \tag{4}$$

Where S(t+1) is the system sate at time (t+1), functioned by the state probability of any time (N) (Hamad et al. 2018).

Several studies have been performed that have used the CA model to assess urban expansion and LULC changes (Barredo et al. 2003; Clarke et al. 1997; White, Engelen, and Uljee 1997). These studies illustrated that this model is capable of describing and modeling the complex process of LULC change, urban systems, and patterns in an intelligible perspective (He et al. 2006; Sui and Zeng 2001; S. Q. Wang et al. 2012; Xian and Crane 2005; Yuan 2010). The major limitation of this model is that it cannot incorporate the macroscale driving factors, such as social, economic, and culture, which is responsible for LULC changes and urban sprawl (Liping et al. 2018). However, for simulation and prediction, some of these studies depend on the quantitative models, such as logistic regression (LR), SLEUTH model, multi-criterion evaluation (MCE), and neural network (Aburas et al. 2017; Al-sharif and Pradhan 2014; Omar et al. 2014).

Markov and CA models have proved their ability to provide a quantitative tool to ease the process of decision making regarding urban and environmental planning and suitability assessment of lands for development. This is important for the efficient management of large metropolis regions. However, the drawbacks of a single model are also explained in many studies (Araya and Cabral 2010; Balzter 2000; Triantakonstantis and Mountrakis 2012). Therefore, to overcome the limitations of individual models, integrated modeling approaches are generally used for LULC future prediction (Al-sharif and Pradhan 2015; Basse, Omrani, Charif, Gerber, and Bódis 2014; Guan et al. 2011; Mishra et al. 2014; Wang and Maduako 2018).

2.2.4 CA-Markov model

The combination of dynamic simulation models with factual and observational models, for example, the CA-Markov model, can overwhelm the limitation of a single model. The use of the integrated model supplements each other, provides an enhanced understanding, and improves LULC modeling (Guan et al. 2011). According to Arsanjani et al. (2011), the different study area has a different environmental condition and land characteristics; therefore, the performance of the LULC prediction model is different in different study areas (Al-sharif and Pradhan 2014; Arsanjani, Kainz, and Mousivand 2011).

The integrated CA–Markov model is a vigorous method in which one can assess and model the LULC based on current trends, both spatially and temporally. This model is applicable to model the spatio-temporal LULC simulations and reconstructions (Yang et al. 2015). This model comprises two components: (1) markov chain, and (2) CA (Sun 2008). This model can decode the markov chain model results through a CA model as a spatial distribution output, which is necessary for designing proper LULC planning (Al-sharif and Pradhan 2014; Arsanjani et al. 2011). Based on transition matrices, the markov model controls the temporal change between LULC categories (Lopez et al. 2001). On the other hand, the CA model controls changes in spatial patterns through local rules taking into account neighborhood configuration and transition potential maps (Clarke, Brass, and Riggan 1994; Guan et al. 2011; He et al. 2008; Houet and Hubert-moy 2006; Li and A. G. O. Yeh 2004; X. P. Liu et al. 2007; White and Engelen 1993; Wu 2002).

This model is one of the most commonly used models for predicting future LULC changes "t+1" using the progression from time "t-1" to time "t" (Behera et al. 2012; Houet and Hubert-moy 2006). It depends on the probabilities of land cover that changes from one state to another between two different time periods (Houet and Hubert-moy 2006). The probabilities matrices are created from the past LULC changes and project to forecast future change (Behera et al. 2012). It can simulate numerous land use categories changes (Houet and Hubert-moy 2006). Therefore, providing the potential of stimulating the conversion from one class to another class of LULC (Hyandye and Martz 2017). Recently, many studies have endeavored to use the CA-markov model to integrate natural and socioeconomic data into land use simulations. For example, Kamusoko et al. (2009) incorporated socioeconomic and physical data into the CA-markov model to predict future LULC change for the year 2030 of Zimbabwe. Their result predicts a continuing decreasing trend in woodland and an increasing trend in bare land. Future simulation result yields that if current LULC trend continue without holistic sustainable development measures, severe land degradation will ensue (Kamusoko et al. 2009). Guan et al. (2011) predicted future LULC change 2015—2042 based on the past trend 1976—2006, using the CA-markov model. Simulation results yields continuing decreasing trend in agriculture land and forest area while increasing trend in built-up area. This would help local authorities better understand and address a complex land use system, and develop the improved land use management strategies that can better balance urban expansion and ecological conservation (Guan et al. 2011; Yu 2009).

Compared to other models, which also used for a similar task, this model poses benefits and drawbacks. The advantages of this model are (1) high proficiency, (2) easy calibration, (3) high capability to comprehensively simulate numerous land covers, and complex patterns (Memarian et al. 2012) as compared to other models (e.g., GEOMOD and CLUE) (Mas et al. 2007). The major drawbacks of this model are (1) incapability to integrate the human, social, and economic dynamics factors in the simulation that can be recognized in agent-based models (Arsanjani et al. 2011) and (2) fail to identify the new developments occurring in the studied area (Aburas et al. 2016; Memarian et al. 2012). Therefore, to address these limitations, this model needs to be combined with other types of models (Al-sharif and Pradhan 2014; Hyandye and Martz 2017).

Soe and Le (2006) used the multi-criteria (MCE) technique in CA-Markov for future prediction of land cover (Myint and Wang 2006). The development of criteria based on the weight assignment to the drivers of LULC changes. The more relevant the driver, the higher the weight is assigned (Behera et al. 2012). There are two types of criteria: (1) factors and (2) constraints. It depends on three standards: (1) decomposition, (2) comparative judgment, and (3) synthesis of priorities (Omar et al. 2014). A detailed application of CA-Markov can be found in (Adhikari and Southworth 2012; Guan et al. 2011; Han and Jia 2017; Kamusoko et al. 2009; Kityuttachai et al. 2013; Mas et al. 2014; Myint and Wang 2006; Wang and Murayama 2017; Yang, Wu, et al. 2019; Yang, Fu, and Chen 2017; Yirsaw et al. 2017).

2.2.5 Land Change Modeler (LCM)

LCM is an incorporated model created by Clark Labs in collaboration with Conservation International, originally developed to oversee the impacts on biodiversity and to scrutinize and predict LULC changes

(Anand, Gosain, and Khosa 2018; Megahed et al. 2015; Roy, Fox, and Emsellem 2014). It is embedded in the IDRISI Terrset 18.1 software (Gibson et al. 2018). LCM moves in stepwise: (1) change analysis, (2) transition potential modeling, and (3) change prediction (Dzieszko 2014). This model takes two thematic raster images as input with the same number and same sequential order of LULC classes. LCM evaluates LULC changes of two different period, provides a quantitative assessment of changes of different LULC classes in terms of gains, losses, swap, net changes, and total changes, and shows the results in the form of numerous graphs and maps (Megahed et al. 2015; Wang and Maduako 2018).

LCM breakdown the LULC changes for different classes, calculate and assess their trends and patterns, and then project these changes to predict the future LULC (Mishra et al. 2014). The model envisages the land use pattern in light of the past change trend (Anand et al. 2018). The explanatory variables, such as distance to roads, slope, aspect, and other variables, were added in the model as a rater datasets. The influencing variables were selected based on their availability, relative importance, and their corresponding effect on LULC changes using Cramer's V (a quantitative measure that shows the relationship between explanatory variables and land cover categories) (Anand et al. 2018; Roy et al. 2014).

For each transition, when the underlying driving is presumed to be the same as the land cover transitions grouped into sub-models. For example, the driver responsible for being a change from forest to an urban area is the same as those effects the conversion of farmland into an urban area. Based on Cramer's V values, explanatory variables are assigned to each sub-model, and the transition potential map of each sub-model is determined through MLP neural networks (Gibson et al. 2018). MLP is capable of processing non-linear relationships among variables more adequately, model more than one transition at a time, and transform categorical data into continuous data (Ayele et al. 2019). The generated transition potential maps are an interpretation of time-specific potential for change. Based on these potential maps (Roy et al. 2014) and markov chain analysis, LCM projects future LULC maps (Mishra et al. 2014).

Multi-layer perceptron (MLP) is a feed-forward neural network based on the supervised Backpropagation (BP) algorithm that plays a central role in prediction. It is a non-parametric algorithm and does not consider multicollinearity (Voight et al. 2019). MLP consists of three layers (1) input, (2) hidden (sets of computational nodes), and (3) output. It signifies relationships between transitions of land use and their explanatory variables through a network of weighted relationships modified iteratively by the algorithm (Mishra et al. 2014). Through hidden layers, the data flow in one direction from an input layer to an output layer and determine the non-linear relationships.

LCM generates two types of prediction (1) hard prediction and (2) soft prediction. A hard prediction yields a projected map based on multi-objective land allocation (MOLA) module. This module assigns each pixel one of the land cover classes to whom it shows more probability to become. A soft prediction represents a continuous mapping of vulnerability to change. It designates the likelihood that a pixel is changed to another land cover class. Finally, the transition probability matrix derived from the markov chain decides how much land is assigned to a thematic class over $T_3 – T_2$, and n-year period (Gibson et al. 2018; Megahed et al. 2015).

LCM generated better prediction accuracy over a short period, particularly in the stable land cover than rapidly changing land cover. Compared to other models that forecast LULC changes based on supervised methods such as the weights of the evidence method in which the user adjusts and selects the weights, LCM produced more precise change potential maps. This is because neural network outputs more sufficiently display the changes of various LULC categories than the individual probabilities acquired through the method of weights of evidence (Megahed et al. 2015). Furthermore, according to Eastman et al. (2005), who compared different methods, such as logistic regression, Bayesian analysis, weights of evidence, and a neural network, concluded that neural networks generated more accurate predictions compared to other approaches (Eastman, Fossen, and Solarzano 2005).

Several studies have used LCM to predict future LULC patterns (Dzieszko 2014; Gupta and Sharma 2020; Voight et al. 2019), tropical deforestation (Ayele et al. 2019; Voight et al. 2019), urban growth, erosion, Mediterranean catchment (Azmoodeh et al. 2016; Roy et al. 2014), and habitat modeling (Mas et al. 2014). Anand et al. (2018) used the LCM to simulate the changes in hydrological components in the Ganga basin, India, in response to LULC changes. Their results shows that urbanization and deforestation are the topmost contributor to the increase in surface runoff and water yield. While increased irrigation demands were the dominant contributor to the water consumption and also added to the increased evapotranspiration. Their study provides substantive information to the decision-makers to develop ameliorative strategies (Anand et al. 2018). Hamdy et al. (2017) simulated urban expansion from 2001 to 2013 using LCM in Abouelreesh village, province of Aswan, southern Egypt. Their result revealed that in 2001 urbanization risk area was 59.79%, reached to 65.45% in 2013 (Hamdy et al. 2017). Abuelaish and Olmedo (2016) modeled the land cover changes in the Gaza strip from 1972-2013 using LCM and predicted that urban areas increase to 58.83% by 2023 from 46.2% in 2013(Abuelaish and Olmedo 2016). Kumar et al. (2015) simulate the future urban expansion for the years 2030 and 2040 for Vijayawada, India, using the LCM model based on past trends from 1973 to 2014. The results depict an increase in built up area by 44.15 % and open land decrease by 58.68%. This rapid and massive conversion of vegetative and open land in to built-up area may have serious environmental impacts unless proper environmental management plans were implemented for the urban area (Kumar et al. 2015). According to Mas et al. (2014); Ozturk (2015); Gibson et al. (2018); Wang and Maduako (2018); Ansari and Golabi (2019), for regional case studies LCM is efficient in simulating future LULC changes, patterns, and trends. This is because LCM provides a better understanding of LULC and is helpful for local administrative bodies for decision making (Ansari and Golabi 2019; Gibson et al. 2018; Mas et al. 2014; Ozturk 2015; Wang and Maduako 2018). The results of all these studies showed that LCM is capable of producing highly accurate LULC simulation. Therefore, this study employed an LCM to predict the future LULC of GHKM.

2.3 Ecosystem service value (ESV)

An assessment of ecosystem services pursues to address the problem statement, “How much are nature's services worth?” (Westman 1977). Academically Westman, for the first time, used the term "natural services" in 1981 and its synonym "ecosystem services" formally adopted in 1983. In 1997, two pioneer studies were published: (1) “Nature’s Services: Societal Dependence on Natural Ecosystems” by Daily et al. (1997) (Daily 1997), and (2) “The Value of the World's Ecosystem Service and Natural Capital” by Costanza et al. (1997)(Costanza, D’Arge, et al. 1997). These studies ignited a discussion and research on ecosystems, ecosystem services, and related policies (M. Hu et al. 2019).

Ecosystem service (ES) is defined as the environments, conditions, and procedure through which natural ecosystems and the species that include them maintain and accomplish human life. (Costanza, Batabyal, et al. 1997; Feng et al. 2012; Tianhong, Wenkai, and Zhenghan 2010). Ecosystem gives not only enormous materials (such as food, wood, and other raw materials) but also provides non-material services such as carbon sequestration and water filtration aesthetic welfares that are imperative for health and human beings (Costanza et al. 2014; Song and Deng 2017a). Ecosystem services are classified into four categories: (1) provisioning services; (2) supporting services; (3) regulating services; and (4) cultural services (W. Liu et al. 2019). These services depend on the type and status of the ecosystem. Supporting services have a relatively indirect impact, while other services have a direct impact. Each ecosystem provides unique services that cannot be substituted by others. For example, services offered by the forest ecosystem is different from grassland ecosystem or wetland ecosystem (Gashaw et al. 2018). Ecosystem services assess the association between man and nature and collaborate with different publics for different purposes (Jiang 2018). The phenomena of the growing population, socioeconomic development resulting in the degradation of the natural environment and ascribed to the gap between the provision of ecosystem services and societal demands for these services (Feng et al. 2012). For example, when an ecosystem is handled to provide a single or certain service (for example, for the climate regulation), the other services are adversely influenced. Therefore, the valuation of an ecosystem plays an important role in both supportable ecology and ecological, economic research, and is urgently needed (Feng et al. 2012; Gashaw et al. 2018; Negussie et al. 2019).

The land is not only the emplacement of the natural terrestrial ecosystem, but human beings also utilize it in several ways. Changes in LULC with the accelerated rate of urbanization, industrialization, and socioeconomic development can modify the ecosystem process, structure, and function, and consequently influence the ESV (Costanza, D'Arge, et al. 1997; Negussie et al. 2019; P. Zhang et al. 2015). These anthropogenic disturbances of the natural environment are becoming more prominent, resulting in an increasing trend of domestication and vulnerability of ecosystems at both local and global scale and has created large ecological footprints on the earth (Deng and Gibson 2018; Zeng et al. 2016). Moreover, for many years, people used only to consider the monetary estimation of the environment and natural resources, but have neglected their potential social, ecological, and environmental values (Salles 2011; Yoshida et al. 2010). This short-sighted conduct causes excessive degradation of natural resources and damage to ecosystem service and endangers human sustainability in the biosphere (W. Liu et al. 2019; P. Zhang et al. 2015), gaining much attention from researchers to determine the impact of LULC changes on ESVs (Song and Deng 2017a) and creating public awareness. Studies that quantify and analyze the impacts in terms of ES changes are still scarce. Therefore, the research is profoundly required on the quantitative assessment of ESV, especially in urbanization territories, which can enlighten land use management, policy decision-makers for sustainability, and to improve the ecological environment (Ye, Zhang, et al. 2018).

Different types of LULC play a different role in the provision of ecosystem services. For example, forest cover plays a vital role in the supply of wood and climate regulation, whereas farmland plays a key role in the provision of food. LULC types act as a proxy for ecosystem services by coordinating them equal to biomes (Polasky et al. 2011; Song et al. 2015). Thus, LULC gave a significant amount of ecosystem services information (Cai et al. 2013) and was subsequently used as supplementary data for assessing ecological transactions in the investigation (Lü et al. 2015).

The ESV assessment method can be classified into four types: (1) cost-based methods; (2) revealed preference methods; (3) stated preference methods; and (4) the benefits transfer method (BTM) (Lin et al. 2018). Costanza et al. (1997) has assessed global ESV using the benefits transfer method. They classified the biosphere into 16 ecosystems and 17 ecosystem functions and calculated the ESV of each (Costanza, Batabyal, et al. 1997; Song and Deng 2017a). Since then, the literature on the assessment of ESV has started to grow (Arunyawat and Shrestha 2016; Estoque and Murayama 2013; Gashaw et al. 2018; de Groot et al. 2012; Kindu et al. 2016; Mendoza-González et al. 2012; Tolessa, Senbeta, and Kidane 2017; Vihervaara, Rönkä, and Walls 2010; Yi et al. 2017). Several researchers have examined the ESV of forest, grassland, and wetland by using Costanza et al. (1997) method (Calvet-Mir, Gómez-Baggethun, and Reyes-García 2012; Long et al. 2014a; Polasky et al. 2011; Song and Deng 2017a; Viglizzo et al. 2012; Zang et al. 2011). Their derived coefficient value has been applied for the evaluation of ecosystem services on a global scale as compared to the regional level.

The results of (Costanza, Batabyal, et al. 1997) have been severely criticized by many researchers, especially when applied to China. This is because they underestimated farmland ESV and overestimated wetland ESV. However, their derived ESV mirrors the developed country's economic level, such as European countries and the United States, instead of developing countries such as China (Chen et al. 2014; Long et al. 2014b). Following the same methodology, the equivalent per-unit-area ESV was established by Xie et al (2003) (XIE et al. 2003) concerning to the Chinese terrestrial ecosystem via a survey of 200 Chinese ecologists. Then, they modified the value of the coefficient of the Chinese ecosystem and can be applied to China's different areas by localizing their average natural food production (Han, Song, and Deng 2016; Tianhong et al. 2010). An assessment of ecosystem services helps policy and decision-makers to integrate environmental, social, and economic apprehensions into land use planning and management (Albert et al. 2016; W. Liu et al. 2019).

Quantitative assessments of the impact of LULC changes on the ESV represent a central point of interest in scientific research on sustainable development (W. Liu et al. 2019). Several studies have been made which have studied the impact of LULC changes on ESV using equivalent per unit value in different regions of China (Cai et al. 2013; Feng et al. 2012; Han et al. 2016; Hao et al. 2012; M. Hu et al. 2019; Li et al. 2010; Mamat, Halik, and Rouzi 2018; Peng et al. 2016; Wang et al. 2015; Ye, Bryan, et al. 2018; Ye et al. 2015). Studies showed that in China during 2000-2008, a 1% change in LULC resulted in a 0.10% average change in ESV (Song and Deng 2017b). Su et al. (2014) determined that in Shanghai, China's total ESV decreased during 1994-2006 and examined the relationship with urbanization (Su et al. 2014). Yun-guo et al. (2011) considered changes in ecosystem service in Changsha, China, predominantly affected by the sprawl of construction land and decreased in woodland and cropland (Yun-guo et al. 2011). Moreover, changes in LULC in northwest China primarily compelled by the growth of oasis agriculture have significantly influenced the ESVs and functions of the Yanqi basin, causing land deterioration and changes in the aquatic environment (S. Wang, Wu, and Yang 2014).

To understand and assess the outcomes/results of these changes in the long term, the availability of reliable and adequate information about LULC change over the years is becoming increasingly necessary (Yirsaw et al. 2017). It is essential to monitor, manage, and utilize ecosystems accurately to halt the ongoing loss of ecosystem services and maintain or balance the supply of different ecosystem services in the landscape. To date, efforts or studies in the quantitative analysis of the effect of LULC changes on ESV and their spatiotemporal variability at the regional level (in GHKM) are very limited. Therefore, this study also aims to study the impact of LULC changes on ESV based on regional coefficient value. This could have significant practical ramifications for protecting ecological civilization.

Chapter 3

3 Study Area[1]

Guangdong, Hong Kong, and Macao geographically situated between 20°13′N–25°31′N and 109°39′E–117°19′E in the southernmost part of mainland China (Figure 2). GHKM covers a total area of approximately 196,342 km^2. GHKM is bounded by/share borders with Fujian province in the east, Jiangxi and Hunan provinces in the north, Guangxi in the west, and the South China Sea in the south (Shobairi and Li 2016). It consists of 23 cities, divided into four groups in accordance with their geographical location. This includes 11 cities in the Pearl River Delta (PRD), four cities in mountainous regions, four cities on the eastern side, and four cities on the western side (Chen et al. 2013b; Li et al. 2013; Shobairi and Li 2016). The cities in Pearl River Delta are Guangzhou, Foshan, Dongguan, Shenzhen, Zhongshan, Zhuhai, Huizhou, Jiangmen, Zhaoqing, Hong Kong, and Macao. Qingyuan, Shaoguan, Heyuan, and Meizhou cities in the mountainous region. However, Zhanjiang, Maoming, Yunfu, and Yangjiang are western side cities, whereas; Chaozhou, Shantou, Jieyang, and Shanwei are eastern side cities. Its climate varies from tropical to subtropical with hot, humid summers and cold, windy, dry winters. The monsoon rainy season begins in April and ends in September. The annual average temperature is 22°C, and annual average precipitation ranges from 1500—2000 mm (Li et al. 2013; Li and Wang 2015; Shen et al. 2019). Forest coverage varies from north to south, in relation to the local climatic conditions (Peng, Hou, and Chen 2008). Guangzhou is

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Hasan, S., Shi, W., Zhu, X., & Abbas, S. (2019). Monitoring of Land Use/Land Cover and Socioeconomic Changes in South China over the Last Three Decades Using Landsat and Nighttime Light Data. *Remote Sensing*, 11(14),1658. https://doi.org/10.3390/rs11141658

Hasan, S., Shi, W., & Zhu, X. (2020). Impact Of Land Use Land Cover Changes On Ecosystem Service Value – A case study of Guangdong, Hong Kong, And Macao In South China. *PLOS ONE*, *15*(4), 1–20. https://doi.org/10.1371/journal.pone.0231259

Hasan, S., Shi, W., Zhu, X., Abbas, S. & Khan, H.U.A. (2020). Future simulation of land use changes in rapidly urbanizing South China based on Land Change Modeler and remote sensing data. *Sustainability*, *12(11)*, 4350; https://doi.org/10.3390/su12114350 the capital and the Pearl River, flowing through the GHKM, is the largest river in South China. The topography of this region is mixed and characterized by rivers, mountains, hills, plateaus, and plains (Li and Wang 2015).

This region is one of the largest political, economic, and cultural centers with the most innovation capacity and strongest comprehensive strength across China (K. Yang et al. 2018). After the opening of economic reform in 1978, GHKM has practiced prompt increase in population, socioeconomic development, and changes in land use land cover. The increase in population mainly caused by increase in immigrants. The tremendous surge in urban area has predominantly come from the conversion of farmland into built-up area (Chang-ping 2010; Hasan et al. 2019). The total population of the Guangdong, Hong Kong, and Macao by 2017 was 9164.90 (10,000 persons) (Xiowei, Xiangxin, and Jianfu 2017). The region has been already encountered ever more jam-packed transportation systems and environmental pollution (Wu et al. 2006). However, the availability of infrastructure supported by government and local authorities has facilitated its economic prosperity and its economy currently ranked 14th in the world (Shen et al. 2019).

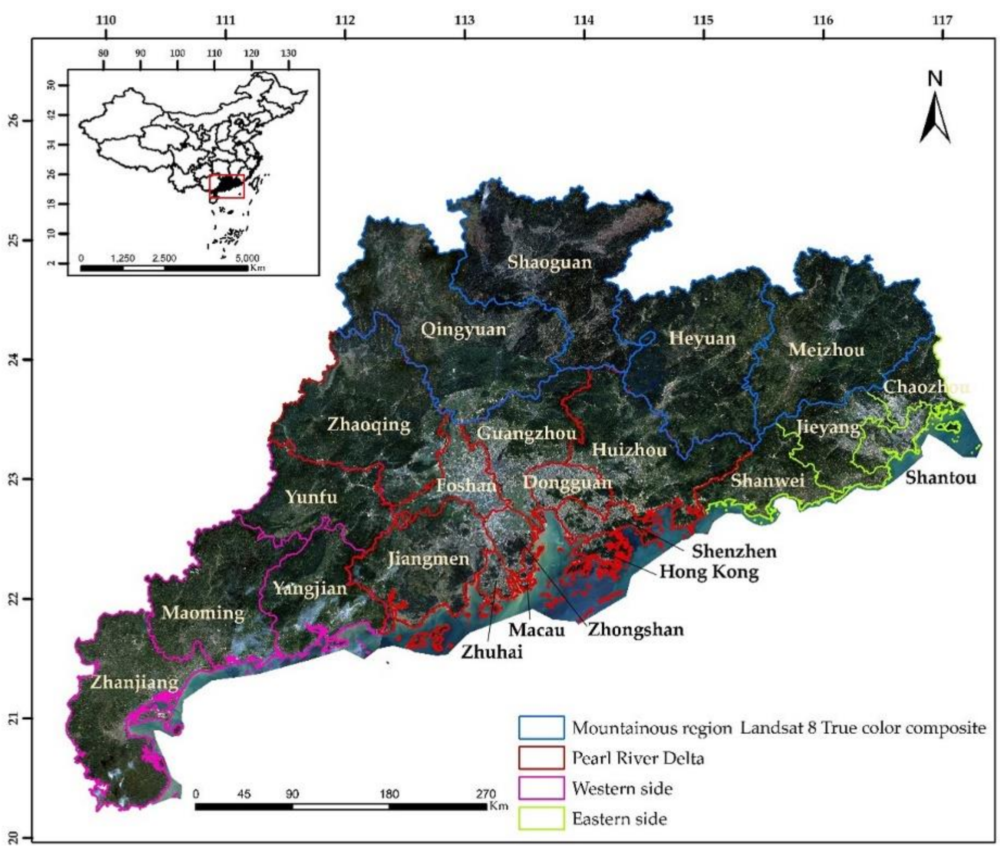

Figure 2. Location map of the Guangdong, Hong Kong, and Macao.

Chapter 4

4 Monitoring of Land Use/ Land Cover and Socioeconomic Changes in South China over the Last Three Decades Using Landsat and Nighttime Light Data[2]

4.1 Introduction

Land use and land cover changes (LULCC) have increasingly become a global challenge. They are the most direct expression of the effects of human activity on the natural ecosystems (J. Liu et al. 2014; Mooney, Duraiappah, and Larigauderie 2013; Tian et al. 2012). The United Nations 'Agenda of the Twenty-First Century' in 1992 officially stimulated research activities related to land use and, therefore, the effects of land cover change (LCC). In 1995, two main international organizations, the International Geosphere-Biosphere Programme (IGBP) and the International Human Dimensions Programme (IHDP), initiated the joint program: the Land Use/Land Cover Change (LUCC) Research Program, as the core of a study related to the global LULC. Thus, since 2000, the monitoring and simulation of LULC change has become a key focus in the field of land change science (Dou and Chen 2017; J. Liu et al. 2014; Wu et al. 2016).

Over the last few decades, land use changes and developments have resulted in population pressure (Wu et al. 2016). Both positive and negative health and welfare effects have arisen, as a result of random industrialization, economic development, modernization, and urban planning policies. It has been found that changes in land use have negative impacts on the climate, ecosystems, surface radioactivity (e.g., increased atmospheric greenhouse gasses and depletion of the ozone layer), agricultural activities, and biodiversity on both local and global scales. Such situations are more

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[2] This chapter is based on a published study and being reproduced with the permission of MDPI.

Hasan, S., Shi, W., Zhu, X., & Abbas, S. (2019). Monitoring of Land Use/Land Cover and Socioeconomic Changes in South China over the Last Three Decades Using Landsat and Nighttime Light Data. *Remote Sensing*, 11(14),1658. https://doi.org/10.3390/rs11141658 prevalent in developing countries such as China (Dou and Chen 2017; Salih, Ganawa, and Elmahl 2017; Yu et al. 2016; Zhu et al. 2016; Zhu and Woodcock 2014).

Since the opening up of economic reform of China in 1978, radical changes in the economy, industrialization, and urbanization have taken place, which in turn have produced a highly noticeable LULCC, well-illustrated by the results of the rapid widespread development, mentioned above. Examples are found in coastal areas such as the Pearl River Delta (PRD) region in Guangdong, Shanghai, Jiangsu, and Zhejiang provinces of southeastern China (Fan et al. 2007; Li et al. 2013). China's inherent problem, namely, the availability of land resources per capita being far below the world average, has influenced the current economic development and unprecedented urbanization. Development appears to have been almost uninhibited and characterized by a lack of planning for the betterment of the areas in which it has taken place. A consequence of this lack of planning is what appears to be random development, resulting in a lack of cohesion and subsequent inhibition of the preservation of the land resources of the newly urbanized areas (Li and A. G. Yeh 2004). During the five decades between 1949 and 1996, the total extent of the urban area of the cities of China nearly tripled (Lin and Ho 2003). During 1980–2011, the urban population increased by 500 million, thus, exceeding the total population of most countries. It is expected to rise by a further 300 million by 2050 (S. Du et al. 2014). This rapid urbanization, combined with LULCC, reflects a depletion of natural resources and subsequent eco-environmental changes (Wu et al. 2016).

During the same period, Guangdong, Macao, and Hong Kong (GHKM) have had similar experiences to those mentioned above, and, LULCC are especially notable in the form of urban land expansion and population growth. These areas were once rich in land resources and were a major source of commercial grain production before the opening of economic reform. The speed of urbanization and land use change (LUC) has been most significant in the PRD region, with the urban area increasing by more than 300% between 1988 and 1996 (Fan et al. 2007; Jiang and Wu 2015; Li et al. 2013; Zhu et al. 2016). More than 40% of farmland was converted to a different land type between 1978 and 2013. Between 1978 and 1998, approximately 92 km^2 of water sites adjacent to the PRD were transformed to islands, most of which have now been urbanized (Zhu et al. 2016). Such changes have obviously reduced areas of fishponds and farmland, and consequently the associated resources and crop yield, at an increasing rate. As a result, sustainable development has been constrained (Hu and Zhang 2013; Li and Wang 2015), with such trends expected to continue during the coming decades. Contradictions in the realm of sustainable development and secure land use policy reform (S. Du et al. 2014) leads to further LULC changes (Jiang and Wu 2015; Li and A. G. Yeh 2004; Wenhua 2004; Zhu et al. 2016).

Aggravating the above complex land structure and intensive urbanization, industrialization, and economic development have, therefore, highlighted the importance of the LULCC of the GHKM over the past 30 years and the "from-to" change in order to determine the socioeconomic factors that will contribute to the necessary changes to ensure future sustainable development.

In the continuing development of remote sensing technology, satellite remote sensing has been widely used to detect LULC change both qualitatively and quantitatively (Al-Bakri et al. 2013; Dewan and Yamaguchi 2009a; Fan et al. 2007; Özyavuz et al. 2011; Seto et al. 2002; Treitz, Howarth, and Gong 1992; XU et al. 2000; Yu et al. 2016), as well as urban expansion (Xiao et al. 2006), and to validate the modeling of urban growth (Dewan and Corner 2014; Poelmans and Van Rompaey 2009). Various methods and algorithms, broadly classified into two types, have been developed for use in detecting such changes. They include (1) change detection without classification, and (2) post-classification (Yu et al. 2016). Change detection without classification includes the normalized difference vegetation index (NDVI), normalized difference water index (NDWI), normalized difference built-up index (NDBI), tasseled cap transformation, principal component analysis, and change vector analysis (CVA). Post-classification techniques include post-classification comparison, image differentiation, aerial difference calculation, image rationing, and image regression (Haque and Basak 2017). All change detection techniques provide the basis for an understanding of the relationships and interactions between humans and natural phenomena (Fan et al. 2007; Hussain et al. 2013; Yu et al. 2016). Landsat images collected by Landsat 5 Thematic Mapper (TM), 7 Enhanced Thematic Mapper Plus (ETM+), and 8 Operational Land Imager (OLI) are often used to detect change, because they provide continuous, consistent, and long-term data over the past selected decades (Chen et al.

