

Quantifying the relationship between urban forms and carbon emissions using panel data analysis

Jinpei Ou · Xiaoping Liu · Xia Li · Yimin Chen

Received: 7 February 2013 / Accepted: 21 September 2013 / Published online: 28 September 2013
© Springer Science+Business Media Dordrecht 2013

Abstract Carbon emissions are increasing in the world because of human activities associated with the energy consumptions for social and economic development. Thus, attention has been paid towards restraining the growth of carbon emissions and minimizing potential impact on the global climate. Currently there has also been increasing recognition that the urban forms, which refer to the spatial structure of urban land use as well as transport system within a metropolitan area, can have a wide variety of implications for the carbon emissions of a city. However, studies are limited in analyzing quantitatively the impacts of different urban forms on carbon emissions. In this study, we quantify the relationships between urban forms and carbon emissions for the panel of the four fastest-growing cities in China (i.e., Beijing, Shanghai, Tianjin, and Guangzhou) using time series data from 1990 to 2010. Firstly, the spatial

distribution data of urban land use and transportation network in each city are obtained from the land use classification of remote sensing images and the digitization of transportation maps. Then, the urban forms are quantified using a series of spatial metrics which further used as explanatory variables in the estimation. Finally, we implement the panel data analysis to estimate the impacts of urban forms on carbon emission. The results show that, (1) in addition to the growth of urban areas that accelerate the carbon emissions, the increase of fragmentation or irregularity of urban forms could also result in more carbon emissions; (2) a compact development pattern of urban land would help reduce carbon emissions; (3) increases in the coupling degree between urban spatial structure and traffic organization can contribute to the reduction of carbon emissions; (4) urban development with a mononuclear pattern may accelerate carbon emissions. In order to reduce carbon emissions, urban forms in China should transform from the pattern of disperse, single-nuclei development to the pattern of compact, multiple-nuclei development.

Keywords Urban forms · Carbon emissions · Panel data analysis

J. Ou (✉) · X. Liu · X. Li · Y. Chen
School of Geography and Planning, and Guangdong Key Laboratory for Urbanization and Geo-simulation, Sun Yat-sen University, 135 West Xingang Rd., Guangzhou 510275, People's Republic of China
e-mail: happyojp@163.com

X. Liu
e-mail: yiernanh@163.com

X. Li
e-mail: lixia@mail.sysu.edu.cn

Y. Chen
e-mail: bikeychen73@gmail.com

Introduction

Climate warming is a global issue, which has become a serious threat to human health and the environment

of the world. In addition to the natural factors, global climate warming is closely related to the increase of carbon emissions produced by human activities. According to the report from the Intergovernmental Panel on Climate Change (IPCC), human activities and fuel burning, especially in cities, are the major sources of global carbon emissions (IPCC 2007). Previous studies showed that urban areas were estimated to consume 67 % of global energy and emit 71 % of carbon dioxide (CO₂) worldwide (Agency (IEA) 2008). It should be a major task to reduce carbon emission from cities. Many scholars and policy makers have paid great attention on dealing with the impact of global climate change by investigating carbon emission mitigation strategies, including transforming the pattern of economic development, optimizing the energy structure, promoting technological progress, and developing a low-carbon economy (Guo et al. 2010). For example, Hou et al. (2011) suggested a long-term effective mechanism for China to boost energy-saving technologies and products, and to promote the economic development toward a low-carbon mode. Such strategies could contribute substantially to the reduction of carbon emissions.

In addition, during the last few decades, scholars have learned about the interactions between carbon emissions and urban forms. Urban forms can be defined as the spatial configuration of human activities (including the spatial pattern and density of land uses, and spatial design of transport and communication infrastructure), which can reflect economic, environmental, technological, and social processes at a certain time (Tsai 2005). The influence of urban forms on carbon emissions is inevitable and profound. Some researchers believe that smaller, more compact, and less disperse urban forms are associated with lower levels of carbon emissions (Anderson et al. 1996; Banister 1996; Dhakal 2009). Christen et al. (2011) found that as much as 50 % of CO₂ emissions in cities are attributable to urban forms, land-use mix, building types, transportation networks, and vegetation. Kennedy et al. (2009) also analyzed the relationship between carbon emissions and land use, and found that, when constraints on land use were stricter, the level of carbon emissions of the residents living was lower.

The above studies indicate that carbon abatement must be achieved, not only through more efficient use of fuel and transformation of the pattern of economic

development, but also through urban planning and spatial optimization. Thus, research on the relationships between urban forms and carbon emissions has become increasingly important. The demand for quantifying the carbon emissions in the atmosphere with urban morphology has likewise been raised by the scientific and policymaking communities. However, few studies have systematically examined the spatial–temporal interplay of urban forms with the specific aim of quantifying the carbon impacts of expanding urban areas (Alberti and Hutyrá 2009; Heath et al. 2011; Lucy et al. 2011). For example, Glaeser and Kahn (2010) attempt to quantify carbon dioxide emissions associated with new construction in different locations across the country (Glaeser and Kahn 2010). However, they merely viewed emissions from the perspectives of driving, public transit, home heating, and household electricity usage, and ignore the impact of urban spatial structure. In another study on carbon emissions in the State of Louisiana, Shu and Lam (2011) presented a new method based on a multiple linear regression model to disaggregate traffic-related CO₂ emission estimates from the parish-level scale to a $1 \times 1 \text{ km}^2$ grid scale (Shu and Lam 2011). However, the factors involved did not consider the patterns of land use, and uncertainty regarding the emission estimates at grid cell level remains because of the error and gaps in the original data. These studies on carbon emissions don't well provide the explicit evidence of how urban land and transportation work together to affect carbon emissions.

Therefore, in order to deal with the existing problems, this paper attempts to quantify the relationships between carbon emissions and urban forms using panel data analysis. Panel data analysis is a regression method of studying observations from multiple entities over multiple periods, which has several advantages over conventional statistical analysis using only cross-sectional or time series data (Chen et al. 2011). For instance, panel data usually contain more degrees of freedom and more sample variabilities than cross-sectional data, which can improve the efficiency of estimates. In addition, the panel data model can reduce the effects of multicollinearity and estimate error. Moreover, panel data analysis can verify and measure some factors that cannot be recognized in pure cross-sectional and time series data models (Hsiao 2003; Baltagi 2005). In this study, four fastest-growing cities (i.e., Beijing, Shanghai, Tianjin, and Guangzhou) are

selected as study areas. As the most important cities in China, these four cities suffer from a series of environmental problems, and their carbon emissions continue to grow due to the rapid development of their economies. Therefore, this study attempts to reveal the relationship between urban forms and carbon emissions for the panel of these four cities using the time series data from 1990 to 2010. Since urban form is primarily affected by urban land use and transportation (Anderson et al. 1996), we used the land use classification of remote sensing images and the digitization of transportation maps to obtain and analyze the spatial distribution of urban land use and transportation network. Then, a set of spatial metrics for quantifying urban land use and transportation network data is utilized. After considering the allocation factors together, we further implemented the statistical method of panel data analysis to estimate whether and to what extent the spatial patterns of urban forms are associated with carbon emissions. The purpose of this study is to create a better understanding on the issues that we are currently facing and to provide a reference for decision makers to prepare appropriate policies on developing a low carbon economy.

Study areas

Four cities (i.e., Beijing, Shanghai, Tianjin, and Guangzhou), located in eastern coastal areas of China (Fig. 1), are selected as the study area in this study. These four cities are the most developed metropolis areas in China, with a total population of 40.67 million and a total gross domestic product (GDP) of 5125.23 billion RMB in 2010. Beijing, the political, cultural, and educational capital of China, is located in the northern part of the North China Plain. It covers an area of 16,410 km², with 14 urban and suburban districts and 2 rural counties. In 2010, it had a population of 19.62 million and a GDP of 1411.36 billion RMB. Shanghai is the largest city by population (over 23 million in 2010) in China. Located in the Yangtze Delta area, Shanghai is also a global city, serving as the most influential economic, financial, international trade, cultural, science and technology centre. Tianjin, which borders Beijing, is a metropolis in Northern China. It covers an area of 1,191 km², with a population of approximately 13 million and a GDP of 922.45 billion RMB in 2010. Guangzhou, located in the Pearl River

Delta, is Southern China's largest city, with an area of 7434.40 km², a population of 8.06 million, and a GDP of 1,074 billion RMB in 2010.

These four cities consume a vast volume of natural resources in order to sustain economic growth. For example, the total area of urban land use in four cities was approximately 1954.40 km² in 1990, but increased to 5714.84 km² in 2010. The rapid urbanization process has not only led to the conversion of natural ecosystems, farmland, and water into urban areas, but also given rise to a series of environmental problems, especially the greenhouse effect and air pollution (Li and Liu 2008). Thus, to protect natural resources and improve environmental quality, it is necessary to identify the factors that influence the carbon emissions in these fast-growing regions. In this study, these four cities are chosen as the study area to determine whether there is a important relationship between urban forms and carbon emissions.

