

Land Use Management Strategies Based on Land Use/Land Cover Types and Assessment of Urban Ecosystem Services

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Abstract

As metropolitan governance models gain popularity for urban development, metropolitan areas increasingly influence regional planning, land-use management, and environmental protection. This study examined three major metropolitan areas in Japan: the Tokyo Metropolitan Area (TKM), Chubu Metropolitan Area (CBM), and Kinki Metropolitan Area (KKM). It explored land use/land cover (LULC) analysis methods and associated policies through an ecological planning and ecosystem services framework, proving insights and methodologies to enhance LULC planning and management. The objectives included analyzing LULC dynamics and developing management strategies. Data and methods were derived from field investigations, geostatistical techniques, remote sensing data, and ecosystem services models like i-Tree Eco and InVEST. Key findings include:

Chapter 2 provides a comprehensive analysis of LULC dynamics from 2000 to 2020 in the three metropolitan areas. It identifies trends such as the decline in cultivated land and the increase in forest and artificial surface, examines changes in spatial patterns of LULC types, and evaluates the influence of 20 driving factors on LULC change, highlighting correlations with population distribution, climate factors and topographic features. This chapter lays the groundwork for the subsequent analyses.

In Chapter 3, the study focuses on the three metropolitan areas for the years 2000 and 2020. It develops land use management strategies aimed at achieving an ecological security pattern through ecological network construction assessments and ecosystem health evaluations. The results show that forest patches account for up to 70% of the LULC types within potential corridors, while green space makes up 90%, indicating favorable conditions for ecological network construction. Additionally, the study proposes pressure-vitality-organization model to assess the ecosystem health, finding that high-quality cultivated lands patches are generally located around artificial surfaces, with grassland and shrubland exhibiting overall high ecosystem health levels.

Chapter 4 focuses on the KKM, examining the relevance of future LULC simulation results for regional policies. It introduces a simulation framework combining the PLUS and InVEST models, forecasting significant decreases in cultivated land and increases in forest and artificial surfaces. This chapter discusses the applicability of these results to policy requirements and guidelines for wide-area planning, offering insights for policy-making and improved LULC planning in the KKM.

Chapter 5 highlights the role of urban forests in enhancing urban ecosystem services, with a case study in Kyoto city. The study employs field investigations, i-Tree Eco model, and geostatistical interpolation to quantify ecosystem services, identifying Empirical Bayesian Kriging as the most accurate interpolation method. The results reveal a positive spatial correlation between urban forest ecosystem services and urban spaces, except for public service spaces. Additionally, this study identifies areas with high-density urban spaces but low ecosystem services, providing strategies for tree planting planning.

In conclusion (chapter 6), this study provided an understanding of LULC changes and management in Japan's metropolitan areas. By integrating ecological principles with empirical methods, it contributed to sustainable urban development and offered practical insights for regional planning and landscape ecology.

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List of Abbreviations and Acronyms

AI	Aggregation Index	LULC	Land Use/Land Cover
AWMSI	Area-Weighted Mean Shape Index	LULCC	Land Use/Land Cover Change
CARS	Multi-Type Random Patch Seeds	LUTM	Land Use Transfer Matrix
CBM	Chubu Metropolitan	MAE	Mean Absolute Error
CMIP6	Coupled Model Inter-Comparison Project Phase 6	MCRM	Minimum Cumulative Resistance Model
COP10	Convention on Biological Diversity 10	MEA	Millennium Ecosystem Assessment
CS	Carbon Storage	MLIT	Ministry of Land, Infrastructure, Transport and Tourism
DBH	Diameter at Breast Height	MSPA	Morphological Spatial Pattern Analysis
dIIC	Delta Values for IIC Index	NP	Number of Patch
dPC	Delta Values for PC Index	NPP	Net Primary Productivity
EBK	Empirical Bayesian Kriging	OK	Ordinary Kriging
ESP	Ecological Security Pattern	PANCES	Predicting and Assessing Natural Capital and Ecosystem Services
ESs	Ecosystem Services	PC	Probability of Connectivity
ESV	Ecosystem Service Value	PD	Patch Density
GDP	Gross Domestic Product	PLUS	Patch Generation Land Use Simulation
GEE	Google Earth Engine	PSS	Public Service Space
GHG	Green House Gas	P-V-O	Pressure-Vitality- Organization
IDW	Inverse Distance Weighting	RBF	Radial Basis Function
IEW	Information Entropy Weight	RCP	Representative Concentration Pathways
IIC	Integral Index of Connectivity	RMSE	Root Mean Square Error
InVEST	Integrated Valuation of Ecosystem Services And Tradeoffs	SHDI	Shannon Diversity Index
IPCC	Intergovernmental Panel on Climate Change	SHEI	Shannon Evenness Index
JAXA	Japan Aerospace Exploration Agency	SS	School Space
KDE	Kernel Density Estimate	SSP	Shared Socioeconomic Pathway
KKM	Kinki Metropolitan	TAS	Tourist Attraction Space
LAI	Leaf Area Index	T-C-K	Tokyo-Chubu-Kinki
LC	Landscape Connectivity	TKM	Tokyo Metropolitan
LCP	Least-Cost Path	UES	Urban Ecosystem Service
LEAS	Land Expansion Analysis Strategy	UPS	Urban Park Space
LH	Landscape Heterogeneity	V-O-R	Vitality-Organization-Resilience
LISA	Local Indicators of Spatial Association		
LO	Landscape Organization		
LPI	Patch Index		
LS	Landscape Shape		
LSI	Landscape Shape Index		
LUH2	Land-Use Harmonization2		

Chapter 1

General Introduction

1.1 Research Background and Issues

1.1.1 Urbanization

The latest report from the United Nations highlights the exponential growth of the global population, which reached 7.6 billion in 2018, with urban residents accounting for a significant portion at 4.2 billion. Projections indicate an even more dramatic increase, with estimates suggesting that by 2050, the global population will surge to 9.7 billion, with a staggering 68% expected to reside in urban areas, amounting to approximately 6.6 billion individuals (Sun et al., 2020; Szkop, 2020a). Urban expansion, driven by intense human activity, continues to deplete land resources (Li et al., 2015; Pauleit et al., 2005). The influx of people into urban centers has spurred their growth and expansion. The allure of urban environments, coupled with employment opportunities, attracts a larger populace, further propelling the process of urbanization (Antrop, 2004; Dadashpoor et al., 2019). Consequently, this urbanization trend leads to the gradual replacement of the original landscape, once dominated by natural vegetation, with buildings and concrete surfaces (Zhao et al., 2012). In recent years, urban expansion has been particularly pronounced in developing countries, where urbanization rates are skyrocketing (Angel et al., 2011; Connop et al., 2016), especially in low- and middle-income countries in Asia, Africa, and Latin America (Li et al., 2015; Lorenz and Lal, 2009; Pauleit et al., 2005). However, it is crucial to recognize that while urban development in developed countries has reached a relatively stable phase, phenomena such as population concentration and alterations in green spaces persist (Chen et al., 2020; Sun et al., 2020). Moreover, certain developing countries are currently facing demographic and economic conditions like those observed in developed countries, including population aging, declining birth rates, and economic slowdowns (Wang et al., 2023; Wolff and Mykhnenko, 2023). Therefore, investigating the existing characteristics of urbanization development in developed countries holds significant importance. These research findings have the potential to offer valuable empirical insights for future land use management strategies in developing countries and to provide theoretical and data-based foundations for land use planning initiatives in developed countries.

1.1.2 Metropolitan Area in Urbanization

The emergence of the metropolis concept represents a significant milestone in the ongoing urbanization process. In 1961, Jean Gottmann introduced the notion of the metropolis to elucidate the phenomenon of extensive urbanization in the northeastern United States (Lang et al., 2020). He defined a "metropolitan area" as a contiguous large urban region comprising multiple interconnected cities, emphasizing the intrinsic relationships among urban centers and highlighting the integrated nature of the metropolitan area (Lang et al., 2020). With the rapid advancement of global urbanization, various countries and regions have formulated methodologies for delineating metropolitan areas, which reflect the unique characteristics and requirements of urbanization across diverse regions (Figure 1.1). These methodologies typically consider factors such as population density, city size, economic

interconnections, functional integration, transportation networks, administrative divisions, and urban development trends (Moreno-Monroy et al., 2021; Zhen et al., 2017).

Currently, the concept of the metropolitan area holds profound implications for urban planning, land use management, and ecological environment protection (Dadashpoor et al., 2019; Dewan and Yamaguchi, 2009; Geymen and Baz, 2007; Yin et al., 2019). This is particularly evident in its coverage of intricate ecological system interconnections among different cities, encompassing elements such as species migration corridors and forest ecosystems. These ecological system interconnections play a pivotal role in sustaining the health and stability of ecosystems (Araki et al., 2018; Dadashpoor et al., 2019). However, the formation of metropolitan areas often coincides with rapid large-scale development and urbanization processes (Antrop, 2004; Güneralp et al., 2020). Furthermore, relatively developed metropolitan areas tend to attract greater population influxes due to economic prosperity and infrastructure enhancements. Consequently, this trend not only accelerates urbanization but also poses a myriad of challenges and risks to the ecological environment.

Research focusing on urban green spaces and ecological environments at the metropolitan scale holds paramount importance. Such studies not only foster a deeper understanding of the connectivity and landscape patterns of urban ecosystems but also facilitate the identification and resolution of ecological environmental issues within metropolitan areas. Augmenting the analysis with additional empirical evidence and statistical data could further enrich the discourse and bolster the arguments presented.

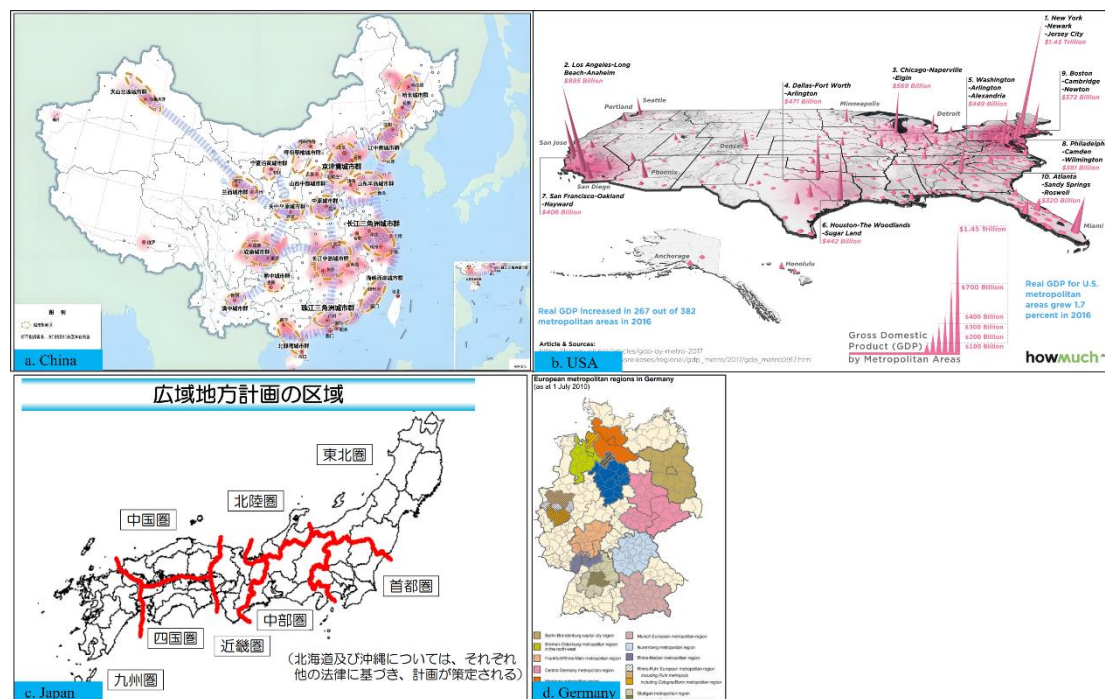


Figure 1.1 Metropolitan Areas Across Diverse Nations

(Source: a: (The State Council, The People's Republic of China 2016); b: (Jeff Desjardins 2017); c: (MLIT, Japan, n.d); d: (Federal Institute for Research on Building, Urban Affairs and Spatial Development (BBSR) within the Federal Office for Building and Regional Planning (BBR), Bonn 2011)).

1.1.3 Land Use/Land Cover

Land use refers to the intentional development and utilization of land resources by humans to meet specific needs. This includes various types of land such as residential, agricultural, transportation facilities, and public management and service areas. On the other hand, land cover represents the natural coverage conditions formed on the Earth's surface, including forests, grasslands, artificial surfaces, and various types of crops (He et al., 2022). In wide-area scale land cover studies, the term 'land use/land cover (LULC)' is commonly used to collectively represent the land cover categories within the region (García-Álvarez et al., 2022; He et al., 2022; Ul Din and Mak, 2021a; Yang et al., 2022).

The rapid socio-economic development of human societies has led to extensive exploitation and utilization of land resources on the Earth's surface, resulting in fragmentation of green spaces within LULC types and subsequent ecological degradation (Verburg et al., 2015; Zhang et al., 2018). Therefore, in the context of sustainable LULC, efforts are focused on detecting land use/land cover change (LULCC), evaluating the ecological security pattern and ecosystem service functions of green spaces, and exploring strategies to maximize the protection and management of land resources while meeting development needs (Ersoy et al., 2019; García-Álvarez et al., 2019; Zhang et al., 2018). Furthermore, amid the complex global economic conditions and escalating climate issues, there is a growing interest in investigating the correlation between LULC characteristics, climate, and socio-economic development (Chen et al., 2020; Dale, 1997; Kim et al., 2013; Liao et al., 2020; Millward, 2006). This exploration aims to regulate climate and formulate regional development policies through land use planning. In conclusion, researches surrounding the LULC has garnered widespread attention across governmental, societal, industrial, and scientific organizations, with extensive discussions in the fields of ecology, urban planning, and landscape architecture (Lambin et al., 1999; Wilkerson et al., 2018).

1.1.4 The Application of Ecosystem Services

In the 1970s and 1980s, scholars initiated a significant shift in research paradigm by adopting an economic perspective to investigate ecological issues, underlining the societal reliance on natural ecosystems for biodiversity conservation efforts (Braat and De Groot, 2012). Subsequently, Westman, (1977) introduced the concept of "ecosystem values", which was subsequently refined into "ecosystem services (ESs)" through systematic studies by Ehrlich (1981), and Ehrlich and Mooney (1983), gaining widespread recognition (Costanza et al., 2017). In the early 21st century, the United Nations Environment Programme conducted the groundbreaking Millennium Ecosystem Assessment (MEA), providing a comprehensive evaluation of ecosystems and their societal significance, thereby emphasizing the intricate interdependencies between ESs and human well-being (Millennium Ecosystem Assessment, 2005). Following closely, the launch of "The Economics of Ecosystems and Biodiversity" initiative in 2007 aimed to underscore the economic importance of biodiversity and ESs and their integration into policy-making processes (Braat and De Groot, 2012). These pivotal studies not only enriched discussions surrounding ESs research but also underscored the indispensable role of ESs in environmental management. The ESs concept stands as a robust framework guiding policy formulation and conservation strategies to tackle diverse environmental challenges (Ahern, 2014; Costanza et al., 2017).

ESs encompass the ecological features, functions, or processes that directly or indirectly promote human well-being, deriving benefits from functioning ecosystems (Costanza et al., 2017). These services include provisioning services such as food and water; regulating services like flood and drought regulation; supporting services like soil formation and nutrient cycling; and cultural services such as recreation, spiritual enrichment, and aesthetic appreciation (Millennium Ecosystem Assessment, 2005) (Figure 1.2).

The Intergovernmental Panel on Climate Change (IPCC) has emphasized the profound impact of human activities, particularly greenhouse gas emissions, on global climate warming (IPCC, 2023). This warming trend has led to disrupted the structure, functionality, and processes of ESs, with significant consequences for both global ecology and human well-being (Li et al., 2021). Notably, terrestrial ecosystems have emerged as critical regulators of the global carbon cycle and vital mitigators of climate change. Green spaces, in particular, serve as primary reservoirs for terrestrial carbon storage regulation (Wang et al., 2022; Tian et al., 2022a). As urbanization progresses, the conversion of natural landscapes into artificial surfaces alters the distribution and abundance of green spaces, which in turn affects their capacity for carbon sequestration and storage. The loss of green spaces and vegetation cover in urban areas reduces the overall carbon sink capacity and exacerbates the concentration of greenhouse gas in the atmosphere (Bai et al., 2020; Xie et al., 2023). Furthermore, urbanization-induced LULCC can disrupt the balance of other ES functions, such as water purification, air quality regulation, and biodiversity conservation, with cascading effects on human health (Collins et al., 2019; Thaiutsa et al., 2008; Wolf et al., 2020). Given the urgency of addressing climate change and its associated impacts, there is a growing recognition of the need to integrate ecosystem-based approaches into urban planning and development strategies (Tian et al., 2022; Ul Din and Mak, 2021).

Research in ES conducted at wide-area scales sometimes neglects the significance of green spaces within built-up areas, possibly due to challenges related to accuracy and data precision (Ul Din and Mak, 2021). However, as urbanization continues to intensify gradually, it is predicted that by the year 2050, approximately two-thirds of the global population will be residing in built-up area (Sun et al., 2020; Szkop, 2020a). This rapid urbanization trend presents a host of increasingly severe and intricate environmental and climatic challenges within these densely populated urban areas (Elmqvist et al., 2015). However, urban ecosystem services (UESs) have received less attention than global ESs research (Haase et al., 2014). UEs encompass the multifaceted benefits derived from the blue-green infrastructure within urban environments, comprising diverse features such as water bodies and natural green spaces like parks, urban forests, and community greenery (Cimburova and Barton, 2020; Elmqvist et al., 2015; Livesley et al., 2016). These integral components of urban landscapes play a pivotal role in shaping the quality of life and overall well-being of urban residents through various direct and indirect mechanisms. Urban blue-green infrastructure serves as a critical component in the regulation of urban microclimates, mitigation of the urban heat island effect, and filtration of air pollutants (Collins et al., 2019; Thaiutsa et al., 2008; Wolf et al., 2020).

Conducting research and discourse on ESs across wide-area scale and within built-up area provides an opportunity to explore the intricate interconnections among urbanization, ES, and human well-being. This exploration can advance the understanding of how urbanization impacts ES and human well-being, hereby advancing the research and formulation of urban planning strategies through the lens of ES.



source: *Final Recommendations of the Interagency Ocean Policy Taskforce, 2010*

Figure 1.2 Explanation of ecosystem service functions.

1.2 Literature Review and Research Gaps

1.2.1 Literature review

Studies on LULC and Related Research

The spatial analysis of LULC primarily relies on remote sensing data and Geographic Information Systems (GIS) technology. Currently, the most common research methods and approaches include the following aspects:

- I. LULC classification: Using remote sensing images to generate LULC maps at different resolutions (Andreatta et al., 2022; Gerardo and De Lima, 2023; Niroumand-Jadidi et al., 2022; Ul Din and Mak, 2021a).
- II. LULCC Detection: Comparing remote sensing images from multiple time points to detect changes in LULC (Lambin et al., 1999; Zhang et al., 2018).
- III. Spatial Distribution Analysis (Abdullah and Nakagoshi, 2006; Dadashpoor et al., 2019; Gandini et al., 2018).
- IV. Landscape Metrics: Description and quantification of the spatial structure and characteristics of LULC types (physical properties of patches) (Hu et al., 2023; Jia et al., 2019).
- V. LULC Simulation: Conducting simulation studies to project future LULC scenarios (Cunha et al., 2021; Liang et al., 2021; Yang et al., 2022).

Previous studies have predominantly focused on regions within developing countries (Geymen and Baz, 2007; Talebi Khiavi and Mostafazadeh, 2021). Among these, research conducted on a wide-area scale in China has been most widespread (Cunha et al., 2021; Jia et al., 2019; Liao et al., 2020). Additionally, inquiries into LULCC often

consider the temporal variations, further integrating the physical attributes of LULC types, spatial patterns, LULC simulation, and ecosystem services calculation. For example, Dadashpoor et al., (2019) utilized LULC data spanning from 1996 to 2016 to examine the impacts of LULCC and urbanization on landscape patterns within the Tehran Metropolitan Area, contributing to sustainable regional planning. Huang and Liao. (2019) focused on Yangtze River Basin in China, projecting LULC scenarios for 2020 using data from 2010 and 2015, and exploring potential changes in functional connectivity across various urban expansion scenarios. Sohl et al. (2016) conducted a comparative analysis of multiple LULC simulation models in the United States, simulating LULC from 2000 to 2100. Meanwhile, Wang et al. (2018) predicted the LULC data for 2030 in Wuhan Province, China, based on an evaluation of LULCC from 2000 to 2015, and conducted assessments of ecosystem services. In essence, research methodologies and strategies concerning LULC types are continually evolving, with the aim of promoting sustainable development in land use planning and management.

Studies on Ecosystem Services

This study searches the ISI Web of Knowledge platform (<http://www.isiknowledge.com>) for papers using the term "ecosystem services" revealed a substantial upsurge in research publication spanning from 2000 to 2023, with notable contributions from the United States and China, among other countries (De Araujo Barbosa et al., 2015) (Figure1.3). The researches surrounding ecosystem services are characterized by its diversity and complexity, contingent upon specific research objectives, ES categories, and the methodological approaches employed. Commonly utilized methods for assessing ecosystem services include qualitative analysis, social surveys, statistics, economic valuation, biophysical indicators, proxy valuation, and model calculations (Shoyama et al., 2017; Wolff et al., 2015).

Presently, there is a prevalent trend in the assessment and mapping of ecosystem service functions leveraging remote sensing and LULC data through modeling and data collection (Malinga et al., 2015; Shoyama et al., 2017; Wangai et al., 2016). This approach has been adopted in some studies conducted at wide-area scales, utilizing the functionalities of ecosystem services across various LULC types and accounting for the physical characteristics, soil structures, and topographical differences to quantify ecosystem service functionalities (Abelleira Martínez et al., 2016; Gilman and Wu, 2023; Malinga et al., 2015; Tian et al., 2022b). Notably, regulating services emerge as a prominently studied category among these assessments. However, it is imperative to acknowledge that the assessment of ES based on remote sensing and LULC data is subject to the precision and accuracy of the underlying data, necessitating careful interpretation (Malinga et al., 2015). Furthermore, there exists a notable dearth of research on ES focusing on urban areas compared to studies centered on blue-green infrastructure, such as forests and cultivated land (Shoyama et al., 2017).

UES are closely linked to human well-being, encompassing critical functions such as mitigating air pollution, alleviating the urban heat island effect, providing direct health benefits (e.g., reducing asthma rates), and enhancing public ecological knowledge and awareness of sustainable development (Su et al., 2010). Currently, urban forests are widely recognized as crucial components of urban green infrastructure, playing pivotal roles in delivering ecosystem services (Livesley et al., 2016). Urban forests offer a myriad of public benefits, including temperature reduction, amelioration of the urban heat island effect, pollution mitigation, carbon sequestration and storage, flood attenuation, as well as providing recreational opportunities and inspiration for culture, art, and design (Raum et al.,

2019). The i-Tree eco software, developed in the United States, has emerged as a prominent tool for assessing urban forest ES functions (Cimburova and Barton, 2020; Livesley et al., 2016). Widely utilized in various European countries and the United States, this software has been integrated into assessments of UES and urban planning research (Cimburova and Barton, 2020; Lin et al., 2021; Szkop, 2020b).

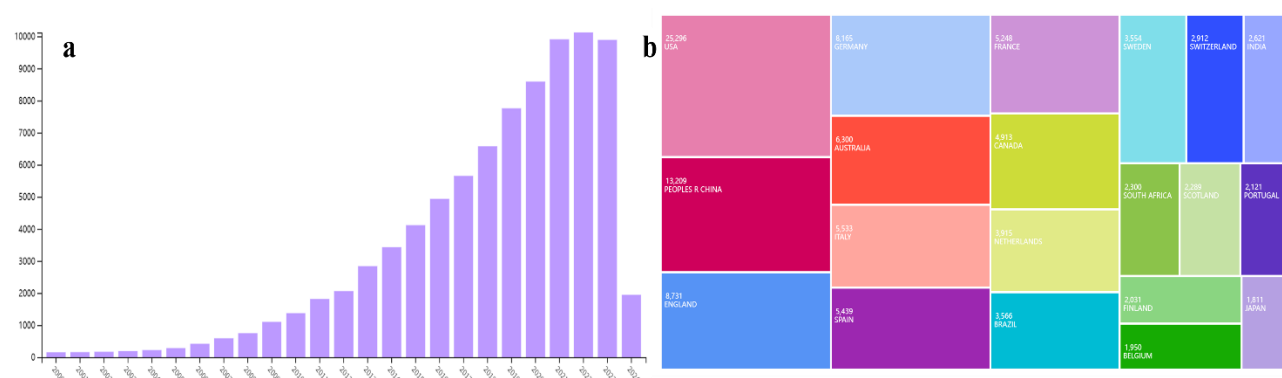


Figure 1.3 Number of studies in ESs found in the literature review (a. Publication Years, b. Countries and Regions).

Studies on LULC in Japan

Japan initiated the development of national land data in the early 1970s, and currently, various institutions worldwide offer extensive and diverse national numerical data (Saizen, 2001; Saizen et al., 2006). This has fostered extensive scholarly inquiry and discourse on LULC typologies within Japan. For instance, in LULCC, Saizen (2001) have examined the dynamics of LULCC in Japan and urban areas from 1974 to 1996 using spatial data, encompassing both national numerical and detailed numerical information. Shimizu (2015) have employed the third mesh data of national numerical information to analyze LULCC patterns in Japan from 1976 to 2009. Ohbi and Suzuki (2002) have conducted analyses of LULCC at the basin level utilizing LULC data from 1976 and 1991. Furthermore, studies have emerged examining the spatial patterns of LULC in Japanese cities, employing landscape patterns or corresponding indices, thereby inciting discourse in realms such as biodiversity conservation and disaster risk reduction. For instance, Yamaura et al. (2008) investigated the influence of forest patch morphology on species diversity, while Yoshioka et al. (2013) devised the "Satoyama Index" based on LULC to gauge the degree of satoyama across different regions of Japan. In recent years, amidst the adjustments in the global economic landscape and the complexities of climate change, research on future LULC simulation in Japan has witnessed a gradual upsurge (Chen et al., 2021; Hori et al., 2021; Yamasaki et al., 2023). For example, a five-year research project called "Predicting and Assessing Natural Capital and Ecosystem Services" (PANCES) has devised several national-level future scenarios to explore potential changes in LULC by 2050 (Shoyama et al., 2019). Yamasaki et al., (2023) simulated the outcomes of LULC in Japan from 2015 to 2100 based on scenarios provided by the Shared Socioeconomic Pathways (SSPs).

Furthermore, considering Japan's fundamental national conditions, analyses and research on LULC in Japan often target farmland and built-up area (Hanashima and Tomobe, 2012; Su et al., 2018). Overall, research related to LULC is comparatively more abundant and covers a wider range of topics in Japan.

Studies on Ecosystem Services in Japan

With the successful convening of the tenth Conference of the Parties to the Convention on Biological Diversity (COP10) in Nagoya, Japan in 2010, research on biodiversity and ES has garnered widespread attention in Japan. Common methodologies for ES evaluation include qualitative analysis, questionnaire surveys, and the utilization of biophysical indicators (Shoyama et al., 2017). For instance, Kitamura et al. (2020) conducted economic evaluations of ES in Lake Kasumigaura, utilizing publicly available data spanning from 1996 to 2016. Ito and Hayashi. (2015) undertook a factor analysis to assess subjective values of biodiversity and ES in the Isoragihama tidal flats of Aichi Prefecture through online surveys. Sase(2023) investigated the influence of atmospheric environments in Japan and East Asia on forest ES. Moreover, with the increasing prevalence of ES mapping, Japanese scholars have recently ventured into the assessment of ES using remote sensing data or LULC data. For example, Huang et al. (2021) employed natural methods to mitigate flood risks in Shiga Prefecture while evaluating ES. Hashimoto et al. (2015) provided depictions and descriptions of ES within social-ecological production landscapes in Noto. Hirabayashi (2021) evaluated the air purification levels of urban forests in Tokyo. Natuhara (2013) assessed ES in Japanese rice paddies. Research in the spatial mapping of ES in Japan is gradually increasing. Furthermore, previous studies related to UES in Japan mainly focus on middle-small scales, such as surveys of species diversity and ES evaluations of street trees and urban green spaces (Kang et al., 2022; Kawaguchi et al., 2020; Tan et al., 2021). These studies provide scientific evidence for the management of street trees and urban green spaces and an objective understanding of the benefits of urban forests. Discussions on ES in Japan span various scales and continue to gain momentum.

1.2.2 Research gap

In Japan, extensive analysis and discussion have been conducted in the fields of LULC analysis and UES, resulting in the accumulation of valuable experience. However, several gaps persist in the following aspects:

Study Area and Period Span: LULC research primarily focuses on national and administrative scales, with limited emphasis on wide-area scale differences, such as metropolitan area scale. Additionally, the research time span often centers around the years 1970-2010, with fewer investigations into contemporary LULC characteristics and the driving factors for LULCC, like 2000-2020.

Practical Application of Ecological Planning Methods: Currently, there is limited exploration in wide-area scale ecological security pattern planning and LULC simulation. Furthermore, there is inadequate discussion on the adaptability of research findings to current spatial planning and policies.

Limitations and Disparities in Multi-scale Studies: There are few case studies addressing LULC-related research from wide-area scales to small-to-medium scales, highlighting methodological differences and research limitations associated with scale.

Utilization of UES in Planning: There is a lack of exploration from the perspective of ES in urban green space planning, including methodologies and contributions.

1.3 The Purpose of Study

1.3.1 Study Area

Since the enactment of the "Capital Construction Law" in 1950, the Japanese government has engaged in broad regional planning based on metropolitan areas. Japan's government divides its territory into metropolitan areas based on population, including three major metropolitan areas: the Tokyo metropolitan area (TKM), the Kinki metropolitan area (KKM), and the Chubu metropolitan area (CBM), as well as regional central metropolitan areas ("Sapporo- Sendai-Fukuoka" and others) (National Spatial Planning), totaling eight metropolitan areas. The total population of the three major metropolitan areas constitutes more than half of Japan's population, and their combined GDP accounts for 67.14% of Japanese total GDP in 2013 (MLIT, 2018). These three major metropolitan areas are highly concentrated regions for the Japanese population, economic activities, transportation, and educational institutions.

Hence, this study delves into research and discourse within the realms of LULC and ES across various scales, encompassing the overarching scale of the three metropolitan areas, the metropolitan area scale, prefectural scale, and the built-up areas scale (Figure 1.4).

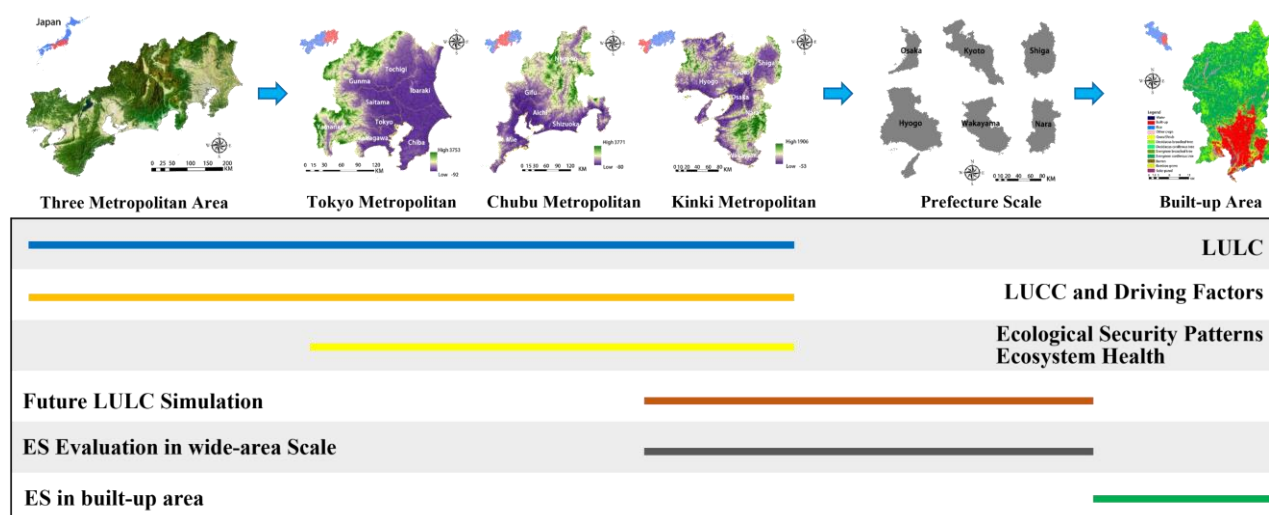


Figure 1.4 Research Area and Research Keywords in This Thesis.

1.3.2 Study Objectives

This study aims to investigate and comprehend the land use management policies and planning legislation in Japan's metropolitan areas. Additionally, it will focus on the metropolitan areas scale, prefectures, and built-up areas to explore the potential applications of various LULC analysis methods in land use management and policy planning. The research results aim to provide insights and methodologies for enhancing LULC planning and management in metropolitan areas. Furthermore, this research hopes to serve as instructive case studies for guiding future land use management strategies and considerations in developing countries.

The specific objectives are as follows:

- I. Clarify LULC change Characteristics from 2000 to 2020 in Japanese metropolitan area.
- II. Explore how spatial analysis based on LULC categories can guide land use planning in Japan.
- III. Develop future LULC simulation scenarios for Japan and explore their potential applications in policies and planning.
- IV. Explore methods to guide land use planning and management through ESs.

1.4 Thesis Structure and Overview

The structure of this thesis is graphically summarized in Figure 1.5. This study consists of six chapters:

The first chapter introduces the background and necessity of this study, providing an overall understanding and motivation.

In the second chapter, a brief overview of land use management policies in Japan's metropolitan areas is provided, with a focus on the dynamic characteristics of LULCC during the period of economic slowdown and population aging (2000-2020). Additionally, it explores the driving factors behind these changes, laying important groundwork and background knowledge for subsequent studies.

The third chapter takes a perspective based on LULC categories to dynamically construct the ecological security patterns of forests in Japan's three major metropolitan areas, and evaluates the ecological health of six types of green spaces. The study combines ecological security patterns and ecological health evaluations to propose feasible methods for LULC type management in Japan's metropolitan areas, providing reference for relevant policy formulation.

Chapter four delves into the KKM Area, Japan's second-largest economic zone, and simulates future LULCC based on four different development scenarios. Furthermore, the integration of study results with relevant regional policies highlights the practical value of LULC simulation research, offering crucial support for future land use planning and management.

Chapter five focuses on the built-up areas in the Kyoto City of KKM Area. By collecting urban forest data through field surveys and calculating ES (regulating services), this study elucidates methods for formulating green space management strategies through ES assessments, providing practical guidance for urban green space planning and management.

Finally, in chapter six, a discussion and summary of the research results are presented.

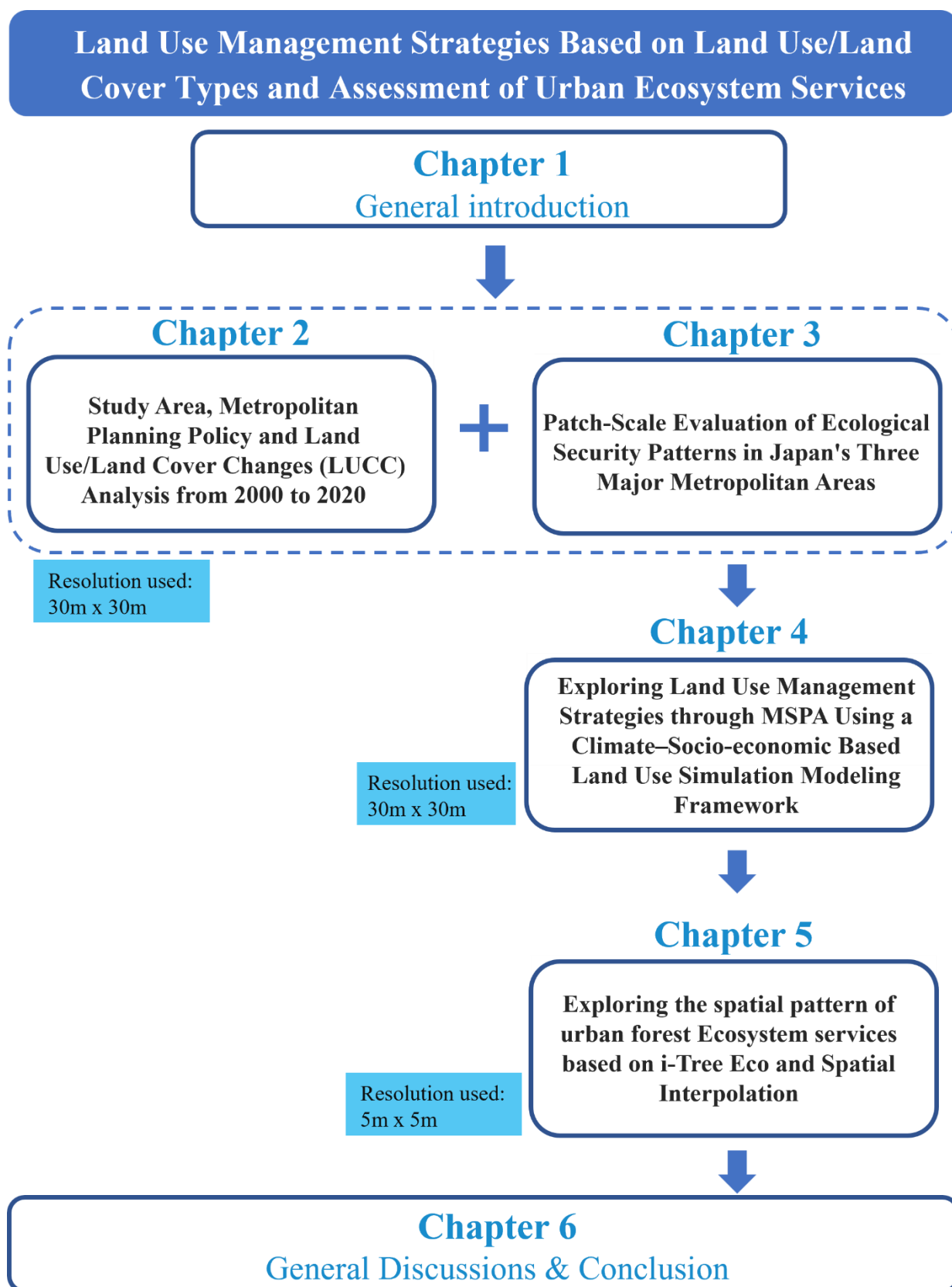


Figure 1.5 The structure of this thesis.

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Chapter 2

Study Area, Metropolitan Planning Policy and Land Use/Land Cover Changes Analysis

This chapter offers a comprehensive overview and basic analysis of the three major metropolitan areas, including their fundamental characteristics, upper-planning legal frameworks, and Land Use/Land Cover Changes (LULCC) from 2000 to 2020. Furthermore, it delves into a study investigating the contribution of driving factors to LULCC. The information presented in this chapter serves as the foundational background for the following chapters.

2.1 Study area

"The metropolitan area" represents an advanced form of urban spatial evolution. It typically refers to an integrated region closely linked, with one or more major cities as its core and its radius extending radially (Kanemoto and Tokuoka, 2001). The scope of Japan's major metropolitan areas consists of central cities and surrounding municipalities (Kanemoto et al., 1996). The central cities refer to the Tokyo Special Wards (the 23 wards of Tokyo) and "government-designated city" (such as Nagoya, Osaka, Kyoto, etc.) (Figure 2.1) (MLIT, Japan, 2015). If the central cities are adjacent to each other, separate metropolitan areas will not be established; instead, they will be integrated. Therefore, the three major metropolitan areas structurally form the following: the Tokyo Metropolitan (TKM) area, with the Tokyo Special Wards (the 23 wards of Tokyo) as the core, forming a "primary dependent structure"; the Kinki Metropolitan (KKM) area, centered around Osaka, Kyoto, and Kobe, forming a "tripolar axis structure"; and the Chubu Metropolitan (CBM) area, forming a "dual-axis structure" with the KKM and TKM areas as axes (MLIT, Japan, 2021). These three major metropolitan areas are intricately intertwined, collectively serving as the bedrock of Japan's economy and cultural landscape. TKM area stands as the largest and most populous in Japan, functioning not only as the nation's political, economic, cultural, and financial nucleus but also as one of the world's foremost urban economics (MLIT, Japan, 2016a). The KKM area emerges as one of Japan's most dynamic and pivotal commercial, cultural, and industrial epicenters, featuring pivotal ports and industrial districts, as well as thriving manufacturing and service sectors, amidst its rich historical and cultural legacy (MLIT, Japan, 2016(b)). Meanwhile, the CBM area plays a crucial role as a pivotal industrial, commercial, and transportation nexus, offering indispensable support to Japan's economy (MLIT, Japan, 2016c).

The geographical characteristics of Japan's three major metropolitan areas exhibit significant diversity (Figure 2.1). TKM Area boasts an expansive and predominantly flat coastal plain. Bordered by the Pacific Ocean to the east, it is characterized by densely populated urban centers. As one moves from the southwest to the north, the terrain gradually shifts to encompass mountainous regions and agricultural lands. CBM showcases a varied landscape, including mountains, plateaus, and coastal plains. It is geographically bisected by the Japanese Alps, dividing it into northern mountainous terrain and southern plains. KKM is marked by a blend of plains, hills, and mountains. Historically, it has been recognized for its fertile plains, which have long been integral to the region's agricultural pursuits (MLIT, Japan, 2021). The area boundaries of this study were analyzed and statistically based on the boundaries restricted in the Greater Regional Plans (MLIT, Japan, n.d.a).

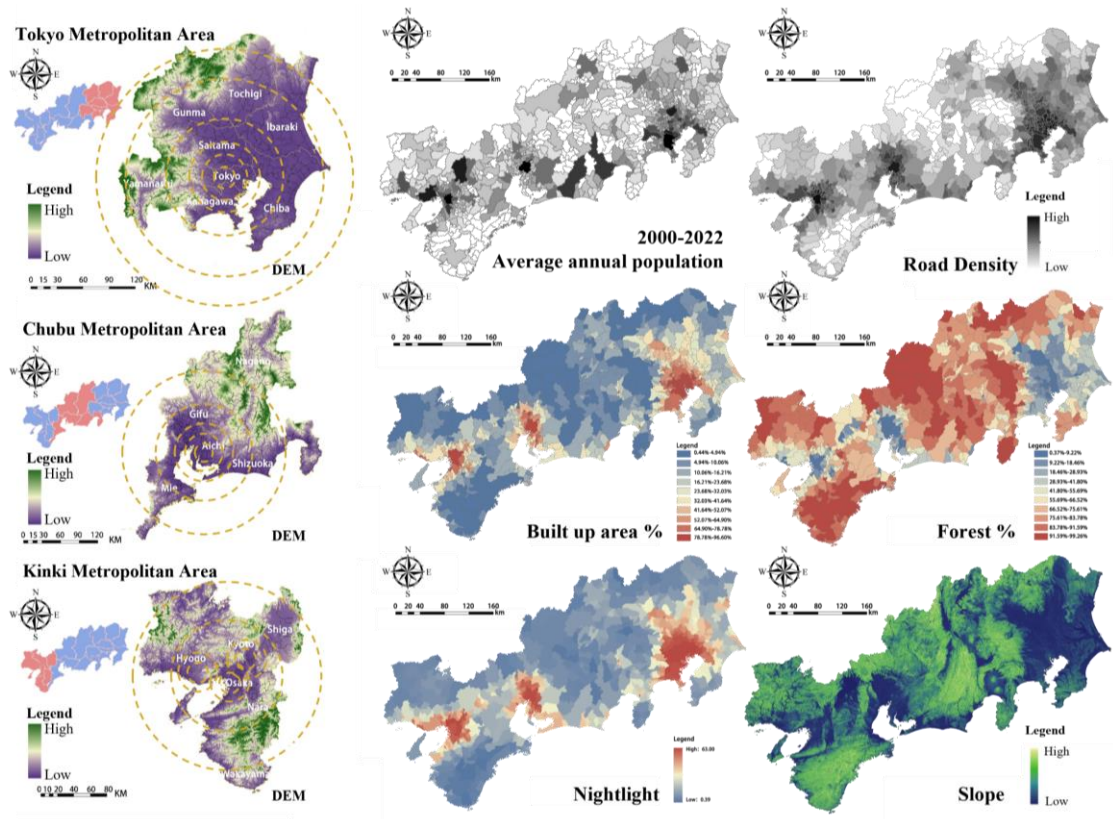


Figure 2.1 The study area: Tokyo metropolitan area, Chubu metropolitan area and Kinki metropolitan area.

2.2 Metropolitan Area Acts and Plans

2.2.1 Acts Related to Land Use Management for Metropolitan Area

2.2.1.1 Legislative Framework

After the Second World War, Japan underwent a process of urban recovery, aiming to effectively address prominent conflicts within its national spatial planning. To achieve this, spatial planning adopted a framework guided by three key acts: the Basic Act for Land (土地基本法), the National Comprehensive Development Act (国土総合開発法) (later renamed the National Spatial Planning Act (国土形成計画法), and the National Land Use Planning Act (国土利用計画法). These three fundamental acts established regulations concerning land ownership, functionality, management, and development standards.

In 1950, Japan formulated and promulgated the National Comprehensive Development Act, with the goal of expanding national land development, serving as an engine for promoting territorial development. This act provided unified guidance for a wide range of policies related to national land from a long-term perspective. However, since 2005, Japan has been grappling with significant and conspicuous challenges such as population decline, social aging, urban population concentration, and overcrowding. In response to these challenges, the National Comprehensive Development Act underwent five revisions and ultimately evolved into the National Spatial Planning Act, which aimed to improve the quality of national land by comprehensively advancing measures for the utilization, maintenance, and protection of land resources (MLIT, Japan, 2023).

Subsequently, Japan revised the framework of the national land planning system based on the National Spatial Planning Act (Figure 2.2). It served as the basis for formulating National Spatial Plans and Greater Regional Plans, which played a complementary role with metropolitan area development plans prepared based on the Metropolitan Area Development Act.

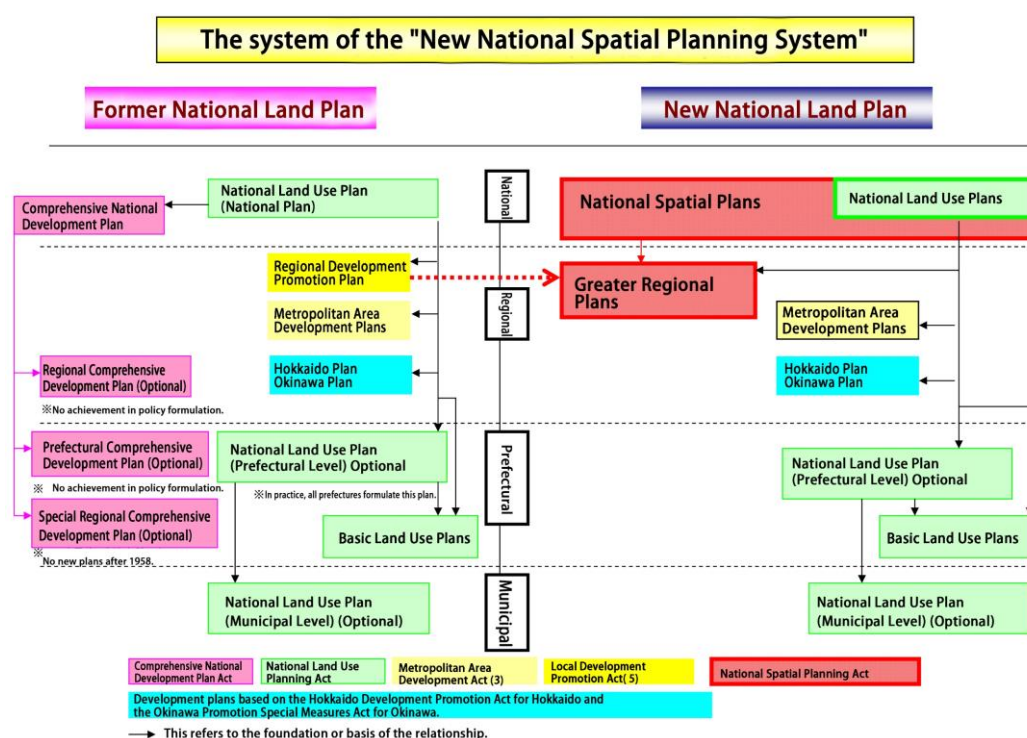


Figure 2.2 National Land Planning System in Japan (Source: Adapted and translated from https://www.pref.chiba.lg.jp/seisaku/shingikai/kokudoriyou/2007/documents/h19_03siry04-1_2.pdf)

2.2.1.2 Metropolitan Area Development Act

Metropolitan Area Improvement Act is the fundamental legislation implemented by the Ministry of Land, Infrastructure, Transport and Tourism (MLIT) for the execution of comprehensive development plans within Japan's three metropolitan areas. This act comprises the Metropolitan Area Development Acts for the TKM (Act No. 83 of 1956), KKM (Act No. 129 of 1963), and CBM (Act No. 102 of 1966). The Metropolitan Area Development Acts serve as a crucial legal framework for the planning of the three metropolitan areas. The legal framework for the existence of the three major metropolitan areas provides a consistent framework, elucidating the purposes, subjects, and review processes of legal enactment (Table 2.1). Additionally, based on the Metropolitan Area Development Acts, corresponding policy areas have been established within the three metropolitan areas, and the implementation of the TKM Development Plan, KKM Development Plan, and CBM Development Plan has been formulated. By implication, it can be divided into established urban area, suburban redevelopment zone, urban development areas and conservation areas (Table 2.2). Furthermore, the planning-related laws formed based on the "Metropolitan Area Development Acts" can be classified into acts related to the development of policy areas, acts related to special financial measures, and acts related to established urban areas (such as industrial restrictions).