2003; Dou and Chen 2017; Haque and Basak 2017; Hussain et al. 2013; Seto and Fragkias 2005). They are available in multispectral, multi-resolution, and multi-temporal forms, which make them useful for LULC change monitoring (Dou and Chen 2017). Extensive studies have been conducted regarding LULCC (Dai, Wang, and Gao 2010; Fan et al. 2008; Lin and Ho 2003; J. Liu et al. 2014; Seto et al. 2002; Seto and Fragkias 2005; Sodango et al. 2017; Weng 2002) and their driving forces, such as urban expansion, population growth (Dou and Chen 2017; S. Du et al. 2014; Li and A. G. Yeh 2004; Ma and Xu 2010), socioeconomic determinants (Li and Wang 2015; Seto and Kaufmann 2003), transformation of farmland to urban land (S. Du et al. 2014), and policy changes (J. Wang et al. 2012; Wang et al. 2018). Wu et al. (2016) assessed urban expansion and LULC changes in Guangzhou from 1979 to 2013 using differently dated Landsat images and concluded that urban expansion increased by 1512.24 km^2, at an annual rate of 11.25% (Wu et al. 2016). Zhang et al. (2015) evaluated the long-term LULC changes, and their results showed that the urbanized area in Dongguan had increased by more than 52% between 1979 to 2013 (H. Zhang et al. 2015). Du et al. (2014) revealed further LULC changes and concluded, positively, that changes in land use were closely related to population growth, economic development, and the implementation of policies (S. Du et al. 2014).

For the classification of remote sensing data, both parametric and non-parametric statistical learning techniques have been developed and used in different contexts (Mountrakis et al. 2011). Parametric statistical learning techniques such as the maximum likelihood classifier (MLC) fail due to an inability to resolve the interclass confusion. This limitation can be overcome by applying a non-parametric classifier such as a support vector machine (SVM), which does not depend on any assumptions of the class distributions of data (Bahari et al. 2014; Q. Liu et al. 2014; Mountrakis et al. 2011). The support vector machine is an advanced machine learning algorithm, binary classifier, and a relatively new supervised classification technique (Pal and Mather 2005). The SVM outperforms the other methods due to its robustness, high classification accuracy, and effective output results, even when using a small training sample (Bahari et al. 2014; Hussain et al. 2013; Q. Liu et al. 2014; Mountrakis et al. 2011). It operates on the principle of structural risk minimization (SRM) (Ustuner et al. 2015) and has overcome the problem of overfitting (Mountrakis et al. 2011; Pal and Mather 2005). Therefore, the SVM has recently attracted the attention of researchers in the community of remote sensing (Gidudu, Hulley, and Marwala 2007). Several studies have employed an SVM (Candade and Dixon 2004; Devadas et al. 2012; Griffiths et al. 2010; Hao et al. 2016; Huang et al. 2008; Megahed et al. 2015; Mohammadimanesh et al. 2018).

Guangdong, Hong Kong, and Macao land use has undergone a significant development over the past 30 years, substantially influenced by the changing polices enabling industrialization, urbanization, and socioeconomic activities. This region has become one of the richest regions in China, contributing 14% of the country's gross domestic product (GDP) (Xiowei et al. 2017). To understand the impacts of LULCC related to changes in policies and socioeconomic dynamics, this study is based on an integrated analysis as follows. First, we estimate the continuous monitoring of LULC changes in GHKM over the past 31 years (1986–2017). Second, we analyze the driving factors and mechanisms of the change. Third, we determine the relationship between light index, urbanization, and socioeconomic determinants. This study also aims to provide reference data regarding the implementation of sustainable socioeconomic and urban development for policy and decisions makers, and to map the relationships between factors that result in the reduction of farmland.

4.2 Materials and Methods

4.2.1 Data Acquisition and Pre-processing

4.2.1.1 Landsat Data

Atmospherically corrected Landsat (TM, ETM+, and OLI) level 2 images with 30 m spatial resolution were collected in the dry season (October to March) from 1986 to 2017 from USGS Earth Explorer (Anon n.d.). The study area was covered with 15 tiles of Landsat images for the corresponding study year. The dry season (winter) is considered the best period to study LULCC, due to minimal cloud and a better capacity to differentiate between grasses and evergreen forest (Li and Wang 2015). Mosaics of cloud-free images were produced every five years. However, due to serious cloud contamination during some years, the collected images were based on intervals that were one or two years longer or shorter during the selected five years (Table 20-S1).

4.2.1.2 DMSP/OLS NTL Data

Defense Meteorological Satellite Program/Operational Linescan System (DMSP/OLS) version 4 data with 1 km spatial resolution and 6-bit radiometric resolution were downloaded from the National Geophysical Data Center (NGDC) website of National Oceanic and Atmospheric Administration (NOAA) (Anon n.d.). Nighttime light (NTL) data from 1994 to 2010, used as an annual NTL image composite, were only available for the period from 1992 to 2013. The stable night light product was used with six sensors F10, F12, F14, F15, F16, and F18; all background noise is removed from this product (Shi et al. 2016), thus it comprises only light emitting from residential areas, cities, town, and persistent lightning areas (Li and Zhou 2017).

DMSP NTL images cannot be used directly because of the absence of onboard intercalibration and sensor, orbit, and magnitude discrepancies, and the digital numbers (DN) values of lit pixels of different satellites even when no changes occur on the ground (Elvidge et al. 2014; Faouzi and Washaya 2017; Jiang et al. 2017; Pandey, Joshi, and Seto 2013; Shi et al. 2016; Zhang and Seto 2011). Therefore, intercalibration, inter-annual composition, and inter-annual series correction was performed to calibrate the NTL data (Faouzi and Washaya 2017; Jiang et al. 2017; Pandey et al. 2013; Shi et al. 2016).

4.2.1.3 Other Data Sets

Other data used in this study includes vector data of the GHKM administrative division boundary and socioeconomic data such as population and GDP data extracted from Guangdong, Hong Kong, and Macao Statistical Yearbooks 1986–2017. All satellite data, including Landsat and NTL images, were clipped by the study area boundary. The projection system used was WGS-1984-UTM-Zone-49N.

4.2.2 Land Use Land Cover Classification from Landsat Images

An a priori classification scheme was devised following similar studies in the Guangdong, Hong Kong, and Macao (S. Du et al. 2014; Fan et al. 2007; Li and Wang 2015). LULC classes were defined as forest, grassland, water, fishponds, built-up, bareland, and farmland (Table 2). The obtained images were classified by a supervised support vector machine (SVM) (Burges 1998). The SVM algorithm has flexible supervised classifier options with high accuracy when classifying the multispectral data, compared to other supervised classification methods (such as a decision tree and maximum likelihood classifier (MLC)). It is an advanced machine learning statistical algorithm that separates the classes by an optimal decision hyperplane surface (Rimal, Zhang, Keshtkar, B. Haack, et al. 2018). High-resolution Google Earth imagery was used to assist with the selection of regions of interest (ROIs) as training samples. In the SVM, a radial bias function (RBF) was used as a kernel function as this kernel yielded higher performance with respect to convergence speed, robustness, and fewer parameter values to predefine (Huang et al. 2008). The cost parameter (C) tells the SVM optimization how much we want to avoid misclassifying each training example. For large values of C, the optimization will choose a smaller-margin hyperplane, whereas a very small value of C will cause the optimizer to look for a larger margin separating the hyperplane. The gamma parameter defines the influence of a single training example. With a low gamma value, points far away from a plausible separation line are considered in the calculation for the separation line. On the other hand, a high gamma value considers the points close to the separable line (Huang et al. 2008; Pal and Mather 2005). Therefore, an RBF with the adjusted parameters C factor = 100, gamma = 0.167, and threshold = 0 were used in this study, as these parameters give the best results and high classification accuracy. The threshold = 0 was set so that it uses the full resolution image. To eliminate the random noise and isolated pixels from a classified map, a majority filter of 8 by 8 was applied (S. Du et al. 2014).

The accuracy of the classified maps was assessed by means of the producer's accuracy, user's accuracy, and kappa statistics derived from the confusion matrix (Abbas, Nichol, and Wong 2018; Lillesand, Kiefer, and Chipman 2008). The accuracy assessment samples were selected by stratified random sampling of the reference image verified with the high-resolution images of Google Earth and the land use data from the provincial Department of Land and Resources (Anon n.d.). The low spatial resolution on Google Earth historical imagery made it more difficult to obtain reference information for 1986, 1989, and 1994. However, it was managed by doing visual interpretation of the Landsat image using different band combinations. A similar approach was taken by (Dissanayake et al. 2019; Estoque and Murayama 2017; FAO 2016; Thapa and Murayama 2007).

Table 2. Description of land use land cover classes.

Class	Description	Abbreviation
Forest	Forest, tree cover	F
Grassland	Natural shrubs and grassland	G
Water	Natural water bodies, oceans, lakes, rivers, and reservoir. Water bodies that are not used for intensive aquaculture	W
Fishponds	Water bodies that are used for intensive aquaculture. Dike pond, including mulberry	FP
Built-up	Land covered by buildings and other man-made structures	BU
Bareland	Exposed soil, sand, rocks, landfill sites, and areas of active excavation	BL
Farmland	Land used for farming, cropland, and orchards	FL

4.2.3 Change Detection from Classification Map

Temporal changes in the spatial extent of the landscape thematic classes were determined through post-classification comparison of the classified maps. The maps were paired sequentially, i.e., 1986–1989, 1989–1994, 1994–2000, 2000–2005, 2005–2010, and 2010–2017, and transition matrices were then produced (Abbas et al. 2018; Pontius, Shusas, and McEachern 2004). To summarize the transition and for further analysis, gain (Equation (5)), loss (Equation (6)), net change (Equation (7)), swap (Equation (8)), and total change (Equation (9)), of each LULC class, for each of the periods (Pontius et al. 2004) were calculated. Also calculated was the annual rate of change using Equation (10), based on the compound interest law; therefore, there is an insensitivity to different time periods (Puyravaud 2003; Teferi et al. 2013).

$$\boldsymbol{G_j = P_{+j} - P_{jj}} \tag{5}$$

$$\boldsymbol{L_j = P_{j+} - P_{jj}} \tag{6}$$

$$\boldsymbol{ANc_j = \left|P_{+j} - P_{j+}\right|} \tag{7}$$

$$\boldsymbol{S_i = 2min\,(P_{j+} - P_{jj};\ P_{+j} - P_{jj})} \tag{8}$$

$$\boldsymbol{(Tc)_j = (P_{j+} - P_{jj}) + (P_{+j} - P_{jj})} \tag{9}$$

$$\boldsymbol{R = \left(\frac{1}{T_2 - T_1}\right) \times \left(ln\frac{A_2}{A_1}\right) \times 100} \tag{10}$$

Where, *G* represents a gain, *L* represents loss, *ANc* represents absolute net change, *S* represents swap, *Tc* represents total change, *A1* and *A2* represent areas corresponding to time *T1* and time *T2*, respectively, and *R* represents the rate of change in percentage terms per year. Gain (*G*) is defined as the landscape thematic class percentage at time 2 after subtracting its proportion from the time 1 landscape. Loss (*L*) is defined as the difference between the percentage of a class of time 1 landscape and its persistent proportion after the transition period. Absolute net change (*ANc*) is defined as the absolute difference of class landscape amount between the time 1 and time 2 landscapes. Swap (*S*) represents the amount of a loss of class at one location and the same amount is added to a different class in the landscape. The total change (*Tc*) characterizes the overall change, calculated by adding gain and loss (Abbas et al. 2018). In this study, the forest growth, expansion of urban area, and loss of farmland were explained both temporally and spatially through the transition matrix.

4.2.4 Light index from DMSP NTL data

The light index is defined based, simultaneously, on two parameters: (1) the brightness of the night light, and (2) the urban area of lit pixels. The light index shows a close relationship with urban population, urban area, and economic activities (Wei et al. 2014; Q. Zhang, Pandey, and Seto 2016). Therefore, changes in the light index over time show the trends of population density and economic growth (Shobairi and Li 2016). The light index was calculated using the following formula:

$$\boldsymbol{Light\ Index = I * S} \tag{11}$$

where, *I* is the average night light brightness:

$$\boldsymbol{I = \frac{1}{N_L \times DN_M} \times \sum_{i=P}^{DN_M} (DN_i \times n_i)} \tag{12}$$

where, $\boldsymbol{DN_M}$ is the maximum DN value, $\boldsymbol{DN_i}$ is the DN value of the i^{th} gray level, $\boldsymbol{n_i}$ is the number of lit pixels belonging to that i^{th} gray level, *P* is the optimal threshold used to extract the urban area from the NTL images, and $\boldsymbol{N_L}$is the number of lit pixels with a DN value between *P* and $\boldsymbol{DN_M}$. *S* is the proportion of lit urban areas to the total area of a study region:

$$\boldsymbol{S = \frac{Area_N}{Area}} \tag{13}$$

where, $\boldsymbol{Area_N}$ is the lit urban areas and *Area* is the total area of the study region (Shobairi and Li 2016).

4.3 Results

4.3.1 LULC Changes from 1986 to 2017

The LULC maps for the years 1986, 1989, 1994, 2000, 2005, 2010, and 2017 were produced by supervised image classification (Figure 3), followed by transition and persistence matrices of the LULC classes (Table 22-S3). The accuracy assessment based on a confusion matrix, having overall accuracy of 91% and kappa of 0.88 (Table 21-S2), suggests each classified LULC map is satisfactory. The transformation between the different LULC maps reflect the direction of change, which can be best explained using a space-time change process. The results (Table 22-S3) reveal that during 1986–2017, the major transition occurred between built-up land, farmland, and forest. The diagonal numbers in Table 22-S3 show a class persistence (i.e., the area remained the same), and the off-diagonal numbers in the matrix represent conversion from one class to another. The main characteristics of the transference are described below.

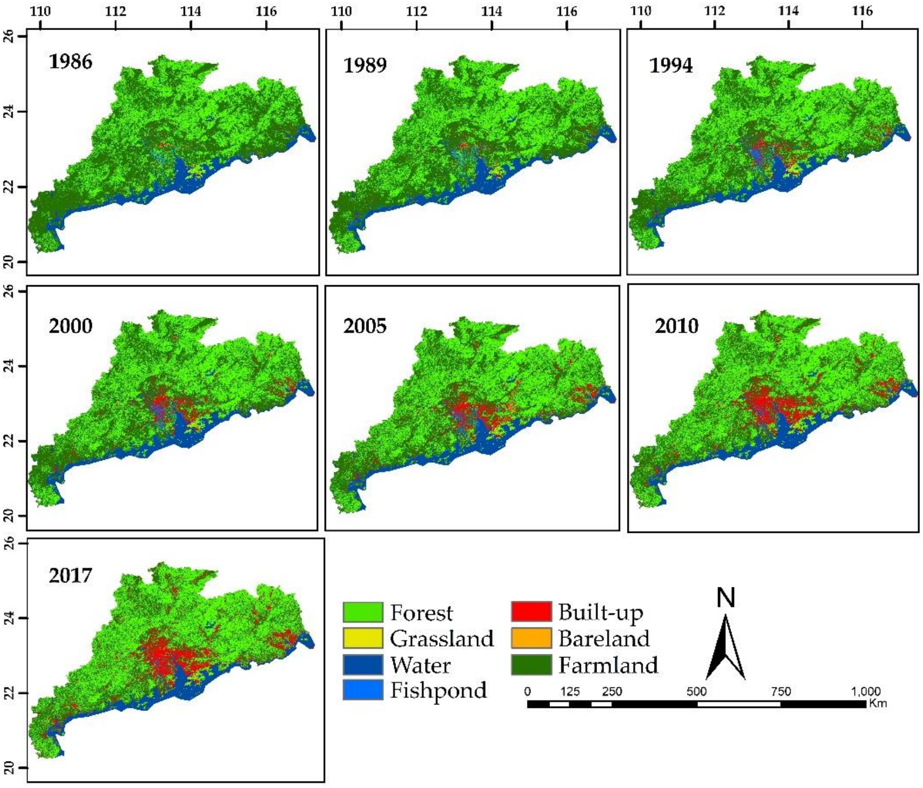

Figure 3. Land use land cover classification map of the Guangdong, Hong Kong, and Macao from 1986 to 2017.

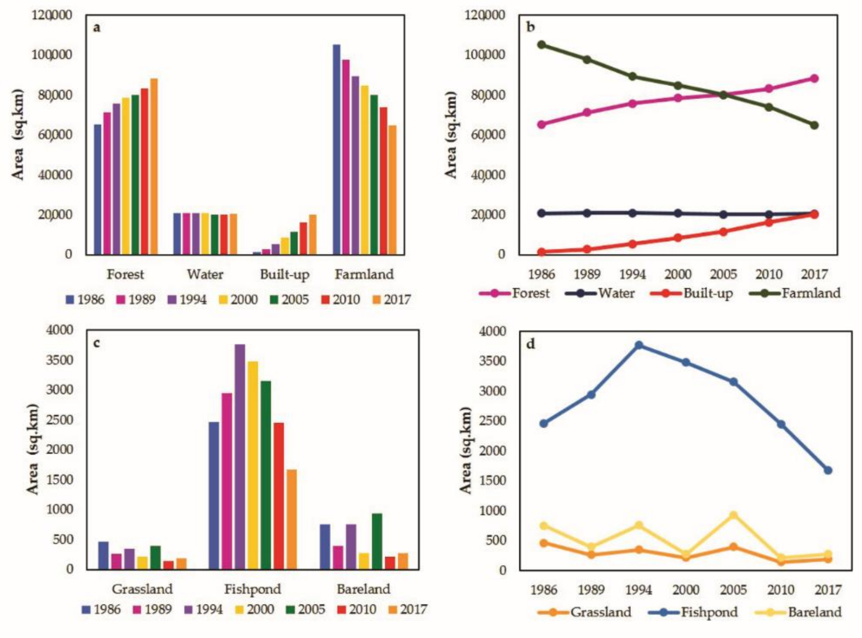

Figure 4. Area distribution of different land use land cover classes and change trends in the Guangdong, Hong Kong, and Macao from 1986 to 2017: (**a**) land use land cover area of forest, water, built-up land, and farmland; (**b**) land use land cover change trends in forest, water, built-up land, and farmland; (**c**) land use land cover area of grassland, fishponds, and bareland; and (**d**) land use land cover change trends in grassland, fishponds, and bareland.

Figure 3 shows a series of maps, while Figure 4a, c is a bar chart and 4b, d gives LULC trends, showing that the GHKM land cover changed significantly during the study period. The economic reform policies, rapid economic development, and urbanization have changed the history of the study area socially and economically, resulting in LULCC (Ramakrishnan et al. 2001; J. Wang et al. 2012). The LULCC over the past 30 years indicates that forest, farmland, and built-up land remain the dominant cover types in the study area. The results reveal that in 1986, built-up land had the least coverage (Figure 3, Table 22-S3) and, over the years, it increased from 0.76% in 1986 to 10.31% in 2017. Compared to other land cover classes, the built-up area increased, with the highest annual rate of change i.e., 8.45%, during 1986–2017 (Table 3). Its highest annual rate of change was observed between 1986 and 1989, i.e., 19.15%. From the late 1980s to the 2000s, the GHKM built-up area grew at an annual rate of around 8–10%, decreasing to 5.19% in 2000–2017 but still maintaining a high rate. The built-up area attained its maximum gain from 0.59% to 2.05% over the entire study period, with the highest being in 2005–2010. Its continuous expansion from an area of scattered downtown (central part or commercial of a town or city) to megacities is due to economic growth and the increasing population.

The most socioeconomic development, industrialization, and urbanization have been observed in the greater bay region, Pearl River Delta (PRD), while other areas such as the eastern flank, western flank, and mountainous region have also grown. The Pearl River Delta (PRD) is characterized by intense human activities. The proportion of built-up areas varies significantly over time in different cities. In Shenzhen, Dongguan, Foshan, Zhongshan, and Macao, the built-up area was less than 5% in 1986. Since then, the urban area in these cities have expanded to a greater degree than that of other cities. The built-up land in these cities rose more than 50% by 2017 (Figure 5). In Guangzhou and Foshan, the built-up areas were significantly higher than in other cities in 1986. They remain higher in built-up area than other cities of the Guangdong, Hong Kong, and Macao in 2017. The overall proportions of their built-up areas were significantly lower than those in Shenzhen, Dongguan, Zhongshan, and Macao due to the relatively slower rates of urban growth and the imbalanced internal development. The built-up area in small cities such as Zhuhai is relatively smaller but proportionally close to that of Guangzhou. The built-up area of Jiangmen, Jieyang, Huizhou, and Chaozhou is close to that of Zhuhai but the proportion of their built-up land is smaller than that of the other PRD regions. The proportion of built-up areas in the mountainous regions, on the western side, and in Shanwei city on the eastern flank are much smaller than that of the other 12 cities in this study area. Thus, it is clear that the opening up of reform, and the introduction of the new economic policies, especially in the PRD, have attracted a significant influence of population from the inner provinces of China.

During the 31-year study period, among all the land use types the highest change in cover occurred in farmland. The area covered by farmland decreased by about 21%, i.e., from 53.54% (105,123.39 km^2) to 33.07% (64,932.38 km^2), with a net loss of 4.26% to 4.73% over the study period (Table 22-S3). This was mainly the result of the expansion of built-up areas, urbanization, and forest growth (at the rate of 0.98% annually) (Figures 4, 5). From the transition matrix (Table 22-S3), the conversion of farmland to other land types is most noticeable. As previously mentioned, a huge amount of farmland was transformed into built-up area: a probable 615 km^2 (0.31%), 1804 km^2 (0.92%), 1690 km^2 (0.86%), 1796 km^2 (0.91%), 3211 km^2 (1.63%), and 2840 km^2 (1.44%) in 1986–1989, 1989–1994, 1994–2000, 2000–2005, 2005–2010, and 2010–2017, respectively. The per capita area of farmland decreased to 0.000708 km^2 in 2017 from 0.001831 km^2 in 1986. The net loss of farmland decreased significantly, whereas its conversion to built-up land accelerated.

Figure 5 shows that the proportion of farmland varied significantly over time in different cities of the study area. The situation was worse in the PRD (coastal) region and on the eastern side of the province, due to a significantly higher population density, higher economic development, and well-established farmland traditions. From 1986 to 2017, the area of farmland loss in these regions was greater than that in other regions of the study area, as officials took full advantage of making a financial profit, regardless of the total effect on society. Other matters such as sustainability were not considered.

The forest areas and built-up land have increased greatly. The gains in forest were 3.81%, 3.27%, 1.93%, 1.85%, 2.17%, and 3.42% during 1986–1989, 1989–1994, 1994–2000, 2000–2005, 2005–2010, and 2010–2017, respectively (Table 22-S3). The forest cover, converted from farmland, increased at rates of 3.58%, 2.96%, 1.61%, 1.48%, 1.80%, and 3.05% during 1986–1989, 1989–1994, 1994–2000, 2000–2005, 2005–2010, and 2010–2017, respectively (Table 22-S3). The highest annual rate of change in forest areas was 2.95% between 1986 and 1989 (Table 3). The changes in the proportion of forest cover over time differed in each prefecture during each of the six periods. In the PRD region, forest decreased, and more noticeably in Shenzhen, Dongguan, Zhuhai, and Zhongshan, but increased in peripheral counties (Figure 5). This is mainly because of conversion to built-up area, agricultural production, and unused land. From 1994 to 2017, forest cover also decreased on the eastern flank of the study area, but increased in some of the surrounding counties. In Foshan and Guangzhou, forest decreased from 1986 to 2000 and then increased between 2000 and 2017 because of an increase in urban forestry within the urbanized area.

The area of fishponds changed slightly, decreasing from 1.25% (2463.37 km^2) to 0.85 % (1674.61 km^2) during the study period. This shows that the net loss in fishponds increased from 0.68% to 0.85% from 1986 to 2017. Therefore, a net loss of fishponds and farmland accelerated the growth of urban area and forest cover. Considerable changes were also observed in both grassland areas and bareland. Grassland was reduced from 0.23% (460.11 km^2) in 1986 to 0.10% (189.72 km^2) in 2017, whereas bareland was reduced to 0.14% (275.40 km^2) in 2017 from 0.38% (752.17 km^2) in 1986 (Table 24-S3). Grassland and bareland are located at areas of low elevation such as the PRD, which is the main reason for their shrinkage in areas. However, the change in water bodies was relatively stable (Figure 4).

The intermixing of forest, grassland, and farmland was also observed, mainly because of the nearly identical signature and the phenological difference in the image acquisition. The transition probabilities for forest to grassland are 0.03, 0.07, 0.02, 0.07, 0.02, and 0.03 (Table 22-S3); for grassland to forest they are 0.05, 0.02, 0.08, 0.04, 0.06, and 0.03 (Table 24-S3) and for farmland to forest they are 3.58, 2.96, 1.61, 1.48, 1.80, and 3.05 during 1986–1989, 1989–1994, 1994–2000, 2000–2005, 2005–2010, and 2010–2017, respectively (Table 22-S3). A variation was observed in the trend of grassland and bareland as the acquisition of Landsat images was done in the dry season (Li and Wang 2015).

Table 3. The annual rate of change of each class as a percentage.

	1986–1989	1989–1994	1994–2000	2000–2005	2005–2010	2010–2017	1986–2017
	(% change per year)						
Forest	2.95	1.23	0.58	0.42	0.75	0.86	0.98
Grassland	−19.02	6.51	−8.21	11.96	−21.00	5.10	−2.69
Water	0.19	−0.02	−0.19	−0.50	0.06	0.30	−0.02
Fishponds	6.08	4.94	−1.36	−2.02	−4.94	−5.51	−1.24
Built-up	19.15	14.37	7.21	6.26	6.93	3.17	8.41
Bareland	−21.40	13.36	−17.08	24.64	−29.47	3.45	−3.22
Farmland	−2.38	−1.83	−0.86	−1.16	−1.60	−1.85	−1.55

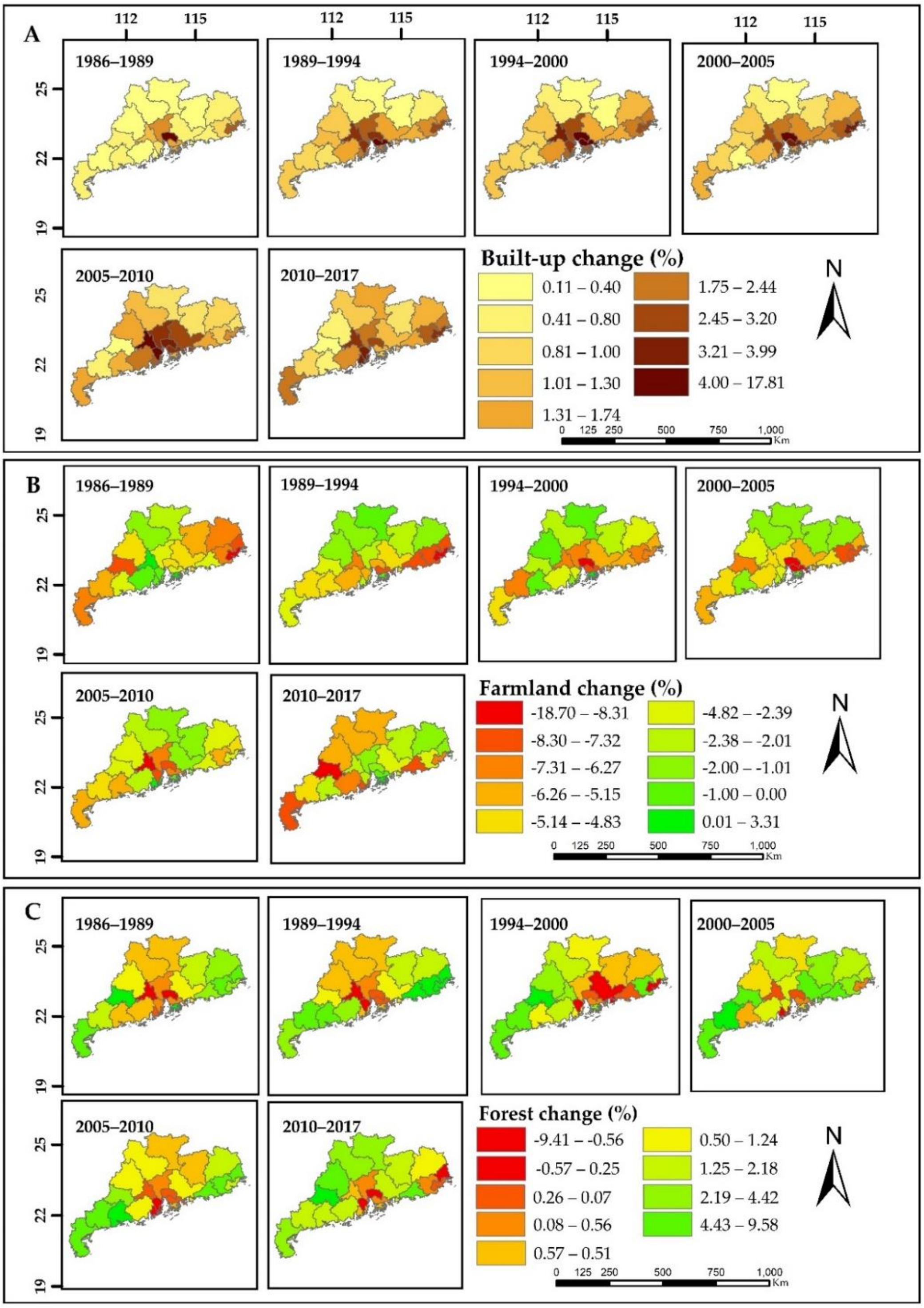

Figure 5. Relative land use change at prefecture (city) level in (A) built-up, (B) farmland, and (C) forest.

4.3.2 Socioeconomic Change

Several types of socioeconomic factors collected from Guangdong, Hong Kong, and Macao Statistical Bureaus for 1986 to 2017, as listed in Table 4, are responsible for LULCC in GHKM.

Table 4. Socioeconomic indicators of the Guangdong, Hong Kong, and Macao.

