IMPACT OF URBAN SPATIAL STRUCTURE ON CARBON EMISSIONS AND PLANNING STRATEGIES

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CERTIFICATE OF ORIGINALITY

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Abstract

Since the Second Industrial Revolution, rapid industrialization and urbanization have significantly increased global carbon dioxide emissions. In response, the international community has reached a consensus on the urgent need to reduce carbon emissions. As the largest developing country, China is undergoing rapid urbanization and industrialization, making it the world’s largest emitter of carbon dioxide. Investigating the patterns of China’s carbon emissions is therefore crucial for global climate change mitigation. Urban spatial structure, as a key element of urbanization, plays a significant role in shaping carbon emissions and provides valuable insights for low-carbon urban planning, with implications for global sustainable development.

Despite its importance, research on the impact of urban spatial structure on carbon emissions in China remains limited. Most studies rely on correlation analyses and lack in-depth exploration. This thesis systematically examines the relationship between urban spatial structure and carbon emissions using remote sensing data, geographic information systems (GIS), and econometric methods. The research is framed within the thematic framework of "spatial distribution—quantitative impact—planning strategy."

The study is structured into four main components: First, a literature review synthesizes existing research on urban spatial structure and related theories, establishing the focus of this study. Second, a multi-tiered indicator system is developed to analyze the impact of urban spatial structure on carbon emissions, incorporating factors such as population size, land area, land form, and green space. Third, an

empirical investigation is conducted using spatial analysis, principal component analysis, and mediation effect analysis to evaluate the characteristics of urban spatial structure and its effects on carbon emissions from multiple sources. Fourth, urban planning and management strategies for carbon reduction are formulated, grounded in the empirical findings.

Using prefecture-level cities in China as the study sample, this research examines the spatio-temporal distribution characteristics of carbon emissions, urban land expansion, and spatial morphology. It further explores the impact of urban spatial structure on carbon emissions and proposes carbon reduction planning strategies from the perspective of urban spatial structure. The following conclusions are drawn:

First, a sub-linear relationship between city size and total carbon emissions is observed, with emissions increasing at a slower rate than city size. City innovation mediates the relationship between city size and industrial emissions, producing both increasing and decreasing effects. In less developed cities, the effect of city size on innovation increases emissions, whereas in more developed cities, the reduction effect is yet to be fully realized. Scale effects are evident in heating carbon emissions, with increasing urban population density potentially mitigating heating emissions for the same city size. Larger cities exhibit greater transportation efficiency due to developed public transit systems, although the overall effect remains limited.

Second, a super-linear relationship between urban land area and carbon emissions is found, with regional disparities. The western region is most affected, followed by the northeast, central, and eastern regions in China. Urban land area has a stronger impact on transportation emissions in small- and medium-sized cities, while higher urban density significantly reduces heating-related emissions in colder regions.

Third, greater complexity in urban land shape is associated with lower transportation emissions but may hinder urban development efficiency, making it a less viable strategy. Conversely, compact urban land form reduce transportation emissions, particularly in smaller cities. Polycentric urban structures lower transportation emissions but increase residential emissions. Urban green space ratios show mixed effects, positively influencing transportation emissions while negatively impacting residential emissions. Compact green space layouts mitigate transportation emissions, while balanced distributions reduce residential emissions.

Finally, based on the empirical findings, spatial planning strategies for carbon emission reduction are proposed, with recommendations focused on urban population size and urban land area/form.

In conclusion, this research provides a comprehensive analysis of the relationship between urban spatial structure and carbon emissions in China. The findings contribute empirical evidence and multidimensional strategies for carbon reduction, supporting China's sustainable development and global climate mitigation efforts.

Publications arising from the thesis

Papers has appeared in print arising from the thesis

Hong S.F., Hui E.C.M., & Lin Y.Y. (2022). Relationships between carbon emissions and urban population size and density, based on geo-urban scaling analysis: A multi-carbon source empirical study [Article]. Urban Climate, 46, 15, Article 101337.

Hong S.F., Hui E.C.M., & Lin Y.Y. (2022). Relationship between urban spatial structure and carbon emissions: A literature review [Review]. Ecological Indicators, 144, 8, Article 109456.

Papers under peer review arising from the thesis

Urban Size and Industrial Carbon Emissions: The mediating effect of innovation.(submitted)

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Chapter 1. Introduction

1.1 Background

Global climate change has gained widespread attention in recent years. Commencing with the Industrial Revolution in the 18th century, humanity has witnessed unparalleled growth in economic and technological realms. A significant escalation in energy demand accompanied this progress. The widespread utilization of fossil fuels has led to substantial carbon dioxide and other greenhouse gas emissions. At the same time, urbanization has led to a rapid increase in urban populations. Activities related to urban infrastructure and transportation have become prominent sources of carbon emissions. Notably, since 1950, there has been a steep ascent in global cumulative carbon emissions (Figure 1-1). Carbon dioxide emissions increased from approximately 200 billion tons in 1950 to 1.6 trillion tons by 2021. Such sustained and rapid surge in the accumulation of carbon dioxide signifies that the increase in global carbon emissions has reached a level of concern, with its implications for global climate change and environmental impact becoming increasingly pronounced. Consequently, this issue has drawn considerable attention worldwide, gradually initiating international efforts to curb carbon emissions.

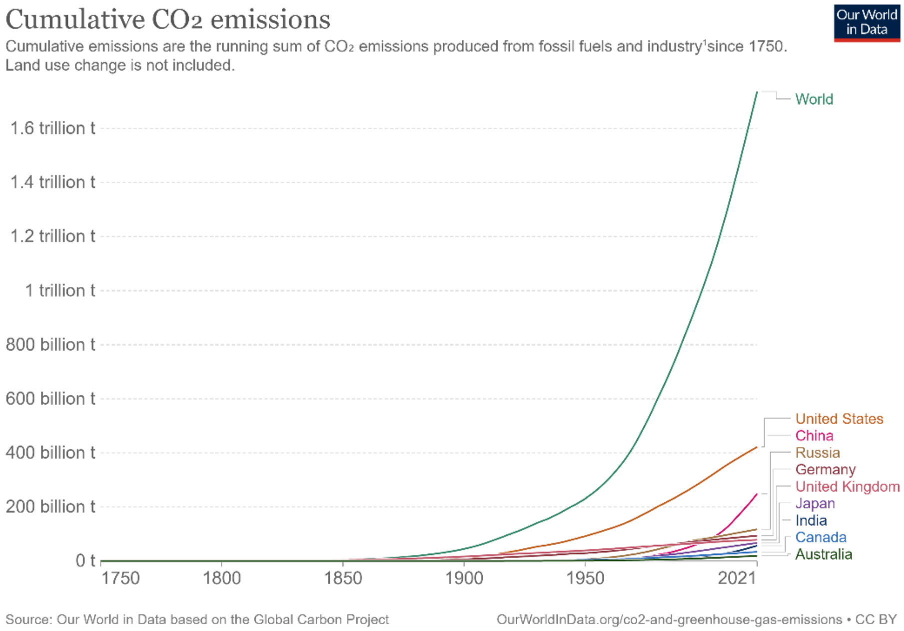

Figure 1-1 Accumulated carbon emissions of the world and major countries[1]

1.1.1 Carbon Emission Reduction: A Key Aspect of Carbon Neutrality and Peak Emissions

The world is currently on a trajectory of rapid carbon dioxide accumulation. Reducing carbon dioxide emissions and mitigating climate change has become a consensus among societies worldwide. Carbon dioxide is a byproduct of urbanization, and its excess can lead to the greenhouse effect, causing systemic global climate change and severe ecological and environmental damage. Since 1990, global carbon dioxide (CO2) emissions have increased by nearly 50%. From 1880 to 2012, global temperature rose by 0.85°C[2]. The United Nations' new flagship report indicates that harmful carbon

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1 Data source: "Data Page: Annual CO_2 emissions", part of the following publication: Hannah Ritchie, Pablo Rosado and Max Roser (2023) - "CO_2 and Greenhouse Gas Emissions". Data adapted from Global Carbon Project. Retrieved from https://ourworldindata.org/grapher/annual-co2-emissions-per-country [online resource]

2 https://www.un.org/sustainabledevelopment/zh/climate-change-2/

emissions from 2010 to 2019 were unprecedented in human history. It warns that the world is on the fast track to disaster and immediate action is needed to limit global warming to within 1.5°C[3]. Specifically, Goal 13 of the United Nations Sustainable Development Goals calls for integrating climate change measures into national policies, strategies, and planning.

In 1988, the United Nations Environment Programme and the World Meteorological Organization established a specialized agency to address climate change, the Intergovernmental Panel on Climate Change (IPCC). This organization serves as a significant platform for international cooperation on climate change, with its third working group focusing on climate response strategies to limit greenhouse gas emissions. In December 1997, the Kyoto Protocol, the first treaty to reduce greenhouse gases was established in Kyoto, Japan. This protocol is a supplement to the United Nations Framework Convention on Climate Change (UNFCCC). Since the signing of the Kyoto Protocol, there has been a deepening consensus among nations on addressing climate change and reducing carbon dioxide emissions. Building on this momentum, the Paris Agreement was later adopted in 2015, aiming to further unite countries in the battle against climate change by setting more ambitious climate goals and enhancing support to meet these objectives globally. According to the *2023 Global Carbon Neutrality Annual Progress Report*, more than 150 countries had announced or planned carbon neutrality targets. These countries account for 88% of the world's total carbon emissions, 85% of the world's population, and 90% of the global economy. For example,

3 https://news.un.org/en/story/2022/04/1115452

China has proposed achieving carbon neutrality by 2060, while the United States, Japan, the United Kingdom, Canada, and the European Union aim for carbon neutrality by 2050. Other countries with carbon neutrality targets are listed in the table.

Table 1-1 Carbon neutrality goals of major countries around the world

Country	**Target Year**	**Policy or Occasion Proposed**	**Details of Carbon Neutrality Goal**
China	2060	75th United Nations General Assembly Debate	Achieve peak carbon emissions before 2030, carbon neutrality by 2060, and strive for a transition to low-carbon development.
USA	2050	Earth Day Leaders Climate Summit (April 22, 2021)	Achieve net-zero carbon emissions by 2050, vigorously develop clean energy and infrastructure, and improve energy efficiency.
EU	2050	European Green Deal (December 2019)	Achieve climate neutrality by 2050, including increasing the proportion of renewable energy, enhancing energy efficiency, and reducing greenhouse gas emissions
Japan	2050	Parliamentary Speech (October 26, 2020)	Achieve carbon neutrality by 2050, promote green energy technology, and reduce dependence on fossil fuels
UK	2050	Carbon Neutrality Legislation (June 27, 2019)	Achieve carbon neutrality by 2050, reduce greenhouse gas emissions, improve energy efficiency, and expand renewable energy use
Canada	2050	Canada's Climate Plan (November 19, 2020)	Achieve carbon neutrality by 2050, strengthen carbon pricing mechanisms, develop clean technologies, and improve energy efficiency
South Korea	2050	Presidential Address (October 28, 2020)	Achieve carbon neutrality by 2050, expand renewable energy use, enhance energy efficiency, and reduce coal use
India	2070	26th United Nations Climate Change Conference (COP26, November 2021)	Achieve carbon neutrality by 2070, vigorously develop clean energy, enhance energy efficiency, and strengthen carbon sink forestry
Brazil	2060	Earth Day Leaders Climate Summit (April 22, 2021)	Achieve carbon neutrality by 2060, reduce deforestation, improve energy efficiency, and develop sustainable agriculture

The Chinese government has also long been attentive to energy saving and carbon reduction. In June 2007, the State Council of China officially issued the "National Climate Change Program," with controlling greenhouse gas emissions being a key component. In September 2007, Hu Jintao, then President of China, advocated the development of a "low-carbon economy" at the Asia-Pacific Economic Cooperation (APEC) meeting. In 2008, China's Ministry of Construction, in conjunction with the World Wildlife Fund, initiated pilot projects for "low-carbon cities" in Baoding and Shanghai, drawing increasing attention to the practice and theory of low-carbon cities from both Chinese governments at all levels and the world. In July 2010, the National Development and Reform Commission (NDRC) officially issued a notice on launching pilot projects for low-carbon provinces and cities, initially identifying Guangdong, Liaoning, Hubei, Shaanxi, Yunnan, and the cities of Tianjin, Chongqing, Shenzhen, Xiamen, Hangzhou, Nanchang, Guiyang, and Baoding as pilot areas. This initiative expanded with the second and third batches of low-carbon city pilots in 2012 and 2017, respectively.

On September 22, 2020, Xi Jinping, the President of China, put forward a significant strategic at the 75th United Nations General Assembly, proposing to achieve "carbon peak" by 2030 and "carbon neutrality" before 2060. The goals of carbon neutrality and carbon peaking have become a societal consensus and represent a further deepening of the concept of green development among the five development concepts(innovation, harmonization, green, openness and sharing). This initiative aims to build a community with a shared future for humanity and achieve harmonious development between humans and nature.

1.1.2 Urban Carbon Emission Reduction: A Broad Consensus in Tackling Climate Change

Under the dominance of "anthropocentrism," urban spatial planning has long been oriented towards specific socioeconomic objectives. In China, while socioeconomic development has made significant strides under the push of urbanization, the ecological environment has also been compromised. Urban ecology and sustainability have become important contents and objectives of urban development, and studying the carbon emission effects of urban spatial structure is a crucial component of urban ecological planning.

Cities, as the focal points of human social development, are engines of economic growth and significant sources of carbon emissions. Urbanization encompasses complex socioeconomic evolution processes, including population, land use, infrastructure, and the built environment. Currently, about 55% of the global population lives in urban areas, which is expected to rise to 70% by the middle of this century. In China, over 40 years of reform and opening-up, the socio-economic pattern has rapidly developed, urbanization levels have continuously increased, and the size and number of cities have grown. Data from the National Bureau of Statistics show that from 1978 to 2020, China's urbanization rate increased from 17.9% to 63.89%, with the urban permanent population exceeding 900 million. The operation and development of cities require raw materials from the natural environment for production and life, and they discharge waste into it. Carbon dioxide is one of the primary gaseous wastes, leading to global climate warming. Cities are a principal aspect of carbon emissions, with studies showing that they consume 66% of energy and emit over 70% of carbon dioxide (Yu et al., 2020).

Therefore, studying urban carbon emissions is crucial to the development-emission reduction paradox. An essential part of urban planning is the organization and arrangement of urban space. Urban design and planning can is regarded as an efficient way for reducing carbon dioxide emissions (Falahatkar & Rezaei, 2020). For example, improving public transportation efficiency through rational land planning, and promoting low-carbon innovation through population planning. Technological Reduction involves developing and implementing advanced technologies to reduce emissions. Examples include carbon capture and storage (CCS), improving energy efficiency in industrial processes, buildings, and transportation, and transitioning to renewable energy sources like solar and wind. Moreover, some scholars believe that the space for technical emission reduction is gradually limited (Shen et al., 2021). Market-based approaches use economic incentives to reduce emissions. These include carbon trading schemes, where companies can buy and sell emission allowances, and carbon taxes that put a price on emitting carbon. Both mechanisms aim to encourage businesses to invest in cleaner alternatives by making pollution more costly. Urban planning is often seen as a third option for carbon reduction outside of technology and the market (Liu et al., 2020). Additionally, urban design and planning can significantly reduce carbon dioxide emissions, thereby achieving low-carbon cities(Falahatkar & Rezaei, 2020).

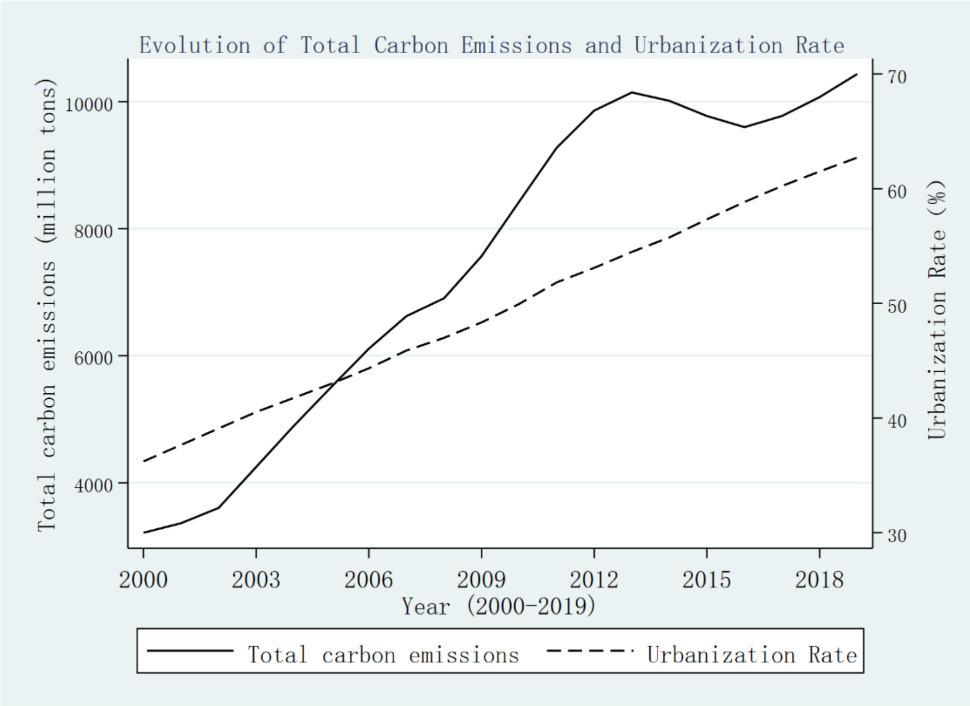

Figure 1-2 Evolution of total carbon emissions and urbanization rate in China(source：created by author)

1.1.3 The Relationship Between Urban Spatial Structure and Carbon Emissions: Scientific Basis for Planning Emission Reductions

As the core areas of economic and social development, cities are major sources of carbon emissions. In the fields of urban planning and environmental management, the relationship between urban spatial structure and carbon emissions has been receiving increasing attention. Not only does urban spatial structure affect residents' daily lives and socioeconomic activities but it also profoundly impacts urban energy consumption patterns and carbon emission levels. Planning emission reduction refers to reducing urban carbon emissions and minimizing environmental impacts through urban planning, design, and management, enhancing urban sustainability. Theoretical and empirical research provides the basis for planning. Before undertaking planning emission reduction efforts, it is essential to thoroughly study the impact of urban spatial structure on carbon emissions, as this forms the premise and scientific foundation for planning emission reduction.

1.2 Literature Review

1.2.1 Review of Theories Related to Urban Spatial Structure

1.2.1.1 Garden City Theory — The Enlightenment of Modern Urban Planning Thought

Addressing the progressively deteriorating urban environment was a primary objective in the early urban planning and development stages. Urban planning during this phase pursued an ideal city, considering various urban diseases from the perspective of urban spatial structure. In 1898, Ebenezer Howard proposed the Garden City theory in response to the issues of overcrowding and poor sanitary conditions arising during urban development. This theory stemmed from dissatisfaction with the environmental destruction caused by 19th-century industrialized cities. Howard focused on the problems of urban spatial structure, believing that the deterioration of the urban environment was due to uncontrolled urban expansion, and he advocated for preventing disorderly urban sprawl.

Howard introduced pioneering planning ideas, presenting significant viewpoints from key aspects of urban planning such as urban size, structure, population density, and greening. His contributions enlightened modern urban planning thought. Subsequently, ideal urban models were proposed, such as the Radiant City (representing urban centralism), Neighborhood Unit, Plug-In City, and Walking City et al. (Huang &

Du, 2009).

1.2.1.2 Sustainable Development Theory — Focusing on Human-Environment Relationships

The theory of human-environment relations delves into the dynamic interaction between human development and the Earth's ecological environment. Humans rely on the natural resources and energy provided by the Earth to sustain life and must address the impacts of their activities on the environment. As society, economy, culture, and politics advance, maintaining and protecting the natural environment increasingly comes to the fore. The core of this interaction is to promote harmonious coexistence between humans and the natural environment.

Sustainable development theory focuses on the balance between human socioeconomic activities and the natural environment. Early on, in 1798, Thomas Malthus, through analyzing the relationship between food production and population growth, pointed out the potential conflict between the finiteness of natural resources and economic development. In 1962, Rachel Carson's book "Silent Spring" revealed the threats of pesticides to birds and other animal groups and the destructive impact on ecosystems, emphasizing that humans should coexist harmoniously with nature rather than exploit it unilaterally.

The 1972 United Nations Conference on the Human Environment and subsequent international discussions heightened the focus on the impact of industrialization on the environment. The book "Careless Technology: Ecology and International Development" included case studies showing that while technological advancement increased the efficiency of resource exploitation, it also led to over-extraction of natural resources. Later, the United Nations Environment Programme, in its 1978 report, first introduced the concept of "eco-development," further advancing the development of the sustainable development concept.

In 1987, the World Commission on Environment and Development (WCED) explicitly defined sustainable development in its report "Our Common Future," emphasizing the importance of meeting current needs without compromising the ability of future generations to meet their own. Reducing carbon dioxide emissions and combating the greenhouse effect have become key tasks in achieving sustainable development.

1.2.1.3 Composite Ecosystem Theory — Systematic Perspective on Urban Issues

The Composite Ecosystem Theory is a critical theoretical foundation for sustainable development. This theory was first proposed in 1984 in response to the worsening ecological environment(Ma & Wang, 1984). It emerged from the recognition that human-centered methodologies were no longer sufficient to guide the sustainable development of society and the economy. The Composite Ecosystem Theory posits that cities and regions form a comprehensive ecosystem where human behavior is dominant and supported by the natural environment. In this system, the flow of resources is vital, with social and cultural elements interwoven like meridians. This system comprises social, economic, and natural subsystems, each following its unique operational rules, yet they are intertwined to form an interactive whole(Wang & Ouyang, 2012). This theory emphasizes the coupled relationship between humans and nature, providing a new perspective for studying their interaction.

1.2.1.4 Urban Metabolism/Urban Organism Theory — An Analogous Perspective

As cities increasingly face severe ecological challenges, the immense pressure on resources and environmental degradation have limited urban development. Researchers have attempted to draw analogies between urban systems and living organisms or ecosystems to seek solutions for urban ecological problems(Lu & Chen, 2015).

The concept of Urban Metabolism was introduced by Wolman in 1965. It can be understood as a comprehensive process involving materials inflow and energy into a city (inputs) and the outflow of products and waste (outputs), illustrating the city's impact on and interaction with its surrounding environment(Lu & Chen, 2015; Wolman, 1965). The Urban Organism theory is more direct, viewing the city as a living entity. It borrows the concept of "metabolism" from ecology to describe and analyze the functions and processes of a city. The core of this theory is to understand how a city consumes inputs like energy, water resources, and food and produces outputs like waste and carbon dioxide, analogous to the metabolic processes in a biological organism. To some extent, research on the relationship between urban spatial structure and carbon emissions can also be considered a type of urban metabolism study. If the city is viewed as a living organism, this research analyzes the intensity and efficiency of carbon emissions under different urban spatial characteristics from an overall urban perspective.

1.2.2 Studies on the Relationship Between Urban Spatial Structure and Carbon Emissions

Urban researchers have conducted extensive studies on urban spatial structure, exploring its influencing factors and impacts on social, economic, and ecological aspects in identifying and studying the current state of urban spatial structures. Yuan and Qiao (2023) analyzed the evolving trends of spatial structures in over 290 Chinese cities at or above the prefectural level. Lan et al. (2023) examined the evolution of Xi'an's multi-centered urban spatial structure. Studies on the environmental impact of urban spatial structures include research on the effects of urban spatial structure on PM2.5 (Han et al., 2020), and the impact of urban spatial structure on carbon emission efficiency (Dong & Zhang, 2023). Research on the urban economic aspect includes analysis of urban spatial structure and the upgrading of the global value chain(Fan et al., 2023), the impact of urban spatial structure on labor skill bargaining(Luo et al., 2023), the influence of urban spatial structure on co-creation spaces(Zhu & Zhang, 2023), and its effect on corporate innovation(Han & Zhuang, 2023).

In summary, research on the role of urban spatial structure at various levels of urban systems, including social, economic, and ecological aspects, has garnered widespread attention. Scholars generally agree that as the basic framework of urban development, urban spatial structure broadly impacts all aspects of urban operation. Exploring the relationship between urban spatial structure and other urban system variables is fundamental to urban planning and policy development.

Urban spatial structure research encompasses two main aspects: the scale of the city and its geometric form. This thesis reviews the relationship between urban spatial structure and carbon emissions from these two perspectives.

1.2.2.1 City Size and Carbon Emissions

Size is the most significant characteristic of urban agglomerations and cities. Ranked before history, geography, and design, size determines most of a city's features (Bettencourt & West, 2010). For example, doubling a city's population requires only an 85% increase in infrastructures, such as roads and power poles (Bettencourt et al., 2007). The reason may be that cities benefit from economies of scale, the concentration of people, and large-scale infrastructure, which promotes innovation and efficiency(Fragkias et al., 2013). In studies of urban carbon emissions, urban size is mainly defined by population and land, two key dimensions of urbanization. Population urbanization is the driving force of land urbanization, the spatial carrier of population urbanization.

Studies on the relationships between city size and carbon emissions were often based on the urban scaling hypothesis: Is there a scaling relationship between city size and carbon dioxide? Is it possible to explain the relationship in simple mathematics? In what ways does city size affect carbon emission efficiency? Given the trade-offs between carbon emissions and socioeconomic development, what is the optimal size for a city? Those answers to these questions form the basic framework of quantitative theoretical research on the relationship between city size and carbon emissions. Efficiency and aggregate perspectives are two main directions for research.

(1) The aggregate perspective

Increasing urban population sizes is believed to increase carbon dioxide emissions, so limiting urban size has been advocated. Human activities cause urban carbon emissions, so there is no doubt that the number of people living in cities affects carbon dioxide emissions and economic activities(Murtaugh & Schlax, 2009). Thirteen cities in the Yangtze River Delta were selected as the study area, the panel regression model was used to analyze the effect of urban population size on the aggregate amount of urban carbon emissions. The results showed that an increase in urban population would increase aggregate carbon emissions, so controlling urban populations and urban land expansion was proposed(Xia et al., 2019).

Urban land use affects urban carbon emissions by influencing the number of carbon sinks and sources(Arneth et al., 2017). Urbanization is when forestland, grassland, and other vegetation-covered lands are replaced by built-up areas, thus resulting in urban expansion and reductions in carbon sinks, which means the land has less capacity to absorb carbon dioxide. A 12.5 percent increase in CO_2 emissions between 1990 and 2010 is thought to be the indirect result of land use changes(Houghton, 2017). Similarly, a positive correlation between urban areas and CO_2 emissions has been found(Falahatkar & Rezaei, 2020).

Expanding urban built-up areas increases transportation infrastructure, production, and living activities, thus directly bringing energy demand and carbon dioxide emissions. Controlling urban area expansion can directly reduce carbon dioxide emissions. Meanwhile, The influences of urban area distributions and spatial arrangements on carbon dioxide emissions should be examined. Through the adjustment of the spatial distribution of urban size, urban expansion can reduce carbon emissions on the premise of meeting the needs of human life.

(2) The efficiency perspective

With the expansion of city size, the aggregate carbon emissions of a city increase, but carbon emission efficiency may also be improved. As the size of urban population increases, per capita CO_2 emissions decrease(Liu Jianghua et al., 2021). This scaling relationship becomes a tool for understanding the holistic relationship between urban expansion and carbon emissions. From a global perspective, urban population growth may also be a way to reduce emissions owing to a nonlinear relationship between urban population size and energy consumption(Gately et al., 2015). Likewise, Wang et al. (2016)found that urban carbon dioxide increased by only 0.2% when a city's population increased by 1%. One of the reasons may be that an increasing urban population size promoted technological advances and improved the efficiency of public facilities, thereby reducing carbon dioxide emissions to some extent(Zhou et al., 2019; Zhou & Liu, 2016). However, this result seems to differ from the following study. Using 366 metropolitan statistical areas and 576 micropolitan areas in the United States, the elastic coefficient method was employed to analyze the relationship between CO_2 emissions and population size. Yet, no relationship involving economies of scale was found(Fragkias et al., 2013). From the perspective of dynamic changes in urban population scales, another study examined the relationship between shrinking cities and carbon emissions. The study found that carbon emission efficiency was lower in shrinking cities and a changing population size had a key effect on carbon emission efficiency(Liu et al., 2020).

In sum, population and land use are the roots of urban carbon emission demand, so there is a significant relationship between urban size and urban carbon emissions. There is no doubt that the growth of city size leads to an increase in carbon dioxide emissions. This level of understanding has limited guiding significance for urban planning and management practice. If a single city reduced its carbon emissions by controlling its size, the carbon emissions of the city itself would fall. Increases in urban size result from migrations between cities or from rural areas to the cities. Population mobility leads to an increase in carbon emissions in a city after population inflow, but the aggregate global carbon emissions do not necessarily increase. Increases in carbon emissions may be determined by the difference between the carbon emission efficiencies resulting from the relative rates of population inflow and population outflow. This implication leads to the following two questions. First, are there any carbon savings resulting from urban population growth? Second, does the change in urban population size bring about changes in carbon emission efficiency, especially for shrinking cities?

1.2.2.2 Urban Form and Carbon Emissions

Urban form, which generally refers to the two-dimensional spatial layout of land use in cities, can significantly impact urban areas' socioeconomic conditions and environmental aspects. The Environmental Protection Agency (2001) highlighted that urban form could influence habitats, ecosystems, endangered species, and water quality(Rafeq, 2006). Due to its potential in promoting urban sustainability and reducing carbon dioxide emissions, urban form is increasingly gaining attention from researchers(Fang et al., 2015). Moreover, it can affect the socioeconomic conditions and environment in urban settings(Camagni et al., 2002; Ou et al., 2013). Urban spatial layout is a crucial component of urban spatial structure(Mariaflavia, 2020). Its planning should also be considered in developing low-carbon cities.

(1) Urban land shape

Scholars have used landscape metrics to analyze the relationship between urban spatial structure and carbon emissions(Wang G. et al., 2019; Zhang et al., 2018). They have focused on the relationships between morphology complexity, irregularity, fragmentation, and carbon dioxide emissions. Studies in several countries consistently show that urban fragmentation and irregularity increase carbon dioxide emissions. Number of Patches, Edge Density, Mean Perimeter-Area Ratio, Percentage of Similar Adjacencies, Patch Cohesion Index and Largest Patch Index were used to quantify urban form, while panel data were employed for the analyses of carbon emissions in Beijing, Tianjin, Shanghai, and Guangzhou. The results showed that fragmentation and irregularity would increase carbon emissions(Ou et al., 2013). Satellite remote sensing was used to extract urban built-up areas and the landscape index was used to quantify urban forms in 55 Japanese cities. The results revealed that a less fragmented public transportation sector emitted less carbon dioxide than sprawling cities, but urban form complexity had little effect on carbon emissions(Yasuyo et al., 2012). Using data from

30 provincial capitals in China from 1990 to 2010, Fang et al. (2015) found that increased urban complexity and irregularity led to increased carbon dioxide emissions. The fragmentation and compactness of cities, for example, in northern Iran were found to increase carbon dioxide emissions(Falahatkar & Rezaei, 2020).

Urban sprawl leads to fragmentation, complexity, and irregularity in urban spatial forms. Wang Shaojian et al. (2019)found that urban sprawl has adverse effects on both the economic and social efficiency of carbon emissions. The complexity of urban forms was significantly correlated with the carbon emissions of all cities and the effect increased with the size of urban population(Shi et al., 2020).

In sum, landscape metrics are mostly combined with remote sensing images to explore urban spatial forms' complexity, irregularity, continuity, connectivity, and fragmentation. A basic consensus has been reached. The irregularity, fragmentation, and complexity of cities lead to increases in urban carbon emissions, while contiguous and connected urban areas have higher carbon dioxide emission efficiency. However, urban form was measured only at the level of urban area contours, and its influence mechanism is seldom analyzed. Many empirical studies have revealed the relationship between urban form and carbon emissions. However, the question remains: how does urban form, as measured by landscape metrics, affect urban socioeconomic functions and, ultimately, carbon emissions?

(2) The compactness of urban land use

Landscape metrics are commonly used to quantify urban compactness. Four landscape indicators were used to measure the compactness of a city: the Aggregation

Index, Percentage of Similar Adjacencies, Patch Cohesion Index, and Proximity Index. The higher the degree of urban compactness, the lower the carbon dioxide emissions(Falahatkar & Rezaei, 2020). Other researchers found similar results (Yasuyo et al., 2012).

Quantified by the ratio of the urban area to the smallest circumcircle, urban compactness is found to be negatively correlated with the social efficiency of its carbon emissions. Specifically, the smallest circumcircle is positively correlated with economic efficiency. Urban compactness is related to higher private costs, although it can reduce environmental costs(Veneri, 2010). It is believed that policymakers should recognize compactness as a trade-off between social and economic efficiency(Liu et al., 2014). The study found that in high-density cities, compact urban development reduces traffic emissions but increases air pollution, so environmental exposure should be considered when adopting such methods(Yuan et al., 2017).

Urban compactness may reduce CO_2 emissions by improving the connectivity of cities. This idea is supported by Mariaflavia (2020), who states that less compact cities have longer commuting distances and times, resulting in lower quality of life and higher potential costs for family welfare. An analysis of the patch cohesion index found that a 1% increase in connectivity could reduce CO_2 emissions nationwide by 28.5 tons per hectare(Shi et al., 2020). Therefore, the degree of a city's compactness is considered by researchers to be an effective measure for low-carbon city construction. In contrast, compactness may raise the temperature of a city, thus increasing the pressure for carbon emissions. Climate factors may influence carbon emissions by influencing fossil energy consumption(Liu Quanwen et al., 2021). For example, temperature differences can lead to differences in demand for fossil fuels. Improvements in city contiguity would enhance urban heat islands(Debbage & Shepherd, 2015), thus reducing carbon emissions.

First, the definition of urban compactness mainly uses planar urban area measurements, but this lacks the analysis of urban architectural indicators such as building density, floor area ratio, and building height. The compactness measured by different indicators varies greatly in an urban built-up area. Future studies must quantify urban density or compactness through urban building indicators and investigate its effect on carbon emissions. Second, most existing studies agree that increasing urban compactness would reduce urban carbon emissions and improve carbon emission efficiency(Falahatkar & Rezaei, 2020; Yi et al., 2021). However, studies found that high compactness may bring about lower social efficiency, more environmental exposure(Yuan et al., 2017), and other factors negatively affecting the quality of life. In addition, the quantitative relationship between the degree of compactness and carbon emissions is still unclear. Previous studies have found that the degree of compactness would also increase the urban heat island effect(Debbage & Shepherd, 2015; Zhou et al., 2017) that can result in more carbon emissions. The influence mechanism should be investigated for the positive and negative effects of the degree of compactness on carbon emissions. Third, it is necessary to study the mechanism of how urban compactness affects carbon emissions.

(3) Polycentricity/monocentricity

The urban center is a key element of a city. Monocentric and polycentric urban forms are universal perspectives of urban spatial structure(Han et al., 2020). "Polycentricity refers to balanced hierarchical relationships among centers in a regional system" (Burgalassi & Luzzati, 2015). Polycentricity can be defined by morphological polycentricity and functional multi-centroidism(Burger & Meijers, 2011). For morphological polycentricity, economy, population, and employment are indicators that are usually used to describe the concentration degree(Wang et al., 2022). For example, as the opposite of compactness, polycentricity is seen as a description of uniformed and centralized population distributions, including the distance of a city's sub-centers to the main center, the number of a city's centers, the population distribution between the main center and the sub-centers(Sha et al., 2020). Meanwhile, the functional approach is usually quantified by the interactions among centers (Green, 2016). Besides, two Common quantitative methods of polycentricity are the urban primacy index (Meijers, 2008) and the rank-size distribution(Meijers & Burger, 2010; Wang et al., 2022). Although not well defined(Veneri, 2010) and regarded as a fuzzy concept(Taubenböck et al., 2017), polycentricity has been promoted as a planning tool to enhance competitiveness and sustainability. There were two opposite views about the effect of polycentricity on carbon emissions.

Polycentric development is often believed to be conducive to higher CO_2 emission efficiency(Sha et al., 2020; Wang et al., 2022). Similarly, it is confirmed that polycentric structures help reduce the mean CO_2 concentrations(Sun et al., 2020). Polycentric spatial planning can reduce ecological footprint(Muñiz & Garcia-López, 2019). A step forward, the effect of polycentricity on carbon reduction was believed to be regulated by urban distance and transportation infrastructure(Chen et al., 2021). Furthermore, the carbon reduction effect of polycentric structures lies in the reductions in commuting duration(Sun et al., 2020). In a study on the effect of urban polycentricity on commuting costs, it is empirically found that a higher degree of polycentricity benefits the reduction of private and external mobility costs (Veneri, 2010).

On the contrary, some studies found no evidence of the effect of polycentricity leading to carbon reduction. In the 2000s, the proxies for polycentricity were found to have significant and positive coefficients for CO_2 in the NUTS-3 of Italian(Burgalassi & Luzzati, 2015). In 24 metropolitan areas, a study did not find significant nexus between polycentricity and driving or energy consumption(Lo, 2016). Similar results were found at the NUTS-5 regional level in Turkey(Sat, 2018). Polycentric structures have only a moderate impact on GHG emissions in the 125 largest urbanized areas in the United States(Lee & Lee, 2014). One of the core reasons for disparities in those analyses can be attributed to selections of spatial scale. Urban polycentricity is sensitive to spatial scale. What looks monocentric on a lower scale may be polycentric on a higher scale.

1.2.3 Literature Summary

After a review of literature on urban spatial structure, the research findings are summarized as follows:

Firstly, this chapter begins by summarizing theories related to this topic, including the Garden City Theory, Sustainable Development Theory, Composite Ecosystem Theory, and Urban Metabolism Theory. Historical developments in urban planning show that early urban planning primarily aimed to address the gradual deterioration of the natural environment. The Garden City Theory, a classic example of early urban planning, reflected concerns about environmental degradation in industrialized cities and proposed improving urban environments by controlling urban expansion. The introduction of this theory not only marked the beginning of modern urban planning thought but also laid the foundation for subsequent development in urban planning. Subsequently, the introduction of Sustainable Development Theory and Composite Ecosystem Theory further emphasized the balance between human activities and the natural environment in urban planning. These theories suggest that cities are not only centers of socioeconomic activity but also parts of the natural environment. Thus, urban development should be coordinated with environmental protection. The Composite Ecosystem Theory mainly provides a more comprehensive perspective to understand the workings of cities as socio-economic-natural complexes. In this context, the introduction of Urban Metabolism or Urban Organism Theory provides an essential theoretical basis for understanding the relationship between urban spatial structure and carbon emissions. Urban Metabolism Theory views the city as an ecosystem, emphasizing the consumption of resources and generation of waste in cities, closely related to carbon emissions. This theory helps us understand how cities consume energy and produce carbon emissions and offers a perspective for analyzing carbon emissions under different urban spatial characteristics.

Secondly, the study of urban spatial structure has received attention in urban planning, covering its impacts on the environment, economy, and society. Research shows that urban spatial layouts influence environmental quality, such as air pollution and carbon emissions, and play a significant role in economic activities and urban competitiveness. These findings underscore the critical role of optimizing urban spatial structure in promoting sustainable development and improving urban functionality. As the basic framework of urban development, urban spatial structure broadly impacts various aspects of city operations, forming an essential basis for urban planning and policy development. These research outcomes provide new perspectives for understanding the impacts of urban spatial structure and offer theoretical foundations for formulating effective urban development strategies.

Thirdly, a review of studies on the relationship between urban spatial structure and carbon emissions reveals that urban size is one of the most critical factors of urban spatial structure, pre-determining most of the city's characteristics. (1) urban land expansion increases carbon sources but decreases carbon sinks, thereby increasing carbon dioxide emissions. Urban planners and policy makers should carefully consider urban land expansion. However, controlling urban population size seems less effective than reducing land size for carbon emissions. Shrinking cities have lower carbon emission efficiency than growing cities. (2) Compact cities have higher connectivity, which helps reduce carbon emissions by reducing commuting distances and times. However, these cities also have negative impacts, such as the heat island effect and reduced social efficiency. (3) Studies on the impact of urban density on carbon emissions are still inconsistent. Research on the impact of polycentricity on carbon reduction is relatively limited, with opposite results. (4) Studies on urban form focus on the relationship between carbon emissions and urban surface characteristics (such as complexity, irregularity, and fragmentation), which are believed to increase carbon emissions. Landscape metrics are the most widely used method to quantify urban spatial form.

Existing research in this field, while comprehensive, presents certain areas for further exploration and development. There are several research gaps as following.

(1) The research on the impact of urban population size on carbon emissions is limited in depth. Currently, many studies primarily focus on exploring the quantitative relationship between urban population size, age, household structure, and carbon emissions. Although some studies have investigated the effects of urban population size on urban system variables (such as education and technological innovation), the specific impact on carbon emissions has not been thoroughly explored. This constitutes the research gaps for the thesis.

(2) Existing research on the impact of urban spatial structure on carbon emissions mainly focuses on the "total amount," while studies that consider multiple carbon emission sources are still relatively few. The breadth of research needs to be further expanded. The nature of different carbon emission sources and urban connotations within cities exhibit significant differences. Conducting comprehensive analyses of multiple carbon emission sources, such as industrial carbon emissions, transportation carbon emissions, and residential carbon emissions, can not only improve the accuracy,

relevance, and effectiveness of the research results but also help compare the impact of urban spatial structure on different carbon emission sources. This, in turn, facilitates a comprehensive understanding of the focal points, which is beneficial for making balanced planning and decision-making.

(3) Urban spatial structure should encompass both the "quantity" and "form" of land. Existing studies generally emphasize "form" over "scale," and discussing urban land morphology without considering the scale of urban land is of limited significance to planning practice. Empirical research typically remains at the level of determining the positive or negative impacts of land area and land morphology on carbon emissions. It fails to discuss the influence of different urban land "forms" on carbon emissions from the "quantity" perspective, taking into account various urban land areas.

1.3 Research Purpose and Significance

1.3.1 Research Purpose

The impact of urban spatial structure on carbon emissions is one of the key scientific propositions in low-carbon urban planning(Ye, Chen, et al., 2012). This study aims to define the concept of urban spatial structure further and systematically construct an index system for it based on the theoretical and practical research of urban spatial structure both domestically and internationally. By employing quantitative methods such as statistical and geographical spatial analysis, this study seeks to delve into and reveal the influence of urban spatial structure on carbon emissions, thereby enriching the foundational theoretical system of urban planning. Following this foundational research, the study will explore planning strategies using urban planning tools to achieve carbon reduction and provide theoretical and empirical support for mitigating climate change. The specific research objectives are as follows:

(1) Clarify the concept of urban spatial structure, further explore and clarify its connotation and extension, and further clarify the research direction.

(2) Reveal from multiple dimensions the extent and mechanisms of the impact of urban spatial structure(both urban size and urban land form) on carbon emissions, summarizing and refining these to enhance the advancement of urban planning theory.

(3) From the perspective of "structural carbon reduction," propose planning strategies to improve carbon emission efficiency and mitigate climate change, thereby enriching the existing toolkit for urban planning.

1.3.2 Research Significance

Research on the impact of urban spatial structure on carbon emissions, based on the "population-land" nexus, tightly integrates urban planning theory and practice and plays a pivotal role in advancing the quantification and measurement of the ecological effects of urban spatial structure.

Studies on how urban spatial structure affects carbon emissions include summarizing the concept of urban spatial structure and systematically constructing an index system and revealing whether and how urban spatial structure impacts carbon emissions. This research area, fundamental to urban planning and management, aims to clarify the concept and indicators of urban spatial structure and unveil the interaction between urban systems and natural ecosystems. It falls within the realm of theoretical foundational research. Building on this theoretical groundwork and exploring specific strategies for urban carbon reduction through planning and management approaches are also key focuses of this study, belonging to the domain of planning practice. Based on this, the theoretical and practical significance of this study is as follows:

Theoretical Significance: This research reveals the impact of urban spatial structure on carbon emissions and synthesizes findings, addressing the value orientation and development pathways of urban spatial development from the perspective of carbon emissions. It can provide reference material for sustainable development, ecological planning, and composite ecosystem theories.

Practical Application Value: Firstly, from the perspective of the carbon reduction effects of urban space, the findings of this study can directly provide guidance for urban planning practitioners in carbon reduction planning, offer ecological considerations for government departments responsible for economic development planning, and facilitate the construction of low-carbon cities. Secondly, the specific planning strategies derived from this study for reducing urban carbon dioxide emissions through spatial adjustments can serve as practical references for healthy, harmonious, and sustainable urban development, contributing to constructing low-carbon and livable cities.