Table 2.1 Metropolitan Area Development Act in Three Metropolitan Area

frameworks		TKM	KKM	CBM
Purpose		TKM serves as the political, administrative, and economic hub. With the goal of driving the Japanese economy, enhancing Japan's international competitiveness, and effectively addressing issues related to an aging society, long-term and comprehensive regional development is pursued to establish a sound Capital Region (Article 1).	KKM as one of Japan's major centers alongside the TKM in terms of economy and culture, should promote its construction and orderly development (Article 1).	Promote the close connection between the Tokai region and the Hokuriku region in terms of industrial economy, while enhancing their locational function between the TKM and KKM, strengthening their important position in Japan's industrial economy. Aim to build a livable and balanced development in the CBM (Article 1).
Legal delineated area		TKM: Tokyo Metropolis and its surrounding areas (Article 2, Item 1)	KKM: Around Kyoto, Osaka, and Kobe, as well as their surrounding regions (Article 2, Item 1).	CBM: Nagoya and its surrounding regions (Article 2, Item 1).
Policy zone		Suburban redevelopment zone, Urban development area (Article 2, Items 4 and 5)	Suburban redevelopment zone, Urban development zones, Conservation areas (Article 2, Items 4-6).	Urban redevelopment areas, Urban development zones, Conservation areas (Article 2, Items 3-5).
National Land Council investigation and review		Article 3-17, 19-20 deleted (Article 18).	Delete Sections 3-5 and 7 (Article 6).	Delete Section 7 (Article 6).
Local Council Planning		None	None	Article 8
Planning		TKM Development Plan (Content, Decision, and Amendment) (Articles 21-23).	KKM Development Plan (Content, Decisions, and Amendments) (Articles 8-10).	CBM Development Plan (Content, Proposal, Decision, and Amendments) (Articles 9-12).
Implementation of the plan	Designation of Policy Zones and Legislation	Suburban redevelopment zone, Urban development area (Articles 24-26, Article 27 deleted).	Suburban redevelopment zone, Urban development zones, Conservation areas (Articles 11-14, Article 15 Deleted).	Urban redevelopment areas, Urban development zones, Conservation areas (Articles 13-16).
	Implementation of Projects	Implementing Entities (Article 28) and Support Measures, etc (Articles 29-33).	Implementing Entities (Article 16) and Support Measures, etc (Article 17, Items 1, and Articles 19-21).	Implementing Authorities (Article 17) and Support Measures, etc (Article 18, Item 1, and Articles 20-22).
Others		Reports to the National Diet, etc (Article 30-2).	Publication of Implementation Status of KKM Area Development Plan (Article 17, Item 3).	Publication of Implementation Status of CBM Area Development Plan (Article 18, Item 3).

Source: Adapted and translated from (Yoshida, 2015), Act No. 83 of 1956

(https://elaws.e-gov.go.jp/document?law_unique_id=331AC0000000083_20150801_0000000000000000),

Act No. 129 of 1963 (https://elaws.e-gov.go.jp/document?law_unique_id=338AC0000000129_20150801_0000000000000000),

and Act No. 102 of 1966 (https://elaws.e-gov.go.jp/document?law_unique_id=341AC1000000102_20150801_0000000000000000).

Table 2.2 Policy Zone Names and Meanings

Policy Zone Names	Meanings
Established Urban Area	Areas to prevent excessive concentration of industry and population, and to maintain and promote urban functions.
Suburban redevelopment zone	Areas planned for development to prevent the disorderly expansion of existing built-up areas.
Urban development zone	Areas intended for development as industrial cities, residential cities, and other artificial surfaces.
Conservation areas	Areas deemed necessary for the preservation or development of cultural heritage, green spaces, and tourist resources.
Suburban green space conservation area	In suburban green spaces, where there is a high risk of uncontrolled urban expansion, the protection of green areas that significantly contribute to maintaining, promoting, or preventing residential pollution and disasters is prioritized.

Source: Adapted and translated from Act No. 83 of 1956, Act No. 129 of 1963, and Act No. 102 of 1966.

2.2.1.3 The other acts related to land use development and management

In addition, based on the "National Land Use Planning Act", a comprehensive legal framework for LULC and transactions control is formed, considering LULC types such as urban areas, agricultural land, forest area, natural park areas, and natural conservation (Figure 2.3). Greater regional planning implemented based on acts like the "National Spatial Planning Act" and the "Metropolitan Area Development Act" is also subject to the constraints of the specialized legal framework. For instance, policy areas are not only restricted by the "Metropolitan Area Development Act" but also by specific National Land Use Planning Act such as the "City Planning Act", "Nature Conservation Act", and "Forest and Forestry Basic Act". The implementation of overarching planning acts alongside other specialized laws shapes the current landscape of spatial planning in Japan.

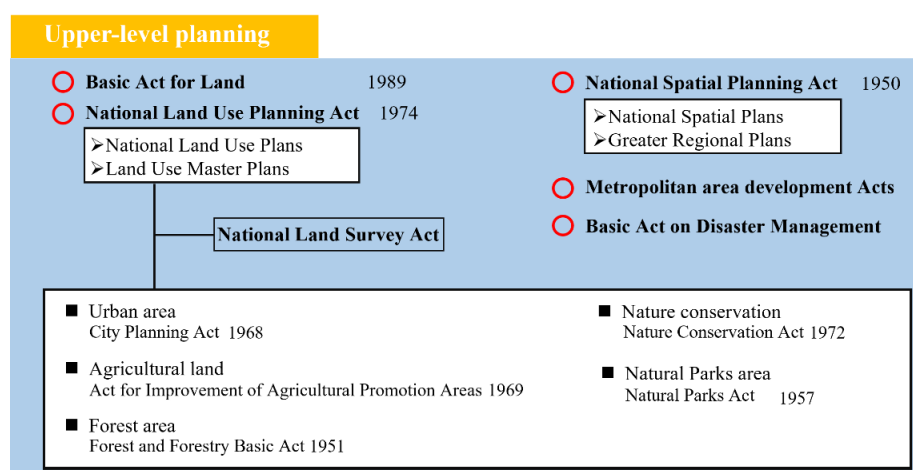


Figure 2.3 Upper-level Planning System in Japan

(Source: Adapted, translated and summarized from

<https://www.city.yokosuka.kanagawa.jp/4805/tokei/honbun/08toshikeikakuhouitaikei.html>)

2.2.2 Greater Regional Plans

2.2.2.1 National Spatial Plans and Greater Regional Plans

The National Spatial Plans is a comprehensive and fundamental planning framework aimed at advancing land

formation across various sectors such as construction, industry, culture, information communication, energy, environment, and landscape (MLIT, Japan, 2016a; MLIT, Japan, 2016b; MLIT, Japan, 2016c). It is devised to promote national development and achieve long-term and coordinated growth in land-related areas.

In 2015, the 7th National Land Formation Planning (National Plan) was enacted by the MLIT, and approved by the Cabinet. The plan comprises three main sections: the fundamental principles of planning, the basic directions for specialized implementation, and the promotion of planning and greater regional plans. The National Plan serves as a strategic outline for implementing national objectives and goals, while greater regional plans break down the specialized implementation and basic directions outlined in the National Plan, considering the characteristics of urban areas, detailing specific projects, and realizing the objectives of the national plan. The National Spatial Planning divides Japan, excluding Hokkaido and Okinawa, into eight broad regional units. Its objective is to formulate land planning measures that align with contemporary needs (MLIT, Japan, 2016a; MLIT, Japan, 2016b; MLIT, Japan, 2016c). By fostering communication and collaboration among these regional units, the plan aims to collectively address the diverse developmental challenges faced by each unit, leveraging their unique territorial characteristics. The National Spatial Planning serves as the foundation for Greater Regional Plans. Furthermore, there is a clear transition of responsibilities and hierarchy between the two planning levels, and mechanisms for coordinating proposals and changes to proposals are well-established. The planning process fosters effective communication through reasonable and efficient platforms, enabling diverse stakeholders (government, citizens, scholars, etc.) to engage in collaborative decision-making.

2.2.2.2 Metropolitan Area Development Plan

Evolution and Objectives of Development Plans

Since the first Metropolitan Area Development Plan was issued in 1958, the Metropolitan Area Development Plans for the three major metropolitan areas have undergone multiple revisions in response to changes in the economy, society, national values, and adjustments in national strategies, including shifts in the focus of the National Spatial Planning (Comprehensive National Development Plan). The evolution and adjustment of the plans reflect the gradual maturation and improvement of urban development in Japan, with each major metropolitan area developing its own characteristics while also being interrelated (MLIT, Japan, 2016(d); MLIT, Japan, 2016(e); MLIT, Japan, 2016(f)). Following a general developmental trajectory of "embryonic stage - growth stage - formation stage - maturity stage" (Xiao and Liu., 2013) (Figure 2.4), the development of the Japanese metropolitan areas can be summarized as follows (Figure 2.5):

For the Tokyo Metropolitan Area Development Plan: Embryonic Stage: The first and second editions aimed to curb the excessive expansion of the TKM. Growth Stage: The third and fourth editions aimed to build a city network with multiple cores and layers, shifting the focus from centralization to outward expansion. Formation Stage: The fifth edition aimed to achieve a sustainable networked spatial structure, transitioning from a single-level dependency to a dispersed network. Maturity Stage: The sixth and seventh editions aimed to construct a convection-type metropolitan area, strengthening cooperation, integration, and transformation among metropolitan areas.

For the KKM Development: Embryonic Stage: The first to third basic development plans aimed to prevent urban congestion and uneven regional development. Growth Stage: The fourth development plan emphasized strengthening the region's economic and cultural ties with the TKM, highlighting unique national and global core

functions. Formation Stage: The fifth basic development plan emphasized the integration of industry, culture, and life, aiming to create a "world-class city." Maturity Stage: In 2016, measures were proposed to address Japan's prominent contradictions and maximize the use of accumulated experience and potential to promote convection.

For the CBM Development: Embryonic Stage: The implementation of the first and second development plans aimed to alleviate uneven regional development and problems of over-concentration and under-population in towns. Growth Stage: The third development plan aimed to form a central and diverse core layer structure. Formation and Maturity Stages: The fourth and fifth development plans emphasized multi-axis national land formation construction and the role of central hubs in metropolitan areas. Under the policy guidance of the "Super Mega-Region" concept, the goal of constructing a super metropolitan area consisting of the TKM, KKM, and CBM was formed.

The stable development of Japan's three major metropolitan areas has highlighted their unique characteristics, with clear strategies for inter-metropolitan cooperation and integration, aiming to enhance mutual exchanges and cooperation between metropolitan areas and gradually forming a networked multi-center spatial structure.

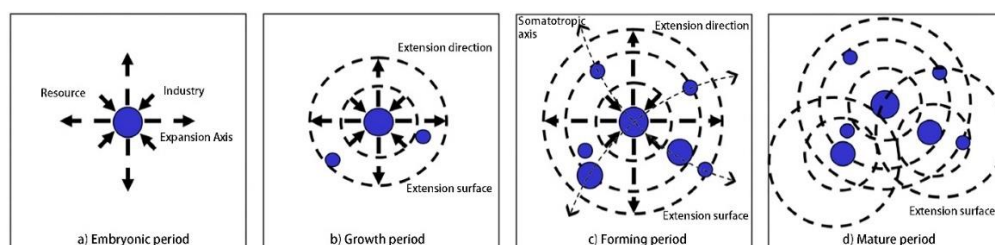


Figure 2.4 Illustration of the Spatial Growth Process of Metropolitan Area (Source: Adapted and translated from Xiao and Liu., 2013)

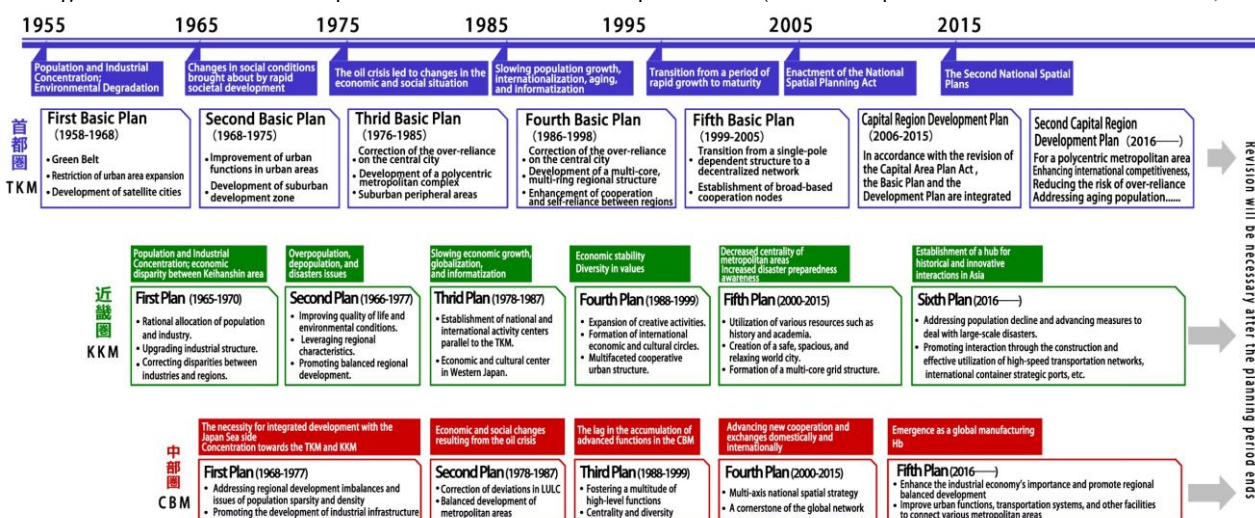


Figure 2.5 Background of the development of the Tri-Area Plan

(Source: Adapted and translated from <https://www.mlit.go.jp/common/001119894.pdf> and MLIT, Japan, 2016(d); MLIT, Japan, 2016(e); MLIT, Japan, 2016(f))

Components and Content of the Development Plans

The Metropolitan Area Development Plan determines the basic planning principles for metropolitan areas, specifies the implementation of specific projects, and regulates the development of related facilities. It serves as the fundamental plan for the development of the national land space planning in metropolitan areas. The Metropolitan Area Development Plans consist of an introduction and two main parts (Figure 2.6). The first part has a planning period of 10 years, while the second part covers a period of 5 years (based on the latest issued development plan). The first part, which includes problem analysis, planning expectations, strategies, and basic principles, is consistent

with the content of greater regional plans. Additionally, the first part defines, delineates, and statistically analyzes the policy areas within the metropolitan areas (Figure 2.7). The second part focuses on facility development planning, outlining expectations and requirements for specific facilities such as roads, railways, and green spaces within the metropolitan areas. To accurately monitor the implementation of the Metropolitan Area Development Plans, annual reports on the implementation status of these plans have been published since 2000, 2008, and 2012 for the TKM, KKM, and CBM. These reports include metropolitan trends (Tokyo area), summaries of the current development plans, details of specific project implementations for the given year, and compiled data (maps of roads, railways, ports, urban parks, etc.). They serve as comprehensive and timely statistical documents that reflect regional development dynamics and facilitate the dynamic supervision of planning implementation. Moreover, they provide the basis for the midterm evaluation (every 5 years) of broader regional planning.



Figure 2.6 The structure of Metropolitan Area Development Plans

(Source: Adapted and translated from MLIT, Japan, 2016(d); MLIT, Japan, 2016(e); MLIT, Japan, 2016(f), designed and summarized by author)

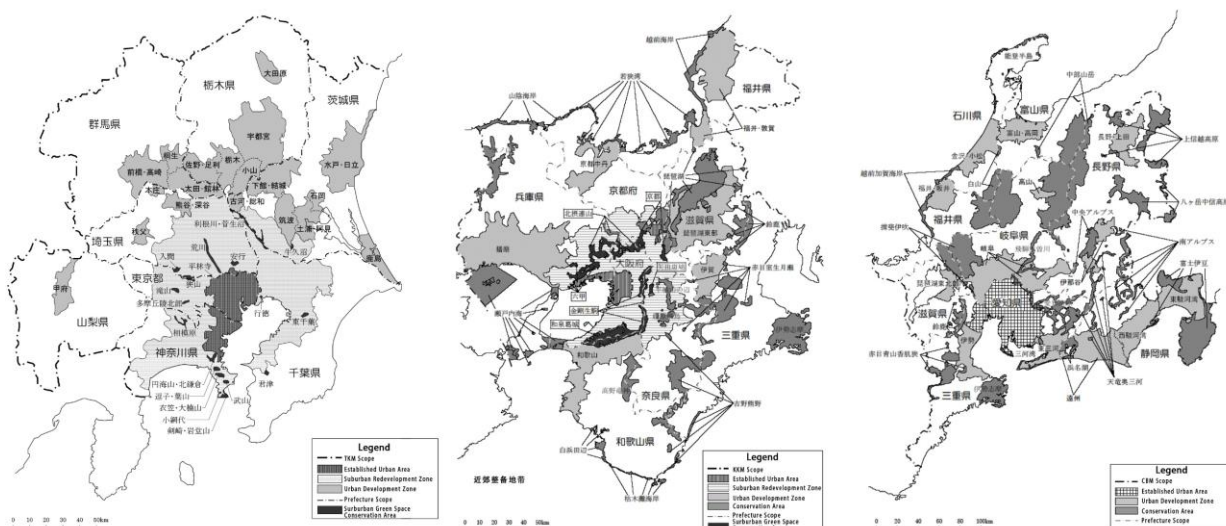


Figure 2.7 The Policy Division from Metropolitan Area Development Plans
(Source: Adapted and translated from <https://www.mlit.go.jp/common/000049179.pdf>)

The construction and development of Japan's three major metropolitan areas exhibit distinctive attributes and tailored content, responsive to local environmental, geographical, economic, and cultural considerations. Strategic policies tailored to each metropolitan area's planning have been proposed accordingly. Nevertheless, there exists a

coherent framework across the planning structure, content, and execution of comprehensive development plans for these major metropolitan areas. These plans are aligned with national spatial plan and greater regional plans, ensuring precise content and clear delineation of responsibilities without conflicts.

2.3 Research Methods for LULCC

2.3.1 Data Sources

This study utilizes spatial data encompassing LULC, topography, climate, soil, vegetation, and socio-economics categories of indicators. The textual data sources are obtained from prefectural yearbooks and related official websites (Table 2.3). Spatial data for climate, temperature, soil and socio-economics are processed to a resolution of $30\text{m} \times 30\text{m}$ using the kriging interpolation method. Road network data sourced from OpenStreetMap (OSM) are employed to calculate "road distance". All datasets are standardized to a $30\text{m} \times 30\text{m}$ spatial resolution to ensure consistency. MODIS NPP and night light data are processed using the Google Earth Engine (GEE).

Table 2.3 Data used in this research and sources.

Data	Data Resources	Description
Land use classification map	Obtained from GLOBELAND30: http://www.globallandcover.com/	Raster, $30\text{ m} \times 30\text{ m}$ (2000,2010,2020)
Digital Elevation Model (DEM)/Evaluation	Obtained from JAXA: https://www.eorc.jaxa.jp/	Raster, $30\text{ m} \times 30\text{ m}$ (2020)
Monthly precipitation/Temperature dataset	Obtained from WorldClim 2.1: https://www.worldclim.org/	Raster, 2.5 minutes (2000-2020)
Clay content, Sand content, Depth to bedrock.....	Obtained from ISRIC-World Soil Information: https://data.isric.org/	Raster, $250\text{ m} \times 250\text{ m}$ (2017)
Road network datasets, residential, open water	Obtained from OpenStreetMap (OSM): https://www.openstreetmap.org/	Shapefile
Administrative unit	Obtained from Ministry of Land, Infrastructure, Transport and Tourism (MLIT of Japan): https://nlftp.mlit.go.jp/	Shapefile
Net primary production (NPP)	Obtained from NASA: (https://ladsweb.modaps.eosdis.nasa.gov/)	Raster, $500\text{ m} \times 500\text{ m}$ (2001, 2010, 2020)
Population distribution	Obtained from WorldPop hub: https://hub.worldpop.org/	Raster, $1\text{ km} \times 1\text{ km}$ (2000, 2010, 2020)
Gross domestic product (GDP) data	Global $1\text{ km} \times 1\text{ km}$ gridded revised real gross domestic product 1992–2019 based on calibrated nighttime light data (Chen et al., 2022)	Raster, $1\text{ km} \times 1\text{ km}$ (2000, 2010, 2019)

2.3.2 Land use conversion matrix

This study employs the Land Use Transfer Matrix (LUTM), grounded in the conceptual framework of spatial analysis and land use modeling, to capture and interpret the intricate dynamics of LULC transformation (Zhou et al. 2020). Essentially, it employs a matrix-based approach to quantify changes in LULC types over successive time intervals. Each cell of the matrix denotes the magnitude of land transferred from one LULC category to another, facilitating the tracking of temporal trends, assessment of spatial patterns, and evaluation of drivers of LULCC (Lin and Peng, 2022).

The LUTM not only encapsulates information on LULC types at the study period's onset and conclusion but

also provides detailed insights into changes in each LULC type throughout the study duration (Talebi Khiavi and Mostafazadeh, 2021). This research utilizes land use maps spanning three periods from 2000 to 2020, analyzing the characteristics of LULCC across the three major metropolitan areas, the TKM, KKM, and CBM areas.

$$S_{ij} = \begin{bmatrix} S_{11} & S_{12} & \cdots & S_{1n} \\ S_{21} & S_{22} & \cdots & S_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ S_{n1} & S_{n2} & \cdots & S_{nn} \end{bmatrix}$$

where S denotes the area; n is the number of LULC types; and i and j denote the LULC types of the two periods (beginning and end, respectively).

2.3.3 Landscape pattern analysis

Landscape pattern analysis involves the systematic quantification of the spatial characteristics of LULC elements within a specific area, primarily through the study of landscape metrics and indices (McGarigal and Marks, 1995). This analytical approach primarily focuses on the inherent arrangement, connectivity, fragmentation, and diversity within landscapes. It serves as a primary means and tool for investigating the distribution and layout of land use coverage, habitats, and prominent landscape attributes (Jiao et al., 2019; Zhou et al., 2020).

This study utilized landscape pattern analysis to evaluate five spatial dimensions of LULC types (area, perimeter, patch density, shape, and intersectionality). Specifically, this study calculated and compared the largest patch index (LPI), patch density (PD), the number of patch (NP), area-weighted mean shape index (AWMSI), and aggregation index (AI) for each LULC type within the three major metropolitan areas in 2000, 2010, and 2020 (Table 2.4) (Dadashpoor et al., 2019; Hou et al., 2020). This allows for further exploration of the changing characteristics of LULC in highly developed urban areas. FRAGSTATS was employed in this study to assess the spatial characteristics and patterns of landscapes based on raster or vector data inputs (McGarigal and Marks, 1995).

Table 2.4 Showing landscape patch metrics (extracted through Fragstat)

Categories	Metrics	Abbreviations	Definitions	Equations	Unit
Area	Landscape Patch index	LPI	LPI approaches 0 when the largest patch of the corresponding patch type is increasing small. LPI = 100 when the entire landscape consists of a single patch of the corresponding patch type; that is, when the largest patch comprises 100% of the landscape.	$LPI = \frac{\max_{j=1}^n a_{ij}}{A} \times 100$ $a_{ij} = \text{area}(m^2) \text{ is the patch } ij, \text{ and } A \text{ is the total landscape area.}$	%
Perimeter	Edge Density	ED	ED = 0 when there is no class edge in the landscape; that is, when the entire landscape and landscape border, if present, consists of the corresponding patch type and the user specifies that none of the landscape boundary and background edge be treated as edge.	$ED = \frac{\sum_{j=1}^{m'} e_{ij}}{A} (10\,000)$ $e_{ij} \text{ is the total length of edge between patch } i \text{ and } j. m' \text{ is the number of patch classes present in the landscape. } A \text{ means the total landscape area.}$	Meters per hectare.
Density	Number of Patch	NP	NP = 1 when the landscape contains only 1 patch of the corresponding patch type; that is, when the class consists of a single patch.	$NP = n_i$ $n_i \text{ is the number of the patch type } i.$	None
Shape	Area-weighted mean shape index	AWMSI	AWMSI = 1 when all patches of the corresponding patch type are circular (vector) or square (raster); AWMSI increases without limit as the patch shapes become more irregular.	$AWMSI = \sum_{j=1}^n \left[\left(\frac{25P_{ij}}{\sqrt{a_{ij}}} \right) \left(\frac{a_{ij}}{\sum_{j=1}^n a_{ij}} \right) \right]$ $P_{ij} \text{ is the perimeter(m) of patch } ij. a_{ij} = \text{area}(m^2).$	None
Interspersion	Aggregation Index	AI	An adjacency matrix, which displays the frequency with which various pairings of patch types (including similar adjacencies between the same patch type) occur side-by-side on the map, is used to determine the aggregation index. Only similar adjacencies involving the focus class are considered in the aggregation index, not adjacencies with the other patch classes.	$AI = \left[\sum_{i=1}^m \left(\frac{g_{ii}}{\text{Max}g_{ii}} \right) P_i \right] (100)$ $g_{ii} \text{ is the number of similar adjacencies (joins) between patch type (class) } i \text{ pixels using the single-count approach. } \text{Max}g_{ii} \text{ is the greatest amount of likes pixels with adjacencies (joins) depending on patch type (class) } i \text{ based on the single-count approach. } P_i \text{ is the percentage of the landscape that is constituted i.e. of patch type (class).}$	%

* LPI: largest patch index, PD: patch density, NP: the number of patches, AWMSI: area-weighted mean shape index, AI: aggregation index.

2.3.4 Morphological Spatial Pattern Analysis

Recently, there has been growing interest in the analysis of LULC spatial patterns based on Morphological Spatial Pattern Analysis (MSPA) (Wei et al., 2022; Wu et al., 2017). MSPA offers an efficient approach to delineate patches and corridors, relying solely on LULC data. Furthermore, MSPA can be effectively integrated with other methodologies, such as landscape connectivity analysis and the least-cost path method (An et al., 2021; Xie et al., 2023). MSPA is an image processing methodology that partitions binary raster imagery into seven distinct and non-overlapping categories: core, islet, loop, bridge, perforation, edge, and branch (Soille and Vogt, 2009; Vogt et al., 2007) (Figure 2.8, Table 2.5). In MSPA, forms such as cores, islets, edges, and perforations correspond to patches in ecology, while linear forms such as bridges, loops, and branches represent corridors in ecology (Dytham and Forman, 1996). To further refine the MSPA-derived map, ArcMap10.5 was utilized to reclassify the MSPA results for the three metropolitan areas.

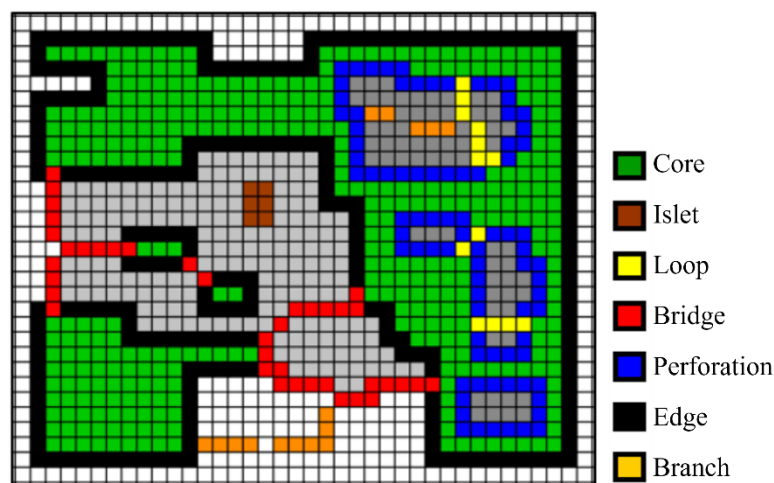


Figure 2.8 MSPA classes (Source: <https://forest.jrc.ec.europa.eu/en/activities/lpa/mspa/#Description>).

Table 2.5 Definition of MSPA classes.

MSPA classes	Definition
Core	Foreground pixels surrounded on all sides by foreground pixels and greater than the specified edge width distance from background
Islet	Foreground pixels that do not contain core. Islet is the only unconnected class. Edges and perforations surround core, and loops, bridges and branches are connected to core
Edge	Pixels that form the transition zone between foreground and background
Perforation	Pixels that form the transition zone between foreground and background for interior regions of foreground. Consider a group of foreground pixels in the shape of a doughnut. The pixels forming the inner edge would be classified as perforations, whereas those forming the outer edge would be classified as edge
Bridge	Foreground pixels that connect two or more disjunct areas of core
Loop	Foreground pixels that connect an area of core to itself
Branch	Foreground pixels that extend from an area of core, but do not connect to another area of core

2.3.5 The Contribution of driving factors

While LULCC is indeed influenced by a multitude of factors, it is commonly categorized into five primary aspects: topography, climate, soil characteristics, socioeconomic conditions, and spatial accessibility (Nasiakou et

al., 2022; Shi et al., 2022; Zhang et al., 2022). This study conducted data analysis using relevant literature and available datasets to identify 20 factors contributing to LULCC in Japanese metropolitan areas (Figure 2.9). These factors encompass topographical features, soil composition including sand content, GDP density, and distance from villages or towns. This study aim is to explore the driving forces behind LULCC in these urban regions.

Next, this study employed the Land Expansion Analysis Strategy (LEAS) model to prioritize the contribution of driving factors (Xie et al., 2023). The model used in this study reflects the impact of various driving factors on different types of LULCC, specifically indicating positive correlations. This means that the driving factors analyzed in the model, such as topography, climate, socioeconomic conditions, and spatial accessibility, contribute to an increase in specific LULC types. The LEAS model involves the preparation of LULC data for two periods (2000, 2020), serving as the Transitions Analysis Strategy, and aims to explore driving factors. Initially, land expansion maps for both periods need to be obtained, with cells indicating areas of change extracted from the later period's LULC data, delineating regions of LULC type alterations (Tian et al., 2022). Random sampling points are chosen, subsets are defined by LULC types, and data mining techniques are applied for individual analyses. When investigating the relationship between the expansion of a certain LULC type and its driving factors, samples of expansion are labeled as "1", while others are labeled as "0". These labeled samples are then used to reconstruct the training dataset, extracting multiple driving factors from the same locations. Subsequently, data mining algorithms are applied to the training dataset to obtain the rules for LULC type conversion (Liang et al., 2021). Finally, this study utilizes the Random Forest Classification algorithm to assess the influence of individual driving factor on land expansion (Figure 2.10). RFC, an ensemble learning technique comprised of numerous decision trees, operates with each tree learning independently and subsequently combining their prediction outcomes. The calculation formula is as follows:

$$P_{i,k}^d(x) = \frac{\sum_{n=1}^M I(h_n(x) = d)}{M}$$

The value of d is either 0 or 1; a value of 1 indicates that there were other land use types that changed to land use type k , while 0 represents other transitions; x is a vector that consists of multiple driving factors; $I(.)$ is the indicative function of the decision tree set; $h_n(x)$ is the prediction type of the n -th decision tree for vector x ; and M is the total count of decision trees. In addition, the RF algorithm has the advantage of measuring the importance of independent variables to the variation of dependent variables, which can be calculated according to the variation of the out-ofbag error caused by stochastic noise. This method has been implemented in many studies (Liang et al., 2021; Yao et al., 2017).

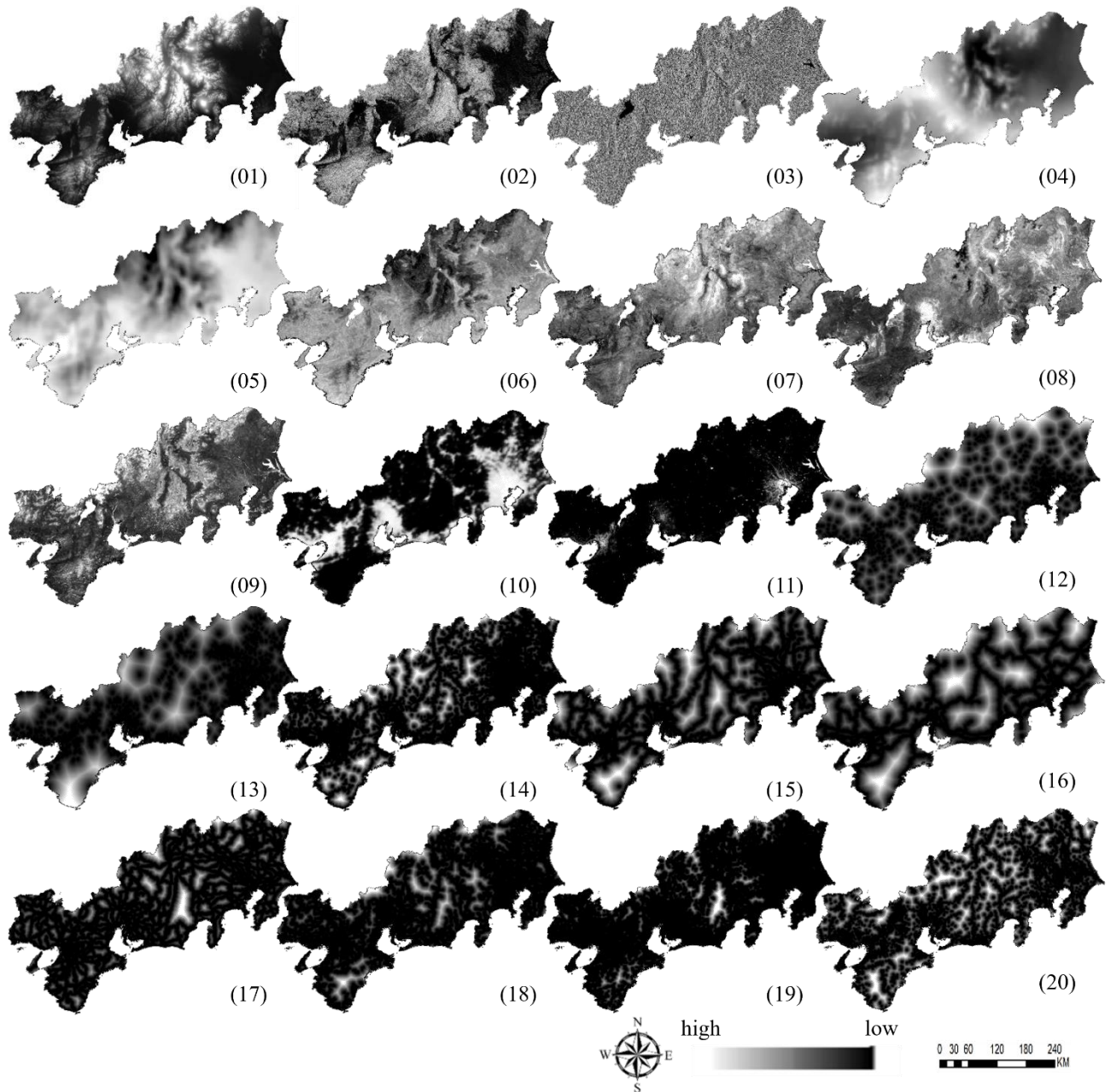


Figure 2.9 The driving factors in metropolitan areas.

((01) Elevation, (2) Slope, (3) Aspect, (04) Precipitation, (05) Temperature, (06) Clay content, (07) Sand content, (08) Soil depth, (09) Soil organic carbon stock, (10) GDP, (11) Population, (12) Distance to townhall, (13) Distance to residential, (14) Distance to transportation node, (15) Distance to railway, (16) Distance to motorway, (17) Distance to trunk road, (18) Distance to primary road, (19) Distance to other road, (20) Distance to open water).

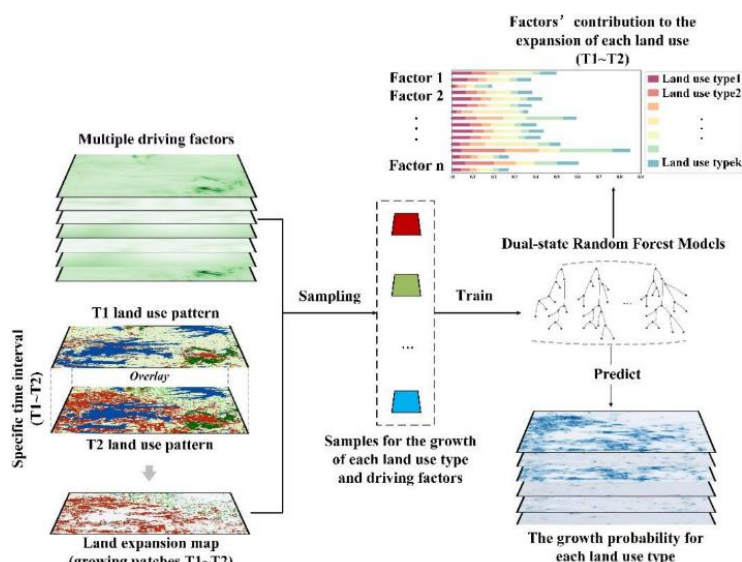


Figure 2.10 Workflow of the rule mining framework based on a land expansion analysis strategy with random forest models (Source: Liang et al. 2021).

2.4 Results

2.4.1 LULCC mapping

In the Tokyo-Chubu-Kinki (T-C-K) region, forest cover approximately 61% of the total area, while cultivated land accounts for about 18%, and artificial surface make up roughly 13% (Figure 2.11, Table 2.6). However, shrubland, grassland, water body, and bare land occupy significantly smaller areas compared to these primary LULC types. Although wetland areas expanded by approximately 40 km² from 2000 to 2020, their overall extent remains limited. In terms of LULCC, there has been a notable increase of 364 km² in forest, a reduction of 1385 km² in cultivated land, and a rise of 1036 km² in artificial surface across the T-C-K region. Cultivated land primarily transition into artificial surface and forest, while forest predominantly convert into shrubland, grassland, and cultivated land, with fewer transitions into artificial surface. Artificial surface primarily converts into cultivated land, with minor shifts into other LULC types.

Among the three major metropolitan areas (Figure 2.12, Table S2.1-2.3), the CBM area encompasses the largest area, covering 42,853.46 km², followed by the TKM area with 36,575.61 km² and the KKM area with 27,263.63 km². From 2000 to 2020, cultivated lands decreased in all three major metropolitan areas, with the most significant reduction observed in the CBM area (1011.70 km²), followed by the KKM area (268.68 km²), and the TKM area (98.48 km²). Artificial surface has expanded in all areas, notably in the CBM area by 790.85 km², while the TKM area witnessed a minor increase of approximately 60 km². Regarding forest, stability was observed in the forest area of the TKM area, while both the CBM and KKM areas experienced increases of over 200 km². Other LULC types underwent relatively minor fluctuations in conversions due to their smaller areas. Additionally, there are significant differences in LULCC among the regions (Figure 2.13).

In the TKM area, minimal changeable differences are observed in forest, cultivated land, and artificial surface. Cultivated land primarily converts into artificial surface, while shrubland and grassland contribute to the increase in forest area. The conversion from artificial surface is relatively small, with cultivated land being the primary

2.4 Results

category. Forests mainly convert into shrubland, cultivated land, and grassland, with minimal conversion involving water bodies.

In the CBM area, cultivated land predominantly converts into artificial surface, followed by forests. Forest conversion is relatively balanced, involving cultivated land, grassland, and shrubland. The conversion of artificial surface to cultivated land (298km²) is much smaller than the conversion of cultivated land to artificial surface (1052km²).

Similarly, in the KKM area, LULC proportions resemble those of the Chubu metropolitan area, with relatively high proportions of shrubland and water bodies. Cultivated land experiences a greater outflow than inflow, primarily towards artificial surfaces. Forest conversion mainly involves the exchange between shrubland and forested areas.

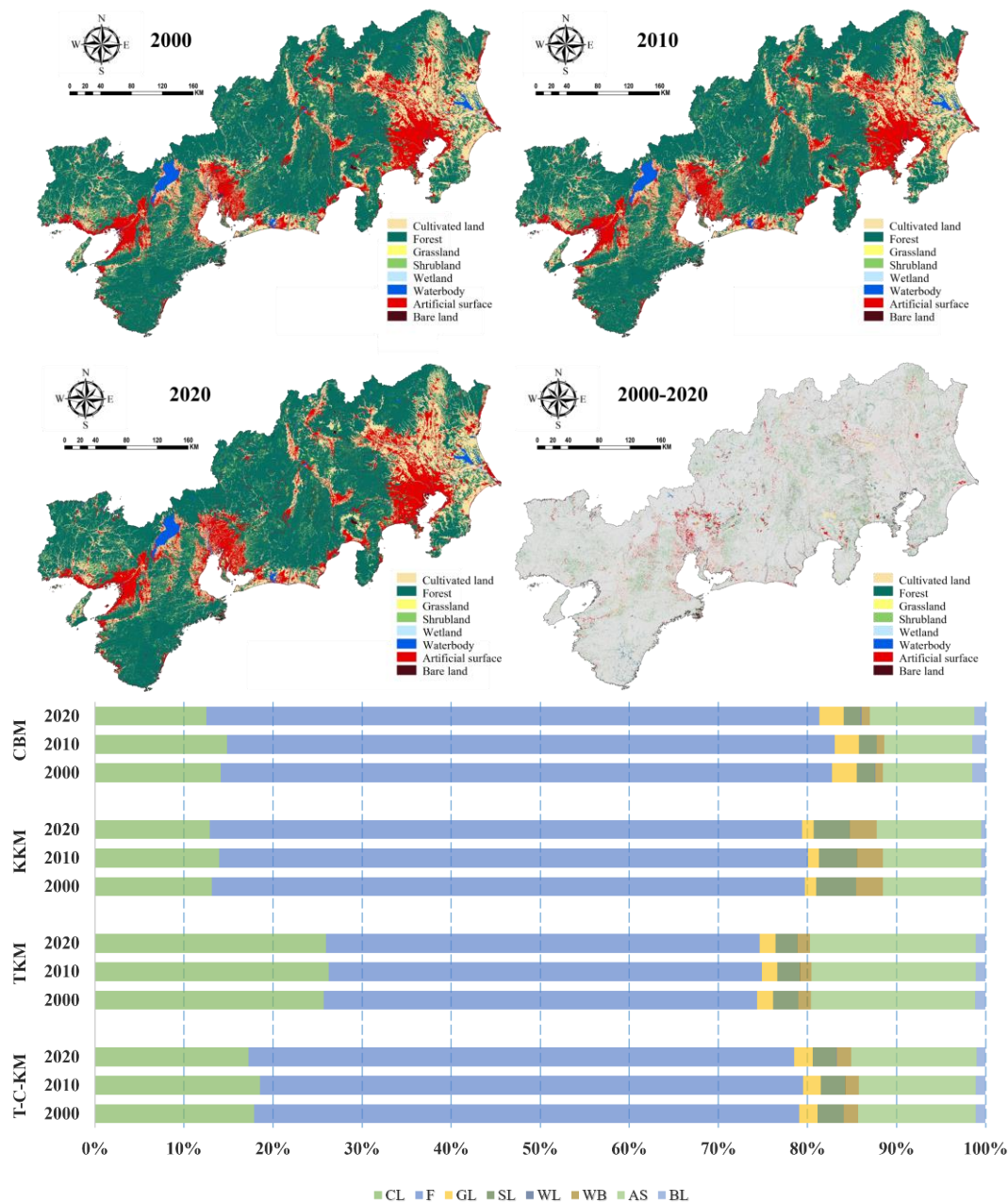


Figure 2.11 The LULCC from 2000 to 2020 (CL: Cultivated Land, F: Forest, GL: Grassland, SL: Shrubland, WL: Wetland, WB: Waterbody, AS: Artificial surface, BL: Bare land).

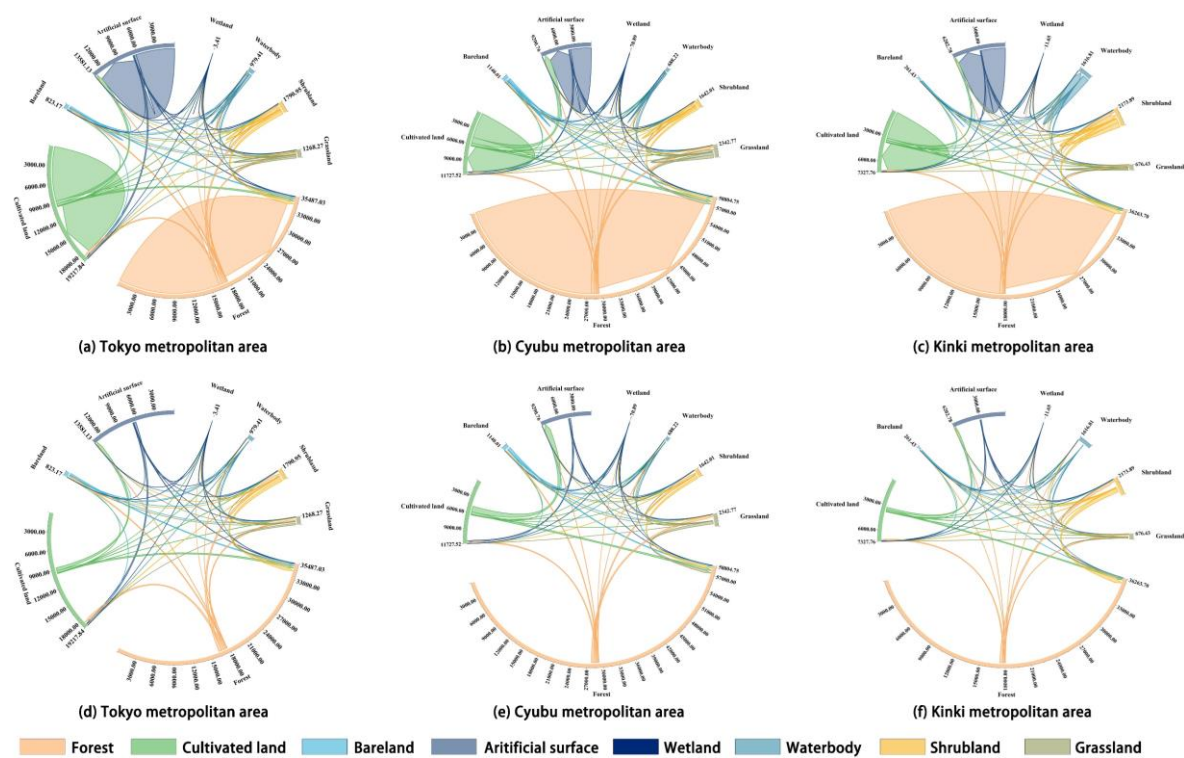


Figure 2.12 The LULCC map of three metropolitan and the LULC changes from 2000 to 2020.

Table 2.6 The LULC transition matrix of the TCK metropolitan from 2000 to 2020/km².