	1986	1989	1994	2000	2005	2010	2017
Gross Domestic Product (100 million Yuan)	667.53	1381.39	4619.02	10,741.25	22,557.37	46,036.25	79,512.05
Primary Industry	188.37	351.73	692.25	986.32	1428.27	2286.98	3694.37
Secondary Industry	255.88	554.13	2253.25	4999.51	11,356.60	22,821.77	34,001.31
Tertiary Industry	223.28	475.53	1673.52	4755.42	9772.50	20,927.50	41,816.37
Total Population (10,000 persons)	5740.70	6024.98	6691.46	7498.54	7899.64	8521.55	9164.90
Total Investment in Fixed Assets (100 million yuan)	216.50	347.34	2141.15	3233.70	7164.11	16,113.19	33,008.86
Government Revenue (100 million yuan)	82.41	136.87	298.70	910.56	1807.20	4517.04	10,390.35
Gross Agricultural output value (100 million yuan)	279.15	548.60	1151.38	1701.18	2447.57	3754.86	6078.43
Gross Industrial output value (100 million yuan)	632.89	1647.24	7273.95	16,904.47	41,661.74	93,462.97	144,926.10
Total Retail Sales of Consumer Good (100 million yuan)	327.02	636.15	1991.33	4379.81	7915.51	17,458.44	34,739.00

During the past 31 years (1986–2017), the GHKM GDP grew from 667.53 (100 million yuan) to 79,512.05 (100 million yuan) (Table 4), with an annual growth rate above 15%. Economic development and population are closely related. With the increase in economic development, GDP increases. This increase in economic development also resulted in population growth through migration, as delineated in Table 4. This unprecedented increase of migrant population caused gradual expansion of cities, urban sprawl, and loss of farmland. Figure 6 shows the GDP, built-up land, and farmland trends from 1986 to 2017, further confirming the influence of the increasing GDP and population growth on the GHKM land cover. Compared to the GDP, however, the annual population growth is relatively low and varies significantly in different stages (Table 5) and in each city of the GHKM (Figure 7). Shenzhen, Dongguan, Hong Kong, Foshan, Guangzhou, Macao, and Zhuhai (monocentric cities) have experienced the greatest and most rapid increase over the past three decades; their annual GDP and population growth rate is close to the average growth rates of the whole region. The rest of the cities in the study area, however, have significantly lower growth rates than the regional averages and that of the population.

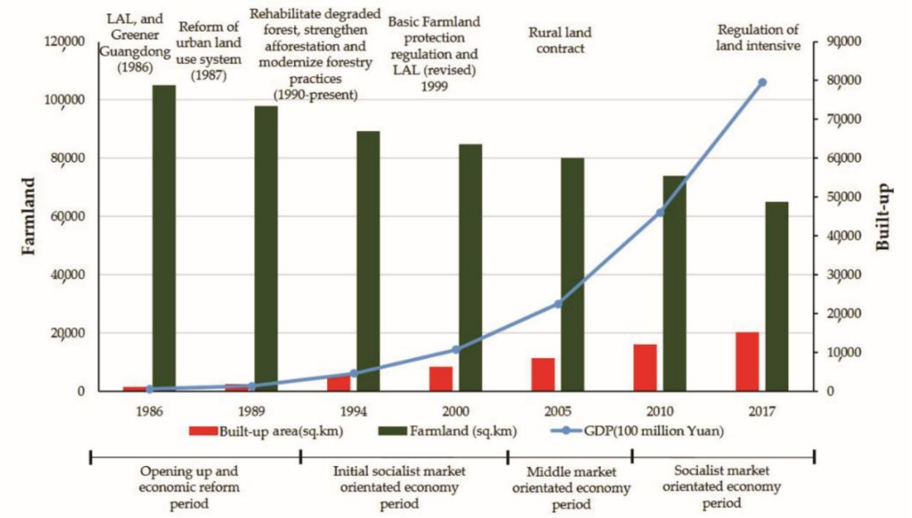

Figure 6. Summary of land policies, gross domestic product, urban area (urbanization), and farmland trend in different economic development periods from 1986 to 2017 (where, LAL = Land administration Law).

Table 5. Population growth rate during different period.

	1986−1989	1989−1994	1994−2000	2000−2005	2005−2010	2010−2017
Population growth rate (%)	4.95	11.06	12.06	5.35	7.87	7.55

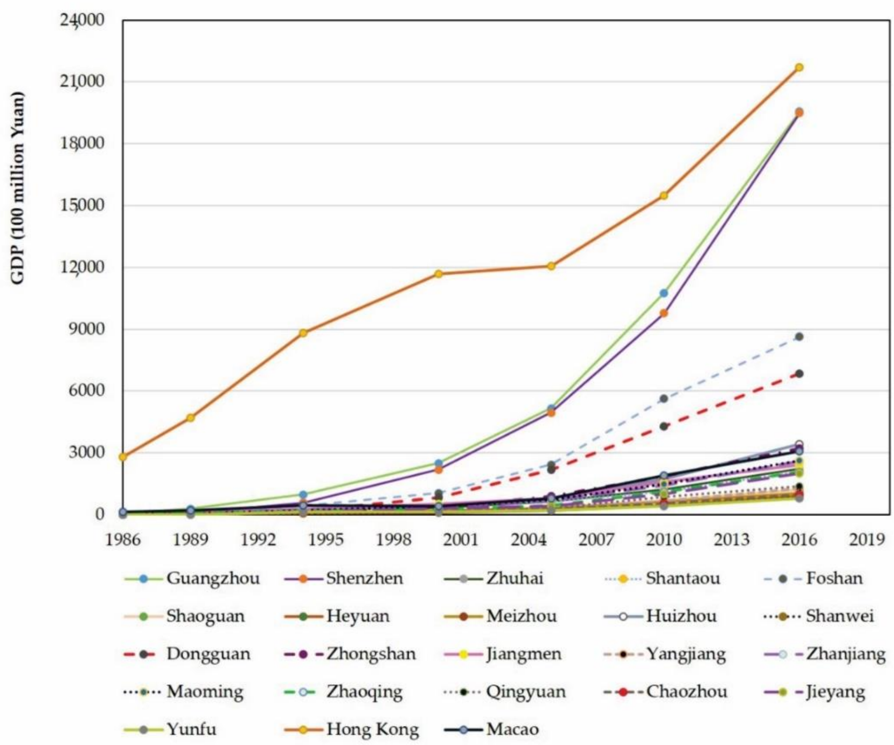

Figure 7. Changes of gross domestic product in each city of the Guangdong, Hong Kong, and Macao.

Based on the urban extent dataset from NTL, an increasing trend of light index related to urbanization has been observed (Figure 25-S1, Table 6), which reflects human activities and development (Figure 8). The reason for the increase in the light index is new lighting projects such as at malls, scenic spots, and streets in order to make the cities seem more glamorous. Consequently, after 30 years of development, a new pattern of urban sprawl has been observed in GHKM, especially in the PRD region, now named the "Greater Bay area" (Figure 3). This area accounts for 57% of the Guangdong, Hong Kong, and Macao population. The Guangdong, Hong Kong, and Macao government revenue has increased to 10,390.35 (100 million Yuan) from 82.41 (100 million Yuan) during the study period (Table 4).

Table 6. Light index of the study area for the years 1994, 2000, 2005, and 2010.

Year	Light index	NTL* Built-up area (km^2)	Average	SDV**
1994	3.42	7860	53.00	4.77
2000	4.40	1024	52.84	4.90
2005	6.21	15,104	54.27	4.53
2010	8.38	17,431	55.34	4.07

***NTL = nighttime light, **SDV = Standard deviation**

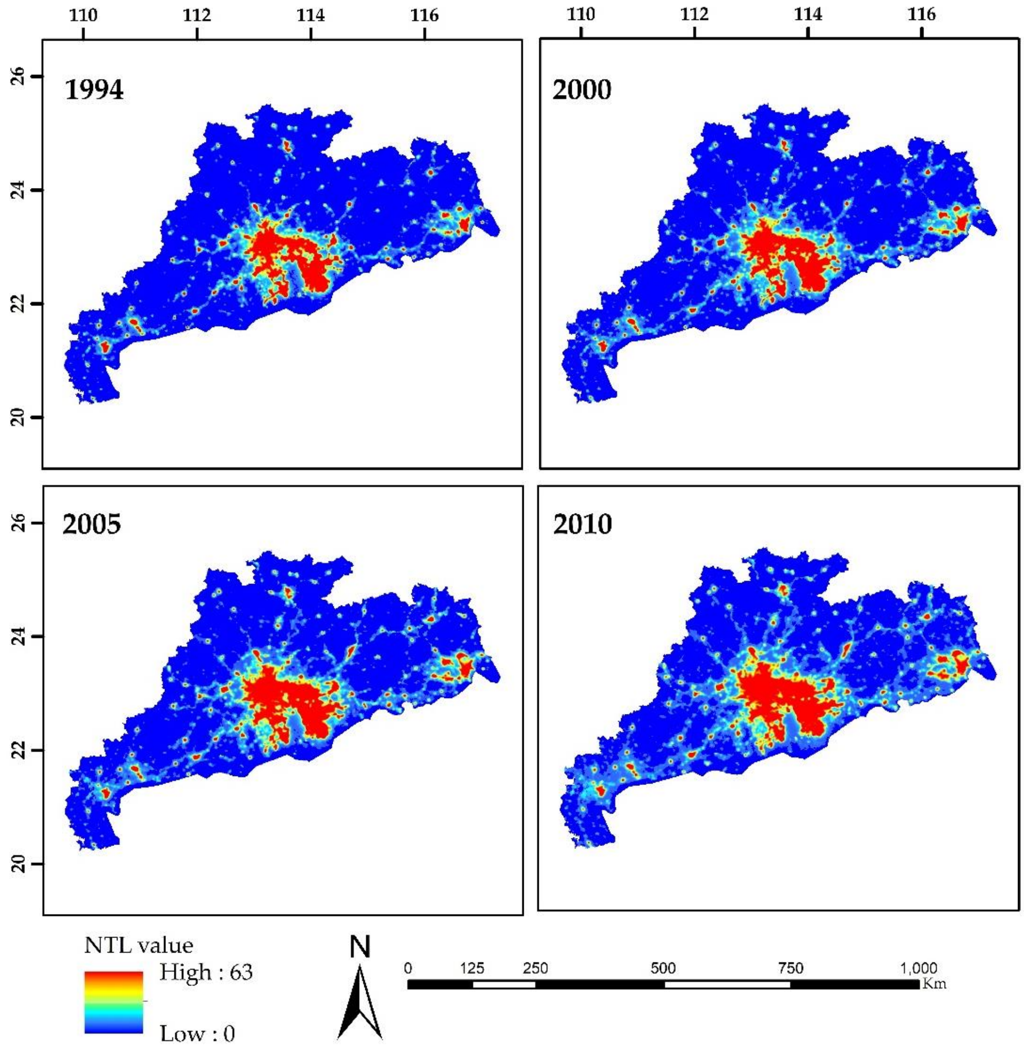

Figure 8. Night light urban expansion images of the study area for the years 1994, 2000, 2005, and 2010.

The total investment in fixed GHKM assets has increased from 216.50 (100 million Yuan) to 33,008.86 (100 million Yuan) during 1986–2017. This significant increase in annual investment is the direct result of (a) more infrastructure and construction projects, (b) urbanization from low density to high density, and (c) conversion of farmland to other land types during the study period (Li and Wang 2015; Liu et al. 2016; J. Wang et al. 2012). There is a significant logarithmic relationship with a coefficient of determination R^2 = 0.93 and R^2 = 0.98 between the fixed assets investment and the built-up area (Figure 9a) and between GDP and population (Figure 9b), respectively. Figure 9c indicates that the coefficient of determination between population and farmland is 0.98. The light index has a strong relationship with urban areas extracted from DMSP NTL data, total population, and socioeconomic indicators (i.e., secondary and tertiary industry), with a coefficient of determination of 0.94, 0.94, and 0.83 (during 1994–2010) (Figure 9d–f).

During the study period, the total retail sales of consumer goods surged from 327.02 (100 million Yuan) in 1986 to 34,739.00 (100 million Yuan) in 2017, reflecting the demand for consumer goods such as cars and houses. This increase in spending power has promoted real estate. Due to the above-mentioned factors, GHKM has also experienced significant socioeconomic development, by encouraging industry. A large migrant population and increasing demand for labor have further increased secondary and tertiary industries, rather than the primary industries (Table 4). As a result, the total population increased from 5740.70 (10,000 persons) in 1986 to 9164.90 (10,000 persons) in 2017 (Table 4), with a population density of 612 (persons/km^2) in 2017.

In summary, policy changes, law enforcement, land use planning, and development strategy shifting may have great impact on the LULC change.

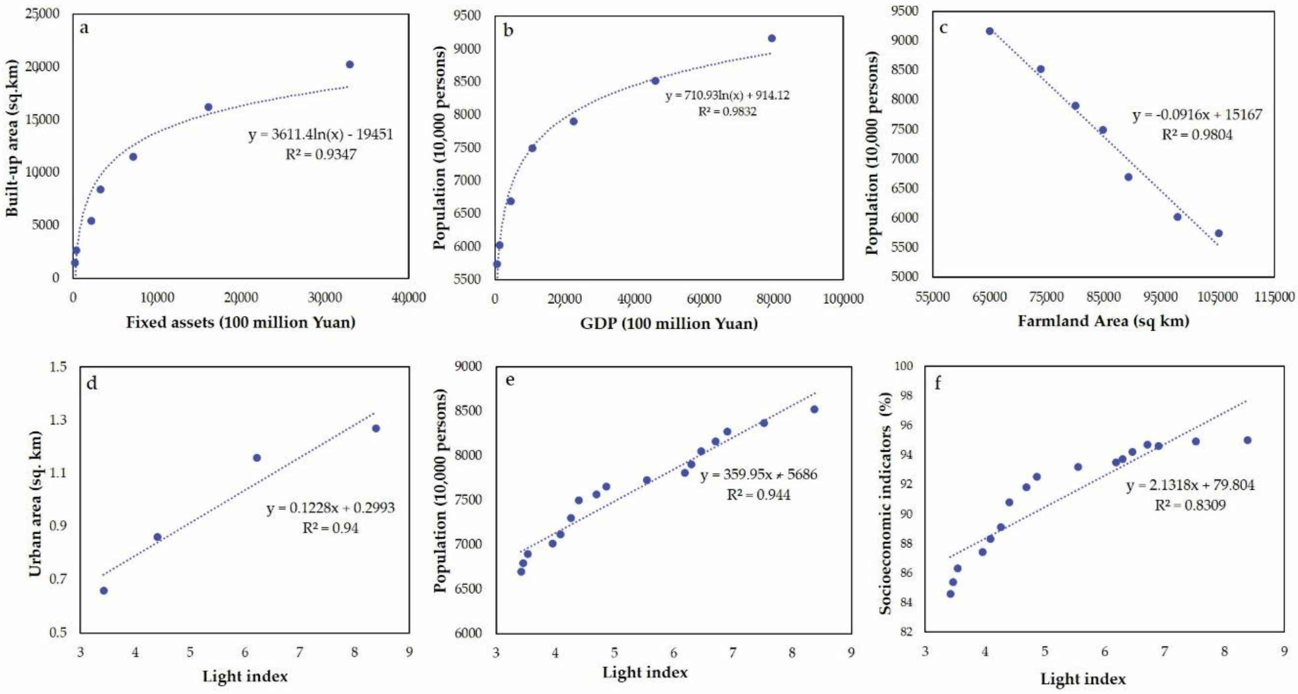

Figure 9. The correlation between (**a**) fixed assets and built-up area (1986−2017), (**b**) GDP and population (1986−2017), (**c**) farmland and population (1986−2017), (**d**) light index and urban area (1994−2010), (**e**) light index and population (1994−2010), and (**f**) light index and socioeconomic indicators (1994−2010).

4.4 Discussion

4.4.1 Driving Forces of LULCC: The Link Between Socioeconomic Factors and LULC

Previous studies have suggested that the processes of industrialization, urbanization, macro-economic policies, and economic fluctuations may be the major driving forces of land use and, therefore, land cover changes (J. Wang et al. 2012). In the current study, the results from LULC maps (Figure 3) and NTL images (Figure 8) shows the increasing trend of built-up area. This increase in built-up area reflects that socioeconomic development and the upgrading of industrial structures affected the land use structure and the provision of land resources. During the study period, fishponds decreased to 0.85% from 1.25% and forest cover increased to 45.02% from 33.24% (Figure 3). GHKM shows the relationship between the different periods of modernization and the relationships with political movements, socioeconomic development, and urbanization (Table 7 and Figure 10). The year 1986 marked the beginning of the economic “soft landing” that was intended to control unconstrained growth in the initial reform period. However, the years 1996 and 1997 marked the beginning of administrative changes that required approved integrated land use planning (LUP) at both regional and county levels and a shift to regional urbanization and pro-urbanization in the development policy (Wang et al. 2018). The detected LULCC results reveal a close relationship between urbanization and socioeconomic activities.

The primary reason for urbanization is the land price differences between cities and downtown areas. The land prices of rural and backward areas were almost half, or even less than, that of established urban areas. This huge difference in land prices attracted investors to install their industries in commercially backward areas and towns. It also created the mixed land use patterns in which villages were absorbed within cities and cities imposed on villages. In so doing, the expansion of urban areas into the surrounding rural areas created strong pressure on farmland and provided an open space for conversion to other land types (Li and Wang 2015). Mixed land use patterns are more pronounced in highly populated regions, further enabled by fast economic development. In circumstances of relatively cheap land, it is difficult to control expansion owing to the interest of industrial investors. This rapid industrial growth further drove the conversion of more farmland and the subsequent rise of built-up areas. Additionally, such developments are encouraged in that they provide a significant contribution to government revenue.

The increase in monthly income has increased the demand for a luxurious lifestyle. This includes beautiful, spacious, and comfortable houses and more convenient transportation. This results in an increase in demand for urban land. Thus, urban sprawl and economic development have moved the GHKM away from an agrarian society. The light index has also delineated the land use policies that have been the product of political, economic, and social conditions in different periods of modernization and development since the opening of reform (Table 7) (Wang et al. 2018). Over the last three decades, economic growth is reflected in the marked increase in GDP, total investment in fixed assets, total retail sales of consumer goods, and other socioeconomic determinants.

However, as urban land is more beneficial to the economic output of an area than areas of arable, farming, agricultural land, and bareland in the urban fringes, these land types provided obvious potential for urbanization (Li and Wang 2015; Liu et al. 2016; J. Wang et al. 2012). Urban land accounts for 30–70% of government revenue (Ng and Hang Hui 2007). The latter would probably be invested in industrialization and infrastructure projects to promote GDP growth, and, in so doing, further the corresponding urban sprawl. GHKM leads the country in retail sales and pays the most taxes to central government (Ramakrishnan et al. 2001). This causes an increase in the rate of land cover change and, subsequently, the furthering of urban expansion. This facilitated urban growth, not only in the PRD region but also in the outskirts of that region, which has been a major driving force in the reduction of farmland. The PRD, the central part of the province, became the main urbanization core, replacing the farmland of previous decades (Li and Wang 2015).

Developments in science and technology in terms of economic development have promoted urbanization. New built-up areas were mainly concentrated in the center (PRD) and on the eastern side of the study area because of their geographical location. For instance, areas of low elevation were considered suitable for urban projects and development. The geography of each area resulted in the expansion of urban areas at decreasing rates. In these two regions, farmland and fishponds were the primary contributors to new built-up areas (Chen et al. 2013a; S. Du et al. 2014). By comparing the

PRD urbanized area with other densely urbanized areas of the world such as the UK (7.5% built-up area), the Netherlands (11.5%), and Belgium (20%), the PRD can be described as the most rapidly urbanized region, with built-up areas rising to 10.31% over the entire study period (S. Du et al. 2014). However, it has been observed that urbanization has, to a degree, become out of control, due to the inefficiency of land use management and failure of policies. Further reasons are related to the growing industries, foreign direct investment, job opportunities, desire for a better lifestyle, facilities, and road networks, and also the uniqueness of the location, i.e., neighboring Hong Kong and Macao (Fan et al. 2007; Ramakrishnan et al. 2001).

Table 7. Changing land use policies from 1978 to 2017.

Years	Periods	Land use policies	Issues
1978−1991	Opening up and economic reform	Local entrepreneurship	Initial productivity but effect development of town and village enterprises
1992−2002	Initial period of the socialist market-oriented economy	Farmland protection and land-use planning	Conflict over farmland protection and land development
2003−2008	Mid-term of the socialist market-oriented economy	Urbanization and regional development Regulating land markets, use rights and property law	Uneven urban-rural and regional social and economic development
2009−now	Socialist market-oriented economy	Intensive land use under construction of civilization Regulating land markets, use rights and property	Conflict over farmland conversion, protection and land development Uneven urban–rural and regional social and economic development

The spatial planning modes in China is related to three planning systems: (1) the socioeconomic development plans, national spatial plans (land use plans), and the urban and rural plans. The 12th (2011—2015) and 13th (2016—2020) Five-year plan, the National New Urbanization Planning (2014-2020), the urban and rural plans aim to regulate economic development, urbanization, safe construction of the ecosystem, reducing urban rural gap, the efficient distribution of land resources, the rational structuring of space, the ability to secure energy resources, the promotion of the general preservation of land, the securement of implementing national spatial plan, etc. On the one hand, the government hopes to transfer more rural people settling into cities as rural-urban migration could help stimulate domestic demand. Moreover, economic growth will continue to matter for future urban development but has to be balanced with social and environmental sustainability. This shift towards sustainable urbanization, with a more consumer-driven and service-oriented economy with less social inequality and sharp reductions in energy and resource use, requires an innovative planning system (Douay and Qi 2018; Harbers et al. 2017).

The current planning system and does not fully allow policymakers and planners to deal with rapid urbanization along the lines described above. The current situation may not be sustainable. GHKM industrial and urban development has been overly dependent on land- use modes characterized by extensive expansion rather than the coordinated and intensive use of scarce land resources. Land-use modes must become more efficient and intensive to secure strategic development goals of coordinated industrialization, urbanization, and agricultural modernization. One of the strategies proposed for more intensive and efficient land use should be 'brownfield' re-development through the recycling of polluted, abandoned, unused and idle urban sites. In addition, the optimization and improvement of the industrial structure will promote a transformation of the economic development mode. Future land-use policy should be shifted to more efficient and effective utilization of inventoried lands and move away from the wasteful practice of extensive utilization of increased amounts of developed lands (Wang et al. 2018).

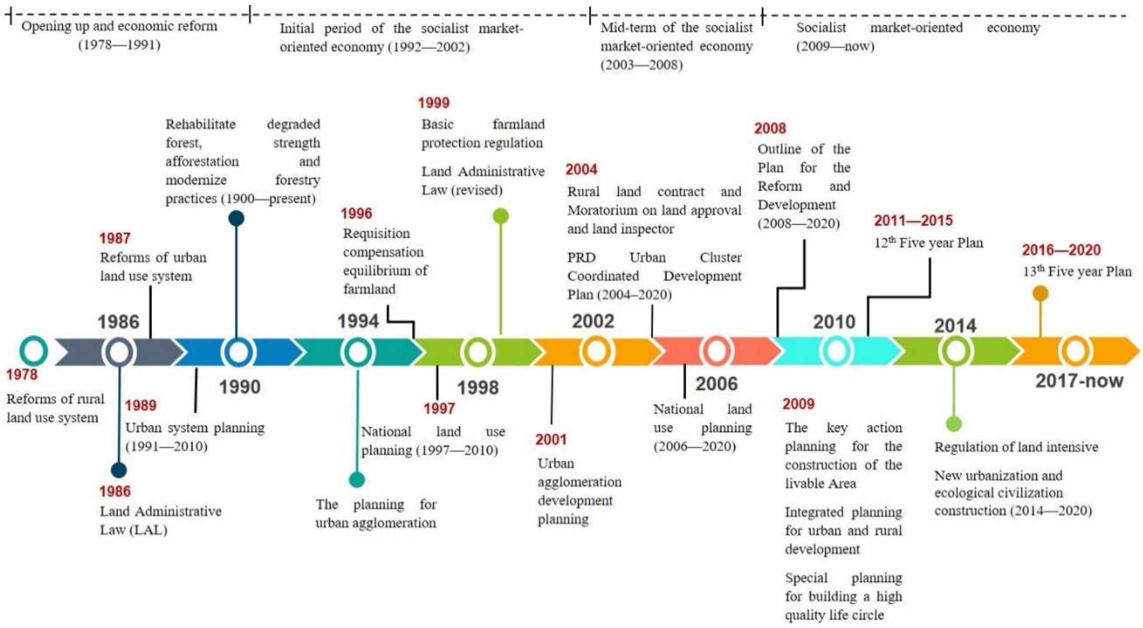

Figure 10. Changing land use and spatial policies during the study period.

4.4.2 Consequence of LULCC: Farmland Reduction and Replacement

Before the "open door" policy, Guangdong was an important region, dominated by open space, and farming activities, and was the largest grain-growing region in China. It was an important production base for rice, sugar cane, and tropical fruits (S. Du et al. 2014). More than 50% of the country's grain was grown in its southern part (Ramakrishnan et al. 2001; J. Wang et al. 2012). After the economic reform process initiated a surge in industry and technology, shifts in local economy, and a massive influx of overseas migrants, pressure was placed on farmland. The pressure became more serious as planning and management functions lagged behind economic development, making farmland unprotected and vulnerable (Dou and Chen 2017; J. Liu et al. 2014; Salih et al. 2017; Tian et al. 2012; Wu et al. 2016), with the result that, during the study period, it became a consistent source of new built-up areas, in line with the performance of other similar regions (S. Du et al. 2014; Fan et al. 2007; Li and Wang 2015).

The conversion of farmland to another land use type was eventually restrained by additional and different land policies and legislation. The most influential of these were the "Land Administration Law (LAL)", the "Basic Farmland Protection Regulation (BFPR)", the "Returning Farmland to Forest Program (RFFP)" and "The Notice on Stabilizing and Improving the Contract of Rural Land issued by central government" (J. Wang et al. 2012). These programs were initiated by the government of China in 1999. These programs aimed (1) to control the expansion of urban areas, and (2) to protect farmland and its conversion. Furthermore, the aim was to promote market development and increase forest cover. According to article no. 33 of LAL, there should be no net loss of farmland. To control the urban sprawl, the stakeholders allowed the development of farmland, only if a substitute area could be developed more efficiently elsewhere in the province. The basic hypotheses of the above policies were rejected due to high investment and the implementation of different development policies that led to a significant occupation of land for construction activities. The result was a constant increase in urban and rural area settlements at the cost of a large reduction of the proportion of farmland and a widening of the urban–rural gap (Bai, Chen, and Shi 2012; S. Du et al. 2014; Lin and Ho 2003; Ramakrishnan et al. 2001; J. Wang et al. 2012). Thus, at the above juncture, urbanization was given priority over the protection of farmland in the current stage of economic development (S. Du et al. 2014).

Unfortunately, farmland being displaced to other regions would not necessarily ensure grain production, as the new sites may be less fertile, or dry and require irrigation facilities. Hence, because of a lack of land suitability, a significant decline in grain yields from 4.6 million tons to 2 million tons was seen in the early 2000s, causing adverse effects on the food production capacity. Additionally, a major shift from traditional double-season rice cropping to a single season directly caused the decrease in total grain production, even in more fertile and appropriate areas of farmland, such as in the higher areas of the PRD region. The indication is that farmers in these areas had changed the agricultural structure from food production to market-oriented farming, which included vegetables and animal husbandry. Additionally, this substantial reduction in grain yield was also due to the changes in food demands of high-income urban residents. For instance, larger sections of local communities began to consume less rice, maize, root crops and wheat, focusing more on poultry, meat, and fish. Moreover, output of cotton, edible oils, vegetables, fruit, meats, and fishery products grew even faster. Direct demand for rice, wheat and other food grains will be declining with positive implications for food security. The main uncertainties are about the indirect demand for cereals, the evolution of per caput demand for livestock products, and future gains in feed use efficiency (Norse, Lu, and Huang 2013; Wang et al. 2021). Together with the effects of environmental pollution, which led to a serious decline in food quality. Also, development of eucalyptus plantations on a large scale because of the high demand for timber products and high ecological value. This also prompted the conversion of farmland.

In addition, the government is facing difficulties in maintaining a constant supply of farmland, due to rapid urbanization as indicated above. The central government gives a “farmland redline” (the minimal area of farmland) in each province. Urbanization, however, has increased the tension between the need to protect farmland and the demand for land for development. Although it is important to improve agricultural productivity and food security, as indicated above, there is an urgent need to strictly implement the protection policies regarding the quantity and quality of farmland (S. Du et al. 2014; J. Wang et al. 2012; Wang et al. 2018).

However, new agro-technologies as well as series of reform policies since 1978 has had greatly shaped agriculture throughout time to support agricultural growth. These agro-technologies demonstrates the importance of technological development in addition to improved incentives, institutional reform, rural economic development, and other policies that increase food availability. These technologies base grew rapidly during the reform and pre-reform periods. These technologies have changed the agriculture structure. The implementation of the household responsibility system (HRS) after its introduction in 1979 that gave individual farmers control over income rights of formerly collective owned land was a major policy driver for the rise in productivity based on improved crop varieties and high inputs of industrial fertilizers. The other major sources of growth were public agricultural research and development (R&D), investment in irrigation, shifts in technologies, transport infrastructure, and the use of off-farm production inputs (Norse et al. 2013).

However, China has virtually no additional land to develop for crop production so the continuing loss of highly productive cropland to urban development and non-agricultural uses could undermine long-term food security (Norse et al. 2013). To ensure the food security government should impose the heavy taxes on the reduction of farmland and reclamation of farmland by establishing its use in other places or by changing the preference of industry regarding the use of arable areas; to control the demand of timber products using numerous methods, such as, decreasing the usage of disposable chopsticks; avoid the wastage of paper; tighter application of the existing legislation and the removal of the perverse economic incentives to local governments that encourage such transfers; to overcome the potentials risks of land use right transfer; governments should create more employment opportunities in rural areas (in both agricultural and non-agricultural sectors)improvement of the rural social security system; raises farmers income; mobilized labor; optimizing agricultural production linkages; substantial expansion of irrigation infrastructure; adopting improved crop varieties; provide price incentives to increase the multiple cropping index and Strengthen scientific and technological support to agriculture (Norse et al. 2013).

Irregularities and a lack of coordination with a market-oriented system have been unavoidable. Prevention tactics regarding the transfer of rural, collectively owned land by means of a market-oriented mechanism, have led to significant inequities between urban and rural activities. The policy "Proper law of 2007" has led to the phenomenon of "financing through land," and impoverishing farmers by taking their land from them, apparently for the betterment of society, has caused an aggravation of the social divide between the urban and rural populations (Wang et al. 2018). Thus, there appears to be a necessity to modify the previously mentioned land policies and address or remove the urban–rural gap, not only to better ensure sustainable economic development, but also to remove social division between them.

4.4.3 Benefits of LULCC: Forest Cover Increases

GMHK has been ahead of the country in terms of socioeconomic development and urbanization, but also in its contribution to the deterioration of the environment. To solve such problems, the government established the program "Greener Guangdong in 10 years" in 1985. By the end of 1993, 3.33 million hectares of degraded forest lands had been re-planted. To maintain this momentum, urban forestry considerations were given priority by the government. The objective was to introduce tree and shrub planting in cities to enhance the quality of life (Bui et al. 2003; Chokkalingam et al. 2006). A focus was placed on obtaining a Greener Guangdong (S. Du et al. 2014; Trac et al. 2013). Thus, during the period of this current study (1986–2017), forest cover increased from 33.24% to 45.02%. The government's encouragement of urban forestry was designed to play a critical role in lessening the urban–rural gap, providing more job opportunities, improving the environment, maintaining the ecological balance, beautifying urban regions (Bui et al. 2003), and controlling the expansion of cities. The increase in the pattern of urban forestry reveals an increase in the demand for forest resources in the urbanized areas and a willingness to control and preserve natural ecosystems (Li and Wang 2015).

From 1990 to the present, a wide range of forest programs were launched and implemented in GHKM, thus supporting afforestation achievements and the modernization of forestry practices. The focus was on both forest industry development (ecological forest) and plantations by adjusting tree species and forest structure to support different economic and recreational purposes. These programs also increased people's incentives and interests regarding forestry development and encouraged the recognition of public ownership. Industrialization and urbanization, therefore, have promoted forestry development and the rehabilitation of degraded forest land in GHKM (Chokkalingam et al. 2006; Peng et al. 2008). However, the development of urban forestry is only one strategy for solving the many problems facing cities new to the urbanization process.