1.4 Research Content

Population and land are key components of urban spatial structure. This study systematically investigates the impact of changes in urban spatial structure on carbon emissions during the urbanization process from the perspective of "population size - land area - land morphology." Building upon a synthesis and summary of existing research, it examines the influence of urban space on changes in carbon emissions. From the perspective of spatial structure adjustment, the study aims to provide theoretical underpinnings and practical planning strategies for carbon reduction in urban planning and development.

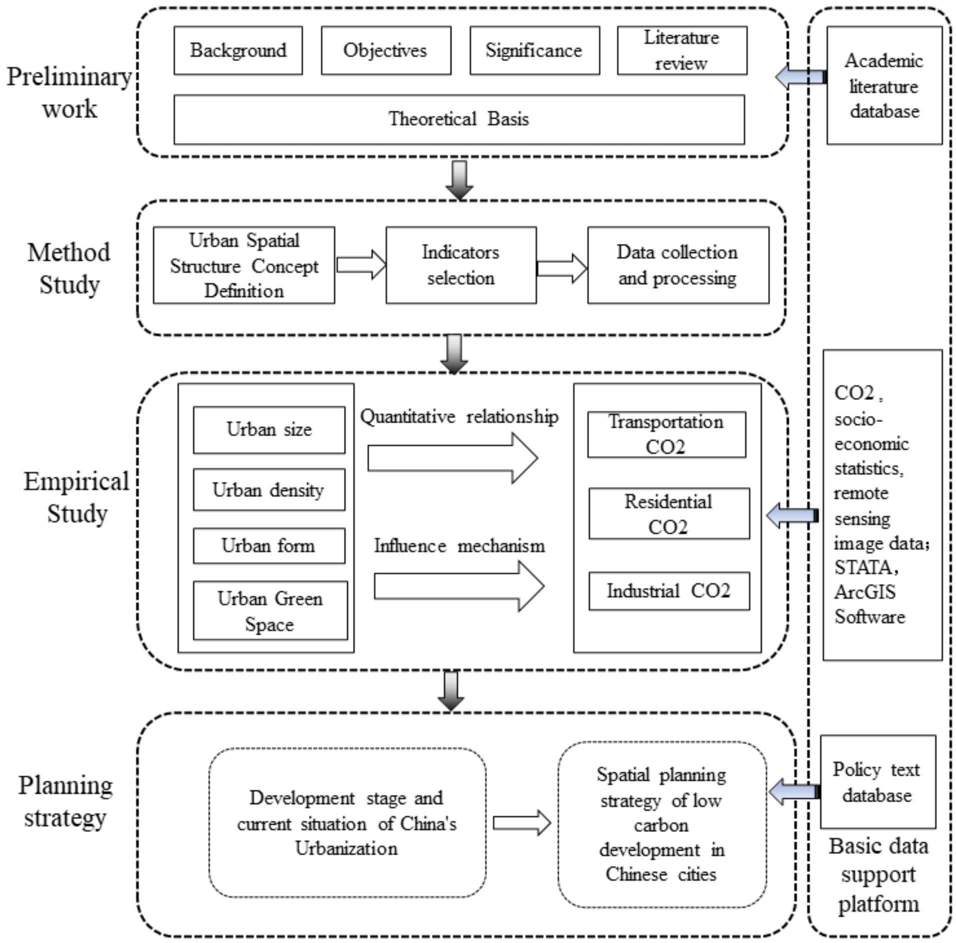

Figure 1-3 Research framework(source: created by author)

Chapter 1: Introduction. This chapter serves as the foundation for practical research, acting as a preliminary study that provides reference and guidance for subsequent sections. It primarily introduces the research background related to urban carbon emissions, the objectives and significance of this study. It reviews the theories and practices related to urban carbon emissions, including a review of theories related to cities and existing research on the impact of urban spatial structure on carbon emissions. This chapter also constructs the research content and framework.

Chapter 2: Urban spatial structure and related concepts. This chapter elaborated related concepts, consist of urban spatial structure, urban spatial form, urban built environment and urban land use. Through this chapter, we can achieve the research objective to a certain extent, laying the foundation for subsequent research. Through this chapter, we can achieve the research objective 1 to a certain extent, laying the foundation for subsequent research.

Chapter 3: The Spatiotemporal Evolution Characteristics of Carbon Emissions in Chinese Cities. This chapter aims to provide data support for the entire study. Firstly, it calculates and obtains all the data required for this research. Secondly, it conducts a spatiotemporal dynamic analysis of carbon emissions in Chinese cities, thereby clarifying the current state of carbon emissions within the Chinese urban system. This serves to provide a foundational understanding for the subsequent empirical research and planning strategy studies.

Chapter 4: The Impact of Urban Size on Carbon Emissions. This chapter first explores the scaling relationships between urban size and total carbon emissions, industrial carbon emissions, transportation carbon emissions, and residential carbon emissions. It then examines the impact of urban population size on each of these emission sources separately. By this chapter, We can answer some of the content of research objective 2 from the perspective of urban size.

Chapter 5. The Impact of Urban Form on Carbon Emissions. Based on the study of the impact of urban size on carbon emissions, this study investigates the impact of urban spatial form on industrial carbon emissions, transportation carbon emissions, and residential carbon emissions. The heterogeneity of the impact of urban morphology on carbon emissions under different land area constraints. Finally, the impact of urban green space scale on carbon emissions was analyzed. By this chapter, We can answer some of the content of research objective 2 from the perspective of urban land form.

Chapter 6. Urban Carbon Reduction Strategies Based on Urban Spatial Structure. This chapter combines the previous analysis and empirical research on carbon emissions to propose strategies for urban carbon reduction. By this chapter, We can answer some of the content of research objective 3.

Chapter 7. provides a summary of the thesis.

1.5 Summary of This Chapter

Population and land are key components of urban spatial structure. This study systematically investigates the impact of changes in urban spatial structure on carbon emissions during the urbanization process from the perspective of "population size - land area - land morphology." Building upon a synthesis and summary of existing research, it examines the influence of urban space on changes in carbon emissions. From the perspective of spatial structure adjustment, the study aims to provide theoretical underpinnings and practical planning strategies for carbon reduction in urban planning and development.

Chapter 2. Urban spatial structure and related concepts

This section analyzes the concepts of urban spatial structure, urban morphology, built environment, and land use, and further defines the specific meaning of urban spatial structure within the context of this study.

2.1 Urban Spatial Structure: Elements and Their Relationships

Urban spatial structure is an interdisciplinary research subject, and many scholars have sought to define it. Among the earliest attempts to conceptualize urban spatial structure, Foley divided it into four levels(Foley, 1964). First, urban spatial structure encompasses the physical environment, functional activities, and cultural values. Second, it includes not only spatial attributes, which are the spatial characteristics of the three elements above but also non-spatial attributes, which refer to cultural and social activities that occur in space. Third, urban spatial structure comprises both form and process. Building on Foley's framework, Webber Melvin (1964) believed that form and process refer to the distribution and interaction of material and activities in space. Fourth, urban spatial structure has a temporal aspect, necessitating a focus on its evolution over time(Foley, 1964).

Bourne (1982) adopted a systems theory perspective to define urban spatial structure, constructing three core concepts of the urban system. The first is urban form (urban form), referring to the spatial layout patterns among various elements within the urban system, including physical facilities, social groups, economic activities, and public institutions. The second is the interaction of urban elements (Interaction), which realize the functions of a city and form functional entities or subsystems. Lastly, urban spatial structure is a set of spatial organization rules that determine urban elements' spatial distribution and interaction, thereby combining various subsystems into the entire urban system. The first level can be seen as the spatial characteristics of places where urban functions are realized, providing a framework for human activities in cities. The second level is the interaction patterns generated by human activities in urban spaces. The third level explains the formation and development of the first layer's form and the second layer's connections.

In recent years, the definition of urban spatial structure has become akin to that of spatial form. It refers to the distribution of phenomena in geographical space(Horton & Reynolds, 1971). Similar definitions have emerged in recent research, with urban spatial structure being defined as the layout of city components(Yousefi & Dadashpoor, 2019). Some studies on urban spatial structure, even without providing a conceptual definition, focus on the physical spatial structure of cities(Camagni et al., 2002; Hankey & Marshall, 2010; Lemoy & Caruso, 2020), typically characterized from a morphological perspective. For instance, some scholars use "hand-shaped" or "fan-shaped" to describe the internal spatial structure of cities(Feng & Zhou, 2013). As a measurable unit and substitute for changes in landscape composition(Seitz et al., 2011), landscape metrics are a typical and widely used method for quantifying urban spatial structure, such as land use patterns(Herold et al., 2016).

In a broader definition of urban spatial structure, the interaction of different urban components is also part of the spatial structure, related to Webber's concept of "process" and Bourne's interactive models. This definition mainly involves human elements, with the spatial layout or patterns of interaction in the movement of people, goods, materials, and information often considered part of urban spatial structure(Zhong et al., 2014). Important factors include population distribution and migration, with related research using population distribution to quantify urban polycentricity and dispersion(Li & Liu, 2018), as well as urban density(Kim & Kim, 2013). With the development of data analysis techniques, large datasets like social media and commuting data are being used to analyze urban connected spatial structures. Urban spatial structure is defined as the spatial layout of internal elements (physical environment) and their interaction within the city system (perceived environment) (Chen et al., 2019).

In summary, urban spatial structure (Urban Spatial Structure) is a core concept in urban planning and geography, involving elements within and between cities and their spatial organization, functional distribution, and relationships. On a macro scale, it encompasses how various elements are distributed within urban geographical space, such as concentrated, dispersed, or uniform spatial distribution patterns. From the perspective of land and people relationships, it includes elements like urban population size and density.

2.2 Urban Spatial Form: Attribute Concepts

The term "Morphology" originates from the Greek words "Morphe" (form) and "Logos" (logic). Initially, morphological studies were primarily in biology, focusing on human anatomy to understand organisms' structure, size, and shape and, thereby, their functions. The application of the morphological perspective in urban studies began to emerge in the early 19th century, viewing cities as organisms and studying their growth mechanisms(Duan & Qiu, 2008).

In 1894, the French historian J. Fritz heavily utilized town plans in his publication "German Town Facilities," studying the spatial characteristics of German towns from a morphological perspective, which influenced urban research. In 1898, Howard published "Tomorrow: A Peaceful Path to Real Reform," proposing the idea of "Garden Cities" to address urban congestion and environmental degradation. He attributed urban environmental deterioration to urban expansion.

The birth of Urban Morphology as a field occurred in 1899, primarily using the terms 'urban morphology' (predominantly in Europe) and 'urban form' (mainly in the USA). A landmark in its development was the publication of "Urban Layouts" by the German geographer O. Schlüter. In 1960, Conzenian established the framework for urban morphological research in "Town Plan Analysis: Alnwick, Northumberland," introducing innovative concepts like 'plan unit,' 'morphological regions,' and 'fringe belts' for analyzing urban form(Duan & Qiu, 2008). Conzenian classified the physical landscape of cities into three levels: town plan, buildings, and land use, with the town plan being the most stable and land use the most changeable(Zhang et al., 2012). The Urban Morphology Research Group (UMRG) was founded in 1971 by Slater and Whitehand, followed by the International Seminar on Urban Form (ISUF) in 1994, gradually forming the Conzenian school.

In architectural studies, the focus is often on micro variables like buildings and streets. For example, Ding et al. (2012) explored the impact of micro-urban texture morphology on thermal comfort, including indicators like sky view factor and urban roughness. On the other hand, urban planners and geographers tend to study macro aspects of urban form, such as town land use layout patterns, scale, and density(Xiu et al., 2018). In recent years, urban spatial morphology has broadened beyond physical space to describe economic, work-residence, and population movement characteristics in space.

2.3 Urban Built Environment: A Relative Concept

As a multi-dimensional concept, the urban built environment has not yet attained a unified definition in academic research. It is often perceived as a relative concept closely linked to human perception and interaction. This concept encompasses not only the physical elements of a city, such as land use, architectural structures, and green spaces but also includes dynamic factors of urban operation, like traffic flow and environmental temperature. Thus, the urban built environment is a composite of physical and functional characteristics and people's perceptions and responses to these characteristics.

In research on the built environment at the metropolitan scale, the urban built environment includes features of polycentric spatial structure(Yang & Zhou, 2020). Wang and Mei (2018) describe variables of the built environment at the campus scale, including road network connectivity, facility functionality, public transportation quality, and land use mix. In the study by Shen et al. (2022) on the relationship between characteristics of the urban built environment and carbon emissions, the concept is broader, encompassing key factors of urban form (such as urban density, size, sprawl, and work-residence balance), urban functions (industrial and commercial levels), urban traffic conditions, and urban greening. Boarnet et al. (2009), in their research on driving behavior and the built environment, primarily focus on the city's compactness as the primary variable of the built environment.

Therefore, as a concept relative to "people," the urban built environment has a wide-ranging scope in academic research yet faces challenges in being precisely defined. Its application often merges with concepts such as urban form, land use, and spatial structure. As research progresses, the concept of the urban built environment increasingly tends to integrate these spatial concepts, such as the city's physical layout, functional allocation of land, and the organizational structure of various spaces.

2.4 Urban Land Use: Functional Zoning

The concept of urban land use focuses on "utilization." Practical research mainly concentrates on assessing the current state of urban land use, such as functional zoning. Li Linchao et al. (2023) utilized remote sensing imagery and Points of Interest (POI) data to classify urban land use, identifying categories such as commercial service land and public administration land. Tan et al. (2023) further employed land use classification data for ecosystem service assessments. On a more granular scale, Yang et al. (2023) analyzed the impact of land uses such as finance, office buildings, hotels, and commercial services on subway passenger flow. Although these studies often do not fully define "urban land use," they generally accept a unified concept scope. This concept refers to the functional characteristics and macro-zoning attributes of land in an urban environment, representing the outcomes of human utilization of land, and emphasizing the human element.

Therefore, in the study of land use, the focus is on the outcomes of land utilization and their impacts on the environment and society, mainly revolving around human activities. This contrasts with the concept of urban form, which concentrates more on the spatial form and physical attributes of land. Research on land use emphasizes the comprehensive effects of land utilization methods on urban ecology, economy, and social structure, while studies on urban form focus on understanding the arrangement and allocation of land within spatial structures. In summary, land use represents the spatial characteristics projected by human activities in space.

2.5 Summary of This Chapter

The above analysis shows that while the concepts of urban spatial structure, urban spatial morphology, urban built environment, and urban land use often overlap in practical research, distinguishing the relationships among these concepts is beneficial for this and future studies. Such distinction aids in fostering academic dialogue.

Space is a broad concept; defining this element is key to unifying the above concepts. Space is an ambiguous term that can refer to both the perceived space of socio-economic activities and the physical space of urban land use. In this thesis, 'space' is called 'physical space.'

In studying urban spatial structure, research includes the intrinsic characteristics of urban space and the relationships between urban spatial elements. Studying urban spatial characteristics forms the foundation for analyzing relationships between these elements. In empirical research, urban spatial morphology often encompasses both the physical and perceived spatial forms of cities. However, this study specifically refers to the physical spatial form of cities. Urban land use typically refers to functional elements. The functionality of a city is a manifestation of human activities in space, which bears similarities to the perceived space within cities. Therefore, in this study, the concept of urban spatial structure encapsulates the research content more aptly.

Chapter 3. The Spatiotemporal Evolution Characteristics of Carbon Emissions in Chinese Cities

This chapter aims to provide data support for the entire study. Firstly, it calculates and collects all the data necessary for this research. Second, the chapter conducts a spatio-temporal dynamic analysis of carbon emissions in Chinese cities. This analysis serves as a foundational reference for examining the impact of urban spatial structures on carbon emissions and formulating relevant planning strategies.

3.1 General Methods and Data for Carbon Emission Calculation

Production-based emissions (PBE) primarily focus on emissions generated within a city's boundaries from producing goods and services(Shan et al., 2018). This approach emphasizes the environmental impact of urban production activities, including emissions from energy production and consumption, industrial processes, transportation, and buildings. PBE is commonly used to assess a city's contribution to global greenhouse gas emissions and the effectiveness of local-level emission reduction policies. The PBE method concentrates on emissions from local production activities, overlooking the impact of urban consumption activities on global emissions. For instance, it does not account for emissions generated by city residents purchasing and consuming goods produced in other regions, potentially leading to emission responsibility shifting and inequities in emission reduction policies.

Researchers have proposed Consumption-based emissions (CBE) to address this issue, linking local consumption to emissions across the entire supply chain, including input-output or life cycle analysis(Mi et al., 2016). This method considers the impact of urban residents' consumption activities on global emissions, encompassing local and cross-border emissions.

The IPCC Administrative Scope approach captures direct emissions from human economic activities within a city's boundaries but excludes emissions from international aviation or maritime transport. The Administrative Scope approach focuses on direct emissions within a city's boundaries. This method helps governments understand local emissions and provides a basis for formulating and monitoring local emission reduction policies.

This thesis focuses on the impact of urban spatial structure on carbon emissions, specifically direct carbon emissions. The Administrative Scope approach, which focuses on direct emissions within a city's boundaries, aids in analyzing how urban spatial structure affects energy consumption and carbon emissions. For example, different building types, transportation modes, and land use practices can lead to varying energy demands and emissions. This approach provides a foundation for formulating and monitoring local emission reduction planning policies.

Existing research on carbon emission inventories in China includes national, provincial, city, and county studies, with smaller-scale studies facing data acquisition challenges. National and provincial energy use statistics are more readily available, making carbon emission data relatively complete at these levels. However, city and county-level carbon emission data are relatively scarce. Some scholars use high-scale carbon emission data from provincial or national levels and allocate it to lower-scale regions, a process known as Down-Scaling. This method spatially decomposes high-scale carbon emission data based on socio-economic statistical data related to emissions, such as population density, GDP(Shan et al., 2019), land use, and nighttime lights(Chen et al., 2020). Using these emission proxy variables is questionable(Zheng et al., 2021). Moreover, since this study focuses on the impact of urban spatial structure on carbon emissions, using such data could lead to circular reasoning problems, as some proxy variables are also research variables of urban spatial structure. Therefore, this study excludes such data sources in its data utilization.

3.2 Data Selection and Calculation in This Study

This study utilizes urban carbon emission data compiled by the China Greenhouse Gas Working Group, which is detailed at the city scale and differentiated by sector. The foundational data of the China Greenhouse Gas Working Group integrates three sources. First is the CHRED 3.0 database, a bottom-up compiled database from survey and point source data, ensuring high precision and accuracy(Gao et al., 2022). Second, city-scale government statistical data, such as published statistical yearbooks, government documents, and research reports. Third, data obtained by the China City Greenhouse Gas Working Group (CCG) through field surveys, interviews, telephone consultations, and correspondence with relevant departments(Cai et al., 2019), providing comparable and highly reliable primary data for city-level carbon reduction research.

The dataset includes sectoral urban carbon emissions data for agriculture, services, industrial energy, industrial processes, urban life, rural life, transportation, and indirect carbon emissions (net electricity trade). For urban spatial structure research, emissions from agriculture and rural life fall outside the scope of urban study. Industrial carbon emission data encompasses energy data during industrial production processes and carbon emissions from industrial processes, primarily cement and lime production. The carbon emissions from these production processes largely depend on chemical reaction norms and have a weak correlation with urban operational status. Therefore, in this study, emissions from the industrial system are calculated only based on energy data during industrial production processes. Carbon emissions from traded electricity are apportioned into industrial and urban living carbon emissions based on the proportion of electricity consumption data for each city as reported in the "China City Statistical Yearbook."

3.3 Calculation of Residential Heating Carbon Emissions

Given that heating carbon emissions are a significant component of residential carbon emissions and that urban spatial structure has a considerable impact on them, existing research on heating carbon emissions is relatively scarce. Furthermore, current urban carbon emission data products do not separately calculate urban heating carbon emissions. Therefore, this chapter calculates heating carbon emissions. The heating data in this study come from the China City Statistical Yearbook and various provincial statistical yearbooks, calculated using the following method:

According to the "People's Republic of China Environmental Protection Standards" by the Ministry of Ecology and Environment, the carbon dioxide emission factor for the combustion of fossil fuels is calculated using the formula:

Equation 3.1

$$EF_i = CC_i * OF_i * \frac{44}{12}$$

Where EF_i is the carbon dioxide emission factor of the i^{th} type of fossil fuel, measured in tons of carbon dioxide per gigajoule (tCO_2/GJ). CC_i is the carbon content per unit calorific value of the i^{th} type of fossil fuel, measured in tons of carbon per gigajoule (tC/GJ). OF_i is the carbon oxidation rate of the i^{th} type of fossil fuel, expressed as a percentage. The carbon oxidation rate is the ratio of carbon in the fuel that combines with oxygen to form carbon dioxide. Theoretically, the carbon oxidation rate is 100% under complete combustion. However, in actual combustion processes, carbon in coal may not fully convert into carbon dioxide due to various reasons (e.g., insufficient oxygen supply, presence of impurities in fuel). According to the standards, the carbon oxidation rates for crude oil, fuel oil, gasoline, kerosene, diesel, liquefied petroleum gas, and natural gas are 98% and 99%, respectively. The factor 44/12 is the ratio of the molecular mass of carbon dioxide to carbon, used to convert the mass of carbon into the mass of carbon dioxide, with the molecular mass of carbon dioxide (44) divided by the atomic mass of carbon (12).

The formula for calculating carbon dioxide emissions from the combustion of fossil fuels is:

Equation 3.2

$$E_{fuel} = \sum_{i=1}^{n} (AD_i * EF_i)$$

Where E_{fuel} is the carbon dioxide emission from the combustion of fossil fuels, measured in tons of carbon dioxide (tCO_2); AD_i is the activity data for the EF_i type of fossil fuel, measured in gigajoules (GJ); EF_i is the carbon dioxide emission factor for the i^{th} type of fossil fuel, measured in tons of carbon dioxide per gigajoule (tCO_2/GJ); i represents the type of fossil fuel.

According to the "China Clean Heating Industry Development Report (2020)," the main energy sources for heating in northern China are coal, natural gas, natural gas, electricity and other energy sources accounting for 56%, 30%, 8%, and 6% respectively. For the sake of simplifying carbon emission calculations in this study, the 6% from other energy sources is included with coal usage, making coal usage 62%, natural gas 30%, and electricity 8%. The coal used for heating is bituminous coal.

The formula for calculating heating emissions in northern Chinese cities is:

Equation 3.3

$$E_{heating,\ m}=\sum_{i=1}^{n}(AD_m*EP_i*EF_i)$$

Where $E_{heating,\ m}$ is the carbon dioxide emission from heating energy sources in city m, measured in tons of carbon dioxide (tCO_2); AD_m is the total heating amount, measured in gigajoules (GJ); EP_m is the proportion of energy source i used for heating, measured as a percentage; EF_i is the carbon dioxide emission factor for the i^{th} type of fossil fuel, measured in tons of carbon dioxide per gigajoule (tCO_2/GJ); i represents the type of fossil fuel.

Table 3-1 Energy-related carbon emission factors

Energy Type	Carbon Content per Unit Calorific Value *CC* (tC/TJ)	Carbon Oxidation Factor (*OF*)	Average CO_2 Emissions per Unit of Electricity Generated (kg/kWh)	CO_2 Emission Factor (tCO_2/GJ)
Natural Gas	15.32[a]	99%[a]		0.05617[b]
Bituminous Coal	25.77[a]	83%[a]		0.09277[b]
Electricity	/	/	1.0096[a]	0.28

Data sources: a. "Provincial Greenhouse Gas Inventory Compilation Guide (Trial)" Climate Change Office [2011] No. 1041; b. Calculated based on the formula; 1 kWh = 0.0036GJ.

3.4 Spatio-Temporal Evolution of Carbon Emissions at the Urban Level in China

This chapter utilizes GIS spatial analysis methods to reveal the spatiotemporal evolution of urban carbon emissions in China, laying a crucial foundation for subsequent research on the impact of urban spatial structure on carbon emissions. After understanding the spatiotemporal evolution of total carbon dioxide emissions, per capita carbon dioxide emissions, and carbon dioxide emissions per unit of GDP, we can reveal the fundamental laws and patterns of urban carbon emissions. First, from a total volume perspective, we will analyze the overall trend of urban carbon emissions in China from the standpoint of total carbon dioxide emissions. Then, from an efficiency perspective, we will examine per capita and carbon dioxide emissions per unit of GDP to analyze the spatiotemporal evolution of urban carbon emissions in China from an efficiency standpoint.

(1) Total Carbon Dioxide Emissions

China's total carbon dioxide emissions display a "high in the North and low in the South" distribution characteristic (Figure 3-1). In 2005, cities with high carbon emissions in the North were mainly concentrated in the more developed Bohai Rim region, such as Beijing, Tianjin, Tangshan, and other developed central cities. The highest emissions in the Yangtze River Delta were in Shanghai and Suzhou. Chongqing and Wuhan had the highest emissions in the central and western regions. The regions south of the Yangtze River generally had lower emissions, with Guangzhou being the area with the highest emissions. From 2005 to 2020, carbon emissions generally showed an upward trend, especially in economically rapidly developing urban agglomerations. The overall carbon emission intensity in the Bohai Rim region increased. Cities in the western region began to show dark areas, indicating an increase in carbon emissions, which may be related to the Western Development Strategy and the increased level of industrialization in the region, with typical cities including Ordos and Yulin. High carbon emission areas in the Northeast were mainly concentrated in the Liaodong Peninsula region and Harbin. In the Yangtze River Delta region, high carbon emission areas were centered around Shanghai, including core cities such as Suzhou, Wuxi, Hangzhou, and Ningbo. In the southern region, Guangdong Province's Guangzhou, Dongguan, and Fujian Province's Quanzhou showed significant increases in carbon emissions.

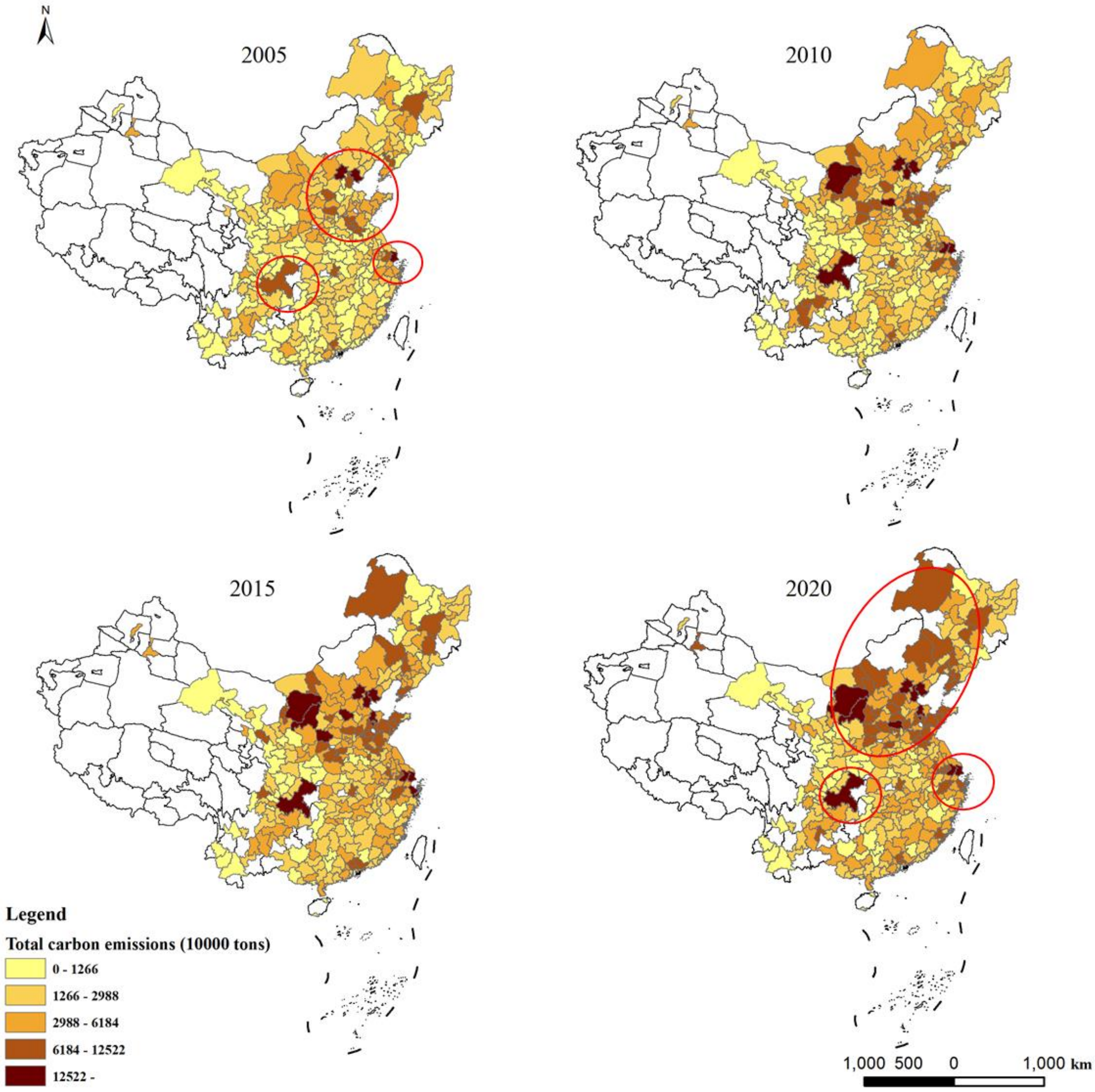

Figure 3-1 Temporal and spatial pattern of total carbon dioxide emissions in Chinese cities

(2) Per capita carbon emissions

Urban per capita carbon emissions show a more pronounced spatial distribution of differences between the north and the south. The northwest region is a high-value area for national per capita carbon emissions. Typical high-value per capita carbon emissions areas are centered around Ordos City in the northwest region, including Yulin City, Yinchuan, and Baotou City. These areas' economies are relatively dependent on resource-based industries, especially energy industries such as coal, oil, and natural gas.

These industries are typically energy-intensive and high in carbon emissions. With its rich coal resources, the Ordos Basin is one of China's largest coal production bases. Large-scale coal mining and consumption have led to high carbon emissions. Simultaneously, the development of the coal chemical industry has also contributed to the increase in carbon emissions in the region. Yulin, similarly dominated by the coal industry, sees coal mining, processing, and use as the area's main sources of carbon emissions. Yinchuan and its surrounding areas, while not as dominated by the coal industry as Ordos City and Yulin City, have a relatively weak industrial base, with heavy industry and energy-intensive industries still occupying a large proportion, which is one of the reasons for the high carbon emissions.

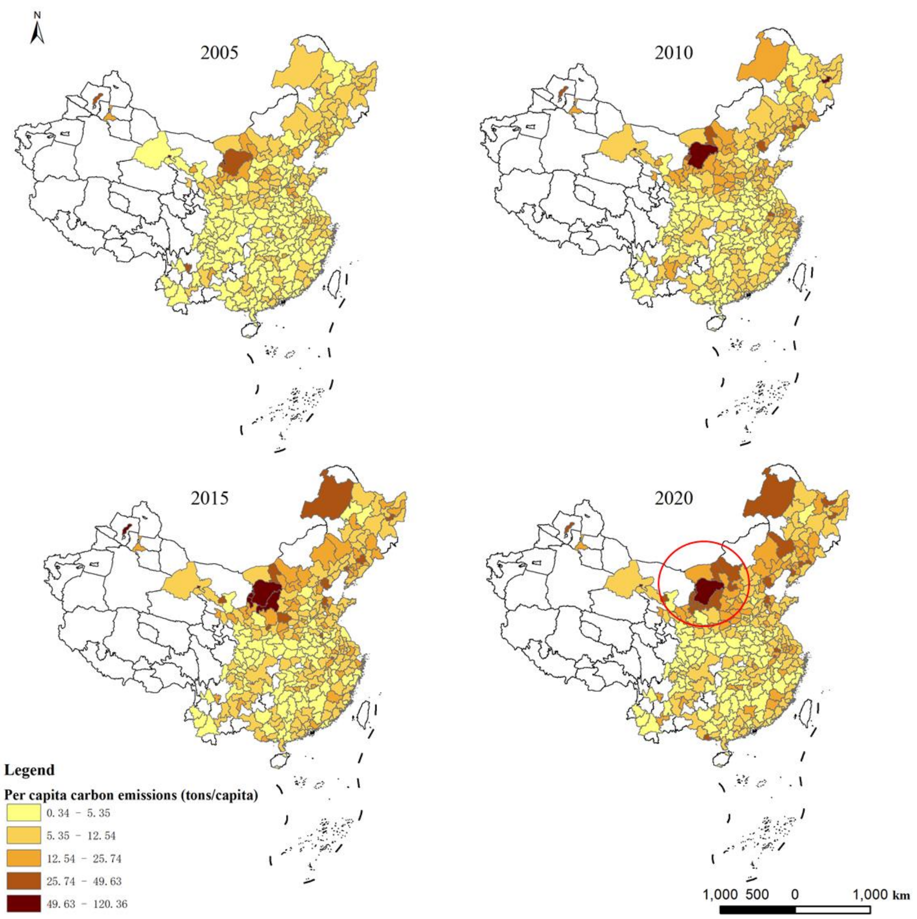

Figure 3-2 Temporal and spatial pattern of per capita carbon dioxide emissions in Chinese cities

(3) Carbon emissions per unit of GDP

From 2005 to 2020, China's overall carbon emissions per unit of GDP showed a downward trend, benefiting from rapid economic growth. The spatial distribution of carbon emissions per unit of GDP still exhibits significant differences between the north and the south. By 2020, the intensity of carbon emissions per unit of GDP presented a clear north-south dividing line, with cities with higher carbon emissions mainly located in the northeast and northwest regions.

Developed regions have relatively lower carbon emissions per unit of GDP. For example, in 2005, the eastern coastal regions generally had lower carbon emissions per unit of GDP than other areas, indicating that the environmental pressure per unit of output is lower in the eastern coastal areas. Possible reasons include the eastern coastal regions having experienced earlier and faster industrial restructuring and upgrading. These areas typically have a higher proportion of services and high-tech industries, which, compared to traditional manufacturing and heavy industry, have lower energy consumption and carbon emissions. Secondly, developed regions often have higher innovation capabilities, more advanced technologies and equipment, higher energy use efficiency, and consequently lower energy consumption and carbon emissions per unit of output. Furthermore, due to their developed economies, the eastern coastal regions have stronger financial capabilities, allowing for investment in environmental protection infrastructure and technology, implementing stricter environmental regulations and policies, promoting clean production and low-carbon technologies, and avoiding becoming "pollution havens."

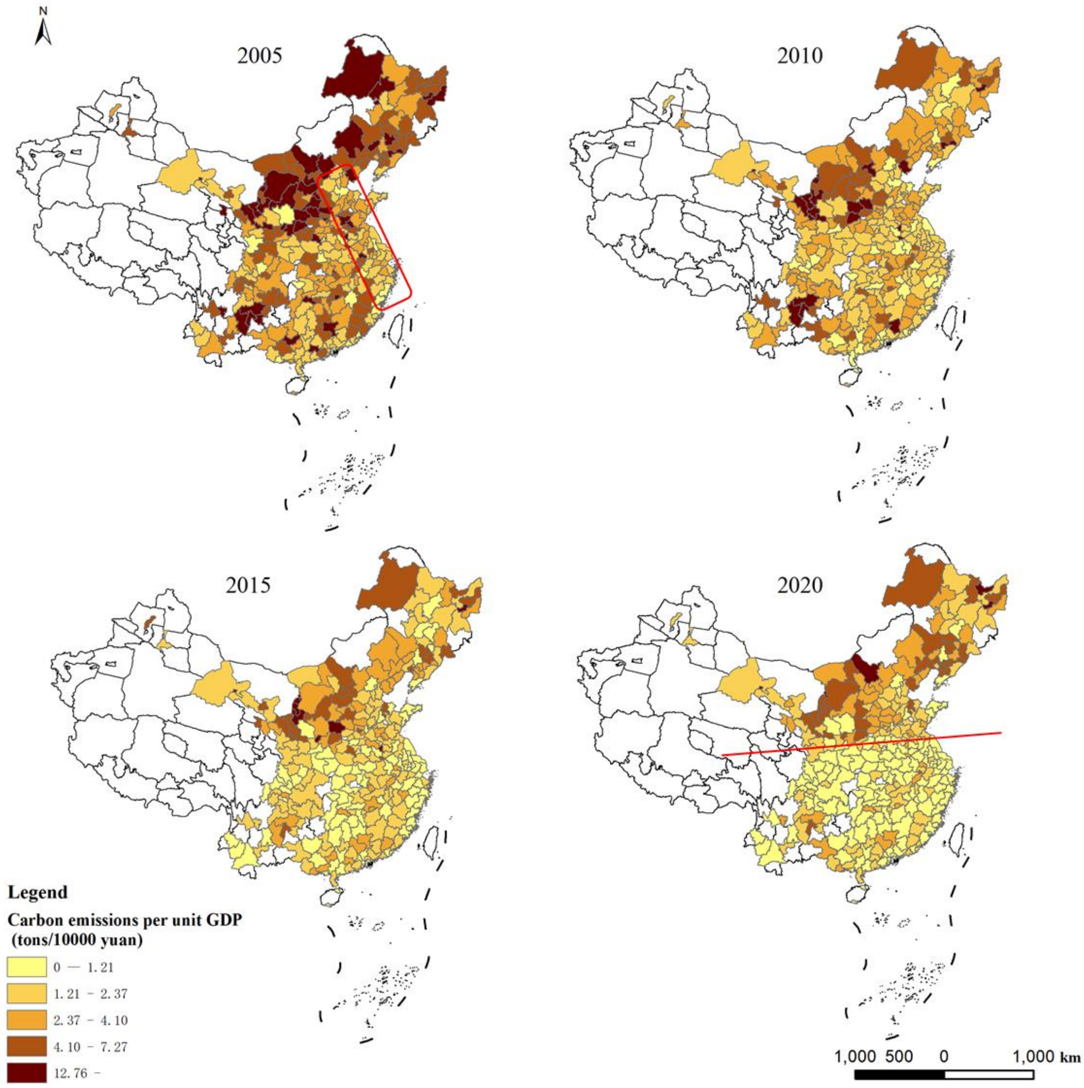

Figure 3-3 Temporal and spatial pattern of carbon dioxide emissions per unit GDP in Chinese cities

3.5 Summary of This Chapter

Appropriate and rational data use is a crucial starting point for research, determining the accuracy and rigor of scientific investigations. This chapter, aligning with the research needs, conducted a comparative analysis of existing carbon emission data products, ultimately selecting the city-scale, sector-specific carbon emission data compiled by the China Greenhouse Gas Working Group as the foundational data for this study. This data, combining bottom-up surveys and point-source data, offers high accuracy. Since this study explores the relationship between urban spatial structure and carbon emissions, the data collection method avoids biases in the research results that could arise from relying on elements of urban spatial structure in the data calculation process.

Urban heating carbon emissions are a significant component of residential carbon emissions. From the perspective of urban systems, existing research has not sufficiently focused on the relationship between urban spatial structure and urban heating carbon emissions. Therefore, this study investigated the impact of urban spatial structure on heating carbon emissions from an urban system perspective. This section calculated urban heating carbon emissions based on the method for calculating carbon dioxide emissions from fossil fuel combustion outlined in the "People's Republic of China Environmental Protection Standards" by the Ministry of Ecology and Environment, combined with the proportion of energy used for heating in Northern China.

After obtaining a complete urban carbon emission dataset, this section examined the overall carbon emissions, per capita carbon emissions, and carbon emissions per unit of GDP within the Chinese urban system, capturing the basic spatial patterns of carbon emissions in Chinese cities. This overview helps to understand and grasp the current comprehensive status of urban carbon emissions in China, laying the foundation for proposing carbon reduction planning strategies. The research findings indicate that total carbon emissions, per capita carbon emissions, and carbon emissions per unit of GDP exhibit a significant "high in the North and low in the South" spatial distribution pattern, particularly with a clear north-south dividing line in carbon emissions per unit of GDP. Developed areas, represented by the eastern coastal regions, generally have lower carbon emissions per unit of GDP.

Chapter 4. The Impact of Urban Size on Carbon Emissions

Population is the most fundamental element of a city. The size of a city's population determines the intensity of socio-economic activities in urban spaces. Urban population size is an essential aspect of research into urban spatial structures, reflecting the structural relationship between 'people' and 'land.' Discussing land use without considering the population significantly diminishes the relevance and guidance of planning practice. However, the research focus on the impact of urban spatial structure on carbon emissions has been primarily on the spatial aspects, with insufficient attention to the size of the urban population. Therefore, it is crucial first to explore the impact of city size on carbon emissions in studies concerning urban spatial structure and its effects on carbon emissions.

4.1 Analysis of the Overall Impact of Urban Size on Carbon Emissions

4.1.1 Theoretical Foundation: Urban Scale Law

The city is a complex mega-system with intricate spatial structures that influence urban metabolism. The foundation of urban planning is understanding complex systems and their dynamic regulation. Among these, the scaling law provides an important theoretical perspective for understanding the relationship between urban size and carbon emission patterns. The renowned theoretical physicist Geoffrey West posited that everything in the world can be measured by immutable standards, known as the Scaling Law. The scaling law is mathematically expressed as:

Equation 4.1:

$$Y \sim X^\beta$$

Here, Y represents a quantifiable indicator within the system, X represents the system's size (e.g., weight, urban population), and β reflects the system's properties. This formula shows that the system's variable Y is directly proportional to the size X raised to the power of β. Depending on the value of β, the scaling law can interpret "sub-linear," "linear," and "super-linear" scenarios. If $\beta<1$, the system is in a sub-linear growth mode, where doubling the system size results in less than double the increase in system variable Y, say an 80% increase. $\beta=1$ denotes a linear growth mode, where the system variable Y grows in direct proportion to the size X. When $\beta>1$, the indicator Y grows at a rate faster than the city size.

One well-known application is Kleiber's Law, which describes the relationship between an animal's metabolic rate and body weight, indicating that an organism's basal metabolic rate is proportional to the three-quarters power of its body weight. This law can be summarized by the formula: $B=a*M^b$. Here, B represents the animal's metabolic rate, M signifies the animal's weight, and a and b are constants, often referred to as Kleiber constants. In daily life, we often fall into the "linear intuition trap," assuming system variables and system size develop linearly. Kleiber's Law helps us escape this trap by viewing the system from the perspective of scaling laws, which is especially necessary for urban systems. Scale is one of the most prominent features of urban spatial structure and is at the core of urban economics and urban planning. Urban size precedes history, geography, and design as determining factors of most city characteristics(Bettencourt & West, 2010).

Research in urban size and socio-economic environments has garnered widespread attention, yielding many results. From a value judgment perspective, the primary intention behind studying the relationship between urban size and other urban system variables is to assist in determining the optimal urban size. The primary debate revolves around whether an optimal city size exists, which has been confirmed to exist(Wang, 2010), originating from Howard's Garden City planning idea and theoretical birth in urban economics of the 1960s. The issue of optimal city size has received broad attention in the socio-economic field, including studies on the relationship between city size and labor productivity(Chen & Zhou, 2017), and the environmental effects of urban size, such as the impact of urban size distribution on $PM_{2.5}$(Zhao et al., 2022), and the relationship between population size and environmental quality(Deng et al., 2020). From the perspective of the scaling law, research indicates that when the urban population doubles, urban infrastructure only needs to increase by 85% such as roads and cables(Bettencourt et al., 2007), demonstrating the infrastructure-saving effect of urban size growth.

The Urban Scaling Law is widely used to examine the attributes of urban systems, gradually becoming the cornerstone of new urban science. The Urban Scaling Law shows how urban attributes change with city size(Lei et al., 2021; Rybski et al., 2019), providing a framework for understanding the relationship between carbon emissions and city size. Urban Scaling Law is suitable for examining the relationship between carbon emissions and urban size because it captures the nonlinear dynamics and efficiencies that arise as cities grow, providing insights into how increased urban density and infrastructure scale with population, which in turn affects carbon emissions. Globally, based on a previous study showing a scaling relationship between urban population size and energy consumption(Gately et al., 2015).

In summary, based on existing research(Bettencourt et al., 2010), this chapter adopts the perspective of the urban scaling law to study the relationship between urban size and carbon emissions from the significant characteristic of urban spatial structure (size). Using a power function, the urban scaling exponent for carbon emissions was calculated:

Equation 4.2:

$$CE=a*US^{\beta}$$

Here, *CE* represents the attribute characteristic of the urban system—that is, carbon emissions. *US* is the urban population size and β is the urban scaling exponent. Since "scale" in English conveys not only the concept of size but also implies stretching or scaling, it expresses the dynamic perspective of urban size; hence, the β value (Urban Scaling Exponents) is translated as urban scaling index in subsequent discussions.

