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The Impact of Urban Dynamics on Green Space in the Munich Region: a Multiple Scenario Modeling Approach

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我见青山多妩媚，

料青山、见我应如是。

情与貌，略相似。

—辛弃疾 (Xin Qiji)

sharing a moment of harmony with nature

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List of Abbreviations

ABM	Agent Based Model
AGA	Adaptive Genetic Algorithm
AHP	Analytic Hierarchy Process
AIC	Akaike Information Criterion
ALR	Autologistic Regression
ANN	Artificial Neural Network
ANOVA	Analysis of Variance
AUC	Area Under the Curve
CA	Cellular Automata
FUZZY	Fuzzy Logit Model
GIS	Geographical Information Systems
GWR	Geographically Weighted Regression
KMO	Kaiser-Meyer-Olkin
LISA	Local Indicators of Spatial Association
LR	Logistic Regression
MC	Markov Chain
MCMC	Markov Chain Monte Carlo
OLR	Ordinary Logistic Regression
OLS	Ordinary Least Squares
PCA	Principal Component Analysis
PCGS	Per Capita Green Space
PCLS	Per Capita Living Space
ROC	Receiver Operating Characteristic
RS	Remote Sensing
SAC	Spatial Autocorrelation
SPAGS	Share of the Population with Access to Green Spaces
SVM	Support Vector Machines
TOL	Tolerance
VIF	Variance Inflation Factor

Summary

As rapid urbanization and population growth have become global issues, changes in land use induced by urban dynamics have critical consequences on landscape patterns and urban environments. Simulating and predicting urban dynamics is helpful for improving our understanding of the dynamic processes and potential future of the urban system, especially for supporting the implementation of sustainable urban development strategies for cities. Thus, modeling of urban dynamics has become an essential tool for decision-makers to understand how urban growth works in overall dense environments and to assess the sustainability of current urban forms.

Green spaces can mitigate the negative effects of urbanization and improve the overall quality of life of urban residents, and have been increasingly considered as “green infrastructure” and a fundamental part of sustainable urban development. The amount and the availability of green spaces is influenced by urban dynamics and their spatial outcomes such as low density development (“sprawl”), densification and monocentric vs. polycentric development. Consequently, their spatial distribution is uneven in most cities and urban regions. This uneven distribution of green spaces has been regarded as an issue of environmental injustice. However, the combined impacts of these different urban dynamics on green space have not yet been systematically and quantitatively assessed. Therefore, this research emphasizes the impacts of urban dynamics on green space in urban regions using a multiple scenario modeling approach.

First, an integrated urban growth model was tested to explain current urban growth for one of the fastest and most dynamically growing urban regions in Germany, the region of Munich. Second, multiple scenarios were developed with respect to the following three dimensions that influence the processes of urban dynamics: housing demand (high, medium, or low), urban spatial structure (monocentric or polycentric), and urban growth form (sprawl, compact sprawl, or compact). The landscape pattern changes were characterized and quantified by using a set of landscape metrics among which the redundancy was reduced by Principal Component Analysis (PCA). Third, by using Per Capita Green Space (PCGS) and the Share of the Population with Access to Green Spaces (SPAGS) as indicators, the availability of green spaces under corresponding scenarios and trade-offs between the two indicators were analyzed at both the regional and sub-regional zone levels. Finally, the Gini coefficient was applied as an indicator of green space equity, and its spatial relationship with socioeconomic variables was explored. Additionally, the impacts of different urban dynamic scenarios on green space equity were comparatively assessed at both levels.

Key findings indicate that, first, incorporating the spatial dependency into the model produced great improvement and the Kappa indexes were higher when separately modeling the growth of different settlement types, as the driving factors for settlement growth of different densities might be dissimilar. Second, urban growth in all scenarios mainly led to the loss of open space, but the specific land use transitions were different in sub-regional zones. The changes of the patch complexity index and the landscape configuration index were mostly similar at both levels. Yet, the landscape diversity index showed contrasting trends between the Urban Core Zone and the other two zones (Peri-Urban and Rural), which is related to whether settlements are the dominant land use in these zones or not. Third, a higher demand for housing placed more pressure on green space availability and equity at both levels. Polycentric scenarios were found to be less limiting than monocentric ones at the regional level. In addition, the relationship between green space equity and socioeconomic variables was spatially heterogeneous and locality-specific. When defining the most advisable urban growth form in terms of green space availability and equity, the trade-offs between the indicators should be considered.

The results also highlight that, without effective greening policies, different degrees of a decline of green space availability and equity were observed in most of the selected scenarios, which were related to the loss of green spaces caused by new construction during urban growth. Moreover, there was not a single growth form that performed best in all the different zones and, thus, urban planning should consider the different impacts of urban dynamics on green spaces and focus more on the development of planning strategies adapted to different sub-regional zones. This novel and straightforward scenario modeling approach provides rare evidence of the respective advantages and disadvantages of different urban dynamics with respect to green spaces. In the urban planning perspective, it is a powerful tool that offers an opportunity for planners and government authorities to gain a more precise understanding of the different urban growth processes and their impacts on green spaces. This is not only crucial for this region in the study but also of great significance for other urban regions that aim to achieve successful green space planning.

Zusammenfassung

Seitdem eine rasche Urbanisierung und eine rasante Zunahme der Weltbevölkerung bedeutende globale Herausforderungen darstellen, haben Landnutzungsänderungen verursacht durch urbane Dynamiken ernsthafte Auswirkungen auf Landnutzungsmuster und städtische Räume. Die Simulation und das Vorhersagen urbaner Entwicklungen sind von Bedeutung für ein verbessertes Verständnis der dynamischen Prozesse und die Zukunft urbaner Systeme, und im Speziellen wesentlich für die Implementierung nachhaltiger städtischer Entwicklungsstrategien. Somit ist das Modellieren urbaner Dynamiken zu einem essentiellen Werkzeug für Entscheidungsträger geworden, da abgebildet werden kann, wie Städtewachstum in dicht bebauten Gebieten funktioniert, und die Nachhaltigkeit gegenwärtiger Nutzungsformen beurteilt werden kann.

Grünflächen können zu einer Abmilderung der negativen Urbanisierungseffekte beitragen und generell die Lebensqualität der Stadtbewohner verbessern. Sie werden zunehmend als „grüne Infrastrukturen“ betitelt und als fundamentaler Bestandteil einer nachhaltigen Stadtentwicklung eingestuft. Das Ausmaß und die Zugänglichkeit von Grünflächen werden beeinflusst von städtischen Dynamiken und ihren räumlichen Folgen, wie beispielsweise der Zersiedlung, der Verdichtung und monozentrischen vs. polyzentrischen Entwicklungen. Als Konsequenz ergibt sich eine ungleichmäßige Verteilung bzw. Zugänglichkeit zu diesen Grünflächen in den meisten Städten und städtischen Regionen. Jenes Phänomen wird als ungerecht wahrgenommen. Die kombinierten Auswirkungen dieser urbanen Dynamiken auf die städtischen Grünflächen wurden jedoch bislang noch nicht systematisch und quantitativ erfasst. Ziel dieser Untersuchung ist somit, die Auswirkungen dieser urbanen Dynamiken auf die Grünflächen in urbanen Gebieten mit Hilfe multipler Szenarioanalysen (engl. multiple scenario modeling) zu untersuchen.

Als erstes wurde ein integriertes urbanes Wachstumsmodell zur Erklärung gegenwärtigen urbanen Wachstums für die Region München getestet – eine der am dynamischsten sich entwickelnden städtischen Regionen in Deutschland. Zweitens wurden multiple Szenarien für die folgenden drei Dimensionen entwickelt, welche urbane Dynamiken beeinflussen:

Wohnungsnachfrage (hoch, mittel oder gering), urbane räumliche Struktur (mono- oder polyzentrisch) und urbane Wachstumsmuster (Zersiedelung, kompakte Zersiedelung oder kompakt). Die Muster der Landschaftsveränderungen wurden charakterisiert und quantifiziert unter Anwendung eines Sets an Landschaftsmetriken, wobei Redundanzen mit Hilfe einer Hauptkomponentenanalyse (engl. principal component analysis, PCA) reduziert wurden. Drittens wurde unter der Verwendung der Grünfläche pro Einwohner (engl. per capita green space, PCGS) und des Anteils an Bewohnern mit Zugang zu Grünflächen (engl. the share of the population with access to green spaces, SPAGS) als zwei Indikatoren die Verfügbarkeit von Grünflächen unter entsprechenden Szenarien und Trade-offs beider Indikatoren sowohl auf der regionalen als auch auf der sub-regionalen Ebene analysiert. Zuletzt wurde der Gini-Koeffizient als ein Gerechtigkeits-Indikator für Grünflächen angewendet und seine räumliche Beziehung zu sozioökonomischen Variablen untersucht. Zusätzlich wurden die Auswirkungen unterschiedlicher Szenarien urbaner Dynamik für einen gerechten Zugang zu Grünflächen vergleichend auf beiden Ebenen analysiert.

Die wesentlichen Ergebnisse zeigen, dass zum einen die Inkorporation räumlicher Abhängigkeiten zu einer beträchtlichen Verbesserung des Modells geführt hat und dass die Kappa-Indizes im Falle einer separaten Modellierung des Wachstums unterschiedlicher Siedlungstypen höher waren, da die Einflussfaktoren für das Wachstum von unterschiedlich dicht besiedelten Gebieten variieren können. Zweitens hat urbanes Wachstum in allen Szenarien hauptsächlich zu einem Verlust offener Flächen geführt, jedoch gab es Unterschiede hinsichtlich der spezifischen Veränderungen in sub-regionalen Zonen. Die Änderungen der Indizes bezüglich der Komplexität des Areals (engl. patch complexity index) und der landschaftlichen Struktur (engl. landscape configuration index) waren weitestgehend gleich auf beiden Ebenen. Allerdings zeigten sich beim landscape configuration index abweichende Trends zwischen der städtischen Kernzone und den anderen beiden Zonen (peri-urban und ländlich), abhängig von der Frage, ob Siedlungen in diesen Zonen der vorherrschende Landnutzungstyp sind oder nicht. Drittens übte eine höhere Wohnungsnachfrage auf beiden Ebenen mehr Druck auf das Vorhandensein von und den gerechten Zugang zu Grünflächen aus. Auf regionaler Ebene stellten sich polyzentrische Szenarien als weniger begrenzend im Vergleich zu monozentrischen heraus. Außerdem war die Beziehung zwischen dem gerechten Zugang zu Grünflächen und sozioökonomischen Variablen räumlich heterogen und ortspezifisch. Für eine Definition der empfehlenswertesten urbanen Wachstumsform für das Vorhandensein und den gerechten Zugang zu Grünflächen sollten die Trade-offs zwischen den Indikatoren berücksichtigt werden.

Die Ergebnisse zeigen auch, dass ohne effektive Begrünungsstrategien in den meisten gewählten Szenarien das Vorhandensein und die gerechte Zugänglichkeit von Grünflächen in unterschiedlichem Maße reduziert wurden, was mit dem Verlust an Grünflächen aufgrund von Neuanlagen im Zuge des Städtewachstums zusammenhing. Darüber hinaus gab es keine einzige Wuchsform, welche sich in allen Zonen als die beste herausstellte und somit sollten bei urbanen Planungsprozessen die unterschiedlichen Auswirkungen urbaner Dynamiken auf Grünflächen berücksichtigt werden und der Fokus stärker auf die Entwicklung von Planungsstrategien angepasst auf unterschiedliche sub-regionale Zonen gelegt werden. Dieser neuartige und direkte Modellierungsansatz ist ein seltener Beleg für die jeweiligen Vor- und Nachteile unterschiedlicher urbaner Dynamiken in Bezug auf Grünflächen. Aus Sicht der Stadtplanung bietet er ein leistungsfähiges Werkzeug, welches den Planern und staatlichen Behörden die Möglichkeit gibt, ein präziseres Verständnis über die unterschiedlichen urbanen Wachstumsprozesse und ihre Auswirkungen auf Grünflächen zu erlangen. Dies ist nicht nur nutzbringend für das ausgewählte Studiengebiet, sondern auch von großer Bedeutung für andere städtische Regionen, welche eine erfolgreiche Grünflächenplanung zum Ziel haben.

Chapter 1

Introduction

1.1 Research Background and Objectives

Rapid urbanization and population growth become global issues that have been receiving increasing attention. Nowadays, the world's population is continuously growing by 1.10% per year, yielding an additional 83 million people annually, and it is projected that the world population will increase to 9.8 billion in 2050 (United Nations, 2017). Urbanization, which refers to the process of increasing number of people move from rural to urban area, is perhaps one of the most important human activities (Tian et al., 2005). As reported by United Nations (2015), for the first time in history the global urban population exceeded the global rural population in 2007. Urbanization is expected to continue globally over the next 35 years and, consequently, one-third of the world's population will reside in rural areas while two-thirds in urban areas by 2050 (United Nations, 2015). The increasing tendencies of population and urbanization result in complex processes of land use and land cover changes across local, regional and global scales, which conversely have severe consequences for the environment (Lauf et al., 2012; Liu and Yang, 2015).

The increasing interest in sustainability assessment for socio-ecological systems of urban areas has shown that the dynamic process of urbanization has various fundamental impacts on ecological systems at a wide range of scales (Gaube and Remesch, 2013; Sun et al., 2013). Therefore, urbanization has been of great concern to researchers due to their significant impacts on land use change and environmental decline. This includes, for example, the loss of agricultural land and green spaces and increases in sealed surfaces (He et al., 2011; Sabet Sarvestani et al., 2011; Xi et al., 2012), the heat island effect (Lee and French, 2009; Yao et al., 2017), flood risk (Haase and Nuissl, 2007; Ohana-Levi et al., 2017; Sathish Kumar et al., 2013), landscape fragmentation and the loss of biodiversity (Dupras et al., 2016; Vimal et al., 2012). Therefore, understanding the causes, processes and consequences of urban growth is crucial for decision-makers to assess the negative impacts and support sustainable urban development (Haase et al., 2012a; Han et al., 2009). For this purpose, urban dynamic modeling approaches are very relevant, since they are capable of simulating historical urban development and predicting the potential future urban dynamics. Urban dynamic modeling, particularly when combined with narratives of future scenarios or development alternatives, has become an attractive and practical approach for planning to assess and visualize future urban development and the potential impacts of implementing different land use policies (Tian and Qiao, 2014).

Although urban dynamics are complex processes with uncertainties (Barreira González et al., 2015), they have been extensively monitored and modeled in a growing body of literature and the following three influencing dimensions have frequently been discussed: housing demand, urban spatial structure and urban growth form (Ewing and Hamidi, 2015; Garcia-López, 2012; Haase et al., 2013). First, the housing demand, which is represented by the increased number of households, can directly affect the extent of urban growth and new land consumption around cities (Nuissl et al., 2009). Second, among various urban spatial structure models, the polycentric model has been frequently suggested as a pre-requisite for a more sustainable and balanced spatial pattern of urban development in contrast to the monocentric model (Meijers and Romein, 2003). Third, different urban growth forms have been extensively debated in literature, among which the main focus was placed on the controversy between "sprawl", i.e. fragmented urban development at low densities (Dupras et al., 2016), and "compact growth" (Salvati and Gargiulo Morelli, 2014). However, different combinations of these three dimensions have rarely been discussed in current literature and their combined impacts on urban ecosystems remain unclear.

Green space plays an essential role in sustainable urban development, which can mitigate the negative impacts of urbanization and positively contribute to life quality of urban residents by providing various benefits to human well-being and supporting biodiversity (Chiesura, 2004; Jim, 2004). Given its well-acknowledged environmental and social services, green space is nowadays more and more regarded as 'green infrastructure,' which has equal importance for cities and city regions as social and technical infrastructures (Pauleit et al., 2017). However, the ecosystem services provided by green spaces are often overlooked and undervalued (Gill et al., 2007), and the availability of green spaces has been extensively influenced by the dynamic process of urban development (Zhao et al., 2013). Accordingly, a considerable loss of green and open spaces can still be found in most urban areas due to the increasing pressure of urbanization and densification processes (Fuller and Gaston, 2009; Lin et al., 2015; McDonald et al., 2010; Zhou and Wang, 2011), which makes efficient management and planning of green spaces become a great challenge nowadays (Shan, 2014). Therefore, understanding the impacts of different urban dynamics on green space availability is of great importance for guiding future greening policies towards a sustainable urban development (Zhou and Wang, 2011). However, most recent studies have focused only on the impacts of different urban growth forms, either sprawling or compact growth, on the availability of urban green space (e.g., Lin et al., 2015; Zhou and Wang, 2011), while a study that accounts for the potential combined impacts of different dimensions of urban dynamics on green spaces is lacking in literature to-date.

Green space is rarely evenly distributed across space within most cities, which has been considered as an issue of environmental injustice (Kabisch and Haase, 2014; McConnachie and Shackleton, 2010). It becomes another challenge for urban planners to provide residents with adequate and equitable access to green spaces across the population (Dony et al., 2015; Kabisch and Haase, 2014; Wolch et al., 2014). Hence, increasing attention has been paid on assessing and understanding the current status of green space distribution and its variations over different socioeconomic groups of urban residents to enhance the benefits of green space for all residents (Li and Liu, 2016). However, a knowledge gap still exists in how green space equity varies along spatial and socioeconomic gradients. In addition, current research tends to focus on the assessment of the status quo or the historical changes of green space equity and a fuller understanding of the impacts of different urban dynamics on green space equity in a futures perspective is still missing (Wei, 2017).

The overall aim of this thesis is to contribute to closing these knowledge gaps by developing and applying a multiple-scenario modeling approach to systematically and quantitatively assess the potential impacts of different population and household dynamics on urban forms and green spaces in the region of Munich, an urban area under high land pressure. The region of Munich is one of the eighteen planning regions in Bavaria, Southern Germany, which is composed of the city of Munich and 186 municipalities in eight administrative districts (in German "Landkreise"). This region is selected as the study area due to; first, it is regarded as one of the fastest growing regions in Europe and the regional population is projected to continuously increase to almost 3.2 million by 2034 (Bavarian State Office for Statistics, 2015), which will consequently contribute to urban growth both near the city of Munich and throughout the region. Second, due to the increasingly intensive interactions between urban and rural areas and the continuous high pressure on open spaces caused by urban growth in most large European cities and urban regions (Kain et al., 2016; Larondelle et al., 2016), green space availability should be considered at the urban regional scale to better account for the complexity of land development between the core city and the peri-urban surroundings.

Third, although the regional urban spatial structure currently follows a monocentric model with the city of Munich at its center (Goebel et al., 2007), this region has the potential of polycentric development as the presence of several subcenters in the surrounding area (RPV, 2005).

Specifically, the following objectives are addressed in this study:

- Objective 1:

  To examine the spatial pattern of historical settlement growth and to develop an integrated urban growth model that accounts for the growth of different settlement types,

- Objective 2:

  To develop multiple urban dynamic scenarios and to assess the impacts of different urban dynamic scenarios on landscape patterns at the regional and sub-regional levels,

- Objective 3:

  To investigate how green space availability varies under different urban dynamic scenarios and to identify the impacts of different urban dynamics on green space availability at the regional and sub-regional levels,

- Objective 4:

  To describe and quantify the pattern of green space equity and its spatial relation with socioeconomic variables and to examine the impacts of different scenarios of urban dynamics on green space equity at the regional and sub-regional levels.

1.2 Structure of the thesis

Besides the Literature Review and Conclusion, the thesis is structured into four major parts according to the four above-mentioned research objectives (Figure 1.1). In **Part I**, the spatial pattern of settlement growth is analyzed, and an integrated model is proposed and applied to simulate the regional urban expansion and the development of different settlement types. Multiple urban dynamic scenarios are developed and modeled in **Part II**, and the land use and landscape pattern changes induced by different urban dynamic scenarios are characterized and quantified. **Parts III** and **IV** build on the modeling results produced in **Parts I** and **II**. In **Part III**, the impacts of different urban dynamic scenarios on green spaces availability are comparatively assessed by using two indicators at both the regional and sub-regional levels. **Part IV** measures the green space equity for each municipality of the region to investigate its relationship with socioeconomic variables across spatial and socioeconomic gradients. In addition, the green space equity under different scenarios is compared to understand the impacts of different urban dynamics on green space equity.

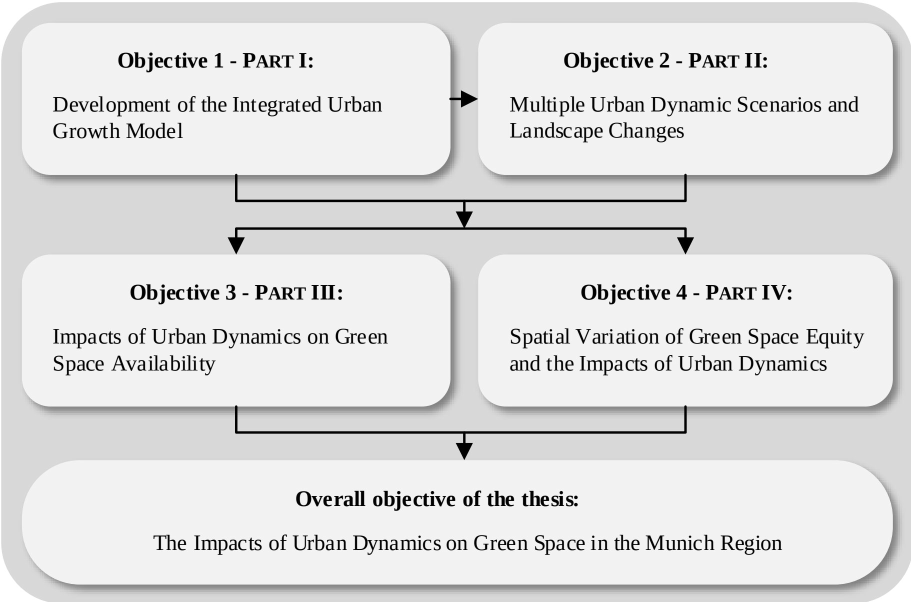

Figure 1.1 Structure and overview of the four major parts of the thesis.

Chapter 2

Literature Review and Analytical Framework

This chapter begins with a literature review of the current state of art and research gaps related to urban dynamic modeling, influencing dimensions of urban dynamics, green space availability and equity under urban dynamics. It is followed by an overview of the analytical framework that presents how relevant research gaps or questions are addressed in this study.

2.1 Urban Dynamic Modeling Approaches

2.1.1 Urban Growth Modeling

In recent decades, the significant technological progress of Remote Sensing (RS) and Geographical Information Systems (GIS) have actively accelerated the advancement of coupled urban socio-demographic and land use modeling techniques (Almeida et al., 2008; Barredo et al., 2003; Loibl and Toetzer, 2003; Zheng et al., 2012). Among these modeling techniques, the Cellular Automata (CA) has gained widespread applications in modeling urban growth and land use changes since the 1990s (Barredo et al., 2003; Batty and Xie, 1994; Clarke et al., 1997; White and Engelen, 2000; Wu and Webster, 1998). The CA was initially developed in the late 1940s and was first applied in geographical modeling by Tobler (1979). The advantages of CA models are clearly to be found in its simplicity, flexibility, intuitiveness, as well as the ability to model and express both spatial and temporal variations in complex dynamic systems (Haase et al., 2012a; Santé et al., 2010). CA models simulate dynamic processes based on the assumption that the change of land use state for each cell is according to the state of the cell itself and the development situation of its neighboring cells in agreement with a set of transition rules (Sathish Kumar et al., 2013; Wu and Webster, 1998). However, the complexity of land cover (particularly the settlement areas of urban regions) and the respective specific importance of the driving forces of urban growth makes the conventional CA model not robust enough to produce plausible simulations of urban growth (Aburas et al., 2016).

Hence, various kinds of quantitative models have been integrated with the conventional CA model to achieve better modeling results, such as Analytic Hierarchy Process (AHP), Markov Chain (MC), Logistic Regression (LR), Fuzzy Logit Model (FUZZY), Support Vector Machines (SVM), Adaptive Genetic Algorithm (AGA), and so on (Aburas et al., 2016). Given the wide range of available quantitative models, the decision on which one to use is important and should consider the local characteristics of urban growth and the respective settlements properties of the study area (Ku, 2016). Nonetheless, the MC model is commonly used over other quantitative models because of its ability to aggregate very complex information into a transition matrix and to consider land use changes over time (Aburas et al., 2016). The assumption behind MC is that the probability distribution of future land use states is based on the current state and the transition between the last two periods (Guan et al., 2011). The combination of MC and CA model was often used to estimate the transitions between different land use types and was regarded as one of the most convenient and efficient modeling approaches due to the large number of already implemented MC-CA models (Guan et al., 2011; Halmy et al., 2015; Mitsova et al., 2011; Zhang et al., 2011, etc.).

It is well known that the trajectories and patterns of urban growth in different parts of the world have been propelled and determined by a set of driving factors (Abhishek et al., 2017; Chen et al., 2016b; Li et al., 2013). Various factors driving urban growth have been considered in literature, including socioeconomic, environmental, and neighborhood factors, as well as urban spatial characteristics (Barredo et al., 2003; Li et al., 2018). First, frequently considered socioeconomic factors include population density and land price. Population density is regarded as a crucial driver of urban growth which has a positive impact on urban growth (Jokar Arsanjani et al., 2013), whereas land price could be expected to have a negative influence (Tian and Qiao, 2014). Second, it has been reported that urban expansion has been influenced by a number of environmental factors such as slope, distance to water bodies and distance to green spaces. Slope is usually considered to have a negative impact on urban expansion (Braimoh and Onishi, 2007; Li et al., 2013). The influence of water bodies on urban expansion could be either negative due to the risk of flooding (Abo-El-Wafa et al., 2017) or positive by providing necessary water resources or a good environmental quality (Li et al., 2015). Green spaces such as parks or woodlands may have a positive influence and thus attract urban developments (Jokar Arsanjani et al., 2013). Third, the neighborhood factor is positively related to urban growth, indicating that urban growth tends to occur close to the existing urban fabric (Cheng and Masser, 2003). Last, urban spatial characteristics such as distance to city centers have found to have a negative impact on urban growth. For example, Luo and Wei (2009) found that distance to major city centers had greater negative influence than distance to subcenters in the city of Nanjing, China, which is in contrast to the findings of Cheng and Masser (2003) who reported that the impacts of subcenters were stronger than major centers in Wuhan City, China. Moreover, urban expansion was found to be guided by transportation accessibility (Wu and Yeh, 1997) and a negative impact of the distance to transportation networks on urban growth could be expected (Li et al., 2018). However, the influences of different levels of transportation system (i.e., railways, highways, major roads and local roads) might be distinct (Li et al., 2015).

However, the differential effects of driving factors of urban growth can still not be satisfactorily identified in the conventional CA model (Balzter, 2000). To overcome this limitation, another quantitative approach called Logistic Regression (LR) has frequently been combined with the CA model that enables the possibility of including driving factors into the model. The LR is a statistical approach for modeling the relationship between a categorical dependent variable and one or more independent variables (Jokar Arsanjani et al., 2013; Li et al., 2017; Luo and Wei, 2009; Vermeiren et al., 2012; Wu and Webster, 1998). It is regarded as a more objective way to estimate the weight of each driving factor based on historical data rather than subjective judgments based on researcher's opinions (Ku, 2016). For instance, Hu and Lo (2007) used an Ordinary Logistic Regression (OLR) model to estimate the relative importance of demographic, econometric and biophysical driving factors, which was later used as the weights to generate an urban growth probability map. Additionally, hybrid models which integrate both MC and LR with CA have been developed in recent studies to improve the performance of MC-CA or LR-CA models in simulating the spatial dynamics of urban growth (Han and Jia, 2017; Jokar Arsanjani et al., 2013).

Moreover, the phenomenon of Spatial Autocorrelation (SAC) is known to widely exist in land use data that tend to be spatially correlated with each other (Overmars et al., 2003). In regression models (particularly when incorporating quantitative approaches to include driving factors of urban growth), SAC in dependent variables may lead to pseudoreplication and spatial dependency in the residuals because the data are not independent. Accordingly, the overall performance of the fitted model will be influenced (Ku, 2016; Naves et al., 2003).

Generally, there are two possible strategies to address the SAC when modeling urban growth. The first one is to retain only the cells that are not autocorrelated using resampling approaches (Aguayo et al., 2007; Hu and Lo, 2007; Liao et al., 2016; Mustafa et al., 2018; Poelmans and

Van Rompaey, 2010). However, this would lead to the loss of information at the fine scale and thus affect the model's performance (Overmars et al., 2003). The second statistically sound approach is the application of a spatial model such as the Autologistic Regression (ALR) in which the SAC issue can be addressed by introducing an autocovariate variable into the model (Augustin et al., 1996). For decades, the ALR model has been widely applied in ecological research, especially in modeling plant species distributions (Dormann et al., 2007; Kissling and Carl, 2008; Wu and Huffer, 1997). However, few studies have integrated the ALR model into land use and in particular urban growth modeling (Jiang et al., 2015; Liu et al., 2015). Therefore, further studies are required to explore whether the integration of this model leads to better performance than other urban growth models and to establish whether it could be widely applied across geographical regions that have different driving factors.

Additionally, for the vast majority of urban growth models, the focus of interest is simply the changes of a single land use type (state) of developed land or settlements, in which case the minutiae of different settlement types (with different house and population densities for example) are thus far not represented in these models (Aburas et al., 2017; Barreira González et al., 2015; Wang et al., 2012). This kind of simplification might give rise to a number of serious problems. For example, the intensity of urban growth cannot be precisely measured because the population densities of various settlement types are not accounted for, and thus housing demand and/or supply are wrongly estimated (Heris, 2017). Also, the developmental preferences of 1-person, 2-person, and larger family households differ according to different settlement types, indicating that the driving factors might be distinct for the growth of each settlement type (Haase et al., 2010; Mustafa et al., 2018). However, few studies have considered the dynamics of the different settlement types (Lauf et al., 2012; Mustafa et al., 2018; Robinson et al., 2012; Zhang et al., 2011). Moreover, the importance and improvement of separately modeling different settlement types in urban growth models have rarely been discussed.

2.1.2 Urban Shrinkage Modeling

Although rapid urbanization currently dominates the scientific debate because they lead to significant changes in land use and environmental deterioration, it is noteworthy that urban shrinkage is another path of urban development which is spreading widely across the world (Haase et al., 2012a; Oswalt and Rieniets, 2006). As reported by Kabisch et al. (2006), urban growth has been replaced by the phase of shrinkage sine 1945 in many countries (as shown in Figure 2.1). In addition to population loss caused by aging population and population migration, the emergence of urban shrinkage may also be related to the interplay of macro-processes, such as the developments in economic, demographic or settlement systems, environmental hazards and changes in political or administrative systems, operating at a local level (Haase et al., 2014).

Figure 2.1 Shrinking cities with more than 100 000 inhabitants between 1950 and 2000 (Source: Office Oswalt and Rieniets, 2006).

Several of the most visible byproducts of urban shrinkage are vacant residential estates or industrial buildings, vacant land due to demolition and leaving spaces unused (Haase et al., 2012a), which offer an opportunity for the development and extension of green and open spaces that can improve environmental quality (Hollander et al., 2009) and provide recreational facilities for the residents (Haase et al., 2012a). Therefore, greening strategies are frequently discussed recently as one solution in planning literature that addresses the challenges brought about by urban shrinkage and brownfield management (Florentin, 2010; Frazier and Bagchi-Sen, 2015; Rall and Haase, 2011; Riley et al., 2017; Schilling and Logan, 2008).

For better understanding the temporal and spatial dynamics of urban shrinkage and its either positive or negative environmental impacts, quantitative studies, particularly more appreciate modeling approaches, are required to support sustainable urban management. However, the number of such applications is rare for urban shrinkage (Haase et al., 2012a). Only a few urban shrinking models have been developed recently due to a lack of empirical evidence except from rare examples and challenges for modelers in developing new approaches, indicator sets, and rule systems (Kabisch et al., 2006). For example, Haase et al. (2012a) simulated the urban shrinkage and its impacts on land use change in Leipzig using a loosely coupled System Dynamic-CA model and an Agent Based Model (ABM). Also, Lee and Newman (2017) predicted the urban decline in Chicago, USA with the land transformation model, an Artificial Neural Network (ANN) based land use change model, using vacant land as a proxy. However, due to lacking empirical evidence of urban shrinkage in the study region, common urban shrinkage models were not suitable (Lauf et al., 2012) and a specific model should be developed to address urban shrinking scenarios.

2.1.3 Scenario Based Urban Dynamic Modeling

Proposition and implementation of effective planning strategies for sustainable urban development require advanced understandings of the dynamic processes and possible future of urban systems (Haase et al., 2012a; Han et al., 2009). One way of investigating the potential future urban contexts is simulating and predicting urban dynamics. However, exclusively extrapolating from the historical trends of urban dynamics into the future may not provide sufficient information for planners to obtain an adequate view of the future scenarios that are possible. In particular, the changing of urban land use patterns is a complex process with uncertainties that are related to political and administrative decision-making processes, unforeseen economic circumstances or the emergence of new influential factors (Barreira González et al., 2015). Scenario simulation is a powerful tool for planning that addresses this uncertainty by providing plausible, descriptive narratives or pathways to the future, specifically when supported by visual outputs such as maps (Cowling et al., 2008; Larondelle et al., 2016). Such approach provides good information on future in which today's decisions might be played out (Verburg et al., 2006).

In combination with urban dynamic models and narratives of future scenarios or development alternatives, scenario-based modeling has become an attractive and practical approach for assessing and visualizing future urban contexts and contributing to the decision-making process to minimize and mitigate the harmful impacts (Sakieh et al., 2015). When applying this approach, it is important to keep in mind that scenarios need to be effectively translated into modeling language and must logically represent the uncertainties associated with probable futures. At the same time, engaging local and regional stakeholders in the process of scenario development plays an important role. Based on their local expertise, they could help to create, maintain and progressively improve the relevance, consistency, and usefulness of scenarios as planning tools (Reed et al., 2013).

There is a wide range of qualitative and quantitative participatory methods that have been used to engage stakeholders in scenarios development, for example, future workshops, multi-criteria evaluation, cooperative discourse, and so forth (Reed et al., 2013). However, the outcomes of scenario studies would be significantly affected by the choice of the involved stakeholders and the results might be biased without systematic and representative stakeholder selection (Prell et al., 2009). It has also been highlighted that the engagement of stakeholders should take place at the beginning of the scenario development process (Reed et al., 2013).

2.2 Urban Dynamics and Change of Landscape Patterns

2.2.1 Influencing Dimensions of Urban Dynamics

Urban dynamics have been extensively monitored and modeled in a growing body of literature (Barreira González et al., 2015; Berberoğlu et al., 2016; Luo and Wei, 2009; Sun et al., 2013; Tian et al., 2005). The primary purpose of these studies is to assess the potential environmental, social and economic impacts of urban dynamics, and thus aiming to find alternative approaches towards achieving more sustainable, and most importantly green, future development. Among these studies, three dimensions that influence the regional dynamics of an urban system have frequently been discussed: housing demand, urban spatial structure and urban growth form (Ewing and Hamidi, 2015; Garcia-López, 2012; Haase et al., 2013).

Housing Demand

One of the most critical driving forces of global environmental change is population growth, which has direct impacts on the consumption of natural resources and goods (Haase et al., 2013). Although urban growth is driven by many factors, including cultural, economic, social and demographic ones, in most cases the need to accommodate more residents is regarded as the main driver (Broitman and Koomen, 2015; Hennig et al., 2015). Typically, higher population growth rates are expected to lead to higher rates of urban growth (Seto et al., 2011). Apart from population growth, other processes that are related to demographic changes have also significant impacts on urban growth (Haase et al., 2013). For instance, it has also been reported that even when population sizes are stable or declining, a larger number of households will also intensify land consumption for housing, resulting in urban growth (Haase et al., 2013; Liu et al., 2003). Haase et al. (2013) further revealed that per capita living space is an invisible variable that also independently has an impact on land consumption for housing, and concluded that smaller households (1 or 2 person), on average, consume more urban land area per capita than larger ones. It is also indicated that the increasing per capita living space is mainly related to positive income development. Therefore, the housing demand, which is represented by the increased number of households rather than population growth, can directly affect the extent of urban growth and new land consumption around cities (Nuissl et al., 2009). The housing demand has a variety of ecological and environmental impacts and influences on the subsequent policies of land use, which is also reversely influenced by planning policies (Lee et al., 2016). Accordingly, it is of particular interest to urban and land use planners. However, the effects of household dynamics on green space, particularly the combined impacts with other influencing dimensions of urban dynamics, have not yet been explored.

Urban Spatial Structure

Although the term “Spatial Structure” has been defined by geographers in a number of ways, in all cases, it is viewed as “an abstract or generalized description of the distribution of phenomena in geographic space” (Horton and Reynolds, 1971). In the case of urban dynamics study, the formation of urban spatial structure can be viewed as a dynamic process during which urban activities are distributed through the development process into urban forms (Wu and Yeh, 1999). Among various urban spatial structure models, the polycentric model, which refers to urban systems with multiple functionally networked centers of residence, employment and services, has frequently been debated in planning as an alternative to the monocentric model, which is dominated by a central city (Meijers and Romein, 2003). Polycentricity has become a popular concept in spatial policies at a variety of spatial scales, which is acknowledged to be a pre-requisite for a possibly sustainable and balanced spatial pattern of urban development (Meijers and Romein, 2003; Salvati and De Rosa, 2014). For example, the concept of polycentric urban systems is one of the key principles of the European Spatial Development Perspective (ESDP), as it is considered to be more sustainable, more equitable and more capable of reducing the negative impacts of urban dispersion than the monocentric urban system (EEA, 2006; Shaw and Sykes, 2004). In fact, urban development over the past few decades has progressively moved from the standard monocentric pattern towards the polycentric pattern in most urban regions (Salvati and De Rosa, 2014). The emergence of polycentric development has been observed in both southern Europe (Garcia-López, 2012; Salvati, 2013) and developing countries (Schneider et al., 2015; Todes, 2012). Even though, the debate on the polycentric urban structure is continued and strongly intertwined with a broader discussion about whether cities should be seen as mere morphological entities with clear and detectable borders or as functional urban regions incorporating large areas around the central city (Vasanen, 2012). In addition, the impacts of the two urban spatial structure models have been studied in literature, including the consumption of land and energy (Salvati and Carlucci, 2014; Yin et al., 2015), air quality (Lefebre et al., 2007), landscape fragmentation (Liu and Wang, 2016), economic productivity (Li and Liu, 2018) and so on. However, their impacts on green space have rarely been investigated (Schneider et al., 2015).

Urban Growth Form

Different urban growth forms have been extensively debated in literature, among which the main focus was placed on the controversy between "sprawl" and "compact growth" that representing the two main schemes by which cities all over the world have evolved (Salvati and Gargiulo Morelli, 2014). According to Ewing (1997), sprawl was defined as forms of growth including leapfrog or scattered development, commercial strip development, or large expanses of low-density or single-use development. However, urban sprawl has been criticized as unsustainable for a number of reasons, including the non-efficient use of resources, e.g., land and energy (Haaland and van den Bosch, 2015), landscape fragmentation and losses of biodiversity (Dupras et al., 2016; Sushinsky et al., 2013; Troupin and Carmel, 2016), related environmental problems, such as increasing greenhouse gas emissions, urban water runoff, the urban heat island effect and urban air pollution (Haase and Nuissl, 2007; La Greca et al., 2011; Lee and French, 2009; Martins, 2012), and, last but not least, increasing social inequality (Frenkel and Israel, 2017). In addressing these issues, the concept of compact growth or the compact city, which is characterized by a high density and mixed-use urban development (Milder, 2012), has been extensively discussed as an alternative form to counteract these negative effects of urban sprawl and excessive land use. Nevertheless, compact growth also has its disadvantages, such as feelings of overcrowding, increasing levels of air pollution and heat stress, and traffic noise and traffic jams, resulting in a lower quality of life and a considerable lack of urban green and open spaces in increasingly dense urban areas and central city districts (Chen et al., 2008; Haaland and van den Bosch, 2015; Pauleit et al., 2005; Shi et al., 2016). So far, the debates on different urban growth forms and associated environmental impacts are mainly driven by theoretical reasoning, and the first necessary step would be the validation and comparison of different theories through empirical studies (Milder, 2012).

