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Summary

CO_2 emission reduction is bound up with sustainable development, and cities increasingly become the main battlefields for combating CO_2 emission-related issues. It is argued that urban form is strongly interconnected with CO_2 emission reduction utilizing energy consumption, transportation behaviour and land utilization. As elements of urban form, urban size and density are considered closely related to CO_2 emission performance. There have been constant discussions about the optimal urban size and density as well as their relations with CO_2 emission, but no consensus has been reached. Moreover, with the increasingly important role of urban agglomeration in urbanization, the pros and cons of urban agglomeration in CO_2 emission reduction are worth understanding.

This study aims to make a contribution to the existing body of knowledge of the relationships between urban form and CO_2 emission, and also aims to find out whether urban agglomeration can play a positive role in improving the efficiency of CO_2 emission. The results of this study can add fresh blood to strategies in combating climate change, give insight on how urban form strategies can be used to reduce emission for urban sustainable development, and help urban policy-makers move forward in making right decisions in creating urban forms to reduce CO_2 emissions.

The secondary analysis and the policy analysis methods are both used in this study. In the method of the secondary analysis, temporal analysis and spatial analysis are applied to the analysis of the temporal and spatial changes of the urban form CO_2 emissions, while regression analysis is conducted to figure out the relationship between urban form and CO_2 emissions both by non-spatial model and spatial model. Additionally, the policies related to CO_2 emissions mitigation and urban agglomeration development will be analysed in policy analysis to investigate the aspects for further improvement.

The research identified several findings, mainly including: (1) There is U-shape relation between population size and CO_2 emissions, and the ideal population size of cities for lowest CO_2 emissions in Yangtze River Delta (YRD) urban agglomeration is 2.716 million. (2) There is a negative relationship between CO_2 emissions and density, which shows that when population density increases 1%, the CO_2 emissions will decrease 0.426% approximately. (3) urban agglomeration played a positive role in CO_2 emissions mitigation, by controlling the total CO_2 emissions, improving the emissions efficiency as well as eliminating the spatial agglomeration of CO_2 emissions.

These findings confirm the significantly important roles of population size and density as elements of urban form for CO_2 emissions reduction in urban agglomeration areas and provide policymakers with the scientific basis for future spatial plan and sustainable development in YRD urban agglomeration.

Keywords

CO_2 emission; Urban form; Population size; Population density; Urban agglomeration

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Abbreviations

IHS	Institute for Housing and Urban Development
UESC	Urban Environment, Sustainability and Climate Change
CO_2	Carbon Dioxide
YRD	Yangtze River Delta
EKC	Environmental Kuznets Curve
IPCC	Intergovernmental Panel on Climate Change
GDP	Gross Domestic Product
FE	Fixed Effects
RE	Random Effects
SAR	Spatial Autoregression Model

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Chapter 1: Introduction

1.1Background

The city is the milestone of human being heading for maturity and civilization. According to World Urbanization Prospects (United Nations, 2018), by 2050, nearly 70% of the world's population is expected to live in cities with a rapid increase by 13% from 2018, indicating a formidable force of urbanization and much more significant roles of cities for human development. People are drawn to cities mainly due to the benefits of more job opportunities, higher medication level, adequate education resources, richer cultural blend, more convenient lifestyle, higher living standards, etc. The aggregation of various elements forms cities, and then cities as the gathering centres attract more elements, improve the aggregation scale, quality and efficiency, and produce greater benefits with positive feedback. Meanwhile, the exchange between different cities promotes the formation of the network economy and the development of the industrial chain, resulting in a mutually beneficial and win-win situation.

However, despite the important role of cities, the sharp increase of population in cities also comes with a series of problems such as violent competition, mental and social pressure, cultural conflict, excessive energy consumption and environmental pollution. Specifically, in terms of environmental issues of cities, the carbon dioxide (CO_2) related issues such as the climate change which may be proved as the greatest global challenge facing by humanity are frequently mentioned (Karl and Trenberth, 2003). Hunt and Watkiss (2011) summarize the various potential effects of climate change on cities from the Intergovernmental Panel on Climate Change (IPCC)'s assessment reports, as well as some previous research achievements of scholars, mainly including the following five points: (1) the influence of sea-level rise to coastal cities. Billions of people might lose their home when the sea level rises over 1 meter this century. (2) The impact of extreme events on established infrastructure. For instance, after extreme storms, floods and drought, the infrastructures in cities such as water apply system and electrical system are usually damaged to some extent, which disturbs the lives of people seriously. (3) The health problems due to increasing average temperatures and extreme events. The heat-related and cold-related mortality and morbidity, food-borne and water-borne diseases, vector-borne diseases happen more frequently. (4) Impacts on energy consumption. That is to say, more energy is used to heating and cooling the cities, leading to more greenhouse gas emissions in return. (5) Impacts on water resources of cities. For example, extreme floods, droughts and diseases influence drinking water volume and quality seriously.

Climate effects strike cities prominently, and reducing CO_2 emissions is recognized as a significant means for combating climate change in urban areas as well. There are several aspects to explain the definitive role of cities in CO_2 emission reduction. Firstly, cities are the centres of economic and political activities, where the implements of related policies and actions seem to be more efficient and effective. Additionally, there is huge potential for improving the efficiency of CO_2 emissions in cities since advanced technology and intelligence are highly gathered urban area. Moreover, CO_2 emissions are mainly concentrated in cities, because CO_2 mostly come from human activities including energy activity, industrial production activity, and the waste disposal process (Cellura, Cusenza, et al., 2018, Lu and Li, 2019). Last but not least, urban forms such as city size and density play a great important part in the performance of CO_2 emissions (Han, 2014).

Furthermore, as the urban agglomeration become the main spatial form of urbanization in many countries, the urban forms of the cities in urban agglomerations are more or less influenced by the interactions among these cities, which may further impact the behaviours of CO_2 emissions.

1.2Problem statement

As stated before, cities play an increasingly important role in sustainable development under the challenges of rapid urbanization and environmental issues. In particular, urban form is widely believed to be strongly interconnected with CO_2 emission reduction.

Many studies have been conducted to find out the relationships between urban form and CO_2 emission, but it is still hard to reach an agreement. Some scholars voiced their opinions that larger cities are less green. For instance, Oliveira et al. (2014) firmly argued that high productivity in big cities was at the cost of higher CO_2 emissions. However, Rybski et al. (2017) deemed that the CO_2 emission efficiency in different sizes of cities was closely related to the urban economic level. Besides, as for urban density, some scholars strongly support the contribution of urban density to CO_2 emission reduction, but some not. Lee, et al. (2014) found that when density is doubled, CO_2 emissions would decrease by 40% approximately, which was in line with the study by Gudipudi and Fluschnik (2016). Most scholars believed the significant influence of urban form on CO_2 emission, but some doubted that urban form is not such an important factor for the mitigation of urban CO_2 emission (Baur, Thess, et al., 2013). It is far from enough to reach a consensus on the relationship between CO_2 emission and urban form. Thus, more statistical investigates are needed to understand the complex interactions between them.

In addition, as the urban agglomeration become the main urbanization form in many countries these years, the relations between urban form and CO_2 emission in urban agglomeration are necessary to be analysed. However, there is a lack of attention in the literature about the relevant topic. Whether urban agglomeration plays a positive role in CO_2 emission mitigation is still lacking discussion. Therefore, it is critical to conduct a study to contribute to the body of knowledge in this field.

To conclude, researches aiming to further understand the impacts of urban form on CO_2 emission in urban agglomeration area are strongly needed.

1.3Research Objective

This research aims to make a contribution to the existing knowledge systems concerning the relationships between urban form and CO_2 emission. Besides, this study also targets to find out whether urban agglomeration can play a positive role in improving efficiency of CO_2 emission, by conducting desk research, choosing YRD urban agglomeration with 26 cities as research scope, collecting the data related to CO_2 emission and urban form from 2006 to 2016. The results of this study can add fresh blood to strategies in combating climate change, give insight on how urban form strategies can be used to reduce emission for urban sustainable development, and help urban policy-makers move forward in making right decisions in creating urban forms to reduce CO_2 emissions.

1.4Provisional research question(s)

Based on the problem statement and research objective, the main research question is: **To what extent do urban forms affect CO_2 emissions in YRD urban agglomeration of China?**

To answer the main question, sub-questions are as followed:

1. What are the temporal changes of CO_2 emissions and urban forms (population size and density) of YRD urban agglomeration from 2006 to 2016?
2. What are the spatial variations of CO_2 emissions in YRD urban agglomeration from 2006 to 2016?
3. Is the amount of CO_2 emission in one city influenced by that in the surrounding cities

(spatial autocorrelation) in YRD urban agglomeration?

4. Does urban agglomeration development play a positive role in improving the efficiency of CO_2 emissions in YRD urban agglomeration?
5. What aspects of YRD urban agglomeration development plan can be emphasized and improved from the perspective of reducing CO_2 emissions?

1.5 Significance of the Study

Scientific significance:

Firstly, this study provides a piece of empirical evidence from China to further explain the relationships between urban forms and CO_2 emissions considering the inconclusive results of previous studies. Secondly, this study contributes to enriching the existing body of knowledge about the important role of urban agglomeration in CO_2 emissions mitigation. Last but not least, it also contributes to the scientific knowledge about the urban form and CO_2 emissions reduction in YRD urban agglomeration as the study location for future urban development.

Policy relevance:

Under the challenges of climate change and rapid urbanization, strategy and policy are needed to address the related issues. To begin with, the findings of the thesis will help urban policy-makers move forward in making right decisions in creating urban forms to reduce CO_2 emissions. In addition, this thesis provides scientific evidence and support to the smooth implementation of the YRD urban agglomeration development plan. Moreover, the national urbanization plan can be more effectively implemented learning from YRD urban agglomeration development experience.

1.6 Scope and limitations

1.6.1 Scope

(1) Physical boundary

According to *the Yangtze River Delta urban agglomeration Development Plan* approved by the state council in May 2016, the YRD urban agglomeration includes 26 cities which are selected as the research area to explore the impact of urban forms on CO_2 emissions. There is one city with population more than 10 million, 10 cities with a populations between 5 million and 10 million, 14 cities with populations between 1 million and 5 million, and one city with population less than 1 million according to the population data in 2016.

The YRD urban agglomeration is centred in Shanghai and located on the alluvial plain before the Yangtze river enters the sea, with only 2.2% of total land, but gathering 11.0% of people and even producing 18.5% of Gross Domestic Product (GDP) of whole China. The YRD urban agglomeration is also an important intersection zone between " The Belt and Road " and the Yangtze River Economic Belt, and it has a pivotal strategic position in the overall situation of China's national modernization and all-round opening pattern.

(2) Time boundary

In this study, data from 2006 to 2016 are selected to be the time boundary, owing to the fact that, on the one hand, it is in 2006 that urban agglomeration was first to be proposed as the main spatial form to promote urbanization in China by *the Outline of the People's Republic of China 11th Five Year Plan for National Economy and Society Development*. On the other hand, the data is available and detailed from 2006 to 2016, which can be collected from official statistical yearbooks.

1.6.2 limitation

1. Calculation of CO_2 emissions: CO_2 emissions are calculated from energy consumption aspects due to the lacking of city-level CO_2 emissions data. Although energy-related CO_2 emissions are the most dominating parts of total CO_2 emissions, other sources of CO2 emissions are ignored in this study, which can be refined in further study.
2. The limitation of the dimensions of urban form: urban form includes more elements than size and density which are selected in this paper. In the following, mixed land use, compactness and other aspects of urban form can be included as independent variables.
3. The limitation of generalizability: the growth patterns of these cities YRD urban agglomeration may be quite similar due to the close interaction of infrastructures, trading, policy, etc. The regional exposure to external pressures leads to some unique characteristics among these cities, which thwarts generalizability. Therefore, the results of this study only show the influence of the urban form on CO_2 emissions of the cities in YRD urban agglomeration, which cannot completely represent corresponding relations in other cities.
4. The exclusion of other greenhouse gases than CO_2: Besides CO_2, greenhouse gases also include methane, nitrous oxide, etc., which are closely related to climate change and sea-level rise. In future studies, the impacts of urban form on more kinds of greenhouse gases can be analysed.

Chapter 2: Literature review

2.1State of the Art of the Theories/Concepts of the Study

2.1.1 Urban form

The definition of urban form that "the spatial configuration of fixed elements within a metropolitan region" (Anderson, Kanaroglou, et al., 1996: pg.9) is well recognized by most scholars. Elements mentioned therein mainly include size, density, compactness, mixed land use, clustering, etc. (Lo, Alex Y., 2016, Emmanuel and Steemers, 2018).

Urban form is listed as one of the important driving forces of mature cities (Silva, Oliveira, et al., 2017). Besides, in the report *Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change* (Edenhofer, Pichs-Madruga, et al., 2014a), urban form is considered as one of the four influential factors of climate change (the other three are economic geography, sociodemographic indicators and technology). Therefore, understanding and improving urban form is considered as one of the ways to realize the goal of urban sustainability.

Urban size and density are the two main elements of urban forms. In this section, urban size and density are as representatives of urban forms, and the literature review about size and density are summarized as follows.

2.1.1.1 Urban Size

Urban size can be defined as the number of elements that aggregated in a certain space, which is commonly quantified from the perspective of population size, economic size and land use size (Li, L., Lei, Wu, He, ChenYan, 2018a). Among them, population size is the most common aspect to represent the urban size in numerous studies (Batty, 2008, Batty, 2013, Fragkias, Lobo, et al., 2013, Louf and Barthelemy, 2014, Bettencourt, L. M., 2013). Furthermore, population size refers to the number of people in the city. The population is closely related to the intensity of social-economic activities in cities, while social and economic activities have a significant impact on energy consumption and environmental issues such as CO_2 emissions. Therefore, the population size is considered as one of the main drivers of energy-related environmental problems in urban areas. Along with the predicts that nearly 70% of the world's population is expected to live in cities by 2050, the pressure of rapid growth of population leads to an increasingly important role of population size played in CO_2 emissions mitigation.

Mang arguments about the efficient and optimal city size are put forward by scholars, and questions about what would happen as a city grows have been raised. An interesting 'scaling law'-based theory of urban size emerges in this situation.

Scaling law describes a seemingly simple but profound situation: a power-law relationship between dependent variable Y and independent variable X, showing as the form :

$$\mathrm{Y} = \mathrm{A}X^{\beta} \tag{1}$$

where A and β are constants in X. This relationship is widely used in many disciplines, which not only show the general relations between two variables but also reveals the self-similarity, that is, a phenomenon replicates itself on different space-time scales. This simple yet appealing and reasonable law resonates with our understanding of cities. Scholars conduct discussions based on the scaling law on urban sizes from various aspects such as social economy, urban infrastructure, environmental pollution, etc., and carry out a large number of empirical studies to explore the relationship between various variables and urban size with data from a wide range of cities.

β is the most important parameter to explain the relations between X (urban size) and Y (social-economy, urban infrastructure, environmental pollution, etc). there are three types of scaling relationships. Firstly, if $|\beta| < 1$, it means there is a sublinear relationship between X and Y. For example, when Y refers to structural quantities of cities such as road, cable, space for residential living, etc., β in related studies is most be less than 1, scaling sublinearly with respect to population (Bettencourt, L. M., 2013, Bettencourt, L. M., Lobo, et al., 2007, Bettencourt, Luis MA, Lobo, et al., 2007). It means that physical infrastructures tend to grow more slowly than city size, which might be a limiting factor of sustainable development in metropolises (Batty, 2008). Secondly, when $|\beta| > 1$, it refers to the superlinear relationship between X and Y. For instance, when Y represents the socioeconomic quantities and X represents the population, the general results of β is usually greater than 1. That is, the relationship between socio-economic attributes (e.g. income, patents, financial services, crime, etc.) and the city size in terms of population exhibits a superlinear growth, which means these indicators increase faster than city size in terms of population, indicating that larger cities are more wealth, creative, but also more expensive and unsafe (Bettencourt, L. M., 2013, Bettencourt, L. M., Lobo, et al., 2007, Bettencourt, Luis MA, Lobo, et al., 2007). Thirdly, linear scaling ($\beta = 1$) means the growth rates of X and Y are the same. For example, some scholars (Fragkias, Lobo, et al., 2013, Mohajeri, Gudmundsson, et al., 2015) find that when Y refers to some environmental quantities, the scaling law follows the linear rule. However, some experts have different conclusions about the relationship between city size and environmental factors (Oliveira, Andrade Jr, et al., 2014, Rybski, Reusser, et al., 2017).

Overall, the superlinear relations between socioeconomic quantities and city sizes as well as the sublinear relations between structural attributes and city sizes have been widely recognized among scholars by a large number of previous empirical studies. However, in terms of the relationship between environmental factors, the conclusions remain questionable. Therefore, further researches about the impact of population size on environmental factors are conducted. Besides the scaling relationships, the U-shaped and N-shaped relationships between them are also discussed in recent studies (Lantz and Feng, 2006, Ahmed and Long, 2013). Recently, more empirical studies about the urban size have been carried out due to the increasing ability to collect data related to various aspects of cities, which enable more mysteries hidden in urban science to be revealed.

2.1.1.2 Urban Density

Urban density can be measured by many ways from several aspects, such as population density, street density, residential density, employment density, patent intensity, etc. (Churchman, 1999, Carlino, Chatterjee, et al., 2007). Among these, density is most commonly defined as a term to represent the number of people who inhabit or use that area (Churchman, 1999), followed by numerous researches where population density is used to be the most representative indicator of urban density (Dodman, 2009, Gudipudi, Fluschnik, et al., 2016).

Density is a significantly appealing and important concept for urban planners, which helps to describe, foretell and control the utilisation of land (Boyko and Cooper, 2011). The inappropriate density affects people's lives seriously: crowding, traffic congestions, energy waste, ill health, crime, social deprivation, etc., while a suitable degree of density contributes to the high productivity and efficiency. For instance, when the population in the city centre is too dense to exceeds the capacity, the overcrowding, traffic jams and pollutions will come one after another. On the other hand, compared with dispersed cities, denser cities take the advantages of maximizing the use of resource and minimizing cost, because the public infrastructures such as road, sewage system and electricity system are more efficient and effective. As for the impacts of density on the environment, many scholars are in favour of the environmental benefits of the density from the perspective of energy saving. With the increase of population density, the per capita energy consumption decreases (Kenworthy and Newman, 2015), which can be explained as, on the one hand, the higher residential density and the proximity of the home to the employment centre reduce the energy consumption of daily travel(Holden and Norland, 2005). On the other hand, residents, living in areas with high population density prefer to commute by energy-saving means such as public transports, bicycles, walking, are less likely to drive (Buliung and Kanaroglou, 2006). By contrast, some scholars argue the negative effect of high-density urban form on the environment for the sake of liveability. Firstly, high-density cities leave relatively few green spaces, which is not conducive to urban air quality, biodiversity, etc. (Jim, 2004, Lo, Alex YH and Jim, 2012, Swanwick, Dunnett, et al., 2003). Moreover, Neuman (2005) argues that high-density negatively influences the liveability of cities and reduces the living quality of residents. For example, it is rare for people in high-density residential areas to possess private gardens, and they are forced to share public gardens (Holden and Norland, 2005). Therefore, more research evidence is needed to further discuss the pros and cons of dense cities.

2.1.2 Relationships between population size, density and CO_2 emission

Human activities influence CO_2 emission in urban areas mainly by way of energy consumption. About three-quarters of anthropogenic CO_2 emissions put into the atmosphere is caused by burning fossil fuels (Houghton, Ding, et al., 2001, Edenhofer, Pichs-Madruga, et al., 2014b). Energy consumption is used to support human activities, but meanwhile, it emits CO_2 emission. The high-intensity energy activities mainly occurring in urban areas make cities become the largest energy consumer of and the main emitters of CO_2 (Conti, Holtberg, et al., 2016).