In a sub-linear scenario, urban carbon emissions' growth rate is less than urban size's growth rate. If the city size doubles, the increase in urban carbon emissions is less than double, say 80%, indicating a 20% carbon-saving effect due to urban growth. Conversely, when $\beta>1$, the growth rate of urban carbon emissions exceeds the growth rate of urban size, indicating that growth at this stage leads to a faster increase in urban carbon emissions, i.e., a super-linear mode.

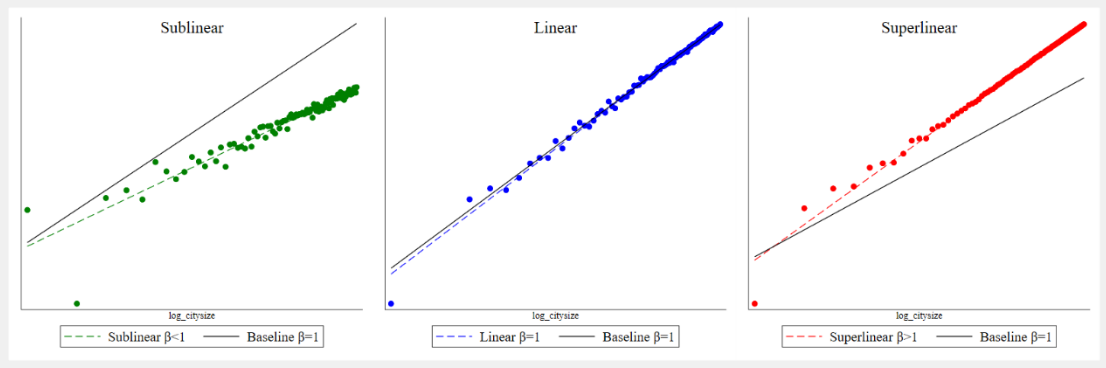

Figure 4-1 Three models of urban carbon emissions with increasing urban size

4.1.2 Empirical Analysis of the Overall Effect of Urban Size on Total Carbon Emissions

In this research, we applied panel data models for our analysis, specifically adopting fixed-effects regression methods. Our panel data encompasses the years 2005, 2010, 2015, and 2020. This data format efficiently leverages both time series and cross-sectional information to enhance the estimation accuracy of the model. In our model, the dependent variable is the total carbon emissions of cities, with urban population size as the independent variable. We also introduced time-fixed effects (year) to control for potential temporal trends that might affect the dependent variable. The regression equation is defined as:

Equation 4.3

$$\ln(\mathit{Carbon\ emission}) = \alpha + \beta \ln(\mathit{pop}) + \varepsilon$$

where α represents the intercept, β signifies the impact of population size on total carbon emissions, essentially the focus of our study, which is the urban size-carbon emission scaling index, and ε is the error term. The regression was performed using a fixed-effects model, assuming unobserved individual-specific effects correlate with explanatory variables within the model. This approach helps eliminate biases caused by unobserved individual differences, yielding more accurate estimations. Furthermore, robustness checks were conducted on the regression outcomes to reduce heteroscedasticity's impact on standard errors, ensuring more stable results.

The urban size-carbon emission scaling coefficient results are as follows: Overall, the relationship between urban size and urban activities (carbon emissions) exhibits a sub-linear pattern. After adjusting for temperature variables, the coefficients for urban population size (Population) across four different models (total carbon emissions, household carbon emissions, transportation carbon emissions, and industrial carbon emissions) are 0.528, 0.971, 0.780, and 0.528, respectively. The scaling indices for total carbon emissions, transportation carbon emissions, and industrial carbon emissions are below 1, indicating a "sub-linear" relationship. The variance in urban scaling indices between transportation and industrial carbon emissions is notable. The coefficient for urban size and transportation emissions is 0.780, implying that a doubling in urban size results in only a 78% increase in transportation carbon emissions. A doubling of urban size leads to only a 52.8% industrial carbon emissions increase. This discrepancy might be attributed to changes in industrial structure rather than the efficiency gains associated with urban size growth, necessitating further analysis to exclude factors related to industrial upgrades. The scaling index for household carbon emissions is nearly 1, suggesting that a doubling of urban size results in a 97.1% increase in household carbon emissions, almost a linear growth pattern.

Table 4-1 Results of urban population size-carbon emission scaling index

Variables	Total Emission	Household	Transport	Industrial
Population	0.528***	0.971***	0.780***	0.528***
	(-0.0329)	(-0.0218)	(-0.0531)	(-0.0367)
Constant	4.557***	-1.602***	0.392	4.232***
	(-0.194)	(-0.129)	(-0.313)	(-0.217)
Observations	1,114	1,114	1,114	1,114
R-squared	0.143	0.279	0.371	0.089
Number of years	4	4	4	4

Robust standard error in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Scale-Adjusted Metropolitan Indicators (*SAMIs*) were used for the deviations of the individual city and the predicted value by scaling law(Bettencourt et al., 2010; Lei et al., 2021). Unlike other per capita indicators, *SAMIs* are Dimensionless, which means the value of *SAMIs* has nothing to do with the scale of an individual city. This indicator can be used for a more meaningful ranking of a single city in a city system, including carbon emissions. *SAMIs* index was calculated as follows：

Equation 4.4

$$\xi_i = \ln\left(\frac{CE_i}{K^*S_i^{\beta}}\right)$$

Where ξ_i is SAMIs of the *i* city, CE_i is the observed value of carbon emission of the *i* city, $K^*S_i^{\beta}$ is the predicted value of carbon emission of *i* city through urban scaling law. We can classify cities of diverse carbon emissions efficiency by comparing ξ_i . When the observed CE_i greater than the predicted $K^*S_i^{\beta}$, $\xi_i > 0$, that means carbon emissions in city *i* is greater than counterparts, called “low carbon emissions efficiency” city. When ξ_i =0, we call city i an “Average carbon emission efficiency” city. When ξ_i

<0, we call city *i* “high carbon emissions efficiency” city.

SAMIs is an evaluation of urban efficiency based on urban scaling law. The core point of *SAMIs* is that urban index and population size have a nonlinear scaling relationship. The comparison of urban carbon efficiency based on *SAMIs* is based on relative quantity rather than an absolute quantity and does not depend on the initial city size value. Such comparison gives up the assumption that urban carbon emission has a linear relationship with city size, which is therefore more meaningful.

SAMIs were calculated to estimate carbon emissions efficiency based on the urban scaling perspective. Figure 4-2 reveals the urban CO_2 emission efficiency based on *SAMIs*. For total carbon emissions efficiency, cities in northern China showed more “low CO_2 emission efficiency” mode than those in southern China, especially when SAMIs were greater than 0.797, meaning that cities in northern China produced more CO_2 on average than their similar-sized cities in southern China. For industrial carbon emissions, cities with “low industrial CO_2 emission efficiency” mode mainly lay in Guangxi and Guizhou that is to the northwest of Guangdong, Jilin in the northeast of China, and Shanxi, Shaanxi, the south of Gansu in the Loess Plateau. For household carbon emissions, cities with "Low CO_2 emission efficiency" mode were mainly distributed in inland and northeast China, including Hunan, Guizhou, Jilin, and Heilongjiang, relatively underdeveloped areas in China. Meanwhile, household carbon emissions are relatively highly efficient in Beijing, the Pearl River Delta. For transportation carbon emission, the Pearl River Delta, the Yangtze River delta, and Jilin were agglomeration zones of Cities with "Low CO_2 Emission efficiency" modes.

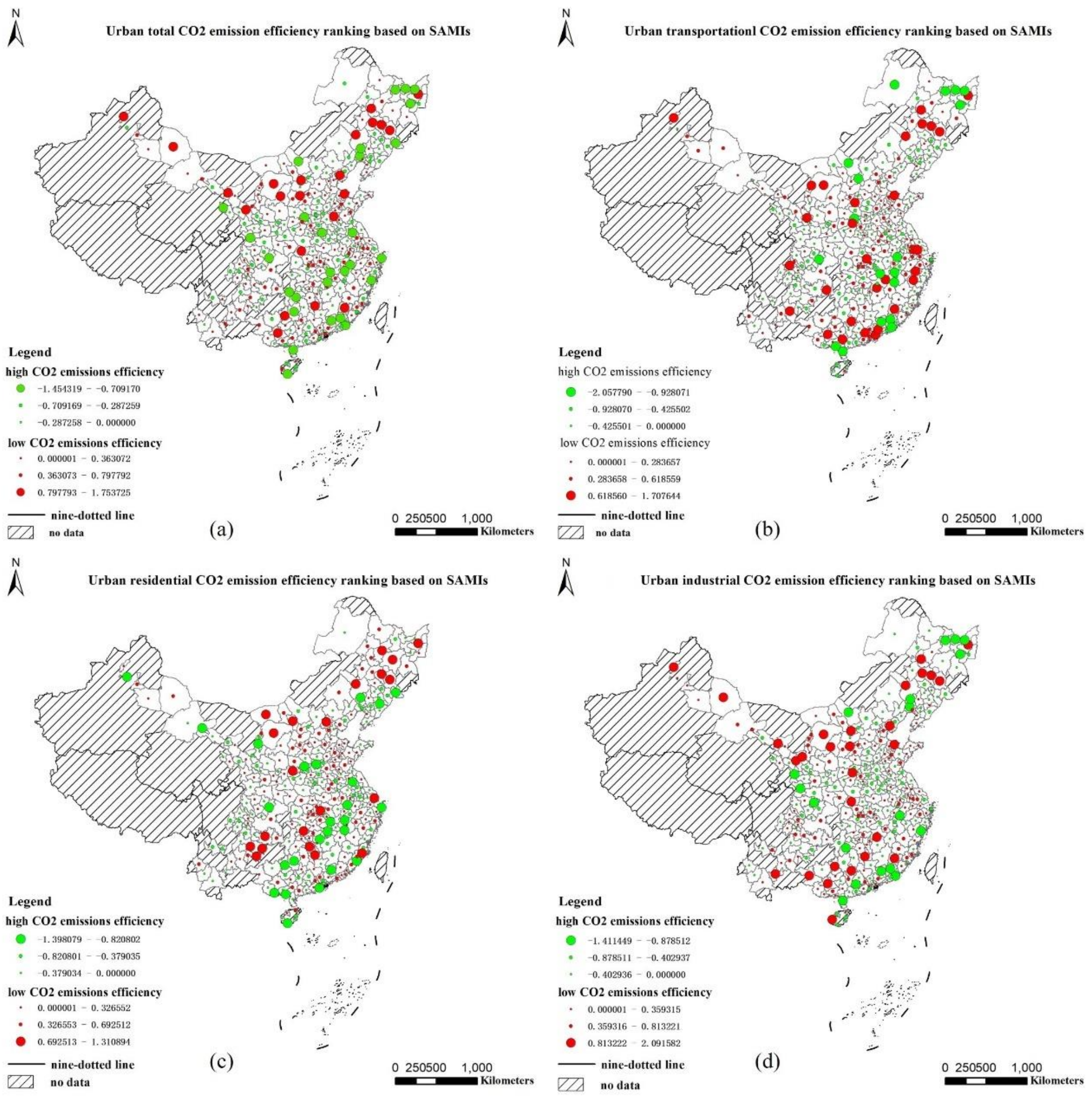

Figure 4-2 Urban CO_2 emission efficiency based on SAMIs

To further detect spatial patterns of carbon emissions efficiency, we calculated the local *moran I* of *SAMIs*(LISA cluster map)(Figure 4-3) in ArcGIS. "High-high cluster(HH)" represents the urban spatial agglomeration distribution of "Low CO_2 Emission efficiency" modes. A city with a “High-Low cluster(HL)” characteristic means this city has a low carbon emission efficiency(high in *SAMIs*) and is surrounded by cities with high CO_2 Emission efficiency" modes. Shanxi, Shaanxi, Ningxia, and Inner Mongolia of the Loess Plateau are HH areas of total and industrial CO_2 emissions, which denotes that total and industrial carbon emission efficiency in this region is lower than its surroundings. For household carbon emissions, HH and HL modes are distributed in northwest Guizhou, the middle of Hunan and Hubei, northeast Jiangxi, and Jilin Heilongjiang in northeast China. For transportation carbon emission, the Pearl River Delta, the southeast and northwest Guangxi, the north of Zhejiang, and so on.

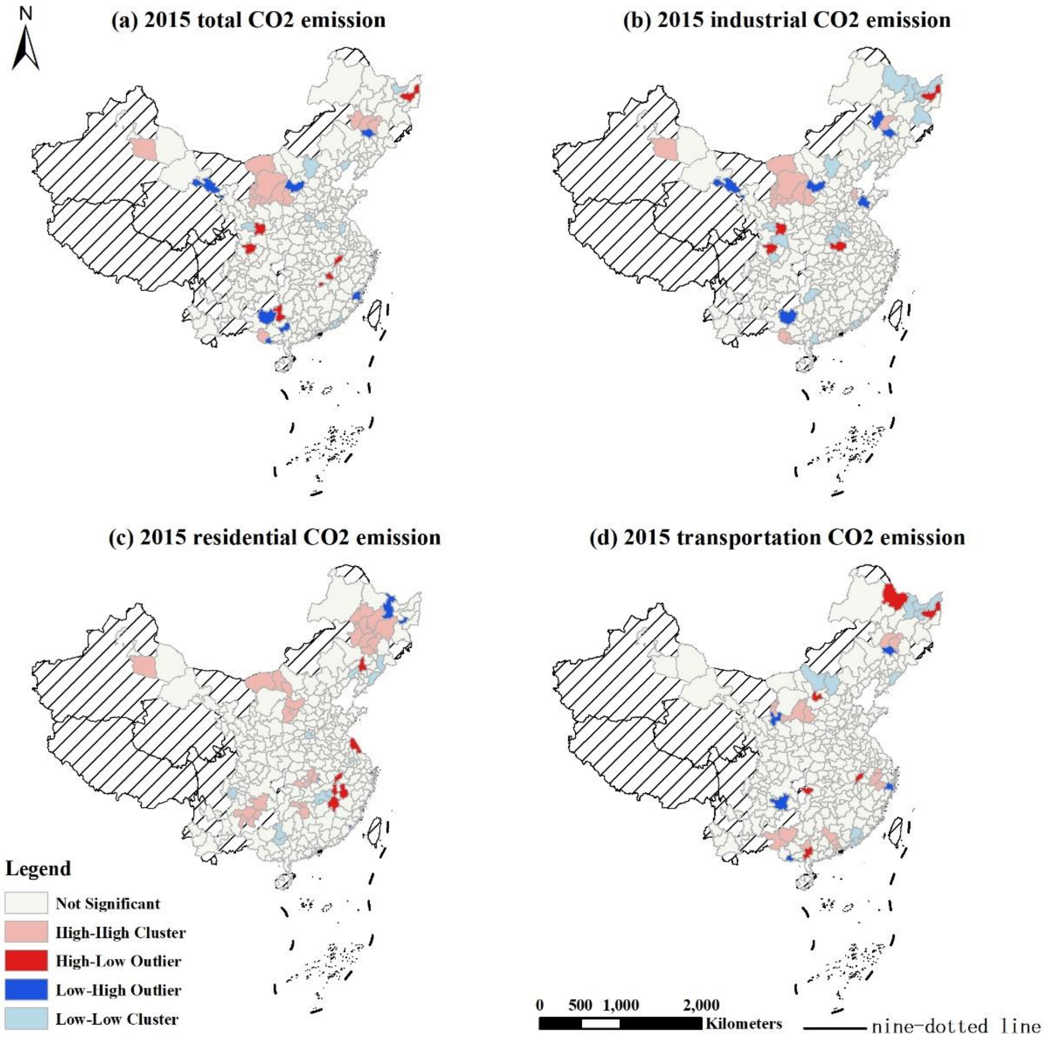

Figure 4-3 LISA cluster map of SAMIs

4.2 The Influence of Urban Size on Industrial Carbon Emissions: An Analysis Based on Mediating Effects

Carbon emissions from industrial production are more complex than household and transportation carbon emissions, as they involve factors such as the level and structure of economic development and urban innovation. Understanding the relationship between urban size and industrial carbon emissions necessitates a mechanism analysis of how urban size affects industrial carbon emissions.

Mediation effect analysis is employed in exploring the influence of variable *X* on variable *Y*, particularly in assessing whether *X* affects *Y* by indirectly affecting another variable, *M*, a phenomenon referred to as the “mediation effect.” Pathway analysis frequently applies mediation effect analysis to capture direct and indirect effects (Peng et al., 2019). Various scholars have used mediation effect analysis to dissect the interrelationships among the natural environment, socio-economic factors, and health. Liu et al. (2022) examined the mediating role of nature contact in the relationship between nature connection and happiness. Triguero-Mas et al. (2017) investigated how natural exposure could influence mental health by modulating stress levels. Guo et al. (2022) inquired as to whether exposure to environmental air pollution mediated socio-economic indicators with health outcomes. In studies closely related to carbon emissions, the intermediary role of innovation between economic development and the ecological environment was evaluated (Wang et al., 2021).

Consequently, mediation effect analysis has been extensively adopted for delineating processes and mechanisms, especially for establishing links between disparate systems such as natural environments and economies. An increase in urban population size does not directly affect a city's carbon emissions, so there must be intermediary factors that influence them. Moreover, identifying the intermediary factors between urban size and carbon emissions is more instructive for understanding the nature of urban systems and for urban planning. The relationship between urban size and carbon emissions is a typical problem for mediation effect analysis.

4.2.1 Theoretical Analysis and Model Construction

Urban spatial structure includes urban size, density, form, and spatial layouts and relationships of urban elements. The main objective of studies on urban spatial structure is to explore the relationship between the spatial distribution of the urban elements and the socio-economic environment of a city to optimize the spatial structure for urban development. Urban operations include city functions and services covering aspects such as the city's society, economy, and culture. The efficiency of urban operations profoundly affects the factors of urban metabolism, such as pollution emissions and energy utilization. Urban spatial structure is the framework that plays a fundamental role in urban operations, while urban metabolism is an interactive process with the natural environment. This study constructed the Spatial-Operational-Metabolic (SOM) Framework as a basic theoretical framework for examining the environmental effects of urban spatial structures. This framework emphasizes the continuity and interdependence between the spatial structures of cities and their metabolic processes, thus highlighting the bridging role of urban operational elements.

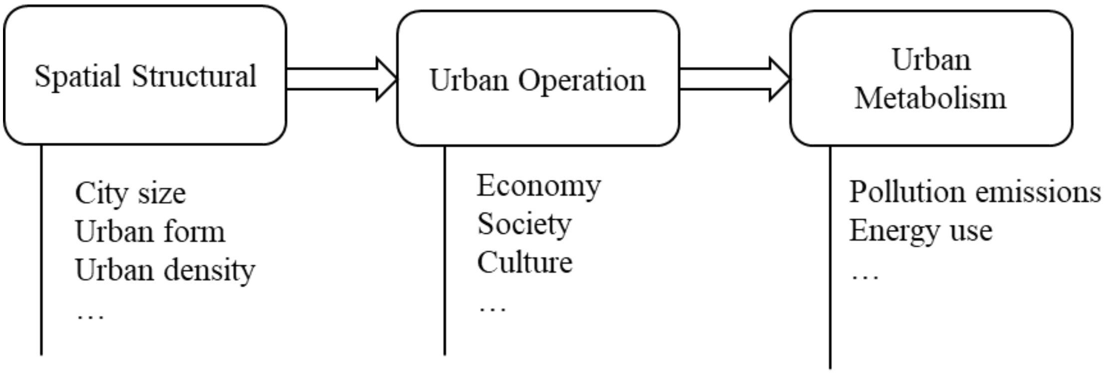

Figure 4-4 Spatial-Operational-Metabolic (SOM) framework

According to this theoretical framework, urban size is the most fundamental element of urban spatial structure. The most direct effect on industrial carbon emissions is the production scale and structure. Industrial carbon emissions are a component of urban metabolism. The elements of urban operations that directly affect industrial carbon emissions include production scale, production structure, and the level of production innovation. Industrial carbon emissions are a critical factor in urban metabolism. The overall innovation capacity of a city is closely related to its size. We believe urban expansion affects industrial carbon emissions through three main pathways: production scale expansion, industrial structure upgrading, and innovation.

The expansion of urban size leads to increased industrial carbon emissions through production scale expansion and structural effects. Expanding the industrial production scale will increase pollution emissions (Yang et al., 2019). Because of superior conditions such as labor supply, product market size, and infrastructure, the expansion of urban size is often accompanied by the expansion of production scale. Firstly, larger cities have larger and higher-quality labor forces, which can support larger industrial enterprises, thereby aggregating more industrial production. Larger cities also have higher labor demands (Huang et al., 2021). Secondly, larger cities usually have larger markets, including urban residents and consumers outside the cities.

Moreover, larger cities tend to have more developed infrastructure and a wider range of services, including transportation infrastructure, public utilities, and financial and consulting services. These factors support larger-scale production. From the perspective of structural upgrading, urban population expansion facilitates industrial upgrading, thereby reducing industrial carbon emissions. The tertiary sector, or the service industry, is generally more carbon-efficient than the primary (agriculture) and secondary (manufacturing) sectors. The service industry primarily relies on knowledge and technology rather than physical resources, resulting in lower carbon emissions. As urban populations grow, the proportion of the tertiary sector typically increases, contributing to a reduction in overall carbon emissions.

The increase in urban size is conducive to the accumulation of innovation. According to Cai et al. (2021), there is a significant positive correlation between urban size and the level of innovation. Regional central cities often have better technical and knowledge bases (Wang & Yang, 2022). Although the sources and degrees of this advantage in innovation in large cities are still controversial, empirical research has shown that the outputs of innovation in large cities are significantly higher, and this relationship is often super-linear to a considerable extent (Broekel et al., 2023; Gomez-Lievano et al., 2016). From a macro-perspective, a larger urban size can attract more innovative elements such as talent, corporate headquarters, and research institutions to promote urban innovation (Zhai & Zhang, 2020). From a micro-perspective, enterprises or institutions in larger cities are more likely to make world-leading innovations than those in smaller cities (Therrien, 2005).

Innovation is a crucial factor affecting carbon emissions, especially industrial carbon emissions. At the national scale, Jiang et al. (2022)found that innovation did not reduce carbon dioxide emissions in low- and middle-income countries. Fernández et al. (2018) found that innovation reduced carbon emissions in high-income countries. In a study of sub-sectors, Erdogan et al. (2020) surveyed G20 countries and found that innovation significantly reduced industrial carbon emissions but had no significant effect on transportation carbon emissions. The sectoral variations in innovation's influence on carbon emissions may be due to its effect being more pronounced at the production end. Zhou et al. (2023) used the number of patents to quantify technological innovation at the provincial level. The empirical results showed that every 1% increase in technological innovation at the provincial level reduced regional carbon emissions by 0.17%. A study at the city level, Gu (2022) examined 275 cities in China and found that technological innovation was conducive to carbon emission reduction and inhibited the growth of carbon emissions. Scholars agree that innovation is an essential factor affecting carbon emissions, but the direction of influence needs further research and discussion.

Innovation can directly promote carbon reduction by developing carbon capture and sequestration technologies. Moreover, it can indirectly mitigate carbon dioxide emissions through clean production techniques and management (Xu et al., 2021). Jin et al. (2014) proposed that the influence of technological innovation on carbon emissions exhibited a double-edged effect. On the one hand, it escalates carbon emissions by stimulating economic growth; conversely, it curtails emissions through enhanced energy efficiency. The adjustments in industrial structure directly affect energy consumption (Li Tao. et al., 2023). As urban size expands, the city witnesses a decline in its secondary industry but a rise in its tertiary industry. As levels of urban innovation ascend, the application of advanced technologies gradually elevates the proportion of the tertiary industry and promotes industrial upgrading (Li & Zhao, 2023). Su et al. (2023) employed a mediation effect model to analyze how innovation affects carbon emissions via economic growth and industrial structure transformation. In summary, scientific research has a widespread consensus that innovation can affect carbon emissions and plays a dual role. It increases emissions by expanding production scale but may also concurrently reduce emissions by fostering industrial structure upgrading.

In summary, this study posits that urban size influences industrial carbon emissions through innovation, which affects carbon emissions through two chain mediation processes: expanding production scale and upgrading industrial structure. Drawing upon (Wen & Ye, 2014), we constructed a mediating effect model between urban size and industrial carbon emissions(Figure 4-5). Urban size can significantly affect the expansion of production and the upgrading of industrial structures, thereby affecting industrial carbon emissions. We established a chain multiple mediation model. In Figure 4-5, a, b, and c are path coefficients denoting degrees of influence. Expressly, a_1, a_{21}, and a_{22} represent the path coefficients of urban size's effect on innovation, industrial structure upgrading, and production expansion. a_{31} and a_{32} are the path coefficients of innovation's effect on industrial structure upgrading and production expansion. The coefficients b_1, b_{21}, and b_{22} represent the influences of innovation, industrial structure upgrading, and production expansion on carbon emissions. Lastly, 'c' represents the direct effect of urban size on industrial carbon emissions after the mediation effects have been considered.

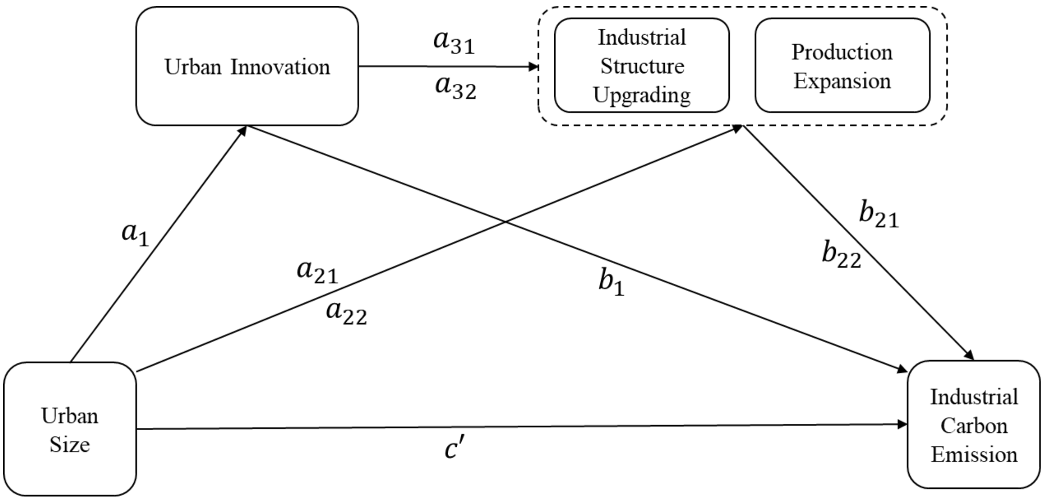

Figure 4-5 Chain multiple mediation model

Compared with the single mediation effect model, the chain multiple mediation effect model has the following advantages. First, the chain mediation effect model can describe academic relationships and processes that are more complex than a single path. Second, the chain model is more flexible because it can capture multiple, possible, and intermediary pathways between variables. Third, chain models allow for comparability and ranking among multiple mediating effects by assessing the effect size of each mediation pathway.

4.2.2 Model and Data Sources

In alignment with the proposed theoretical model, we formulated a chain multiple mediation model as follows:

Equation 4.5

$$\ln(ICE) = c \ln(US) + e_1$$

Equation 4.6

$$\ln(UI) = a_1 \ln(US) + e_2$$

Equation 4.7

$$\ln(PE) = a_{22} \ln(US) + a_{32} \ln(UI) + e_4$$

Equation 4.8

$$\ln(ISU) = a_{21} \ln(US) + a_{31} \ln(UI) + e_3$$

Equation 4.9

$$\ln(ICE) = c' \ln(US) + b_1 \ln(UI) + b_{21} \ln(ISU) + b_{22} \ln(PE) + e_5$$

ICE (Industrial Carbon Emissions) represents the industrial carbon emissions produced within a given urban area. *US* (Urban Size) represents the urban population size. *UI* (Urban Innovation) denotes the area's level of innovation. *PE* (Production Expansion) represents the growth or expansion of industrial production. *ISU* (Industrial Structure Upgrading) describes the transformation of industrial structure from the economy's secondary sector to the economy's tertiary sector, which is measured by the proportion of the tertiary sector in the economy.

To better grasp the link between urban size and carbon emissions, this study formulated carbon emission efficiency to determine an exponent for industrial carbon emissions relative to urban size:

Equation 4.10

$$\ln(CEE) = \alpha + \beta * \ln(US) + \varepsilon$$

where *CEE* (Carbon Emission Efficiency) represents the city's carbon emission efficiency per unit of GDP and β is the scaling coefficient, which represents the power-law relationship between urban size and carbon emission efficiency.

The bootstrap method is a statistical technique that repeatedly resamples subsets of data from their original dataset. The advantage of this approach is its ability to operate without assuming that the data conform to a specific probability distribution. This method is particularly useful for addressing complex issues or those where classical statistical methods may not directly apply, so it is more effective than other methods for testing mediation effects (Alfons et al., 2021). Traditional tests like the Sobel test may yield inaccurate results if certain data distribution assumptions are unmet. Therefore, we employed the bootstrap method to assess the significance of mediation effects, which are prevalent in social science, medical, and business research. They occur when a variable influences an outcome by affecting one or more other variables.

This study's carbon emission data were sourced from the city-scale sector-specific carbon emission dataset collated and curated by the China Greenhouse Gas Working Group. This dataset (available at http://www.cityghg.com/toCauses?id=4) provides data on city-scale sector-specific carbon emissions for 2005, 2010, 2015, and 2020. 137 researchers from 76 institutes gathered and analyzed the data, then cross-validated for accuracy and precision. According to the industrial electricity consumption ratios from the China Urban Statistical Yearbooks, indirect emission data were proportionally allocated to industrial carbon emissions. The employment figures of the secondary industry denoted the production expansion indicator. Population scale, industrial structure data, and employment numbers in the secondary sector were all extracted from the China Urban Statistical Yearbooks. Data on urban innovation were taken from the innovation index in the "Report on Chinese City and Industry Innovation Capacity"(Kou & Liu, 2017), which quantified levels of urban innovation from output-side data.

4.2.3 Empirical Study Results

4.2.3.1 the Impact Mechanism of Urban Size on Industrial Carbon Emissions

In general, an expansion in urban size leads to an increase in industrial carbon emissions according to a sub-linear pattern. The scaling exponent of urban size to industrial carbon emissions is only 0.528, implying that a 100% increase in city size leads to only 52.8% growth in industrial carbon emissions and indicates a growth gap of 47.2% compared to a linear increase pattern. Hence, industrial carbon emissions in cities exhibit sub-linear growth trends, which suggest that as city size expands, the growth rate of industrial carbon emissions slows down. However, the relationship between city size and industrial carbon emission efficiency is a sub-linear scaling with a scaling coefficient of -0.409 (as per Eq. 4.10). Therefore, even though the expansion of city size results in a rise in the total volume of industrial carbon emissions in China, the overall efficiency of carbon emissions improves.

Table 4-2 Regression results for mediation effects

Variable	Equation 4.5 ln(*ICE*)	Equation 4.6 ln(*UI*)	Equation 4.7 ln(*PE*)	Equation 4.8 ln(*ISU*)	Equation 4.9 ln(*ICE*)	Equation 4.10 ln(*CEE*)
ln(*US*)	0.528***	1.326***	0.342***	-0.096**	-0.149**	-0.409***
	(0.0367)	(0.0553)	(0.0593)	(0.011)	(0.028)	(0.049)
ln(*UI*)			0.436***	0.055***	0.111*	

Variable	Equation 4.5 ln(*ICE*)	Equation 4.6 ln(*UI*)	Equation 4.7 ln(*PE*)	Equation 4.8 ln(*ISU*)	Equation 4.9 ln(*ICE*)	Equation 4.10 ln(*CEE*)
			(0.00926)	(0.0110)	(0.0479)	
ln(*PE*)					0.597**	
					(0.124)	
ln(*ISU*)					-0.573*	
					(0.202)	
_cons	4.232***	-7.425***	9.609***	3.891***	3.246	3.155
	(0.217)	(0.326)	(0.346)	(0.064)	(1.812)	(0.287)
N	1114	1114	1114	1114	1114	1114
R-sq	0.089	0.255	0.708	0.152	0.386	0.128

Note: *** p<0.01, ** p<0.05, * p<0.1. Robust standard errors are in parentheses

Table 4-3 is a summary of results generated by the Bootstrap test, and presents the results of the coefficient test for the chain multiple mediation model, by which we examined the mediating effects of various paths in the model on the relationship between industrial carbon emissions and urban size. We employed the bootstrap method for 1,000 resamples and calculated the mediating effect for each sample. The p-value associated with our mediating effect is less than 0.001 and the confidence interval does not encompass zero. Therefore, our mediating effect is statistically significant and offers robust evidence to support our hypothesis.

Table 4-3 Summary of mediation effect analysis

Effect	Pathways	Effect	Standard Error	z	p	LLCI	ULCI
Direct effect	1. Urban size ⇒ Industrial CO_2	-0.149	0.051	-2.91	0.004	-0.250	-0.049
Mediation Effects	2. Urban size ⇒ Innovation ⇒ Industrial CO_2	0.147	0.042	3.50	0.000	0.065	0.229
	3. Urban size ⇒ Production expansion ⇒ Industrial CO_2	0.204	0.027	7.52	0.000	0.151	0.258
	4. Urban size ⇒ Industrial upgrading ⇒ Industrial CO_2	0.023	0.010	2.19	0.028	0.002	0.043
Chain Mediation Model	5. Urban size ⇒ Innovation ⇒ Industrial Structure Upgrading ⇒ Industrial CO_2	-0.042	0.012	-3.51	0.000	-0.065	-0.018
	6. Urban size ⇒ Innovation ⇒ Production expansion ⇒ Industrial CO_2	0.345	0.037	9.20	0.000	0.271	0.418

Note: LLCI and ULCI refer to the lower and upper limits, respectively, of the 95% confidence interval.

For every 1% expansion in city size, urban innovation increases super-linearly by 1.326%(Table 4-2). The effect of innovation on industrial carbon emissions is double-edged, as it embodies both emission-increasing and emission-reducing effects, with the former significantly outweighing the latter. The overall effect of city size on urban industrial carbon emissions via elevation of the overall level of urban innovation is 0.45(Pathway 2,5,6 in Table 4-3). Overall, the effect coefficient of city size on innovation to industrial carbon emissions is positive, thus signifying that city size propels industrial carbon emissions through innovation. With a 1% growth in population size, industrial carbon emissions increase by 0.45% through the mediation mechanism of innovation.

Innovation's effect on industrial carbon emissions predominantly manifests as a significant emission-increasing factor with an effect magnitude of 0.492, which encompasses the drive of innovation toward production expansion (as seen in Pathway 6 Table 4-3) and other unaccounted factors (in Pathway 2 in Table 4-3). Of the innovation emission-increasing effects, 70.12% are generated through stimulating production expansion (highlighted in Pathway in Table 4-3). Conversely, the emission-reducing effect of innovation is seen in its fostering of industrial structure upgrading. When controlling for the city size variable, a 1% surge in the level of innovation results in a 0.055% increase in industrial upgrading. This industrial structural evolution, in turn, contributes to a decline in urban industrial carbon emissions.

Innovation's emission-reducing effect is primarily evident in promoting industrial structure upgrading (as seen in Pathway 5 in Table 4-3). Theoretically, besides facilitating industrial structure upgrading, innovation harbors other emission-reducing mechanisms. For instance, innovation can introduce more advanced and cleaner production technologies and better management practices, leading to energy conservation in industrial production. Nevertheless, excluding the factors of production expansion and industrial structure upgrading, the direct effect of city size on industrial carbon emissions via innovation is positive with an effect magnitude of 0.147 ((as seen in Pathway 2 in Table 4-3)). This positive coefficient implies a masking effect. Specifically, the emission-increasing effects associated with innovation overshadow the emission-reducing effects of cleaner production resulting from innovation.

The expansion of city size increases industrial carbon emissions primarily through the pathway of production expansion, with a total effect of 0.549 (Paths 3 and 6), which indicates that this increase has been achieved mainly through production expansion. The emission-increasing effect from city size expansion is 0.719 (Paths 2–4 and 6), of which the effect of production expansion accounted for 76.3%. Excluding the production expansion effect brought about by innovation, the effect of city size expansion on industrial carbon emissions through the production expansion path is 0.204.

The expansion of city size results in a slight carbon emission reduction effect in urban industries through industrial structure upgrading primarily achieved via innovation. For every 1% increase in city size, industrial carbon emissions decrease by 0.042% because of the industrial structure upgrading brought about by innovation (Path 5). However, excluding innovation, the mediation effect of city size through industrial structure upgrading has positively affected industrial carbon emissions (Path 4) because, without the innovation factor, the growth in city size would not have been conducive to industrial upgrading. When controlling for innovation, every 1% increase in city size decreases industrial upgrading by 0.096%. When excluding the mediating effects of innovation, production expansion, and industrial structure upgrading, the direct effect of city size on industrial carbon emissions is negative, with a value of -0.149, which suggests other unobserved effects. Specifically, for every 1% growth in city size, industrial carbon emissions decrease by 0.149%.

4.2.3.2 Heterogeneity analysis of the impact of urban size on carbon emissions through innovation

Previous studies have found that urban size boosts urban innovation in a super-linear manner and leads to an overall increase in industrial carbon emissions. On the other hand, research has shown that innovation's effects on carbon emissions display significant heterogeneity. A policy-focused study by Wei and Kong (2022) examined the effects of innovative city construction on carbon emissions. They found that the effects of innovative urban construction on carbon emissions were more pronounced in the western regions, which are poorer and have smaller populations. At the national scale, innovation has had carbon reduction effects in both low- and high-income countries (Ali et al., 2016; Fernández et al., 2018). The effects of urban innovation on carbon emissions seem to differ significantly across regions with varying levels of development. Hence, to better understand the differences in the mediation effects of urban-size-innovation-emissions across regions with different levels of development, we used per capita GDP data from 2020 and divided the sample into four groups using the quartile method. As shown in Table 4-4, the quartiles' average per capita GDP is 2.825, 4.069, 6.281, and 14.835 ten thousand yuan, respectively.

Table 4-4 Descriptive statistics of GDP per capita by quartiles (in 10,000 yuan)

Subgroup	N	Mean	Min	Max
0% to 25% percentile	282	2.825	1.451	3.428
25% to 50% percentile	276	4.069	3.436	4.835
50% to 75% percentile	280	6.281	4.935	8.268
75% to 100% percentile	276	14.835	8.460	50.218

To delve deeper into the variations in the mediation effects, we employed the bootstrap method for grouped mediation effect testing, the results of which are shown in Table 4-5. After controlling for factors such as industry structure and production scale expansion, the population sizes of cities still exerted significant positive effects on industrial carbon emissions via innovation, with a specific effect coefficient of 0.147. Further subgroup analysis revealed the disparity in these mediation effects. Notably, for the sample group of the first quartile, the path coefficient of this mediation effect is 0.363, which considerably exceeds 0.147 of the ungrouped tests. This finding suggests that the emission-increasing effects of innovation have been primarily concentrated in cities with lower levels of development. Specifically, the emission-increasing effects driven by innovation are particularly pronounced for cities with a per capita GDP of about 30,000 yuan. However, the mediation effects are insignificant for the other three quartile groups. Cities in the highest income group do not show the anticipated carbon reduction due to innovation. This outcome does not imply that urban innovation has had no effect on carbon emissions, but the carbon-reducing effects brought about by innovations in green production technologies and management may have been masked by the emission-increasing effects.

Cities with relatively high levels of development primarily benefit from carbon emission reduction when urban growth fosters innovation and upgrades the industrial structure. As shown in Table 4-5, the mediation effects via Pathway 5 are insignificant in the first three percentiles. However, in the fourth quartile, the mediation effect is significant at -0.144(Pathway 5 Table 4-5). This group's minimum and average GDP per capita are 84,600 and 148,300 yuan, respectively, which shows that in cities with higher levels of development, using innovation to drive industrial structure upgrading is a practical approach to achieving carbon reduction as city size expands.

By promoting innovation and stimulating production expansion, urban-scale expansion increases carbon emissions in cities with low and medium levels of development more significantly than in cities with high levels of development. Path 6 of Table 4-5 shows that the mediating effects are significant in all grouped cities. In the city samples in the first and second quartiles, the mediating effects are nearly twice as large as those in the third and fourth quartiles, thus implying that green production should receive more attention in small and medium-sized cities.

In cities with low and medium levels of development, urban size expansion reduces carbon emissions by fostering innovation and boosting production. These effects are more pronounced than in cities with higher levels of development. Path 6 of Table 4 indicates that these mediating effects are significant across all city groups. For samples in the first and second quartiles, the mediating effects are nearly double those in the third and fourth quartiles, thus implying that green production should be prioritized in smaller cities.

Table 4-5 Mediation effects of innovation across subgroups

Subgroup	Effect	Standard Error	z	p	LLCI	ULCI
Pathway 2. Urban size ⇒ Innovation ⇒ Industrial CO_2						
0% to 25% percentile	0.363	0.086	4.21	0.000	0.194	0.532
25% to 50% percentile	0.111	0.093	1.20	0.232	-0.071	0.292

Subgroup	Effect	Standard Error	z	p	LLCI	ULCI
Pathway 2. Urban size ⇒ Innovation ⇒ Industrial CO_2						
0% to 25% percentile	0.363	0.086	4.21	0.000	0.194	0.532
50% to 75% percentile	0.138	0.097	1.41	0.157	-0.053	0.329
75% to 100% percentile	0.104	0.096	1.09	0.278	-0.084	0.291
Pathway 5. Urban size ⇒ Innovation ⇒ Industrial Structure Upgrading ⇒ Industrial CO_2						
0% to 25% percentile	-0.040	0.024	-1.66	0.097	-0.086	0.007
25% to 50% percentile	0.005	0.008	0.65	0.516	-0.011	0.022
50% to 75% percentile	-0.0003	0.028	-0.01	0.991	-0.546	0.540
75% to 100% percentile	-0.144	0.047	-3.06	0.002	-0.237	-0.052
Pathway 6. Urban size ⇒ Innovation ⇒ Production expansion ⇒ Industrial CO_2						
0% to 25% percentile	0.179	0.046	3.88	0.000	0.089	0.270
25% to 50% percentile	0.207	0.048	4.27	0.000	0.112	0.302
50% to 75% percentile	0.117	0.044	2.66	0.008	0.031	0.204
75% to 100% percentile	0.121	0.061	2.00	0.045	0.003	0.240

Note: LLCI and ULCI refer to the lower and upper limits, respectively, of the 95% confidence interval.

The impact of urban population size on carbon emissions is examined under different industrial structures. According to the descriptive statistics of industrial structure proportions in Chinese cities, most cities have entered a stage dominated by the secondary and tertiary industries. The average proportions of the secondary and tertiary industries are 45.13% and 40.84%, respectively. To explore the differences in the impact of urban population size on industrial carbon emissions under varying industrial structures, this study classifies city samples into secondary industry-dominant and tertiary industry-dominant categories using the maximum value comparison method. Specifically, cities where the proportion of the secondary industry exceeds that of the tertiary industry are categorized as secondary industry-dominant, while those where the tertiary industry proportion is higher are classified as tertiary industry-dominant.

Table 4-6 Descriptive statistics of industrial structure proportions in Chinese cities

Industrial structure	Mean(%)	Standard Error	Maximum (%)	Minimum (%)
Primary Industry	14.01	8.86	0.04	48.7
Secondary Industry	45.13	11.17	9	85.92
Tertiary Industry	40.84	9.97	11.05	85.34

The research findings indicate that in cities with a higher proportion of the tertiary industry, the increase in urban population size has a more pronounced effect on industrial CO_2 emissions through innovation. Specifically, in secondary industry-dominant cities, the impact of innovation on industrial CO_2 emissions remains relatively limited as urban population size increases. However, in tertiary industry-dominant cities, this effect becomes more significant. This suggests that in cities where the tertiary industry accounts for a larger proportion, the expansion of urban population size enhances the role of innovation in driving industrial CO_2 emissions. The growth of urban population size is typically accompanied by greater resource agglomeration, higher talent density, and broader market demand, all of which provide a more favorable environment for innovation activities. As a result, larger cities tend to better accommodate and support innovation, further driving industrial development and expansion. This finding is also empirically validated in both secondary and tertiary industry-dominant cities. As industries grow and expand, CO_2 emissions generally increase correspondingly.

