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Exploring the Spatial Heterogeneity and Influence Factors of Daily Travel Carbon Emissions in Metropolitan Areas: From the Perspective of the 15-min City

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Abstract: Most of the residents' daily travel is concentrated within their 15-min walking distance. In China, derived from the 15-min city concept, the 15-min walkable area is often referred to as the 15-min pedestrian-scale neighborhood, and it has become a basic planning unit. Understanding the factors that influence the built environment of the 15-min pedestrian-scale neighborhood on the residents' daily travel carbon emissions is critical to reduce urban carbon emissions. There may be spatial heterogeneity in daily travel carbon emissions as a dependent variable due to the spatial heterogeneity of built environment factors. Therefore, this study used data from the Wuhan City Resident Travel Survey to describe the spatial pattern of daily travel carbon emissions among Wuhan residents. The study examined the spatial heterogeneity of daily travel carbon emissions and explored the spatial differentiation of the built environment's impact on daily travel carbon emissions within the 15-min pedestrian-scale neighborhood of the residents using spatial autocorrelation analysis and multi-scale geo-weighted regression (MGWR). The results indicate that Wuhan residents' daily travel carbon emissions show an increasing circle structure from the center outward. In general, built environment elements in the 15-min pedestrian-scale neighborhood are closely related to the daily travel carbon emissions, and the direction and degree of impact of the built environment varies spatially. This study provides empirical evidence for controlling transportation carbon emissions.

Keywords: 15-min city; 15-min pedestrian-scale neighborhood; travel carbon emissions; built environment; spatial heterogeneity

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1. Introduction

Transportation-related carbon emissions are major contributors to global climate change. The transportation sector is now the second largest source of carbon emissions worldwide, accounting for 25% of total emissions [1]. More importantly, traffic-related emissions have increased at an annual rate of 10% in some areas over the past three decades [2]. Controlling transportation carbon emissions has become an increasingly critical issue in urban planning and transportation [3–5].

In recent years, land use and sustainable community policies aimed at reducing carbon emissions have become a hot topic of urban planning concern [6–8]. The "15-min city" has become a spatial concept for low-carbon green urban planning in different regions. Carlos Moreno introduced the 15-min city concept as a framework to combat greenhouse gas emissions [9,10]. It is also an adaptive planning adjustment in the face of strict health protocols and blockade measures in the COVID-19 pandemic shock. The planning goal of the 15-min city is to focus on meeting neighborhood-based infrastructure needs, safeguarding the physical needs of residents in their daily lives, and avoiding infection. At the same time, the "15 Minute City" plan rethinks the urban transportation system, aiming to create more active travel, build sustainable ecosystems in cities, reduce carbon emissions, and improve urban livability [10]. Similarly, originally developed in Japan, a "15-min pedestrian-scale neighborhood" is a space or behavioral form formed by residents' home-centered activities, such as shopping, leisure, commuting (to school), social interaction, and medical care [11]. As opposed to traditional residential planning, which uses population as a criterion for determining facility needs, 15-min pedestrian-scale neighborhood planning is based on residents' daily needs [12,13]. In China, many large cities have proposed allocating public service facilities within a 15-min pedestrian-scale neighborhood accessible to residents every day, thus forming a basic living unit for their daily needs which is more livable, while reducing motorized travel demand, therefore effectively reducing travel carbon emissions. In this situation, the built environment within the 15-min pedestrian-scale neighborhood will have a significant impact on residents' travel behavior [8,14]. Several studies have shown that the different levels of urban built-environment elements influence residents' travel behavior, such as travel distance, travel mode, travel frequency, and travel time, thereby affecting travel carbon emissions [3,15,16]. Although the 15-min pedestrian-scale neighborhood has become the basic spatial unit of China's carbon emission reduction planning policy, the choice of car travel within 15 min walking distance is still prominent. Unlike developed countries where urban environments change slowly and demand for car travel is relatively saturated, China has experienced unprecedented urbanization in the past few decades [17,18]. Almost every major city in China is undergoing rapid urban expansion and spatial reorganization, while the quality of public transportation services has failed to keep pace with the dramatic changes in urban space. In addition, the poor quality of walking and cycling spaces discourages people from choosing active travel. More importantly, driving a car is perceived as a social status symbol rather than a convenient, time-saving mode of transportation in China. It is a common phenomenon that many people still choose to travel by car even though driving may take longer than taking public transportation due to traffic congestion [19]. Therefore, how to control travel carbon emissions through changes in the built environment has become a critical issue.

However, it is rare for studies to be conducted on the built environment within the actual walkable areas of residents. As no empirical studies have been conducted on the correlation between travel carbon emissions and the built environment of the 15-min pedestrian-scale neighborhood, it remains a technical challenge to construct a 15-min city with low-carbon travel. In addition, the theory of residential self-selection has confirmed that residential areas with similar socio-economic characteristics have similar built environments [3,20,21], resulting in spatial heterogeneity of built environment and travel behavior. Due to the widespread spatial heterogeneity of the residence built environment [22], the daily travel carbon emissions of residents as the dependent variable may also be spatially heterogeneous [23]. However, few studies in the previous literature have addressed the spatial differentiation of daily travel carbon emissions and their influence factors. These research gaps pose difficulties for differentiated and customized sustainable community planning.