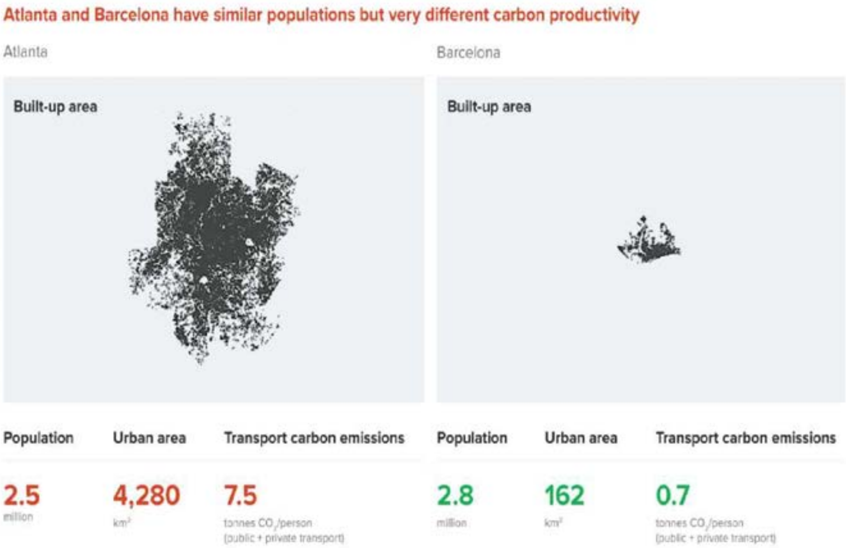
The relationship between population size and CO_2 emission has been expansively researched. Overall, previous research papers which analysed the relationship between population and CO_2 emission aim to find out whether larger cities are greener or less green, as well as the optimal urban size.

On the one hand, many scholars take advantages of scaling law mentioned before to find the answer to the former point. Oliveira et al. (2014) firmly argue that there is a superlinear scaling between CO_2 emissions and population size based on power law for U.S. cities, which suggests that high productivity in big cities was at the cost of higher CO_2 emissions. In contrast, some scholars (Fragkias, Lobo, et al., 2013, Mohajeri, Gudmundsson, et al., 2015) find that the scaling law follows from the fact that the CO_2 emission is proportional to city size, which means CO_2 emissions grow in the same pace with population sizes. However, Rybski et al. (2017) deems that for cities of economically less developed countries, the scaling of CO_2 emissions and population size shows super-linearity, while for cities of developed countries, the relationship turns to linearity or sub-linearity, indicating that the urban CO_2 emission efficiency was closely related to the urban economic level. It is far from enough to reach a consensus on the relationship between CO_2 emission and population size. The reasons for the above contradictory conclusions are summarized in the following two points by Louf and Barthelemy (2014). First, the estimation of urban CO2 emissions is not accurate due to the different considerations of scholars. Second, the error lies in the vague definition of the geographical scope of the city, which lead to inaccurate estimation of CO_2 emissions and population in the corresponding geographical area. But these two issues are tricky. The process to figure out whether big cities are greener or less green still has far to go.

On the other hand, to test the exists of ideal population size for the lowest CO_2 emissions, a quadratic relationship between the two variables are under discussion. That is, based on a quadratic model, U-shaped or inverted U-shaped relationship and the optimal population size can be obtained. Lantz and Feng (2006) explored the forces of CO_2 emission in Canada using panel data set with five-region over 30 years. The result showed that there is an inverted U-shaped relationship between population and CO_2. This method was first used for testing the Environmental Kuznets Curve (EKC) hypothesis, but its application has become more flexible (Farhani, Mrizak, et al., 2014, Halkos, 2003, Maddison, 2006, Ahmed and Long, 2013).

The relationship between population density and CO_2 emission are still debatable. Some scholars strongly support the positive role of high-density cities in CO2 emission reduction, but some not. Lee, et al. (2014) examined the influence of population density on individual household's CO_2 emission in the 125 cities in the U.S., finding that when population density is doubled, CO_2 emissions from the energy consumption in the household will decrease by 40% approximately. Additionally, Gudipudi and Fluschnik (2016) employed the City Clustering Algorithm (CCA) to analysis relationship between population density and the CO_2 emissions and concluded that doubling the population density would lead to reducing at least 42% of CO_2 emissions. Another piece of strong evidence illustrates that the population of Barcelona and Atlanta is approximately the same, but Barcelona with a high-density pattern of built-up area has lower carbon emissions (Bertaud and Richardson, 2004) as shown in Figure 1. Most studies showed that the higher population density, the lower CO_2 emission. However, some researchers argued that population density is not an important factor for the reduction of urban CO_2 emission in Europe when compared with the role of household size and personal wealth. (Baur, Thess, et al., 2013).

Figure 1 The comparison of density in Atlanta and Barcelona



(Source, Bertaud and Richardson, 2004)

In addition, population size and density as the two important elements of urban forms supplement each other. Without considering either, the results are incomplete. For example, in Fragkias and Lobo's study (2013), with or without considering the density, the relationship between population size and CO_2 emission are different, changing from sub-linearity to super-linearity.

Overall, the correlations between population size, density and CO_2 emission have arguable conclusions. More strong pieces of evidence are necessarily provided to find out the more convincing conclusions.

2.1.3 Other urban drivers of CO_2 Emission

Cities lie in a key position to solve the global challenge of climate change due to the concentration of CO_2 emissions. Cities only account for 2% world's surface area, but agglomerate 50% global population and concentrate about 80% the whole CO_2 emissions(Li, L., Lei, Wu, He, ChenYan, 2018a). Besides the urban form, the influence factors of CO_2 emissions are summarized in economy, industrial structure, and land use aspects as follows based on various previous researches. These three aspects are needed to be taken into account as control variables when studying the relationship between urban form and CO_2 emissions.

2.1.3.1 Economic drivers

Urbanization is the result of rapid economic development and the driving force of further economic development. The environmental problems accompanying urbanization are more or less related to economic development.

Most researchers hold the opinion that rapid economic growth turned cities into main energy consumers as well as CO_2 emission emitters (Hubacek, Feng, et al., 2012, Shan, Guan, et al., 2017). Zheng (2016) concludes that the economic level has positive but non-linear effects on CO_2 emissions in Chinese cities. To be more precise, it shows an inverted U-shaped relationship between GDP per capita and CO_2 emissions, which is the so-called EKC confirmed by numerous studies (Maddison, 2006, Kang, Zhao, et al., 2016, Halkos, 2003, Farhani, Mrizak, et al., 2014). Besides, Li (2018b) believes that economic growth in urban areas brings industrial agglomeration changes which have positive externality. It means that more industrial agglomeration leads to the higher efficiency of energy consumption and CO_2 emissions. In Li's work, economic density (GDP per unit area) and employment density (ratio of employment in the pillar industry) are chosen to be the indicators of economic aspect.

2.1.3.2 Industrial structure drivers

The shift from energy-intensive heavy industry to the services and innovation directions has been recognized as one of the main drivers of CO_2 emission reductions (Green and Stern, 2017, Zheng, J., Mi, et al., 2019).

Scholars usually use structural decomposition analysis, econometric analysis, empirical analysis methods, etc. to find the impact of industrial structure changes on CO_2 emissions. For example, an optimization model is developed by Mi (2015) to assess the possible impacts of industrial structure on CO2 emission, showing that industrial structure adjustment can reduce CO2 emission by 46.06% from 2010 to 2020 in Beijing. Most scholars believe that industrial structure is a useful way to control and reduce CO_2 emissions (Liaskas, Mavrotas, et al., 2000, Adom, Bekoe, et al., 2012, Shan, Guan, et al., 2017)). In Li's (2018b) study, the primary and secondary industry as the percentage to GDP and the employment rates in the primary industry and the secondary industry are taken as the indicators of industrial structure to analysis their effects on reducing CO_2 emissions, finding that secondary industry plays the significant role of CO_2 emissions reduction. Similarly, Li (2017) points to China as an example of how the secondary industry contributes more to carbon dioxide emissions than any other sector, accounting for more than 80% of the total emissions.

2.1.3.3 Land use drivers

Land-use change has spectacularly transformed the regional landscape and will continue to have a profound influence on regional climate (Heald and Spracklen, 2015). Land-use change is one of the symbols of urbanization, the impacts of which on CO_2 emissions cannot be ignored during the process of urbanization. Previous researches show that the expansion of construction area, land reclamation and wetland degradation lead to CO_2 emissions increase to a great extent (Watson, Noble, et al., 2000, Li, L., Lei, Wu, He, ChenYan, 2018b)

The land use for green space of cities not only play a critical role in reducing CO_2 emissions but also affecting human health (Nieuwenhuijsen, 2016). Similarly, Nowak (2002) confirms that with the increase of trees in cities, the process of accumulation of atmospheric carbon slows down, which means more land for trees, less CO_2 concentration in cities.

2.1.4 Urban agglomeration

Urban agglomeration as a new style of urbanization is on the rise. This emerging but not entirely new notion is based on polycentrism. It expands the structure of a polycentric city (multiple central business districts in one city) to polycentric urban regions at a larger scale, considering different metropolises as multiple centres (Kloosterman and Musterd, 2001). Hall and Pain (2006) define this new form as a series of cities, ranging from 10 to 50, are physically independent but functionally united, grouped around one or more metropolises and emerging from the new functional classification of labour to form a strong economic strength.

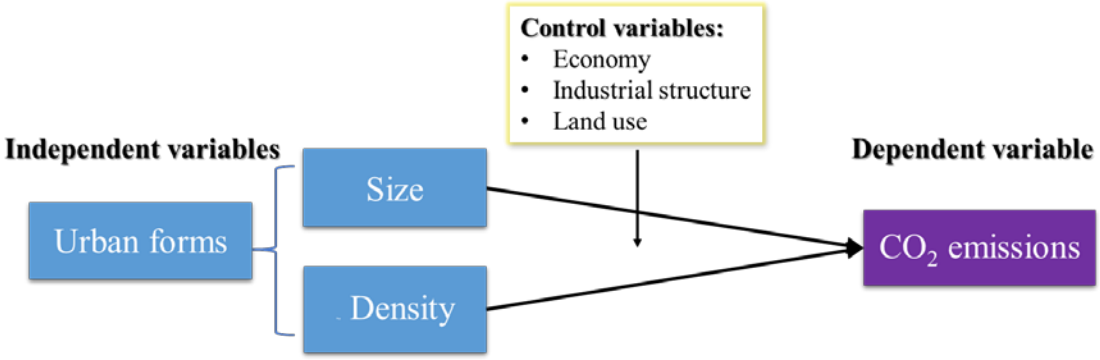
In reality, the polycentric metropolis regions, such as YRD urban agglomeration and Pearl River Delta region (Guangzhou–Shenzhen–Hong Kong–Macau) in China, Naga–Legaspi–Iriga–Daet region in the Philippines, South East England, Jakarta-centered region in Indonesia, National Capital Region of Delhi, etc., are developing rapidly, and their urban structures have been widely concerned (Hall and Pain, 2006, Choe, 2008). Furthermore, Banister (2012) attempts to divide the urban clustering structures into three categories, namely Radial Cities (with one city that acts as a strong centre in clustering region), City Clusters (multi-centre urban clustering region), and Axial Cities (double-centre clustering region). Due to the complexity and diversity of the linkage between cities, this classification is unable to cover all clustering structures, but it provides an idea to further explore the sustainable urban form.

As a matter of fact, urban agglomeration has become the main spatial mode of urbanization in many countries, especially in China. Since 2006, when *the Outline of the People's Republic of China 11th Five Year Plan for National Economy and Society Development* first proposed to take urban agglomerations as the main form to promote urbanization in China, urban agglomerations as the core areas of economic growth have attracted much attention in terms of economic agglomeration, intercity trade, industry specialization, long-term development and planning, etc. In order to scientifically guide the urbanization in China, the *National New-type Urbanization Plan (2014—2020)* was released in March 2014, followed by several urban agglomeration plans. These plans aim to form the urban pattern of reasonable division of labour, mutual supplement and common development between core cities and other cities within the city cluster. In November 2018, the Central Committee of the Communist Party of China and the State Council issued *the Opinions on Establishing More Effective New Mechanisms on Regional Coordinated Development* to push ahead integrated development of significant national strategies through the development of urban agglomerations, and promote the inter-regional integration and mutual complement. Taking the Beijing-Tianjin-Hebei, YRD and Pearl River Delta urban agglomerations in China as examples, with 5.2% of the whole land of China, these regions gather 23% of the population, contribute to 39.4% of the GDP, and realize more than 70% of invention patents. In the next 15 years, China's urban areas will continue to attract billions of people for employment and residence.

The advantages and limitations of urban agglomeration development are comprehensively sorted out in the book *City Cluster Development* (Choe, 2008) initiated by the Asian Development Bank. The advantages mainly include the following points. First, integrated manner contributes to more cost-effective infrastructure and services when clustered cities act together. For example, water management will exert more effect at a regional scale as river basins often cross multiple urban areas. Second, urban agglomeration fosters inclusive development. Urban agglomeration takes the places often neglected places in urban development into consideration, such as the adjacent environment around cities and rural areas, which promotes the sharing of development benefits and fosters inclusive development. Moreover, urban agglomeration development can strengthen environmental protection. It makes local government agencies attach more importance to common interests and examine the impact of specific actions on the environment. For instance, more concern about air pollution will be paid when highways are under construction in one certain city, because air pollution affects surrounding cities of the urban agglomeration at the same time. However, urban agglomeration development also has limitations, including administrative decentralization at varies levels hindering inter-agency cooperation and coordination, as well as the poor infrastructure and information networks which cannot support clustering form, etc.

2.2Conceptual framework

Figure 2: Conceptual framework



(Source, the author)

Chapter 3 Research design and methods

3.1 Revised research question(s)

The main research question is: **To what extent do urban forms affect CO_2 emissions in YRD urban agglomeration of China?**

To answer the main question, sub-questions are as followed:

1. What are the temporal changes of CO_2 emissions and urban forms (population size and density) of YRD urban agglomeration from 2006 to 2016?
2. What are the spatial variations of CO_2 emissions in YRD urban agglomeration from 2006 to 2016?
3. Is the amount of CO_2 emission in one city influenced by that in the surrounding cities (spatial autocorrelation) in YRD urban agglomeration?
4. Does urban agglomeration development play a positive role in improving the efficiency of CO_2 emissions in YRD urban agglomeration?
5. What aspects of YRD urban agglomeration development plan can be emphasized and improved from the perspective of reducing CO_2 emissions?

3.2 Operationalization

The procedure of operationalization mainly includes three steps which are the definition of the theoretical concepts, operationalization from variables to indicators and the scales of measurement (Van Thiel, 2014).

3.2.1 Definition of the theoretical concepts

According to the main research question, the theoretical concepts include two important aspects, urban form as the independent variable and CO_2 emissions as the dependent variable. The definitions of variables of these concepts are shown in table 1, which can help to further transform the complicated concepts or variables into quantifiable indicators.

Table 1 Definition of concepts/variables

Concepts/Variables	definition	Source
Urban form	The spatial configuration of certain elements within urban areas. Elements mentioned therein mainly include mainly including size, density, compactness, mixed land use, clustering, etc.	(Anderson, Kanaroglou, et al., 1996, Lo, Alex Y., 2016, Emmanuel and Steemers, 2018).
CO_2 Emission	CO_2 emission related to fossil energy consumption.	(Jing, Bai, et al., 2018)
	Emissions are estimated using fuel-specific emission factors.	(Cellura, Cusenza, et al., 2018)
	Energy-related emissions are emissions correlated with two aspects. One is the extraction and production of fuel for any purpose, and the other is the production of useful energy from fuel.	(IPCC, 2006)

Source: the author

3.2.2 Operationalization from variables to indicators

According to the above definitions of concepts, the transition from the dependent and independent variables to indicators are detailly presented in table 2.

In table 2, the dependent variable is energy-related CO_2 emission. Based on the general method for calculating CO_2 emissions from the fossil fuel consumption perspective issued by IPCC, CO_2 Emission calculated from energy consumption of 27 fuel types and 17 categories are referred to be the indicator for the dependent variable. Meanwhile, for the independent variable, although the definition and connotation of urban form are rich, there are many pieces of research on the city size and city density as the representatives of urban forms, and the influence of urban size and density on CO_2 emission have unclear conclusions. Therefore, city size and density are chosen to be the main dimensions of urban form, and the population size and density are referred to be the indicators of independent variables.

Table 2 Operationalisation of dependent and independent variables

Variable		Dimension	Indicator
Dependent	CO_2 Emission	Energy-related CO_2 Emission	Energy consumption from 27 fuel types and 17 categories
Independent	Urban form	City size	Population size
		City density	Population density

Source: the author

In addition, considering the impact of urban economy, industrial structure and land use on CO_2 emissions, this paper takes these three aspects as control variables. GDP, GDP per capita, secondary industry as the proportion to GDP, tertiary industry as the proportion to GDP, built-up area which refers to the area within a city administrative boundary that has been continuously developed and constructed, and green area are chosen to be the corresponding indicators of control variables, as shown in table 3.

Table 3 Operationalisation of control variables

Control variable	Dimension	Indicator	Main reference
Economy	GDP	GDP	(Hubacek, Feng, et al., 2012, Zheng, H., Hu, et al., 2016)
		GDP per capital	
Industrial structure	Composition of GDP	The secondary industry as the proportion to GDP	(Green and Stern, 2017, Li, L., Lei, Wu, He, ChenYan, 2018b)
		The tertiary industry as the proportion to GDP	
Land use	Built-up area	The area within a city administrative boundary that has been continuously developed and constructed	(Watson, Noble, et al., 2000, Nieuwenhuijsen, 2016)
	Green area	Area of green land	

Source: the author

3.2.3 Scales of measurement

Observing the values or scores of variables is called measuring the variable. There are four kinds of scales of measurement, including nominal, ordinal, interval and ratio scale (Van Thiel, 2014). Specifically, nominal scale is to labelling variables which are called qualitative; ordinal scale variables are the ones can be arranged in a certain order; interval-level variables are with same distance between consecutive scores but not used for absolute computations; variables with ratio scale have a fixed zero point and fixed intervals between scores as well (Van Thiel, 2014). Therefore, the ratio scale is the most suitable scale for the indicators in this research (Table 4).

Table 4 Scales of measurement

Dependent/ Independent/control	Variable	Dimension	Indicator	Data scale
Dependent	CO_2 Emission	Energy-related CO_2 Emission	Energy-related CO_2 Emission	Ratio scale
Independent	Urban form	City size	Population size	
		Density	Population density	
Control	Economy	GDP	GDP	
			GDP per capital	
	Industrial structure	Composition of GDP	The secondary industry as the proportion to GDP	
			The tertiary industry as the proportion to GDP	
	Land use	Built-up land	Built-up land in urban areas	
		Green space	Area of green land	

3.3Research strategy

Desk research is the research strategy in this study. The reasons for choosing desk research as research strategy are as follows.

To begin with, desk research is considered as the most fitting strategy when data is already available (Van Thiel, 2014). The indicators of this study include city-level energy-related CO_2 emissions, city population size, population density, GDP, GDP per capita, secondary industry as the proportion to GDP, tertiary industry as the proportion to GDP, built-up area, green area which will be collected or calculated based on China Energy Statistical Yearbook, China Statistical Yearbook; China City Statistical Yearbook. Then, a database of all variables will be created for the following analysis. Secondly, desk research is adequate for temporal analysis. The changes in CO_2 emissions and urban forms over a long time need the information based on existing datasets because we cannot collect related data for the past 11 years by survey or interview. Moreover, desk research is one of the most efficient and feasible research strategies when handling with the quantitative data of a wide variety of aspects. In this study, the aspects of the data are broad, such as the data of CO_2 emissions, urban form, economy, industrial structure, and land use in 26 cities over the past 11 years. Therefore, the most effective and feasible method for this study is desk research.

However, the quality of data and the matching data of the corresponding variables are the key points to keep in mind. On the one hand, the methods for collecting original data are unclear to some extent in the statistical yearbooks used in this study, which means that there might be some discrepancy among the data due to different statistical methods in different regions. But given that the data come from official national statistics, they are more reliable than data from other sources. On the other hand, the existing databases are produced by other people for some specific reasons, the data might not match the subjects completely.

To conclusion, although choosing desk research as the research strategy in this study has some weaknesses, the availability of the data and the efficiency when handling mass data make the desk research the best research strategy in this study.

3.4 Data collection methods

Based on the desk research strategies, the sources of data are summarized in table 5, followed by the collection methods of each kind of data.

