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The Impact of Street Network Structure on Carbon Emissions from Commuting

Evidence from Three Chinese Cities

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ABSTRACT

Around 75 per cent of global carbon emissions are produced by cities, which are thus the determinant of Earth's climate change. Currently, scant attention has been paid to the role of the street network in carbon emissions. As an essential urban infrastructure, the street network can affect people's commuting modes and thus carbon emissions from commuting. Therefore, this study aims to understand the relationship between street centrality and carbon emission. Our study area consists of three Chinese cities: Shenzhen, Dongguan, and Huizhou. Street network centralities (i.e., closeness and betweenness) were calculated through sDNA. Finally, a stepwise regression analysis was computed to explore the relationship between variables.

Our results showed that street centrality could predict carbon emissions from commuting. The carbon emissions from commuting were positively influenced by global closeness centrality and negatively impacted by both global and local betweenness centrality. One possible explanation is that the road network structure can affect carbon emissions by affecting the process of car idling. Specifically, roads with a high closeness centrality would potentially gather more cars and more idling, contributing to high carbon emissions. However, this process rarely occurs on high-betweenness roads where vehicles usually pass through without stopping, which can reduce carbon emissions. The result of this paper could help design healthier urban street network systems to reduce carbon emissions from commuting and develop a sustainable commuting mode.

KEYWORDS

Carbon Emissions; Space Syntax; Street Network; Centrality; Commuting

1 INTRODUCTION

At the 75th United Nations General Assembly, the Chinese government announced that the country would implement more effective policies and measures to achieve a carbon dioxide emissions peak by 2030 and carbon neutrality by 2060 (BBC News, 2021). Since then, almost all industries have begun to transform into a low-carbon production mode. One of the primary sources of greenhouse gases is transportation activities (Notte et al., 2018). Daily commuting in cities, for example, produces massive carbon emissions. China's annual carbon dioxide emissions exceed 10 billion tons, of which the carbon emissions of the transportation industry account for about 15% in 2020, ranking third among all industries. In the past nine years, the average annual growth rate of carbon emissions in the transportation sector has exceeded 5%, and it is expected to increase by 50% on the existing basis by 2025 (SINA finance, 2021). Therefore, controlling the carbon emission of the transportation industry is necessary to achieve the goal of carbon peak and carbon neutrality.

In response to the "low-carbon experimental city" policy of the central government, many cities and regions in China have issued a series of policies to control carbon emissions. Most transportation-related policies focus on reducing carbon emissions from the perspective of energy and vehicles (Zhang and Liu, 2015; Sorrell, 2015; Andersen et al., 2009; You et al., 2011). However, few relevant policies or studies have been conducted on the role of road networks in carbon emissions. As an essential urban infrastructure, the road network is suggested to affect people's commuting modes, distance and speed, thus carbon emissions from commuting. This study thus aims to understand the relationship between road network centrality and carbon emissions.

To achieve this aim, we analysed the relationship between carbon emissions from commuting and road network in three Chinese cities (i.e., Shenzhen, Dongguan, and Huizhou) through space syntax analysis and a stepwise regression model. The findings of this paper can help policymakers reduce emissions from the perspective of road network structure, design environment-friendly urban roads and promote sustainable commuting modes.

Following this introductory section, the next section reviews the current research on reducing carbon emissions in transportation, especially the research based on the road network. The third section introduces the research sites, data, methodology and variable description. The fourth section shows the results of road network analysis based on space syntax and the results of causal analysis based on the stepwise regression model. The fifth section discusses the credibility of the research results and their possible application in practice. The sixth section summarizes the main findings, limitations of this paper and suggestions for future research.