Table 4-7 Bootstrap industrial structure grouping test for mediating effects

Subgroup	Effect	Standard Error	*z*	*p*	*LLCI*	*ULCI*
Pathway 2. Urban size ⇒ Innovation ⇒ Industrial CO_2						
Secondary Industry-Dominant	0.082	0.037	2.26	0.024	0.011	0.155
Tertiary Industry-Dominant	0.182	0.102	1.79	0.074	-0.017	0.383
Pathway 6. Urban size ⇒ Innovation ⇒ Production expansion ⇒ Industrial CO_2						
Secondary Industry-Dominant	0.217	0.032	6.65	0.000	0.153	0.281
Tertiary Industry-Dominant	0.476	0.083	5.72	0.000	0.312	0.638

Note: LLCI and ULCI refer to the lower and upper limits, respectively, of the 95% confidence interval.

There is a sub-linear relationship between urban size expansion and industrial carbon emissions. Such relationship suggests that urban size expansion inevitably increases total industrial emissions while improving carbon emission efficiency. This finding is consistent with the research on urban size and industrial carbon emissions at the provincial level in China (Li, 2016). However, carbon emission intensity is also believed to increase when the urban size increases excessively. Most cities in China are still not large enough. Although the increase in a city’s size would lead to an increase in its carbon emissions, the growth of urban size has improved the overall carbon emission efficiency of the entire urban system and reduced the total carbon emissions to a certain extent.

Our study preliminarily found that the effects of innovation on carbon emissions are heterogeneous among cities at different levels of development and contradicts other studies that have found that urban innovation has promoted carbon emission reduction (Fernández et al., 2018). Previous studies have also confirmed the super-linear relationship between urban size and innovation (Bettencourt et al., 2007; Broekel et al., 2023). However, China's urban innovation has not generally shown a significant carbon emission reduction effect. Our findings are consistent with previous research that has found technological innovation to increase carbon dioxide emissions directly or indirectly (Su et al., 2023). The reason may be China's current stage of rapid development in which investment in urban production expansion is given priority over urban innovation. Innovation in green production technology is still in its infancy. Moreover, green innovations have the attributes of public goods and often generate positive environmental externalities, such as reduced pollution, improved resource efficiency, or lower greenhouse gas emissions. These positive effects benefit society but usually do not directly bring economic returns to innovators. Therefore, such positive externalities may lead to the underestimation of green innovation, market failure, and insufficient supply. To encourage green innovation, the government and other public institutions must provide incentives and subsidies to ensure that green innovation is fully supported and promoted. Future research should further explore the effects of innovation on industrial carbon emissions at different levels of urban development.

Why is the indirect effect of urban size affecting carbon emissions through innovation only significant in smaller cities? First, small cities' initial levels of industrial technology may be relatively backward, and innovations are more likely to focus on improving production performance rather than focusing on environmental benefits, thus resulting in increased carbon emissions in the short term. Second, small cities may have relatively loose environmental standards and enforcement compared to larger cities, so the former may attract some high-polluting enterprises. This phenomenon aligns with the Pollution Paradise Hypothesis and has been confirmed in China (Wu & Zhang, 2021). Nie et al. (2022) more directly verified the hypothesis by analyzing China's spatial transfers of carbon emissions. Therefore, small and medium-sized cities should pay more attention to their increases in carbon emissions due to innovation. It is necessary to consider innovation's positive and negative effects comprehensively. In such light, the local governments should strengthen the relevant policies and regulations to ensure that innovation contributes to reducing carbon emissions.

4.3 Analysis of the Impact of Urban Size on Household Heating Carbon Emissions

4.3.1 The Necessity of Studying Urban Heating Carbon Emissions

Urban heating is a basic necessity for the residents of towns and cities in the colder northern regions. The household heating system in China has undergone four stages. From 1952 to 1970, the first stage was the initial phase, where heating was predominantly decentralized, characterized by low thermal efficiency and high pollution. The second stage, from 1971 to 2002, saw a gradual increase in the construction of thermal power plants and an expansion in heating demand, but it was still a rough expansion phase, lacking long-term planning. The third stage, from 2003 to the present, marked the cessation of welfare heating and the beginning of the commercialization of heating. The document "Guiding Opinions on the Pilot Work of Reforming the Urban Heating System (Jiancheng [2003] No. 148)" pointed out the need to promote the commercialization and socialization of heating. After that, the construction of heating infrastructure and urbanization process advanced rapidly. This eventually led to a pattern of centralized heating in the north, roughly divided by the Qinling-Huaihe line. The demand for heating in northern China is enormous, and its relationship with urban space has not yet received widespread attention. Heating carbon emissions have not yet peaked. The heating industry lacks "dual carbon" planning, specific carbon reduction targets, and top-level guidance(Zhu, 2023). Due to their individuality and dispersion, planning for emission reduction in residential energy use lacks focus. Unlike the individual characteristics of carbon emissions from cooking and lighting, China's centralized heating has a strong public characteristic, providing convenient conditions for the operability of carbon reduction planning.

In urban carbon emission reduction research, at the macro scale, there are many studies on the reduction of total carbon emissions, household carbon emissions, and even transportation carbon emissions. However, due to its strong regional nature, heating is adopted only in some areas of China in the form of centralized heating, making research relatively rare. At the macro level of urban research, Zheng et al. (2011) carried out income-heating carbon emission elasticity estimation as a sub-item of household carbon emissions. This is a beneficial attempt to understand how the urban economic system affects urban metabolism. Most research on heating carbon emissions focuses on the micro level, such as studies on air-source heat pumps and gas boilers(Yang et al., 2018) and groundwater-source heat pumps(Chai & Ma, 2012) at the engineering and technical level, which are not part of urban planning research. Research on how urban spatial structure affects heating carbon emissions is still lacking. Theoretically and practically, an urgent need is to understand the interaction between urban heating carbon emissions and urban spatial characteristics to support planning practice.

Therefore, the following study focuses on heating, a key yet under-researched area within household carbon emissions, exploring how urban spatial structure affects household heating carbon emissions.

4.3.2 Theoretical Analysis and Model Construction

From the perspective of heating carbon emissions, the total carbon emissions and per capita carbon emissions of heating cities nationwide generally show an upward trend. The total carbon emissions increased from 150 million tons in 2006 to nearly 300 million tons in 2019, and the per capita heating carbon emissions rose from 1 ton per person to close to 1.5 tons per person. This results from the gradual improvement of China's heating infrastructure and the expansion of the heating coverage area, showing a trend over time. This study focuses on the impact of urban spatial structure on heating carbon emissions, and controlling for time trends can effectively control the impact of gradually increasing total heating volumes, thereby comparing the impact of urban heating volumes under different city sizes and densities. In the Stata statistical software, the "i(year)" command is used as an indicator variable (also known as a dummy variable or categorical variable) in models to control for specific effects of the year. Each year has an indicator variable (except for a base year, usually the first year in your data). This approach allows the model to capture potential fixed effects for each year, thereby controlling for time trends. For instance, if policies, economic environments, or other macro variables changed in specific years, causing systemic changes in heating carbon emissions, then by using i(year), you can capture these effects. This can ensure that the model estimates are not disturbed by these unobserved factors.

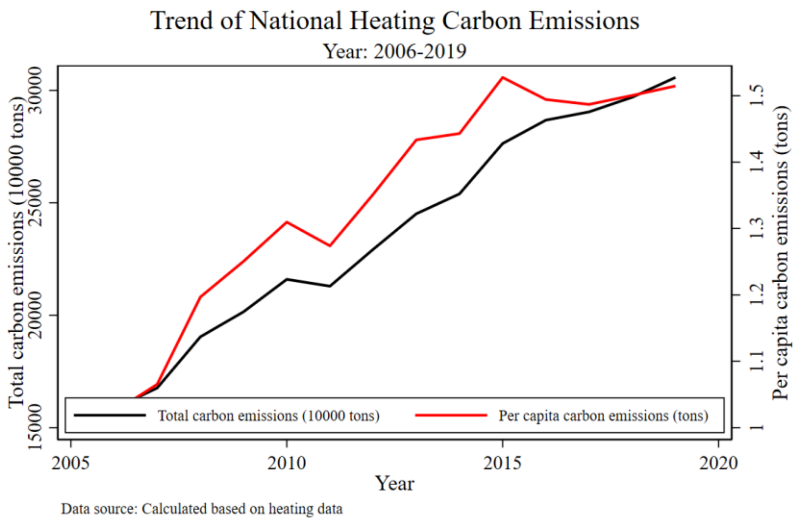

Figure 4-6 Trend of heating carbon emissions in China from 2006 to 2019

Looking at the carbon emissions from heating across cities, urban heating carbon emissions are significantly correlated with city levels. According to the spatial pattern map of urban heating carbon emissions classified by natural breakpoints, the cities with the highest household heating carbon emissions, exceeding 9.73 million tons, were mainly provincial capitals and cities of higher levels. For example, Beijing (18.15 million tons), Tianjin (16.90 million tons), Harbin (17.64 million tons), Shenyang (15.94 million tons), and Changchun (9.73 million tons). This result is related to the larger city size, which comes with a greater demand for heating. The heating carbon emissions in North China and Northeast China are significantly higher than those in regions with lower latitudes, such as Henan and Anhui, which are significantly influenced by temperature. Areas with lower local temperatures have significantly more heating days and a higher heating intensity than the warmer southern regions. Future research should exclude the impact of temperature as a factor.

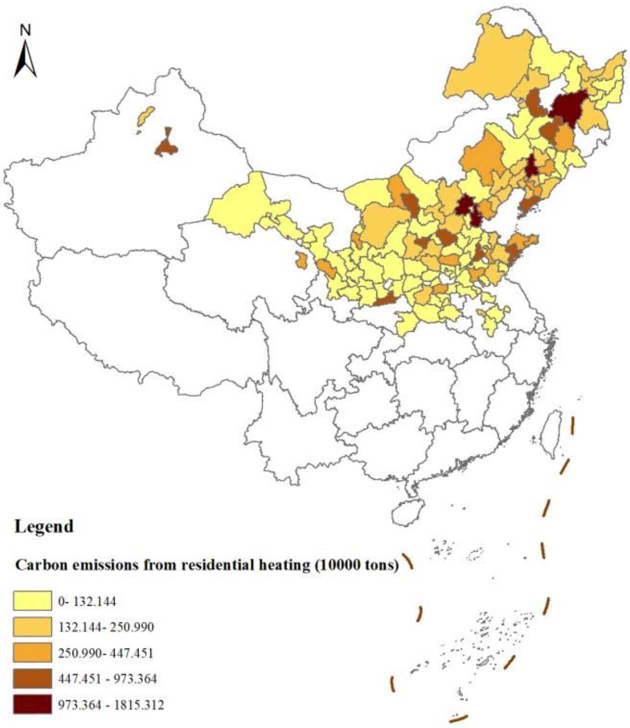

Figure 4-7 Urban heating carbon emission pattern(2019)

Urban size is often significantly related to its infrastructure and energy demands, especially heating requirements, which in turn affect the carbon emissions level of the heating system. In large cities, the heating system is usually more complex and extensive. Urban density refers to the spatial layout of urban elements, often affecting the nature of the city. Cities of the same size may exhibit different heating carbon emissions characteristics due to their varying urban densities. For example, high density could lead to more concentrated heating demands, less loss in heat during transportation, or a slower overall rate of urban heat dissipation, resulting in improving heating efficiency and reducing carbon emissions. Therefore, this study posits that urban size is a key factor affecting heating carbon emissions, while urban density determines the extent of the impact of urban size on heating carbon emissions, acting as a moderating effect. Therefore, this chapter use moderation effect analysis instead of mediation effect analysis.

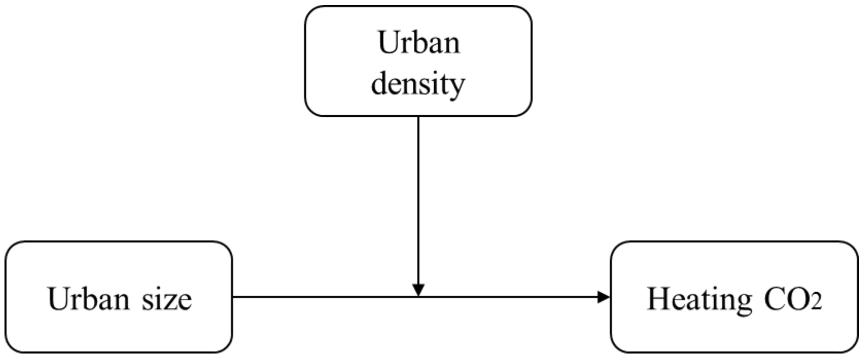

Figure 4-8 Theoretical models of urban size, density, and heating carbon emissions

Based on the theoretical model presented above (Fig 4-8), we employ multiple linear regression models, specifically fixed-effects models, to assess the impact of urban size (measured by population), population density, and temperature on heating carbon emissions. All models underwent robustness checks and utilized year as a grouping variable for error clustering. This chapter also considered logarithmic regression models. Logarithmic regression models are advantageous for explaining how a 1% change in spatial structure indicators translates into a percentage change in carbon emissions.

The multiple linear regression models are as follows:

Equation 4.11

$$Heating\_CO_{2_{it}}=\beta_{10}+\beta_{11}*US_{it}+\beta_{12}*T_{it}+u_{it}$$

Equation 4.12

$$Heating\_CO_{2_{it}}=\beta_{20}+\beta_{21}*US_{it}+\beta_{22}*UD_{it}+\beta_{23}*T_{\mathrm{it}}+u_{it}$$

For the logarithmic form regression models:

Equation 4.13

$$\ln(Heating\_CO_{2_{it}})=\beta_{30}+\beta_{31}*\ln(US_{it})+\beta_{32}*\ln(T_{it})+u_{it}$$

Equation 4.14

$$\ln(Heating\_CO_{2_{it}})=\beta_{40}+\beta_{41}*\ln(US_{it})+\beta_{42}*\ln(UD_{it})+\beta_{43}*\ln(T_{it})+u_{it}$$

For the moderation effect regression:

Equation 4.15

$$Heating\_CO_{2_{it}}=\beta_{50}+\beta_{51}*US_{it}+\beta_{52}UD_{it}+\beta_{53}(US_{it}*UD_{it})+\beta_{54}*T_{it}+u_{it}$$

Combining for the polynomial form:

Equation 4.16

$$Heating\_CO_{2_{it}}=\beta_{50}+\left(\beta_{51}+\beta_{53}UD_{it}\right)*US_{it}+\beta_{52}*UD_{it}+\beta_{54}*T_{it}+u_{it}$$

Deriving the partial derivative of heating carbon emissions (*HeatingCO*$_2$) with respect to urban size (*US*) yields:

Equation 4.17

$$\frac{\partial Heating\_CO_{2_{it}}}{\partial US}=\beta_{51}+\beta_{53}*UD$$

In the above equations:

$Heating\_CO_{2it}$ represents the heating carbon emissions of city *i* in year t.

US_{it} represents the urban size of city *i* in year t, measured by population indicators.

UD_{it} represents the urban density of city i in year t, measured by the ratio of population to land area.

T_{it} represents the average temperature of city i in year t, serving as a control variable.

The moderation effect provides insights into how urban density (*UD*) influences the impact of urban size (*US*) on heating carbon emissions ($HeatingCO_2$). If β_{53} is positive, an increase in urban density enhances the impact of urban size on heating carbon emissions; conversely, it weakens the impact. This could mean that in high-density cities, there might be more efficient heating systems or other emission reduction measures in place, leading to an increase in urban size that does not result in a proportional increase in carbon emissions. Furthermore, the moderation effect could provide important implications for urban planning and environmental policy, especially in terms of balancing urban growth with sustainability. For example, if β_{53} is positive, this might imply that heating carbon emissions management in high-density cities should receive more attention.

4.3.3 Empirical Study Results

Heating carbon emissions exhibit sub-linear growth with the increase in urban size. The scaling exponent for heating carbon emissions is 0.945, which means that when the urban size increases by 100%, the average increase in urban heating carbon emissions is 94.5%, resulting in a 5.5% carbon emission saving effect. This phenomenon can be attributed to several factors. First, larger cities typically have higher energy efficiency, especially in heating systems. Technologies such as centralized heating, geothermal heating, or heat recovery are more easily implemented and popularized in larger cities. Second, large cities are more likely to implement carbon emission controls, such as setting stricter building standards or using renewable energy sources. Lastly, large cities are more likely to invest in new technologies and infrastructure that improve energy efficiency due to economies of scale.

Second, the sublinear relationship between heating-related carbon emissions and urban population size is stronger than that for total household carbon emissions. As analyzed in Section 4.1, the scaling exponent for household carbon emissions is 0.971, whereas that for heating-related emissions is 0.945, indicating that heating emissions are more sensitive to urban population expansion. Other components of household carbon emissions, such as lighting and cooking, are relatively independent of urban population size. Regardless of city size, people's cooking habits and methods tend to remain consistent, and the fuels (e.g., natural gas or electricity) and appliances (e.g., kitchen stoves) used in different-sized cities exhibit little variation. Similarly, lighting demand remains relatively uniform across cities of varying sizes. Thanks to the widespread adoption of energy-efficient technologies, lighting efficiency has significantly improved across diverse urban environments. Compared to heating, cooking and lighting are typically managed within individual households and thus do not benefit significantly from efficiency gains associated with urban population growth. As a result, the effect of urban population size on carbon emissions from lighting and cooking is relatively small. Instead, these emissions are primarily driven by individual household behaviors and choices rather than the direct influence of overall urban scale.

These findings highlight the importance of considering the heterogeneity and complexity of emissions from various household activities in low-carbon urban planning.

Table 4-8 Empirical results of the impact of urban size on heating carbon emissions

Variables	Equation 4.11	Equation 4.12	Equation 4.13	Equation 4.14	Equation 4.15
	Heating_CO_2	*Heating_CO_2*	ln(*Heating_CO_2*)	ln(*Heating_CO_2*)	*Heating_CO_2*
Urban Size	1.798***	1.800***			2.196***
	(0.0750)	(0.0770)			(0.0967)
Urban Density		-0.00303			0.0515***
		(0.00424)			(0.00516)
Urban Size Urban Density*					**-0.000364***
					(2.36e-05)
Ln(Urban Size)			0.945***	0.930***	
			(0.0222)	(0.0173)	
Ln(Temprature)			-1.254***	-1.288***	
			(0.0441)	(0.0602)	
Ln(Urban Density)				0.0286	
				(0.0225)	
Temprature	-21.71***	-21.39***			-22.50***
	(1.279)	(1.428)			(1.516)
Constant	216.1***	214.7***	3.283***	3.253***	179.4***
	(17.65)	(18.84)	(0.142)	(0.148)	(19.71)
Observations	1,761	1,761	1,761	1,761	1,761
R-squared	0.747	0.747	0.411	0.411	0.766
Number of years	14	14	14	14	14

Robust standard errors in parentheses； *** p<0.01, ** p<0.05, * p<0.1

The impact of urban size on heating carbon emissions is moderated by urban density. The term $-0.000364\times UD$ in the partial derivative indicates that urban density (UD) reduces the impact of urban size (US) on heating carbon emissions ($HeatingCO_2$). Specifically, each unit increase in urban density reduces the impact of urban size on heating carbon emissions by 0.000364 units. In practical terms, an increase in urban population density by 1000 people per square kilometer results in a relative decrease of 0.364 tons in heating carbon emissions for every increase of 10,000 people in urban size. The growth in urban density weakens the positive growth effect of urban size on heating carbon emissions. The concentration of population from low-density cities to high-density cities overall reduces the level of heating carbon emissions.

$$\frac{\partial HeatingCO2}{\partial US}=2.196\text{-}0.000364*UD$$

This study employs a non-parametric estimation method for cross-validation of the conclusion. Interflex, utilizing non-parametric kernel estimation, offers a flexible and intuitive approach to examine moderating effects or interaction effects. It does not rely on any preset functional form. Thus, it can capture more complex relational dynamics. According to Figure 4.9, the impact of urban density on the effect of urban size on heating carbon emissions shows a U-shaped relationship, with the turning point at a density of 7500 people per square kilometer. The population density of most cities in China is far below this threshold. This means that, in the context of China, the increase in urban population density weakens the demand for heating carbon emissions driven by urban size growth (at least up to such a turning point).

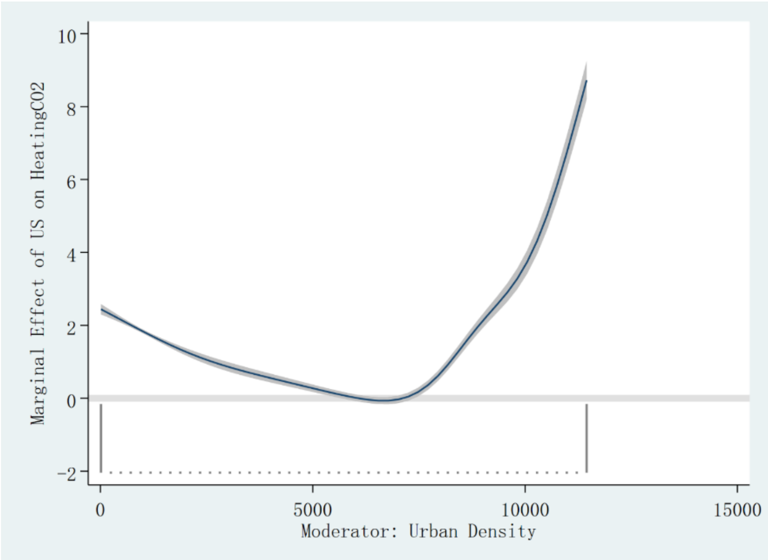

Figure 4-9 Adjusting marginal effect estimation (Interflex plot)

In general, expanding high-density cities exerts less pressure on heating carbon emissions. In contrast, the expansion of low-density cities contributes more significantly to the pressure on heating carbon emissions. Equation 4.11 results show that the current expansion of Chinese cities leads to an average increase in heating carbon emissions of 17.98 tons of CO_2 per 10,000 people. By incorporating this into the partial derivative equation, it is determined that when urban density is approximately 1093 people per square kilometer, urban size and the consequent growth in heating carbon emissions align with the national average level. The expansion of cities with a population density lower than 1093 people per square kilometer will elevate the overall level of heating carbon emissions. Conversely, increasing the population size of cities with a density higher than 1093 people per square kilometer will reduce heating emissions. To reach the 2019 average heating carbon emissions growth rate of 15 tons per 10,000 people, the population density must be 1912 people per square kilometer.

From the perspective of the human-environment relationship, urban density serves as a moderating variable in the impact of urban population size on heating-related carbon emissions, reflecting the interaction between human activities and spatial configurations and their environmental implications. The human-environment relationship theory emphasizes the interplay between population distribution, land use patterns, and geographical conditions, which collectively shape urban energy consumption patterns and carbon emissions levels.

In high-density cities, residents and buildings are more spatially concentrated, optimizing the energy distribution efficiency of centralized heating systems. The shorter transmission distances reduce heat loss during distribution, leading to higher overall heating efficiency. Additionally, high-density areas are often associated with stricter building standards, including better insulation performance and the adoption of advanced energy technologies, further lowering per-unit heating demand and carbon emissions.

In contrast, low-density cities are characterized by more dispersed populations and buildings, making it more challenging to implement centralized heating systems efficiently. In these areas, heating demand is widespread yet scattered, and independent heating systems—such as electric heaters or gas boilers—are commonly used. These systems typically have lower efficiency and higher carbon emissions due to energy conversion losses and less effective energy utilization. Moreover, urban planning and building design in low-density areas may not fully integrate energy-saving considerations, resulting in lower energy efficiency and higher heating-related carbon emissions.

From a heating perspective, urban planning and land-use strategies in regions with significant heating demand should consider how to optimize population distribution and urban spatial organization to reduce heating-related carbon emissions. While the practical application of this study's findings in heating carbon emission planning may face certain limitations, they provide valuable insights for understanding the dynamics of heating emissions from the perspectives of urban scale and density. This understanding is crucial for accurately identifying and assessing planning targets, thereby enhancing the practical value of planning efforts.

4.4 The Impact of Urban Size on Transportation Carbon Emissions

4.4.1 Theoretical Analysis of Urban Transportation Carbon Emissions

Previous research on urban transportation carbon emissions has primarily focused on the quantitative measurement of carbon emissions and analyzing influencing factors. The goal of the studies on the quantitative measurement of transportation carbon emissions is to precisely calculate the current status of carbon dioxide emissions from various transportation components. For example, there are calculations of carbon emissions from public transportation(Chen et al., 2023; Wang & Zheng, 2023), as well as specific measurements of carbon emissions in areas such as the Yangtze River Economic Belt(Jiang et al., 2020) and Gansu Province(Wu et al., 2015). The research on measuring transportation carbon emissions is a foundation for understanding the current state of regional and urban transportation carbon emissions. However, planning for carbon emission reduction also requires an understanding of the connections between transportation carbon emissions and other factors. Many studies have been conducted on the factors influencing transportation carbon emissions. Neverthelss, a framework has not yet been established for studying urban transportation carbon emissions from the perspective of the urban system.

Research on transportation carbon emissions can be conducted in three dimensions: demand side, supply side, and supply efficiency. First, the larger the city size, the greater the total demand for transportation carbon emissions. The number of people is positively correlated with transportation demand; more people mean more demand for passenger and freight transport(Su et al., 2011), thus increasing carbon emissions. Second, the higher the level of affluence, the greater the demand for transportation and, consequently, the higher the demand for transportation carbon emissions. Wu et al. (2015)found that the level of economic development has a greater pull on transportation carbon emissions than the factor of population size.

Moreover, as income levels increase, people tend to buy and use personal transportation (such as cars) rather than public transportation. Higher incomes can afford higher travel costs and may lead to more frequent and longer-distance travel, thereby increasing carbon emissions. Third, the supply of transportation services affects carbon emissions. It has been found that developed public transportation helps to reduce carbon emissions(Su et al., 2011). Fourth, elements of urban spatial structure affect the efficiency of transportation supply, which in turn affects the demand for transportation carbon emissions. For example, the larger the city, the longer the commuting distance.

The denser the city, the more pronounced the congestion effect.

The first and second dimensions represent the demand-side analysis of factors driving transportation carbon emissions. At the same time, the third point analyzes the pressure on transportation carbon emissions from the perspective of transportation supply structure. The fourth point suggests that urban spatial structure is the fundamental framework for socio-economic activities and transportation carbon emissions, constraining transportation supply efficiency and impacting carbon emissions. Through this comprehensive theoretical framework, we can understand the multifaceted factors affecting transportation carbon emissions more comprehensively and provide more accurate evidence for policy-making. This framework can also serve as a basis for more in-depth quantitative research. Based on the analysis of the spatiotemporal pattern of urban transportation carbon emissions in China, this chapter explores the impact of city size on transportation carbon emissions.

4.4.2 Current Status of Urban Transportation Carbon Emissions in China

China's transportation carbon emissions have shown a significant upward trend. In 2020, the carbon emissions from transportation amounted to 894 million tons, 2.58 times the amount in 2005. Looking at the per capita level, the per capita transportation carbon emissions for 2005, 2010, 2015, and 2020 were 0.291, 0.410, 0.557, and 0.676 tons per person, respectively. The level of per capita transportation carbon emissions also shows an increasing trend.

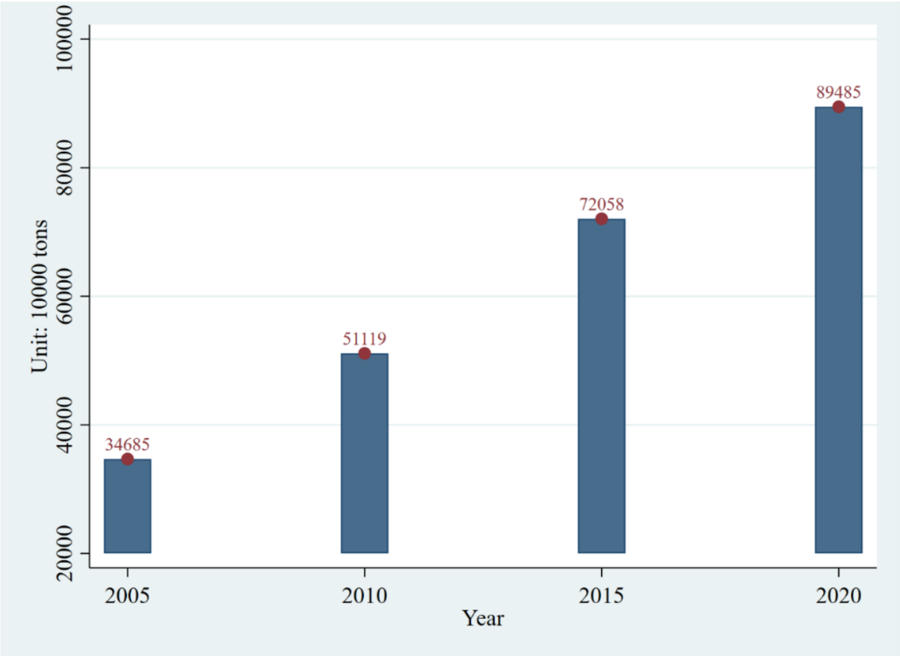

Figure 4-10 Urban transportation carbon emission pattern

The spatial distribution of transportation carbon emissions in China exhibits characteristics of "dense in the east and sparse in the west, continuous along the coast, and clustered at four poles." The east-west disparity indicates that the coastal areas in the eastern part of China have significantly higher transportation carbon emissions compared to the central and western regions. The continuous coastal zone in the east essentially forms a contiguous area of high transportation carbon emissions, making it a hotspot for China's transportation carbon emissions. Regarding clustering at four poles, in 2020, the eight cities with the highest transportation carbon emissions were Beijing and Tianjin, Shanghai and Suzhou, Guangzhou and Shenzhen, Chengdu and Chongqing. These areas are essential centers within their respective regions or economic sectors, serving as growth poles for the economy and as high points for transportation carbon emissions.

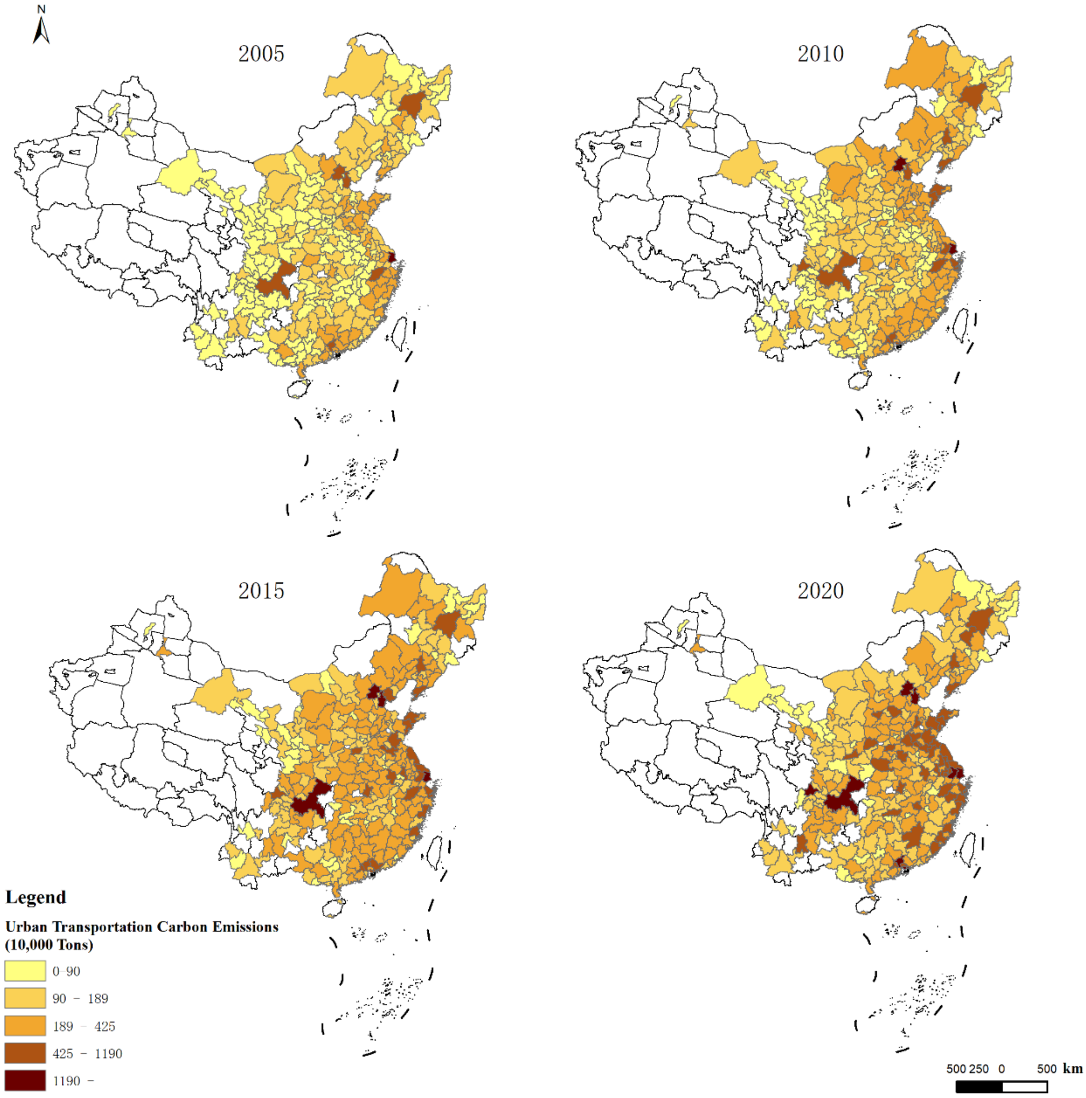

Figure 4-11Temporal and spatial characteristics of urban transportation carbon emissions in China

4.4.3 Analysis of the Impact Mechanism of Urban Size on Transportation Carbon Emissions

In the overall analysis presented in Section 4.1, transportation-related carbon emissions exhibit a significant sublinear relationship with urban population size. The scaling exponent for the relationship between urban population size and transportation carbon emissions is 0.78, indicating that when the urban population doubles, transportation carbon emissions increase by 78%. From an efficiency perspective, urban population growth leads to a reduction in per capita transportation carbon emissions. This sublinear relationship is primarily attributed to the well-developed public transportation systems in large, densely populated cities, which reduce residents' dependence on private vehicles. Due to their larger population base, these cities can support extensive and efficient public transportation networks, such as subways, buses, and light rail systems. These systems provide convenient and widely accessible mobility options, effectively reducing vehicle miles traveled and alleviating traffic congestion, thereby lowering carbon emissions. Additionally, population growth is often accompanied by higher levels of urban development and more advanced transportation management technologies, such as intelligent traffic systems, which enhance road usage efficiency and further reduce emissions. Thus, the expansion of urban population size not only fosters greater economic and social activity but also facilitates relative reductions in transportation-related carbon emissions through efficient public transit systems, demonstrating the synergy between population growth and environmental sustainability.

It is widely recognized that larger cities tend to have more developed public transportation systems, which contribute to lower transportation-related carbon emissions. This understanding is well-supported both theoretically and empirically. As urban populations grow, improvements in transportation infrastructure, such as the expansion of subway lines and the increase in bus fleets, help accommodate larger populations while reducing reliance on private vehicles, thereby mitigating carbon emissions.

However, relatively few studies have empirically tested the mediating effect of public transportation systems in the relationship between urban population size and transportation carbon emissions. Moreover, public transportation systems are a key component of urban planning and can be influenced through policy interventions. While individual travel behaviors—such as trip frequency, mode choice, and travel distance—also affect carbon emissions, they are more challenging to regulate directly through urban planning tools.

Considering this, this section aims to construct and empirically test a mediation model to examine the role of public transportation systems in mitigating transportation-related carbon emissions in Chinese cities. Specifically, the model explores how urban population growth potentially reduces transportation carbon emissions by improving public transportation systems. This analysis considers both direct effects and indirect effects, in which public transportation usage mediates this relationship. The study thus seeks to verify whether, in the Chinese context, the expansion of public transportation can effectively contribute to reducing transportation carbon emissions, as conceptualized in the mediation model illustrated in Figure 4-12.

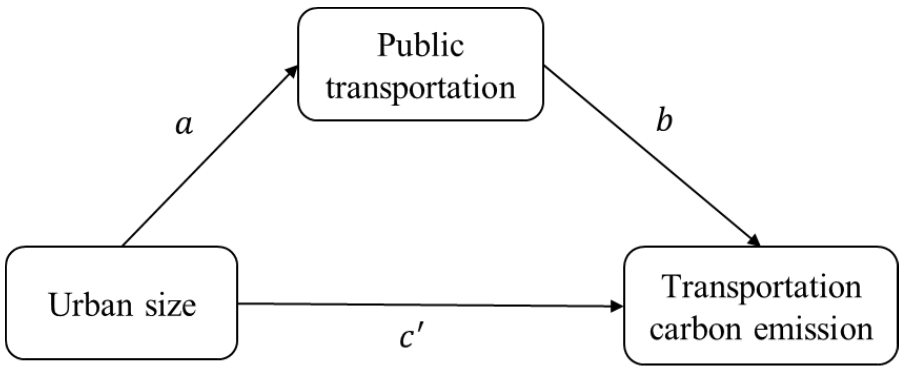

Figure 4-12 Mediating effect model of urban size on transportation carbon emissions.

Based on the mediation effect theoretical framework mentioned above, this study will establish a corresponding econometric model to quantitatively assess the effect of the mediating variable—urban public transportation—on the relationship between city size expansion and transportation carbon emissions reduction.

Equation 4.18

$$\ln(\textit{Transport emission})_{\mathrm{it}}=\beta_{01}+c*\ln(US)_{it}+\beta_{11}\ln(\textit{GDP per capita})_{it}+\mu_{i1}+\gamma_{t1}+\epsilon_{it1}$$

Equation 4.19

$$\ln(\textit{Public Transportation})_{it}=\beta_{01}+a*\ln(US)_{it}+\beta_{11}\ln(\textit{GDP per capita})_{it}+\mu_{i1}+\gamma_{t1}+\epsilon_{it1}$$

Equation 4.20

$$\ln(\textit{Transport emission})_{\mathrm{it}}=\beta_{01}+c^{'}*\ln(US)_{it}+b*\ln(\textit{Public Transportation})_{it}$$
$$+\beta_{11}\ln(\textit{GDP per capita})_{it}+\mu_{i1}+\gamma_{t1}+\epsilon_{it1}$$

In the formula, *US* represents the urban population size, *GDP per capita* is used as a control variable for per capita carbon emissions, Transport emission refers to the amount of carbon emissions from transportation, and the total volume of bus and trolleybus passengers represents Public Transportation. The mediating effect is denoted as ab, the direct effect as c', and the total effect as $ab + c'$.

The regression results show that urban public transportation acts as a mediating variable in the impact of city size on transportation carbon emissions. According to the regression results in Table 4-9, after controlling for the city's wealth level (per capita GDP), the regression coefficient for city size is 0.81, and this coefficient has passed the 1% significance test. This means that the total effect of city size on transportation carbon emissions is 0.81, with a 1% increase in city size leading to a 0.81% increase in urban transportation carbon emissions. The regression results from Equation 4.19, with the total volume of urban passenger transportation as the dependent variable, show that the coefficient for city size is 0.834, which has passed the 1% significance test. In China's urban system, city size positively affects urban public transportation. With a 1% increase in urban population size, the scale of urban public transportation increases by 0.834%, i.e., a=0.834. In Equation 4.20, the regression coefficient for public transportation is -0.0354, which has passed the significance test at the 5% level (b=-0.0354). This means that, after controlling for urban population size and wealth level, urban public transportation can reduce transportation carbon emissions to a certain extent. The value of the mediating effect $a*b$ is -0.0295. This indicates that with the growth of city size, increasing the use of urban public transportation can reduce urban transportation carbon emissions. With a 1% increase in city size, transportation carbon emissions can be reduced by 0.0295% through the mediation pathway of urban public transportation.

Table 4-9 Regression results of the mediating effect of urban size on transportation carbon emissions

Variables	Equation 4.18 ln(*Transport Emission*)	Equation 4.19 ln(*Public Transportation*)	Equation 4.20 ln(*Transport Emission*)
ln(*US*)	0.810***	0.834***	0.840***
	(0.0244)	(0.0468)	(0.0277)
ln(*Public Transportation*)			-0.0354**
			(0.0157)
ln(*GDP per capita*)	0.568***	1.299***	0.613***
	(0.0227)	(0.0438)	(0.0307)
Constant	-0.406***	2.429***	-0.320**
	(0.148)	(0.284)	(0.153)

Variables	Equation 4.18 ln(*Transport Emission*)	Equation 4.19 ln(*Public Transportation*)	Equation 4.20 ln(*Transport Emission*)
Observations	1,114	1,110	1,110
R-squared	0.598	0.511	0.599
Number of years	4	4	4

Note: Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

In China, the growth of urban population size leads to an increase in public transportation usage, which, to some extent, mitigates the growth of transportation-related carbon emissions. As a result, the relationship between urban population size and transportation carbon emissions exhibits a sublinear growth pattern. This finding aligns with empirical observations. Urban population growth is often accompanied by the development and expansion of public transportation systems, encouraging residents to adopt more environmental friendly travel modes. As cities grow in both population and economic activity, governments and urban planners tend to allocate more resources to the construction and optimization of public transportation infrastructure, such as subways, buses, and light rail systems. These investments not only enhance urban transport efficiency but also reduce residents' reliance on private vehicles. Such measures effectively improve per capita travel efficiency and decrease carbon emissions per trip. Consequently, while urban expansion increases economic activities and transportation demand, a well-developed public transportation system enables the growth of urban population size to outpace the rise in transportation carbon emissions. This sublinear relationship suggests that with sound urban planning and policy guidance, cities can achieve both economic growth and environmental sustainability by controlling and slowing the increase in transportation-related carbon emissions.

However, the coefficient of this mediation effect is small, indicating that the effect on reducing transportation carbon emissions is limited. This means that urban public transportation has not yet been able to fully provide sufficient convenience for residents' travel and meet their living needs, resulting in public transportation being unable to replace private modes of transport on a large scale. One reason might also be the inefficiency of public transportation systems, especially the subway, due to the rush to launch subway projects without adequate planning. Firstly, public transportation, especially subways, also requires carbon emissions during operation. In the rush to build subway projects, there might be a push to reclassify counties as districts without fully considering the actual socio-economic development, making the urban population meet the criteria needed for constructing subways. However, the functional connections between different urban areas remain relatively weak. In such cases, the subway system may operate inefficiently due to insufficient passenger numbers. This affects the financial sustainability of the subway system itself and may also reduce the potential contribution of the entire urban public transportation system to carbon emission reduction.

4.5 Summary of This Chapter

This chapter first analyzes the relationship between urban population size and total carbon emissions, industrial carbon emissions, transportation carbon emissions, and household carbon emissions from the perspective of urban scaling laws. It further examines the differences in urban carbon emission efficiency in China using Scale-Adjusted Metropolitan Indicators (SAMIs) (Section 4.1). Subsequently, the mechanisms and heterogeneity of industrial carbon emissions (Section 4.2), household carbon emissions (Section 4.3), and transportation carbon emissions (Section 4.4) are analyzed in detail based on different emission sources. The findings indicate a sublinear relationship between urban population size and carbon emissions, with urban population size affecting industrial, heating, and transportation carbon emissions through different pathways. The key research findings are summarized as follows:

First, Urban population size influences industrial carbon emissions through innovation, production expansion, and industrial upgrading.

(1) Overall, urban innovation in China has not yet demonstrated a significant carbon reduction effect. (2) Innovation has a dual impact on industrial carbon emissions, exhibiting both emission-promoting and emission-reducing effects, with the former significantly outweighing the latter. As urban population size grows, innovation levels rise, driving production and increasing industrial carbon emissions. This effect is particularly pronounced in cities with lower development levels. (3) The expansion of urban population size not only stimulates industrial carbon emissions through production growth but also generates a limited carbon reduction effect through industrial upgrading.

Second, Higher urban population density weakens the heating carbon emission demand associated with urban population growth.

This section examines the impact of urban population size on heating carbon emissions and the moderating role of urban density. The findings reveal that the scale effect of heating carbon emissions is stronger than that of overall household carbon emissions. The influence of urban population size on heating carbon emissions exhibits a U-shaped relationship with urban density. In general, increasing urban density mitigates the demand for heating carbon emissions resulting from population growth.

Third, Urban population growth reduces transportation carbon emissions through public transportation systems, but the effect is limited.

A mediation model is constructed to empirically test the relationship between urban population size, public transportation, and transportation carbon emissions. The results show that as urban population size increases, the use of public transportation also rises, contributing to a reduction in transportation carbon emissions. However, the overall effect of this reduction remains limited.