Table 5 The sources of data

concepts	Data category	Data source	Data type
CO_2 Emission	Energy-related CO_2 Emission	China Energy Statistical Yearbook; China Statistical Yearbook; China City Statistical Yearbook; China provincial statistical yearbooks	quantitative
Urban form	Population size	China City Statistical Yearbook;	
	Population density	China City Statistical Yearbook;	
Control variables	GDP	China City Statistical Yearbook;	
	GDP per capital	China City Statistical Yearbook;	
	The secondary industry as the percentage to GDP	China City Statistical Yearbook;	
	The tertiary industry as the percentage to GDP	China City Statistical Yearbook;	
	Built-up area	China City Statistical Yearbook;	
	Green area	China City Statistical Yearbook;	
Policy analysis	National policies about CO_2 emission reduction	the website of the State Council of People's Republic of China (http://www.gov.cn/)	qualitative
	Yangtze River Delta Urban Agglomeration Development Plan		

3.4.1 CO_2 emission data collection

In this study, CO_2 emissions are calculated through a model recommended by IPCC from the perspective of energy consumption (Simon, Leandro, et al., 2006). This method is one of the most commonly used ones for CO_2 emissions accounting. However, due to the fact that the basic city-level energy-related data for accounting CO_2 emissions has serious consistent and accuracy problems in China, data scale conversion from province-level to city-level becomes a key point for scholars to figure out the accurate data of CO_2 emissions in Chinese cities (Wong, 2016, Shan, Guan, et al., 2017). Accordingly, we reference a reliable method developed by Jing (2018) to calculate city-level CO_2 emissions by combining provincial Energy Balance Tables (EBTs), distribution coefficients and an approach recommended by IPCC.

The calculation the city-level CO_2 emissions are summarily into two steps. The first one is to figure out the city-level EBTs with consumption of 27 kinds of fossil fuel. The second step is to account city-level CO_2 emissions by IPCC recommended approach. The concrete steps of calculation of CO_2 emissions are shown in Annex 1.

3.4.2 Urban form data collection

The indicators of the urban form include population size and population density, which are collected from existing China City Statistical Yearbook. There are several aspects data of 292 main cities of China in the database, from which urban form data of 26 cities in YRD urban agglomeration are selected. The period of data collection is from 2006 to 2016. Then, the data of urban form as independent variables are put into the new dataset especially for these cities in YRD urban agglomeration.

3.4.3 Control variable data collection

The indicators of control variables cover urban economy, industrial structure, land use and policy aspects. In terms of urban economy, industrial structure and land use, the indicators include GDP, GDP per capita, secondary industry as the proportion to GDP, tertiary industry as the proportion to GDP, built-up land in urban area, and green area, all of which are collected from existing China City Statistical Yearbook from 2006 to 2016. Moreover, all the data of control variables are sorted into the new dataset.

3.4.4 Policy analysis data collection

The policy analysis data are qualitative data about the content of the National plan involving CO_2 emissions and YRD urban agglomeration development, which is to find out what aspects of the urban agglomeration strategy and planning can be emphasized and improved from the perspective of reducing CO_2 emissions. The documents can be downloaded through the website of the State Council of People's Republic of China (http://www.gov.cn/)

3.5 Validity and reliability

Desk research is believed to have comparatively higher validity and reliability (Van Thiel, 2014). The validity and reliability of this study are demonstrated as follows.

3.5.1 Validity

Internal validity is to find out whether the concepts have been adequately operationalized, and whether the relations between variables truly does exist (Van Thiel, 2014).

All the operationalizations of variables in this study are based on many previous pieces of research, and we try to find the most comprehensive and adequate operationalization way with limited accessible data. For instance, CO_2 emissions variable is adapted to calculate based on energy consumption and also transform the data from the provincial level to city level. During this process, the operationalization is not adequate to some extent, but we include the types of fossil fuel and categories of energy consumption as wide as possible, combining with official EBTs, to try to overcome the limitation of the CO_2 emissions data. In addition, the existence of the correlation between dependent and independent will be tested before the regression analysis in this study. Actually, the relations between these variables have been studied a lot by scholars.

External validity is also important for quantitative research, which is to rethink about the generalization of findings. In this study, the triangulation method will be used to compare the conclusions of this study with those of relevant literature.

3.5.2 Reliability

The reliability of this study is relatively high because all the data are collected from are official sources such as several national statistical yearbook and official website. The process of data collection or calculation was consistent within the time scope and double-checked. Although original collecting methods of the secondary data are not well known, these available official data are most reliable compared with other data sources.

3.6Data analysis techniques

The secondary analysis and the content analysis methods are both used in this desk research to analysis data. In the secondary analysis, temporal analysis and spatial analysis are applied to the analysis of the spatial-temporal changes of CO2 emissions as well as the urban forms in the field of urban size and density in YRD urban agglomeration from 2006 to 2016, while regression analysis is conducted to figure out what kind of relationships are there between urban forms and CO2 emissions. Additionally, the policies related to urban agglomeration will be analysed by the method of policy analysis to understand the guidance and emphasis in terms of the urban forms and CO_2 emissions reduction in national urbanization strategies of China, and the YRD urban agglomeration development plan (2016-2020) will be detailly analysed.

3.6.1 Temporal analysis

Temporal analysis usually uses information over a long time, resulting in time-varying characteristics of data. For research sub-question 1 and 2, the temporal changes of total CO_2 emissions, CO_2 emissions per capita, CO_2 emissions per GDP, urban size, urban density, as well as their corresponding growth rate trends from 2006 to 2016 are required to be analysed, which can be realized by the temporal analysis presented by diagrams.

3.6.2 Spatial analysis

For the research sub-question 2, the spatial variations of CO_2 emissions can be analysed in terms of the spatial distribution and agglomeration. The characteristics of the spatial distribution of CO_2 emissions and urban forms in YRD urban agglomeration are found out visually by taking advantages of ArcGIS Pro. The natural breaks classification method is used in spatial distribution analysis to classify the level of CO_2 emissions and urban forms. It is a commonly used data classification method which aims to classify the values into “natural” classes, which is good for revealing the real distribution characteristics of the values (Jenks, 1967).

Besides, Moran’s I measurement is used as the method to find out the agglomeration pattern of CO_2 emissions in YRD urban agglomeration also by ArcGIS Pro. Moran's I is a broadly used mothed for testing spatial autocorrelation developed by Patrick Alfred Pierce Moran (1950), which is symbolized by a spatial connection in an indication among nearby positions in space. Values of Moran’s I range from -1 (revealing wonderful dispersed pattern) to 1 (revealing great clustered pattern). Negative or positive quantities imply negative or positive spatial autocorrelation respectively.

Local Moran’s I is a local spatial autocorrelation measurement on the strength of the Moran’s I statistic. It was progressed by Anselin (1995). Given a set of features of CO_2 emissions and an analysis field (the map of cities in YRD urban agglomeration), the Cluster and Outlier Analysis tool (Anselin Local Moran's I) in ArcGIS identifies spatial clusters of features with higher or lower values compared with average values, and displays the clusters and outliers at local level visually.

3.6.3 Regression analysis

Regression analysis is a common approach to test associations between quantitative dependent and independent variables under the consideration of control variables. It is appropriate to use regression analysis to find the answer to sub-question 3 which is the main part of this study. Regression analysis is conducted by taking advantage of STATA, a kind of software for statistics and data science. Considering that there are more than one independent and control variables, multiple regression function is needed to find out the interactions between variables.

3.6.3.1 Regression models

The basic multiple regression model (M.1) is as follows.

$$Y = a + \beta * X + \gamma * C + \varepsilon \quad (M.1)$$

Where Y stands for the dependent variable; X stands for independent variables; C stands for control variables; a stands for the alleged constant; β stands for the coefficient of the independent variables, which shows the positive or negative relations between Y and X; γ is the coefficient of the control variables, which shows the associations between Y and C; ε is the estimation error.

Furthermore, in order to explore whether there is "U-shape" relations between dependent and independent variables, and to find out the existence of the turning point of the independent variables, the quadratic model M.2 is established as follows.

$$Y = a + \beta_1 * X + \beta_2 * X^2 + \gamma * C + \varepsilon \quad (M.2)$$

Where Y, X, C, a, γ, ε, β have the same meanings as the ones in M.1. However, if $\beta_2 > 0$, the relationship between Y and X will be "U-shape", and if $\beta_2 < 0$, the relationship between Y and X will be "inverted U-shape". Moreover, If the figures of β_1 and β_2 are negative and positive differently, the turning point of the independent variable with realistic significance will exist.

In addition, taking the spatial distribution and agglomeration of dependent variable into account, if the dependent variable at a particular location is influenced by the value of the dependent variable of its neighbourhood, the Spatial autoregression model (SAR) which is also called Spatial lag model (SLM) is appropriate to be applied in the analysis.

The basic SAR is given by

$$Y = a + \rho * W * Y + \beta * X + \gamma * C + \varepsilon \quad (M.3)$$

where the meanings of Y, X, C, a, γ, ε, β are the same as the ones in M.1. Moreover, ρ is the coefficient of space factor of the dependent variable, and W is the spatial weight which can be obtained by Queen contiguity method which is to account the number of its links with neighbours both by edges and corners by using GeoDa software. More specifically, the ratio of the number of links of one city to the total number of links is the spatial weight of the city, which is from 0 to 1.

Moreover, in order to explore whether there is "U-shape" relation between dependent and independent variables as well as the turning point of the independent variables, the model M.4 is established as follows when combined with the spatial autoregression model.

$$Y = a + \rho * W * Y + \beta_1 * X + \beta_2 * X^2 + \gamma * C + \varepsilon \quad (M.4)$$

where the meanings of Y, X, C, a, γ, ε, β_1, β_2, ρ, W are the same as the ones mentioned above. Similarly, if $\beta_2 > 0$, the relationship between Y and X will be "U-shape", and if $\beta_2 < 0$, the relationship between Y and X will be inverse "U-shape". Moreover, If the figures of β_1 and β_2 are negative and positive differently, the turning point of the independent variable with realistic significance will exist.

Summarily, Model 1 is the basic linear regression model; Model 2 is to further analysis the " U-shape" relations between dependent and independent variables, as well as the turning point of the independent variables; Considering the spatial influence, SAR model is chosen as Model 3 to analysis the correlations among variables; Model 4 is the overall model which combines the factors from Model 1,2,3. Additionally, the application of Model 3 and 4 should be according to the results of the spatial autocorrelation test which are described in the above spatial analysis section.

3.6.3.2 Hausman test

After the determination of regression models, it is worth considering whether the methods used to analyse panel data are fixed effects (FE) or random effects (RE). Firstly, FE assume that something within the entity (country, city, person, etc.) which may affect or bias the independent variable should be controlled. Besides, another crucial supposition of FE is that the time-invariant attributes in one entity are unique and should not be connected with other particular entities. In other words, each entity is separate, which means that the entities' error terms and the constants should not be interrelated with each other. Accordingly, if the two assumptions are not satisfied, FE is no appropriate (probably using RE). Comparatively, the rationale behind RE is that the difference among entities is unrelated to the independent variables and assumed to be random.

Hausman test can be applied to make a decision between FE or RE helpfully, whose null hypothesis is that the preferred model is RE, while the alternative model is FE. Taking advantage of Stata, if the prob > chi2 statistic of the Hausman test is significant, then reject the null hypothesis and use FE.

3.6.4 Policy analysis

There are two main aspects included in the policy analysis. First, the contents of national policies involving CO_2 emission mitigation are summarized in this section. Second, the aspects of Yangtze River Delta Urban Agglomeration Development Plan (2016-2020) that were emphasized and would be improved from the perspectives of CO_2 emission reduction are put forward.

The former one can be conducted by collecting the national documents related to emission reduction by searching from the website of the State Council of People's Republic of China (http://www.gov.cn/). Some important documents can be detailed investigated. The second part is to concretely analysis the Yangtze River Delta Urban Agglomeration Development Plan (2016-2020) and then make a conclusion about its role in CO_2 emission reduction some aspects for further improvement.

Chapter 4: Research Findings

In this chapter, the findings are narratively presented involving temporal analysis, spatial analysis, descriptive analysis, correlation analysis, regression analysis and policy analysis.

It is secondary data research, and the data are almost collected from several official statistic yearbooks and website as mentioned in chapter 3. However, few specific data are missed in the database. For instance, the build-up area of Shanghai city from 2013 to 2015 are unavailable. In this case, the interpolation method is applied to fill missing values.

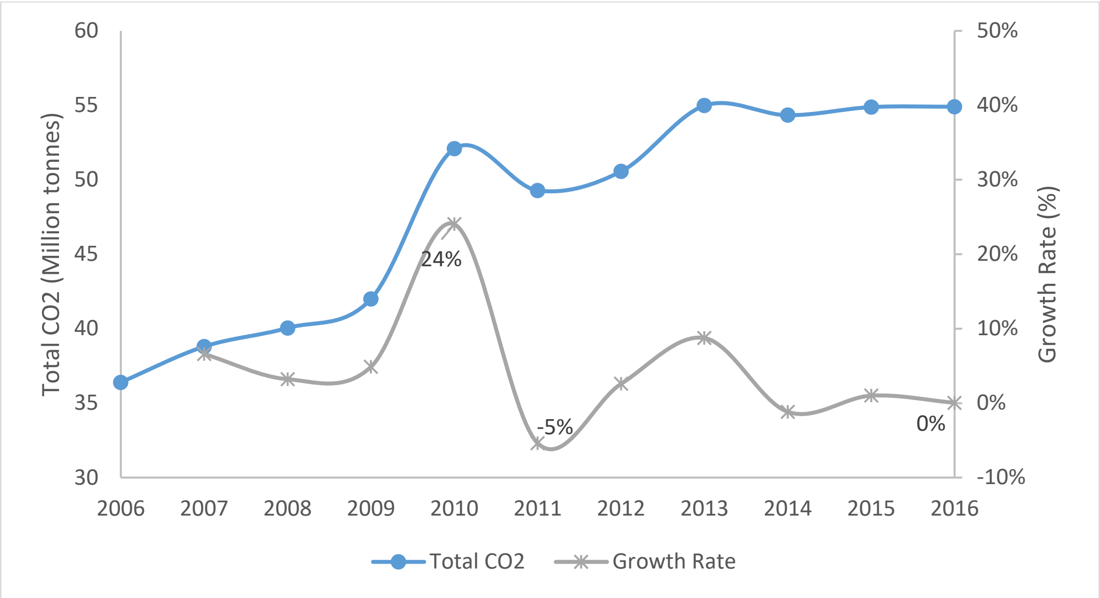
4.1Temporal analysis

The temporal changes of CO_2 emissions and population size and density from 2006 to 2016 are analysed by time series plots in this section, which aims to find out the overall characteristics and behaviours of CO_2 emissions and urban form changed over time when the YRD urban agglomeration area is considered as a whole.

4.1.1 Temporal analysis of CO_2 emissions

From Figure 3 in the below, total CO_2 emissions are on the left Y-axis, and the growth rates of CO_2 emissions are on the right Y-axis. The years from 2006 to 2016 are on the X-axis. It could be seen that there was a general rising trend of the total CO_2 emissions of YRD urban agglomeration from 36,399,219 tons in 2006 to 54,906,862 tons in 2016. Besides, the years 2010 and 2013 seem to be two turning points. More specifically, the total CO_2 emissions rise stably before the sharp increase from 2009 to 2010 with a growth rate at 24%. Then the total CO_2 emissions decrease by 5% from 2010 to 2011, followed by a significant increase from 2011 to 2013. After 2013, the total CO_2 emissions remained stable with 0% growth rate in 2016. The time series of the total CO_2 emissions suggests that the total CO_2 emissions have been brought under control to some extent in YRD urban agglomeration in recent years.

Figure 3: The temporal variation of total CO_2 emission in YRD urban agglomeration



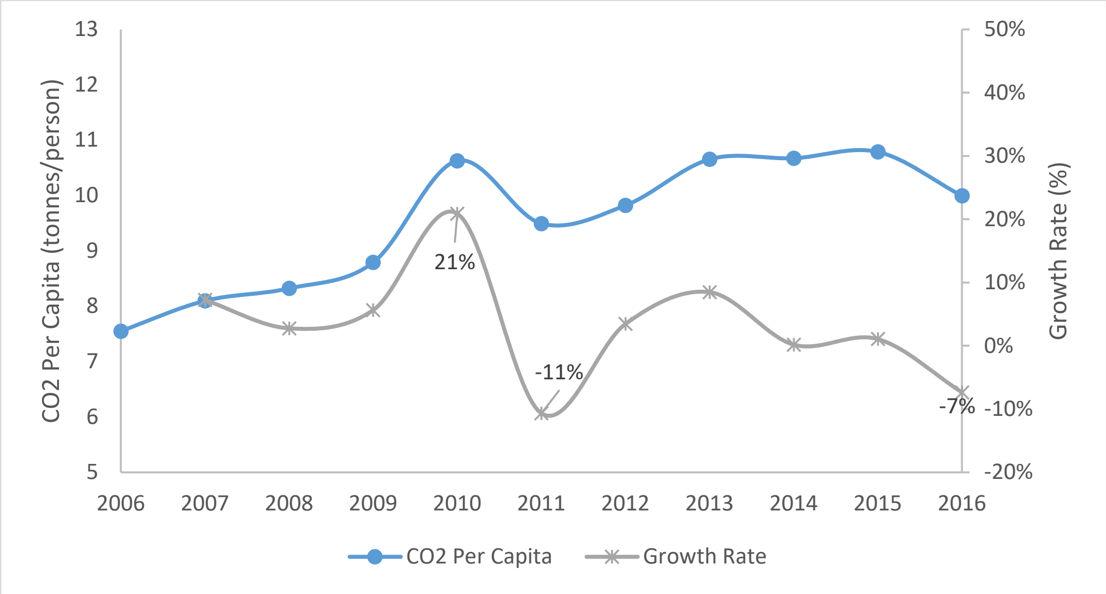
(Source: the author)

In addition, since the YRD urban agglomeration is a highly developed economic region in China's eastern coastal region and gathers a large number of population， economy as well as the pollution emissions, only looking at total CO_2 emissions does not tell the full story of CO_2 emissions. Therefore, to find more meaningful information about the efficiency of CO_2

emissions in YRD urban agglomeration, the changes of CO_2 emissions in tons per capita and CO2 emission in tons per Yuan are also analysed as follows.

On the one hand, the temporal changes in CO_2 emissions per capita were shown in Figure 4. The CO_2 emissions per capita are on the left Y-axis, and the growth rates of CO_2 emissions per capita are on the right Y-axis. The years from 2006 to 2016 are on the X-axis. It could be seen that there was a similar turning point in 2010 as the one in Figure 3, which showed a significant increase by 21% and decrease by 11% of CO_2 emissions per capita before and after 2010 respectively. Then, the CO_2 emissions per capita grew slightly from 2011 to 2013, followed by a stable status from 2013 to 2015 and an obvious drop by 7% to 2016. CO_2 emissions per capita is a common useful measurement and indicator to show the situation of CO_2 emission-related issues. These stable and drop trends of CO_2 emissions per capita from 2013 to 2016 indicated that the efficiency of CO_2 emissions was getting improved in recent years from the perspective of CO_2 emissions per capita.

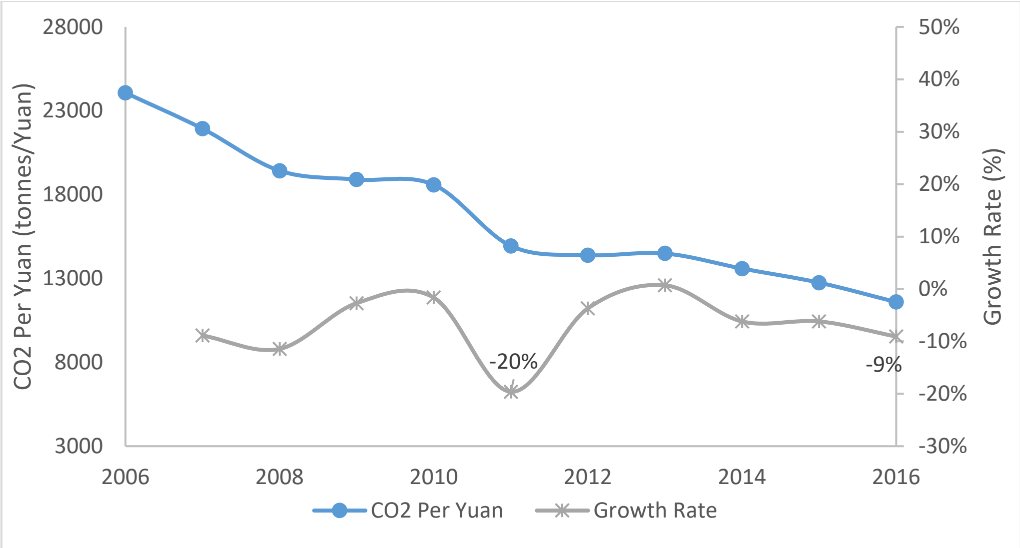
Figure 4: The temporal variation of CO_2 emission per capita in YRD urban agglomeration



(Source: the author)

On the other hand, the temporal variation of CO_2 emission in tonnes per Yuan could be seen from Figure 5, which showed a sustained downward trend from 24,072 tonnes/Yuan in 2006 to 11,596 tonnes/Yuan in 2016. The CO_2 emissions in tonnes per Yuan are on the left Y-axis, and the growth rates of CO_2 emissions in tonnes per Yuan are on the right Y-axis. The years from 2006 to 2016 are on the X-axis. Besides, CO_2 emission per Yuan fell fastest by 20% from 2010 to 2011, and the rates of decline were increasing gradually from 2013 to 2016. This trend of CO_2 emission in tonnes per Yuan reflected that the CO_2 emission and economic development in YRD urban agglomeration were moving towards a more balanced and scientific development mode.