LULC types	Cultivated	Forest	Grassland	Shrubland	Wetland	Waterbody	Artificial surface	Bare land	Total (2020)
Cultivated	16967.23	651.27	36.90	88.66	0.35	40.44	655.41	31.31	18471.56
Forest	876.48	61911.10	835.79	1265.85	0.98	36.77	163.32	428.30	65518.58
Grassland	75.09	786.33	993.45	193.19	0.02	7.47	42.93	90.79	2189.27
Shrubland	88.94	1195.98	167.46	1215.67	0.39	11.07	25.75	86.77	2792.04
Wetland	24.97	4.32	3.67	3.41	1.96	5.41	6.23	11.10	61.08
Waterbody	95.42	66.59	8.29	17.71	1.95	1450.00	30.53	24.00	1694.49
Artificial surface	1697.78	149.52	20.28	40.42	0.21	27.15	13107.63	36.92	15079.91
Bare land	30.46	389.53	59.43	82.17	13.91	17.15	11.62	461.14	1065.41
Total (2000)	19856.37	65154.64	2125.26	2907.07	19.78	1595.46	14043.42	1170.33	106872.32

2.4.2 Landscape pattern index for LULC types

This study conducted a comprehensive analysis of the spatial patterns of LULC types in the three major metropolitan areas, considering parameters such as area, perimeter, patch density, shape, and intersectionality (Table 2.7). The findings are summarized as follows:

In the three major metropolitan areas, the largest forest patch covered over 30% of the total area, exhibiting notably high AI values, indicating significant clustering and integration of large forest patches. Additionally, forest patches displayed high AWMSI and NP values, reflecting a high abundance of forest patches with considerable variations in morphology and irregular characteristics. The distribution of cultivated land and artificial surfaces demonstrated similarities in LPI, NP, and AI values, suggesting integrated characteristics and relatively low fragmentation levels among patches. Notably, AWMSI values in the TKM and KKM areas were significantly higher for cultivated land compared to artificial surfaces, indicating greater irregularity in cultivated land patches and larger

variations in patch shapes among them. Grassland, shrubland, and bare land exhibited high NP and ED values, alongside low LPI, AWMSI, and AI values. Indicating severe fragmentation, poor clustering, and scattered small patches with relatively consistent shapes. Wetlands constituted a small portion of the total areas, concentrated with their numbers increasing from 2000 to 2020. Water body displayed high NP and AI values, indicating numerous but clustered patches, along with low ED and AWMSI values, suggesting relatively uniform patch morphology and high clustering. Specifically, LPI values were high in the TKM and KKM areas, indicating the presence of substantial large water body patches within these regions. This study explored the spatiotemporal changes in landscape patterns of forests, cultivated land, and artificial surfaces within the three major metropolitan areas (Figure 2.13).

In the TKM area, the proportion of the largest cultivated land patches exhibited an inverted-V-shaped increase from 2000 to 2020. By 2020, the perimeter, density, and shape values were relatively high, while the aggregation index declined, indicating fragmentation in cultivated land patches over time, with a decrease in the integration level of the largest patches from 2010 to 2020. In 2000, forests showed the highest values in terms of the proportion of the largest patches, perimeter, density, and shape, but with a decrease in aggregation. By 2010, the proportion of the largest forest patches reached its minimum, with declines in perimeter and density, gradually increasing by 2020, reflecting the initial integration of forest patches followed by an increase in smaller fragmented patches. By 2020, the proportion of the largest artificial surface patches was the smallest, with the highest patch density and perimeter, and the lowest aggregation index, indicating the emergence of smaller artificial surface patches and decreased spatial heterogeneity.

For the CBM area, by 2020, the patch density reached its maximum value, while the proportion of the largest patches, perimeter, and dispersion decreased, reflecting fragmentation in cultivated land patches. From 2000 to 2020, there was a decrease in the density and perimeter of forest patches, while dispersion increased, and the proportion of the largest patches increased, indicating integration and high aggregation of forest patches. The artificial surface in the CBM area experienced a decrease in patch density and an increase in aggregation from 2000 to 2020. The proportion of the largest patches initially declined rapidly, followed by a slow increase from 2010 to 2020, reflecting an exacerbation followed by gradual improvement in the scattered nature of artificial surface patches.

For the KKM area, between 2000 and 2010, the indicators of the largest patches, perimeter, and aggregation of cultivated land reached their maximum values, while the density was at its minimum. reflecting decreased fragmentation and increased integration of cultivated land during this period. From 2010 to 2020, cultivated land patches began to exhibit scattered fragmentation. By 2020, the density, perimeter, and shape of forest patches reached their minimum values, while the indicators of the largest patches and dispersion reached their maximum values, reflecting a gradual integration and clustering of forest patches. By 2020, the patch density, perimeter, and dispersion indicators of artificial surface reached their maximum values, indicating an increase in artificial surface patches.

Table 2.7 The change in landscape pattern indices in three metropolises from 2000 to 2020.

LULC types	Year	Tokyo metropolitan					Chubu metropolitan					Kinki metropolitan				
		LPI	ED	NP	AWMSI	AI	LPI	ED	NP	AWMSI	AI	LPI	ED	NP	AWMSI	AI
Cultivated land	2000	3.8595	9.4764	2319	16.167	97.2896	1.0423	7.4529	5447	15.3032	94.4249	1.1663	9.7094	5144	14.4454	93.1914
	2010	5.4587	9.3852	2129	18.3168	97.3703	1.0131	7.6632	6033	14.7961	94.5429	1.6335	9.8924	4612	16.4612	93.4595
	2020	5.2271	9.9916	3051	20.5808	97.1665	0.397	6.9728	8251	9.5857	94.0545	1.5587	9.4309	4734	15.5201	93.2833
Forest	2000	33.7323	29.5013	23338	100.385	95.4642	37.4015	23.6872	22837	136.4954	96.3073	31.4959	28.4083	16687	84.1339	96.0283
	2010	30.9127	28.2934	20832	88.4711	95.6476	37.2064	23.4527	21429	136.268	96.3243	31.3434	27.7867	15511	83.0451	96.0873
	2020	30.7401	28.3640	20909	86.989	95.634	37.5413	22.0286	19807	128.0761	96.5516	31.6779	26.8476	15336	78.8633	96.2426
Grassland	2000	0.0273	10.2938	113265	3.0734	56.9014	0.0202	11.6264	207491	2.8154	54.7459	0.018	6.8499	78277	2.1379	50.0409
	2010	0.0287	9.7185	106940	3.1574	57.2333	0.0202	11.4725	204403	2.7756	55.049	0.0277	6.6478	75395	2.2567	50.4986
	2020	0.0307	9.7175	105874	3.3086	59.4635	0.0202	10.9219	192094	2.7575	57.4604	0.0508	6.4200	71187	2.5231	54.5996
Shrubland	2000	0.0398	18.5025	192590	3.4092	49.9603	0.0074	11.0225	230516	2.3538	42.7215	0.0172	23.4032	193681	3.2647	51.2291
	2010	0.0151	16.9285	182490	2.7374	49.1199	0.0075	10.6031	223083	2.3171	42.5394	0.0183	22.2791	185629	3.1953	51.354
	2020	0.0114	16.6450	181087	2.6044	48.9372	0.0071	10.0531	213853	2.2891	42.6072	0.012	21.0096	172991	3.1845	51.7708
Wetland	2000	0.0034	0.0398	22	3.3592	86.9541	0.0054	0.0523	56	4.0126	88.405	0.0001	0.0010	3	1.6257	80.3279
	2010	0.0019	0.0058	21	1.79	88.5736	0.0046	0.0500	66	3.4942	88.3051	0.0001	0.0010	3	1.5885	78.4884
	2020	0.0018	0.0116	52	2.1007	84.2659	0.01	0.1725	321	5.823	85.5157	0.0032	0.0305	21	2.8833	88.7599
Waterbody	2000	0.7552	1.8090	5048	9.8609	90.3965	0.1164	1.1096	4808	5.1392	86.0571	1.9591	1.2690	2981	3.4646	96.1713
	2010	0.7358	1.3739	4389	9.0146	92.1062	0.1158	0.9843	4381	4.5497	86.9001	1.9614	1.0386	2897	3.4711	96.7734
	2020	0.7708	1.5675	3590	9.3821	91.6404	0.1178	1.2077	3912	5.0427	86.1195	1.9659	1.3014	2663	3.6742	96.0667
Artificial surface	2000	3.1544	5.2901	2481	7.7879	97.8168	2.0543	4.3349	3900	14.324	95.4609	2.0459	4.5159	2455	7.3861	96.2575
	2010	3.1568	5.2187	2471	7.6536	97.8471	1.1443	4.209	3697	11.1961	95.5332	2.01	4.5137	2580	7.0076	96.2756
	2020	3.0744	5.8525	2809	7.6473	97.6207	1.3476	4.4635	3593	11.3483	95.9777	2.0255	4.6452	2665	7.1145	96.3783
Bare land	2000	0.028	6.7263	74374	2.2779	56.6121	0.0412	6.0173	107468	2.4139	58.0708	0.0056	2.7289	28883	1.9506	53.2045
	2010	0.0282	6.5511	72028	2.3533	57.1727	0.0382	5.8472	104501	2.5377	58.2833	0.0143	2.5284	26564	2.2055	54.0735
	2020	0.0275	6.4330	71643	2.3628	57.1158	0.0414	4.7147	85297	2.8409	60.4131	0.0056	2.4417	24974	1.9804	55.4873

* LPI: Landscape patch index,% (area); ED: Edge density, m/ ha (perimeter); NP: Number of patch, None (Patch density); AWMSI: Area-weighted mean shape index, None (shape); AI: Aggregation index, % (Interspersion).

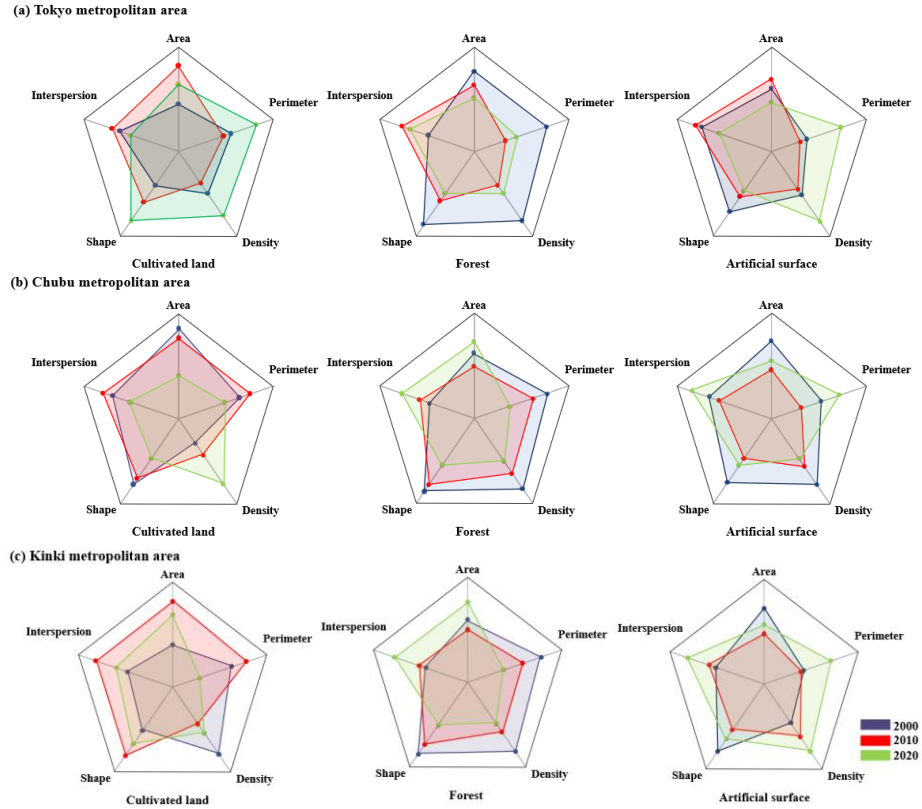


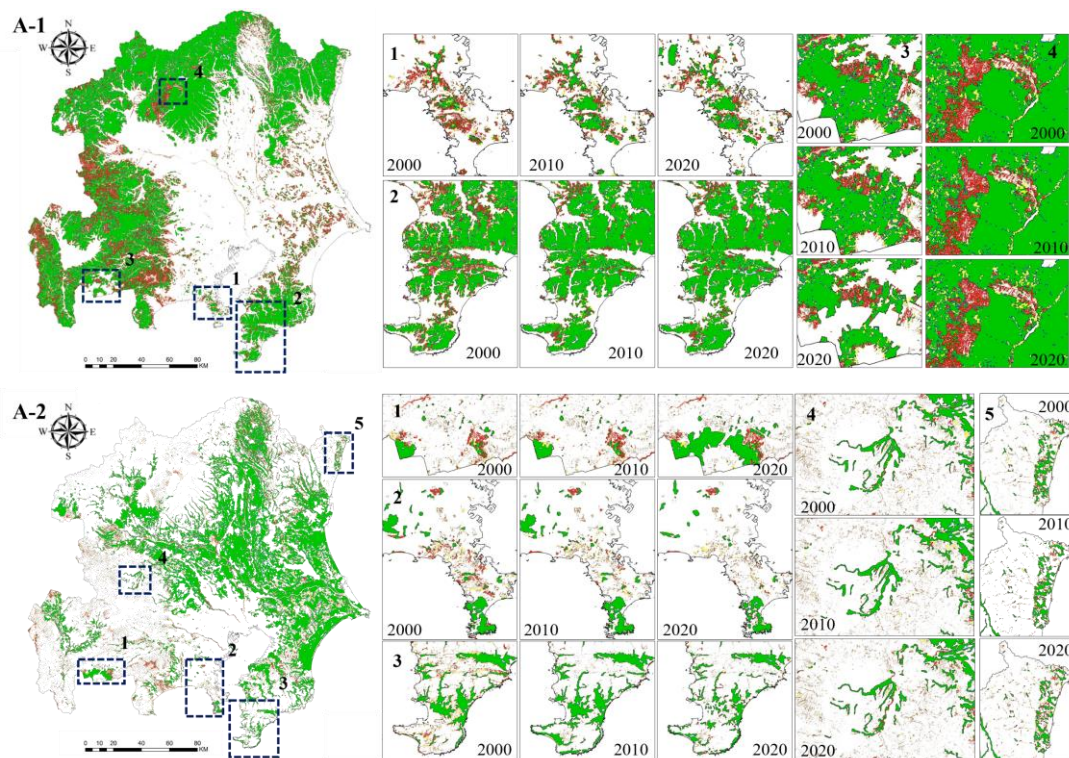
Figure 2.13 The landscape pattern indices of the main LULC types from 2000 to 2020.

2.4.3 MSPA types for Forest and green spaces

LULCC in the three major metropolitan areas has exhibited a relatively slow pace. To further explore the morphological characteristics of LULC, this study focused on extracting forest land and other green spaces, emphasizing changes in their MSPA classes. Due to the scarcity and dispersion of other green space forms such as wetlands and grasslands, they were combined with cultivated land for comprehensive analysis as green space. Through MSPA, it was observed that the MSPA classes changes in forest within the three metropolitan areas have been relatively sluggish, particularly noticeable near artificial surfaces, such as the southern parts of the TKM, central parts of the CBM, and the central parts of the KKM (Figure 2.14). Forest changes mainly occurred between 2000-2010 or 2010-2020, with few instances of consistent changes in MSPA classes from 2000 to 2020. For example, in TKM's A-1(1) area, the core area of forest increased from 2000 to 2010 and remained relatively stable from 2010 to 2020; the changes in the morphology of forest in the A-1(3) area were insignificant from 2000 to 2010, yet experienced a decrease in core areas and perforations from 2010 to 2020. The forest core in the B-1(2) area disappeared significantly from 2010 to 2020, while the perforations in the B-1(3) area increased during the same period. The MSPA classes changes in green space were more likely to occur near artificial surfaces, with noticeable increases in the core and edge areas of green space in regions closer to artificial surfaces, such as areas A-2(1), B-2(3), and C-2(4), with changes primarily concentrated in specific time periods between 2000 and 2010 or 2010 and 2020.

Considering the slow changes in forest and green space, as well as the characteristic concentration of MSPA classes changes within specific time intervals, this study further statistically analyzed the mutual transformation

processes of MSPA classes from 2000 to 2020 (Figure 2.15). Regarding forest, the principal transformation types in the three metropolitan areas are core, bridge, perforations, and edge. Notably, the phenomena of mutual transformation between core, perforation, and edge were pronounced due to their unique morphological interdependencies, while other linear features such as bridge, branch, and loop predominantly transitioned into backgrounds with poor stability. In green space, a significant proportion of transformations in the three metropolitan areas led to backgrounds. Moreover, the main MSPA classes changes were concentrated in core, islet, and edge areas, with the mutual transformation between islet and background and between core and edge representing the primary characteristics of MSPA classes change. Linear features primarily transitioned into backgrounds, with transformations into other MSPA classes accounting for a small proportion of the total changes.



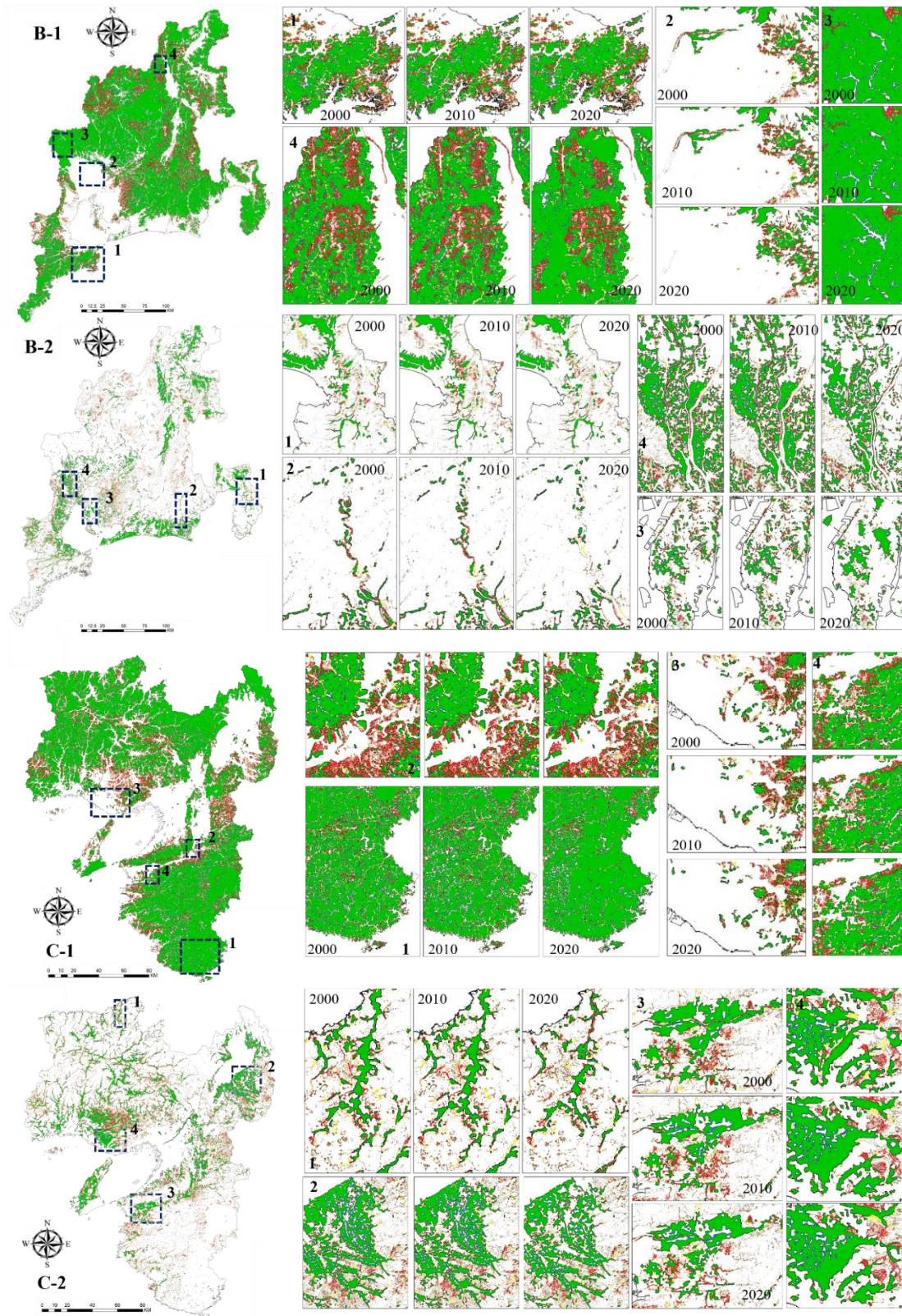


Figure 2.14 MSPA classes and spatial distribution of forest and green spaces in three major metropolitan areas in 2000, 2010, 2020 (A-1 Forest in TKM, A-2 Green Space in TKM; B-1 Forest in CBM, B-2 Green Space in CBM, C-1 Forest in KKM, C-2 Green Space in KKM).

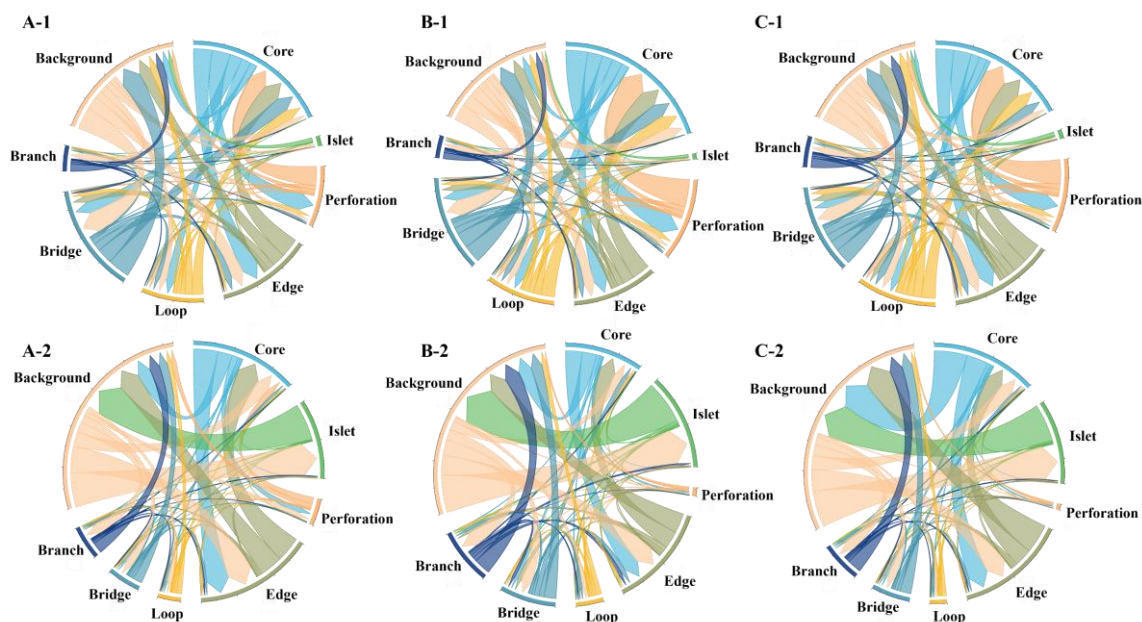


Figure 2.15 MSPA classes changes in three major metropolitan areas from 2000 to 2020 (A-1 Forest in TKM, A-2 Green Space in TKM; B-1 Forest in CBM, B-2 Green Space in CBM, C-1 Forest in KKM, C-2 Green Space in KKM).

2.4.4 The contribution of driving factors in metropolitan area

This study conducted separate analyses of the driving factors contributing to LULCC in the T-C-KM areas, the TKM area, the CBM area, and the KKM area, spanning the years 2000 to 2020 (Figure 2.16). The results revealed significant variations in the impact of driving factors on LULCC within each area. Notably, topographic factors exerted the most substantial influence on changes in cultivated land across the T-C-KM area, while alterations in forest were notably influenced by topography features. Moreover, specific characteristics of LULC exhibited distinct sensitivities to particular driving factors, particularly evident in changes observed in artificial surfaces. Population density distribution emerged as the primary driving force across the four regions under discussion. Additionally, alterations in water bodies within the T-C-KM areas, the TKM area, and the CBM area were notably influenced by climate factors, followed by topography and distance from open water.

Furthermore, this study identified both commonalities and significant differences in the contribution of driving factors to changes in the same LULC type across different regions. For example, for cultivated land, the most critical driving factors across all regions were DEM, temperature, precipitation, and population. Similarly, changes in grassland were most notably influenced by population density distribution and DEM. Regarding bared land, while DEM and precipitation significantly impacted changes across all regions, population emerged as a notable influencing factor, particularly outside the TKM area. For wetlands, driving factors contributing to LULCC in the KKM and CBM areas included distance from motorways, DEM, and GDP, whereas DEM remained the predominant influencing factor in the TKM area.

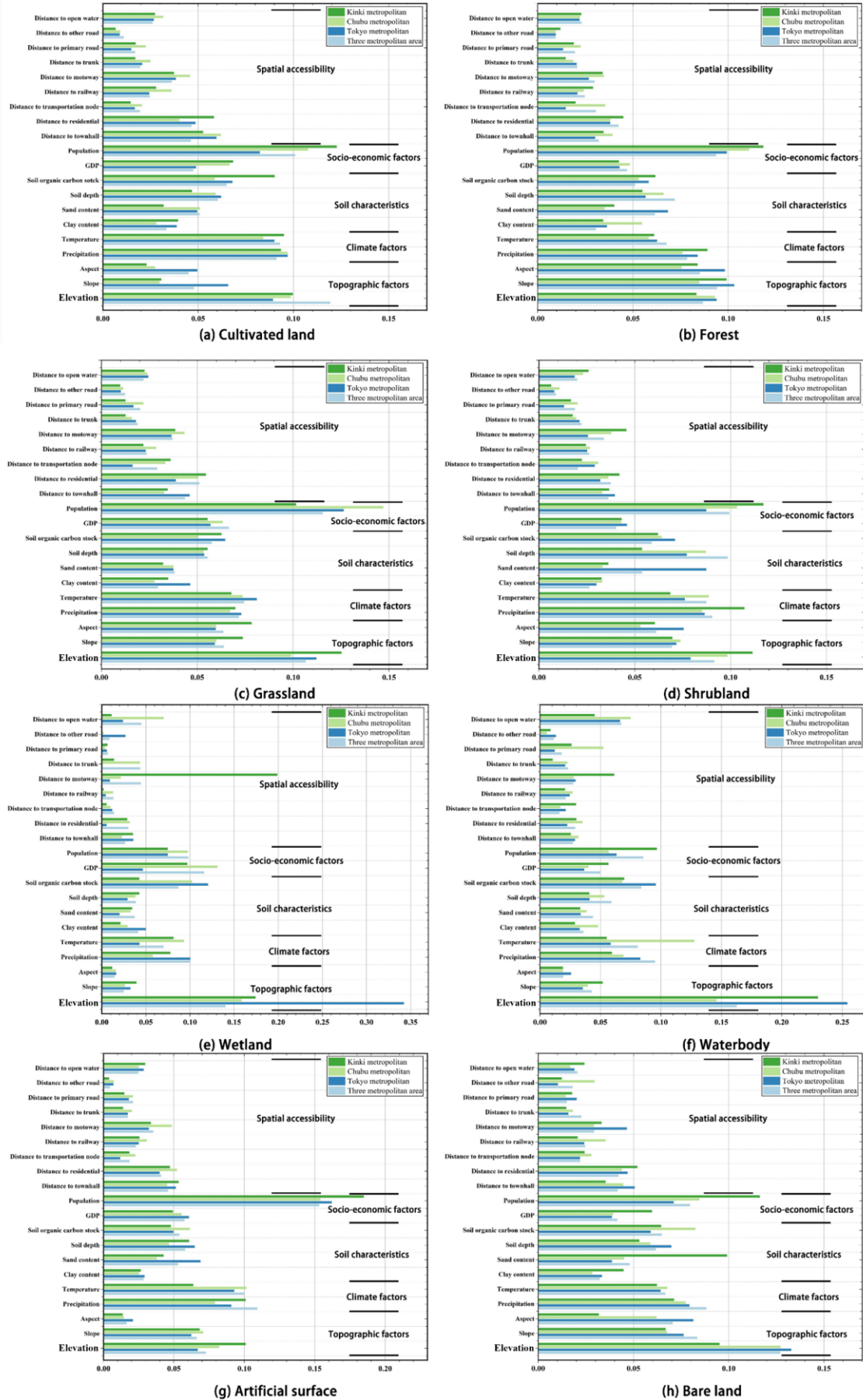


Figure 2.16 The contribution of driving factors for the LULCC from 2000 to 2020.

2.5 Discussion

Since the early 21st century, rapid urban development in densely populated developing countries has precipitated significant alterations in LULCC (Angel et al., 2011; Connop et al., 2016). This transformation predominantly entails the conversion of green spaces into artificial surfaces to meet the escalating demands of urban population and economy (Kong et al., 2010; Li et al., 2020; Liao et al., 2020). In contrast, developed countries have undergone more stabilized changes in land use types after rapid urbanization, with shifts in land use and land cover reflecting societal needs and urban trends (Millward, 2006).

Japan, characterized by its rugged archipelagic terrain, encompasses three major metropolitan areas where forests cover 60% of the total area (Table 2.6). Japan's urban development has traversed five distinct phases (MLIT, 2014), accompanied by rigorous legal frameworks and planning guidelines for land use development and management. Despite challenges such as aging demographics and population concentration, major metropolitan areas in Japan continue to grapple with significant pressures on LULC owing to population and economic development (Hori et al., 2021; Kobayashi et al., 2020). This study observed that LULC in Japan's major metropolitan areas still manifest characteristics of cultivated land, forest, and artificial surfaces (Figures 2.11-2.12, Tables S2.1-2.3), consistent with trends observed in numerous other countries (Dadashpoor et al., 2019; Koga et al., 2020; Yang et al., 2022). However, from 2000 to 2020, there has been an augmentation in forest and artificial surfaces, while cultivated land has diminished, unlike in other developed countries such as China (Jiao et al., 2019; Li et al., 2020). Additionally, forecasts regarding future trends of LULC types in Japan suggest a potential increase in forest and a decrease in cultivated land in most scenarios (Shoyama et al., 2019). Furthermore, as LULCC in Japan decelerate, it becomes increasingly imperative to regulate land use patterns. This study also unveiled intricate MSPA classes changes in forest and green space, distinct from subtle changes in LULC types. Clearly delineating the characteristics and functions of different forms and comprehending their responses to driving factors may furnish valuable insights for land use management from a morphological perspective.

Moreover, the study scrutinized the contributions of driving factors to LULCC. It is evident that human activities remain the primary impetus behind urban land use transformation, including in Japan's major metropolitan areas (Liang et al., 2021; Lin and Peng, 2022). However, meticulous analyses of the impacts of LULC driving forces divulge that in certain cities in China, for instance, the construction of basic infrastructure has influenced changes in major LULC types such as cultivated land, forest, and construction land (Liang et al., 2021; Lin and Peng, 2022). In contrast, in Japan's major metropolitan areas, population density distribution plays a pivotal role, particularly in influencing LULCC outside wetlands and waterbodies (Figure 2.16). Additionally, natural factors such as topography and climate also exert significant influence on LULCC in Japanese metropolitan area.

The topographical characteristics of Japan's three major metropolitan areas significantly influence LULC distribution and urban development. Firstly, variations in elevation directly impact regional suitability. High-elevation areas, characterized by lower temperatures and shorter growing seasons, are typically utilized for forestry and pastures, whereas low-elevation areas are more suitable for urban construction and agricultural activities (Schlecht et al., 2014; Xiao et al., 2008). The low-elevation terrain and extensive cultivated land of the Kanto Plain have provided a foundation for the development of TKM. Similarly, the low-elevation regions around Nara and

Lake Biwa also contain vast cultivated land, highlighting the importance of low-elevation areas for farming. Additionally, the central urban areas of TKM, CBM, and KKM are all located in low-elevation regions, reflecting the influence of low elevation on human settlement patterns (Figure2.1, figure2.11). Secondly, slope gradient has impact on LULCC primarily because steep slopes are unsuitable for mechanized agriculture and large-scale cultivation due to the risk of soil erosion. These areas are usually designated as forest or terraced fields (Latocha et al., 2016). In the three metropolitan areas, regions with significant slopes are often classified as forest, emphasizing the importance of slope gradient in the distribution of LULC types (Figure2.1, Figure2.9, Figure2.11). Lastly, aspect significantly affects solar radiation, especially in the Northern Hemisphere. South-facing slopes receive more sunlight and are suitable for light-loving crops, while north-facing slopes are better for shade-tolerant crops or forestry. However, in this study, while aspect influenced the type of natural vegetation, such as forests and shrubland, it was not a major driver of LULCC in densely populated cultivated land areas from 2000 to 2020. This indicates that in highly developed areas, human activities have a greater impact on LULC than natural topographical factors (Figure2.16).

For the climate factors, while temperature may not show a direct relationship with LULC, its significant indirect effects on regional planning, agricultural productivity, forest health, and infrastructure development make it a crucial factor in LULC simulations (Santamouris, M.,2015; Lobell, D. B., & Field, C. B.,2007; Schlenker, W., & Roberts, M. J. 2009). The inclusion of temperature in these models provides a more holistic and accurate representation of the driving forces behind LULCC. As shown in Figure 2.16, the distribution of temperature, artificial surfaces and various green areas has similar distribution characteristics, and areas with higher temperatures are mainly artificial surface and cultivated land (Figure 2.9, Figure 2.11). In Japan, high-temperature areas are often located in warm climates suitable for human habitation. With population growth and rapid urbanization, these areas are extensively developed for urban construction, resulting in widespread artificial surfaces (Oda et al., 2018). Additionally, these high-temperature regions, such as the Pacific coastal areas, typically have abundant water resources and fertile soil, making them ideal for agricultural production and leading to extensive land development for farming (Chao et al., 2020). With temperature variations affecting crop viability and human comfort, shifts in land use patterns are inevitable. For instance, changes in temperature can necessitate the relocation of agricultural zones to areas with more suitable growing conditions. Additionally, urban areas may need to expand green spaces to mitigate the urban heat island effect and improve livability. Consequently, temperature is recognized as a possible driver of LULCC, influencing both agricultural practices and urban planning strategies to adapt to evolving environmental conditions.

Generally, areas with optimal precipitation support intensive cultivated land and urban development, while areas with slightly less rainfall are more suitable for forest (Liang et al., 2021; Lin and Peng, 2022). However, in Japan, where precipitation is generally high, precipitation is often not a direct factor in LULCC. Instead, it influences other factors such as topography, soil type, and human activities, which in turn lead to indirect changes in LULC types (Kimura T, 2024). For example, the Kanto Plain benefits not only from high precipitation but also from flat terrain and fertile soil, resulting in extensive cultivated land (Figure 2.9). Artificial surfaces like Tokyo and Osaka benefit from high precipitation, which supports the large water demands of dense populations and industrial activities (Figure 2.9). Urban planning in these regions often includes infrastructure to manage and efficiently utilize

the abundant water resources. Steep terrain and abundant precipitation make certain areas less suitable for cultivated land and urban development, thus preserving natural landscapes and biodiversity hotspots (Pande, C.B et al, 2021)). Additionally, high precipitation maintains soil moisture levels critical for both agriculture and forestry. Therefore, precipitation is an important factor to consider in LULC studies. In addition, although temperature and precipitation are not direct causes of LULCC, their potential impact on other driving forces has been demonstrated in numerous studies (Jiao et al., 2019; Liang et al., 2021; Lin and Peng, 2022). Therefore, they have been included as factors that may influence LULCC in many LULC simulation studies.

Furthermore, Global climate change and socioeconomic fluctuations are among the most severe environmental and social challenges of our time, significantly impacting ecosystems and human societies. In densely populated areas, such as the three major metropolitan areas in Japan, urban expansion requires converting forests or agricultural land, reducing carbon sinks. Concurrently, extensive industrial activities emit greenhouse gases, leading to increased temperatures and the urban heat island effect. Climate change has heightened the frequency and intensity of extreme weather events, such as hurricanes, floods, and droughts, significantly impacting economic activities and population distribution. For instance, extreme weather can cause fluctuations or declines in crop yields, affecting food security and potentially expanding the range of disease transmission, thereby influencing population distribution and economic development. LULCC epitomizes the complex interactions between climate and socioeconomic factors (Justice et al., 2015).

2.6 Conclusion

This study offers a thorough analysis of planning policies and legal frameworks in the TKM, CBM, and KKM Areas. It examines LULCC from 2000 to 2020, identifying trends in cultivated land, forests, and artificial surfaces. The study also explores landscape patterns and driving factors, emphasizing the impact of population distribution, topography, and climate. Overall, it provides valuable insights into the planning dynamics and environmental trends of these metropolitan regions. Furthermore, this chapter's research provides data support on LULCC for Chapter 3's investigation into current ecological security patterns. The influence of climate and population distribution drivers informs Chapter 4's exploration of LULCC scenarios under social fluctuations and climate change.

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Chapter 3

Patch-Scale Evaluation of Ecological Security Patterns in Japan's Three Major Metropolitan Areas

Many studies on LULCC in Japan have focused on long-term trends over 50 to 100 years, primarily starting from the 1970s (Ohbi and Suzuki, 2002; Saizen, 2001; Shimizu, 2015). While these studies offer valuable historical insights, they may not fully capture recent changes or divergences influenced by contemporary factors. Since 2000, Japan's LULC patterns have stabilized, making data from this period more pertinent for guiding future short-term land use planning. Therefore, this study concentrates on LULCC occurring after 2000.

Land use planning in Japan operates within specific legal frameworks and research methodologies at various scales. Besides nationwide planning, the metropolitan scale is a crucial research focus, especially for the three major metropolitan areas. These regions, with their high economic activity and population density, are key areas for land use planning and management. Currently, comprehensive land use management policies and corresponding legal frameworks are in place for these metropolitan areas. These policies and laws provide detailed guidance on LULC in the three major metropolitan regions and serve as a basis for specific spatial discussions and implementations. Consequently, focusing on these metropolitan areas is significant for policy discussion and practical applications.

3.1 Introduction

Due to high density and rapid growth in urban populations, coupled with rising consumption levels, remaining urban green spaces such as forest, cultivated land, wetland, shrubland and grassland are increasingly vulnerable to erosion and fragmentation (Kong et al., 2010; Li et al., 2015). Habitat fragmentation and the loss of biodiversity can lead to ecosystem degradation, negatively impacting ecosystem health. Moreover, these issues exacerbate climate-related disasters within urban areas, such as flooding and the urban heat island effect (Liu et al., 2023). In order to mitigate the ecological damage and natural resource consumption caused by urban development, and to promote sustainable land use/land cover (LULC) practices, the concept of ecological security pattern (ESP) has gained increasing attention (Zhao et al., 2024). ESP involves the thoughtful and strategic allocation of ecological spatial components to build a system that effectively resists natural disasters and anthropogenic disturbances (Wen and Hou, 2021; Zhao et al., 2024). The core objective of ESP is to enhance regional ecological security by protecting key ecological sources, maintaining corridors, and optimizing spatial configurations. By integrating ecological assessments and network construction, ESP offers a comprehensive strategy for ecological protection, crucial for maintaining stable and resilient ecosystems in urban and regional planning.

Ecological network construction and ecosystem health assessment are critical components of ESP. As early as the 1980s and 1990s, cities in the United States and Europe initiated discussions and practices regarding ecological network construction (Peng et al., 2017). Ecological network construction is considered to have a multitude of benefits in enhancing biodiversity, improving human well-being, increasing economic benefits, and strengthening urban environmental resilience (Harrison and Bruna, 1999; Mackovc̃in, 2000). Initially, the focus of ecological

network construction was primarily on biodiversity conservation (Liu et al., 2023). However, with a growing understanding of the importance of ESP in maintaining ecosystem services and ensuring ecological security, enhancing the integrity and resilience of regional ecosystems through ecological network constructions has been widely studied and implemented in both developed and developing countries (Li et al., 2022; Peng et al., 2018). This approach is now considered a crucial means for achieving sustainable and resilient urban environments (Teng et al., 2011). The core objective of ecological network construction is to create an interconnected urban ecosystem network by linking ecological core areas, corridors, and buffer zones (Li et al., 2022; Liu et al., 2023). The primary steps include: identifying and evaluating ecological sources, determining potential ecological corridor pathways by constructing resistance surface models, applying least-cost path analysis to identify optimal routes, and incorporating species' random walk characteristics to define the potential boundaries of corridors (Li et al., 2024; Peng et al., 2018; Zhang et al., 2022). The continuous refinement and in-depth discussion of these research steps provide a solid theoretical foundation and technical support for ecological network construction.

Ecosystem health is a critical measure for quantifying and achieving the goals of land use optimization and ecological source protection within an ESP (Morán-Ordóñez et al., 2022; Rapport et al., 1998). Ecosystem health is the capacity of an ecosystem to maintain its structural integrity, functional processes, and resilience against external disturbances, thereby sustaining biodiversity and providing essential ecosystem services such as nutrient cycling, water purification, and habitat provision. It reflects the ecosystem's ability to self-regulate, adapt to changes, and recover from disruptions, ensuring long-term environmental stability and human well-being (Hasani et al., 2023). It represents the structure, regulation functions, and resilience of ecosystems in maintaining spatial organization and quality in the face of external disturbances, serving as a crucial indicator of sustainable development potential (Hasani et al., 2023; Rapport et al., 1998). Additionally, the evaluation methods and selected factors for assessing ecosystem health vary across different scales. For example, in specific green spaces such as forests or cultivated land, indicators like species diversity, food chain complexity, and stability are crucial (Lawton, J. H., 1989; McHugh et al., 2010). On a large scale, spatial organization and structural complexity become more important, while factors like food chains and species diversity are less emphasized. Based on the concept of ecosystem health, scholars have developed various assessment frameworks for large-scale evaluations. The Pressure-State-Response model focuses on external pressures on ecosystems and their current state. The Driving Force-State-Response model emphasizes the root driving forces behind ecological changes and their impacts on ecosystem conditions. The Vitality-Organization-Resilience (V-O-R) model assesses the overall health, structural complexity, and resilience of ecosystems. The Driving Force-Pressure-State-Impact-Response model provides a comprehensive analysis of ecosystem health conditions and the impacts of human activities (Khatun and Das, 2022; Xu et al., 2022). Among these, the V-O-R model assesses the overall health, structural complexity, and resilience of ecosystems, it is particularly effective in ecosystem restoration and is widely used in the construction and optimization of ESP due to its comprehensive approach to assessing ecosystem health (Xu et al., 2022).

Despite significant research in ecological network construction and ecosystem health assessment, there remain areas that require further improvement. Firstly, discussions and analyses of LULC differentiation are still lacking (Dong et al., 2020; Ersoy et al., 2019). For instance, some of research sometimes homogenizes green space into the concept of green infrastructure, overlooking the functional differences of various LULC types in achieving

sustainable development within the ESP (Li et al., 2024; Liu et al., 2023). Different LULC types, such as forests and cultivated land, have distinct functional characteristics; forests play a decisive role in material cycling and ecological resilience, while cultivated land focuses on food production efficiency and security (Hoshino, 2001; Jin and Song, 2023; Li et al., 2021). Secondly, while the V-O-R model is widely used in ESP, it has limitations due to its insufficient consideration of socio-economic factors and the subdivision and refinement of LULC types, leading to a lack of comprehensiveness and limitations in result discussions and practical applications (Hasani et al., 2023; Khatun and Das, 2022; Xu et al., 2022). Lastly, most previous studies on ESP have focused on developing countries' cities (Dai et al., 2021; Peng et al., 2019). However, in recent years, Japan's national strategy and planning have increasingly emphasized ESP, as highlighted in key policies such as the "National Biodiversity Strategy 2023-2030" and Japan's national spatial planning (MOEJ, 2023). These policies repeatedly stressed the importance of ESP in climate change adaptation, biodiversity conservation, and establishing sustainable urban development. Therefore, discussing ESP in cities of developed countries like Japan is equally crucial (MOEJ, 2023).

Based on the above background, this study aims to evaluate and analyze ESP through the construction of ecological networks and assessment of ecosystem health, focusing on different LULC types. It discusses the changes in ESP from 2000 to 2020 in the three representative metropolitan areas in Japan (Tokyo, Chubu, and Kinki) at the LULC type patch scale. The main content of this study includes the following: identifying ecological sources and potential corridors for forests, and discussing the feasibility of constructing these corridors in study area; improving ecosystem health assessment model based on the patch scale of LULC types; and integrating ecological networks construction and ecosystem health assessments to explore the feasibility of applying ESP in regional planning and protection. Through these studies, the study aims to develop a framework for land use management, development, and delineation, providing more effective guidance for managing urban ecological environments.

3.2 Method

This study is organized into three main sections: ecological network construction, ecosystem health evaluation, and spatial characterization analysis (Figure 3.1). The ecological network construction focuses on identifying and linking forest areas to establish corridors and buffer zones, thereby enhancing connectivity and resilience. The ecosystem health assessment targets green spaces in various LULC types, evaluating patches by proposing a Pressure-Vitality- Organization (P-V-O) model. Based on the results from these two sections, the spatial characterization analysis examines different LULC types to understand their spatial distribution and interactions within study area. Sections 3.3.2-3.3.4 provide detailed explanations of each component as illustrated in Figure 3.1.

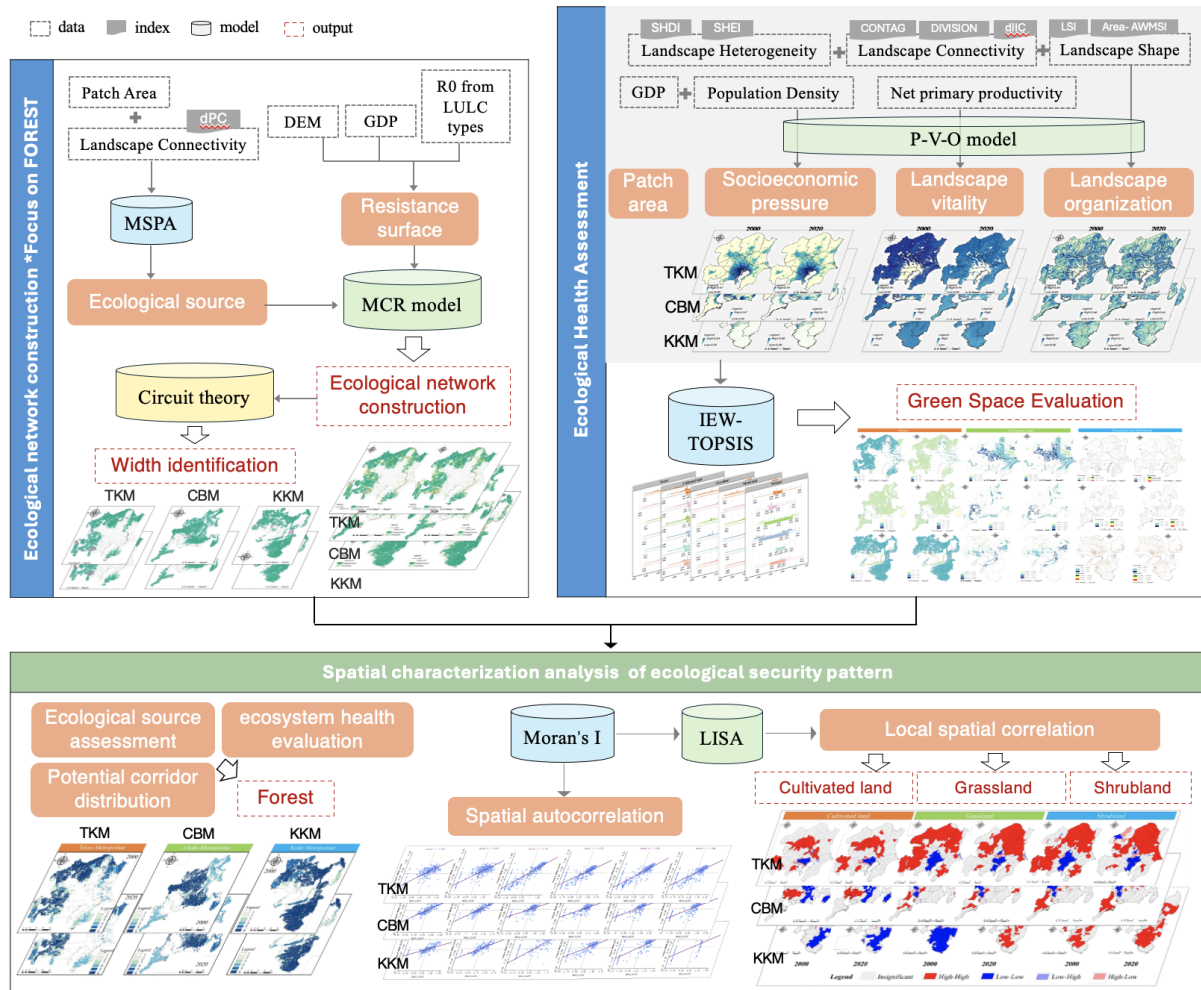


Figure 3.1 The research framework

3.2.1 Ecological network construction

This study investigated the dynamic alterations in ecological network construction across three major metropolitan areas, focusing on forests due to their recognized ecological functions, robust connectivity, high ecological stability, and minimal anthropogenic disturbance (Jin and Song, 2023; Saura and Rubio, 2010). Forests play a crucial role in maintaining biodiversity, supporting biological migration, and ensuring ecosystem resilience, making them ideal subjects for ecological network construction (Ersoy et al., 2019). By prioritizing forests, the study aims to enhance ecological stability and mitigate human-induced disruptions within ecological networks. This approach aligns with broader goals in regional planning and ecology to create sustainable and resilient urban environments (Jin and Song, 2023).