Chapter 5. The Impact of Urban Form on Carbon Emissions

The size of a city determines the demand volume for urban metabolism. In contrast, the urban spatial form, serving as the skeleton of urban operations, has a specific locking effect on urban metabolism. Research in the field of urban carbon reduction is gradually gaining attention. In the domain of urban studies, many researchers believe that urban spatial form is strongly associated with urban elements such as the heat island effect (Liang et al., 2020; Ramirez-Aguilar & Souza, 2019), air quality (Lu & Liu, 2016; McCarty & Kaza, 2015), and the housing market (Jones et al., 2009). Urban spatial form is an indispensable link in analyzing and understanding the impact of urban spatial structure on carbon emissions. Moreover, the real-world relationship between urban spatial form and carbon emissions provides direct and operational guidance for urban planning. It has long-term and structural characteristics regarding its impact on carbon emissions(Qin & Shao, 2012). Therefore, building on the foundation of research into the impact of city size on carbon emissions, this chapter investigates the effects of urban spatial form on industrial, transportation, and household carbon emissions.

5.1 Quantification of Urban Geometric Morphology and Its Spatio-Temporal Evolution

5.1.1 Selection of Urban Geometric Morphology Indicators

The selection of indicators for the geometric morphology of cities begins from the dimensions of "land area-spatial allocation," choosing key variables that reflect the geometric characteristics of urban land use space. These are quantified across four dimensions: the scale of the built-up area, shape complexity, compactness, and polycentricity/monocentricity. The built-up area's land use size reflects the scale of land utilization, serving as the basic framework for urban production and living, and constitutes a fundamental premise for urban development. The complexity of urban land use is represented by the area-weighted mean shape index and the area-weighted mean patch fractal dimension. The description of the compactness of urban built-up areas utilizes the Compactness Index (*AI*), Largest Size Index (*LSI*), and Average Nearest Neighbor Distance (*ENN_AM*). Characterizing urban polycentricity/monocentricity employs the Central Area Index and the Coefficient of Variation of the Central Area. This establishes a quantified indicator system for urban spatial morphology, measuring the geometric form of urban land use from the dimensions of built-up area scale, shape complexity, compactness, and the degree of polycentricity or monocentricity.

(1) City Area： *CA*

Land serves as the spatial foundation for socio-economic activities, as the carrier for various production activities and as the living space for humans. The utilization and management of land are directly related to a region's economic development, environmental quality, and social progress. Therefore, the reasonable use and effective management of land resources play a crucial role in promoting the sustainable development of socio-economic. The urban land area (*CA*: City Area) determines urban development's spatial capacity and boundaries, representing the most significant and intuitive spatial form characteristic of urban space. This study employs land use vector data to extract the urban land area, ensuring data heterogeneity and comparability. The precision of land use vector data extraction is high, though there may be some discrepancies with the statistical data of various cities.

(2) Urban Built-up Area Shape

a. Area-Weighted Mean Shape Index (*SHAPE_AM*)

The Area-Weighted Mean Shape Index (Shape Index - Area Weighted Mean, *SHAPE_AM*) is a landscape index used to measure the shape complexity of landscape patches. This index focuses on expressing the complexity of a patch's shape, taking into account the size of the patch. *SHAPE_AM* is calculated by summing the product of each patch's shape complexity and its relative area, then dividing by the total area of all patches. Thus, the shape index of larger patches has greater weight in *SHAPE_AM*.

Equation 5.1

$$SHAPE\_AM = \frac{\sum_{i=1}^{n}\left(A_i * p_i / (4\sqrt{A_i}\right)}{\sum_{i=1}^{n}(A_i) * n}$$

In the formula, n is the total number of patches. A_i is the area of the i^{th} patch. p_i is the perimeter of a single patch. *SHAPE_AM* describes the degree of clustering, with values of *SHAPE_AM* being equal to or greater than 1. When it equals 1, it indicates that there is only one patch of that type in the landscape and it is close to square. As the dispersion and irregularity of patch types increase, the Area-Weighted Mean Shape Index gradually increases without an upper limit.

b. Area-Weighted Mean Fractal Dimension (*FRAC_AM*)

The Area-Weighted Mean Fractal Dimension (Fractal Dimension Index Area Weighted Mean: *FRAC_AM*) is an indicator used to describe the complexity and shape of urban construction land patches (see Equation 5.2). The value of *FRAC_AM* ranges between 1 and 2, with values closer to 1 indicating more regular urban built-up area edges. Higher Area-Weighted Mean Fractal Dimensions suggest more complex, unplanned urban expansion, while lower fractal dimensions may be associated with well-planned, orderly urban expansion.

Equation 5.2

$$\text{FRAC\_AM}=\frac{\left(\sum_{i=1}^{n}\frac{2\ln 0.25p_i}{\ln A_i}\right)*A_i}{n*\sum_{i=1}^{n}A_i}$$

(3) Urban Built-up Area Aggregation characteristic

a. Urban Construction Land Aggregation Index (*AI*)

The Landscape Aggregation Index (*AI*) indicates the probability of different patch types (including similar nodes among the same type) appearing adjacent in a landscape map. Its unit is a percentage ranging from 0 to 100. When the fragmentation level of a certain patch type is maximized, its Aggregation Index is 0. As the degree of aggregation increases, the Aggregation Index increases, reaching 100 when the patch type aggregates into a compact whole. A higher Aggregation Index for a city's built-up area typically implies that buildings or built-up blocks are spatially closer, forming a more continuous and compact built environment. Conversely, a lower Aggregation Index may indicate that built-up blocks are relatively dispersed in space, potentially showing higher fragmentation.

b. Largest Patch Index (*LPI*)

The Largest Patch Index (*LPI*) of urban construction land is the ratio of the largest construction land patch to the total construction land area, reflecting the intensity of urban construction land aggregation towards a single plot. High *LPI* values usually correspond to higher compactness, where the city's largest patch is dominant. Conversely, low *LPI* values may indicate a relative dispersion among urban plots.

c.Area-Weighted Mean Nearest Neighbor Distance (*ENN_AM*)

The Area-Weighted Mean Nearest Neighbor Distance (Euclidean Nearest Neighbor Distance-Area Weighted: *ENN_AM*) is used in landscape ecology to describe the compactness among landscape elements. This index measures the average distance from each landscape patch or specific land use type to its nearest neighbor of the same type. Shorter nearest-neighbor distances for a patch suggest that patches are closer to each other, making the urban land landscape potentially more compact.

Equation 5.3

$$ENN_{MN}=\frac{\sum_{i=1}^{n} d_i * A_i}{n * \sum_{i=1}^{n} A_i}$$

In the formula, d_i is the distance from urban land patch i to the nearest other patch, and Ai is the area of the i^{th} patch.

(4) Urban Land Polycentric/Monocentric Structure Characteristics

Urban structure often encompasses considerations of both morphological polycentric structures and functional polycentric structures. In this study, the focus is on morphological polycentricity. Urban polycentric and monocentric structures are characterized by center intensity, the number of centers, and distribution evenness. The leading indicators include the Largest Patch Index (*LPI*) of urban construction land, the Number of Core Areas (*NCA*), and the Coefficient of Variation of Core Areas. To ensure comparability among different cities, the urban core areas in this study are determined based on land use data. Empirically, areas within a boundary of 1000 meters are considered core areas.

a. Core Area Percentage of Landscape (*CAPL*)

The Core Area Percentage of Landscape (*CAPL*) refers to the proportion of the central area of urban construction land relative to the total area of construction land. A higher *CAPL* value indicates that the urban central area occupies a more significant proportion of the total built-up area, typically suggesting that the city's core area or central district dominates, showing a monocentric spatial structure of urban development. Conversely, a lower *CAPL* suggests a trend towards a polycentric urban form. In a polycentric structure, in addition to the main urban core area, multiple auxiliary central areas or sub-centers may have relatively independent structures.

b. Number of Core Areas (*NCA*)

The Number of Core Areas (*NCA*) reflects a city's single/polycentric structure characteristics. In urban planning, the relationship between urban land use and infrastructure determines that the urban core areas are the heart of the built-up area. The number of urban core areas intuitively reflects a city's monocentric or polycentric structural features.

c. Core Area Coefficient of Variation (*CACV*)

The Core Area Coefficient of Variation (*CACV*) is the ratio of the standard deviation of the areas of various core areas to the average area of these core areas. This indicator reflects the degree of variation and unevenness in the sizes of different core areas within a city. A higher *CACV* indicates a larger difference in patch sizes, which, in urban planning practice, generally means that the central urban area is much larger than the surrounding smaller centers, presenting a monocentric urban spatial structure. Conversely, a lower *CACV* indicates that urban core areas are more evenly distributed with more minor differences in size, showing the characteristics of a polycentric urban spatial structure.

In addition to these morphological variables of urban land (McGarigal et al., 2012), this chapter explores the impact of urban green spaces and the relationship between green spaces and construction land on carbon emissions, with the selection of indicators discussed in section 5.2.5.

5.1.2 Data Sources and Processing Procedures

(1) Data source

The National Oceanic and Atmospheric Administration (*NOAA*) provides the nighttime light data through the *NPP-VIIRS* (National Polar-orbiting Partnership-Visible Infrared Imaging Radiometer Suite) monthly composite nighttime light remote sensing imagery. *VIIRS*, a scanning imaging radiometer, collects radiation images in visible and infrared wavelengths of land, atmosphere, ice, and oceans. This data filters out interference from stray light, lightning, lunar illumination, and cloud cover. The *NPP-VIIRS* nighttime light data is one of the important products, including monthly composite nighttime light data and daily nighttime light data. Utilizing polar orbits, the *NPP-VIIRS* nighttime light data is stitched together from multiple cloud-free images to form global nighttime light remote sensing imagery, sensitively capturing nighttime lights on Earth, especially in urban areas with high light intensity.

Wuhan University provides a 30m high-precision land use dataset derived from many Landsat images (335,709 images), ensuring a broad representation of land cover. The dataset was trained using stable samples extracted from the China Land Use/Cover Dataset (*CLUDs*) and samples interpreted visually through satellite time series data, Google Earth, and Google Maps, ensuring the reliability and verifiability of its training data (Yang & Huang, 2021). Therefore, this study adopts this dataset as the foundation for this research segment and combines it with the advantages of nighttime lights in determining urban extents to acquire the dataset for this study. The latest dataset is from 2019. Due to minimal urban morphology changes within a year, this study uses 2019 instead of 2020.

(2) Data Processing Procedure

This study aims to quantify urban spatial morphology, where an essential step involves extracting spatial data on urban form and determining the accuracy of related index calculations for urban spatial form. The methods to delineate urban built-up areas in calculating urban spatial morphology mainly include using nighttime light data for extracting urban built-up areas and utilizing existing land use data.

Nighttime light data has advantages in delineating boundaries and studying urban expansion at a coarse granularity, but it has certain limitations in describing the internal morphology of cities. Nighttime lights serve as a valuable data source for urban studies, extensively used by scholars for built-up area extraction research in various locations and at different scales, such as global scale(Sharma et al., 2016), four major metropolitan areas in Eurasia(Liu et al., 2019). In summary, nighttime light data can achieve an error within 5% at the urban area quantity level, satisfying the needs for the general area, expansion direction, and rough shape calculation. Therefore, nighttime lights can broadly reflect the intensity of human activity in urban and non-urban areas, especially in urban peripheries and transition zones. However, due to the overflow characteristic of nighttime lights, they often do not well represent the internal morphology of cities. For example, large green areas like Wanshi Mountain and Dongping Mountain inside Xiamen Island cannot be well identified in nighttime light data.

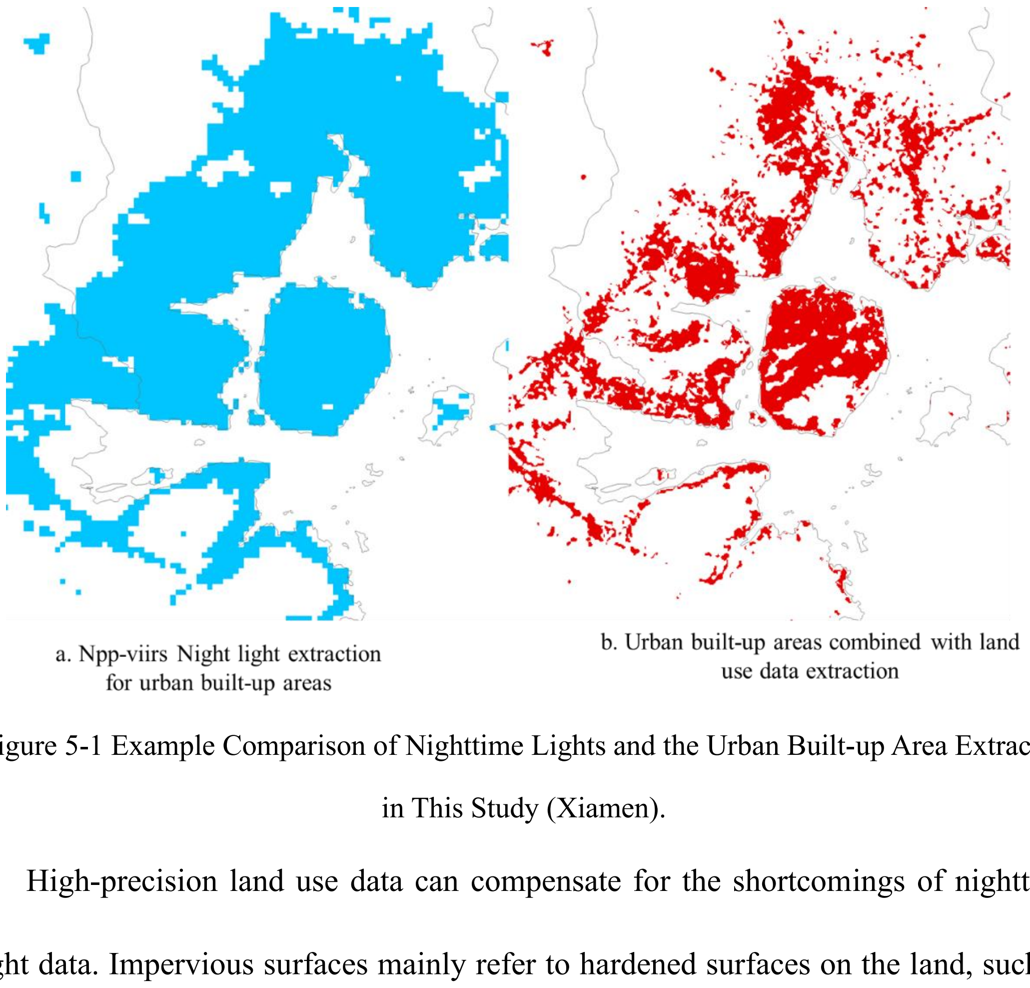

Figure 5-1 Example Comparison of Nighttime Lights and the Urban Built-up Area Extracted in This Study (Xiamen).

High-precision land use data can compensate for the shortcomings of nighttime light data. Impervious surfaces mainly refer to hardened surfaces on the land, such as buildings, roads, squares, et al. This method primarily uses remote sensing technology, such as high-resolution satellite imagery, to determine. Land use vector data can more accurately reflect urban buildings and hardened ground distribution. In studying the internal morphology of cities, land use vector data has significant advantages that nighttime light data cannot achieve. However, land use data also includes rural lands. Therefore, this study combines the advantages of nighttime light data and land use data to generate a foundational dataset for urban built-up areas. The process for handling this study's foundational dataset for urban built-up areas is as follows.

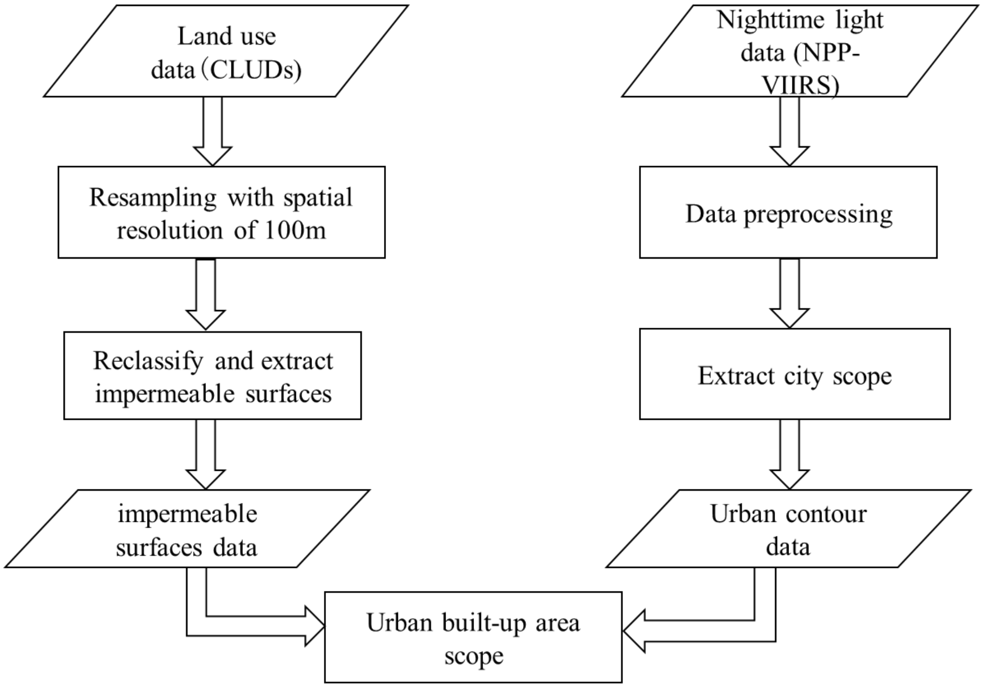

Figure 5-2 The process of extracting urban built-up areas scope

(2) Data Processing Procedure

Firstly, processing of nighttime light data. The *NPP-VIIRS* nighttime light data is released monthly, but due to differences in the months of capture, there can be seasonal systematic differences in city nighttime lights. Additionally, higher latitude areas may experience poorer quality in global nighttime light data, sometimes resulting in "truncated" data loss. Firstly, considering both data month consistency and quality, data from January, April, and December are chosen. Secondly, for ease of later statistical calculations, the *NPP-VIIRS* nighttime light data undergo projection transformation to Albers equal-area conic projection, and the grid size is resampled to 100 meters by 100 meters. Thirdly, *NPP-VIIRS* nighttime light data contains background noise, and in pitch-black non-urban spaces, there might be negative *DN* values, which would produce errors if directly included in calculations. Thus, negative *DN* values were set as 0. To eliminate the excessively high-intensity outliers in *NPP-VIIRS* nighttime light data, this study placed the pixel *DN* values from lowest to highest, selecting the *DN* value at the 99.9% percentile of light-emitting pixels as the threshold *DNmax* and brightness above this threshold were set as *DNmax*, thus eliminating excessively bright outliers. Fourthly, not involving quarterly analysis, using monthly data can introduce bias.

Additionally, nighttime light data can have random errors in each capture, which can be eliminated through annual synthesis. Therefore, this study uses the "Raster Calculator" to average the cropped monthly Bohai Rim area nighttime light data into an annual composite, obtaining yearly data. Fifthly, since this study uses nighttime light data only to extract urban extents and reference existing research(Liu et al., 2018), it adopts a generic threshold of nighttime light *DN* value greater than or equal to 6 for urban areas.

Second, processing of land use data. Since this study aims to explore urban spatial morphology, requiring area statistics and using 30-meter spatial resolution data does not significantly enhance the study results, and large data volumes pose a considerable test to hardware. (1) Considering the difficulty of data processing, the China Land

Use/Cover Dataset (CLUDs) is resampled to 100 meters by 100 meters grid data. (2) Resampling. Since urban built-up areas are mostly impervious surfaces, this study replaces urban built-up areas with impervious surfaces. The impervious surface data is resampled, assigning a value of 1 to impervious surface grids and 0 to others. (3) Filtering. Since there is sporadic white noise in the data, which is not conducive to grasping the overall morphology of the city, the image undergoes filtering. (4) Nighttime light data was used to clip, excluding non-urban impervious areas, thus obtaining this study's foundational urban built-up area dataset. Data examples are shown as follows for China's three major urban agglomerations. It should be noted that there is a quantitative difference between the land use vector data and statistical data used in this study.

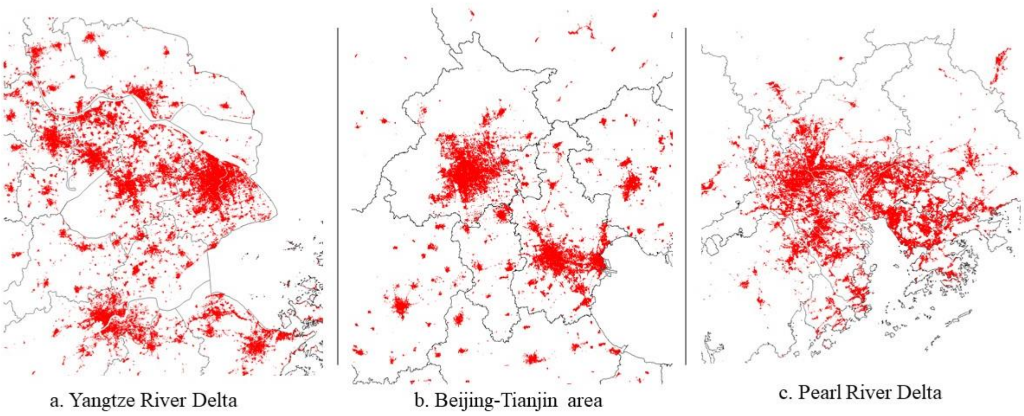

Figure 5-3 Example of Urban Built-up Area Data

(3) Urban form Indicators Calculation

Firstly, this study uses vector data at the scale of Chinese prefecture-level city administrative districts as the boundary to clip the urban built-up area data obtained from previous calculations, resulting in over 300 independent urban built-up area raster datasets for calculating morphology indices.

Secondly, these 300 urban built-up area vector datasets are imported into the landscape index calculation software Fragstats to calculate the landscape indices selected in the previous sections. The final output includes landscape index data for the years 2005-2020.

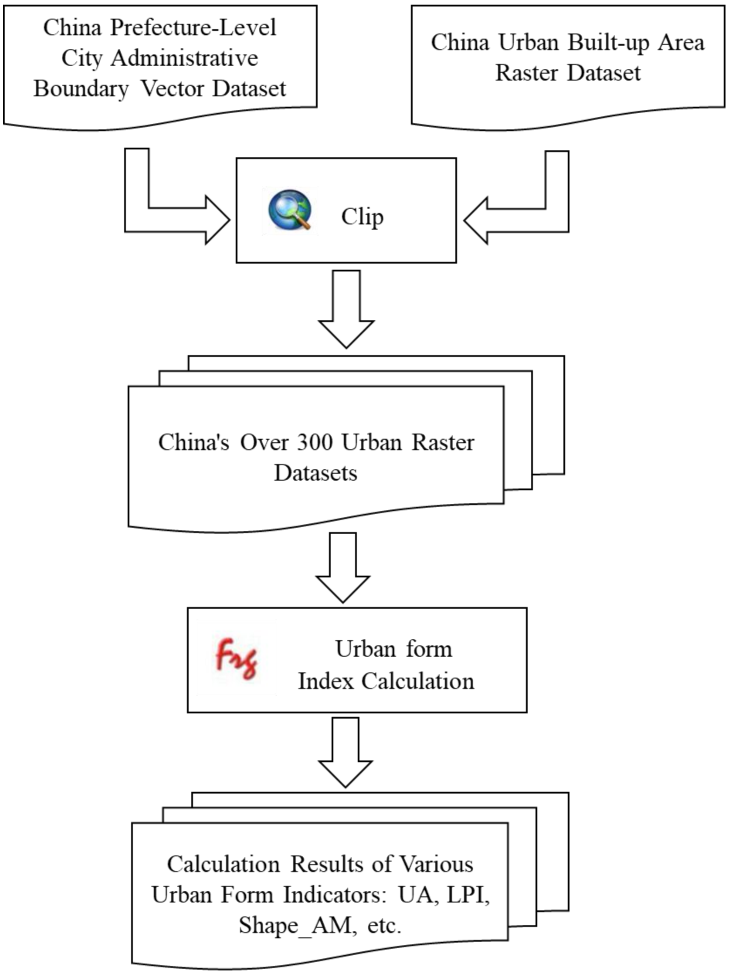

Figure 5-4 Urban Built-up Area Landscape Indicators Calculation Process(source：created by author)

Before formally initiating the analysis, given that the units and magnitudes of the spatial morphology indices vary, to increase the comparability between data and reduce errors, this study adopts the Max-Min (*MAX-MIN*) method to normalize the calculated data on urban spatial morphology to a range between 1 and 11.

Equation 5.4

$$Y=\frac{X\text{-}MIN(X)}{MAX(X)\text{-}MIN(X)}+1$$

In this formula, Y represents the normalized dimensionless data, which can be used for regression analysis; X is the original data for a certain spatial form index of a city; min(X) and max(X) respectively denote that variable's minimum and maximum values.

5.1.3 Spatio-Temporal Evolution Characteristics of Urban Land Use Geometry in China

Understanding the geometric morphology of Chinese cities and their spatiotemporal evolutionary characteristics is beneficial for grasping the current state of urbanization in China from a spatial perspective, thereby proposing targeted spatial arrangement strategies for carbon emission reduction. This section will reveal several morphological characteristics of Chinese cities through urban built-up area (*CA*), morphological complexity, aggregation, and polycentricity.

(1) Overall Significant Growth in Urban Land Area in China from 2005-2020

At a national level, the urban built-up area in China shows a steady growth trend from 2005 to 2020. In 2005, the urban built-up area was 46,348.62 square kilometers. By 2010, this figure had grown to 59,466.05 square kilometers, representing an approximate 28.3% increase over five years. In the following five years, the urban built-up area continued to grow, reaching 72,225.46 square kilometers by 2015, an increase of about 21.4% compared to 2010. However, from 2015 to 2020, although the urban built-up area increased to 78,099.36 square kilometers, the growth rate slightly slowed down. Overall, in the 15 years from 2005 to 2020, the urban built-up area increased by about 68.5%, with an average annual growth rate of about 4.6%. This data reveals the continuous advancement of urbanization in China and the stable expansion of the urban size.

From a provincial perspective, the distribution of urban construction land in China is significantly more concentrated in the eastern regions than in the central and western regions. Provinces such as Jiangsu, Zhejiang, and Guangdong have significant and dense urban built-up areas, which aligns with the higher economic development and population density in these areas. Coastal areas, due to their economic, transportation, and logistics conveniences, have fostered a larger demand for urban construction land. In central provinces, such as Hubei, Henan, and Anhui, the development of urban built-up areas is also relatively significant. However, their distribution is slightly sparser compared to the eastern regions. Sichuan Province has seen a major increase in urban construction land in the western region.

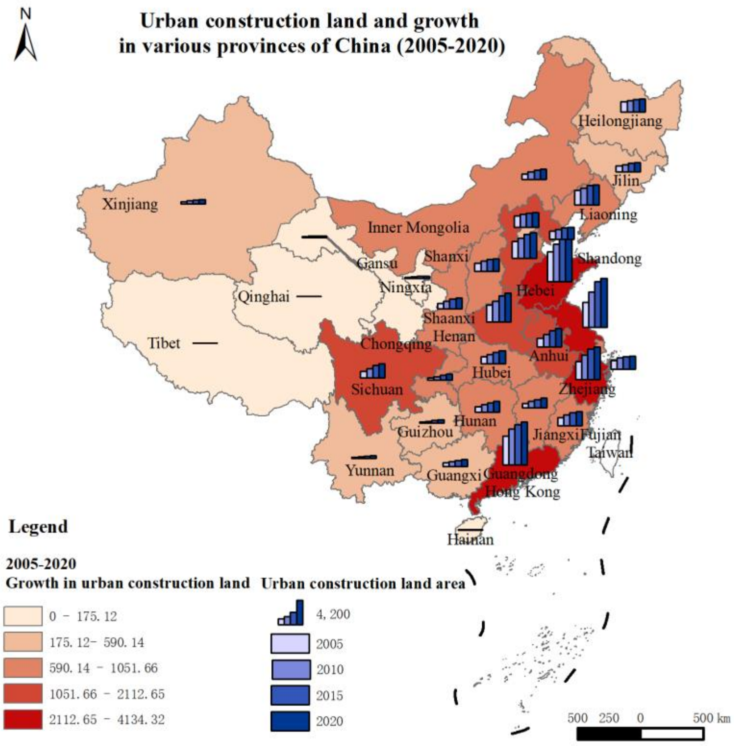

Figure 5-5 Urban Construction Land Area and Growth in Chinese Provinces, 2005-2020(source：created by author)

Paying attention to the recent trends in urban construction land expansion is beneficial for understanding the current situation and serving urban policy formulation. Therefore, this study calculated the growth trend of urban construction land from 2015 to 2020. The top ten provinces in terms of urban construction land growth rate over the past five years are Chongqing (20.68%), Guizhou (18.68%), Jiangxi (15.10%), Yunnan (14.96%), Guangxi (13.48%), Sichuan (13.03%), Hunan (12.27%), Anhui (12.13%), Hubei (11.17%), and Henan (11.15%). The spatial distribution shows that although the total amount of urban construction land in the central and western regions is lower than in the eastern region, the growth rate is faster. The spatial distribution mainly includes the southwestern regions of Yunnan, Guizhou, Sichuan, Chongqing, and Guangxi and the central regions of Jiangxi, Anhui, Hunan, Hubei, and Henan. The southwestern region, represented by Chongqing, has the fastest growth rate, while in the central region, Jiangxi has the fastest growth rate.

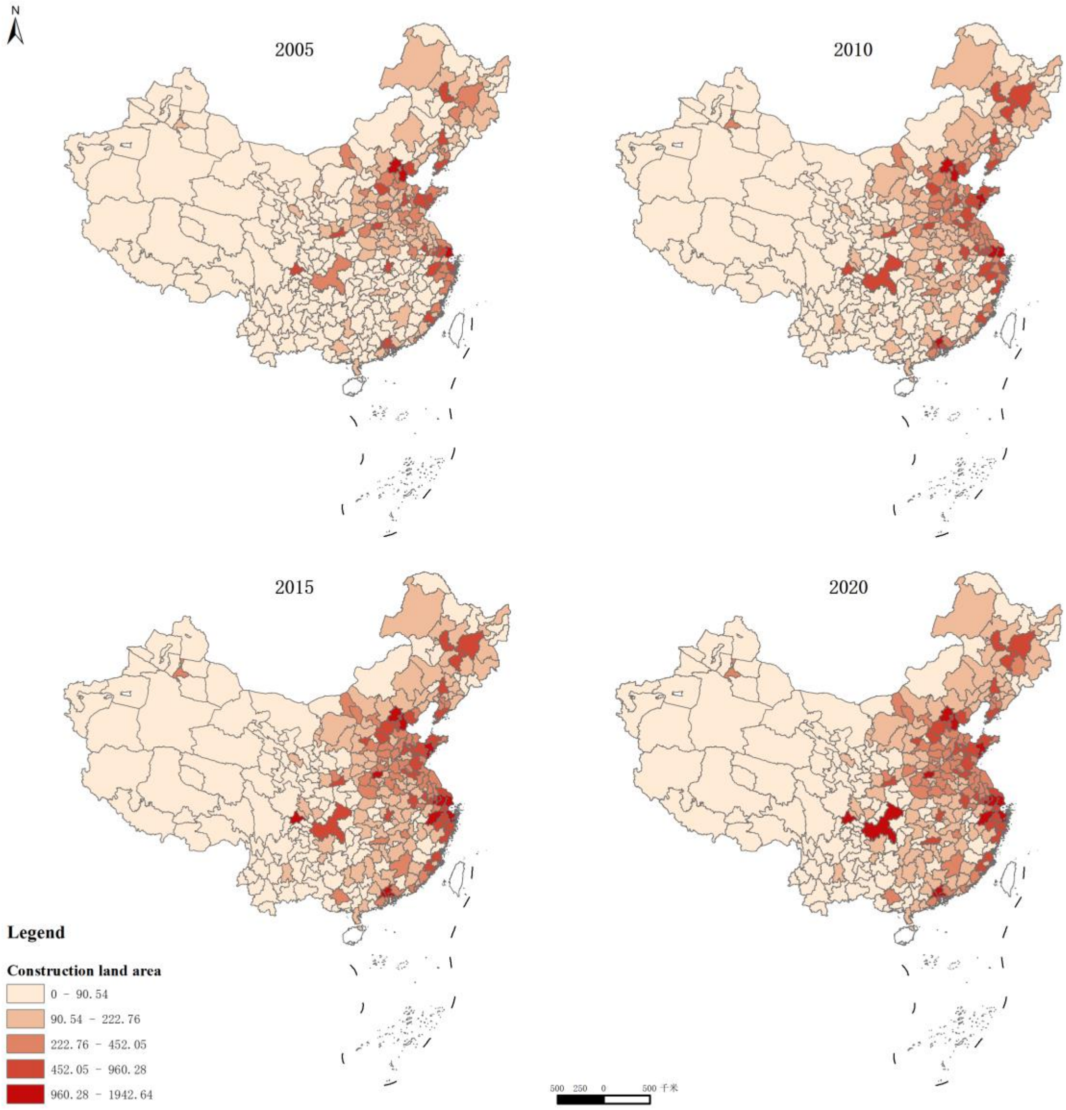

Figure 5-6 The spatial pattern of construction land in prefecture-level cities in China from 2005 to 2020(source: created by author)

Over the past two decades, urban construction land expansion in China has shown significant regional differences, especially in the eastern coastal areas. The Yangtze River Delta, Pearl River Delta, and Bohai Rim region, as China's most economically active regions, have experienced urbanization processes that are significantly faster and larger in scale than other regions. Urban construction land growth speed is particularly prominent in provincial capitals and regional central cities, reflecting their role as engines in the regional urbanization process. In 2005, the urban construction land size in the Bohai Rim and the Yangtze River Delta had already reached a certain scale and continued to grow rapidly in the subsequent twenty years or so. This growth trend gradually spread to inland cities, with the expansion of cities in the central region, such as Zhengzhou, Chengdu, and Chongqing, being particularly notable. By 2020, the Yangtze River Delta, Pearl River Delta, Bohai Rim, and Chengdu-Chongqing area became the main highlands of urban construction land.

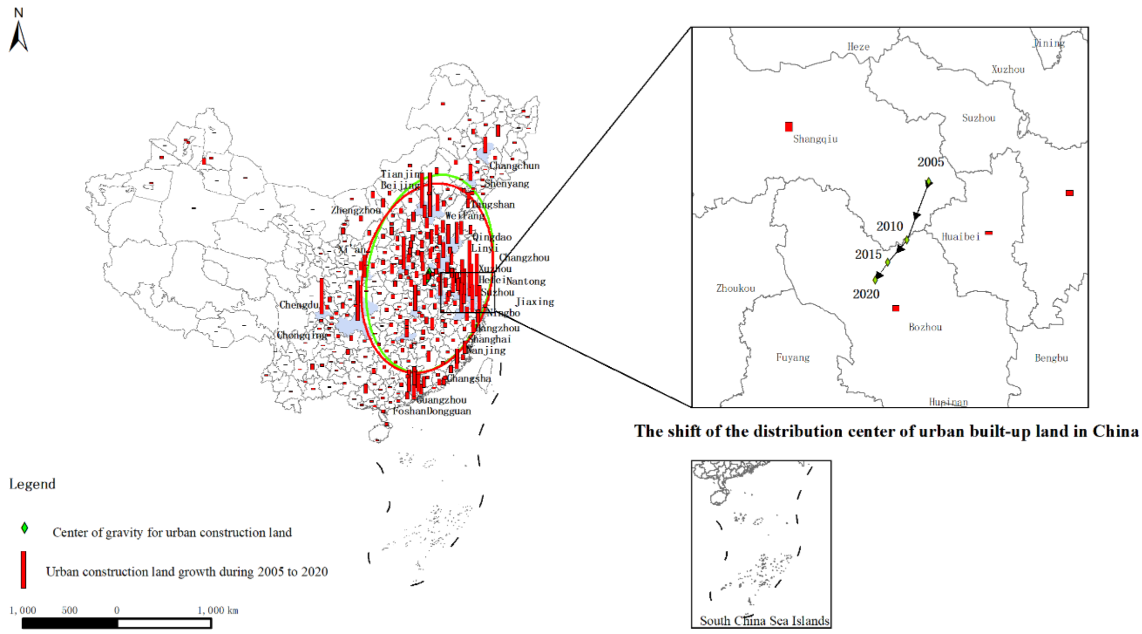

Figure 5-7 Trend of urban construction land use over time in Chinese cities(source: created by author)

The center of gravity for urban construction land in China has been moving towards the southwest. The movement of the urban construction land's center of gravity reveals China's urbanization development dynamics. To intuitively display the trend of change in urban construction land, this chapter calculated the net growth of urban construction land from 2005 to 2020 and the migration trend of the center of gravity of China's urban construction land. As shown, the period 2005 to 2010 witnessed the largest movement of the urban construction land's center of gravity, showing a significant trend of moving southward. After 2010, the center of gravity continued to move southward but with an enhanced trend towards the west. Considering the net growth of urban construction land, the Yangtze River Delta has seen a trend of dense and rapid growth of urban construction land over the past twenty years, with cities around Shanghai in Jiangsu and Zhejiang also rapidly expanding. In the southern Pearl River Delta region, including Guangzhou, Foshan, Dongguan, Zhuhai, and Shenzhen. In the western region, Chengdu, Chongqing, and Xi'an experienced rapid growth. In the central region, Zhengzhou, Hefei, Wuhan, and Changsha ranked the highest.

Overall, the growth of urban construction land in China shows a trend of gradual diffusion from east to west and from the coast to the inland. This change maps the spatial pattern of China's economic development and reflects the effects of regional development strategies and policy orientations. Future urban planning and land use policies must consider this dynamic trend to achieve more balanced and sustainable urban development.

(2) Spatiotemporal Evolution Characteristics of Urban Land Shape Complexity in China

This chapter employs the Area-Weighted Mean Shape Index (*AWMS*) and Area-Weighted Patch Fractal Dimension (*AWMPFD*) to quantify the complexity of urban shapes. To present the current state and evolution trend of shape complexity within the Chinese urban system, this chapter visualizes the Area-Weighted Mean Shape Index

(*AWMS*) and Area-Weighted Patch Fractal Dimension (*AWMPFD*) for 2020. It calculates the changes in these indices from 2005 to 2020. This allows for a better understanding of the complexity of urban land shapes in terms of spatial patterns and temporal trends. Although there are some differences in the research results of the two indices, the overall outcomes are largely consistent and corroborate each other. The study finds that the shape complexity of land use in large cities in China is higher than those in medium and small cities.

Moreover, the complexity of urban land north of the Yangtze River is higher than in the region south. Typical examples include the Yangtze River Delta, encompassing Shanghai, the Suzhou-Wuxi-Changzhou to Hefei area, the Hangzhou-centered urban cluster; the Shandong Peninsula urban cluster; and the Beijing-Tianjin area. In the south, urban land shapes in the Pearl River Delta urban cluster tend to be more complex. Other regions are primarily represented by central cities such as Wuhan, Nanchang, Changsha, Zhengzhou, and Chongqing.

Between 2005 and 2020, the shape complexity of urban land in the vast majority of cities showed an increasing trend(Figure 5-8). However, a small portion of cities, mainly medium- and small-sized, exhibited a declining trend in land complexity. Cities where urban land shape complexity increased rapidly from 2005 to 2020 are primarily new first-tier or second-tier cities, such as Zhengzhou, Xi'an, Quanzhou, Kunming, Dongguan, Foshan, Nanchang, Suzhou, et al. A possible reason is that these cities, following the development of first-tier cities, are rapidly urbanizing and expanding. Economic development, diversification of industries, and increased commercial activities have led to a growth in urban spatial demand, further driving the complexity of urban spatial structures. New first-tier and second-tier cities might be more flexible and proactive in urban planning and land use policies to support rapid urban development, leading to continuous changes and complexity in urban shapes. Regions with a significant decrease in land complexity include Qingdao and its surrounding cities like Rizhao and Weifang, as well as the northern Guangdong cities of Qingyuan and Zhaoqing. The smoothness of the peripheries in these cities is reducing, and the regularity of urban land use is increasing. This may reflect a gradual transition to more planned, orderly, and infill stages of development in these cities, emphasizing the effective use of urban land and spatial planning.

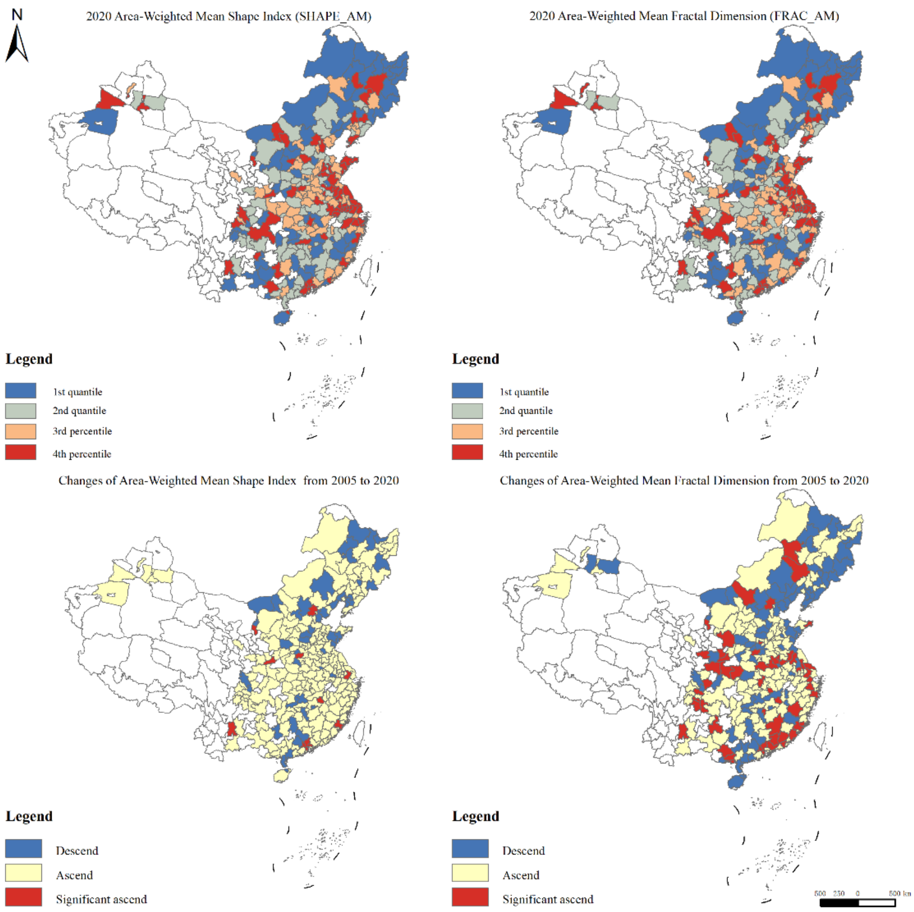

Figure 5-8 Spatial-temporal pattern of urban land shape complexity in Chinese cities(source: created by author)

(3) Spatiotemporal Evolution Characteristics of Urban Land Compactness in China

The compactness of urban development has always been an important direction in the study of urban spatial structure. This research uses the Urban Land Aggregation Index (*AI*) and the Core Area Percentage of Landscape (*CAPL*) to quantify the compactness of urban land. As illustrated below, the research results indicate significant spatial differences in the compactness of urban land across China. Regions such as Shandong, Henan, the Beijing-Tianjin-Hebei area, and cities in the Northeast exhibit higher levels of land aggregation, where urban plots are closer to each other, facilitating the formation of a compact entity. Combined with the Core Area Percentage Index, cities in Henan, Shandong, and the Yangtze River Delta exhibit higher compactness. The possible reason for the Beijing-Tianjin area is its long history, dense population, and concentrated economic development, which tends to maintain or increase land compactness during urban planning and expansion. The urban development in the Northeastern region is influenced by its industrial base and historical development pattern, resulting in a more concentrated urban land spatial structure.

In the southern regions, such as Fujian, Guangdong, and the Southwest, the compactness of cities is relatively lower compared to the Central and Northern regions. The southern region, especially Fujian and the Southwest features complex terrain dominated by mountains and hills. This mountainous and hilly terrain restricts the spatial expansion of cities, leading to more dispersed urban development and making it difficult to form a compact urban structure. For example, the mountains surrounding the Sichuan Basin and the terrain of the Yunnan-Guizhou Plateau have a significant impact on urban layout. Numerous rivers and lakes in Guangdong Province's and Fujian Province's coastal areas also influence urban development and expansion to some extent. Cities must plan around these natural geographical conditions, which may lead to more dispersed urban land use.