Figure 5: The temporal variation of CO_2 emission in tonnes per Yuan in YRD urban agglomeration



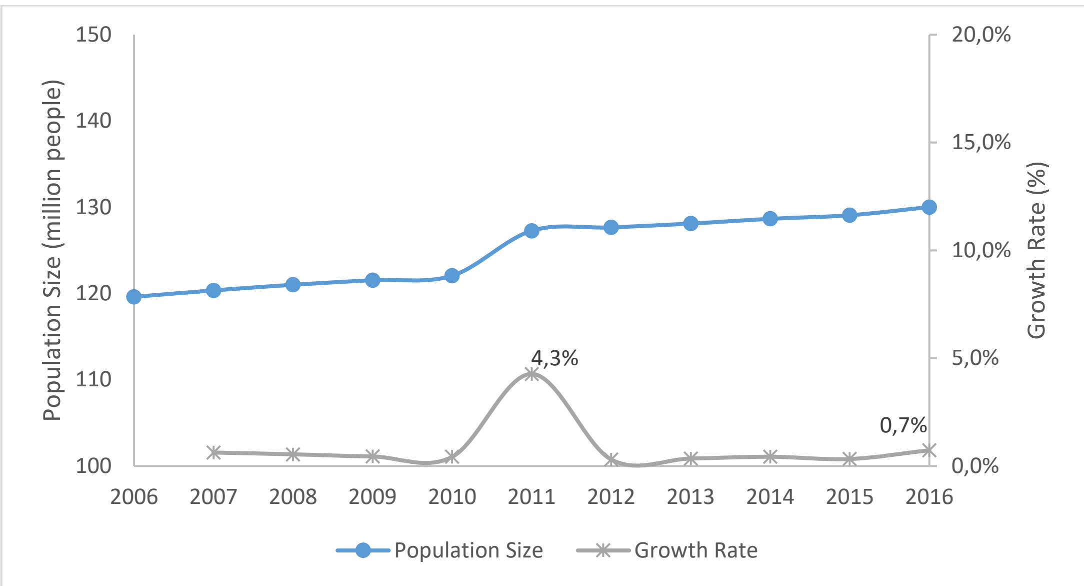
(Source: the author)

To conclude, although the total CO_2 emissions and the CO_2 emissions per capita in YRD urban agglomeration showed an increasing trend from 2006 to 2016, the growth rate went down in recent years, which suggested an effective control of CO_2 emissions in YRD urban agglomeration. Moreover, the gradual decrease of CO_2 emissions in tonnes per Yuan implied a more balanced and scientific development mode between CO_2 emission and economic development in YRD urban agglomeration recently.

4.1.2 Temporal analysis of population size and density

In figure 6, the population size is on the left Y-axis, and the growth rate of the population size is on the right Y-axis. The years from 2006 to 2016 are on the X-axis. During 2006-2013, the population size of the whole YRD urban agglomeration area grew gradually from 120 million people in 2006 to 130 million people in 2016. Moreover, an obvious increase with a growth rate at 4.3% in 2011 seemed to divide the population size in YRD urban agglomeration into two levels.

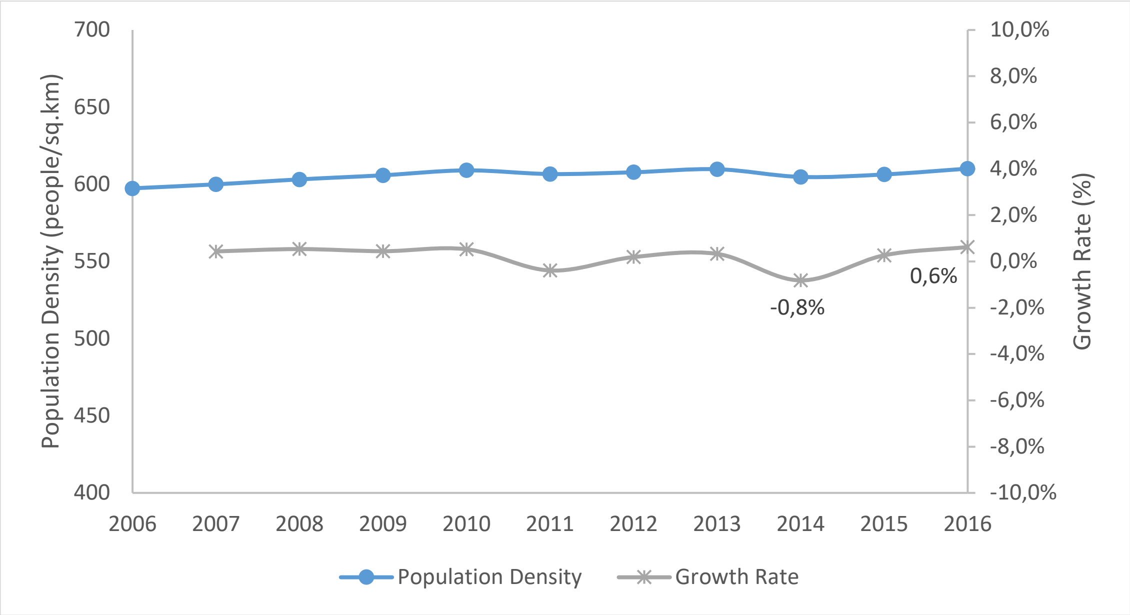
Figure 6: The temporal variation of population size in YRD urban agglomeration



(Source: the author)

From Figure 7, the population density is on the left Y-axis, and the growth rate of the population density is on the right Y-axis. The years from 2006 to 2016 are on the X-axis. The population density of the whole YRD urban agglomeration area experienced a slight increase from 597.37 people per sq.km in 2006 to 610.13 people per sq.km in 2016. The growth rate of every year is within ±1%. After a slight rising from 2006 to 2010, it fell slightly from 2010 to 2011. Then, a small increase for two years is followed by a tiny decline of 0.8% in 2014. Finally, the population density of the whole YRD urban agglomeration area in 2015 and 2016 went back with 0.6% growth rate.

Figure 7: The temporal variation of population density in YRD urban agglomeration



(Source: the author)

4.2 Spatial analysis

In this section, spatial distribution and the agglomeration of CO_2 emissions are analysed by ArcGIS Pro to find out the characteristics and regulations of the distributions of CO_2 emissions, the clustering patterns of CO_2 emissions, and the potential relationships between CO_2 emissions and urban size and density in terms of spatial distributions.

4.2.1 Spatial distribution of CO_2 emissions

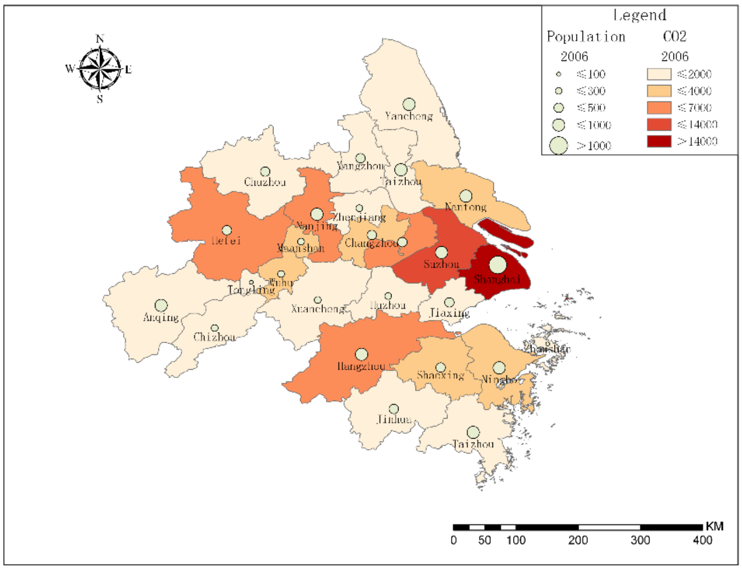
The spatial distribution of CO_2 emissions and its spatial relations between urban size and density are shown respectively as follows, which aims to find changes of the distribution of total CO_2 emissions, urban size and density from 2006 to 2016 visually. The years of 2006, 2011 and 2016 are chosen as the representatives. In addition, to find more spatial information about the level of CO_2 emissions in YRD urban agglomeration, the distribution of CO_2 emissions per capita and CO_2 emissions per GDP from 2006 to 20016 are also shown in this part.

4.2.1.1 CO_2 emissions and population size

The spatial distributions of CO_2 emissions and population size from 2006 to 2016 are analysed in this part. Considering the natural breaks classification method mentioned in chapter 3 and the consistency, the total CO_2 emissions and the population size are divided into 5 fixed levels respectively. The darker the red colour is, the higher the CO_2 emissions are. The bigger the circle is, the larger the population size is.

From Figure 8 in the below, it is clear that the cities with a higher level of CO_2 emissions distributed in the east part of YRD urban agglomeration in 2006, mainly including Shanghai and Suzhou cities. Moreover, the levels of CO_2 emissions in most cities were low. In general, many areas with larger circles were with darker red, which suggested that the distribution pattern of CO_2 emissions might be similar and related to that of urban population to some extent.

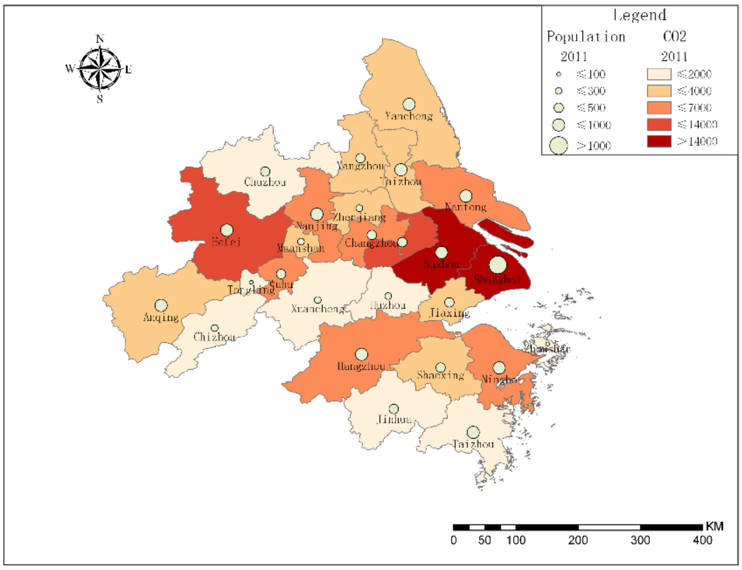
Figure 8: The spatial distribution of CO_2 emissions and population size in 2006



(Source: the author, based on ArcGIS Pro)

Figure 9 in the below shows the spatial distribution of CO_2 emissions in 2011. The higher level of CO_2 emissions mainly distributed in the east part but expanded westward compared with the situations in 2006. The CO_2 emissions in northern cities also increased significantly. Additionally, the city with the largest population also was the one with the highest CO_2 emissions, and where there were fewer people, there were fewer CO_2 emissions generally.

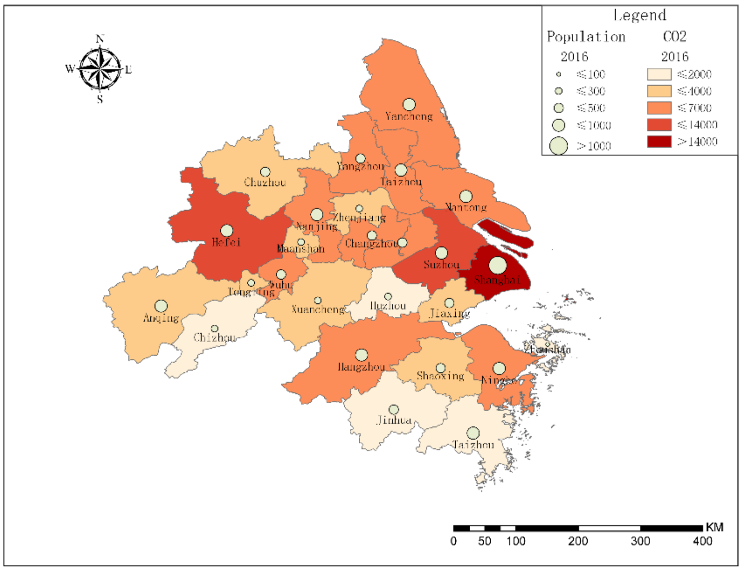
Figure 9: The spatial distribution of CO_2 emissions and population size in 2011



(Source: the author, based on ArcGIS Pro)

In Figure 10, it can be seen that the numbers of cities at the middle level of CO_2 emissions increased significantly in 2016 when compared with that in 2011, especially for the cities in the north part. However, the CO_2 emissions in some cities at a higher level in 2011 dropped down in 2016, such as Suzhou and Changzhou cities. It suggested that the gap of CO_2 emissions between cities were narrowed. By contrast, the changes in population size from 2006 to 2016 are not obvious from the map.

Figure 10: The spatial distribution of CO_2 emissions and population size in 2016



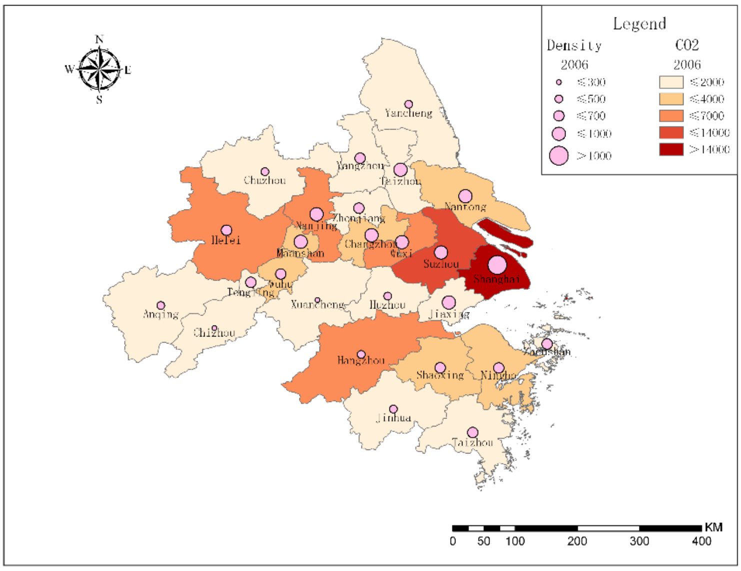
(Source: the author, based on ArcGIS Pro)

4.2.1.2 CO_2 emissions and population density

The distribution of CO_2 emissions has already been described in the above section. In this part, the changes in population density and the spatial correlation between CO_2 emissions and density from 2006 to 2016 are discussed as main points. The spatial distributions of CO_2 emissions and population density are shown visually in figure 11-13. Considering the natural breaks classification method and the consistency, the total CO2 emissions and the population density are divided into 5 fixed levels respectively. The darker the red colour is, the higher the CO_2 emissions are. The bigger the pink circle is, the larger the population density is.

From Figure 11, it is clear that Shanghai had the highest CO_2 emissions as well as the highest density in 2006. Generally, many areas with larger circles were with darker red, which suggested that the distribution pattern of CO2 emissions might be similar and related to that of urban density to some extent.

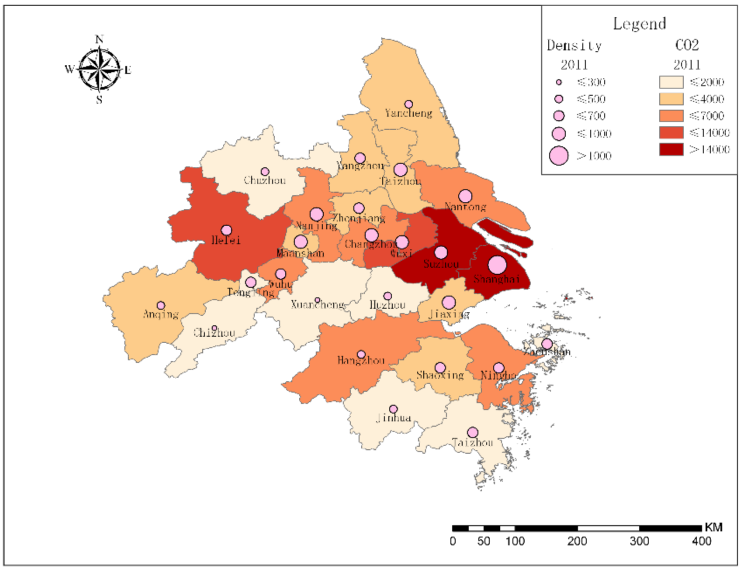
Figure 11: The spatial distribution of CO_2 emissions and population density in 2006



(Source: the author, based on ArcGIS Pro)

In 2011 (Figure 12), some cities' density increased obviously, such as Wuxi, where the CO_2 emissions also increased to some extent. However, some cities, such as Suzhou, which had a high level of CO_2 emissions were with low density as well. It indicated that the correlation of the spatial distribution of CO_2 emissions and density became not obvious in 2011.

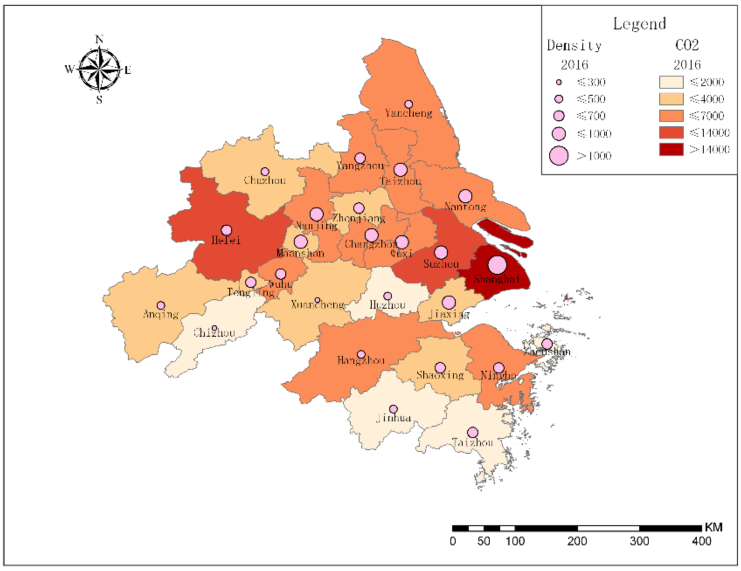
Figure 12: The spatial distribution of CO_2 emissions and population density in 2011



(Source: the author, based on ArcGIS Pro)

It can be seen from figure 13 that the CO_2 emissions in northern cities of YRD urban agglomeration grew significantly from 2011 to 2016, while the density of the corresponding cities did not change much. Moreover, some cities with less CO_2 emissions even became denser in population in 2016, such as Nanjing. All in all, the relationship between CO_2 emissions and density is unclear from the perspective of spatial distribution. Therefore, further analysis of the relationship between them is necessary to be conducted.