Data and method

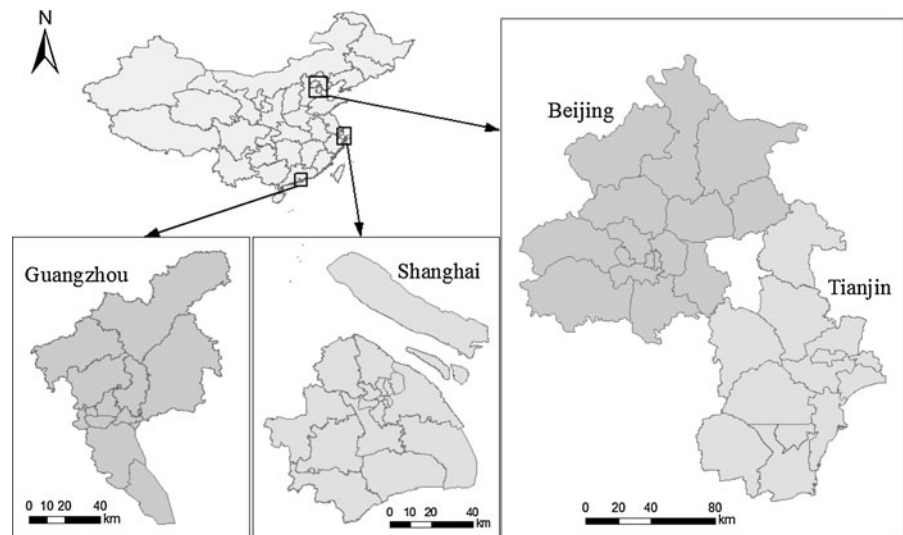
Carbon emissions

In this study, the carbon emissions are described by carbon dioxide equivalent emissions, which referring to the carbon content of greenhouse gases that would have the same global warming potential. The carbon dioxide equivalent emissions are normally used when attributing aggregate emissions from the particular sources over a specified timeframe. Currently, it is very difficult to acquire precise data of carbon emissions. However, because carbon emissions are mainly released from the fossil energy consumption, it is a useful method to approximate the carbon emissions through energy-related statistical data (Bi et al. 2011; Chun et al. 2011). In this paper, we calculated the carbon emissions only from fossil energy consumption using a unified standard method recommended by the IPCC Guidelines (IPCC 2006):

$$C = \sum_{w=1}^W \alpha_w \beta_w E_w \quad (1)$$

where w is the different categories of energy sources; W is the total number of energy sources; C represents the amount of carbon emissions; α_w and β_w are the appropriate calorific value and carbon emission factor

Fig. 1 The location of research areas (Beijing, Tianjin, Shanghai, and Guangzhou)



for each fuel type respectively, as shown in Table 1 (Dhakal 2009); E_w is the amount of fossil energy w obtained from total primary energy supply of the original energy balance tables expressed in the physical units, and these tables are derived from the China Energy Statistical Yearbook and some statistics yearbooks of each city (Table 2). Specially, total primary energy supply contain some fossil energy consumption used to produce thermal power and heating. So the total carbon emissions we obtained would include the part of emissions from the electricity and heating consumption. In addition, the consumption of electricity and heating bought from other regions could also lead to some of carbon emissions. But this part of the emissions only account for a small proportion of total carbon emissions, so was ignored in this study.

As shown in Fig. 2, the estimated results of carbon emissions of each city are obtained from Eq. (1). In Fig. 2, we find that the carbon emissions of these cities from 1990 to 2010 show an increasing trend. Shanghai is the largest emitter, with its emission increasing from 12.85 million tons in 1990 to 62.87 million tons in 2010. In addition, the carbon emission of Guangzhou was lower than those of other three cities before 2005, but more than that of Beijing in 2010.

Urban land use and transportation data

In this study, a spatial distribution data of urban land use and transportation network is used to develop spatial metrics for quantifying urban forms.

The spatial distribution of urban land use is acquired from the land use classification of remote sensing images. Remote sensing is the acquisition of information on an object or phenomenon that can support detailed and accurate urban land mapping at different spatiotemporal scales. These data can be useful in acquiring the spatial distribution of urban land use through the land use classification (Herold et al. 2002). First, land use and cover of four cities are mapped by the use of cloud-free Landsat Thematic Mapper data with corresponding 30 m resolution for five time points: 1990, 1995, 2000, 2005, and 2010. After all images are geometrically corrected to Universal Transverse Mercator map projection system, land use classification of these images is then implemented using the object-oriented classification software Definiens Developer 7.0. The classification procedure involves the following steps: image segmentation, sample selection, feature optimization, and objects classification. In the process of image segmentation, the image is subdivided into objects consisting of similar pixels. Then, the image objects are selected manually as samples for each land use class. To maximize the distance between land use class and another, the next step is to determine a set of features using the tool of Feature Optimization in the software. Finally, according to the selected samples and features, nearest-neighbor classification is performed to achieve the classification results. Once the land use classification completed, the output images are further converted into two land categories (urban and non-urban) based on the differences in land use

Table 1 Calorific value and emission factors of fuel types

	Calorific value	Carbon emission factor (not CO ₂) (t-C/TJ)
Raw coal	20,934 kJ/kg	26.8
Cleaned coal	26,377 kJ/kg	26.8
Other washed coal	8,374 kJ/kg	26.8
Briquettes	20,934 kJ/kg	26.8
Coke	28,470 kJ/kg	29.5
Coke oven gas	17,375 kJ/cu m	13
Other gas	5,234 kJ/cu m	13
Other coking products	28,470 kJ/kg	29.5
Crude oil	41,868 kJ/kg	20
Gasoline	43,124 kJ/kg	18.9
Kerosene	43,124 kJ/kg	19.6
Diesel oil	42,705 kJ/kg	20.2
Fuel oil	41,868 kJ/kg	21.1
Liquefied petroleum gas	50,241 kJ/kg	17.2
Refinery gas	46,055 kJ/kg	18.2
Other petroleum products	41,868 kJ/kg	25.8
Natural gas	38,979 kJ/cu m	15.5

properties of each city and the research objective in urban forms analysis. As shown in Figs. 3, 4, 5 and 6, the final classification results provide an overview of urban land use for each city in 5 years.

To evaluate the reliability of the classification results, an accuracy assessment for the urban category is then performed using a method proposed by Pontius and Millones (2011). This method divides the disagreements between classification and reference into quantity disagreement and allocation disagreement, which is more helpful than Kappa indices just using a single ratio to represent the classification accuracy. The quantity disagreement and allocation disagreement can be derived from the following equations (Pontius and Millones 2011):

$$p_{uv} = \left(\frac{n_{uv}}{\sum_{v=1}^V n_{uv}} \right) \left(\frac{N_u}{\sum_{u=1}^V N_u} \right) \tag{2}$$

$$Q = \frac{1}{2} \sum_{g=1}^V q_g = \frac{1}{2} \sum_{g=1}^V \left| \left(\sum_{v=1}^V p_{ug} \right) - \left(\sum_{v=1}^V p_{gv} \right) \right| \tag{3}$$

$$A = \frac{1}{2} \sum_{g=1}^V a_g = \frac{1}{2} \sum_{g=1}^V 2 \min \left[\left(\sum_{u=1}^V p_{ug} \right) - p_{gg}, \left(\sum_{v=1}^V p_{gv} \right) - p_{gg} \right] \tag{4}$$

where V is the number of land use classes; n_{uv} is the number of sample classified as u and referenced as v ; N_u is the population of land use class u ; q_g and a_g are the quantity disagreement and the allocation disagreement of land use class g ; p_{uv} is the estimated proportion of the study area classified as u and referenced as v ; Q and A are the overall quantity disagreement and the allocation disagreement, respectively.

We calculated the quantity and allocation disagreements for the accuracy of the urban category. In each image we constructed several sampling data and collected the samples' reference information based on visual inspection of the raw images. Through comparing the classification result and reference information in each point, each sampling data was evaluated and summarized in an estimated population matrix. According to Eqs. (2), (3) and (4), the results of the overall quantity and allocation disagreements of the urban category in each image were listed in Table 3. From the table, the minimum of quantity disagreement is 1.17 %, while the maximum one is 5.01 %. The values of allocation disagreement range from 4.56 to 9.14 %. On the whole, the total disagreements are approximately 12 %.

In addition, transportation network data with vector format are obtained from the digitization of the transportation maps of each city. However, it is difficult to acquire the complete transportation maps for each year due to the absence of establishment or update of traffic road database. Thus, we integrate the transportation maps and remote sensing images to extract main city roads. Firstly, we obtained the latest transportation maps from the transportation bureau of each city. After the overlaying of the latest transportation maps and Landsat TM images, we then modified digitally the transportation maps based on the visual inspection of the Landsat TM images. Such that, we could get the main roads of each city in the five time points. The digital results shown in Figs. 3, 4, 5 and 6 present the spatial distribution of the main roads of each city.