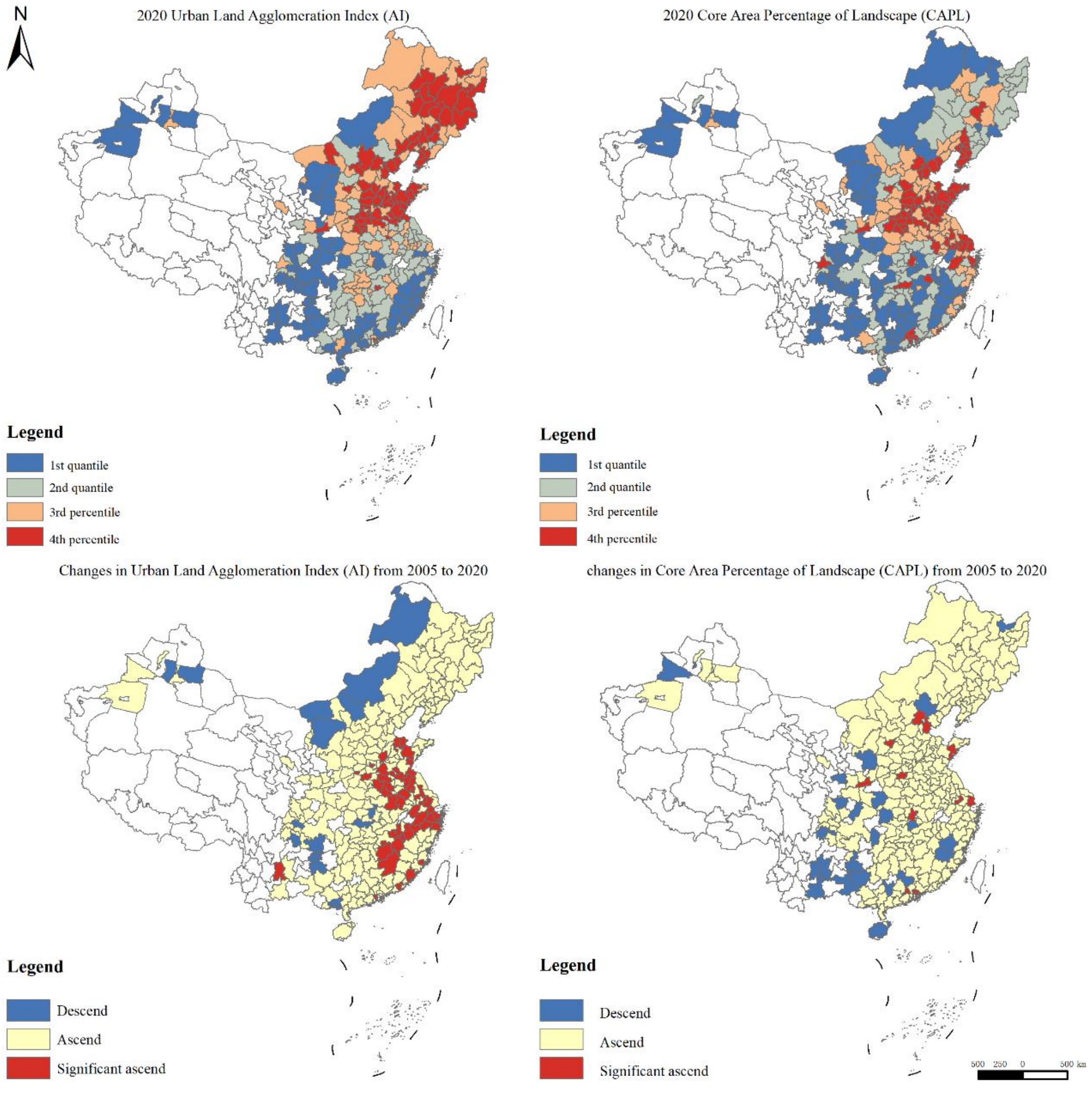

Figure 5-9 Spatial-temporal pattern of urban land form agglomeration in China(source：created by author)

From the perspective of change trends, from 2005 to 2020, urban land in China has evolved towards a more compact development model. Only a few cities still developed towards a looser urban spatial structure, all located in the central and western regions, such as Xiaogan in Guizhou, Qinzhou in Guangxi, and Jingzhou in Hubei. The relatively lagging economic development and slower urbanization processes in these areas may have resulted in less concentrated urban planning and construction. Regions where urban compactness significantly increased are mainly in the central and eastern areas, such as Jiangxi, Anhui, Henan, and Zhejiang.

(4)Spatiotemporal Evolution Characteristics of Urban Land Polycentricity in China

This study uses the Number of Core Areas (*NCA*) and the Coefficient of Variation of Core Areas (*CACV*) to characterize the polycentric nature of cities. A smaller number of core areas and a higher *CACV* mean a city tends towards a monocentric spatial structure. Conversely, a larger number of core areas and a smaller *CACV* mean that a city tends towards a polycentric spatial structure development model.

The eastern coastal region to the Bohai Rim area has a high value of core area numbers, indicating that urban functions and activities are distributed across multiple areas. In polycentric cities, commercial, administrative, cultural, and entertainment facilities are not concentrated in a single central area but are spread across multiple city areas. Northern Jiangsu, Jiangsu, and Henan exhibit low *CACV*, meaning these areas feature a balanced distribution of polycentric characteristics. The Yangtze River Delta area has a high *CACV*, indicating that although there are multiple centers in these areas, there is a significant difference in the scale and function of these centers, comprising a polycentric urban spatial structure with high-grade urban core areas and other lower-grade urban sub-centers.

The southeastern coastal region generally shows a low number of core areas and a high *CACV*, meaning these cities typically have fewer urban centers, and there is a significant difference in the scale and function of these urban centers, with the main urban area occupying an absolute core position, showing monocentric development spatial structure characteristics. A possible reason is the geographical condition of "eight mountains, one water, and one field" in the southeastern coastal region, limiting cities' ability to expand in all directions. Especially in some coastal cities, the topography (such as mountains and bodies of water) limits the city's spatial layout, leading to a high concentration of urban core areas.

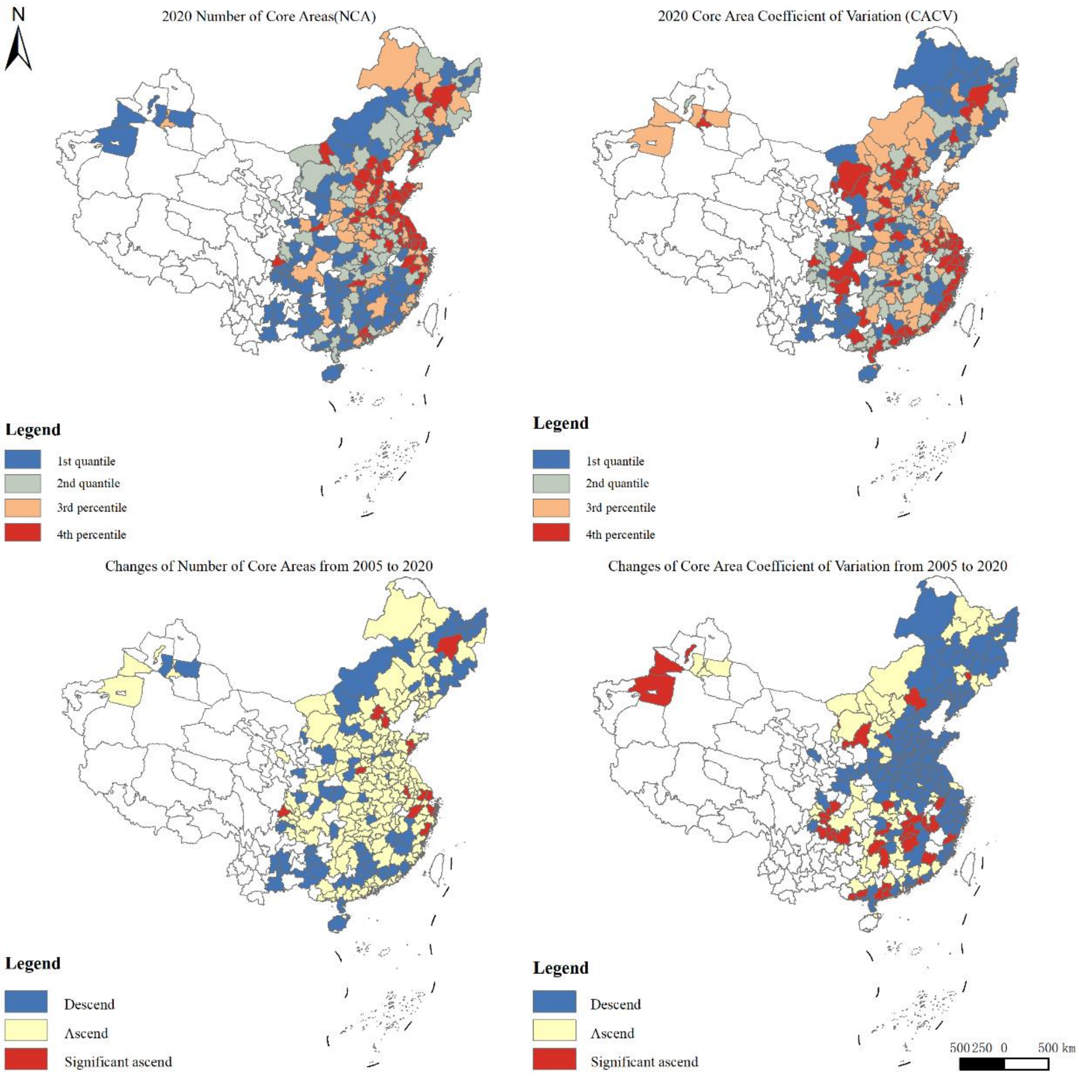

Figure 5-10 Spatial-temporal pattern of poly-centric/mono-centric spatial structure characteristics in Chinese cities(source：created by author)

Observing the changes in core areas, the number of core areas in most cities generally increases, while in some regions, the number of core areas decreases. For instance, the number of core areas is declining in the western part of Fujian, northern Guangdong, Guangxi, and the northeastern region. Cities experiencing a significant increase in the number of core areas include Shanghai, Suzhou, Hangzhou, Ningbo, Hefei in the Yangtze River Delta; Qingdao in Shandong; Zhengzhou in Henan; Chengdu in Sichuan; Beijing, Tianjin, and Harbin. These relatively developed cities within their regions serve as economic centers that have undergone rapid economic growth. Economic prosperity has brought more commercial activities, job opportunities, and population aggregation, which has promoted the development of new commercial and household areas, thereby increasing the number of urban core areas.

5.2 Empirical Analysis of the Impact of Urban Geometric Morphology on Carbon Emissions

Urban construction land's expansion and morphological expression manifest urban socio-economic activities in space. Building on the overall understanding of urban spatial geometry obtained in the previous sections, this chapter constructs a quantitative model to explore the impact of urban spatial structure characteristics—land area, land shape complexity, land compactness, and polycentric/monocentric structure—on total carbon emissions, industrial carbon emissions, transportation carbon emissions, and household carbon emissions.

As a foundational element of urban spatial structure, urban land area plays a fundamental role in influencing urban carbon emissions. Research on the urban land area has focused chiefly on provincial-level and economic development studies, with fewer studies directly exploring the relationship between urban construction land expansion and its effects on energy consumption and carbon emissions(Zhang & Chen, 2017), and even fewer conducting a systematic analysis of the impact of urban construction land expansion on the detailed sectors of industrial carbon emissions, transportation carbon emissions, and household carbon emissions. Therefore, this study begins by exploring the impact of urban geometry on carbon emissions, starting with urban land area.

5.2.1 Impact of Urban Land Area on Carbon Emissions

The size of urban land(CA: City Area) determines the capacity of urban space and, to a certain extent, determines the carrying capacity of urban socio-economic activities, making it the most basic characteristic of urban spatial structure. From the total urban land area perspective, this section first explores its scaling relationship with carbon emissions. The study uses a panel data model for analysis, including observations from 2005, 2010, 2015, and 2020, totaling 984 observations. The panel data model was constructed as follows：

Total carbon emissions:

Equation 5.5

$$\ln(Total\_Emission)_{it}=\beta_{01}+\beta_{11}\ln(CA)_{it}+\mu_{i1}+\gamma_{t1}+\epsilon_{it1}$$

Industrial carbon emissions:

Equation 5.6

$$\ln(Industrial\_Emission)_{it}=\beta_{02}+\beta_{12}\ln(CA)_{it}+\mu_{i2}+\gamma_{t2}+\epsilon_{it2}$$

Transportation carbon emissions:

Equation 5.7

$$\ln(Transport\_Emission)_{it}=\beta_{03}+\beta_{13}\ln(CA)_{it}+\mu_{i3}+\gamma_{t3}+\epsilon_{it3}$$

Household carbon emission:

Equation 5.8

$$\ln(Household\_Emission)_{it}=\beta_{04}+\beta_{14}\ln(CA)_{it}+\mu_{i4}+\gamma_{t4}+\epsilon_{it4}$$

The research results show a strong positive correlation between urban land use and carbon emissions. The R-squared values in the study results are 0.416, 0.284, 0.469, and 0.338, corresponding to total, household, transportation, and industrial carbon emissions, respectively. This means that the model has successfully explained the variability of various types of carbon emission data to different extents. For example, an R-squared value of 0.416 for the total carbon emissions model indicates that the model explains 41.6% of the variability in total carbon emissions. Contrary to the sub-linear relationship between urban population size and carbon emissions discussed earlier, there is a super-linear relationship between urban land area and carbon emissions. From the preliminary super-linear relationship between urban land use and carbon emissions, it can be found that the expansion of urban land use overall contributes to a significant increase in urban carbon emissions.

Table 5-1 Results of urban land area carbon emission scaling index

Variable	Equation 5.5 ln(*Total Emission*)	Equation 5.6 ln(*Household Emission*)	Equation 5.7 ln(*Transport Emission*)	Equation 5.8 ln(*Industrial Emission*)
ln(*CA*)	1.277***	1.465***	1.280***	1.388***
	(0.0974)	(0.00814)	(0.0980)	(0.111)

Variable	Equation 5.5 ln(*Total Emission*)	Equation 5.6 ln(*Household Emission*)	Equation 5.7 ln(*Transport Emission*)	Equation 5.8 ln(*Industrial Emission*)
Constant	7.132***	3.369***	4.371***	6.718***
	(0.0554)	(0.00463)	(0.0557)	(0.0631)
Observations	984	984	984	984
R-squared	0.416	0.284	0.469	0.338
Number of years	4	4	4	4

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

（1）Total carbon emission

The regression coefficient between total carbon emissions and urban land area is 1.277, indicating that for every 1% increase in urban land area, the total carbon emissions of a city will correspondingly increase by 1.277%. This result suggests that as urban land area expands, related economic activities likely increase, including expanding industries such as construction, manufacturing, and transportation, thereby leading to higher energy consumption and carbon emissions.

To gain a more comprehensive understanding of the dynamics between urban spatial structure and carbon emissions, this chapter further explores the relationship between urban land area and carbon emission efficiency. The econometric model constructed is as follows:

Equation 5.9

$$\ln(Carbon\ Efficiency)_{it}=\beta_{01}+\beta_{11}\ln(CA)_{\mathrm{it}}+X_{it}\beta+\mu_{i1}+\gamma_{t1}+\epsilon_{it1}$$

Formula 10 establishes the relationship between urban land area and GDP, helping to determine the economic reasons for changes in carbon emission efficiency caused by variations in urban land area.

Equation 5.10

$$\ln(GDP)_{\mathrm{it}}=\beta_{01}+\beta_{11}\ln(CA)_{\mathrm{it}}+X_{it}\beta+\mu_{i1}+\gamma_{t1}+\epsilon_{it1}$$

In the formula, carbon emission efficiency is represented by carbon emissions per unit of gross domestic product (*GDP*), meaning that lower carbon emissions per unit of *GDP* indicate less environmental pressure to achieve a unit of societal welfare. "*X*" includes other control variables that may influence carbon emissions or carbon emission efficiency. This chapter controls for population (*pop*) and industrial structure (the proportion of the tertiary sector) as two fundamental variables affecting the urban economy and carbon emissions.

Table 5-2 Results of urban land use and carbon emission efficiency

Variables	Equation 5.9		Equation 5.10	
	ln(*Carbon Efficiency*)	ln(*Carbon Efficiency*)	ln(*GDP*)	ln(*GDP*)
ln(*CA*)	-0.486***	-0.183**	1.761***	1.520***
	(0.0287)	(0.0322)	(0.0804)	(0.106)
ln(*pop*)		-0.372**		0.335***
		(0.0660)		(0.0510)
ln(*Industrial structure*)		-0.168		0.00230
		(0.114)		(0.0585)
Constant	0.996***	3.667***	6.137***	4.266***
	(0.0163)	(0.615)	(0.0458)	(0.300)
Observations	984	984	984	984
R-squared	0.080	0.156	0.762	0.806
Number of years	4	4	4	4

Robust standard errors in parentheses； *** p<0.01, ** p<0.05, * p<0.1

From the regression results, while the growth of urban land area has led to a rapid increase in total carbon emissions, it has also achieved improvements in carbon emission efficiency, mainly due to the city's economy growing faster than its carbon emissions. The regression analysis shows that urban land area is negatively correlated with carbon emissions per unit of *GDP*, even after controlling for population and industrial structure variables. This indicates that the expansion of urban land area has contributed to the rapid growth of urban *GDP*. The R-squared values reach nearly 80%, suggesting the model can explain 80% of the variability in carbon emission efficiency, which is relatively high explanatory power. This may imply that a city's economic growth is largely related to land development. In China, land finance—where the government raises fiscal revenue by selling land use rights—has been an essential source of city income. Thus, this high correlation may reflect the close link between urban economic growth and land expansion, highlighting the significance of land expansion in driving urban economic growth. This could also suggest a pattern where the expansion of urban land use is a key driver of economic growth.

In analyzing the overall relationship between urban land area and carbon emissions in China, this study aims to provide empirical support for urban low-carbon spatial planning. To this end, we will explore the spatial heterogeneity of the impact of urban land area on carbon emissions, conducting grouped regression analysis for China's eastern, central, western, and northeastern regions. Research results show the impact of urban land expansion on carbon emissions in descending order: Western (1.678) > Northeastern (1.405) > Central (1.359) > Eastern (1.268) regions.

The highest elasticity coefficient in the western region (1.678) may relate to the area's economic development mode, energy structure, and industrial layout. Due to geographical location, historical factors, and socio-cultural influences, the western region has long been socio-economically underdeveloped. The Western Development Strategy, implemented in 1999 and further promoted by the "Guidelines for Further Promoting the Development of the West in the New Era" issued by the State Council in 2020, aimed to address these imbalances. From 1999 to 2020, the regional GDP of the western area increased from 1.58 trillion to 21.3 trillion. However, according to the *Western Blue Book: China Western Development Report*, despite overall innovation insufficiency, lower levels of industrial structure, higher pollutant emissions, lower levels of green production, and insufficient supply of ecological products in the western region, which confirms the research finding that urban development in the western region tends to follow a "high-carbon expansion" trend. Combined with the findings that innovation has both emission reduction and increase effects, the western region should consider green innovation in urban expansion, especially in transferring state-owned land, to break away from the high-carbon model.

The elasticity coefficient for the northeastern region (1.405) follows, historically a base for China's heavy industry. Although industrial restructuring has been ongoing in recent years, the proportion of heavy industry remains substantial. In recent years, the traditional place-based economy, driven by resource endowments, has gradually been replaced by an economy driven by dynamic factors such as innovation, location, and talent, leading to regional urban shrinkage in the Northeast, an objective geographical reality(Sun et al., 2023). With significant urban population outflow in the Northeast, research using census data found urban shrinkage in 32 out of 34 prefecture-level cities(Gong et al., 2022). When dynamic factors withdraw from urban land, the land cannot reduce accordingly, often resulting in an anchoring effect on energy consumption and carbon emissions. The research found a paradox of "population shrinkage-space expansion" in shrinking cities, where urban populations decrease, but construction land further increases, leading to inefficient land use and development issues(Long et al., 2015). Against general shrinkage, the Northeast should strictly review and cautiously expand urban construction land. Identifying elements that still have comparative advantages in the region, revitalizing resources, achieving economic increments based on stock construction land, and avoiding ineffective land expansion could prevent economic stagnation and maintain high carbon emissions.

The lowest elasticity coefficient in the eastern region (1.268) may reflect the maturity and advancement of urban planning and low-carbon development. Cities in the eastern region, usually with higher economic development, might invest more in new energy and clean technologies, helping reduce carbon emissions per unit of land area.

Table 5-3 Results of urban land area carbon emissions grouping

Variable	Eastern China	Central China	Western China	Northeast China
	ln(*Total Emission*)	ln(*Total Emission*)	ln(*Total Emission*)	ln(*Total Emission*)
ln(*CA*)	1.268***	1.359***	1.678***	1.405***
	(0.117)	(0.177)	(0.207)	(0.116)
Constant	7.089***	7.104***	7.074***	7.057***
	(0.0990)	(0.0793)	(0.0715)	(0.0566)
Observations	340	308	200	136
R-squared	0.519	0.267	0.234	0.475

Variable	Eastern China ln(*Total Emission*)	Central China ln(*Total Emission*)	Western China ln(*Total Emission*)	Northeast China ln(*Total Emission*)
Number of years	4	4	4	4

Robust standard errors in parentheses； *** p<0.01, ** p<0.05, * p<0.1

Urban population density plays a vital role in the impact of land expansion on carbon emissions. It directly reflects the intensity of population aggregation and other productive factors in urban space, directly affecting urban land's utilization intensity and efficiency. Therefore, the impact of urban land expansion on carbon emissions varies under different urban population densities. Current research in urban planning has focused more on the characteristics and driving mechanisms of urban construction land expansion, with less attention given to the impact of urban carbon emissions under different urban population densities. This chapter categorizes cities into quartiles based on urban population density—sorting cities from low to high density and dividing them into groups 0-25%, 25%-50%, 50%-75%, and 75%-100%.

Table 5-4 Urban land area and carbon emissions: quantile regression results

Variable	1st quartile ln(*Total Emission*)	2nd quartile ln(*Total Emission*)	3rd quartile ln(*Total Emission*)	4th quartile ln(*Total Emission*)
ln(*CA*)	1.809**	1.336***	1.229***	1.192***
	(0.237)	(0.0879)	(0.106)	(0.0245)
Constant	6.933***	7.018***	7.168***	7.289***
	(0.0790)	(0.0503)	(0.0737)	(0.0162)
Observations	246	245	245	245
R-squared	0.234	0.479	0.419	0.447
Number of years	4	4	4	4

Robust standard errors in parentheses； *** p<0.01, ** p<0.05, * p<0.1

The research findings indicate that as urban density increases, the impact of urban land expansion on carbon emissions diminishes. In cities within the 1st quartile (cities with the lowest density), the coefficient for ln(CA) is the highest (1.809), significant at the 5% level, indicating that in cities with the lowest population density, each 1% increase in urban land area leads to a 1.809% increase in carbon emissions. This may reflect the greater environmental pressure of land use in expanding low-density cities. In cities within the 2nd quartile, the coefficient for ln(CA) is 1.336, significant at the 1% level, indicating that the impact of urban land area increase on carbon emissions in cities with lower population density is reduced compared to the 1st quartile. In the 3rd quartile cities, the coefficient for ln(CA) further decreases to 1.229, significant at the 1% level, showing that as urban population density increases, the impact of urban land area increase on carbon emissions becomes progressively smaller. In the 4th quartile cities (cities with the highest density), the coefficient for ln(CA) is the smallest (1.192), significant at the 1% level, indicating that in cities with the highest population density, the impact of urban land area increase on carbon emissions is the smallest. This could be due to more compact urban planning, efficient energy use, and more developed public transportation systems in high-density cities. Urban spatial structure arrangements should comprehensively consider urban population density to align land supply with population flow, carefully evaluating the land demand of low-density cities. Low-density cities should focus on intensification, maximizing benefits on existing land to avoid extensive expansion.

(2) Industrial carbon emission

Research on the impact of industrial carbon emissions tends to analyze socio-economic factors such as industrial and energy structures(Yuan et al., 2019), technological progress(Ma et al., 2019), et al. There is a lack of exploration from the perspective of urban physical space—construction land—on its impact on industrial carbon emissions. This section explores the relationship between urban land area and industrial carbon emissions, providing theoretical and empirical support for urban planning and sustainable development strategies. In this research, three fixed-effect regression models were constructed to explore the impact of urban land area and population size on industrial carbon emissions. Equation 5.11 aims to depict the quantitative relationship between urban land area and industrial carbon emissions. Equation 5.12 controls for population size, i.e., exploring how urban land area impacts industrial carbon emissions when population size remains constant. Equation 5.13 uses industrial carbon emissions per unit output (industrial carbon emissions/total value of secondary and tertiary industries) as a variable to explore how urban land affects changes in industrial carbon emission efficiency.

Equation 5.11

$$\ln(\textit{Industrial emission})_{it}=\beta_{01}+\beta_{11}\ln(CA)_{it}+\mu_{i1}+\gamma_{t1}+\epsilon_{it1}$$

Equation 5.12

$$\ln(\textit{Industrial emission})_{it}=\beta_{02}+\beta_{12}\ln(CA)_{it}+\beta_{12}\ln(pop)_{it}+\mu_{i2}+\gamma_{t2}+\epsilon_{it2}$$

Equation 5.13

$$\ln(\textit{Industrial emission per unit output})_{it}=\beta_{03}+\beta_{13}\ln(CA)_{it}+\beta_{23}\ln(pop)_{it}+\mu_{i3}+\gamma_{t3}+\epsilon_{it3}$$

Table 5-5 The impact of urban land area on industrial carbon emissions

Variable	Equation 5.11 ln(*Industrial Emission*)	Equation 5.12 ln(*Industrial Emission*)	Equation 5.13 ln(*Industrial emission per unit output*)
ln(*CA*)	1.388***	1.535***	-0.159
	(0.111)	(0.0728)	(0.0678)
ln(*pop*)		-0.204**	-0.477**
		(0.0626)	(0.115)
Constant	6.718***	7.855***	3.458**
	(0.0631)	(0.407)	(0.652)
Observations	984	984	984
R-squared	0.338	0.350	0.134
Number of years	4	4	4

Robust standard errors in parentheses； *** p<0.01, ** p<0.05, * p<0.1

The research finds that the coefficient for ln(*CA*) (the logarithm of urban land area) is 1.53, indicating that a 1% increase in urban land area is expected to lead to an approximate 1.53% increase in industrial carbon emissions. This might be because expanding urban land area provides more space for industrial and commercial activities. Such expansion may accompany the construction of new industrial facilities, increased production capacity, and broader logistics demands. On the expanded land, there could be more energy-intensive industrial activities, such as manufacturing and processing industries, which are usually closely associated with higher carbon emissions. In Equation 5.12, the coefficient for ln(*pop*) (the logarithm of urban population) is -0.20, suggesting that with every 1% increase in urban population (on a logarithmic scale), after controlling for land area, industrial carbon emissions are expected to decrease by about 0.20%. After controlling for population size, the coefficient for *ln(CA)* increases to 1.535, meaning that expanding urban land area increases industrial carbon emissions to a greater extent when the population size remains constant. Since the population remains unchanged, expanding urban land also implies a decrease in urban density, so the research results also mean that the expansion of low-density urban land is a cause of more industrial carbon emissions. In Equation 5.13, the value of *ln(pop)* is negative, indicating that increasing the population on the constant urban land reduces the industrial carbon emissions per unit output. This suggests that, overall, in the Chinese urban system, maintaining efficient use of urban land helps to improve energy use efficiency and reduce carbon emissions.

(3) Transportation carbon emission

Urban transportation emissions, as one of the major sources of carbon emissions, have become a key area for reducing greenhouse gas emissions and achieving sustainable development goals. The scale of urban land sets the geographical boundaries for urban socio-economic activities. This section constructs the following models to analyze the relationship between urban land area and transportation carbon emissions. Equation 5.14 explores the quantitative relationship between urban land area and the evolution of transportation carbon emissions in a sample of Chinese cities. Population is the source of carbon emissions, and urban transportation carbon emissions result from the metabolism of human or goods movement activities. Controlling the population size variable can further reveal the impact of urban land expansion on carbon emissions under constant population size. Therefore, Equation 5.15 controls for the urban population variable.

Equation 5.14

$$\ln(Transport\ Emission)_{it}=\beta_{01}+\beta_{11}\ln(CA)_{\mathrm{it}}+\mu_{i1}+\gamma_{t1}+\epsilon_{it1}$$

Equation 5.15

$$\ln(Transport\ Emission)_{\mathrm{it}}=\beta_{02}+\beta_{12}\ln(CA)_{it}+\beta_{12}\ln(pop)_{\mathrm{it}}+\mu_{i2}+\gamma_{t2}+\epsilon_{it2}$$

Table 5-6 Results of the impact of urban land area on transportation carbon emissions

Variable	Equation 5.14 ln(*Transport Emission*)	Equation 5.15 ln(*Transport Emission*)
ln(*CA*)	1.280***	0.969***
	(0.0980)	(0.0913)
ln(*pop*)		0.432***
		(0.0377)
Constant	4.371***	1.964***
	(0.0557)	(0.223)
Observations	984	984
R-squared	0.469	0.554
Number of years	4	4

Robust standard errors in parentheses； *** p<0.01, ** p<0.05, * p<0.1

The study finds that the impact of urban land expansion on transportation carbon emissions is not homogeneous across cities of different urban land sizes; significant variations in the impact may exist. To further explore the influence of urban land area on transportation carbon emissions from the perspective of urban diversity, this research first categorized urban land area into quartiles and then conducted regression analyses separately for each. The results exhibit a "high at both ends, low in the middle" characteristic, meaning that the regression coefficients for the 1st and 4th quartile groups are significantly higher than those for the middle two quartiles. This indicates that overall, urban land area expansion in cities with both smaller and larger land sizes generally leads to faster growth in transportation carbon emissions. The reason may be that in smaller cities, urban land expansion could accompany an increase in private car usage and a relative lack of public transportation services, resulting in a larger amount of transportation carbon emissions. While larger cities might have a more comprehensive public transportation system, further expansion of urban land area could lead to the development of new suburbs and satellite towns that may not be close to efficient public transportation networks. These results suggest that when formulating urban planning and transportation strategies, cities must consider specific conditions and development stages to achieve more effective carbon reduction and sustainable development.

Table 5-7 Group regression results of the impact of urban land area on transportation carbon emissions

Variable	1st quartile ln(*Transport Emission*)	2nd quartile ln(*Transport Emission*)	3rd quartile ln(*Transport Emission*)	4th quartile ln(*Transport Emission*)
ln(*CA*)	3.785***	1.137	0.989**	1.462***
	(0.453)	(0.944)	(0.227)	(0.0564)
Constant	3.746***	4.515***	4.584***	4.175***
	(0.0843)	(0.325)	(0.129)	(0.0663)
Observations	246	246	246	246
R-squared	0.064	0.008	0.044	0.611
Number of years	4	4	4	4

Robust standard errors in parentheses； *** $p<0.01$, ** $p<0.05$, * $p<0.1$

（4）Household carbon emission

This section discusses the impact of urban land area on household carbon emissions. This study designed a series of fixed-effect regression models to quantify these impacts systematically. Through these models, we can statistically analyze the impact of urban land area on household carbon dioxide emissions. This research first comprehensively grasps the quantitative relationship between urban land area and household carbon emissions in Chinese cities (Equation 5.16). According to general laws and experiences of urban development, the growth of urban land area often accompanies the aggregation of the urban population. In Equation 5.17, urban population size is introduced to explore the impact of urban land area on carbon emissions, excluding the influence of population size. A significant portion of household carbon emissions comes from carbon emissions due to temperature regulation, including carbon emissions from air conditioning in summer and heating in northern cities during winter. This part of household carbon emissions is directly affected by urban temperature. Therefore, in Equation 5.18, the temperature variable is controlled. The economic level also influences household carbon emissions. Thus, in Equation 5.19, per capita Gross Domestic Product (GDP) is further included as a control variable.

Equation 5.16

$$\ln(Household\ Emission)_{\mathrm{it}}=\beta_{01}+\beta_{11}\ln(CA)_{it}+\mu_{i1}+\gamma_{t1}+\epsilon_{it1}$$

Equation 5.17

$$\ln(Household\ Emission)_{it}=\beta_{02}+\beta_{12}\ln(CA)_{it}+\beta_{12}\ln(pop)_{it}+\mu_{i2}+\gamma_{t2}+\epsilon_{it2}$$

Equation 5.18

$$\ln(Household\ Emission)_{it}=\beta_{03}+\beta_{13}\ln(CA)_{it}+\beta_{23}\ln(pop)_{it}+\beta_{33}\ln(Temperature)_{it}+\mu_{i3}+\gamma_{t3}+\epsilon_{it3}$$

Equation 5.19

$$\ln(Household\ Emission)_{it}=\beta_{04}+\beta_{14}\ln(CA)_{it}+\beta_{24}\ln(pop)_{it}+\beta_{34}\ln(Temperature)_{\mathrm{it}}$$
$$+\beta_{44}\ln(GDP\ per\ capita)_{it}+\mu_{i4}+\gamma_{t4}+\epsilon_{it4}$$

The study finds a significant correlation between urban land area and household carbon emissions, showing a super-linear relationship. In Equation 5.16, a 1% increase in urban land area leads to a 1.465% increase in household carbon emissions. This value is significantly higher than the quantitative relationships between urban land area and both transportation and industrial carbon emissions. After controlling for the population variable, the ln(*CA*) regression coefficient remains significant but decreases to 0.971, transitioning to a sub-linear relationship. This suggests that part of the quantitative relationship between urban land expansion and household carbon emissions is due to the increase in urban population size. After controlling for the temperature variable, the regression coefficient for ln(*CA*) further reduces but remains significant and relatively high. Overall, the impact of average temperature on household carbon emissions is negative, meaning higher urban average temperatures result in lower household carbon emissions. Notably, the effects of cooling and heating due to average temperature are opposite, and the impact on household carbon emissions is the result of this dual balance. After further controlling for *per capita GDP*, the coefficient for ln(*CA*) remains significant but decreases from 0.904 to 0.355. This implies that in larger cities, higher incomes lead to lifestyle changes, further increasing energy use and thus causing increased carbon emissions. Related research has found that this difference in carbon emissions tends to diminish with economic growth (Mi et al., 2020).

Table 5-8 Results of the impact of urban land area on household carbon emissions

Variable	Equation 5.16 ln(*Household Emission*)	Equation 5.17 ln(*Household Emission*)	Equation 5.18 ln(*Household Emission*)	Equation 5.19 ln(*Household Emission*)
ln*(CA)*	1.465***	0.971***	0.904***	0.355**
	(0.00814)	(0.0305)	(0.0383)	(0.0781)
ln(*pop*)		0.687***	0.804***	1.061***
		(0.0486)	(0.0689)	(0.0834)
ln(*Temperature*)			-0.637**	-0.757***
			(0.141)	(0.109)
ln(*GDP per capita*)				0.353***
				(0.0433)
Constant	3.369***	-0.454	0.685	-0.607
	(0.00463)	(0.276)	(0.444)	(0.606)
Observations	984	984	984	984
R-squared	0.284	0.384	0.423	0.434
Number of years	4	4	4	4

Robust standard errors in parentheses； *** p<0.01, ** p<0.05, * p<0.1

After controlling for population, economic level, and temperature variables, the urban land area remains significantly related to the level of household carbon emissions. This impact likely mainly stems from carbon emissions due to temperature adjustment, including cooling and heating. Cities with larger urban land area experience more severe urban heat island effects in the summer, requiring more cooling energy consumption and thus leading to higher carbon emissions. Meanwhile, the scale of land in cities within heating regions might affect the efficiency of heating systems. Based on this, the study conducted group regression on Equation 5.19 based on whether heating is provided, with the following results. Although the ln(CA) coefficient in group regression is insignificant, its coefficients show opposite characteristics. In the heating group, urban land area and household carbon emissions are positively correlated, which may reflect that cities with larger areas require more household carbon emissions for heating under the same conditions. The non-heating group presents a negative value, contrary to our hypothesis that more cooling energy consumption due to the heat island effect leads to more carbon emissions. However, these regression results are insignificant, and their explanatory power is limited. The lack of significance could be due to the reduced sample size after grouping, which might lead to decreased statistical power, making it difficult to detect the true relationship between variables. More importantly, the dependent variable includes all household carbon emissions, mixing non-temperature-regulated carbon emissions, which affects the statistical significance.

Table 5-9 Impact of urban land area on household carbon emissions: grouped results

Variable	Groups of cities with heating	Group of unheated cities
	ln(*Household Emission*)	ln(*Household Emission*)
ln(*CA*)	0.379	-0.0942
	(0.190)	(0.217)
ln(*pop*)	0.947***	1.218***
	(0.0949)	(0.161)
ln(*Temperature*)	0.0116	-1.237
	(0.0717)	(0.574)
ln(*GDP per capita*)	0.231	0.602**
	(0.138)	(0.167)
Constant	-1.618*	-0.280
	(0.566)	(1.210)

Variable	Groups of cities with heating ln(*Household Emission*)	Group of unheated cities ln(*Household Emission*)
Observations	444	540
R-squared	0.586	0.369
Number of years	4	4

Robust standard errors in parentheses； *** p<0.01, ** p<0.05, * p<0.1

Based on the availability of heating data, this section further analyzes the relationship between urban land area and heating carbon emissions, using heating carbon emissions as the dependent variable instead of the total household carbon emissions to construct the following model. Through this analysis, we can understand the relationship between household carbon emissions and urban land area from the decomposition of household carbon emissions. Similarly, we first examine the quantitative relationship between urban land area and heating carbon emissions(Equation 5.20). Population size to some extent determines the scale of heating needed. The level of economic development determines the coverage of heating. Temperature determines the intensity of heating; theoretically, the lower the temperature, the higher the heating intensity and carbon emissions, and vice versa, the higher the temperature, the lower the heating intensity and carbon emissions. Therefore, we have progressively controlled these three variables.

Equation 5.20

$$\ln(Heating\ Emission)_{it}=\beta_{01}+\beta_{11}\ln(CA)_{it}+\mu_{i1}+\gamma_{t1}+\epsilon_{it1}$$

Equation 5.21

$$\ln(Heating\ Emission)_{it}=\beta_{02}+\beta_{12}\ln(CA)_{it}+\beta_{12}\ln(pop)_{it}+\mu_{i2}+\gamma_{t2}+\epsilon_{it2}$$

Equation 5.22

$$\ln(Heating\ Emission)_{it}=\beta_{03}+\beta_{13}\ln(CA)_{it}+\beta_{23}\ln(pop)_{it}+\beta_{33}\ln(Temperature)_{it}+\mu_{i3}+\gamma_{t3}+\epsilon_{it3}$$

The regression results show a strong correlation between urban land area and heating carbon emissions. Overall, a 1% increase in urban land area leads to a 1.641% increase in heating carbon emissions. After adding control variables, the coefficient did not decrease but instead increased. In Equation 5.21, the ln(*CA*) coefficient reaches 2.663, indicating that after controlling for population factors, the expansion of urban land area leads to a significant increase in urban heating. This implies that the low-density expansion of cities puts greater pressure on heating carbon emissions. In regions requiring heating, the importance of compact urban development is significant. Temperature is an important factor affecting heating carbon emissions. With all other conditions being constant, a 1% increase in temperature reduces the carbon emissions required for heating by 1.11%.

Table 5-10 Results of the impact of urban land area on household carbon emissions (heating)

Variable	Equation 5.20 ln(*Heating Emission*)	Equation 5.21 ln(*Heating Emission*)	Equation 5.22 ln(*Heating Emission*)
ln(*CA*)	1.641***	2.663***	2.590***
	(0.133)	(0.108)	(0.0952)
ln(*pop*)		-0.917***	-0.631**
		(0.0376)	(0.123)
ln(*Temperature*)			-1.111***
			(0.0768)
Constant	3.571***	8.339***	9.540***
	(0.0830)	(0.261)	(0.556)
Observations	444	444	444

Variable	Equation 5.20 ln(*Heating Emission*)	Equation 5.21 ln(*Heating Emission*)	Equation 5.22 ln(*Heating Emission*)
R-squared	0.302	0.427	0.519
Number of years	4	4	4

Robust standard errors in parentheses；*** p<0.01, ** p<0.05, * p<0.1

5.2.2 Influence of Urban Land Shape Complexity on Carbon Emissions

Researchers often include many related explanatory variables in quantitative research in statistical models to consider influencing factors and comprehensively describe phenomena. Although this approach makes the analysis more comprehensive, it also introduces complexity. This is particularly the case where multicollinearity among these variables can lead to overlapping information reflected in the data. To address this issue, Principal Component Analysis (PCA) is often used to simplify a large set of indicators into a few independent principal components. Therefore, to extract the main information about urban spatial forms and reduce redundancy and multicollinearity issues, this study first conducts a principal component analysis on various spatial form indicators and then carries out subsequent quantitative regression analysis based on this.

This section first conducted a principal component analysis on the complexity indicators of urban land area form, specifically the Area-Weighted Mean Shape Index (*AWMS*) and the Area-Weighted Mean Patch Fractal Dimension (*AWMPFD*). The results show that the first principal component, Component1_Complexity, explains 96.03% of the information of the two variables. From the factor loading matrix, it is known that the Area-Weighted Mean Shape Index (*AWMS*) and the Area-Weighted

Mean Patch Fractal Dimension (*AWMPFD*) are highly correlated in explaining the complexity of urban land form, with both variables contributing equally and symmetrically distributed across the two principal components. Therefore, this chapter uses the first principal component, which reflects the majority of the complexity of urban land, for regression analysis. Before conducting the regression analysis, the same standardization and logarithmic transformation were applied.

Table 5-11 Total variance explained by the principal component of urban land complexity

Principal Component	Eigenvalue	Percentage of Variance（%）	Cumulative Percentage（%）
Component1_Complexity	1.921	96.03	96.03
Component2_Complexity	0.0786	3.93	100

Table 5-12 Factor loading matrix for urban land complexity

Variable	Component1_Complexity	Component1_Complexity
AWMS	0.7071	0.7071
AWMPFD	0.7071	-0.7071

(1) Total Carbon Emissions

This section first analyzes the impact of urban land complexity on total carbon emissions from an overall perspective. The following quantitative regression models are constructed. Equation 5.23 includes only the indicator of urban land complexity, which helps understand the dynamic quantitative relationship between urban land complexity and total carbon emissions. Equation 5.24 further controls for population size, a fundamental variable affecting urban carbon emissions.

Equation 5.23

$$\ln(Total\ Emission)_{it}=\beta_{01}+\beta_{11}\ln(Component1\_Complexity)_{it}+\mu_{i1}+\gamma_{t1}+\epsilon_{it1}$$

Equation 5.24

$$\ln(Total\ Emission)_{\mathrm{it}}=\beta_{02}+\beta_{12}\ln(Component1\_Complexity)_{it}+\beta_{12}\ln(pop)_{it}+\mu_{i2}+\gamma_{t2}+\epsilon_{it2}$$

The research results show that the increase in urban land complexity generally promotes an increase in total urban carbon emissions. Overall, a 1% increase in urban land complexity leads to a 0.96% increase in total urban carbon emissions. After controlling for the total population factor, the urban land complexity regression coefficient decreases but remains significant.

Table 5-13 Impact of urban land complexity on carbon emissions

Variables	Equation 5.23 ln(*Total Emission*)	Equation 5.24 ln(*Total Emission*)
ln(*Component1_Complexity*)	0.960***	0.838***
	(0.0971)	(0.101)
ln(*pop*)		0.241***
		(0.0282)
Constant	6.734***	5.438***
	(0.114)	(0.246)
Observations	984	984
R-squared	0.194	0.222
Number of years	4	4

Robust standard errors in parentheses； *** p<0.01, ** p<0.05, * p<0.1

The evolution of urban land shape complexity might be related to the expansion of urban land area. Rapid expansion of urban boundaries can lead to more complex urban shapes in the early stages of urbanization. However, urban development enters a filling phase as urbanization progresses, affecting urban edges. Therefore, the shape of urban land under different urban land area varies, and the impact on carbon emissions differs. Based on this, this section categorizes urban land area into quartiles and conducts regression analysis accordingly. The research results show that the impact of urban land complexity on carbon emissions is not significant for cities in the 1st to 3rd quartiles. Significance is only found in the 4th quartile group of cities, with a positive value. This indicates that in cities with higher levels of urbanization, urban land complexity has a greater impact on carbon emissions. The possible reason is that in cities with larger urban land area, the density of socio-economic activities is high, urban land use intensity is significant, and there are higher requirements for transportation accessibility and insulation. Other sections of this chapter analyze carbon emissions split into industrial, transportation, and household carbon emissions.