4.4.4 Recommendation for Sustainable Development and Open Space Protection

Hong Kong can be considered reasonably successful in controlling unplanned urbanization and protecting open spaces, despite the population growth, economic development and the resulting urban sprawl to cater for them. The government should impose heavy taxes on the urban development of farmland to prevent further loss of farmland. The government needs to set up a new administrative body for the effective planning of land use. In this process, public contributions and making and executing plans for land use and sustainable development will play a dominant role. Transferring industrial activities from the PRD to lagging regions will help to reduce urban–rural inequality and increase rural household income. This would result in lessoning rural poverty. Thus, fast urbanization helps poverty alleviation and increasing the productivity. Furthermore, a detailed study at the city level is required to adapt policies more effectively and to control the negative impacts of land cover changes.

4.5 Conclusion

The results show that over the past three decades, GHKM, a large tropical and sub-tropical region in China, has undergone dramatic LULCC, mainly dominated by built-up land, farmland, and forest. During the study period, the built-up area has increased from 0.76% to 10.31% and farmland and fishponds decreased from 53.54% to 33.07% and from 1.25% to 0.85%, respectively. On the other hand, at the expense of the reduction of farmland and different afforestation programs, forest cover increased from 33.24% in 1986 to 45.02% in 2017. The primary reasons for such changes in land use and land cover were the development of the socioeconomic corridor, industrialization, job opportunities, urban sprawl, and different land policies. The transition of farmland to built-up area and the increase in light index reveal that urbanization provides more benefits to the government in terms of economic development. To some extent, the decrease in farmland mirrors the irreversible trends of industrialization, urbanization, and marketization. Moreover, a spatial analysis and statistical data revealed that the marked increase in GDP, total investment in fixed assets, and total retail sales of consumer goods have to a large extent led to the expansion of cities. On the other hand, there has been a loss of farmland and an increase in forest cover. Such changes have caused notable land cover changes in GHKM. These trends may also be projected into the future. These findings revealed in this paper are designed to help policy and decision makers to analyze the relationship between socioeconomic drivers and LULCC. Also, this paper provides a scientific basis for land resource optimization, not only in GHKM but also in other parts of China.

Chapter 5

5 Future simulation of land use changes in rapidly urbanizing South China based on Land Change Modeler and remote sensing data[3]

5.1 Introduction

Today, urban growth represents powerful engines for economic prosperity and growth. However, changes in land use land cover (LULC) are pervasive and subjects of great concern worldwide (Hossein Shafizadeh Moghadam and Helbich 2013). This is more pronounced in rapidly growing countries, such as China (Rimal et al. 2017), where urban land transactions and local land leasing revenue have exploded sharply (Chen et al. 2018), after the opening of economic corridor policy in 1978. The phenomena of socioeconomic development and industrialization has resulted in an increasing urban population, rural to urban migration, reclassification of administrative rural zones to urban zones, and subsequent expansion of urban areas and cities in peri-urban pockets, at unparalleled rates (Araya and Cabral 2010; Li et al. 2014; Rimal et al. 2017; Zheng et al. 2018). According to the United Nations Department of Economic and Social Affairs Population Division, (2017) China's total urban population has increased from 11.80% (7,726 (10,000 persons)) in 1950 to 58.52% (139,008 (10,000 persons)) in 2017, and is predicted to reach 76.10% by the end of 2050 (Anon 2017). This situation has simultaneously strengthened economic localism, as built-land produces more revenue (Chen et al. 2018). However, these significant changes cause continuous stress on agricultural land

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[3] This chapter is based on a published study and being reproduced with the permission of MDPI.

Hasan, S., Shi, W., Zhu, X., Abbas, S. & Khan, H.U.A. (2020).Future simulation of land use changes in rapidly urbanizing South China based on Land Change Modeler and remote sensing data. *Sustainability*, *12(11)*, 4350; https://doi.org/10.3390/su12114350 and other natural and semi natural resources (Ahmed and Ahmed 2012; Aithal, Vinay, and Ramachandra 2013; Wang and Maduako 2018).

In China, the fragmentation of farmland into urban fringe and loss of other natural and semi natural resources have a strong prospective of weakening an enduring coherence of human beings and their environment, as well as a serious threat to food security (Wu et al. 2006). Immense anthropogenic activities have generated many ecological and environmental issues on different spatial scales, resulting in the increased scarcity of land resources. These include unplanned land development, employment opportunities, the escalation of slums, and insufficient infrastructure and houses (Dewan and Yamaguchi 2009a; Dewan et al. 2012; Guan et al. 2011; Hossein Shafizadeh Moghadam and Helbich 2013; Rimal et al. 2017; Wang and Maduako 2018). The prevailing high dynamic economic growth, urbanization, and industrialization has posed a great challenge to policy and decision makers to achieve the goal of sustainable development (Araya and Cabral 2010; Kumar et al. 2015; Rahman 2016; Rimal et al. 2017; Wang and Maduako 2018). Therefore, the modeling and future prediction of land use land cover and urban growth is a pressing need to enable comprehensive view regarding a more competent administration of urban planning, preservation of natural resources (such as farmland), and the espousal of long-term sustainable policies.

Recently, to better understand the functioning of the land use system, the modeling of land use land cover change is growing rapidly in the spatially explicit scientific field (Kumar et al. 2015; Verburg et al. 2004). Land change models are simplifications of reality that offers an important means of predicting future land use land cover change pressure points (Han et al. 2015; Nourqolipour et al. 2015) and develop ex-ante visions of urbanization process implications (Hossein Shafizadeh Moghadam and Helbich 2013). Models usefully simplify the complex suite of socioeconomic and biophysical forces that influence the rate and spatial patterns of land use land cover change and, also enable the estimation of the impacts of changes in land use land cover (Aburas et al. 2018; Al-sharif and Pradhan 2014; Megahed et al. 2015; Shivamurthy and Kumar 2013; Verburg et al. 2004; Xin, Xin-qi, and Li-na 2012). To date, a variety of models have been developed, and are classified into the following types, (1) machine learning model, (2) cellular based model, (3) spatial based model, (4) agent based approaches (Aithal et al. 2013; Brown et al. 2004; Han et al. 2015; Mas et al. 2014; Megahed et al. 2015), and (5) hybrid approaches (Council 2014). The performance of different modelling tools however, are difficult to compare because land use land cover change models can be fundamentally different in a variety of ways (Ansari and Golabi 2019; Kumar et al. 2015; Sun 2008). Several studies have revealed that Land Change Modeler (LCM), based on integrated multilayer perceptron (MLP) with markov chain (MC), is a strong model for the analysis and prediction of land use land cover change, urban growth, and the validation of results (Kumar et al. 2015; Mas et al. 2014; Megahed et al. 2015; Mishra et al. 2014; Ozturk 2015; Wang and Maduako 2018). This is because outputs of neural networks, acquired through the Weights of Evidence technique (where a user can select and modify the weights) (Megahed et al. 2015; Pérez-vega, Mas, and Ligmann-zielinska 2012; Roy et al. 2014), more effectively show the transition of different types of land cover than do individual probabilities.

Landscape morphological and structural metrics are also used to directly compute the structure, spatio-temporal patterns of urban change, and land use land cover change from thematic maps. The metrics, however, provide a better illustration and explanation of spatial heterogeneity at a particular resolution and scale. They may give a connection among the physical structure of a landscape and urban pattern, shape, functionality, and process (Barnsley et al. 1997; Geoghegan, Wainger, and Bockstael 1997; Parker, Evans, and Meretsky 2001). These simple quantitative indices i.e. landscape metrics have also been used to interpret, asses, and verify urban models (Aithal et al. 2013; Alberti and Waddell 2000; Araya and Cabral 2010; Geri et al. 2010; Herold, Goldstein, and Clarke 2003; Jain, Kohli, and Rao 2011; Jia et al. 2019; Reis, Silva, and Pinho 2016). Herold et al. (2003) applied landscape metrics and an urban growth model in Santa Barbara, California from 1930 to 2001 and predicted the urban growth to the years 2030. They concluded the more compact growth around existing urban cores, rather than a leap frog urban development (Herold et al. 2003). Aithal et al. (2013) analyzed the land use dynamics in the rapidly urbanizing of Bangalore, India using multilayer perceptron, based on Cellular Automata (CA)-Markov and landscape metrics. Their results showed that from 2012 to 2020, urban land would expand 108% (Aithal et al. 2013). Megahed et al. (2015)

modeled the urban growth of Greater Cairo, Egypt, using landscape metrics and a Land Change Modeler. They concluded that urbanization had accelerated from 4.64% to 17.30% during 1984—2014 and would continue to increase to 21.93% in 2025 (Megahed et al. 2015).

Guangdong, Hong Kong, and Macao (GHKM) is one of the most significant and rapidly developing region in China. Guangdong, Hong Kong, and Macao has undergone a transformation from its planned economy to a market oriented economy, fast regional economic and social development policy/strategy, and urbanization acceleration process, all of which have had a significant impact on the spatial pattern of the land use land cover change (Han et al. 2015; Hasan et al. 2019; J. Liu et al. 2014; Rimal et al. 2017). The economic center of China, especially the Pearl River Delta (PRD) region of the Guangdong, Hong Kong, and Macao has remained the primary destination region for local and international immigrants thus, causes intense settlement (Braimoh and Onishi 2007). The migration occurred because of the potential of remunerative job opportunities, a better education system, and other daily life facilities. This unprecedented urbanization and industrialization has caused the fragmentation of farmland into an urban fringe, with the loss of traditional farming activities and a shift in the character of rural communities (Wu et al. 2006). Consequently, the characteristics of land use land cover in Guangdong, Hong Kong, and Macao have changed significantly. If such circumstances continue, Guangdong, Hong Kong, and Macao will then quickly become an urban slum with the least suitable living conditions for urban residents (World Bank 2011). Slums exist in the neighborhood of posh areas and the exterior of big cities because the latter attract people for economic reasons. Both pull and push factors of rural urban migration, land price differences, non-affordable prices at densely urbanized area are underlying factor of growth of slums in urban areas, spiraling urban poverty, the inability of the urban poor to access affordable land for housing, and insecure land tenure. The various push factors operating at the place of origin include natural rate of population growth, creating population pressure on the existing resources, exhaustion of natural resources; natural calamities such as floods. The following may be counted as the pull factors: establishment of new industries with the provision of new opportunities for gainful employment; facilities for higher education in cities; pleasant climatic conditions, etc. Slums are the products of failed policies, inappropriate regulation, dysfunctional land markets, unresponsive financial systems, and a fundamental lack of political will. Each of these failures adds to the toll on people already deeply burdened by poverty and forces them to live in slums.

Thus, knowing the state of the future land use land cover of the Guangdong, Hong Kong, and Macao is a paramount requirement to enable the adequate design of potent urban, demographic, and economic policies and also an increase in or protection of farmland, to ensure sustainable development (Hyandye and Martz 2017; World Bank 2011). Therefore, the main objective of this study is to forecast future land use land cover changes, particularly urban growth, based on Land Change Modeler. Moreover, in the detailed analysis of the land use land cover change patterns, landscape metrics were also used to decipher and analyze model predicted land cover patterns in the study area, and was further extended to the year 2031. This study also aims to provide a scientific basis to decision and policy makers to enable the development of strategies that will ensure regional ecological protection and sustainable development.

5.2 Materials and Methods

5.2.1 Data Acquisition

The land use land cover data for Guangdong, Hong Kong, and Macao for the years 2005, 2010, and 2017 have been produced in the chapter 4, which was based on the supervised classification of multi-temporal Landsat data (thematic mapper (TM)/enhanced thematic mapper (ETM+)/operational land imager (OLI)) at a 30m resolution (Hasan et al. 2019). Other data sets include Shuttle Radar Topographic Mission (SRTM) 30m Digital Elevation Model (DEM) downloaded from the 30m SRTM Tile downloader (Anon n.d.), roads network data and water channel network data obtained from the “Open Street Map (OSM)” (Anon n.d.). Slope, aspect, and hillshade were derived from the DEM. All the data were projected to Universal Transverse Mercator (UTM) projection i.e., WGS-1984-UTM-Zone-49N, with the spatial resolution of 30m.

5.2.2 Land use land cover change modelling and future scenarios

Land Change Modeler (LCM) in TerrSet (formerly known as IDRISI) software was originally designed to manage biodiversity influences, and to analyze and forecast land use land cover changes

(Gibson et al. 2018; Hamdy et al. 2017; Mishra et al. 2014; Roy et al. 2014; Shivamurthy and Kumar 2013). This model is based on the artificial neural network (ANN), Markov Chain matrices, and transition suitability maps, generated by training multilayer perceptron (MLP) or logistic regression (Ansari and Golabi 2019; Mas et al. 2014; Megahed et al. 2015). This model predicts the land use land cover changes from the thematic raster images having the same number of classes in the same sequential order (Mas et al. 2014). In this study, the Land Change Modeler is used to forecast the future land use land cover changes in Guangdong, Hong Kong, and Macao for the next fourteen years (for 2024 and 2031) by following the four steps: (1) change analysis, (2) transition potential and determination of explanatory variables, (3) change prediction, and (4) model validation (Dzieszko 2014; Megahed et al. 2015).

5.2.2.1 Change analysis

In the change analysis panel, the changes between two different time periods time 1 and time 2 land use land cover maps were calculated. The change analysis give a quick evaluation of quantitative change, by charting gains and losses, among different land cover types (Mishra et al. 2014). It also estimates net change, persistence, and the specific transition of land cover information both in map and geographical forms (Hamdy et al. 2017). These changes are important to identify the dominant transition from one class to another, all the dominant transitions are then grouped and targeted (Dzieszko 2014; Megahed et al. 2015). The spatial trend of change provides the trend in the form of a map, with the best fit polynomial trend surface adhering to the pattern of change (Hamdy et al. 2017).

5.2.2.2 Transition potential modeling and driving forces determination

5.2.2.2.1 Transition Potential

The transition potential determines the area of change (Megahed et al. 2015). Land cover transitions can be grouped into sub-models, if it is assumed that for each transition, the underlying drivers of change are the same (Pérez-vega et al. 2012). For example, the processes that influence the land use land cover to change from farmland to built-up land may be the same as those that affect the change of forest to built-up land. Thus, land use land cover changes with common driving variables were grouped into sub-models (Gibson et al. 2018). In addition, evidence likelihood was selected to determine the relative frequency of different land use land cover types which had occurred within the transitional areas (Megahed et al. 2015).

5.2.2.2.2 Selection of explanatory variables

Explanatory variables or drivers, responsible for land use land cover change, were selected on the basis of factors that increase or decrease the appropriateness of a specific alternative for the activity of concern (Mishra et al. 2014; Wang and Maduako 2018). Factors, such as, topography is a significant factor for urban change. Topography influences the city size and its spatial distribution, by possible restraints of water supply and provision of adequate land (Müller, Steinmeier, and Küchler 2010). In general, the slope, aspect, and elevation are recognized as the most imperative topographic factors affecting urban sprawl (Braimoh and Onishi 2007; Reilly, Mara, and Seto 2009; Ye et al. 2013). Proximity factors such as distance to water channels and distance to roads also play an imperative role in urban sprawl, as each provide convenience to dwellers to access resources and everyday needs. Neighborhood effects generally show that if a non-built-up pixel surrounded by built-up land, it is more likely to eventually to transform into a built-up area. As regards, land use land cover planning and policy, factors differ because of the different institutional contexts of the different study areas. For example, in this study area (GHKM), urban development can be influenced by different planning guidelines and regulations, including master plans and zoning (Mishra et al. 2014; Ozturk 2015; Wang and Maduako 2018). In this study, both topographic and proximity factors were selected to scrutinize the urbanization and land use land cover change impacts. These variables are expected to have a significant influence on futures changes (Gibson et al. 2018; Maria et al. 2014). The significance of each variable is tested using Cramer's V, a quantitative measure (Gibson et al. 2018; Hamdy et al. 2017). However, Cramer's V does not assure a strong performance of the variables, since it cannot represent the scientific prerequisites and the multifaceted nature of the relationships. It simply helps to determine whether or not to include the particular variable as a driving factor of land use land cover change (Kumar et al. 2015; Megahed et al. 2015; Raschio and Alei 2016).

5.2.2.2.3 Multilayer perceptron (MLP)

Multilayer perceptron (MLP) neural network is a feedforward neural network with one or more layers between the input and output layers. MLP depends on the back propagation (BP) algorithm that is a supervised training algorithm (Ahmed 2011; Eastman 2009; Mishra et al. 2014). It plays a central role in the land change modeler, and consists of three layers (1) input, (2) hidden, and (3) output (Mishra et al. 2014). Through feed-forward algorithms, networks calculate weights for input values, input layer nodes, hidden layer nodes, and output layer nodes, all of which propagate through the hidden layer, (set of computational nodes) to output layers. For modeling, multilayer perceptron allows more than one transition at a time (Megahed et al. 2015; Raschio and Alei 2016). In multilayer perceptron, through hidden layers, the data flows in one direction, from an input layer to an output layer and determines non-linear relationships. Within the layers, the nodes are assembled and every node receives an input signal from the different nodes and yields a transformed signal to other nodes. After assigning weight to each original input layer, which includes a threshold, it passes through either a linear or non-linear stimulation function. To reduce the error between the observed and the expected results, the weights must be resolved in the training process, before the system can be utilized for forecast purposes (Megahed et al. 2015; Raschio and Alei 2016). After the multilayer perceptron has been trained with various influencing factors (Mas et al. 2014), for each of the sub-models it therefore produces time-explicit transition potential maps that represent time-explicit change potential (Council 2014; Eastman 2009; Gibson et al. 2018; Rimal et al. 2017).

5.2.2.3 Change prediction

Change prediction is the last step in which the future prediction is executed on the basis of Markov chain, and using the historical rate of change and the transition potential maps (Dzieszko 2014).

5.2.2.3.1 Markov Change Model

The Markov chain model, is a stochastic modelling procedure, extensively used for land use land cover change modelling. This model forecast the future land use land cover from time t=1 to another time t+1 (Falahatkar and Soffianian 2011), on the basis of the transition probability matrix and the transition area matrix of each land use land cover class (Hyandye and Martz 2017). The transition matrix represent the probability of land use land cover change in the observed time period from one land use group to another (Behera et al. 2012; Han et al. 2015; Wang and Murayama 2017). Transition probability maps, generated through multilayer perceptron, provide a probability estimation that each pixel will either be converted into another land cover type or persist be adjusted during annual time steps (Gibson et al. 2018).

5.2.2.4 Future Scenario

Land Change Modeler produce two kinds of predictions: (1) hard prediction, and (2) soft predictions. A hard prediction produces a predicted map, (Megahed et al. 2015) based on a multi-objective land allocation (MOLA) module (Gibson et al. 2018). One of the land cover classes is assigned to each pixel, on the basis of their most likely probability. Soft prediction determines the probability of the pixel changing to another land category, by producing a vulnerability map, where the value from 0-1 is assigned to each pixel (Megahed et al. 2015).

5.2.2.5 Model validation

Model validation is needed to assess the accuracy. Thus, the objective of the validation process is to determine the quality of 2017's simulated map in comparison with 2017's actual land use land cover map. For model validation, there are two well recognized methods: (1) Kappa statistics and (2) relative operating characteristics (ROC) (Mishra et al. 2014; Omar et al. 2014). Kappa statistics is a quantitative method that measures the goodness of fit or the best value between the model prediction and the observed maps, revised for precision by possibility in the form of K no (overall accuracy), kappa location (kappa for grid cell level location), K location Strata (kappa location strata), and K standard (kappa standard). The range of Kappa values is from 1 to -1, where positive values show, by chance, an unusual greater improved agreement, and negative values are a bad agreement (Araya and Cabral 2010; Chaudhuri and Clarke 2014; Omar et al. 2014; Roy et al. 2014; Sun 2008). Kappa values were categorized as poor below 0.40, fair to good from 0.40 to 0.75, and excellent over 0.75 (Roy et al. 2014). Relative operating characteristics, however, is well able to compare a Boolean map of "reality" with a suitability map. It is defined as a graph between the rate of true positives on the vertical axis and the rate of false positives on the horizontal axis. Its value ranges between 0 and 1, where, 1 shows a perfect fit and 0.5 shows a random fit (Aburas et al. 2018; Hamdy et al. 2017;

Martínez, Suárez-seoane, and Luis 2011; Mas et al. 2014; Sun 2008). The threshold value for the relative operating characteristics used in this study is 100. If the assessment of the simulation yields valid results (Ozturk 2015; Sahalu 2014), the calibrated model with the same driving forces then predicts the 2024 and 2031 land use land cover map, modelling the changes between 2005 and 2017 land use land cover maps.

5.2.3 Landscape metrics

Landscape metrics are used to illustrate and compute the spatial characteristics of patches, land use land cover class area, and the whole land cover over time. This is useful for monitoring, measuring, and analyzing land use land cover change, such as changes in urban sprawl and its structure (Akin, Erdoɪan, and Berberoɪlu 2013). They illustrate significant landscape information such as the composition and configuration, heterogeneity, diversity, compactness, fractal dimensions, linearity and squareness, complexity, fragmentation, and morphological characteristics. However, their selection, interpretation, analysis, and evaluation depend on the specific study context, classified map, and the inherent process of change (Aithal et al. 2013; Araya and Cabral 2010; Geri et al. 2010; Herold et al. 2003; Megahed et al. 2015; Nichol, Abbas, and Fischer 2017). The matrices used for this study are listed in Table 8, and are based on similar studies (Akin et al. 2013; Alberti and Waddell 2000; Anon 2019; Araya and Cabral 2010; Fang et al. 2014; Herold et al. 2003; Herold, Scepan, and Clarke 2002; JACK, Laack, and Zimmerman 2005; Jain et al. 2011; Lombardi, Perotto-Baldivieso, and Tewes 2020; Kevin McGarigal, Cushman, and Ene 2012; Megahed et al. 2015; Nichol et al. 2017; Perotto-Baldivieso et al. 2011; Reis, Silva, and Pinho 2015). These metrics were computed using the FRAGSTATS software (K. McGarigal, Cushman, and Ene 2012) based on land use land cover maps for the years 2005, 2010, 2017, and predicted 2024 and 2031.

Table 8. The description of landscape metrics used for morphological analysis (where, CL = class level, LL = landscape level).

Category	Metric Name	Acronym Unit	Level Used	Description	Range
Patch Size and Density	Patch Density (PD)	Number of patches per 100 ha	CL	The number of patches per unit area	PD ≥1, no limit
	Percentage of Landscape (PLAND)	%	CL	The aggregated area of landscape.	0—100

Shape and Edge	Mean Patch Area (MPA)	ha	CL	An average patch size in each class	MPA > 0, no limit
	Edge Density (ED)	m/ha	CL	Calculate the total lengths of all edge segments of corresponding patch type per unit area. Edge density explained the complexity of each patch shape.	ED ≥1, no limit
	Largest Patch Index (LPI)	%	CL	Ratio between the largest patch of the corresponding patch type and the total landscape area.	0 < LPI ≤ 100
	Area Weighted Mean Fractal Dimension Index (AWMPFD)	None	LL	Measure the average fractal dimensions of patches of a particulate patch type divided by the total sum of the patch area.	1 ≤ AWMPFD ≤ 2
Proximity	Mean Euclidean Nearest Neighbor Distance (ENN_MN)	m	CL	Measure the minimum edge to edge distance to the nearest neighbor same patch type. It explains isolation of corresponding patch type or landscape.	ENN_MN > 0
Diversity and Texture	Contagion (CONTAG)	%	LL	Measure the total probability that a patch of cells neighboring the same type of cells.	0 < CONTAG ≤ 100
	Shannon's Diversity Index	None	LL	Indicate diversity in a landscape from the abundance of patch types. It increases as the number of different patch types increases or the distribution of area/land among patch types/classes becomes more equitable.	Shannon's Entropy ≥ 0, no limit

5.3 Results

5.3.1 Land cover change analysis

The land use land cover maps for the years 2005, 2010, and 2017 (Hasan et al. 2019) are shown in Figure 3 (Chapter 4). The area statistics of different land use land cover categories between different years are shown in Table 9. During 2005—2017, the built-up area increased from 5.84% (11475.77 km^2) to 10.31% (20228.95 km^2), with a significant annual rate of change of 4.72%. The growth of built-up area is different in different periods i.e., 2.41% during 2005—2010 (period 1) and 2.06% during 2010—2017 (period 2). This significant rise in built-up area has resulted in a decline in both farmland and fishponds. Farmland covered an area of 40.77% (80043.82 km^2) in 2005, but decreased substantially to 37.63% (73890.27 km^2) in 2010 and 33.03% (64938.68 km^2) in 2017, respectively. Thus, farmland declined by 3.13% during 2005—2010, 4.60% in 2010—2017, and 7.73% in 2005—2017. Similarly, fishponds decreased from 1.56% (3059.93 km^2) in 2005 to 0.97% (1902.79 km^2) in 2017, with a significant change of 3.96% (1157.13 km^2). Furthermore, as a result of different afforestation programs, forest cover increased from 40.84% (80180.31 km^2) in 2005 to 42.39% (83223.94 km^2) in 2010 and 45.02% (88390.98 km^2) in 2017, respectively (Table 9).

Table 9. Area statistics of the land use land cover classes for the years 2005, 2010, and 2017.

Year	2005		2010		2017		Change 2005—2010	Change	Change 2010—2017	Change	Change 2005—2017	Change
Classes	**Km^2**	**%**	**Km^2**	**(%)**	**Km^2**	**(%)**	**Km^2**	**%**	**Km^2**	**%**	**Km^2**	**%**
Forest	80180.31	40.84	83223.94	42.39	88391.98	45.02	3043.63	1.55	5168.03	2.58	8211.67	4.13
Grassland	399.84	0.20	143.26	0.07	189.47	0.10	-256.58	-0.13	46.21	0.02	-210.37	-0.11
Water	20249.86	10.31	20211.49	10.29	20656.34	10.51	-38.37	-0.02	444.84	0.21	406.47	0.19
Fishponds	3059.93	1.56	2453.32	1.25	1902.79	0.97	-606.61	-0.31	-550.53	-0.28	-1157.14	-0.59
Built-up	11475.77	5.84	16203.51	8.25	20228.95	10.31	4727.74	2.41	4025.44	2.06	8753.18	4.45
Bareland	934.47	0.48	218.44	0.11	275.21	0.14	-716.03	-0.36	56.77	0.03	-659.26	-0.34
Farmland	80043.82	40.77	73890.27	37.63	64938.68	33.03	-6153.55	-3.13	-8951.59	-4.60	-15105.14	-7.73

The gains and losses of different land use land cover thematic classes were calculated, as shown in Table 10. Major land use land cover changes include (1) expansion of built-up land, (2) reduction in farmland and fishponds, and (3) increase in forest cover. During 2005—2017, gain and loss in forest cover was 10092.25 km^2 (2.09%) and 1880.78km^2 (-0.39%), with a net gain of 8211.47 km^2 (1.70%). Fishponds loss 2276.21 km^2 (-0.47%) and gained 880.06km^2 (0.18%), with a net loss of 1396.15 km^2 (-0.29%). Farmland lost 15672.26 km^2 (-3.25%) and gained 566.94 km^2 (0.12%) with a net loss of 15105.30 km^2 (-3.13%). Built-up land however, increased with a net gain of 8753.13 km^2 (1.81%). During the same period, the classes that contributed to the net change of built-up area are listed as: forest 1067.32 km^2 (0.22%), grassland 47.42 km^2 (0.01%), water 272.06 km^2 (0.06%), fishponds 867.93 km^2 (0.18%), bareland 346.48 km^2, and farmland 6151.92 km^2 (0.07%) were transformed to built-up area. The contribution to the net change of other classes are shown in Table 10 (2005—2017). In summary, the reduction in farmland concurs with the expansion of radioactivity aligned to the urbanization growth.

Table 10. Land use land cover gains, losses and contributions to net change in each category during periods 2005—2010, 2010—2017, and 2005—2017.

2005—2010									
	Gain	**Loss**	**Net contribution**						
Classes			**Forest**	**Grassland**	**Water**	**Fishponds**	**Built-up**	**Bareland**	**Farmland**
	%	%	%	%	%	%	%	%	%
Forest	0.88	0.25	0.00	-0.02	0.00	0.00	0.12	0.00	-0.73
Grassland	0.01	0.06	0.02	0.00	0.00	0.01	0.00	0.00	0.02
Water	0.18	0.19	0.00	0.00	0.00	-0.01	0.02	0.00	-0.01
Fishponds	0.23	0.36	0.00	-0.01	0.01	0.00	0.11	0.00	0.01
Built-up	0.98	0.00	-0.12	0.00	-0.02	-0.11	0.00	-0.06	-0.67
Bareland	0.03	0.18	0.00	0.00	0.00	0.00	0.06	0.00	0.09
Farmland	0.21	1.48	0.73	-0.02	0.01	-0.01	0.67	-0.09	0.00
2010—2017									
Forest	1.39	0.32	0.00	0.00	0.04	-0.02	0.14	0.02	-1.24
Grassland	0.03	0.02	0.00	0.00	0.00	0.00	0.00	0.00	-0.01

Water	0.27	0.18	-0.04	0.00	0.00	-0.07	0.04	0.00	-0.02
Fishponds	0.18	0.35	0.02	0.00	0.07	0.00	0.06	0.00	0.01
Built-up	0.83	0.00	-0.14	0.00	-0.04	-0.06	0.00	-0.01	-0.59
Bareland	0.05	0.04	-0.02	0.00	0.00	0.00	0.01	0.00	-0.01
Farmland	0.07	1.92	1.24	0.01	0.02	-0.01	0.59	0.01	0.00
2005—2017									
Forest	2.09	0.39	0.00	-0.02	0.03	-0.05	0.22	-0.04	-1.84
Grassland	0.03	0.07	0.02	0.00	0.01	0.00	0.01	0.00	0.01
Water	0.27	0.19	-0.03	-0.01	0.00	-0.07	0.06	0.00	-0.03
Fishponds	0.18	0.47	0.05	0.00	0.07	0.00	0.18	0.00	-0.01
Built-up	1.81	0.00	-0.22	-0.01	-0.06	-0.18	0.00	-0.07	-1.27
Bareland	0.05	0.18	0.04	0.00	0.00	0.00	0.07	0.00	0.02
Farmland	0.12	3.25	1.84	-0.01	0.03	0.01	1.27	-0.02	0.00

5.3.2 Simulation

5.3.2.1 Transition potential modelling and determining driving variables

The land use land cover change results indicated that the significant changes in urban areas occur mainly from the deterioration of farmland and fishponds. The transition considered in the Land Change Modeler are: Forest – Built-up, Grassland – Built-up, Water – Built-up, Fishponds – Built-up, Bareland – Built-up, Farmland – Built-up, and Farmland – Forest. All these transitions, based on visual evidence of the urban spatial trend, had the same driving force. Table 11 illustrates the potential explanatory power of each driving force, represented by Cramer's V. The variable that has a Cramer's V value of about 0.15 or higher are useful, while those with values of 0.4 or higher are good. Thus, the selected factors were found to be relevant (Figure 11). Slope show significant influence on urban growth especially in the Pearl River Delta and on the eastern side of the study area. This could be attributed to their relatively flat terrain where the constraints of slope are not as significant as that in the mountainous regions. Both hillshade and aspect indicate exposure to sunlight, which can play a significant role in the selection of land for farmland and urban area encroachment. On the other hand, it is also important factor for the increasing growth of tropical/subtropical forest types in the study area. Hillshade may be correlate with slope and aspect as it reflect the topographic patterns associated with both of them. Other variables are also found to be an important spatial determination of urban growth. After the selection of the predictor variables, transitions were modelled in one transition sub-model, and generated the transitions potential maps through multilayer perceptron with an accuracy of above 70% (Figure 12).