3.2.1.1 Identification of potential corridor direction

Morphological Spatial Pattern Analysis (MSPA): In MSPA analysis, core, islet, edge, and perforation correspond to patches, while bridge, loop, and branch represent corridors (Dytham and Forman, 1996). To further refine the MSPA-derived map, ArcGIS was employed for reclassification purposes. Forest patches were selected as candidate ecological sources.

Ecological source: This study determines ecological source areas through patch area and landscape

connectivity. Initially, morphological spatial pattern analysis (MSPA) is employed to identify various features of forested areas (Wu et al., 2017). In MSPA analysis, core, islet, edge, and perforation correspond to patches, while bridge, loop, and branch represent corridors (Dytham and Forman, 1996). To further refine the MSPA-derived map, ArcGIS was employed for reclassification purposes. Forest patches are selected as candidate ecological sources. Subsequently, landscape connectivity can be quantified using graph theory-based indices such as the Integral Index of Connectivity (IIC), probability of connectivity (PC), and betweenness centrality (Saura and Pascual-Hortal, 2007). These metrics play a vital role in identifying critical ecological connections and quantifying potential ecological flux among different patches. Additionally, the delta values for PC index (dPC) are utilized to evaluate the connectivity of individual forest patches. The dPC considers habitat quantity, accessibility, and the likelihood of dispersal among patches (Saura and Rubio, 2010). It can be used to select ecological sources in combination with patch area. These data were computed using the cone for (<http://www.cone for.org/>), with a threshold distance set at 1000 m and a distance probability value of 0.5 (Jin and Song, 2023; Mohammadi et al., 2021).

$$PC = \frac{PC_{num}}{A_L^2} = \frac{\sum_{i=1}^n \sum_{j=1}^n a_i a_j p_{ij}^*}{A_L^2}$$

Here, PC represents the connection index value of all patches in the landscape, n represents the total number of patches in the landscape, a_i and a_j represent the areas of patch i and patch j , p_{ij} represents the number of connections between patch i and patch j , and A_L represents the size of the study area.

$$dPC = \frac{PC - PC_{remove}}{PC} \times 100\%$$

Here, dPC represents the change in landscape connectivity after a patch is removed and is used to evaluate the importance of the patch for maintaining landscape connectivity. PC_{remove} represents the connectivity index value of the remaining patches after one is removed.

Forest patches in the three metropolitan areas were classified into six levels based on patch area and dPC index (Table 2). Patches graded at Level 4 or higher were prioritized as ecological sources for constructing the ecological network, considering their spatial distribution and quantity comprehensively.

Table 3.1 Indices of forest patch importance evaluation (ecological sources)/km².

Landscape connectivity	area ≥ 100	50 ≤ area < 100	10 ≤ area < 50	0.5 ≤ area < 10	0.15 < area < 0.5
dPC ≥ 25	level-1	level-1	level-2	level-2	level-3
15 ≤ dPC < 25	level-1	level-2	level-2	level-3	level-4
5 ≤ dPC < 15	level-2	level-2	level-3	level-4	level-5
2.5 ≤ dPC < 5	level-2	level-3	level-3	level-5	level-5
dPC < 2.5	level-3	level-4	level-4	level-5	level-5

Resistance surface: Resistance surface quantifies the obstacles organisms face when navigating their environment, with higher resistance values indicating greater difficulty for movement (Ersoy et al., 2019; Gurrutxaga et al., 2010). Initially, this study assigned uniform resistance values to all patches with the same LULC type to derive a basic resistance surface (Dong et al., 2020). The initial resistance values were set as follows: cultivated land (40), forest (5), shrubland (10), grassland (20), wetlands (50), water bodies (100), artificial surfaces (500), and bare land (300) (Dong et al., 2020; Peng et al., 2019). However, initial resistance surface overlooks inherent natural and anthropogenic variations within the same LULC type, which also can significantly influence species migration (Li et al., 2024; Xie et al., 2023). Generally, the intensity of human activity and terrain complexity increase ecological resistance levels (Dong et al., 2020). Therefore, we revised the initial resistance surface by

incorporating these factors. To account for human activity intensity, this study used Gross Domestic Product (GDP) as a proxy, derived from nighttime light data, with higher GDP values indicating higher activity intensity (Chen et al., 2022). For terrain complexity, surface curvature was calculated based on DEM data. Greater absolute values of surface curvature indicate more convex or concave surfaces, which are unfavorable for species migration (Barbarella et al., 2019; Shary et al., 2002). The specific revision formula used is as follows:

$$R = R_0 \times \left(0.5 \times \frac{GDP_i}{GDP_{mean}} + 0.5 \times \frac{C_i}{C_{mean}} \right)$$

where R is the modified resistance surface, R_0 is the initial resistance surface associated with LULC types, GDP_i is the GDP of grid i , GDP_{mean} is the average GDP for each LULC types, C_i is the absolute value of the surface curvature of grid i , C_{mean} is the average absolute value of the surface curvature for each LULC type.

Ecological network construction: The Minimum Cumulative Resistance Model (MCRM) evaluates species movement dynamics within landscapes, particularly focusing on the connectivity between ecological sources (Dai et al., 2021; Dong et al., 2015). By integrating ecological sources, spatial distances, and resistance surfaces, the MCRM provides valuable insights into movement patterns and associated costs across various habitats. This study employed the MCRM to simulate Least-Cost Paths (LCPs), representing optimal routes for organism movement between ecological sources (Li et al., 2024; Wang et al., 2022). These paths effectively navigate around or mitigate disturbances caused by human activities or spatial features. Additionally, the MCRM aids in identifying critical corridors and improving habitat connectivity, thereby contributing to ecosystem restoration efforts. The specific revision formula is as follows:

$$MCRM = f_{min} \sum_{j=n}^{i=m} D_{ij} \times R_i$$

Here, f is a function of the positive correlation, min denotes the minimum value of cumulative resistance produced in different processes of the landscape unit i transforming into a different source unit j , D_{ij} is the Euclidean distance between landscape unit i and source unit j , and R_i is the ecological resistance of spatial unit i to a species migration.

3.2.1.2 Width identification by circuit theory

Circuit theory is widely applied in ecology to identify pinch points and probability width within LCP corridors, complementing MCRM analysis results by providing effective resistance values for potential ecological corridors (An et al., 2021). Previous research has leveraged the stochastic random walk properties of charges in circuit theory to model ecological processes in heterogeneous landscapes. Current density, within this study, reflects the connectivity strength of potential ecological corridors. Concepts such as resistance, current, and voltage are associated with ecological processes in large-scale population networks or landforms, including individual movement and gene flow (McRae et al., 2008). In this study, resistance surfaces acted as conductive surfaces, assigning higher resistance values to grid cells with lower probabilities of individual movement and lower resistance values to areas with higher movement probabilities. Ecological source areas were regarded as nodes, where current represented the likelihood of species moving randomly between nodes, and voltage indicated the probability of attracting species undergoing random migration along corridor pathways between nodes (An et al., 2021; McRae et

al., 2008).

3.2.2 Ecosystem health assessment based on P-V-O model

This study developed a method for evaluating ecosystem health at the patch scale from three aspects: socioeconomic pressure, landscape vitality, and landscape organization. Initially, indicators for the P-V-O model were selected and evaluated. Then, R software was used to extract the levels of socioeconomic pressure, landscape vitality, and landscape organization for patches of forests, cultivated land, grasslands, shrublands, and wetlands. Finally, the patch area was integrated, and the Information Entropy Weight-Technique for Order Preference by Similarity to an Ideal Solution (IEW-TOPSIS) was applied to comprehensively overlay the P-V-O results and rank the ecological health levels of green space patches.

3.2.2.1 P-V-O model

Socioeconomic pressure: This study selected GDP and spatial distribution of population density as representative indicators of social and economic factors (Chen et al., 2020; Xie et al., 2023). GDP measures economic activity within a region, indirectly reflecting levels of urbanization, industrialization, and infrastructure development, all of which impact the availability and quality of green spaces. Population density represents the concentration of inhabitants in a given area, influencing land use patterns, urban expansion, and demand for recreational spaces, thereby affecting urban green space development (Salem et al., 2019). To address the dimensional variations among the two indicators, this study employed fuzzy membership functions to standardize indicator values onto a scale from 0 to 1 (Fu et al., 2021). This approach allows for the integration of diverse attributes while accounting for inherent differences in scale and magnitude.

Landscape vitality: In this study, Net primary productivity (NPP) was utilized as a proxy indicator to measure landscape vitality (Zhao et al., 2024). NPP refers to the total energy acquired by plants through photosynthesis from sunlight, subtracting the energy consumed during metabolic processes, resulting in the net energy remaining. This surplus energy is utilized for plant growth, reproduction, and providing food for other organisms. NPP represents the rate at which plants store energy as biomass within an ecosystem. It serves as a crucial indicator of ecosystem productivity and health.

Landscape organization (LO): LO plays a pivotal role in understanding the structure, functionality, and ecological processes within landscapes. It encompasses the spatial arrangement, composition, and configuration of various landscape elements and serves as a fundamental indicator for assessing landscape health and resilience to disturbances (Cadenasso et al., 2006; Xu et al., 2022). Evaluating LO involves assessing landscape heterogeneity (LH), landscape connectivity (LC), and landscape shape (LS).

In consideration of the ecological relevance of landscape patterns, this study employed several key indices to quantify LO. The Shannon diversity index (SHDI) and Shannon evenness index (SHEI) to quantify LH. Landscape Division Index (DIVISION), Contagion Index (CONTAG), and the delta values for IIC index (dIIC) of key patches in forests and cultivated land were utilized to characterize LC. Furthermore, Landscape Shape Index (LSI) and Area-weighted mean shape index (AWMSI) were utilized to measure as LS. Except for the dIIC, all other indicators were computed using a 1000-meter square moving window in Fragstats (Tang et al., 2023; Zhao et al., 2024). The calculation of the dIIC was conducted in conefor2.6 software and strictly controls the number of patches (Saura and

Torné, 2009). Thus, the area of forest patches greater than or equal to 0.15 km² and cultivated land patches greater than or equal to 0.1 km² were separately computed to obtain the dIIC of important patches. Finally, the following weights were used for aggregation (Khatun and Das, 2022; Tang et al., 2023):

$$LO = 0.35 \times LH + 0.35 \times LC + 0.3 \times LSI$$

$$LO = SHDI \times 0.2 + SHEI \times 0.15 + DIVISION \times 0.15 + CONTAG \times 0.15 + dIIC1 \times 0.025 + dIIC2 \times 0.025 \\ + LSI \times 0.15 + AWMSI \times 0.15$$

3.2.2.2 Evaluation based on the IEW-TOPSIS method

In this study, this study employed the IEW-TOPSIS method to evaluate the ecosystem health of various green space types (Geng et al., 2021). First, this study used the Information Entropy Weight (IEW) method to calculate the weights of V-O-R. The IEW method effectively transforms diverse indicators into comparable data, enabling accurate weight allocation by utilizing information entropy and the context of the original data (Xie et al., 2023). Then, the Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS) ranked and selected alternatives based on their Euclidean distance to an ideal solution, identifying those closest to the positive ideal solution (PIS) and farthest from the negative ideal solution (NIS) (Behzadian et al., 2012; Vavrek and Chovancová, 2019). PIS and NIS represent the best and worst patch results in ecosystem health within the same year. TOPSIS is suitable for evaluating patch plans by establishing a hierarchy through comparisons against PIS and NIS (Zhang et al., 2011).

In this study, the ecosystem health of each LULC patch was assessed by comparing its characteristics with those of the optimal LULC patch during the same period. This comparative analysis effectively determined the relative level of ecosystem health of patches within the study area. Previous research indicated that high levels of socioeconomic indicators can negatively affect all types of green spaces, excluding cultivated land (Peng et al., 2017). Therefore, it is crucial to perform reverse transformation on these indicators when evaluating green spaces, excluding cultivated land.

Here, x_{ij} was the evaluation matrix x for the alternative i with evaluation index j . Dimensionless processing was adopted to obtain different index values as follows: x'_{ij} is the matrix after dimensionless processing.

$$x'_{ij} = \frac{x_{ij} - \min_{1 \leq j \leq n} x_{ij}}{\max_{1 \leq j \leq n} x_{ij} - \min_{1 \leq j \leq n} x_{ij}} \quad (\text{Generate variables - forward MMS})$$

$$x'_{ij} = \frac{\max_{1 \leq j \leq n} x_{ij} - x_{ij}}{\max_{1 \leq j \leq n} x_{ij} - \min_{1 \leq j \leq n} x_{ij}} \quad (\text{Generate variables - Reverse NMMS})$$

The IEW was then used to determine weight objectively. In information theory, entropy is a measure of the uncertainty associated with a random variable. IEW was calculated using:

$$H_j = -(\ln(n))^{-1} \left(\sum_i^m f_{ij} \ln f_{ij} \right); i = 1, 2, \dots, m; j = 1, 2, 3, 4; n = 4$$

The following was used to avoid the insignificance of $\ln f_{ij}$:

$$f_{ij} = \frac{x'_{ij}}{\sum_{i=1}^m (x'_{ij})}$$

Higher degrees of deviation in j equate to lower values of information entropy H_j . This indicates that the greater amounts of information provided by index j equate to greater weights in the index. The weight W_j is defined as:

$$W_j = \frac{1 - H_j}{n - \sum_{j=1}^n H_j}$$

x_j^+ indicates the most preferable alternative and x_j^- the least preferable. To calculate separation, n -index evaluation distance was used. This represents the separation from PIS and NIS for each alternative.

$$d_i^+ = \sqrt{\sum_{j=1}^n W_j (x_{ij} - x_j^+)^2}; 0 \leq d_i^+ \leq 1.$$

$$d_i^- = \sqrt{\sum_{j=1}^n W_j (x_{ij} - x_j^-)^2}; 0 \leq d_i^- \leq 1.$$

The relative closeness of the i th alternative with respect to the ideal solution is defined as c_i .

$$c_i = \frac{d_i^-}{d_i^+ + d_i^-}; i = 1, 2, \dots, m; 0 \leq c_i \leq 1$$

If the value of c_i is closer to 1, the alternative i will be closer to the PIS.

3.2.3 Exploratory spatial data analysis method

This study evaluated and identified forest patches that are crucial for achieving ESP from the perspectives of ecological network construction and ecosystem health assessment. The P-V-O model was applied to evaluate patches of cultivated land, grassland, shrubland, and wetland, identifying their importance for ESP.

For forest patches, the ESP evaluation results were integrated with the ecological sources assessment, potential corridor distribution, and ecosystem health evaluation. Additionally, the concept of the metropolitan area was considered to ensure coordinated planning among multiple municipalities, as forest planning is generally based on wide-area planning in practical applications. Forest patches, characterized by aggregation and large areas, were thus discussed at the metropolitan area scale.

Conversely, cultivated land, grassland, and shrubland patches differ significantly from forest patches in size and distribution pattern, lacking clear characteristics in spatial distribution and interaction. Relevant protection policies are also mostly implemented at smaller scales, such as municipal areas or by controlling patch areas, as seen in Japan's land use revitalization plan for cultivated land patches. The univariate Moran's I index was used to measure spatial autocorrelation, quantifying the similarity or dissimilarity of variable values between adjacent areas. This is useful for identifying clustered, dispersed, or random patterns in the spatial distribution of ESP levels across different LULC patches (Li et al., 2017; Xie et al., 2020). Additionally, the Local Indicators of Spatial Association (LISA) were used to measure local spatial correlation, further refining the spatial analysis (Gruebner et al., 2011; Zhong et al., 2020). Therefore, this study used these indicators to discuss LULC types such as cultivated land at the municipal scale. The univariate Moran's I index and the LISA was calculated as (Xie et al., 2020):

$$I = \frac{N}{W} \times \frac{\sum_i \sum_j w_{ij} (x_i - \bar{x})(x_j - \bar{x})}{\sum_i (x_i - \bar{x})^2}$$

$$I_i = \frac{(x_i - \bar{x})}{m_2} \sum_j w_{ij} (x_j - \bar{x})$$

Where I is Univariate Moran's I, N is the total number of spatial units (administration units), W represent the sum of all spatial weights, w_{ij} is the spatial weight between spatial units i and j . x_i and x_j are the values of the variable being analyzed for spatial units i and j . $\bar{x}$ is the mean value of the variable across all spatial units.

I_i is the local Moran's I value for spatial unit i , m_2 is the variance of the variable.

3.3 Results

3.3.1 Forest ecological network construction

3.3.1.1 Landscape connectivity in forest

The change in forest land across the three major metropolitan areas exhibits minimal fluctuations. Specifically, the proportion of forest land decreased by 0.02% and 0.13% in the TKM area and the KKM area, respectively, while it increased by 0.22% in the CBM area. However, the IIC and PC indicators for all three major metropolitan areas improved from 2000 to 2020 (Table 3.2). Among them, the dynamics of overall forest landscape connectivity indicator in the CBM area experienced the greatest fluctuations, which correlates with the intensity of changes in area.

Table 3.2 Changes in forest landscape connectivity based on the values of IIC_{num} and PC_{num} .

Landscape connectivity index	Year	Tokyo metropolitan	Chubu metropolitan	Kinki metropolitan
IIC_{num}	2000	5.239E+07	2.533E+08	5.696E+07
	2020	5.496E+07	2.882E+08	5.699E+07
PC_{num}	2000	1.006E+08	3.811E+08	1.056E+08
	2020	1.055E+08	4.168E+08	1.061E+08

3.3.1.2 Direction lines of ecological corridors

Potential ecological corridors in three metropolitan areas, identified by the MCRM for the years 2000 and 2020, revealed significant trends in the spatial distribution and length characteristics of these corridors over the specified period (Figure 3.2, Table 3.3).

In both 2000 and 2020, certain potential corridor locations in the TKM area remained consistent, such as the corridor in the southwest area. However, by 2020, many potential corridors had disappeared. The longest potential corridor in this area exceeded 110 km, approximately ten times longer than the second-longest corridor. This extensive corridor spatially connects the southern and northern regions of forests, forming a closed, continuous forest ecosystem layer around the periphery of the TKM area. Compared to 2000, there was a significant decrease in the length and number of potential corridors in the 5-20 km range in 2020. Particularly those 10-15 km and 5-10 km ranges, each decreasing by nearly 40 km. The central and western areas showed notable corridor deficiencies.

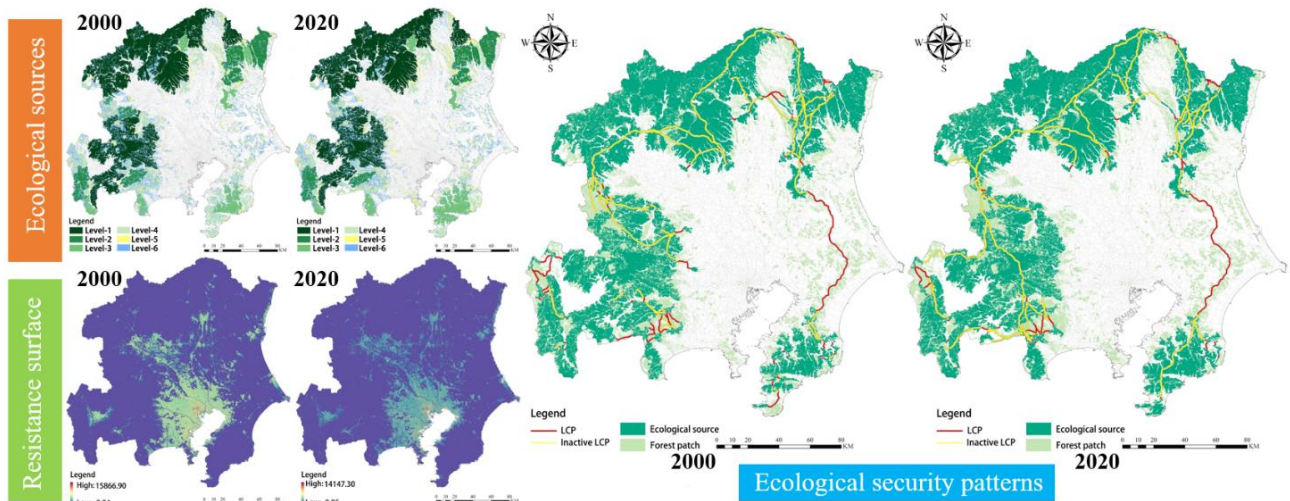
In the CBM area, a well-developed forest ecological network was observed, with corridors primarily on the outskirts of non-forest areas. The 2000 distribution was denser around the urban center than in 2020. The longest potential corridor measured 35.13 km in 2000 and 37.06 km in 2020, situated on the outskirts of the urban center and along the coastline, respectively. Additionally, in 2020, there was an increase in the number of the 10-20 km and less than 1 km ranges, while other lengths ranges decreased. Northern and eastern longer corridors observed in 2000 had reduced or disappeared by 2020.

In the KKM area, the total length of corridors increased by about 10 km, with dense corridors in the northern and eastern regions. The spatial distribution of potential corridors in 2000 and 2020 exhibited significant consistency and similarity. For instance, potential corridors on islands in the KKM area were remarkably similar, and although

corridors longer than 20 km increased in 2020, their spatial distribution remained largely consistent with that of 2000, primarily situated in the northern and eastern parts of the KKM area.

Table 3.3 The number and direction lines length of potential ecological corridors computed based on LCP.

Area	Length/km	$L \geq 20$	$15 \leq L < 20$	$10 \leq L < 15$	$5 \leq L < 10$	$1 \leq L < 5$	$L < 1$	ALL
TKM_2000	Number	1	2	9	11	25	49	97
		1.03%	2.06%	9.28%	11.34%	25.77%	50.52%	100.00%
	Length/km	112.03	34.51	113.87	83.07	64.07	14.05	421.59
TKM_2020	Number	1	1	6	6	17	43	74
		1.35%	1.35%	8.11%	8.11%	22.97%	58.11%	100.00%
	Length/km	113.52	15.24	74.51	45.34	51.33	15.49	315.41
CBM_2000	Number	3	3	4	11	26	75	122
		2.46%	2.46%	3.28%	9.02%	21.31%	61.48%	100.00%
	Length/km	79.43	49.29	53.9	75.7	68.88	17.32	344.53
CBM_2020	Number	2	3	3	6	19	61	94
		2.13%	3.19%	3.19%	6.38%	20.21%	64.89%	100.00%
	Length/km	61.13	52.21	37.25	39.95	55.05	18.46	264.05
KKM_2000	Number	4	3	6	9	30	73	125
		3.20%	2.40%	4.80%	7.20%	24.00%	58.40%	100.00%
	Length/km	99.25	53.56	75.83	64.23	74.43	16.69	383.99
KKM_2020	Number	4	5	5	10	22	69	115
		3.48%	4.35%	4.35%	8.70%	19.13%	60.00%	100.00%
	Length/km	107.19	87.01	62.77	68.19	49.79	18.28	393.23



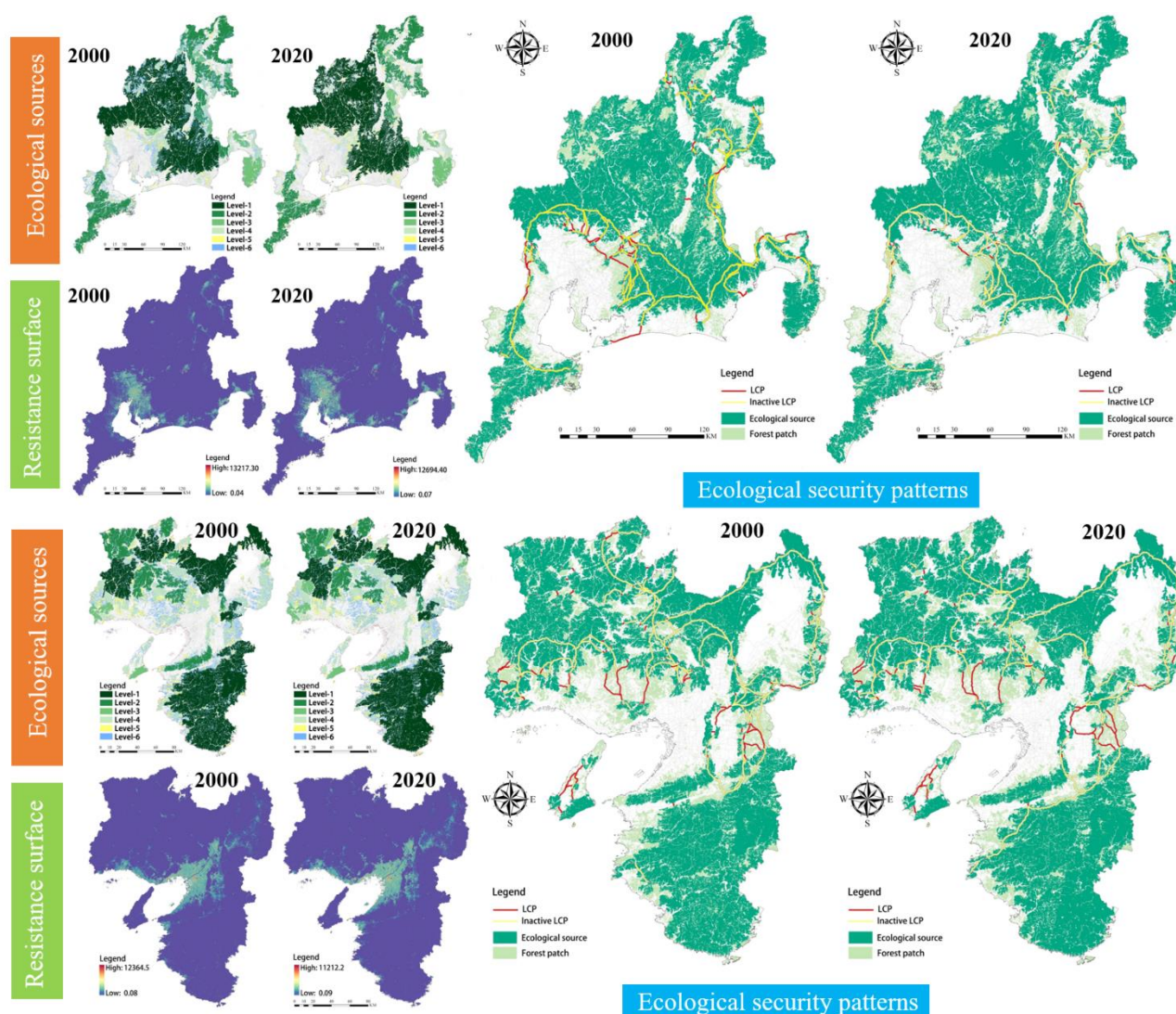


Figure 3.2 Ecological source, resistance surface and direction lines of ecological corridors from in 2000 and 2020.

3.3.1.3 Identification of optimal width of ecological corridor

This study investigates the width and area of important potential ecological corridors in three major metropolitan areas in 2000 and 2020 using circuit theory and the pinchpoint mapper tool in Linkage Mapper. By setting ranges for ecological corridors and cumulative current thresholds from 1km to 5km, five threshold widths for ecological network constructions in forest were established for 2000 and 2020, respectively (Figure S3.1). The results showed that as the threshold increases, the area of ecological corridors increases while the cumulative current decreases. Under the 3km cumulative current threshold, the change becomes relatively stable. Additionally, the width of corridors in the three metropolitan areas are generally less than 3km even under 4km and 5km thresholds, leading to the selection of 3km as the threshold for defining corridor spatial extent (Figure 3.3).

Japan's extensive forest saw significant urban forest expansion from 2000 to 2020. The study found that certain potential corridors shortened due to increased forest areas. For example, this occurred in southern Chiba Prefecture in TKM (TKM-c), northern Mie and southern Gifu Prefectures in CBM (CBM-d), and western Hyogo Prefecture in KKM (KKM-b). Despite these changes, the orientation and morphology of many potential corridors remained stable, such as in Kobe City in Hyogo Prefecture (KKM-a) and northern regions of CBM (CBM-a). However, the width of

corridors varied, with some areas in the southern TKM (TKM-c) and northern Aichi Prefecture (CBM-b) exhibiting wider corridors in 2020 compared to 2000.

Overall, potential corridors in the three metropolitan areas are generally short (less than 5km) with modest changes in orientation and area, highlighting the intricate dynamics of urban forest expansion and the need for nuanced management strategies to maintain ecological connectivity. The study also analyzed the current LULC types of potential corridors (Table 3.4), finding a decrease in potential corridor areas from 2000 to 2020, particularly in CBM. Moreover, the results revealed that over 70% of potential corridors are fragmented forest patches, and green spaces make up over 90% of the total area. Except for CBM in 2020, artificial land cover within potential corridors is below 1%. The consistency and stability of potential corridors, coupled with the feasible establishment of green spatial patterns, underscore the importance of strategic planning in urban and landscape ecology.

Table 3.4 Statistics of LULC Types within the Potential Forest Ecological Corridor Area/km².

Metropolitan/LULC		Cultivate d land	Forest	Grass land	Shrub land	Wetland	Water body	Artificial surface	Bare land	Total area
Tokyo metropolitan	2000	52.61	484.77	31.70	51.08	0.00	32.55	0.23	4.35	657.29
		8.00%	73.75%	4.82%	7.77%	0.00%	4.95%	0.03%	0.66%	100.00%
	2020	46.25	354.83	23.06	34.64	0.00	29.48	0.35	3.98	492.59
		9.39%	72.03%	4.68%	7.03%	0.00%	5.98%	0.07%	0.81%	100.00%
Chubu metropolitan	2000	37.26	222.75	13.41	25.67	0.17	1.09	0.14	2.14	302.63
		12.31%	73.60%	4.43%	8.48%	0.06%	0.36%	0.05%	0.71%	100.00%
	2020	26.57	152.33	9.86	17.49	0.00	2.18	0.35	1.41	210.20
		12.64%	72.47%	4.69%	8.32%	0.00%	1.04%	0.17%	0.67%	100.00%
Kinki metropolitan	2000	67.74	389.39	17.39	73.14	0.00	0.73	0.23	1.88	550.51
		12.30%	70.73%	3.16%	13.29 %	0.00%	0.13%	0.04%	0.34%	100.00%
	2020	62.64	362.08	18.04	63.83	0.34	0.61	0.25	1.71	509.49
		12.29%	71.07%	3.54%	12.53 %	0.07%	0.12%	0.05%	0.33%	100.00%

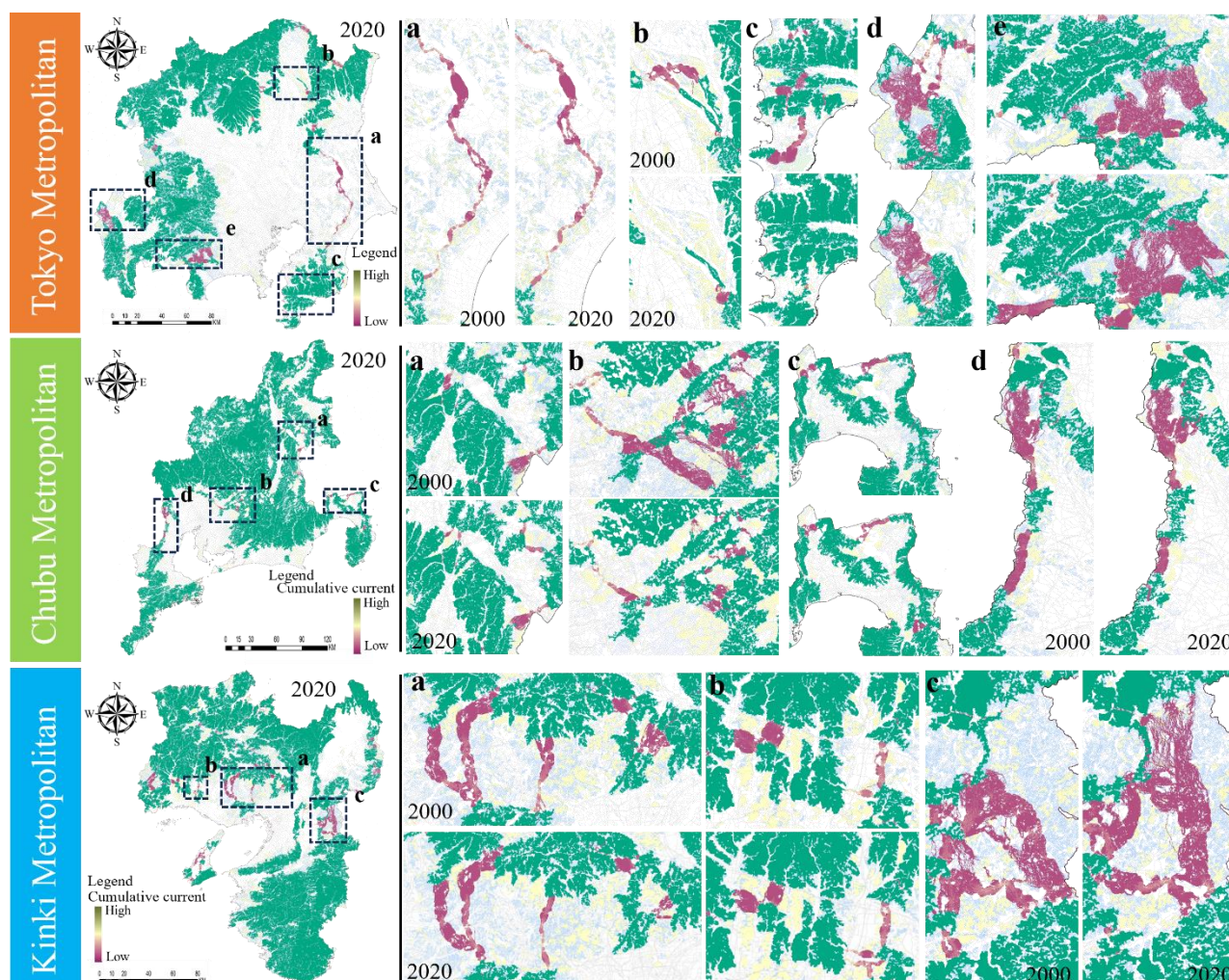


Figure 3.3 Ecological corridors and cumulative current at the 3km thresholds.

3.3.2 Assessing LULC patches under P-V-O model

3.3.2.1 The results of P-V-O models

This study conducted comprehensive computations and analyses on ecological health assessment in 2000 and 2020 (Figure S3.2, Figure 3.4). Overall, the socio-economic indicators of the metropolitan areas did not exhibit significant spatial changes within the specified timeframe. Urban development has resulted in a spatial pattern characterized by the concentration of activities in the central areas of the metropolitan region (23 wards of Tokyo; Nagoya, Osaka, Kyoto, and Kobe city), alongside scattered urban points. However, the trend of central areas driving regional growth and urban expansion over the last two decades has been relatively weak. Furthermore, the study identified a heightened increase in the high values of socio-economic factors in the TKM and CBM, signifying an intensified economic development within the current spatial framework.

KKM sustains stable spatial configurations of landscape vitality indicators, although there is an overall decline in the TKM and CBM. Notably, a significant decrease in landscape vitality can also be observed in the southern region of the KKM. The spatial arrangement of landscape organization in the TKM exhibited relative stability, accompanied by additional increments in high values; conversely, the low-value spectrum of landscape organization expanded in the northern sector of the CBM and towards the southeast of the KKM.

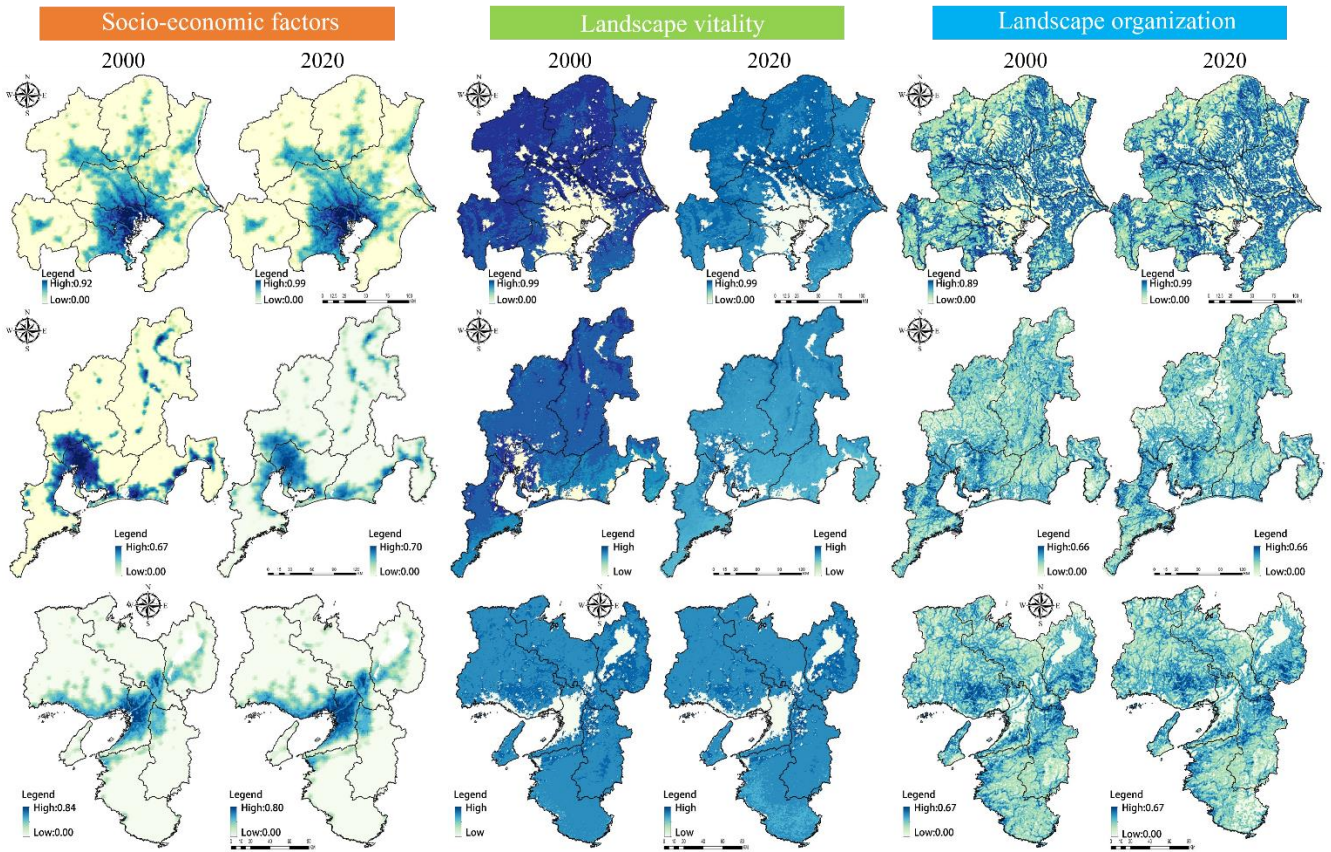


Figure 3.4 Socio-economic factors, landscape vitality, and landscape organization in three metropolitan areas.

3.3.2.2 The assessment of ecosystem health based on the IEW-TOPSIS method

This study applies the IEW-TOPSIS method to assess green space patches in three major metropolitan areas for 2000 and 2020 (Figure 3.5). For forest patches, over 75% had a c_i index above 0.7. Furthermore, the range of c_i values for forest patches in 2020 was consistently larger compared to 2000, indicating increased variability. In the TKM, forest patches in 2000 were predominantly clustered within the c_i range of 0.669-0.900, but the distribution of patches shifted to a narrower range of c_i values in 2020 (0.68-0.84), showing decreased overall concentration. In the CBM, the distribution of c_i values exhibited the highest degree of dispersion. Peak points and ranges of c_i values for both CBM and KKM shifted towards lower values in 2020, with a reduction in the number of patches in the high-value regions. Cultivated land patches showed wide variability in both years with 50% of patches having c_i values below 0.46. Peak c_i values decreased in 2020, and dispersion increased, indicating more divergence.

Grassland patches in TKM showed the greatest variability, with an expanded concentration range in 2020, suggesting greater uniformity. The accumulation patterns in the CBM and KKM remained similar, with the CBM more aggregated in 2000, whereas the opposite was observed for the KKM. For shrubland patches, 50% had c_i values above 0.784. Specifically, In the TKM, the c_i values of the accumulation peak points were higher and ranges were wider in 2000, with increased dispersion in 2020. The CBM and KKM trends were consistent over time. Wetland patches increased in number, with expanded c_i ranges (except in the TKM), indicating more variability. Its limited number of patches allows for targeted observation and precise protection.

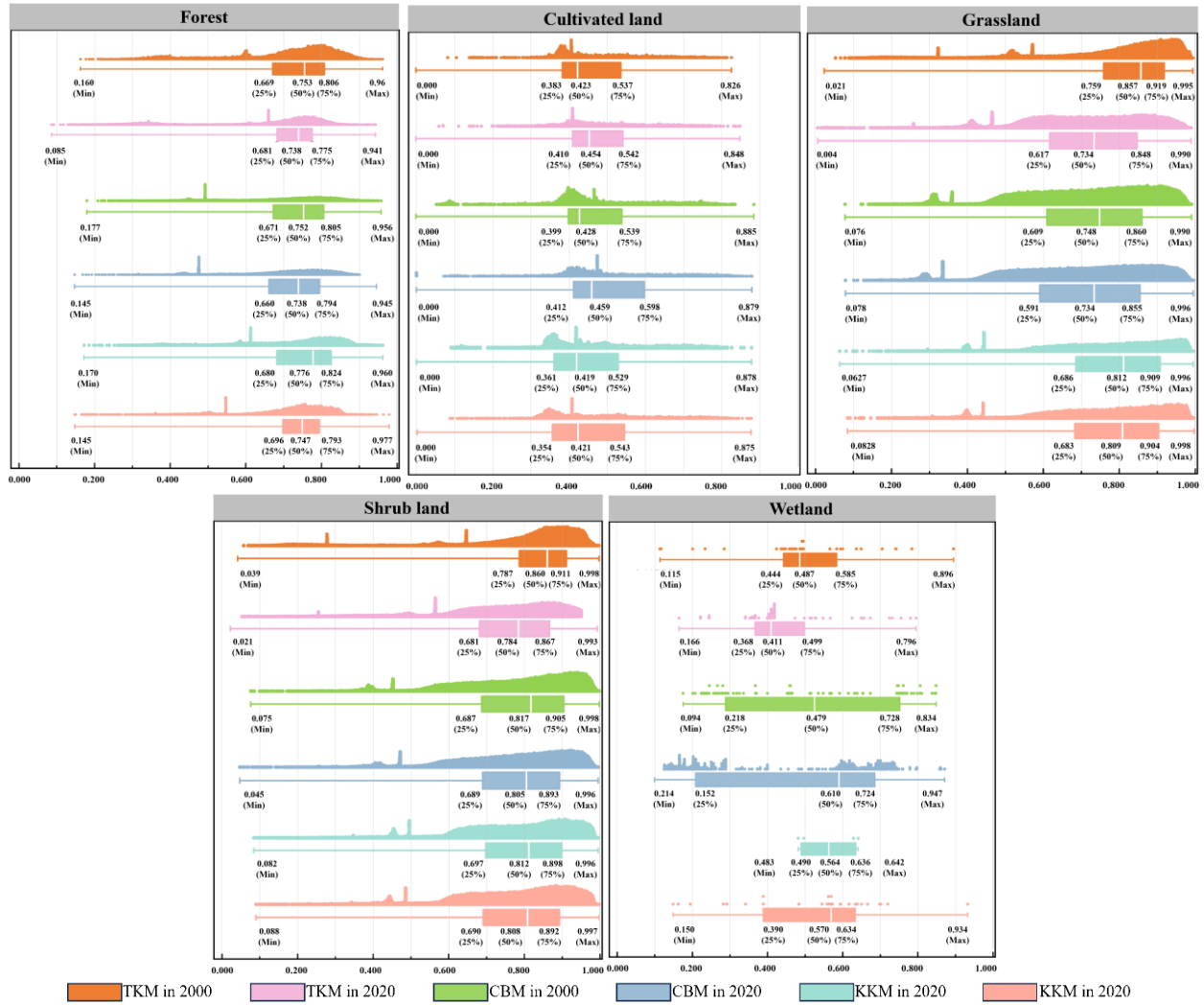


Figure 3.5 c_i values span in forest, cultivated land, grassland, shrubland and wetland of three metropolitan areas.

The study conducted an evaluation of green space patches in 2000 and 2020 (Figure 3.6). To address the challenge of relatively low c_i values observed for cultivated land, a natural break method based on TOPSIS results was utilized to classify cultivated land. High-quality patches for forest, grassland, and shrubland were identified with c_i values exceeding 0.8, while those falling below the 25% were categorized as low-quality patches or requiring targeted management.

Forest patches revealed relatively cohesive spatial structures across the three metropolitan areas. Large forest patches often located on the outskirts of urban boundaries. Forest patches maintained relatively stable c_i results between 2000 and 2020 in the CBM and KKM. In the TKM and KKM, forest patches proximal to urban areas tended to exhibit lower c_i values. The CBM area exhibited patches with high c_i values around the urban areas, while the eastern region contained patches with lower c_i values.

Cultivated land patches were closely linked to human activities, with higher c_i values observed in proximity to urban areas. In the TKM, there were large high c_i value patches in the central region, which expanded in 2020. In the CBM, although patches with high c_i values were primarily clustered around the urban area, their quantity decreased compared to 2000. In the KKM, patches with high c_i values were widely dispersed around urban area and the northwestern area.

Grassland and shrubland are characterized by dispersed distribution and relatively smaller extents. In the TKM, grassland with high c_i values predominantly clustered in the northeastern and southern area. Shrubland tended to distribute near forests, with quality improvements in the southern area. In the CBM, high c_i value grassland patches demonstrated consistent stability, particularly along riverbanks. Conversely, shrubland patches in the southern and southeastern areas generally exhibited favorable attributes, indicating a need for optimization and enhancement initiatives. In the KKM, grassland patches were predominantly in mountainous terrain. Grassland patches along riverbanks and shrubland patches near central urban area correlated with lower c_i values.