Table 5-14 Impact of urban land shape complexity on total carbon emissions: grouped results

Variable	1st quartile ln(*Total Emission*)	2nd quartile ln(*Total Emission*)	3rd quartile ln(*Total Emission*)	4th quartile ln(*Total Emission*)
ln(*Component1 _Complexity*)	0.297	-0.133	-0.315	0.484**
	(0.200)	(0.199)	(0.173)	(0.125)
ln(*pop*)	0.0137	-0.241**	-0.226*	0.475***
	(0.0256)	(0.0652)	(0.0753)	(0.0760)
Constant	6.802***	9.201***	9.766***	4.834***
	(0.253)	(0.343)	(0.630)	(0.675)
Observations	246	246	246	246
R-squared	0.016	0.040	0.037	0.224
Number of years	4	4	4	4

Robust standard errors in parentheses； *** p<0.01, ** p<0.05, * p<0.1

(2) Industrial carbon emissions

The research identified urban land area as a significant determinant influencing industrial carbon emissions. Initially, the analysis incorporated urban land area as a control variable within the first model (Equation 5.25). Subsequently, Equation 5.26 extended the analysis by additionally controlling for the size of the urban population. In Equation 5.27, the investigation delved into the effects exerted by the number of employees engaged in urban industries and the composition of the industrial sector, specifically focusing on the share of the tertiary sector.

Equation 5.25

$$\ln(\textit{Industrial Emission})_{it}=\beta_{01}+\beta_{11}\ln(\textit{Component1\_Complexity})_{it}+\beta_{21}\ln(CA)_{it}+\mu_{i1}+\gamma_{t1}+\epsilon_{it1}$$

Equation 5.26

$$\ln(\textit{Industrial Emission})_{it}=\beta_{02}+\beta_{12}\ln(\textit{Component1\_Complexity})_{it}+\beta_{22}\ln(CA)_{it}$$
$$+\beta_{32}\ln(pop)_{it}+\mu_{i2}+\gamma_{t2}+\epsilon_{it2}$$

Equation 5.27

$$\ln(\textit{Industrial Emission})_{\mathrm{it}}=\beta_{03}+\beta_{13}\ln(\textit{Component1\_Complexity})_{it}+\beta_{23}\ln(CA)_{it}$$
$$+\beta_{33}\ln(pop)_{it}+\beta_{43}\ln(\textit{Industrial Employment})_{\mathrm{it}}+\beta_{53}\ln(\textit{Industrial Structure})_{it}+\mu_{i3}+\gamma_{\mathrm{t3}}+\epsilon_{it3}$$

The research results indicate that among the factors of urban spatial structure, the impact of urban land complexity on industrial carbon emissions is generally insignificant. In the first model, with urban land area controlled, the impact of urban land complexity on industrial carbon emissions was insignificant (P=0.444). When the population was further controlled, the regression coefficient increased but still did not pass the significance test. After controlling for industrial structure and the number of industrial employees, the regression coefficient for urban land complexity on industrial carbon emissions increased further, with a P-value of 0.11, significantly narrowing. The coefficient is negative, which may be because the increase in urban land complexity affects transportation efficiency and the synergy between industries, possibly leading to a relative reduction in industrial activities. This "hindrance effect" on industrial production activities could result in relatively lower industrial carbon emissions.

Table 5-15 Impact of urban land shape complexity on industrial carbon emissions

Variable	Equation 5.25	Equation 5.26	Equation 5.27
	ln(*Industrial Emission*)	ln(*Industrial Emission*)	ln(*Industrial Emission*)
ln(*Component1_Complexity*)	-0.194	-0.220	-0.366
	(0.220)	(0.217)	(0.168)
ln(*CA*)	1.514***	1.683***	1.408**
	(0.0321)	(0.0681)	(0.270)
ln(*pop*)		-0.211**	-0.291***
		(0.0660)	(0.0491)
ln(*Industrial Employment*)			0.301
			(0.145)
ln(*Industrial Structure*)			-0.433**
			(0.0882)
Constant	6.873***	8.069***	6.861**
	(0.242)	(0.593)	(2.017)
Observations	984	984	984
R-squared	0.341	0.353	0.386
Number of years	4	4	4

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

(3)Transportation Carbon Emission

Research on urban transportation carbon emissions primarily focuses on measurement, spatial patterns, and the impact analysis of socio-economic factors. Jiang et al. (2020) analyzed the spatial pattern of urban transportation carbon emissions in the

Yangtze River Economic Belt. Scholars have also analyzed the impact of population size and Gross Domestic Product (GDP) on transportation carbon emissions(Su et al., 2011). In studies based on major metropolitan areas in the United States, urban spatial structure is considered an important factor affecting transportation carbon emissions(Sevtuk & Amindarbari, 2021). Scholars in China have likewise focused on the impact of urban spatial structure on transportation carbon emissions from a case study perspective(Ye, Zhang, et al., 2012). There is a lack of comprehensive examination from the perspective of urban space on how urban spatial structure affects transportation carbon emissions. This section focuses on one of the indicators of urban spatial structure—urban land complexity and its impact on transportation carbon emissions, constructing the following model.

Equation 5.28

$$\ln(\textit{Transport Emission})_{it}=\beta_{01}+\beta_{11}\ln(\textit{Component1\_Complexity})_{it}+\beta_{21}\ln(CA)_{it}+\mu_{i1}+\gamma_{t1}+\epsilon_{it1}$$

Equation 5.29

$$\ln(\textit{Transport Emission})_{it}=\beta_{02}+\beta_{12}\ln(\textit{Component1\_Complexity})_{it}+\beta_{22}\ln(CA)_{it}$$

$$+\beta_{32}\ln(pop)_{it}+\beta_{42}\ln(GDP)_{\mathrm{it}}+\mu_{i2}+\gamma_{t2}+\epsilon_{it2}$$

Equation 5.28 includes only indicators of urban spatial structure, namely land complexity and urban land area. Equation 5.29 includes two fundamental variables influencing transportation demand: population and GDP. The regression results show that the coefficient for urban land shape complexity (*ln(Component1_Complexity)*) is -0.225, but this impact is not significant (P-value greater than 0.1). This means that, without controlling for other factors, the negative impact of urban land shape complexity on transportation carbon emissions has not reached statistical significance. In Equation 5.29, when controlling for population and GDP factors, the impact of urban land shape complexity on transportation carbon emissions becomes significant ($P<0.1$), with the coefficient increasing to -0.401(Table 5-16). This indicates that after considering basic economic and population factors, the role of urban land shape complexity in reducing transportation carbon emissions becomes more apparent. Population growth and economic expansion are foundational factors that increase transportation carbon emissions. A larger population and greater economic growth typically lead to higher transportation demand, which is reflected in the positive regression coefficients in Equation 5.29. The negative impact of urban land complexity on carbon emissions might be due to the more complex urban forms reducing transportation accessibility and suppressing traffic activities.

Table 5-16 Impact of urban land shape complexity on transportation carbon emissions

Variable	Equation 5.28 ln(*Transport Emission*)	Equation 5.29 ln(*Transport Emission*)
ln(*Component1_Complexity*)	-0.225	-0.401*
	(0.187)	(0.170)
ln(*CA*)	1.427***	0.498**
	(0.145)	(0.134)
ln(*pop*)		0.257**
		(0.0502)
ln(*GDP*)		0.487**
		(0.0956)
Constant	4.551***	0.273
	(0.168)	(0.226)
Observations	984	984
R-squared	0.474	0.605
Number of years	4	4

Robust standard errors in parentheses； *** p<0.01, ** p<0.05, * p<0.1

After verifying that urban land shape complexity has a certain suppressive effect on transportation-related carbon emissions, this study further explores the heterogeneity of this effect under urban land area constraints. To investigate how the impact of land shape complexity on urban transportation carbon emissions varies with different urban land sizes, this section classifies the sample cities into quartiles based on land area and conducts a quartile regression analysis. The descriptive statistics for urban land area quartiles are as follows.

Table5-17 Descriptive statistics of urban land area in the quartile

Quartile	Mean (km^2)	Standard Deviation	Minimum	Maximum
1st Quartile	52.08	14.56	21.49	76.48
2nd Quartile	104.62	17.66	76.52	137.45
3rd Quartile	196.70	42.04	137.51	284.23
4th Quartile	630.59	409.13	285.71	2532.83

The quartile regression analysis reveals that in cities with an urban land area of approximately 100 square kilometers, transportation carbon emissions are more significantly influenced by land shape complexity. From a value-oriented perspective, urban land shape complexity imposes certain constraints on travel behavior, which may reduce social welfare and lower overall societal efficiency. The outcomes associated with increasing land shape complexity run counter to the objectives of ecological civilization development. Therefore, urban land shape complexity cannot serve as a viable planning tool for reducing transportation carbon emissions. On the contrary, this finding suggests that urban land shape complexity has a considerable impact on urban transportation efficiency. Consequently, for cities with an urban land area of approximately 100 square kilometers, special attention should be given to ensuring the smooth operation of urban transportation in course of urban development.

Table5-18 Impact of urban land shape complexity on transportation carbon emissions: grouped results

Variable	1st quartile ln(Transport Emission)	2nd quartile ln(Transport Emission)	3rd quartile ln(Transport Emission)	4th quartile ln(Transport Emission)
ln(*Component1_Complexity*)	-0.403	-0.763***	-0.193	-0.141
	(0.225)	(0.0720)	(0.181)	(0.180)
ln(*CA*)	2.269***	0.540	0.357	0.477**
	(0.208)	(1.126)	(0.244)	(0.112)
ln(*pop*)	0.398***	0.165**	0.198*	0.309**
	(0.0673)	(0.0401)	(0.0838)	(0.0614)
ln(*GDP*)	0.477***	0.491*	0.342**	0.590***
	(0.0750)	(0.189)	(0.0676)	(0.0914)
Constant	-0.800***	1.191	1.502**	-1.341*
	(0.101)	(0.707)	(0.390)	(0.442)
Observations	246	246	246	246
R-squared	0.389	0.209	0.232	0.754
Number of years	4	4	4	4

Robust standard errors in parentheses； *** p<0.01, ** p<0.05, * p<0.1

（4）Household Carbon Emission

The construction of regression models analyzing the impact of urban land complexity on carbon emissions is as follows. Equation 5.30 incorporates the principal component of urban land complexity indicators and urban land area as basic variables. Since household carbon emissions are constrained by population size and the level of economic development, Equation 5.31 includes population size and Gross Domestic Product (GDP) as control variables. Temperature is an important factor influencing household carbon emissions, and this study also includes it as a control variable. Heating carbon emissions are a major component of household carbon emissions in the north, and this chapter explores the relationship between urban land complexity and heating carbon emissions in Equation 5.32. Since heating is commonly implemented in northern cities and has a smaller correlation with the level of economic development, Equation 5.32 only includes urban land area, urban population size, and temperature as control variables.

Equation 5.30

$$\ln(\mathit{Household\ Emission})_{it}=\beta_{01}+\beta_{11}\ln(\mathit{Component1\_Complexity})_{it}+\beta_{21}\ln(CA)_{it}+\mu_{i1}+\gamma_{t1}+\epsilon_{it1}$$

Equation 5.31

$$\ln(\mathit{Household\ Emission})_{it}=\beta_{02}+\beta_{12}\ln(\mathit{Component1\_Complexity})_{it}+\beta_{22}\ln(CA)_{it}+\beta_{32}\ln(pop)_{it}$$
$$+\beta_{42}\ln(GDP)_{it}+\beta_{52}\ln(\mathit{Temperature})_{it}+\mu_{i2}+\gamma_{t2}+\epsilon_{it2}$$

Equation 5.32

$$\ln(\mathit{Heating\ Emission})_{it}=\beta_{03}+\beta_{13}\ln(\mathit{Component1\_Complexity})_{it}+\beta_{23}\ln(CA)_{it}+\beta_{33}\ln(pop)_{it}$$
$$+\beta_{43}\ln(\mathit{Temperature})_{it}+\mu_{i3}+\gamma_{t3}+\epsilon_{it3}$$

Overall, urban land complexity has increased household carbon emissions. The coefficient for ln(Component1_Complexity) is 0.115, but not significant ($p>0.1$), indicating an uncertain statistical relationship between urban land shape complexity and household carbon emissions. This might be due to missing important variables. In the regression results of Equation 5.31, the coefficient for *ln(Component1_Complexity)* is 0.643, and it passes the significance test. The R-squared value of the equation is 0.441, a significant improvement compared to the results of Equation 5.30, indicating that the model can explain a considerable portion of the causes of household carbon emissions.

Overall, a 1% increase in urban land complexity leads to a 0.643% increase in urban household carbon emissions.

Heating carbon emissions are significantly affected by urban land complexity. Heating carbon emissions are an important component of household carbon emissions. The regression results of Equation 5.32 show that the coefficient for ln(Heating Emission) is 0.856, and it passes the 1% significance test. This means that for every 1% increase in urban land complexity, heating carbon emissions increase by 0.856%. Complex urban land may mean that heating infrastructure (such as pipelines and thermal power stations) is more dispersed, which could lead to decreased heating efficiency. Heat loss during energy transmission might increase, leading to higher carbon emissions. In complex urban lands, buildings may be more exposed to wind and shade, possibly increasing the demand for indoor heating, especially in winter. To maintain a comfortable indoor temperature, more energy consumption is required.

Table 5-19 Results of the impact of the complexity of urban land shape on household carbon emissions

Variable	Equation 5.30 ln(*Household Emission*)	Equation 5.31 ln(*Household Emission*)	Equation 5.32 ln(*Heating Emission*)
ln(*Component1_Complexity*)	0.115	0.643***	0.856***
	(0.101)	(0.0840)	(0.0754)
ln(*CA*)	1.391***	0.450**	1.871***
	(0.0697)	(0.110)	(0.0567)
ln(*pop*)		0.859***	-0.495**
		(0.0786)	(0.145)
ln(*Temperature*)		-0.826**	-1.412***

Variable	Equation 5.30 ln(*Household Emission*)	Equation 5.31 ln(*Household Emission*)	Equation 5.32 ln(*Heating Emission*)
		(0.148)	(0.0680)
Constant	3.277***	0.395	8.983***
	(0.0782)	(0.517)	(0.751)
Observations	984	984	444
R-squared	0.285	0.441	0.551
Number of years	4	4	4

Robust standard errors in parentheses；*** p<0.01, ** p<0.05, * p<0.1

To explore the impact of urban land complexity on urban carbon emissions across different urban land sizes, this section divides the research sample into quartiles based on urban land area and then conducts quartile regression analysis. The descriptive statistics for the quartiles of urban land area are as follows.

Table 5-20 Descriptive statistics of urban land area in the quartile

	Mean (km^2)	Standard Deviation	Minimum Value	Maximum Value
1st quartile	52.08	14.56	21.49	76.48
2nd quartile	104.62	17.66	76.52	137.45
3rd quartile	196.70	42.04	137.51	284.23
4th quartile	630.59	409.13	285.71	2532.83

The results of the quantile regression analysis on the impact of urban land area on carbon emissions are as follows: The regression coefficients for urban land complexity are consistent in sign with the ungrouped results, indicating that urban land complexity leads to an increase in heating carbon emissions across all scenarios of urban land area. From a significance-level perspective, the regression coefficients of urban land complexity are statistically significant in the regressions for the second and fourth quartiles. In the second quartile, for every 1% increase in urban land complexity, urban heating carbon emissions increase by 1.238%. In cities within the fourth quartile, for every 1% increase in urban land complexity, heating carbon emissions increase by 0.713%.

In the descriptive statistics table for urban land area quartiles, the average urban land area for cities in the second quartile is 104.62 square kilometers. The average urban land area for cities in the fourth quartile is 630.59 square kilometers. Thus, from the perspective of urban land complexity, urban planning efforts aimed at reducing heating carbon emissions should mainly focus on reducing the complexity of urban land use in cities with areas around 100 square kilometers and 600 square kilometers.

Table 5-21 Quartile regression results of urban land shape complexity on transportation carbon emissions

Variable	1st quartile ln(*Heating Emission*)	2nd quartile ln(*Heating Emission*)	3rd quartile ln(*Heating Emission*)	4th quartile ln(*Heating Emission*)
ln(*Component1_Complexity*)	0.184	**1.238****	0.441	**0.713***
	(0.192)	(0.301)	(0.207)	(0.298)
ln(*CA*)	4.213**	2.280	2.806**	1.579***
	(1.202)	(1.032)	(0.579)	(0.214)
ln(*pop*)	-0.343*	-0.436	-0.854**	-0.313
	(0.123)	(0.224)	(0.242)	(0.188)
ln(*Temperature*)	-0.734*	-1.430***	-1.703**	-1.767***
	(0.294)	(0.146)	(0.307)	(0.145)
Constant	6.458***	8.205***	11.82***	9.446***
	(0.408)	(1.337)	(1.297)	(0.673)

Variable	1st quartile ln(*Heating Emission*)	2nd quartile ln(*Heating Emission*)	3rd quartile ln(*Heating Emission*)	4th quartile ln(*Heating Emission*)
Observations	67	110	145	122
R-squared	0.344	0.258	0.472	0.630
Number of years	4	4	4	4

Robust standard errors in parentheses； *** p<0.01, ** p<0.05, * p<0.1

5.2.3 Impact of Urban Land Compactness on Carbon Emissions

The Principal Component Analysis (*PCA*) method is advantageous for extracting sufficient information among variables while eliminating the impact of redundant information. This section first uses the *PCA* method to analyze indicators of urban land compactness. Indicators used to describe urban land compactness include the Compactness Index (*AI*), Largest Patch Index (*LSI*), and Average Nearest Neighbor Distance (*ENN_AM*). The higher the Compactness Index (*AI*), the more the urban land tends to form a cohesive whole, indicating higher urban land compactness. A larger Largest Patch Index suggests that urban patches tend to be more centrally distributed, which also explains urban land compactness to some extent. The Average Nearest Neighbor Distance more intuitively explains the distance of urban land distribution. The closer the average distance between patches, the higher the compactness of urban land.

In the total variance explained by the principal component of urban land compactness, Principal Component 1 (*Component1_Compactness*) accounts for 41.67% of the information. In the factor loading matrix of urban land compactness, Principal

Component 1 (*Component1_Compactness*) is positively related to the Compactness Index (*AI*) and the Largest Patch Index (*LSI*), and negatively related to the Average Nearest Neighbor Distance (*ENN_AM*). Such a quantitative relationship reflects the content of urban land compactness, where higher values of Principal Component 1 (*Component1_Compactness*) indicate greater urban compactness. In regression analysis, we use Principal Component 1 (*Component1_Compactness*) as the variable reflecting urban compactness.

Table 5-22 Total variance explained by the principal component of urban land compactness

Principal Component	Eigenvalue	Percentage of Variance	Cumulative Percentage
Component1_Compactness	1.249	41.67	41.67
Component2_Compactness	1.048	34.96	76.63
Component3_Compactness	0.701	23.37	100

Table 5-23 Factor loading matrix for urban land compactness

Variable	Component1_Compactness	Component2_Compactness	Component3_Compactness
AI	0.4637	0.7212	-0.5146
LSI	0.7379	0.0072	0.6749
ENN_AM	-0.4905	0.6927	0.5288

After extracting and reducing the variable information on urban compactness using Principal Component Analysis, this section first analyzes the impact of urban land compactness on carbon emissions from the perspective of total carbon emissions. Equation 5.33 controls for the basic urban spatial structure indicator related to urban carbon emissions—urban land area. Equation 5.34 further controls for the urban population size.

Equation 5.33

$$\ln(Total\ Emission)_{it}=\beta_{01}+\beta_{11}\ln(Component1\_Compactness)_{it}+\beta_{21}\ln(CA)_{it}+\mu_{i1}+\gamma_{t1}+\epsilon_{it1}$$

Equation 5.34

$$\ln(Total\ Emission)_{it}=\beta_{02}+\beta_{12}\ln(Component1\_Compactness)_{it}+\beta_{21}\ln(CA)_{it}$$

$$+\beta_{12}\ln(pop)_{it}+\mu_{i2}+\gamma_{t2}+\epsilon_{it2}$$

The research results show that after controlling for urban population and land area, the regression results of urban land compactness with total urban carbon emissions are insignificant. In Equation 5.33, the coefficient for the logarithmic transformation of urban compactness, *ln(Component1_Compactness)*, is -0.254, with a standard error of 0.124. In Equation 5.34, this coefficient is -0.296, with a standard error of 0.162. In both models, this indicates that the impact of urban compactness on overall carbon emissions is statistically insignificant. Considering urban land area and population, the impact of urban land compactness on total carbon emissions is statistically insignificant. The lack of significant impact on the aggregate level does not mean that urban compactness has no effect on carbon emissions. Below, the research on urban land compactness and carbon emissions will be carried out from the perspectives of industrial carbon emissions, transportation carbon emissions, and household carbon emissions.

Table 5-24 The impact of urban land use shape complexity on total carbon emissions

Variable	Equation 5.33	Equation 5.34
	ln(*Total Emission*)	ln(*Total Emission*)
ln(*Component1_Compactness*)	-0.254	-0.296
	(0.124)	(0.162)
ln(*CA*)	1.339***	1.388***

Variable	Equation 5.33 ln(*Total Emission*)	Equation 5.34 ln(*Total Emission*)
	(0.0782)	(0.0518)
ln(*pop*)		-0.0533
		(0.0426)
Constant	7.481***	7.835***
	(0.216)	(0.502)
Observations	984	984
R-squared	0.418	0.419
Number of years	4	4

Robust standard errors in parentheses； *** p<0.01, ** p<0.05, * p<0.1

（2）Industrial Carbon Emission

The study of the relationship between urban compactness and industrial carbon emissions constructs the following econometric models. Equation 5.35 includes only urban compactness (ln(*Component1_Compactness*)) and urban land area (ln(*CA*)) as indicators of urban spatial structure, aiming to reveal the direct quantitative relationship between urban land compactness and carbon emissions. Equation 5.36 further controls for the population variable, as population size may affect the scale and intensity of industrial activities, thereby influencing carbon emissions. Equation 5.37 adds variables affecting industrial carbon emissions, such as the number of industrial employees and industrial structure.

Equation 5.35

$$\ln(Industrial\ Emission)_{\mathrm{it}}=\beta_{01}+\beta_{11}\ln(Component1\_Compactness)_{it}+\beta_{21}\ln(CA)_{it}+\mu_{i1}+\gamma_{t1}+\epsilon_{it1}$$

Equation 5.36

$$\ln(Industrial\ Emission)_{it}=\beta_{02}+\beta_{12}\ln(Component1\_Compactness)_{it}+\beta_{22}\ln(CA)_{it}$$

$$+\beta_{32}\ln(pop)_{it}+\mu_{i2}+\gamma_{t2}+\epsilon_{it2}$$

Equation 5.37

$$\ln(\mathit{Industrial\ Emission})_{it}=\beta_{03}+\beta_{13}\ln(\mathit{Component1\_Compactness})_{it}+\beta_{23}\ln(CA)_{\mathrm{it}}$$
$$+\beta_{33}\ln(pop)_{it}+\beta_{43}\ln(\mathit{Industrial\ Employment})_{it}+\beta_{53}\ln(\mathit{Industrial\ Structure})_{it}+\mu_{i3}+\gamma_{t3}+\epsilon_{it3}$$

The study results indicate that the regression results for urban land compactness and industrial carbon emissions are insignificant, but the signs are negative. The results show that urban land area, population size, and industrial structure are important factors affecting industrial carbon emissions. However, the regression results for urban land compactness did not pass the significance test. From Equation 5.35 to Equation 5.37, it can still be observed that the regression coefficient between urban land compactness and industrial carbon emissions gradually increases and is negative. This may explain to some extent that an increase in urban land compactness is beneficial for reducing industrial carbon emissions, but the impact is limited. A compact urban layout promotes the agglomeration of economic activities, which can bring benefits of scale and scope economies. Agglomeration economies, by sharing resources and facilities and improving production efficiency, help reduce carbon emissions per output unit. Areas with higher urban compactness often mean shorter commutes and transportation distances, reducing energy consumption and related carbon emissions. The close layout of industrial units and supply chains can reduce logistics costs, improving energy efficiency.

Table 5-25 The impact of urban land compactness on household carbon emissions.

Variable	Equation 5.35 ln(*Industrial Emission*)	Equation 5.36 ln(*Industrial Emission*)	Equation 5.37 ln(*Industrial Emission*)
ln(*Component1_Compactness*)	-0.140	-0.315	-0.357
	(0.134)	(0.209)	(0.213)
ln(*CA*)	1.422***	1.624***	1.349**
	(0.0876)	(0.0326)	(0.273)
ln(*pop*)		-0.221*	-0.289**
		(0.0725)	(0.0525)
ln(*Industrial Employment*)			0.253
			(0.174)
ln(*Industrial Structure*)			-0.488**
			(0.105)
Constant	6.910***	8.380***	7.768*
	(0.238)	(0.727)	(2.586)
Observations	984	984	984
R-squared	0.338	0.352	0.379
Number of years	4	4	4

Robust standard errors in parentheses； *** p<0.01, ** p<0.05, * p<0.1

（3）Transportation Carbon Emission

The urban spatial structure most directly influences transportation carbon emissions. In this section, the study constructs a quantitative model with urban land compactness as the independent variable and transportation carbon emissions as the dependent variable. Equation 5.38 includes urban land area as a control variable. Equation 5.39 incorporates city population size and Gross Domestic Product (GDP), two fundamental variables affecting urban transportation demand, into the regression.

Equation 5.38

$$\ln(Transport\ Emission)_{it}=\beta_{01}+\beta_{11}\ln(Component1\_Compactness)_{it}+\beta_{21}\ln(CA)_{it}+\mu_{i1}+\gamma_{t1}+\epsilon_{it1}$$

Equation 5.39

$$\ln(Transport\ Emission)_{it}=\beta_{02}+\beta_{12}\ln(Component1\_Compactness)_{it}+\beta_{22}\ln(CA)_{it}$$

$$+\beta_{32}\ln(pop)_{it}+\beta_{42}\ln(GDP)_{it}+\mu_{i2}+\gamma_{t2}+\epsilon_{it2}$$

The research results show that urban land compactness is an important factor affecting transportation carbon emissions. In both regression models, the regression coefficient of urban land compactness (*ln(Component1_Compactness)*) passed the significance test, with coefficients of -1.189 and -0.815, both statistically significant ($p<0.05$). This indicates that the more compact the urban land, the lower the transportation carbon emissions. Specifically, for every 1% increase in urban compactness, transportation carbon emissions are expected to decrease by about 0.815%. Possible reasons include: (1) A compact urban layout usually means proximity of household areas, work areas, and commercial zones, reducing residents' commuting distance and time. Shorter commuting distances directly lead to reduced transportation energy consumption and, thus lower transportation carbon emissions. (2) In compact cities, public transportation systems (such as subway buses) are easier to build and maintain and are more efficient. This improves the convenience and attractiveness of public transport for residents and reduces the use of private cars, thereby reducing carbon emissions. (3) Good urban planning and compact city structure help to reduce traffic congestion. Traffic congestion increases energy consumption and leads to vehicles emitting more carbon dioxide in inefficient states. Our research is consistent with existing studies; Qiao and Jiao (2023) found that the compactness of urban spaces contributes to reducing transportation carbon emissions.

Table 5-26 The impact of urban land compactness on transportation carbon emissions.

Variable	Equation 5.38 ln(*Transport Emission*)	Equation 5.39 ln(*Transport Emission*)
ln(*Component1_Compactness*)	-1.189**	-0.815**
	(0.206)	(0.220)
ln(*CA*)	1.572***	0.635***
	(0.0740)	(0.108)
ln(*pop*)		0.264**
		(0.0481)
ln(*GDP*)		0.372***
		(0.0547)
Constant	6.004***	1.735***
	(0.324)	(0.234)
Observations	984	984
R-squared	0.512	0.608
Number of years	4	4

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

The impact of urban spatial structure on transportation carbon emissions demonstrates significant scale effects, indicating that the impact of compactness varies significantly across cities with different land use scales. This study adopted a grouped regression analysis method to delve deeper into this phenomenon, dividing the urban land area by quartiles. This approach allows exploring how spatial structure compactness affects transportation carbon emissions in cities of different land area.

The research findings reveal that the impact of urban land compactness on transportation carbon emissions varies significantly in cities of different land area. In smaller-scale cities (the 1st and 2nd quartiles), urban compactness is significantly negatively correlated with transportation carbon emissions, indicating that increasing urban compactness helps reduce transportation carbon emissions in these cities. Specifically, a 1% increase in urban land compactness leads to decreased transportation carbon emissions by 1.017% and 1.167% in cities of the 1st and 2nd quartiles, respectively. The impact of urban compactness on transportation carbon emissions is more significant in cities of the second quartile. From the descriptive statistics of urban land area quartiles, the average urban land area in cities of the 1st and 2nd quartiles is 52 square kilometers and 104 square kilometers, respectively. In terms of reducing transportation carbon emissions, urban planning practices should pay more attention to cities with an urban land area of 100 square kilometers and below, emphasizing urban land compactness. Urban land patches should be as close as possible to form a compact whole.

However, in larger-scale cities (the 3rd and 4th quartiles), the impact of urban compactness on transportation carbon emissions is no longer significant. This may reflect that complex transportation networks and diversified travel modes in these cities make urban compactness no longer a significant factor for transportation carbon emissions, which are more influenced by other factors.

Table 5-27 Quartile regression results of urban land compactness on transportation carbon emissions

Variable	1st quartile ln(*Transport Emission*)	2nd quartile ln(*Transport Emission*)	3rd quartile ln(*Transport Emission*)	4th quartile ln(*Transport Emission*)
ln(*Component1_Compactness*)	**-1.017****	**-1.167*****	-1.304	0.0155
	(0.272)	(0.181)	(0.786)	(0.202)
ln(*CA*)	3.573***	0.719	0.728*	0.411**
	(0.544)	(1.154)	(0.259)	(0.0845)
ln(*pop*)	0.414***	0.205***	0.188	0.341***
	(0.0485)	(0.0200)	(0.0888)	(0.0477)
ln(*GDP*)	0.290**	0.248	0.264**	0.566***
	(0.0558)	(0.156)	(0.0576)	(0.0741)
Constant	1.089	3.478**	3.686*	-1.503**
	(0.647)	(0.986)	(1.508)	(0.340)
Observations	246	246	246	246
R-squared	0.406	0.205	0.297	0.752
Number of years	4	4	4	4

Robust standard errors in parentheses； *** p<0.01, ** p<0.05, * p<0.1

(4) Household Carbon Emissions

The impact of urban land compactness on carbon emissions is constructed from two dimensions: total household and heating carbon emissions. Equation 5.40 includes indicators of urban spatial structure. Equation 5.41 incorporates population size, gross domestic product (GDP), and temperature as control variables. Equation 5.42 uses heating carbon emissions as the dependent variable, with urban compactness as the independent variable, and controls for population size, GDP, and temperature.

Equation 5.40

$$\ln(Household\ Emission)_{it} = \beta_{01} + \beta_{11}\ln(Component1\_Complexity)_{it} + \beta_{21}\ln(CA)_{it} + \mu_{i1} + \gamma_{t1} + \epsilon_{it1}$$

Equation 5.41

$$\ln(Household\ Emission)_{it} = \beta_{02} + \beta_{12}\ln(Component1\_Complexity)_{it} + \beta_{22}\ln(CA)_{it}$$
$$+ \beta_{32}\ln(pop)_{it} + \beta_{42}\ln(Temperature)_{it} + \mu_{i2} + \gamma_{t2} + \epsilon_{it2}$$

Equation 5.42

$$ln(Heating\ Emission)_{it} = \beta_{03} + \beta_{13}\ln(Component1\_Complexity)_{it} + \beta_{23}\ln(CA)_{it}$$
$$+ \beta_{33}\ln(pop)_{it} + \beta_{43}\ln(Temperature)_{it} + \mu_{i3} + \gamma_{t3} + \epsilon_{it3}$$

The research findings indicate a positive correlation between urban land compactness and household carbon emissions. A possible reason is that a compact urban environment may promote high socio-economic vitality, which could lead to increased energy consumption and, consequently, more carbon emissions. The impact of urban compactness on heating carbon emissions is not significant.

Table 5-28 Results of the impact of urban land compactness on household carbon emissions

Variable	Equation 5.40 ln(*Household Emission*)	Equation 5.41 ln(*Household Emission*)	Equation 5.42 ln(*Heating Emission*)
ln(*Component1_Compactness*)	-0.127	0.872***	0.926
	(0.239)	(0.148)	(0.453)
ln(*CA*)	1.497***	0.648***	2.333***
	(0.0595)	(0.0384)	(0.169)
ln(*pop*)		0.864***	-0.564**
		(0.0617)	(0.165)
ln(*Temperature*)		-0.712**	-1.314***
		(0.141)	(0.173)
Constant	3.543***	-0.637*	8.404***

Variable	Equation 5.40 ln(*Household Emission*)	Equation 5.41 ln(*Household Emission*)	Equation 5.42 ln(*Heating Emission*)
	(0.329)	(0.259)	(1.138)
Observations	984	984	444
R-squared	0.284	0.433	0.529
Number of years	4	4	4

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

5.2.4 Effect of Urban Poly/mono-centricity Spatial Structure on Carbon Emissions

The indicators for measuring urban polycentric characteristics include (1) the central area coefficient and (2) the coefficient of variation of central areas. A larger central area coefficient suggests a tendency towards a monocentric spatial structure. A larger coefficient of variation of central areas indicates greater differences between the central areas' patches, with the core patch dominating, suggesting a tendency towards a monocentric spatial structure; conversely, it indicates a polycentric structure. Before conducting econometric analysis, principal component analysis was used to analyze these two variables reflecting urban polycentric/monocentric spatial characteristics, extracting the principal component. According to the table explaining the total variance of urban land polycentricity's principal component, the first principal component (*Component1_Polycentricity*) explains 74.59% of the variance, reflecting most of the information (data). From the factor loading matrix of urban land polycentricity, both the central area index and the coefficient of variation of central areas are positively related to the first principal component, indicating that the larger *Component1_Polycentricity*, the more evident is the monocentric spatial structure characteristics.

Table 5-29 Total variance explained by the principal component of poly-/mono-centricity

Principal Component	Eigenvalue	Percentage of Variance	Cumulative Percentage
Component1_Polycentricity	1.491	74.59	74.59
Component2_Polycentricity	0.581	25.41	100

Table 5-30 Factor loading matrix for poly-/mono-centricity

Variable	*Component1_Polycentricity*	*Component2_Polycentricity*
CPLAND	0.7071	0.7071
CORE_CV	0.7071	-0.7071

(1) Total Carbon Emissions

This section explores the relationship between urban polycentric/monocentric spatial structures and total carbon emissions through the following two models. Equation 5.43 incorporates the urban polycentric/monocentric indicators along with the most fundamental characteristics of urban spatial structure. Equation 5.44 includes a population control variable.

Equation 5.43

$$\ln(Total\ Emission)_{it}=\beta_{01}+\beta_{11}\ln(Component1\_Polycentricity)_{it}+\beta_{21}\ln(CA)_{it}+\mu_{i1}+\gamma_{t1}+\epsilon_{it1}$$

Equation 5.44

$$\ln(Total\ Emission)_{it}=\beta_{02}+\beta_{12}\ln(Component1\_Polycentricity)_{it}+\beta_{21}\ln(CA)_{it}$$
$$+\beta_{12}\ln(pop)_{it}+\mu_{i2}+\gamma_{t2}+\epsilon_{it2}$$

The research findings indicate that after controlling for urban population and urban land area, the degree of urban polycentric spatial structure is not significantly correlated with total urban carbon emissions. In both models, the coefficient of the logarithmic transformation of urban polycentric spatial structure, ln(Component1_Polycentricity), was 0.0436 and 0.0397, respectively, but these results were not statistically significant (with high p-values). This suggests that the relationship between the degree of a city's polycentric or monocentric spatial structure and its total carbon emissions is not significant after accounting for urban land area and population size. The potential reason for the insignificance in total carbon emissions may be that the effects of a polycentric structure are more pronounced in specific sectors (such as transportation carbon emissions) rather than in overall carbon emissions. The following sections will explore the impact of polycentric spatial structure on carbon emissions from industrial, transportation, and household carbon emissions perspectives.

Table 5-31 The impact of urban land polycentric/monocentric structure on household carbon emissions

Variable	Equation 5.43	Equation 5.44
	ln(*Total Emission*)	ln(*Total Emission*)
ln(*Component1_Polycentricity*)	0.0436	0.0397
	(0.131)	(0.134)
ln(*CA*)	1.239***	1.269***
	(0.121)	(0.118)
ln(*pop*)		-0.0366
		(0.0351)
Constant	7.118***	7.322***
	(0.0797)	(0.273)
Observations	984	984
R-squared	0.416	0.417

Variable	Equation 5.43 ln(*Total Emission*)	Equation 5.44 ln(*Total Emission*)
Number of years	4	4

Robust standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

(2) Industrial Carbon Emissions

The econometric model for the impact of urban polycentric spatial structure on industrial carbon emissions is as follows. Equation 5.45 takes the principal component analysis of urban polycentricity as the main independent variable, with industrial carbon emissions as the dependent variable, and includes urban land area as a control variable. Equation 5.46 further controls for urban population size. Equation 5.47 additionally controls for the number of employees in the secondary sector of the city and the industrial structure.

Equation 5.45

$$\ln(\mathit{Industrial\ Emission})_{it}=\beta_{01}+\beta_{11}\ln(\mathit{Component1\_Polycentricity})_{it}+\beta_{21}\ln(CA)_{it}+\mu_{i1}+\gamma_{t1}+\epsilon_{it1}$$

Equation 5.46

$$\ln(\mathit{Industrial\ Emission})_{it}=\beta_{02}+\beta_{12}\ln(\mathit{Component1\_Polycentricity})_{it}+\beta_{22}\ln(CA)_{it}+\beta_{32}\ln(pop)_{it}+\mu_{i2}+\gamma_{t2}+\epsilon_{it2}$$

Equation 5.47

$$\ln(\mathit{Industrial\ Emission})_{it}=\beta_{03}+\beta_{13}\ln(\mathit{Component1\_Polycentricity})_{it}+\beta_{23}\ln(CA)_{\mathrm{it}}+\beta_{33}\ln(pop)_{it}+\beta_{43}\ln(\mathit{Industrial\ Employment})_{it}+\beta_{53}\ln(\mathit{Industrial\ Structure})_{it}+\mu_{i3}+\gamma_{t3}+\epsilon_{it3}$$

The study found that the degree of polycentricity in cities is generally insignificant concerning total industrial carbon emissions. The regression coefficients in all three models are less than 0.1, specifically 0.0852, 0.0636, and 0.0324, and none passed the significance test of the models. The variables ln(*CA*) (urban land area) and ln(*pop*) (population) are significant in the models. Urban land area positively correlates with industrial carbon emissions, possibly because larger urban land area indicate more extensive industrial activities. The impact of population on industrial carbon emissions is significant and negatively correlated in Equation 5.46 and Equation 5.47, which may reflect that industrial activities are more concentrated and efficient in cities with higher population densities.

Table 5-32 The impact of urban land polycentric/monocentric structures on industrial carbon emissions

Variable	Equation 5.45 ln(*Industrial Emission*)	Equation 5.46 ln(*Industrial Emission*)	Equation 5.47 ln(*Industrial Emission*)
ln(*Component1_Polycentricity*)	0.0852	0.0636	0.0324
	(0.169)	(0.177)	(0.160)
ln(*CA*)	1.314***	1.479***	1.223**
	(0.149)	(0.129)	(0.267)
ln(*pop*)		-0.203**	-0.268***
		(0.0629)	(0.0422)
ln(*Industrial Employment*)			0.250
			(0.177)
ln(*Industrial Structure*)			-0.483**
			(0.108)
Constant	6.690***	7.825***	7.170*
	(0.0948)	(0.432)	(2.336)
Observations	984	984	984
R-squared	0.339	0.350	0.377

Variable	Equation 5.45 ln(*Industrial Emission*)	Equation 5.46 ln(*Industrial Emission*)	Equation 5.47 ln(*Industrial Emission*)
Number of years	4	4	4

Robust standard errors in parentheses； *** p<0.01, ** p<0.05, * p<0.1

(3) Transportation Carbon Emissions

The econometric research framework for the impact of urban polycentric spatial structures on transportation carbon emissions is structured as follows. Equation 5.48 incorporates the principal component indicators of urban polycentric structure and urban land area. Equation 5.49 further controls for factors affecting urban transportation demand, such as population (*pop*) and economic development (*GDP*).

Equation 5.48

$$\ln(Transport\ Emission)_{it}=\beta_{01}+\beta_{11}\ln(Component1\_Polycentricity)_{it}+\beta_{21}\ln(CA)_{it}+\mu_{i1}+\gamma_{t1}+\epsilon_{it1}$$

Equation 5.49

$$\ln(Transport\ Emission)_{it}=\beta_{02}+\beta_{12}\ln(Component1\_Polycentricity)_{it}+\beta_{22}\ln(CA)_{it}$$
$$+\beta_{32}\ln(pop)_{it}+\beta_{42}\ln(GDP)_{it}+\mu_{i2}+\gamma_{t2}+\epsilon_{it2}$$

In both models, the coefficients for the logarithmic transformation of urban polycentric structure ln(*Component1_Polycentricity*) were -0.171 and -0.163, respectively, neither of which reached statistical significance. This indicates that, after controlling for other variables, the direct correlation between the city's polycentric structure and transportation carbon emissions is insignificant. The growth in population and economic activity directly drives the increase in transportation carbon emissions, while the expansion of urban land area reflects the spatial diffusion effects in the process of industrialization and urbanization. The impact of a polycentric urban spatial structure on transportation carbon emissions may exhibit different effects in cities with different urban land area. Therefore, the entire sample is divided into quartiles based on urban land area, and regression analysis is conducted accordingly.

Table 5-33 Impact of urban land polycentric/monocentric structure on transportation Carbon Emissions Results

Variable	Equation 5.48	Equation 5.49
	ln(*Transport Emission*)	ln(*Transport Emission*)
ln(*Component1_Polycentricity*)	-0.171	-0.163
	(0.0811)	(0.0814)
ln(*CA*)	1.428***	0.507**
	(0.0601)	(0.107)
ln(*pop*)		0.295***
		(0.0396)
ln(*GDP*)		0.399***
		(0.0654)
Constant	4.427***	0.335
	(0.0800)	(0.236)
Observations	984	984
R-squared	0.471	0.591
Number of years	4	4

Robust standard errors in parentheses； *** p<0.01, ** p<0.05, * p<0.1

The quartile regression results indicate that in the first quartile, the coefficient for urban polycentricity (ln(*Component1_Polycentricity*)) is -0.201. This suggests a negative correlation between urban polycentric structures and transportation carbon emissions in the smallest urban land area group, significant at the 10% level. This may imply that in relatively smaller cities, a polycentric structure can reduce transportation carbon emissions. In the second quartile, the coefficient for urban polycentricity is -

0.266, but not significant, indicating that the relationship between urban polycentric structure and transportation carbon emissions is unclear in cities of the second quartile. In cities of the third quartile, the coefficient for urban polycentricity is -0.549, significant at the 5% level (** $p<0.05$), suggesting that urban polycentric structures significantly reduce transportation carbon emissions in the medium urban land area group. The coefficient for urban polycentricity in the fourth quartile is 0.08, but not significant, indicating that in the largest urban land area group, the impact of urban polycentric structures on transportation carbon emissions is not significant.

Table 5-34 Grouped regression results of the impact of urban polycentric/monocentric structure on transportation carbon emissions

Variable	1st quartile ln(*Transport Emission*)	2nd quartile ln(*Transport Emission*)	3rd quartile ln(*Transport Emission*)	4th quartile ln(*Transport Emission*)
ln(*Component1_Polycentricity*)	-0.201*	-0.266	-0.549**	0.0800
	(0.0745)	(0.289)	(0.170)	(0.140)
ln(*CA*)	3.179***	0.556	0.689	0.364*
	(0.198)	(1.018)	(0.309)	(0.118)
ln(*pop*)	0.426***	0.212***	0.189*	0.339***
	(0.0443)	(0.0303)	(0.0739)	(0.0380)
ln(*GDP*)	0.311***	0.355	0.337**	0.561***
	(0.0216)	(0.162)	(0.0578)	(0.0802)
Constant	-0.376*	1.239	1.678***	-1.477*
	(0.142)	(0.747)	(0.243)	(0.545)
Observations	246	246	246	246
R-squared	0.370	0.133	0.257	0.753

Variable	1st quartile ln(*Transport Emission*)	2nd quartile ln(*Transport Emission*)	3rd quartile ln(*Transport Emission*)	4th quartile ln(*Transport Emission*)
Number of years	4	4	4	4

Robust standard errors in parentheses；*** p<0.01, ** p<0.05, * p<0.1

（4）Household Carbon Emission

Econometric models for the impact of urban polycentric spatial structure on household Carbon Emissions. Equation 5.50 incorporates indicators of urban spatial structure, including the main component of urban polycentricity and urban land area. Equation 5.51 adds control variables for population size and temperature. Equation 5.52 focuses on heating carbon emissions, a significant component of household carbon emissions, to explore the impact of urban polycentric spatial structure on heating carbon emissions.