Figure 13: The spatial distribution of CO_2 emissions and population density in 2016



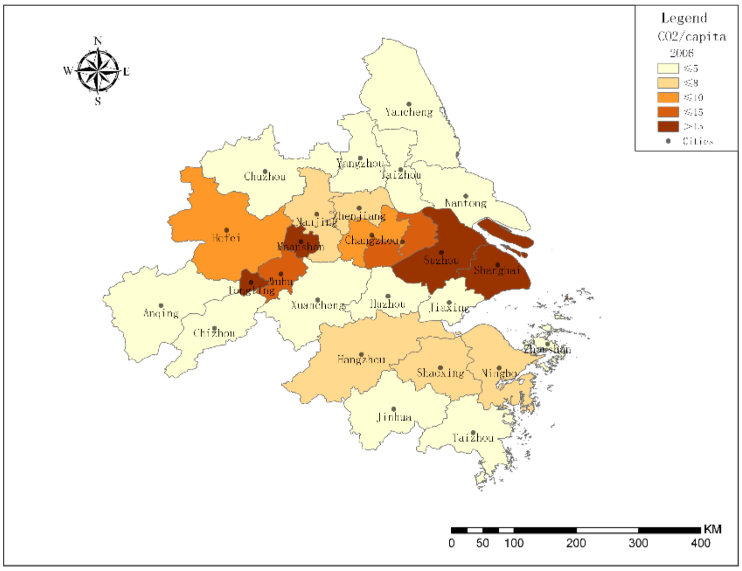
(Source: the author, based on ArcGIS Pro)

4.2.1.3 CO_2 per capita

The spatial distributions of CO_2 per capita from 2006 to 2016 are analysed in this part. The years of 2006, 2011 and 2016 are chosen as the representatives to show these distributions and the changes visually (Figure 14-16). Considering the natural breaks classification method and the consistency, the CO_2 per capita and the population size are divided into 5 fixed levels respectively. The darker the brown colour is, the higher level of the CO_2 per capita is.

In 2006 (Figure 14), the cities with the high level of the CO_2 per capita are mainly situated in the east and west part of YRD urban agglomeration, including Shanghai, Suzhou, Maanshan, Toling cities, etc., just like a belt across the middle part the YRD urban agglomeration. Moreover, the levels of CO_2 per capita in most cities were low.

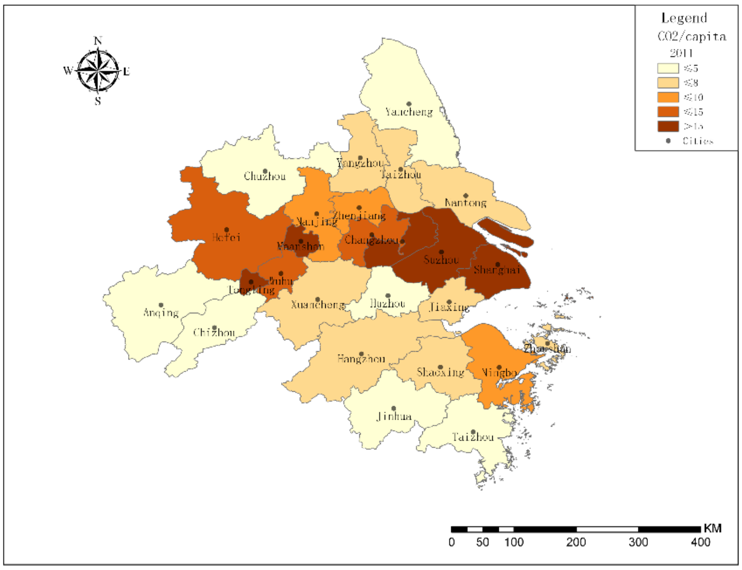
Figure 14: The spatial distribution of CO_2 per capita in YRD urban agglomeration in 2006



(Source: the author, based on ArcGIS Pro)

The spatial distributions of CO2 per capita in 2011 are shown in Figure 15. The high level of the CO_2 per capita mainly gathering in a belt across from east to west of YRD urban agglomeration. From 2006 to 2011, the belt expanded to the north and south to some extent. The level of the CO_2 per capita in most cities got higher over the 6 years.

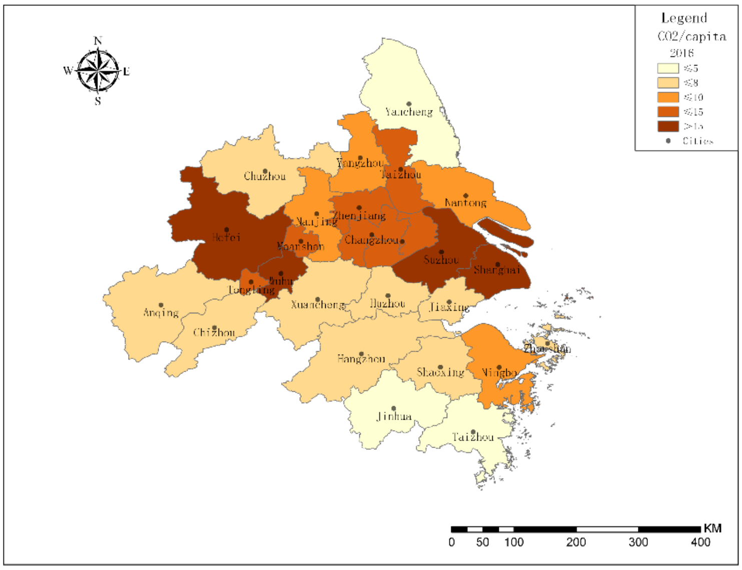
Figure 15: The spatial distribution of CO_2 per capita in YRD urban agglomeration in 2011



(Source: the author, based on ArcGIS Pro)

In Figure 16, the overall level of the CO_2 per capita in YRD urban agglomeration increased. Besides, the scope of cities with a higher level of the CO2 per capita became larger, especially for some cities in the west part. However, some cities' level decreased from 2011 to 2016, such as Changzhou, Tongling, Maanshan and Huzhou cities.

Figure 16: The spatial distribution of CO_2 per capita in YRD urban agglomeration in 2016



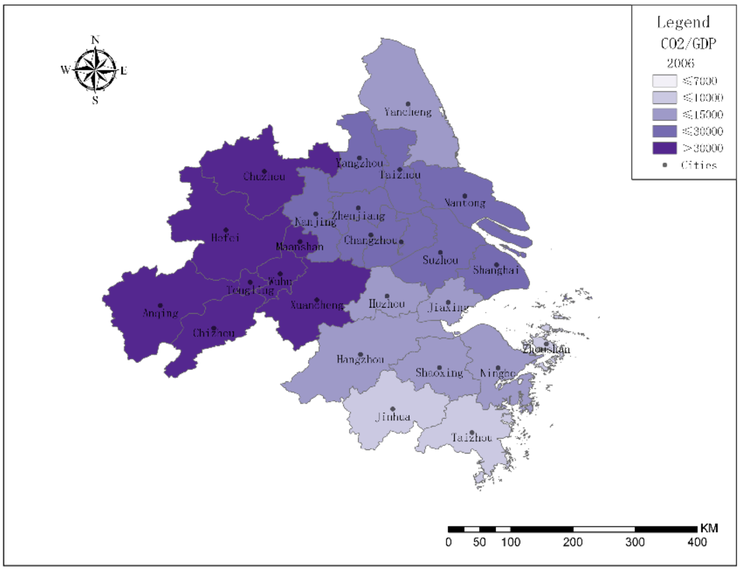
(Source: the author, based on ArcGIS Pro)

4.2.1.4 CO_2 per GDP

The spatial distributions of CO_2 per GDP from 2006 to 2016 are analysed in this part. The years of 2006, 2011 and 2016 are chosen as the representatives to show the distributions and the changes visually (Figure 17-19). Considering the natural breaks classification method and the consistency, the CO_2 per GDP and the population size are divided into 5 fixed levels respectively. The darker the purple colour is, the higher the level of the CO_2 per GDP is.

In Figure 17, it is clear that the distribution of CO_2 per GDP had obvious regional dividing lines. The cities with the high level of the CO_2 per capita mainly located in the west and middle part of YRD urban agglomeration in 2006, while the northern and southern cities were at the lower level of CO_2 per GDP comparatively.

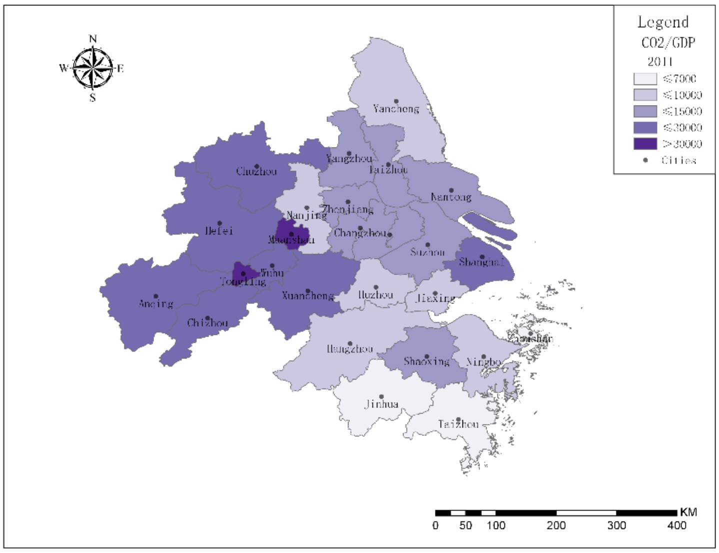
Figure 17: The spatial distribution of CO_2 per GDP in YRD urban agglomeration in 2006



(Source: the author, based on ArcGIS Pro)

The spatial distributions of CO_2 per GDP in 2011 are shown in Figure 18. It could be clearly seen from the map that the overall levels of CO_2 per GDP in 2011 were significantly lower than that in 2006, which means that most cities in YRD urban agglomeration controlled and adjusted the balance between the economic development and CO_2 emissions issues over these 6 years. However, the west and middle parts of YRD urban agglomeration were still with a higher level of CO_2 per GDP than the rests.

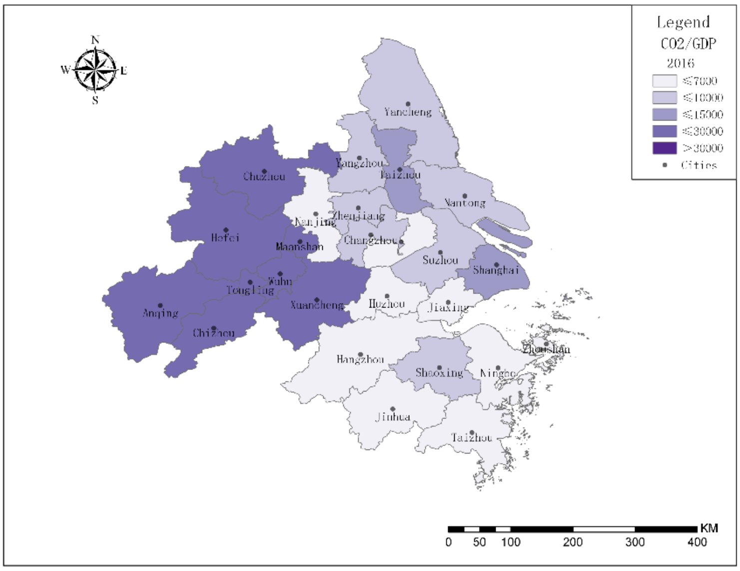
Figure 18: The spatial distribution of CO_2 per GDP in YRD urban agglomeration in 2011



(Source: the author, based on ArcGIS Pro)

From Figure 19 in the below, it is clear that there was no city at the highest level of CO_2 per GDP in 2016, and only the west part of was with relatively higher levels. It suggested that the balance between economic development and CO_2 emissions issues were continually improved from 2011 to 2016 in YRD urban agglomeration.

Figure 19: The spatial distribution of CO2 per GDP in YRD urban agglomeration in 2016



(Source: the author, based on ArcGIS Pro)

4.2.2 Agglomeration of CO_2 emissions

According to the figures in the last section of spatial distribution, the level of CO_2 emissions varies in different regions, presenting that CO_2 emissions cluster in east part but less distribute in north and south, which implies that there may be agglomeration pattern of CO_2 emissions in YRD urban agglomeration. If the agglomeration existed in the spatial distribution of CO_2 emissions, the spatial factor should be considered in the later regression analysis.

Meanwhile, the level of agglomeration can be judged by the results of the spatial autocorrelation test. Spatial autocorrelation is an important spatial statistical approach in Geographic Information Systems, which can reveal spatial patterns of regional variables. As mentioned in Chapter 3, Global and Local Moran's I are the commonly used methods to evaluate the overall and local level of spatial autocorrelation which presents spatial agglomeration. With these methods, this section calculates the CO_2 emissions' spatial autocorrelation for city-level units in YRD urban agglomeration from 2006 to 2016 with the years of 2006, 2011 2016 as representatives, demonstrates the characteristics and changes of the global and local spatial correlation, provides further evidence for the choice of regression model whether with or without the concern of spatial factor.

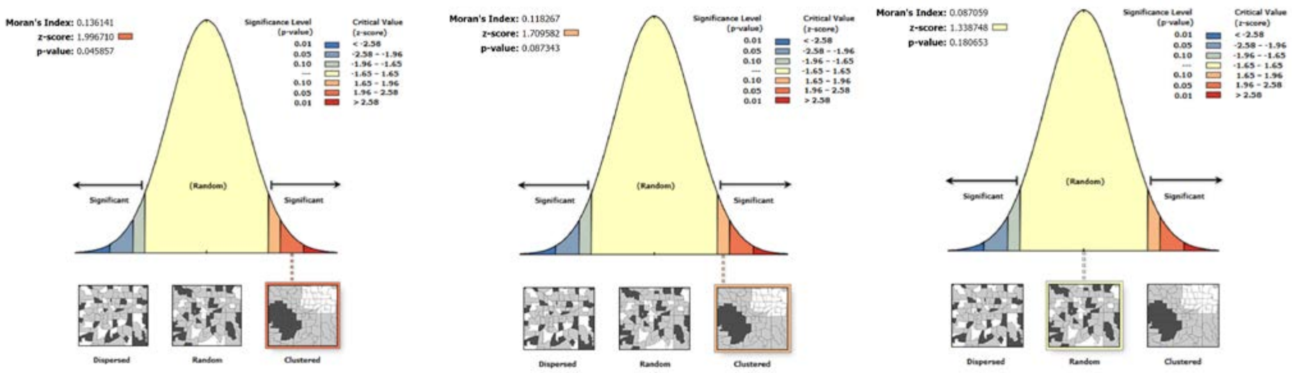
4.2.2.1The global agglomeration

The global agglomeration level of CO_2 emissions from 2006 to 2016 are shown in Figure 20. Firstly, it can be seen from Figure 20 (a) that the Global Moran's Index is about 0.136 in 2006 and that there is a less than 5% likelihood that this clustered pattern could be the result of random chance. The result suggests that spatial autocorrelation of CO_2 emissions in YRD urban agglomeration in 2006 is significant with a clustered pattern. In addition, the Moran's Index is about 0.118 in Figure 20 (b), indicating a clustered pattern of CO_2 emissions in YRD urban agglomeration in 2011 at the 10% level of significance. Moreover, the Moran's Index about

0.087 in Figure 20 (c) implies that the pattern does not appear to be significantly different from random, which means that there seems no significant spatial agglomeration of CO_2 emissions in YRD urban agglomeration in 2016.

The Global Moran's Index from 2006 to 2016 decrease apparently with the changes of the spatial agglomeration pattern from clustered to random, which means that the spatial distribution of CO_2 emissions changes from significant clustered pattern to random characteristic. This kind of transform also suggests that the influence of spatial factor is worth discussing in the later regression analysis.

Figure 20: The global agglomeration level of CO_2 emissions from 2006 to 2016



(a)2006-Clustered (b)2011-Clustered (c)2016-Random

(Source, the author, based on ArcGIS Pro)

4.2.2.2The local agglomeration

Local Moran's Index is used to find more details of the agglomeration of CO_2 emissions in each city of YRD urban agglomeration from 2006 to 2016 are shown in Figure 21-23 visually. The coloured cities in Figure 21-23 are all core units which have strong special autocorrelations in terms of CO_2 emissions at a significant level ($P \leqslant 0.05$). The clarification of the legend is in Table 6.

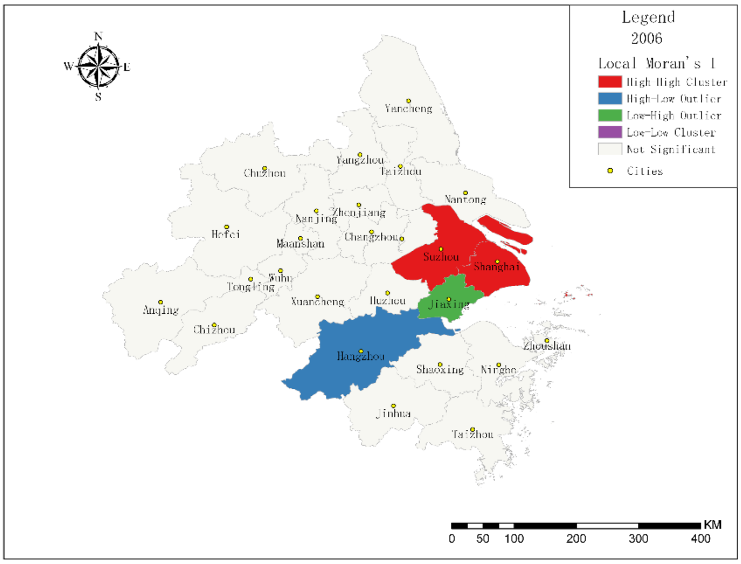
Table 6 The clarification of local agglomeration map legend

Category	Colour	Autocorrelation	Explanation
High-high Cluster	Red	positive	CO_2 emissions in this city are high and in its neighbours are high as well
High-low Outlier	Blue	negative	This city is a high outlier among low neighbours
Low-high Outlier	Green	negative	This city is a low outlier among high neighbours
Low-low Cluster	Purple	positive	CO_2 emissions in this city are low and in its neighbours are low as well
Not significant	Grey	-	There no significant spatial association in terms of CO_2 emissions between this city and its neighbours

(Source, the author)

In Figure 21, it is clear that, in 2006, there were two core high CO_2 emissions clusters which were Shanghai and Suzhou cities, while the high-low and low-high outliers were Hangzhou and Jiaxing respectively. It means that the CO_2 emissions mainly agglomerated around the Shanghai and Suzhou cities in 2006, but dispersed in the regions around Hangzhou and Jiaxing. Additionally, most cities in YRD urban agglomeration illustrated no significant spatial autocorrelation pattern in 2006.

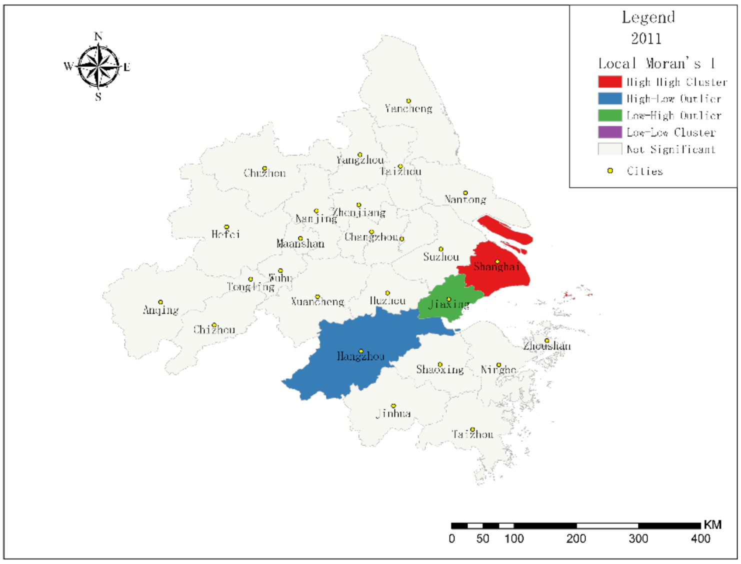
Figure 21: The local agglomeration of CO_2 emissions in 2006



(Source, the author, based on ArcGIS Pro)

In Figure 22, it is clear that, in 2011, there was only one high-high CO_2 emissions cluster which was Shanghai city, while the high-low and low-high outliers were Hangzhou and Jiaxing respectively. It means that the CO_2 emissions mainly agglomerated around the Shanghai city in 2011, but dispersed in the regions around Hangzhou and Jiaxing. Apparently, the area of clusters decreased from 2006 to 2011, and most cities in YRD urban agglomeration showed no significant spatial autocorrelation pattern in 2011.