To address the above issues, this study analyzed Wuhan daily travel survey data, and used spatial autocorrelation analysis to examine the spatial pattern and spatial heterogeneity of residents' daily travel carbon emissions. Then the actual 15-min walkable areas of residents' daily travel were calculated. Furthermore, this study developed a MGWR method to quantify the spatial heterogeneity of the built environment of the 15-min pedestrian-scale neighborhood on daily travel carbon emissions. The spatial pattern of daily travel carbon emissions was accurately reflected in this study. With the consideration of spatial heterogeneity, the mechanism of the influence of 15-min pedestrian-scale neighborhood built-environment factors on daily travel carbon emissions is further clarified, offering insight for the development of regionally differentiated low-carbon transportation policies.

The organizational structure of this study is as follows: Section 2 provides a literature review, identifying research gaps. Section 3 presents the data, variables, and the MGWR method. Section 4 provides the results, analysis of the results, and details of the results obtained, Section 5 summarizes the main findings and discusses their implications for planning theory and planning practice.

2. Literature Review

2.1. 15-min City and 15-min Pedestrian-Scale Neighborhood

Rapid urbanization of the world has resulted in an increase in urban pollution, emissions, and congestion. There is an increasing demand for quality of life among people. Therefore, urban planning has shifted from focusing on economic development to focusing on human needs [13,24]. In recent years, the concept of the 15-min city has gained much attention and has been increasingly accepted by scholars and planners [10].The 15-min city concept was developed from early urban planning practices, such as Howard's garden cities [25], Clarence Perry's neighborhood units [26], Walter Christall's central location theory, "New Urbanism", and Peter Calthorpe's pedestrian pockets [27]. It advocates an urban structure that allows residents to access basic services within a limited 15-min time frame by walking, biking or taking the green bus. Currently, the Paris government has launched the 15-min city policy, which aims to encourage residents to walk or ride to meet their daily needs in 15 min or less [28]. In China, learning from the 15-min city lessons of Europe, America and Japan, planning policies have changed the previous three-level classification of residential areas, residential subdivisions and residential clusters based on population to an organizational model of residential areas with 5-min, 10-min and 15-min pedestrian-scale neighborhood [29]. The 15-min pedestrian-scale neighborhood originated in Japan and is based on the actual needs of residents, including employment, medical care, shopping, entertainment, and other daily needs [11,30]. The basic planning unit is the physically accessible area where residents live every day [11].

Although one of the original purposes of 15-min pedestrian-scale neighborhood planning was to reduce travel demand, urban pollution and emissions, most of the current research has focused on the definition and shape of living circles [13,31], as well as the configuration of facilities [13,32]. The low-carbon-travel-oriented 15-min pedestrian-scale neighborhood is very poorly studied. In recent years, many planning policies suggest that the spatial layout of a neighborhood should meet the daily travel needs of residents and minimize the need for long-distance travel; however, gaps in the literature result in the implementation of policies lacking detailed empirical evidence to support them.

2.2. Built Environment and Travel Carbon Emissions

Research indicates that the built environment influences residents' travel behavior, which, in turn, influences travel carbon emissions [3,5]. Therefore, it is likely that built-environment variables that impact individual travel behavior will also impact CO_2 emissions [4]. Most academics focus on travel mode selection, travel distance, travel frequency, travel purpose, and travel time when studying the relationship between the built environment and travel behavior [6,33,34]. Regarding travel behavior, most of the literature examines the impact of "5D" built environment elements (density, diversity, design, destination accessibility, and transit proximity) [35,36]. According to the literature, built environment factors, such as residential and job density [37,38], land use mix [39], intersection density [39], and public transportation accessibility [38], are all negatively correlated with energy consumption and carbon emissions. Research from Zahabi et al. [40] in Montreal, Canada, showed that a 10% increase in residential density, land-use mix, and transport accessibility leads to 3.5%, 2.5%, and 5.8% reductions in GHG emissions from household transport, respectively. Hong and Goodchild [41] arrived at a similar conclusion in their study conducted in Puget, USA. Transport emissions can be reduced by 31.2–34.4% by doubling the land use mix and intersection density.

Moreover, Chinese travel preferences are different from those in the West [19], and the built environment and transport carbon emissions in China are different from those in the developed West [42,43]. Academic studies of Chinese cities have come to different conclusions to those in Western countries, and several density studies conducted in China have shown that the relationship between density and CO_2 emissions is not significant [42,44]. Ma et al. [16] and Xiao et al. [45] arrived at opposing conclusions regarding the provision of public transport. The former shows a negative relationship between public transport accessibility and CO_2 emissions, whereas the latter has a positive impact on CO_2 emissions. In addition, some studies have shown that spatial heterogeneity of CO_2 emissions exists to different degrees among and within cities [46]. Moreover, academics who study residential self-selection argue that, since residents with similar socioeconomic characteristics choose similar residential areas, this results in a heterogeneous spatial distribution of the built environment characteristics of residential areas [3,20,21]. Ignoring spatial heterogeneity is likely to lead to fallacious research results [22]; therefore, it is necessary to consider spatial heterogeneity in research [23,47].