2 LITERATURE REVIEW

The factors affecting carbon emissions from commuting are complex and diverse (Chow,2016; Cao and Wang,2017; Kissinger et al.,2019; Wang and Zeng,2019). The existing studies have used various modelling tools and multi-source data to explore this topic. For example, Ewing and Cervero (2001) summarized that trip frequencies, trip distance and travel mode choice can be used to estimate carbon emissions from transportation, which are mainly determined by socio-demographics, the built environment and socioeconomics. Cao and Yang (2017) found that CO2 emissions were negatively affected by mixed land-use, residential density, metro station density and road network density through survey data from 2015 in Guangzhou. Xia et al (2020) focused on relevant public policies (including mixed land use policies, urban density control and spatial planning policies) through the geographically weighted regression model and taxi GPS data, providing insights into reducing carbon emissions from daily travel. Jia et al (2018) collected questionnaire-based survey data in Beijing, Hangzhou and Jinan, and found that travellers' low-carbon awareness, low-carbon knowledge and low-carbon habits were important factors driving them to choose sustainable commuting modes through the binary logistic regression analysis. However, there is still a lack of research on carbon emissions from commuting and the road network. Most studies have focused on the relationship between the basic attributes of road and traffic carbon emissions. For example, the road network density has been widely found to affect traffic carbon emissions in previous studies (Yang and Cao, 2017; Wang et al., 2020; Shu and Lam, 2011; Wu et al., 2016). Furthermore, the length of the road can also be a factor in estimating carbon emissions (Lu et al., 2017). Additionally, Alam et al. (2020) have found that rolling resistance caused by uneven roads is the main source of carbon emissions.
Moreover, studies have examined the indirect impact of roads on traffic carbon emissions through pedestrian activities. For instance, Zhang et al (2013) found that low-carbon constraints in policies can affect the route and mode selection of pedestrians, thus affecting the performance of the composite transportation network composed of public and private vehicles. Specifically, when low-carbon constraints are used, the travel time and carbon emissions of crowded road networks can be reduced. However, for non-congested networks, the use of low-carbon constraints would increase the travel time of the road network. Yamagata et al. (2019) focus on pedestrian movements through GPS data and various walking ability indexes (centrality, betweenness, angle, etc.) based on road network data, designing a walking oriented, low-carbon intelligent community.

In summary, most previous studies on carbon emissions have focused on the basic characteristics of roads (such as length and density) or indirectly analysed the impact of the road network on carbon emissions through the pedestrian travel mode. At present, there is a need to analyse the structural characteristics of the road networks and explore the direct impact of road structure on carbon emissions. Therefore, to fill these research gaps, this study takes the structural characteristics of the road networks as the research object, using space syntax analysis to explore the impact of the road layout on carbon emissions from commuting. Noteworthily, the carbon emissions considered in this paper are mainly concentrated in carbon dioxide and carbon monoxide.

3 DATASETS AND METHODS

3.1 Research site

The research site is located in Guangdong Province, the east of the Pearl River Delta in southern China (Figure 1). The research area is a part of the Shenzhen metropolitan area, including five cities: Shenzhen, Dongguan, and Huizhou are three central cities; Heyuan and Shanwei are two marginal cities. Whilst the Shenzhen metropolitan area is an important economic pillar of Guangdong Province, the environmental pressure has increased with industrial development in recent years. In particular, the central area is facing urgent needs for energy conservation and emission reduction. Therefore, this paper focuses on the carbon emissions in these three central cities (i.e. Shenzhen, Dongguan and Huizhou) (Figure 1) and explores how the road networks of these three cities influence carbon emissions from commuting.

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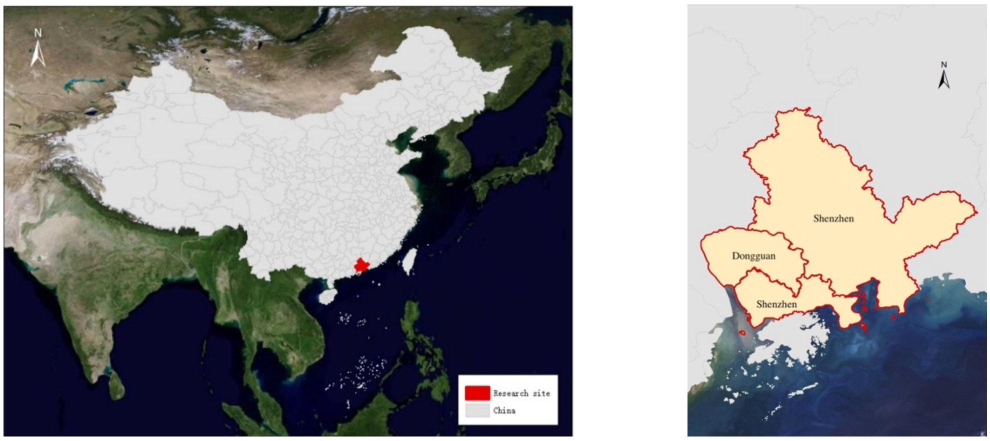

Figure 1. Location of research site.