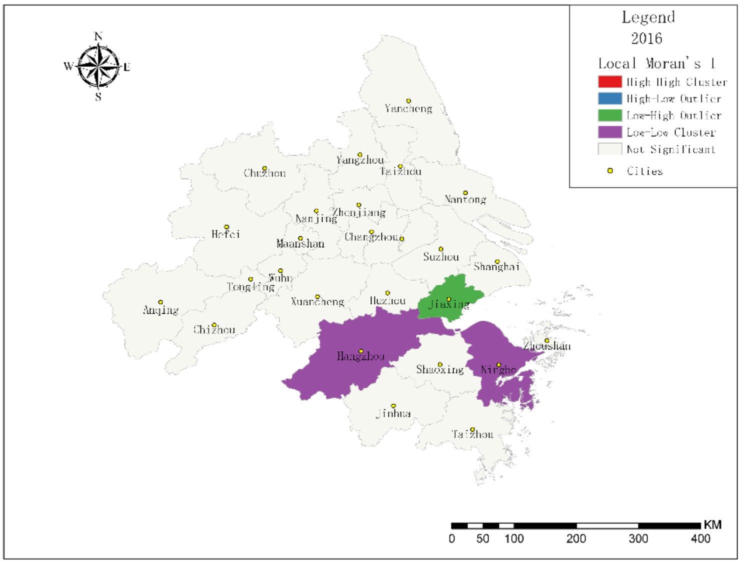
Figure 22: The local agglomeration of CO_2 emissions in 2011



(Source, the author, based on ArcGIS Pro)

In Figure 23, there were two low-low CO_2 emissions clusters which were Hangzhou and Ningbo cities and one low-high CO_2 emissions outlier which was Jiaxing city in 2016. It means that the regions with lower CO_2 emissions levels mainly clustered around Hangzhou and Ningbo cities and that less CO_2 emissions were in Jiaxing city compared to its neighbours. Most cities in YRD urban agglomeration showed no significant spatial autocorrelation pattern in 2016.

Figure 23: The local agglomeration of CO_2 emissions in 2016



(Source, the author, based on ArcGIS Pro)

From 2006 to 2016, according to the above local agglomeration maps, it is clear that the areas of high-high clusters and high-low outlier decreased obviously, but the low-low clusters appeared in 2016. These phenomena suggested that the spatial agglomeration of the high level of CO_2 emissions decreases, but the clusters with lower CO_2 emissions levels increased. Additionally, the spatial agglomeration of CO_2 emissions is significant in some parts of YRD urban agglomeration, but most cities revealed no significant spatial agglomeration pattern.

To conclude, combining the results of global and local agglomeration obtained by Global Moran's I and Local Moran's I methods, there was a significant spatial agglomeration of CO_2 emissions with clustered pattern in YRD urban agglomeration in 2006, but the spatial agglomeration gradually became less obvious. With these in mind, whether to consider spatial autocorrelation of CO_2 emissions as an influence factor needs to be further discussed in the following regression analysis.

4.3 Descriptive statistics

The descriptive statistics including the mean, the standard deviation, the minimum, the maximum of the dependent, independent and control indicators as well as the corresponding units are summarized in table 7. It is a panel data set with 26 cities and 11 years, so the total observations are 286.

Table 7 Descriptive statistics of indicators

	Indicator	Abb.	Mean	Std. Dev.	Min	Max	Unit
Dependent	CO2	C	48.0	62.6	2.5	368.0	Million Tonnes
Independent	Population size	P	4.8	2.7	0.7	14.5	Million People
	Density	D	683.7	376.4	189.9	2286.7	People/Sq.km
Control	GDP	G	366.0	420.8	13.0	2817.9	Billion Yuan
	GDP/capita	GP	61458.7	32794.5	8503.0	199017.0	Yuan/Person
	The secondary industry as the proportion to GDP	S	52.1	7.5	29.8	74.7	%
	The tertiary industry as the proportion to GDP	T	40.8	7.8	23.4	69.8	%
	Built-up area	B	192.7	206.1	19.0	999.0	Sq.km
	Green area	GA	130.9	244.5	6.1	1316.8	Sq.km

Deserved to be mentioned, the logarithm to the base *e* of all variables was taken for the following analysis in this paper. There are three main reasons for the logarithm of indicators. To begin with, it is good to eliminate the influence of heteroscedasticity, which is to satisfy one of the basic assumptions of the linear model, that is, the variance of the random error term is not different with the changes of independent indicators. For instance, in terms of cities with small population size, the change in CO_2 emissions may be small, but for cities with large population size, the change in CO_2 emissions may be very large. Secondly, the Scaling Law which describes as a power-law relationship between dependent and independent indicators mentioned in Chapter 2 can be applied in the regression analysis by linearizing the exponential relationship with the logarithm of the indicators. Moreover, the logarithmic form of indicators is more suitable for some regression model test, such as testing spurious relationship by unit root test which will be explained more detailly in the regression analysis section. To conclude, considering the above three points, subsequent data analysis will be based on the logarithmic form of indicators. Meanwhile, the unit conversion is implemented to make the order of magnitude of the variable after taking the logarithm relatively close. The descriptive statistics of indicators in the logarithmic form are shown in table 8.

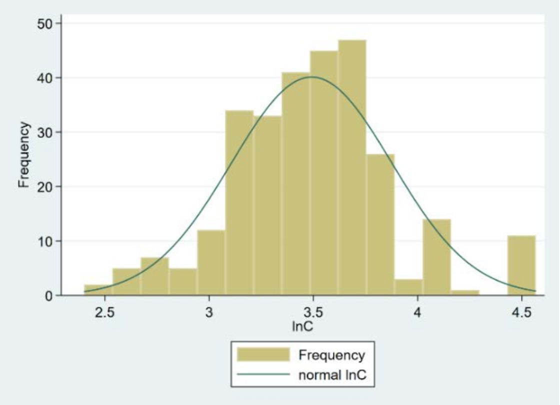
Table 8 Descriptive statistics of indicators in logarithm

	Indicator	Abb.	Mean	Std. Dev.	Min	Max
Dependent	ln(CO2)	lnC	8.04	0.89	5.53	10.51
Independent	ln(Population size)	lnP	6.00	0.65	4.29	7.28
	ln(Density)	lnD	6.41	0.48	5.25	7.73
Control	ln(GDP)	lnG	7.70	1.03	4.87	10.25
	ln(GDP/capita)	lnGP	10.86	0.61	9.05	12.20
	ln(secondary industry as the percentage to GDP)	lnS	3.94	0.15	3.40	4.31
	ln(tertiary industry as the percentage to GDP)	lnT	3.69	0.19	3.15	4.25
	ln(built-up area)	lnB	4.86	0.86	2.94	6.91
	ln(Green area)	lnGA	8.76	1.02	6.42	11.79

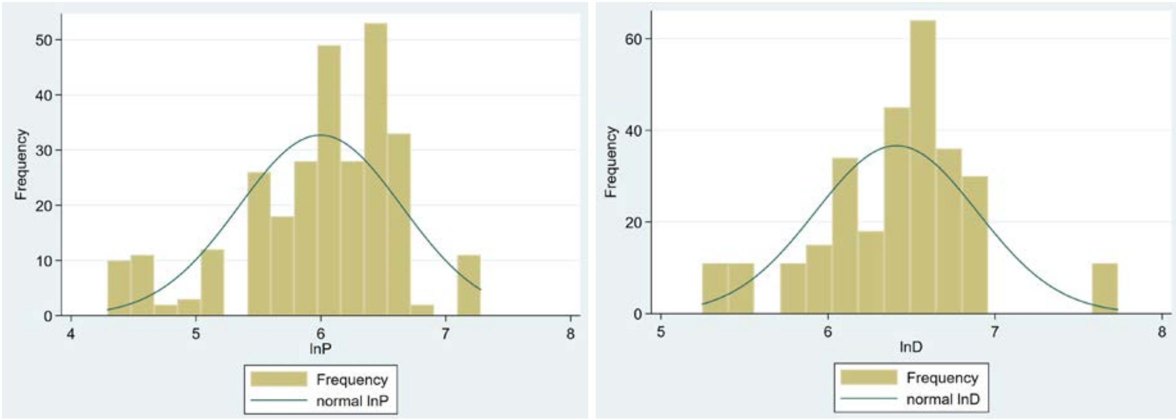
(Source, the author, based on Stata)

Furthermore, an important assumption of the regression analysis in the next section is the normality of dependent and independent indicators. The histograms of the frequency of dependent indicator (lnC) and independent indicators (lnP, lnD) are used to check the normality. As seen from Figure 24, these histograms are approximately bell-shaped, which refers to the approximately normal distribution of the dependent and independent indicators.

Figure 24: The normality of dependent and independent variables



(a)lnC



(b)lnP (c)lnD

(Source, the author, based on Stata)

4.4 Correlation analysis

Correlation analysis is one of the essential steps before conducting multiple regression analysis. Pearson Correlation test is the commonly used method to show how significant and strong the linear dependence between two variables is. The value of Pearson correlation (r) ranges from –1 that reveals a strong negative relation to +1 that indicate an obvious positive relation. Along with the Pearson correlation, the p-value has to be taken into account in the analysis to indicate the significance of the relationship. With a number from 0 to 1, a p-value below 0.05 reveals a significant relationship, while p-value that is larger than 0.05 means that there is no significant correlation.

In this section, the Pearson Correlation test is applied among independent, dependent, and control variables, the results are shown in Table 8 below.

4.4.1 The correlation between dependent variables and other variables

It can be seen clearly from Table 9 that the dependent variable (lnC) has strong and significant relationships with independent and control variables, except for lnS. For instance, the significant positive correlation between CO_2 emissions (lnC) and size and density (lnP and lnD) are 0.6828 and 0.6358 respectively. The strong and significant dependences indicate that these independent and control variables are likely to be the potential factors which impact the CO_2 emissions. However, the weak correlation between lnC and lnS by Pearson Correlation test is not sufficient to show that there is no relationship between them, because the relationship between the two may emerge when controlling for other variables. Therefore, further correlations between variables in multiple regression analysis can be judged more accurately when holding all of the other variables constant.

4.4.2 The correlation between independent variables

In order to avoid the multicollinearity between independent variables, the independent variables should be independent. If the degree of correlation between variables is high enough, it can cause problems that model estimation is distorted or it is difficult to interpret the results accurately. The Pearson Correlation test between independent variables is one way to check the multicollinearity.

It is clear that the correlation result between two independent variables (lnP and lnD) is only 0.3395, and the correlation is significant at 5% level, which means that multicollinearity between two independent variables is unlikely to exist.

Table 9 The correlations of all variables

Variable	lnC	lnP	lnD	lnG	lnGP	lnS	lnT	lnB	lnGA

lnC	1.0000								
lnP	0.6828*	1.0000							
	0.0000								
lnD	0.6358*	0.3395*	1.0000						
	0.0000	0.0000							
lnG	0.8194*	0.7389*	0.6271*	1.0000					
	0.0000	0.0000	0.0000						
lnGP	0.5350*	0.1235*	0.5662*	0.7484*	1.0000				
	0.0000	0.0369	0.0000	0.0000					
lnS	-0.0131	-0.3515*	0.0650	-0.2234*	0.0452	1.0000			
	0.8252	0.0000	0.2736	0.0001	0.4463				
lnT	0.3562*	0.4530*	0.3629*	0.6600*	0.5005*	-0.7446*	1.0000		
	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000			
lnB	0.8454*	0.6526*	0.6239*	0.8856*	0.6531*	-0.2255*	0.6346*	1.0000	
	0.0000	0.0000	0.0000	0.0000	0.0000	0.0001	0.0000		
lnGA	0.7734*	0.5045*	0.6443*	0.7870*	0.6414*	-0.2829*	0.6222*	0.9181*	1.0000
	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	

*Correlation is significant at the 0.05 level

(Source, the author, based on Stata)

4.5 Regression analysis

A regression analysis of strongly balanced panel data which refer to the fact that all 26 cities have data for all 11 years is conducted in this section, which mainly includes five steps. Firstly, the unit root test is to check the stationary of data to avoid the spurious relationships between variables. Secondly, the Non-Spatial Regression and Spatial Regression analysis are both considered in this section, owing to the fact that the overall influence of spatial autocorrelation on CO_2 emissions in YRD urban agglomeration was still unclear. Specifically, it displayed a significant clustered pattern in earlier years but gradually became less obvious and finally turned to a random pattern. It means that whether the spatial autocorrelation of dependent variables is an influencing factor is worth further discussing. Thirdly, in both kinds of regression, the models are specified and determined into details based on the model M.1-M.4 in Chapter 3. Then, the fixed effects or random effects of each model are decided by the Hausman test for avoiding model misspecification and endogenous regressors. Finally, the results of the regression are illustrated and discussed.

4.5.1 Unit root test

The purpose of regression analysis is to find the degree of the influence between independent and dependent variables. However, when we do regression analysis, spurious regression may occur. Spurious relationship refers to that there is no causal relationship between independent and dependent variables, but for some reason, regression analysis shows that there is a statistical correlation between them, leading people to mistakenly believe that there is a correlation between these variables. Actually, spurious regression tends to occur when non-stationary data are used, while the unit root is one of the characteristics of non-stationary data. Therefore, without unit root means the good stationarity of the data, and also means spurious regression occurs unlikely.

In this section, Levin-Lin-Chu (LLC) and Im-Pesaran-Shin (IPS) are chosen to test the unit-root of data series. For LLC, the null hypothesis is that panels contain unit roots, and the alternative hypothesis is that the panels are stationary. If the P-value is less than 0.01(at 1% significant level) or less than 0.05(at 5% significant level), the null hypothesis can be rejected, meaning that the panel data are stationary. For IPS, the null hypothesis is that all panels contain unit roots, and the alternative hypothesis is that some panels are stationary. If the P-value is less than 0.01 (at 1% significant level) or less than 0.05 (at 5% significant level), the null hypothesis can be rejected, meaning the data are stationary. The two test methods are complementary to each other. Only both methods conclude that there is no unit root, can the tested data be considered stable.

The results in table 10 of the two types of unit-root test methods both illustrate that there is no unit root in each variable. Therefore, the panel data are stationary, and the regression analysis can be carried on then.

Table 10 Unit-root test

Variable	Unit-root test		Conclusion
	Levin-Lin-Chu (LLC)	Im-Pesaran-Shin (IPS)	
lnC	-3.4697***	-2.8153***	stationary data
lnP	-7.6697***	-3.4985***	stationary data
lnD	-7.4032***	-3.4353***	stationary data
lnG	-2.0262**	-5.7363***	stationary data
lnGP	-4.3559***	-1.9196**	stationary data
lnS	-2.9038***	-2.933***	stationary data
lnT	-3.587***	-3.0174***	stationary data
lnB	-5.992***	-2.016**	stationary data
lnGA	-12.9262***	-3.1599***	stationary data

*** at 1% significant level; ** at 5% significant level

(Source, the author, based on Stata)

4.5.2 Non-Spatial Regression analysis

One side of the results in spatial analysis shows that the spatial agglomeration gradually became less obvious and the spatial agglomeration pattern was random in 2016. Based on these, the regression analysis without the effect of spatial autocorrelation on dependent variables is conducted in this section, including two models based on M.1 and M.2.

4.5.2.1Non-spatial regression model specification

The model (M.1) mentioned in Chapter 3 is specified as follows.

$$\ln C = \mathrm{a} + \beta_1 \ln P + \beta_2 \ln D + \gamma_1 \ln G + \gamma_2 \ln GP + \gamma_3 \ln S + \gamma_4 \ln T + \gamma_5 \ln B + \gamma_6 \ln GA + \varepsilon \qquad \text{(M.1s)}$$

Where $\ln C$ is the dependent variable; $\ln P$ and $\ln D$ are the independent variables; $\mathrm{lnG, lnGP, lnS, lnT, lnB, lnGA}$ are the control variables; a is the so-called constant; ε is the estimation error; β_i are the coefficients of the two independent variables, which shows the relationships between dependent and independent variables; γ_i is the coefficient of the control variables, which shows the positive or negative relations between dependent and control variables. More precisely, if $\beta_1 > 0$, it means that when population size increases 1%, the CO_2 emissions will increase β_1%; if $\beta_1 < 0$, it means that when population size increase 1%, the CO_2 emissions will decrease β_1%. Similarly, if $\beta_2 > 0$, it means that when population density increases 1%, the CO_2 emissions will increase β_2%; if $\beta_2 < 0$, it means that when population density increase 1%, the CO_2 emissions will decrease β_2%.

Furthermore, quadratic the model (M.2) mentioned in Chapter 3 is specified as M.2s. On the one hand, the purpose of the following model is to test the inverted U-shaped relationship between environmental factors in terms of CO_2 emissions and economic growth from GDP and GDP per capita. On the other hand, more importantly, it aims to explore empirically whether there are "U-shaped" or "inverted U-shaped" relationships between CO_2 emissions and urban size and density and try to find the ideal urban size and density.

$$\ln C = a + \beta_1 \ln P + \beta_2 \ln D + \beta_3 (\ln P)^2 + \beta_4 (\ln D)^2 + \gamma_1 \ln G + \gamma_2 \ln GP + \gamma_3 (\ln G)^2 + \gamma_4 (\ln GP)^2 + \gamma_5 \ln S + \gamma_6 \ln T + \gamma_7 \ln B + \gamma_8 \ln GA + \varepsilon \quad \text{(M.2s)}$$

Where the meanings of parameters in M.2s are the same as the ones in M.1s. Additionally, if $\beta_3 > 0$, the relationship between absolute CO_2 emissions and population size is likely to be "U-shape", and if $\beta_3 < 0$, the relationship may be "inverted U-shape". Moreover, If the negative or positive figures of β_1 and β_3 are different, the turning point or the so-called ideal population size for CO_2 emissions will exist with realistic significance. Similarly, if $\beta_4 > 0$, the relationship between CO_2 emissions and population density is likely to be "U-shape", and if $\beta_4 < 0$, the relationship may be "inverted U-shape". Moreover, If the negative or positive values of β_2 and β_4 are different, the turning point or the so-called ideal population density for CO_2 emissions will exist with realistic significance. Meanwhile, the inverted U-shaped relationships between CO_2 emissions and economic growth in terms of GDP and GDP per capita can be tested by the values of γ_1, γ_2, γ_3, and γ_4.

4.5.2.2Hausman test for non-spatial regression

To decide whether fixed effects (FE) or random effects (RE) is the best technique to be used for non-spatial regression of model M.1s and M.2s, the Hausman test is conducted for both models. As mentioned in Chapter 3, the null hypothesis is that the preferred model is RE, and if the prob > chi2 statistic of the Hausman test is significant, reject the null hypothesis and use FE. The results of prob > chi2 statistics of Hausman test for M.1s and M.2s are both significant at 1% level, which means that FE is better to be applied in non-spatial regression.

4.5.2.3Non-spatial regression analysis results

The results of non-spatial multiple regression analysis between CO_2 emissions as the dependent variable as well as population size and density as the independent variables are showed in table 11. There are two models to be explicated. One (M.1s) is to examine the basic linear correlation between CO_2 emissions and population size and density, and the other one (M.2s) is to explore whether there is "U-shape" relations between CO_2 emission and population size and density, as well as their turning points. The R-square of M.1s and M.2s are both above 0.8, which indicate good fitness of the regression models. On the other hand, the R-square of M.2s is higher than that of M.1s, which suggests that taking the square of population, density, GDP and GDP per capita into consideration can improve the fitness of the model.