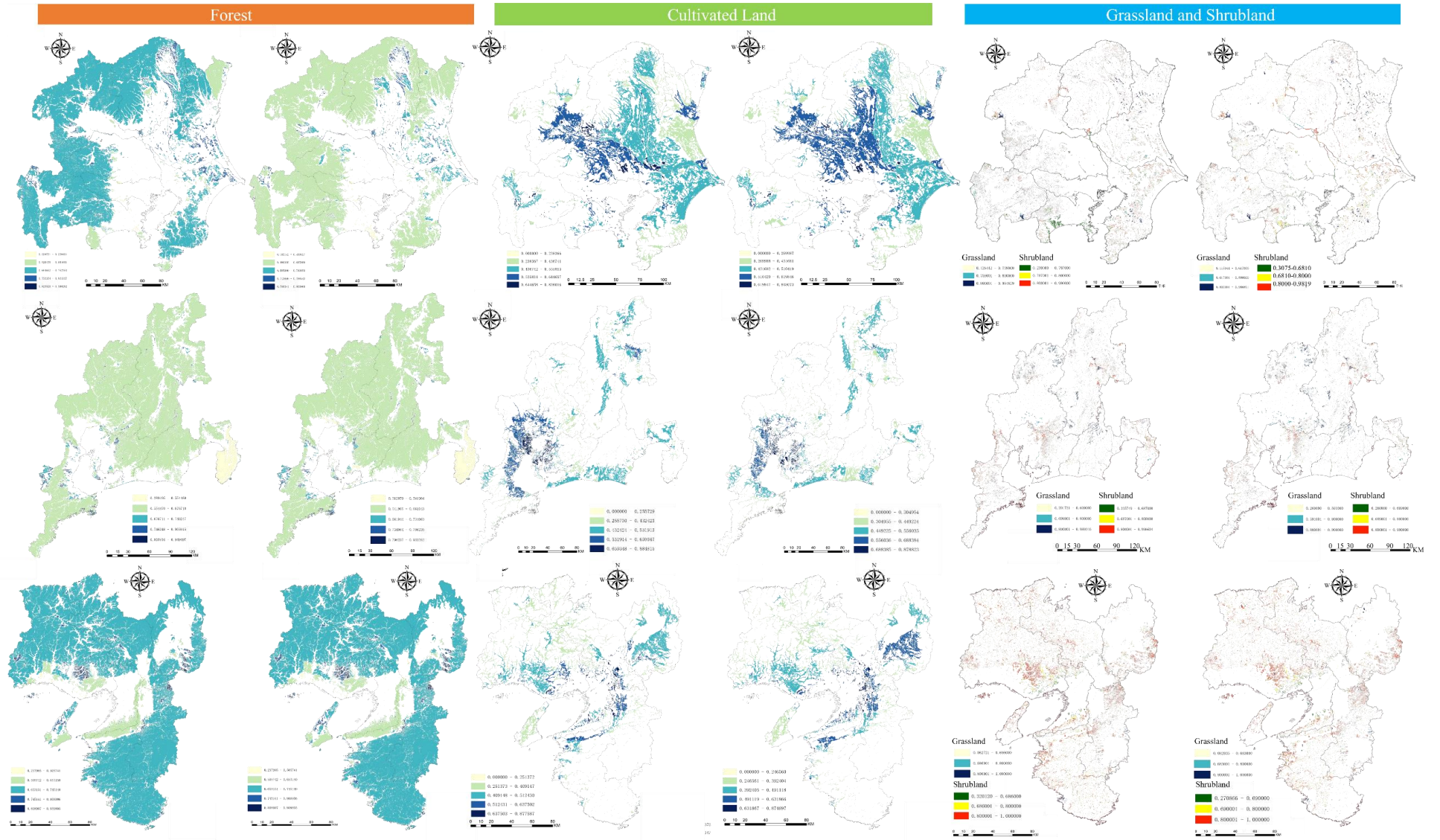


Figure 3.6 c_i values span in forest, cultivated land, shrubland and grassland of three metropolitan areas.

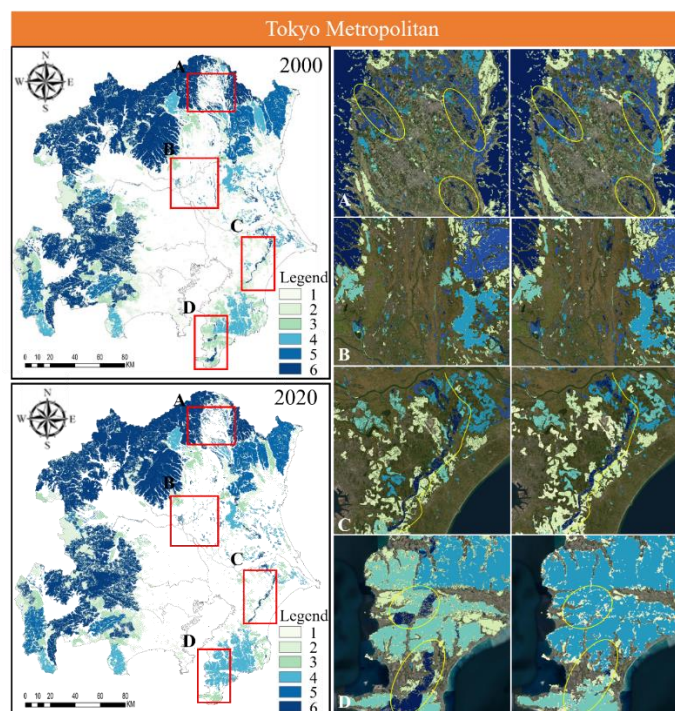
3.3.3 Analysis spatial characterization of ESP

This study stratified forest patches into six levels of the importance for ESP, ranging from low to high (1-6) (Figure 3.7). Overall, forest patches in the three major metropolitan areas demonstrate favorable conditions. The majority of forest evaluation results remained consistent between 2000 and 2020. However, notable disparities persist among these regions.

The important patches of forest in the TKM are predominantly located in the southwestern to northern large forest patches, and their distribution has remained consistent between 2000 and 2020. Attention should be focused on constructing potential corridors or implementing island hopping functions for some forest patches in other areas. For instance, in TKM's C of Figure 9, the potential corridors have remained consistent between 2000 and 2020, highlighting the need for integrating these patches. The change in importance observed in TKM's D of Figure 9 is due to the integration of high-level patches from 2000 to 2020, warranting special attention to these significantly altered patches.

In the CBM, important patches are concentrated in the large-scale forest patches to the northwest and southeast, maintaining consistency between 2000 and 2020. The fragmentation and notable changes in importance of forest patches in the central area, as illustrated in Figure A, are closely related to dynamic changes in potential corridors and patch integration, necessitating focused attention during conservation and management. Additionally, high-importance small patches in Figures B-D require dynamic monitoring and on-site surveys of their characteristics.

In the KKM, there has been an increase in forest patch-level differences in 2020, particularly evident in the fragmentation around the central urban areas. For example, forest patches in areas A, B, and C of the KKM may require specific protection and integration efforts due to the influence of potential corridors. Changes in potential corridor areas depicted in Figure D of the KKM in 2020, indicate the need to consider establishing protection areas based on the 2000 potential corridor trends and emphasizing focused attention accordingly.



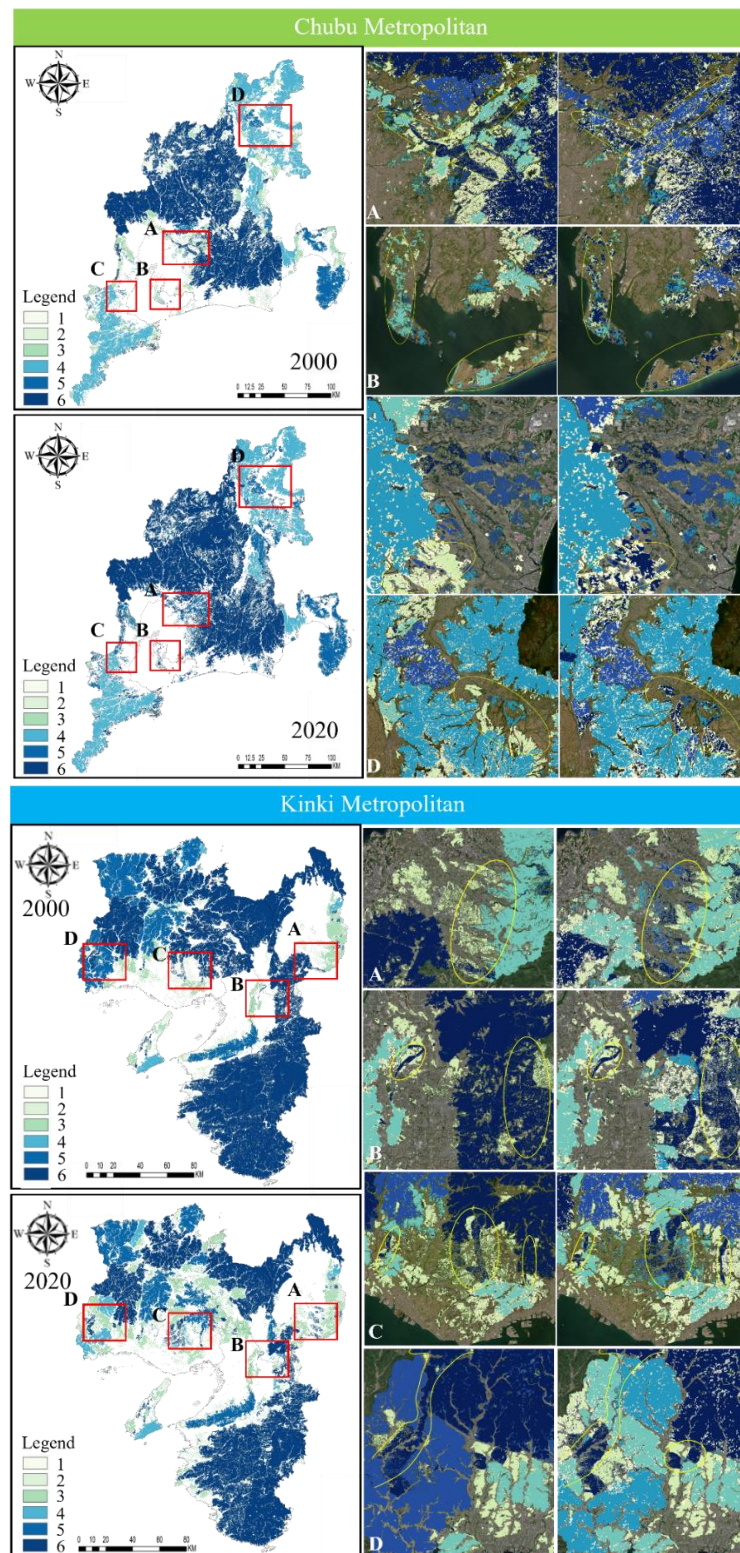


Figure 3.7 Spatial Distribution Map of comprehensive forest Evaluation Based on ecological network and ecosystem health assessment.

For cultivated land, grassland, and shrubland, the study discusses spatial management on municipal scale. The three major metropolitan areas encompass 334, 237, and 198 cities, respectively. The study analyzed and statistically examined the ecosystem health results of green space patches within each municipality, calculating their Moran's I index (Table 3.5). The results found that the z-values are all significantly higher than 6, with p-values all less than

0.001, passing the significance test at the 1% level, indicating clear clustering characteristics. The Global Moran's I index has the defect of ignoring the instability of local spatial processes. Therefore, it is necessary to draw a LISA cluster map to explore their spatial distribution characteristics (Figure 3.8).

Regarding cultivated land, in the TKM, high-value regions of cultivated land c_i show clear clustering characteristics in the northern region, while central low-value areas remained stable between 2000 and 2020, with high-value regions of cultivated land c_i existing around the periphery. Additionally, high-value regions of cultivated land c_i in the western region began to show clustering. High-value regions of cultivated land c_i in the CBM and KKM areas are located on the highly developed peripheries of artificial surfaces, while low-value areas exhibit clear spatial clustering characteristics.

For grassland, due to its large patch numbers, it is subject to various disturbances. In the TKM, there are evident high-value regions of grassland c_i in the peripheral areas from west to northeast, while the central area remains stable as a low-value region. The clustering characteristics of grassland in the CBM are not particularly strong, with significance remaining stable. In the southern region of the KKM, there has been a significant increase in grassland c_i values. Regarding shrubland in the TKM, high-value regions of c_i exhibit clustering characteristics similar to grassland, while in the CBM, high-value regions of shrubland c_i mainly cluster in the southern areas. In the northern and southern regions of the KKM, there are numerous clusters of high-value regions.

Table 3.5. Univariate spatial autocorrelation estimates of P-V-O model.

LULC types	Year	TKM		CBM		KKM	
		Moran's Index	z-score	Moran's Index	z-score	Moran's Index	z-score
Cultivated land	2000	0.625	17.9262	0.5572	13.0472	0.3298	6.7718
	2020	0.6189	18.5161	0.5728	13.2397	0.47	9.9274
Grassland	2000	0.7408	20.9592	0.3886	9.1907	0.7043	14.5402
	2020	0.5725	16.8849	0.41	9.5726	0.4673	9.7539
Shrubland	2000	0.6825	19.5905	0.4355	9.8486	0.5781	12.2913
	2020	0.5943	17.6319	0.4766	10.8365	0.5288	11.1743

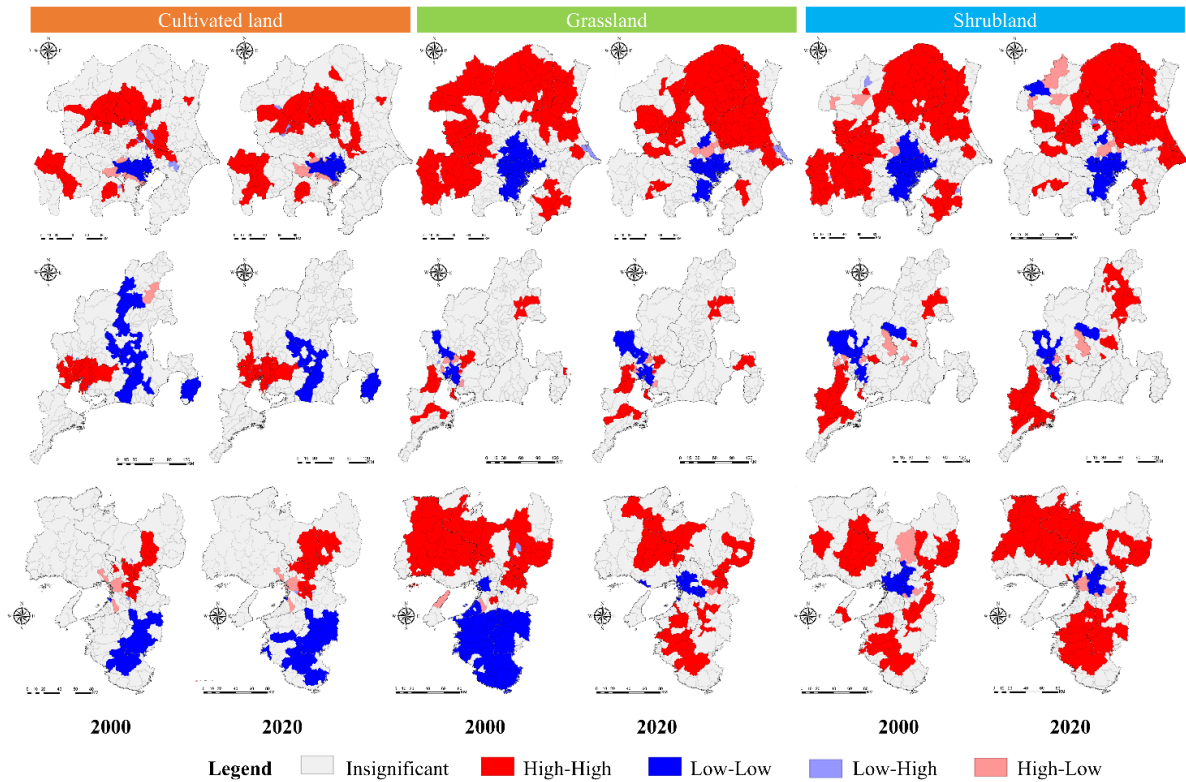


Figure 3.8 LISA agglomeration diagram illustrates the distribution characteristics of ESP on municipal scale.

3.4 Discussion

3.4.1 Ecological network construction guides urban land use management

The construction of ecological networks plays a crucial role in mitigating climate change, maintaining biodiversity, and facilitating species migration (Ersoy et al., 2019; Perault and Lomolino, 2000; Xie et al., 2023). Although there is limited research on ecological network construction for the purpose of sustainable and stable urban structure in developed countries, particularly in Japanese cities, Japan has repeatedly emphasized the importance of ecological network in key documents and regional planning strategies (Ministry of the Environment., 2023), highlighting the necessity and urgency of conducting ecological network construction research in Japan. As a developed country, Japan frequently experiences natural disasters such as earthquakes and typhoons, underscoring the importance of considering their impact on ecological network (Moej, 2023). A stable network is crucial for sustainable urban development and for mitigating and adapting to natural disasters (Dai et al., 2021; Peng et al., 2018). Strategies to address these challenges include strengthening the planning and protection of ecological corridors, promoting ecological restoration projects, and improving the zoning of preservation areas in wide-area local plans.

This study found that Japan has a solid foundation for constructing ecological networks (Table 3, Figure 3). Despite the presence of numerous potential corridors, those less than 1 km in length constitute over 50% of the total, with forest patches inside these potential corridors accounting for over 70% of the area (Table 4, Table 5). These characteristics indicated that Japan primarily needs to integrate and maintain the green space within these potential corridors to build an effective ecological network. This high proportion of shorter corridors indicates the relatively proximity between ecological source areas, suggesting a well-connected network of natural habitats crucial for

maintaining biodiversity and ecological processes. Compared to studies in developing countries, which often show a more fragmented and complex corridor distribution, such as in China, ecological network construction faces greater challenges due to the complex LULC types within potential ecological corridors (Peng et al., 2019; Xie et al., 2023; Zhao et al., 2024). the shorter corridor lengths in Japan's metropolitan areas reflect a more intact ecological network beneficial for ESP. Shorter corridors require less extensive intervention to maintain connectivity, making their integration into regional planning more feasible and cost-effective. While both short and long corridors are vital for ecological connectivity, the prevalence of short corridors underscores an advantage in these metropolitan areas by facilitating easier implementation of ecological network plans and contributing to a robust ESP.

Furthermore, the ecological network construction results of the three major metropolitan areas exhibit distinct characteristics (Figure 3.3, Figure 3.4). For example, in the TKM area, the forest network surrounds the artificial surfaces, while the lack of forest corridors in the eastern region results in an incomplete ecological network. In the CBM, potential corridors are primarily located near artificial surfaces. In the KKM, with Osaka Prefecture, Kyoto City, and Kobe city as the core development centers, large areas of intact forest patches exist in the north and south, and potential corridors are also predominantly located near artificial surfaces. These metropolitan areas demonstrate significant differences in forest spatial structure, reflecting varied strategies in managing economic and population growth alongside ecological issues (Lang et al., 2020).

3.4.2 ESP evaluation of three major metropolitan area

Currently, in multiple countries, land use management is conducted by distinguishing and managing various LULC types for planning and development. For instance, in Japan, there are systems like the agricultural promotion regional system and the agricultural land conversion permission system to protect and manage cultivated land (Hirabayashi, 2021; Liu et al., 2020). These regulatory practices acknowledge the roles of various ecological and socio-economic factors in urban environments and emphasize the importance of tailored land use management and planning methods. However, there remains a notable gap in extensive research concerning the differentiation of LULC categories, particularly regarding critical issues like ecological network construction and ecosystem health assessments. While these research findings can provide spatial maps with relatively clear regional disparities, their practical application in planning is challenging and lacks precise planning (Cao et al., 2018; Xu et al., 2022). Therefore, within this context, differentiated research on LULC types has become one of the focal points of this study.

This study evaluated five types of green spaces in the three major metropolitan areas in 2000 and 2020 at the patch scale. Regarding forest, the study integrated ecological network and ecosystem health assessment results, providing graded results for forest areas in 2000 and 2020, reflecting the areas of controlled and protected forests at the patch scale (Figure 3.7). Forests, known for their rich biodiversity, play a crucial role in maintaining ESP and mitigating natural disasters in future land use planning (Jin and Song, 2023). This study highlights the disparity in protection levels between large and small forest patches identified through ESP. Large patches are often protected by national policies, such as national parks, whereas small patches lack clear protection and maintenance measures. Detailed maps pinpointing small patch areas are provided, underscoring the need for further field surveys and biodiversity assessments (Figure 3.7). Given that many small patches are in urban fringes and urban inners, their management and protection should be integrated with urban development plans, like Metropolitan area develop

plans. Additionally, the study emphasizes the importance of integrating fragmented forest patches and establishing robust management practices. This includes legal constraints, physical barrier implementations, and boundary adjustments based on analytical results to harmonize development and conservation efforts. The comprehensive plans of the three metropolitan areas should precisely define the natural reserve boundaries. In Japan, land use management involves multiple stakeholders, including government, residents, and businesses. Promoting the importance of ESP and establishing forest negotiation platforms are crucial for effectively managing forest development and protection. For example, in Chiba Prefecture, the southeast of TKM, a long potential forest corridor intersects with various LULC types. Although the artificial surface and cultivated land within this corridor are relatively small (Table 3.4, Figure 3.7), integrating patches among the potential corridor's ranges to forest corridor will inevitably impact People's daily life, business operations, and forestry operations. Active collaboration and communication platforms are essential for the successful implementation and adjustment of potential corridors.

This study evaluates the ESP of various green spaces by assessing patch structure, vitality, and potential threats. The results indicate that key cultivated land patches are predominantly located around artificial surface. In recent years, a pressing issue has emerged concerning the simultaneous expiration of the 30-year cultivation obligation mandated by the Productive Green Land Act, which has been instrumental in maintaining agricultural land within Japanese cities (Nakashima et al., 2023; Satake et al., 2018). From the perspective of securing designated green spaces within urban areas, revitalizing peri-urban agriculture is an essential agenda. Promoting “local production for local consumption” is anticipated not only to contribute to reducing CO₂ emissions, but also to align with the concept of food mileage, which reduces environmental burdens by shortening transportation distances, etc. This approach is increasingly recognized as an integral part of efforts towards achieving the Sustainable Development Goals (Nakajima et al., 2023; Shiraki et al., 2006). This study provides the location of key cultivated land patches (Figure 3.8), allowing for the delineation of high-quality cultivated land protection areas, particularly in stable high-quality peri-urban regions and municipalities from 2000 to 2020. This ensures these areas continue to serve as critical agricultural output zones, enhancing cultivated land management and ensuring food supply for nearby residents. For areas with ESP mismatches, such as low cultivation regions surrounding high-quality clusters, issues generally stem from population distribution, soil quality, and nature factors leading to concentrated mismatches in cultivated land. By integrating ESP evaluations at the patch scale (Figure 3.6), this study identifies high-quality patches for targeted protection, preventing further degradation and abandonment of farmland, thereby maintaining the integrity of key cultivated land wherever possible. Finally, the regional drawings provide reference materials for policy-making. For example, cultivated land development permits typically offer guidance on managing and maintaining cultivated land areas. If the protection of cultivated land is carried out under more comprehensive evaluation indicators, it will be particularly meaningful for some high-quality and small cultivated land areas. For example, evaluations combined with the ESP mentioned in this study can enhance the protection strategies.

In the TKM and KKM, highly rated grassland and shrubland regions are predominantly located near forests, reflecting the natural transition from grasslands and shrublands to mixed forests in Japan (Okubo, 2002). This distribution pattern highlights the dynamic equilibrium between grasslands, shrublands, and forests. In the CBM, high-value grassland and shrubland clusters are less frequent but are associated with the richness of forest resources. Identifying and evaluating high-quality areas can promote livestock development and diversify the regional

economy. Shrublands are rich in biodiversity and are crucial for ecosystem conservation. For instance, in Hyogo Prefecture, northern Kinki region, ESP evaluations from 2000 to 2020 show an increase in high-value shrubland areas, potentially indicating improvements in shrubland quality (Figure 3.8). Combining regional results with patch-scale evaluations can more precisely protect high-quality grasslands and shrublands. This method helps balance ecological conservation with resource utilization, providing a scientific basis for the sustainable development of grasslands and shrublands. It also offers important references for regional planning and land use decisions.

3.4.3 Limitations and future works

This study provides evaluation methods of LULC types differentiation on a broad scale by considering ecological network construction and ecosystem health assessments. However, several limitations and areas for future research need to be addressed. One limitation is the use of broad LULC classifications, which may not capture nuanced differences within each category. Future research should focus on more detailed LULC classifications, such as differentiating natural forests, secondary forests, plantations, bamboo forests, and orchards. Additionally, the study primarily assessed LULC types based on physical characteristics and potential factors, without deeply analyzing how socio-economic and demographic influences, such as the abandonment of cultivated land due to population decline and aging in Japan, affect these results. Future research should delve deeper into these root causes of LULCC to more accurately discuss and interpret results related to species diversity distribution and land use dynamics. While the study focused on three major metropolitan areas in Japan, the findings may not be directly applicable to other regions with different ecological and socio-economic contexts. Conducting cross-regional comparisons in future research will help validate findings and provide broader insights into the applicability of ecological network construction and ecosystem health assessments across different contexts. Incorporating socio-economic factors and their interactions with physical characteristics will also provide a more holistic understanding of land use dynamics, including analyzing urbanization patterns, economic activities, and policy impacts. By addressing these limitations and focusing on these future research directions, the study aims to enhance the understanding and application of differentiated LULC types in ecological network construction and ecosystem health assessments, contributing to more effective land use management and sustainable development practices.

3.5 Conclusion

This study proposed an evaluation method based on the patch scale of LULC types for constructing ecological networks and evaluating ecosystem health. It discussed the importance of different LULC types in achieving the stability of the ESP and explored methods of planning, regional division, and protection. The results emphasized the need for fine planning at broad scale by distinguishing LULC differences. The findings showed that (1) the three major metropolitan areas in Japan have superior forest ecological network spaces, with 70% of the LULC types in potential forest corridors being fragmented forest patches, and more than 50% of the corridors being less than 1 km long. (2) Additionally, the study proposed a P-V-O model based on the patch scale and integrated and evaluated the importance of five types of green space patches in the ESP using the IEW-TOPSIS method. The important green space areas under the municipal area were divided by the LISA index, identifying critical areas such as important cultivated land patches located in city centers and grassland concentrated in the northern areas of TKM and KKM.

The results of the study will be combined with the zoning and adjustment of current spatial planning to explore the adjustment and management of protected areas and development zones, ensuring the long-term stability of the ecological network through policies and regulations. The research also provides an opportunity for future discussions on ESP at the patch scale, emphasizing the importance of patch-scale evaluation. This approach aims to enhance the understanding and application of differentiated LULC types in ecological network construction and ecosystem health assessments, contributing to more effective land use management and sustainable development practices.

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Chapter 4

Exploring Land Use Management Strategies through MSPA Using a Climate–Socio-economic Based Land Use Simulation Modeling Framework

The KKM Area is Japan's second-largest economic zone and a vital center of Japanese economy and culture, alongside the TKM area. Anchored by Osaka, Kyoto, and Kobe, it forms a 'three poles, one axis' urban structure. The KKM Area shoulders the responsibility of driving Japan's future development, aiming to reduce the risk of over-reliance on Tokyo as a single hub, making it a primary core region for development. The KKM Area exhibits a relatively optimistic trend in economic development, historical and cultural dissemination, as well as ecosystem conservation. Furthermore, as previously mentioned, land use/land cover changes in metropolitan areas are significantly influenced by socioeconomic and climate factors. The KKM also exhibits characteristics of a multi-centered city. Despite its high green space coverage, important green spaces are relatively scattered, posing potential challenges to the future development of multi-centered cities. With the deepening research on the TTKM, exploring the characteristics of future urban development in the KKM under global climate change and socioeconomic fluctuations has become a highly significant topic.

4.1 Introduction

Future LULC simulations are considered an important initiative that provide a scientific basis for supporting governmental decision-making. Moreover, they have the potential to promote environmentally sustainable development and protection (Shi et al. 2021). In scenario selection, scenarios that describe the possible future development of anthropogenic drivers of climate change, aligned with socioeconomic development, are critical (Popp et al. 2017). The Coupled Model Inter-comparison Project Phase 6 (CMIP6), launched in 2013 by the World Climate Research Program and its core project, the Working Group on Coupled Modeling, served as an essential scientific resource for the IPCC to assess and synthesize the latest climate science and inform global climate policy discussions (Eyring et al. 2016). The CMIP6 links shared socioeconomic pathways (SSP) to representative concentration pathways (RCP) used in the CMIP5, generating a range of future climate scenarios, namely the SSP–RCP (O'Neill et al. 2016; Tebaldi et al. 2021). Notably, researchers have widely applied SSP–RCP scenarios in LULC simulation studies to explore the characteristics of LULCC (Liao et al. 2020; Hurtt et al. 2020; Gong et al. 2023; Kumar et al. 2023). In addition, several methodologies have been commonly used in LULCC simulations, including the Land Change Modeler, the Conversion of Land Use and its Effects model, the Meta-cellular Automata, the Future Land Use Simulation model, and the Patch Generation Land Use Simulation (PLUS) model (Shi et al. 2021; Sobhani et al. 2021; Nasiakou et al. 2022; Sun et al. 2022; Xiang et al. 2022). In this study, the PLUS model was used, which was combined with the cellular automata (CA) model based on multiclass random patch seeding, to better simulate changes in the level of multiclass LULC patches (Sun et al. 2022). It improves the accuracy of simulating changes in LULC distribution. In addition, this model can compare and identify the influence of various driving factors on LULCC (Liang et al. 2021).

Over the past five years, there has been a significant increase in study focusing on predicting future LULC changes (Gomes et al. 2021). However, the majority of studies focus on cities in developing countries; fewer studies have explored the patterns of LULC change and simulation prediction in cities in developed countries (Li et al. 2021a; Sun et al. 2022). Urban development in developed countries provides valuable insights into the dynamics of LULC patterns, the effectiveness of LULC policies, and the complex interplay among urbanization, socioeconomic factors, and environmental considerations. The experiences learned from developed countries can provide valuable guidance for adjusting LULC policies and informing future LULC planning in both developed and developing countries. Furthermore, there is often a lack of institutional fit-related analyses. Most studies have focused on future ecosystem services evaluation and landscape patterns change, overlooking the specific planning requirements and legal framework of the studied areas (Tian et al. 2022; Hou et al. 2022). Particularly for some developed countries like Japan and the United Kingdom, artificial surface development and management are subject to strict legal regulations and planning constraints (Millward 2006).

The Basic Act for Land, the National Spatial Planning Act, and the National Land Use Planning Act create a comprehensive set of territorial planning legislation in Japan. This study focuses on conducting extensive LULC simulations and discussions in the KKM of Japan. As the limitations stemming from the long-term concentration of development in the Tokyo metropolitan area become more evident, being the second-largest economy in Japan, the KKM is presented with amplified opportunities for urban growth and the reinvigoration of social capital (Kansai Greater Regional Plans). Nevertheless, in comparison to other metropolitan regions across Japan (Chen et al. 2021), research addressing LULC changes and their management remains inadequate in the KKM. Within the context of territorial planning legislation, the KKM development plans, as well as national park and green space preservation plans, provide essential guidance for future wide-area LULC development and management. Additionally, in response to the challenges of an aging population and other emerging issues (Saiki 2009; Ito et al. 2016), the agricultural land conversion permit system is implemented to restrict the conversion of agriculturally productive land with high output or large areas into other LULC types, in order to address the decline in cultivated land availability. Land management through morphological characteristics is still the most common method, although the spatial division considered various factors, such as the regional economy and population structure. In addition, the formulation and implementation of laws have certain foresight, so the analysis of land use simulation and simulation results has reference value for the formulation and implementation of regional policies to a certain extent.

Based on the background, this study focuses on the KKM area, and aims to conduct LULC simulations under four future SSP–RCP scenarios from the CMIP6. These scenarios considered variations in the population, economy, climate characteristics, and LULC demands. Furthermore, this study places particular emphasis on exploring and discussing the spatial patterns under the basis of wide-area planning. The primary objectives of this study are as follows: (1) to simulate LULC from 2020 to 2100; (2) to analyze changes in the distribution of terrestrial carbon storage (CS) under four scenarios and explore their correlation with the MSPA classes of forest; and (3) to analyze and discuss the spatial pattern changes of LULC types guided by wide-area planning. This study will contribute to a comprehensive understanding of the future dynamic changes in the LULC in the KKM, emphasizing the significance of formulating localized land management strategies and providing valuable references for policymakers, landowners, and land managers.

4.2 Study Area and Materials

4.2.1 Study Area

KKM area, which comprises six prefectures (regional authorities comprising municipalities) including Osaka, Kyoto, Hyogo, Nara, Shiga, and Wakayama, is the second-largest economic region in Japan (National Spatial Strategy) (Figure 4.1). This metropolitan plays a crucial role in Japanese politics, economy, culture, and global communication (Kansai Greater Regional Plans). Its total area is approximately 27,329.71 km², with a population of 20,554,346 people as of 2020, accounting for 16.28% of the total population of Japan (Statistics Bureau of Japan 2020). The KKM is in central and western Honshu, Japan, and is surrounded by mountains, the Sea of Japan to the north, the Seto Inland Sea to the west, and the Pacific Ocean to the south (Figure 4.1). Its geography is diverse, with rugged terrain around the central lowland such as Osaka Plain, Kyoto Basin, Nara Basin, and Omi Basin, and the largest lake of Japan, Lake Biwa, located in the northeastern area. There are regional differences due to the amount of precipitation and its seasonal distribution due to the relationship with the topography and the ocean, which includes Japan's representative climate types. The main climate zones are divided into the Sea of Japan climate in the northern part and the Pacific coastal climate in the southern part. The Pacific coast-type climate is further subdivided into the Nankai climate zone, the Tokai climate zone, and the Setouchi climate zone.

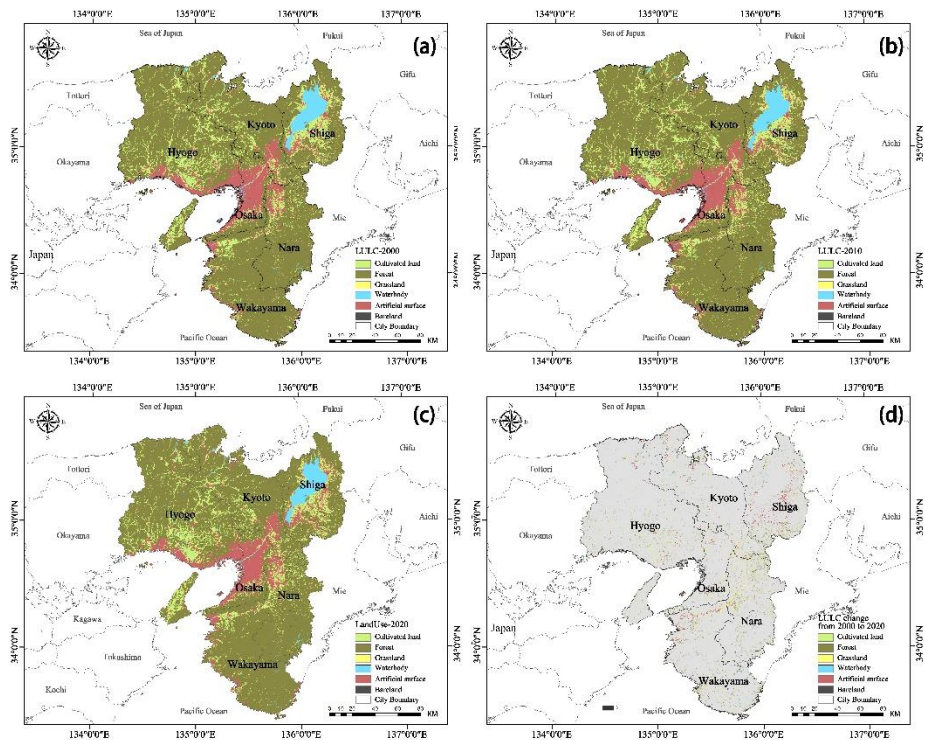


Figure 4.1 The LULC map of KKM and the LULC changes from 2000 to 2020 ((a) LULC in 2000, (b) LULC in 2010, (c) LULC in 2020, (d) LULC change from 2000 to 2020).

In the 21st century, KKM, like other Japanese regions, is also facing various challenges like a declining population, significant aging, economic stagnation, and a reduction in regional status and urban vibrancy, which are of widespread concern. Nevertheless, the Kansai Greater Regional Plans has proposed to establish the KKM area as the core of Japan's future economic growth and enhance its vitality. This plan presents both opportunities and

challenges for regional development, making the future LULC trajectory worthy of attention under the complex economic development and climate change.

4.2.2 Data Acquisition

The boundary shapefile of the KKM was obtained from the Ministry of Land, Infrastructure, Transport, and Tourism (<https://nlftp.mlit.go.jp/ksj/>, accessed on 10 September 2022), and the land dataset was obtained from GLOBELAND30 (<http://www.globallandcover.com/>, accessed on 25 September 2022). Based on previous studies and the consideration of a comprehensive selection of driving factors, we selected a total of 25 driving factors (Table 4.1), including 3 topographic factors, 2 climatic factors, 9 soil factors, 2 socioeconomic factors, and 9 spatial accessibility factors. After a series of data preprocessing steps in ArcMap10.5 software (ESRI), including projection transformation, Euclidean distance, resampling, and clipping—all the above data were converted to raster data with the same projected coordinate system and a spatial resolution of 30 m.

In this study, data on population density, GDP density, temperature, and precipitation were collected for four scenarios in 2040, 2060, 2080, and 2100, which were used as driving factors for LULC simulation. The population density and GDP density data were obtained from kilometer-scale grid data of future climate change scenarios from SSPs (Wang et al. 2022; Wang and Sun 2022). Future temperature and precipitation data were obtained from WorldClim 2.1 based on the MRI-ESM2-0 model (<http://worldclim.org/>, accessed on 22 January 2023).

Table 4.1 Data sources and processing.

Category	Data	Year(s)	Original Resolution	Data Resource
Land dataset	Land use/cover data	2000, 2010, 2020	30 m	GLOBELAND30 (http://www.globallandcover.com/ , accessed on 25 September 2022)
Topographic factors	DEM	2022	30 m	JAXA-DEM (https://www.eorc.jaxa.jp/ALOS/en/aw3d30/ , accessed on 13 October 2022)
	Slope		30 m	
	Aspect		30 m	
Climate factors	Annual mean precipitation	2000–2018	30 arc-sec	WorldClim 2.1(https://www.worldclim.org/ , accessed on 16 November 2022)
	Annual mean temperature		30 arc-sec	
Soil characteristics	soil type	2011	30 m	National Agriculture and Food Research Organization (https://soil-inventory.rad.naro.go.jp/offer.html , accessed on 28 November 2022)
	Soil water capacity	2017	250 m	ISRIC-World Soil Information (https://data.isric.org/ , accessed on 10 December 2022)
	Depth to bedrock		250 m	
	Cumulative probability of organic soil		250 m	
	Soil organic carbon stock		250 m	
	Soil PH		250 m	
	Texture class		250 m	
	Sand content		250 m	
	Clay content		250 m	
Socioeconomic factors	GDP density	2015	5 km	(Kummu et al. 2018)
	Population density	2020	100 m	WorldPop (https://hub.worldpop.org/)

Spatial accessibility	Proximity to town hall		30 m	OpenStreetMap (https://download.geofabrik.de/ , accessed on 21 December 2022)
	Proximity to residential		30 m	
	Proximity to transportation node		30 m	
	Proximity to railway	2022	30 m	
	Proximity to trunk/motorway		30 m	
	Proximity to primary road		30 m	
	Proximity to secondary road		30 m	
	Proximity to tertiary road		30 m	
	Proximity to open water		30 m	
	Annual mean precipitation		30 arc-sec	
Future climate and socioeconomic factors under SSP-RCP Scenarios	Annual mean temperature	2040, 2060, 2080, 2100	30 arc-sec	WorldClim 2.1 based on the MRI-ESM2-0 model (http://worldclim.org/ , accessed on 22 January 2023) (Wang et al. 2022; Wang and Sun 2022)
	GDP density		1 km	
	Population density		1 km	

The driving factors collected were allowed to be inconsistent with the time period of the land use data, but the time period was as close as possible to the time period of the LULC data (Tian et al. 2022).

4.3 Methodology

This study has three parts: (1) Future LULC simulations under four SSP–RCP scenarios, (2) carbon storage calculation by future LULC, (3) Spatial patterns analysis and morphological spatial patterns from the perspective of LULC types (Figure 4.2).

Step 1 LUCC simulation_ LUH2/Markov chain—PLUS

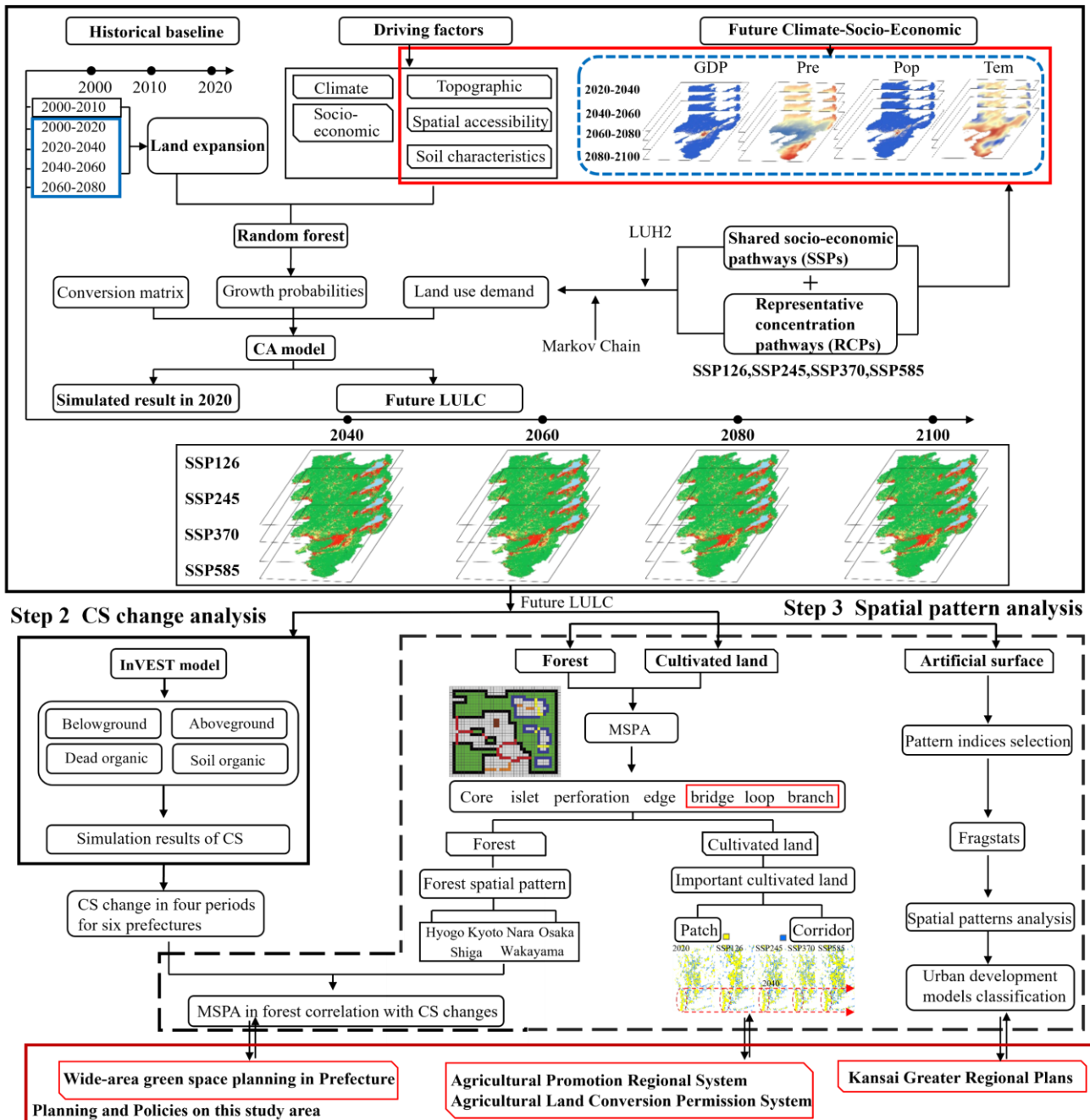


Figure 4.2 Technical analysis pathway and modeling framework.

4.3.1 Future LULC Scenarios

4.3.1.1 LULC Demand from LUH2-Markov Chain

This study selected the basic scenarios for climate model projections in Tier 1 (SSP126, SSP245, SSP370, and SSP585) of the Scenario Model Inter-comparison Project (O'Neill et al. 2016; Li et al. 2021b).

SSP126 (Sustainability - Taking the Green Road) envisions a future where the world swiftly adopts sustainable development practices. This scenario emphasizes the widespread use of green technologies, strong international collaboration, and significant reductions in global inequality. Population growth is kept low due to substantial

investments in education and health, leading to improved human well-being overall. Climate policies are highly effective, resulting in minimal greenhouse gas emissions and considerable efforts to mitigate climate change. By 2100, this scenario achieves a radiative forcing of 2.6 W/m², leading to global warming of approximately 1.5°C to 2°C. This scenario highlights the potential for a sustainable future through coordinated global efforts and investments in green growth strategies (O'Neill et al. 2016).

SSP245 (Middle of the Road) projects a future that follows historical trends with moderate economic growth and demographic shifts. This pathway balances regional solutions with international cooperation, facing moderate challenges in both mitigation and adaptation. Population growth and economic development are steady, with no significant changes in global inequality. Climate policies are moderately implemented, resulting in intermediate levels of greenhouse gas emissions. By 2100, this scenario reaches a radiative forcing of 4.5 W/m², corresponding to global warming of about 2.5°C to 3°C. SSP245 represents a future where global efforts are sufficient but not aggressive enough to avert significant climate impacts (O'Neill et al., 2017; IPCC, 2018).

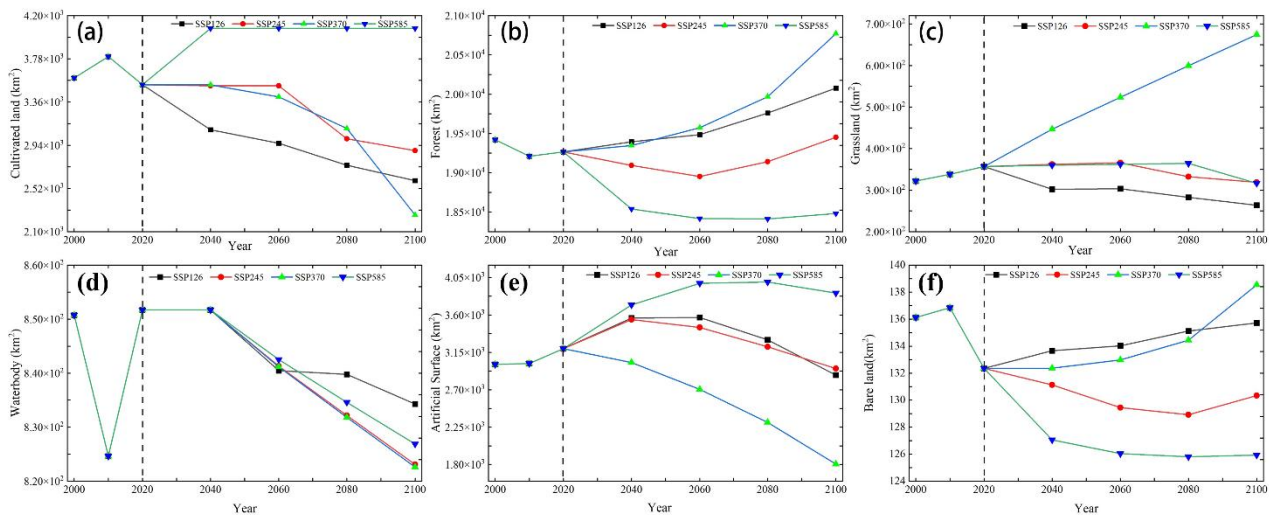
SSP370 (Regional Rivalry - A Rocky Road) describes a world characterized by regional rivalry, nationalism, and limited international cooperation. Economic growth is uneven, with moderate to high population growth due to lower investments in education and health. This scenario faces substantial challenges in both mitigation and adaptation, with fragmented climate efforts leading to relatively high greenhouse gas emissions. By 2100, radiative forcing in this scenario reaches 7.0 W/m², resulting in global warming of approximately 3.5°C to 4°C. SSP370 highlights the difficulties in addressing climate change in a world divided by regional competition and insufficient global cooperation (O'Neill et al., 2016; IPCC, 2018).

SSP585 (Fossil-fueled Development - Taking the Highway) outlines a future driven by rapid economic growth based on fossil fuels, leading to high greenhouse gas emissions. This scenario features significant technological advancements but also substantial inequality and environmental degradation. Population growth is high, with minimal investments in sustainable development. This pathway faces very high challenges in both mitigation and adaptation, with continued reliance on fossil fuels and limited efforts to reduce emissions. By 2100, radiative forcing in this scenario reaches 8.5 W/m², corresponding to global warming of approximately 4°C to 5°C. SSP585 illustrates a world where economic growth is prioritized over environmental sustainability, resulting in severe climate impacts (Table 4.2) (Riahi et al. 2017; Tebaldi et al. 2021).