3.2 Description of the variables

The data used in this study include road network, carbon emissions, location, excess commuting rate and commuting time spent on multiple means of public transport. The road network data was extracted from Open Street Map, and other data were provided by the China Academy of Urban Design&Planning (CAUPD).

(1) Carbon Emission Variable

The developed carbon emission accounting models in the current studies include the model issued by the Intergovernmental Panel on Climate (IPCC), The World Resources Institute and Boston University. Among them, the IPCC model is jointly suggested by the World Meteorological Organization (WMO) and the United Nations Environment Programme (UNEP). As a greenhouse gas calculation model, it provides an authoritative method for countries around the world to calculate greenhouse gas. The calculation of carbon emissions based on IPCC is:

Carbon emissions = activity data × Emission factor,

where the activity data represents the data of emissions caused by human activities (commuting activities in this study), and the emission factor represents the coefficient to quantify the gas emissions per unit activity. We adopted the carbon emission factor coefficient from Beijing Ecological Environment Bureau, as follows:

Table 2. Carbon dioxide emission per capita of different travel modes.

Private car	Bus	Metro	Bicycle
0.2500	0.540	0.0286	0.0072

Source: Beijing Ecological Environment Bureau, Beijing low carbon travel carbon emission reduction methodology.

In this study, the carbon emissions from commuting are calculated as follows:

Carbon emission of a commuter = activity data × Emission factor = The distance the commuter moves * the emission factor of the vehicle used by the commuter (1)

Total carbon emissions from commuting in a region = the sum of carbon emissions of all commuters in the region (2)

The distribution of carbon emissions is shown in Figure 2. Some regions of Shenzhen and Huizhou have high carbon emissions (the red and orange parts in Figure 2), and Dongguan has the lowest carbon emissions among the three cities. Overall, most of the high carbon emission regions of the three cities are located in peripheral areas, and the carbon emissions in the central areas are generally lower than those in peripheral areas.

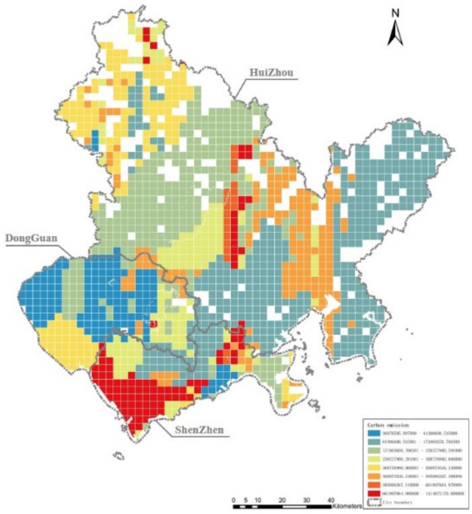

Figure 2. Distribution of carbon emissions in three cities

(2) Road Network Variable

we used Spatial Design Network Analysis (sDNA) (Cooper, 2021) to clean the network through the ‘prepare network tool’ and then quantified the street centrality in ArcGIS 10.7. In this paper, we mainly focused on two types of centralities:

① *Closeness centrality* represents the accessibility of a street network to the rest of the street network within a given radius. The street network with high closeness tends to have higher potentials to attract traffic flow coming to the area (i.e., to-movement). In sDNA, the closness centrality is measured by NQPDA, which is commonly referred to as a gravity model considering both the quantity and accessibility of the network weight.

② *Betweenness centrality* measures the probability that the street network has been circulated within a given radius. The higher the betweenness degree means greater traffic flow would potentially pass through the area (i.e., through-movement). sDNA measures a two-phase betweenness (TPBt) of a destination by considering the competition between destinations to attract origions.