Table 11. Cramer's V values of explanatory variables.

Explanatory variables	Cramer's V
Slope	0.3448
Aspect	0.3107
DEM	0.2665
Hillshade	0.2526
Distance to roads	0.2162
Distance to water channel	0.1787

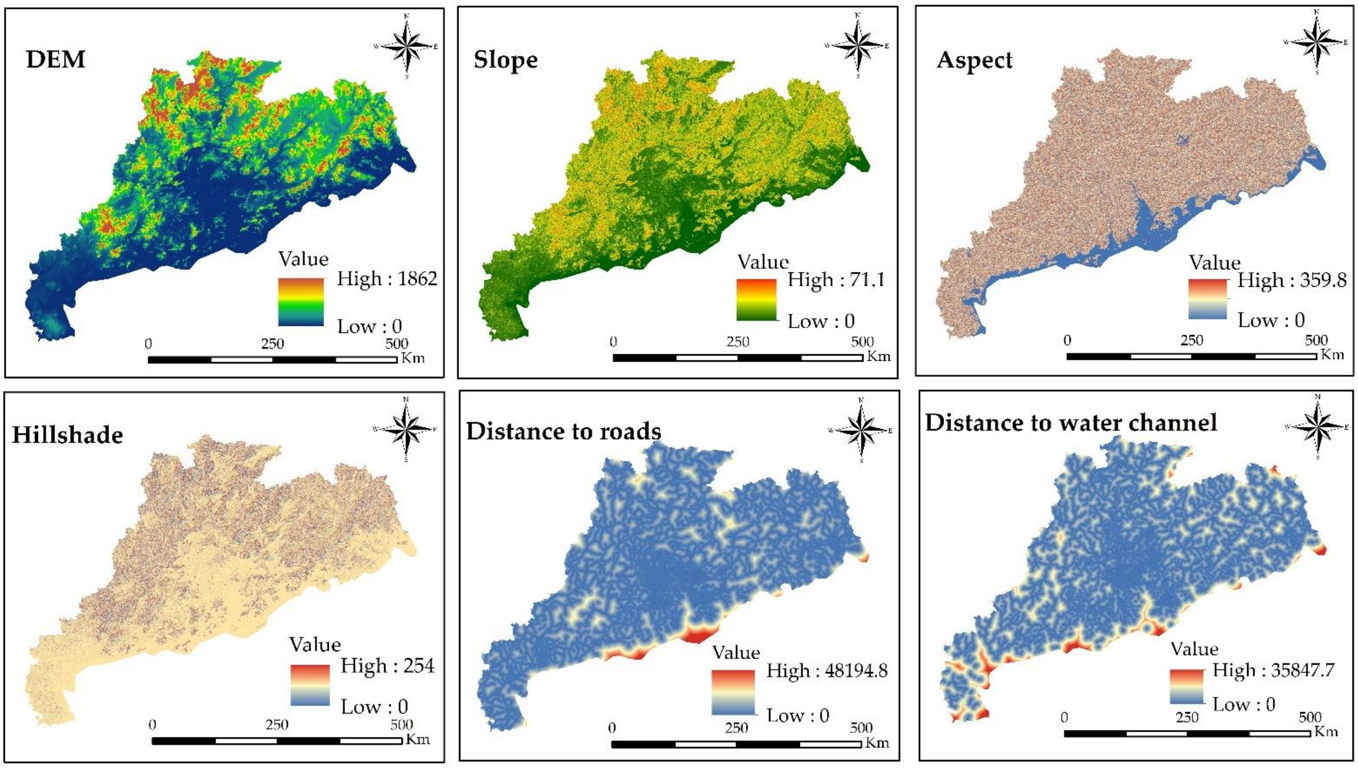

Figure 11. Maps of the variables used for the spatial distribution of land change modeling DEM, slope, aspect, hillshade, distance to roads, and distance to water channel.

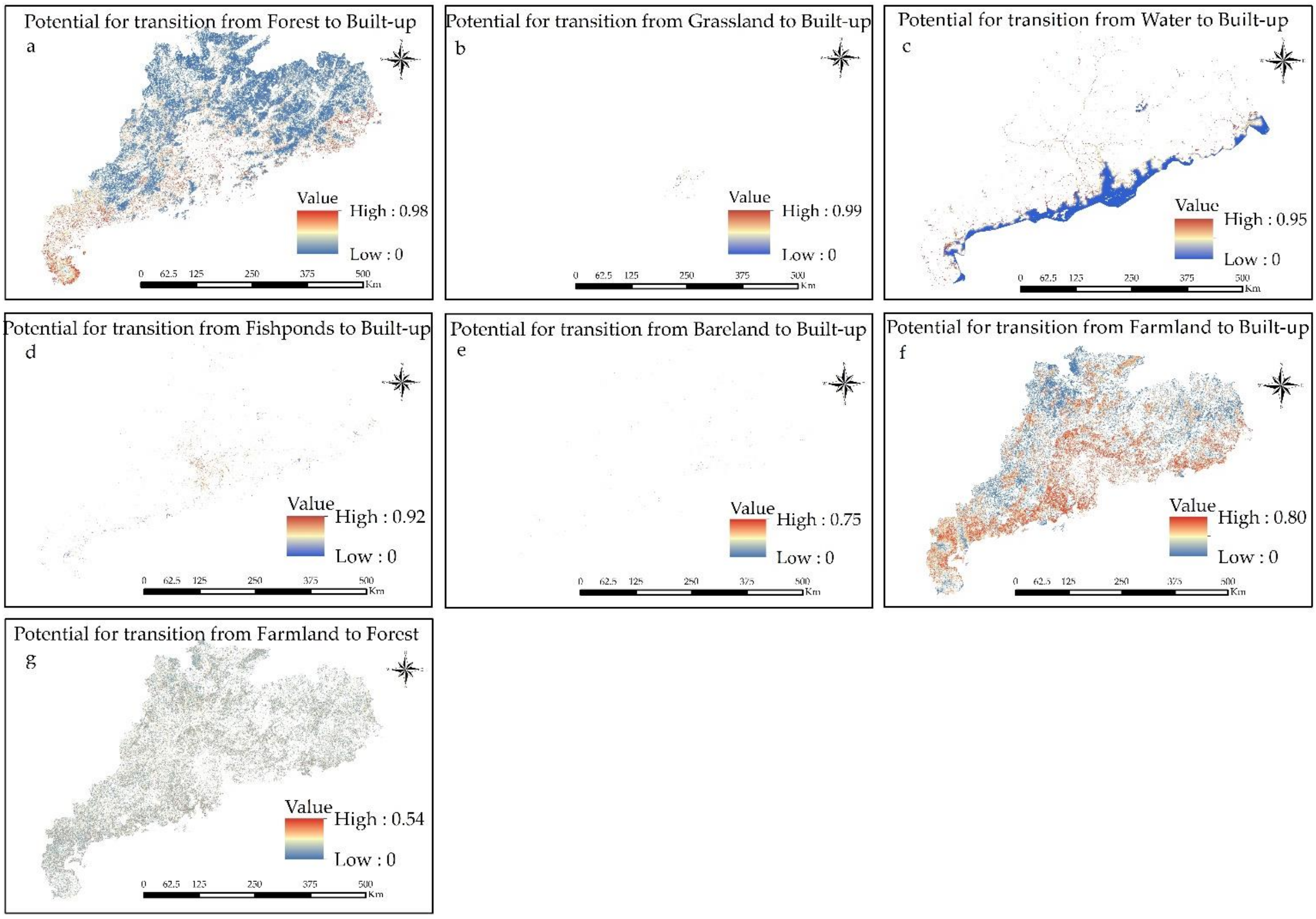

Figure 12. Transition potential maps from (a) forest to built-up (b) grassland to built-up, (c) water to built-up, (d) fishponds to built-up, (e) bareland to built-up, (f) farmland to built-up, and (g) farmland to forest.

5.3.2.2 Land use land cover Transition Analysis

In this study, the transition probability matrices were produced for the years 2017 (using 2005 and 2010 land use land cover layers), 2024 (using 2010 and 2017 land use land cover layers), and 2031 (using 2010 and 2017 land use land cover layers) (Table 12). The transition probability matrix shows the probability of a conversion for each land use land cover class to another class, within the specified time. The change of probabilities, between two different time periods reveal the significant increase of urban areas at the cost of a decrease in farmland and fishponds in the Guangdong, Hong Kong, and Macao region.

Table 12 (For 2017) shows that forest and built-up are the most stable classes with respective probabilities of 0.97 and 1.00. Water, farmland, and fishponds are the most dynamic classes with transition probabilities of 0.93, 0.87, and 0.28. In these land cover classes, farmland was mainly converted into built-up land and forest cover, whereas, fishponds were primarily transformed into built-up land. The occupation of both farmland and fishponds by an urban sprawl is evident. From Table 12 (for 2024 and 2031) the transition of several land use land cover classes shows a consistency with the previous periods. Forest and built-up land are still the most stable classes with respective transition probabilities 0.96 and 1.00 (for 2024) and 0.94 and 1.00 (for 2031). The most dynamic classes are farmland and fishponds, which primarily transformed into built-up land with respective transition probabilities 0.1057 and 0.2956 (for 2024) and 0.151 and 0.3319 (for 2031). Transformation of farmland into forest had a probability of 0.113 for 2024 and 0.1582 for 2031 indicates that different afforestation policies will continue to play a significant role in making greener Guangdong, Hong Kong, and Macao.

Table 12. Transition probability matrix of land use land cover classes for the years 2017, 2024, and 2031.

Transition Probability Matrix 2017							
	Forest	**Grassland**	**Water**	**Fishponds**	**Built-up**	**Bareland**	**Farmland**
Forest	0.9789	0.0007	0.0033	0.0054	0.0104	0.001	0.0000
Grassland	0.3594	0.0926	0.054	0.0708	0.0712	0.0026	0.3495
Water	0.0141	0.0001	0.9385	0.0306	0.0087	0.0004	0.0076
Fishponds	0.1502	0.0006	0.2139	0.2888	0.2244	0.0017	0.1204
Built-up	0.0000	0.0000	0.0000	0.0000	1.0000	0.0000	0.0000
Bareland	0.0851	0.0016	0.0242	0.024	0.3149	0.0098	0.5404
Farmland	0.0606	0.0000	0.0025	0.0035	0.0555	0.0008	0.877
Transition Probability Matrix 2024							
Forest	0.9615	0.0007	0.0076	0.0069	0.0223	0.001	0.0000
Grassland	0.4148	0.0152	0.0715	0.0347	0.1167	0.0012	0.3459
Water	0.0324	0.0001	0.8876	0.037	0.0246	0.0005	0.0178
Fishponds	0.1982	0.0004	0.2587	0.106	0.2956	0.0009	0.1403
Built-up	0.0000	0.0000	0.0000	0.0000	1.0000	0.0000	0.0000
Bareland	0.1211	0.0004	0.0294	0.0114	0.3541	0.001	0.4827
Farmland	0.113	0.0001	0.0055	0.0045	0.1057	0.0008	0.7705
Transition Probability Matrix 2031							
Forest	0.9445	0.0007	0.0119	0.0075	0.0344	0.0010	0.0000
Grassland	0.4389	0.0017	0.0776	0.0166	0.1502	0.0008	0.3142
Water	0.0509	0.0001	0.8411	0.0381	0.0421	0.0005	0.0272
Fishponds	0.2224	0.0002	0.2667	0.0396	0.3319	0.0006	0.1385
Built-up	0.0000	0.0000	0.0000	0.0000	1.0000	0.0000	0.0000
Bareland	0.1502	0.0001	0.0317	0.0066	0.3853	0.0006	0.4256
Farmland	0.1582	0.0001	0.0084	0.0048	0.151	0.0008	0.6767

5.3.3 Validation

Simulated and actual land use land cover maps of 2017 is shown in Figure 13. Their area statistics of different land use land cover classes are shown in Table 13. Visual interpretation of the modeling results shows that the simulated map for the year 2017 is reasonably similar to the actual map for that year. A more detailed analysis was accomplished using the Kappa variations and relative operating characteristics. Kappa variations that compared the projected land use land cover map with the actual land use land cover map of the year 2017 resulted in Kappa value = 0.97, K_{no} = 0.97, kappa location = 0.99, and k standard = 0.96, whereas the relative operating characteristics value i.e., area under the curve is 0.914 (Figure 14). Thus, high values of both Kappa and relative operating characteristics interpret that the majority of the study area experienced no change representing the consistency is quite strong between the predicted results and the actual land use situation. However, model predict less forest cover and more built-up area and fishponds than the actual land cover map. Both Kappa and relative operating characteristics results confirms that the model is reliable for the Guangdong, Hong Kong, and Macao and can be used to predict future land use land cover change under different scenarios.

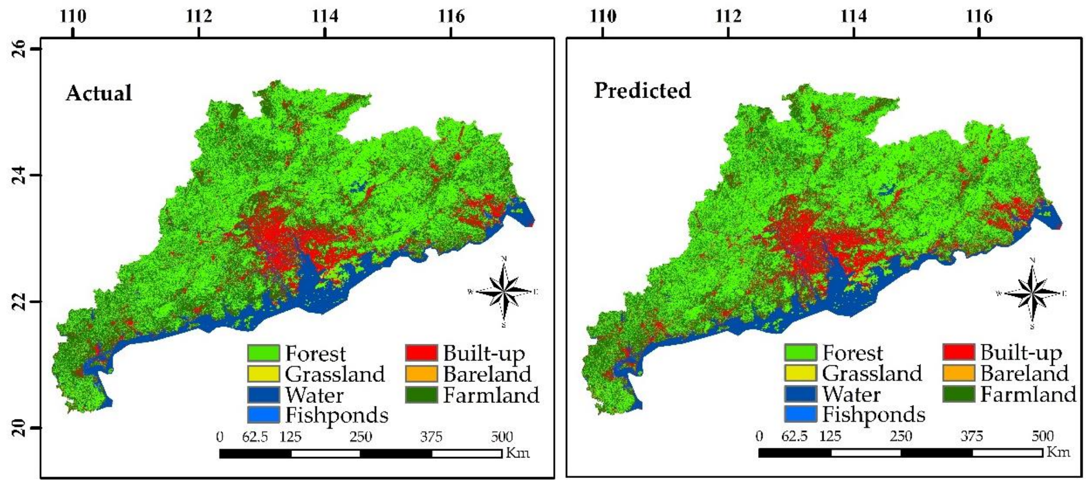

Figure 13. Actual and simulated land use land cover map for the year 2017 of the Guangdong, Hong Kong, and Macao.

Table 13. Area statistics of actual and predicted land use land cover map of 2017.

Classes	Actual (km^2)	Predicted (km^2)
Forest	88391.98	86835.34
Grassland	189.47	133.06

Water	20656.34	20035.57
Fishponds	1663.83	1902.80
Built-up	20228.95	21975.24
Bareland	275.21	149.66
Farmland	64938.68	65311.12

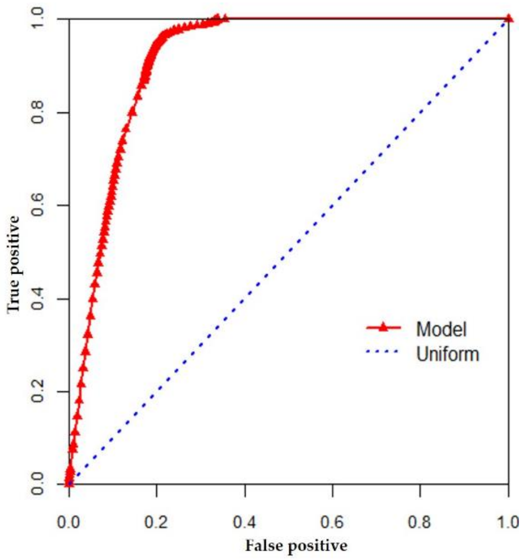

Figure 14. Relative operative characteristics (ROC) curve which provide the correlation between predicted and actual land use land cover map. The closer the curve approaches the upper left corner, the stronger is the predictive power of the model. For this study relative operative characteristic value is 0.914, indicating strong consistency between predicted and actual land use land cover map.

5.3.4 Future Scenario /simulation

After successful validation of the model, based on real land use land cover maps the model predicted the urban growth and the land use land cover maps for the years 2024 and 2031 (Figure 15). The markov model also provides the transition probability matrix for the years 2024 and 2031 (Table 12 for 2024 and 2031). The statistical change analysis of projected land cover is shown in Table 14. The model predicts that built-up land will continue to increase by 15710.20 km^2 (136.90%) in 2024 and 20518.78 km^2 (178.80%) in 2031, compared to 11475.77 km^2 in 2005, to the detriment of a decrease of farmland and fishponds (Table 14). Farmland will decrease by 22313.79 km^2 (-11.36%) in 2024 and 29000.81 km^2 (-36.25%) in 2031, compared to the 80043.82 km^2 in 2005. Fishponds will decrease by 1331.81 km^2 (-0.68%) and 1420.87 km^2 (-0.72%) in 2024 and 2031, compared to 3059.93 km^2 in 2005. However, forest cover will continue to increase by 9536.49 km^2 (4.86%) and 11869.30 km^2 (6.05%) in 2024 and 2031, compared to 80180.31 km^2 in 2005 (Table 14). The overall change in the land use land cover in the predicted years is shown in Figure 16. In summary, the predicted results confirm that such patterns will continue in future because of the results of China's economic hub, economic policy, housing, industry, and development of the infrastructure. These changes have adverse impacts on the urban environment. Therefore, with the help of future prediction results, proper planning and environmental management plans can control the adverse effect of these changes.

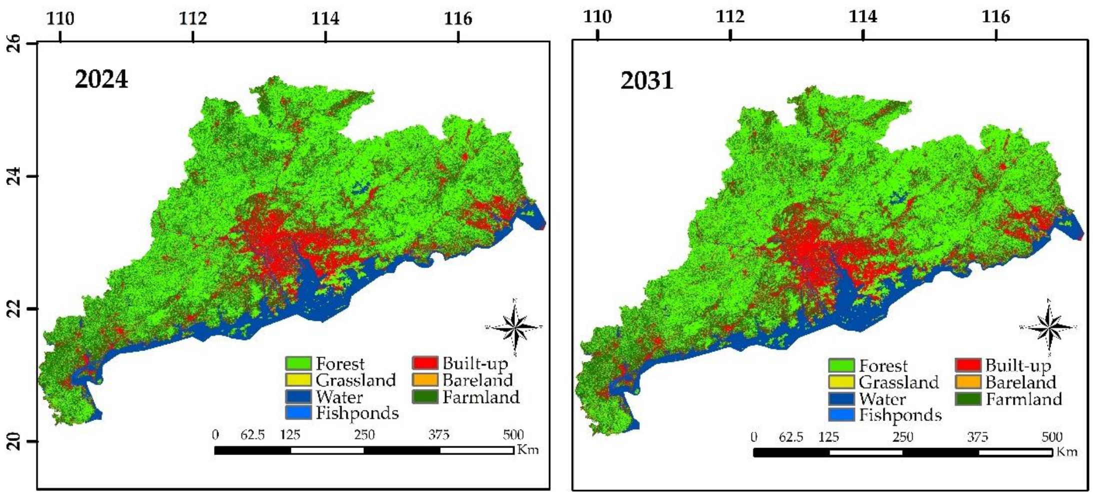

Figure 15. Predicted land use land cover map for the years 2024 and 2031.

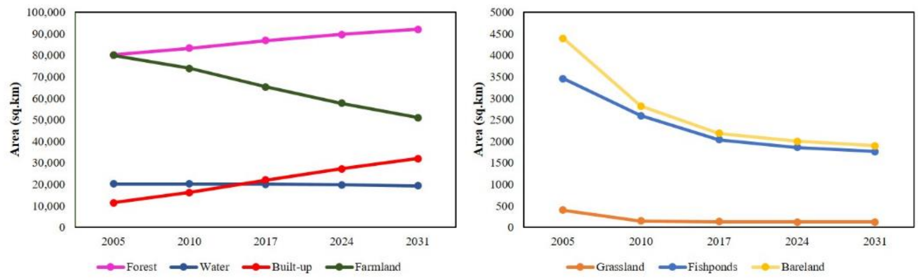

Figure 16. Area of the land use land cover classes (a) forest, water, built-up, and farmland, (b) grassland, fishponds, and bareland over the years 2005, 2010, 2017, and predicted 2024 and 2031.

Table 14. Area statistics of the projected land use land cover classes in 2024 and 2031.

	2017	**2024**	**2031**	**Change 2017—2024**		**Change 2017—2031**	**Change**	**Change 2005—2031**	**Change**
Classes	**km²**	**km²**	**km²**	**km²**	**%**	**km²**	**%**	**km²**	**%**
Forest	88391.98	89716.81	92049.62	1324.83	1.50	3657.64	4.14	11869.30	14.80
Grassland	189.47	126.54	121.74	-62.93	-33.21	-67.72	-35.74	-278.10	-69.55
Water	20656.34	19714.21	19360.51	-942.13	-4.56	-1295.82	-6.27	-889.35	-4.39
Fishponds	1663.83	1728.12	1639.06	64.29	3.86	-24.77	-1.49	-1420.87	-46.43
Built-up	20228.95	27185.97	31994.55	6957.03	34.39	11765.61	58.16	20518.78	178.80
Bareland	275.21	141.09	134.27	-134.12	-48.73	-140.94	-51.21	-800.20	-85.63
Farmland	64938.68	57730.03	51043.01	-7208.65	-11.10	-13895.67	-21.40	-29000.81	-36.23

Furthermore, it can be concluded from gain and loss Table 15 that farmland will be adversely influenced by an upsurge in other land use types, specifically built-up areas. A significant gain in both built-up and forest, has been recorded because of the socioeconomic development process and different land use policies such as the Land administration Law (LAL). Table 15 also shows the contribution to net change in each land use land cover category, both positively and negatively in the Guangdong, Hong Kong, and Macao during 2005—2031. It is worth noticing that the loss of farmland was mostly transferred into two classes i.e., (1) forest (18093.67 km^2) and (2) built-up (11323.29 km^2). Table 15 shows that loss of fishponds dominantly converted into built-up area (1320.78 km^2). Due to continuous increase in urban growth and development, the green ecosystem in the Guangdong, Hong Kong, and Macao will be significantly influenced, making it crucial for local institutions to establish exacting policies to protect and preserve the local environment in the long haul.

Table 15. Gains, losses, and contributions to net change in each land use land cover types in the Guangdong, Hong Kong, and Macao during 2005—2031.

2005—2031	**Gain**	**Loss**	**Net contribution**						
Classes			**Forest**	**Grassland**	**Water**	**Fishponds**	**Built-up**	**Bareland**	**Farmland**
	%	%	%	%	%	%	%	%	%
Forest	3.95	0.52	0.00	-0.02	0.03	-0.03	0.37	-0.04	-3.75
Grassland	0.02	0.07	0.02	0.00	0.01	0.00	0.02	0.00	0.00
Water	0.24	0.24	-0.03	-0.01	0.00	-0.08	0.15	-0.01	-0.03
Fishponds	0.15	0.49	0.03	0.00	0.08	0.00	0.27	0.00	-0.03
Built-up	3.27	0.00	-0.37	-0.02	-0.15	-0.27	0.00	-0.11	-2.35
Bareland	0.03	0.19	0.04	0.00	0.01	0.00	0.11	0.00	0.01
Farmland	0.05	6.20	3.75	0.00	0.03	0.03	2.35	-0.01	0.00

In order, to examine and understand the influence of land use land cover change on green lands (i.e., forest and farmland) and the key role of urbanization, Figure 17 shows the conversion of farmland and forest into other land use types. The spatial visualization provided by the Land Change Modeler shows that in the next 14 years built-up areas are the most momentous land use land cover class and will negatively affect the farmlands. Figure 17b shows that the forest cover will continue to increase in the Guangdong, Hong Kong, and Macao over the next 14 years.

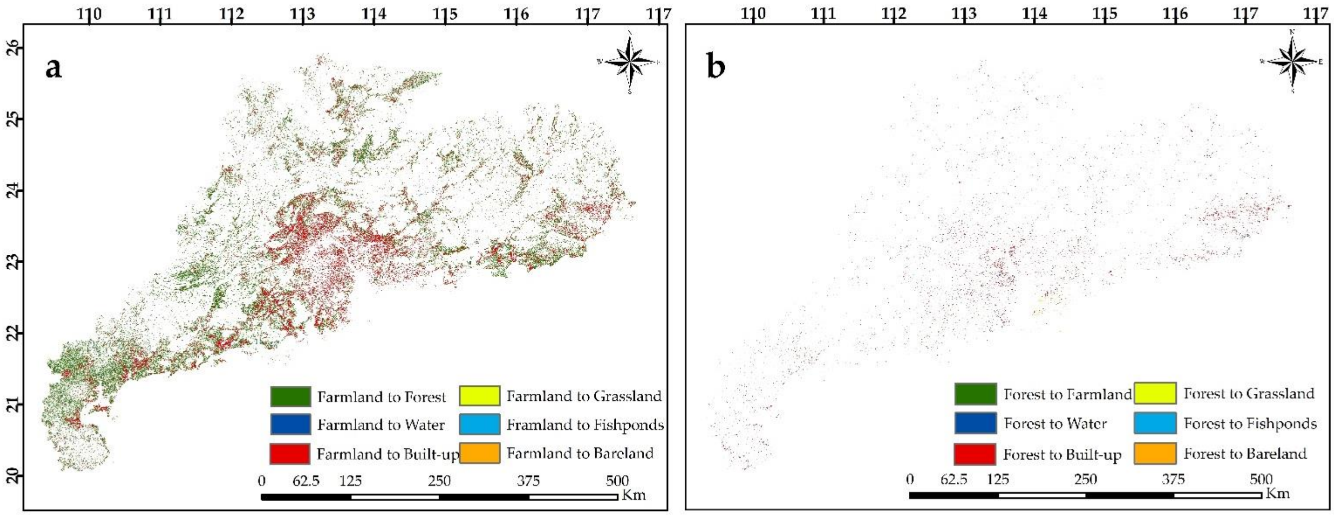

Figure 17. Transition from (a) farmland to all categories and (b) forest to all categories between 2005 and 2031.

5.3.5 Landscape metrics and urban analysis

Figure 18 reflects the changes in spatial morphology of the landscape at class and landscape level. With the increase in the 'percentage of the landscape' of both forest cover and built-up land, the 'patch density' and 'edge density' increased significantly (Figure 18a-c). The patch density for forests cover increased from 0.46 to 0.53 and for built-up from 0.35 to 0.49 during 2005—2017 and will continue to increase during 2017—2031 (Figure 18b). This signifies the considerable growth of landscape complexity with the increasing human-induced activities. The largest patch index increases for both forest cover (from 4.06% to 7.33%) and built-up land (from 0.35% to 1.03%) during 2005—2017 and predicted result show that it will continue to increase to 11.60% in 2024 and 12.21% in 2031 (Figure 18d). This indicate the corresponding patch type uniformity. A 'mean patch area', which is a critical measure of habitat fragmentation, will be decrease for forest cover from 36.17 ha in 2005 to 30.72 ha in 2031and increase for built-up land from 6.71 ha in 2005 to 11.10 ha in 2031. Smaller 'mean patch area' together with larger 'patch density' and 'largest patch index' for forest cover revealed fragmentation. However, larger 'mean patch area' together with larger 'patch density' and 'largest patch index' for built-up land reflects that the landscape is expected to gradually became urban dominated as the intensity of urbanization in the fringe as well as densification within already urbanized area increased tremendously, leading to the dominance of urban landscape. The mean Euclidian nearest neighbor distance (ENN_MN) shows an expected decrease for both forest and built-up land during 2005—2031 (Figure 18g). This indicating that the spaces between their neighbors is decreases with time due to high industrialization and unprecedented population density, thus suggesting coalescence.

The ‘percentage of landscape’ of both farmland and fishponds decreased substantially during the study period. For farmland, the decrease in the ‘mean patch area’, ‘largest patch index’ and increase in ‘patch density’ reflect that farmland is highly fragmented (Figures 18b, d, and f). The ‘mean patch area’ decreased from 38.94 ha in 2005 to 24.04 ha in 2017 and will continue to decrease to 16.64 ha in 2024 and 12.03 ha in 2031. The ‘largest patch index’ showed the similar trend as a result of gradual urban encroachment. In contrast ‘edge density’, increases from 16.77 m/ha to 21.17 m/ha during 2005—2031 indicating that the landscape patches turn to be complex. However, the value of ‘mean Euclidian nearest neighbor distance’ decreases from 220.56 m in 2005 to 211.41 m in 2031, indicating coalescence. For fishponds, the ‘patch density’ decreases substantially i.e., from 0.17 in 2005 to 0.09 in 2031, indicating aggregated fishponds areas. Similarly, a significant reduction occurred in the ‘mean patch area’, ‘largest patch index’, and ‘edge density’ during 2005—2017 and they will continue to decrease during 2017—2031 (Figure 18c, e, f).

Due to more dispersed distribution, fragmentation, and heterogeneity in the landscape, ‘Shannon’s diversity index’ and ‘area weighted mean fractal dimension’ increases while, ‘contagion value’ decreases during 2005—2017 and predicted result shows that such trend will continue during 2017—2031 (Figure 18 i-k). This indicating that urban growth will continue in the form of increasing number of clusters as well as expansion of existing urban centers. On the other hand, forest patches will increase and merged to form contiguous patches thus increasing proportion in the landscape and dominating land cover type. Decrease in farmland can be exacerbated due to isolation as indicated by increasing trend in patch density and reduction in the relative proportion in the landscape. This demonstrating that land development will continue to spread over the urban peripheral areas and into the neighboring rural areas. It will be important for policy makers to carefully design and monitor urban growth with least impact on the farmland fragmentation.