Table 2 the consumption of each energy obtained from the original energy balance tables of each city

Cities	Years	Raw coal (10 ⁴ tons)	Cleaned coal (10 ⁴ tons)	Other washed coal (10 ⁴ tons)	Briquettes (10 ⁴ tons)	Coke (10 ⁴ tons)	Coke oven gas (10 ⁸ cu m)	Other gas (10 ⁸ cu m)	Other coking products (10 ⁴ tons)	Crude oil (10 ⁴ tons)
Beijing	1990	1379.36				231.44	15.29		21.53	122.74
	1995	2185.21	494.60	0.08		92.85			3.07	654.65
	2000	2068.44	569.80	8.85		46.45			-1.41	755.20
	2005	2563.37	455.02	8.42		49.15			-8.98	799.62
	2010	2416.88	201.29	6.42	3.63	56.49	1.46		-8.32	1117.24
Tianjin	1990	1203.77				126.83	5.52			22.17
	1995	2192.83	230.11	5.12		-25.33				488.38
	2000	2218.15	249.38			-46.45	-0.27		-8.81	698.11
	2005	3289.00	512.18			11.77	-0.22	21.55	-11.43	863.17
	2010	4361.30	424.06	16.87	3.31	425.69	1.09		172.39	1566.81
Shanghai	1990	858.75				419.32				
	1995	2879.78	1065.46			61.12	-0.94	39.36		975.71
	2000	3279.96	1219.57	2.52		-54.24	-0.80	60.88	-0.34	1310.39
	2005	4128.78	1159.79		34.00	-140.46		92.00	-14.45	1967.00
	2010	4794.59	1059.83	9.86	10.69	83.93		0.82	70.32	2126.50
Guangzhou	1990									
	1995	1204.16	31.68			20.82	10.17			440.39
	2000	1418.96	31.14	0.01		17.93				659.44
	2005	1685.79				21.43				308.27
	2010	1986.50				18.46				461.60
Cities	Years	Gasoline (10 ⁴ tons)	Kerosene (10 ⁴ tons)	Diesel oil (10 ⁴ tons)	Fuel oil (10 ⁴ tons)	Liquefied petroleum gas (10 ⁴ tons)	Refinery gas (10 ⁴ tons)	Other petroleum products (10 ⁴ tons)	Natural gas (10 ⁸ cu m)	
Beijing	1990		208.47			21.26		0.72	0.83	
	1995	-24.62	65.70	-34.64	-22.89	-2.56		-26.65	1.21	
	2000	-24.30	116.22	-100.50	11.04	-8.49		-19.86	10.97	
	2005	93.45	179.33	-27.83	-6.20	-9.76		94.56	31.74	
	2010	114.48	273.69	-111.89	31.27	8.17		-24.81	75.03	
Tianjin	1990	32.12	1.96	60.34	124.14	5.17		26.39	2.28	
	1995	-16.62	-6.15	-53.85	18.94	-1.54		-22.20	3.93	
	2000	-1.92	-13.35	-51.95	39.12	-2.97		-47.05	6.40	
	2005	-26.46	-10.66	-121.89	107.00	-16.62		-29.22	9.05	
	2010	40.66	-59.76	-269.47	123.22	-31.08		9.83	22.96	
Shanghai	1990	50.68	20.53	99.59	219.03			104.59		
	1995	-33.15	2.89	-5.86	80.05	-4.14		-180.18		
	2000	-131.38	7.90	-225.49	353.75	11.62	-2.47	-67.06	2.54	
	2005	-21.10	44.07	-388.44	646.35	15.06	-1.90	-60.73	18.74	
	2010	154.69	249.86	-265.07	714.73	48.92	-0.06	-115.69	45.01	
Guangzhou	1990									
	1995	-63.17	14.54	-67.25	151.74	3.99		2.01		
	2000	-56.96	15.67	-97.96	208.09	3.09		1.98	0.10	
	2005	-42.93		-46.15	106.22	2.33				
	2010	-38.71		-67.23	145.66	1.80				

The blank denotes the null record in statistics yearbooks

Spatial metrics for quantifying urban forms

Urban forms can affect the social, economic conditions and environment of the city (Camagni et al. 2002). Particularly, urban forms directly affect the travel behavior, which, in turn, affect carbon emissions (Cervero 1998). Therefore, in order to deal with the relationships between urban forms and carbon emissions, city planners need a deep understanding on the characteristics and rules of urban forms. Currently, the use of spatial metrics is very useful for

representing urban forms (Galster et al. 2001; Holden and Norland 2005). Based on previous studies, spatial metrics can constitute critical independent measures of the urban socioeconomic landscape and can also be used for an improved representation of a variety of urban spatial characteristics (Geoghegan et al. 1997; Parker and Meretsky 2004). Thus, in this study, several spatial metrics for quantifying urban forms in different dimensions(i.e. size, shape, density) are chosen based on the published literatures about this theme (Seto and Fragkias 2005; Dietzel et al. 2005) and the characteristics of the study area. These spatial metrics include Total (urban) Class Area (CA), Number of Patches (NP), Edge Density (ED), Mean Perimeter-Area Ratio (PARA_MN), Percentage of Like Adjacencies (PLADJ), Patch Cohesion Index (COHESION), Largest Patch Index (LPI), Urban Road Density (RD), and Traffic Coupling Factor (CF).

CA represents the total area of all patches of the corresponding patch type, and here is an important measure in representing the expansion of urban land use. NP is equal to the number of urban patches, and is used to measure the extent of subdivision or fragmentation of urban land. ED is equal to the sum of the lengths of all edge segments involving the urban patch, divided by the total landscape area (i.e., a measure of the sprawl and shape of urban land use). PARA_MN is

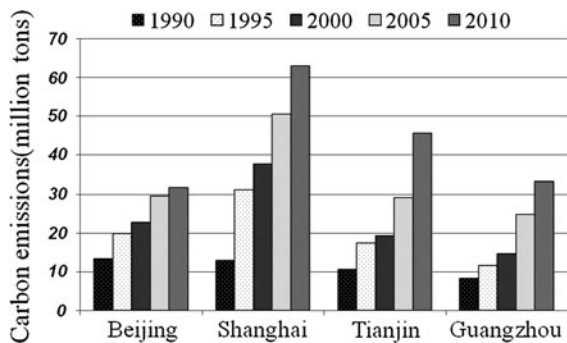
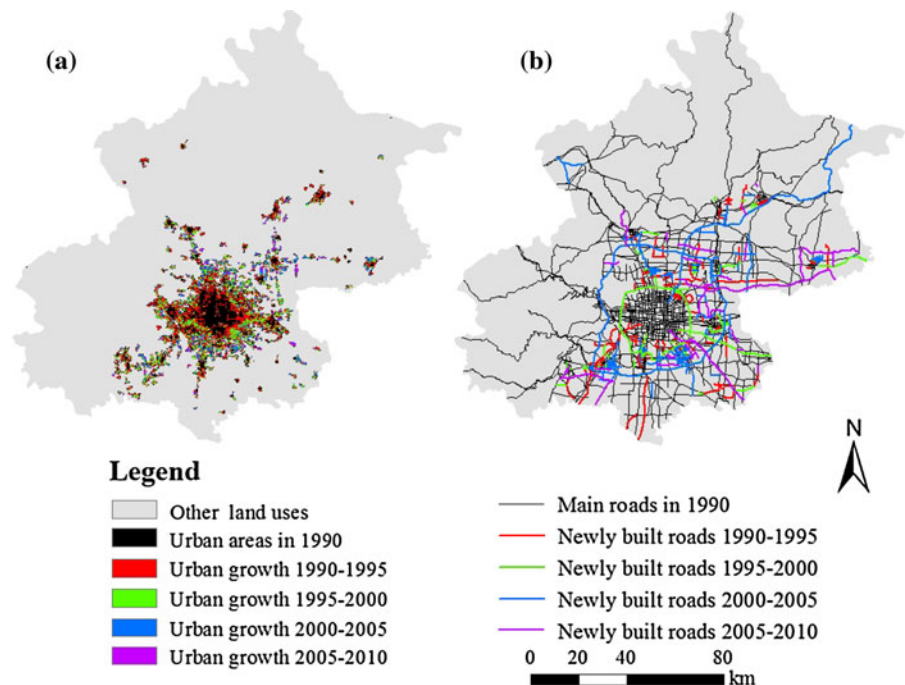


Fig. 2 Carbon emissions in four cities for selected years. *Notes* because the statistics yearbooks don't record any energy data of Guangzhou in 1990, here we estimate a value based on its economic and population for the data consistency in panel analytic

Fig. 3 The change of urban land use (a) and transportation network (b) in Beijing for 1990–2010



the average perimeter-to-area ratio of urban patches in the landscape, which can quantify urban landscape configuration in terms of the complexity of patch shape. PLADJ is a contagion index equal to the percentage of cell adjacencies involving urban patch that are similar adjacencies (Turner 1989). PLADJ can be used to represent the degree of aggregation of the urban patch. Regardless of the amount of landscape comprising urban land use, this index will be at a minimum if the urban patch is maximally dispersed and will be at a maximum if the urban patch is maximally contagious. COHESION is proportional to the area-weighted mean perimeter-to-area ratio divided by the area-weighted mean patch shape index. This index can be a measure of the physical connectedness of urban land, which would increase as the urban patch becomes more clumped or aggregated in its distribution. LPI quantifies the percentage of total landscape area comprised by the largest patch. In urban landscape, it can be used to describe the extent to which an urban area is characterized by a mononuclear pattern of development (Gustafson 1998). Table 4 shows a more detailed description including the specific mathematical equations of the metrics (McGarigal et al. 2002) used in this research.