Equation 5.50

$$\ln(\mathit{Household\ Emission})_{it}=\beta_{01}+\beta_{11}\ln(\mathit{Component1\_Polycentricity})_{it}+\beta_{21}\ln(CA)_{it}+\mu_{i1}+\gamma_{t1}+\epsilon_{it1}$$

Equation 5.51

$$\ln(\mathit{Household\ Emission})_{it}=\beta_{02}+\beta_{12}\ln(\mathit{Component1\_Polycentricity})_{it}+\beta_{22}\ln(CA)_{it}+\beta_{32}\ln(pop)_{it}+\beta_{42}\ln(\mathit{Temperature})_{it}+\mu_{i2}+\gamma_{t2}+\epsilon_{it2}$$

Equation 5.52

$$\ln(\mathit{Heating\ Emission})_{it}=\beta_{03}+\beta_{13}\ln(\mathit{Component1\_Polycentricity})_{it}+\beta_{23}\ln(CA)_{it}+\beta_{33}\ln(pop)_{it}+\beta_{43}\ln(\mathit{Temperature})_{it}+\mu_{i3}+\gamma_{t3}+\epsilon_{it3}$$

The regression results indicate that in the model, the coefficient for urban polycentric structure is 0.262, but it does not reach the traditional level of significance.

After further controlling for temperature and population variables, in Equation 5.51, the coefficient for polycentric structure is 0.411 and is significant at the 10% level (* $p<0.1$), suggesting a positive correlation between urban polycentric structure and household carbon emissions. This implies that an increase in the degree of polycentricity may increase household carbon emissions. Regarding heating carbon emissions, in Equation 5.52, the coefficient for polycentric structure is -0.0140, indicating that its impact on heating carbon emissions is not significant.

Table 5-35 Regression results of the impact of urban land polycentric/monocentric structure on household carbon emissions

Variable	Equation 5.50 ln(*Household Emission*)	Equation 5.51 ln(*Household Emission*)	Equation 5.52 ln(*Heating Emission*)
ln(*Component1_Polycentricity*)	0.262	0.411*	-0.0140
	(0.230)	(0.153)	(0.201)
ln(*CA*)	1.239***	0.538**	2.602***
	(0.208)	(0.165)	(0.227)
ln(*pop*)		0.818***	-0.632**
		(0.0636)	(0.127)
ln(*Temperature*)		-0.660**	-1.109***
		(0.138)	(0.104)
Constant	3.282***	0.535	9.542***
	(0.0715)	(0.428)	(0.573)
Observations	984	984	444
R-squared	0.287	0.431	0.519
Number of years	4	4	4

Robust standard errors in parentheses； *** p<0.01, ** p<0.05, * p<0.1

5.2.5 Analysis of the Impact of Urban Green Spaces on Carbon Emissions

Urban green spaces, as an essential component of urban ecosystems, play a crucial role in absorbing carbon dioxide, mitigating climate change, improving urban environments, and enhancing the quality of life for residents. Understanding the relationship between green space morphology and urban carbon dioxide emissions can help us better plan and manage urban green systems, achieve urban carbon reduction, and thus promote sustainable development. This study selects indicators such as urban green space area, urban green coverage rate, and Shannon diversity index to explore their relationship with carbon dioxide emissions.

5.2.5.1 Indicator Selection

a. Urban Green Space Ratio (*UGSR*)

Urban Green Space Ratio (*UGSR*) is an indicator used to quantify and describe the coverage of green spaces within a city or other areas. Green spaces include parks, grasslands, trees, gardens, and other areas that positively impact the environment and quality of life. The green space ratio is expressed as a percentage based on the proportion of all green space areas to the total urban built-up area.

b. Green Space - Built-up Land - Shannon Diversity Index (*SHDI*)

Green Space - Built-up Land - Shannon Diversity Index (*SHDI*) calculates the total sum of the area proportion of each patch type in the landscape multiplied by its natural logarithm, then takes the negative of that sum. It is unitless, with a range of $SHDI \geqslant 0$. When the landscape contains only one patch type, Shannon's diversity is 0. As the number of patch types in the landscape increases and the area proportion of each type becomes more balanced, Shannon's diversity increases.

Equation 5.53

$$SHDI=-\sum_{i=1}^{n} P_i \ln(P_i)$$

Where n is the number of patch types, focusing here on the combination of urban green space and built-up land, making n=2. P_i represents the area proportion of each patch type. In this study, it represents the proportion of built-up land and green space. This study uses it to calculate the distribution state of green space and built-up land, whether mixed or balanced.

c. Urban Green Space Spatial Compactness Index (*AI_UGS*)

Urban Green Space Spatial Compactness Index (*AI_UGS*) indicates the spatial distribution pattern of urban green spaces, significantly affecting their ecological regulation functions. The Aggregation Index of Urban Green Space (*AI_UGS*) describes the spatial distribution relationship of urban green spaces. A lower *AI_UGS* value indicates fragmented, dispersed green space distribution. Conversely, a higher *AI_UGS* value indicates urban green spaces are forming a more compact whole.

5.2.5.2 Data Source and Processing

This study's data on urban green space area was sourced from the "China City Statistical Yearbook." The Urban Green Space Ratio (*UGSR*) was calculated by dividing the urban green space area by the urban built-up area.

Shi et al. (2023) utilized deep learning methods to calculate urban green space data for 31 major cities in China, providing urban green space data with a spatial resolution of 1 meter, representing highly accurate urban green space data. This study employs this data to analyze urban green space spatial morphology.

Figure 5-11 Example of Local Urban Green Space Data (Beijing)

Before calculating the spatial morphology of urban land use, this chapter matched the spatial resolution of urban green space data with urban built-up land data, uniformly setting it to a spatial resolution of 50m*50m. This data was then imported into Fragstats to calculate the Urban Green Space-Built-up Land Shannon Diversity Index (*SHDI*) and the green space compactness index.

5.2.5.3 Empirical Research Results on the Impact of Urban Green Spaces on Carbon Emissions

5.2.5.3.1 Research on the Impact of Urban Green Coverage Rate on Carbon Emissions

To explore the impact of urban green space ratio on carbon emissions, this section constructs the following econometric model to analyze the influence of urban green space ratio (*UGS_Rate*) on urban carbon emissions (*Carbon Emission*), including total carbon emissions (*Total Emission*), industrial carbon emissions (*Industrial Emission*), transportation carbon emissions (*Transport Emission*), and household carbon emissions (*Household Emission*). Control variables include factors affecting urban population size (*pop*), urban land area (*CA*), and affluence level (*AGDP*). Such a model design helps accurately assess the impact of various urban factors on carbon emissions, providing data support for urban planning and environmental policies.

Equation 5.54

$$\ln(carbon\ Emission)_{it}=\beta_{02}+\beta_{12}\ln(UGS\_Rate)_{\mathrm{it}}+\beta_{22}\ln(CA)_{\mathrm{it}}+\beta_{32}ln(pop)_{it}$$
$$+\beta_{42}ln(AGDP)_{it}+\mu_{i2}+\gamma_{t2}+\epsilon_{it2}$$

The impact of urban green space ratio on different components of carbon emissions shows certain heterogeneity. For total carbon emissions (*Total Emission*): The regression coefficient of *UGS_Rate* is -0.126, but its p-value is greater than 0.1 (standard error is 0.108), indicating it is not statistically significant(Table 5-36). For industrial carbon emissions (*Industrial Emission*): The regression coefficient of *UGS_Rate* is -0.199, but also not statistically significant (standard error is 0.135), suggesting the impact of urban green space ratio on industrial carbon emissions is not statistically meaningful.

For transportation carbon emissions (*Transport Emission*), the regression coefficient of *UGS_Rate* is 0.270, with a p-value less than 0.1 (standard error is 0.0890), showing a positive correlation between urban green space ratio and transportation carbon emissions, passing the significance test. This indicates that in the urban system of China, cities with a larger urban green space ratio have relatively higher transportation carbon emissions. Cities with a higher green space ratio might focus on the layout of green spaces in urban planning, but this does not necessarily mean that transportation planning is equally efficient. The regression results suggest that population size and affluence level are the main factors affecting transportation carbon emissions, with regression coefficients of 0.695 and 0.373, respectively, passing the significance test. First, larger population sizes in cities typically mean higher transportation demand. As population numbers increase, the frequency and distance of travel and the usage of transportation vehicles all increase, leading to higher transportation carbon emissions.

Moreover, densely populated areas may experience traffic congestion, further increasing car carbon emissions. Second, cities with higher levels of economic development usually have higher personal or household income levels, which may affect residents' travel choices. For instance, residents may prefer private cars over public transportation in more economically developed areas, thereby increasing transportation carbon emissions. Economic development can also lead to more business activities and logistics needs, similarly increasing transportation carbon emissions.

The impact of the urban green space ratio on household carbon emissions is significant and opposite to its impact on transportation carbon emissions. The regression coefficient of *UGS_Rate* is -0.663, with a p-value less than 0.1 (standard error is 0.209), indicating a negative correlation between urban green space ratio and household carbon emissions, with a strong correlation. In cities with more green spaces, households may reduce reliance on air conditioning and heating devices due to better natural shading and cooling effects brought by urban greening. In other words, this lowers energy consumption and related carbon emissions. Among the factors affecting household carbon emissions, urban land area, population, and affluence level are also important, with regression coefficients being 0.797, 0.764, and 0.161, respectively, and all passing the significance level tests.

Table 5-36 Regression results of the impact of urban green space ratio on carbon emissions

Variable	*Total Emission*	*Industrial Emission*	*Transport Emission*	*Household Emission*
ln(*UGS_Rate*)	-0.126	-0.199	0.270*	-0.663*
	(0.108)	(0.135)	(0.0890)	(0.209)
ln(*CA*)	0.755**	1.010**	0.370	0.797***
	(0.190)	(0.276)	(0.176)	(0.0931)
ln(*pop*)	0.201	0.0235	0.695***	0.764***
	(0.139)	(0.206)	(0.0424)	(0.0723)
ln(*AGDP*)	0.377*	0.368	0.373**	0.161**
	(0.147)	(0.196)	(0.0693)	(0.0463)
Constant	5.845***	6.453**	0.187	-0.717
	(0.864)	(1.273)	(0.215)	(0.420)

Variable	*Total Emission*	*Industrial Emission*	*Transport Emission*	*Household Emission*
Observations	982	982	982	982
R-squared	0.446	0.369	0.592	0.397
Number of years	4	4	4	4

Robust standard errors in parentheses； *** p<0.01, ** p<0.05, * p<0.1

5.2.5.3.2 Research on the Impact of Urban Green Space Morphology on Carbon Emissions

To explore the impact of urban green space morphology on carbon emissions, considering the characteristics of the sample, this study constructs an ordinary least squares regression model:

Equation 5.55

$$\ln(\mathit{carbon\ emission}) = \beta_0 + \beta_1 \cdot \ln(\mathit{AI\_UGS}) + \beta_2 \cdot \ln(\mathit{SHDI}) + \beta_3 \cdot \ln(\mathit{CA}) + \beta_4 \cdot \ln(\mathit{pop}) + \beta_5 \cdot \ln(\mathit{A\_GDP})$$

In this formula, carbon emission refers to the total urban carbon emissions. Subsequent studies will conduct regression analysis on four dimensions: total carbon emissions (*Total Emission*), industrial carbon emissions (*Industrial Emission*), transportation carbon emissions (*Transport Emission*), and household carbon emissions (*Household Emission*). *AI_UGS* is an index of urban green space compactness, indicating whether urban green spaces are fragmented and evenly distributed or large and compactly concentrated. *SHDI* represents the balance of urban green spaces and built-up areas. The model includes control variables, such as urban land area (*CA*), population size (*pop*), and *per capita GDP*. Regression results show that the R-squared values of the models are relatively high, at 0.644, 0.652, 0.803, and 0.766, respectively, indicating that the model adequately explains the factors affecting urban carbon emissions and fits well.

Table 5-37 Impact of urban green space morphology on carbon emission: regression results

Variable	(1) *Total Emission*	(2) *Industrial Emission*	(3) *Transport Emission*	(4) *Household Emission*
ln(*AI_UGS*)	-0.0478	-0.225	-0.164	**0.725*** **
	(0.105)	(0.174)	(0.170)	**(0.117)**
ln(*SHDI*)	0.125	0.224	0.0667	**-0.670*** **
	(0.189)	(0.256)	(0.169)	**(0.135)**
ln(*CA*)	1.324***	2.130***	0.797*	0.134
	(0.239)	(0.319)	(0.430)	(0.356)
ln(*pop*)	-0.782***	-1.604***	0.394	0.965***
	(0.202)	(0.282)	(0.253)	(0.266)
ln(*AGDP*)	-0.179	-0.460	0.296	0.750***
	(0.201)	(0.284)	(0.255)	(0.249)
Constant	12.58***	17.28***	2.483	-3.027*
	(1.425)	(2.041)	(1.952)	(1.465)
Observations	26	26	26	26
R-squared	0.644	0.652	0.803	0.776

Robust standard errors in parentheses； *** p<0.01, ** p<0.05, * p<0.1

From the regression results, the impact of urban green space morphology on carbon emissions mainly manifests in its effect on household carbon emissions. In models (1), (2), and (3), neither the compactness of urban green spaces nor the Shannon diversity index of green and built-up areas showed significant regression coefficients. However, looking at the regression coefficients, the impact of urban green space morphology on industrial and transportation carbon emissions is opposite to that on household emissions, suggesting that compact green space layouts may reduce industrial and transportation emissions. For industrial emissions, compact green layouts can make urban spaces more organized, reducing fragmentation and improving land use efficiency. This is particularly important for industrial area planning as it helps reduce necessary transportation distances, thus reducing energy consumption and increasing production efficiency. For transportation emissions, the compact and centralized layout of urban green spaces allows for less urban space being squeezed by green areas, thereby reducing transportation carbon emission efficiency.

Model (4) shows significant effects of urban green space morphology on household carbon emissions. The logarithmic regression coefficient for the compactness index (*AI_UGS*) is 0.725, significant at the 1% level. This indicates that urban green spaces' compact and centralized distribution somehow increases household carbon emissions. Firstly, a compact distribution of urban green spaces also means a compact and dense distribution of urban built-up land, which in some cases might reduce energy efficiency. Dense building layouts may lead to poor ventilation and heat island effects, increasing reliance on air conditioning and cooling systems, thereby increasing energy consumption and carbon emissions. Secondly, under compact, centralized green layouts, due to the limited regulatory effect of heat island phenomena, residents may need to rely more on air conditioning and cooling devices to regulate indoor temperatures, leading to increased energy consumption and carbon emissions. In contrast, a dispersed and balanced green layout might more effectively reduce the city's average temperature, reducing reliance on air conditioning and cooling devices, thus helping to reduce household energy consumption and carbon emissions.

In model (4), the regression coefficient for the balance index of green and built-up land distribution (*SHDI*) is -0.67%, significant at the 1% level. A balanced quantitative allocation of urban green spaces and built-up land helps reduce household carbon emissions. This result emphasizes the importance of achieving a balanced allocation of green and built-up areas in urban planning. Urban green spaces provide ecological services such as air purification, temperature regulation, rainwater management, and biodiversity protection but also play a crucial role in reducing urban heat islands and improving the urban microclimate. Green spaces help lower household energy consumption and carbon emissions by reducing reliance on air conditioning and cooling systems. This finding corroborates with related research; for instance, Yao et al. (2023) discovered that the reduction of urban green space area led to intensified heat island effects in Hefei's urbanization process. Therefore, balanced green space layouts are vital for achieving sustainable urban development.

5.3 Summary of This Chapter

The selection of indicators for urban geometric morphology starts from the "land area-spatial allocation" dimension, choosing key variables that reflect the geometric morphological characteristics of urban land use. These variables quantify urban geometric morphology from four dimensions: built-up area size, shape complexity, compactness, and polycentricity/mono-centricity, exploring their impact on carbon emissions and urban green space morphology. This study leverages the advantages of nighttime light data and land use data to generate a foundational dataset for urban built-up areas. With the help of ArcGIS and Fragstats software, geometric morphological indices are calculated to explore their relationship with carbon emissions after analyzing urban geometric morphology spatiotemporal patterns.

First, Urban land growth and carbon emissions exhibit a "super-linear" relationship, with improvements in carbon emission efficiency.

Previous research in this chapter found a "sub-linear" relationship between urban population growth and carbon emissions. However, studies on urban land show a "super-linear" relationship between urban land growth and carbon emissions, meaning that as urban land grows, carbon emissions increase at a faster rate.

The improvement in carbon emission efficiency mainly comes from the city's economy growing faster than its carbon emissions. Measuring carbon emission efficiency with carbon emissions per unit of GDP, carbon emission efficiency improves as urban land area grows, largely due to land finance playing a significant role in driving urban economic growth.

Research on different sources of carbon emissions found that (1) increasing urban population density can improve carbon emissions per unit of industrial output. (2) urban land growth has a more pronounced effect on transportation carbon emissions in smaller and larger cities. (3) For household carbon emissions, urban land expansion has the greatest impact on heating carbon emissions. In heating areas, moderately increasing urban density significantly reduces heating carbon emissions.

Second, Complex urban land inhibits transportation carbon emissions but

increases household emissions, especially heating carbon emissions.

This section selects the Area-Weighted Mean Shape Index (AWMS) and Area-Weighted Mean Patch Fractal Dimension (AWMPFD) as indicators of urban land complexity. Principal Component Analysis (PCA) extracts effective information and eliminates redundant information. Research findings indicate: (1) Urban land complexity does not significantly impact total and industrial carbon emissions. (2) Urban land shape complexity is more evident in reducing transportation carbon emissions, possibly because more complex urban forms reduce transportation accessibility, inhibiting traffic activities. (3) Urban land complexity increases household carbon emissions but to a lesser extent. Complex urban land significantly impacts heating carbon emissions, possibly because complex urban land means heating infrastructure (like pipelines and thermal power stations) is more dispersed, leading to reduced heating efficiency.

Third, Compact urban land is beneficial for reducing transportation carbon emissions and positively correlates with household carbon emissions.

The section has selected the Compactness Index (AI), Largest Patch Index (LSI), and Mean Nearest Neighbor Distance (ENN_AM) as indicators of urban land compactness. PCA is used to reduce dimensions and eliminate redundant information. Research shows: (1) Urban land compactness does not significantly impact total or industrial carbon emissions. (2) Compact urban land helps reduce transportation carbon emissions, especially in small and medium-sized cities. Urban planning practices should pay more attention to cities with an urban land area of 100 square kilometers or less, emphasizing urban land compactness. (3) Urban land compactness positively correlates with household carbon emissions but is not significantly related to heating carbon emissions.

Fourth, The impact of polycentric/monocentric spatial structures on carbon emissions is generally insignificant.

Urban polycentricity/mono-centricity spatial structure characteristics are depicted using the Center Area Coefficient and Center Area Variation Coefficient, with PCA used to extract principal components and reduce redundancy. Research shows: (1) Polycentric/monocentric spatial structures do not significantly impact total carbon emissions or industrial carbon emissions. (2) urban polycentric spatial structures in smaller cities can reduce transportation carbon emissions. (3) Urban polycentric structures are positively correlated with household carbon emissions, meaning that an increase in polycentricity may lead to an increase in household carbon emissions. The impact of the city's polycentric/monocentric spatial structure features on heating carbon emissions is insignificant.

Fifth, An increase in urban green space ratio increases transportation carbon emissions but reduces household carbon emissions.

Urban green space, a key element of urban spatial components, can regulate the urban microclimate, impacting carbon emissions. This chapter selects the urban green space ratio to describe the supply level of urban greening; the Urban Green Space-Built-up Land-Shannon Diversity Index (*SHDI*) to measure the balanced relationship between urban green space and built-up land; and the Urban Green Space Spatial

Compactness Index (*AI_UGS*) to describe the spatial distribution characteristics of urban green space as compact or dispersed. Research findings show: (1) The urban green space ratio does not significantly impact total or industrial carbon emissions. (2) In the Chinese urban system, cities with a larger urban green space ratio also have relatively larger urban transportation carbon emissions. (3) Increasing the urban green space ratio helps reduce household carbon emissions. (4) Cities with a more balanced distribution of green space and built-up land have lower household carbon emissions. Cities with a more evenly distributed green space have lower household carbon emissions.

Chapter 6. Urban Carbon Reduction Strategies Based on Urban Spatial Structure

This article combines the analysis results from the previous chapters of empirical research and proposes urban carbon reduction planning strategies from two dimensions: urban size and urban form.

6.1 Urban Carbon Reduction Strategies from the Perspective of Urban Size Dimension

6.1.1 Improving Carbon Emission Efficiency by Urban Population Agglomeration

According to the National Bureau of Statistics of China, the urbanization rate in China has reached 65.22%. The phase of large-scale rural population migration to cities has passed, and the future will see an increase in population movement between cities, with adjustments in urban size occurring nationwide. Initially, urbanization was characterized by rural-to-urban migration, with inter-city migration playing a secondary role, mainly manifesting as rural population aggregation in towns. However, in the later stages of urbanization, the dynamics of "rural-to-urban" and "urban-to-urban" population movements change, with the speed and scale of inter-city population movement exceeding that of rural-to-urban migration. Rational inter-city population movement can enhance urban efficiency, including carbon emission efficiency. Chapter 3 has found a "sub-linear" relationship between urban population size and carbon emissions, meaning the growth rate of urban carbon emissions is slower than that of urban population growth. As urban size increases, carbon emissions per unit of GDP decrease, indicating that the carbon emission pressure associated with producing the material life humans require is diminishing.

Population policy planning should be adaptive, scientifically predicting future population and socio-economic development trends, and rationally guiding population concentration towards cities with higher quality of regional development. This optimizes the allocation of resources and thus reduces carbon emissions. Leveraging the scale effect of urban population aggregation can improve energy efficiency and reduce carbon emissions. Cities experiencing population inflow should focus on enhancing regional development efficiency. Zhong Yuejun et al. (2023)[194] similarly believe that entering the post-industrial development stage, reallocating resources towards more efficient areas can improve economic growth while also enhancing energy utilization efficiency and reducing energy consumption per unit of GDP through scale effects and reallocation effects.

To promote rational population mobility, bridging the gap between the inevitable growth assumed in overall urban planning and the reality that urban populations may decrease is necessary. Inevitably, inter-city population movement results in growth in some cities and decline in others, i.e., the central cities' suction effect on surrounding cities. However, in overall urban planning, cities experiencing population decline are often still planned for growth. This creates a scenario of shrinking cities but expanding plans[182]. Urban planners and managers should base their decisions on the laws of urban development and reality, considering constraints of resources and environmental carrying capacity to rationally predict and plan future urban populations, thereby effectively guiding urban development.

Urban carbon neutrality planning should consider the regional urban system as the basic unit, not individual cities. As China's urbanization level increases, the growth of one city is, to some extent, at the expense of shrinkage in other cities, marking an adjustment in the urban system's scale distribution in the middle and later stages of urbanization. The growth in urban size that leads to increased industrial production also accompanies industrial shrinkage in other regions. Although this study finds that industrial carbon emissions in growing cities are increasing, carbon emission efficiency is improving. Therefore, when planning for carbon reduction, urban planning and management should consider the entire urban system, taking into account the distribution of urban size.

6.1.2 Urban innovative Agglomeration Promotes Industrial Carbon Reduction

This thesis has identified a mechanism through which urban size growth facilitates industrial carbon reduction by promoting urban innovation and upgrading industrial structures(section 4.2). However, these studies also highlight the dual nature of urban innovation in reducing industrial carbon emissions. On one hand, innovation leads to increased production and, consequently, more industrial carbon emissions. On the other hand, innovation contributes to carbon emission reduction by advancing the upgrade of urban industrial structures. Nevertheless, it was also found that even in cities with higher income levels, the carbon reduction driven by innovation is insufficient due to a lack of green innovation supply.

Therefore, cities should be guided towards innovative agglomeration focusing on green innovation, which often suffers from market failure and insufficient supply due to its public good characteristics. To ensure sustainable urban development, the government provides specific green innovation subsidies and policy support to growing small cities to promote the development of green production and management technologies. This policy aims to balance urban expansion with industrial carbon emissions while recognizing the positive impact of innovation on carbon emissions, ensuring that cities can achieve carbon reduction while pursuing economic growth. Cities with a per capita GDP of over 80,000 RMB should focus on promoting industrial structure upgrades through innovation to achieve carbon reduction.

There should be a collaborative effort towards green innovation in the urban system among large, medium, and small cities. Large cities should guide and drive the development of green innovation in medium and small cities. Previous research has also found that the promotive effect of innovation on carbon emissions is primarily observed in cities with lower levels of development. Specifically, for cities with a per capita GDP of about 30,000 RMB, the effect of innovation on increasing industrial carbon emissions is particularly pronounced(Section 4.2.3.2). Large cities, with their rich experience in balancing economic development and environmental protection, should lead in providing technological support and collaborative guidance to smaller cities. Smaller cities, which may have more lenient environmental standards and insufficient motivation for green innovation, should avoid becoming "pollution havens" through the spatial transfer of carbon emissions.

6.1.3 Heating Cities Increase Population Density to Reduce Heating Carbon Emissions

In China, the per capita carbon emission is 7.8 tons, while in cities with heating systems, the per capita heating carbon emission reaches 1.5 tons, accounting for about 20% of the total. Research on carbon reduction in heating from the perspective of spatial structure is relatively scarce. This study finds that the scale effect of heating carbon emissions is larger than that of household carbon emissions, and increasing urban density can reduce the impact of urban size growth on heating carbon emissions. Therefore, for heating cities, it is necessary to reasonably guide the concentrated distribution of urban population and improve urban population density. Large cities, with their more complete infrastructure and technology, can adopt more efficient and cleaner heating systems, which helps reduce carbon emissions.

Moreover, under the current overall urban density in China, there should be a general increase in the population density of cities with heating needs, guiding population concentration towards core areas. Increased urban density helps improve heating efficiency by reducing thermal energy loss during transmission. A high-density urban layout can also promote more concentrated energy use, reduce energy waste, and thus lower carbon emissions. This is especially important in cities with lower temperatures, where their levels of heating carbon emissions are high.

6.1.4 Large cities Should Focus on Improving Public Transportation Efficiency to Reduce Transportation Carbon Emission

Based on the intuitive experience that using urban public transportation systems in large cities helps reduce overall carbon emissions, this study constructs a mediation effect model to test the impact mechanism of "urban size-public transportation-transportation carbon emissions". The research finds that the increase in urban size does indeed reduce transportation carbon emissions to a certain extent-- through the use of urban public transportation. However, the impact is still relatively small, indicating that in China's urban system, the role of public transportation systems has not been effectively played, and efficiency is low.

Therefore, it is recommended to reduce transportation carbon emissions from the following aspects: (1) Efforts should be made to improve the coverage and accessibility of the public transportation system, expand the public transportation network, especially in densely populated areas, to ensure that transportation services cover a broader area. Improve the convenience of public transportation, such as reducing waiting times, increasing the frequency of services, and optimizing route design. (2) In small and medium-sized cities, further promote the concentrated distribution of the population and shorten the distance of urban populations to urban public services, thereby reducing transportation demand. (3) For cities where the urban population and economic development level are not yet developed, a detailed assessment of the city's public transportation needs should be conducted before approving subway planning. For cities with lower population and economic development levels, more economical and efficient public transportation solutions, such as Bus Rapid Transit (BRT), trams, or enhanced bus services, can be considered.

6.2 Urban Carbon Reduction Planning Strategies from the Urban Land Morphology

6.2.1 Reducing Land shape Complexity to Promote Household Carbon Emission Reduction in Cities of 100 and 600 km²

The study finds that urban land shape complexity suppresses urban transportation carbon emissions to some extent but increases carbon emissions from urban residents, particularly those related to heating (Section 5.4). Although greater urban complexity reduces transportation-related carbon emissions, it also inhibits urban transportation activities and reduces overall economic development efficiency when considering urban development comprehensively. Additionally, increased land-use complexity leads to higher residential carbon emissions, especially from heating.

Considering these factors, this study suggests that urban planning should aim to reduce the complexity of urban land morphology to lower carbon emissions from the residential sector. This is particularly important for northern cities with heating demands, where land morphology should be designed to be more regular. Preventing urban sprawl and the resulting increase in land complexity is crucial, especially for cities with land area of approximately 100 and 600 square kilometers..

6.2.2 Enhancing Land-Use Compactness in Small and Medium-Sized Cities to Reduce Transportation Carbon Emissions

The research on urban land compactness found that compact and close-knit urban land layouts are conducive to reducing transportation carbon emissions. Therefore, from the perspective of enhancing land compactness and aiming to reduce urban transportation carbon emissions, this chapter proposes the following planning suggestions:

1. urban land expansion should be closely integrated geographically and functionally with the existing urban core areas to achieve a positive interaction between new urban land and urban functions and the existing urban core.

2. Newly Added new construction land in cities should prioritize "infill development" over "outward expansion." Urban built-up areas often do not exhibit completely continuous spatial characteristics, and "urban voids" may exist internally. These urban voids are often characterized by irregularity, fragmentation, and abundance, frequently becoming socio-economic-ecological grey spaces, representing potential resources for enhancing urban sustainability. These urban voids can be redeveloped as incremental construction land, revitalizing and supplementing the need for new outward expansion of construction land, enhancing urban land compactness, and reducing transportation carbon emissions.

3. Strict control over creating "urban enclaves" is necessary. Urban enclaves, being geographically distant from the main urban area, not only increase the difficulty of interaction with the main urban area, but hindering the improvement of urban economic

development performance and increase transportation carbon emissions. Therefore, the approval of urban enclaves should be strictly controlled.

6.2.3 Increasing Urban Green Space Supply and Optimizing Spatial Patterns to Reduce Household Carbon Emissions

Urban green spaces, as "quasi-natural" elements in urban spaces, play a regulatory role in urban climate. This research on the impact of urban green spaces on urban carbon emissions found that cities with a higher ratio of green space have relatively lower household carbon emissions. This indicates that increasing the urban green space ratio can effectively reduce carbon emissions from the urban household sector. In urban land planning, improving urban spatial order through constructing urban green spaces and appropriately increasing the urban green space ratio can create urban green spaces in fragmented vacant lands and link these green spaces to form a beneficially interactive urban green space system. Particularly in cities with higher summer temperatures and larger urban built-up areas, an adequate urban green space ratio can effectively mitigate the urban heat island effect in summer, reducing the increase in carbon emissions caused by indoor cooling. The study also found that an increase in the urban green space ratio relatively increases transportation and industrial carbon emissions. During the construction of urban green spaces, it is also necessary to consider the positive interaction between urban green spaces and other land uses, avoiding the inefficiencies caused by urban fragmentation due to urban green spaces.

From the perspective of green space spatial allocation, the research found that an overly concentrated distribution of urban green spaces is not conducive to reducing carbon emissions in the household sector, while a relatively uniform spatial distribution has a greater effect on reducing household carbon emissions. Therefore, when planning urban green space layouts, the balanced integration of urban construction land and urban green spaces should be considered, avoiding the spatial imbalance between urban construction land and green spaces to reduce the regulatory effects of urban green spaces.

6.3 Summary of This Chapter

This chapter, based on the empirical research results regarding the impact of urban spatial structure on industrial carbon emissions, transportation carbon emissions, and household carbon emissions, proposes spatial planning strategies for carbon reduction from four dimensions: urban population size, urban land area, urban land form, and urban green space.

Chapter 7. Conclusions and Discussion

7.1 Major Conclusions of the thesis

This study utilizes remote sensing, geographic information systems (GIS), and econometric methods to investigate the impact of urban spatial structure on carbon emissions, framed within the "spatial distribution-quantitative impact-planning strategies" framework. The analysis draws on data from over 220 Chinese cities to examine the systemic effects of urban spatial structure on various categories of carbon emissions, including total emissions, transportation, industrial, and household emissions. The study develops a multi-tiered indicator system for urban spatial structure in relation to carbon emissions, incorporating factors such as population size, land area, land form, and urban green space.

Second, through spatial analysis, principal component analysis, and mediation effect analysis, this thesis provides an empirical assessment of the current state of China's urban spatial structure and its impact on various sources of carbon emissions. The findings offer valuable insights for urban planning and management strategies aimed at carbon reduction. The chapter also proposes practical planning and management approaches that leverage urban spatial structures to mitigate carbon emissions, serving as useful references for sustainable urban development in China.

Lastly, the research advocates for a holistic approach to urban planning, focusing on low-carbon and efficient urban performance. It emphasizes the need to rethink urban land use expansion, optimize citizen-engaged planning processes, and prioritize sustainable urban spatial structures in achieving these goals. The key findings highlight the importance of integrating urban spatial planning with carbon reduction objectives to promote sustainable urban development. The main conclusions are as follows:

(1) Urban Population Size and Carbon Emissions

This section explores the impact of urban population size on carbon emissions and finds that the relationship between urban population size and carbon emissions is sublinear. Furthermore, urban population size influences industrial, heating, and transportation carbon emissions through distinct pathways.

First, urban population size affects industrial carbon emissions through innovation, production expansion, and industrial upgrading. As the urban population grows, it leads to superlinear innovation agglomeration, which, in turn, stimulates production and increases industrial carbon emissions. This effect is particularly pronounced in less developed cities. Meanwhile, the carbon reduction effect of innovation is mainly reflected in its role in industrial upgrading, which leads to emission reductions—an effect more evident in highly developed cities. Thus, while urban expansion drives industrial carbon emissions through increased production, industrial upgrading has only a limited mitigating effect.

Second, the scale effect of heating carbon emissions is more pronounced than that of overall household carbon emissions. The impact of urban density on the relationship between urban size and heating carbon emissions follows a U-shaped pattern. Overall, increasing urban population density weakens the demand for heating-related carbon emissions associated with urban expansion.

Third, urban expansion reduces transportation carbon emissions through improvements in the public transportation system, but this effect remains limited. The potential of urban public transportation systems to mitigate transportation-related carbon emissions has not been fully realized, constraining their effectiveness.

(2) Urban Land Form and Carbon Emissions

This study also examines the overall impact of urban land area on industrial, transportation, and household carbon emissions, as well as the influence of land form under land area constraints on multi-source carbon emissions. The findings indicate that urban land area has a superlinear effect on carbon emissions and that land area constraints limit the impact of urban land morphology on multi-source carbon emissions.

First, urban land expansion is the primary driver of significant increases in total urban carbon emissions, following a superlinear relationship. The impact of land expansion on carbon emissions varies by region, with the ranking as follows: Western China > Northeastern China > Central China > Eastern China. Regarding multi-source carbon emissions, land expansion has the greatest impact on transportation carbon emissions in both small and large cities, while for household carbon emissions, land expansion primarily influences heating carbon emissions. In regions with heating demand, moderate increases in urban density can significantly reduce heating carbon emissions.

Second, greater complexity in land morphology leads to higher household carbon emissions, though the effect is relatively minor. However, complex land morphology has a more significant impact on heating carbon emissions, especially in cities with land areas of 100 km² and 600 km². A more fragmented land morphology results in a more dispersed distribution of heating infrastructure (e.g., pipelines and cogeneration plants), leading to lower heating efficiency and higher carbon emissions.

Third, higher urban land compactness is beneficial for reducing transportation carbon emissions, with stronger effects observed in small and medium-sized cities. Urban planning should place greater emphasis on enhancing land compactness in cities with land areas of 100 km² or less, as this can significantly improve transportation efficiency and reduce emissions.

7.2 Innovative Points of the Thesis

(1) This study examines the impact of urban spatial structure on multi-source carbon emissions from the perspective of urban population size and land morphology, yielding a more comprehensive set of findings. Compared to previous studies that focused solely on total carbon emissions, this research provides a more nuanced and detailed understanding of the relationship between urban form and carbon emissions.

(2) A multiple mediation model was constructed to quantify the impact of urban population size on carbon emissions through urban system variables, expanding the research framework. An innovative finding of this study is that urban population size influences industrial carbon emissions through innovation activities in a dual manner, exhibiting both emission-promoting and emission-reducing effects.

(3) The study explores the impact of urban land morphology on carbon emissions

under land area constraints, offering an innovative perspective compared to previous research that treated the "shape" and "size" of urban land independently. The findings reveal that the effects of urban land morphology on carbon emissions vary across different land area, providing deeper insights into the relationship between urban land use and carbon emissions.

7.3 Discussions

The carbon emission reduction effects of urban innovation require certain urban development conditions. In this study, it was found that, overall, urban innovation in China has led to an increase in industrial carbon emissions, with a more significant effect observed in middle- and low-income cities, while no significant carbon reduction effects were observed in high-income cities. This finding is consistent with the research of Jiang et al. (2022), which showed that urban innovation reduced carbon emissions in high-income countries, while no carbon reduction effects were observed in middle- and low-income countries. The study by Ali et al. (2016) found that in the developing country of Malaysia, the relationship between technological innovation and carbon emissions was not significant. In Bangladesh, Raihan et al. (2022) showed that technological innovation could reduce carbon emissions and achieve environmental sustainability. In the BRICS countries, Erdogan (2021) found that increased technological innovation could reduce carbon emissions in the construction industry. Awan et al. (2022) found that in 33 high-income countries, innovation reduced carbon dioxide emissions in the transportation sector.

The study by Lin and Ma (2022) provides a deeper explanation of this phenomenon, suggesting that the marginal alleviating effect of green technological innovation on carbon emissions becomes significant only when the level of human capital in a city reaches a certain threshold. The Pollution Haven Effect suggests that in developing cities or countries with relatively lax environmental regulations and lower production costs, high-pollution industries tend to cluster more easily, while in high-income regions, stricter environmental standards lead some high-pollution industries to shift to middle- and low-income areas.

By comparing our results with those of other developed and developing countries, we find that the carbon emission reduction effects of innovation are influenced by the Pollution Haven Effect. Future research should explore the Pollution Haven Effect of innovation and identify how technological innovation can play a role in carbon emission reduction in cities at different levels of development.

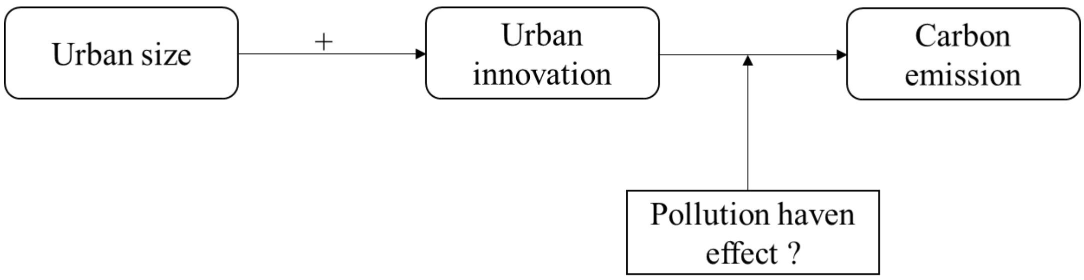

Figure 7-1 Exploratory research process for urban innovation effects

The physical spatial structure of urban land includes not only the total "quantity" of land but also its spatial "form". The area and morphology of urban land together constitute the physical framework of urban socio-economic life. This study confirms that, under different urban land areas, urban form has a significantly varied impact on carbon emissions. Urban spatial form refers to the spatial distribution of urban land scale. The scale of urban land often constrains the intensity of the impact that urban form has on carbon emissions. Most existing studies tend to overlook the role of land scale when discussing the effect of urban spatial form on carbon emissions. Urban land scale and form are not isolated concepts; they are closely intertwined. While much attention has been paid to the shape or morphology of urban spaces, particularly in relation to urban expansion and land use intensity, less emphasis has been placed on role quantity of urban land.

This study highlights that urban spatial form plays a crucial role in shaping carbon emissions, but its impact is moderated by the size of the urban land area. For example, cities with larger land areas may face different challenges related to urban sprawl, resulting in higher carbon emissions due to increased travel distances, whereas cities with more compact forms may have reduced emissions as a result of more efficient land use and transportation systems.

In fact, the physical structure of urban space—how land is utilized and organized—directly affects carbon efficiency. In larger cities, the spatial spread of land may lead to greater dependence on private transportation and energy-intensive infrastructure. In contrast, smaller cities or those with a more integrated urban form may benefit from more sustainable practices, such as higher-density development, mixed land use, and better public transportation networks.

Thus, it is crucial for future research to not only consider the spatial arrangement and form of urban areas but also the constraint of urban land quantity when examining their impact on carbon emissions(Figure 7-2). A more nuanced understanding of how land size interacts with spatial distribution can provide valuable insights for policymakers aiming to create more sustainable urban environments.

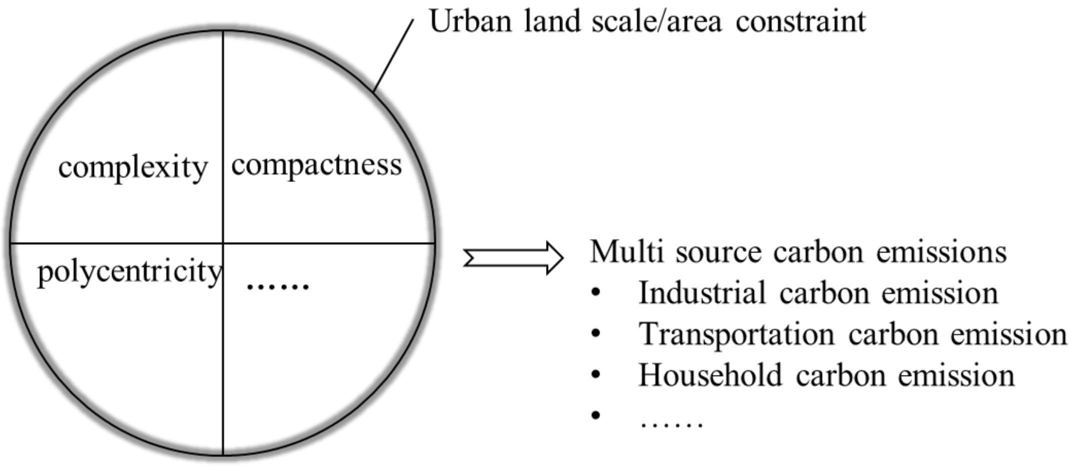

Figure 7-2 Research framework on the indirect impact of urban land on carbon emissions

This thesis, with the support of remote sensing and geographic information systems, combined with quantitative methods and focusing on the theme of "spatial distribution - quantitative impact - planning strategies," analyzes the relationship between urban spatial structure and carbon emissions in more than 200 Chinese cities, in light of the stages of urban development in China. It explores planning strategies that align with low-carbon development and supporting strategies for planning implementation. However, due to space limitations, this study still has the following needed further research in the future:

First, this study carefully selected carbon emission data, excluding those derived using urban spatial structure indicators, to prevent biased or invalid analyses. However, the reliance on discontinuous data points from the years 2005, 2010, 2015, and 2020, while statistically valid for exploring the impacts of urban spatial structure on carbon emissions, limits the ability to conduct a time series analysis. Consequently, this approach does not fully capture the dynamic evolution of the relationship between urban spatial structure and carbon emissions in China. For future studies, conducting a continuous time series analysis could offer deeper insights and more robust empirical evidence on how urban spatial structure influences carbon emissions over time.

Second, this study acknowledges the significance of the interplay between urban green spaces and urban construction land within urban spatial structures. This thesis ventures into analyzing the effects of urban green space ratio, form, and its interaction with urban construction land on carbon emissions. Nonetheless, due to the constraints of acquiring high-precision data for urban green spaces, the analysis was limited to a sample of 26 cities, all of which are provincial capital cities. While the results are statistically significant, their applicability is mainly relevant to larger urban contexts similar to provincial capital cities, and caution should be exercised when extrapolating these findings to smaller cities. Future studies should aim to dissect the underlying mechanisms linking urban green spaces with carbon emissions, potentially broadening the scope to include diverse urban settings and enhancing the granularity of the data used.

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