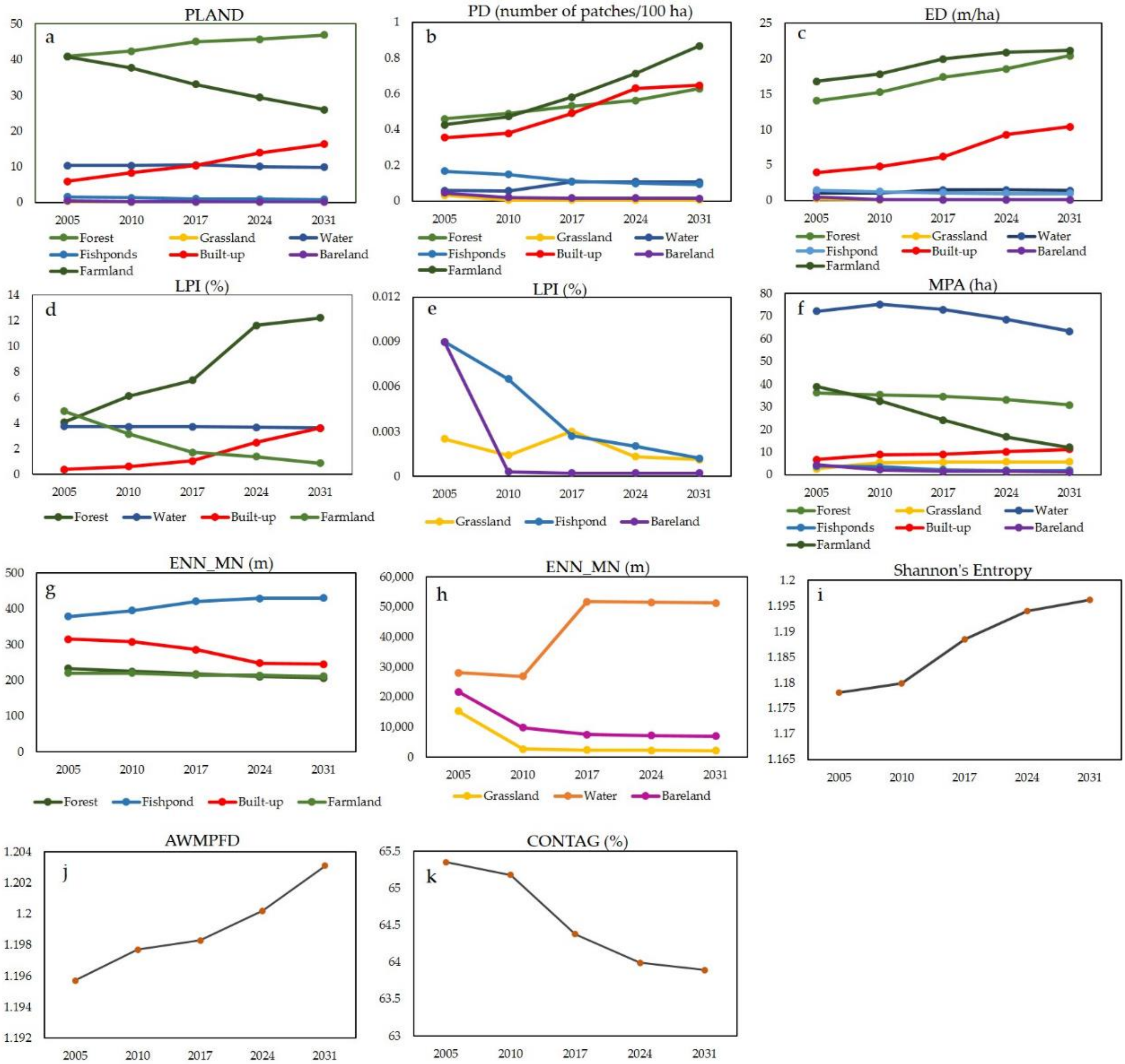

Figure 18. Temporal patterns of landscape metrics from 2005 to 2031 (a) Percentage of landscape (PLAND), (b) Patch density (PD), (c) Edge density (ED), (d, e) Largest Patch Index (LPI), (f) Mean patch area (MPA), and (g, h) Mean Euclidian Nearest Neighbor Distance (ENN_MN) at class level, whereas, (i) Shannon's diversity index (SDI), (j) Area Weighted Mean Fractal Dimension (AWMPFD), and (k) Contagion (CONTAG)) at landscape level.

5.4 Discussion

After the settlement of political insurgency in 1978, the pace of infrastructure development, socioeconomic development, industrialization, and urbanization accelerated in the Guangdong, Hong Kong, and Macao. There is a complex relationship between land use land cover change, anthropogenic activities, and a sustainable future environment (Rimal et al. 2017). Today, a large number of land use land cover and urban growth models have been developed which provide ability to choose a model according to the characteristics of the area of interest and the research questions (Han et al. 2015; Verburg et al. 2004; Verburg and Overmars 2007). In this study, Land Change Modeler was used to predict the land use land cover changes for the next fourteen years. Long-term simulations can be used as a guide for urban studies by giving future forecasts of possible changes under existing patterns and circumstances (Basse, Omrani, Charif, Gerber, and Bodis 2014; Ozturk 2015). However, with the increase in simulation periods, the simulated results may be adversely affected. For example, land use land cover and transportation system are the two utmost imperative sub-systems that influences the long-term shape of a city. With time, they commonly influence each other, (Demirel et al. 2008) and may also affect the demands for travel and access. Construction or expansion of new or existing roads, for example, directly influences the settlements location and density. Thus, it is assumed, that the network of static transportation makes a substantial drawback for simulations of long haul urban development. In this regard, models have shortcoming in temporal dynamics (Basse, Omrani, Charif, Gerber, and Bodis 2014; Ozturk 2015; Rui and Ban 2011). Thus, for this study, on the basis of the continuity of the past trends of 2005—2017, projected maps for the years 2024 and 2031 have been simulated. To validate the model, the simulated image was compared with the actual land use land cover image of the same year i.e., for 2017, all the Kappa values and relative operating characteristics value were greater than 80%. The accuracy of this study shows consistency with previous studies, in which Land Change Modeler and Landsat images were used (Ahmed 2011; Ahmed and Ahmed 2012; Dewan and Yamaguchi 2009a; Dzieszko 2014; GÜLENDAM BAYSAL 2013; Han et al. 2015; Kumar et al. 2015; Megahed et al. 2015; Ongsomwang and Pimjai 2015; Ozturk 2015; Wang and Maduako 2018).

5.4.1 Future consequences of land use land cover changes: built-up and farmland

After the opening of the economic corridor, the Chinese government launched a series of policies such as the "Household Production Responsibility System (HPRS)" and the "market-directed economic system". These policies have headed explicit conversion of land use land cover, such as transformation of farmland into built-up land (Y. Hu et al. 2019). During 2005—2017, the built-up area boomed from 5.84% to 10.31% and the modeling results confirm that it will continue to increase to 16.30% by 2031, at a cost of substantial reduction in both farmland (from 40.77% in 2005 to 26.00% in 2031) and fishponds (from 1.56% to 0.83% during 2005—2031). This trend is also reflected in the landscape metrics i.e., patch density, largest patch index, and edge density increases for built-up land and decreases for fishponds whereas, mean patch area decreases for both of them. Therefore, in each successive period, a high industrialization rate and socioeconomic development causes the expansion of built-up land beyond the administrative boundary of the counties, and urban growth exceeded the outskirts of the surrounding regions. This is also because of increase in household income/personal income level, living standards, and a reduction in traditional farming activities (Wang and Maduako 2018). However, the continuous development of historical city centers, more fragmented growth, and increasing coalescence between land cover neighbor's causes decrease in mean euclidian nearest neighbor distance of built-up land and farmland. Moreover, increase in Shannon's diversity index claims a high urban rate and dispersion of urban development within the period of study, causing a noteworthy influence on the urban peripheral (Araya and Cabral 2010). With the increase in fragmentation, the contagion value decreased due to more individual units such as urban units.

These changes are more pronounced in the Pearl River Delta (PRD) and on the east flank of the Guangdong, Hong Kong, and Macao. These two regions account for 57% of the Guangdong, Hong Kong, and Macao total population (Hasan et al. 2019). The probable reason is that these regions lie at a low elevation, and are more suitable for settlement than the high-elevated areas. Thus, unprecedented growth of built-up areas has overwhelmed the primitive rural areas and encompass an economic corridor from the PRD and the eastern sides towards the surrounding outskirts (Han et al. 2015; Wang and Maduako 2018). However, increase in the proportion of urban dwellers have confirmed a rising competition between consumers in the property and land market (Chen et al. 2018).

Such changes in land cover are attributed to the land use land cover regulations, which allowed the sale of the state ownership land in the property market, while the sale of collective land ownership is not allowed (Wu et al. 2006). This rapid development of built-up land has significantly contributed to provide much lose space for other land use types, such as built-up areas. Additionally, the reason for the conversion of farmland into urban land is that the local government confiscated collectively owned farmland for public and commercial purposes and remunerated farmers for the loss of the affected lands. The confiscated land, then became state-owned and the rights of its land use transferred by sale, tender or agreement. A special market substance was established by the government and its related operational departments (Wu et al. 2006).

Thus, these simulated results helped urban planners and policy decision makers to learn that further expansion of urban land and urban population could result in increased traffic jams, transformation of open spaces, increased travel time, residential energy consumption (Poelmans and Van Rompaey 2009), and changes in living standards (Wu et al. 2006).

5.4.2 Proximate and underlying factors

Proximate and underlying factors of communal facility availabilities and rural urban connections (Rimal et al. 2017) have also ominously played a key role in the population migration in the Guangdong, Hong Kong, and Macao. Distance from roads and distance from water channels are also consider an imperative spatial determinant for urban development, thus indicating that non-urban area near to the city center has the higher probability of being converted into built-up land. Such areas were ripe for further urban planning (Wang and Maduako 2018). The next important factors for urban growth were slope, aspect, and hillshade (Rimal et al. 2017; Wang and Maduako 2018). The unparalleled combination of economic development, population, and the unintended byproducts of the growth of government policies has contributed to the social structure change of the Guangdong, Hong Kong, and Macao from a largely rural society to an urban society. Most importantly, urbanization and industrialization have significantly provoked farmland reduction in the Guangdong, Hong Kong, and Macao (Y. Hu et al. 2019; Wu et al. 2006). All the above mention drivers were should considered by policy decision makers when addressing land use development and the resulting key sustainability problems (Rimal et al. 2017).

5.4.2.1 Forest cover increases

During 2005—2017, forest cover increased to 45.02% from 40.84% and simulation results show that it will continue to increase to 46.88% in 2031. This trend can also be observed in the increasing patch density, largest patch index, and edge density of forest cover. Of further interest, mean euclidian nearest neighbor distance of forest cover decreased as the distance between forest neighbors shrank. This increase in forest cover indicates that forest policies and afforestation programs is likely to continue in the study area. These programs may include “China Biodiversity Conservation Action Plan (1994) (CBCAP)” (Bentai, W. & Chunyu 1994), the “Forestry Action Plan for China’s Agenda 21 (1995) (FAPCA)” (Klawitter 2004), the “China Ecological Environment Conservation Plan (1998) (CEECP)”, the “China Wetland Protection Action Plan (2000) (CWPAP)”, the “China Mangrove Protection Management (CMPM)”, and the “Utilization Plan (2002) (UP)” (Y. Hu et al. 2019; Jia et al. 2015). Forest cover in China, also increased because of the development of eucalyptus plantations on a large scale. Plantation of eucalyptus is not only limited to Guangdong but are also planted in most of southern China, such as, Guangxi, Sichuan, Yunnan, Hainan, and Fujian provinces, because of the high demand for timber products and high ecological value. Development of eucalyptus plantations on large scale for logging, however, also prompted the conversion of farmland. Therefore, to protect farmland conversion, it is essential to control the demand of timber products using numerous methods, such as, decreasing the usage of disposable chopsticks and avoid the wastage of paper (Y. Hu et al. 2019). The significant growth of eucalyptus has caused a set of potential ecological issues, such as water deprivation, biodiversity loss, and fertilizer consumption (Y. Hu et al. 2019).

In summary, the future simulation of land use land cover change, based on the Land Change Modeler, have significant ramifications for urban planning and management of the Guangdong, Hong Kong, and Macao (Wu et al. 2006). The simulated results, given above in section 5.3.4 and 5.3.5 provide significant insights into the future land use land cover development, and will hence provide a better understanding of the area’s growth patterns and the necessity for suitable sustainable development, together with the protection of farmland during planning developmental. To a large extent, when planning a city or city growth the consequence of urban sprawl is a necessary consideration.

5.5 Conclusions

During the last two decades, the Guangdong, Hong Kong, and Macao (GHKM) has experienced substantial changes in land use land cover with induced socioeconomic activities. This study has examined the features of land use land cover change and simulated future land use land cover and urban growth of the GHKM using Land Change Modeler (LCM). To validate the model, the projected 2017 land use land cover map was compared with 2017 actual land use land cover map. After successful model validation, the land use land cover map for the years 2024 and 2031 are predicted. The simulated results showed an expected increase in built-up areas from 10.31% in 2017 to 16.30% in 2031 with the substantial decrease in farmland from 33.03% to 26.00% and fishponds from 0.97% to 0.83% during 2017—2031. Forest cover, however, will increase from 45.02% in 2017 to 46.88% in 2031 due to afforestation programs and reduction in farming activities. The spatial structure analysis of the landscape exhibits more disperse, heterogeneous, and fragmented landscape in future. Such changes in land use land cover are attributed to intense socioeconomic development, industrialization, and continuously sprawling urban fabric in urban pockets at suburban and peripheral areas. This unprecedented urbanization and an alarming loss of farmland could ultimately threaten to natural resources and food security. However, timely actions must be taken by urban planners and policy-decision makers to enable sustainable development as well as the protection of farmlands and other natural resources.

Chapter 6

6 Impact Of Land Use Land Cover Changes On Ecosystem Service Value – A case study of Guangdong, Hong Kong, And Macao In South China[4]

6.1 Introduction

Ecosystem services (ES) can be described as the condition and processes through which natural ecosystems, and the species that comprise them, sustain and fulfill human well-being (Costanza, Batabyal, et al. 1997; Costanza, D'Arge, et al. 1997; Daily 1997). Ecosystem services can be considered as the goods and services that benefit human life both directly and indirectly (Feng et al. 2012; Zhan 2015). These services include supporting services, regulating services, provisioning services, and cultural services. These services incorporate benefits to the society (Lin et al. 2018; Zhan 2015; Y. Zhang et al. 2015). In connection to rapid economic development, intense human activities and urbanization in the fastest burgeoning developing countries has placed pressure in the deterioration of key ES (Łowicki and Walz 2015; Ye, Zhang, et al. 2018; Zorrilla-Miras et al. 2014). Thus, the endowment of ES, its structure, and functions greatly influenced by changes in patterns, practices, and intensity of land use land cover (LULC) (Costanza et al. 2014; Fu et al. 2015; Gaglio et al. 2017; Li et al. 2010; Ye, Zhang, et al. 2018). Such changes in land cover have put both ecosystems and humans at risk and are expected to continue to increase in the future (Mamat et al. 2018; Yirsaw et al. 2016; Zhan 2015). Therefore, increasing imbalance provision of ecosystems under the rapidly growing urbanization and development have become a focus of concern (Y. Zhang et al. 2015). Such situations are more pronounced in developing countries such as China.

Since China initiated the opening of economic reform and policy in 1978, socioeconomic development and adaptation of several land use policies have driven significant changes in LULC

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[4] This chapter is based on a published study and being reproduced with the permission of PLOS ONE.

Hasan, S., Shi, W., & Zhu, X. (2020). Impact Of Land Use Land Cover Changes On Ecosystem Service Value – A case study of Guangdong, Hong Kong, And Macao In South China. *PLOS ONE, 15*(4), 1–20. https://doi.org/10.1371/journal.pone.0231259 with increasing speed, breath, and depth (Chen et al. 2018). These changes have resulted in the urban expansion, loss of farmland (Mamat et al. 2018; Song and Deng 2017a), ecological damage (Y. Zhang et al. 2015), and horticultural development without proper planning and management of prevailing land resources (Yirsaw et al. 2016). China’s total urban population has increased from 11.80% in 1950 to 58.52% in 2017, which is predicted to reach 76.10% by the end of 2050 (Anon 2017). The increasing human populace and socioeconomic development have confronted genuine difficulties in ecological land, various ecosystem services value, and food security both in space and time (Mamat et al. 2018; Zhan 2015). Thus, knowledge of economic valuation, analysis, and quantification of the effect of ongoing development on ES are necessary for policy decision makers in both the exploration of the means to achieve socioeconomic and ecological sustainable development (Elmqvist et al. 2015; Gómez-Baggethun and Barton 2013; Ye, Bryan, et al. 2018). Therefore, in recent year, ecosystem services have started gaining importance in order to reveal the coevolution process of both nature and human (Zhan 2015).

Several studies have been performed to monitor the impact of LULC changes on the structure and functions of ESV in numerous regions of China (Cai et al. 2016; Chang-ping 2010; Chen et al. 2014; Feng et al. 2012; Hao et al. 2012; Hu et al. 2013; Li et al. 2014; Liu, Li, and Zhang 2012; Song and Deng 2017a; Wang et al. 2006; Wang and Sun 2016; Wu et al. 2013; Yan-qiong, Jia-en, and LI Yun 2011; Ye, Zhang, et al. 2018) and around the world (Baró et al. 2015; Cai et al. 2013; Estoque and Murayama 2013; Hu et al. 2013; Kreuter et al. 2001; Liu, Li, et al. 2012; Long et al. 2014b; Mendoza-González et al. 2012; Su et al. 2014; Sudhira and Nagendra 2013; TEEB 2013; Tianhong et al. 2010; Wu et al. 2013; Ye et al. 2015; Yi et al. 2017; Yirsaw et al. 2016). Due to LULC changes and urbanization, most of these studies showed moderate to significant decrease in ESV (Hu et al. 2013; Mamat et al. 2018; Su et al. 2014; Tianhong et al. 2010; Wu et al. 2013; Yirsaw et al. 2016) while others found almost no change (Han et al. 2016). Some studies have also revealed an increase in ESV (Fang et al. 2014; Li and Ding 2017; Y. Wang et al. 2014; Xia et al. 2018). Such variations in the services value are of the following reasons. Firstly, in terms of fast urbanization and industrialization, several changes in LULC occur concurrently, as a result of not only limited to urban sprawl but also include various contending demands. These include reforestation and protection, natural indemnity, infrastructure development, comfort, and tourism and recreation (Bryan et al. 2015; Bryan and Crossman 2013). Secondly, there is a very close relationship between ESV types and LULC utilization (J. Liu et al. 2007; Ye, Bryan, et al. 2018). Given their profound implication and distinct nature and characteristics, the capability to summarize and apply the results of these case studies to other regions is limited. Thus, indicating the importance of studying the impact of LULC changes on ESV, which is essential to inform policy and decision-makers for sustainable planning and management and safe ecological system.

Several methods exist to enable the quantification of the global terrestrial ecosystem services value but the method most commonly used is the “benefit transfer” developed by Costanza’s et al. (1997) (Costanza, D’Arge, et al. 1997). They classified the world ecosystems into 16 types and 17 subtypes as their services functions. Their results, however, have been seriously condemned when applied to China. For example, bias in some cases such as underestimated farmland ESV and overestimated wetland ESV (Cai et al. 2013). Their derived ESV mirrored the economic level of developed countries (e.g., United States and European countries) instead of developing countries such as China (Liu, Li, et al. 2012; Song and Deng 2017a; Wang et al. 2015). For Chinese terrestrial ecosystem services Xie et al. (2003) developed the equivalent per-unit-area following the same methodology proposed by Costanza et al. (1997) (Costanza, D’Arge, et al. 1997). They extracted the equivalent weight factor via a survey of 200 Chinese ecologists. Combined with land use data, equivalent per-unit-area values were widely used in a different regions of China to calculate ESV (Cai et al. 2013; Feng et al. 2012; Ye et al. 2015; Ye, Zhang, et al. 2018; Zhou et al. 2017). Using this method, LULC can act as a proxy by coordinating the land cover type proportional to the biomes. The later then assign the economic values centered on a standard, adjusted locally, and value of coefficients set. This method provide a type of multi-criteria technique, enabling the integration of diverse distinctive measurements into a solitary money related unit. Furthermore, this approach provides repeatable and comparable results, an assessment of change with time, and crosswise over a heterogeneous urbanization perspective.

Hence, it gives a constant mode to enhance knowledge with time through different case studies (Liu, Li, et al. 2012; Ye, Bryan, et al. 2018; Ye, Zhang, et al. 2018).

The present study focus on Guangdong, Hong Kong, and Macao (GHKM) located in South China. Since 1978, economic development and urban expansion in GHKM has caused this region to become one of the fastest developing regions in the world. This has resulted in harsh natural conditions, overconsumption, and deterioration of provisioning services from nature and put both ecosystems and well-being at risk (Ye, Bryan, et al. 2018; Ye, Zhang, et al. 2018; Zhan 2015). The Chinese government has initiated different measures to improve the deteriorated ecological environment, by means of such as an increase in forest cover and to protect high productive cropland. The imbalance provision of ES is the main restricted factor both in social and economic sustainable development in the GHKM (Y. Zhang et al. 2015). Therefore, limited/not enough studies have been conducted in the GHKM that provides a comprehensive understanding and estimating the impact of such changes in land cover and policies on the ES. Hence, the objective of this study are as follows: to evaluate and quantify the effect of LULC changes on ESV in GHKM from 1986 to 2017, to assign the specific coefficient of ESV to each land use category using the established unit-value transfer method, and to scrutinize the impact of LULC changes on ESV. The contribution of individual ecosystem service functions changes during the study period based on modified coefficient. The coefficient of sensitivity is then assessed to estimate the uncertainty in the value coefficient. On the bases of the results, this study also aims to provide information useful to urban planners and decision-makers for the regional coordinate and sustainable development.

6.2 Materials and Methods

6.2.1 Acquisition of Data and land use land cover classification

LULC data play a pivotal role to evaluate the ESV and the availability of historical LULC data provides an adequate ground to analyze changes in ESV (G. Li, Fang, and Wang 2016). The LULC data for the GHKM have been produced in the chapter 4 (Hasan et al. 2019) which is based on the classification of multi-temporal Landsat images (TM/ETM+/OLI) at 30m resolution for the years 1986, 1989, 1994, 2000, 2005, 2010, and 2017. Each LULC map comprises of the seven classes

(Table 2). The overall accuracy of the classified LULC maps was about 91% and Kappa 0.88 (Hasan et al. 2019). To detect LULC changes, a cross-tabulation detection method was used to quantify the transitions. The LULC changes, related to seven images, were also mapped and graphed (Hasan et al. 2019). The data was then used to estimate changes in various ESV and spatial analyses.

6.2.2 Assigning ecosystem service value (ESV)

In this study, we used the ES classification which is based on nine ecosystem services (Table 16) proposed by Xie et al. (2003) (their meaning and importance described in Table 25-S6). By tailoring the localized average natural grain yield, the equivalent weight factor, as shown in Table 16, can be applied to different regions of China. As a benchmark, the economic value of average natural grain production of farmland per year was set at 1.0 (Chen et al. 2014; Estoque and Murayama 2013; Han et al. 2016; Liu, Li, et al. 2012; Tianhong et al. 2010; Ye, Zhang, et al. 2018). Based on this factor, all other coefficients were adjusted accordingly. Xie et al. (2003) proposed that in general, the natural food production should be 1/7 of the actual food production (Liu, Li, et al. 2012; XIE et al. 2003).

From 1986 to 2017, GHKM's average actual grain production was 5529.76 kg/ ha and the average grain price in 2017 was 2.65 CNY/kg. Thus, the ESV of one equivalent weight factor for GHKM is 2093.41 CNY ha^{-1} (5529.76*2.65/7).

On the basis of the linkage between LULC types and biome types, the ESV per unit area of each LULC class in GHKM was assigned (Table 16). Specifically, LULC types "forest", "grassland", "water", "fishponds", "built-up", "bare land", and "farmland" equal to biome types "woodland", "grassland", "water body", "wetland", "construction land", "unused land", and "cropland", respectively. For built-up, the coefficient value proposed by following Dong et al. (2007) (Dong et al. 2007) and Deng (2012) (Deng 2012) was considered. In this study, although the biomes used as proxies for each type of LULC do not perfectly match in each case however, they are related (Kreuter et al. 2001). Their use has been proven feasible in other case studies (Liu, Li, et al. 2012; Song and Deng 2017a; Tianhong et al. 2010; Wu et al. 2013).

Table 16. Equivalent weighting factor per hectare ESV of Chinese terrestrial ecosystems (Xie et al. (2003)).

	Forest	Grassland	Water	Fishponds	Built-up	Bareland	Farmland
Food	0.1	0.3	0.1	0.3	0.01	0.01	1
Raw material	2.6	0.05	0.01	0.07	0	0	0.1
Gas regulation	3.5	0.8	0	1.8	-2.42	0	0.5
Climate regulation	2.7	0.9	0.46	17.1	0	0	0.89
Water supply	3.2	0.8	20.4	15.5	-7.51	0.03	0.6
Waste treatment	1.31	1.31	18.2	18.18	-2.46	0.01	1.64
Soil formation and retention	3.9	1.95	0.01	1.71	0.02	0.02	1.46
Biodiversity protection	3.26	1.09	2.49	2.5	0.34	0.34	0.71
Recreation and culture	1.28	0.04	4.34	5.55	0.01	0.01	0.01
Total	21.85	7.24	46.01	62.71	-12.01	0.42	6.91

6.2.3 Ecosystem service value calculation

By using Equation (14), Equation (15), and Equation (16) the ecosystem service value, ecosystem function, and total ESV for each thematic class was determined after evaluating the ESV per unit area for each land cover class (Feng et al. 2012; Tianhong et al. 2010; P. Zhang et al. 2015; Zhu et al. 2017).

$$ESV_k = \sum_f A_k * VC_{kf} \tag{14}$$

$$ESV_f = \sum_k A_k * VC_{kf} \tag{15}$$

$$ESV = \sum_k \sum_f A_k * VC_{kf} \tag{16}$$

Where, ESV_k represents the ESV for LULC class “k”, ESV_f represents the value of ecosystem function type “f”, and ESV represents the total ESV respectively. $A_k$represents the area for LULC class “k” and VC_{kf} represents the value coefficient (CNY/ha/a) for LULC class “k” and ecosystem function type “f” (Feng et al. 2012; Tianhong et al. 2010; P. Zhang et al. 2015).

6.2.4 Sensitivity analysis

Since the biomes used as proxies do not perfectly match the LULC class (as mention above in section assigning ecosystem service value (ESV)) and there exist uncertainties in the coefficient values, sensitivity analysis is needed to determine the dependence level of the change of the ESV upon the coefficient values. Therefore, the standard economic elasticity concept was used to calculate the coefficient of sensitivity (CS) as follows:

$$CS = \left| \frac{(ESV_j - ESV_i)/ESV_i}{(VC_{jk} - VC_{ik})/VC_i} \right| \tag{17}$$

The percentage change in the ESV calculated resulting from ± 50% change in the coefficient value and LULC class 'k'. "i" and "j" indicate the respective initial and adjusted values. If CS > 1, the estimated ESV is elastic, relative to that coefficient, whereas if CS < 1 than the estimated ESV is considered to be inelastic. The more prominent the corresponding change in the ESV with respect to a relative change in the coefficient value, the more serious is the utilization of a precise ecosystem value coefficient. However, in previous studies, the sensitivity analysis has been widely used (Aschonitis et al. 2016; Feng et al. 2012; Kreuter et al. 2001; Liu, Li, et al. 2012; Mamat et al. 2018; Tianhong et al. 2010; Wang et al. 2015; Ye, Bryan, et al. 2018; Zhu et al. 2017).

6.3 Results

6.3.1 Land use land cover change

Guangdong, Hong Kong, and Macao LULC changed substantially between 1986 and 2017 (Figure 4). Farmland had the greatest decline in the area among the seven LULC classes (-40191.84 km^2, -38.23%), followed by fishponds (-788.61 km^2, -32%) and water (-152.22 km^2, -0.73%). On the other hand, forest exhibited the largest increase (23126.88 km^2, 35.40%), followed by built-up land (18753.44 km^2, 1260.02%). As compared to other thematic classes, the built-up area increases with the highest annual growth rate i.e., 8.41% (Table 3). The estimated size of both water and fishponds were relatively small but they both play a vital role in ES and often have high service value. Their cumulative area accounts for only 11% of GHKM's total area, which even seemed to declines during socioeconomic development and urbanization. The major transformation observed were farmland into built-up land and forest whereas, fishponds into built-up land (Table 23-S4). Thus, farmland and fishponds are the primary contributors to the new built-up areas. The transformation among different LULC classes certainly affects ecosystems structures and functions as well as variation in the total ESV. Therefore, estimating changes in the ESV in response to LULC changes are described in the below sections.

6.3.2 Variations in ecosystem service value

In this study, based on the Equations (14)–(16) the ESV of each land cover class and total ESV of the GHKM for the years 1986, 1989, 1994, 2000, 2005, 2010, and 2017 were calculated using the modified value coefficients (Table 17) and the area of each LULC (Figure 4). According to the results, shown in Table 18, it can be indicated that the general ESV trend is characterized by a variable change process. During the study period, in GHKM's total ESV surged from 680.23 billion CNY in 1986 to 713.68 billion CNY in 1994, then declined to 668.45 billion CNY in 2017. In the first eight years (1986—1994), the total value of ESV increased by approximately 33.45 billion CNY. The ESV net benefits per hectare was 1703.38 CNY. In the following 23 years (1994—2017), ESV loss was about 45.22 billion CNY, and the net loss of ESV per hectare was 2303.04 CNY. This net gain and loss in ESV are due to the LULC changes during the study period.

Table 17. Per unit area ESV of different LULC classes in the Guangdong, Hong Kong, and Macao (CNYha^{-1}year^{-1}).

	Forest	**Grassland**	**Water**	**Fishponds**	**Built-up**	**Bareland**	**Farmland**
Gas regulation	7326.94	1674.73	0.00	3768.14	-5066.05	0.00	1046.71
Climate regulation	5652.21	1884.07	962.97	35797.31	0.00	0.00	1863.13
Water supply	6698.91	1674.73	42705.56	32447.86	-15721.51	62.80	1256.05
Soil formation and retention	8164.30	4082.15	20.93	3579.73	41.87	41.87	3056.38
Waste treatment	2742.37	2742.37	38100.06	38058.19	-5149.79	20.93	3433.19
Biodiversity protection	6824.52	2281.82	5212.59	5233.53	711.76	711.76	1486.32
Food	209.34	628.02	209.34	628.02	20.93	20.93	2093.41
Raw material	5442.87	104.67	20.93	146.54	0.00	0.00	209.34
Recreation and culture	2679.56	83.74	9085.40	11618.43	20.93	20.93	20.93
Total	45741.01	15156.29	96317.79	131277.74	-25141.85	879.23	14465.46

Table 18. Total ESV for each land use type in the Guangdong, Hong Kong, and Macao from 1986 to 2017.