The two metrics, RD and CF, are constructed to describe the interrelationship between urban spatial structure and traffic organization. Because of rapid economic growth, fast urbanization, and quick motorization, the urban transportation sector has currently become one of the sectors with the highest amount of carbon (Svensson et al. 2004). In addition, traffic organization change can play an important role in the development of urban spatial structure. But at the same time it is also affected by urbanization, which can provide the development space and objective necessity of urban traffic organization (Han and Liu 2009). Thus, the analysis of the influence of traffic organization and urban spatial structure on carbon emissions is very important. In this research, we used urban road density and traffic coupling factor to represent the interrelationship between traffic organization and urban spatial structure. Urban road density (RD) refers to the total length of the regional road network divided by the area of urban land use (not the total area of a city). Higher road density should generally imply a higher availability and connectivity of short alternative routes (Jenelius 2009). Traffic coupling factor (CF) is defined as a proportion of the total area of road effect buffer

zones and the area of urban land use, indicating the extent of interaction in urban spatial structure and urban traffic organization. The higher the value of CF is, the more harmonious the development of urban forms is (Kenworthy and Laube 1996). The equations of RD and CF are presented as follows:

$$RD = \frac{L}{A_{urban}} \quad (5)$$

$$CF = \frac{A_{buffer}}{A_{urban}} \quad (6)$$

where L is the total length of the regional road network, A_{buffer} represents the total area of road effect buffer zones, and A_{urban} represents the area of urban land use. Specifically, because no criteria for determining buffer distance when conducting road effect buffer zones have been identified in previous studies (Li et al. 2004), we set the buffer distance as 500 m, which does not account for road width.

With the support of the data we need, some spatial metrics, such as CA, NP, ED, PARA_MN, PLADJ, COHESION and LPI, are computed individually for each city using the public domain spatial metrics program FRAGSTATS (McGarigal et al. 2002). And the value of the metrics RD and CF are obtained from the use of the spatial analyst and buffer analyst in ArcGIS. Finally, the specific calculation results, further used as the explanatory variables for carbon emissions in panel data analysis, are shown in Fig. 7.

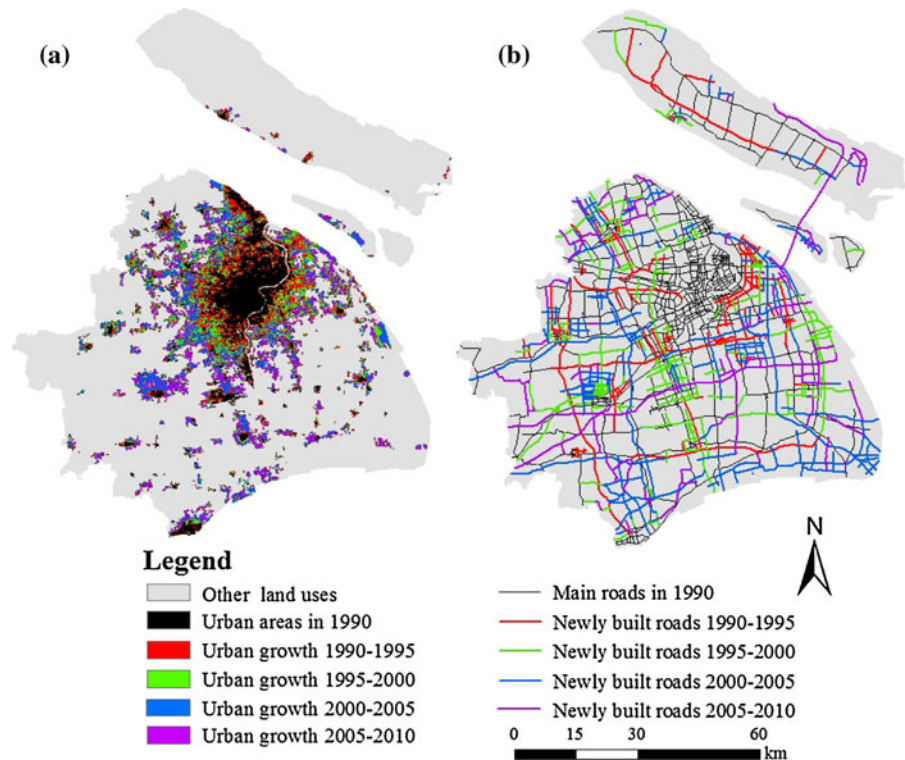
Panel data analysis

Panel data analysis employed in this paper is to examine the relationships between carbon emissions and urban forms. Firstly, panel unit root tests and panel cointegration tests of the variables should be conducted to confirm the validity of the panel data model estimation before establishing the panel regression model. Next, all data must undergo natural logarithm transformation to avoid non-stationarity and heteroskedasticity phenomena in the time series variables (Hsiao 2003). Finally, the parameters of interacting variables are estimated by using the panel regression model.

Panel unit root tests

On account of the non-stationary nature of time series data, their stationary nature must be examined before

Fig. 4 The change of urban land use (a) and transportation network (b) in Shanghai for 1990–2010



panel data models are established. Panel unit root test has recently attracted attention because it is more powerful than the normal time series unit root. In general, the panel unit root test is based on the following autoregressive model:

$$y_{it} = \rho_i y_{it-1} + \delta_i X_{it} + \varepsilon_{it} \quad (7)$$

where $i = 1, 2, \dots, N$ indicates entities observed in the time points $t = 1, 2, \dots, T$; X_{it} represents exogenous variables in the model including any fixed effects or individual trends; δ_i is the vector of regression parameters; ρ_i is the autoregressive coefficients, and ε_{it} is a stationary process. If $\rho_i < 1$, y_i is said to be weakly trend-stationary. Conversely, if $\rho_i = 1$, then y_i contains a unit root (Mahadevan and Asafu-Adjaye 2007).

One of the most widely applied tests within this field of research is the Levin et al. (2002) (LLC) test, which is improved on Eq. (7). The test is designed to examine the null hypothesis of a common unit root in the panel versus the alternative of stationarity when the cross-sectional units are independent of one another (Levin et al. 2002). In this paper, the LLC panel unit root test is applied to examine whether the data are difference-stationary or trend-stationary and to determine the number of unit roots at their level. We

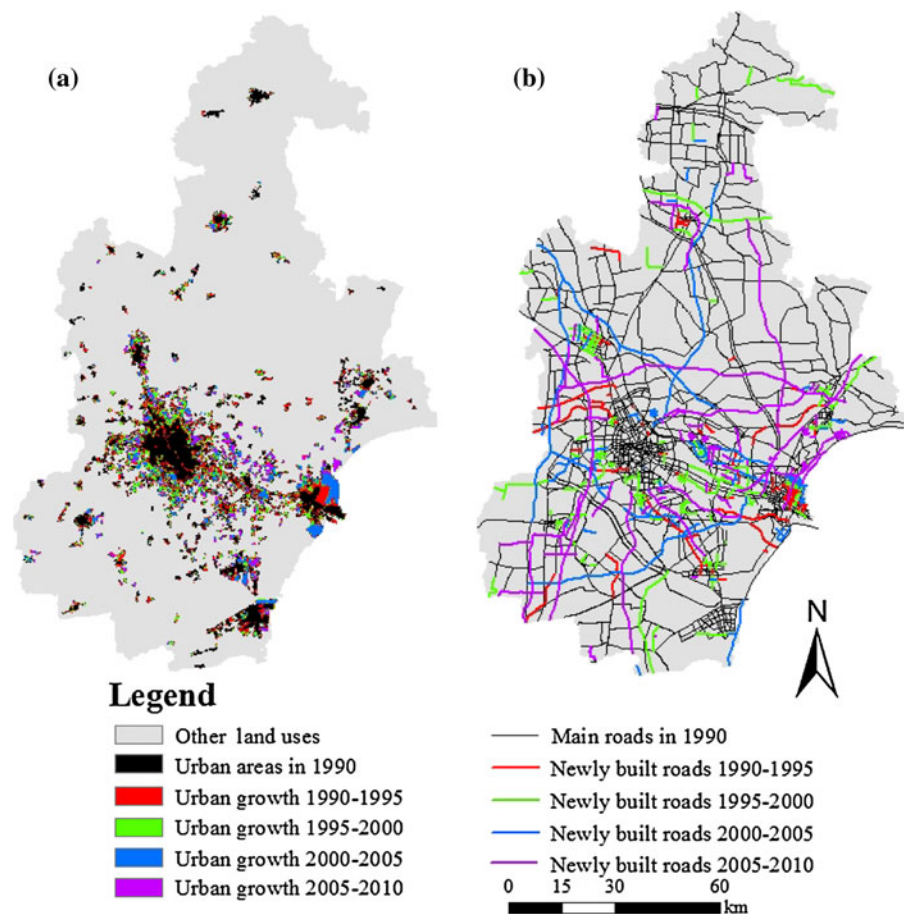
likewise check if any of the variables are integrated from the same order to satisfy the premise of cointegration test.

Panel cointegration tests

From the result of the unit root tests, if the variables are integrated of order one, then the next step is to utilize cointegration tests to analyze whether a long-run relationship exists among them. The analysis is conducted by applying Pedroni's heterogeneous panel cointegration tests, which allow for cross-section interdependence with heterogeneous slope coefficients, fixed effects, and individual specific deterministic trends. Pedroni's framework provides cointegration tests for both heterogeneous and homogenous panels with seven repressors based on seven residual-based statistics (Pedroni 1999).

In these seven statistics, the panel v-statistic, panel r-statistic, panel PP-statistic, and panel ADF t-statistic are based on pooling the residuals of the regression along the *within*-dimension of the panel. The other three (Group rho-Statistic, Group PP-Statistic and Group ADF-Statistic) are based on pooling the residuals of the regression along the *between*-

Fig. 5 The change of urban land use (a) and transportation network (b) in Tianjin for 1990–2010



dimension of the panel (Al-mulali and Binti Che Sab 2012). In both cases, the basic approach is to first estimate the hypothesized cointegrating relationship separately for each panel member, and then to pool the resulting residuals for conducting the panel tests. See Pedroni (1999) for details on these tests and the relevant critical values.