2.2.2 Assessment of Landscape Changes

One of the key topics of landscape ecology is to establish the correlation between spatial patterns and ecological processes (Wu and Hobbs, 2002), of which the first step is to quantify landscape patterns (Hulshoff, 1995). Quantifying the landscape pattern accurately in a region is essential for land use planning and resource management (Liu et al., 2016) that has attracted substantial attention from landscape ecologists (Turner, 2005). The features and changes of landscape patterns could be assessed by the combined use of land use maps and landscape metrics (Fan and Myint, 2014). Landscape metrics are algorithms that can be straightforwardly and quickly computed to quantify the spatial characteristics of landscape elements at different levels (patch, class, and landscape) using categorical land use maps (Weber et al., 2014b). They have become common tools in landscape pattern monitoring, assessment and planning since the 1990s (Peng et al., 2010), which can provide objective descriptions of different aspects of landscape structure and patterns (Plexida et al., 2014).

In recent years, the concept of ecosystem services has gained increasing attention, and landscapes are found to have many essential functions that provide various "goods and services" (Bolliger and Kienast, 2010; de Groot, 2006). The use of landscape metrics provides a possible approach to account for the landscape structures and related ecosystem services, which can give valuable information to improve the assessment of the ecological functioning (Frank et al., 2012). It is argued by Syrbe and Walz (2012) that landscape metrics can be used as measures of biodiversity and related ecosystem services. For example, landscape metrics have been successfully used as indicators for assessing landscape patterns and their impacts on biodiversity (Gimona et al., 2009), pollen distribution (Viaud et al., 2008), aesthetic value (Dramstad et al., 2006), and water quality (Uuemaa et al., 2005). Moreover, landscape metrics have also been broadly used in urban ecosystem studies to investigate, for instance, different urban structures (Liu and Yang, 2015), the process of urbanization (Yu and Ng, 2007), patterns of urban green space (Zhou and Wang, 2011), as well as urban environmental issues regarding urban air quality (Weber et al., 2014a), traffic-induced noise (Weber et al., 2014b), and urban surface temperature (Liu and Weng, 2008; Weber et al., 2014c).

However, it has been reported that many landscape metrics may be empirically redundant (Cushman et al., 2008). This is mainly because some of these metrics measure multiple aspects of landscape structure that might overlap with each other. Another possible reason is that the different structural aspects of the landscape under investigation are correlated. Therefore, there is still a need for further analysis on reducing such redundancy and selecting appropriate and effective landscape metrics for specific landscape studies.

2.3 Green Space Availability under Urban Dynamics

2.3.1 Functions of Green Spaces

As defined by Wu and Jackson (2017), green spaces refer to "land partly or completely covered with grass, trees, shrubs or other vegetation (e.g., parks, forests, green roofs, and community gardens)". Green spaces play a crucial role in the global ecosystem and particularly in the urban ecosystems where they are considered as a remedy to urban environmental problems (Xu et al., 2016). By supporting biodiversity and providing various ecosystem services, green spaces can mitigate the negative impacts of urbanization and improve the quality of life of urban residents, which are seen as a fundamental part of sustainable urban development (Chiesura, 2004; Jim, 2004). The environmental and social services of green spaces that contribute to the quality of life have been well acknowledged by a number of research studies (Kabisch and Haase, 2014). Vital environmental services provided by green spaces include, among others, air purification (Jim and Chen, 2008; Tallis et al., 2011), temperature mitigation (Gill et al., 2007; Rahman et al., 2017; Sun and Chen, 2017), noise reduction (Margaritis and Kang, 2017), carbon storage (Strohbach and Haase, 2012), flood regulation (Gittleman et al., 2017; Zölch et al., 2017; Zhang et al., 2015), and biodiversity conservation (Nielsen et al., 2014). Meanwhile, the valuable social services involve the provision of recreational service (He et al., 2016), mental and physical health improvement (Coppel and Wüstemann, 2017; Maas et al., 2006), fostering the social interaction and integration by offering meeting places for local residents (Bijker and Sijtsma, 2017; Peschardt et al., 2012), potentially improving the population's sense of safety (Branas et al., 2011; Kuo et al., 1998), and alike. Because of the vital services it can provide, green space is also increasingly considered as 'green infrastructure,' which is just as important for cities and city regions as social and technical infrastructure (Pauleit et al., 2017).

However, the ecosystem services provided by green spaces are often overlooked and undervalued, and thus a considerable loss of green and open spaces can still be found in most urban areas due to the increasing pressure of urbanization and densification processes (Gill et al., 2007). In view of this situation, on the one hand, targeted or threshold values for green space provision had been developed in Europe, at national and subnational levels (Wüstemann et al., 2016). For example, the targeted values of the per capita provision of public green space vary between 6 and 15 m^2 among different German cities (Deutscher Rat für Landespflege, 2006). In addition to the amount of provision, the accessibility of green space, which is often defined as distance or proximity from residents' home to green space (Koppen et al., 2014), is another key factor that influences the frequent use of green space and improves the well-being among its users (Barbosa et al., 2007; Gupta et al., 2016). It is regarded to be particularly critical for the recreational use of green space (Handley et al., 2003). Therefore, it is suggested by Handley et al. (2003) that a minimum of 2 ha natural green space should be accessible within 300 m distances for all residents in the UK. On the other hand, some studies and policies aim to improve the green infrastructure's multifunctionality which can perform multiple environmental, social and economic functions and provide multiple ecosystem services on the same spatial area (European Commission, 2012; Hansen et al., 2017a; Hansen and Pauleit, 2014; Meerow and Newell, 2017). For example, different ways of connecting green spaces, biodiversity, people and the green economy were identified, developed and tested in the GREEN SURGE project that is funded by the European Union's Seventh Framework Programme (Hansen et al., 2015, 2017b).

2.3.2 Impacts of Urban Dynamics on Green Space Availability

The dynamic process of urban development has extensive influences on the availability of green spaces (Zhao et al., 2013). As urban growth forms are the central concepts in today's debate regarding urban dynamics, the majority of recent studies have only focused on the impacts of different urban growth forms on the availability and distribution of urban green space. For instance, McDonald et al. (2010) examined the loss of open space (including agricultural land, forest, grassland and additional more natural land-cover) between 1990 and 2000 for all 274 metropolitan areas in the US, and indicated that 1.4 million hectares of open space were lost due to urban expansion. Another study conducted in the Chinese city of Kunming by Zhou and Wang (2011) also found that rapid expansion of built-up areas caused a considerable loss of green spaces and a more fragmented landscape, especially in the city's outer belt. On the other hand, several other studies have indicated that compact urban growth could lead to a general loss of urban green spaces in residential areas as well. Fuller and Gaston (2009) reported that green space coverage declined mildly as population density increased, and compact cities showed very low per capita green space across 386 cities in Europe. Similar results were also found in another study by Lin et al. (2015), who explored the potential loss of green spaces with urban densification in Sydney and highlighted that the area of green spaces, including public parkland and residential tree cover, decreased as urban areas become more densely populated.

Although it is reported by Tan et al. (2013) and Zhao et al. (2013) that public green space increased during urban growth in some instances, which is mainly related to the overall increase in the total city area and to the implementation of greening policies. Without effective greening policies, it is very likely that urban sprawl will pose enormous threats to green spaces in the countryside, while compact growth will lead to a reduction of urban green spaces within urban areas (Nuissl et al., 2009). In other words, some green spaces are always lost during urban growth, no matter which growth form has been adopted (Zhao et al., 2013). However, relevant studies have so far mainly focused on either sprawling or compact growth, while comparative studies that consider the impact of both urban growth forms on green space availability are rare. A few studies have compared the consequences of compact and sprawling development on landscape pattern, landscape connectivity and biodiversity (Park et al., 2014; Sushinsky et al., 2013; Troupin and Carmel, 2016), rather than the availability of green spaces. Moreover, previous studies have mainly been carried out at the city level, and lack a systematic analysis of the impacts of different development trends and urban dynamics on the availability of green spaces at the regional level.

2.4 Green Space Equity under Urban Dynamics

2.4.1 Definition of Green Space Equity

At present, efficiently managing and planning green spaces face great challenges in the case of increasing pressure that related to rapid urbanization, diversification of the society, and up-and-coming city densification (Shan, 2014). Given the link between green spaces and the welfare benefits for residents, endeavoring to provide residents with adequate and equitable access to green spaces across the population has been increasingly recognized as an important issue for urban planners, which is also due to growing concerns related to environmental justice (Dony et al., 2015; Kabisch and Haase, 2014; Wolch et al., 2014). Traditionally, the primary focus of environmental justice refers to the distribution of toxic-emitting facilities, waste dumps, and other environmental hazards that are disproportionately located near socially disadvantaged groups, while recent studies have expanded the scope of this conception by including issues such as equitable access to green spaces and other natural resources (Boone et al., 2009; Davis et al., 2012; Jennings et al., 2012). However, the green spaces are rarely evenly distributed across space within most cities, which correspondingly results in the disproportionate provision of green spaces to different subsets of urban population (Kabisch and Haase, 2014; Li and Liu, 2016; McConnachie and Shackleton, 2010). For example, Wüstemann et al. (2017) identified inequalities in green space provision across major German cities that related to income, age, education and children in the household. Also, You (2016) reported that the provision of public green spaces declined with district disadvantage degrees and the accessibility for socioeconomically disadvantaged districts were more restricted in Shenzhen, China.

To enhance the benefits of green spaces for urban residents, relevant researches on green space equity and its variations over space has been drawing increasing attention from scholars and governors (Li and Liu, 2016). An increasing amount of literature has been contributing to the research on green space equity. The majority of these studies have mainly focused on associating the spatial disparities of green space provision or accessibility with different social groups based on socioeconomic status (Barbosa et al., 2007; Kimpton, 2017), racial/ethnic or religious characteristics (Comber et al., 2008), migration background (Schüle et al., 2017), age (Shen et al., 2017), (dis)ability (Byrne et al., 2009; You, 2016), population density (Xiao et al., 2017) and other axes of difference. For example, Li and Liu (2016) analyzed the relationships between neighborhood socioeconomic disadvantage and public green space availability and accessibility at the district level in Shanghai, China and highlighted that the abundance and accessibility were lower in districts with higher levels of neighborhood socioeconomic disadvantage. Similar findings have also been reported by a number of other case studies (Dai, 2011; McConnachie and Shackleton, 2010; Pham et al., 2012; Schüle et al., 2017; Shanahan et al., 2014; You, 2016). Significant positive relationships have been reported between population density and the provision or accessibility of urban green spaces (Chen and Hu, 2015; Ngom et al., 2016). Moreover, it has also been highlighted that areas with larger proportions of elderly or deprived (unemployed) population tend to have more access to public green spaces (Barbosa et al., 2007; Xiao et al., 2017). However, contrasting findings have been reported by Shen et al. (2017), who disclosed that low public green space access were found in sub-districts with high level of aged or unemployed population in a case study in Shanghai, China.

The other strand of literature identifies, characterizes and compares the degree of green space equity among different resident groups within a city (Kabisch and Haase, 2014) or different cities at the national level (Wüstemann et al., 2017) by employing equality indicators. Among a number of existing indices which measure an unequal distribution, the Gini coefficient has gained a broad application in different fields. The Gini coefficient is prevalent in economics to measure inequality of income distribution (Molero-Simarro, 2017), which has also been applied to assess inequality of sustainable urban development (Li et al., 2009), biodiversity (Barr et al., 2011), carbon dioxide emissions (Chen et al., 2016a), and also in the context of green space provision. For example, Kabisch and Haase (2014) and Xing et al. (2018) explored the inequality of green space distribution for different resident groups by applying the Gini coefficient in the cities of Berlin, Germany and Wuhan, China, respectively. In addition, Yao et al. (2014) analyzed the inequality of urban green space distribution across the urban area in Beijing, China, while Wüstemann et al. (2017) compared the inequalities in green space provision across German major cities. Compared to other studies which focus on the spatial disparities of green space provision (Kimpton, 2017; Li and Liu, 2016), applying the Gini coefficient is a simple way to get an overview of the overall degree of inequality (Kabisch and Haase, 2014), particularly when attempting to associate the spatial inequality with other socioeconomic variables in a quantitative way. However, the complexity of how the green space equity varies along spatial or socioeconomic gradient has been somehow limited (Wei, 2017). Thus, a knowledge gap still exists regarding the spatial relationship between the green space equity of different spatial units (e.g., districts or municipalities) and their socioeconomic characteristics.

2.4.2 Impact of Urban Dynamic Process on Green Space Equity

The recent research tends to focus on the assessment of the status quo or the historical changes of green space equity. For example, Wei (2017) comparatively evaluated the park accessibility across the 41 sub-districts in Hangzhou, China of the years 2000 and 2010, and highlighted that significant spatial inequality in terms of park access was found among socioeconomic groups. The overall accessibility of parks had improved from 2000 to 2010, yet changes in spatial inequalities of park access had not been detected.

As underlined in the literature, the dynamic processes of urban development have extensive influence on green space availability and distribution (Dallimer et al., 2011; Qian et al., 2015; Zhao et al., 2013). Consequently, green space equity will also be affected by the process of urban dynamics. However, the process analysis which provides a fuller understanding of the impacts of urban dynamics on green space equity is still rare (Wei, 2017). Particularly, it offers a useful tool to assess the impacts of proposed policies or planning strategies on green space equity when associated with different scenarios. As a recent global phenomenon, the ongoing urbanization presents a challenge to urban planning which, in turn, offers great opportunities for sustainable urban management to incorporate the improvement of life quality through equitable provision of green spaces (Kabisch and Haase, 2014). In practice, the causes of the unequal distribution of green spaces may differ from place to place, but optimizing the provision and accessibility and reducing the spatial and social inequality should be primary goals of green space planning (Wei, 2017). Bearing this in mind, understanding the impacts of different urban dynamics on green space equity enables the assessment of current policies and offers useful reference and guidance for green space planning. It is also crucial for policymakers and planners in providing appropriate services, supports and opportunities for local residents (Wei, 2017).

2.5 Overview of the Analytical Framework

Based on the literature review, relevant research gaps or questions and the methods that are used to address them are shown in Figure 2.2. In **Part I**, the spatial modeling approach was developed. For this purpose, the Spatial Autocorrelation (SAC) in the pattern of settlement growth was examined by Moran's *I* coefficient and the Local Indicators of Spatial Association (LISA) analysis. Autologistic Regression (ALR) was incorporated in the model to correct the impact of the SAC. Moreover, the growth of both high- and low-density settlements was modeled separately. Multiple scenarios that account for different influencing dimensions of urban dynamics were developed through a focus group meeting with stakeholders in **Part II**. Then, a set of landscape metrics were employed to comparatively quantify the modeled landscape patterns under different scenarios, before which the redundancy among these landscape metrics was tested and reduced. **Part III** explored how green space availability varies across different scenarios using regression analysis. In addition, the impacts of different urban dynamic scenarios on green space availability were comparatively assessed at both the regional and sub-regional levels by using two indicators. In **Part IV**, the pattern of green space equity at the municipal level was characterized by the Gini coefficient and its spatial relationship with socioeconomic variables was investigated using a Geographically Weighted Regression (GWR). Meanwhile, the impacts of different urban dynamic scenarios on green space equity were comparatively studied at both levels.

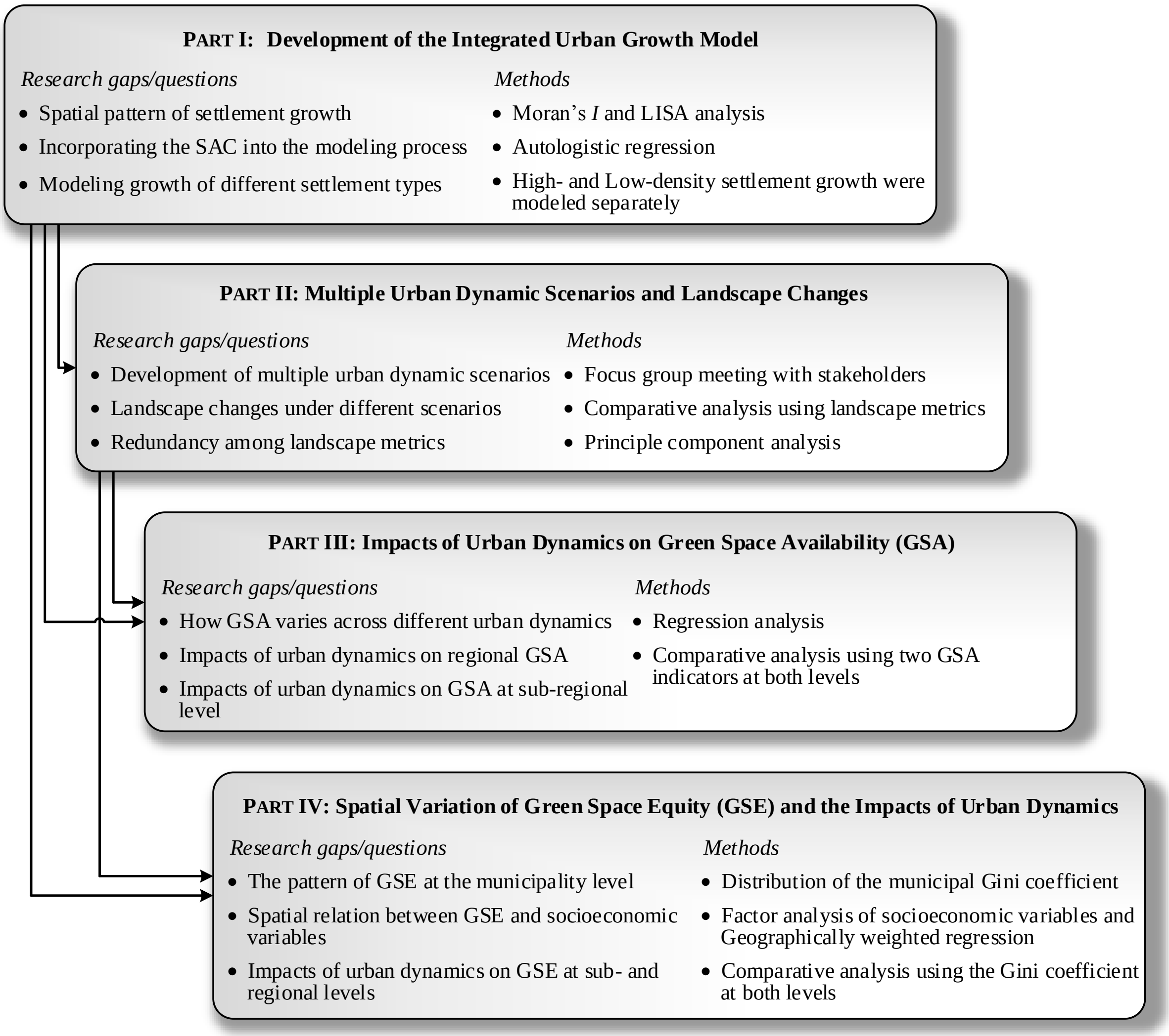

Figure 2.2 Overview of the analytical framework of the thesis.

Chapter 3

Methods

3.1 Study Area and Workflow

The study area is located in Bavaria, Southern Germany, between 47°49′–48°37′N and 10°45′–12°16′E (Figure 3.1). According to the Bavarian state development scheme, the region of Munich (also called Planning Region 14), composed of the city of Munich and 186 municipalities in eight administrative districts (in German "Landkreise"), is one of the 18 planning regions in Bavaria. It extends over 5,500 km^2 and is home to around 2.85 million inhabitants by the end of 2015 (Bavarian State Office for Statistics). This region is regarded as one of the fastest growing and most economically competitive regions in Europe. As the major city of this region and the capital of the Bavarian state, the city of Munich is the third largest, and one of the most populous, cities in Germany, with approximately 1.45 million residents in 2015 and an average population density of approximately 4,668 inhabitants per km^2 (Bavarian State Office for Statistics, 2015).

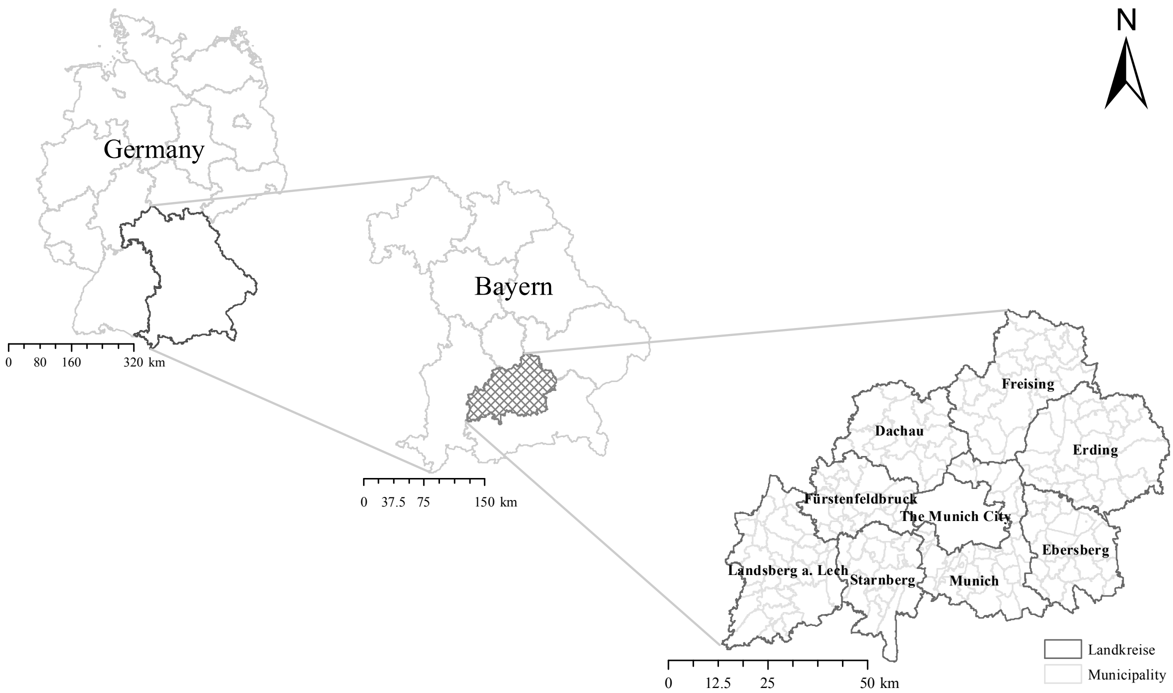

Figure 3.1 Location of the region of Munich.

The region of Munich has been experiencing steady population growth with an average annual population growth rate of approximately 1.0% over the past decade. As a result, a series of problems have emerged, including the loss of natural resources, intensification of land use, and threats to the quality of life (Schaller and Mattos, 2010). However, this trend can be expected to continue, as it is projected by the Bavarian State Office for Statistics that the population will continuously increase, to almost 3.2 million by 2034. This will inevitably contribute to urban growth not only near the city of Munich but also throughout the region. Accordingly, the problems that caused by population and urban growth might be exacerbated in the future unless active and effective urban planning and management strategies being developed and implemented. Therefore, a comprehensive study of urban dynamics in the whole region is important for decision-makers and planners to mitigate its negative impacts on both humans and ecosystems. In addition to urban growth, other possible urban development pathways such as urban shrinkage that generates a number of vacant lands and brownfields were also involved by introducing multiple urban dynamic scenarios.

In this region, the present urban spatial structure clearly follows a monocentric model with the city of Munich at its center (Goebel et al., 2007). The city of Munich is located in the center of this region and is defined as the regional center in the regional plan (RPV, 2005). However, this region has polycentric development potential due to the presence of several subcenters, as shown in Figure 3.2, which are identified with high urban development potentials in the regional plan.

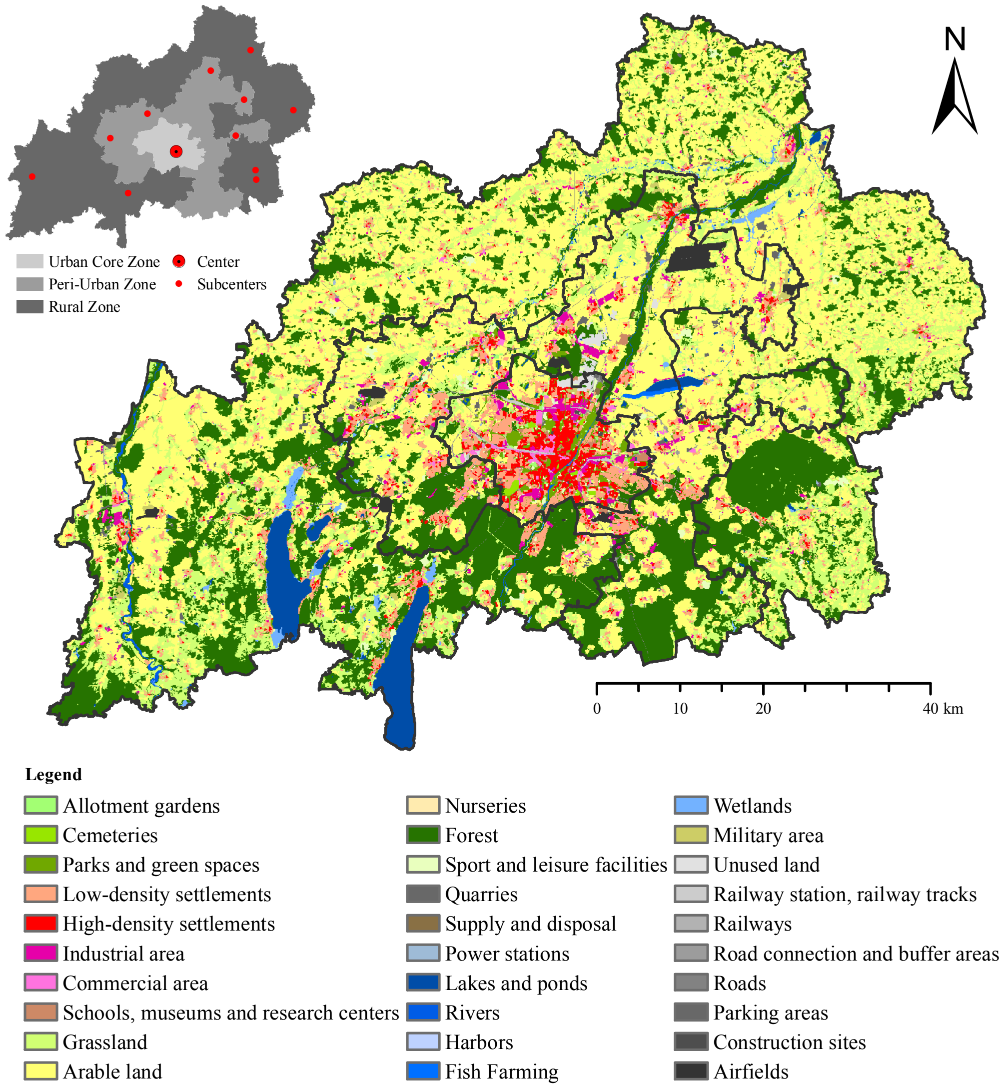

Figure 3.2 Land use and land cover map of 2013.

Regional land use and land cover data for the years 2003 and 2013 have been derived from the Landscape Development Atlas of the Munich Region (LEK 14) and Digital Orthophotos data (DOP) from Bavarian State Office for Digitizing, Broadband and Survey. A total number of thirty land use classes were classified into vector maps based on visual interpretation of the high-resolution aerial photography, which offers much more detailed information of the distribution and changes of different land uses (Figure 3.2). The settlement areas were classified into high-density settlements, such as multistory housing and multistory blocks, and low-density settlements, such as row housing, single-family housing and detached houses. For urban growth modeling and further analysis, the original vector land use maps were converted to the raster format with a grid size of $30m \times 30m$ in ArcGIS 10.3.

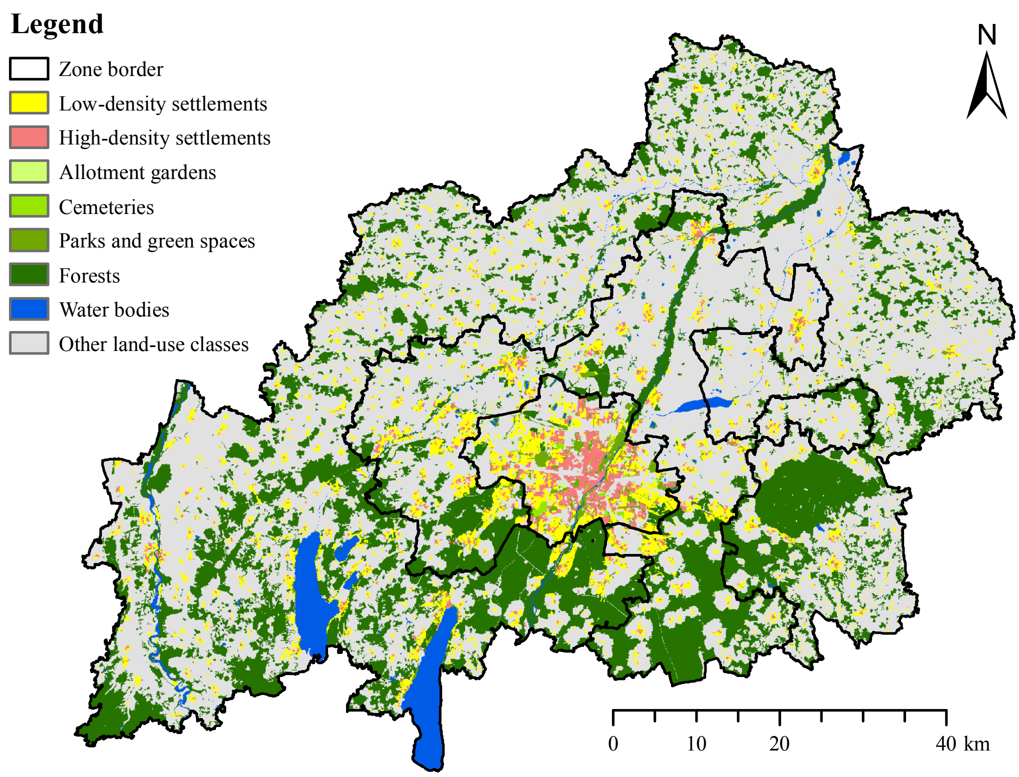

Figure 3.3 Spatial distribution of green spaces in 2013.

The regional distribution of green spaces of the year 2013 is shown in Figure 3.3. This study focuses on four key land use categories that related to green spaces, including "parks and green spaces", "allotment gardens", "cemeteries" and "forests". Other land use categories which could potentially serve as green spaces were excluded from analysis because of either low recreational value (e.g., "arable land", "grassland" and "wetland") or low vegetation coverage and a lack of public accessibility (e.g. "sports and leisure facilities") (Kabisch et al., 2016). In the Urban Core Zone, the main types of green space are large parks, as well as the continuous greenbelt along the Isar River, which runs from south to north across the region. It is evident from Figure 3.3 that more green spaces are available in the Peri-Urban and Rural Zones. Compared to the northern part of this region, relatively more green spaces exist in the southern part as the forests in the southern region are protected based on their special environmental functions and for recreation. Protected green spaces, such as nature reserves, natural monuments, protected landscape areas and elements, were excluded when modeling urban growth. All datasets used in this study are listed in Table 3.1.

Table 3.1 Summary of datasets used in this study.

Data	Scale	Reference year/period	Source
Population number	Municipality level	2003 –2013	Bavarian State Office for Statistics
Population projection	Regional level	2014 –2033	
Household structure data	Regional level	2003 –2013	
Residential building data	Municipality level	2003, 2013	
Residential land price	Municipality level	2013	Planning Association of Greater Munich (PV), Real estate market data (IMV GmbH)
Land use maps	Regional level	2003	Landscape Development Atlas of the Munich Region (LEK 14)
	Regional level	2013	Digital Orthophotos data (DOP) from Bavarian State Office for Digitizing, Broadband and Survey
Transportation network map	Regional level	2004	Landscape Development Atlas of the Munich Region (LEK 14)
Constraint maps (including nature reserves map, flooding risk map, habitat maps, etc.)[a]	Regional level	2003, 2004, 2005	Landscape Development Atlas of the Munich Region (LEK 14)
Digital elevation model	Regional level	2003	The United States Geological Survey

[a] see Appendix A.

The systematic workflow of this study is shown in Figure 3.4. The integrated model that was proposed in **Part I** incorporates three sub-models including the Autologistic Regression (ALR), Markov Chain (MC), and Cellular Automata (CA). Various model evaluation methods were used to assess the performance of the integrated model. In **Part II**, the multiple urban dynamic scenarios were first developed in consideration of the three dimensions that influence the processes of urban dynamics, including housing demand, urban spatial structure, and urban growth form. Then, the land use changes under different scenarios were modeled and the landscape patterns were characterized and quantified by a set of landscape metrics. In addition, the redundancy among those landscape metrics was tested and reduced using the Principal Component Analysis (PCA). **Part III** assessed the impacts of different urban dynamic scenarios on green space availability by using two indicators. In **Part IV**, the Gini coefficient was employed to evaluate the spatial equity of green space distribution. Factor analysis was utilized to reduce the redundancy of the socioeconomic variables and to facilitate the interpretation of the resulting factors. In addition, the spatial relationship between green space equity and socioeconomic factors was explored using a Geographically Weighted Regression (GWR). More details are given in the following sub-sections.

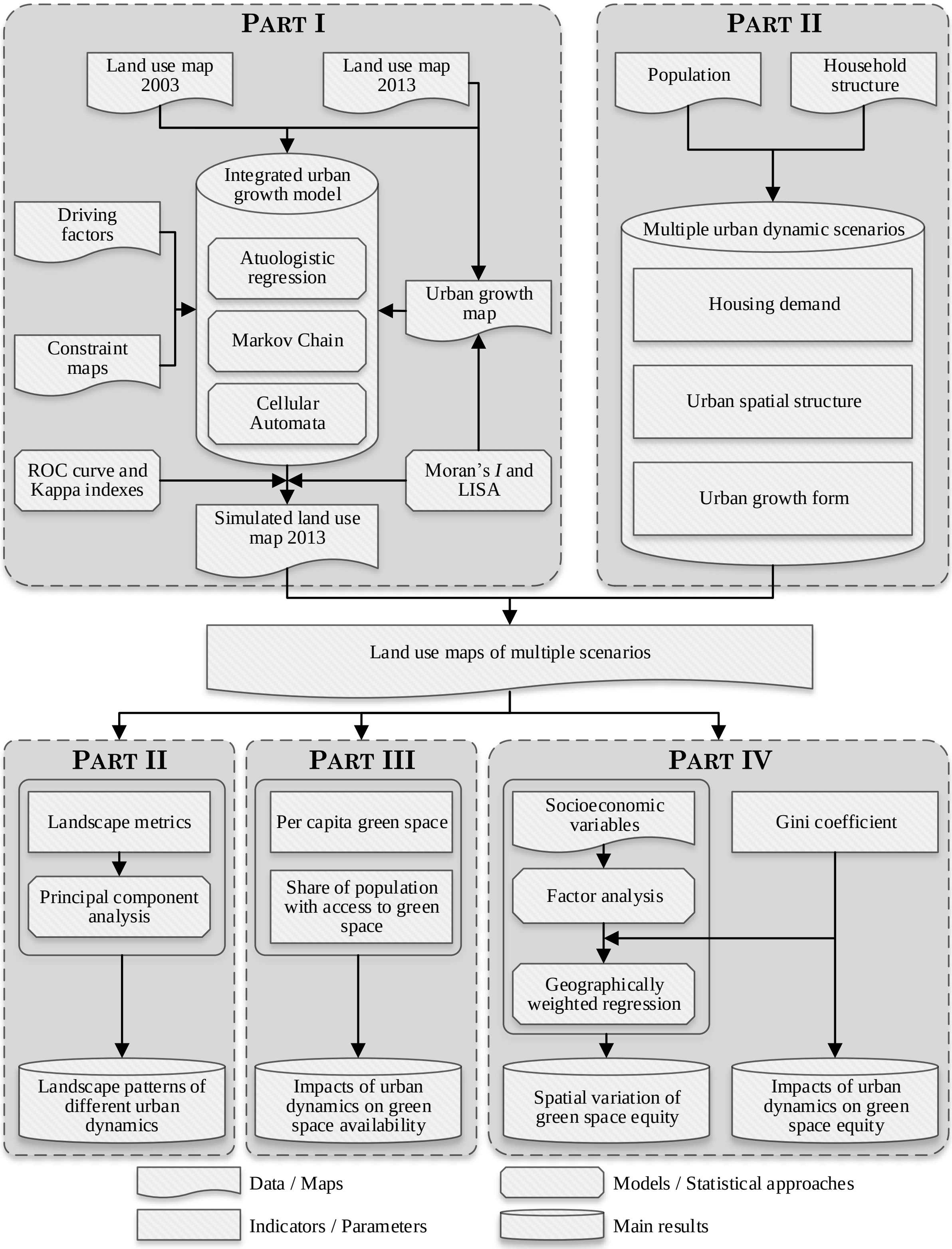

Figure 3.4 Overview of the systematic workflow of this study.

3.2 Development of the Integrated Urban Growth Model (Part I)

The focus of this part is modeling the urban growth that is mainly dominated by the settlement growth for housing and infrastructure. Therefore, the original land-use maps were further reclassified into high-density settlements (such as multistory housing and multistory blocks), low-density settlements (such as row housing, single-family housing and detached houses), and non-settlements. Then, the reclassified vector land use maps were converted to the raster format with a grid size of $30m \times 30m$. In this part, the Spatial Autocorrelation (SAC) in the pattern of historical settlement growth was assessed and a set of potential driving factors of urban growth were collected. To correct the impact of the SAC, an integrated urban growth model was built by incorporating the Autologistic Regression (ALR) with an Markov Chain (MC) based Cellular Automata (CA) model. The modeling accuracy was evaluated by two different approaches. The spatial analysis processes were conducted in ArcGIS 10.3.

3.2.1 Assessing Spatial Autocorrelation

Two techniques were employed for detecting the SAC in the pattern of settlement growth and the residuals of regression models. The first one is the global Moran's I coefficient, which is very commonly used as a global parameter for the assessment of SAC. Second, the Local Indicators of Spatial Association (LISA) analysis can provide more detailed insights into spatial dependency with the neighboring samples (Anselin, 1995; Moran, 1948). The value of Moran's I varies from -1.0 and 1.0. Positive autocorrelation in the data leads to positive values and negative autocorrelation results in negative values. As suggested by Glazier et al. (2004), the absolute value of Moran's I more than 0.2 indicates that significant SAC occurred. In addition to the original data, SAC can also be found in the residuals of a regression model (Overmars et al., 2003). In this study, the SAC in the patterns of settlement growth was analyzed by the global Moran's I at various lag distances, while both indicators (the global Moran's I and the LISA) were used to measure the SAC in the residuals of regression models.

3.2.2 Collecting Potential Driving Factors

Before constructing the model, factors that might impact the process of settlement growth were collected according to the local characteristics of the study area, the nature of the models, and the purpose of the research (Ku, 2016). A number of 17 potential driving factors of urban growth were collected (Table 3.2) and resampled into $30m \times 30m$ grid layers (as shown in Appendix B). Following Barredo et al. (2003), these driving factors could be organized into four groups, including 1) Environmental factors, 2) Local-scale neighborhood factors, 3) Spatial characteristic factors, and 4) Socioeconomic factors. All factors that generated as grid maps were then converted into continuous explanatory variables to be used in the regression analysis.

Table 3.2 List of driving factors used in this study.

Driving factors	Abbreviation	Description
Environmental factors		
Slope	SLP	Slope in degrees
Distance to water	DisWT	Euclidean distance in Meters
Distance to green spaces[a]	DisGS	Same as above
Local-scale neighborhood factors		
Neighborhood	NBH	Number of settlement cells in a 5 × 5 cell neighborhood (i.e., the neighborhood size normally used in the CA model)
Spatial characteristics factors		
Distance to the S-bahn (suburban train) station	DisSB	Euclidean distance in Meters
Distance to the U-bahn (metro) station	DisUB	Same as above
Distance to the main center	DisMC	Same as above
Distance to the subcenters	DisSC	Same as above
Distance to the settlement centers	DisSTC	Same as above
Distance to the commercial area	DisCA	Same as above
Distance to the industrial area	DisIA	Same as above
Distance to the highway	DisHW	Same as above
Distance to the major road	DisMR	Same as above
Distance to the local road	DisLR	Same as above
Distance to the urban edge	DisUE	Same as above
Socioeconomic factors		
Population density[b]	PPD	Population per km^2 for each Municipality
Residential land price[b]	RLP	Euro per m^2 of ground for each Municipality

[a] It includes the land use classes of ”parks and green spaces”, ”allotment gardens”, ”cemeteries” and ”forests”. Other land use categories were excluded because of either low recreational value (e.g., ”arable land” and ”grassland”) or low vegetation coverage and a lack of public accessibility (such as ”sports and leisure facilities”).