Table 11 Non-spatial regression results for CO_2 emissions

Determinants	M.1s		M.2s	
	Coef.	Sig.	Coef.	Sig.
lnP	-0.111		-2.634	***
$(\ln P)^2$			0.235	***
lnD	-0.426	**	-9.493	
$(\ln D)^2$			0.690	
lnG	0.450	***	0.932	***
$(\ln G)^2$			-0.038	**
lnGP	0.128	*	0.586	
$(\ln GP)^2$			-0.020	
lnS	1.257	***	0.891	***
lnT	0.648	***	0.650	***
lnB	-0.154	**	-0.085	
lnGA	0.022		0.011	

Constant	-0.223	33.133 *
R-square	0.813	0.822

*** at 1% significant level; ** at 5% significant level; * at 10% significant level

(Source, the author, based on Stata)

For model M.1s, there is a negative relationship between CO_2 emissions and population size but the result is not significant, while the relationship between CO_2 emissions and density is statistically significant at 5% level. The coefficient of density in M.1s is -0.426, which means that there is a negative relationship between CO_2 emissions and density and that when population density increases 1%, the CO_2 emissions will decrease 0.426%. On the one hand, the negative relationship suggests that cities with higher density have less CO_2 emissions. On the other hand, figure -0.426 is between -1 and 0, which reveals that with the gradual increase of density, the efficiency of carbon dioxide reduction will be reduced. In other words, the mitigation effect of urban density on carbon dioxide will be gradually weakened with the increase of density of cities. Therefore, it can be seen that for low-density cities, measures by increasing urban density will have a great effect on carbon dioxide reduction, but for cities with high density, the effect of continuing to increase urban density to achieve emission reduction will not be obvious.

Additionally, the relations between CO_2 emissions and some control variables are also at 1% or 5% significant level. For example, the coefficient of lnG is 0.450, which means that 1% growth in GDP leads to increasing CO_2 emission by 0.450%. However, the values 0.450 which is between 0 and 1 suggests a sublinear relationship, which means that the higher level of GDP the city is, the higher efficiency of CO_2 emissions the city has. As another example, the coefficient of lnS is 1.257, which means a superlinear relationship between the secondary industry as the percentage to GDP and CO_2 emission, indicating that with the higher proportion of the secondary industry, the growth rate of CO_2 emission will also increase. By contrast, the sublinear relationship between the tertiary industry as the percentage to GDP and CO_2 emission implies that the growth rate of CO_2 emission will gradually decrease as the increase of the proportion of the tertiary industry. Therefore, the development of the tertiary industry improves the efficiency of CO_2 emission, but the development of the secondary industry does the opposite.

For model M.2s, when the square of population, density, GDP and GDP per capita are included in the model, the relationship between CO_2 emissions and population size become significant. The quadratic coefficient lnP is positive, which shows that there is a U-shape relation between population and CO_2 emissions. Take the derivative of lnP, solve the equation, and the turning point of the population can be finally obtained (shown in table 12). Therefore, the ideal population size of cities for lowest CO_2 emission in YRD urban agglomeration is 2.716 million, which means that if a city's population is less than 2.716 million, with the increase of the population, the CO_2 emission will decline, while once the population exceeds the turning point, CO_2 emissions will increase significantly with the population.

However, in 2016, the average of the population size of cities in YRD urban agglomeration was 5.001 million, and only five cities' population was less than the ideal size (2.716 million), including Huzhou, Zhoushan, Maanshan, Tongling and Chuzhou. Since the population growth is a general trend, it is necessary to control and adjust population in YRD urban agglomeration.

Table 12 The ideal urban form based on M.2s

Term	Population size	Density
Linear term	negative	not significant
Quadratic term	U-shape	not significant

Turning point	2.716×10^6	-

Meanwhile, it shows a significant inverted U-shaped relationship between CO_2 emissions and GDP, which just confirms the conclusion of EKC. More specifically, as the growth of GDP, the CO_2 emissions increase first, but after reaching the peak point, the CO_2 emissions decrease gradually. That is to say, economic growth does not always lead to negative effects on the environment and sometimes the opposite may actually be true. However, the turning point of GDP is far more than the current economic level of cities in YRD urban agglomeration, which means that at this stage economic growth is still leading to an increase in CO_2 emissions, but at a gradually slower rate.

Moreover, the relations between CO_2 emissions and lnS, lnT are both significant. Compared with the results in M.1s, both secondary and tertiary industry show a sublinear relationship with CO_2 emissions in M.2s, indicating that the development of the secondary and tertiary industry both tend to increase the efficiency of CO_2 emissions.

4.5.3 Spatial Regression analysis

On the other side of the results in spatial analysis, it shows that there was significant spatial autocorrelation of CO_2 emissions with clustered pattern in YRD urban agglomeration. Even though the spatial agglomeration gradually became less obvious, the spatial autocorrelation still may be the potential influencing factor of the dependent variable. Therefore, the spatial autoregression model (SAR) for panel data analysis is involved in this section.

4.5.3.1 Spatial regression model specification

The basic SAR model (M.3) mentioned in Chapter 3 is specified as follows.

$$\ln C = \mathrm{a} + \rho W \ln C + \beta_1 \ln P + \beta_2 \ln D + \gamma_1 \ln G + \gamma_2 \ln GP + \gamma_3 \ln S + \gamma_4 \ln T + \gamma_5 \ln B + \gamma_6 \ln GA + \varepsilon \qquad \text{(M.3s)}$$

Where some parameters which are the same as the ones in M.1s have the same meanings mentioned above. Moreover, ρ is the coefficient of space factor of the dependent variable, and W is the spatial weight matrix, obtained by Queen Contiguity method which considers the contiguity with edges and corners by using GeoDa software. If $\beta_1 > 0$, it means that when population size increases one unit, the CO_2 emissions will increase β_1%; if $\beta_1 < 0$, it means that when population size increase one unit, the CO_2 emissions will decrease β_1%. Similarly, if $\beta_2 > 0$, it means that when population density increases one unit, the CO_2 emissions will increase β_2%; if $\beta_2 < 0$, it means that when population density increase one unit, the CO_2 emissions will decrease β_2%.

Furthermore, the quadratic model M.4 mentioned in Chapter 3 is specified as M.4s below. Similar to M.2s, the purposes of the following model are, on the one hand, to test the EKCs relationship, and on the other hand, more importantly, to explore empirically whether there are "U-shaped" or "inverted U-shaped" relationships between CO_2 emissions and urban form, and to find the ideal urban size and density. But the difference is that the influence of spatial autocorrelation of CO_2 emissions is taken into account in M.4s

$$\ln C = \mathrm{a} + \rho W \ln C + \beta_1 \ln P + \beta_2 \ln D + \beta_3 (\ln P)^2 + \beta_4 (\ln D)^2 + \gamma_1 \ln G + \gamma_2 \ln GP + \gamma_3 (\ln G)^2 + \gamma_4 (\ln GP)^2 + \gamma_5 \ln S + \gamma_6 \ln T + \gamma_7 \ln B + \gamma_8 \ln GA + \varepsilon \qquad \text{(M.4s)}$$

Where the meanings of parameters in M.4s are the same as the ones in M.1s, M.2s, and M.3s. Additionally, if $\beta_3 > 0$, the relationship between CO_2 emissions and population size is likely to be "U-shape", and if $\beta_3 < 0$, the relationship may be "inverted U-shape". Moreover, If the negative or positive figures of β_1 and β_3 are different, the turning point or the so-called ideal population size for CO_2 emissions will exist with realistic significance. Similarly, if $\beta_4 > 0$, the relationship between CO_2 emissions and population density is likely to be "U-shape", and if $\beta_4 < 0$, the relationship may be "inverted U-shape". Moreover, If the negative or positive values of β_2 and β_4 are different, the turning point or the so-called ideal population density for CO_2 emissions will exist with realistic significance. Meanwhile, the EKCs relationships between CO_2 emissions and economic growth in terms can be tested by the values of γ_1, γ_2, γ_3, and γ_4.

4.5.3.2Hausman test for spatial regression

To decide whether FE or RE is the best technique to be used for spatial regression of model M.3s and M.4s, the Hausman test is conducted for both models. As mentioned in Chapter 3, the null hypothesis is that the preferred model is RE, and if the prob > chi2 statistic of the Hausman test is significant, reject the null hypothesis and use FE. The results of prob > chi2 statistics of Hausman test for M.3s and M.4s are 0.0097 and 0.0187 respectively, both at 1% significant level, which means that FE is more suitable for spatial regression.

4.5.3.3 Spatial regression analysis results

To begin with, the spatial weight W both in M.3s and M.4s is obtained by Queen contiguity method that is to account the number of its links with neighbours both by edges and corners by using GeoDa software. The summary of the links and the W is shown in table 13. It illustrates that the minimal number of links of a city is 1, and the city has no more than eight neighbours in YRD urban agglomeration. The average links of the cities are 4.385. Based on the number of links with neighbours, the W is calculated by the ratio of the number of links of one city to the total number of links is the spatial weight of the city. The average of W in YRD urban agglomeration is 0.038.

Table 13 Summary of links and W

Number of links	1	3	4	5	6	7	8
Number of cities	1	7	7	6	2	2	1
Average of links	4.385						
Average of W	0.038						

After incorporating spatial factors into the model, the results of spatial multiple regression analysis between CO_2 emissions as the dependent variable as well as population size and density as the independent variables are shown in table 14. There are two models to be explicated. M.3s is the basic SAR model to examine the correlation between CO_2 emissions and population size and density under consideration of spatial autocorrelation. The other one (M.4s) is based on M.3s but adding the square of variables to explore whether there is "U-shape" relations between CO_2 emission and population size and density, as well as their turning points. The R-square of M.3s and M.4s are both above 0.8, which indicate good fitness of the regression models. On the other hand, the R-square of M.4s is little higher than that of M.3s, which suggests that taking the square of population, density, GDP and GDP per capita into consideration can improve the fitness of the model.

Table 14 Spatial regression results for CO_2 emissions

Determinants	**M.3s**		**M.4s**	
	Coef.	**Sig.**	**Coef.**	**Sig.**
lnP	-0.088		-3.086	***
$(\ln P)^2$			0.282	***
lnD	-0.373		-5.403	
$(\ln D)^2$			0.386	
lnG	0.361	***	0.917	**
$(\ln G)^2$			-0.045	*
lnGP	0.126		0.412	

$(lnGP)^2$			-0.012	
lnS	1.238	***	0.833	
lnT	0.650	**	0.663	**
lnB	-0.144		-0.071	
lnGA	0.029		0.018	
Spatial ρ	0.194		0.215	
R-square	0.805		0.810	

*** at 1% significant level; ** at 5% significant level; * at 10% significant level

(Source, the author, based on Stata)

From table 14, the spatial parameter ρ is an important determinant, which refers to the average influence of the neighbours of the spatial units on the given spatial units. It is clear that the values of spatial ρ in M.3s and M.4s are about 0.2, which shows a positive effect of the spatial factor on CO_2 emissions, but the results are not significant. It means that, generally, for the whole 26 cities over the 11 years, the impact of spatial agglomeration on CO_2 emissions is not significant. In other words, the amount of CO_2 emissions in the neighbours around a city has no significant effect on the amount of CO_2 emissions in this city.

Although the spatial factors are not significant, some other important results can still be obtained from table 14.

Firstly, the relationships between CO_2 emissions and three control variables (lnG, lnS and lnT) from model M.3s are analogous to the corresponding results from M.1s. Specifically, the coefficient of lnG is 0.361, which means that 1% growth in GDP results in the growth of CO_2 emission by 0.361%. It also suggests a sublinear relationship, which means that the higher level of GDP the city is, the higher efficiency of CO_2 emissions the city has. In terms of lnS, the coefficient is 1.238, which means a superlinear relationship between secondary industry proportion and CO_2 emission, indicating that with the higher proportion of the secondary industry, the growth rate of CO_2 emission will also increase. By contrast, the sublinear relationship between tertiary industry percentage and CO_2 emission implies that the growth rate of CO_2 emission will gradually decrease as the increase of the proportion of the secondary industry. Therefore, the development of the tertiary industry improves the efficiency of CO_2 emission, but the development of secondary industry does the opposite.

Secondly, from M.4s, it shows a U-shape relationship between population size and CO_2 emissions, which is consistent with the results from M.2s. The coefficients of lnP and $(lnP)^2$ are -3.086 and 0.282 respectively. After taking the derivative of lnP, the turning point of the population can be finally obtained by solving the equation. The results are shown in table 15. Therefore, the results from M.4s show that the ideal population size of cities for lowest CO_2 emission in YRD urban agglomeration is 2.378 million, which means that if a city's population is less than 2.378 million, with the increase of the population, the CO_2 emission will decline, while once the population exceeds the turning point, CO_2 emissions will increase significantly with the population.

Table 15 The ideal urban form based on M.4s

Term	Population size	Density
Linear term	negative	not significant
Quadratic term	U-shape	not significant
Turning point	2.378×10^6	-

Thirdly, there is an inverted U-shaped relationship between CO2 emissions and GDP at 10% significant level, which confirms the conclusion of EKC to some extent.

Moreover, the relationship between CO_2 emissions and lnT shows a sublinear relationship, which is greatly consistent with the results from M.1s, M.2s and M.3s, indicating that the growth rate of CO_2 emissions will decrease as the increase of tertiary industry proportion, and that the development of the tertiary industry has the tendency to increase the efficiency of CO_2 emissions.

4.5.4 Summary

In the regression analysis section, both non-spatial and spatial regression models are applied to analyse the impact of urban population size and density on absolute CO_2 emissions. Due to the fact that the spatial autocorrelation is not a significant influence factor of CO_2 emissions according to the results of spatial regression, the relationships between CO_2 emissions and urban form are finally concluded based on the results of non-spatial regression. Meanwhile, the results of spatial regression can be the supports and supplements to the conclusions. The sub-questions 3 is answered as follows.

4.5.4.1 CO_2 emissions and population size

There is a U-shape relation between population and CO_2 emissions, and the ideal population size of cities for the lowest CO_2 emissions in YRD urban agglomeration is 2.716 million. It means that if a city's population is less than 2.716 million, with the increase of the population, the CO_2 emission will decline, while once the population exceeds the turning point, CO_2 emissions will increase significantly with the population. However, in 2016, the average of the population size of cities in YRD urban agglomeration was 5.001 million, and only five cities' population was less than the ideal size (2.716 million), including Huzhou, Zhoushan, Maanshan, Tongling and Chuzhou. Because population growth is a general trend (figure 6), it is necessary to control and adjust population size in YRD urban agglomeration for CO_2 emissions reduction.

4.5.4.2 CO_2 emissions and population density

There is a negative relationship between CO_2 emissions and density, and that when population density increases 1%, the CO_2 emissions will decrease 0.426%. On the one hand, the negative relationship suggests that cities with higher density have less CO_2 emissions. On the other hand, figure -0.426 is between -1 and 0, which reveals the sublinear relations between CO_2 emissions and density. That is to say, with the gradual increase of density, the reduction rates of CO_2 emissions will decline. In other words, the mitigation effect of urban density on CO_2 emissions will be gradually weakened with the increase of density of cities. Moreover, density growth is a general trend for cities in YRD urban agglomeration according to the temporal analysis (figure 7). Therefore, it can be concluded that measures by increasing urban density will have a great effect on CO_2 emissions reduction for cities with low-density, but the way by increasing population density continually for those cities with higher density may be not effective to achieve the goal of CO_2 emission reduction in YRD urban agglomeration.

4.6 Policy analysis

There are two main aspects included in the policy analysis. First, the contents of national policies involving CO_2 emission mitigation are summarized in this section. Second, the aspects of Yangtze River Delta Urban Agglomeration Development Plan (2016-2020) that were emphasized and would be improved from the perspectives of CO_2 emission reduction are put forward.

In order to achieve green and sustainable development, China has adopted a series of policy measures. From January 1, 2006, to December 31, 2016, there were about 244 national documents related to emission reduction by searching from the website of the State Council of People's Republic of China (http://www.gov.cn/).

Taking some of the important documents for example. Firstly, the *Reply of the State Council on the Plan for Reducing Energy Consumption per GDP in All Regions During the 11th Five-Year Plan Period* which was released on September 17, 2006, stressed that national energy consumption per GDP was requested to be reduced by 20% during the period of 11th five-year plan, which was a formal mandatory policy for energy conservation targets. Secondly, *Circular on the Implementation of Low-carbon Pilot Work in Provinces and Cities* was issued in July 2010, posing the pilot construction period of low-carbon economy development in China. Specifically, five provinces and eight cities listed as pilot areas were required to formulate low-carbon development plans and supporting policies, to accelerate the establishment of low-carbon industry systems, to set up greenhouse gas emissions data statistics and management system, and to advocate low-carbon lifestyles and green consumption patterns. Then, the *White Paper: China's Energy Policy 2012* pointed out that China had made energetic efforts in developing new and renewable energy resources, realising an annual reduction of 600 million tonnes of CO_2 emission. However, fossil energy would continue to dominate the energy consumption mix for many years. A more environment-friendly and sustainable development was urgently needed under the growing challenge for protecting the environment and countering climate change. Moreover, to enhance the ability of sustainable and eco-friendly development and of the industry, the *Industrial Transformation and Upgrading plan (2011-2015)* explicitly emphasized the active promotion of low-carbon technologies. It aimed to explore low-carbon industrial development models as well as the carbon trading measures. In addition, the *13th Five-year Plan for Controlling Greenhouse Gas Emissions*, released in October 2016, sets a target of effectively controlling total carbon emissions by 2020, namely, reducing carbon dioxide emissions per GDP by 18% compared with 2015. In order to achieve this goal, the plan mainly focused on starting the national carbon emission trading market, initially establishing laws, regulations and standards system to cope with climate change, improving the statistical accounting evaluation and accountability system, deepening the low-carbon pilot demonstration, and enhancing the public awareness of low-carbon. On the other hand, it emphasized international cooperation. For example, the implementation of the UN 2030 agenda for sustainable development and the international cooperation of low-carbon projects in the Belt and Road development would be highly promoted.

To conclude, the measures of emission reduction in these policies mainly focus on four aspects, namely, formulating relevant laws, improving statistical systems, establishing a demonstration system, and strengthening international cooperation. Expectantly, China will make unremitting efforts in these aspects to promote carbon emission reduction and obtain international support and recognition.

As a guiding and binding document for the integrated development of YRD urban agglomeration, the Yangtze River Delta Urban Agglomeration Development Plan (2016-2020) mainly emphasised the construction of green and low-carbon ecological city from the aspects of the green city construction, the intensive use of resources, and the low-carbon lifestyle, etc. More specifically, the green city construction focuses on the development of green energy, green building materials, and green transportation systems. Besides, the intensive use of resources aims to control the total consumption, to accelerate the recycling of resources and to promote the venous industry (resources recycling industry). Then, the low-carbon lifestyle is closely linked with every citizen, and the goals of energy conservation and emission reduction will be better achieved from the bottom up through the power of the masses.

On the other hand, this plan pointed out some "big city diseases" including traffic congestion, environmental degradation and high urban operating costs caused by an excessive concentration of population in individual cities. Facing these problems, this plan highly mentioned the rational distribution of population, which means that measures would be taken to guide the population transfer from large cities such as Shanghai to satellite towns. Meanwhile, the plan also supported the infrastructure construction and the development of special industries in small cities to increase the attraction of small cities, which contributed to relieving the pressure of high concentration of population in big cities. Additionally, this plan set the goal of further increasing population density to build a world-class city cluster with intensive and efficient utilization of space. Very coincidentally, based the results of the impacts of population size and density on the CO_2 emissions in this study, these points in terms of planning of urban forms mentioned by the plan do yield benefits to the CO_2 emissions reduction.

Overall, the Yangtze River Delta Urban Agglomeration Development Plan (2016-2020) is highly consistent with the target of CO_2 emissions reduction both in terms of low-carbon city construction and urban form planning.

Even though this plan has made contributions to the CO_2 emissions reduction from several aspects, there are some recommendations for further improvement from the perspective of CO_2 emissions mitigation. Firstly, the development of urban agglomerations cannot be achieved without connectivity and sharing, but when the infrastructure networks such as transportation, information, energy, water conservancy facilities are under construction among cities, the sprawl pattern of urban construction and low efficiency of space utilization should be avoided as far as possible, as well as the problem of excessive reduction of green space caused by extensive overdevelopment. Secondly, compensation mechanism for inter-regional ecological protection has been established in YRD urban agglomeration, but the unified carbon emission data statistics system and the open platform for carbon emission information are still needed to be improved in the future. Meanwhile, as one of the effective means to promote industrial transformation, energy restructuring and emission mitigation, the carbon trading market should be emphasized and supplemented in the plan during the development of YRD urban agglomeration, which can contribute to the establishment of a national unified carbon trading market.