		Forest	**Grassland**	**Water**	**Fishponds**	**Built-up**	**Bareland**	**Farmland**	**Total**
ESV billion CNY	**1986**	298.50	0.70	200.30	32.34	-3.74	0.07	152.07	680.23
	1989	326.18	0.40	201.38	38.59	-6.65	0.03	148.35	708.28
	1994	346.90	0.53	201.21	49.46	-13.69	0.07	129.19	713.68
	2000	359.15	0.33	199.07	45.64	-21.07	0.02	122.69	705.84
	2005	366.72	0.61	194.13	41.38	-28.87	0.08	115.79	689.84
	2010	380.64	0.22	194.65	32.18	-40.75	0.02	106.90	673.84
	2017	404.28	0.29	198.83	21.99	-50.89	0.02	93.93	668.45
1986—1989	billion CNY	27.68	-0.30	1.07	6.25	-2.91	-0.03	-3.72	28.05
	%	9.27	-42.53	0.54	19.32	77.71	-47.15	-2.45	4.12
	%/yr	3.00	-16.86	0.18	6.06	21.13	-19.15	-0.82	1.36
1989—1994	billion CNY	20.72	0.13	-0.17	10.88	-7.04	0.03	-19.15	5.40
	%	6.35	32.48	-0.08	28.19	105.81	90.29	-12.91	0.76

	%/yr	1.24	5.79	-0.02	5.09	15.53	13.73	-2.73	0.15
1994—2000	billion CNY	12.26	-0.20	-2.14	-3.82	-7.39	-0.04	-6.50	-7.84
	%	3.53	-38.54	-1.06	-7.73	53.97	-63.09	-5.03	-1.10
	%/yr	0.58	-7.79	-0.18	-1.33	7.46	-15.30	-0.86	-0.18
2000—2005	billion CNY	7.56	0.28	-4.94	-4.26	-7.80	0.06	-6.90	-16.00
	%	2.11	85.51	-2.48	-9.34	36.99	234.30	-5.62	-2.27
	%/yr	0.42	13.15	-0.50	-1.94	6.50	27.30	-1.15	-0.46
2005—2010	billion CNY	13.92	-0.39	0.51	-9.20	-11.89	-0.06	-8.90	-16.00
	%	3.80	-64.10	0.26	-22.23	41.18	-76.72	-7.68	-2.32
	%/yr	0.75	-18.53	0.05	-4.90	7.14	-25.29	-1.59	-0.47
2010—2017	billion CNY	23.65	0.07	4.19	-10.19	-10.14	0.01	-12.97	-5.39
	%	6.21	32.32	2.15	-31.67	24.87	26.71	-12.13	-0.80
	%/yr	1.21	5.76	0.43	-7.33	4.54	4.85	-2.55	-0.16
1986—2017	billion CNY	105.78	-0.41	-1.47	-10.35	-47.15	-0.04	-58.14	-11.77
	%	35.44	-58.77	-0.73	-32.01	1260.02	-63.39	-38.23	-1.73
	%/yr	0.98	-2.82	-0.02	-1.24	8.78	-3.19	-1.54	-0.06

A substantial decrease in total ESV (1.73%) between 1986 and 2017 was due to loss of semi-natural land cover types, especially shrinkage in farmland and unprecedented increase in urbanization. However, the loss of farmland was far higher than the loss by urbanization (Table 18). This causes a significant effect in loss of ESV. Though the ESV of other LULCs had increased, such as increase in forest cover but increase was too small to counterbalance the decline. Despite the fact that both water and fishponds covered small areas but they had the highest value coefficients. Therefore, they produced a service value nearly equal to that of the forest. High service value was also produced by farmland due to its large area coverage. The accumulated ESV of forest, water, fishponds, and farmland exceeded 90% of the total value, showing that these land cover classes played a key role in ecosystem services. This is particularly true regarding fishponds whose area was only 0.85–1.9%, yet produced 3–7% of the total ESV. It is assumed that the ESV for bareland and built-up land is much lower due to its low value coefficients.

6.3.3 Change in ecosystem function

The individual ecosystem function (computed using Equation 15) contribution rate to the total ESV are ranked on the basis of their estimated average ESV_f for the years 1986, 1989, 1994, 2000, 2005, 2010, and 2017 (Table 24-S5). Water supply, waste treatment, soil formation and retention, and biodiversity protection were the most valuable ecosystem services, affecting the total ESV. However, their combined contribution accounted for 65.07%. The highest decline occurred in the water supply value (-22.30 billion CNY, -14.72%) between 1986 and 2017 followed by waste treatment (-20.77 billion CNY, −14.63%) and food production (-7.96 billion CNY, −33.18%). Conversely, soil formation and retention (6.28 billion CNY, +7.26%) and recreation and culture (5.09 billion CNY, +12.91%) have experienced a significant increase in value (Figure 19). Recreation and culture and food production made the least contribution to the ESV, with their accumulated contribution rate was only approximately 9.14%.

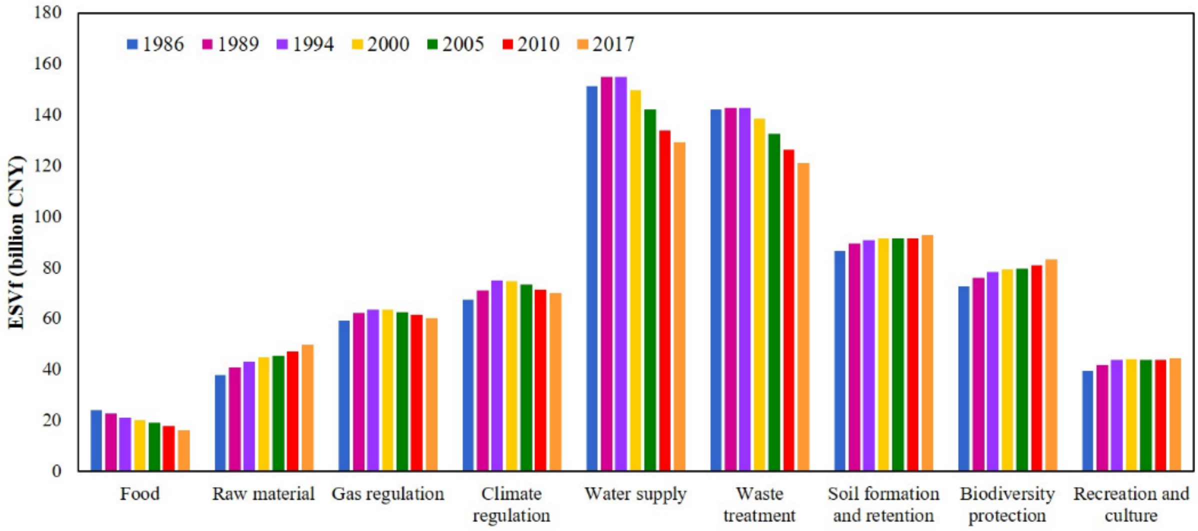

Figure 19. Value of individual ESV in the Guangdong, Hong Kong, and Macao from 1986 to 2017.

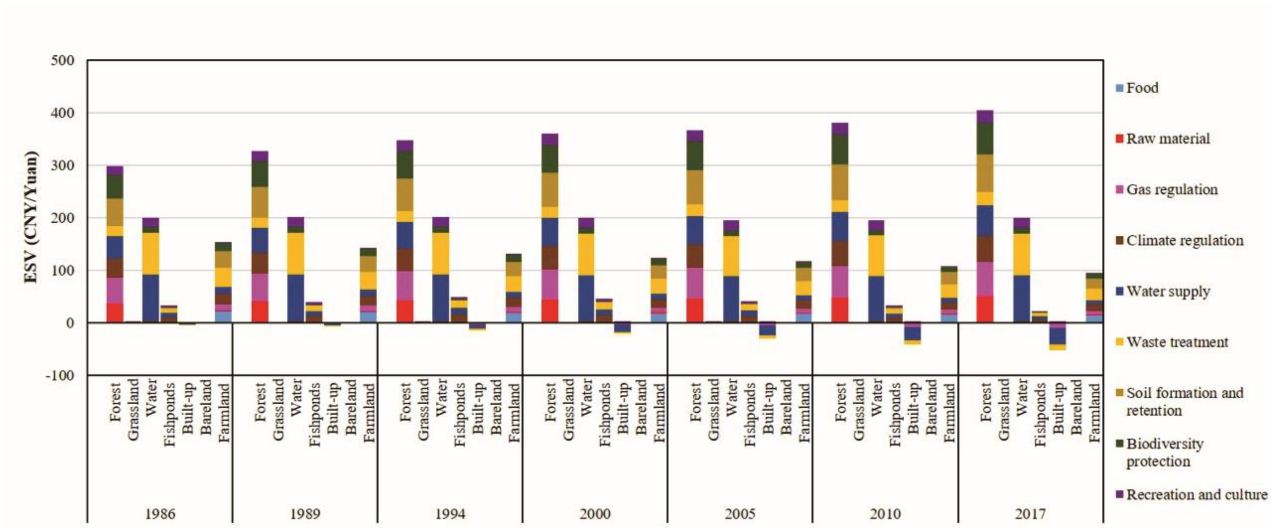

Figure 20. Individual ESV for different land use land cover in the Guangdong, Hong Kong, and Macao from 1986 to 2017.

Due to the large area and the high coefficient value, forest produced the highest ESV among the seven LULC classes i.e., 50% of the total value. It has a significant effect on biodiversity protection, gas regulation, water supply, climate regulation, and soil formation and retention (Figure 20). In 1986 water ESV was 200.30 billion CNY, which decreased by 1.47 billion CNY by 2017 with a robust influence on water supply and waste treatment. Farmland ESV was most affected by LULC changes, decreased by 58.14 billion CNY (38.23%) between 1986 and 2017. This has influenced soil formation and retention, waste treatment, biodiversity protection, and food production. Built-up area, increased by 18,753km^2 (1260.02%) between 1986 and 2017, produced increasingly negative ESV (47.15 billion CNY), notably through effects on water supply, waste treatment, and gas regulation (Figure 20). However, the increase in the built-up area did not increase the ESV, as its coefficient value was zero, close to zero, and less than zero. This resulted in a rapid reduction in the individual value of ecosystem functions.

6.3.4 Spatial Distribution

The ESV varied spatially across the Guangdong, Hong Kong, and Macao. The ESV in the hilly and mountainous areas and in the southern regions of the GHKM was greater mainly due to the forest extent. In the PRD region and on the eastern side, ESV was low because of the development of the built-up area under fast growing urbanization. The urban areas were immediately surrounded by medium value farmland and water (Figures 21 and 22). Furthermore, individual ecosystem functions such as water supply, waste treatment, climate regulation, gas regulation, and food production decreased significantly in the PRD and on the eastern side of the GHKM during the study period (Figure 22). This is mainly because unprecedented industrialization, foreign direct investment, intense human activities, and socioeconomic development have been observed in these regions. Moreover, biodiversity protection, recreation and culture, raw material, and soil formation and retention have increased during 1986 and 2017 more pronounced in the mountainous region and on the southwestern side (Figure 22). This is the result of enaction of different land policies such as the "Forestry action plan for China Agenda 21 (1995)" and "Utilization Plan (2002)". On the other hand, they decreased in the PRD and on the eastern side (Figure 23).

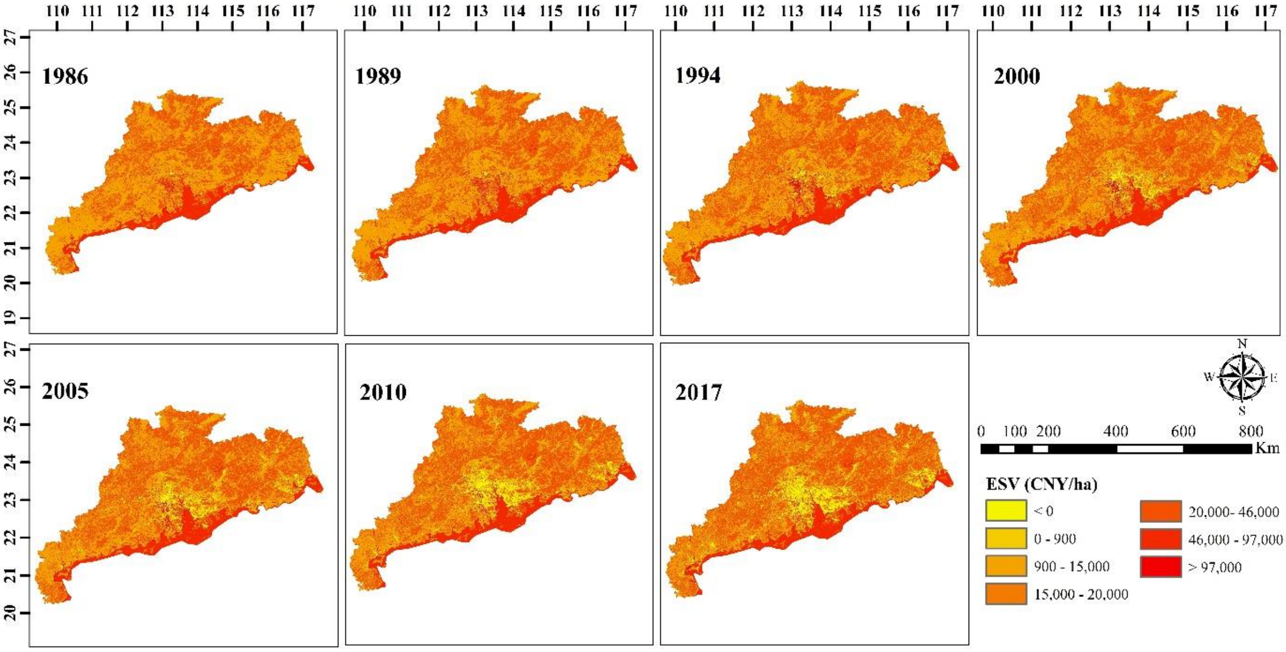

Figure 21. Spatially distributed total ESV in the Guangdong, Hong Kong, and Macao from 1986 to 2017.

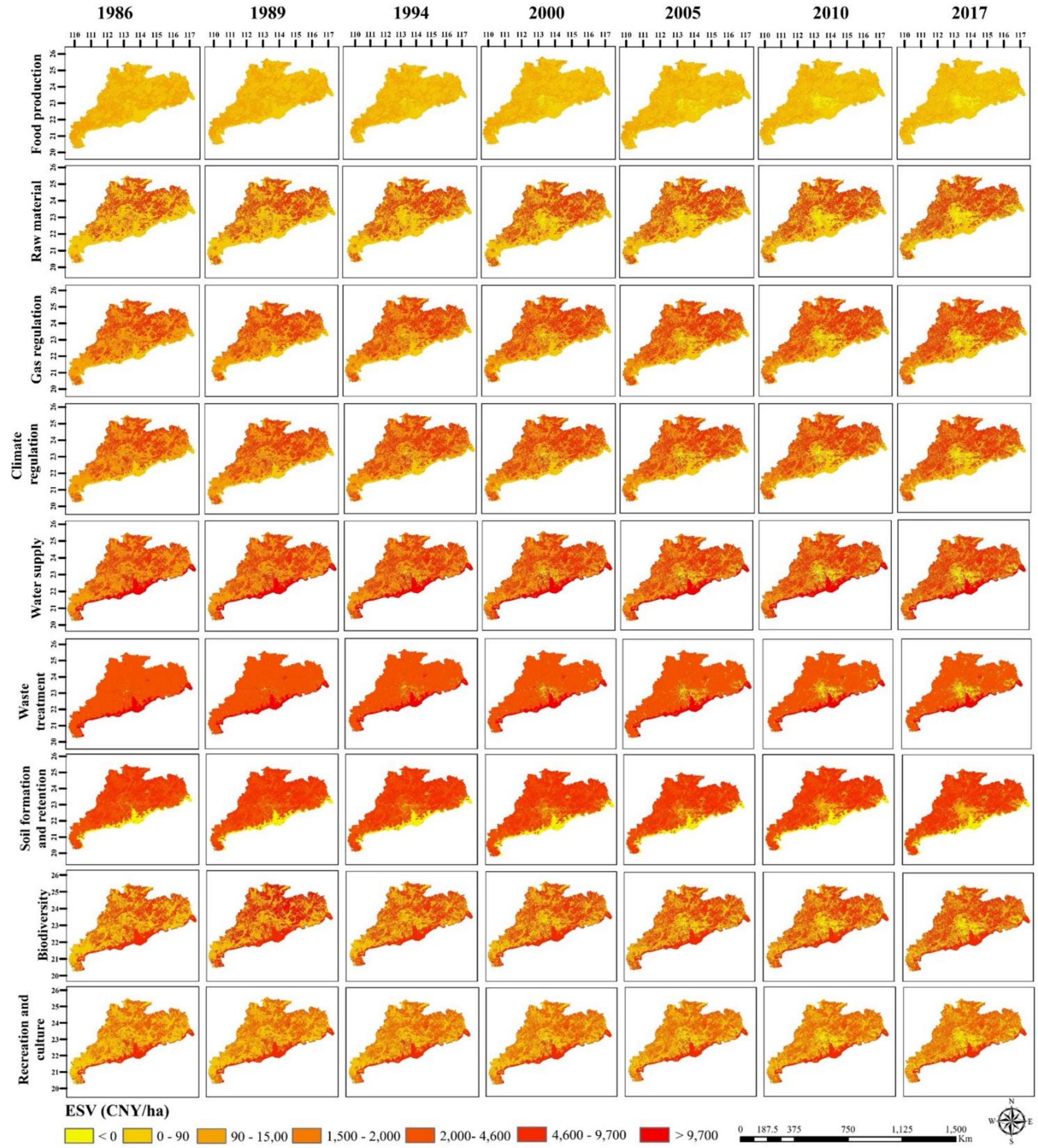

Figure 22. Spatial distribution of individual ecosystem functions in the Guangdong, Hong Kong, and Macao from 1986 to 2017.

6.3.5 Sensitivity analysis

Sensitivity analysis was performed in order to assess the reliability of the results. The changes in the coefficient of sensitivity (CS) value must be relatively low i.e., less than one (in Equation (17)). In all cases, values of CS < 1 and often are near to zero (Table 19). This confirms that the total ESV estimation was relatively inelastic in relation to the coefficient value (Mamat et al. 2018). The CS for forest, water, farmland, and fishponds was relatively large. Forest has the highest coefficient of sensitivity, about 0.5%, due to its high coefficient value and large area. Though the water and fishponds areas were small, their CS was relatively large because of their high value coefficients. Their CS decreased from 0.29 to 0.28 and 0.05 to 0.03 during the study period (Table 19). As compared to forest and water, the CS of farmland is lower, declining from 0.22 to 0.14 during 1986—2017. The decrease in farmland and fishponds CS was mainly the result of an increase in urbanization and industrialization. Thus, in this present study, the sensitivity analysis showed that the estimation was robust despite uncertainties in the value coefficients.

Table 19. Percentage wise change in the coefficient of sensitivity (CS) and estimated total ESV by 50% adjustment in the value of coefficient (VC).

	1986		1989		1994		2000		2005		2010		2017	
	%	CS	%	CS	%	CS	%	CS	%	CS	%	CS	%	CS
Forest VC±50%	21.94	***0.44***	23.03	***0.46***	24.30	***0.49***	25.44	***0.51***	26.58	***0.53***	28.24	***0.56***	30.24	***0.60***
Grassland VC±50%	0.05	***0.00***	0.03	***0.00***	0.04	***0.00***	0.02	***0.00***	0.04	***0.00***	0.02	***0.00***	0.02	***0.00***
Water VC±50%	14.72	***0.29***	14.22	***0.28***	14.10	***0.28***	14.10	***0.28***	14.07	***0.28***	14.44	***0.29***	14.00	***0.28***
Fishponds VC±50%	2.38	***0.05***	2.72	***0.05***	3.47	***0.07***	3.23	***0.06***	3.00	***0.06***	2.39	***0.05***	1.64	***0.03***
Built-up VC±50%	-0.28	***-0.01***	-0.47	***-0.01***	-0.96	***-0.02***	-1.49	***-0.03***	-2.09	***-0.04***	-3.02	***-0.06***	-3.81	***-0.08***
Bareland VC±50%	0.00	***0.00***	0.00	***0.00***	0.00	***0.00***	0.00	***0.00***	0.01	***0.00***	0.00	***0.00***	0.00	***0.00***
Farmland VC±50%	11.18	***0.22***	10.47	***0.21***	9.05	***0.18***	8.69	***0.17***	8.39	***0.17***	7.93	***0.16***	7.03	***0.14***

6.3.6 Patterns of economic growth and its effect on ecosystem service value

With the increase in GDP, the accomplishment in local economic development can be assessed. In the study period, GDP increased by a factor of 119.11 times from 66.75 billion CNY in 1986 to 7951.21 billion CNY in 2017, with a yearly average growth rate of 16.67%. At the same time, ESV per capita decreased by 38.45% from 11849.22 CNY in 1986 to 7293.62 CNY in 2017. Figure 23a shows a negative non-linear relationship between GDP per capita and ESV per capita with a coefficient of determination R^2 = 0.97. Figure 23b, a nonlinear regression analysis, demonstrated that there exists a significant negative correlation between farmland's ESV and the GDP with a coefficient of determination R^2 = 0.98, i.e., when GDP increased, the ESV of farmland decreased. Figure 23c indicated that the coefficient of determination between population density and ESV per capita is 0.99.

Therefore, economic development and urbanization had a significant negative impact on regional ESV. Of further interest, Figure 24a shows a decline in the ratio of total ESV to total GDP during the study period. Figure 24b and c show that with the increase in population and built-up area ESV decreases, whereas Figure 24d reflects that decrease in farmland has a negative impact on ESV i.e., ESV decreases.

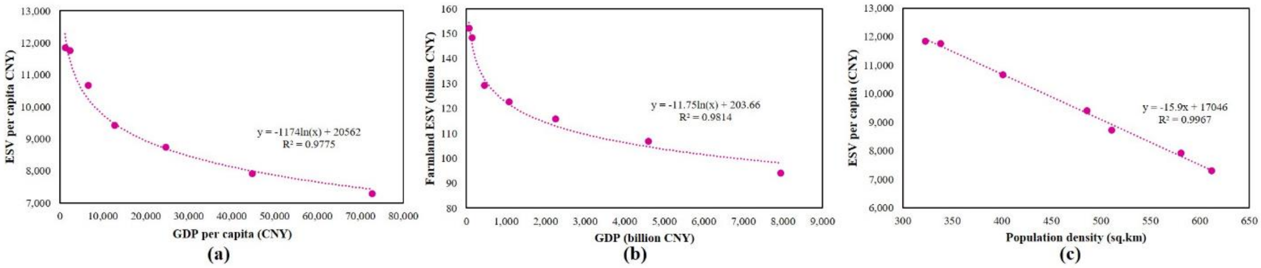

Figure 23. The correlation between (a) GDP per capita (CNY) and ESV per capita (CNY), (b) GDP (billion CNY) and farmland ESV (billion CNY), and (c) population density (sq.km) and ESV per capita (CNY) over the study period (1986—2017).

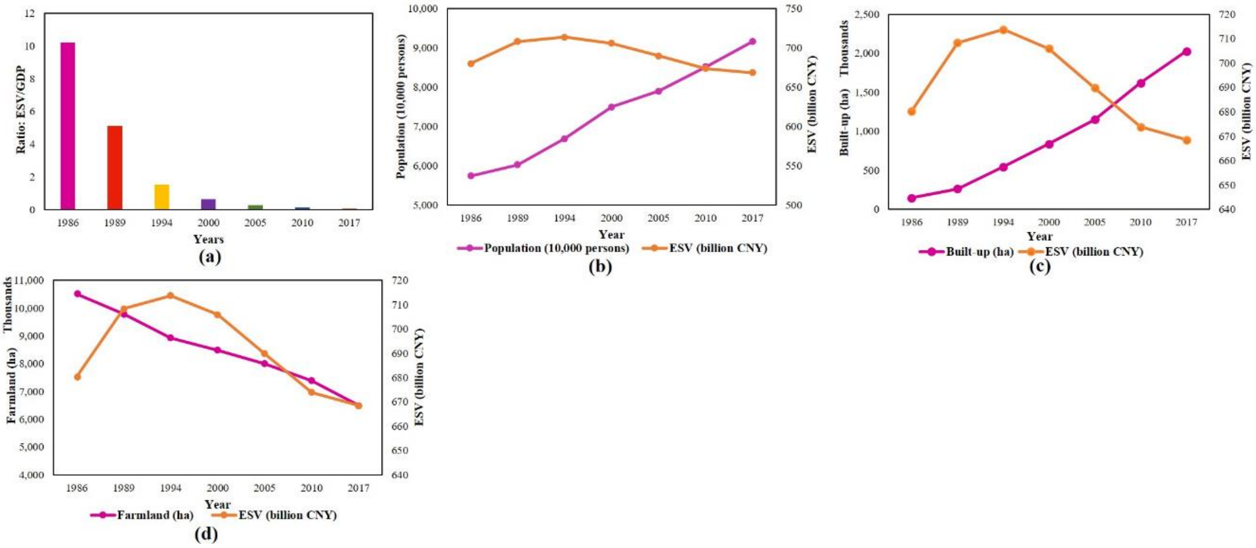

Figure 24. Relationship between (a) changes in the ratio of total ESV and GDP from 1986 to 2017, (b) total population (10,000 persons) and ESV (billion CNY), (c) built-up (ha) and ESV (billion CNY), and (d) farmland (ha) and ESV (billion CNY) over the study period (1986—2017).

In summary, the main reason for the decrease in total ESV is the process of rapid urbanization at the expense of loss of farmland.

6.4 Discussion

We have computed the LULC changes from 1986 to 2017 and their impact on the ESV, in the rapidly developing Guangdong, Hong Kong, and Macao region. Changes in LULC and massive expansion of the built-up area has largely occupied the farmland and other natural and semi natural land cover. This has resulted in a substantial loss of ESV in certain zones while huge gains in others, with a net decrease of 1.73%. This net decrease in ESV is lower than other studies such as in Kashgar Region (Mamat et al. 2018), Ethopia (Negussie et al. 2019), Bordeaux, France (Cabral et al. 2016) and Nenjiang River Basin (Wang et al. 2015). Rapid urbanization processes and industrialization have converted farmland to built-up areas. During the study period, farmland has been significantly decreased, including the conversion of farmland to built-up areas and forest. Forest and water provided the highest ESV, including water supply, waste treatment, soil formation and retention, biodiversity protection, and climate regulation. Thus, water supply, waste treatment, and food production ecosystem services faced the largest loss, while soil formation and retention and culture have achieved the greatest gain. This is because of the gain in new industrial population and to meet the needs and aspiration aligned to those new industries.

6.4.1 Driving forces for land use land cover changes and ecosystem service value

After the implementation of the economic reform policy in China, GHKM region has advanced the furthest, practiced the largest socioeconomic development and population growth (Hasan et al. 2019; Ye, Bryan, et al. 2018). This has increased pressure to the ecology and environment and brought adverse effects on regional total ESV (Wu et al. 2013; Yirsaw et al. 2016). This has created numerous fascinating issues and challenges for researchers and policy and decision makers (Liu, Song, and Arp 2012; Wu et al. 2013; Wu and Yeh 1997). Changes in the extent and composition of the forest, grassland, fishponds, and other ecosystems have large effects on the biophysical conditions, which further influence the provision of ES and biodiversity conversion (Zhan 2015). Fishponds and farmland both give various ES, for example, waste treatment, climate regulation, and biodiversity protection decrease during the study period. Both of them have greater economic benefits; they are being utilized for the construction purposes that further provoke the transformation of land use. Along with the decrease in area, the high value of water supply and waste treatment coefficients that are related with water and farmland (Table 16) have resulted in a high ESV from this land cover. The changes in LULC also influences the water supply ecosystems by shifting the transpiration, interception, and evaporation. These factors tend to increase with the increase in forest cover (Zhan 2015). Forest increases with highest ESV per unit area propelled by local government after implementing “Greener Guangdong” policy promoting the construction of forest protection system. This has encouraged farmers to establish horticultural plantations and forest industry development in the GHKM, especially since 1990 (Bui et al. 2003; Chokkalingam et al. 2006).

In the process of urban expansion and industrialization, rural settlement and agricultural land depletion have experienced significant loss, which has a substantial negative effect on ESV and food security. At the end of 2013, the government established a program, namely “Farmland Protection Red Line 0.12 billion hectares (1.8 billion mu)” with the aim to maintain 1.8 billion mu farmland. Under the current scenario of rapid urbanization process, it would be very difficult to keep a target of 0.12 billion of farmland in the future (Chen et al. 2018; Tan et al. 2017). Therefore, farmland protection as well as fishponds, both need to be considered on a first priority.

The results of this study show consistency with past literature regarding the effect of LULC changes and urbanization on the ESV at a variable rate, ranging from significant decreases to a modest increase in service value, with the majority report a modest decrease in service value. Estoque and Murayama (2013) assessed the ESV in Baguio City, Philippines and result showed that in past 21 years (1988—2009) the ESV decreased by 60%. Such decrease in ESV is due to decrease in forest cover and cropland (Estoque and Murayama 2013). In Argentina, the increased in economic income causes the decreased in ecosystem services (Viglizzo et al. 2012). In northen part of Lao PDR the ESV decreased by 11.74% during 1992 to 2002. The high rate of loss of services have undoubtedly serious negative ecological conservation in the long term (Yoshida et al. 2010). In Texas, USA, with the increase in urbanization the total ESV has dcreased by 4% during 1976 to 1991. In Berlin, Bremen, and Hamburg, Germany, the ESV decreased by 0.51%, 1.68%, and 2.26% respectively; because of the extent of urbanization and the level of economic development (Jiang 2018). In the southern plains of Nepal, the total ESV declined by 1% per year during 2001—2016 with the significant loss of forests, water bodies, and agricultural land (Sharma et al. 2019). Moreover, different methods of evaluation can provide different results. For example, both Li et al. (Tianhong et al. 2010) and Peng et al. evaluated the ESV of Shenzhen for the same year (2000), giving estimates of 2.9 billion and 126.5 billion Yuan, respectively. Similarly, in this study ESV of GHKM for the same year (2017), giving estimate of 668.45 billion (Xie et al. 2003) and 792.52 billion Yuan (Xie et al. 2008), respectively. Absolute numbers of ESVs have less meaning, and the dynamics of ESVs are commonly indicating ecological problems (Y. Wang et al. 2014).

Moreover, economic growth seems to be in conflict with ecological protection as this study also shows that ESV and ESV per capita decreased significantly with the continuous increase in total GDP and GDP per capita over the past three decades in the GHKM. The main reason for such a decrease in ESV is the transformation of natural and semi natural resources into built-up (Feng et al. 2012; Lin et al. 2018; W. Liu et al. 2019; Liu, Li, et al. 2012; Tianhong et al. 2010; Wu et al. 2013; Ye, Zhang, et al. 2018; Y. Zhang et al. 2015), typically resulting in lower or negative values of services. Nonetheless, even in PRD, a fast urbanizing GHKM region, urban expansion is only one of the various LULC change happening concurrently. A range of other LULC changes corresponding with the increase of built-up area also took place. Such changes include a transformation of farmland to forest, a high service value land use. To some extent, this transformation negates the adverse effect of urban expansion on ESV in the GHKM (Ye, Bryan, et al. 2018).

6.4.2 Implication for planning sustainable development

The study presented in this paper clearly demonstrates the net decline in the ESV supply i.e., -1.73. Land use inherently entails trade-offs, with economic benefits inevitably taking precedence over ecosystem benefit. Protection of the natural environment is of equal importance to economic development. If environmental protection is neglected, the economic loss caused by pollution may exceed the economic benefits resulting from the transformation of land use. Therefore, GHKM needs improved planning regarding sustainability of ecosystems and smart land use. Such planning should involve environmental, economic, and social considerations in order that the sustainability of services antagonistically influenced by fast urban expansion, for example, gas regulation, water supply, waste treatment, climate regulation, and food production must be stressed for improvement. Therefore, planning and decisions should focus on protecting farmland and fishponds to reverse the unsustainable deterioration in these ecosystem services. Similarly, the protection of forest and water is also important because they also comprise of high ecosystem services value. This could be accomplished through planning protocols and setting the sustainability targets for local ecosystem services by using different decision analysis methods such as triage planning (Pendleton et al. 2015), spatial optimization algorithms and ecological corridor (Chuai et al. 2016; Ye, Bryan, et al. 2018). This could reduce the future hazard for ESV. In summary, ESV has the great potential to inform policy and decision makers by highlighting the advantages of sustainable ecosystem management.

6.4.3 Limitations

In this study, the method used to calculate the ESV was proposed by Costanza et al. (1997a,b), and adjusted by Xie et al. (2003) according to the Chinese terrestrial terrain. The ESV was then derived by multiplying each land use class with a corresponding ecosystem coefficient value. Although, estimated results produced by this method have been criticized because of used at coarse resolution, uncertainties due to complex, dynamic, and nonlinear nature of ecosystems (Limburg et al. 2002; Turner et al. 2003), limiting economic valuation, and double scale problems (Konarska, Sutton, and Castellon 2002; Liu, Li, et al. 2012; Tianhong et al. 2010; Turner et al. 2003).