[b] collected at the municipal level and limited by data availability.

The multicollinearity of independent variables should be pre-tested in regression models. Otherwise, it can inflate the variances of coefficient estimates and potentially lead to misleading results regarding the effect of any individual predictor in the model (Dormann et al., 2013). The Tolerance (TOL) and the Variance Inflation Factor (VIF) were calculated among the independent variables to eliminate multicollinearity. According to Ozdemir (2011), variables with $VIF > 10$ and $TOL < 0.1$ that indicate a severe multicollinearity were excluded from the regression analysis.

3.2.3 Framework of the Integrated Models

Figure 3.5 shows the framework of the integrated models developed in this study. Land use maps from 2003 and 2013 were overlaid to obtain an urban growth map that was then used as the dependent variable in the Autologistic Regression (ALR) or Ordinary Logistic Regression (OLR) model and as input data for the Markov Chain (MC) analysis. The regression produced local transition probabilities (i.e., the probability value of a cell for being transformed into settlements) where some areas were excluded due to the constraint map (i.e., land development restriction). Then, it was combined with a transition probability matrix from MC (i.e., the probability of each land use type changed into urban settlement) to generate a transition probability map. Furthermore, by considering the transition area matrix (i.e., the number of cells of each land use type that are expected to be changed into settlements over the study period) from the MC, the Cellular Automata (CA) simulation was run to obtain a map of urban growth prediction. For the purpose of testing the improvement caused by the ALR approach, the ALR-MC-based CA model (the ALR-MC-CA model) was compared with another integrated model based on the OLR (the OLR-MC-CA model). The detailed algorithm of each model in the framework is explained at the following sections.

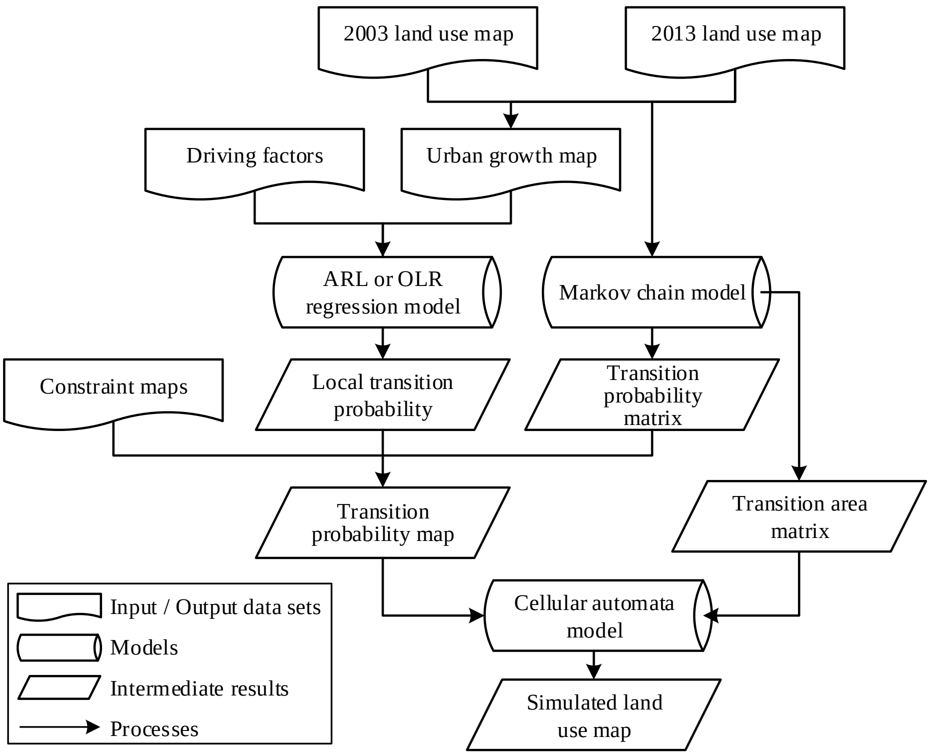

Figure 3.5 Framework of the integrated models.

Logistic and Autologistic Regression

In different urban growth or land use change models, the OLR has been quite commonly used as an empirical approach to estimate the weights of the driving factors. In an OLR model, the predicted dependent variable is calculated as the transition probability using the following equation:

$$log(\frac{p_i}{1-p_i}) = \alpha + \beta_1 x_{1,i} + \cdots + \beta_n x_{n,i} \qquad \text{(Eq. 3.1)}$$

where p_i (ranged from 0 to 1) is the transition probability of the dependent variable y_i ($y_i = 1$ indicates the transition to settlements of grid cell i and $y_i = 0$, otherwise). α is a constant to be estimated and β is a vector of the estimated coefficient for each independent variable x.

Compared to OLR, the ALR model introduces an autocovariate variable as an independent variable into the regression process to correct the impact of SAC (Augustin et al., 1996). The model is defined as:

$$log(\frac{p_i}{1-p_i}) = \alpha + \beta_1 cov_1 + \cdots + \beta_n cov_n + \beta_{n+1} autocov_i \qquad \text{(Eq. 3.2)}$$

The autocovariate at grid cell i is determined as follows:

$$autocov_i = \sum_{j \in N_i} w_{ij} y_i \qquad \text{(Eq. 3.3)}$$

where N_i is the defined neighborhood matrix for cell i, w_{ij} is the inverse of the Euclidean distance between i and its neighboor j and y_j is the presence or absence of the transition at grid cell j.

However, because the observations y_j are conditionally dependent on one another, an analytical form of the maximum likelihood is intractable. Therefore, the Markov Chain Monte Carlo (MCMC) method was applied for estimating the parameters of the ALR model (Huffer and Wu, 1998). The processes of statistical analysis were performed in R (R Core Team, 2017), and the MCMC estimation was performed in R using the MCMCpack package (Martin et al., 2011).

Defining Neighborhood Matrix for ALR

According to the Eq. 3.3, the ALR model incorporates the spatial dependency into the regression process by including an autocovariate variable that is determined by the neighborhood matrix N_i. The definition of N_i should consider the spatial lag to the extent that the independent variable is strongly autocorrelated. Different from Ku (2016) who simply applied the Euclidian distance weighted matrix to define the spatial dependency, I preferred to use the approach of Naves et al. (2003) where a correlation coefficient c_r was calculated to describe the autocorrelation of the dependent variable y with spatial lag r (Figure 3.6). The spatial lag that showed a strong correlation ($c_r > 0.7$) was defined as the neighborhood matrix for calculating the autocovariate variable in the ALR (Aguayo et al., 2007; Naves et al., 2003). The results show that the neighborhood matrices for all settlement growth, high-density settlement growth and low-density settlement growth were 9 × 9 cells, 11 × 11 cells and 7 × 7 cells, respectively.

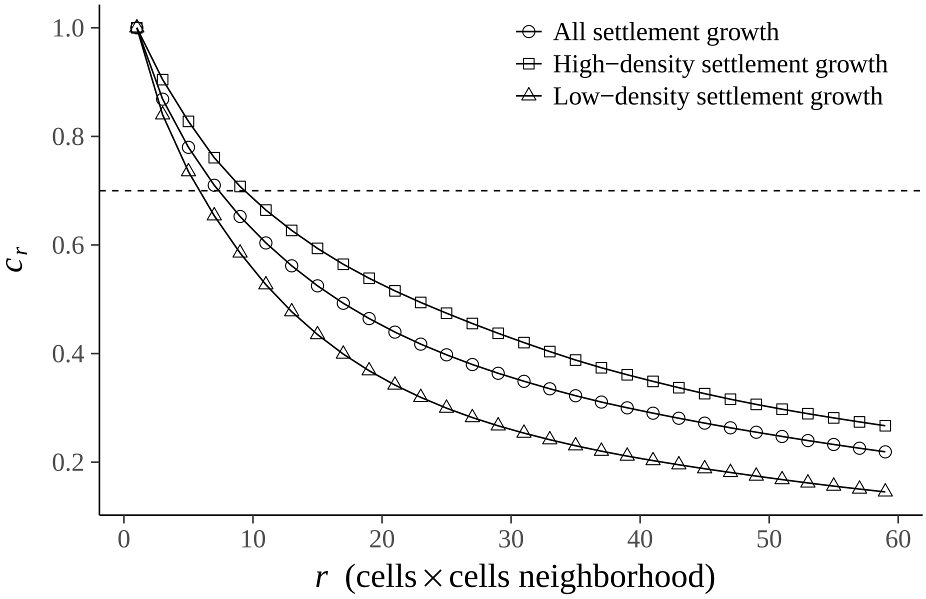

Figure 3.6 Correlation of the dependent variable y with spatial lags.

Markov Chain Model

The MC is defined as a stochastic process that describes the elements of a system transforming from one state to another at each time step (Balzter, 2000). In MC models, it is assumed that the probability distribution of future land use state is based on the current state and the transition between the last two periods (Guan et al., 2011). The output of the MC model is the transition probability matrix that records the probability of transition from each land use class to others in different temporal periods. It is described as follows:

$$P = (p_{ij}) = \begin{bmatrix} p_{11} & \cdots & p_{1n} \\ \vdots & \ddots & \vdots \\ p_{n1} & \cdots & p_{nn} \end{bmatrix}; 0 \leq p_{ij} < 1; \sum_{i=1}^{n} p_{ij} = 1 \quad \text{(Eq. 3.4)}$$

where p_{ij} is the probability of land use i changing to land use j calculated for each grid cell and n is the number of land use classes. The transition area matrix that represents the land use demands (A_{pn}) in the target year of simulation can be defined by multiplying the matrix with the total area of each land use class (A_1 - A_n) (Ku, 2016), as shown in Eq. 3.5.

$$\begin{bmatrix} p_{11} & \cdots & p_{1n} \\ \vdots & \ddots & \vdots \\ p_{n1} & \cdots & p_{nn} \end{bmatrix} \begin{bmatrix} A_1 \\ \vdots \\ A_n \end{bmatrix} = \begin{bmatrix} A_{p1} \\ \vdots \\ A_{pn} \end{bmatrix} \tag{Eq. 3.5}$$

Cellular Automata Model

The CA models have been broadly applied to simulate urban growth patterns and land use changes. Generally, CA models define the new state of land use for each cell according to the state of the cell and the developmental situation of its neighboring cells in agreement with a set of transition rules (Sathish Kumar et al., 2013; Wu and Webster, 1998). It is represented by:

$$S_{ij}^{t+1} = f(S_{ij}^t, \Omega_{ij}^t, T^t) \tag{Eq. 3.6}$$

where S_{ij}^{t+1} and S_{ij}^t are the states of the cell at location ij (i.e., latitude i and longitude j) at time $t+1$ and t, respectively. Ω_{ij}^t is the development situation in the neighborhood space of cells ij, and T^t is a set of transition rules. Furthermore, in the case of the non-deterministic CA, the state at time $t+1$ becomes:

$$S_{ij}^{t+1} = f(P_{ijs}^t, T^t) \tag{Eq. 3.7}$$

where P_{ijs}^t is the probability of transition to the state s for cell ij.

Model Integration

In this study, the models were integrated by the following equation:

$$P_{ijk} = (P_l)_{ij} \cdot (P_{MC})_{ijk} \cdot (\prod_{r=1}^{m} C_{ijr}) \cdot (P_\Omega)_{ij} \tag{Eq. 3.8}$$

where P_{ijk} is the transition probability of cell ij (i.e., latitude i and longitude j) from land use k to settlements. $(P_l)_{ij}$ is the local transition probability of cell ij, which is determined through a set of driving factors using regression models. $(P_{MC})_{ijk}$ is the transition probability matrix calculated by MC analysis and represents the probability of land use k changing to settlements for cell ij. C_{ijr} is a list of constraint factors that take a binary value of 0 or 1 which represents an absolute restriction or not. $(P_{\Omega})_{ij}$ is the neighborhood effect for cell ij which is defined as follows (Wu, 2002):

$$(P_{\Omega})_{ij} = \frac{\sum con(S_{ij}^{t} = Settlement)}{n \times n - 1} \qquad \text{(Eq. 3.9)}$$

where $con(S_{ij}^{t} = Settlement)$ represents the number of settlement cells within the $n \times n$ neighborhood filter. Then, the CA model was performed at the last step by using the IDRISI Selva software, and the neighborhood effect was determined through the default 5 × 5 cells contiguity neighborhood filter (Eastman, 2012; Mitsova et al., 2011).

The allocation process of the integrated models followed some rules consisting of: (1) the total land use demand during the simulation period (which is derived from the MC analysis) is equally allocated to each simulation year (iteration), (2) the neighborhood effect of each cell is calculated in each iteration to re-weight its transition probability score, (3) the allocation is conducted by ranking the transition probability scores, and cells with a higher score have a stronger potential to change, and (4) the simulation continues until the total land use demand is met. Compared to existing urban growth models, the integrated modeling framework developed in this study incorporates the driving factors of urban growth using the ALR, which overcomes the impact of SAC that is widely detected in spatial land use data. In the meantime, the transition probabilities of different land use types to settlements have also been taken into consideration by using the MC model.

3.2.4 Evaluation of Model Performance

The performances of different models were comparatively assessed by two approaches: the Kappa statistic and the Receiver Operating Characteristic (ROC) curve. First of all, the Kappa statistic has been widely used to assess the classification accuracy of thematic land use maps, and is considered suitable to evaluate the accuracy of simulation results (He et al., 2006). Two Kappa indexes were adopted in this study to assess the similarity between the observed map and simulated maps, including the Kappa index and the Fuzzy Kappa index (K fuzzy). First, the Kappa index is calculated based on an error matrix through a cell-to-cell comparison. It is regarded as more robust due to its ability to capture the possible agreement that occurred by chance. Second, the K fuzzy index can assess the similar spatial patterns between categorical maps within a certain vicinity of cells by accounting for both location and category fuzziness (Hagen, 2003). In this study, the K fuzzy index was calculated based on a neighborhood with a 4 cell radius and an exponential decay function with a halving distance of 2 cells using the

Map Comparison Kit software (Visser and de Nijs, 2006).

Second, the ROC curve is, statistically speaking, a graphical plot that tests the ability of a binary classifier system, such as the logistic regression and other binary classification approaches (Pontius and Schneider, 2001). To compute the ROC curve, a series of pairs of the sensitivity (proportion of true positives) and the specificity (proportion of false positives) will be obtained when changing the probability threshold. The ROC curve is generated by plotting the sensitivity against the specificity. The ROC statistic is represented by the Area Under the Curve (AUC), with values ranging from 0.5 to 1. A higher value of AUC indicates a better fit of the model, an AUC of 0.5 indicates a random model and an AUC of 1 indicates an ideal model.

3.3 Multiple Urban Dynamic Scenarios and Landscape Changes (Part II)

To develop the multiple urban dynamic scenarios, a focus group meeting was organized with regional and local experts. For comparative analysis, eight representative scenarios were selected and modeled. To characterize and quantify the landscape pattern changes induced by different scenarios at both the regional and sub-regional levels, a set of landscape metrics were used, among which redundancy was pre-tested and reduced.

3.3.1 Multiple Urban Dynamic Scenarios

Developing Multiple Urban Dynamic Scenarios

As highlighted in the literature review, the engagement of stakeholders in scenario development can improve the relevance, consistency and usefulness of scenarios based on their local expertise (Nilsson et al., 2014; Reed et al., 2013). Therefore, a focus group meeting was held with experts who have in-depth knowledge of the regional and local urban development in this region. A regional land use map and the pattern of historical settlement growth were provided and the research objectives were introduced in the meeting as necessary information for further discussion. To ensure the plausibility and accuracy of the scenarios developed, the experts were engaged at the very beginning of the scenario development process (Reed et al., 2013). Moreover, the experts were selected from both regional and local planning associations and a research institution including the Planning Association of Greater Munich (RPV) which is the key planning organization in the Munich region, the Environmental Consultancy of Professor Schaller Umwelt Consult GmbH (PSU) which is a local environment and landscape planning company, and the Chair for Strategic Landscape Planning and Management from the Technical University of Munich. All of them have expertise in environment or landscape planning and very good knowledge in the urban development of this region. The following two main topics were discussed in the focus group meeting.

First, the delimitation of different sub-regional zones: As urban dynamics in different sub-regional zones have different characteristics and disparate impacts on ecosystems and natural resources (Haase et al., 2012b; Li et al., 2016), a total number of 186 municipalities of this region were assigned to three zones (Urban Core Zone, Peri-Urban Zone and Rural Zone) based on the experts' knowledge and broad expertise in this region and their assessment of future urban development in each municipality (as shown in Figure 3.2). In this study, the Urban Core Zone refers to the city of Munich which is generally a higher-density built environment still under great settlement pressure. The Peri-Urban Zone includes the surrounding municipalities; it has a relatively lower population density but belongs to the functional urban area, which has a great development potential. Moreover, the Rural Zone is comprised of municipalities in more remote areas but within the rural-urban-region that are still accessible within a practical daily commuting time (as previous studies on rural-urban linkages have also suggested (Nilsson et al., 2014; Ravetz et al., 2013)).

Second, the development of realistic regional urban dynamics in terms of housing demand, urban spatial structure, and urban growth form in the future: Based on the analysis of historical change and the experts' knowledge and expertise in this region, "realistic" future urban dynamics were thoroughly discussed. The outcomes were adopted as baseline sub-scenarios for housing demand, urban spatial structure, and urban growth form. For the purpose of the comparative study, additional alternative sub-scenarios were developed based on the baseline sub-scenarios. The detailed settings of each sub-scenario are shown in Table 3.3. Ultimately, a total of eighteen scenarios for various urban dynamics were generated by combining different sub-scenarios (Figure 3.7).

Table 3.3 Description and settings for sub-scenarios.

Sub-scenarios	Description	Detailed settings and information
Sub-scenarios for housing demand		
High housing demand	High population growth with high per capita living space.	Compared with the projected average annual population growth rate, the average annual growth rates of high and low population growth scenarios were 1.2 times higher and 0.8 times lower, respectively. The Per Capita Living Space (PCLS) scenarios were proposed based on the proportions between smaller households (one- or two-person households) and larger households (three or more -person households) in the whole region. When assuming that the average area of one apartment remains static, there is no doubt that a higher proportion of smaller households will lead to a higher PCLS. Compared to their average annual growth rates between 2003 and 2013, the growth rates of smaller and larger households were 1.2 times higher and 0.8 times lower in high PCLS scenarios respectively, while the opposite trend was observed in the low PCLS scenario. In the medium PCLS scenario, the growth of both smaller and larger households followed their average annual growth rate between 2003 and 2013.[a]
Medium housing demand *(Baseline)*	Projected population growth with medium per capita living space.	
Low housing demand	Low population growth with low per capita living space.	
Sub-scenarios for urban spatial structure		
Monocentric *(Baseline)*	Urban growth in this scenario will follow a monocentric model. More economic activities and employment opportunities will be developed in the Urban Core Zone, which attracts people moving towards this area. Consequently, the housing demand will be much higher in the Urban Core Zone than the other two zones.	55% of the housing demand will be accomplished in the Urban Core Zone, with 30% in the Peri-Urban Zone and 15% in the Rural Zone.
Polycentric	This scenario describes a contrasting situation, in which the subcenters in the Peri-Urban and Rural Zones will be developed with more economic activities and more employment opportunities.	40% of the housing demand will be in the Urban Core Zone, with 40% in the Peri-Urban Zone and 20% in the Rural Zone.

Table 3.3 Description and settings for sub-scenarios *(continued)*.

Sub-scenarios	Description	Detailed settings and information
Sub-scenarios for urban growth form		
Sprawl (*<u>Baseline</u>*)	This scenario describes a situation where the urban fabric will continuously expand to non-urban land at low densities.	According to distinct urban growth characteristics in different zones, urban growth in the Urban Core Zone is proposed to be 20% low-density and 80% high-density settlements. Concurrently, urban growth in the Peri-Urban Zone is comprised by half low-density and half high-density settlements, in contrast to 80% low-density and 20% high-density in the Rural Zone.
Compact sprawl	This scenario depicts a strategy in which the urban fabric expands in a dense manner.	Urban growth in all three zones will be developed as high-density settlements.
Compact	This scenario implies a strong urban densification process.	All high-density residential buildings in each zone will add one more floor (2 apartments) to accommodate more residents. On the one hand, if the housing demand is greater than the supply, by adding one more floor, new high-density settlements will be developed to fill the gap. On the other hand, when the housing demand is less than the supply, the corresponding number of households will move from low-density to high-density settlements, and the vacant low-density settlement areas, as a result of this transfer, will be converted into green spaces to improve the living environment quality, which implies the shrinkage of urban areas.

Note: Regional population projection data and regional household structure data were obtained from the Bavarian State Office for Statistics, and the housing demand sub-scenarios were projected through the year 2033 (20 years from 2013).

[a] more details are shown in the Appendix C.

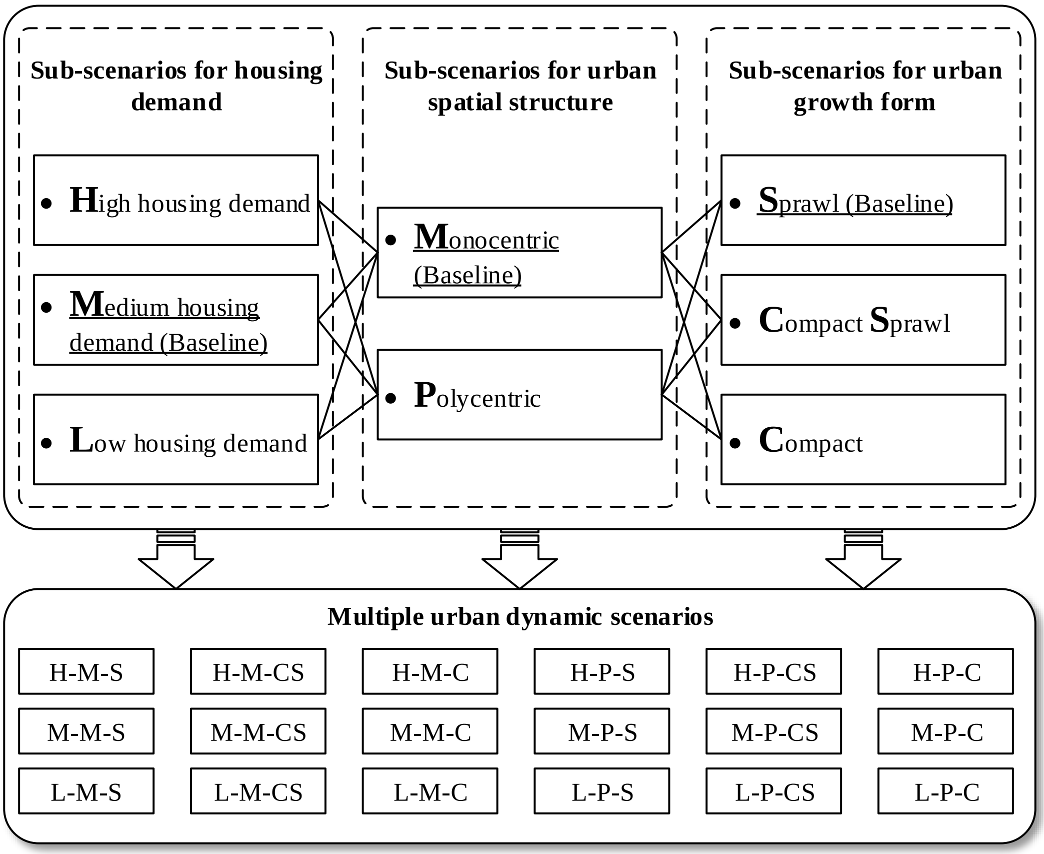

Figure 3.7 Multiple urban dynamic scenarios generated by combining different sub-scenarios (The multiple scenarios were generated by combing different sub-scenarios to embrace as much urban dynamics alternatives as possible. The amount of different housing demand (High, Medium, or Low) is allocated into each sub-regional zone based on alternative urban spatial structure (Monocentric or Polycentric) with different urban growth forms (Sprawl, Compact Sprawl, or Compact). All scenarios were named according to their combinations of sub-scenarios; for example, the combination of high housing demand, monocentric structure, and sprawl growth form scenario was abbreviated as H-M-S).

The land take per household for each scenario was calculated according to the following equation:

$$LTpH_{ij} = \frac{\Delta Residential\ area_{ij}}{\Delta Household\ number_{ij}} \qquad \text{(Eq. 3.10)}$$

where $LTpH_{ij}$ refers to the land take per household in zone i and settlement density j, with $j = 1$ indicating low-density settlements and $j = 2$ indicating high-density settlements. $\Delta Residential\ area_{ij}$ refers to the change in settlement area between 2003 and 2013 in zone i and settlement density j, and $\Delta Household\ number_{ij}$ refers to the change in household number in zone i and settlement density j over the same time period. The area of land converted into settlements in all scenarios is shown in Figure 3.8.

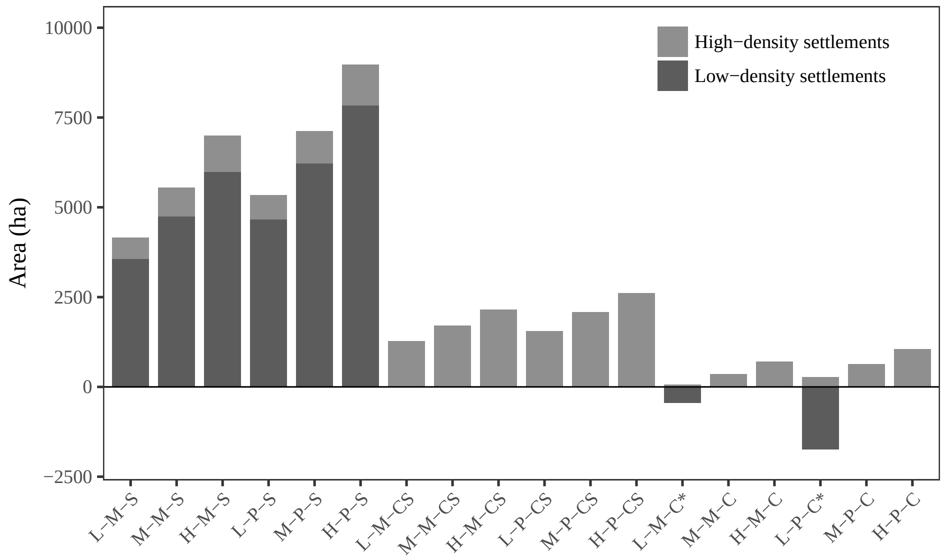

Figure 3.8 Area of land converted into settlements in each scenario projected through the year 2033 (*indicates urban shrinking scenario).

Selecting Scenarios for Comparison

As analyzing all 18 scenarios would make the analysis too broad and too complex, credible results could also be achieved by choosing a smaller number of scenarios that were considered particularly relevant to address the research objectives. Eight scenarios were selected for further comparative analysis in this study. The selection process is performed in two steps. First, landscape fragmentation and correspondingly the loss of biodiversity are two most important negative impacts of urban sprawl. Therefore, the connectance index of green-blue infrastructure (including green spaces and water bodies), which measures the overall connectivity of green-blue infrastructure, and the total settlement area were calculated for each scenario as indicators, and then four extreme cases were subsequently selected, including H-M-CS, H-P-S, L-P-C, and L-M-C (Figure 3.9). The connectance index is defined by the percentage of functional joinings between patches of the same patch type, which measures the overall connectivity of green-blue infrastructure in this study, and was calculated using FRAGSTATS software (McGarigal et al., 2012). Second, for the purpose of examining the impacts of different urban dynamics on green space availability, scenarios should be compared separately by keeping two of the three sub-scenarios the same while varying the remaining ones. For instance, H-P-S, M-P-S, and L-P-S, which have the same urban spatial structure and growth form, were selected to compare the impacts of the three housing demand sub-scenarios. Accordingly, another four scenarios were selected, including H-M-C, H-M-S, M-P-S, and L-P-S. In total, eight scenarios were selected, as shown in Figure 3.9.

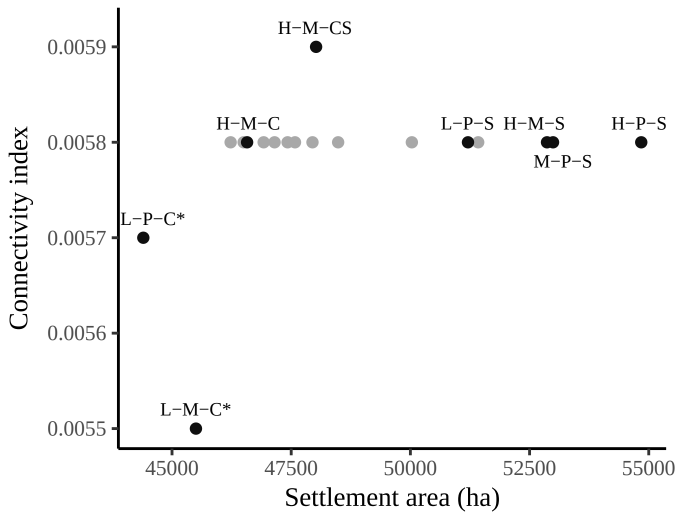

Figure 3.9 Scenarios that were selected for comparison (marked in black, *indicates urban shrinking scenario).

3.3.2 Urban Dynamic Modeling

The integrated urban growth model (the ALR-MC-CA model) that was developed in **Part I** was used to model the urban growth for each selected scenario. However, urban growth does not always follow a fixed model and it is unreasonable to use the same set of rules when a study area is large (He et al., 2015). Therefore, urban growth in different sub-regional zones was modeled independently. The relative weights of the driving factors of urban growth in each sub-regional zone evaluated by the Autologistic Regression (ALR) are summarized in Appendix D. The transition probabilities of different land use types to high- and low-density settlements were considered by using the Markov Chain (MC) model (see Appendix E). Protected green spaces, such as nature reserves, natural monuments, protected landscape areas and elements, were excluded when modeling urban growth (see Appendix A). The final transition probability maps for all sub-regional zones are presented in Appendix F. In the end, urban growths in different sub-regional zones were spatially allocated based on their final transition probability maps, respectively, by the customized Cellular Automata (CA) model.

It is noteworthy that urban shrinkage is another path of urban development that is occurring widely throughout the world (Haase et al., 2012a). In this study, compact growth scenarios may result in urban shrinkage. Several of the most visible byproducts of urban shrinkage are vacant residential or industrial buildings, vacant land due to demolition and unused spaces, which offer an opportunity for the development and extension of green and open spaces that can improve environmental quality (Hollander et al., 2009) and provide recreational facilities for residents (Haase et al., 2012a). Accordingly, as described in the scenario settings, vacant land as the result of urban shrinkage is converted into green spaces in the shrinking scenarios. Based on findings from previous studies (Kabisch et al., 2016; Lauf et al., 2014), the availability of nearby green spaces is considered to be more beneficial for all age-groups of residents, especially in terms of daily short-term recreational services. Therefore, the maximum distance to green spaces was set at 300 meters, and the minimum size of the green spaces was set at 2 ha (Handley et al., 2003; Kabisch et al., 2016; Lauf et al., 2014). As outlined previously, due to the lack of empirical evidence of urban shrinkage in the study region, common urban shrinkage models were not suitable (Lauf et al., 2012). Therefore, in the case of this study, an optimization model was built in the GAMS software environment to maximize the benefits of the newly developed green spaces for residents (see Pribadi and Xu, 2017, for a detailed explanation of the model). There are two basic rules in this model. First, the new green spaces, with a minimum size of 2 ha (as above), were developed within low-density settlement patches that had no access to green spaces (no green space larger than 2 ha available within 300 m). Second, the beneficial areas, settlement areas within 300 m from these new green spaces, were maximized.

3.3.3 Assessing the Landscape Pattern Changes

Calculation of Landscape Metrics

The landscape pattern changes were analyzed with landscape-level metrics to investigate and explore landscape-scale variables (Inkoom et al., 2018). Landscape metrics have been found to be capable of characterizing and quantifying urban land patterns and adding insights to the process of urban dynamics by a large number of studies (Buyantuyev and Wu, 2007; Buyantuyev et al., 2010; Dietzel et al., 2005; Inkoom et al., 2018; Liu and Yang, 2015; Liu et al., 2016; Yu and Ng, 2007). For this study, twenty-four widely used landscape metrics were employed and computed at the landscape level to characterize the changes of landscape patterns under different urban dynamic scenarios. All metrics were calculated in FRAGSTATS 4.2 (McGarigal et al., 2012) and detailed descriptions are listed in Table 3.4. These 24 landscape metrics can be categorized into three groups: patch complexity (LPI, TE, ED, LSI, AREA_MN, AREA_AM, PAFRAC, SHAPE_MN, and FRAC_MN), configuration (CONTAG, IJI, PLADj, AI, DIVISION, SPLIT, and MESH), and diversity (PR, PRD, SHDI, SIDI, MSIDI, SHEI, SIEI and MSIEI).

Table 3.4 List of landscape metrics used in this study representing three aspects (patch complexity, configuration, and diversity) of spatial heterogeneity.

Landscape metrics	Abbreviation	Description (McGarigal and Marks, 1995; Wu et al., 2002)
Patch complexity (area, edge and shape metrics)		
Largest Patch Index	LPI	The percentage of total landscape area comprised by the largest patch
Total Edge	TE	The sum of the lengths (m) of all edge segments in the landscape
Edge Density	ED	The sum of the lengths (m) of all edge segments in the landscape, divided by the total landscape area (m^2)
Landscape Shape Index	LSI	A standardized measure of total edge or edge density that adjusts for the size of the landscape. It measures the shape complexity of the entire landscape
Mean Patch Size	AREA_MN	The sum, across all patches in the landscape, of the area (m^2) of each patch, divided by the total number of patches
Area-Weighted Mean Patch Size	AREA_AM	The sum, across all patches in the landscape, of the area (m^2) of each patch multiplied by the proportional abundance of the patch
Perimeter-Area Fractal Dimension	PAFRAC	The fractal dimension of the whole landscape which equals 2 divided by the slope of regression line between the logarithm of patch area (m^2) and the logarithm of patch perimeter (m)
Mean Patch Shape Index	SHAPE_MN	The sum, across all patches in the landscape, of the patch-level shape index, divided by the total number of patches. Shape index equals patch perimeter (m) divided by the square root of patch area (m^2)
Mean Fractal Dimension Index	FRAC_MN	The patch-level fractal dimension averaged over all patches in the landscape. Patch fractal dimension index equals 2 times the logarithm of patch perimeter (m) divided by the logarithm of patch area (m^2)
Configuration (aggregation metrics)		
Contagion	CONTAG	Measures the extent to which patches are spatially aggregated by computing the probability that two randomly selected adjacent pixels belong to the same patch type
Interspersion and Juxtaposition Index	IJI	Measures the distribution of adjacencies among unique patch types
Percentage of Like Adjacencies	PLADj	Measures the degree of aggregation of patch types by considering only dispersion and not interspersion
Aggregation Index	AI	The area weighted mean class-level aggregation index which equals the number of like adjacencies divided by the maximum possible number of like adjacencies involving the corresponding class
Landscape Division Index	DIVISION	The probability that two randomly chosen pixels in the landscape are not situated in the same patch
Splitting Index	SPLIT	The effective mesh number
Effective Mesh Size	MESH	The size of the patches when the landscape is subdivided into S patches, where S is the value of the splitting index

Table 3.4 List of landscape metrics used in this study representing three aspects (patch complexity, configuration, and diversity) of spatial heterogeneity *(continued).*

Landscape metrics	Abbreviation	Description (McGarigal and Marks, 1995; Wu et al., 2002)
Diversity (diversity metrics)		
Patch Richness	PR	The number of different patch types in the landscape
Patch Richness Density	PRD	The number of different patch types divided by total landscape area (m^2)
Shannon's Diversity Index	SHDI	The proportional abundance of each patch type
Simpson's Diversity Index	SIDI	The probability that any 2 pixels selected at random would be different patch types
Modified Simpson's Diversity Index	MSIDI	Eliminates the intuitive interpretation of Simpson's index as a probability
Shannon's Evenness Index	SHEI	The observed SHDI divided by the maximum SHDI for that number of patch types. It measures the degree of evenness as the complement of dominance
Simpson's Evenness Index	SIEI	The observed SIDI divided by the maximum SIDI for that number of patch types. It measures the degree of evenness as the complement of dominance
Modified Simpson's Evenness Index	MSIEI	The observed modified MSIDI divided by the maximum MSIDI for that number of patch types. It measures the degree of evenness as the complement of dominance

Statistical Analysis for Data Reduction

First, following Plexida et al. (2014) and Inkoom et al. (2018), the Shapiro-Wilk test and the F-test were used to test for data normality and variance homogeneity. As some of the metrics were non-normally distributed among different scenarios, the Spearman's rank correlation coefficient was calculated for each metric group in a pair-wise way to explore the redundancy and multicollinearity among these metrics.

Then, following Cushman et al. (2008), a Principal Component Analysis (PCA) with varimax rotation was applied to each metric group to identify the core components that explained the landscape variability in the dataset. In light of the work of Li and Liu (2016), components with eigenvalues larger than 1 and metrics with loadings greater than 0.75 were retained for further analysis.

Finally, to further reduce the level of redundancy, the retained metrics from each metric group were integrated into a new landscape index by using the following equation (Li and Liu, 2016; Su et al., 2017).

$$Landscape\ Index = \sum_{i=1}^{n} E_i \times (\sum_{j=1}^{k} L_j \times x_j) \qquad \text{(Eq. 3.11)}$$

where E_i refers to the eigenvalue of component i; L_j refers to the loading score of landscape metric j; x_j is the standardized value of landscape metric j.

3.4 Impacts of Urban Dynamics on Green Space Availability (Part III)

To assess the impacts of urban dynamics on the availability of green spaces, different scenarios were comparatively analyzed by using two indicators that offer different information in terms of green space availability at both the regional and sub-regional levels.

3.4.1 Definition of Green Spaces Availability

According to Kabisch et al. (2016), the understanding of green space availability is the amount of green area in a certain defined distance to where people live. In this study, first of all, green spaces are defined as land uses of "parks and green spaces", "allotment gardens", "cemeteries" and "forests". Other land use classes, such as "arable land", "grassland" and "wetland", that could potentially serve as green spaces were excluded from analysis due to their relatively low recreational value (Kabisch et al., 2016). The “sports and leisure facilities” class (e.g., football stadiums, tennis courts, golf courses) was also excluded because of low vegetation coverage and a lack of public accessibility. Second, as mentioned in the section 3.3.2, this study puts more focus on the availability of nearby green spaces that are more beneficial for all age-groups of residents in terms of daily short-term recreational services (Kabisch et al., 2016; Lauf et al., 2014), in which case the maximum distance to green spaces was set at 300 meters and the minimum size of the green spaces was set at 2 ha (Handley et al., 2003; Kabisch et al., 2016; Lauf et al., 2014).

3.4.2 Indicators for Green Space Availability

Different indicators have been used in Europe, at national and subnational levels, to assess the provision of green spaces (Wüstemann et al., 2016). For example, targeted values of the per capita provision of public green space, ranging from 6 to 15 m^2, are used in urban planning in German cities (Deutscher Rat für Landespflege, 2006). However, this indicator does not provide information regarding the spatial distribution and the accessibility of green spaces for residents (de la Barrera et al., 2016). Therefore, the European Environment Agency (EEA) defines that, in Europe, people should have access to green space within 15 min walking distance (Stanners and Bourdeau, 1995), which indicates the overall accessibility of green spaces. As another example, it is recommended by Natural England, a non-departmental public body, that all residents should have access to natural green spaces of a minimum size of 2 ha within 300 m distances in the UK (Handley et al., 2003).

Thereby, two indicators were employed in this study, Per Capita Green Space (abbreviated hereafter as PCGS) and the Share of the Population with Access to Green Spaces (abbreviated hereafter as SPAGS). Different approaches have been used to measure the spatial accessibility of green space, among which buffer analysis and network analysis in the GIS environment are the two most frequently used ones (Koppen et al., 2014). Buffer analysis measures the linear distance without considering the actual routes, while network analysis is based on transportation networks which requires highly detailed data (Gupta et al., 2016). In this study, the buffer analysis was applied due to a lack of detailed road network data for the entire region. Both indicators were calculated according to the following steps (Figure 3.10): first, all green spaces with a minimum size of 2 ha were selected. Then, a buffer analysis was performed using ArcGIS 10.3 to create 300 m rings around the selected green spaces and all settlement areas. Finally, the area of the green spaces ($\geq$ 2 ha) within 300 m distances from the settlement areas and the population within 300 m distances from green spaces ($\geq$ 2 ha) were calculated and divided by the total population, respectively, as PCGS ($\geq$ 2 ha and within 300 m distances) and SPAGS ($\geq$ 2 ha and within 300 m distances).