Land-Use Harmonization2 (LUH2; <http://luh.umd.edu/>, accessed on 30 October 2022) is an important part of the CMIP6; it presents eight LULC scenarios at 0.25° × 0.25° resolution. To obtain the high-resolution simulation results, this study quantified and calibrated each LULC scenario in LUH2 with the historical LULC in 2020, while retaining the original fluctuation rates of LULC types in LUH2 (Liao et al. 2020; Li et al. 2021b). Furthermore, using the historical LULC data in 2020, the SSP–RCP scenarios of land use demand trajectories were obtained. In addition, considering the substantial inaccuracy in grassland due to the low resolution in LUH2 and the missing results of the water body (Liao et al. 2020; Li et al. 2021b), this study used a Markov chain to rectify the LULC demand data, and determined the land use demand trajectories in the KKM (Figure 4.3).

Table 4.2 Some scenarios used in this study (“√” represents this study has chosen)

	sustainability	Middle of the road	regional rivalry	Inequity	Fossil-Fuels
Shared socio-economic pathways	SSP1√	SSP2√	SSP3√	SSP4	SSP5√
Representative concentration pathways	RCP1.9	RCP4.5√	RCP7.0√	RCP3.4	RCP8.5√
	RCP2.6√			RCP6.0	
SSPs-RCPs scenarios used in this study	SSP126	SSP245	SSP370		SSP585

**Figure 4.3** Trajectories of land use demand, which were calibrated based on the 2020 land use map ((a) cultivated land, (b) forest, (c) grassland, (d) waterbody, (e) artificial surface, (f) bare land).

4.3.1.2 Spatiotemporal Dynamic Simulation Based on PLUS

The PLUS model contains two modules: (1) a rule-mining framework based on a land expansion analysis strategy (LEAS); and (2) a CA based on multi-type random patch seeds (CARS) (Liang et al. 2021). Firstly, the LULC maps of two periods were overlaid to extract the cells representing the change areas. Then, the LULC expansion map was used as a transition analysis strategy in the LEAS. The random forest classifier (RFC) algorithm was applied to identify the relationship between the changing area and every driving factor. This process helped determine the contribution value of the driving factors to the change in each LULC type during the two periods (Wang and Sun 2022). Finally, a growth mechanism based on CARS was utilized to dynamically simulate various types of land patches.

4.3.1.3 Model Evaluation

This study used the LULC in 2000 and 2010 to simulate LULC in 2020, and then compared the simulated 2020 results with the actual 2020 results to verify the accuracy of the simulation results. Two evaluation metrics, the overall accuracy and Kappa coefficient, were employed. The overall accuracy measures the ratio of correctly classified cells to the total number of cells. On the other hand, the Kappa coefficient ranges from 0 to 1. Generally, a Kappa coefficient greater than 0.6 indicates acceptable results, while a value above 0.8 suggests a relatively accurate simulation outcome (Lin and Peng 2022).

$$Kappa = \frac{p_0 - p_c}{p_p - p_c}$$

where p_0 and p_c refer to the actual and predicted simulation accuracy in a random state, respectively, and p_p is the proportion of correct simulations in the ideal classification case and is commonly assumed to be 1.

In this study, the calculated Kappa coefficient was found to be 0.92, indicating a high level of agreement between the simulated and actual LULC data. Additionally, the overall accuracy was determined to be 0.96, further confirming the reliability and accuracy of the simulation method employed in this study. These results demonstrate that the method used in this study meets the operational requirements of the model, and can effectively simulate LULC changes.

4.3.2 CS Estimation Based on the InVEST Model

The Integrated Valuation of Ecosystem Services and Tradeoffs (InVEST) model is commonly employed to simulate and analyze the connections between nature and human well-being, including ecosystem services or the contributions of nature to people (Riahi et al. 2017; Tebaldi et al. 2021). One of the most commonly used models in InVEST is the carbon storage and sequestration model, which aggregates the amount of carbon stored in four pools based on LULC maps and the statistics of previous studies (Table 4.3) (Sahle et al. 2019; Li et al. 2021c).

$$C = \sum_{t=1}^n S_t \times (C_{t,a} + C_{t,b} + C_{t,c} + C_{t,d})$$

where C is the total CS; S_t refers to the area of cultivated land, forest, grassland, waterbody, artificial surface, and bare land (km^2); $C_{t,a}$, $C_{t,b}$, $C_{t,c}$, and $C_{t,d}$ are the carbon densities from aboveground, belowground, soil organic, and dead organic matter, respectively, of the t type of LULC (Mg/km^2).

Table 4.3 Carbon densities of each land use/land cover type (Mg/km^2).

Land Types	Use	Aboveground Carbon Density	Belowground Carbon Density	Soil organic Carbon Density	Dead Organic Matter Density	Sources
Cultivated land		21.00	2.52	73.20	2.52	(IPCC (2006) 2006; Koga et al. 2011; Matsui et al. 2021)
Forest		84.60	20.30	90.00	7.01	(Morisada et al. 2004; IPCC (2006) 2006; NOGUCHI et al. 2009; Takahashi et al. 2010)
Grassland		2.91	4.65	114.00	0.00	(IPCC (2006) 2006; Matsuura et al. 2012)
Bare land		0.20	0.00	40.10	0.00	(Takahashi et al. 2008; Wang et al. 2022)

4.3.3 Spatial Pattern Analysis from the Perspective of LULC Types

4.3.3.1 Spatial Pattern Analysis of Artificial Surface

Landscape pattern indices are crucial indicators for analyzing the fragmentation, shape characteristics, aggregation, and shape diversity of LULC patches (McGarigal and Marks 1995). These indices are commonly employed to quantitatively analyze ecological landscape patterns (Jiao et al. 2019; Yin et al. 2019). By considering the calculation principles through the spatial distribution of patches, we utilized several landscape pattern indices, namely the Largest Patch Index (LPI), Landscape Shape Index (LSI), Contagion (CONTAG), and Shannon's

diversity index (SHDI) to analyze the fragmentation, shape, degree of aggregation, and shape diversity of future artificial surface patches. We aimed to explore the spatial pattern under different scenarios. The calculations of all the indices were conducted using Fragstats 4.2 software.

4.3.3.2 Changes in Morphological Patterns of Green Space

MSPA was employed to divide the LULC map into seven MSPA classes, based on the Euclidean distance threshold between raster cells (Vogt et al. 2007; Riitters et al. 2009). It can provide insights into the extraction of LULC patches using mathematical morphology (Xie et al. 2023). This study took one type of LULC as the foreground and the remaining categories as the background; then, these data were converted into raster data in TIFF format. Eight-neighbor connectivity and edge width values of 20 were used in this research, in order to obtain more detailed information at the regional scale in different land use types as much as possible (Chen et al. 2019). Additionally, considering the pixel size and the need for significant MSPA classes for each LULC type in each period, the edge width was uniformly set at 4 m (Chen et al. 2019; Xie et al. 2023). The following equation was used to calculate the cover area of each MSPA class.

$$S_{ti} = S_t \times P_i (i = 1, 2, \dots, 7)$$

where S_t refers to the area of cultivated land or forest (km²); P_i represents the proportion of different MSPA classes under a specific LULC type (%); S_{ti} refers to the area of core, islet, edge, perforation, bridge, loop branch under a specific LULC type (km²).

4.3.3.3 Identification of Important Cultivated Land Patches and Corridors

In response to the decline in cultivated land, Japan has implemented a series of initiatives to protect and regulate its use. Notably, the Agricultural Promotion Regional System and the Agricultural Land Conversion Permission System specifically address the management of cultivated land exceeding 40,000 m². Development activities on such land require local approval following consultation with the Minister of Agriculture, Forestry, and Fisheries. Although evaluating the functionality of cultivated land requires a comprehensive analysis of various factors such as soil composition, crop yield, and market demand, area-based management is considered one of the most direct and effective approaches. This study focused on identifying important cultivated land larger than 40,000 m², and explored its morphology through patches and corridors classification. Within the MSPA framework, the core, islet, edge, and perforation correspond to patches, while the bridge, loop, and branch represent corridors (Dytham and Forman 1996). ArcMap10.5 software (ESRI) was used to further count and extract the areas and numbers of cultivated land patches and corridors above 40,000 m².

4.3.3.4 The Correlation between MSPA Classes in Forest and CS Changes

This study utilized Pearson correlation analysis to explore the relationships between CS changes and MSPA class changes of forest. In conducting this analysis, a crucial step is to select variables for statistical analysis to determine the significance of the correlation coefficient and identify tradeoffs. In this study, it was determined that there is a strong linear correlation when the absolute value of r exceeds 0.4. This threshold serves as a guideline for evaluating the strength and direction of the correlation between CS changes and MSPA class changes, providing insights into the relationship between forest characteristics and carbon storage dynamics.

4.4 Results

4.4.1 Future LULC under Different Scenarios

The future LULC results indicate that except for SSP370, which exhibited significant grassland changes, the primary types of LULC change were cultivated land, forests, and artificial surfaces (Table 4.4). In terms of cultivated land, it showed a trend of growth followed by stabilization in the SSP585, but the other three scenarios exhibited a decline from 2020 to 2100. SSP370 experienced the most substantial decline, with only two-thirds of the cultivated land area in 2020. In contrast, the SSP585 remained stable after initially increasing to 4071.22 km² in 2040. Overall, the forest areas in SSP126, SSP245, and SSP370 increased from 2020 to 2100, except for a decline in SSP585. Artificial surface areas increased in all of the scenarios by 2100, except for SSP370, which experienced a decrease of roughly 660 km². Under SSP126, the artificial surface area reached 3569.00 km² in 2060, and then began to decrease to 3427.89 km² in 2100. Both SSP245 and SSP585 showed an increase in artificial surface area from 2020 to 2100, with SSP585 growing by about 670 km².

Table 4.4 Statistics in LULC under four scenarios.

Time	Scenario	Cultivated Land/km ²	Forest/km ²	Grassland/km ²	Waterbody/km ²	Artificial Surface/km ²	Bare Land/km ²
2020		3529.23	19,264.54	356.82	851.70	3195.05	132.36
2040	SSP126	3091.84	19,369.78	325.54	850.61	3558.43	133.49
	SSP245	3512.60	19,069.68	361.53	850.61	3404.31	130.96
	SSP370	3522.68	19,322.06	445.96	850.61	3056.18	132.20
	SSP585	4071.22	18,515.44	359.67	850.61	3405.86	126.89
2060	SSP126	2993.92	19,484.09	303.38	845.28	3569.00	134.01
	SSP245	3514.56	19,048.89	346.53	841.33	3448.95	129.45
	SSP370	3410.46	19,572.82	523.55	841.17	2862.40	119.29
	SSP585	4076.42	18,417.96	362.18	842.51	3504.59	126.04
2080	SSP126	2746.04	19,760.55	282.73	839.77	3567.81	132.80
	SSP245	3249.17	19,141.93	332.31	832.17	3645.21	128.91
	SSP370	3103.17	19,968.86	599.40	831.83	2723.55	102.89
	SSP585	4076.42	18,412.77	338.44	834.61	3541.65	125.81
2100	SSP126	2595.63	20,078.15	263.49	834.28	3427.89	130.25
	SSP245	2888.57	19,452.38	318.67	823.11	3716.64	130.33
	SSP370	2439.17	20,769.84	674.59	822.59	2535.69	87.82
	SSP585	4076.42	18,119.78	316.38	826.89	3864.29	125.93

The LULC expansion maps show that despite varying types of LULC changes, there were similarities in the change areas and severity (Figure 4.4). For instance, along Lake Biwa in Shiga Prefecture, the southeast area's LULC changes were apparent in all four scenarios. Except for SSP370, which increased forest area, the rest showed mainly artificial surface expansion. In the north of Wakayama, artificial surface expansion occurred under all four scenarios. This study further extracted and calculated LULC changes from 2020 to 2100 under six prefectures by administrative division (Figure 4.5). The results revealed varied LULC changes among the prefectures. For example,

cultivated land decreased in all prefectures except Osaka under the SSP126 scenario, with the largest decrease observed in Shiga. The artificial surface area increased only in Hyogo and Shiga, with a significant increase in Shiga. The main types of LULC changes differed by prefecture. Under the four scenarios, there are significant differences in LULCC. For example, in the SSP126 scenario, which prioritizes ecological protection, there is a notable decrease in cultivated land and an increase in forest in Hyogo, Kyoto, Shiga, and Wakayama, reflecting the potential conversion of cultivated land to forest. However, in regions like Osaka and Nara, although forest increases, it mainly results from the conversion of artificial surface and grassland. In the SSP245 scenario, which predicts future development based on historical experience, cultivated land decreases in all six prefectures of the KKM, but the LULCC vary. For instance, in Hyogo, Kyoto, and Nara, cultivated land is converted to artificial surface and forest, while in Shiga, Osaka, and Wakayama, cultivated land is more frequently converted to artificial surface. In the SSP585 scenario, which prioritizes economic development, cultivated land increases in all areas except Shiga, and the significant decrease in forest reflects that economic development in this scenario leads to a substantial conversion of forest to cultivated land.

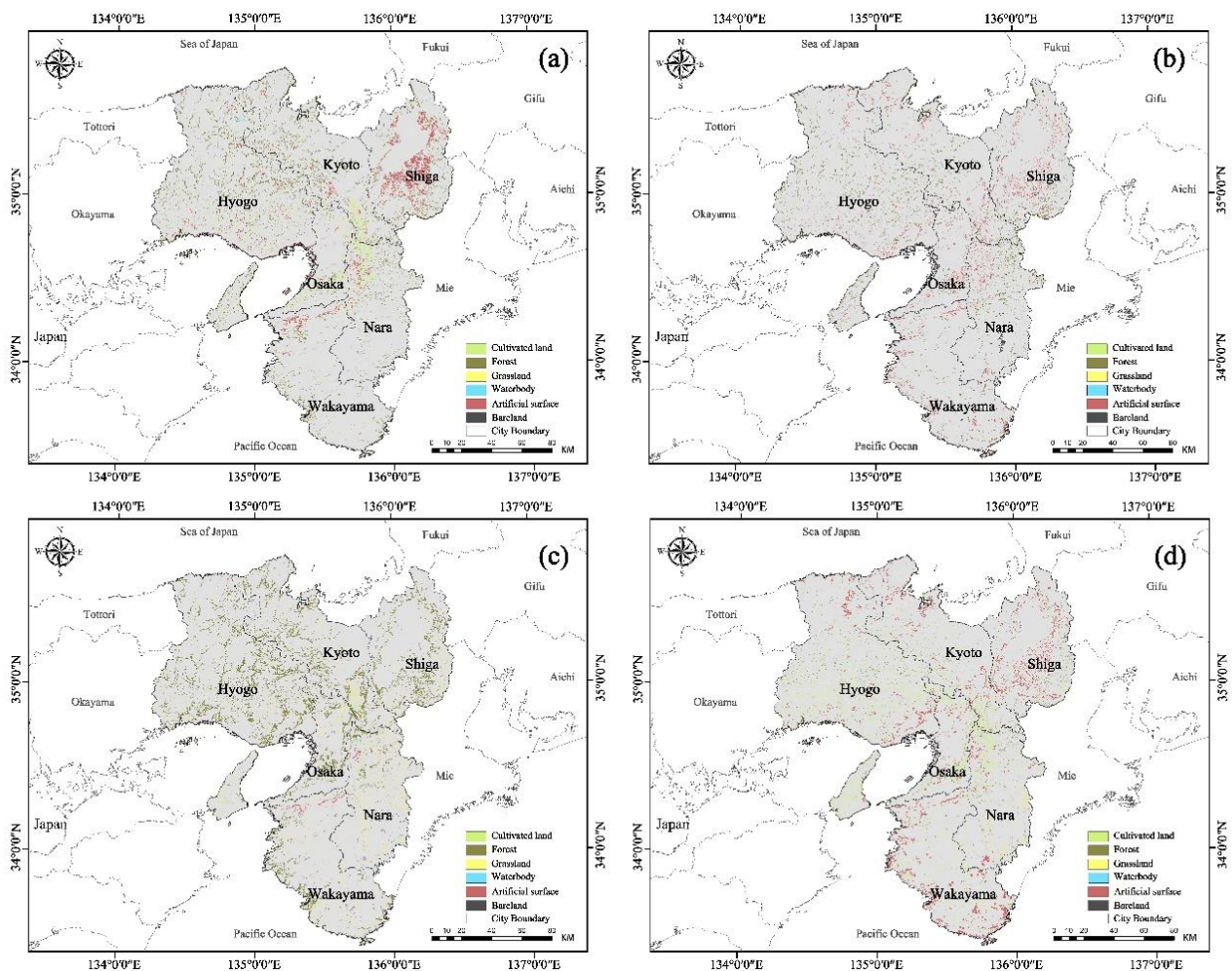


Figure 4.4 Land use expansion map from 2020 to 2100 under four scenarios ((a) SSP126; (b) SSP245; (c) SSP370; (d) SSP585).

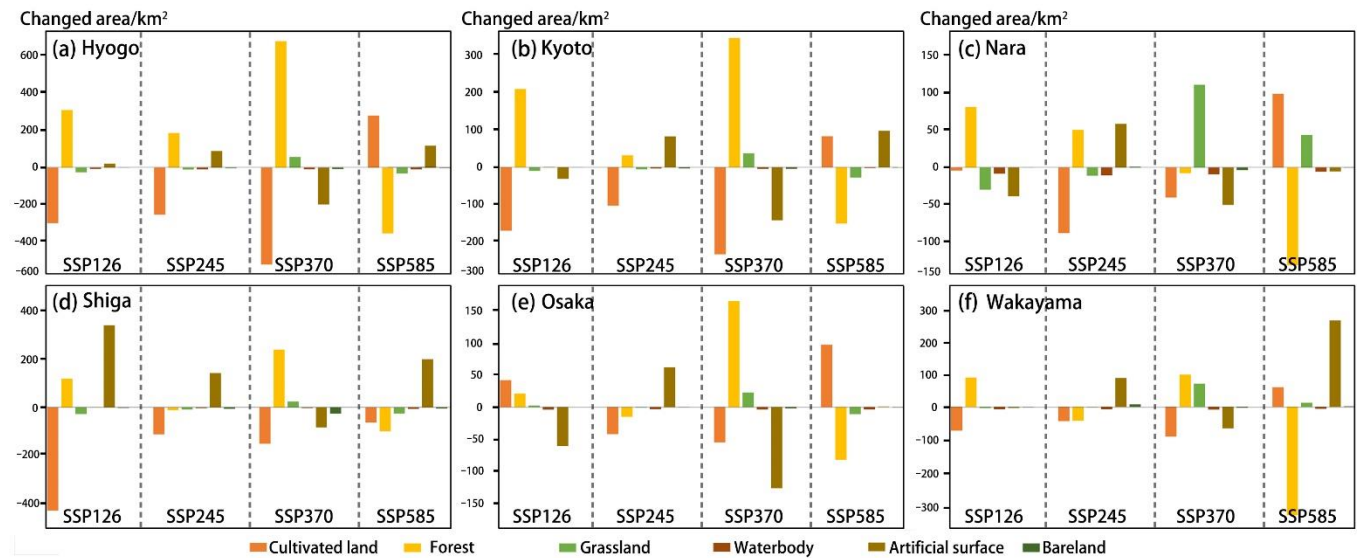


Figure 4.5 LULC changes from 2020 to 2100 in six prefectures).

4.4.2 CS for LULC under CMIP6 Scenarios

The CS results indicate a significant variation in CS levels under different scenarios (Table 4.5 Figure 4.6). CS continues to decrease under SSP585, primarily due to forest decline and the expansion of artificial surfaces. Conversely, the total CS increases in SSP126 and SSP370, mainly due to forest increase, with SSP370 having the highest annual growth rate of 0.29 Tg (106 Mg) associated with the rapid shrinkage of artificial surfaces. The SSP245 scenario results show a steady decrease in CS from 2040 to 2080, followed by a recovery period after 2080, with fluctuations in CS compatible with forest changes. Furthermore, this study calculated the CS in each prefecture under the four scenarios (Figure 4.7). In the SSP126 scenario, although CS increased in all of the prefectures, the magnitude of the increase varied considerably. Hyogo exhibited the highest increase of 3.12 Tg, while Osaka had a modest increase of only 0.37 Tg. Under the SSP245 scenario, the overall CS in Osaka and Shiga decreased, while Kyoto, Nara, and Wakayama experienced slight increases in total CS by 2100, although the changes between 2040 and 2100 were inconsistent. Notably, Hyogo demonstrated the highest growth of 1.88 Tg. In the SSP370 scenario, all of the cities observed an increase in CS, with Hyogo experiencing the most significant rise of 8.64 Tg, and Nara showing a modest increase of 0.70 Tg. In contrast, under the SSP585 scenario, all cities exhibited low CS levels, which decreased between 2040 and 2100. Wakayama experienced the most notable decrease of 2.83 Tg.

Table 4.5 CS dynamic change from 2020 to 2100.

Scenario	Total CS (Tg)				CS Change (Tg)				
	2040	2060	2080	2100	2020–2040	2040–2060	2060–2080	2080–2100	2020–2100
SSP126	426.30	427.37	430.24	434.92	–2.36	1.07	2.87	4.68	6.26
SSP245	424.85	424.26	423.33	425.86	–3.81	–0.59	–0.93	2.53	–2.80
SSP370	431.08	435.92	441.72	452.16	2.41	4.84	5.80	10.44	23.50
SSP585	419.16	417.27	416.88	410.69	–9.50	–1.89	–0.39	–6.18	–17.97

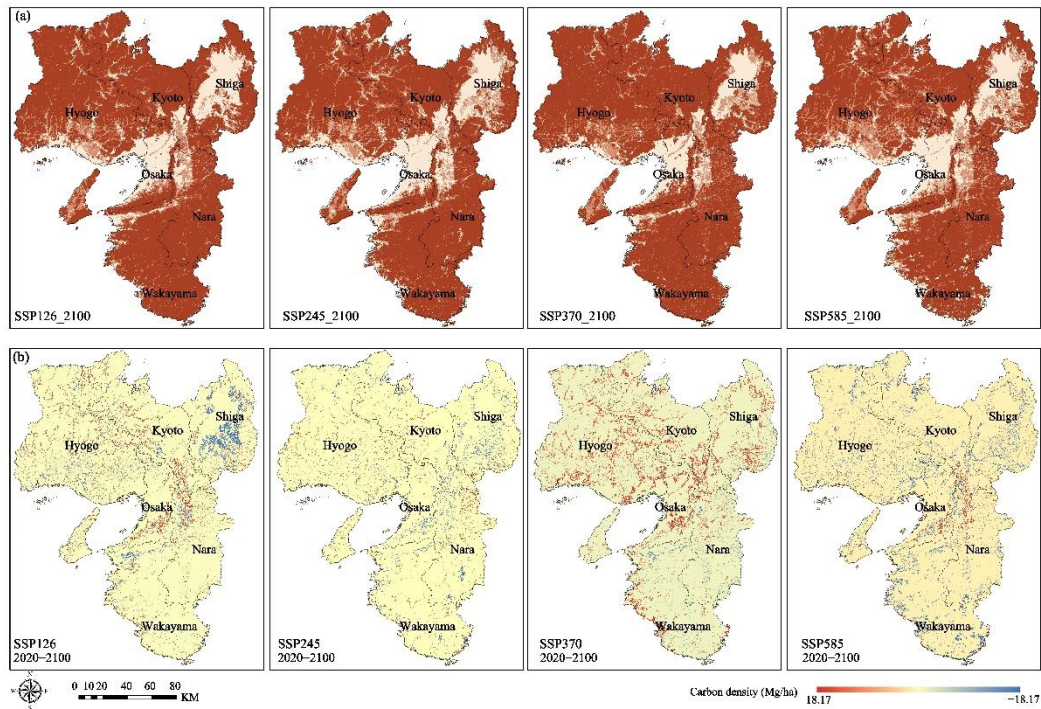


Figure 4.6 CS in 2100 and the distribution changes from 2020 to 2100 under four scenarios.

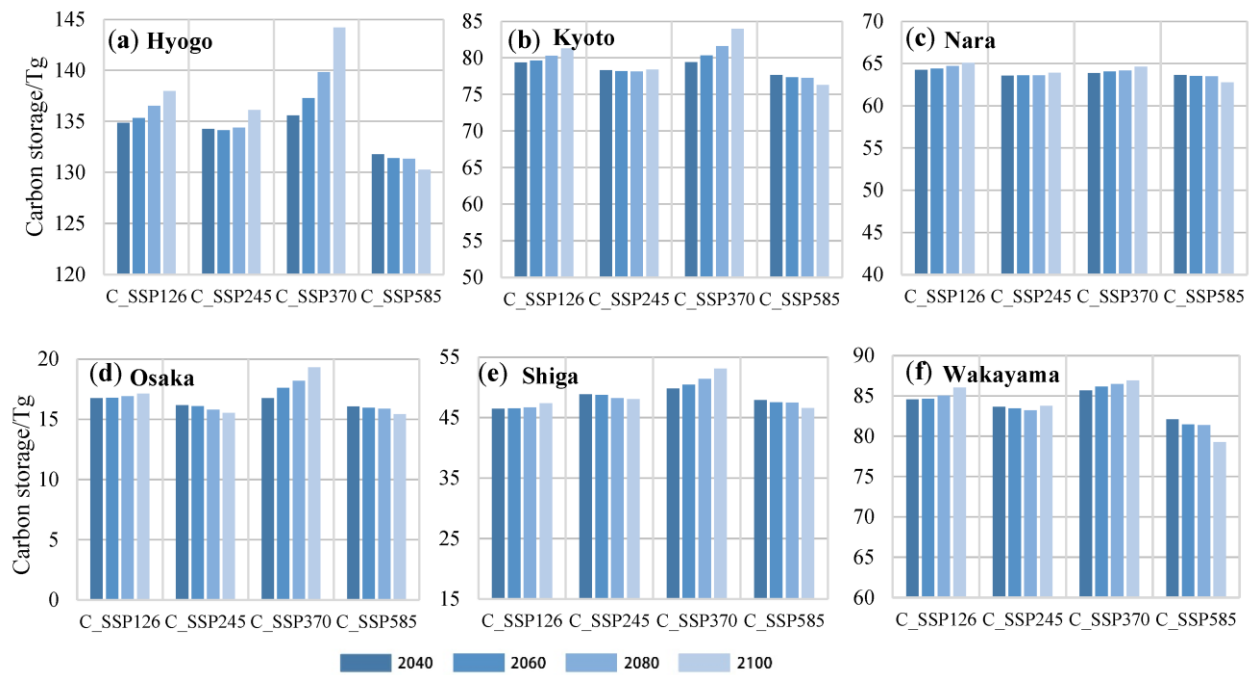


Figure 4.7 CS dynamic change of prefectures in KKM.

4.4.3 The Spatial Patterns of Artificial Surface Changes

In the different simulated periods, the four scenarios exhibited disparities in their changes in spatial pattern indices for artificial surface patches (Figure 4.8). For instance, under the SSP126 scenario, the LPI and CONTAG indices in Wakayama decreased during the 2000–2040 period, remained stable in 2040–2080, and increased in

2080–2100. These results indicate that the artificial surface area in Wakayama becomes increasingly fragmented during 2000–2040, but shows aggregated development by 2080–2100.

Furthermore, the artificial surface patch distributions in the six prefectures are different by 2100. In Hyogo, Shiga, and Wakayama, the change in spatial pattern indices remained largely consistent, with the trend from 2000 to 2020 under the SSP126, SSP245, and SSP585 scenarios. The LPI and CONTAG show a decreasing trend in all of the scenarios except for SSP370, while the value of the LSI and SHDI increased. These findings indicate that the fragmentation of artificial surface patches increases in the SSP126, SSP245, and SSP585 scenarios, and the shapes of the patches become more complex and less aggregated.

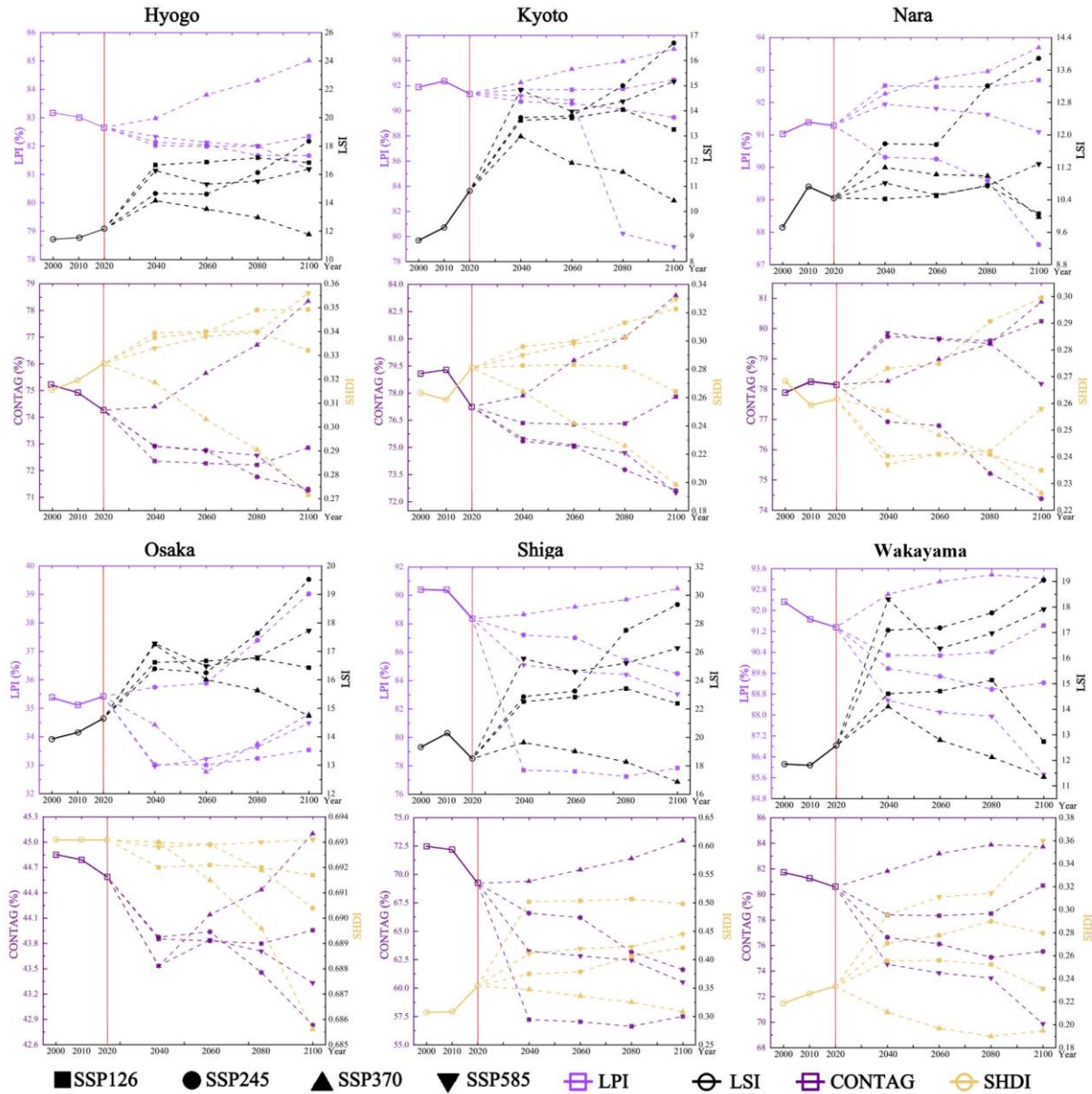


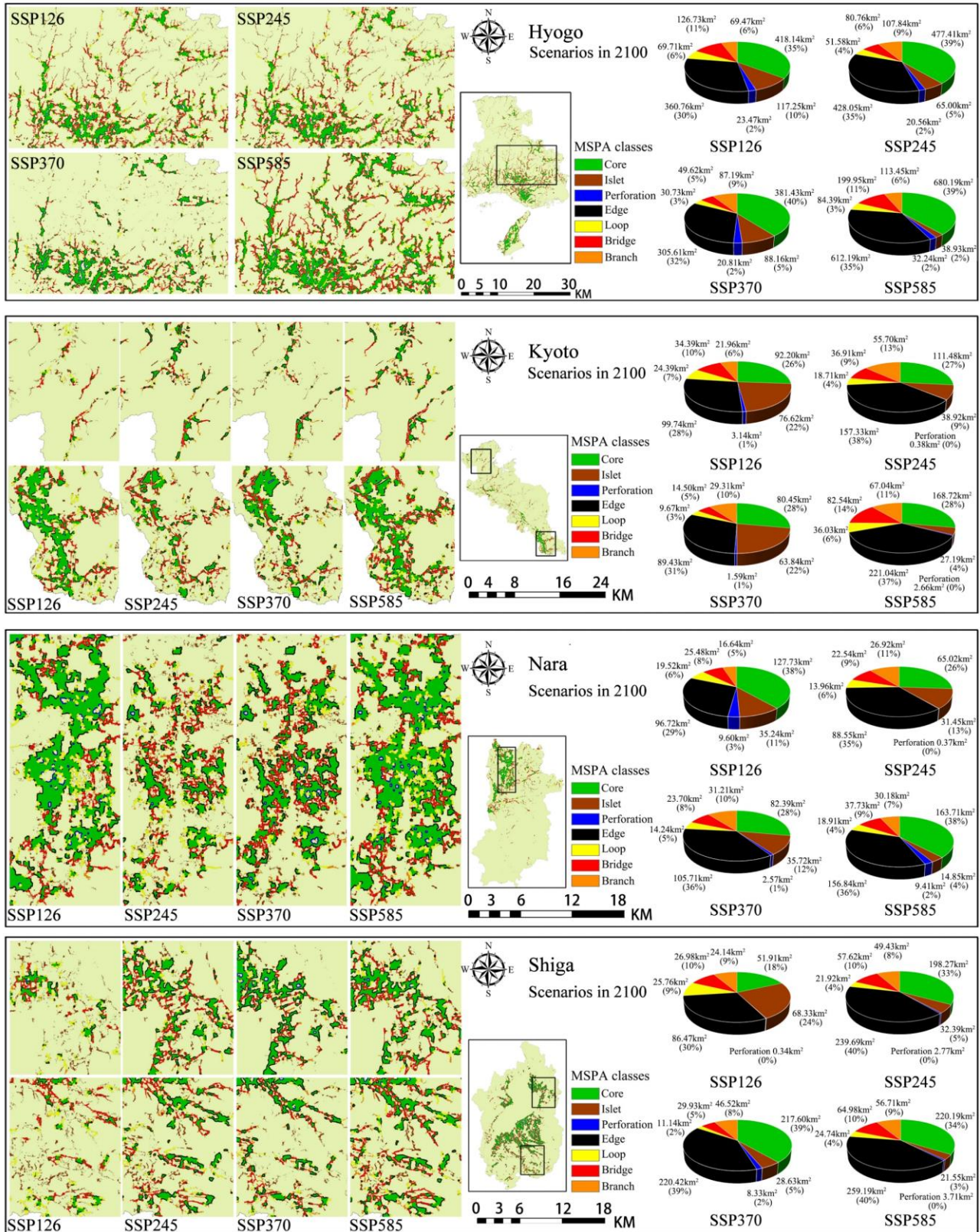
Figure 4.8 Changes in spatial pattern index of artificial surface from 2000 to 2100.

In Kyoto and Nara, there are similarities in terms of changes in the spatial pattern indices. The LPI and CONTAG decreased in the SSP245 and SSP585 scenarios, while the SHDI increased. The results show increased fragmentation of artificial surface patches and decreased aggregation by 2100, while the situation is the opposite for SSP126 and SSP370.

In the SSP126, SSP370, and SSP585 scenarios, the LPI, CONTAG, and SHDI indices fall in Osaka, while the LSI index rises. This indicates that by 2100, artificial surface patches will be fragmented, more complex and diversified in shape, and less aggregated. Under the SSP245 scenarios, the LPI and LSI rise while the other indices fall. These scenarios show large patches of artificial surface expansion, and also an increase in fragmented artificial surfaces.

4.4.4 Key Cultivated Land Patches and Corridors Identification

The spatial patterns of cultivated land in each prefecture are characterized by core areas, edges, perforations, and a small portion of linear patterns (such as loops, bridges, and branches) that account for less than 30% (Figure 4.9). By 2100, in the SSP126 scenario, Shiga, Kyoto, and Hyogo experience significant reductions in cultivated land area specifically, in Shiga and the northern region of Kyoto, the core area decreases significantly, the number of islets increases, and there is severe fragmentation of cultivated land patches. In the SSP245 and SSP370 scenarios, the area of cultivated land decreases, and the cultivated land distribution of MSPA classes was similar. In the SSP585 scenario, cultivated land increases in all prefectures except Shiga. The core, edge, and perforation areas account for more than 65% of the total area, while islets make up less than 6%. This indicates a higher level of integrity in cultivated land.



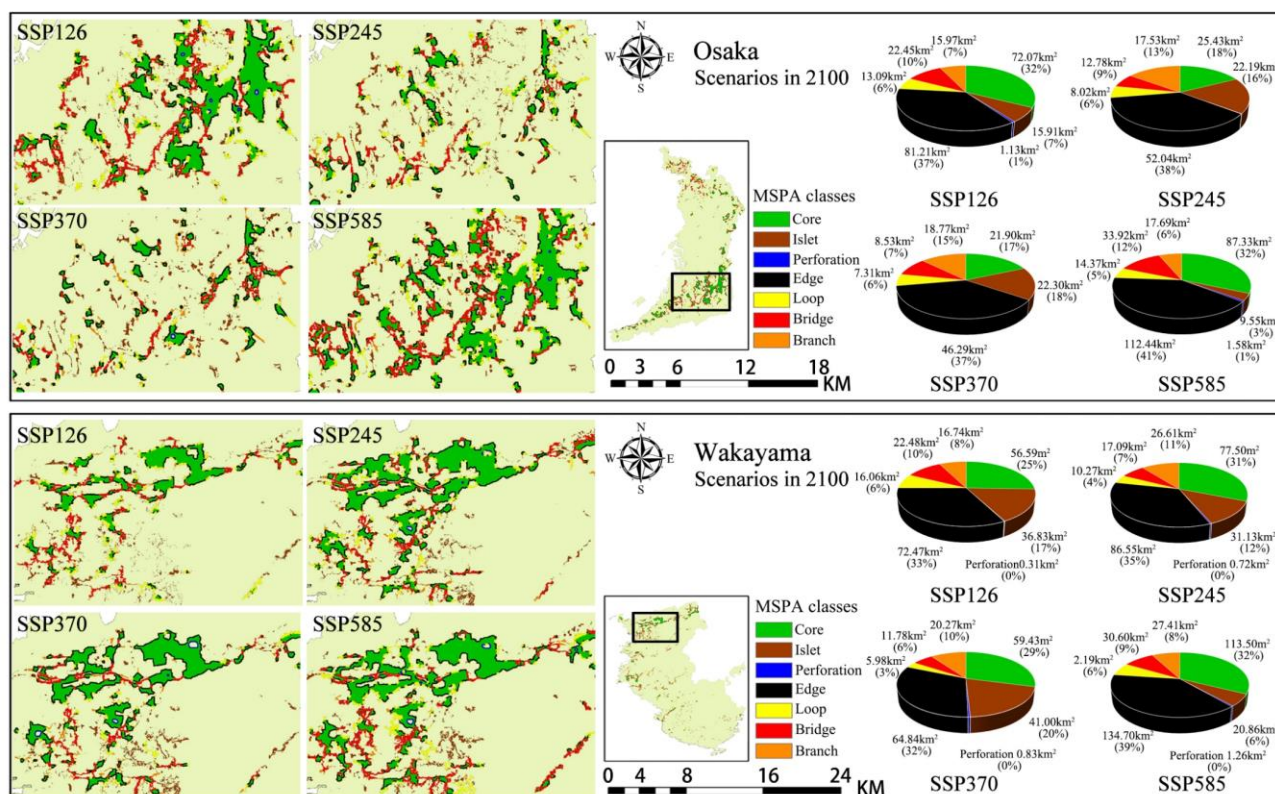


Figure 4.9 MSPA classes of cultivated land in four scenarios at 2100.

Within the KKM area, the majority of cultivated land exists in the form of key patches and corridors, accounting for over 90% of the total area of cultivated land in most prefectures; meanwhile, the number is less than 25%. The number of patches is generally smaller than that of corridors, while the area of patches is larger than corridors (Figure 4.10). Hyogo stands out with the largest area and the numbers of important patches and corridors, while Osaka has the lowest. When comparing the numbers and areas from 2000 to 2020, Hyogo, Osaka, and Wakayama exhibited relatively stable fluctuations, with an increase in area under the SSP126 scenario from 2020 to 2060. Conversely, the number gradually decreased in the remaining prefectures, year by year. Under the SSP245 scenario, both the numbers and areas of key patches and corridors in all of the prefectures showed relatively minor fluctuations from 2020 to 2060. By 2100, the areas decreased in all of the prefectures, while the numbers increased significantly in Shiga and Wakayama. In the SSP370 scenario, the Hyogo and Kyoto prefectures experienced the most rapid decline in area, while the other prefectures showed smaller changes from 2040 to 2080, until 2100, when they begin to decline more significantly. Under the SSP585 scenario, both the areas and the amounts increased in all of the prefectures except for Shiga.

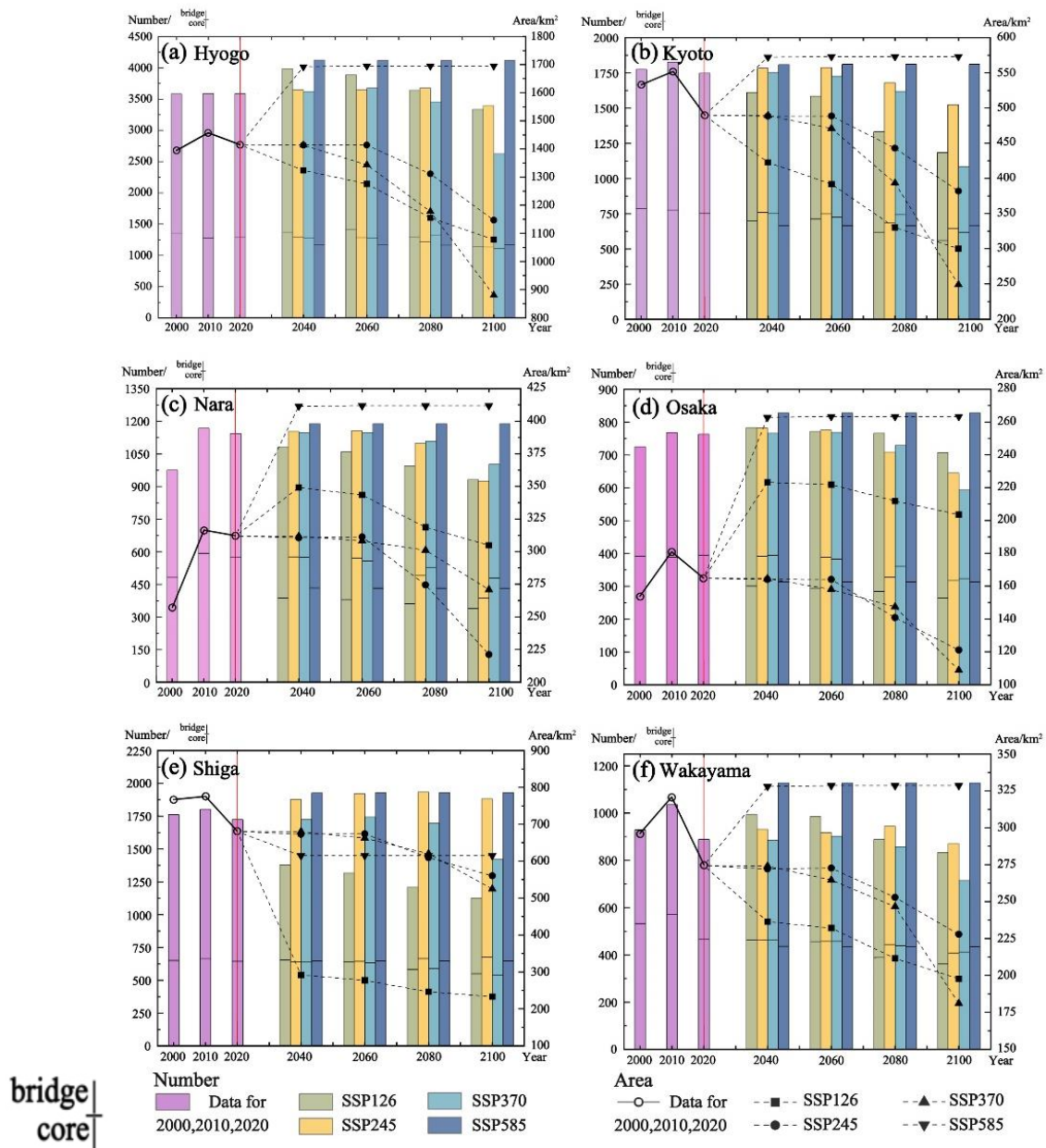


Figure 4.10 Changes in key cultivated land patches and corridors in six prefectures from 2000 to 2100.

4.4.5 Forest MSPA Classes Change and the Influence on CS Changes

The core is the largest area among all the forest MSPA classes (Figure 4.11). The KKM area has good forest integrity. The forest area increased in all the scenarios except for SSP585 from 2020 to 2100 (Table 4.4). Among the prefectures, the core and edge areas increased more, while the areas of MSPA linear classes fluctuated less. However, there were some exceptions, such as the MSPA class changes in Nara under SSP370. While the areas of its core, edge, and islet decreased, the increase in bridges led to an increase in forest area. Furthermore, while the forest area of SSP585 decreased, the forest core remained stable in most prefectures, such as Hyogo, Kyoto, and Shiga, where the woodland acreage decreased while the core area rose.

Among different land types, forests, grasslands, and cultivated land exhibit high carbon density, with forests having the highest. In this study, 24 CS changes and forest MSPA changes were extracted from six prefectures under

the four scenarios to explore the relationship between forest morphological characteristics and CS changes. The correlation analysis revealed that not all MSPA classes had a significant impact on CS changes (Figure 4.12). For instance, only the branch area had a significant influence on CS changes under the SSP126 scenario. Additionally, not all MSPA classes necessarily contributed to the CS density increase. In all of the cases, the forest branch area was negatively associated with CS change; this result means that in most cases, the increase in branch area is related to changes in other MSPA classes in forests. The changes in CS can reflect the conversion patterns of forest morphology. For instance, in three scenarios, the CS change exhibited a positive correlation with core areas, indicating that the increase the proportion of the core area also enhances the CS level of KKM (Figure 4.7, Figure 4.12). Therefore, in the future, emphasizing the integration of fragmented forest patches is a development trend.



Figure 4.11 MSPA classes change of forest in prefectures under four scenarios

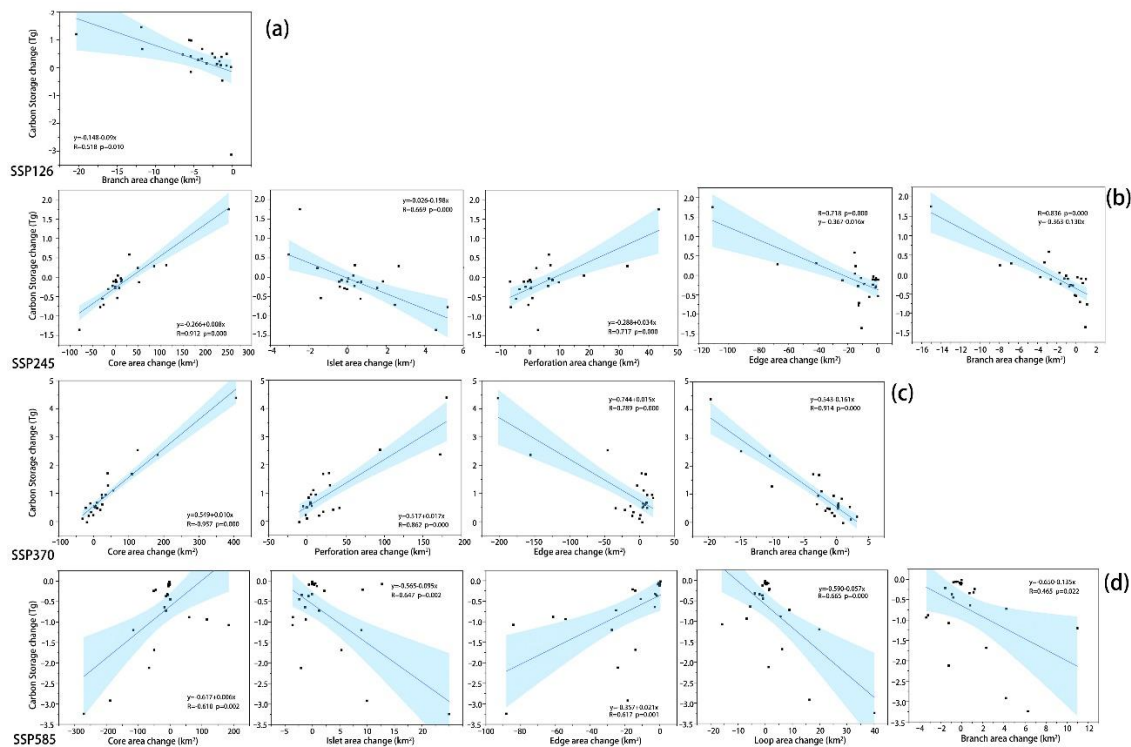


Figure 4.12 Correlations between CS with MSPA classes changes in forests in KKM. The shaded areas represent 95% confidence intervals and are displayed when $r > 0.4$ or $r < -0.4$ ((a) SSP126, (b) SSP245, (c) SSP370, (d) SSP585).