Panel data model

Generally, panel data analytic models can be categorized into three types: pooled regression model, variable intercepts and constant coefficients model, and variable intercepts and variable coefficients model (Baltagi 2005). The pooled regression model has constant coefficients, which are referred to as both intercepts and slopes. The form of the pooled regression model can be expressed as Eq. (8), in which a and b are constant coefficients. Equation (9) is the form of variable intercepts and constant coefficients model,

which has constant slopes but intercepts that differ based on entity and/or time. The third model has differential intercepts and slopes that vary based on both entity and/or time shown as Eq. (10).

$$y_{it} = a + bx_{it} + \varepsilon_{it} \quad (8)$$

$$y_{it} = a_i + bx_{it} + \varepsilon_{it} \quad (9)$$

$$y_{it} = a_i + b_i x_{it} + \varepsilon_{it} \quad (10)$$

where i and t represent the entities and time points; y_{it} and x_{it} are indices for the dependent variable and independent variable, respectively; and a_i is specified as fixed effects or random effects. Similar to the specification of a_i , b_i can also be expressed as a fixed or random effect. Here, ε_{it} is the error term.

Two main hypotheses are used to determine which specific model should be selected. Whether the hypothesis is accepted based on the result of F -test through comparing the residual sum of squares (RSS) of Eqs. (8), (9), and (10).

Fig. 6 The change of urban land use (a) and transportation network (b) in Guangzhou for 1990–2010

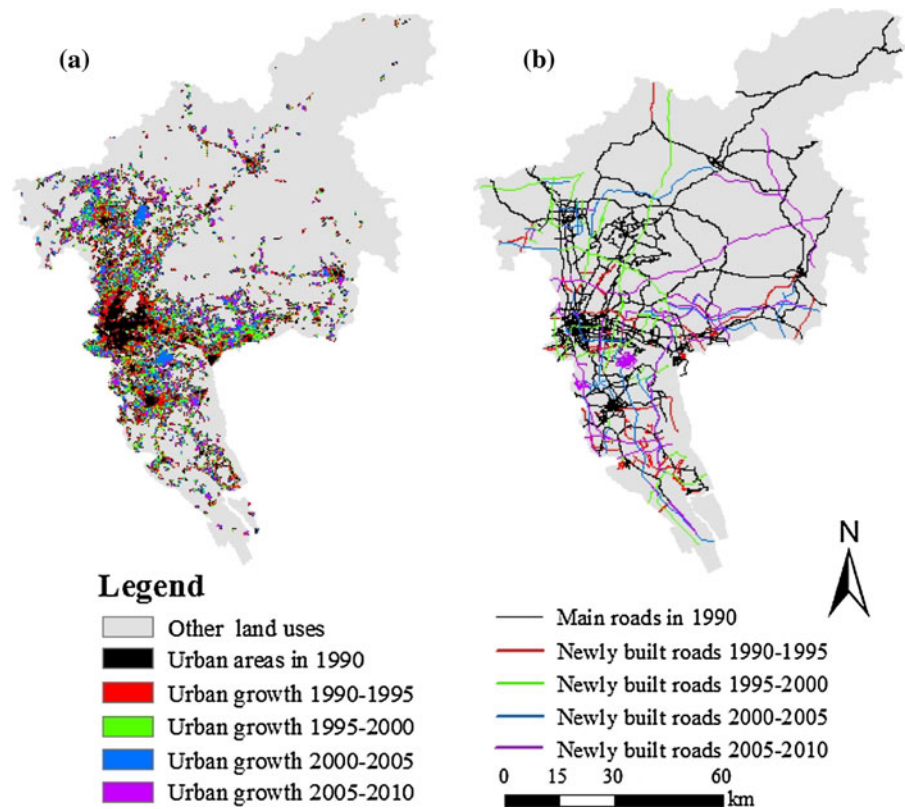


Table 3 Results of the overall quantity disagreement (Q) and allocation disagreements (A) of the urban category in each image (%)

Accuracy assessment	Beijing		Shanghai		Tianjin		Guangzhou	
	Q	A	Q	A	Q	A	Q	A
1990	1.24	4.56	4.12	8.37	3.82	7.31	3.22	7.04
1995	4.15	7.73	2.06	8.03	3.61	7.93	5.01	7.86
2000	2.31	7.91	1.08	5.96	2.87	6.34	2.76	6.32
2005	1.17	6.34	3.26	9.14	3.08	6.99	3.55	7.83
2010	2.46	7.31	2.85	7.30	2.15	5.87	4.18	8.07

$$H_1 : b_1 = b_2 = \dots = b_N$$

$$F_1 = \frac{(S_2 - S_1)/[(N - 1)k]}{S_1/(NT - N(k + 1))} \sim F[(N - 1)k, N(T - k - 1)] \tag{11}$$

$$H_2 : a_1 = a_2 = \dots = a_N \quad b_1 = b_2 = \dots = b_N$$

$$F_2 = \frac{(S_3 - S_1)/[(N - 1)(k + 1)]}{S_1/(NT - N(k + 1))} \sim F[(N - 1)(k + 1), N(T - k - 1)] \tag{12}$$

where F_1 is the statistic for H_1 that intercepts and coefficients are held constant over entities and time; F_2 is the statistic for H_2 that intercepts are variable and coefficients are constant; $S_1, S_2,$ and S_3 are RSS for Eqs. (10), (9), and (8), respectively; and $N, T,$ and k denote the number of entities, the number of time points, and the number of explanatory variables, respectively. The entities are specified as the cities in this study.

Given the confidence level and condition that $T > k + 1,$ if F_2 is larger than or equal to the critical

value, the hypothesis H_2 is accepted and Eq. (8) is selected; otherwise, the hypothesis H_1 must be tested. If F_1 is larger than or equal to the critical value, the hypothesis H_1 is then accepted, and Eq. (9) is selected; otherwise Eq. (10) is selected. Next, we need to decide if the fixed effects or random effects model should be used, which is determined by the Hausman test (Baltagi 1996). The Hausman test mainly asks whether the covariance estimator and GLS estimates of b (the common parameter) are obviously different (Hausman 1978). This statistic analysis is distributed asymptotically as a central χ^2 under the null hypothesis (Hsiao 2003).

Results and discussion

In this study, the statistical method of panel data analysis was implemented through the statistical software EViews. Originally developed and distributed by Quantitative Micro Software (QMS), EViews

offers innovative solutions for econometric analysis, forecasting, and simulation. Therefore, we estimated the relationships between carbon emission and urban forms with the EViews testing. The analysis procedure and experiment results are described below.

Panel unit root analysis

Table 5 reports the results for the LLC panel unit tests. As the table shows, with exception of urban road density and traffic coupling factor, the null hypothesis of non-stationary is rejected at the 10 % significance for the levels of other variables. When the first differences are taken, the null hypothesis of non-stationary is rejected for all the variables. Therefore, we can conclude that all the variables are non-stationary and integrated at an order of one. Based on these results, carbon emissions and other variables are tested to find whether there is a long-run relationship between them.

Table 4 Spatial metrics of urban land use

Indicators	Abbreviation	Formula	Description
Total urban area	CA	$CA = \sum_{j=1}^n a_j(1/10000)$	$a_j = \text{area (m}^2\text{) of urban patch } j$
Number of patches	NP	$NP = n$	$n = \text{number of urban patches}$
Edge density	ED	$ED = (10,000) \sum_{j=1}^n e_j / AREA$	$e_j = \text{total length (m) of edge in landscape involving urban patch } j, \text{ including landscape boundary and background segments of urban patch}$ $AREA = \text{total landscape area (m}^2\text{)}$
Mean perimeter-area ratio	PARA_MN	$PARA_MN = \frac{\sum_{j=1}^n (l_j/a_j)}{n}$	$l_j = \text{perimeter (m) of urban patch } j$ $a_j = \text{area (m}^2\text{) of urban patch } j$
Percentage of like adjacencies	PLADJ	$PLADJ = \frac{d}{\sum_{j'=1}^m d_{j'}} (100)$	$d = \text{number of like adjacencies between pixels of urban patch based on the double-count method}$ $d_{j'} = \text{number of adjacencies between pixels of urban patch and non-urban patch } j' \text{ based on the double-count method}$ $m = \text{number of non-urban patches}$
Patch cohesion index	COHESION	$COHESION = \left(1 - \frac{\sum_{j=1}^n 1}{\sum_{j=1}^n l_j \sqrt{a_j}}\right) \left(1 - \frac{1}{\sqrt{SUM}}\right)^{-1} (100)$	$l_j = \text{perimeter of urban patch } j \text{ in terms of number of cell surfaces}$ $a_j = \text{area of urban patch } j \text{ in terms of number of cells}$ $SUM = \text{total number of cells in the landscape}$
Largest patch index	LPI	$LPI = \frac{\max a_j}{AREA} (100)$	$a_j = \text{area (m}^2\text{) of urban patch } j$ $AREA = \text{total landscape area (m}^2\text{)}$