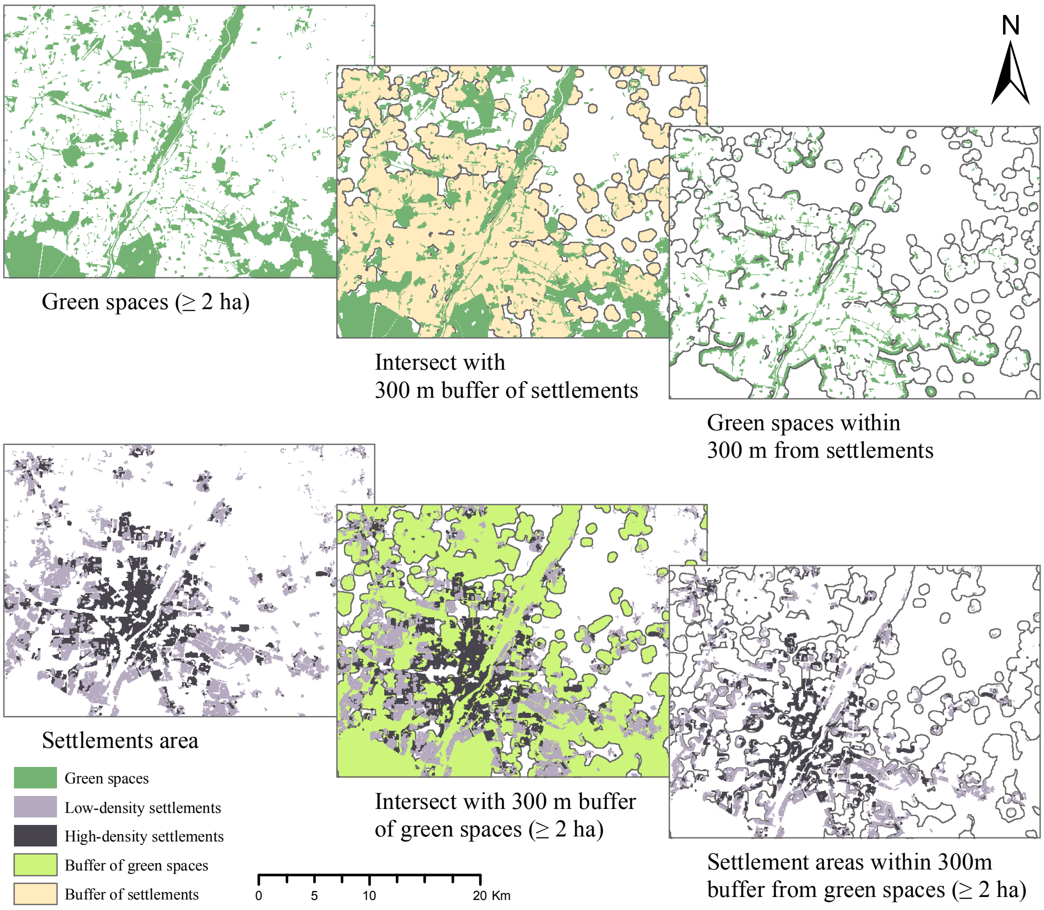

Figure 3.10 Processes of the spatial calculation in ArcGIS.

3.5 Spatial Variation of Green Space Equity and the Impacts of Urban Dynamics (Part IV)

To investigate the spatial equity of green space distribution, the Gini coefficient was adopted as the indicator and its spatial relationship with socioeconomic variables was explored. Moreover, to reveal the impacts of different urban dynamics, the green space equity under different scenarios were compared at both the regional and sub-regional levels.

3.5.1 Measuring the Green Space Equity

The Gini coefficient, which was developed as a measure of the inequality among values of a frequency distribution, was employed to measure the spatial inequality in green space distribution across the population for all municipalities. Although it is prevalent in economics and has been applied in measuring the income inequality of residents, the Gini coefficient has also been proved as an efficient indicator to assess sustainable urban development (Li et al., 2009) and the green space provision as well (Kabisch and Haase, 2014; Wüstemann et al., 2017). The Gini coefficient ranges from 0 and 1, with 0 representing perfect equality of potential access to the same amount of green space and 1 indicating perfect inequality. It can be expressed as:

$$GC = 1 - \sum_{i=1}^{n} {}^{P}/_{P_i}(B_{i-1} + B_i) \tag{Eq. 3.12}$$

where P_i is the population number of grid cell i and P is the total population of the municipality. B is the cumulative share of green space in a 300 m buffer around grid cell i. The higher a municipality's Gini coefficient means the more unequal the green space distribution among its residents.

For calculating the Gini coefficient, the study region was intersected with a $100m \times 100m$ grid file, and grid cells with their centroids located in each municipality were selected. The population number within each grid cell and the amount of green space within a 300 m buffer around the centroid of the grid cell were calculated. The population densities of both high-density and low-density settlements were calculated based on the population and household census data from the Bavarian State Office for Statistics. First, the average number of people living in one household and the household numbers of high-density and low-density settlements were calculated, based on which the population living in high-density and low-density settlement area were computed. Then, the population density was calculated by dividing the population number by the settlement area for high-density and low-density settlements respectively. Grid cells with less than two residents were excluded from the further calculation. The Gini coefficient was calculated for the whole region, sub-regional zones (Urban Core, Peri-Urban and Rural Zones) and municipalities, respectively.

3.5.2 Collecting Socioeconomic Variables

To explore the relationship between the green space equity and socioeconomic factors across different municipalities, eight socioeconomic variables were selected including the percentage of old people above 65, percentage of children and teenagers below 18, percentage of people in long-term unemployment, per capita living space, population density, per capita municipal revenue, per capita income and average housing price. Basic descriptive statistics of these variables are shown in Table 3.5.

Table 3.5 Descriptive statistics of the socioeconomic variables.

Variable	Minimum	Maximum	Mean	Std. Deviation
Percentage of old people above 65 (%)	9.58	26.79	17.80	3.48
Percentage of children and teenagers below 18 (%)	14.85	23.07	19.02	1.44
Percentage of people in long-term unemployment (%)[a]	0.00	0.81	0.26	0.14
Per capita living space ($m^2/inh.$)	36.76	63.94	47.11	4.10
Population density (n/ha)	17.32	112.27	36.19	17.08
Per capita municipal revenue (Euro/$inh.$)	1401.55	30655.59	2995.71	2939.82
Per capita income (Euro/$inh.$)	35076.70	142887.16	48173.96	14000.13
Average housing price (Euro/m^2)	7.22	1385.89	325.08	247.24

Note: n = 183. Average housing price was calculated as the average value from the year 2010 to 2016 due to data availability. All other data are from the year 2013.

[a] Long-term unemployed persons are those who were registered as unemployed with the employment agencies for a year or more.

Then, to reduce the redundancy of the variables and to facilitate the interpretation of the resulting factors, the factor analysis was conducted (Shen et al., 2017; Yao et al., 2013). The Kaiser-Meyer-Olkin (KMO) test was pre-performed to check the appropriateness of the factorial analysis. Principal component analysis and varimax rotation were used as the methods for factor extraction and maximizing the correlation between factors and measured variables. Municipalities with only forest or lake as well as the two municipalities of which the Gini coefficients equal to zero due to the absence of green spaces ($\geq$ 2 ha) within 300 m from settlements were excluded from analysis.

3.5.3 Spatial Correlation Analysis

It is known from literature that the provision of green spaces is mostly unevenly distributed over space and tends to be spatially heterogeneous (Kabisch and Haase, 2014). In this case, simple statistical methods such as global Ordinary Least Squares (OLS) regression may not be applicable, particularly to large-scale analyses. Firstly, the homoscedasticity assumption of OLS may be violated (Gao and Li, 2011; Li and Liu, 2016). Secondly, the OLS can only produce space-constant global relationships that only reflect the average conditions (Fotheringham and Brunsdon, 1999; Li and Liu, 2016; Su et al., 2012). Therefore, a spatial statistic approach, Geographically Weighted Regression (GWR), was applied to detect the varying local relationships between the Gini coefficient and socioeconomic factors across different parts of the region. GWR has been widely applied as a regional level analytical approach to characterize the spatially non-stationary relationship in the field of urban planning and land use studies (Gao and Li, 2011; Lee and Schuett, 2014; Li and Liu, 2016; Nilsson, 2014; Su et al., 2014; Yu, 2006). The general equation of GWR model can be expressed as Eq. 3.13.

$$y_i = \beta_0(\mu_i, v_i) + \sum_{k=1}^{n} \beta_k(\mu_i, v_i) x_{ik} + \varepsilon_i \qquad \text{(Eq. 3.13)}$$

where y_i is the independent variable at the location i, $\beta_0(\mu_i, v_i)$ is the intercept at the location i, $\beta_k(\mu_i, v_i)$ represents the local regression coefficient for the independent variable x_k at the location i, and (μ_i, v_i) denotes the Cartesian coordinate of the ith point, commonly indicating the centroid of the spatial unit. The parameters in GWR are estimated by weighting all observation around the point i through the following equation:

$$\hat{\beta}(\mu_i, v_i) = (X^T W(\mu_i, v_i) X)^{-1} X^T W(\mu_i, v_i) y_i \qquad \text{(Eq. 3.14)}$$

where $\hat{\beta}(\mu_i, v_i)$ represents the estimate of the coefficient value at the location i and $W(\mu_i, v_i)$ is an n by n weighting matrix for all observed data around the point i. In GWR model, it is assumed that observations close to point i have more influence on local parameter estimation at location i and therefore are weighted more than farther ones. Hence, the weight of an observation is valued according to its spatial proximity to point i based on the distance-decay weighting function, also called the kernel function, which follows the Gaussian curve (Brunsdon et al., 1996).

To keep the number of neighbors constant, the adaptive bi-square function was employed as the weighting function (Pribadi and Pauleit, 2016), which can be written as:

$$W_{ij} = \begin{cases} [1 - (d_{ij}^2/d^2)]^2 & d_{ij} < d \\ 0 & otherwise \end{cases} \qquad \text{(Eq. 3.15)}$$

where W_{ij} denotes the weight value for observation j in the neighborhood of observation i, d_{ij} is the Euclidian distance between the observations i and j, d is an adaptive bandwidth that is defined as the distance from the observation i to the kth nearest neighbor. At the meantime, the golden section search method was adopted with the minimum value of Akaike Information Criterion (AIC) as the selection criteria to search for the optimal bandwidth size automatically. The GWR analysis was conducted using ArcGIS 10.3 and GWR4 software developed by Nakaya (2016).

Chapter 4

Results

4.1 Development of the Integrated Urban Growth Model (Part I)

In the following paragraphs, the Spatial Autocorrelation (SAC) that existed among the pattern of the historical settlement growth as well as the modeling improvement by incorporating the spatial dependency into the model and by separately modeling the growths of different settlement types are reported.

4.1.1 Spatial Autocorrelation of Regional Settlement Growth

From 2003 to 2013, the area of settlements has increased by 3.93% (17.33 km^2) in the Munich region. The spatial distribution of the settlement growth during this study period is shown in Figure 4.1. As seen, the spatial pattern of the settlement growth has been quite scattered throughout the region, and the area of the settlement growth only accounted for a rather small proportion (about 0.31%) of the total area.

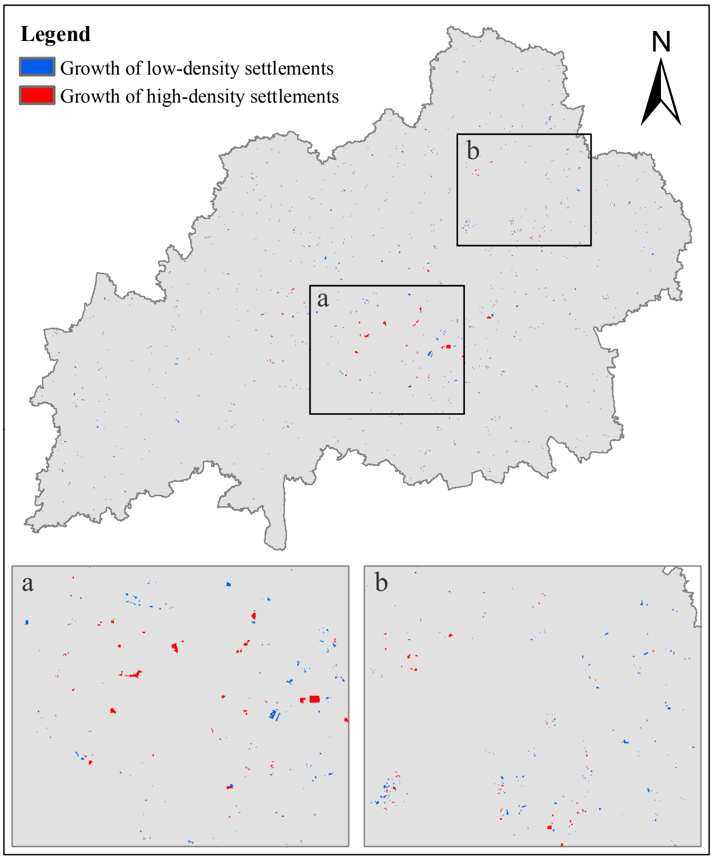

Figure 4.1 Spatial distribution of the settlement growth between 2003 and 2013.

To characterize the SAC of the settlement growth, Moran's *I* analysis was carried out at various lag distances (Figure 4.2). The results show that a strong positive SAC existed among the distribution of the settlement growth within a certain lag distance and gradually decreased while the lag distance increased. It indicated that a regression model that could explain the spatial dependency would be helpful in understanding the spatial pattern of the settlement growth and yield more credible modeling results.

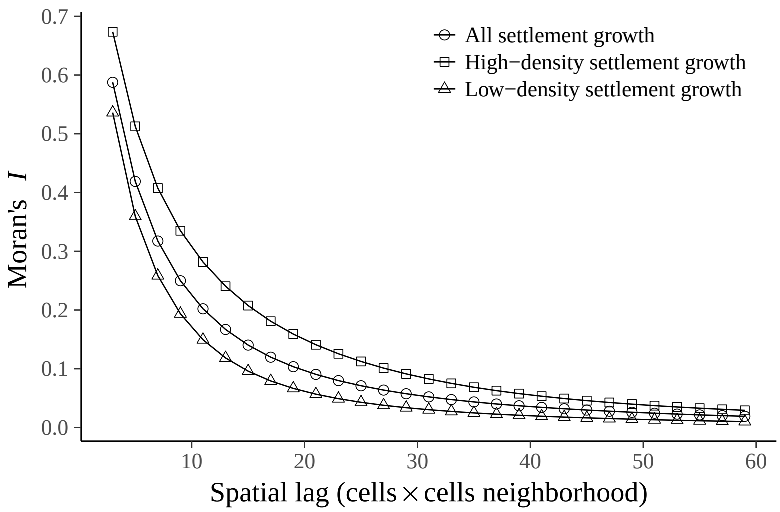

Figure 4.2 Moran's *I* values for the distributions of different settlement growth.

4.1.2 Model Improvement by Incorporating the Spatial Autocorrelation

Table 4.1 shows the results (coefficients and standard errors) of the Ordinary Logistic Regression (OLR) and the Autologistic Regression (ALR) for all settlement growth. The negative coefficients indicate that the settlement growth and the driving factors have an opposing relationship, whereas the positive coefficients indicate that the settlement growth is reinforced by these factors. Not surprisingly, a significant positive correlation was found between the autocovariate variable and the settlement growth, which could be attributed to the strong positive SAC in the spatial pattern of the settlement growth. In addition to the autocovariate variable, the numbers of significant variables were fourteen and thirteen in the OLR and the ALR respectively. Population density (PPD) and distance to the main center (DisMC) were not significant in both regressions. Compared to the OLR, four kinds of results came up when incorporating the autocovariate variable in the ALR. First, some variables were eliminated, including the slope (SLP), distance to the settlement centers (DisSTC) and distance to the commercial area (DisCA). Second, two variables, distance to the S-bahn station (DisSB) and distance to the industrial area (DisIA), became significant in the ALR. Third, the coefficients of the common variables in OLR and ALR were modified. Some of them that were much more significant in the OLR became less significant in the ALR. Fourth, some coefficients show opposite signs (positive or negative) between the OLR and ALR, including distance to water (DisWT), distance to green spaces (DisGS), distance to U-bahn station (DisUB), distance to sub-center (DisSC), distance to highway (DisHW), distance to major road (DisMR) and residential land price (RLP). Overall, both models exhibit very different results and thereby the choice of the right model is a crucial decision.

Table 4.1 Regression coefficients (B) and standard errors (S.E.) of the OLR and the ALR for all settlement growth.

Variable	Ordinary logistic regression		Autologistic regression	
	B	S.E.	B	S.E.
Constant	-2.66E+00***	4.37E-02	-5.68E+00***	7.23E-02
Slope	-8.26E-02***	3.94E-03	—	—
Distance to water	-3.96E-05***	3.57E-06	1.47E-05**	5.44E-06
Distance to green spaces	-6.84E-04***	1.61E-05	1.48E-04***	1.90E-05
Neighborhood	1.02E-01***	1.80E-03	2.12E-01***	2.98E-03
Distance to the S-bahn (suburban train) station	—	—	-6.99E-06*	3.50E-06
Distance to the U-bahn (metro) station	7.33E-06***	1.03E-06	-3.78E-06•	2.11E-06
Distance to the main center	—	—	—	—
Distance to the subcenters	1.99E-05***	1.78E-06	-6.27E-06*	2.81E-06
Distance to the settlement centers	5.70E-05***	2.55E-06	—	—
Distance to the commercial area	-3.68E-05***	3.46E-06	—	—
Distance to the industrial area	—	—	2.42E-05*	1.28E-05
Distance to the highway	-6.96E-06***	1.99E-06	8.50E-06**	3.10E-06
Distance to the major road	-2.10E-04***	1.99E-05	1.21E-04***	3.10E-05
Distance to the local road	-9.25E-03***	1.76E-04	-3.54E-03***	3.10E-04
Distance to the urban edge	-7.68E-03***	1.21E-04	-1.40E-02***	3.33E-04
Population density	—	—	—	—
Residential land price	2.13E-04***	3.28E-05	-3.04E-04***	6.26E-05
Autocov			9.25E-01***	5.17E-03

Note: Significant codes: ***: $p < 0.001$, **: $p < 0.01$, *: $p < 0.05$, •: $p < 0.1$, —: not significant.

The SAC in the residuals of both models were assessed using the Local Indicators of Spatial Association (LISA) analysis to test the improvement of the ALR compared to the OLR. It is clear from Figure 4.3 that more clusters (which indicate different kinds of SAC) existed in the residuals of the OLR-MC-CA model than the ALR-MC-CA model. In addition, the global Moran's I index of the residuals in the OLR-MC-CA model was 0.2415, which implied a high positive SAC according to Glazier et al. (2004) and was much higher than that in the ALR-MC-CA model (0.0358).

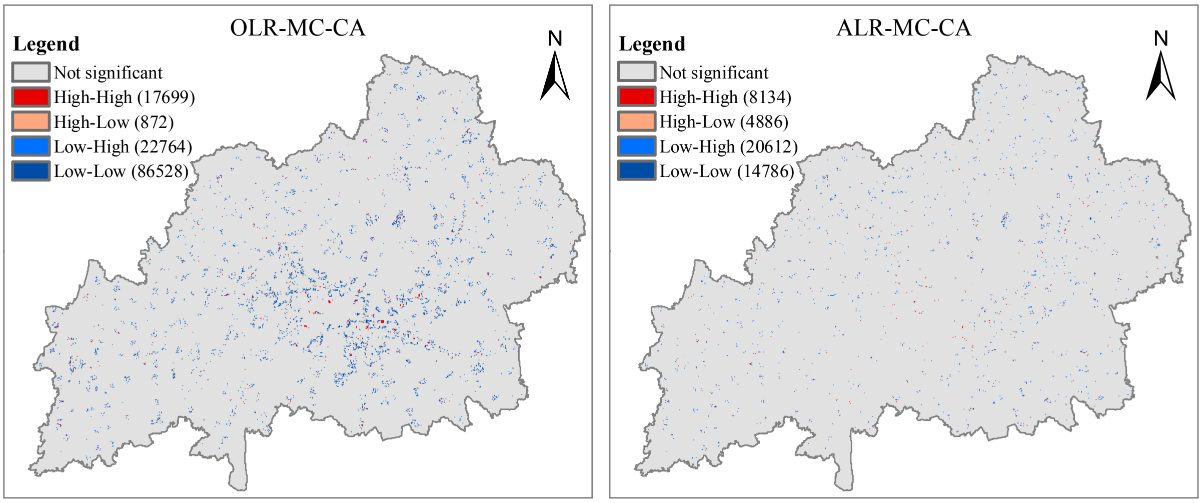

Figure 4.3 Local indicators of spatial association (LISA) cluster maps of residuals in the OLR-MC-CA and the ALR-MC-CA models. The High-High and Low-Low mean cells of high and low values are surrounded by cells with high and low values, respectively, which indicates positive SAC. The High-Low and Low-High mean cells of high and low values are surrounded by cells with low and high values, which indicates negative SAC. The level of significance was set as $p < 0.05$.

The result of the Receiver Operating Characteristic (ROC) curve analysis, which describes how strongly the settlement growth is aggregated around areas with higher transition probability (Han and Jia, 2017), shows that the ALR-MC-CA model (with an AUC value of 0.998) performed better than the OLR-MC-CA model (with an AUC value of 0.962) (Figure 4.4). Figure 4.5 shows the simulated errors of settlement cells by the two models. There are two types of errors in the falsely simulated settlement cells. The first one is non-settlement cells that converted into settlements but were incorrectly simulated as non-settlement cells. Another type of error is that non-settlement cells that did not convert into settlements were wrongly simulated as settlement cells. In general, although the distributions of the falsely simulated cells of both models were somewhat similar to each other, the number of falsely simulated cells by the ALR-MC-CA model was less than that by the OLR-MC-CA model. Moreover, the Kappa indexes were calculated for both models by comparing the simulated settlement growth with real growth (Table 4.2). The ALR-MC-CA model had considerably higher values of Kappa and K fuzzy than the OLR-MC-CA model, indicating that the simulation accuracy of the ALR-MC-CA model was much higher than the other one.

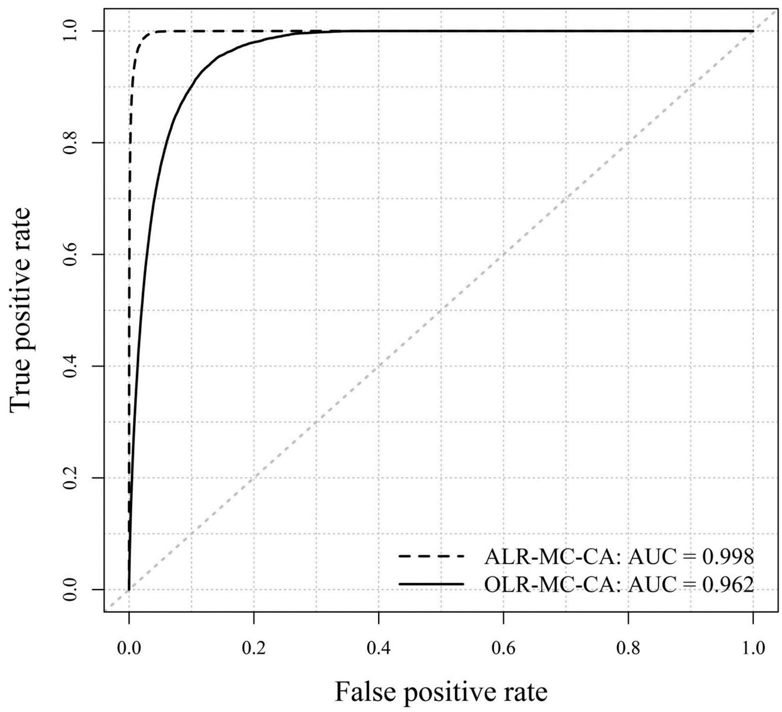

Figure 4.4 ROC curve and values of AUC for the OLR-MC-CA and the ALR-MC-CA models.

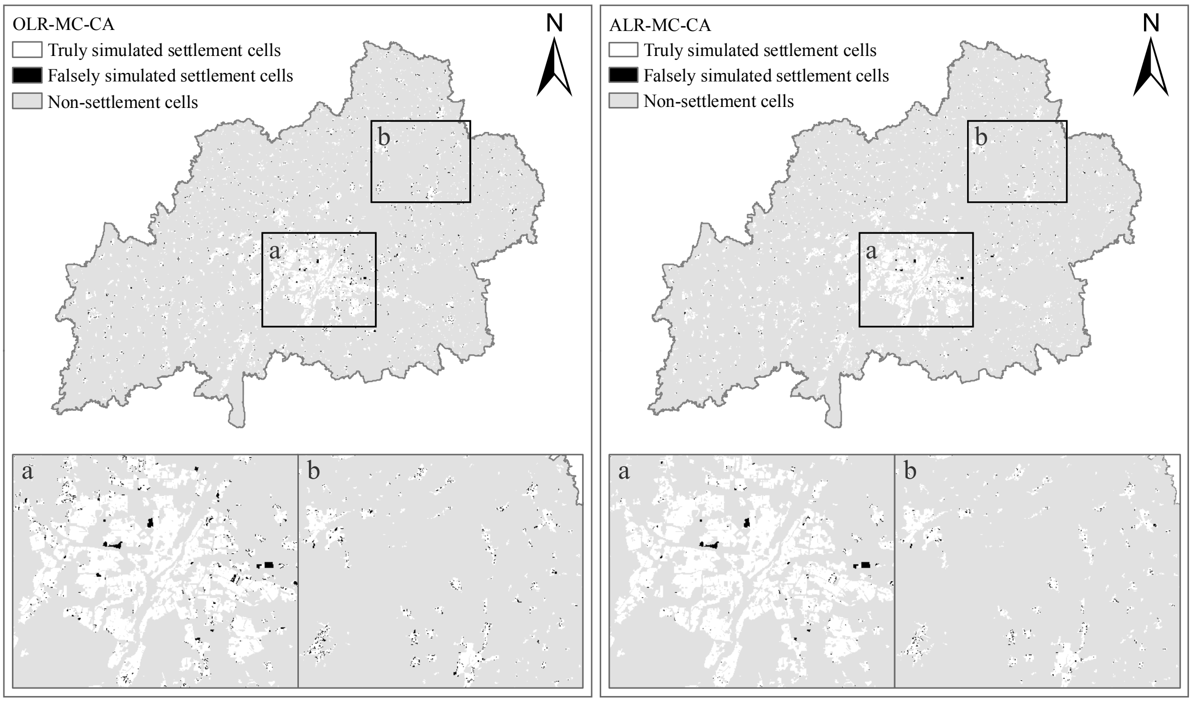

Figure 4.5 Simulated errors of settlement growth by the OLR-MC-CA model and the ALR-MC-CA model (a: city center of Munich, b: peripheral area with subcenter).

Table 4.2 Kappa and K fuzzy values for simulation result of both models.

Index	OLR-MC-CA	ALR-MC-CA
Kappa	0.1820	0.6050
K fuzzy	0.3298	0.7642

4.1.3 Separately Modeling High- and Low-density Settlement Growth

The coefficients (B) and standard errors (S.E.) of the ALR for the growths of different settlement types are shown in Table 4.3. A total of thirteen variables were significant in the regression for high-density settlement growth, while there were only nine significant variables for low-density settlement growth. Four variables were not significant in both regressions, including the slope (SLP), distance to the S-bahn station (DisSB), distance to the main center (DisMC), and distance to the commercial area (DisCA). The distance to water (DisWT), distance to the subcenters (DisSC), distance to the settlement centers (DisSTC), distance to the industrial area (DisIA) and residential land price (RLP) were significant for high-density settlement growth but were insignificant for low-density settlement growth, whilst the distance to the U-bahn station (DisUB) was only significant for low-density settlement growth. In addition, among the common variables that were included in both regressions, distance to the local road (DisLR) and distance to the urban edge (DisUE) had the same correlation with both high-density and low-density settlement growth. However, on the one hand, distance to the green spaces (DisGS), distance to the highway (DisHW) and distance to the major road (DisMR), which had positive correlations with low-density settlement growth, were negatively correlated with high-density settlement growth. This implied that the development of high-density settlements would be close to green spaces, highways and major roads. On the other hand, population density (PPD) had a positive correlation with high-density settlement growth but a negative correlation with low-density settlement growth, indicating that high-density settlements would be developed in areas with high population density and the development of low-density settlements was the opposite.

Table 4.3 Regression coefficients (B) and standard errors (S.E.) of the ALR for high-density and low-density settlement growth.

Variable	High-density settlements		Low-density settlements	
	B	S.E.	B	S.E.
Constant	-5.71E+00***	1.43E-01	-5.53E+00***	7.34E-02
Slope	—	—	—	—
Distance to water	5.87E-05***	1.13E-05	—	—
Distance to green spaces	-5.47E-04***	5.27E-05	2.09E-04***	1.95E-05
Neighborhood	2.10E-01***	5.65E-03	1.93E-01***	3.71E-03
Distance to the S-bahn (suburban train) station	—	—	—	—
Distance to the U-bahn (metro) station	—	—	-8.33E-06***	1.60E-06
Distance to the main center	—	—	—	—
Distance to the subcenters	-2.92E-05***	5.70E-06	—	—
Distance to the settlement centers	-4.68E-05***	8.70E-06	—	—
Distance to the commercial area	—	—	—	—
Distance to the industrial area	9.77E-05***	2.54E-05	—	—
Distance to the highway	-3.11E-05***	6.60E-06	1.45E-05***	3.36E-06
Distance to the major road	-2.86E-04***	7.96E-05	1.29E-04***	3.50E-05
Distance to the local road	-2.69E-03***	6.15E-04	-2.68E-03***	3.70E-04
Distance to the urban edge	-1.33E-02***	5.28E-04	-2.18E-02***	6.33E-04
Population density	2.83E-04***	5.92E-05	-1.47E-04***	2.04E-05
Residential land price	-1.81E-03***	2.15E-04	—	—
Autocov	1.10E+00***	1.05E-02	1.13E+00***	7.16E-03

Note: Significant codes: ***: $p < 0.001$, **: $p < 0.01$, *: $p < 0.05$, •: $p < 0.1$, —: not significant.

Figure 4.6 represents the observed and simulated distributions of high-density and low-density settlements for the year 2013 by the ALR-MC-CA. It is apparent that the distribution of settlement areas in both maps shared a high similarity, and the differences were not quite evident. This is because the settlement growth only accounted for a very small proportion of the total settlement area during the study period. The simulated errors of high-density and low-density settlement growth by the ALR-MC-CA model are shown in Figure 4.7. Compared to the simulated error of all settlement growth by the same model (see Figure 4.5), it is apparent that the falsely simulated settlement cells decreased when separately modeling high-density and low-density settlement growth. The values of Area Under the Curve (AUC), Kappa and K fuzzy that were used to assess the model performance are summarized in Table 4.4. The AUC values for high-density and low-density settlement growth were both higher than that of all settlement growth. Meanwhile, modeling high-density and low-density settlement growth separately showed higher values of all Kappa indexes than integratively modeling all settlement growth.

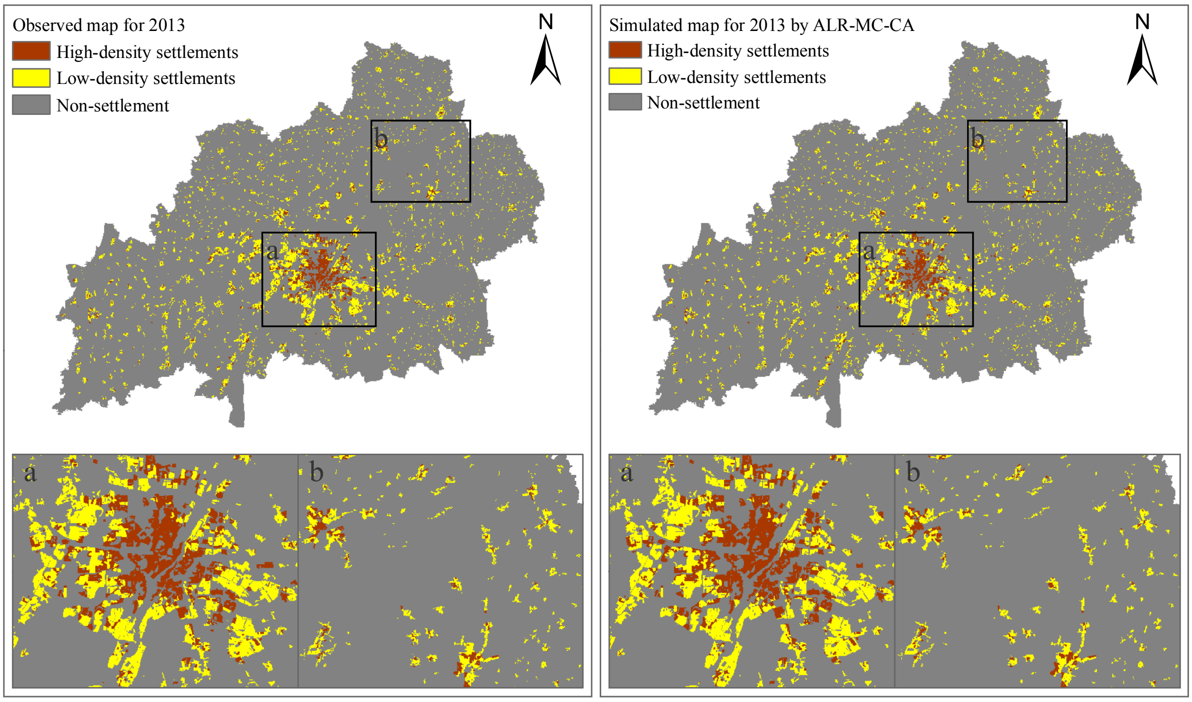

Figure 4.6 High-density and low-density settlements distributions in observed map and simulated map by ALR-MC-CA for the year 2013 (a: city center of Munich, b: peripheral area with subcenter).

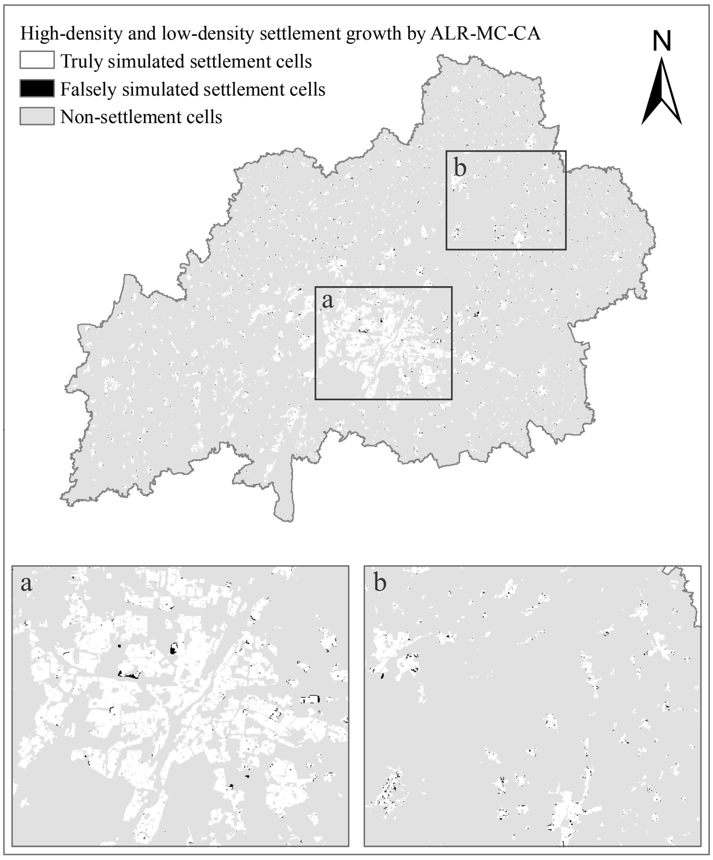

Figure 4.7 Simulated error of high-density and low-density settlement growth by the ALR-MC-CA model (a: city center of Munich, b: peripheral area with subcenter).

Table 4.4 Values of AUC, Kappa and K fuzzy for modeling all settlement growth integratively and the growth of different settlement types separately by the ALR-MC-CA model.

	AUC	Kappa	K fuzzy
Modeling all settlement growth by ALR-MC-CA			
All settlements	0.9980	0.6050	0.7642
Modeling high-density and low-density settlement growth by ALR-MC-CA			
High-density settlements	0.9994	0.6741	0.8023
Low-density settlements	0.9982	0.6350	0.8028
Overall	—	0.6524	0.8046

4.2 Multiple Urban Dynamic Scenarios and Landscape Changes (PART II)

The following paragraphs show the results of historical land use change as a result of urban expansion, and the regional and sub-regional land use and landscape pattern changes under different urban dynamic scenarios.

4.2.1 Urban Expansion between 2003 and 2013

A land use transition matrix for the period of 2003-2013 is shown in Table 4.5. In the entire region, the area of settlements has increased from 44,138 ha to 45,871 ha between the year 2003 and 2013, of which the growth of high-density settlements accounted for 33.19%, while low-density settlement growth accounted for 66.81%. With an average annual growth rate of 0.39%, the area of settlements accounted for 8.33% of the total area of this region in 2013.

Table 4.5 Land-use transition matrix for the period of 2003-2013 in *ha*.

Land use classes / Abbr.	AG	AL	CA	CS	F	G	HS	IA	LP	LS	MA	N	PA	PGS	Q	RSRT	RCBA	R	SMRC	SLF	UL	SD	W	Sum 2003
Allotment gardens	927	/	/	/	/	/	/	/	/	/	/	/	/	/	/	/	/	/	/	/	/	/	/	927
Arable land	11	207841	148	134	41	420	127	418	/	381	/	5	13	60	507	/	132	47	41	184	5	48	/	210561
Commercial area	/	/	2130	10	/	/	/	/	/	/	/	/	/	/	/	/	/	/	/	/	/	/	/	2140
Construction sites	/	6	75	12	/	38	138	44	11	74	/	/	/	39	/	/	25	14	13	61	7	/	/	559
Forest	/	6	/	/	142286	102	/	98	/	8	/	/	/	/	89	/	12	10	/	8	/	/	/	142620
Grassland	/	10844	113	54	201	85857	235	291	/	670	/	/	16	21	156	/	23	14	22	120	/	7	/	98643
High-density settlements	/	/	/	16	/	/	9909	/	/	/	/	/	/	/	/	/	/	/	/	/	/	/	/	9925
Industrial area	/	/	/	27	/	8	38	5655	/	5	/	/	/	/	/	/	/	/	/	/	/	/	/	5733
Lakes and ponds	/	/	/	/	/	/	/	/	12746	/	/	/	/	/	/	/	/	/	/	/	/	/	/	12746
Low-density settlements	/	/	/	/	/	/	/	/	/	34206	/	/	/	/	/	/	/	/	/	/	/	/	/	34206
Military area	/	/	/	12	/	/	/	/	/	/	1061	/	/	/	/	/	/	/	/	/	/	/	/	1074
Nurseries	/	/	/	/	/	/	/	/	/	/	/	518	/	/	/	/	/	/	/	/	/	/	/	518
Parking areas	/	/	/	11	/	/	/	/	/	/	/	/	252	/	/	/	/	/	/	/	/	/	/	264
Parks and green spaces	/	/	/	/	/	/	21	/	/	20	/	/	/	6090	/	/	/	/	/	/	/	/	/	6132
Quarries	/	130	/	/	29	179	/	16	/	/	/	/	/	/	2321	/	/	/	/	6	15	/	/	2696
Railway station, railway tracks	/	/	/	/	/	/	/	/	/	/	/	/	/	/	/	616	/	/	/	7	/	/	/	623
Road connection and buffer areas	/	/	/	/	/	/	/	/	/	/	/	/	/	/	/	/	604	/	/	/	/	/	/	604
Roads	/	/	/	/	/	/	/	/	/	/	/	/	/	/	/	/	/	1512	/	/	/	/	/	1512
Schools, museums and research centers	/	/	/	24	/	/	/	/	/	/	/	/	/	/	/	/	/	/	1485	/	/	/	/	1509
Sport and leisure facilities	/	/	/	6	/	/	8	6	/	6	/	/	/	/	/	/	/	/	/	4426	/	/	/	4452
Unused land	/	39	45	/	16	/	/	9	/	/	/	/	/	/	/	/	/	/	/	/	1519	/	/	1629
Supply and disposal	/	/	/	/	/	/	/	/	/	/	/	/	/	/	/	/	/	/	/	/	/	413	/	413
Wetlands	/	11	/	/	/	/	/	/	/	/	/	/	/	/	/	/	/	/	/	/	/	/	3091	3102
Sum 2013	938	218877	2511	306	142572	86604	10477	6537	12757	35370	1061	523	281	6210	3074	616	796	1598	1561	4811	1547	468	3091	542585

Note: Land uses of Airfields, Cemeteries, Power stations, Fish Farming, Harbors, Railways, and Rivers are excluded in this table due to either no land-use transition or the transitions are quantitatively low and rare (e.g. Airfields converted into Arable land).