The closeness and betweenness centrality were computed with two radii. The radius of 2000 meters was selected as the local scale, which is suitable for cycling commuting. The radius of n was selected as the global scale, which is suitable for vehicle commuting. Therefore, there are four street network variables: local closeness centrality (R=2km), local betweenness centrality (R=2km), global closeness centrality (R=n), and global betweenness centrality (R=n).

(3) Location

Location in this study refers to the specific orientation of each grid in the Shenzhen metropolitan area, which is quantified into three levels, "0" represents that the grid is located in the central area of the metropolitan area; "1" represents that the grid is located in the peripheral area of the metropolitan area; "0.5" represents that the grid is located between the central and peripheral areas of the metropolitan area. This classification of “centre”, “periphery”, and “in-between” is based on the *Commuting Observing Report in the Great Bay Area 2021* by CAUPD.

(4) Excess Commuting Rate

Excess Commuting Rate refers to the proportion of actual commuting distance on average in excess of theoretical optimal commuting distance. This variable is designed to characterize the deviation of actual work-residence spatial distribution from the optimal theoretical distribution, which can reflect the balance between the spatial distribution of the residence and the working place. Specially, the greater the excess commute rate, the farther away the place of residence and work is in the region. The information on users' locations of residence and employment that were used to calculate the excess commuting rate was extracted from the Baidu Map location service. Commuting OD pairs were thus generated from the information of users' locations of residence and employment.

(5) Commuting time spent on multiple public transport

Commuting time spent on multiple public transports refers to the shortest time of travel with multiple public transport based on the street network of OD raster, calculated from the Baidu Map API for trip planning. The means of public transport include metro, regular bus and a combination of multiple modes of public transport through transit connections. The time spent includes time to access stations by walk, waiting time, riding time and time for transfer by walk. This variable can reflect the transfer efficiency between various public transport.

The list of all variables is shown in Table 1.

Table 1. List of the variables

	Variables	Units
1	Carbon emissions from commuting	Ton
2	Closeness (R=2000m)	/
3	Betweenness (R=2000m)	/
4	Closeness (R=n)	/
5	Betweenness (R=n)	/
6	Location	/
7	Excess commuting rate	%
8	Commuting time spent on multiple public transport	Minute

3.3 Analytical approach

To aggregate the data, we divided the study area into 3000m * 3000m grids, which were then used as the unit of analysis. The grid division of 3000m * 3000m is suitable for Chinese cities, Hengyu et al. (2018) used grid division at the same scale to divide Guangzhou in China. Using the ‘join attributes by location’ function, we calculated the average value of all variables for each grid. Subsequently, a stepwise regression model was built through SPSS26.0 to analyse the impact of independent variables on commuter carbon emissions.

Additionally, the results of carbon emissions, commuting time spent on multiple public transport and excess commuting rate were calculated based on OD information. The purchase of the data and the calculation of OD information were provided by the China Academy of Urban Design & Planning (CAUPD).

4 RESULTS

4.1 Results of street network analysis

The multi-scalar closeness and betweenness centralities of the street network were calculated by sDNA, and 2 km and infinity (R=n) were selected as the radius for the local and global centrality, respectively. Two cartographic representation methods based on linear and 3km-radius grids are used for analysis. Linear element mapping takes into account the geometric characteristics of the road network and helps to show the morphological characteristics of a specific road network from a micro perspective (Figure 3); Grid mapping is suitable for expressing the macro characteristics of road network shape by counting the mean value of road network variables passing through each grid (Figure 4). The mapping results are divided into eight categories using the natural break method in ArcGIS.