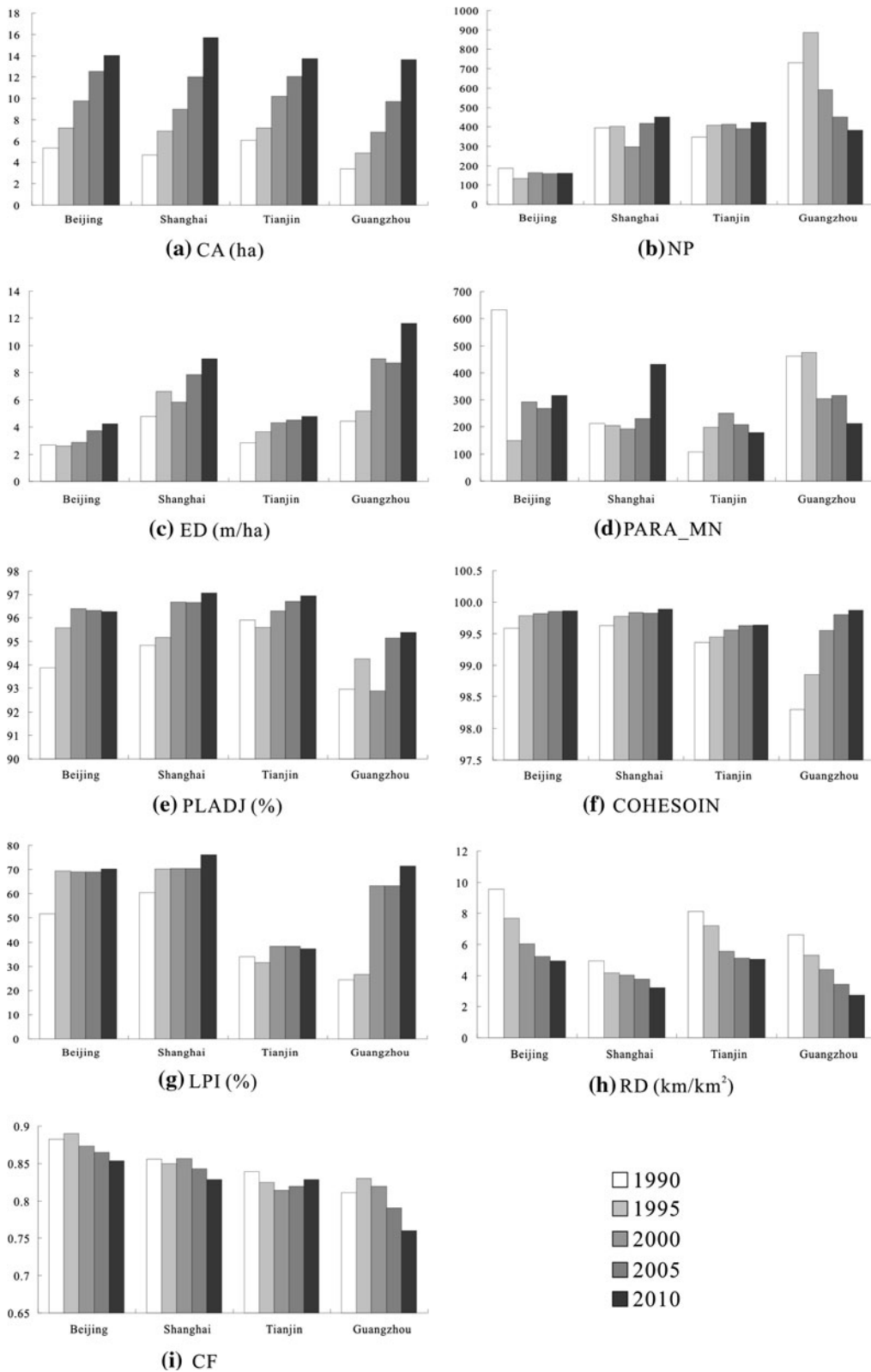


Fig. 7 Values of spatial metrics of four cities

Results of panel cointegration

According to the above results, seven cointegration statistics are calculated to test the long-run relationship among these variables. The results of panel cointegration tests between carbon emissions and other variables are displayed in Table 6. As Table 6 shows, the panel rho-statistic and group rho-statistic of these variables accept the null hypothesis of no cointegration; however, the other five statistics reject this hypothesis. In addition, the significant levels are different among these variables. Considering the Orsal's findings that the panel ADF-statistic performs better than the other three within-dimension-based statistics and three group-mean statistics through a comparison of the relative performance of Pedroni's the test statistic (Orsal 2007), we based our conclusions primarily on the panel ADF-statistics, which shows that the nullity of non-cointegration of the variables is rejected at the 5 % significance level (see the bold numbers in Table 6). This indicates that a long-term equilibrium relationship exists between carbon emissions and other variables.

Parameter estimations of the panel model

Since there is a relationship between carbon emissions and other variables, we establish panel regression models for these variables to estimate influences of patterns of urban land use and transportation on carbon emissions. Given the condition that $T > k + 1$ and $T = 5$, the maximum value of k is 3, which implies that a regression model have, at most, three explanatory variables. The explanatory variables are separated into three regression models in order to analyze the relationship of carbon emissions and urban forms properly. The combinations of explanatory variables are organized as (1) CA, PLADJ, and COHESION; (2) NP, CF, and LPI; and (3) RD, ED, and PARA_MN.

Next, F -tests are performed to determine which specific regression form should be used for these three models. The results of the F -tests are listed in Table 7. For Model 1, given the significance level of 5 %, F_2 is equal to 6.0077, which is greater than $F(12,4)$. Thus, hypothesis H_2 is rejected. In addition, F_1 is greater than $F(9,4)$, given the same significance level; thus, hypothesis H_1 is accepted, meaning that Model 1 should adopt Eq. (9). The F -test results for the other two models are similar to that of Model 1; thus, Eq. (9) is also used for Models 2 and 3. Table 8 presents the

results of the Hausman test for the three models. The probability P values of the three models are less than the critical value at the 5 % level of significance, indicating that it should use the fixed-effect model, rather than the random effects model. Then, generalized least squares (GLS) regression is likewise employed for the above three models.

Table 9 displays the coefficients estimated from panel data analysis, which demonstrate a clear relationship between carbon emissions and urban forms. As expected, Table 9 shows that CA is positively correlated with carbon emissions. Thanks to the market-oriented reform and fast economic development, the urbanization in these four cities is accelerating during the study period. The expansion of urban areas has led, not only to changes in the structure and composition of agriculture and forest, but also to decreases in vegetation carbon storage. Rapid urbanization in these four cities has also caused the fast growth of population, such that daily living, traveling, and working of the population create a great demand for energy and lead to large quantities of carbon emissions. Moreover, as an important industry in these regions, manufacturing has to consume huge land resource and increase the amount of carbon emissions for the industrial production. Thus, unsurprisingly, the rapid growth of urban areas has brought about a corresponding increase in carbon emissions.

The estimation results show that the variables NP, ED, and PRAR_MN also have significant positive impacts on carbon emissions. NP is used to reflect the scattering of the spatial pattern of urban land use. The higher the value of NP is, the more scattered the spatial pattern of urban land use is. The variables ED and PRAR_MN measure the regularity of the shape of urban patches. The shape of urban land use becomes more irregular if the values of ED and PARA_MN increase under the restriction of the same amount of area for urban patch. Accordingly, the estimation results on the variables NP, ED, and PRAR_MN indicate that a more scattered or irregular pattern of urban land use will give rise to more carbon emissions. The main reason for this phenomenon may be the increase in potential transportation requirements when activities are distributed in many different urban patches. For example, in Beijing or Shanghai, many newly built residential areas are distributed in distant suburbs where the living environment is better than that in the central urban area. Thus, the scattered or

Table 5 Results of LLC panel unit root tests

Variable	Levels	First difference
Carbon	−3.6046***	−21.6329***
CA	−2.2333**	−9.6038***
NP	−6.3089***	−21.1611***
ED	−7.8068***	−4.5152***
PARA_MN	−8.4376***	−153.9060***
PLADJ	−10.0509***	−5.4607***
COHESION	−8.9882***	−10.4263***
LPI	−19.5124***	−11.6711***
RD	−0.3959*	−1.2902***
CF	0.1532*	−45.9063***

*** Significance at the 1 % level, ** 5 % level, and * 10 % level

irregular pattern of residential areas lead to recurrent long movements of people from residences to their places of work (Muller 2004). As a consequence, a higher level of person transport is incurred to meet the need of economic activities, which results in higher consumption of energy and increases more carbon emissions.

We further find that urban sprawl with an aggregated and continuous pattern is conducive to the reduction of carbon emissions based on the estimation results that the variables PLADJ and COHESION are negatively correlated with carbon emissions. As discussed above, the variables PLADJ and COHESION are measures of the aggregation and connectedness of urban land, respectively. The lower the values both PLADJ and COHESION are, the more compact the development pattern of urban land is. Currently, a number of studies have stated that a compact urban structure is highly beneficial for sustainable development because, for instance, of the lesser need for car transport, increased accessibility, reuse of existing infrastructure, preservation of green areas outside the cities, and regeneration of urban areas (Gordon and Richardson 1997; Van Der Waals 2000; Think et al. 2002). These benefits contribute substantially to the decrease in carbon emissions. Thus, the estimation results suggest that a compact urban structure would help reduce carbon emissions.