At the sub-regional level, almost half of the area of settlement growth was located in the Rural Zone (49.13%), followed by the Peri-Urban Zone (35.71%) and the Urban Core Zone (15.16%) (Figure 4.8). Although the areas of settlement growth only accounted for a relatively small proportion in the Urban Core and Peri-Urban Zones, it is worth noting that approximately 65% and 25%, respectively, of the regional population growth took place in these two zones during the same period (Bavarian State Office for Statistics, 2015). This is because the population density of these two zones was much higher than that of the Rural Zone. This finding confirms that the form of settlement growth in this region is mainly sprawl during the study period. Figure 4.8 also shows that 60.22% of the area of low-density settlement growth occurred in the Rural Zone while only 6.8% occurred in the Urban Core Zone. Regarding the area of high-density settlement growth, 41.19% occurred in the Peri-Urban Zone, followed by the Urban Core Zone (31.98%), and the Rural Zone (26.83%).

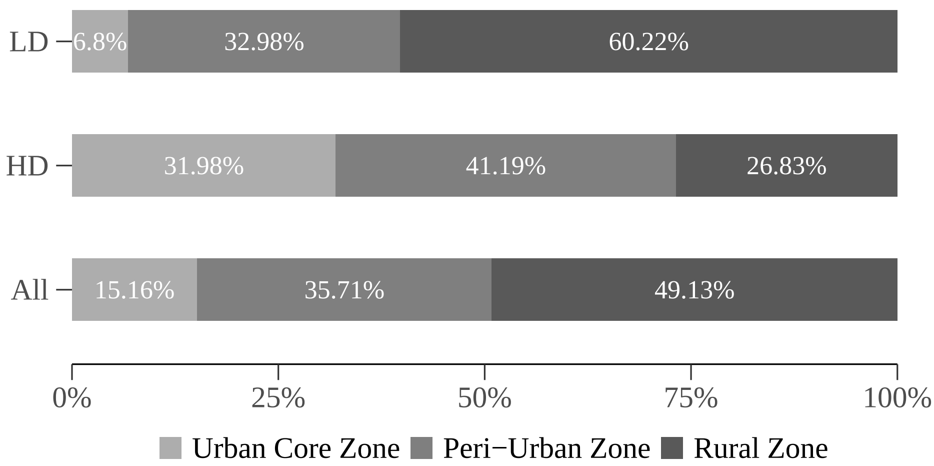

Figure 4.8 Percentage distribution of the area of settlement growth in different sub-regional zones (All: all settlements, LD: low-density settlements, and HD: high-density settlements).

The patterns of land use conversions at both levels as a result of settlement growth are illustrated in Figure 4.9. At the regional level, the growth of high-density settlements was mainly driven by conversions from the land use classes of grassland (40.38%), construction sites (23.65%) and arable land (21.78%). Also at the regional level, the growth of low-density settlements predominantly led to losses of grassland (57.05%) and arable land (32.49%). However, different patterns can be found in different sub-regional zones. Apart from grassland, the main land use classes contributing to high-density settlement growth differed between different zones. For example, the loss of parks and green spaces in the Urban Core Zone was mainly caused by the growth of high-density settlements, which differs from the other two zones (Figure 4.10). Meanwhile, the growth of low-density settlements came primarily from the conversion of grassland and arable land in all three zones, except for construction sites, which were the third leading contributor in the Peri-Urban Zone. The latter finding indicates that significant conversion from arable land and grassland to low-density settlements had already started before the study period and had been ongoing in the Peri-Urban Zone.

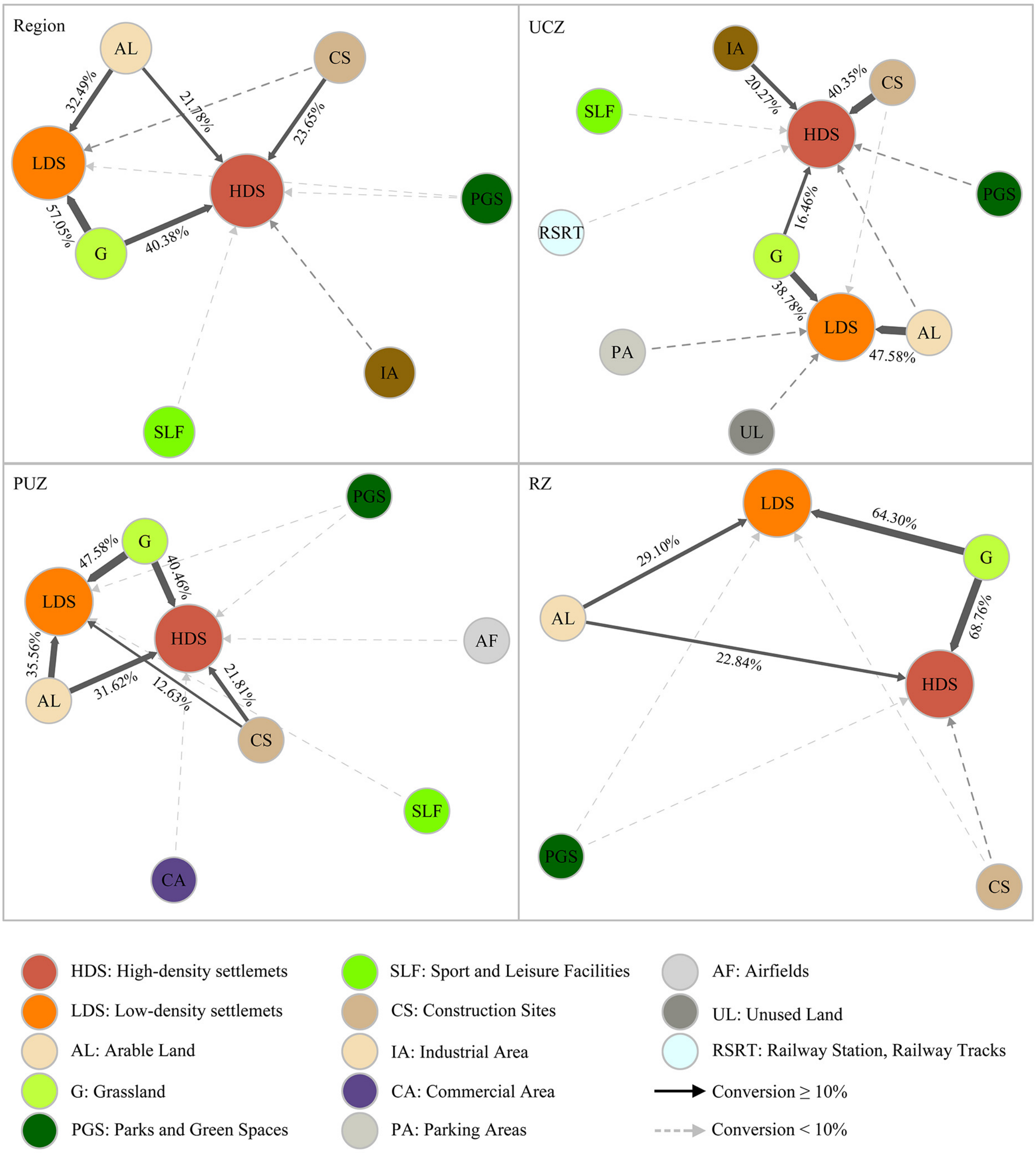

Figure 4.9 Patterns of land use conversion caused by settlement growth in the entire region and sub-regional zones (UCZ: Urban Core Zone, PUZ: Peri-Urban Zone, and RZ: Rural Zone. Only land use transitions accounted for more than 1% are shown).

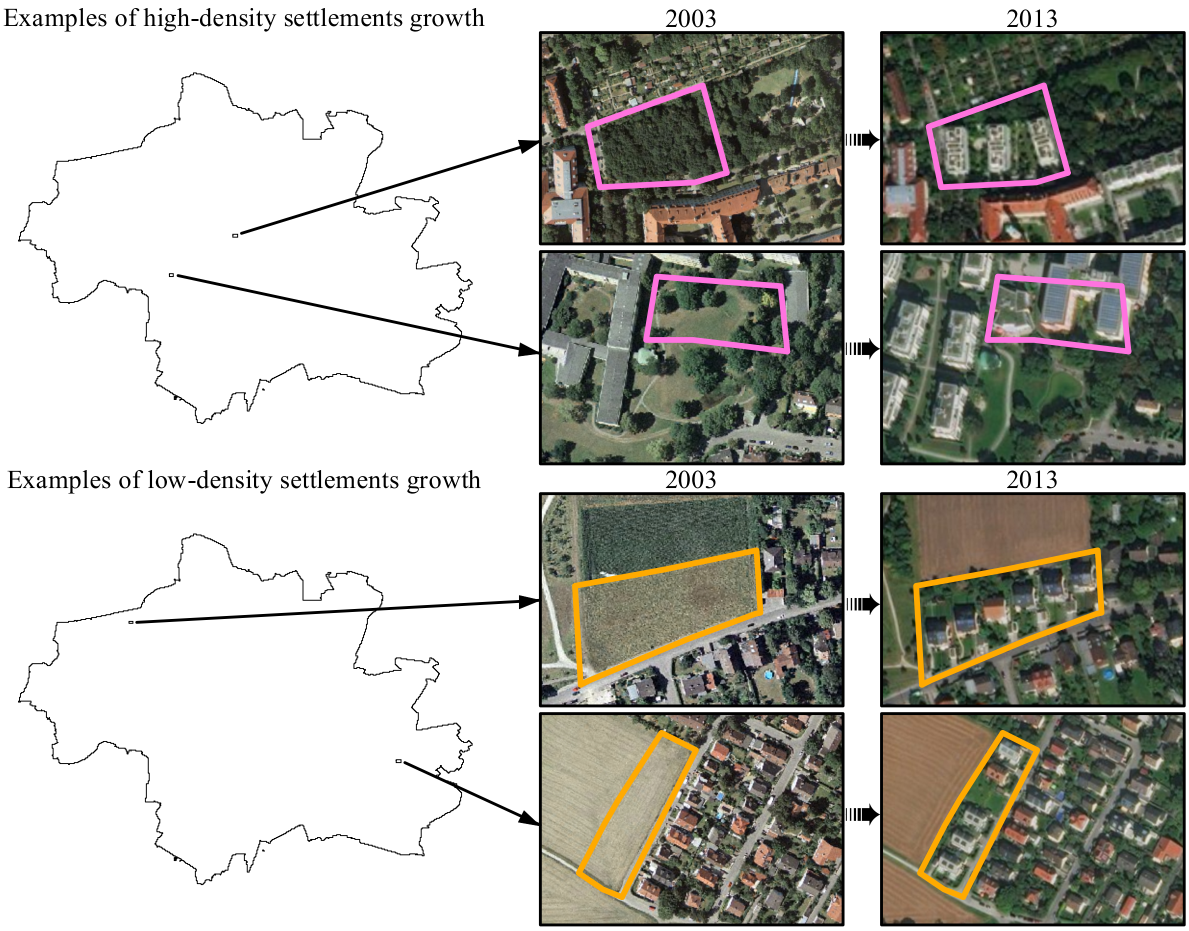

Figure 4.10 Examples of the growth of different settlement types between 2003 and 2013 in the Urban Core Zone (High-density settlement growths were more close to the city center and led to a significant loss of green spaces, while the growths of low-density settlements were mainly converted from arable land and grassland).

4.2.2 Urban Expansion under Different Scenarios

The spatial distribution of settlement growth under different scenarios is presented in Figure 4.11. As can be seen, the patterns of settlement growth in all scenarios were quite scattered throughout the entire region, which follows the historical urban growth pattern during the past decade (as shown in Figure 4.1, section 4.1.1).

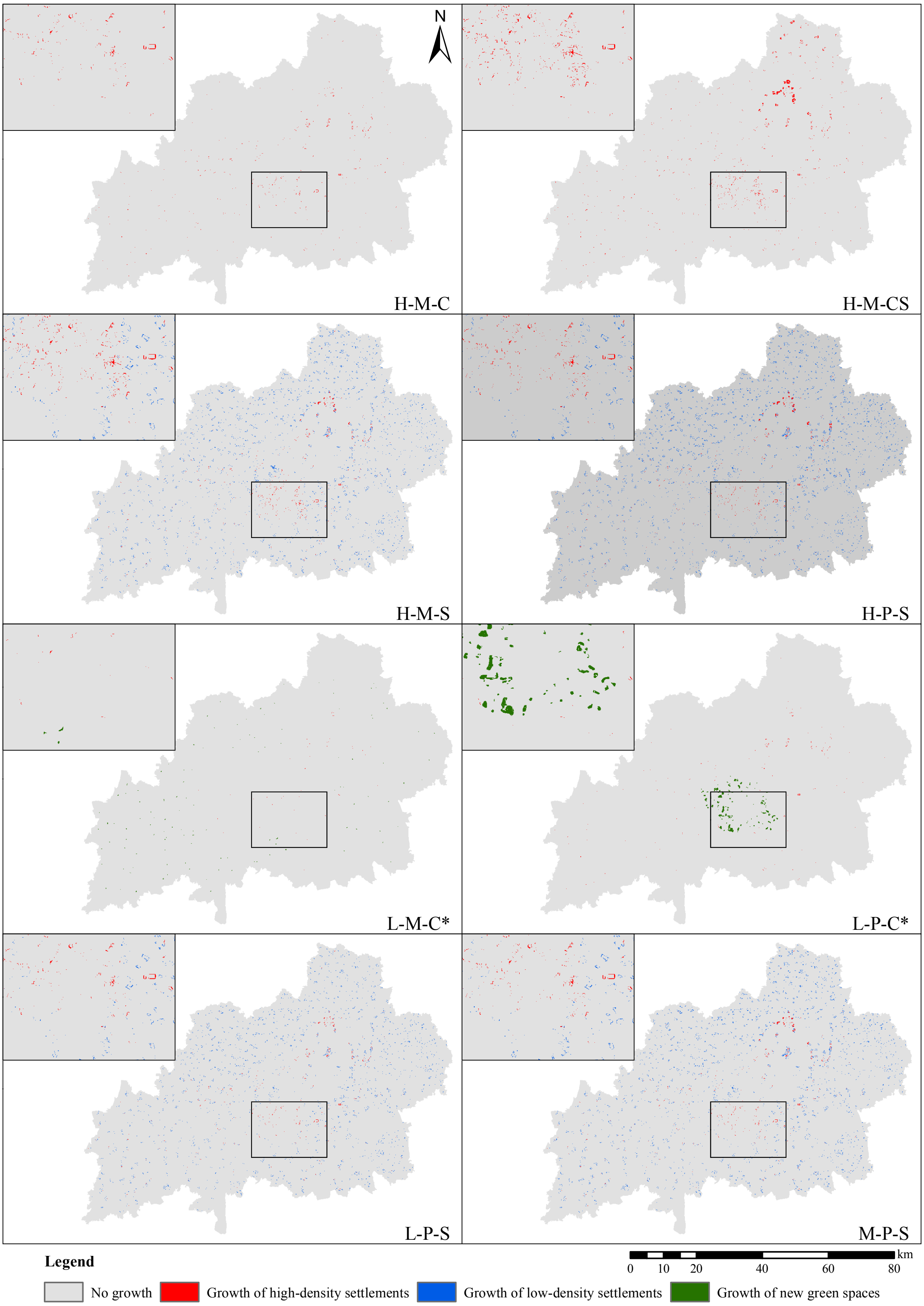

Figure 4.11 The spatial distribution of settlement growth in the eight selected scenarios (In the L-C-M and L-C-P scenarios, there were new green spaces generated due to urban shrinkage. The zoom-in window shows the settlement growth in the Munich urban core zone in details).

Figure 4.12 illustrates the land use transitions of the eight selected scenarios at both the regional and sub-regional levels. At the regional level, the settlement growth was, in most of the scenarios, mainly conversions from grassland, arable land, and parks and green spaces. The negative values in the L-M-C and L-P-C scenarios were due to the development of new green spaces because of urban shrinkage. At the sub-regional level, first, more land use classes that mainly contributed to the settlement growth were found in the Urban Core Zone than in the other two zones. Second, in the Urban Core Zone, the losses of parks and green spaces were much higher than the losses of other land uses in most scenarios (except for the two shrinking cases) especially in the compact growth (H-M-C) and compact sprawl growth (H-M-CS) scenarios. In comparison, the settlement growth in the other two zones mainly led to the loss of arable land and grassland. However, the losses of arable land were higher than the losses of grassland in the Peri-Urban Zone, whereas the opposite was true in the Rural Zone.

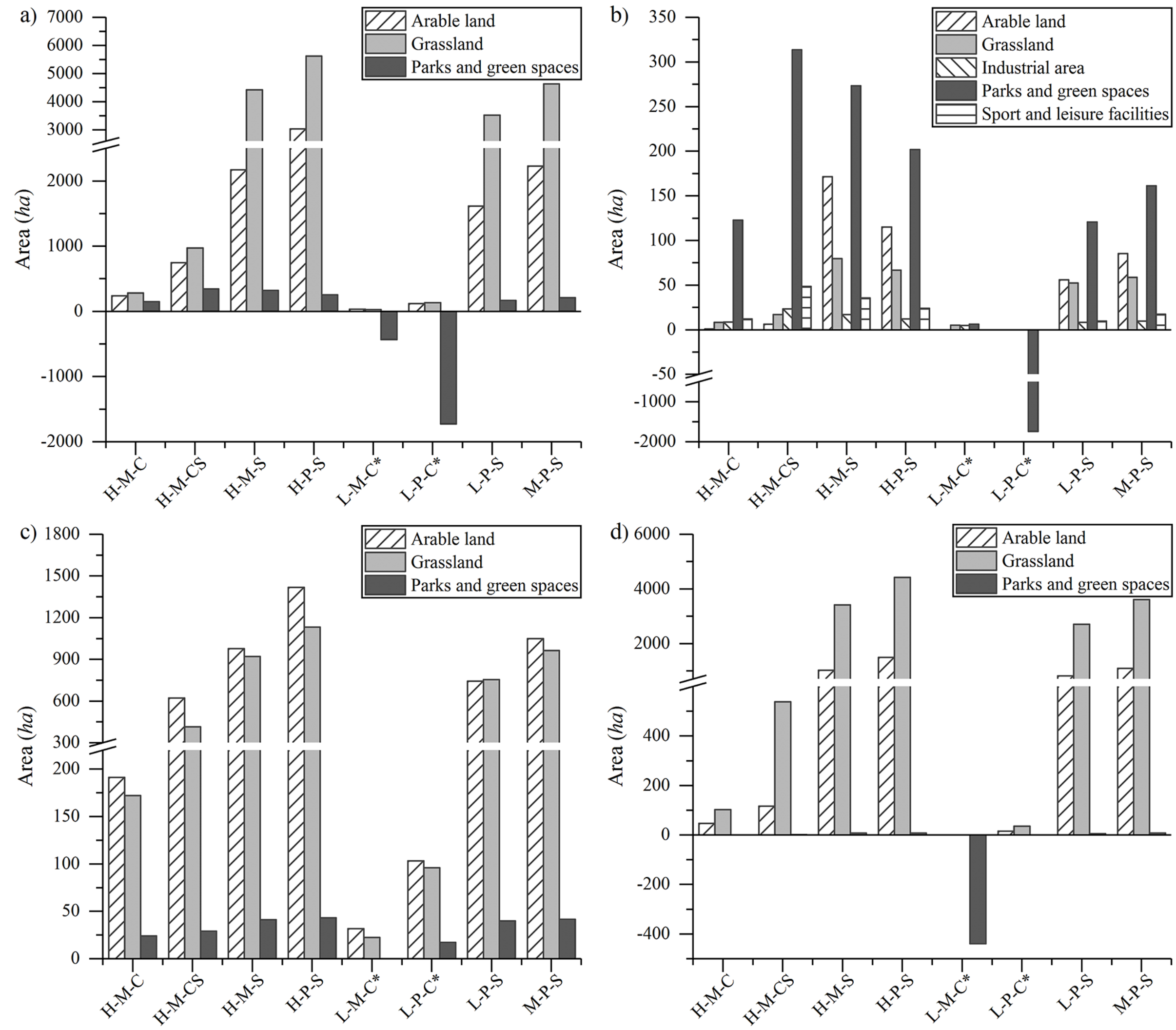

Figure 4.12 Land use changes in the eight selected scenarios at the regional level and in different sub-regional zones (Only land uses with transitions that account for more than 5% of the total changes in at least one scenario are shown. a): Region, b): Urban Core Zone, c): Peri-Urban Zone, and d): Rural Zone).

4.2.3 Elimination of Redundancy among Landscape Metrics

The results of the metric correlation assessment indicate that most of the metric pairs were significantly correlated for all three metric groups (Figure 4.13). Since the landscape metrics exhibited varying levels of redundancy and multicollinearity, each metric group was subjected to the Principal Component Analysis (PCA) to eliminate or reduce the multicollinearity and redundancy among the final predictor variables (Vanderhaeghe et al., 2012; Yao et al., 2013). The results demonstrate that, for each metric group, only one principal component was extracted with an eigenvalue larger than 1, and at least 82% of the total variance was explained (Table 4.6). Seven metrics were found with loadings greater than 0.75 for the patch complexity group, while only two and five metrics were identified for the configuration group and the diversity group, respectively. Consequently, three new landscape indexes were formulated according to Eq. 3.11 as follows:

$$\begin{aligned}\textit{Patch Complexity Index} = 7.42 \times (&0.95 \times P_{PAFRAC} + 0.93 \times P_{FRAC\_MN} \\ &+ 0.92 \times P_{SHAPE\_MN} + 0.88 \times P_{LSI} + 0.86 \times P_{TE} \\ &+ 0.86 \times P_{LPI} + 0.85 \times P_{AREA\_AM})\end{aligned} \qquad \text{(Eq. 4.1)}$$

$$\textit{Configuration Index} = 6.02 \times (0.96 \times P_{AI} + 0.93 \times P_{PLADj}) \qquad \text{(Eq. 4.2)}$$

$$\begin{aligned}\textit{Diversity Index} = 7.90 \times (&0.78 \times P_{SHDI} + 0.78 \times P_{SIDI} + 0.78 \times P_{SIEI} \\ &+ 0.77 \times P_{SHEI} + 0.76 \times P_{MSIDI})\end{aligned} \qquad \text{(Eq. 4.3)}$$

where P indicates the standardized value of the corresponding landscape metric.

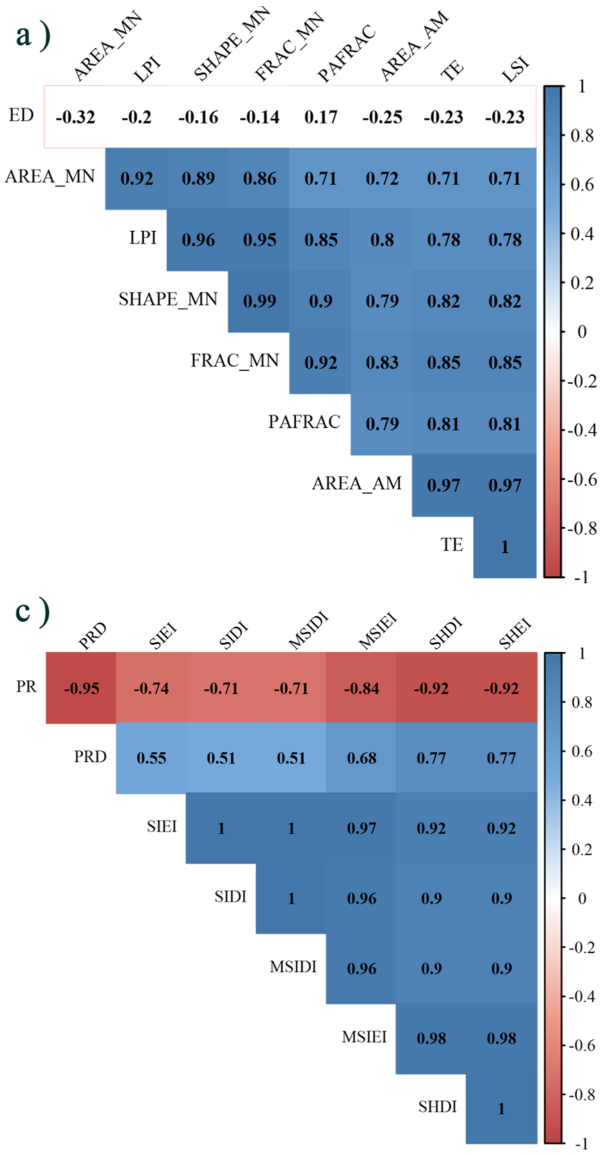

Figure 4.13 Matrixes of Spearman correlation coefficients for a) patch complexity metrics, b) configuration metrics, and c) diversity metrics (blue: positive correlation, red: negative correlation, and white: not significant).

Table 4.6 Results of varimax rotated PCA for the three groups of landscape metrics.

Patch complexity		Configuration		Diversity	
Component 1	Loadings	Component 1	Loadings	Component 1	Loadings
Perimeter-Area Fractal Dimension	0.95	Aggregation Index	0.96	Shannon's Diversity Index	0.78
Mean Fractal Dimension Index	0.93	Percentage of Like Adjacencies	0.93	Simpson's Diversity Index	0.78
Mean Patch Shape Index	0.92	Splitting Index	-0.74	Simpson's Evenness Index	0.78
Landscape Shape Index	0.88	Contagion	0.73	Shannon's Evenness Index	0.77
Total Edge	0.86	Effective Mesh Size	0.19	Modified Simpson's Diversity Index	0.76
Largest Patch Index	0.86	Interspersion and Juxtaposition Index	-0.47	Modified Simpson's Evenness Index	0.75
AreaWeighted Mean Patch Size	0.85	Landscape Division Index	-0.61	Patch Richness	-0.63
Edge Density	-0.16			Patch Richness Density	0.63
Mean Patch Size	0.65				
% Cumulative variance explained	82.45	% Cumulative variance explained	85.96	% Cumulative variance explained	98.76
Eigenvalue	7.42	Eigenvalue	6.02	Eigenvalue	7.90

Note: Shaded values denote loadings greater than 0.75 and only components with eigenvalue more than 1 are shown in the table.

4.2.4 Changes of Landscape Patterns among Scenarios

Figure 4.14 compares the landscape pattern changes under different urban dynamic sub-scenarios at the regional level while keeping the other two sub-scenarios the same. Based on the descriptions of the landscape metrics (see Table 3.4) and their loadings within each principal component (Table 4.6), higher patch complexity index values indicate that the area, edge, and shape of the patches in the landscape of corresponding scenarios are more complex and irregular. The configuration index measures the degree of aggregation of the entire landscape including all land use classes; that is, the higher the value, the more aggregated the entire landscape. Moreover, the diversity index is a measure of landscape composition, which is influenced by the richness and evenness of the landscape. The value of the diversity index increases as the number of different patch types increases and the distribution of the area among patch types becomes more even (McGarigal and Marks, 1995).

It appears that contrasting trends can be found between the patch complexity index and the other two indexes (Figure 4.14). First, scenarios with different levels of housing demand but the same urban spatial structure and urban growth form (H-P-S, M-P-S, and L-P-S) were compared with each other. A higher housing demand scenario reduced the patch complexity but improved the aggregation and diversity of the landscape. Second, H-M-S and L-M-C were compared with H-P-S and L-P-C, respectively, to evaluate the differences between scenarios with different urban spatial structures. The monocentric scenarios led to higher levels of patch complexity but lower levels of landscape aggregation and diversity than the polycentric ones. Furthermore, the differences between scenarios with different urban growth forms were identified by comparing H-M-C, H-M-CS, and H-M-S. The compact growth scenario (H-M-C) had the highest patch complexity index value, followed by the compact sprawl scenario (H-M-CS) and sprawl scenario (H-M-S). However, the opposite results were found for the configuration and diversity indexes.

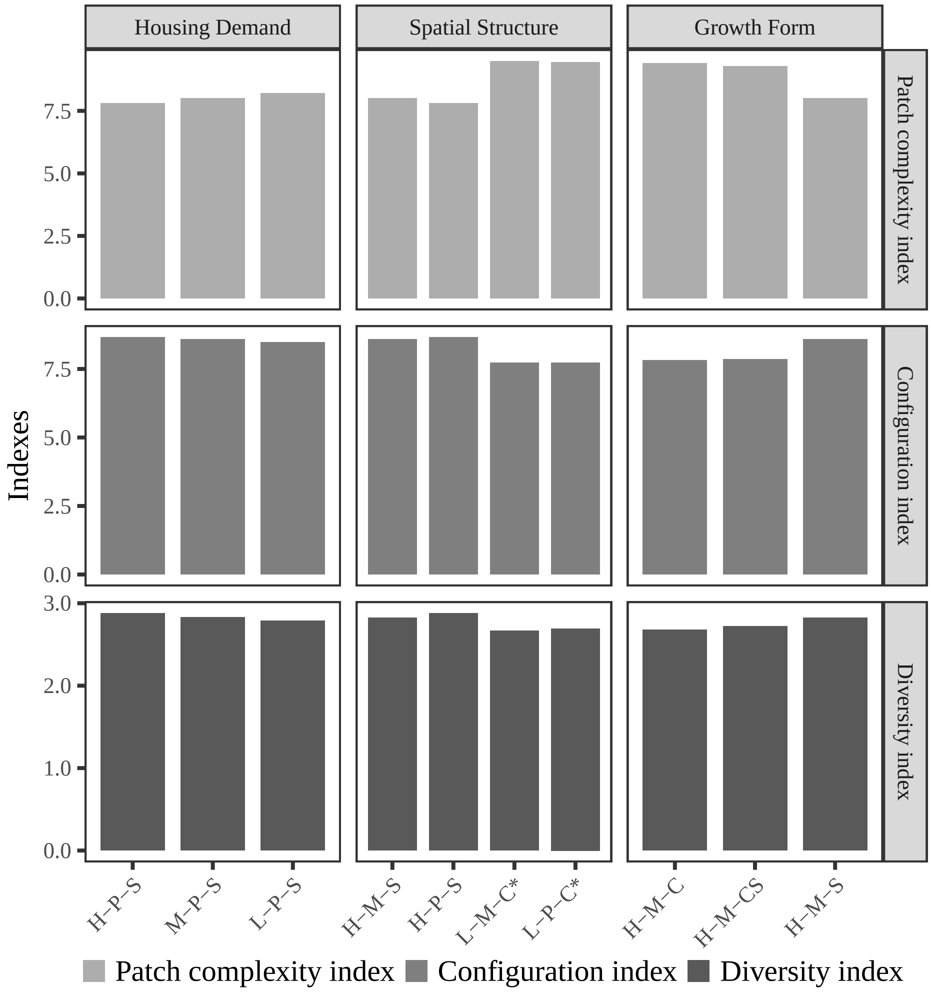

Figure 4.14 Values of the three landscape indexes under scenarios at the regional level with different levels of housing demand, spatial structure, and growth forms (*indicates urban shrinking scenario).

For each landscape index, significant differences were found between the mean values of the eight scenarios in different sub-regional zones (Figure 4.15). Moving from the Urban Core Zone outwards, the patch complexity index increased along the urban-rural gradient, while the landscape diversity index declined. In addition, the mean value of the landscape configuration index was the highest in the Peri-Urban Zone, followed by the Rural Zone and the Urban Core Zone.

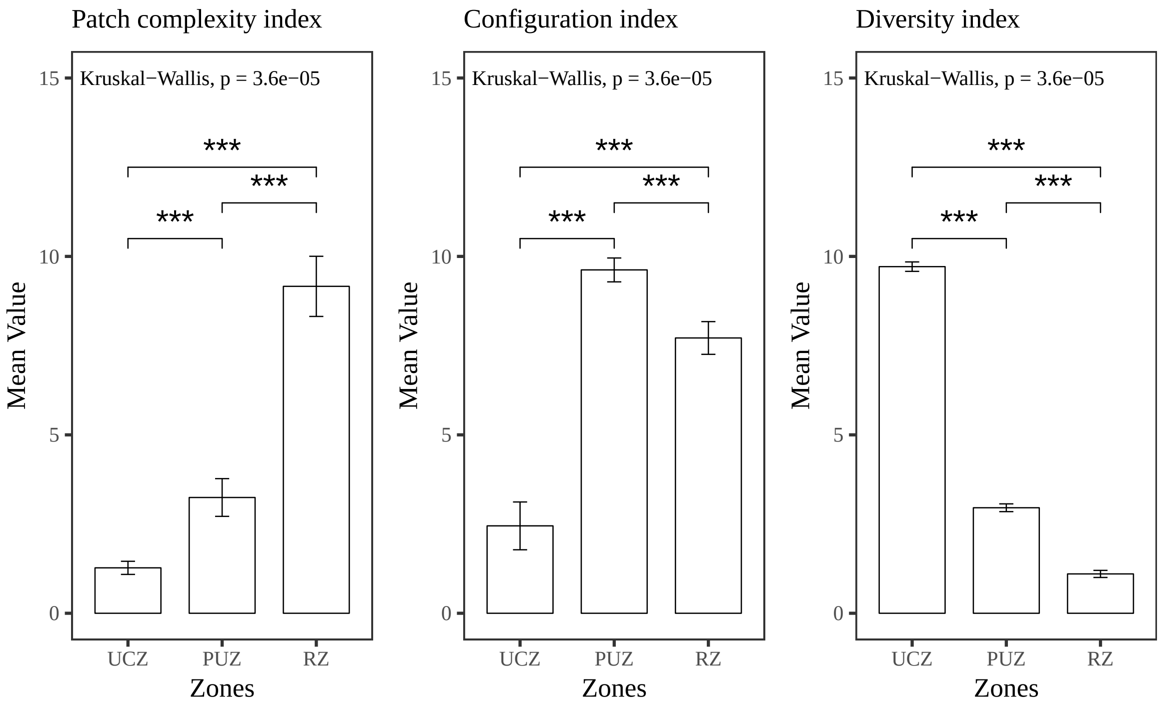

Figure 4.15 The mean values for each index of the eight scenarios in different sub-regional zones (UCZ: Urban Core Zone, PUZ: Peri-Urban Zone, and RZ: Rural Zone). The nonparametric Kruskal-Wallis test followed by post hoc Mann-Whitney U tests was used. Results represent mean ± SD (n = 8), and ***: $p < 0.001$, **: $p < 0.01$, *: $p < 0.05$.

Figure 4.16 presents the changes of each landscape index under different scenarios in different sub-regional zones. First, the changes of the patch complexity index in all zones were largely similar to those at the regional level (Figure 4.16a). More specifically, the patch complexity index declined when increasing the housing demand. Additionally, the compact growth scenario had the highest patch complexity index value while the sprawl growth scenario had the lowest value. The only difference is that the patch complexity index value of the polycentric scenarios was higher than for the monocentric scenarios in the Urban Core Zone, which was contrary to the changes in the other two zones and the region. Second, for the configuration index, most of the changes in different zones were in line with the regional changes as well (Figure 4.16b). Similar to the patch complexity index, the changes among different spatial structure scenarios in the Urban Core Zone contrasted with those of the other two zones and the region. Third, the changes of the diversity index were more complicated compared to those of the other two indexes (Figure 4.16c). The diversity index increased in the Peri-Urban and Rural Zones when increasing the housing demand, which is in line with the regional change, whereas it declined in the Urban Core Zone. The landscapes of polycentric scenarios were more diverse than those of the monocentric scenarios in most cases, except for the two shrinking scenarios (L-M-C and L-P-C) in the Rural Zone. As for different urban growth form scenarios, the landscape diversity index of the compact growth scenario was the highest in the Urban Core Zone followed by the compact sprawl and sprawl growth scenarios. However, the trends were reversed in the other two zones.

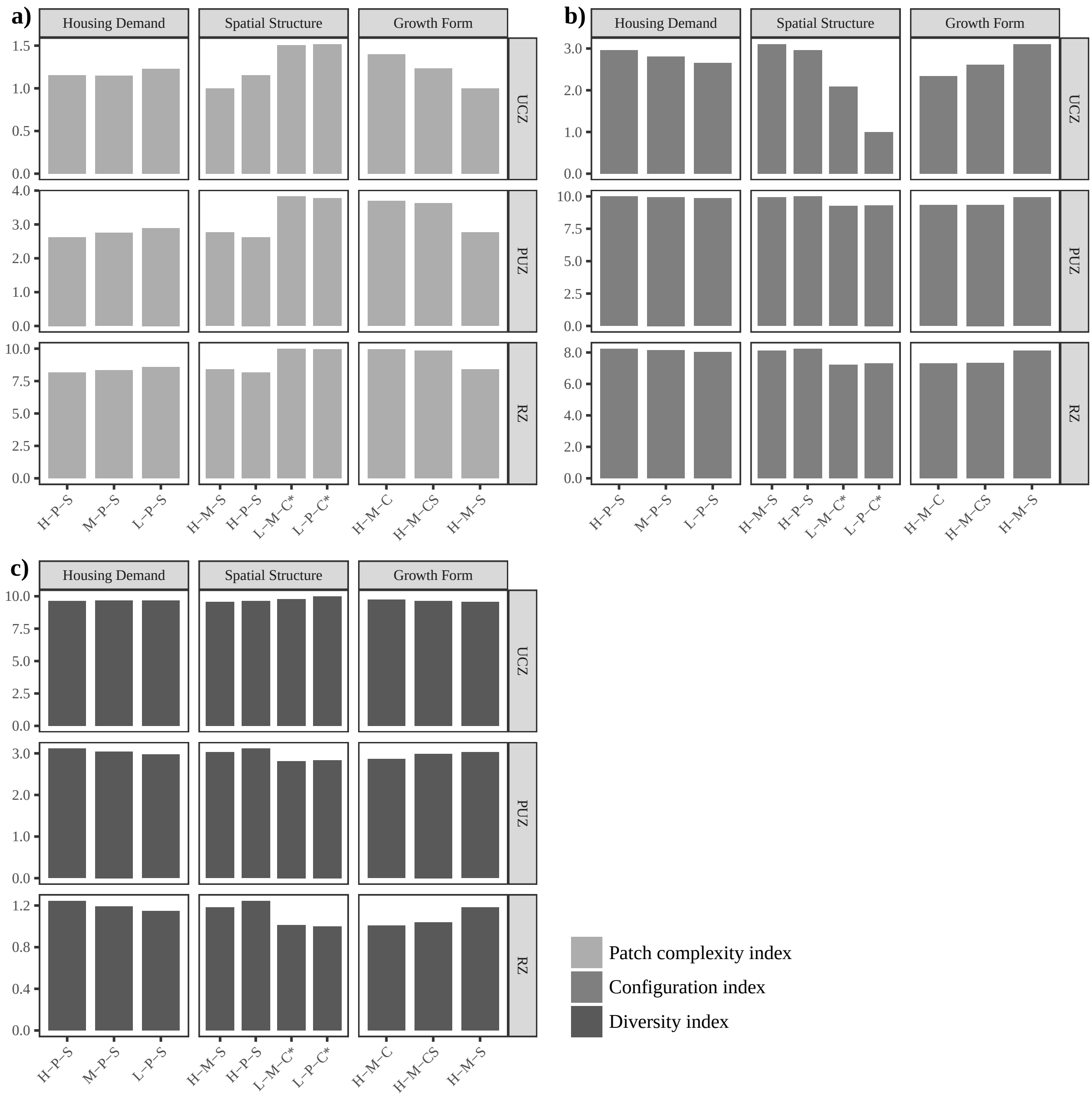

Figure 4.16 Values of the a) patch complexity index, b) configuration index, and c) diversity index under different scenarios in different sub-regional zones (UCZ: Urban Core Zone, PUZ: Peri-Urban Zone, and RZ: Rural Zone, *indicates urban shrinking scenario).