The morphological characteristics of the road network can be summarized as follows: first, on a local scale (R=2km), the southern region of Shenzhen shows high closeness and betweenness centralities, which reflects its regional traffic centrality. Second, on the global scale, Shenzhen shows high regional closeness and betweenness centralities, reflecting its central position in the Shenzhen metropolitan area. Dongguan also shows high closeness, indicating that Dongguan only undertakes to attract long-distance passenger and vehicle flow on the global scale, but lacks attraction to short-distance travel movement flow. Third, on the global scale, the boundary zone between Shenzhen and Dongguan, and the boundary zone between Shenzhen and Huizhou are high-value areas of global betweenness, which can be considered the transportation hubs of the Shenzhen metropolitan area, but they do not reflect the integration and attraction of movement flow on the global scale. Fourth, on the global scale, the result of closeness is more continuous, reflecting the characteristics of "gradually weakening from the west to the East". The result of betweenness is more discrete, and the agglomeration characteristics of high-value grids are weak. The possible reason is that the distribution of trunk road networks (such as expressways) undertaking massive crossing functions is discrete.

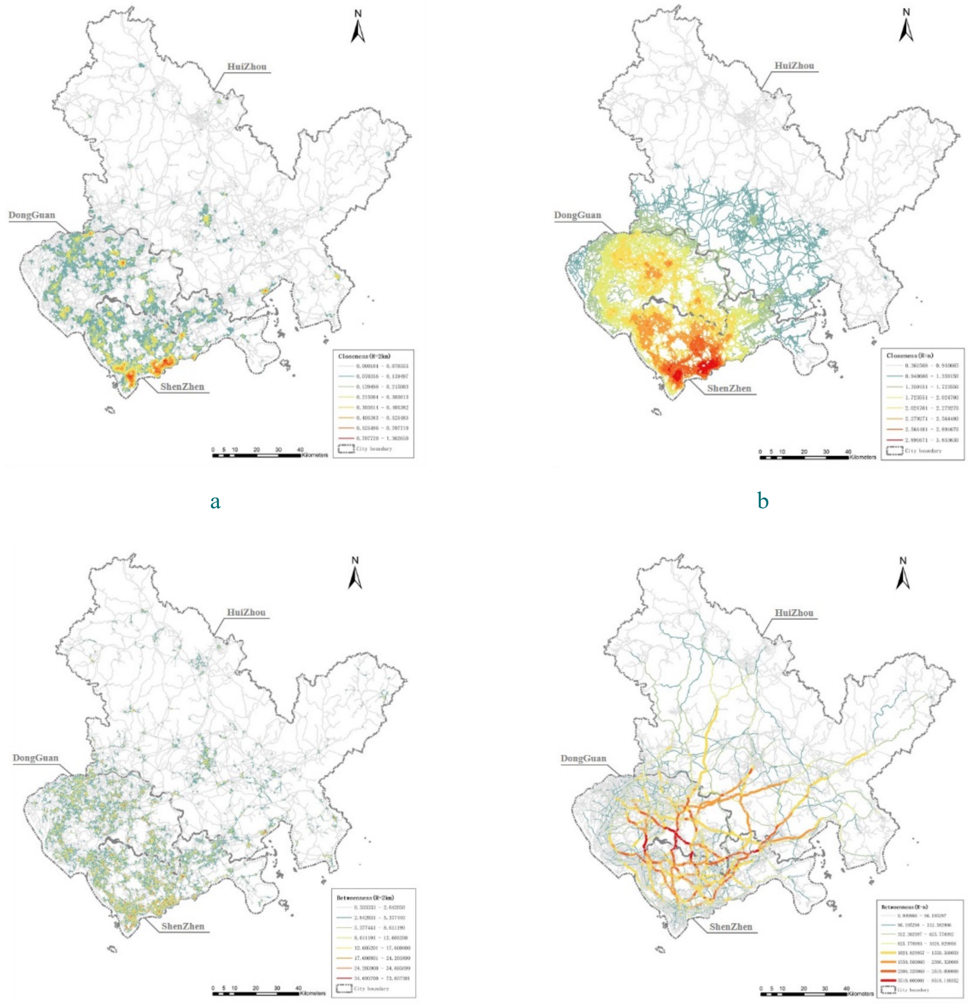

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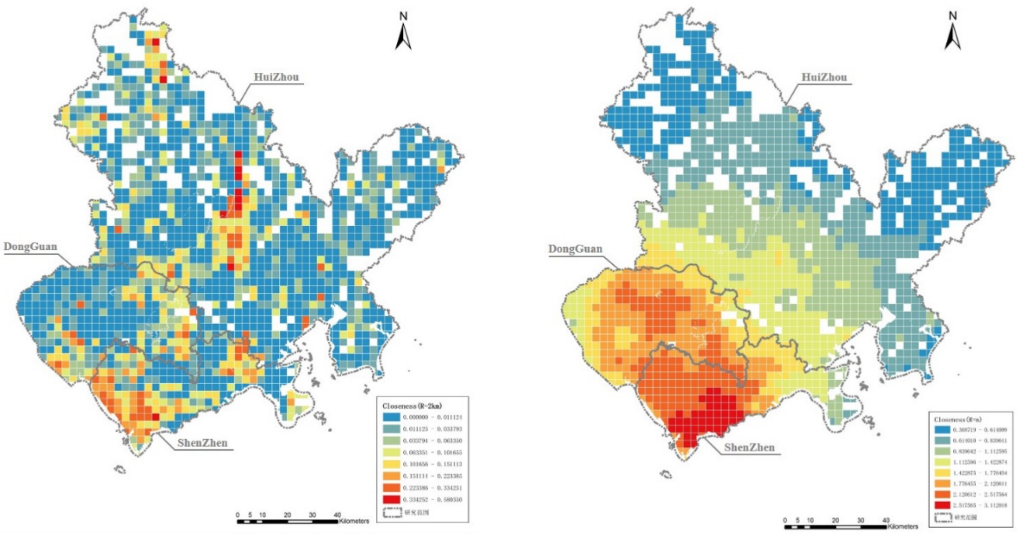