The biomes used as a proxy for LULC classes but does not match precisely in each case (Kreuter et al. 2001). Additionally, heterogeneity in an ecosystem made the accuracy of the adjusted coefficient values in doubt (Tianhong et al. 2010). Although, a diverse range of valuation methods are available but, each and every method may prompt “refer” to different estimated values, hence causing a criticism in the ecosystem service valuation method. Thus it is essential to realize that the precise evaluation of the coefficients for time series analysis is less critical than the cross-sectional analysis. This is because the coefficients will, in general, have less influence regarding the estimation of directional change than that of the magnitude of ecosystem values (Liu, Li, et al. 2012; Tianhong et al. 2010). In this study, the supposition that coefficient of ESV remains constant over time, allows a comparison of minimal change with time. However, in reality, it is unlikely that values remain constant (Zank et al. 2016). This study attempted to adjust the value of coefficients on the basis of study area data, but still it remains a general estimation and unable to capture the spatial heterogeneity among the supply of ecosystem services within the LULC classes (Tianhong et al. 2010; Ye, Bryan, et al. 2018). This method, however, will remain a convenient mode to integrate the effect of LULC changes across numerous ecosystem services and also identify minimal change with time in the provision of ecosystem services. Moreover, sensitivity analysis demonstrates that total ESV estimated in this study were relatively inelastic with respect to the value coefficient and despite of uncertainties our estimation up to some extent is robust.

The reliability of a proxy based method can be increased by using remotely sensed high resolution images in combination with field survey. The field survey can empower LULC mapping at high accuracy. The methods used in this study also suppose that the value of each ecosystem service, given by each LULC over the study area is homogeneous, as the value coefficients are regionally downscaled values. Instead, in reality, values change spatially. This is a drawback of methods which can be overcome by incorporating biophysical and economic systems spatial models (Bryan and Crossman 2013) and by doing field survey for higher scale economic valuation of the supply of ecosystem services on local level (Bryan, Grandgirard, and Ward 2010; Raymond et al. 2009; Ye, Bryan, et al. 2018).

In summary, based on Costanza’s et al. (1997) research, Xie et al. (2003, 2008) improved the calculation model by conducting a professional questionnaire survey of 700 ecologists and other relevant scholars in China that evaluated the status of China's ecosystem and socio-economic development. The coefficients from Xie et al. (2008) were estimated according to a survey of 700 ecologists or relevant scholars in China. Although these coefficients have been widely used in scientific studies (Fei et al. 2018; Wang et al. 2017). The equivalent coefficient was considered the estimated value of a certain ES of a specific ecosystem from the literature, indirect comparison with ecosystem biomass and experts’ knowledge (Xie et al. 2017). Equivalent coefficients for China's ES research were developed (M. Hu et al. 2019; Xie et al. 2017). The ecosystems were divided into 6 primary categories, including farmland, forest, grassland, wetland, barren land and water area, after that 14 secondary categories were subdivided (Xie et al. 2017).

Using the Xie et al. (2003, 2008) value coefficients, however, may not be precise enough, because the land use classification was only applied to the first-level classification (e.g. forest land and grassland). The structural and functional differences of different ecosystems at the same level, e.g. the forest land type includes broad-leaved forests, coniferous forests, bush forests, etc., may lead to uncertain ESVs (Y. Wang et al. 2014). However, coefficient value derived by (Xie et al. 2017) can be applied to the second level classification.

6.5 Conclusions

This study has revealed the impact of LULC changes on ESV resulting from urban expansion, industrialization, and socioeconomic development in the GHKM between 1986 and 2017. The changes in the ESV show a close relationship with socioeconomic growth in the study area. The result showed that the built-up area had expanded by 1260.02% over the last three decades, with an average annual growth rate of 8.41%, produced mainly at the expense of the reduction of farmland, together with other concurrent non-urban LULC changes. This has placed strong pressure on both natural and semi-natural ecosystems.

The total ESV decreased by 1.73% (11.77 billion CNY) between 1986 and 2017. This decrease in the value of ecosystem services is associated with a decrease in the total area of farmland, fishponds, and water. This also signifies the dynamics and complexity of the individual ESV as notably some services value decreased significantly while others increased substantially. Forest generated the highest percentage of the total ESV (approximately 50%) and together with fishponds, water, and farmland produced more than 90% of the total ESV, showing that these four LULC classes have an important role in supplying ecosystem services.

Regarding the total ESV, the highest contribution is made by water supply followed by waste treatment ecological function. Their contribution represents approximately 45% of the total. The result shows that there exists a substantial negative correlation between farmland ESV and the GDP. The ESV for farmland was higher in 1986, but tended to decrease rapidly during the study period as a consequence of the burgeoning industrialization and development. In regional land use planning and decision analysis, priority must be given to those services which can contribute to the sustainability of everyday life, particularly which can be adversely influenced by urban expansion such as water supply, gas regulation, climate regulation, and food production. Therefore, the fragile ecological environment in the GHKM clearly indicate that stakeholders and planners need to highlight the protection of such as farmland and fishponds to achieve the sustainable utilization of land resources and organized economic and environmental development.

Furthermore, by using remote sensing data, the land cover class can be utilized as a proxy for ecosystem services, with corresponding land cover classes equal to biomes, thus, making the ecosystem valuation possible for larger regions. Further research should expand or design such methods that can more precisely evaluate these coefficients for the authenticity of the resulting estimate reliant upon the precision of the coefficient value.

Chapter 7

7 Conclusion and Recommendations

Guangdong, Hong Kong, and Macau (GHKM) has undergone significant LULC changes after the opening of economic reform policy in 1978. The massive land transformations caused by socioeconomic development, natural and human induced factors. This study has demonstrated the characteristics of LULC change over the past three decades (1986—2017), simulated future scenario using Land change modeler (LCM) and the impact of these tremendous changes on ecosystem service values. During 1986—2017, the built-up area has increased from 0.76% (1488.35 km^2) to 10.31% (20,643.28 km^2) and farmland and fishponds decline substantially from 53.54% (105,123.93 km^2) to 33.07% (64,932.19 km^2) and from 1.25% (2463.35 km^2) to 0.97% (1902.79 km^2), respectively. On the other hand, due to different afforestation programs and at the expense of farmland reduction, forest cover increased from 33.24% (65,257.55 km^2) in 1986 to 45.02% (88,384.19 km^2) in 2017. The most dominant transformation observed were farmland to built-up and forest. The reasons for such changes in LULC were the socioeconomic development, cheap land rate, employment opportunities, better life style, urbanization, industrialization, facilities, and different land use policies. Moreover, land ownership and transfer policies have played their own role in changing land cover and real estate market. A marked increase in GDP, total investment in fixed assets, and total retail sales of consumer goods have led to the widespread expansion of cities and substantial loss of natural resources. However, reduction in farmland mirrors the irreversible trend of marketization and urbanization up to some extent. Thus long term LULC changes has provide a scientific reference for designing rational urban planning at provincial level and improve understanding of LULC changes in relation to socioeconomic determinant and land use policies.

Furthermore, to simulate the future scenario of LULC change Land change modeler (LCM) was used. After model validation, predicted the LULC map for the years 2024 and 2031. The simulated result showed that current patterns will continue in future i.e. an expected increase in built-up area from 10.31% (20,643.28 km^2) in 2017 to 16.30% (31994.55 km^2) in 2031 with the substantial decrease in farmland from 33.03% (64,932.19 km^2) to 26.00% (51043.01 km^2) and fishponds from 0.97% (1902.79 km^2) to 0.83% (1639.06 km^2). Moreover, forest cover will increase from 45.02% (88,384.19 km^2) in 2017 to 46.88% (1639.06 km^2) in 2031.The spatial structure analysis of the landscape exhibits more disperse, heterogeneous, and fragmented landscape in future. Such changes in land cover are attributed to intense socioeconomic development, industrialization, and continuous sprawling urban fabric in urban pockets at suburban and peripheral areas, which may have serious threat to environmental sustainability. A long-term sustainable urban development is essential to promote orderly urbanization and should be linked to similarly urgent plans for farmland protection.

The unprecedented development and urbanization has placed strong pressure on both natural and semi-natural ecosystems. The total ESV decreased by 1.73% (11.77 billion CNY) between 1986 and 2017. This decrease in the value of ecosystem services is associated with a decrease in the total area of farmland, fishponds, and water. This signifies the dynamics and complexity of the individual ESV as notably some services value decreased significantly while others increased substantially. Forest generated the highest percentage of the total ESV (approximately 50%) and together with fishponds, water, and farmland produced more than 90% of the total ESV, showing that these four LULC classes have an important role in supplying ecosystem services. The ESV for farmland was higher in 1986, but tended to decrease rapidly during the study period because of the burgeoning industrialization and development.

Therefore, the findings of this study will help policy decision makers to take some decisive measures for optimal land source optimization and analyze the relationship between LULC changes and socioeconomic determinants. Future prediction would give the information to the urban planner that further expansion of urbanization could result in traffic congestion, transformation of open spaces, increased travel time, and residential energy consumption. In addition, to reduce the further fragmentation of natural resources. For ecosystem services, priority must be given to those services which can contribute to the sustainability of everyday life, particularly which can be adversely influenced by urban expansion such as water supply, gas regulation, climate regulation, and food production. This could enhance the understanding of environmental managers and the general public on the ongoing changes and contribute to establish the ecological corridor and effective strategies to reduce the reduction of ESV. Therefore, in the fragile ecological environment stakeholders need to highlight the protection of natural resources such as farmland and fishponds to achieve the sustainable economic and environmental development. Additional research is needed to cover marine ecosystems and to include the resilience of ecosystems to environmental change in spatially explicit assessments.

Further research should expand at county, district level, and systematic cross-city comparisons using high spatial resolution data that integrates more accurate historical LULC changes. This could help to bring better insight to understand the current environmental issues and plan for future risks associated with farmland reduction, loss of key ecosystems and biodiversity, and urban sprawl. Moreover, as the reliability of the estimated ESV result mainly depend upon the precision of the coefficient value, therefore, future research should design such methods that can evaluate these coefficient value more accurately.

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Appendices

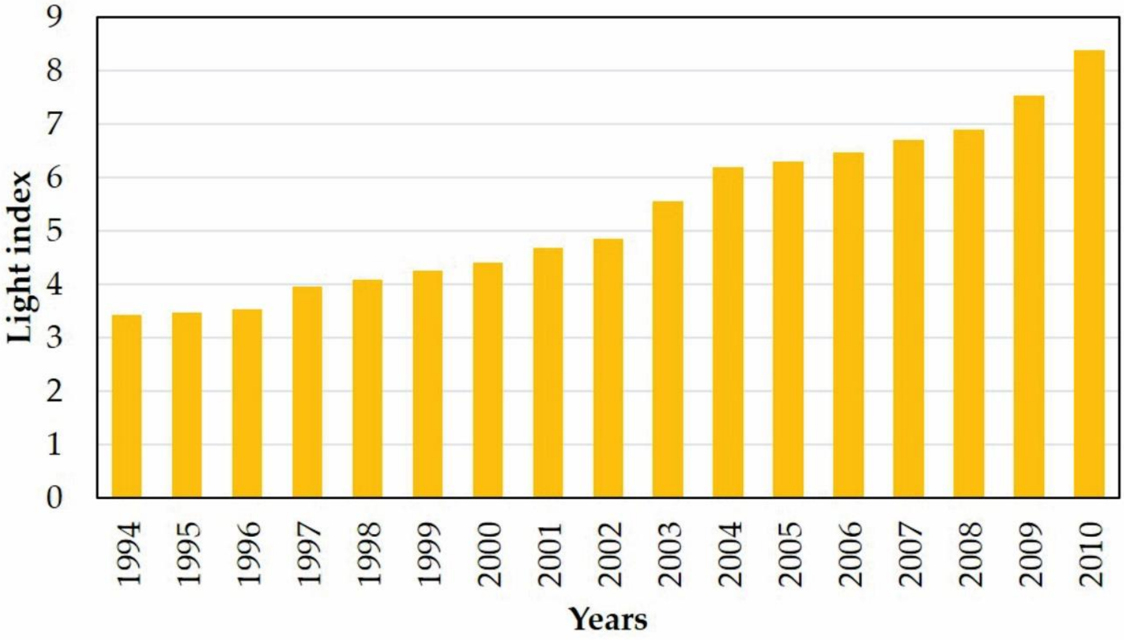

Figure 25-S1. Light index of the Guangdong, Hong Kong, and Macao from 1994 to 2010.

Table 20-S1. Description of the Landsat datasets scene used for land use land cover change detection.

Path/Row	1986		1989		1994		2000		2005		2010		2017	
	Date	Sensor	Date	Sensor	Date	Sensor	Date	Sensor	Date	Sensor	Date	Sensor	Date	Sensor
	YYMNDD*		YYMNDD*		YYMNDD*		YYMNDD*		YYMNDD*		YYMNDD*		YYMNDD*	
120/043	19861105	TM	19891129	TM	19941111	TM	20001103	ETM+	20050306	ETM+	20101209	TM	20171025	OLI
120/044	19861223	TM	19891129	TM	19941111	TM	20001010	TM	20061222	ETM+	20101209	TM	20171110	OLI
121/043	19861214	TM	19891120	TM	19941102	TM	20001102	TM	20051124	ETM+	20101208	ETM+	20171101	OLI
121/044	19861214	TM	19891120	TM	19941102	TM	20000915	TM	20050116	TM	20101208	ETM+	20171101	OLI
121/045	19861214	TM	19891120	TM	19941102	TM	20000915	TM	20051124	ETM+	20101029	TM	20171101	OLI
122/043	19861103	TM	19891108	TM	19941109	TM	19991225	TM	20051123	TM	20101231	ETM+	20171226	OLI
122/044	19861103	TM	19891213	TM	19941024	TM	20000914	ETM+	20051217	ETM+	20101231	ETM+	20171023	OLI
122/045	19861124	TM	19890228	TM	19941024	TM	20001101	ETM+	20051123	TM	20101231	ETM+	20160326	OLI
123/042	19861217	TM	19891204	TM	19941031	TM	20001124	ETM+	20051208	ETM+	20101222	ETM+	20161128	OLI
123/043	19861217	TM	19891204	TM	19941031	TM	20001226	ETM+	20061219	TM	20111225	ETM+	20180323	OLI
123/044	19861228	TM	19891204	TM	19941223	TM	19991224	ETM+	20061219	TM	20111225	ETM+	20171030	OLI
123/045	19861228	TM	19891204	TM	19941031	TM	19991208	ETM+	20051122	ETM+	20101112	TM	20171030	OLI
124/044	19861219	TM	19891125	TM	19941107	TM	20001030	ETM+	20051129	ETM+	20101111	ETM+	20170122	OLI
124/045	19861206	TM	19891030	TM	19961214	TM	20001030	ETM+	20051121	TM	20091124	ETM+	20171208	OLI
124/046	19861028	TM	19891018	TM	19941022	TM	20001123	TM	20061218	ETM+	20101229	ETM+	20161205	OLI

- **YYMNDD = Year Month Day**

Table 21-S2. Accuracy assessment of classified images for the years 1986, 1989, 1994, 2000, 2005, 2010, and 2017 (where, F = Forest, G = Grassland, W = Water, FP = Fishponds, BU = Built-up, BL = Bareland, and FL = Farmland).

	Reference Pixels								
	F	G	W	FP	BU	BL	FL	Total	UA* (%)
1986 Classified Pixels									
F	137	5	0	0	0	0	9	151	90.73
G	1	33	0	0	0	1	2	37	89.19
W	0	0	24	3	0	0	0	27	88.89
FP	0	0	1	41	2	0	0	44	93.18
BU	0	0	0	1	51	3	0	55	92.73
BL	0	1	0	0	1	24	1	27	88.89
FL	7	1	0	0	0	0	55	63	87.30
Total	145	40	25	45	54	28	67	404	
PA (%)**	94.48	82.50	96.00	91.11	94.44	85.71	82.09		
OA* (%)**	90.35	Kappa coefficient = 0.88							

	Reference Pixels								
	F	G	W	FP	BU	BL	FL	Total	UA* (%)
1989 Classified Pixels									
F	140	3	0	0	0	0	8	151	92.72
G	1	35	0	0	0	2	3	41	85.37
W	0	0	27	1	0	0	0	28	96.43
FP	0	1	2	37	1	0	0	41	90.24
BU	0	0	0	3	45	1	0	49	91.84
BL	0	1	0	0	1	30	1	33	90.91
FL	7	0	0	0	2	0	52	61	85.25
Total	148	40	29	41	49	33	64	404	
PA (%)**	94.59	87.50	93.10	90.24	91.84	90.91	81.25		
OA* (%)**	90.57	Kappa coefficient = 0.88							

	Reference Pixels								
	F	G	W	FP	BU	BL	FL	Total	UA* (%)
1994 Classified Pixels									
F	133	3	0	0	0	0	6	142	93.66
G	2	39	0	0	0	1	3	45	86.67
W	0	0	32	2	0	0	0	34	94.12
FP	2	0	3	42	1	0	0	48	87.50
BU	0	0	0	2	47	1	0	50	94.00
BL	0	1	0	0	1	24	2	28	85.71
FL	5	0	0	3	1	0	48	57	84.21
Total	142	43	35	49	50	26	59	404	
PA (%)**	93.66	90.70	91.43	85.71	94.00	92.31	81.36		
OA* (%)**	90.35	Kappa coefficient = 0.88							

	Reference Pixels								
	F	G	W	FP	BU	BL	FL	Total	UA* (%)
2000 Classified Pixels									
F	148	3	0	0	0	0	9	160	92.50
G	1	30	0	0	0	2	1	34	88.24
W	0	0	23	1	0	0	0	24	95.83
FP	0	0	2	35	1	0	1	39	89.74
BU	0	0	0	1	50	1	0	52	96.15

BL	0	1	0	0	2	23	0	26	88.46
FL	6	0	0	1	2	0	60	69	86.96
Total	155	34	25	38	55	26	71	404	
PA (%)**	95.48	88.24	92.00	92.11	90.91	88.46	84.51		
OA* (%)**	91.34	Kappa coefficient = 0.89							

				Reference Pixels					
	F	G	W	FP	BU	BL	FL	Total	UA* (%)
2005 Classified Pixels									
F	127	3	0	0	0	0	7	137	92.70
G	3	29	0	0	0	2	0	34	85.29
W	0	0	35	3	0	0	0	38	92.11
FP	0	0	2	39	2	0	0	43	90.70
BU	0	0	0	2	55	3	0	60	91.67
BL	0	1	0	0	2	22	1	26	84.62
FL	6	0	0	0	1	0	59	66	89.39
Total	136	33	37	44	60	27	67	404	
PA (%)**	93.38	87.88	94.59	88.64	91.67	81.48	88.06		
OA* (%)**	90.59	Kappa coefficient = 0.88							

				Reference Pixels					
	F	G	W	FP	BU	BL	FL	Total	UA* (%)
2010 Classified Pixels									
F	141	4	0	0	0	0	7	152	92.76
G	3	28	0	0	0	0	0	31	90.32
W	0	0	35	3	0	0	0	38	92.11
FP	1	0	2	43	1	0	0	47	91.49
BU	0	0	0	1	53	3	0	57	92.98
BL	0	0	0	0	1	19	1	21	90.48
FL	5	0	0	1	2	0	50	58	86.21
Total	150	32	37	48	57	22	58	404	
PA (%)**	94.00	87.50	94.59	89.58	92.98	86.36	86.21		
OA* (%)**	91.34	Kappa coefficient = 0.89							

				Reference Pixels					
	F	G	W	FP	BU	BL	FL	Total	UA* (%)
2017 Classified Pixels									
F	129	3	0	0	0	0	8	140	92.14
G	1	35	0	0	0	2	1	39	89.74
W	0	0	25	2	0	0	0	27	92.59
FP	0	0	1	36	1	0	0	38	94.74
BU	0	0	0	1	57	2	0	60	95.00
BL	0	1	0	0	2	31	1	35	88.57
FL	4	0	0	1	2	0	58	65	89.23
Total	134	39	26	40	62	35	68	404	
PA (%)**	96.27	89.74	96.15	90.00	91.94	88.57	85.29		
OA* (%)**	91.83	Kappa coefficient = 0.90							

***UA = User Accuracy, **PA = Producer Accuracy, and ***OA= Overall Accuracy**

Table 22-S3. Change detection matrix of land use land cover during different time period (percentage).

1986/1989	F	G	W	FP	BU	BL	FL	Total/PLSE[1]	L*	Tc**	Nc***	ANc****	S*****
F	32.51	0.03	0.06	0.45	0.16	0.03	0.00	33.24	0.71	4.52	3.09	3.09	1.43
G	0.05	0.09	0.00	0.00	0.01	0.00	0.08	0.23	0.14	0.18	-0.10	0.10	0.08
W	0.04	0.00	10.19	0.23	0.04	0.01	0.08	10.59	0.40	0.86	0.06	0.06	0.80
FP	0.13	0.00	0.29	0.58	0.04	0.01	0.20	1.25	0.68	1.59	0.24	0.24	1.35
BU	0.00	0.00	0.00	0.00	0.76	0.00	0.00	0.76	0.00	0.59	0.59	0.59	0.00
BL	0.00	0.00	0.02	0.01	0.03	0.09	0.23	0.38	0.29	0.41	-0.18	0.18	0.23
FL	3.58	0.00	0.10	0.23	0.31	0.07	49.26	53.54	4.26	4.85	-3.67	3.67	1.18
Total/PLSL[2]	36.32	0.13	10.65	1.50	1.35	0.20	49.85	100					
G******	3.81	0.04	0.46	0.92	0.59	0.11	0.59						
Persistence = 93.48%, Total change = 6.51%, Absolute net change = 3.97%, Swap = 2.54%													
1989/1994													
F	35.35	0.07	0.06	0.47	0.27	0.10	0.00	36.32	0.97	4.25	2.30	2.30	1.94
G	0.02	0.10	0.00	0.00	0.01	0.00	0.00	0.13	0.03	0.11	0.04	0.04	0.07
W	0.07	0.00	10.15	0.30	0.06	0.02	0.04	10.65	0.50	0.98	-0.01	0.01	0.97
FP	0.21	0.00	0.23	0.77	0.11	0.02	0.15	1.50	0.72	1.87	0.42	0.42	1.45
BU	0.00	0.00	0.00	0.00	1.35	0.00	0.00	1.35	0.00	1.43	1.43	1.43	0.00
BL	0.01	0.00	0.02	0.01	0.07	0.05	0.05	0.20	0.15	0.49	0.18	0.18	0.30
FL	2.96	0.00	0.17	0.36	0.92	0.20	45.25	49.85	4.60	4.85	-4.36	4.36	0.48
Total/PLSL[2]	38.62	0.18	10.64	1.92	2.77	0.39	45.49	100					
G******	3.27	0.08	0.49	1.14	1.43	0.33	0.24						
Persistence = 93.02%, Total change = 6.98%, Absolute net change = 4.38%, Swap = 2.61%													
1994/2000													
F	38.05	0.02	0.08	0.22	0.23	0.02	0.00	38.62	0.57	2.50	1.37	1.37	1.14
G	0.08	0.08	0.00	0.00	0.01	0.00	0.00	0.18	0.09	0.12	-0.07	0.07	0.05
W	0.04	0.00	10.12	0.36	0.05	0.01	0.06	10.64	0.52	0.93	-0.11	0.11	0.82
FP	0.19	0.00	0.27	1.06	0.18	0.00	0.21	1.92	0.86	1.57	-0.15	0.15	1.42
BU	0.00	0.00	0.00	0.00	2.77	0.00	0.00	2.77	0.00	1.50	1.50	1.50	0.00
BL	0.01	0.00	0.01	0.01	0.16	0.05	0.14	0.39	0.33	0.43	-0.24	0.24	0.18
FL	1.61	0.00	0.05	0.12	0.86	0.06	42.79	45.48	2.70	3.11	-2.29	2.29	0.82
Total/PLSL[2]	39.99	0.11	10.53	1.77	4.27	0.14	43.20	100					
G******	1.93	0.03	0.41	0.71	1.50	0.09	0.41						
Persistence = 94.92%, Total change = 5.08%, Absolute net change = 2.86%, Swap = 2.22%													
2000/2005													
F	38.98	0.07	0.07	0.26	0.39	0.21	0.00	39.99	1.00	2.85	0.85	0.85	2.00
G	0.04	0.06	0.00	0.00	0.01	0.00	0.00	0.11	0.05	0.20	0.09	0.09	0.11
W	0.10	0.01	9.82	0.40	0.08	0.02	0.09	10.52	0.70	1.14	-0.26	0.26	0.89
FP	0.22	0.03	0.31	0.81	0.16	0.01	0.23	1.77	0.96	1.75	-0.17	0.17	1.58
BU	0.00	0.00	0.00	0.00	4.27	0.00	0.00	4.27	0.00	1.58	1.58	1.58	0.00
BL	0.01	0.00	0.01	0.00	0.02	0.04	0.07	0.14	0.11	0.55	0.33	0.33	0.21
FL	1.48	0.04	0.06	0.13	0.91	0.20	40.38	43.20	2.82	3.20	-2.43	2.43	0.78
Total/PLSL[2]	40.83	0.20	10.27	1.61	5.85	0.48	40.77	100					
G******	1.85	0.15	0.44	0.79	1.58	0.44	0.39						
Persistence = 94.36%, Total change = 5.64%, Absolute net change = 2.85%, Swap = 2.78%													
2005/2010													
F	40.21	0.02	0.09	0.17	0.30	0.04	0.00	40.83	0.62	2.80	1.55	1.55	1.25
G	0.06	0.05	0.01	0.01	0.01	0.00	0.06	0.20	0.16	0.18	-0.13	0.13	0.05
W	0.10	0.00	9.80	0.25	0.06	0.00	0.05	10.26	0.46	0.95	0.03	0.03	0.92

FP	0.18	0.00	0.31	0.69	0.27	0.00	0.15	1.61	0.92	1.48	-0.36	0.36	1.12
BU	0.00	0.00	0.00	0.00	5.85	0.00	0.00	5.85	0.00	2.41	2.41	2.41	0.00
BL	0.03	0.00	0.01	0.01	0.14	0.03	0.25	0.48	0.44	0.52	-0.36	0.36	0.16
FL	1.80	0.00	0.07	0.11	1.63	0.03	37.13	40.77	3.64	4.16	-3.13	3.13	1.02
Total/PLSL[2]	42.38	0.07	10.29	1.25	8.26	0.11	37.64	100					
G******	2.17	0.03	0.49	0.56	2.41	0.08	0.51						
Persistence = 93.75%, Total change = 6.25%, Absolute net change = 3.98%, Swap = 2.26%													
2010/2017													
F	41.59	0.03	0.20	0.16	0.34	0.06	0.00	42.38	0.79	4.21	2.63	2.63	1.58
G	0.03	0.03	0.00	0.00	0.01	0.00	0.00	0.07	0.04	0.11	0.02	0.02	0.08
W	0.11	0.00	9.85	0.21	0.09	0.00	0.03	10.29	0.44	1.10	0.22	0.22	0.88
FP	0.22	0.00	0.37	0.40	0.15	0.01	0.10	1.25	0.85	1.31	-0.40	0.40	0.91
BU	0.00	0.00	0.00	0.00	8.26	0.00	0.00	8.26	0.00	2.05	2.05	2.05	0.00
BL	0.02	0.00	0.00	0.00	0.03	0.02	0.03	0.11	0.09	0.21	0.03	0.03	0.18
FL	3.05	0.02	0.08	0.08	1.44	0.05	32.90	37.64	4.73	4.90	-4.57	4.57	0.34
Total/PLSL[2]	45.02	0.10	10.51	0.85	10.31	0.14	33.07	100					
G******	3.42	0.07	0.66	0.46	2.05	0.12	0.17						
Persistence = 93.06%, Total change = 6.94%, Absolute net change = 4.96%, Swap = 1.98%													
[1]PLSE = Percentage of earlier landscape, [2]PLSL = Percentage of later landscape, *L = Loss, **Tc = Total change,													
*****Nc = Net change, ****ANc = Absolute net change, *****S = Swap, and ******G= Gain**													

Table 23-S4. Land use transitions in Guangdong, Hong Kong, and Macao between 1986 and 2017(km^2).

		2017							
	Classes	**Forest**	**Grassland**	**Water**	**Fishponds**	**Built-up**	**Bareland**	**Farmland**	**Total/LSE[1]**
1986	**Forest**	62,031.53	60.13	211.53	310.49	2586.82	57.05	0.00	65,257.55
	Grassland	285.24	63.82	2.69	2.30	80.75	2.37	22.93	460.11
	Water	167.71	14.26	19,268.44	420.14	838.32	9.89	76.72	20,795.47
	Fishponds	299.74	8.88	532.01	456.97	1074.51	5.75	85.50	2463.35
	Built-up	0.00	0.00	0.00	0.00	1488.35	0.00	0.00	1488.35
	Bareland	149.99	1.27	84.13	18.32	330.99	15.90	151.56	752.16
	Farmland	25,449.98	41.35	544.48	466.39	13,841.81	184.44	64,595.48	105,123.93
	Total/LSL[2]	88,384.19	189.72	20,643.28	1674.61	20,241.55	275.40	64,932.19	196,340.94
[1]LSE = Earlier landscape, [2]LSL = Later landscape									

Table 24-S5. Value of ecosystem function from 1986 to 2017.

ESV$_f$ billion(CNY/Yr)	**1986**	**1989**	**1994**	**2000**	**2005**	**2010**	**2017**	**%**	**Rank**	**Tendency**
Food	23.99	22.63	20.99	20.08	19.11	17.83	16.04	2.91	9	⬇
Raw material	37.80	40.95	43.25	44.61	45.41	46.92	49.54	6.39	8	⬆
Gas regulation	59.07	62.31	63.64	63.51	62.56	61.44	60.36	8.99	6	⬇
Climate regulation	67.38	71.13	75.07	74.66	73.53	71.55	70.07	10.41	5	⬇
Water supply	151.47	154.78	154.97	149.66	142.08	133.82	129.17	21.00	1	⬇
Waste treatment	141.96	142.71	142.69	138.37	132.45	126.21	121.19	19.55	2	⬇
Soil formation and retention	86.53	89.35	90.78	91.44	91.31	91.57	92.81	13.12	3	⬆
Biodiversity protection	72.55	75.93	78.41	79.45	79.74	80.79	83.11	11.39	4	⬆

Recreation and culture	39.47	41.73	43.88	44.05	43.65	43.70	44.57	6.23	7	⬆
Total	680.23	701.51	713.68	705.84	689.84	673.84	668.45	100.00		

Table 25-S6. Meaning and importance of weigh factors.

Regulation	Gas regulation	Regulation of atmospheric chemical composition e.g. CO2/O2 balance,O3 for UVB protection, and SOx levels
	Climate regulation	• Regulation of global temperature, precipitation, and other biologically mediated climatic processes at global or local levels. • Capacitance, damping and integrity of ecosystem response to environmental fluctuations
	Water supply	• regulation of hydrological flows • Storage and retention of water
	Waste treatment	• Recovery of mobile nutrients and removal or breakdown of excess or xenic nutrients and compounds. • Movement of floral gamets
Support	Soil formation and retention	• soil formation process • Storage, internal cycling, processing and acquisition of nutrients. • Retention of soil within an ecosystem
	Biodiversity protection	• Trophic-dynamic regulations of populations • Sources of unique biological materials and products • Habitat for resident and transient populations.
Provision	Food	That portion of gross primary production extractable as food.
	Raw materials	That portion of gross primary production extractable as raw materials e.g. The production of lumber, fuel or fodder
Culture	Recreation and culture	Providing opportunities for recreational activities. Providing opportunities for non-commercials uses.