4.3 Impacts of Urban Dynamics on Green Space Availability (Part III)

In this part, the overall changes of green space availability under different urban dynamic scenarios are firstly reported. Then, the impacts of different urban dynamics on green space availability are revealed at both the regional and sub-regional levels.

4.3.1 Green Space Availability under Different Scenarios

A number of, predominantly inner-urban, green spaces have been and most likely will continue to be lost during urban growth, no matter which growth form is adopted. It was apparent in this study that green space declined as a result of urban growth in six out of eight scenarios, with the exceptions of L-M-C and L-P-C, which follow a process of shrinkage resulting in new green spaces (Figure 4.17).

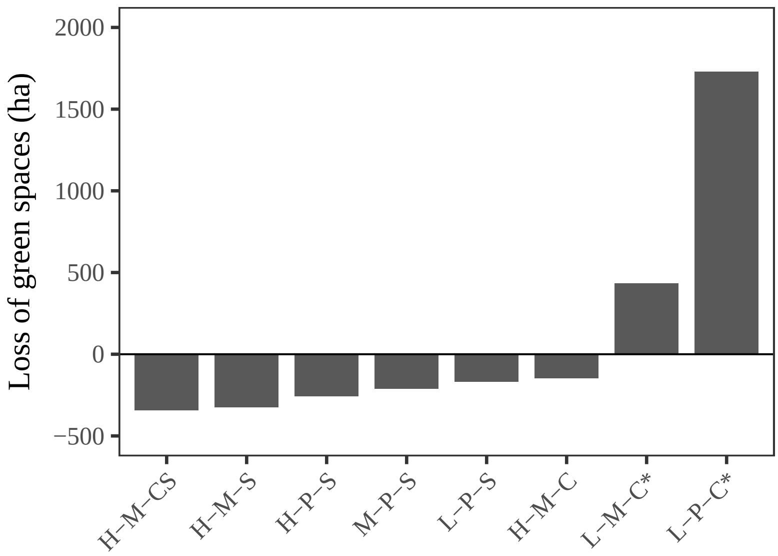

Figure 4.17 Changes in green space areas by 2033 in each scenario relative to 2013 (*indicates urban shrinking scenario).

The percentage changes of Per Capita Green Space (PCGS) and the Share of the Population with Access to Green Spaces (SPAGS) for each scenario compared to the year 2013 are shown in Figure 4.18. In most cases, both indicators showed negative percentage change values, which implies decreases compared to 2013. As mentioned above, the shrinkage-driven L-M-C and L-P-C were two exceptions wherein SPAGS increased due to the development of new green spaces. Overall, L-P-C was the scenario that showed the lowest decrease in PCGS and the highest increase of SPAGS.

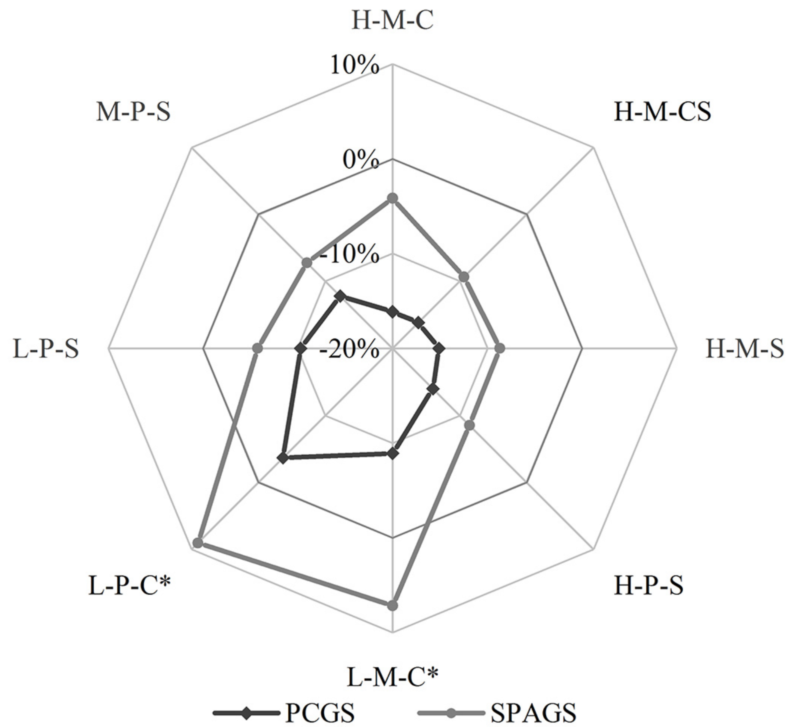

Figure 4.18 Percentage changes in PCGS and SPAGS between each scenario and 2013 (*indicates urban shrinking scenario).

The correlations between the two main indicators, PCGS and SPAGS, and other variables, including settlement area, population density, and area of green spaces, were investigated in this study (Figure 4.19). Settlement area was found not to be significantly correlated to PCGS but to be negatively correlated to SPAGS ($p < 0.05$), which implies that scenarios with smaller settlement areas do not indeed lead to higher PCGS but automatically result in a higher SPAGS. With regard to population density, there was no significant correlation with either PCGS or SPAGS. Furthermore, significant positive relationships were identified between the area of green spaces and both indicators. In other words, scenarios with a larger area of green spaces usually had higher values of PCGS and SPAGS as well. Generally speaking, PCGS was mainly correlated to the area of green spaces, while both the area of green spaces and settlement area had significant correlations with SPAGS.

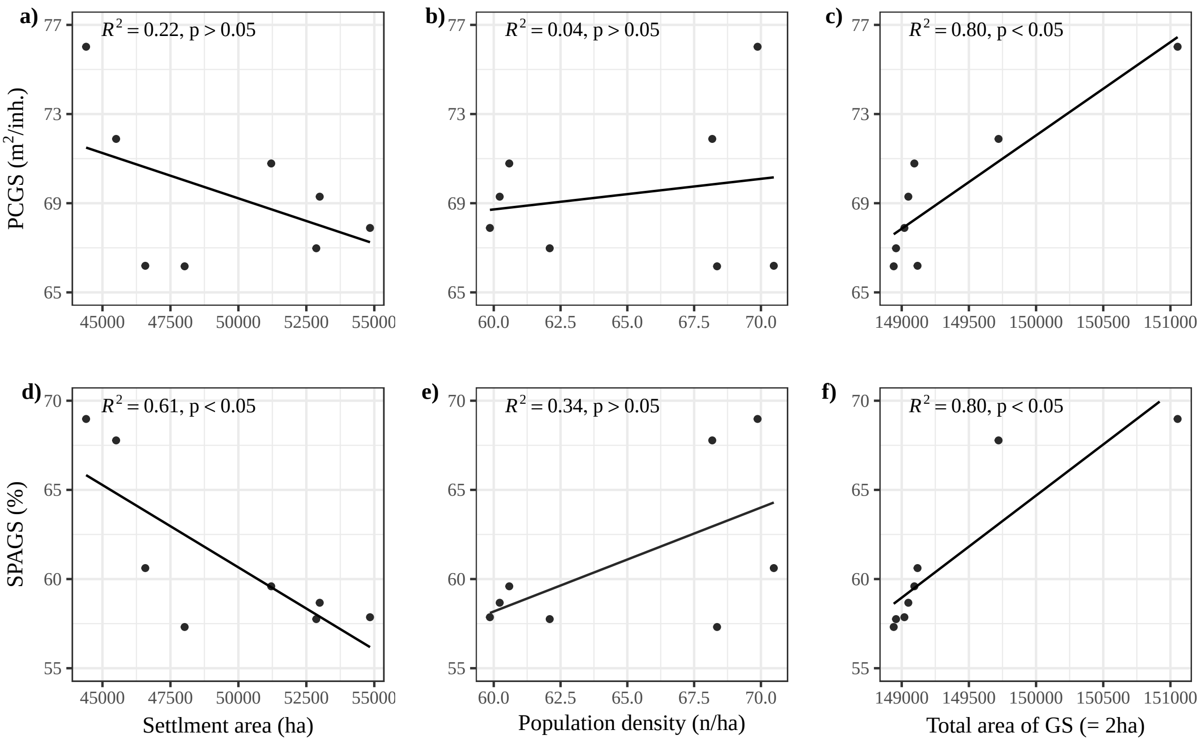

Figure 4.19 Linear regression between the two indicators and settlement area, population density, as well as area of green spaces (dots represent the eight scenarios).

4.3.2 Impacts of Urban Dynamics on Regional Green Space Availability

Figure 4.20 compares the impacts of different urban dynamic sub-scenarios on green space availability. For clarity, changes in green spaces within 300 *m* distances from settlements and population numbers with access to green spaces compared to 2013 are displayed in Figure 4.21. First, it is evident from the results that both indicators declined when the housing demand increased (Figure 4.20a). Despite the fact that a higher housing demand scenario led to a higher net increase in green spaces within 300 *m* distances from settlements (Figure 4.21a), the value of PCGS was lower, due to the larger population size it included. At the same time, scenarios with higher housing demand resulted in greater net decreases in the total population number with access to green spaces (Figure 4.21b), thereby resulting in lower values of SPAGS.

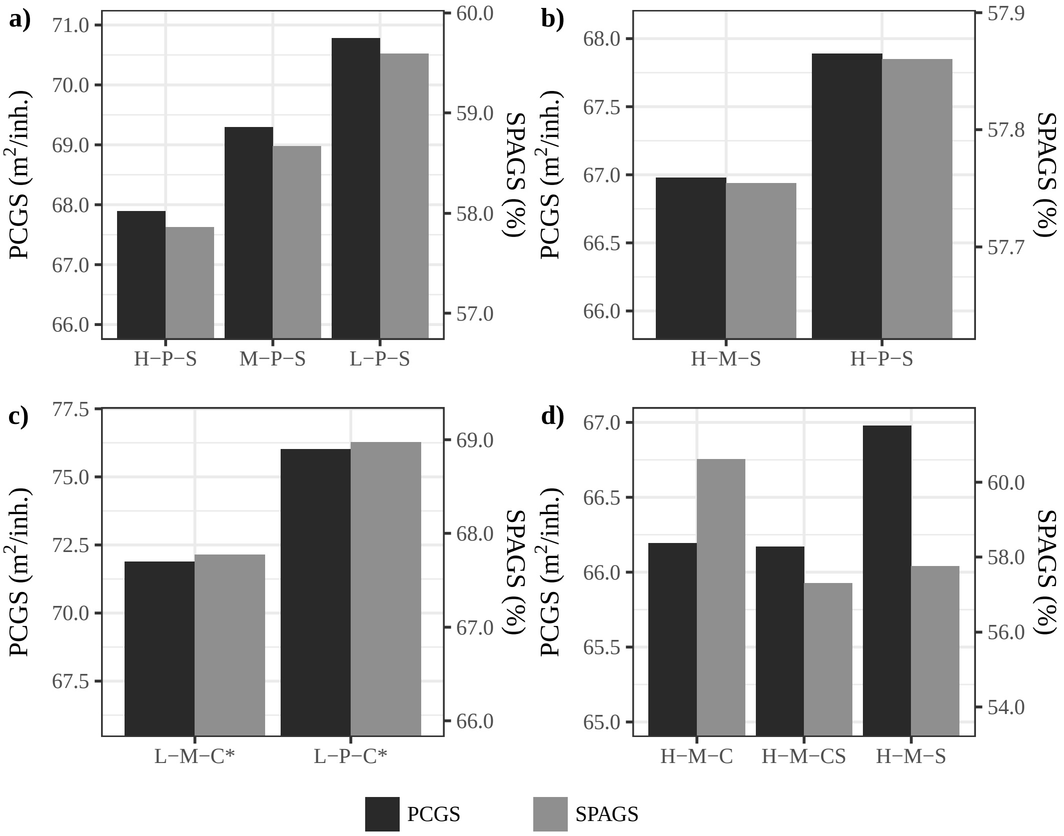

Figure 4.20 Values of PCGS and SPAGS in scenarios with a) different housing demands, b) & c) different spatial structures, and d) different growth forms (*indicates urban shrinking scenario).

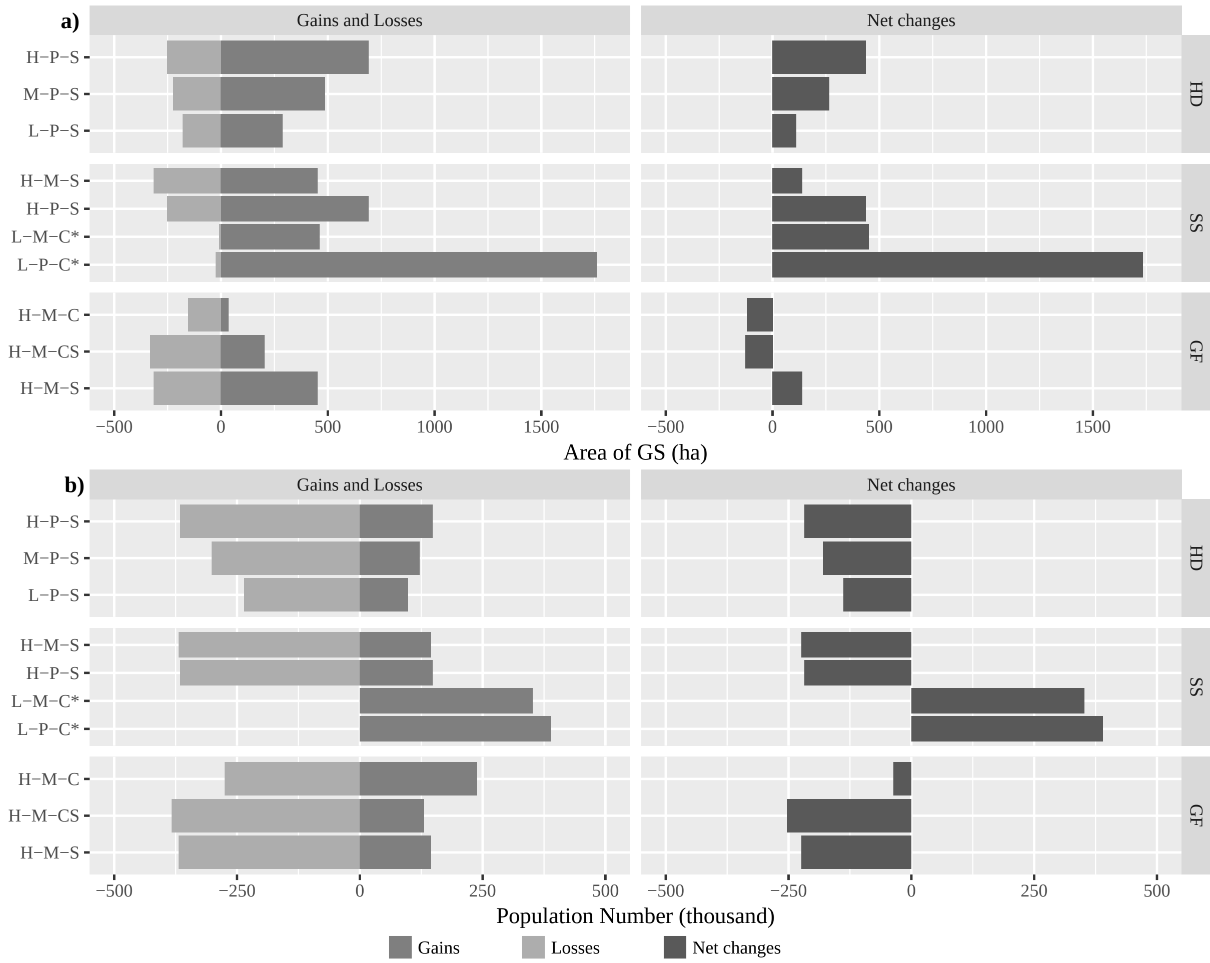

Figure 4.21 Gains, losses and net changes in a) green spaces within 300 *m* distances from settlements and b) population numbers with access to green spaces for all scenarios compared to 2013 (HD: different housing demand scenarios, SS: different spatial structure scenarios, GF: different growth form scenarios, *indicates urban shrinking scenario). Note: The gains in green spaces within 300 *m* distances from settlements were mainly due to new settlements developed closer to (within 300 *m* in this study) green spaces that used to be more than 300 *m* from settlement areas, and the losses primarily stemmed from green spaces within 300 *m* that were converted into settlements. For populations with access to green spaces, new settlements developed within 300 *m* distances from green spaces, as well as the increase in population density or new green spaces constructed in shrinking cases, contributed to the gains, while the losses were due to new settlements developed in areas far from green spaces (more than 300 *m*), increases in population density in settlement areas without access to green spaces, or the loss of green spaces.

Second, it can be concluded from Figure 4.20b&c that the polycentric scenarios (H-P-S and L-P-C) demonstrate both higher PCGS and SPAGS values compared to the monocentric scenarios (H-M-S and L-M-C). According to Figure 4.21, a greater net increase in green spaces within 300 *m* distances from settlements and a smaller net decrease in population numbers with access to green spaces were found in H-P-S compared to H-M-S. It indicates that a polycentric structure will substantially increase the area of green spaces within 300 *m* distances from settlements and reduce the loss of population with access to green spaces. In addition, as there were shrinking cases and new green spaces developed in L-M-C and L-P-C, both green spaces within 300 *m* distances from settlements and population numbers with access to green spaces were increased in these two scenarios. However, the increases were higher in L-P-C than in L-M-C.

Third, growth in the form of “sprawl” (H-M-S) showed the highest value of PCGS, and “compact” growth (H-M-C) showed the highest value of SPAGS; in contrast, “compact sprawl” growth (H-M-CS) showed the lowest values for both indicators (Figure 4.20d). As shown in Figure 4.21a, green spaces within 300 m distances from settlements increased in H-M-S, while decreases were observed in the other two scenarios (the decrease was greater in H-M-CS). Interestingly, the loss of green spaces in H-M-CS was even greater than that in H-M-S. According to the difference between “compact sprawl” and “sprawl” in this study, it appears very likely that the development of high-density settlements would result in even more green spaces being encroached than the development of low-density settlements in the study region. Therefore, H-M-S had the highest value of PCGS, while H-M-CS had the lowest value among these three scenarios (Figure 4.20d). Regarding the population number with access to green spaces, H-M-C showed the lowest net decrease and, accordingly, the highest value of SPAGS. In contrast, H-M-CS had the largest net decrease and the lowest value of SPAGS (Figure 4.21b, Figure 4.20d).

4.3.3 Impacts of Urban Dynamics in Sub-regional Zones

As shown in Figure 4.22, significant differences were found for both indicators among the mean values of the eight scenarios in different sub-regional zones. While moving outwards from the Urban Core Zone, the values of PCGS increased in all scenarios due to the presence of more forest areas in the Peri-Urban and Rural Zones (see Figure 3.3). However, the values of SPAGS declined along the urban-rural gradient in seven of eight scenarios, as there were less green spaces (≥ 2 ha) available within 300 m distances from homes, with the exception of L-M-C, in which new green spaces developed in the Rural Zone.

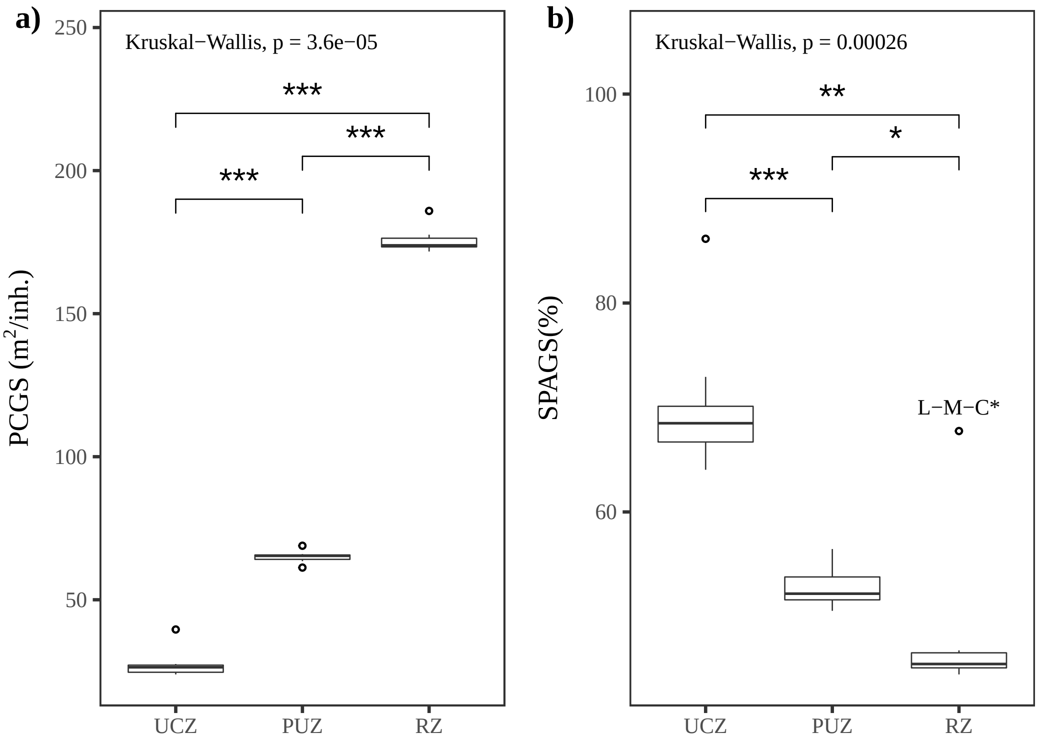

Figure 4.22 Boxplot of the mean values of a) PCGS and b) SPAGS of the eight scenarios in different zones (UCZ: Urban Core Zone, PUZ: Peri-Urban Zone, RZ: Rural Zone). The nonparametric Kruskal-Wallis test followed by post hoc Mann-Whitney U tests was used (n = 8, and ***: $p < 0.001$, **: $p < 0.01$, *: $p < 0.05$).

Figure 4.23a compares the changes in PCGS and SPAGS among different housing demand sub-scenarios in each zone. In line with the regional change, both indicators declined as the housing demand increased in all three zones. When comparing scenarios with different urban spatial structures, the changes in both indicators were always in agreement with each other in the same zone (Figure 4.23b&c). However, contrasting trends were found between the Urban Core Zone and the other two zones. According to the scenario settings, monocentric scenarios allocated more housing demand in the Urban Core Zone and less in the other two zones compared to polycentric scenarios. As both indicators declined while the housing demand increased in all three zones, thereby the values of both indicators in monocentric scenarios were lower in the Urban Core Zone but higher in the other two zones than polycentric scenarios (Figure 4.23b&c).

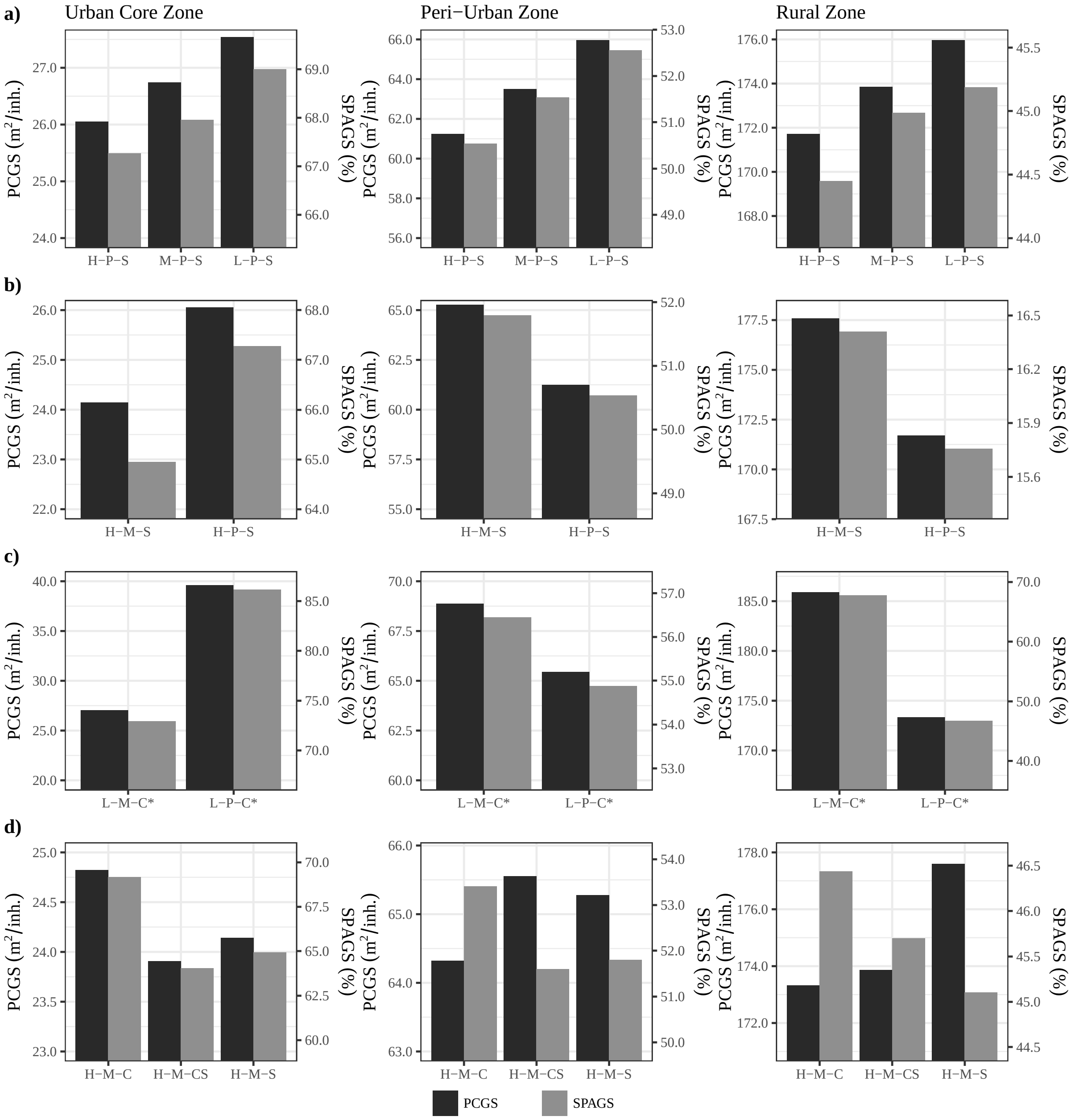

Figure 4.23 PCGS and SPAGS values under scenarios with a) different housing demands, b) & c) different urban spatial structures, and d) different urban growth forms in different sub-regional zones (*indicates urban shrinking scenario).

The changes of both indicators among scenarios with different urban growth forms were distinct in different zones (Figure 4.23d). In the Urban Core Zone, H-M-C had the highest values of both PCGS and SPAGS, due to the smallest net decrease of green spaces within 300 *m* of settlements and the net increase in population with access to green spaces (Figure 4.24), whereas H-M-CS had the lowest values. In the Peri-Urban Zone, H-M-C had the lowest value of PCGS but the highest value of SPAGS, because of the net decrease of green spaces within 300 *m* from settlements and the smallest net decrease in the population number with access to green spaces, respectively. In contrast, H-M-CS had the highest value of PCGS but the lowest value of SPAGS. In the Rural Zone, H-M-C had the lowest value of PCGS but the highest value of SPAGS, which is similar to the Peri-Urban Zone. However, in contrast to H-M-CS in the Peri-Urban Zone, H-M-S had the highest value of PCGS but the lowest value of SPAGS in the Rural Zone. Generally, "compact" growth (H-M-C) was most likely to be the best option in the Urban Core Zone in terms of both indicators; however, defining the optimal approach for the other two zones must consider the relative trade-offs between the two indicators.

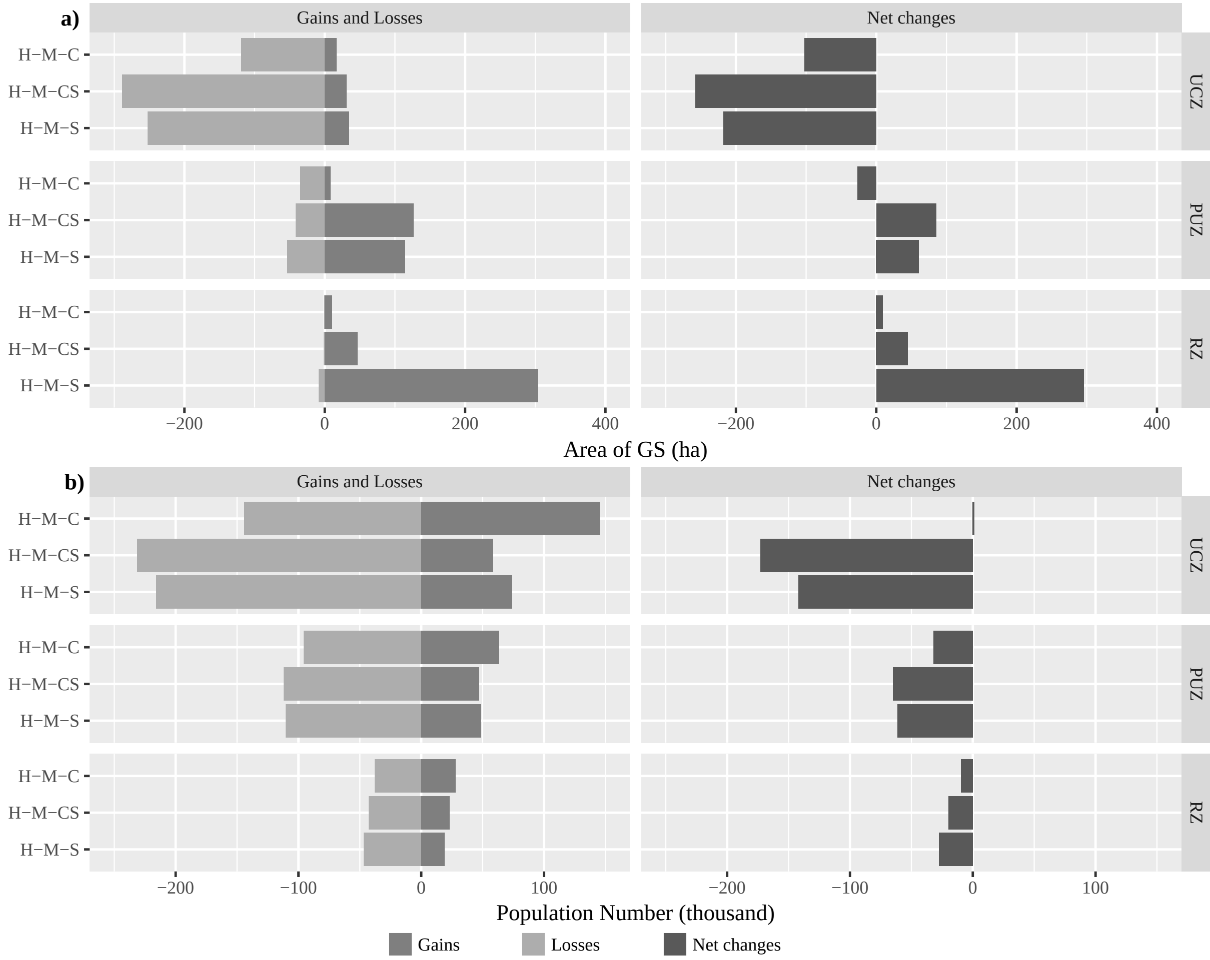

Figure 4.24 Gains, losses and net changes of a) green spaces within 300 m distances from settlements and b) population numbers with access to green spaces relative to 2013 among scenarios with different urban growth forms in the three zones (UCZ: Urban Core Zone, PUZ: Peri-Urban Zone, RZ: Rural Zone, *indicates urban shrinking scenario).

4.4 Spatial Variation of Green Space Equity and the Impacts of Urban Dynamics (Part IV)

This section presents the spatial correlation between green space equity and socioeconomic factors as well as the impacts of different urban dynamic scenarios on green space equity at both levels.

4.4.1 Spatial Correlation between Green Space Equity and Socioeconomic Factors

Figure 4.25 shows the distribution of the Gini coefficient of the year 2013. Lower Gini coefficient values were found in the central and southern municipalities of the region, indicating that green spaces were more equally distributed in these areas. Municipalities in their surrounding areas showed higher values of the Gini coefficient, in particular in the northwest and central-east parts of this region.

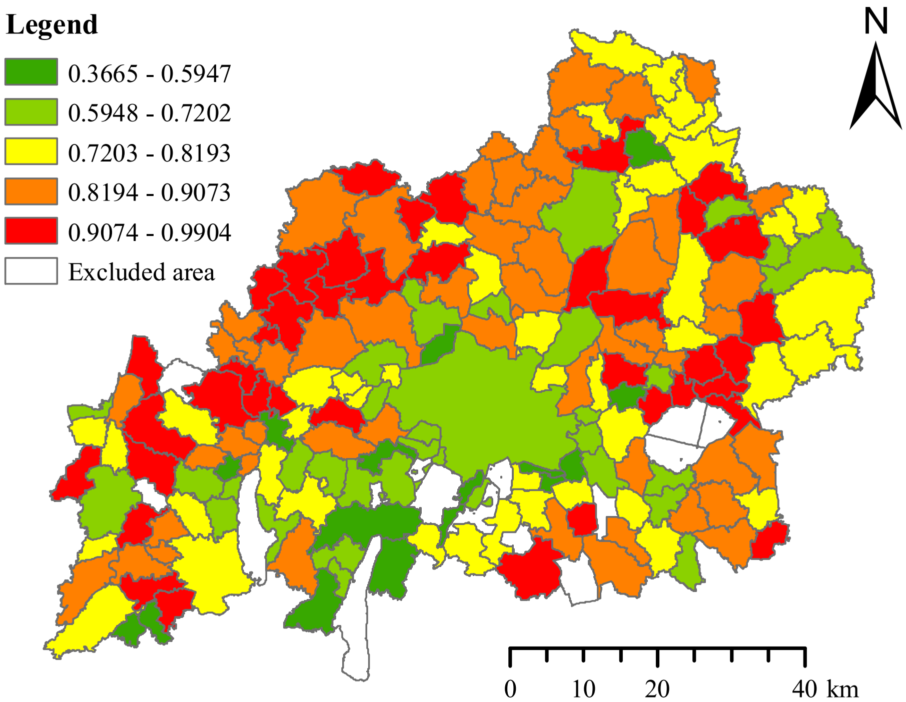

Figure 4.25 Distribution of Gini coefficient of the year 2013.

The Kaiser-Meyer-Olkin (KMO) test was found to be 0.655, signifying that a factor analysis is appropriate. Three rotated factors were extracted with eigenvalues greater than 1 and 79.74% of the total variance in the original data explained. The results of factor analysis are shown in Table 4.7. Factor 1 accounted for 28.63% of the variance with high positive loadings on the percentage of old people above 65 and the percentage of people in long-term unemployment while high negative loading on the percentage of children and teenagers below 18, which can be identified as the "Demographic factor". Factor 2 is defined as "Social-spatial factor" which explained 25.86% of the variance with high positive loading on per capita living space and high negative loading on population density. Explaining 25.25% of the variance, Factor 3 is termed "Economic factor" as it had high positive loadings on the variables of per capita municipal revenue, per capita income and average housing price.

Table 4.7 Rotated Component Matrix of Factor Analysis.

Variables	Factor 1	Factor 2	Factor 3
Percentage of old people above 65 (%)	0.850	0.215	0.291
Percentage of children and teenagers below 18 (%)	-0.736	0.251	0.165
Percentage of people in long-term unemployment (%)	0.703	-0.432	0.110
Per capita living space ($m^2/inh.$)	-0.012	0.934	0.181
Population density (n/ha)	0.418	-0.828	0.250
Per capita municipal revenue (Euro/$inh.$)	-0.192	-0.083	0.799
Per capita income (Euro/$inh.$)	0.257	0.416	0.794
Average housing price (Euro/m^2)	0.504	-0.190	0.729

Note: The mainly loaded variables are shaded for each factor. The total variance explained is 79.74%.

The Geographically Weighted Regression (GWR) was used to explore the spatial relationship between the Gini coefficient and the three factors across all municipalities. Compared to the global regression, the GWR model showed a better performance. It provided a smaller AIC value (-294.73) and a higher R^2 value (0.41) than the global regression (-280.19 and 0.26 respectively). Moreover, the results of ANOVA (Analysis of Variance) also implied that the GWR model had significantly improved the performance of the global regression model (Table 4.8).

Table 4.8 GWR ANOVA of the relationship between the Gini coefficient and socioeconomic variables.

Source	Sum of Square	Degree of Freedom	Mean Square	F-value	p-value
Global Residuals	2.194	179.000			
GWR Improvement	0.466	20.598	0.023		
GWR Residuals	1.728	158.402	0.011	2.073749	0.000000

Note: Global regression: AIC = −280.19, R^2 = 0.26; GWR: AIC = −294.73, R^2 = 0.41.

Figure 4.26 shows the distribution of significant parameter estimates of the GWR model. First, the demographic factor had a significant negative correlation with the Gini coefficient across the municipalities in the middle, west and northwest parts of the region. As mentioned previously, this factor had high positive loadings on the percentage of old people above 65 and percentage of people in long-term unemployment, and a high negative loading on the percentage of children and teenagers below 18. Therefore, the percentage of old people above 65 and percentage of people in long-term unemployment had negative correlations while the percentage of children and teenagers below 18 showed a positive correlation with the Gini coefficient in these areas. Second, a significant positive correlation was found across the southeast municipalities between the Gini coefficient and the social-spatial factor which had a high positive loading on per capita living space and a high negative loading on population density. Accordingly, it indicates that per capita living space had a positive correlation with the Gini coefficient while population density had a negative one. Third, the economic factor was found to have a significant negative correlation with the Gini coefficient in the southwest half of the region. This factor had high positive loadings on the variables of per capita municipal revenue, per capita income and average housing price, thereby all these three variables were negatively correlated with the Gini coefficient across the southwest municipalities.

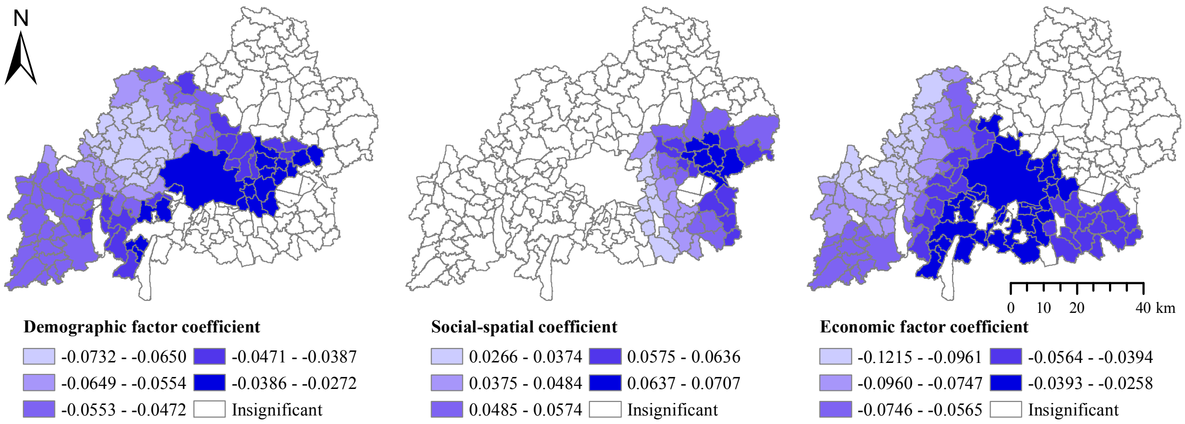

Figure 4.26 Distribution of significant coefficients based on t-test at $\alpha = 0.05$.

4.4.2 Impacts of Urban Dynamics on Regional Green Space Equity

As shown in Figure 4.27, most of the scenarios showed higher values of the Gini coefficient compared to the year 2013, with the exceptions of L-P-C and L-M-C, which have new green space developed as the result of urban shrinkage. A higher value of the Gini coefficient indicates the more uneven spatial distribution of green spaces.