Figure 1. Results of centrality analyses at segment level, showing (a) local closeness centrality (R=2km), (b) global closeness centrality (R=n), (c) local betweenness centrality (R=2km), (b) global betweenness centrality (R=n)



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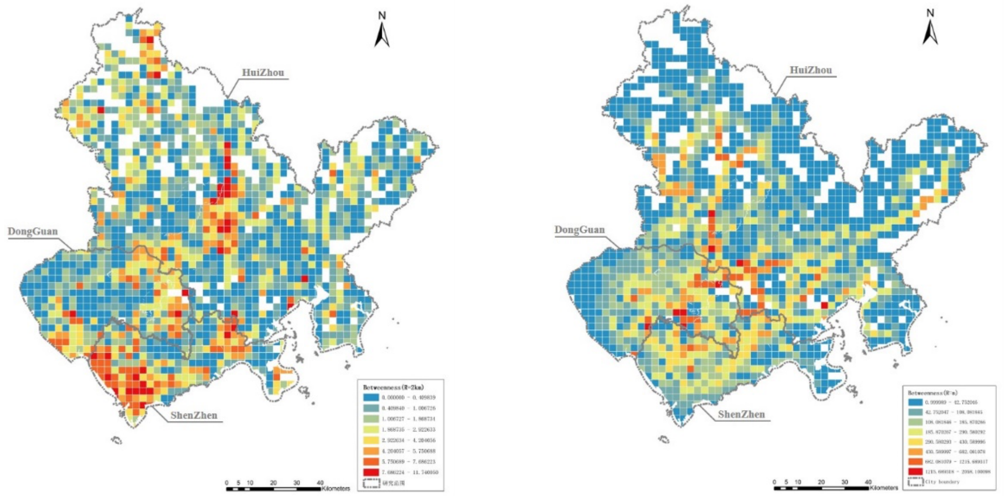

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Figure 2. Results of centrality analyses at grid level, showing (a) local closeness centrality (R=2km), (b) global closeness centrality (R=n), (c) local betweenness centrality (R=2km), (b) global betweenness centrality (R=n)

4.2 Results of model

Table 3 summarizes the variables that pass the significance test after six steps in the stepwise regression model. The R-square of the final model is 0.583 (see Table 4). Table 5 shows the coefficients of the variables finally retained and the results of VIF. Firstly, the result confirmed the impact of street network variables on carbon emissions from commuting. More specifically, the global closeness centrality (R=n) significantly and positively correlated with the carbon emissions from commuting. Furthermore, both local (R=2km) and global (R=n) betweenness centrality demonstrated significant negative impacts on carbon emissions. However, judging from the standard coefficient (Beta), the betweenness centrality at the local scale was a stronger predictor of carbon emissions than at the global scale. Meanwhile, it is also noted that the impact of betweenness centrality on carbon emissions is weaker than that of closeness centrality.