4.5 Discussion

4.5.1 The potential applications of LULC simulation results in forest, artificial surface, and cultivated land management

The future LULC results for most scenarios in the KKM area are in line with the current development trends, such as the gradual decrease in cultivated land and the increase in forested areas (Table 4.4) (Takata et al. 2011; Kobayashi et al. 2020). These findings are consistent with the results of previous LULC simulations conducted in Japan (Shoyama et al. 2019; Chen et al. 2021). Additionally, the higher carbon densities observed in forests, attributed to differences in plant growth and underground soil characteristics (Takeshi et al. 2007; Li et al. 2021c), indicate a strong potential for the carbon density to increase in the future of the KKM area. In this context, the emphasis of future climate regulation within the KKM will be on enhancing climate regulation within densely developed urban areas. The expansion of the artificial surfaces, coupled with the establishment of urban forests, holds the potential to ameliorate the thermal climate within the city. Furthermore, a noticeable surge in the volume of studies concentrating on LULC simulations has been evident in recent years. As researchers delve into this field, it becomes crucial to not only analyze the outcomes of these studies, but also to discuss their practical implications.

For forested land, since 1968, urban development in Japan has been strictly regulated (Millward 2006; Takeshi et al. 2007), and the LULC has been carefully planned and governed by legislation (Seta 2010). In terms of forests, until 2100, the future LULC changes under the four scenarios have less disruptive impacts on the conservation areas

established in the Regional Green Space Planning; forested areas within artificial surface areas are not significantly encroached upon (Figure 4.13). We also found that with the exception of the SSP585 scenario, the rise in forests is paralleled by a decline in cultivated land in most scenarios. This trend could be attributed to the ongoing decrease in Japan's population, leading to farmland abandonment. Concurrently, the demand for land for construction has reached a saturation point. Consequently, the abandoned farmland is translated into forest. Based on this background, it is important to note that while the Regional Green Space Planning of each prefecture has well-defined boundaries for conservation areas, there is a lack of clarity when it comes to delineating future conservation areas and optimizing existing conservation area boundaries. For example, the study results can support setting conservation priorities, policy formulation, and attracting diverse stakeholders. In the SSP245 scenario, based on historical development experience, forest in Shiga, Osaka, and Wakayama decreases and is mostly converted to artificial surfaces. Therefore, future forest management policies in these prefectures should focus on monitoring and protection. By identifying areas of forest reduction on maps, setting up forest development risk zones, conducting field surveys, and coordinating with multiple stakeholders, the necessity of development versus protection can be discussed, and policies can be formulated to achieve the management and protection of these areas. In Hyogo, Kyoto, and Nara, forest increases, primarily due to the conversion of cultivated land. In these areas, more emphasis will be placed on the protection and management of cropland to prevent land abandonment. For instance, key patches and corridors of cultivated land should be identified to assess the need for focused conservation efforts. Through field surveys and consultations with residents, specific management measures and strategies for LULC can be discussed and implemented. In addition, within the KKM area, there are interconversions between different MSPA classes of forests, and linear forests (Loop, Branch, Bridge) are identified as a relatively unstable category (Figure 4.12). By analyzing the dynamic changes of linear forests, we can ensure the connectivity between large forest patches by defining the boundaries of forest corridor protection.

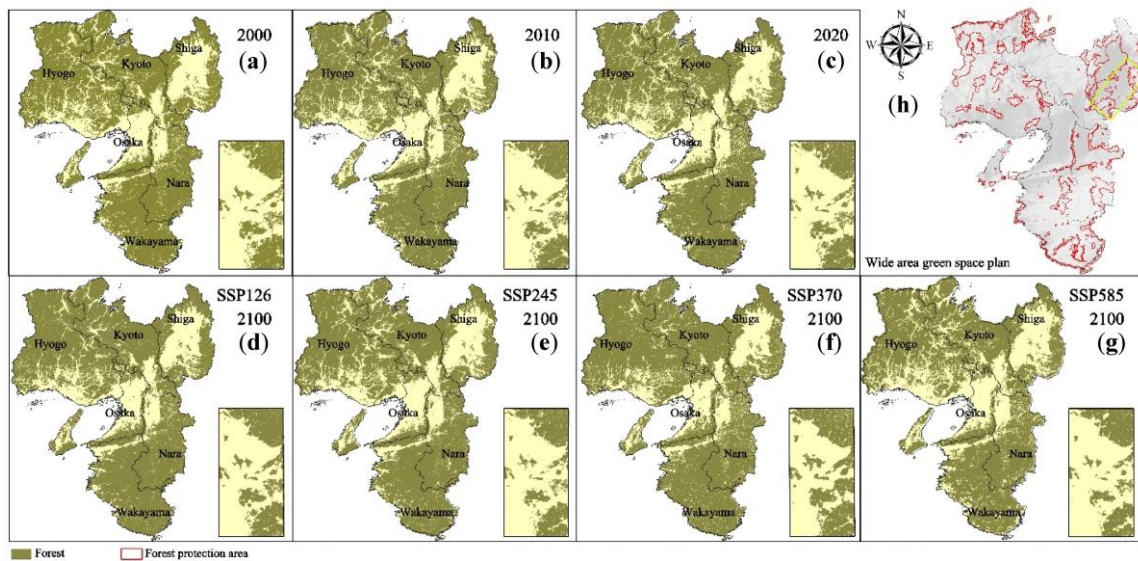


Figure 4.13 Distributions of forest in 2000–2020 and 2100 under four SSP–RCP scenarios ((a) 2000, (b) 2010, (c) 2020, (d) SSP126 in 2100, (e) SSP245 in 2100, (f) SSP370 in 2100, (g) SSP585 in 2100, (h) wide-area green space plan).

For artificial surfaces, under all four of the scenarios, urban expansion tends to be concentrated in the central region of the KKM area, the north of Wakayama, and the southeast of Lake Biwa in Shiga (Figures 4.4 and 4.14); these results are consistent with the development areas identified in the Kinki Area Adjustment plan (Figure 4.8). In the future, the expansion of artificial surface area in the KKM is projected to continue under all of the scenarios except for SSP370. While Japan's population is experiencing a decline, and the immediate demand for artificial surfaces is not pressing, it is plausible that adjustments in the development of artificial surfaces are taking place in accordance with policy shifts. Such changes in land use functions could be contributing to the abandonment of certain artificial surfaces. Additionally, the significant economic costs associated with demolishing existing structures or concrete surfaces have likely contributed to these areas persisting as artificial surfaces.

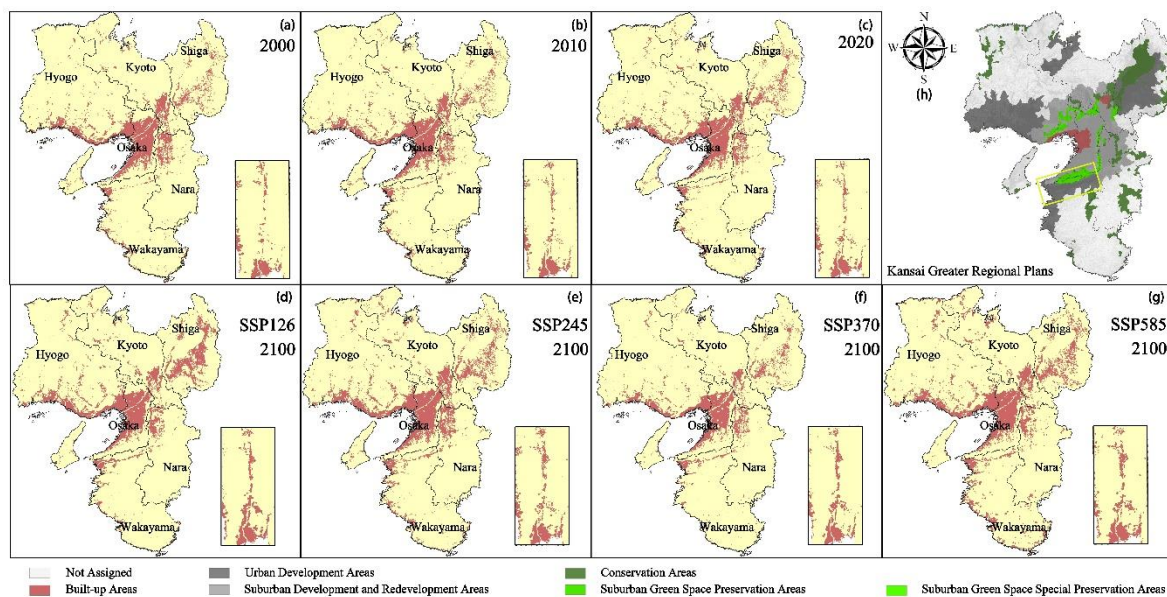


Figure 4.14 Distribution of artificial surface areas in 2000–2020 and 2100 under four SSP–RCP scenarios ((a) 2000, (b) 2010, (c) 2020, (d) SSP126 in 2100, (e) SSP245 in 2100, (f) SSP370 in 2100, (g) SSP585 in 2100, (h) Kansai greater regional plans).

In addition, there are notable variations in the development characteristics among different prefectures within the region. This study identifies three categories of prefecture based on the fluctuating indices related to the spatial distribution change of artificial surfaces, including (1) Hyogo, Shiga, and Wakayama; (2) Kyoto and Nara; and (3) Osaka. These differences reflect the functional characteristics and regional positioning of different prefectures. It emphasizes the importance of synergistic planning among cities to ensure coordinated and sustainable regional development.

For cultivated land, Japan is a heavily depopulated country in rural areas suffering from serious abandonment and reduced cultivated land (Su et al. 2018). In addition, food shortages are expected to become more serious due to extreme weather caused by global warming. Along with progress in the development of new crops and approaches to address food problems, it is also important to discuss conservation policies for cultivated land within the Agricultural Promotion Regional System and the Agricultural Land Conversion Permission System (Van Dijk et al. 2021). In recent years, there has been an increase in studies on how to use abandoned cultivated land, improve agriculture production, and protect cultivated land (Nishihara 2012; Hanioka et al. 2018). Based on the study results,

relevant maps have the potential for application in the following areas: Dynamic monitoring of cultivated land patches and corridors: The study identified changes in key cultivated land patches and corridors under four scenarios for the years 2040, 2060, 2080, and 2100. For example, by 2100, except for SSP585, most key cultivated land areas are projected to decline (Figure 4.10), indicating the potential for land abandonment. Policies can be formulated to incentivize the maintenance of productive cultivated land. This may involve providing financial incentives to farmers who cultivate the land or implementing land management plans that encourage sustainable cultivated land practices. Urban-Rural Interface Planning: Using simulation results to create buffer zones and green belts to protect farmland from urban encroachment can improve planning at the urban-rural interface. Policies can be developed to support cultivated land, which serves as a bridge between urban and rural areas, provides local food production, and maintains open space. Supporting stakeholder participation: Presenting different LULC scenarios can help stakeholders understand the long-term impacts of various LULC decisions. Engaging with local farmers, communities, and other stakeholders through participatory planning processes ensures that their knowledge and needs are incorporated into LULC policies. Tools such as participatory GIS and scenario planning workshops can facilitate this engagement. By implementing these strategies, the use of maps and study results can effectively guide land use planning and policy development, ensuring sustainable cultivated land practices and balanced urban-rural development.

4.5.2 Effectiveness and Limitations

The effectiveness of the LULC simulation method is reflected in several key aspects: Firstly, methodological rigor: This study employs a LULC simulation method based on cellular automata modeling software, which integrates historical LULC data with widely recognized global socioeconomic trends and climate change scenarios (Doelman et al., 2018; Kim et al., 2013). This model and its scenarios have been extensively validated and recognized through peer-reviewed research (Chen et al., 2021; Liang et al., 2021). Secondly, scenario-based approach: The study uses multiple scenarios to capture various possible future development patterns, enhancing the validity of the simulation. Each scenario represents different assumptions about future societal trends and climate change, allowing for a comprehensive assessment of potential LULC outcomes. Validation and calibration: The simulation uses historical LULC data to model future LULCC. Additionally, it compares model predictions with observed changes (e.g., comparing 2020 simulation results with actual 2020 data) to assess the model's accuracy.

However, the study has certain limitations: Uncertainty in projections: Despite the robustness of the simulation model, uncertainties in future socioeconomic trends, climate change fluctuations, and dynamic policy adjustments introduce limitations to the predictions. Additionally, unexpected events (e.g., economic crises, significant policy shifts, natural disasters) can increase the unpredictability of the results, so the projections should be considered potential outcomes rather than precise forecasts. Data limitations: The accuracy of simulation results depends on the quality and availability of input data. Incomplete or outdated data can affect the reliability of predictions. For example, using data from 1987-1990 for LULC simulation in Japan would result in more dramatic LULCC. Therefore, while the LULC simulation method provides a valuable tool for predicting future LULCC and informing policy decisions, its limitations must be acknowledged. Understanding these limitations allows for more nuanced interpretations of the results and helps guide the development of more robust and adaptive land use policies.

4.6 Conclusions

The CMIP6 has been widely adopted and used in LULC simulations in response to complex climate, social, and economic changes. This study focuses on the KKM of Japan, which is characterized by significant aging and slow urbanization. This study simulated and analyzed LULC and CS changes for the years 2040, 2060, 2080, and 2100 using the PLUS-InVEST model. The results reveal that, except under the SSP585 scenario, the cultivated land area in the KKM will decrease, while the forest area will increase. The artificial surface area decreases only in the SSP370 scenario. There are consistent change characteristics between the CS change and forest area change. Based on wide-area planning and the LULC management policies in KKM, this study further analyzed and discussed the spatial patterns of artificial surfaces, the identification of important patches and corridors of cultivated land, and the dynamic changes in area and number, as well as the transformation patterns of forest MSPA classes. The above analysis provides a reference for LULC management and planning policy formulation in the KKM area in the face of different future climate changes and socioeconomic scenarios.

The LULC simulation results of this study serve as fundamental information for collaborative regional planning, the planning and adjustment of nature reserve areas, and the dynamic regulation and protection of cultivated land. This study contributes to a comprehensive understanding of the future dynamic changes in the LULC area in KKM under different climate change and economic development scenarios, emphasizing the significance of formulating localized land management strategies and providing valuable references for policymakers and land managers.

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Chapter 5

Exploring the Spatial Pattern of Urban Forest Ecosystem Services Based on I-Tree Eco and Spatial Interpolation

The data utilized in the preceding chapters are all remote sensing and LULC data with a resolution of 30 m or higher. However, due to limitations in data accuracy, green spaces within built-up area are often overlooked. Kyoto City, as an important city for cultural dissemination and economic development in the KKM area, possesses abundant green spaces within its built-up area. Therefore, employing more refined data to assess urban ecosystem services (UES) becomes particularly necessary. Currently, although UES assessment holds potential feasibility in regional planning, the field remains popular yet lacks in-depth exploration. In this context, conducting exploration and development of an UES assessment framework within built-up area, along with providing corresponding regional planning and management methods, holds significant importance.

5.1 Introduction

Urban forest is an important component of urban green infrastructure, which improves urban air quality by modifying the rate of pollution deposition and dispersion (Ma et al., 2021; Riondato et al., 2020). Other than air pollutant removal, urban forests are also critical for other ecosystem services (ESs) such as runoff reduction (Yao et al., 2019). Considering this, many countries have adopted various laws, incentives, and initiatives to promote tree mass planting in cities (Eisenman 2019). The Greater London Authority, for example, expects to increase forest cover from 20% in 2006 to 30% in 2050 (Tallis et al. 2011). Numerous cities in the United States have reviewed the advantages of the urban forest canopy and developed goals for the planting and management of urban forest (Locke et al. 2009). China has increased its forest area by 19% from 1999 to 2013 (Chen et al. 2019), and a large number of cities have started urban forestry projects and proposed targets for improving urban forest cover (Wu et al., 2019; Yao et al., 2019; Zhang et al., 2018).

Japan's population density is 7.5 times higher than the world average, and the population is highly concentrated in cities, which has led to urbanization problems such as serious urban flooding and heat island effect (Honjo and Takakura 1984; Saiki 2009). To mitigate the negative effects of urbanization, urban green space planning is emphasized in Japanese cities. For example, the 23 wards of Tokyo intends to raise the green space rate from 29% in 2006 to 30% in 2050 (Tokyo Metropolitan Bureau of Environment, 2018). Osaka City plans to achieve a higher green space rate in 2025 than the 2012 benchmark value of 10.4% (Osaka City 2021). Kyoto City plans to increase the green space rate from 35% to 37% by 2025, which means planting 10,000 trees annually (Kyoto City Official Website 2010).

Evaluation of urban forest ecosystem services is critical for urban forest management and greening goal setting. Field investigation can provide an accurate assessment of ecosystem services. The i-Tree Eco is one of the most used tools for urban forest ecosystem service assessment based on field investigation data (Baró et al. 2015; Parsa et al. 2019; Kang et al. 2022). The i-Tree Eco uses two alternative methods to evaluate ecosystem services, namely full inventory-based and sample-based methods. The full inventory-based method is applied to fully investigated projects, such as street trees or parks (Tan et al. 2021). While the sample-based method is used to estimate the

ecosystem services of the urban forest across a whole city, the results are not provided in a spatially explicit manner. From a perspective of urban forest management and investment, the spatial pattern of urban forest ecosystem services is critical for decision-makers. To this end, recent studies have attempted to incorporate spatial analyses with the i-Tree Eco. There are three main approaches for improvement. The first is incorporating the i-Tree Eco model into GIS software. For example, Wu et al. (2019) applied a modified dry deposition model derived from i-Tree Eco in GIS to evaluate the spatiotemporal dynamics of PM_{2.5} in Shenzhen City, China. Gong et al. (2022) built a spatial analysis model based on the NO₂ deposition model of i-Tree Eco. The second approach is dividing the research area into sub-areas and applying i-Tree Eco respectively. In this way, researchers can get the results of the sub-areas and thus are capable of spatial analyses to some extent. An example is that Yao et al. (2021) divided Shenyang metropolitan, China into sub-districts before applying i-Tree Eco so that the analysis of within-metropolitan heterogeneity is possible. The third approach is to inter/extrapolate the evaluation results from i-Tree with geostatistics. For instance, Ma et al. (2021) analyzed the spatial pattern of carbon storage and carbon sequestration in the built-up area of Beijing.

Among the three approaches, the geostatistical interpolation is the most extensively utilized method in ecology and geology (Li et al., 2020; Ma et al., 2019; Qiao et al., 2019; Shabankareh et al., 2018). The spatial interpolation method is mainly used to analyze, elucidate, and explain complex phenomena associated with the spatial heterogeneity (Ma et al., 2021). A summarization of previous studies (Table 5.1) found that the use of interpolation methods is common and useful for research objects with a spatial autocorrelation, such as air pollutants (Abushammala et al. 2013; Laurent et al. 2016) and soil chemicals (Wang et al. 2014). However, for the i-Tree Eco-related studies, the practice of conducting spatial predictions using different interpolation methods is not common (Riondato et al. 2020; Szkop 2020). The application of the spatial interpolation method can help substitute or reduce the necessity for the limited sample sizes in a highly heterogeneous system and large amount of field investigation needs in the implementation of the i-Tree Eco approach (Speak et al. 2018; Jin and Yang 2020). The performance of different spatial interpolation methods varies and highly depends on the research objective, location, and model parameters (Yanto et al. 2022). Choosing an appropriate interpolation method can improve the accuracy of interpolation results (Abushammala et al. 2013; Namdar-Khojasteh et al. 2022). Furthermore, most i-Tree Eco related studies concentrate on calculating ecosystem service value (ESV) using field investigation data and analyzing the spatial pattern of ecosystem services in urban forest, however, they rarely consider the link between the spatial pattern of ecosystem services and the distribution of urban space types (Song et al. 2020; Lin et al. 2021; Gong et al. 2022). By investigating the relationship between ecosystem services and urban spatial types or land use types, the i-Tree Eco method can be effectively applied to the urban planning (Ma et al., 2021).

This study, based on i-Tree Eco, geostatistical interpolation, and spatial correlation analysis, aims to mapping the spatial pattern of the urban forest ecosystem services and ESV, and provide insight for the ecosystem services-oriented urban planning. The primary objectives of this study are to explore (1) the assessment of urban forest ecosystem services, as well as the application and comparison of various spatial interpolation methods. (2) the relationship between urban forest characteristics, forest ecosystem service values, and land use types. (3) the link between urban space types and forest ESV. This study supplements and refines the i-Tree Eco-based technology approach to studying urban forest ecosystem services, giving direction for urban forest planning and design.

Table 5.1 Review of past studies on pollutant prediction based on spatiotemporal analysis.

Location	Target pollutant	Interpolation methods*	Study focus	Major finding	Remarks	Reference
Beijing, China	Carbon storage, Carbon sequestration	OK	To explore available methods for assessing the orientation, magnitude, and role of urban forests in abating climate change	Urban forest carbon storage and carbon sequestration are influenced by urban planning and urban forest structure	OK provides a method for mapping	(Ma et al., 2021)
Delhi, India	PM _{2.5}	IDW, OK	To map the PM _{2.5} profile and compare the average deviation of Kriging and IDW	Thematic maps may serve as a foundation for effective activities to control air pollution, and the prediction error of the two methods is the same	IDW and OK are widely used	(Shukla et al. 2020)
Kuala Langat, Selangor, Malaysia	CH ₄ , CO ₂	IDW, Kriging	To quantify CH ₄ and CO ₂ emissions throughout the dry season in open dumping landfill	Higher CO ₂ emissions than CH ₄ emissions	IDW provides a more precise result	(Abushammala et al. 2013)
Mexico City, Mexico	PM ₁₀ , PM _{2.5} , O ₃ , CO, NO ₂ , and SO ₂	citywide average, nearest monitor, IDW, OK	To compare interpolation models To assess several exposure windows during pregnancy	OK is the most recommended approach and the selected zone where pregnant women stay can affect interpolation error	OK proved reliable	(Rivera-González et al. 2015)
Terni, Italy	PM ₁₀	OK	To analyze the spatial distribution of elements and trace the various PM ₁₀ sources	Identification and characterization localization of the main local PM ₁₀ sources	OK is used to map the spatial variability	(Massimi et al. 2020)
California, USA	Air pollutants	EBK (PM _{2.5} , O ₃ , NO ₂)	To explore whether effects might vary among air pollution sources and components on Preterm birth	Primary traffic-related pollutants might increase preterm birth risk	EBK proved reliable	(Laurent et al. 2016)
Tehran city, Iran	air pollutants (NO _x , CO, SO ₂ , O ₃ , PM _{2.5} , and PM ₁₀)	IDW, RBF	To explore the associations between COVID-19 instances and both short-term and long-term exposures to air pollutants	Air pollutants can increase the number of infected people	Using different interpolation methods to improve accuracy	(Namdar-Khojasteh et al. 2022)

*Note: OK, IDW, EBK, and RBF are the abbreviation of Ordinary kriging, Inverse distance weighting, Empirical Bayesian Kriging, and Radial basis function, respectively.

5.2 Study area

Kyoto City (135°33'33" E-135°52'43" E, 35°19'16" N-34°52'30" N) is located in the south of Kyoto Prefecture, Japan (Figure 5.1). It is a typical mountainous basin with a subtropical monsoon climate characterized by warm, humid summers and cold, dry winters. The total area is 827.8 km², 147.4 km² of which is the built-up area. The population of Kyoto City was 1.45 million in 2021, accounting for 56.77% of the total population of Kyoto Prefecture, and the population density is 1,756 per km² (Kyoto City Statistics Portal, 2021). Kyoto city has formed a mono-centric city in modern times. The built-up has formed a stable layout with the center as commercial area, surrounded by industrial and residential areas. In addition, as the typical representative of Japanese history and culture, more than 60% of shrines and temples in Kyoto Prefecture are located in Kyoto City, and shrines and temples can be seen everywhere in the built-up area (Kyoto Prefecture 2016). Therefore, other than trees in urban parks and street trees, some spaces, like private yards, shrines, and public service spaces, are also crucial for achieving the urban forest planning goal in the built-up area of Kyoto City.

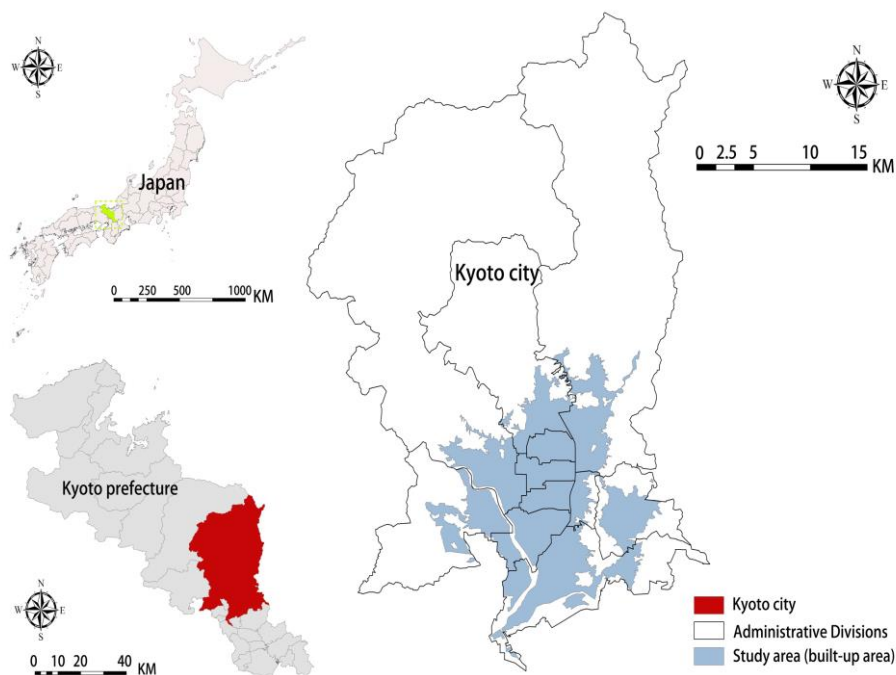


Figure 5.1. Map of Kyoto Prefecture, Kyoto City, and the study area.

5.3 Method

5.3.1 Field investigation

As shown in Figure 5.2, the first step is the field investigation. According to the urban planning system and City Planning Law of Japan, the land use of the built-up area was categorized into 6 types, namely 3 types of residential areas (ResLow, for low-rise residential area; ResHigh, for mid- and high-rise residential

area; ResOther, for other residential area), Ind (industrial area), and 2 types of commercial areas (ComNbr, for neighborhood commercial area; Com, for commercial area) (Akashi 2007) (Table 5.2). It should be noted that the land use categorization is mainly based on the regulation of building form of the land use types based on criteria related to building coverage, height, floor space ratio, etc. Land use zoning is not usually consistent with the regulation since there could be existing ‘unqualified’ buildings built before the law’s introduction. The total number of plots is 151. Considering the operability of field investigation, instead of circular plots, we used quadrangular plots in this study, and the size of a plot is 20 meters by 20 meters. We applied a land use area-based stratified sampling method to determine the sample plots number (Figure 5.3(b), Figure 5.3(c)). The species name, height, diameter at breast height (DBH), percentage of canopy missing, light exposure, size and health condition of crown for each tree in the plots were measured between May and August of 2019 following i-Tree Eco workbook (i-Tree 2019). The species names are validated with TPL (The Plant List) database (Kalwij 2012).

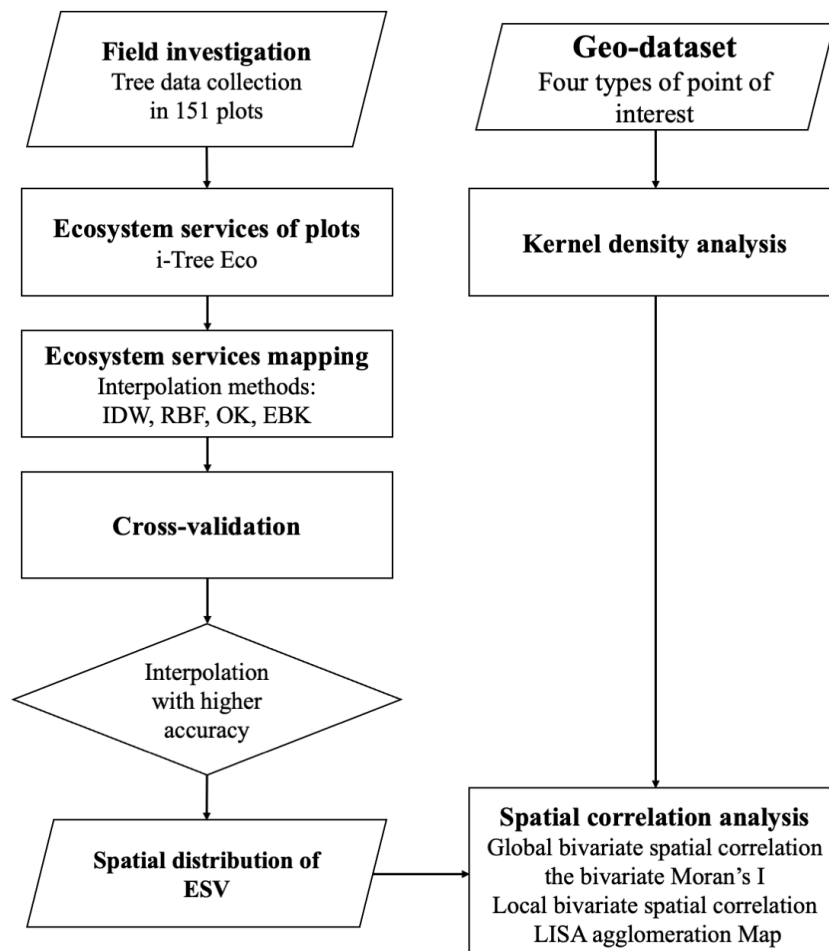


Figure 5.2 Flowchart of the data analysis of this study.

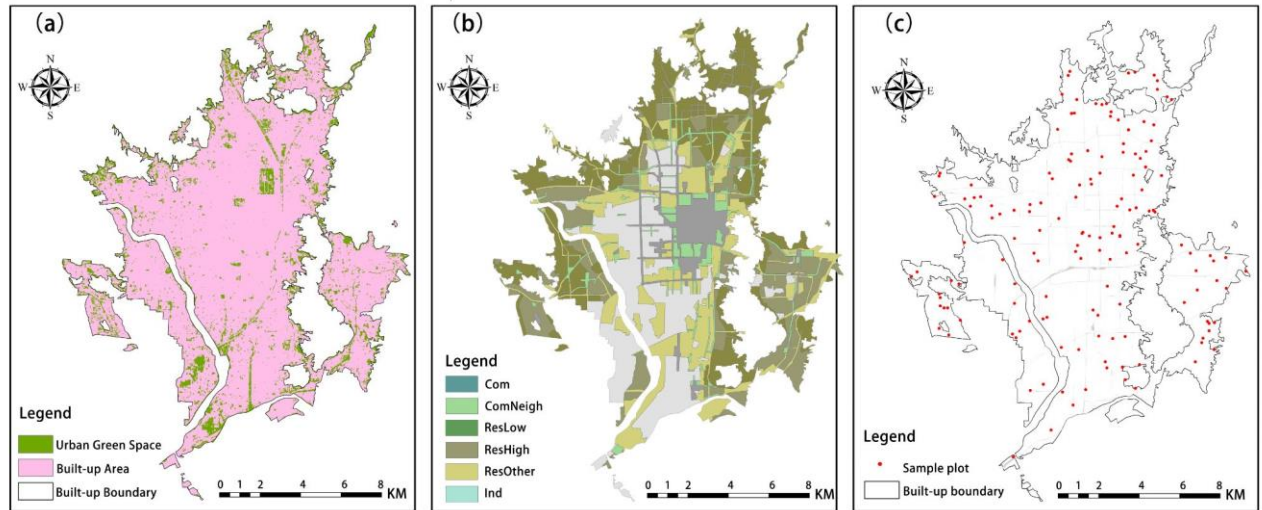


Figure 5.3 Maps of (a) land cover, (b) land use, and (c) distribution of sample plots.

Table 5.2 Land use classification.

Land use type	Land use subtype	Number of plots
ResLow	Category I exclusively low-rise residential area Category II exclusively low-rise residential area	35
ResHigh	Category I mid/high-rise oriented residential area Category II mid/high-rise oriented residential area	38
ResOther	Category I residential area Category II residential area	34
Ind	Quasi-residential area Quasi-residential area Industrial area Exclusively industrial area	23
ComNbr	Neighborhood commercial area	9
Com	Commercial area	12

5.3.2 Tree attribute indices and plot ecosystem services

For each land use type, the following indices were calculated based on the field investigation data. Relative abundance of a species is calculated by $RA_{ij} = A_{ij}/A_j$, where RA_{ij} is the relative abundance of species i in land use type j , A_{ij} and A_j is the abundance (number of trees) of species i and all species in land use type j , respectively. Species richness is the number of species in each land use. Tree density is the average number of trees per plot. Besides, the mean and median value of DBH, height, and leaf area index (LAI) are also calculated.

Carbon storage, and annual ecosystem services including carbon sequestration, air pollutants removal, and runoff reduction for each tree of each plot were assessed and valued using i-Tree Eco. Carbon storage

is calculated based on tree biomass (which is calculated based on tree size-related data collected in ground investigation, such as DBH and height) and species-specific carbon content provided by i-Tree Eco. Carbon sequestration is calculated with species-specific allometric equations (built-in data of i-Tree Eco), DBH, crown coverage, and canopy missing percentage. With the allometric equations and the data, the growth rate is estimated for each tree, thus annual carbon sequestration can be calculated (Nowak et al. 2013). The air pollutant removal module of i-Tree Eco is based on the dry deposition model (Hirabayashi et al. 2012). The key data for the module are local weather conditions, air pollutant concentration, and LAI. Removal of NO₂, SO₂, O₃, and PM_{2.5} were included in this study. Runoff reduction is calculated as the rainwater intercepted by trees by simulating the difference between the actual runoff with current tree cover and that without trees. The calculation is mainly based on precipitation, LAI, and impervious cover rate estimated with Japan Aerospace Exploration Agency (JAXA) satellite imagery (https://www.eorc.jaxa.jp/ALOS/jp/dataset/lulc_j.htm). Since the default parameters of i-Tree eco mainly support North American and European cities, we revised the model with local parameters of climate zone, phenology (leaf-on and leaf-off date of trees), meteorology, air quality, precipitation, in this study for a more accurate assessment (Kang et al., 2022).

For the valuation of ecosystem services, we applied local benefit-related parameters in the revised i-Tree Eco model. The social cost for carbon in Japan (10,600 Yen per ton carbon = 97 US dollars per ton carbon) (Ministry of the Environment, Government of Japan 2019) was applied to calculate monetary values for the carbon storage and carbon sequestration. The monetary value of air pollutant removal is calculated as the avoided cost of human health damage due to air pollutants reduction using the United States Environmental Protection Agency's BenMAP model (Nowak et al. 2014). While we followed the framework of the model, the parameters were changed to fit the situation of Japan. We adopted the local population and its structure, medical expenses, household income, and the value of statistical life to the revised i-Tree Eco model (Kang et al., 2022). The monetary metric of runoff reduction service was calculated based on the cost of stormwater control facilities, and the value was taken from a case study of Suita City of Japan (719 yen per m³ = 7 US dollars per m³) (Kawaguchi et al. 2021).

5.3.3 Spatial interpolation of ecosystem service

Spatial interpolation is the method to predict the values of unmeasured points based on the values of observed points. They are divided into deterministic methods and probabilistic interpolation methods (Krivoruchko 2012). Deterministic methods use predefined functions based on the distance between the observed and predicted positions. Probabilistic-based methods are based on statistical theory, quantifying the uncertainty related to the prediction position value (Krivoruchko 2012). Using the plot ecosystem service results calculated by i-Tree as observed values, 4 interpolation methods of those two interpolation types were applied and compared to determine the most accurate interpolation method for each ecosystem service.

5.3.3.1 Deterministic interpolations

Regarding the deterministic interpolation methods, inverse distance weighting (IDW) and radial basis function (RBF) were used. IDW interpolation is based on the principle of similarity, for which an observed point has a certain impact on the interpolation points in the adjacent area, and the impact decreases when distance increases (Johnston et al. 2001). The distances between the predicted points and the observed points are used as the weight for the weighted average calculation. The weight is greater when the distance is smaller (Qiao et al. 2019). RBF is a radial symmetric scalar function that varies with distance (Broomhead and Lowe 1988). It requires that the interpolation surface passes across all the observed points. As the final interpolation surface, the fundamental functions with minimal total surface curvature are chosen. The values of interpolation points calculated by IDW are within the range of observed point values, while the predicted values of RBF can exceed the range of observed values.

5.3.3.2 Probabilistic interpolations

Regarding the probabilistic interpolation methods, we used ordinary kriging (OK) and empirical Bayesian kriging (EBK). OK is a linear estimation method of regionalized variables. It is a structural analysis based on the spatial correlation of observed data, that is, semivariogram. It uses variance analysis to interpolate and provides suitable interpolation estimates according to the observed values and their spatial relationships (Wang et al. 2014; Ding et al. 2018; Shukla et al. 2020). Its interpolation process is comparable to the weighted moving average, and the weight value is determined by spatial data analysis. EBK differs from OK in that it accounts for the error generated by the estimation of the semivariogram model. This is accomplished by estimation, followed by the application of many semivariogram models as opposed to a single semivariogram (Krivoruchko 2012; Gribov and Krivoruchko 2020; Agyeman et al. 2021). Krivoruchko (2012) proposes a 3 steps interpolation process for EBK. (1) The data are used to estimate a semivariogram model. (2) A new value is predicted for each position of the input data using the semivariogram, and (3) The predicted data are used to estimate a new semivariogram model. The weight for this semivariogram is then determined using Bayes' rule, which reveals the probability that the observed data can be derived from the semivariogram.

5.3.3.3 Comparison of interpolation methods

The mean absolute error (MAE) and the root mean square error (RMSE) are commonly used with the cross-validation results to compare different interpolation methods (Stone 1974; Ding et al. 2018; Qiao et al. 2019). Regarding the cross-validation, we used the “leave-one-out” method. The process of leave-one-out cross-validation is as follows. (1) For the results of a certain ecosystem service, the measured value of an investigated plot (Z_i) is temporarily removed. (2) The value of the removed plot point ($\hat{Z}_i$) is estimated by applying an interpolation method based on the measured values of the plots left. (3) The removed plot is added back to the field investigation data set. The steps from (1) to (3) were repeated until all the plots have been removed once. In that way, we got an array of the measured values of 1, 2, 3, ..., i th sample plots (Z_1 ,

$Z_2, Z_3, \dots, Z_i$), and estimated values ($\hat{Z}_1, \hat{Z}_2, \hat{Z}_3, \dots, \hat{Z}_i$). Then an MAE and an RMSE were calculated for the interpolation method and the ecosystem service.

$$MAE = \frac{1}{n} \sum_{i=1}^n |\hat{Z}_i - Z_i|$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (\hat{Z}_i - Z_i)^2}$$

where $\hat{Z}_i$ and Z_i are estimated and measured values at the location point of plot i , respectively, and n is the number of sample plots. The accuracy of an interpolation method for an ecosystem service is higher when it has a lower MAE or RMSE. The values of RMSE are compared first, while MAE values are compared when the RMSE values are the same. The ecosystem service interpolation results with the highest accuracy were then used for the following analysis.

5.3.4 Ecosystem service value (ESV) calculation

Based on the metrics and monetary valuation of ecosystem services for the sample plots (in section 5.3.2), we calculated the monetary value per unit metric of each ecosystem service as follows.

$$V_j = \frac{1}{n} \sum_{i=1}^n \frac{ESV_{i,j}}{ES_{i,j}}$$

where V_j is the average per unit monetary value of the ecosystem service j , n is the number of the plots, $ESV_{i,j}$ is the monetary value of ecosystem service j of the i th plot, $ES_{i,j}$ is the metric of the ecosystem service j of the i th plot.

Spatial estimate of ESV for each ecosystem service was calculated as the product of the average per unit monetary value and the spatial interpolation result of the ecosystem service metric with the highest accuracy in section 5.3.3. The total ESV is calculated as the sum of ESV for each ecosystem service. After mapping the spatial distribution of ESV, the Getis-Ord G_i^* statistic of hot spot analysis was applied to locate the area where clustering of high- or low-value elements of ESV in urban forests occurred. In addition, the total ESV of different land use types were calculated and compared using ArcMap 10.5 and R (version 4.2.2)

5.3.5 Spatial correlation analysis

5.3.5.1 Geo-datasets

In this study, the geographic data were collected based on the research purpose of exploring the correlation between the urban forest ESV and the distribution of urban space types. The distribution of urban space types was calculated from point of interest data. Four types of point of interest data were collected, including tourist attraction space (TAS, including ruins, shrines, and touristy places), urban park space (UPS), school space (SS, including kindergartens, schools, colleges, and universities), and public service space (PSS, including museums, hospitals, town halls, libraries, etc.) (Figure 5.4). The data of UPS is from the Ministry

of Land, Infrastructure, Transport, and Tourism of Japan (<https://nlftp.mlit.go.jp>), and other data sources are from OpenStreetMap (<https://download.geofabrik.de/>). All data includes area size.

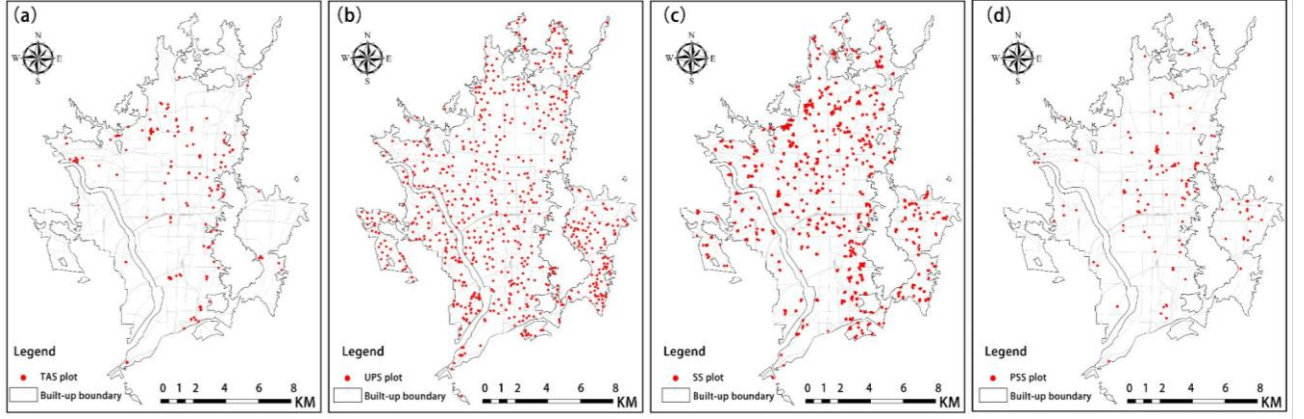


Figure 5.4 Maps of the point of interest in the built-up area of Kyoto City. (a) TAS: tourist attraction space; (b) UPS: urban park space; (c) SS: school space; (d) PSS: public service space.

5.3.5.2 Kernel density (KDE) analysis

Based on the interpolation results and point of interest, this study further explored the relationship between the ESV and urban space types. Firstly, urban space distribution of each point of interest was estimated by the KDE detection tool. KDE is a widely used non-parametric estimating method for determining the probability density function of variables (Zhang et al., 2021). KDE can calculate the probability density around the point and polygon features in each output cell grid (Zhong et al. 2020), and turn discrete points and polygons into a continuous density surface, resulting in a smooth and comprehensible representation (Zhang et al., 2021; Zhong et al., 2020). Considering the purpose and operability of this study, we assumed that the ESV is correlated with the area of urban space, thus took the area attribute as the “population field” of KDE in ArcGIS. KDE estimates the intensity inside each grid using a “moving window” that weights events within its sphere of impact based on their distance from each grid (Li et al., 2017; Ma & Tong, 2022). The KDE function was calculated based on the point of interest as follows.

$$P_i = \frac{1}{n\pi R^2} \times \sum_{j=1}^n K_j \left(1 - \frac{D_{ij}^2}{R^2}\right)^2$$

where P_i is the kernel density, i is the search radius, K_j represents the weight of the point object j , R is the bandwidth, D_{ij} is the distance between i and j ($D_{ij} < R$), n is the number of point objects in the bandwidth R range. Based on the area range of each point of interest type, bandwidth was set at 500 m after a pre-examination between 400 m and 1000 m with a 100 m-interval.

5.3.5.3 Global bivariate spatial correlation

This study used the bivariate Moran’s I statistics to evaluate the global spatial correlation between the ESV and KDE of each urban space type. Instead of assessing a spatial autocorrelation within the variables, the two-variable Moran’s I analysis examines how two variables in the space are clustered according to high

and low values (Li et al., 2017). The Moran's I values range between -1 and 1. If the bivariate Moran's I is greater than zero, there is a positive spatial correlation between ESV and KDE of urban space type. The correlation is stronger when the bivariate Moran's I is higher. Inversely, if the bivariate Moran's I is negative, ESV and KDE have a negative correlation (Zhong et al. 2020). It was calculated as:

$$I_{kl}^i = \frac{O_k^i W_{ij} O_l^j}{n}$$

where I_{kl}^i is the bivariate Moran's I, $O_k^i = [y_k^i - \bar{y}_k]/\sigma_k$ and $O_l^j = [y_l^j - \bar{y}_l]/\sigma_l$ represent the standardized values, y_k^i is the observation k (KDE) at location i, y_l^j is the observation l (ESV) at location j, σ_k and σ_l represent the variance of y_k and y_l , W_{ij} is the spatial unit weight matrix, and n is the number of objects being analyzed. To robust the test results, Z-value and P-value were tested when the "permutations" was set as 999 (Zhong et al. 2020).

5.3.5.4 Local bivariate spatial association

The bivariate local indicators of spatial association (LISA) was used to estimate the spatial correlation between ESV and urban space distribution across the city (Gruebner et al. 2011; Zhong et al. 2020).

$$LISA_{kl}^i = O_k^i \sum_{j=l}^n W_{ij} O_l^j$$

where $LISA_{kl}^i$ is the bivariate LISA, O_k^i , W_{ij} , and O_l^j are described in the equation of bivariate Global Moran's I in section 5.3.5.3. The bivariate LISA results were then visualized according to the pair of high- or low-value clusters of ESV and urban space distribution: high-high, low-low, low-high, and high-low value aggregation. For example, high-high value aggregation indicates the high ESV with high KDE of an urban space type.

5.4 Results

5.4.1 Tree attribute indices

In the 151 plots, 1240 trees (118 plant species of 48 families) were recorded. From the perspective of abundance, the most common families were *Oleaceae* (191 trees), followed by *Fagaceae* (151 trees), *Berberidaceae* (95 trees), *Rosaceae* (91 trees), and *Cupressaceae* (74 trees). According to the most common species of each land use measured by relative abundance (Figure 5.5), the abundance of species in ResLow, ResHigh, and ResOther were more evenly distributed. In contrast, ComNbr had an obvious dominant species, *Quercus glauca*, accounting for more than 50 percent of the total number of trees. Ind and Com areas also had an uneven species abundance distribution compared to residential areas.