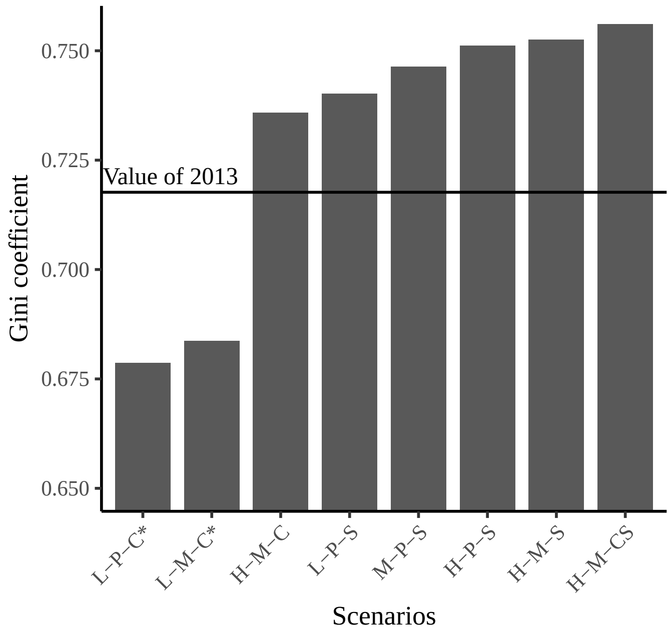

Figure 4.27 The values of Gini coefficient for eight scenarios (The horizontal line indicates the value of Gini coefficient in the year 2013 and *indicates urban shrinking scenarios).

The impacts of different sub-scenarios of urban dynamics on green space equity are compared in Figure 4.28. A lower housing demand scenario led to a lower value of the Gini coefficient, indicating that green spaces were more equally distributed across the region. Polycentric scenarios showed lower values of the Gini coefficient than monocentric ones. Moreover, the compact growth scenario (H-M-C) performed the best with the lowest Gini coefficient among the other two urban growth form sub-scenarios (H-M-CS and H-M-S).

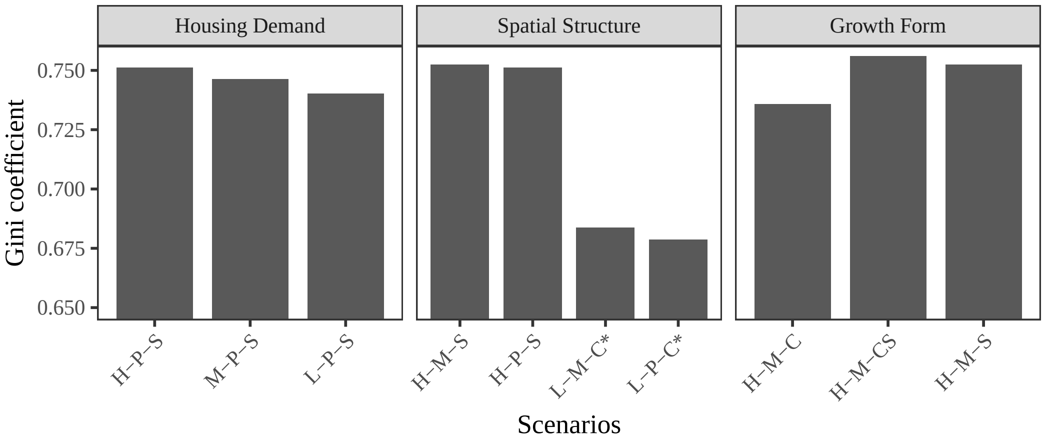

Figure 4.28 Values of Gini coefficient in scenarios with different housing demand, different urban spatial structure and different urban growth form at the regional level (*indicates urban shrinking scenarios).

4.4.3 Impacts of Urban Dynamics on Green Space Equity in Sub-regional Zones

Figure 4.29 compares the mean values of the Gini coefficient of the eight selected scenarios in different sub-regional zones and shows that the differences were significant. Moving outwards from the Urban Core Zone, the mean values of the Gini coefficient showed an increasing trend along this urban-rural gradient in most of the scenarios. Exceptions were found to be the two shrinking scenarios in which new green spaces have developed.

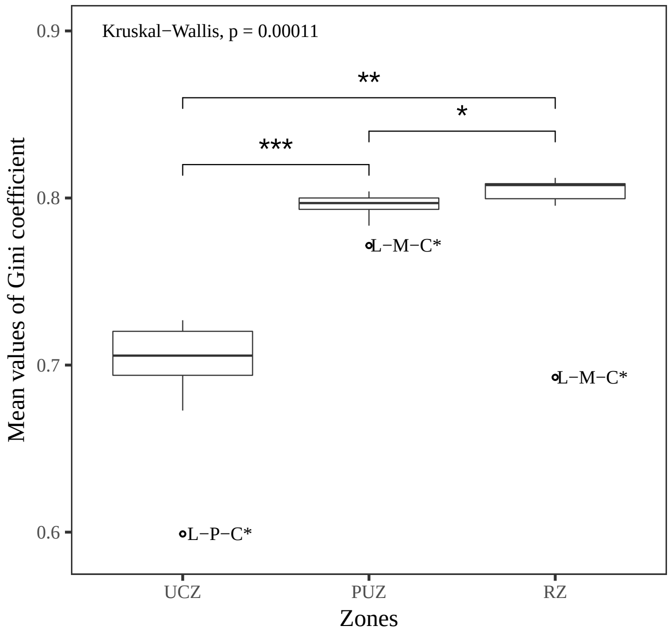

Figure 4.29 Boxplot of the mean values of the Gini coefficient of the eight selected scenarios along different sub-regional zones (UCZ: Urban Core Zone, PUZ: Peri-Urban Zone, and RZ: Rural Zone). The nonparametric Kruskal-Wallis test followed by post hoc Mann-Whitney U tests was used (n = 8, and ***: p < 0.001, **: p < 0.01, *: p < 0.05). The scenario names of outliers are labeled.

Figure 4.30 represents the impacts of different urban dynamic scenarios on the green space equity in different sub-regional zones. In line with the change at the regional level, the Gini coefficient rose with increasing housing demand in all three zones. Lower values of the Gini coefficient were found under the polycentric scenarios in the Urban Core Zone while the other two zones showed contrasting results. Among scenarios with different urban growth forms, the "compact" growth form (H-M-C) showed the lowest value of the Gini coefficient in all three zones. However, it is noteworthy that the compact sprawl growth scenario had the highest values of the Gini coefficient in the Urban Core and Peri-Urban Zones, whereas the sprawl scenario obtained the highest value in the Rural Zone, thus indicating the worst situation in terms of green space equity.

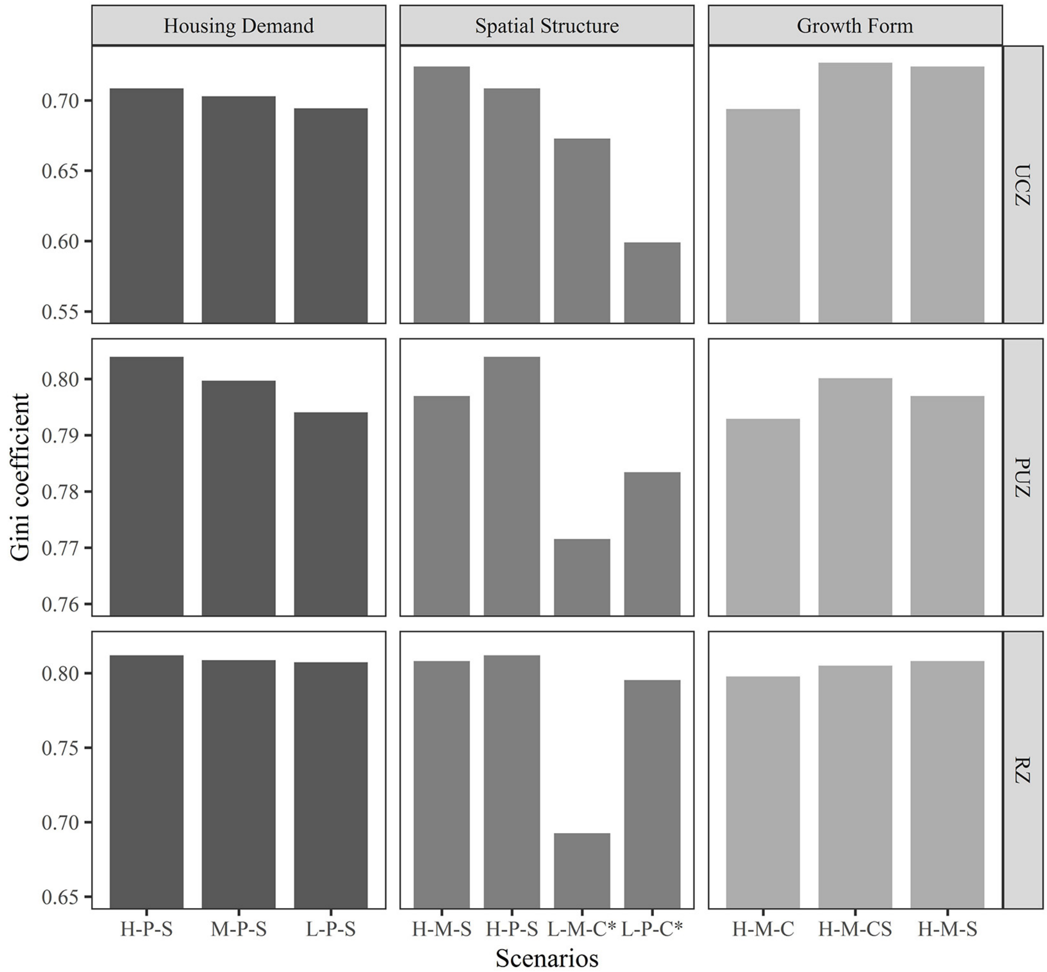

Figure 4.30 Values of the Gini coefficient under scenarios with different housing demand, different urban spatial structure and different urban growth form in different sub-regional zones (UCZ: Urban Core Zone, PUZ: Peri-Urban Zone, and RZ: Rural Zone, *indicates urban shrinking scenarios).

Chapter 5

Discussion

Globally, persistent population growth and urbanization put increasing pressure on ecological systems on a wide range of scales, which leads to severe environmental consequences (Gaube and Remesch, 2013; Lauf et al., 2012; Liu and Yang, 2015; Sun et al., 2013). By providing various ecosystem services, green spaces play a crucial role in the global ecosystem. Particularly in urban ecosystems, green spaces are considered to be a remedy to urban environmental problems (Xu et al., 2016). In recent years, the increasing interest in sustainability science has sharpened the focus on sustainable urban development, of which green spaces are regarded as a fundamental part (Jim, 2004). Therefore, this empirical study aims to contribute to the advancement of knowledge about the impacts of different urban dynamics on green spaces. The study was conducted in the region of the fast-growing Bavarian capital city of Munich, an urban area with intense land pressure, based on a multiple-scenario modeling approach.

In this chapter, the advantages of incorporating the spatial dependency into the model and modeling the growths of different settlement types separately are discussed first (**Part I**). Then, the main characteristics of the historical urban growth and the landscape pattern changes under multiple urban dynamic scenarios are explored (**Part II**). Next, the impacts of different urban dynamics on green space availability at both levels and the trade-offs between the two green space availability indicators are discussed (**Part III**). Further, the spatial correlation between green space equity and socioeconomic factors as well as the impacts of different urban dynamics on green space equity are investigated (**Part IV**). Finally, general limitations of this study are discussed.

5.1 Development of the Integrated Urban Growth Model (Part I)

By combining urban growth driving factors using the Autologistic Regression (ALR) and the transition probability matrix from the Markov Chain (MC), an integrated urban growth model was proposed in this study based on the Cellular Automata (CA) approach. Several reasons contribute to the robust and reliable results that are provided by this model. First, urban growth is a complex dynamic system that is influenced by a series of driving factors, including human decisions and some degree of stochasticity (Barredo et al., 2003). From a practical point of view, incorporating driving factors into urban growth modeling is of great importance and its ability to improve modeling accuracy has been proved in previous studies (Aburas et al., 2017; Han and Jia, 2017; Lauf et al., 2012; Luo and Wei, 2009). Second, it is also known from the literature that the transition probabilities of different land use classes to urban land use differ (Guan et al., 2011; Halmy et al., 2015; Mitsova et al., 2011). The simulation accuracy could be effectively improved by coupling the CA models with the transition probabilities of each land use type through the transition probability matrix that is provided by the MC (Guan et al., 2011).

5.1.1 Incorporating the Spatial Dependency into Urban Growth Modeling

A significant positive Spatial Autocorrelation (SAC) was found in the spatial pattern of settlement growth, indicating that the Ordinary Logistic Regression (OLR) that assumes the data to be statistically independent was unable to capture all spatial dependency in the data (Overmars et al., 2003). By introducing an autocovariate variable, the ALR incorporates the SAC into the regression process and consequently obtained a higher AUC (Area Under the Curve) compared to the OLR. It resulted in great improvement in model accuracy that was illustrated by the significant increases in the Kappa indexes. It is worth noting that the Kappa indexes of the OLR-MC-CA model were quite low, which might be attributed to the short simulation period and the small amount of observed net change in the reference map (García et al., 2012; Lauf et al., 2012; Pontius et al., 2008). Therefore, the incorporation of the ALR in urban growth models shows a great potential in regions where the growth pattern is spatially autocorrelated, in particular when the actual growth accounts for a scattered and small proportion of the total area. Moreover, a significant SAC was found in the residuals of the OLR-MC-CA model, while there was a lower SAC in the residuals of the ALR-MC-CA model, indicating that the explanatory power of the later model was much improved. This improvement is because an extra part of variance is explained by the autocovariate variable that takes into account the SAC within a neighborhood matrix (de Frutos et al., 2007; Hubbell et al., 2001; Wu et al., 2009). In the case of this study, the neighborhood matrices were defined based on the analysis of the autocorrelation of the dependent variable with different spatial lags (Naves et al., 2003). As the value of global Moran's I in the model residuals being close to zero (0.0358), it is shown to be a promising approach for determining the neighborhood matrix of the ALR.

In this study, certain differences were found between the OLR and ALR, including the significant variables, the sign of the coefficients and their significance levels (Table 4.1). The ALR shows a better result both with regards to quantitative model evaluation and the agreement with observed settlement development during this time in Munich. The new settlements that have developed in the past decade have tended to move away from bodies of water (DistWT) to get closer to public transportation such as the U-bahn (DisUB) and S-Bahn (DisSB) stations. Furthermore, they tend to locate in areas with a lower land price (RLP) but that are relatively far from urban green spaces (DisGS). All of these tendencies have been fully reflected in the ALR result.

The results also show that, when ignoring the SAC in regression models, more variables were included to explain the variation and their significance were overestimated due to the inflation of the Type I error, which is in line with other studies (Hubbell et al., 2001; Jiang et al., 2015; Lennon, 2000; Overmars et al., 2003; Wu et al., 2009). It should also be noted that the magnitude of estimated coefficients had been adjusted owing to the incorporation of the SAC. In good agreement with Wu et al. (2009), for most of the variables that were included in both the OLR and ALR, the absolute values of the estimated coefficients in the OLR were higher than those in ALR. This indicates that the precision of the coefficients estimated in the OLR would be affected by the SAC in the model's residuals. Thus, before using the OLR to identify the drivers in land use change and urban growth models, the SAC should be carefully examined (Jiang et al., 2015; Wu et al., 2009).

5.1.2 Incorporating Settlements Type Segregation into Urban Growth Modeling

As a significant positive SAC was found in the spatial patterns of low-density and high-density settlement growth (see Figure 4.2), the growth of both settlement types was modeled by the ALR-MC-CA model. The results showed that separately modeling the growth of different settlement types obtained higher model accuracy than integratively modeling all settlement growth, as indicated by the higher values of AUC and the Kappa indexes (Table 4.4). When separately modeling different types of settlement growth, both the overall Kappa and the respective Kappa indexes for high-density and low-density settlement growth were higher than that of integratively modeling all settlement growth together. This can be explained with the fact that the development paradigms and developers preferences are distinct for different types of settlement growth (Haase et al., 2010; Mustafa et al., 2018). In addition, high-density settlement growth showed higher values of the AUC and the Kappa index than low-density settlement growth, indicating that the model had a better explanatory power in modeling compact and high-density settlement types than modeling more scattered, less compact low-density settlements. This is in agreement with Lauf et al. (2012) who found that compact structures are generally more readily reproducible in spatial models.

As the growth patterns of both high-density and low-density settlements were strongly autocorrelated, it is not surprising to find that the autocovariate variables were significant in both ALR regressions. Compared to the growth of low-density settlements, high-density settlement growth depended on more variables (see Table 4.3). This suggests that the growth pattern of high-density settlements was driven by more factors. Meanwhile, apparent differences of included variables and their coefficients were found between the two regressions. First, some variables were only significant with either high-density or low-density settlement growth. For example, the distance to water (DisWT) variable had a significant positive impact on high-density settlement growth, indicating that high-density settlements have mostly developed further away from water bodies (Li et al., 2018), but no significant relationship was found for low-density settlement growth. This is probably due to the main types of water bodies being the lakes in the south part of this region which traditionally have been an area where affluent people settle in the form of low-density settlements. As another example, unlike the low-density settlements, the development of high-density settlements was close to the subcenters (DisSC) and settlement centers (DisSTC) as populated areas have higher demand on the provision of public services. This is in line with Mustafa et al. (2018) who reported that the high-density built-up areas were found in the major built-up cores surrounded by lower density built-up areas. Second, variables that were similarly significant in both regressions might have contradictory impacts. For instance, the development of high-density settlements tends to be close to all road networks, while low-density settlements also tend to develop close to local roads but away from highways and major roads which is in line with Li et al. (2015). Furthermore, the distance to green spaces (DisGS) had a negative correlation with high-density settlement growth which is in accordance with Jokar Arsanjani et al. (2013) who revealed that green spaces have a positive influence and thus attract general urban development whereas a positive correlation was found between the distance to green spaces (DisGS) and low-density settlement growth. A possible explanation would be that more public green spaces are required or being developed to improve the environmental quality of high-settlement areas, while more private green cover is available in low-density settlement areas such as private gardens (Lin et al., 2015).

5.2 Multiple Urban Dynamic Scenarios and Landscape Changes (Part II)

5.2.1 Main Characteristics of Urban Expansion

During the past decade, although almost 90% of the regional population growth took place in the Urban Core and Peri-Urban Zones, the area of settlement growth in these two zones only accounted for 50.87% of the total area of settlement growth. The factors that may contribute to this situation include the relatively larger housing size and the correspondingly lower population density, as well as the lower land price in the Rural Zone. The latter reason would also partially explain why most of the high-density settlements were developed in the Urban Core and Peri-Urban Zones while the majority of the low-density settlements were developed in the Rural Zone. At the regional level, both the high-density and low-density settlement growth mainly led to the losses of grassland, arable land, construction sites, and parks and green spaces. This finding is in line with McDonald et al. (2010), who observed considerable losses of open space due to urban expansion between 1990 and 2000 for all 274 metropolitan areas in the United States. At the sub-regional level, the number of land use classes that were converted by settlement growth in the Rural Zone was much less than in the other two zones, indicating that the land use changes caused by urbanization were less intensive in the rural area (Yu and Ng, 2007). Interestingly, unlike in the other two zones, the loss of parks and green spaces in the Urban Core Zone was mainly caused by the growth of high-density settlements (as shown in Figure 4.10). This is because, as discussed in the last section, the development of high-density settlements was closer to city centers, where the availability of other open spaces was very limited.

The spatial patterns of settlement growth under all urban dynamic scenarios were very dispersedly distributed across the region, which follows the pattern of historical growth. At the regional level, the settlement growth in most scenarios continuously led to losses of grassland, arable land, and parks and green spaces, except for the two urban shrinking scenarios that saw new green spaces developed. However, the patterns of land use transitions differed between different sub-regional zones. The losses of parks and green spaces were considerably higher than the losses of other land use categories in the Urban Core Zone which has already been highly urbanized and has limited open spaces (i.e., grassland and arable land) available. In the Peri-Urban and Rural Zones, the growth of settlement areas mainly led to conversions of arable land and grassland, and the losses of parks and green spaces only accounted for a small proportion. However, in contrast to the Rural Zone, the losses of arable land were higher than those of grassland in the Peri-Urban Zone, which could be attributed to the fact that the Peri-Urban Zone had already been going through the process of suburbanization and the grassland close to urban areas had already been mostly converted. These findings confirm that the patterns of urban dynamics and their impacts on ecosystems and natural resources are disparate in different sub-regional zones along the urban-rural gradient (Haase et al., 2012b; Li et al., 2016).

5.2.2 Changes in Landscape Patterns under Multiple Scenarios

Most of the landscape metrics from each metric group demonstrated strong pair-wise correlations in this study. First, this is because some of them may be empirically redundant as they fundamentally measure the same aspect of the landscape structure (Cushman et al., 2008). Second, this study only focused on land use changes induced by urban growth, which actually took up a small proportion of the whole study area, and correspondingly the landscape patterns under different urban dynamic scenarios were somewhat correlated. The Principal Component Analysis (PCA) has been demonstrated to be a practical approach to reduce the redundancy among landscape metrics (Inkoom et al., 2018; Plexida et al., 2014). By avoiding the redundancy that existed among the initially selected multiple landscape metrics, the three new landscape indexes developed in this study were found to be incapable of quantifying, or at least comparatively assessing, the landscape pattern changes efficiently.

Landscape metrics have been successfully used as indicators for assessing landscape functions. As reviewed by Uuemaa et al. (2013), patch complexity metrics have been used to assess the animal diversity and pollen distribution (Gimona et al., 2009; Viaud et al., 2008). Landscape configuration metrics are found to be correlated to urban heat islands, amphibian habitat selection, and landscape aesthetics (Dramstad et al., 2006; Hoss et al., 2010; Liu and Weng, 2008). Moreover, landscape diversity metrics can be used for assessing bird diversity, water quality, and landscape aesthetics (Uuemaa et al., 2005; Wrbka et al., 2008). However, landscape metrics were employed in this study to characterize and quantify the changes in landscape patterns under different scenarios, which could improve our understandings of the impacts of urban dynamics on landscape pattern changes and potentially provide valuable information to the design of sustainable planning strategies (Inkoom et al., 2018).

The changes of the patch complexity and configuration indexes in different sub-regional zones were largely similar to their trends at the regional level. The difference was found in the Urban Core Zone where the patch complexity was lower and the landscape was more aggregated in the monocentric scenarios than in the polycentric ones. This is because more housing demand (55%) was allocated to this zone in the monocentric scenarios than the polycentric ones (40%), while the patch complexity was lower and the landscape was more aggregated when the housing demand was higher. Regarding the diversity index, in line with the regional change, its value increased in the Peri-Urban and Rural Zones when increasing the housing demand. The reason for this is that the settlement area only accounted for a small proportion of these two zones, and increasing the settlement area improved the richness of patch types and led to the more even distribution of the area among different patch types. However, the diversity index value declined in the Urban Core Zone as the settlement area became the dominant land use, and increasing the settlement area reduced both the richness of patch types and the evenness of the distribution of the area among different patch types. This could also help to explain why the landscape diversity index of the polycentric scenarios was higher in the Urban Core Zone even though relatively less housing demand (40%) was allocated in this zone. The landscape diversity index of the compact growth scenario was the highest in the Urban Core Zone as a result of the area of settlement growth being the smallest under this scenario. Nevertheless, the trends were reversed in the other two zones because the settlements were no longer the dominant land use.

5.3 Impacts of Urban Dynamics on Green Space Availability (Part III)

As known from literature, the process of urban dynamics has significant influences on the availability of green spaces (Zhao et al., 2013). However, the majority of current studies of green space availability have been performed at the city level (de la Barrera et al., 2016; Kabisch et al., 2016; Richards et al., 2017), while neglecting the zoning within urban regions as well as the influence of urban spatial patterns beyond the city level (Haase, 2016). Nowadays, the interactions between urban and rural areas become increasingly intensive and the urban growth in a majority of large European cities and urban regions continuously puts high pressure on open spaces (Kain et al., 2016; Larondelle et al., 2016). Thus, green space availability should be considered at the urban regional scale in order to better account for the complexity of land development between the core city and peri-urban surroundings. In this study, a broad analysis of regional green space availability under different urban dynamics was performed based on a multiple-scenario modeling approach.

5.3.1 Green Space Availability among Scenarios at the Regional Level

In six out of the eight selected scenarios, the reductions in green spaces were found as a consequence of urban growth and land take. This is in agreement with Zhao et al. (2013) who emphasized that some green spaces are always encroached due to urban expansion regardless of which growth form or configuration of the city is adopted. Exceptions were found in two shrinking scenarios in which new green spaces were developed. As we know from shrinking cities, the shrinkage and space availability do not necessarily indicate a creation or enhancement of urban green space *per se*. Yet, the pressure on land is lower and a larger number of brownfields leads more frequently to considerations of greening vacant land (Haase et al., 2012a; Wolff et al., 2017), at least for interim use (Nassauer and Raskin, 2014; Rall and Haase, 2011). Both indicators in this study, Per Capita Green Space (PCGS) and the Share of the Population with Access to Green Spaces (SPAGS), decreased in most scenarios, which also illustrated the decline of green space availability under growth pressure. Despite the increase of SPAGS in the two shrinking scenarios as a result of new green space construction, PCGS still declined due to the considerable increase in the population density caused by "compact" growth. This latter finding shows how densification within the living space (splitting large flats into smaller ones) or increasing the height of houses in preferred living areas impacts the availability and accessibility of public green spaces in cities. A densification as such also indicates reduced green space within the housing areas and will, overall, diminish urban green space in residential areas, which is in line with Lin et al. (2015).

The results of regression analysis showed that the settlement area was not significantly correlated to PCGS which might be due to the fact that a larger settlement area does not necessarily lead to a bigger population size as the urban growth forms are dissimilar. However, it was negatively correlated to SPAGS ($p < 0.05$) which suggested that access to green spaces declines as cities grow as reported by Fuller and Gaston (2009) and as argued in the section before. In good agreement with prior research by Kabisch and Haase (2013), no significant correlation was found between population density and either PCGS or SPAGS. Contrastingly, significant positive relationships were identified between the green space area and both indicators; namely, scenarios with a higher amount of green spaces could be expected to have higher values of both PCGS and SPAGS, which implied the great importance of maintaining existing (large) green spaces that should be adopted in planning policies (Kabisch et al., 2016; Lin et al., 2015).

The results also showed that the availability of regional green spaces varied according to different urban dynamic scenarios. When urban spatial structures and growth forms remained the same, it is apparent that a higher housing demand posed more pressure on green space availability (cf. Westerink et al., 2013). Although higher housing demand led to higher net increases in green spaces within 300 m distances from settlements (Figure 4.21a), which was related to the physical expansion of urban areas that incorporated more existing green spaces from the surrounding areas (Kabisch et al., 2016), the values of both PCGS and SPAGS were lower in the higher housing demand scenarios due to the larger population sizes they included. Compared to the monocentric scenario, the polycentric scenario could help to disperse the housing pressure from the inner city to the subcenters in peri-urban surroundings or rural areas, where more green spaces (including forests) are available and the prevailing population density is comparatively low. Although the polycentric urban structure may lead to more fragmentation and isolation of green spaces in the Peri-Urban and Rural Zones than the monocentric structure (Liu and Wang, 2016), it resulted in greater regional green space availability in this study. For different urban growth forms, "compact" growth showed the highest SPAGS due to the largest gain and smallest loss of populations with access to green spaces, and therefore the smallest net decrease compared to the other two alternative growth forms. This is very much in line with the findings of Westerink et al. (2013), who advocated the more sustainable compact growth compared to sprawling peri-urbanization. However, it is notable that "sprawling" growth was more favorable in terms of PCGS, which showed the highest value as a result of the net increase in green spaces within 300 m distances from settlements. It could also be attributed to the fact that the incorporated area of green spaces by urban expansion was larger than the concurrent loss. This comparative study provides rare evidence of the respective advantages and disadvantages of different growth forms with respect to green space availability and accessibility, which contributes to the current debate on different urban growth forms that mainly focused on "sprawl" and "compact growth" (Ewing, 1997; Haase, 2016; Milder, 2012; Westerink et al., 2013).

5.3.2 Green Space Availability among Scenarios in Sub-regional Zones

When comparing the growth effects in sub-regional zones, it showed that PCGS increased when moving from the Urban Core Zone outwards in all scenarios, whereas SPAGS decreased along this urban-rural gradient, except for L-M-C because it had new green spaces developed in the Rural Zone. The higher values of PCGS in the Peri-Urban and Rural Zones were attributed to more green spaces and lower population numbers. Even so, the lower values of SPAGS in almost all scenarios highlighted the fact that the spatial inequality and injustice of green space provision was more critical in these zones. Previous reports have suggested that spatial inequality and injustice might be correlated with the dissimilarities in neighborhood socioeconomic conditions as well as ecological prerequisites among different sub-regional zones (de la Barrera et al., 2016; Kabisch and Haase, 2014; Kabisch et al., 2016; Lin et al., 2015).

The housing demand was found to have the same impact on green space availability in all zones. That is, both indicators declined while the housing demand was increasing, which is in accordance with the impacts at the regional scale. In addition, polycentric scenarios tended to have a better performance in the Urban Core Zone, with both indicators exhibiting higher values than in any monocentric scenario. This is because less of the housing demand (40%) was allocated to this zone in polycentric scenarios than in the monocentric ones (55%). Correspondingly, as more housing demand was allocated to the Peri-Urban and Rural Zones compared to the monocentric scenarios, the values of both indicators were lower in the polycentric scenarios in these two zones.

Compared to the other two urban growth form scenarios, the compact growth scenario showed higher values of SPAGS in all three zones. In each zone, “compact” growth increased the population density in areas that had already been settled, leading to the highest net increases or the lowest net decreases of population numbers with access to green spaces (Figure 4.24b). However, the values of PCGS showed that different zones had their own most sustainable growth forms. In the Urban Core Zone, “compact” growth showed the highest PCGS value due to the smallest net decrease of green spaces within 300 m from settlements. As argued in the previous section, the physical expansion of urban areas could incorporate new green spaces. However, the incorporation did not compensate for the loss in this zone, which was already highly urbanized (Pauleit and Duhme, 2000) and for which most of the green spaces were already quite close to the settlement areas (Figure 3.3). In the Peri-Urban Zone, “compact sprawl” growth led to the highest net increase of green spaces within 300 m distances from settlements and therefore the highest value of PCGS. This value was even higher than that of “sprawl” growth. A possible explanation for this is that high-density settlements were closer to green spaces than low-density settlements in this zone. Interestingly, in the Rural Zone, the highest value of PCGS was found with “sprawl” growth due to the increased availability of green spaces in the surrounding areas. Moreover, incorporation of green spaces into the urban fabric exceeded losses elsewhere in this zone . However, the SPAGS value was the lowest with “sprawl” growth in this zone. Therefore, it can be noted that there is not one preferred urban type of growth form for all zones. Even in the same zone, except for the Urban Core Zone in which “compact” growth obtained the highest values of both indicators, different urban growth alternatives showed relative advantages depending on which indicator was used for the assessment. This finding has important implications for both urban and regional planners to understand the spatially heterogeneous impact of urbanization on green space availability. It also implies that targeted planning strategies should be proposed for different sub-regional zones by addressing their specific spatial characteristics, such as the population density and the provision of green spaces (Li et al., 2016).

5.3.3 Trade-offs between the Two Green Space Availability Indicators

The results also highlighted that the changes in the two indicators were not consistent with each other within each scenario, and certain trade-offs were suggested, especially in the following two aspects. First, PCGS increased in all scenarios when moving from the Urban Core Zone outwards to the Rural Zone, whereas SPAGS decreased along the urban-rural gradient in seven of eight scenarios. Second, with regard to urban growth form scenarios, a scenario with a higher value of PCGS usually yielded a lower value of SPAGS and vice versa in most cases at both the regional and sub-regional zone scale. High values of PCGS did not necessarily lead to high values of SPAGS, indicating an uneven distribution of green spaces across the urban area, i.e., spatial inequality is present (de la Barrera et al., 2016; Kabisch and Haase, 2014; Lin et al., 2015).

Per capita green space does not provide information concerning the spatial distribution and the accessibility, or the quality of green spaces, which influences the ecosystem services they deliver (Badiu et al., 2016; de la Barrera et al., 2016). Therefore, adopting it as an indicator to assess green space availability has been controversial. However, due to its simplicity and intuitiveness, this indicator is still widely used and various target values have been provided for better and more straightforward management of urban green spaces. In German cities, the targets related to per capita green space vary from 6 to 15 m^2 per resident (Deutscher Rat für Landespflege, 2006). In this study, in addition to Per Capita Green Space (PCGS), the Share of the Population with Access to Green Spaces (SPAGS) was employed as an additional complementary indicator, which reflects the overall accessibility of green spaces for all residents in an area. To address the trade-offs between the two indicators, it can be suggested that once the value of PCGS is above the target value or in an acceptable range in which no target values are given, promoting the overall accessibility to green spaces should be considered a priority to improve the spatial justice of green space provision (Kabisch and Haase, 2014). For example, although "compact" growth led to relatively lower values of PCGS at the regional level, it may be still more advisable to adopt this strategy, as the value of SPAGS was the highest and the PCGS value was still at a high level.

5.4 Spatial Variation of Green Space Equity and the Impacts of Urban Dynamics (Part IV)

5.4.1 Correlations with Socioeconomic Variables

As discussed previously, green space studies should be conducted at the urban regional scale to better understand the complexity of land development between the urban cores and peri-urban surroundings, due to urban areas continue to develop into urban regions and open spaces are under high pressure by urban growth (Kain et al., 2016; Larondelle et al., 2016). By employing the Gini coefficient as an indicator, the spatial variation of green space equity across the region was analyzed. The findings revealed that green spaces were more equally distributed in municipalities of the central and southern parts of the region than the surrounding ones, particularly than those in the northwest and central-east parts of this region. A possible explanation is that more green spaces (e.g. the woodlands in the south of Munich) are protected in those areas due to their special environmental functions and recreational uses (see Figure 3.3) which consequently contribute to the spatial equity of green space distribution and, accordingly, attract more affluent people living there (Buettner et al., 2013). In turn, municipalities with a better socioeconomic condition may be dedicated to the protection and maintenance of green spaces as other studies suggested that socioeconomic advantages are more likely associated with better availability and accessibility to green spaces (Kabisch and Haase, 2014; Pauleit et al., 2005; Schüle et al., 2017; Wüstemann et al., 2017). This pattern clearly reflects the divergence between the affluent south part and the less affluent north part of this region. The northwest part is of less relevance as it is sparsely populated, while the east part should be of more concern for green planning as it is rapidly developing.

The result of Geographically Weighted Regression (GWR) analysis showed that the relationships between green space equity and socioeconomic variables were not always consistently significant across space and the coefficients reflect great spatial heterogeneity indicating the relationships are locality-specific (Li and Liu, 2016). First, the significant correlation of the demographic factor with green space equity across the municipalities in the middle, west and northwest parts of the region accords with previous findings that areas with larger percentages of an elderly population tend to have more access to and more equitable distribution of parks and green spaces, whereas areas with higher shares of a younger population tend to have less (Kabisch and Haase, 2014; Xiao et al., 2017; Xing et al., 2018). In addition, a negative correlation was found between the percentage of people in long-term unemployment and the Gini coefficient. These findings are in line with Xiao et al. (2017) who found that the proportion of aged or deprived (unemployed) residents was significantly higher in neighborhoods that were more accessible to public green spaces, whereas Shen et al. (2017) reported that sub-districts with larger proportions of aged or unemployed population show worse public green space access in Shanghai, China. In the case of this study, on the one hand, there is a trend that retired people with limited financial resources and individuals with lowest income level move outwards from urban centers to reduce the housing costs and have a good quality environment (Zhao et al., 2017). On the other hand, young families also tend to move from city centers to peri-urban areas where the housing price is lower, but they prioritise theirs needs for access to work places, schools, etc. over the access to green spaces (Ravetz et al., 2013).

Second, the social-spatial factor was found to be significantly correlated with the Gini coefficient in the southeast part of the region. As a higher population density will most probably lead to a lower value of per capita living space, contrasting correlations were found between the Gini coefficient and these two variables. This result suggested that, in the southeast part of the region, municipalities with higher population density were associated with more equitable green space distribution. Chen and Hu (2015) and Xiao et al. (2017) reported that areas with higher population densities were correlated with better green space provision and accessibility, respectively. Third, the negative correlations of the economic factor (including per capita municipal revenue, per capita income and average housing price) with the Gini coefficient in the southwest half of the region is consistent with previous researches that economically disadvantaged neighborhoods suffered from disparities in green space distribution (Li and Liu, 2016; Pauleit et al., 2005; Pham et al., 2012; Schüle et al., 2017; Wüstemann et al., 2017; You, 2016).

Considering specific socioeconomic factors throughout the region is required to build spatially-specific greening strategies that effectively safeguard green spaces equally accessible by all residents (Li and Liu, 2016). Regarding the results, greening strategies should put emphasis on increasing the green space provision for municipalities with economic disadvantages and a high percentage of a young population in the middle, west and northwest parts of the region, while improving equitable access to green spaces is important for municipalities with low population density and greater per capita living spaces in the southeast. When promoting such strategies, priority should be given to municipalities with a higher level of green space inequality as well as a bigger population size to enhance the benefits for more residents. Although it might be argued that more industry and commerce would be required for municipalities with economic disadvantages to boost their economic growth, a balanced development among economic growth, environmental quality, and social equity is required to achieve the goal of sustainability (Chen and Hu, 2015). Therefore, improving the green space availability and equity should also be considered in the process of promoting economic development (Chen and Wang, 2013).

GWR is a powerful tool for exploring the spatial non-stationary and scale-dependent phenomena across space and the behavior of variables at a local level (Ivajnšič et al., 2014; Jaimes et al., 2010). In this study, it provides more information on the spatial variability of the green space equity in correlation to socioeconomic gradients, which shows great potential for better green space planning in a policy context. From the results, the Gini coefficient is shown to be a robust indicator that assesses the spatial equity of green space distribution. It would be of great interest to include this indicator in the Eurostat Urban Audit Database (EUROSTAT, 2004), a project that aims to collect comparable statistics and indicators of socioeconomic, environmental, and other aspects for European cities, to provide more comprehensive information on urban green spaces in addition to green space availability and accessibility.

5.4.2 Impacts of Urban Dynamics on Green Space Equity at the Regional Scale

Nowadays, it has become a challenge for cities or urban regions that are undergoing rapid urbanization to provide sufficient and equitable green spaces to all residents with limited land resources. In particular, for the cities and urban regions at the stage of socioeconomic inequalities, improving the green space equity might be more desirable in promoting life quality through equitable provision of green spaces (Kabisch and Haase, 2014). Compared to the status of 2013, the green space equities became worse in six out of the eight scenarios as a consequence of the loss of green spaces caused by urban expansion no matter which growth form or configuration the city adopted (Zhao et al., 2013). Two exceptions were found in the shrinking scenarios, in which new green spaces were developed for the purpose of improving green space provision in areas with limited access to green spaces. In practical terms, urban shrinkage does not necessarily mean a creation or enhancement of urban green space *perse*, but the lower pressure on land resource and the emergence of a great number of brownfields provide an opportunity for the consideration of greening vacant land (Haase et al., 2012a; Wolff et al., 2017) or for interim use (Nassauer and Raskin, 2014; Rall and Haase, 2011). It is noteworthy that urban shrinkage is another path of urban development which is spreading widely across the world (Haase et al., 2012a; Oswalt and Rieniets, 2006). Although the results of this case study are mainly for urban growth, the multiple scenario modeling approach could also be applied in other geographic regions that undergo different pathways of urban development, such as urban shrinkage or regrowth.

Compared among different sub-scenarios at the regional level, it is apparent that a higher housing demand led to a more inequitable green space distribution when urban spatial structures and growth forms remained the same. This is due to the fact that a higher housing demand poses more pressure on green spaces (cf. Westerink et al., 2013). The green space distributions were more equal in the polycentric scenarios than the monocentric ones, as the housing pressure in the polycentric scenarios were dispersed from the inner city to the subcenters in peri-urban surroundings or rural areas where more green spaces are available. With regard to different urban growth forms, the compact growth scenario was the most favorable one in terms of green space equity. As discussed in the previous section, "compact" growth has less pressure on green spaces by increasing population density in areas that had already been settled. This finding supports the advocates of compact growth who regard it as a more sustainable way compared to a sprawling peri-urbanization (Westerink et al., 2013). Considering the other two growth forms, "sprawl" performed better than "compact sprawl", which might be owing to the reason that the greater physical expansion of urban area in the sprawl scenario more strongly reduces the distance to green spaces from the surrounding areas (Kabisch et al., 2016).