Notably, the variable LPI has significant positive impact on carbon emissions. Contrary to previous research conclusions by Chen et al. (2011), this estimation result indicates that increasing the percentage of

urban landscape accounted by the urban core (largest urban patch) can lead to an increase in carbon emissions. The difference of urbanization level between the different study areas could be a reason why this study reached a different conclusion from Chen. But most importantly, the research of Chen ignored the core influence of traffic congestion in a city. Certainly, we cannot deny that a larger urban core can provide more functions of economic activities. However, this can also lead to an increase in traffic. For example, according to the statistical yearbooks, the total number of vehicles of the four cities is about 4.49 million in 2000, but increased to 11.57 million in 2010. A large number of people driving to the urban center for work, study, or shopping could easily result in traffic congestion due to insufficient road resources. Traffic congestion, characterized by slower speeds, longer trip times, and increased vehicular queuing, not only raises fuel consumption, but also increases exhaust emissions (Ang 1990; Baranovskii et al. 1995). Besides, the research of Makidoo et al. (2012) has endorsed the view that too dense settlements in mono-centric form may lead to greater per capita CO₂ emissions. Therefore, to some degree, the urban form development with a mononuclear pattern can increase the amount of carbon emissions.

The estimation results of urban road density and traffic coupling factor for carbon emissions support the above analysis. The variables RD and CF both have significant negative effects on carbon emissions, indicating that higher RD and CF values can result in lower carbon emissions. Obviously, improvements in urban road density can effectively raise the flow speed of vehicles and reduce traffic congestion, which could improve the efficiency of fuel consumption of vehicles and reduce the carbon emissions. However, if a new road is constructed far from the functional sites of economic activities, the value of RD metric may be increase. But this construction could also result in a waste of energy and resources, instead of the reduction of carbon emissions, because of the increase in travel time. Thus, the coupling degree of urban spatial structure and traffic organization is a very important factor in carbon emissions. Specifically, the coupling development of urban spatial structure and traffic organization can enable traffic to flow freely and improve accessibility to a transport node or agglomeration of economic activities (Kenworthy and Laube 1996). Thus, improvements in urban road density and the coupling degree of urban spatial structure and

Table 6 Testing for bivariate cointegration between carbon emissions and other variables

Test statistics	Panel v-statistic	Panel rho-statistic	Panel PP-statistic	Panel ADF-statistic	Group rho-statistic	Group PP-statistic	Group ADF-Statistic
CA	8.7098***	1.0925	-5.417***	-2.1965**	1.8136	-5.5792***	-5.4475***
NP	13.1406***	0.8966	-3.7768	-1.7858**	1.9360	-1.7221**	-7.3278***
ED	5.5646***	1.2313	-1.3403*	-21.8732***	1.6820	-4.5718***	124.88
PARA_MN	16.8802***	1.0389	-3.5769***	-12.7876***	1.9095	-1.8802**	-23.6619***
PLADJ	0.5566	-0.2907	-5.3368***	-3.3066***	0.9365	-7.6116***	-9.4248***
COHESION	9.9246***	0.4797	-13.3733***	-2.8358***	1.3960	-11.9594***	-12.6061***
LPI	19.0783***	0.5069	-10.5988***	-17.1068**	1.6738	-6.8216***	0.6440
RD	2.0251**	-0.1328	-1.5698*	-1.9111**	0.7255	-4.5544***	-5.2425***
CF	12.8857***	0.7913	-4.7404***	-6.6392***	1.5998	-7.6745***	-16.8097***

*** Significance at the 1 % level, ** 5 % level, and * 10 % level

Table 7 *F*-test results for Model 1, 2 and 3

<i>F</i> -test	Model 1	Model 2	Model 3
Hypothesis H_2	F(12,4) < 6.0077 (0.05)	F(12,4) < 8.4167 (0.05)	F(12,4) < 6.1291 (0.05)
Hypothesis H_1	F(9,4) > 0.9582 (0.05)	F(9,4) > 3.4554 (0.05)	F(9,4) > 1.6773 (0.05)

Table 8 Hausman test results

	χ^2 statistic	Prob.	Conclusion
Model 1	27.5762	0.0000	Fixed effect model
Model 2	25.8901	0.0000	Fixed effect model
Model 3	20.6890	0.0001	Fixed effect model

traffic organization could be a particularly effective method of reducing traffic congestion, as well as carbon emissions.

At present, there have already existed some researches on the energy consumption or carbon emissions from cities (Huang et al. 2013). But researches on quantifying the relationship between carbon emissions and urban forms using panel data analysis, especially for Chinese cities, have been still little reported so far. One recent study used somewhat similar approach to estimate the impacts of urban forms on energy consumption in five cities of Pearl River Delta (Chen et al. 2011). Its analysis showed the same views that the growth of the urban size, fragmentation, and irregularity of urban land use patterns can lead to increased energy consumption. However, one conclusion that increasing the percentage of urban landscape accounted by the urban core can help reduce the energy consumption in their study

is different from ours. In the results of our study, the urban form development with a mononuclear pattern may increase the amount of carbon emissions because of the core influence of traffic congestion in the four large cities. Besides, we also confirmed this view by the estimation results of urban road density and traffic coupling factor for carbon emissions, and suggested urban forms in China should transform from the pattern of disperse, single-nuclei development to the pattern of compact, multiple-nuclei development. Thus, these results of our study are credible and representative, which is not presented in the previous researches.

In fact, the study has certain limitations that remain to be fixed. For example, industrial activities are usually the major sources of carbon emissions in Chinese cities, but less affected by the urban forms. So it is a limitation when analyzing the relationship between city's total emissions and urban forms. Considering the difficulty in classifying accurately the industrial land through Landsat TM images with a 30 m resolution and collecting land use data on earlier years, in this study we could also not figure out the impact of spatial distribution of industrial activities on carbon emissions. Furthermore, because of the difference of urbanization in different regions, the results of the empirical results do not represent the common

Table 9 Coefficients estimated from panel data analysis

Variable	Model 1	Model 2	Model 3
CA	1.2361*** (5.1557)		
NP		2.0489*** (3.147317)	
ED			0.5980* (1.0652)
PARA_MN			0.0710 (0.4239)
PLADJ	−0.4986 (−0.0619)		
COHESION	−15.4681** (−0.8050)		
LPI		3.3070*** (3.8720)	
RD			−1.2514*** (−2.0042)
CF		−0.3391 (−0.0596)	
Constant	67.1392* (0.6598)	−2.1476* (−0.6880)	8.4131*** (4.7012)
R-squared	0.9360	0.8020	0.8611
F-statistic	31.6755	8.7773	13.4268
Prob(F-statistic)	0.0000	0.0006	0.0001

* Significant at 0.10

** significant at 0.05

*** significant at 0.01

mechanism and need thorough examination. Thus, in the future study, we will anticipate the collection of more finer land use data and focus on building models in order to provide general understandings about the relationship between urban forms and carbon emissions.

Conclusions and policy implications

In response to global climate change, carbon emission mitigation strategies have been studied and formulated from social and economic perspectives. Increasing attention has been given to the effects on carbon emissions caused by different urban forms. However, quantifying the carbon impacts of urban forms accurately and systematically remains relatively unexplored. Therefore, this paper attempts to quantify the relationships between urban forms and carbon emissions empirically for the panel of four cities (i.e., Beijing, Tianjin, Shanghai, and Guangzhou) using the time series data for four time intervals.

In this study, panel data analysis was implemented to estimate the relationships between urban forms and carbon emissions after several selected spatial metrics for quantifying urban forms were obtained from the spatial distribution data of urban land use and transportation network. Panel unit root test and panel cointegration analysis of the spatial metrics variables were conducted before panel data models were established. These test results support the view that all panel variables are non-stationary and integrated of

order one. The results further demonstrate that a long-term equilibrium relationship exists between these spatial metrics and carbon emissions.

Additionally parameter estimations of the panel data model reveal that the individual variable coefficients have important but different impacts on carbon emissions. Urban expansion (high CA) inevitably leads to increased carbon emissions because of the consumption of resources and the accretion of population in rapid urbanization. Fragmented (high NP) or irregularly shaped (high ED and PARA_MN) patterns of urban land use likewise result in more carbon emissions. Conversely, we found an urban sprawl that has an aggregated and continuous pattern (high PLADJ and COHESION) would be conducive to the reduction of carbon emissions. Increases in both urban road density (RD) and traffic coupling factor (CF) also promote the reduction of carbon emissions. However, because it can easily cause traffic congestion, urban form development with a mononuclear pattern (high LPI) may accelerate carbon emissions. Therefore, in the foundation of compact development, the urban forms should transform from the pattern of single-nuclei development to that of multiple-nuclei development.

From the analytical results, we can conclude that planning for future development should consider the effects of different urban forms to reduce carbon emissions. Currently, China is facing many serious issues on ecology and environment resulting from its rapid economic growth and urbanization process. Maintaining a balance between sustainable development and cutting down total carbon emissions remain

important challenges for policy makers. One direct solution to reduce carbon emissions is the reduction of energy consumption. However, such a measure could have a negative impact on economic growth. As shown in this paper, constructing an ideal urban form through urban planning and spatial optimization is a critically important method of handling the carbon emissions problem. Thus, the planning of future development in China should take into account the effects of urban forms, and make the urban pattern more compact rather than disperse. Meanwhile, it suggests that urban forms should be a spatial pattern of the spool thread with poly-centers. From the above, the findings obtained in this study could provide important decision support in building China's low-carbon society.

Acknowledgments This study was supported by the National Natural Science Foundation of China (Grant No. 41171308 and 41371376), the Foundation for the Author of National Excellent Doctoral Dissertation of PR China (Grant No. 3149001), and the National Science Fund for Excellent Young Scholars (Grant No. 41322009).