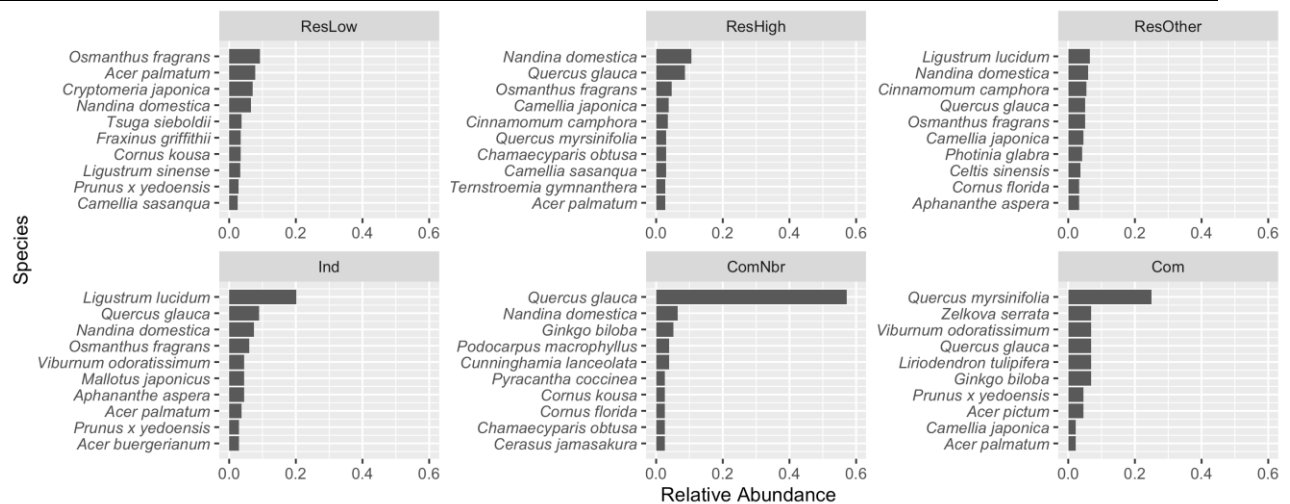


Figure 5.5 Top 10 species of Kyoto City by the relative abundance of each land use type.

The other tree attributes were further calculated for each land use (Table 5.3). Residential areas generally had higher richness and LAI. ResLow and ResHigh had higher density but relatively lower DBH and height. Trees in the Ind area had low density but relatively higher DBH and height.

Table 5.3 Tree attribute indices across land use types.

Land use	Richness	Density (tree/plot)	DBH mean (cm)	DBH median (cm)	Height mean (m)	Height median (m)	LAI mean	LAI median
ResLow	81	11.40	10.23	7.00	4.33	2.90	3.88	3.51
ResHigh	77	9.68	11.90	8.83	4.35	3.00	3.62	3.13
ResOther	68	6.41	15.03	8.00	4.91	3.55	3.14	2.92
Ind	43	5.83	14.07	11.09	5.53	4.00	3.06	2.49
ComNbr	18	8.56	11.28	7.00	4.36	2.70	3.14	2.54
Com	22	3.67	14.16	9.75	4.44	3.35	3.13	2.65

5.4.2 Mapping urban forest ecosystem services

5.4.2.1 Performance of interpolation methods

Table 5.4 compares the cross-validation results of carbon storage, carbon sequestration, removal of NO₂, O₃, PM_{2.5}, SO₂, and runoff reduction in urban forests under four interpolation methods (IDW, RBF, OK, and EBK). According to the RMSE values, the accuracy test results for removal of NO₂, O₃, PM_{2.5}, SO₂, and runoff reduction in the urban forest were EBK < RBF < IDW < OK, and the test results for Carbon storage and Carbon sequestration are EBK < RBF < OK < IDW and EBK < IDW < RBF < OK, respectively. These results suggested that the accuracy of EBK was consistent and superior in all seven ecosystem services. Further combining the MAE results, although the rank of the accuracy of the methods was different across ecosystem services, EBK for Carbon storage, Carbon sequestration, O₃, SO₂, and runoff reduction still showed high performance. Though RBF for NO₂ and PM_{2.5} removal had the smallest MAE values, they are very close to those of EBK. The results of RMSE and MAE suggested that EBK had an advantage among the spatial interpolation methods for all ecosystem services of the urban forest in Kyoto City.

Table 5.4 Results of cross-validation metrics for four interpolation methods.

Metrics for cross- validation	Interpolatio n methods*	Carbon storage	Carbon sequestration	NO ₂ remo val	O ₃ remov al	PM _{2.5} remov al	SO ₂ remo val	Runoff Reductio n
MAE	IDW	632.48	52.74	45.76	152.64	10.91	19.97	1.82
	RBF	627.64	53.18	45.53	153.09	10.69	19.91	1.78
	OK	643.86	53.89	51.3	167.18	11.88	21.6	1.94
	EBK	608.35	50.67	46.22	153.06	10.73	19.67	1.75
RMSE	IDW	1088.82	77.16	80.13	258.45	17.49	34.22	2.91
	RBF	1026.94	77.92	78.91	257.21	17.32	33.75	2.88
	OK	1062.09	81.02	83.83	275.92	18.13	35.86	3.01
	EBK	996.23	74.47	77.57	251.91	16.93	33.14	2.82

*IDW: inverse distance weighting, RBF: radial basis function, OK: ordinary kriging, EBK: empirical bayesian kriging.

5.4.2.2 Mapping ecosystem services using EBK

Based on the maps of urban forest ecosystem services from EBK interpolation, the ecosystem services had relatively similar spatial characteristics (Figure 5.6). High-value regions were in the northeast and southern regions, and ecosystem services in the central, eastern, and western regions were lower. However, ecosystem services still differed in the direction and extent of the distribution of the high values. For example, the high value region of carbon storage and carbon sequestration was wider than the others ecosystem services.

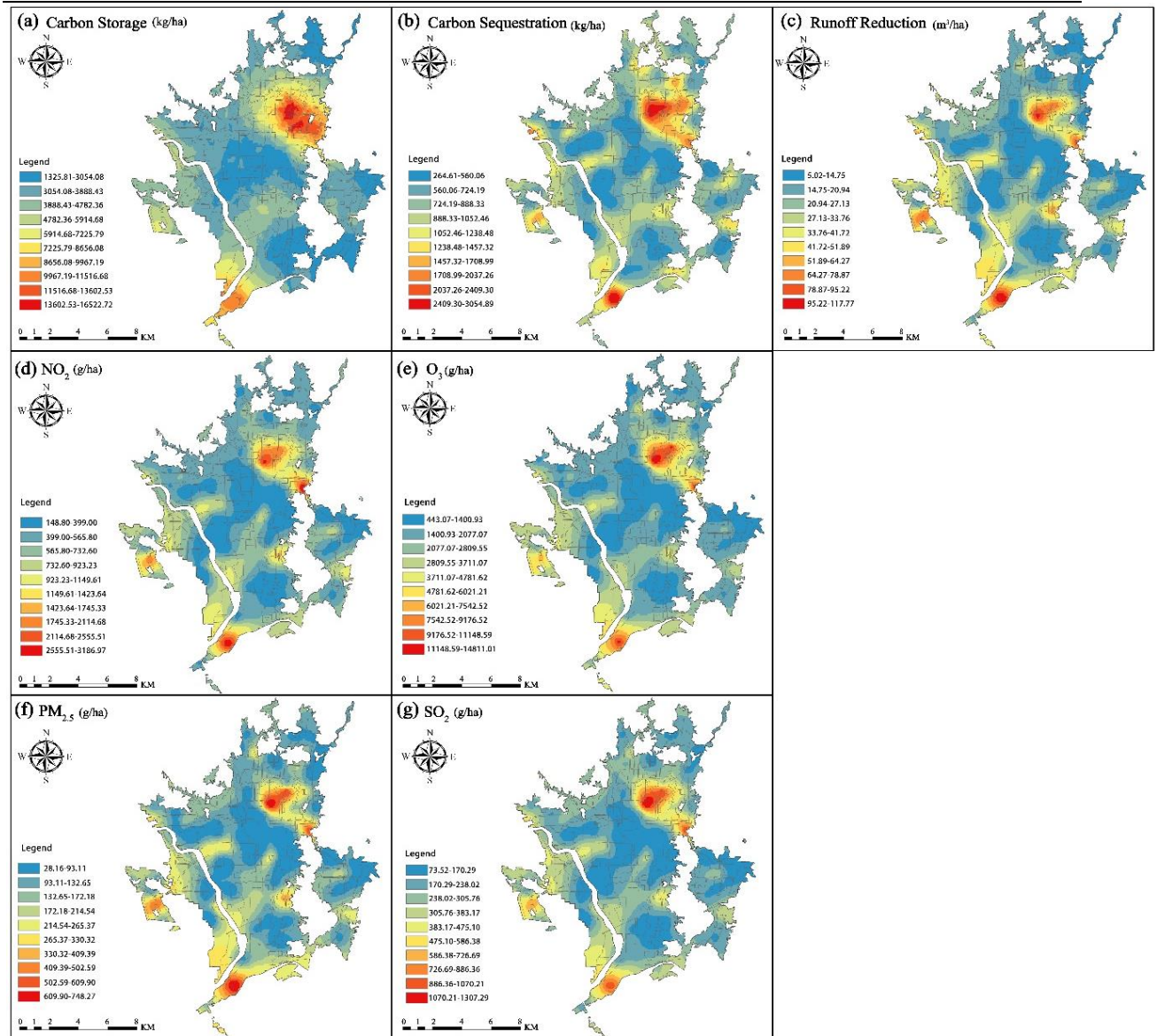


Figure 5.6 Predictive mapping of seven types of ecosystem services in urban forest based on EBK interpolation.

(a) Carbon Storage, (b) Carbon Sequestration, (c) Runoff Reduction, (d) NO₂, (e) O₃, (f) PM_{2.5}, (g) SO₂ removal.

5.4.3 ESV of the urban forest

5.4.3.1 Spatial pattern of ESV

The spatial distribution of ESV in the built-up area of Kyoto City was characterized by some clusters (Figure 5.7). The peak areas were northeast and south, including large green spaces like Kamomioya-jinja and Kyoto Gyoen National Garden, while the central area and the northern, eastern, and southeastern areas had lower ESV. Figure 5.7(b) also shows the hot and cold spots identified using statistically significant ESV high- and low-value areas based on the Getis-Ord Gi*. In the built-up area of Kyoto city, the southwest surrounds and the northeastern region were where the high concentration hotspots were found, with the northeastern region having the greatest hotspot area.

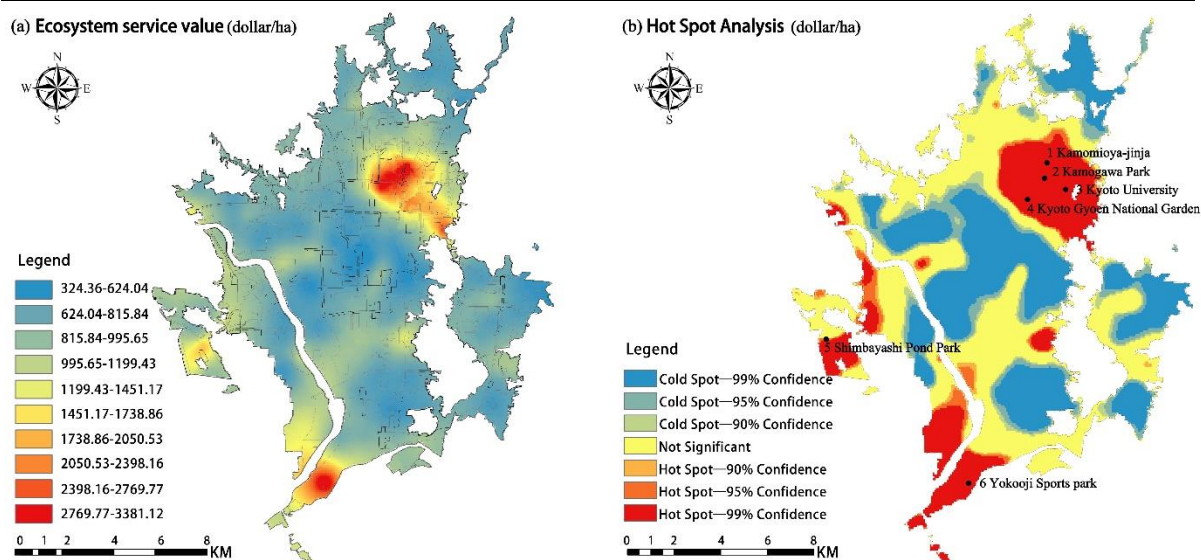


Figure 5.7 Maps of (a) ESV (dollar/ha) and (b) high- or low-value cluster areas for ESV (dollar/ha).

5.4.3.2 ESV of land use types

Ecosystem services and total ESV of each land use type were calculated and compared (Figure 5.8). It is found that ResLow, ResHigh, and ResOther exhibited higher total ESV. The reason might be that the residential areas are mostly private residences with larger available planting spaces, and have a larger total land area than the other land use types. The Ind area also has a high level of ESV, which might be related to larger trees (Table 5.3) and the dominance of high-ecosystem-service species (Figure 5.5).

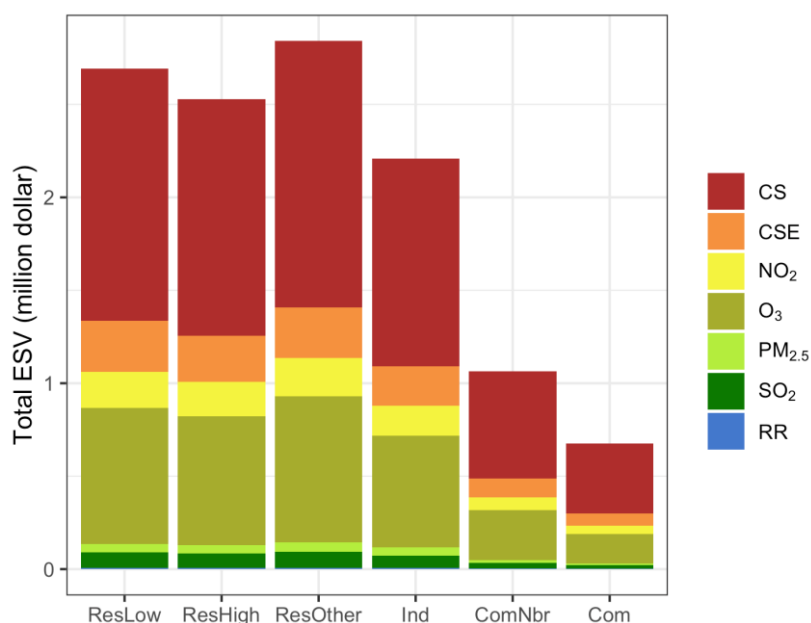


Figure 5.8 Total ecosystem service value (ESV) across land use types of Kyoto City. CS: carbon storage; CSE: carbon sequestration; RR: runoff reduction.

5.4.4 ESV and urban space types

5.4.4.1 Global bivariate spatial correlation

The Z-values for TAS, UPS, SS, and PSS were 62.96, 118.92, 57.42, and -30.79, respectively. The P-values are all less than 0.001 at a confidence of 99%. Therefore, these results were considered statistically significant. TAS, UPS, and SS were positively correlated with the aggregation of ESV (Figure 5.9), among which the Moran's I was relatively higher (0.266) for UPS. In addition, a negative correlation between the PSS and ESV of the urban forest was detected. According to the number of scatter plots, it was found that 2.45%, 6.83%, 11.12%, and 2.84% of TAS, UPS, SS, and PSS, respectively, were located in the first quadrant (high-KDE, high-ESV). This suggests that UPS had the highest aggregation in areas with high aggregation of ESV. In the fourth quadrant (high-KDE, low-ESV), the percentages for the four categories were 2.61%, 10.80%, 20.96%, and 10.79% respectively. This indicates that, except for TAS, the high aggregation of other urban spaces is surrounded by weaker ESV in the urban forest.

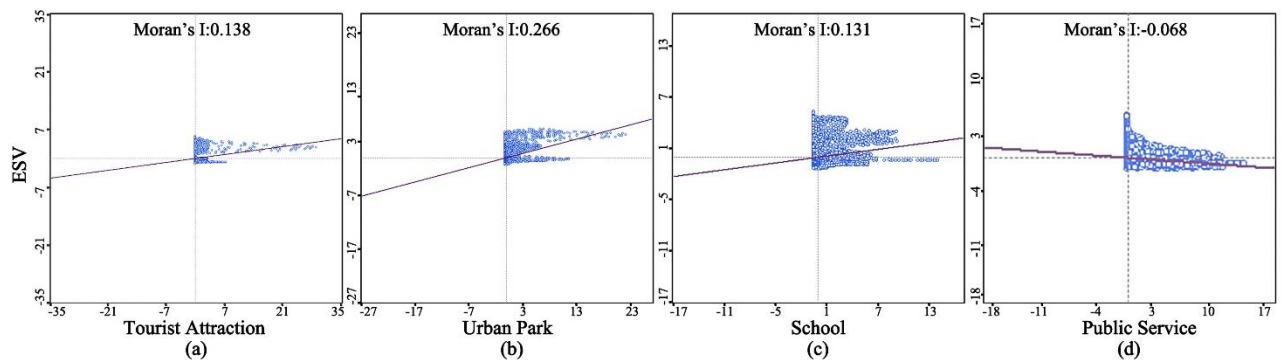


Figure 5.9 The Moran's I scatter plots for the urban forest ESV and (a) TAS, (b) UPS, (c) SS, and (d) PSS correlations.

5.4.4.2 Local bivariate spatial association

The bivariate LISA agglomeration maps (Figure 5.10) illustrate the relationship between the areas of high and low aggregation of ESV in the urban forest and four urban space types. The high aggregation area of ESV showed a higher KDE of SS (high), followed by UPS, TAS, and PSS. In the western and southern areas of the high aggregation area of ESV, UPS and SS exhibited high aggregation characteristics and contributed to the ESV. In the low aggregation area of ESV, all urban space types, except for TAS, displayed significant levels of high aggregation. However, the aggregation of these urban space types did not enhance the ESV of the urban forest.

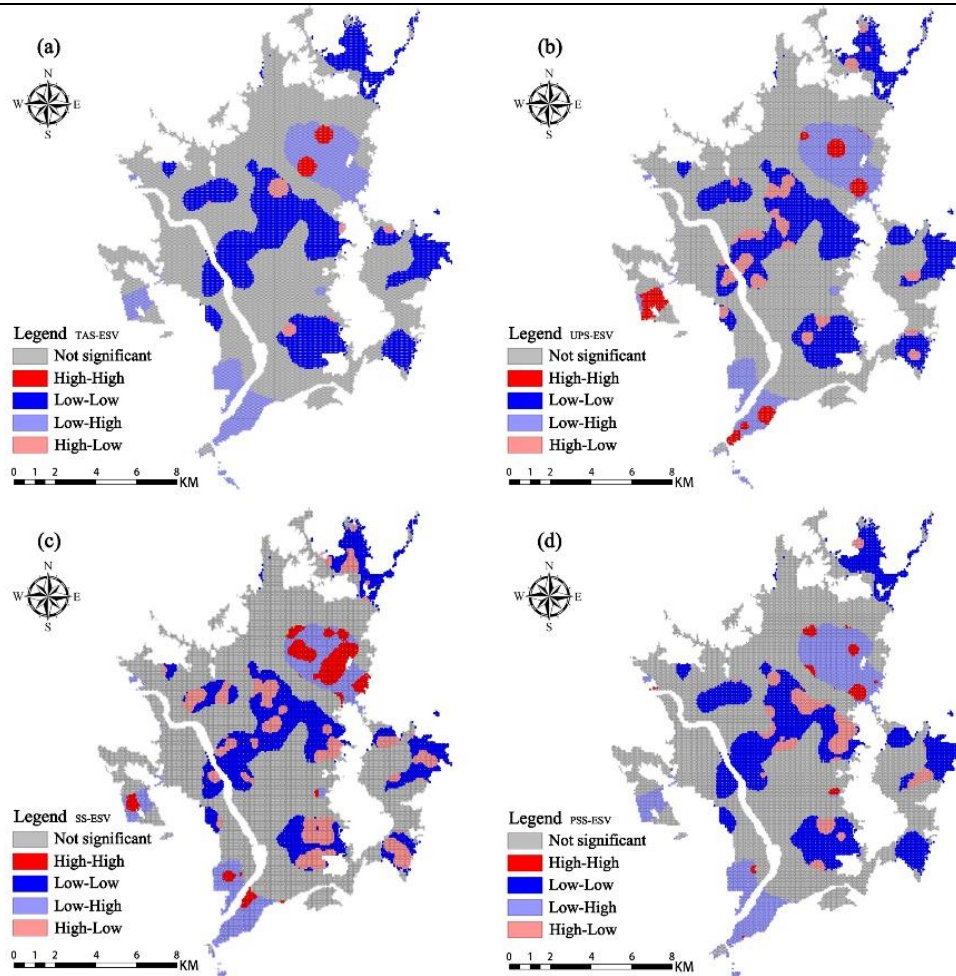


Figure 5.10 LISA agglomeration maps for the correlation between the urban forest ESV and (a) TAS, (b) UPS, (c) SS, and (d) PSS.

5.5 Discussion

5.5.1 Empirical Bayesian kriging

Ecologists recognized that almost all macro-ecological data show strong spatial patterns, driven by spatially structured biological processes, and therefore tend to be spatially auto-correlated (Webster 1985; Rangel et al. 2006). The essence of geostatistics is the study of the spatial relationships of these variables by assuming that adjacent data are spatially correlated and that the relationship expressing the degree of this correlation can be analyzed and counted using a function (Johnston et al. 2001; Krivoruchko 2012). Therefore, geostatistics can predict spatial patterns based on macroecological data. EBK, one of the reliable automatic interpolation methods in geostatistics, has unique advantages. Firstly, it requires smaller interaction modeling, and automatic modeling of spatial relationships, especially for small or non-stationary data, and is often considered more accurate. Besides, its application of local models to capture small-scale effects, rather than applying only a single model, makes the predictions more accurate in terms of standard errors than other kriging methods (Krivoruchko 2012; Krivoruchko and Gribov 2019; Gribov and Krivoruchko 2020; Agyeman et al. 2022). In this study, MAE and RMSE were used to assess the accuracy of the results of

interpolation methods, and it was verified that EBK has advantages (Table 5.3). Comparing the measured data with the predicted data further showed that the error of EBK was predicted.

In addition, the spatial pattern depends on the spatial sampling scheme of the data collection. In this study, the results of ESV were essentially consistent with the distribution of urban forests. That is, Kyoto University, Kamomioya-jinja, Kamogawa Park, and other large green areas were identified as hotspot areas (Figure 5.7). However, on the other hand, some large green areas were located at the edge rather than the center of the hotspot, like Shimbayashi Pond Park and Kyoto Gyoen National Garden (Figure 5.7). The results indicate that there may be some discrepancy between the study results and the reality, which also reflects the bias of the spatial prediction results due to insufficient sampling data in the above areas.

5.5.2 Ecosystem services and land use

The impact of i-Tree-related studies on urban forest policy and practice has been limited, despite the widespread application of i-Tree Eco (Raum et al. 2019). This limitation arises from the focus on a single ecosystem service and a lack of spatial information, which restricts the practical applicability of i-Tree Eco research findings (Dangulla et al. 2020). Furthermore, to overcome the challenges posed by the method of i-Tree Eco reliance on a limited sample size in highly heterogeneous systems and the high cost of the field investigation, this study employed the spatial interpolation method to calculate the ESV of urban forests. In addition, we compared the species composition (Figure 5.5), tree attributes (Table 5.2), and ESV (calculated by EBK) of the urban forest in different land use types of Kyoto City (Figure 5.8). Exploring the urban forest characteristics and ESV in different land use types can guide the ecosystem services demand and supply of the built-up area. For example, in Com and ComNbr areas, considering the high-volume ratio, frequent human activities, and a lack of green space, urban planning should pay attention to three-dimensional greening to meet the demand for ecosystem services during the daytime. In addition, the species selection should be based on the specific situation of the site and to achieve co-benefits of biodiversity improvement.

5.5.3 ESV and public urban space distribution

Studies have been conducted to investigate the characteristics of forests and assess the ESV of urban forests in specific urban spaces, such as street trees (Thaiutsa et al. 2008; Taylor et al. 2015) and urban parks (Collins et al. 2019; Wolf et al. 2020). However, in a highly developed urban area with limited plant space, to achieve the planning goal of urban green space ratio, it is not negligible to research the flexible use of urban forests for fragmented green space in the built-up area (Wolf et al. 2020). In this study, based on field investigation, it was found that there was a certain area of green space in basic service facilities, such as the forecourts of municipal institutions, public spaces of schools, and atriums of museums, etc. Therefore, we chose four urban space types to analyze their correlation with the ESV of the urban forest. We found that TAS, UPS, and SS in Kyoto city have a positive relationship with the ESV of the urban forest, and PSS has a negative relationship (Figure 5.9). This is significant for understanding the current utilization of urban forests in different urban space types. In addition, we believe that it is urgent and necessary to increase tree planting for the above urban spaces in High (KDE)-Low (ESV) areas (Figure 5.10), which gives a specific direction for tree planning. In addition, we also found that the correlation analysis was carried out based on

the areas of high and low ESV values of the urban forest, so that with the dynamic change of ESV of tree species, the tree planning can also be adjusted and laid out in conjunction with the dynamic analysis of spatial correlation.

5.6 Conclusion

This study presents a comprehensive urban tree planning workflow that incorporates i-Tree Eco, geostatistical interpolation, and spatial correlation analysis. The main objective is to explore the feasibility of using spatial interpolation methods as an alternative approach to address the limitations associated with the i-Tree Eco method. These limitations include the use of limited sample sizes in highly heterogeneous systems, the high cost of collecting field data, and the large amount of data needs. The workflow is applied to the built-up area of Kyoto City, Japan, as a case study. Using the estimates of each ecosystem service in the built-up area of Kyoto City, the distribution map of ESV and the distribution of hot/cold spots of ecosystem services were further calculated and completed. Finally, the composition of urban forest ESV under different land use types and the relevance of ecosystem services to urban space types were discussed.

This study integrates the underlying data and analysis to draw conclusions from the perspectives related to forest planning and management. The key findings are as follows: (1) EBK is better utilized in the spatial interpolation of the urban forest in the built-up area of Kyoto City, and this result matches the characteristics of the current green space distribution. (2) Land use type, plant richness, and species evenness impact the functions of ecosystem services, with a single plant allocation in commercial and industrial areas and a more balanced plant allocation in residential areas. Enhancing plant diversity enhances ecosystem services. (3) TAS, UPS, and SS in Kyoto city have a positive relationship with the ESV of the urban forest, and PSS have a negative relationship, and identified urban spaces (high (KDE)-low (ESV)) that need to increase urban tree planting to enhance the ESV of the urban forest.

Overall, this study provides valuable insights and practical guidance for urban tree planning, highlighting the potential of spatial interpolation methods and their application in understanding and managing ecosystem services in urban forests. The findings contribute to the development of effective strategies for urban forest management and planning.

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Chapter 6

General Discussion and Conclusion

6.1 Summarization of this study

From Chapter 2 to Chapter 5, this study conducts land use/land cover (LULC) research ranging from the metropolitan area to the built-up area scale. It centers around key themes including "Characterizing land use/land cover change (LULCC) and the contribution of driving factors in the Three Major Metropolitan Areas Over the Past 20 Years (2000-2020)", "Establishing a Comprehensive Ecological Security Pattern (ESP) and Evaluating Ecological Health", "Simulating Future LULC Scenarios", and "Analyzing and Applying Urban Ecosystem Services (ESs)".

Chapter 2: providing an overview of three metropolitan areas: Tokyo Metropolitan Area (TKM), Chubu Metropolitan Area (CBM), Kinki Metropolitan Area (KKM), examining the upper-level planning policies and legal frameworks associated with the metropolitan area scale. It analyzes Land Use and Land Cover Change (LULCC) from 2000, 2010, and 2020, showing a decrease in cultivated land and increases in forests and artificial surfaces. The landscape pattern analysis reveals fragmentation of cultivated land and increasing intactness of forests. The chapter also scrutinizes changes in the morphological spatial patterns of forests and green spaces, setting the stage for ecological source selection and landscape organization in subsequent chapters. It employs a land expansion analysis strategy using 20 driving factors from topography, socioeconomic conditions, soil characteristics, climate, and spatial accessibility, identifying significant correlations with population distribution and highlighting topography and climate as key drivers. These findings form the basis for future LULC simulations under complex climate and economic scenarios.

Chapters 3 and 4 extensively utilize methods from LULC to explore their applicability in land use planning for Japan's metropolitan areas. These chapters develop a comprehensive framework for large-scale LULC from the perspectives of ESP and land use detection and simulation. **Chapter 3** extensively explores the applicability of LULC methods in regional planning for Japan's metropolitan areas, emphasizing ESP. The study identifies critical patches of forest, cultivated land, and grassland, highlighting the need for tailored management strategies to protect these areas. Large patches are protected under national policies, while small patches require additional measures like legal constraints and physical barriers. An innovative ESP evaluation framework integrating ecological network construction and ecosystem health assessment is proposed, addressing gaps in fine-scale LULC differentiation and application in precise planning. **Chapter 4** introduces a comprehensive LULC simulation modeling framework using the PLUS and InVEST models, applied to the KKM. It projects future LULC changes under four SSP-RCP scenarios (SSP126, SSP245, SSP370, and SSP585). The findings indicate a general decrease in cultivated land and an increase in forest areas, except under SSP585, while artificial surfaces are expected to increase, except under SSP370. It highlights the need for integrating simulation results with policy discussions to support conservation, sustainable agriculture, and urban planning, promoting stakeholder collaboration and informed policy-making. This research underscores the importance of dynamic monitoring, buffer zones, and stakeholder engagement to ensure sustainable land

Moreover, Chapters 4 and 5 collectively highlight the critical role of integrating ESs into land use planning, particularly using advanced modeling frameworks and participatory approaches. The integration of ESs into land use planning is essential for sustainable urban development. **Chapter 4** uses the InVEST models to project future LULC changes and carbon storage in the KKM under various SSP-RCP scenarios, revealing critical patterns in forest aggregation and cultivated land decline. **Chapter 5** expands on this by focusing on the practical application of ESs in urban planning, particularly within built-up areas often overlooked in broad planning efforts. Using field investigations, i-Tree Eco, and geostatistical interpolation, this chapter examines urban forest ESs in Kyoto City. The study quantifies ESs such as carbon sequestration and air purification, finding higher species richness and ES values in residential areas. The spatial correlations between ES values and urban spaces, including tourist attractions, parks, and schools, underscore the importance of incorporating urban forest ESs into planning efforts. Both chapters highlight the importance of detailed spatial analysis for ES in creating resilient, ecologically informed urban landscapes. These insights offer valuable guidance for policymakers and urban planners aiming to optimize green infrastructure and enhance urban ecological quality.

The study highlights the interplay between natural, socioeconomic, and policy factors in shaping land use patterns in Japan's metropolitan areas. It underscores the importance of integrating ecological considerations and dynamic monitoring into urban planning to achieve sustainable and resilient urban development. These findings provide valuable insights for policymakers and urban planners, emphasizing an inclusive, data-driven, and ecologically focused approach to land use management.

6.2 General Discussion

6.2.1 Potential Application of LULC-Related Research Methodology in Planning Practice

In the fields of urban planning and landscape ecology, extensive research has been conducted on land use, leveraging 3S technologies (remote sensing, geographic information systems, and global positioning systems) and spatial analysis methods (Chen et al., 2021; Dewan and Yamaguchi, 2009). These efforts have led to the development of numerous comprehensive and valuable research methods and frameworks. Planning departments at various scales and regions provide rich regional planning maps for land management, emphasizing ecological protection and building construction (Chapter 2). These maps highlight the importance and immediacy of managing land use through spatial planning and are continuously updated and revised to reflect changing social needs and temporal shifts. Spatial analysis through LULC has become a mainstream approach in urban planning and ecological security protection, showcasing its significant potential and necessity (Arowolo and Deng, 2018; Yang et al., 2022). This study applies cutting-edge land use methodologies to explore relevant frameworks at the metropolitan scale in Japan. The research includes

an evaluation framework for ES based on spatial analysis, landscape pattern assessment, and dynamic monitoring within LULC analysis; a simulation framework for LULC based on various socioeconomic models and climate fluctuations; and a comprehensive framework using i-Tree Eco and spatial interpolation methods to guide urban green space planning from the perspective of ESs.

Regional planning increasingly relies on the integration of LULC analysis to manage and optimize LULC effectively. The use of advanced LULC simulation models like PLUS and InVEST, as demonstrated in this study, allows for projections of future LULCC and their impacts on ESs such as carbon storage (Verburg et al., 2019; Nelson et al., 2009). By applying these models to the KKM and evaluating changes under different SSP-RCP scenarios, this study provides valuable insights into how LULC decisions can influence ecological outcomes. Moreover, the application of spatial pattern analysis and morphological spatial pattern analysis (MSPA) helps in understanding the distribution and connectivity of LULC types, which is crucial for maintaining ecological networks and ensuring the stability of ES (Li et al., 2020; Turner, 2005). This spatial understanding aids in making informed decisions about where to focus conservation efforts and how to design urban areas that support ecological resilience.

In conclusion, the integration of LULC analysis into regional planning is essential for achieving sustainable development goals. By utilizing advanced modeling frameworks and spatial analysis methods, urban planners can make informed decisions that enhance ecological resilience and promote balanced land use. This study provides a comprehensive framework for incorporating these techniques into policy discussions, guiding the development of urban areas that are both environmentally sustainable and socially beneficial.

6.2.2 Prospects of Ecosystem Service Assessment

Although the concept and application of ES are relatively recent, they have rapidly gained attention at various regional and spatial scales (Costanza et al., 2017). Governments worldwide recognize the importance of ES, as seen in initiatives like the Convention on Biological Diversity and the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services (IPBES). These initiatives highlight the need to integrate ES into policy and decision-making processes to achieve sustainable development goals (Costanza et al., 2017).

Assessing ES faces several challenges, including rigorous data requirements and errors across different scales (Bennett et al., 2009; De Araujo Barbosa et al., 2015). For instance, Chapter 4 of this study estimates the carbon storage capacity of land use types in the KKM by collecting specific carbon sequestration rates. These rates vary across Japan due to differences in topography, climate, and vegetation, affecting assessment outcomes. Additionally, Chapter 5 involves field surveys to accurately evaluate urban forest ES.

ES assessments are widely applied at both broad and local scales. Broad-scale assessments provide a macro perspective, aiding in the formulation of national and regional environmental policies, natural resource management strategies, and land use planning (Huang et al., 2021; Sannigrahi et al., 2019; Yang et al., 2018). In contrast, local-scale assessments focus on details and specific environments, such as urban green spaces and forests, directly influencing regional planning and green space management decisions (Gong et al., 2022;

Ma et al., 2021). Chapter 4 of this study evaluates the broad carbon storage capacity and explores its relationship with forest morphology, providing management recommendations and strategies aimed at maintaining ES stability through forest morphology management. Chapter 5 examines the ES benefits of urban forests in Kyoto at a finer scale, highlighting the methodological differences between broad and local scales. By analyzing the correlations between urban forest ESs and four types of urban spaces, this chapter identifies areas where urban space and urban forest ESs do not align, pinpointing potential planting spaces for urban forests and proposing regional planning strategies.

ES assessments are crucial for guiding sustainable development. As research progresses, opportunities to integrate ES into planning and policymaking processes will increase. By incorporating ES considerations into decision-making frameworks, policymakers can enhance the resilience and sustainability of urban ecosystems.

6.3 Limitation and Future studies

The limitations of this study encompass several dimensions:

- Limiting applicability to other regions or countries.
- Overlooking middle-small spatial scale variations and localized phenomena; ESs analysis is confined to built-up areas.
- Predominantly quantitative analysis, potentially neglecting qualitative and socio-cultural factors relevant to land use management.

In response to the limitations mentioned, future study will primarily focus on the following aspects:

- Expanding scope and scales: Expand geographical scope to more regions and scales for broader applicability.
- Small or Middle-Scale analysis: Use fine-scale analysis to evaluate ESs across different LULC types and apply them in regional planning.
- Qualitative Analysis Integration: Integrating qualitative analysis methods (such as stakeholder interviews, questionnaire analysis) to comprehensively understand LULC dynamics and ecosystem service functions.
- Exploring the impact of study findings on policy and planning interventions, including the development of targeted strategies for sustainable land use management and regional planning.

6.4 Conclusion

This study comprehensively analyzes changes and assessments of LULC and ESs from metropolitan regions to built-up areas, aiming to enhance regional planning and land management practices. By employing widely accepted methods in land use science and integrating methods related to ESs assessment, this study explores the dynamic interactions between LULC and ES across broad and middle-small scales, providing references for sustainable urban development strategies. This study shows that over the past two decades,

Japan's major metropolitan areas have seen a decrease in cultivated land and an increase in forests and artificial surfaces due to topography, climate, and socio-economic conditions. On a broad scale, this research integrates LULC dynamic detection, spatial analysis, and simulation, providing strategies for land use management in Japan's three major metropolitan areas. It also discusses the differences in ES assessment methods at broad and middle-small scales, exploring ESs-oriented land use management strategies. This study highlights the importance of incorporating LULC methods and ES considerations into regional planning and policy-making processes to enhance the resilience and sustainability of urban ecosystems. By providing a comprehensive framework for LULC and ES assessment, it offers actionable guidance for policymakers and urban planners. This work delivers practical strategies for effective land use management and sustainable urban development, ultimately supporting the creation of resilient and sustainable urban environments.

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Appendix

Table S2-1. The LULC transition matrix of the TKM areas from 2000 to 2020/km².

LULC	Artificial surface	Bareland	Cultivated land	Forest	Grassland	Shrubland	Waterbody	Wetland	Total (2000)
Artificial surface	6229.66	5.21	356.49	100.62	30.33	19.69	15.87	0.31	6758.18
Bareland	7.35	127.14	15.09	192.85	34.03	30.54	8.01	0.00	414.99
Cultivated land	466.45	12.43	8717.33	343.69	34.71	46.06	37.14	0.33	9658.16
Forest	71.79	204.12	375.80	16293.92	273.76	502.34	26.38	0.06	17748.17
Grassland	12.08	24.38	23.49	291.29	210.54	53.14	3.26	0.03	618.22
Shrubland	23.56	28.37	52.31	501.80	61.76	225.37	11.80	0.01	904.99
Waterbody	12.00	5.85	19.10	14.43	4.92	8.81	405.19	1.41	471.70
Wetland	0.07	0.67	0.07	0.26	0.00	0.01	0.06	0.06	1.19
Total (2020)	6822.96	408.18	9559.68	17738.86	650.05	885.96	507.70	2.21	36575.61

Table S2-2. The LULC transition matrix of the CBM areas from 2000 to 2020/km².

LULC	Artificial surface	Bareland	Cultivated land	Forest	Grassland	Shrubland	Waterbody	Wetland	Total (2000)
Artificial surface	3858.00	5.80	298.00	55.10	9.03	6.35	12.17	5.50	4249.95
Bareland	27.06	222.60	17.09	237.50	50.50	39.76	11.99	11.15	617.65
Cultivated land	1052.00	16.61	4734.00	455.40	28.61	19.08	44.58	19.33	6369.61
Forest	70.23	188.10	255.40	27850.00	474.40	391.50	33.20	4.31	29267.14
Grassland	7.11	28.66	13.56	509.40	531.50	67.45	3.58	3.31	1164.57
Shrubland	12.10	36.58	19.58	409.70	81.48	274.50	3.43	3.39	840.76
Waterbody	14.14	10.99	19.98	19.59	2.66	2.15	252.10	3.70	325.30
Wetland	0.17	13.02	0.30	0.92	0.02	0.46	1.87	1.73	18.48
Total (2020)	5040.80	522.36	5357.91	29537.61	1178.20	801.25	362.93	52.41	42853.46

Table S2-3. The LULC transition matrix of the KKM areas from 2000 to 2020/km².

LULC	Artificial surface	Bareland	Cultivated land	Forest	Grassland	Shrubland	Waterbody	Wetland	Total (2000)
Artificial surface	2876.00	2.14	84.41	31.20	6.27	5.14	6.68	0.43	3012.27
Bareland	4.54	63.01	3.15	31.69	9.31	20.56	3.91	0.00	136.18
Cultivated land	257.60	5.77	3254.00	197.40	19.14	39.07	19.89	5.35	3798.22
Forest	34.23	27.90	144.60	17370.00	88.23	347.80	14.50	0.01	18027.27
Grassland	2.94	6.49	3.94	114.10	160.00	47.98	2.36	0.26	338.06
Shrubland	9.26	18.57	30.18	484.60	54.04	555.50	3.59	0.00	1155.75
Waterbody	5.94	1.38	9.23	7.44	1.37	2.09	768.20	0.15	795.81
Wetland	0.00	0.00	0.02	0.00	0.00	0.00	0.01	0.06	0.08
Total (2020)	3190.51	125.26	3529.54	18236.43	338.37	1018.14	819.14	6.25	27263.63

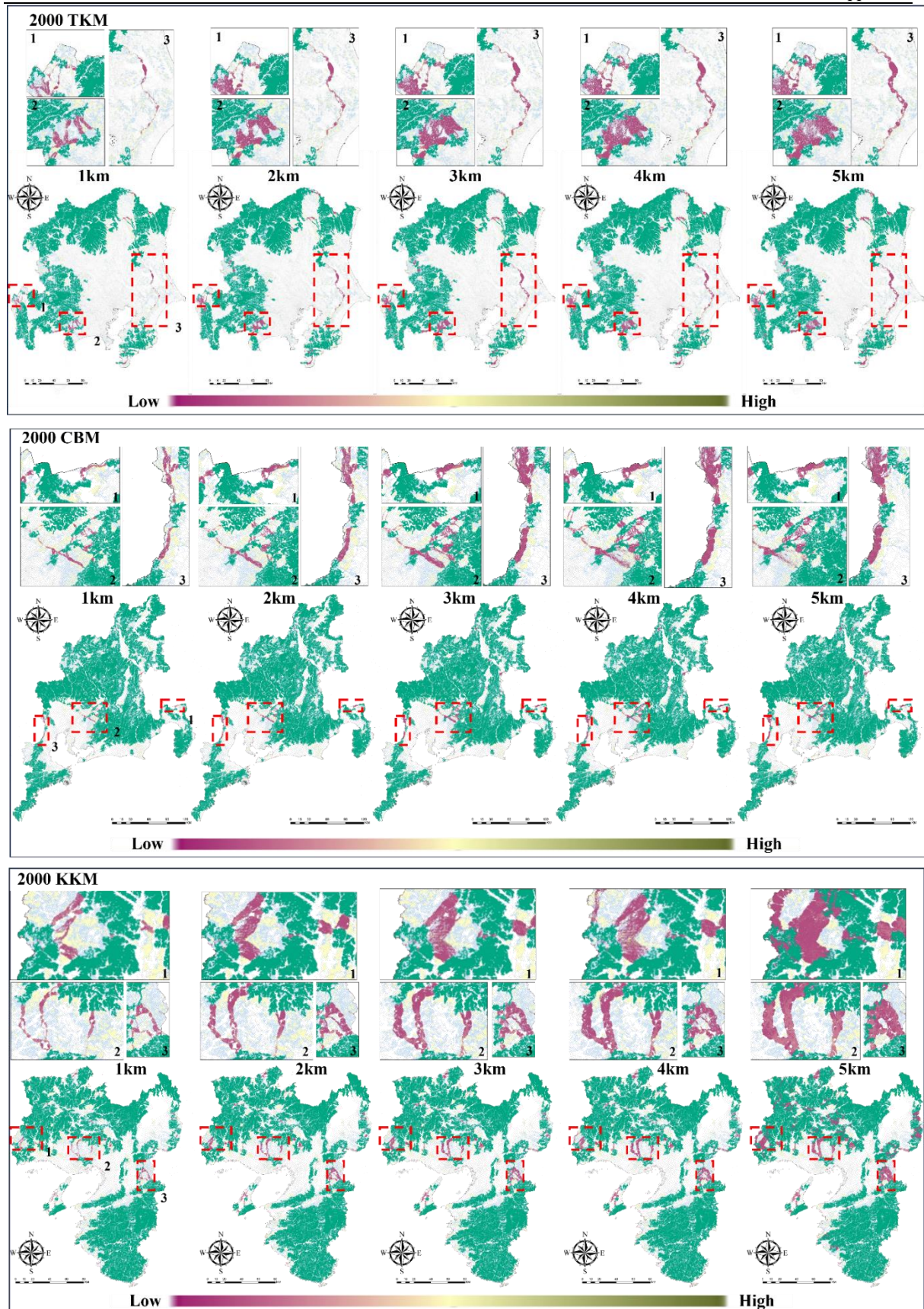


Figure S4-1 The cumulative current thresholds setting from 1 km to 5 km for ecological network constructions (using the year 2000 as an example).

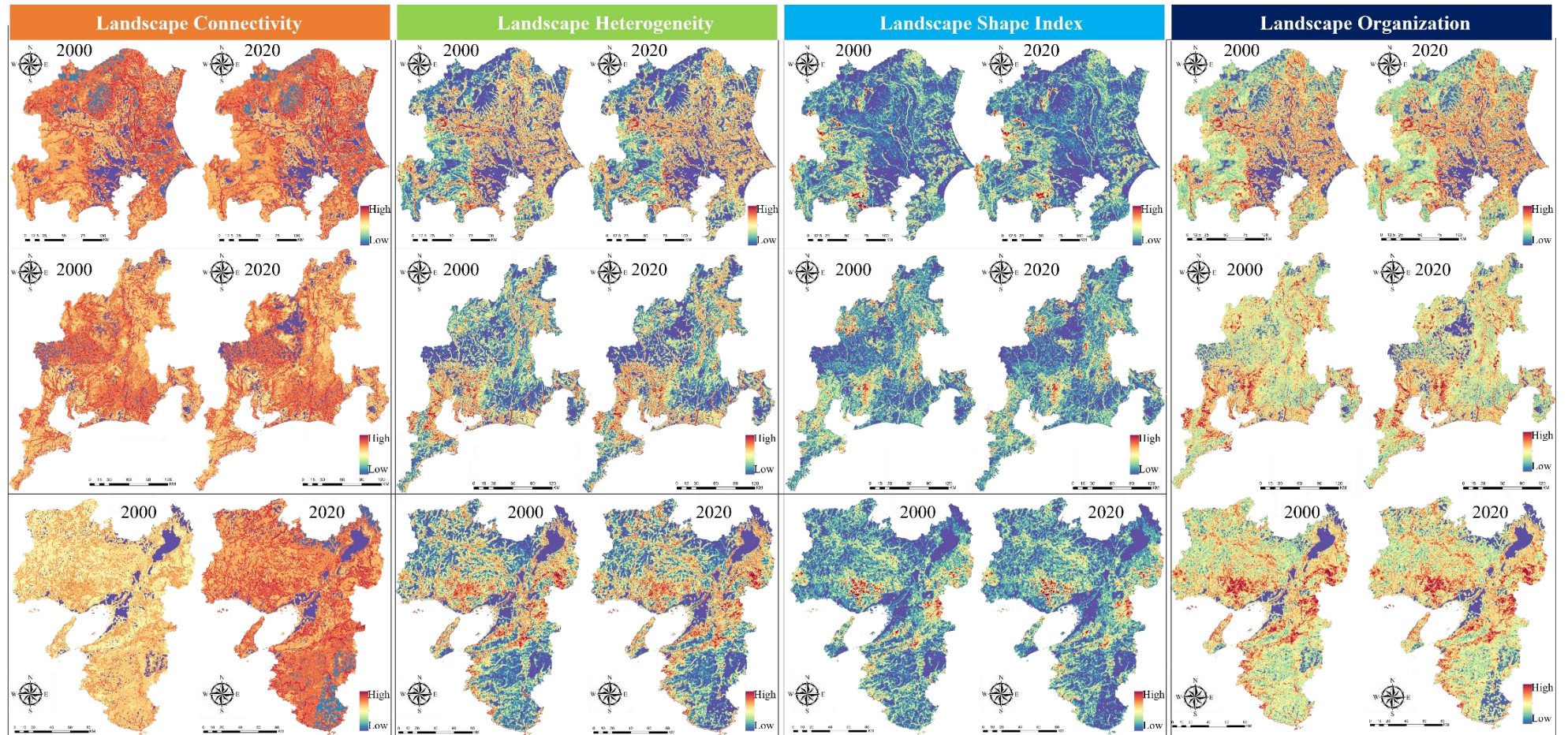


Figure S4.2 The calculation of landscape organization in the three metropolitan areas.