5.4.3 Impacts of Urban Dynamics on Green Space Equity in Sub-regional Zones

Although more green spaces are available in the outer zones, the distribution of green spaces became more and more inequitable when moving outwards from the Urban Core Zone to the

Rural Zone in almost all scenarios, except for L-M-C that had new green spaces developed in the Rural Zone. This trend is found to be consistent with the declining tendency of the population density along this urban-rural gradient as Xiao et al. (2017) revealed that low population density areas are correlated with less accessibility to public green spaces. Although it is also reported that more private green cover (such as private gardens) are available in the low population density areas (Lin et al., 2015), providing more accessible public green spaces should be considered during the future urban development in these areas.

In all three zones, increasing the housing demand led to the decline of green space equity, which is in accordance with the change at the regional scale. Polycentric scenarios had less housing demand (40%) allocated in the Urban Core Zone than monocentric scenarios (55%), and vice versa in the other two zones. As a higher housing demand led to a more inequitable green space distribution, accordingly, polycentric scenarios tended to have a higher green space equity than monocentric ones in the Urban Core Zone whilst it is lower in the other two zones. Among different urban growth form scenarios, "compact" growth was found to be the best option considering green space equity in all sub-regional zones and "sprawl" was better than "compact sprawl" in the Urban Core and Peri-Urban Zones. This is consistent with the findings at the regional level. The only difference is that "compact sprawl" led to higher green space equity than "sprawl" in the Rural Zone, because of high-density settlements were observed to be closer to green spaces than low-density settlements and there are much more green spaces available in the Rural Zone. As different sub-regional zones have different spatial characteristics, the findings presented here disclose the spatially heterogeneous impact of urbanization on green space equity across different sub-regional zones and highlight the necessity of proposing targeted planning strategies that are adapted to these zones (Haase et al., 2012b; Li et al., 2016).

5.5 General Discussion: Limitations and Prospects

The multiple (combined) scenario modeling approach used in this study can provide information concerning the advantages and disadvantages of different urban dynamics with respect to green space availability and equity, which could also be applied in other geographical regions. However, some limitations of and future improvements to the present study are noteworthy.

Limitations Regarding the Data Set

The regional land use and land cover data used in this study were derived from high-resolution aerial photography, which offers detailed information of the distribution and changes of different land uses at very fine scale. However, due to the limitation of computing power, the original vector maps were converted into $30m \times 30m$ raster maps, during which process the loss of information is inevitable. In addition, when calculating the Gini coefficient, as no more precise population density data available, reassigning the population to residential grids based on the area and overall proportion between high-density and low-density settlements may introduce a certain error to the calculation of green space equity. Moreover, although landscape metrics have been successfully used as indicators for assessing landscape functions, the effectiveness of using these metrics to assess changes of landscape functions in the region is not investigated due to a lack of related data and out of the focus of the present study.

Uncertainties of the Scenario Modeling Approach

A number of limitations and uncertainties were included in this approach, which is unavoidable for any simulation approach (Haase and Schwarz, 2009; Schwarz et al., 2010). As highlighted by Haase and Schwarz (2009) in their review of human-nature interaction models, there is a range of comprehensive urban land use change models but no unique approach to representing urban landscapes and human-nature interactions. Clear limitations of this approach included the restricted number of driver variables (population number, number of households, housing space needs, see Schwarz et al., 2010), the coarse representation of the housing spaces per capita (3 classes) (see Lauf et al., 2012) and the aggregated ways of looking at the rural-urban gradient (zoning) as well as the degree of compactness of an urban region. Undoubtedly, more detailed classifications of urban-rural zones, spatial patterns and growth forms could have been used; however, whether these would have changed the variance of the results is not clear, although they might have modified the results or added more options and patterns. Second, as highlighted in the literature review, the outcomes of scenario studies might be biased without systematic and representative stakeholder selection (Prell et al., 2009). When engaging more stakeholders, the uncertainty and variation of the developed scenarios could be increased, however, the significant time necessary to achieve all their aims has been noted by a number of studies (e.g., Kowalski et al., 2009; Reed et al., 2013). Accordingly, as the focus of this study is the urban dynamics at the urban-region scale, the experts that engaged in the scenario development were invited from the key planning associations in this region who have in-depth knowledge of the regional urban development. Third, lacking a third land use map, the predicting accuracy of the urban growth model has not been validated. However, the focus of this study was to systematically and quantitatively assess the potential effects of different population and household dynamics on the urban forms and its green spaces in the study region, rather than predicting the future urban growth pattern. Last, the simulation approach itself is straightforward and includes spatial autocorrelation as the main source of error for a pixel-based Markov-Chain-probability model. It definitely excludes more complex land-use-change-driver feedbacks, so a redistribution of households after initial allocation by incorporating a satisfaction proxy with the housing situation and a respective feedback loop from households to land (use) may have improved the analysis (see again Haase and Schwarz, 2009). However, the limited number of influential parameters in the whole modeling approach permits a high transferability and traceability of the model and a straightforward sensitivity test for the utilized variables. Still, further improvement can be made by incorporating macro-level driving factors of urban growth into the model, such as the effect of government policy, economic growth, technological changes, and global climate changes.

Limitations Regarding the Assessment of Green Spaces

First, this study defines green spaces based on the classification scheme of the land use and land cover data and concentrates on four important green space categories which have higher values of recreational services, including “parks and green spaces”, “allotment gardens”, “cemeteries” and “forests”. It should be noted that some extensively managed grasslands (for example, the Fröttmaninger Heide in this region) may also have considerable recreational values. However, such areas are not easy to distinguish from other grasslands in the land use maps. Second, due to a lack of detailed road network data, the linear distance was calculated as a proxy of accessibility of green space. Although this approach has been used by many researchers to generate serviceable areas around facilities and green spaces (Barbosa et al., 2007; Gupta et al., 2016; Wüstemann et al., 2017), more accurate results might be achieved with more detailed data on the access point of green spaces and traffic networks such as footpaths, cycling paths, and so forth. Moreover, this study focuses on the nearby green spaces which are considered as more important to the daily short-term recreational services as the beneficiaries are often the residents who live in a vicinity of green spaces (Kabisch and Haase, 2014). However, there is evidence that local residents would not extensively utilize the green spaces if they are viewed as unsafe and farther green spaces with relatively large areas may still be frequently visited in a car-oriented culture (Diez Roux et al., 2007; Wen et al., 2013). In this context, one should note that changing the definition or the accessible distance of green spaces may lead to dissimilar results. Third, due to a lack of data, the quality of green spaces which can also vary across the socioeconomic gradient and influences the attractiveness and utilization of green spaces (Schüle et al., 2017) has not been considered in this study. Last, the indicators (PCGS, SPAGS, and the Gini coefficient) were used in this study to assess the green space availability and equity, while other parameters would need to be considered for a fuller assessment, e.g. of the impacts of urban dynamics on ecological quality and biocultural diversity (Elands et al., 2018; Vierikko et al., 2016). For instance, although the polycentric urban structure resulted in greater regional green space availability and equity in this study, it may lead to more fragmentation and isolation of green spaces which might have negative impacts on habitat suitability (e.g., for bigger mammals, bees or birds) than the monocentric structure (Liu and Wang, 2016).

Chapter 6

Conclusions

The integrated model that was developed and applied in this study achieved good accuracy in modeling the urban growth in the region of Munich, an urban area with high land pressure in Germany. Incorporating the spatial dependency into the model showed great improvement compared to the Ordinary Logistic Regression (OLR) model. There is a great potential for applying this model to other geographical regions where the urban growth pattern is spatially autocorrelated, especially when the actual growth is scattered and proportionally small. The Kappa indexes were higher when separately modeling the different settlement growth than an encompassing modeling all settlement growth because the driving factors of different settlement growth might be dissimilar and the minutiae of different settlement growth could be better represented.

Multiple urban dynamic scenarios were developed to assess the changes in landscape patterns caused by urban expansion and their impacts on green spaces. Urban growth in all scenarios demonstrated quite scattered spatial patterns across the region and mainly led to the loss of open spaces including land use categories of grassland, arable land, and parks and green spaces. However, the specific patterns of land use transition differed in different sub-regional zones along the urban-rural gradient. Using the three landscape indexes developed in this study to quantify or at least comparatively assess the changes of landscape pattern was found to be an appropriate and effective method that eliminated the redundancy and confusion that existed among the initially selected multiple landscape metrics. At the regional level, a higher housing demand scenario reduced the patch complexity but improved the aggregation and diversity of the landscape. The monocentric scenarios led to higher levels of patch complexity but lower levels of landscape aggregation and diversity than the polycentric ones. The compact growth scenario had a higher patch complexity index value and lower aggregation and diversity index values than did the other two growth form scenarios. At the sub-regional level, the changes of the patch complexity and configuration indexes were largely similar to their regional changes.

In addition, the changes of landscape diversity index showed adverse trends between the Urban Core Zone and the other two zones, which is attributed to whether urban settlement was the dominant land use in these zones or not. Understandings of the impacts of urban dynamics on landscape pattern changes might potentially provide valuable information for the design of sustainable planning strategies. However, due to a lack of related data, the effectiveness of using these metrics to assess changes of landscape functions in the region is out of the focus of the present study and could be a direction for future work.

The availability of nearby green spaces with high values of daily recreational services under diverse and diverging urban dynamic scenarios was assessed using two complementary indicators at both the regional and sub-regional level. In addition, the Gini coefficient was used to evaluate the green space equity since it has been considered as an issue of environmental justice. Furthermore, the analysis of the spatial correlation between green space equity and socioeconomic factors allows us to shed new light on the variances of green space equity across spatial and socioeconomic gradients at the urban regional level. To my best knowledge, this is a first time study that identifies the spatial variability of green space equity and its locality-specific relationships with socioeconomic variables across the urban region and explores the impacts of different urban dynamics on green space availability and equity to provide policymakers and planners with a useful reference and guidance for more effective green planning strategies.

This study clearly revealed that, without effective greening policies, different degrees of decline in green space availability and equity were observed in most of the selected scenarios, which were related to the loss of green spaces caused by new construction during urban growth, although scenarios that showed shrinkage dynamics did result in new green space development. From the comparative analysis, it is apparent that a higher housing demand posed more pressure on the green space availability and equity at both levels. Moreover, the polycentric urban spatial structure was found to be less limiting in terms of green space availability and equity than the monocentric structure at the regional level. However, to define the most advisable urban growth form, one must consider the trade-offs between the indicators. For example, at the regional level, "compact" growth showed the highest proportion of people with access to green spaces and the most equitable distribution of green spaces, whereas the per capita value of green spaces was the highest under "sprawl" growth. The results also indicated that it may difficult to find a single growth form that performs best in all different zones, and thus, an optimization-oriented approach would fail. Therefore, urban planning and greening policies should consider the physical and socioeconomic heterogeneity across space, and focus more on the development of planning strategies adapted to different sub-regional zones.

In the case of this study, it would be more advisable to adopt polycentric urban spatial structure and “compact” growth form in the Munich region in terms of green space availability and equity. Moreover, increasing the green space provision should be considered for municipalities with economic disadvantages and a high percentage of a young population in the middle, west and northwest parts of the region, while improving equitable access to green spaces is essential for municipalities with low population density and greater per capita living spaces in the southeast. When promoting such greening strategies, priority should be given to municipalities with a higher level of green space inequality as well as a bigger population size to enhance the benefits for more residents.

The indicators applied in this study, particularly their combination, provided general information on green space availability and equity, especially in the cases of comparative studies, by using only a small set of input data. This novel and straightforward scenario approach allows us to shed new light on the respective advantages and disadvantages of different urban dynamics with respect to green space availability and equity. Different analytical approaches have been applied in this study that aims to fill current research gaps related to urban dynamic modeling, influencing dimensions of urban dynamics, green space availability and equity under urban dynamics. To the best knowledge of the author, this is a first time study that explores the combined impacts of different urban dynamic influencing factors on green space availability and equity at both the regional and sub-regional levels and identifies the spatial variability of green space equity and its locality-specific relationships with socioeconomic variables across an urban region. In addition, this multiple scenario modeling approach offers certain flexibility and is capable of adapting to different urban contexts simply by modifying the parameter settings of the scenarios and the modeling tools.

From the urban planning point of view, the multiple-scenario modeling framework presented in this study could be used as a powerful tool that offers an opportunity for planners and governmental authorities to have a more precise understanding of the urban dynamic process and their impacts on green spaces that might occur in an urban region similar to the one tested. Thus, further planning and developmental scenarios can be developed to assess the potential costs, benefits, and risks of corresponding planning strategies. Future works would be focused on incorporating the assessment of green space quality and of ecosystem services to deepen and extend our understandings of the impacts of urban dynamics on the green spaces, such as the attractiveness of different green space types. Moreover, such large-scale study would need to be complemented by qualitative ones that look in-depth into land use changes to better understand their impacts on green space availability and equity at fine scales, which would be another direction for future work.

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Study Statement

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2. Xu, C., Haase, D., Pauleit, S., 2018. The Impact of Different Urban Dynamics on Green Space Availability: a Multiple Scenario Modeling Approach for the Region of Munich, Germany. *Ecological Indicators*. 93, 1-12. (**Part III**)

3. Xu, C., Pribadi, D.O., Haase, D., Pauleit, S., 2018. Spatial variation of green space equity and the impacts of urban dynamics: A case study in the region of Munich. *Ecological Indicators*. 93, 512-523. (**Part IV**)

Author's contribution:

The first author C. Xu conceived the research design and methodological framework under the supervision of D. Haase and S. Pauleit. All computational work, data collection and statistical analyses were conducted by the first author as well as writing and composing the manuscripts. D.O. Pribadi contributed to the proposition of the urban growth model. D. Haase and S. Pauleit assisted in the development of multiple scenario settings. All coauthors contributed to the manuscripts by scientific advice, discussion and language editing.

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Appendix

Appendix A: Constraint maps

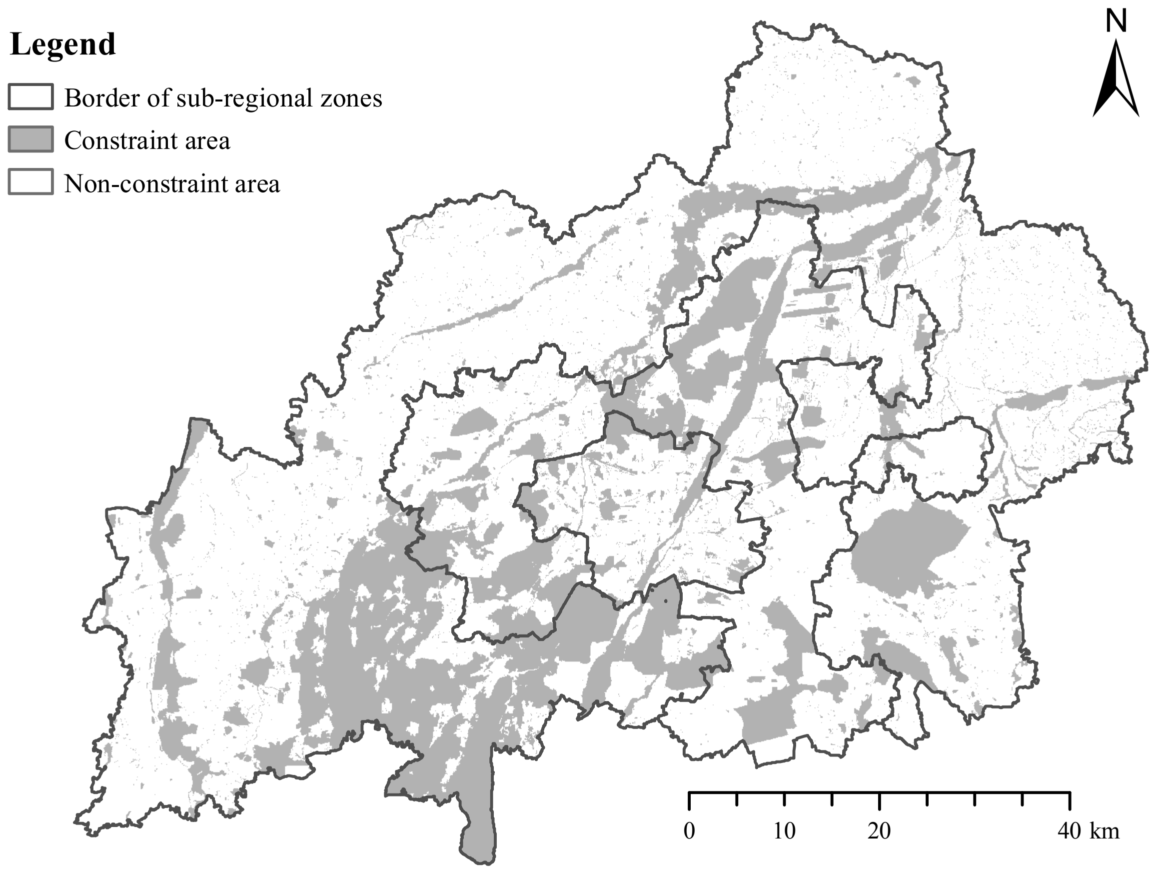

Figure A1 The constraint map that used in urban growth modeling (including nature reserves map, flooding risk map, habitat maps, etc.).

Appendix B: Potential driving factors of urban growth

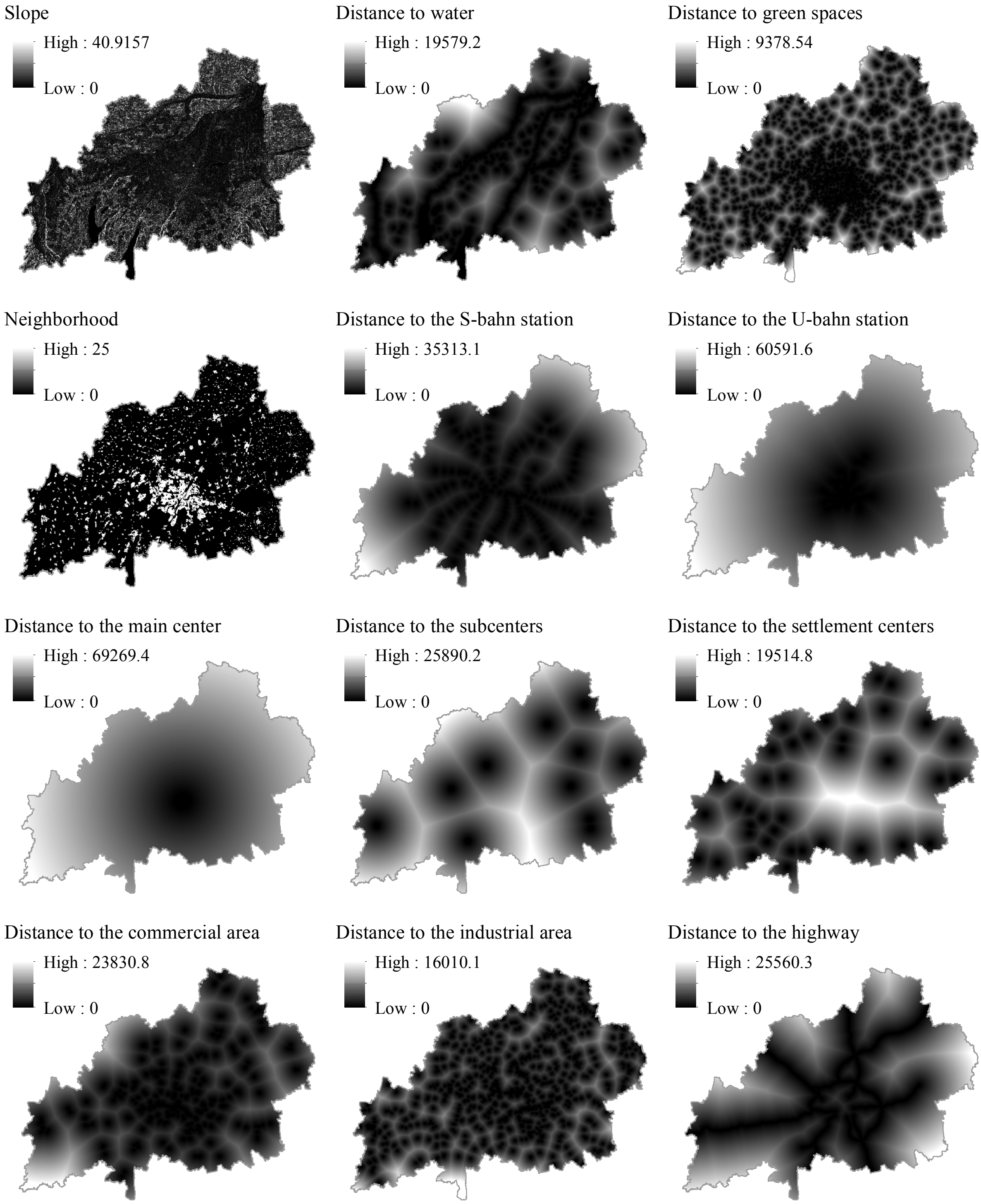

Figure B1 Maps of the potential driving factors of urban growth.

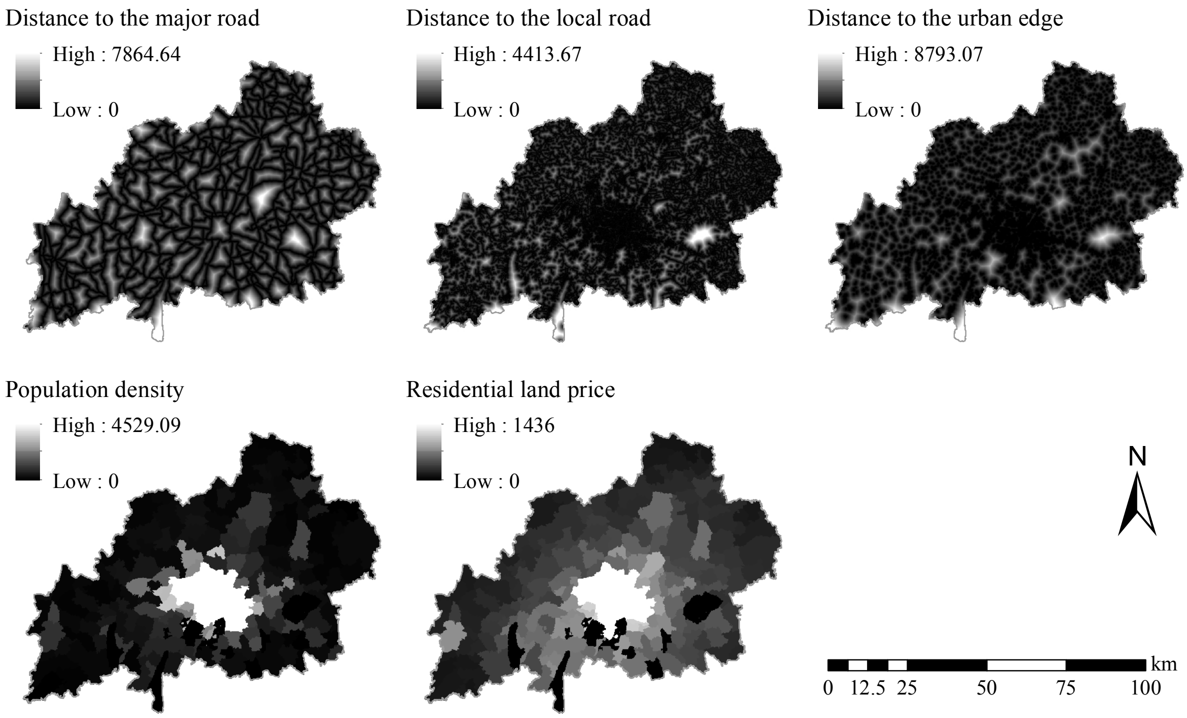

Figure B1 Maps of the potential driving factors of urban growth *(continued)*.

Appendix C: Development of the housing demand sub-scenarios

The Per Capita Living Space (PCLS) scenarios were proposed based on the proportions between smaller households (one- or two-person households) and larger households (three or more -person households) in the whole region. When assuming that the average area of one apartment remains static, there is no doubt that a higher proportion of smaller households will lead to a higher PCLS. Compared to their average annual growth rates between 2003 and 2013, the growth rates of smaller and larger households were 1.2 times higher and 0.8 times lower in high PCLS scenarios respectively, while the opposite trend was observed in the low PCLS scenario. In the medium PCLS scenario, the growth of both smaller and larger households followed their average annual growth rate between 2003 and 2013.

Regional population projection and regional household structure data were utilized for developing housing demand scenarios. Regional population projection data was used as the trend line (projected) scenario of population growth. Compared with the projected average annual population growth rate, the average annual growth rates of high and low population growth scenarios were 1.2 times higher and 0.8 times lower, respectively. (Figure C1).

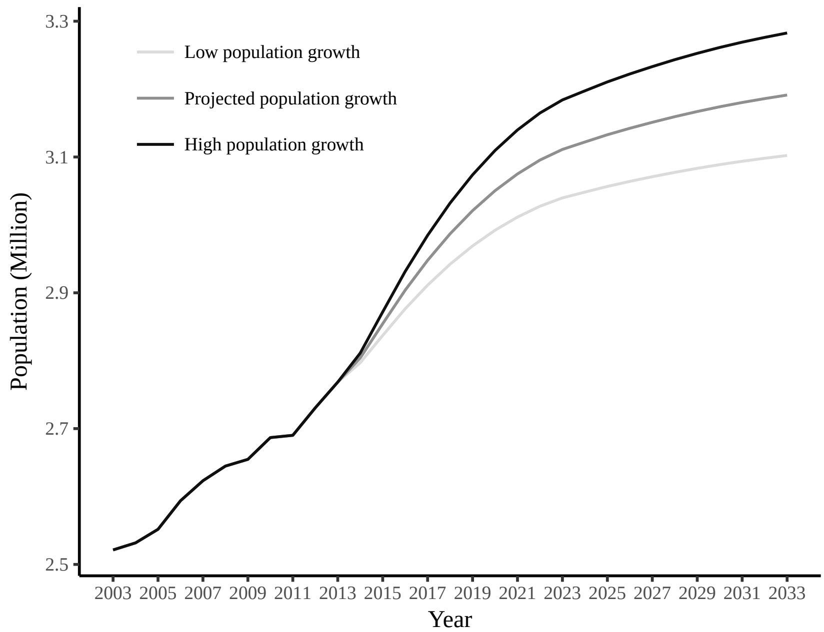

Figure C1 Scenarios of high, projected, and low population growth.

Then, the regional household structure data was utilized for calculating different scenarios of PCLS. They were proposed based on the proportions between smaller households (one- or two-person households) and larger households (three or more -person households) in the whole region When assuming that the average area of one apartment remains static, there is no doubt that a higher proportion of smaller households will lead to a higher PCLS. Compared to their average annual growth rates between 2003 and 2013, the growth rates of smaller and larger households were 1.2 times higher and 0.8 times lower in high PCLS scenarios respectively, while the opposite trend was observed in the low PCLS scenario. In the medium PCLS scenario, the growth of both smaller and larger households followed their average annual growth rate between 2003 and 2013 (Figure C2).

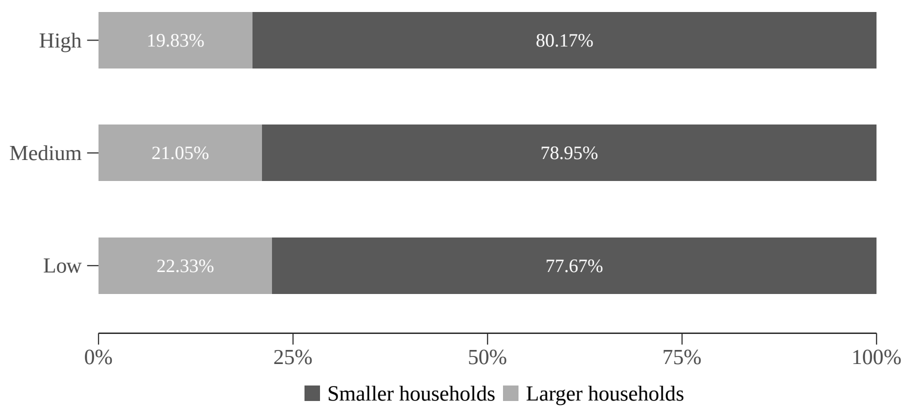

Figure C2 Proportions of smaller and larger households under low, medium, and high Per Capita Living Space scenarios.

At the end, three housing demand scenarios (High, Medium and Low) were developed by combing different scenarios of population growth and PCLS. The high housing demand scenario implies high population growth with high PCLS, while medium and low housing demand scenarios mean projected population growth with medium PCLS and low population growth with PCLS, correspondingly (Figure C3).

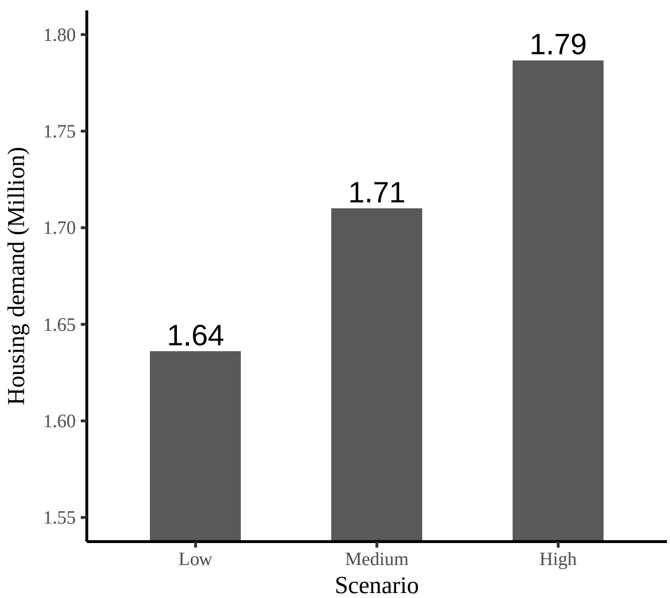

Figure C3 Housing demand scenarios in millions of new households in the year 2033.

Appendix D: The weights of the driving factors for each sub-regional zone

Table D1 Regression coefficients (B) and standard errors (S.E.) of the ALR for high-density settlement growth in each sub-regional zone

Variable	Urban Core Zone		Peri-Urban Zone		Rural Zone	
	B	S.E.	B	S.E.	B	S.E.
Constant	-3.19E+00***	8.26E-01	-4.75E+00***	3.81E-01	-5.10E+00***	2.80E-01
Slope	1.77E-01**	6.19E-02	—	—	-4.60E-02*	1.85E-02
Distance to water	7.65E-04***	5.66E-05	1.92E-04***	3.11E-05	—	—
Distance to green spaces	-1.33E-02***	9.63E-04	-1.23E-03***	1.64E-04	-4.47E-04***	6.55E-05
Neighborhood	2.53E-01***	2.04E-02	2.04E-01***	9.02E-03	2.15E-01***	9.63E-03
Distance to the S-bahn (suburban train) station	-7.69E-04***	1.19E-04	-5.03E-05•	2.73E-05	—	—
Distance to the U-bahn (metro) station	-1.41E-03***	1.94E-04	-4.45E-05**	1.70E-05	—	—
Distance to the main center	-1.35E-04*	5.47E-05	3.13E-05*	1.40E-05	-1.77E-05***	4.35E-06
Distance to the subcenters	-1.79E-04***	3.21E-05	-3.90E-05**	1.22E-05	—	—
Distance to the settlement centers	—	—	—	—	—	—
Distance to the commercial area	1.68E-03***	1.81E-04	—	—	-3.57E-05**	1.27E-05
Distance to the industrial area	1.13E-03***	1.72E-04	1.17E-04•	6.32E-05	—	—
Distance to the highway	—	—	—	—	-3.60E-05***	9.02E-06
Distance to the major road	-1.66E-03***	2.26E-04	-7.88E-04***	1.49E-04	—	—
Distance to the local road	-1.04E-02***	2.17E-03	-5.39E-03***	9.55E-04	—	—
Distance to the urban edge	-1.07E-02***	1.08E-03	-1.04E-02***	7.20E-04	-2.21E-02***	1.81E-03
Population density	—	—	—	—	—	—
Residential land price	—	—	-3.44E-03***	3.64E-04	-3.27E-03***	3.49E-04
Autocov	6.87E-01***	2.27E-02	9.41E-01***	1.49E-02	1.65E+00***	2.26E-02

Note: Significant codes: ***: $p < 0.001$, **: $p < 0.01$, *: $p < 0.05$, •: $p < 0.1$, —: not significant.

Table D2 Regression coefficients (B) and standard errors (S.E.) of the ALR for low-density settlement growth in each sub-regional zone

Variable	Urban Core Zone		Peri-Urban Zone		Rural Zone	
	B	S.E.	B	S.E.	B	S.E.
Constant	-3.04E+00*	1.29E+00	-7.44E+00***	2.70E-01	-4.76E+00***	1.29E-01
Slope	—	—	—	—	—	—
Distance to water	2.18E-04**	7.92E-05	—	—	—	—
Distance to green spaces	-2.51E-03***	6.43E-04	2.00E-04***	4.54E-05	1.77E-04***	2.22E-05
Neighborhood	2.85E-01***	1.93E-02	2.26E-01***	6.93E-03	1.72E-01***	4.55E-03
Distance to the S-bahn (suburban train) station	—	—	-5.27E-05**	1.84E-05	—	—
Distance to the U-bahn (metro) station	—	—	—	—	—	—
Distance to the main center	-2.40E-04***	6.30E-05	3.13E-05***	7.16E-06	-1.33E-05***	2.03E-06
Distance to the subcenters	-1.17E-04***	3.49E-05	2.35E-05***	6.36E-06	—	—
Distance to the settlement centers	-9.23E-05$^{\bullet}$	5.01E-05	3.94E-05***	1.00E-05	—	—
Distance to the commercial area	—	—	1.49E-04***	2.41E-05	—	—
Distance to the industrial area	—	—	—	—	—	—
Distance to the highway	2.93E-04**	9.19E-05	-2.32E-05*	1.17E-05	1.07E-05**	3.65E-06
Distance to the major road	—	—	—	—	1.20E-04**	4.23E-05
Distance to the local road	-7.02E-03**	2.54E-03	—	—	-3.88E-03***	4.85E-04
Distance to the urban edge	-1.52E-02***	3.49E-03	-1.92E-02***	1.01E-03	-2.38E-02***	8.33E-04
Population density	—	—	—	—	—	—
Residential land price	—	—	—	—	-4.23E-04**	1.52E-04
Autocov	8.09E-01***	2.66E-02	1.12E+00***	1.31E-02	1.13E+00***	8.86E-03

Note: Significant codes: ***: $p < 0.001$, **: $p < 0.01$, *: $p < 0.05$, $^{\bullet}$: $p < 0.1$, —: not significant.

Appendix E: The transition probabilities of different land use types

Table E1 Normalized values of the transition probabilities of different land use types to high- and low-density settlements in different sub-regional zones

Land use classes	High-density settlements			Low-density settlements		
	UCZ	PUZ	RZ	UCZ	PUZ	RZ
Allotment gardens	0	0.0020	0	0	0.0012	0
Cemeteries	0	0	0	0	0	0
Parks and green spaces	0.3695	0.0459	0.0312	0.0201	0.0487	0.0310
Low-density settlements	0	0	0	0	0	0
High-density settlements	0	0	0	0	0	0
Industrial area	1.0000	0	0	0.0050	0	0.0172
Commercial area	0	0	0	0	0	0
Schools, museums and research centers	0	0	0	0	0	0
Grassland	0.7559	0.9173	1.0000	0.7575	1.0000	1.0000
Arable land	0.3953	1.0000	0.4661	1.0000	0.9808	0.5944
Nurseries	0.0011	0.0133	0.0010	0.0063	0.0047	0.0006
Forest	0	0.0077	0.0035	0	0.0269	0.0148
Sport and leisure facilities	0.1982	0.0158	0	0	0.0360	0.0029
Quarries	0.0011	0.0026	0.0010	0.0013	0.0030	0.0014
Supply and disposal	0.0437	0	0	0.1005	0	0
Power stations	0	0	0	0	0	0
Lakes and ponds	0	0	0	0	0	0
Rivers	0	0	0	0	0	0
Harbors	0	0	0	0	0	0
Fish Farming	0	0	0	0	0	0
Wetlands	0	0	0	0	0	0
Military area	0	0	0	0	0	0
Unused land	0	0.0005	0	0	0.0003	0
Railway station, railway tracks	0	0	0	0	0	0
Railways	0	0	0	0	0	0
Road connection and buffer areas	0	0	0	0	0	0
Roads	0	0	0	0	0	0
Parking areas	0.0280	0.0179	0.0010	0.0955	0	0.0006
Construction sites	0.4065	0.1918	0.0797	0.0151	0.1037	0.0435
Airfields	0	0	0	0	0	0

Note: UCZ: Urban Core Zone, PUZ: Peri-Urban Zone, RZ: Rural Zone.

Appendix F: Final transition probability maps

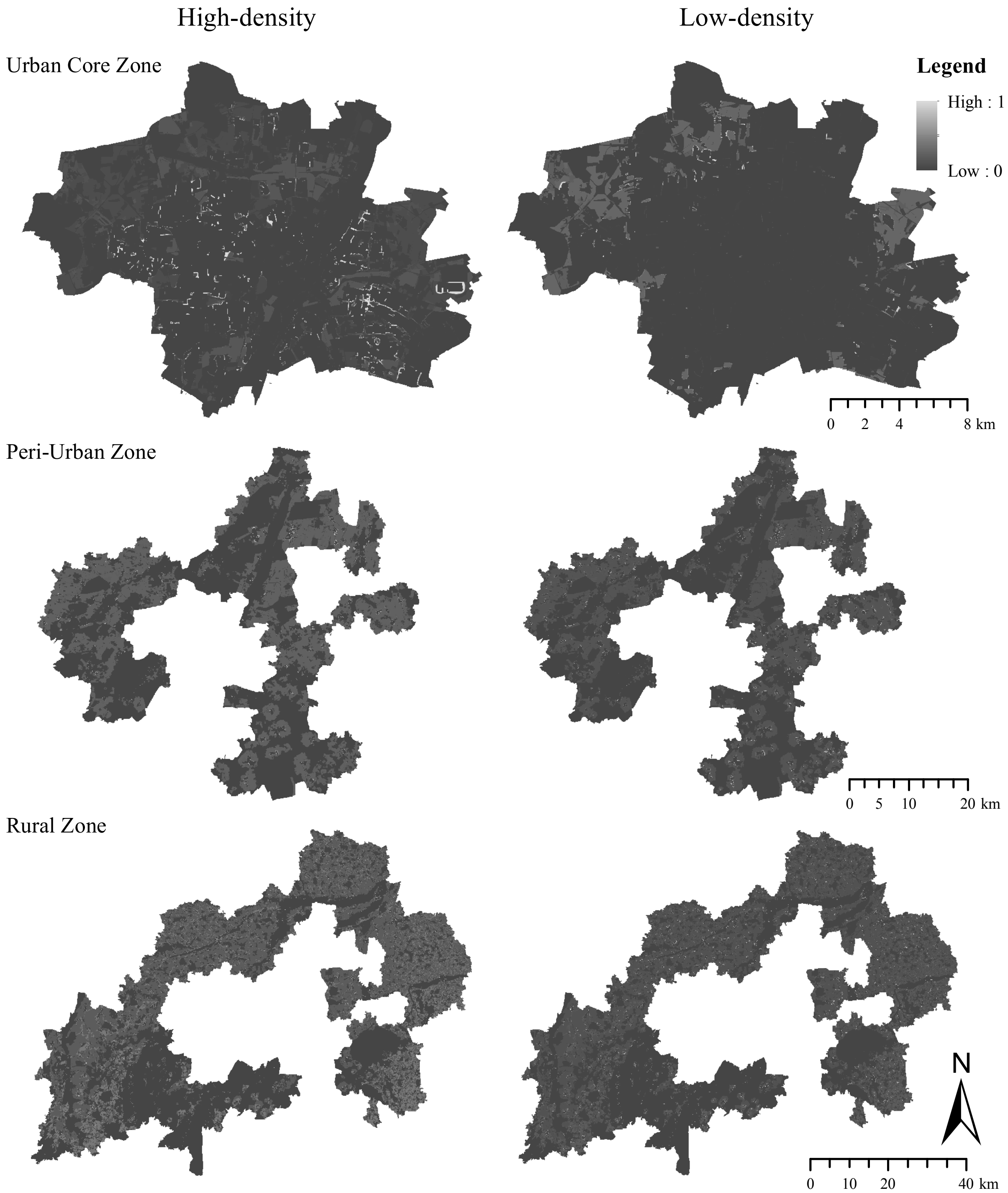

Figure F1 Final transition probability maps of high-density and low-density settlement growth for each zone.