The results also suggested that the carbon emissions from commuting were significantly and positively influenced by the 'location', 'excess commuting rate', and 'commuting time spent on multiple public transport'. Specifically, in the area near the periphery of the city, the higher the excess commuting rate and the longer the commuting time spent on multiple public transports, which may lead to higher carbon emissions from commuting.

Table 3. Summary of the independent variables used in the proposed models

Independent variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Closeness (R=n)	√	√	√	√	√	optimal
Closeness (R=2000m)	×	×	×	×	×	×
Location			√	√	√	optimal
Excess commuting rate				√	√	optimal
Commuting time spent on multiple public transport					√	optimal
Betweenness(R=2000m)						optimal
Betweenness (R=n)						optimal

Note that the six independent variables of model 6 are determined based on the stepwise regression of the other five models.

Tables 4. Summary of final model (Model 6)

R	R Square	Adjusted R Square	Std. Error of the Estimate
.764	.584	.583	256117279.01147

Table 5. Coefficients of final model (Model 6)

Variables	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
	B	Std. Error	Beta			Tolerance	VIF
(Constant)	-2429709646.804	169052595.420		-14.373	.000		
Closeness(R=n)	561111409.427	20110713.787	.928	27.901	.000	.191	5.243
Location	460121214.999	17052627.936	.429	26.982	.000	.833	1.200
Excess commuting rate	1548869778.444	92254070.382	.375	16.789	.000	.424	2.360
Commuting time spent on multiple public transport	27312195.655	2544724.591	.217	10.733	.000	.518	1.931
Betweenness(R=2km)	-22154336.480	3964556.057	-.130	-5.588	.000	.388	2.576
Betweenness(R=n)	-62572.949	26284.141	-.037	-2.381	.017	.871	1.148

a. Dependent Variable: carbon emission form commuting

5 DISCUSSIONS

Our results have shown that the carbon emissions from commuting were positively correlated with closeness centrality and negatively with betweenness centrality. In other words, carbon emissions may be higher if a road is more likely to attract cars coming to this place (i.e., higher to-movement potential). On the contrary, if the vehicles simply pass through a road without stopping (i.e., higher through-movement potential), the carbon emissions would be lower. For this finding, we think that the main reason is that the street centrality would affect the idle of vehicles. Specifically, there are two possible explanations.

On the one hand, the street structure may affect the carbon emission of cars by affecting the process of stopping and starting cars. Specifically, the street with high closeness (high to-movement potential) is easier to become the origin or destination for cars. Streets with high closeness would gather a large number of vehicles to arrive, flameout and restart here. The process of flameout and restarting of the car, and the process of staying but without flameout (e.g., taxi drivers stopping to pick up passengers, cars waiting for traffic lights, etc.) are found to produce more carbon than normal driving (Li et al., 2017; Barth and Boriboonsomsin, 2008). On the contrary, due to the high betweenness of the street, few vehicles would stop here, and there is no process of stopping and restarting vehicles. Therefore, the higher the carbon emission of the high closeness street, the lower the carbon emission of the high betweenness street.

On the other hand, carbon emissions, particularly CO2, are closely connected to vehicle speed (Barthand Boriboonsomsin, 2008; Boriboonsomsin and Barth, 2009; Demir et al., 2011; Harris et al., 2011; Wyatt et al., 2014). Severe congestion usually leads to a slower speed and greater speed fluctuation, resulting in greater CO_2 emissions. Conversely, carbon emissions are relatively low when vehicles move at a steady, medium speed (Barth and Boriboonsomsin, 2008). In the case of the Shenzhen metropolitan area, due to their high accessibility, the roads with high closeness centrality are more likely to suffer from traffic congestion, resulting in vehicles driving at low speed and thereby emitting more carbon. On the contrary, the roads that undertake crossing functions (with high betweenness) are often urban expressways or high-grade trunk roads. These roads have no congestion most of the time, and most vehicles can drive at normal speed, so the carbon emission is relatively low.