References

- Alberti M, Hutyrá L (2009) Detecting carbon signatures of development patterns across a gradient of urbanization: linking observations, models and scenarios. *Cities and Climate Change*
- Al-mulali U, Binti Che Sab CN (2012) The impact of energy consumption and CO₂ emission on the economic growth and financial development in the Sub Saharan African countries. *Energy* 39(1):180–186
- Anderson WP, Kanaroglou PS, Miller EJ (1996) Urban form, energy and the environment: a review of issues, evidence and policy. *Urban Stud* 33(1):7–35
- Ang BW (1990) Reducing traffic congestion and its impact on transport energy use in Singapore. *Energy Policy* 18(9): 871–874
- Baltagi BH (1996) Testing for random individual and time effects using a Gauss–Newton regression. *Econ Lett* 50(2):189–192
- Baltagi HB (2005) *Econometric analysis of panel data* (Third edition). Wiley, Chichester
- Banister D (1996) Energy, quality of life and the environment: the role of transport. *Transp Rev* 16(1):23–35
- Baranovskii SD, Thomas P, Adriaenssens GJ (1995) The concept of transport energy and its application to steady-state photoconductivity in amorphous silicon. *J Non-Cryst Solids* 190(3):283–287
- Bi J, Zhang R, Wang H, Liu M, Wu Y (2011) The benchmarks of carbon emissions and policy implications for China's cities: case of Nanjing. *Energy Policy* 39(9): 4785–4794
- Camagni R, Gibelli M, Rigamonti P (2002) Urban mobility and urban form: the social and environmental costs of different patterns of urban expansion. *Ecol Econ* 40(2):199–216
- Cervero R (1998) *The transit metropolis: a global inquiry*. Island Press, Washington
- Chen Y, Li X, Zheng Y, Guan YY, Liu XP (2011) Estimating the relationship between urban forms and energy consumption: a case study in the Pearl River Delta, 2005–2008. *Landsc Urban Plan* 102(1):33–42
- Christen AN, Coops C, Crawford BR, Kellett R, Liss KN, Olchovski I, Tooke TR, Van Der Laan M, Voogt JA (2011) Validation of modeled carbon-dioxide emissions from an urban neighborhood with direct eddy-covariance measurements. *Atmos Environ* 45:6057–6069
- Chun M, Mei-ting J, Xiao-chun Z, Hong-yuan L (2011) Energy consumption and carbon emissions in a coastal city in China. *Procedia Environ Sci* 4:1–9
- Dhakal S (2009) Urban energy use and carbon emissions from cities in China and policy implications. *Energy Policy* 37(11):4208–4219
- Dietzel C, Oguz H, Hemphill JJ, Clarke KC, Gazulis N (2005) Diffusion and coalescence of the Houston metropolitan area: evidence supporting a new urban theory. *Environ Plan B* 32(2):231–246
- Galster G, Hanson R, Ratcliffe RM, Wolman H, Coleman S, Freihage J (2001) Wrestling sprawl to the ground: defining and measuring an elusive concept. *Hous Policy Debate* 12(4):681–717
- Geoghegan J, Wainger LA, Bockstael NE (1997) Spatial landscape indices in a hedonic framework: an ecological economics analysis using GIS. *Ecol Econ* 23(3):251–264
- Glaeser EL, Kahn ME (2010) The greenness of cities: carbon dioxide emissions and urban development. *J Urban Econ* 67(3):404–418
- Gordon P, Richardson HW (1997) Are compact cities a desirable planning goal? *J Am Plan Assoc* 63(1):95–106
- Guo R, Zhu Q, Cao X, Ren Z, Li F, Pradhan M, Jin F, Zhou Q, Wu B (2010) GIS-based carbon balance assessment and its application in Shanghai. *AIP Conf Proc* 1251(1):246–251
- Gustafson EJ (1998) Quantifying landscape spatial pattern: what is the state of the art? *Ecosystems* 1(2):143–156
- Han F, Liu Y (2009) Study on the coupling mechanism of urban spatial structure and urban traffic organization. *Int J Business Manag* 4(7):134–138
- Hausman JA (1978) Specification tests in econometrics. *Econometrica* 46(6):1251–1271
- Heath LS, Smith JE, Skog KE, Nowak DJ, Woodall CW (2011) Managed forest carbon estimates for the US greenhouse gas inventory. *J For* 109:167–173
- Herold M, Scepan I, Clarke KC (2002) Remote sensing and landscape metrics to describe structures and changes in urban landuse. *Environ Plan A* 34(8):1443–1458
- Holden E, Norland IT (2005) Three challenges for the compact city as a sustainable urban form: household consumption of energy and transport in eight residential areas in the greater Oslo region. *Urban Stud* 42(12):2145–2166
- Hou J, Zhang PD, Tian Y, Yuan X, Yang Y (2011) Developing low-carbon economy: actions, challenges and solutions for energy savings in China. *Renew Energy* 36(11):3037–3042
- Hsiao C (2003) *Analysis of panel data*. Cambridge University Press, Cambridge

- Huang Y, Xia B, Yang L (2013) Relationship study on land use spatial distribution structure and energy-related carbon emission intensity in different land use types of Guangdong, China, 1996–2008. *Sci World J* 2013:15
- IE Agency (IEA) (2008) World energy outlook 2008 *OECD/IEA*: 578
- IPCC (2006) IPCC guidelines for national greenhouse gas inventories. intergovernmental panel on climate change. IPCC, London
- IPCC (2007) Climate change 2007 the fourth assessment report of IPCC. Cambridge University Press, Cambridge
- Jenelius E (2009) Network structure and travel patterns: explaining the geographical disparities of road network vulnerability. *J Transp Geogr* 17(3):234–244
- Kennedy C, Steinberger J, Gasson B, Hansen Y, Hillman T, Havranek M, Pataki D, Phdungsilp A, Ramaswami A, Mendez GV (2009) Greenhouse gas emissions from global cities. *Environ Sci Technol* 43:7297–7302
- Kenworthy JR, Laube FB (1996) Automobile dependence in cities: an international comparison of urban transport and land use patterns with implications for sustainability. *Environ Impact Assess Rev* 16(4–6):279–308
- Levin A, Lin C-F, Chu CSJ (2002) Unit root tests in panel data: asymptotic and finite-sample properties. *J Econom* 108(1):1–24
- Li X, Liu X (2008) Embedding sustainable development strategies in agent-based models for use as a planning tool. *Int J Geogr Inf Sci* 22(1):21–45
- Li S, Xu Y, Zhou Q, Wang L (2004) Statistical analysis on the relationship between road network and ecosystem fragmentation in China. *Prog Geogr* 23(5):77–85
- Lucy RH, Byungman Y, Hepinstall-Cymerman J, Alberti M (2011) Carbon consequences of land cover change and expansion of urban lands: a case study in the Seattle metropolitan region. *Landsc Urban Plan* 103:83–93
- Mahadevan R, Asafu-Adjaye J (2007) Energy consumption, economic growth and prices: a reassessment using panel VECM for developed and developing countries. *Energy Policy* 35(4):2481–2490
- Makidoo Y, Dhakalb S, Yamagatac Y (2012) Relationship between urban form and CO₂ emissions: evidence from fifty Japanese cities. *Urban Clim* 2(12):55–67
- McGarigal K, Cushman SA, Neel MC, Ene E (2002) FRAG-STATS: spatial pattern analysis program for categorical maps
- Muller PO (2004) Transportation and urban form: stages in the spatial evolution of the American Metropolis. Guilford Publications, New York
- Orsal K. (2007) Comparison of panel cointegration tests. <http://sfb649.wiwi.hu-berlin.de>
- Parker DC, Meretsky V (2004) Measuring pattern outcomes in an agent-based model of edge-effect externalities using spatial metrics. *Agric Ecosyst Environ* 101(2–3): 233–250
- Pedroni P (1999) Critical values for cointegration tests in heterogeneous panels with multiple regressors. *Oxf Bull Econ Stat* 61(S1):653–670
- Pontius RG, Millones M (2011) Death to kappa: birth of quantity disagreement and allocation disagreement for accuracy assessment. *Int J Remote Sens* 32(15):4407–4429
- Seto KC, Fragkias M (2005) Quantifying spatiotemporal patterns of urban land-use change in four cities of china with time series landscape metrics. *Landscape Ecol* 20(7):871–888
- Shu YQ, Lam NSN (2011) Spatial disaggregation of carbon dioxide emissions from road traffic based on multiple linear regression model. *Atmos Environ* 45(3):634–640
- Svensson R, Odenberger M, Johnsson F, Strömberg L (2004) Transportation systems for CO₂: application to carbon capture and storage. *Energy Convers Manag* 45(15–16): 2343–2353
- Thinh NX, Arlt G, Heber B, Hennersdorf J, Lehmann I (2002) Evaluation of urban land-use structures with a view to sustainable development. *Environ Impact Assess Rev* 22(5):475–492
- Tsai Y-H (2005) Quantifying urban form: compactness versus sprawl. *Urban Stud* 42(1):141–161
- Turner MG (1989) Landscape ecology: the effect of pattern on process. *Ann Rev Ecol Syst* 20:171–197
- Van Der Waals J (2000) The compact city and the environment: a review. *Tijdschrift voor economische en sociale geografie* 91(2):111–121