4.7 Summary

In this chapter, firstly, the temporal analysis and the spatial analysis are applied to find out the situations of CO_2 emissions and urban forms (population size and density) in YRD urban agglomeration from the perspectives of temporal and spatial changes. Then, the results of regression analysis illustrate that there is a U-shape relation between population and CO2 emissions, and the ideal population size of cities for the lowest absolute CO_2 emissions in YRD urban agglomeration is 2.716 million. The results also show that there is a negative sublinear relationship between absolute CO_2 emissions and density and that when population density increases 1%, the CO_2 emissions will decrease 0.426% approximately. Finally, with the combination of the above findings and policy analysis, the aspects of Yangtze River Delta Urban Agglomeration Development Plan (2016-2020) that can be improved from the perspectives of CO_2 emission reduction become clear, and it also confirms the positive role of urban agglomeration development for CO2 emissions mitigation.

Chapter 5: Conclusions and recommendations

In this chapter, firstly, the research objectives along with the brief background information are reviewed. Then, the research questions get fully answered separately, and these conclusions are linked back to the literature. Last by not the least, the limitations of the thesis and suggestions for further research are stated, followed by some policy recommendations for possible solutions to the research problem.

5.1 Retrospect of research objectives

With the increasingly important role of cities in sustainable development, the potential influence factors of the environment issues such as CO_2 emission in cities are got more and more attention. Many scholars conducted related research about the relationships between CO_2 emission and urban form, but it is still a long way to reach a consensus. On the other hand, since urban agglomeration became the main spatial form of urbanization in many countries these years, whether this new type of urbanization can play a positive role for CO_2 emission reduction is necessary to be further analysed.

Under consideration of the above two aspects, this study is to and examine to what extent the effect of urban size and density have influence on CO_2 emission and to find out whether urban agglomeration can play a positive role in improving efficiency of CO_2 emission, by conducting a desk research, choosing YRD urban agglomeration with 26 cities as research scope, collecting the data related to CO_2 emission and urban form from 2006 to 2016. The main research question and sub-questions are mentioned as follows.

Main research question: To what extent do urban forms affect CO2 emissions in YRD urban agglomeration of China?

Sub-questions 1: What are the temporal changes of CO2 emissions and urban forms (population size and density) of YRD urban agglomeration from 2006 to 2016?

Sub-questions 2: What are the spatial variations of CO2 emissions in YRD urban agglomeration from 2006 to 2016?

Sub-questions 3: Is the amount of CO2 emission in one city influenced by that in the surrounding cities (spatial autocorrelation) in YRD urban agglomeration?

Sub-questions 4: Does urban agglomeration development play a positive role in improving the efficiency of CO2 emissions in YRD urban agglomeration?

Sub-questions 5: What aspects of YRD urban agglomeration development plan can be emphasized and improved from the perspective of reducing CO2 emissions?

The conclusion of this study can add fresh blood to strategies in combating climate change and help urban policy-makers move forward in making right decisions in creating urban forms to reduce CO_2 emissions.

5.2 Conclusions

The answers to the main research question and sub-questions research questions are concluded from six perspectives separately in this part.

(1) The extent of impacts of city size and density on CO_2 emissions in YDR urban agglomeration

The impacts of population size and density on CO_2 emissions are required based on multiple regression analysis of strongly balanced panel data of 26 cities and 11 years. The non-spatial and spatial regression analysis are both conducted to find out the most appropriate relationships. However, the spatial parameter in spatial regression results is not significant, which means the overall impact of spatial autocorrelation on CO_2 emissions is not significant. In other words, the amount of CO_2 emissions in the neighbours around a city generally has no significant effect on the amount of CO_2 emissions of this city in YRD urban agglomeration. Therefore, the extent that the city size and density impact CO_2 emissions are concluded based on the results of the non-spatial analysis. Meanwhile, the results of spatial regression can be the supports and supplements to the conclusions.

CO_2 emissions and population size:

There is a U-shape relation between population size and CO_2 emissions, and the ideal population size of cities for the lowest CO_2 emissions in YRD urban agglomeration is 2.716 million. It means that if a city's population is less than 2.716 million, with the increase of the population, the CO_2 emission will decline, while once the population exceeds the turning point, CO_2 emissions will increase significantly with the population. However, in 2016, the average population size of cities in YRD urban agglomeration was 5.001 million, and only five cities' population was less than the ideal size (2.716 million), including Huzhou, Zhoushan, Maanshan, Tongling and Chuzhou. Moreover, because population growth is a general trend according to the temporal analysis of population size (figure 6), it is necessary to control and adjust population size in YRD urban agglomeration for CO_2 emissions reduction. However, most previous studies argued about a sub-linear or super-linear relationship population size on CO_2 emissions between by linear model, and hard to reach an agreement (Batty, 2008, Batty, 2013, Bettencourt, L. M., 2013, Fragkias, Lobo, et al., 2013, Louf and Barthelemy, 2014). Therefore, this U-shape relationship based on quadratic function adds a relatively new sight in the impact of population size on CO_2 emissions.

CO_2 emissions and population density:

There is a negative relationship between CO_2 emissions and density. Specifically, it shows that when population density increases 1%, the CO_2 emissions will decrease by 0.426% approximately. On the one hand, the negative relationship suggests that cities with higher density have less CO_2 emissions. On the other hand, the coefficient of population density from model M.1s (-0.426) in table 11 is between -1 and 0, which reveals the sublinear relations between CO_2 emissions and density. That is to say, with the gradual increase of density, the reduction rates of CO_2 emissions will decline. In other words, the mitigation effect of urban density on CO_2 emissions will be gradually weakened with the increase of density of cities. Moreover, density growth is a general trend for cities in YRD urban agglomeration according to the temporal analysis (figure 7). Therefore, it can be concluded that measures by increasing urban density will have a great effect on CO_2 emissions reduction for cities with low-density, but the way by increasing population density continually for those cities with higher density may be not effective to achieve the goal of CO_2 emission reduction in YRD urban agglomeration. This result in line with many studies(Lee and Lee, 2014, Gudipudi, Fluschnik, et al., 2016, Mindali, Raveh, et al., 2004, Baur, Thess, et al., 2013), which also found that higher population density would lead to lower CO2 emission.

(2) The temporal changes of CO_2 emissions and population size and density in YRD urban agglomeration

To begin with, the total CO_2 emissions in YRD urban agglomeration experienced an increasing trend from 2006 to 2016 generally, but the growth rate of total CO_2 emissions went down in recent years, which suggested the control of CO_2 emissions took effect to some extent in YRD urban agglomeration these years. Additionally, in terms of CO_2 emissions per capita, there was a stable status from 2013 to 2015, followed by an obvious drop in 2016. These changes indicated that the efficiency of CO_2 emissions was getting improved in recent years from the perspective of CO_2 emissions per capita. Moreover, the gradual decrease of CO_2 emissions per GDP over the 11 years implied a more balanced and scientific development mode between CO_2 emission and economic development in YRD urban agglomeration recently. Meanwhile, for urban forms in terms of population size and density, the former one increased significantly over the 11 years and the latter experienced a slight increase from 2006 to 2016.

In conclusion, as to the temporal change trend, the total CO_2 emissions increased continually from 2006 to 2016, but the growth rate went down and the efficiency of CO_2 emissions was getting improved in recent years. Meanwhile, the population size and density experienced an increasing trend in YRD urban agglomeration.

(3) The spatial variations of CO_2 emissions in YRD urban agglomeration

The spatial distribution changes of CO2 emissions can be seen clearly from the figures 8-10. In 2006, the levels of CO_2 emissions in most cities were generally low, and the cities with a higher level of CO_2 emissions mainly distributed in the east part of YRD urban agglomeration, including Shanghai and Suzhou cities. In 2011, the amount of CO_2 emissions in the northern cities increased significantly, and the higher level of CO_2 emissions mainly distributed in east part but expanded westward. In 2016, many cities' CO_2 emissions increased significantly, especially for the cities in the north part. However, the CO_2 emissions in some cities at a higher level in 2011 dropped down in 2016, such as Suzhou and Changzhou cities. It suggested that the overall level of CO2 emissions in YRD urban agglomeration increased, but the gap of CO_2 emissions among cities were narrowed down over the 11 years. In addition, from the figures 8-12, cities with higher levels of CO_2 emissions also have higher population size and density comparatively, which indicated that the distribution pattern of CO_2 emissions might be related to that of population size and density to some extent. However, specific relationships need to be further studied.

(4) The spatial autocorrelation of CO_2 emissions in YRD urban agglomeration

It can be seen from the spatial distribution maps that CO_2 emissions mainly cluster in the east part but less distribute in north and south, which implies that there might be agglomeration pattern of CO_2 emissions in YRD urban agglomeration. If the agglomeration existed in the spatial distribution of CO_2 emissions, the spatial autocorrelation factor should be considered in the later regression analysis. Therefore, Global and Local Moran's Index methods are used to evaluate the global and local level of spatial agglomeration.

The results of Global Moran's Index illustrated that spatial agglomeration pattern of CO_2 emissions changed from clustered to random apparently, which means that CO_2 emissions influenced by the spatial autocorrelation in the first few years but the influence became not obvious later. From the perspective of Local Moran's, I, it is clear that high-high clusters and low-low clusters of CO_2 emissions did exist from figures 21-23, but only clustered in small parts of YRD urban agglomeration. These phenomena suggested that the influence of spatial autocorrelation on CO_2 emissions is still unclear, and whether it is an influencing factor is worth discussing.

Due to the uncertainty of spatial autocorrelation of CO_2 emissions over the 11 years, non-spatial and spatial models are both conducted in regression analysis. The results of the spatial model show an insignificant spatial parameter ρ of the spatial autocorrelation of CO_2 emissions, which means that, generally, for the whole 26 cities over the 11 years, the impact of spatial autocorrelation on CO_2 emissions is not significant. In other words, the amount of CO_2

emissions in the neighbours around a city has no significant effect on the amount of CO_2 emissions in this city.

(5) The role of urban agglomeration development in improving the efficiency of CO_2 emissions

Urban agglomeration was first proposed to be the main form to promote urbanization in China by *the Outline of the People's Republic of China 11th Five Year Plan for National Economy and Society Development* in 2006. Since then, YRD urban agglomeration aimed to become a world-class city cluster, embracing high-speed economic development, high-tech industrialization, and harmony between humankind and nature. In order to scientifically guide the urbanization in China, the *National New-type Urbanization Plan (2014—2020)* was released in 2014, followed by *YRD urban agglomeration plan* in 2016. Due to the fact that green growth and sustainable development are critical for the future of urbanization, it is necessary to estimate the influence of urban agglomeration this new-type of urbanization on the environment in terms of CO_2 emissions.

On the one hand, urban agglomeration does good to controlling the CO_2 emissions and improving the emissions efficiency in YRD urban agglomeration from 2006 to 2016, which can be explained from three aspects. First of all, the growth rate of CO_2 emissions went down to about 0% in recent years, which suggested the control of CO_2 emissions took effect to some extent with the development of urban agglomeration these years. Additionally, CO_2 emissions per capita experienced a related stable status from 2013 to 2015 and even presented an obvious drop in 2016. This change indicated that the efficiency of CO_2 emissions was getting improved in recent years from the perspective of CO_2 emissions per capita. Moreover, the gradual decrease of CO_2 emissions per GDP over the 11 years implied a more balanced and scientific development mode between CO_2 emission and economic development in YRD urban agglomeration, which cannot happen without the contribution of urban agglomeration by cooperation and sharing.

On the other hand, urban agglomeration brings benefit to eliminating the spatial agglomeration of CO_2 emissions. Based on the results of spatial analysis, the agglomeration pattern of CO_2 emissions changed from cluster to random from 2006 to 2016. Behind this phenomenon, it reveals that urban agglomeration promoted the interaction between cities, shared the sustainable approach for development, and achieved overall green development. The mutually beneficial development mode of urban agglomeration makes CO_2 emissions not highly concentrated in individual cities, but dispersed, which is conducive to the absorption and reduction of CO_2 to some extent.

Overall, urban agglomeration development played a positive role in CO_2 emissions mitigation, by controlling the total CO_2 emissions, improving the emissions efficiency as well as the absorption and reduction of CO_2 by eliminating the spatial agglomeration. These results are to some extent in line with the positive role of urban agglomeration development not only from the perspective of CO_2 emissions reduction, but also from the perspective of economic and productivity growth in many studies (Ahrend, Lembcke, et al., 2017, Wang, Liu, et al., 2017).

(6) the aspects of new-type urbanization strategy and planning which should be improved and emphasized from the perspective of reducing CO_2 emissions

In order to achieve green and sustainable development, China has adopted a series of policy measures. From January 1, 2006, to December 31, 2016, there were about 244 national documents related to emission reduction by searching from the website of the State Council of People's Republic of China (http://www.gov.cn/). The measures of emission reduction in these policies mainly focus on four aspects, namely, formulating relevant laws, improving statistical systems, establishing a demonstration system, and strengthening international cooperation. Expectantly, China will make unremitting efforts in these aspects to promote carbon emission reduction and obtain international support and recognition.

Based on the policy analysis, it can be concluded that the *Yangtze River Delta Urban Agglomeration Development Plan (2016-2020)* is highly consistent with the target of CO2 emissions reduction both in terms of low-carbon city construction and urban form planning. This point further proves the positive effect of the development of urban agglomeration in the YRD area on CO_2 emissions reduction.

Even though this plan has made contributions to the CO_2 emissions reduction from several aspects, there are some recommendations for further improvement from the perspective of CO2 emissions mitigation. Firstly, the development of urban agglomerations cannot be achieved without connectivity and sharing, but when the infrastructure networks such as transportation, information, energy, water conservancy facilities are under construction among cities, the sprawl pattern of urban construction and low efficiency of space utilization should be avoided as far as possible, as well as the problem of excessive reduction of green space caused by extensive overdevelopment. Secondly, compensation mechanism for inter-regional ecological protection has been established in YRD urban agglomeration, but the unified carbon emission data statistics system and the open platform for carbon emission information still need to be improved in the future. Meanwhile, as one of the effective means to promote industrial transformation, energy restructuring and emission mitigation, the carbon trading market should be emphasized and supplemented in the plan during the development of YRD urban agglomeration, which can contribute to the establishment of a national unified carbon trading market.

5.3 An Addition to the Existing Body of Knowledge

This paper contributes to adding more evidence for the influence of urban form on CO_2 emissions. It points out the existence of a U-shaped relationship between CO_2 emissions and population size as well as ideal population size from the perspective of CO_2 emissions reduction. Besides, it indicates that there is a negative sub-linear relationship between CO_2 emissions and population density, which means increasing population density is an effective but not a long-term approach for CO_2 emissions reduction. In addition, it also proves that urban agglomeration this new form of urbanization plays a positive role in improving the efficiency of CO2 emissions and provides policy recommendations for the future development of urban agglomeration.

5.4 Limitations and further research implications

There are some limitations in this study regarding data availability, methodology and the results. Firstly, CO_2 emissions data are not available and calculated based on energy consumption. Fortunately, energy consumption data is from the official statistic yearbook with high reliability, and the method for CO_2 emissions accounting is most commonly used by scholars. It makes up for the data limits to the greatest extent. Secondly, the Moran's I method for spatial analysis is better to be applied in the scope with more than 30 cities according to the best practice guidelines in ArcGIS Pro. In this study, YRD urban agglomeration only includes 26 cities. There may be some errors to some extent when using Moran's I method. Moreover, the results about the relationships between CO_2 emissions and urban form in this study only can be applicable in this scope of the study. More studies about other scopes are needed to confirm these conclusions and generalise the influence rules of urban forms on CO_2 emissions.

For future studies, on the one hand, the scope can be broadened and also include cities that do not belong to urban agglomeration. A comparative analysis can be conducted to further prove the positive effect of urban agglomeration on CO_2 emissions reduction. On the other hand, further research is advised to discuss more urban drivers of CO_2 emissions from the aspects of economic scale and industrial structure, due to the fact that some other interesting results are found in this study, such as the significant impact of GDP and tertiary industry proportion on CO2 emissions.

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Annex 1: The calculation steps of CO_2 emissions

In the first step, it is necessary to download the EBTs of Shanghai city, Jiangsu province, Zhejiang province, Anhui province between 2006 and 2016 from China Energy Statistical Yearbook. In the EBTs, there are 17 categories and 27 types of fuels as shown in table 16 and table 17 respectively. For Shanghai city, there are existing EBTs at the city level, while for other 25 cities, the EBTs should be transferred from provincial level to city level by appropriate distribution indicators which are selected considering the following two principles. On the one hand, the indicators are available at a city level continuously over the years. On the other hand, the meaning of the indicators can almost represent the categories in the provincial EBTs. Under fully considering the above principles, several distribution indicators are chosen from China Statistical Yearbook, China City Statistical Yearbook, or China provincial statistical yearbooks for corresponding categories as shown in table 16.

After the preparation of provincial EBTs data and the city-level distribution indicators, it is possible to obtain the EBTs for each city by following three equations.

$$\alpha_i = \frac{O_i^C}{O_i^P} \tag{1}$$

$$AD_{i,j}^C = AD_{i,j}^P * \alpha_i \tag{2}$$

$$AD_j^C = \sum_{i=1}^{17} AD_{i,j}^C \tag{3}$$

In Eq. (1), *i* represents to the categories in provincial EBTs; α_i is the distribution coefficient in *i*; O_i^C refers to the city-level distribution indicator of *i* in city C; O_i^P refers to the sum of distribution indicator of *i* of all cities in province *P*. In Eq. (2), *j* refers to the fossil fuel types shown in table 7; $AD_{i,j}^P$ refers to the consumption of fossil fuel j in category *i* in province *P*, which is available in provincial EBTs; $AD_{i,j}^C$ is the consumption of fossil fuel *j* in category *i* in city C. In Eq. (3), AD_j^C is the total consumption of fossil fuel j with all 17 categories in city C.

Then, with the city-level EBTs, emission factors (table 17) for each consumption of fossil fuel are taken into account to calculate the CO_2 emissions. The following Eq. (4) is the IPCC (2006) recommended approach.

$$CE^c = \sum_{j=1}^{27} AD_j^c * EF_j \tag{4}$$

Where EF_j refers to the emission factor of fossil fuel j; CE^c represents the total CO_2 emissions in city C, which is related to the total consumption of 27 types of fossil fuel.

Additionally, the CO_2 emissions data as dependent variables of 26 cities in YRD urban agglomeration from 2006 to 2016 are put into a new dataset with independent and control variables.

Table 16 Energy consumption categories of EBT and distribution indicators

Category	*i*	Indicator
Transformation		
Thermal Power	1	Industrial output value
Heating Supply	2	Industrial output value
Coal Washing	3	Industrial output value
Coking	4	Industrial output value
Petroleum Refineries	5	Industrial output value
Gas Works	6	Industrial output value
Natural Gas Liquefaction	7	Industrial output value

Briquettes	8	Industrial output value
Recovery of Energy	9	Industrial output value
Loss	10	Electricity consumption of the whole society
Total Final Consumption		
Agriculture, Forestry, Animal Husbandry and Fishery	11	Agriculture, forestry, animal husbandry, and fishery output value
Industry	12	Industrial output value
Construction	13	General public budget expenditure
Transport, Storage and Post	14	The tertiary industry output value
Wholesale, Retail Trade and Hotel, Restaurants	15	The tertiary industry output value
Others	16	The tertiary industry output value
Residential Consumption	17	Population

Table 17 Types of fuels and emission factors (EF_j)

	Fuel type	EF (10^4 t CO_2/10^4 t or 10^8 m^3)		Fuel type	EF (10^4 t CO_2/10^4 t or 10^8 m^3)
1	Raw coal	1.981	15	Diesel oil	3.096
2	Cleaned coal	2.405	16	Fuel oil	3.170
3	Other washed coal	0.955	17	Naphtha	4.160
4	Briquettes	1.950	18	Lubricants	3.922
5	Gangue	2.860	19	Paraffin waxes	3.785
6	Coke	2.860	20	White spirit	4.069
7	Coke oven gas	8.555	21	Bitumen asphalt	3.690
8	Blast furnace gas	9.784	22	Petroleum coke	3.028
9	Converter gas	2.773	23	LPG	3.101
10	Other gas	9.968	24	Refinery gas	3.012
11	Other coking products	3.833	25	Other petroleum products	2.527
12	Crude oil	3.020	26	Natural gas	21.622
13	Gasoline	2.925	27	LNG	2.889
14	Kerosene	3.033			

LPG: Liquefied Petroleum Gas, LNG: Liquefied Natural Gas.

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