In addition to the street configuration, this paper has also shown that the closer the geographical location is to the periphery of the metropolis, the higher the carbon emissions in the region. Due to the lack of public transport in the periphery of the Shenzhen metropolitan area, most trips to the periphery of the metropolis need to rely on motor vehicles. Although the number of daily commuting trips in the central area of the Shenzhen metropolitan area is higher than that in the marginal area, the carbon emissions in the central area are still lower than those in the peripheral areas (Commuting Observing Report in the Great Bay Area, 2021). Thus, the carbon emissions in the central region are usually lower than those in the peripheral region. However, this does not automatically mean that any locations in the peripheral area will have high carbon emissions. What is more important is whether the public transport facilities in the area can support the travel volume in the area. This finding echoes a previous study by Cao and Yang (2017), who also noticed that carbon emissions usually depend on the balance between the volume of travel and public transport (e.g., metro station density).

Furthermore, our results have also shown that the higher the excess commuting rate, the higher the carbon emissions from commuting. The high excess commuting rate represents that the actual commuting distance in the region is greater than the optimal commuting distance, reflecting the unbalanced distribution of work and residence caused by a monofunctional land use mode. This residence-workplace unbalanced distribution may lead to long commuting distances, which further generates higher carbon emissions from commuting. This finding is in line with the conclusion of a previous study, which suggested that compared with the area with a single land use mode, the higher the mixing degree of land use, the lower the regional carbon emissions (Cao and Yang, 2017).

Finally, we found that if all commuting vehicles are replaced by public transport to calculate the commuting time of each commuter, the longer the commuting time spent on multiple public transports, the higher the carbon emissions generated by commuting. In this study, the time spent commuting using public transport reflects the transfer times of public transport in a commuting trip. The more transfer times, the longer the commuting time. The long commute time suggests that commuters may have transfer many times, or a variety of different public transport during the trip (i.e., commuters cannot use one public transport directly to their destination but need to transfer to another public transport). In Shenzhen, long-distance commuting usually needs to transfer different public transport (e.g., taking the metro first and then transferring to the bus) (Commuting Observing Report in the Great Bay Area, 2021). The extensive use of a variety of public transport may cause more carbon emissions. Another potential negative possibility is that if the use of public transport requires multiple transfers, it may cause the boredom of commuters. They may instead drive or take a taxi to commute, which may lead to higher carbon emissions.

6 CONCLUSIONS

To conclude, this study found that the road network variables can predict the carbon emissions generated by commuting. Specifically, closeness is a positive predictor of carbon emissions from commuting, and betweenness is a negative predictor of carbon emissions from commuting. The finding is relevant to vehicle’s speed. Additionally, location, excess commuting rate and commuting time spent on multiple public transport positively influence carbon emissions from commuting. These findings are speculated to be relevant to the balance between public transport service coverage and commuting volume, residence and workplace, as well as public transport transfer efficiency and commuting distance. Based on the above findings, this paper could provide some implications for the sustainable commuting mode in the future.

First, try to alleviate the urban congestion by optimizing the road network structure and reduce the idling of cars, keeping the car speed at a normal level, rather than too slow or too fast, which will help to effectively reduce the carbon emission from commuting. Second, build public transport base on the commuting travel volume of cities. The coverage of public transport should be improved in the regions with high commuting volume; Third, the mixed use of land contributes to reduce carbon emissions from commuting, especially building residence around the CBD, improving the balance between residence and workplace to shorten commuting distance could effectively reduce carbon emissions from commuting. Fourth, it is suggested to design an efficient public transport system to realize "point-to-point" commuting, reducing unnecessary transfer between various public transport.

There are some limitations in this study. Road network variables based on space syntax theory is a topological network analysis, which lacks the discussion of road variables affecting commuters' activities in practice (such as road width). In future research, relevant variables can be considered to be added to the model. Moreover, future research can also focus on the differences of the impact of road network variables on carbon emissions from commuting in different spatial distribution and different time periods.

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