2.3. Research Gaps

Despite providing some insight into the relationship between the built environment and travel carbon emissions, they do not reach consistent conclusions. Recently, a few studies have attempted to investigate the complex mechanism of the built environment's influence on CO_2 emissions using methods such as structural equation modeling [3,15] and machine learning [48,49]. These models, however, are global models, and using them to analyze spatial CO_2 emissions with heterogeneity will obscure the heterogeneous characteristics of spatial CO_2 emissions. Therefore, the results of the analysis may be distorted by the confounding effect of spatial data, or even result in incorrect conclusions [22,23]. Because of spatial heterogeneity, the direction and degree of association between the independent and dependent variables may vary across spatial locations. This creates difficulties in the implementation of planning policies. For example, where should the mix of land be increased and where should it be reduced in order to reduce daily travel carbon emissions? Which areas should promote population concentration and which should be de-populated?

More importantly, existing studies primarily use communities, streets, traffic districts [15], or buffer zones at a certain distance from the residence [4] as boundaries to measure the built environment around individuals; however, these boundaries cannot accurately reflect residents' actual daily activities. Errors may occur in the measurement of the built environment around an individual when using these simplified "data boundaries". In particular, as mentioned above, studying the link between the built environment in the 15-min pedestrian-scale neighborhood and the carbon emissions of daily travel is essential to reduce carbon emissions. In summary, we urgently need empirical studies that consider spatial heterogeneity and the actual built environment of 15-min pedestrian-scale neighborhoods in order to support sustainable community planning.

To address these issues, this study quantified the spatial heterogeneity of daily travel carbon emissions in Wuhan and used an improved GWR model, MGWR, to analyze the heterogeneity of the direction and degree of association between the 15-min pedestrian-scale neighborhood built-environment variables and daily travel carbon emissions at different spatial locations. This study can provide empirical evidence for low-carbon-travel-oriented 15-min pedestrian-scale neighborhood planning.

3. Materials and Methods

3.1. Research Area and Data Source

This study used residential travel survey data from December 2020 in Wuhan (Figure 1), China, to reveal the spatial pattern of daily travel carbon emissions in Wuhan and the spatial heterogeneity of the influence of the residents' 15-min pedestrian-scale neighborhood built environment on daily travel carbon emissions. Wuhan is a megalopolis in central China that has experienced rapid urbanization and motorization over the past four decades. There was intense pressure to reduce transport emissions, as Wuhan's transport carbon emissions increased at an average annual rate of 11.6% from 2005 to 2017 [50].

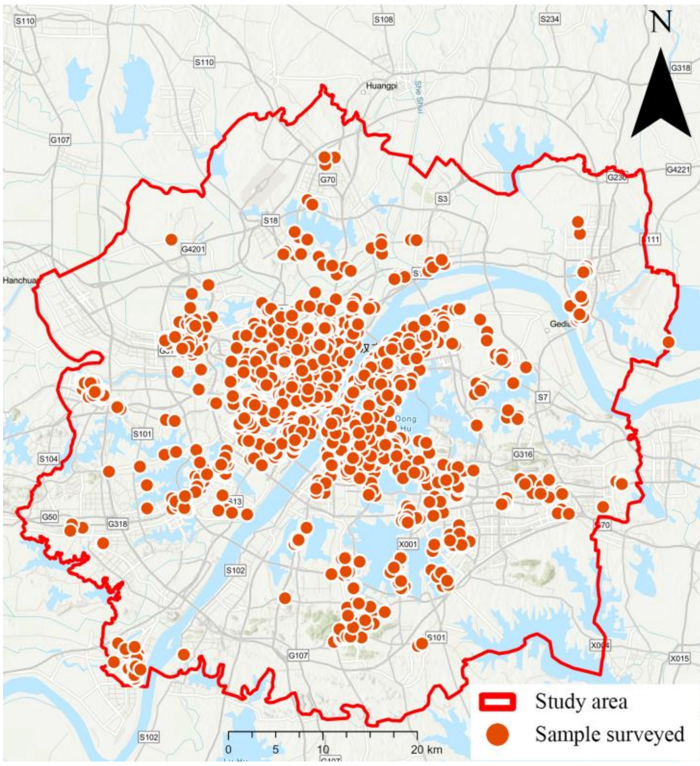


Figure 1. Spatial distribution of residents surveyed.

The travel data in this study came from the fourth travel survey of residents in 2020 conducted by the Wuhan Institute of Transportation Development Strategy. Surveys have been conducted every decade to determine the basic characteristics of daily movements of the population. A structured Family Interview Questionnaire was used to collect daily travel information from residents, such as the origin and destination of daily travel, purpose of travel, selected mode of travel, and social and economic characteristics of families and individuals, including age, gender, personal education level, employment status, household registration, family income, family size, and number of children. The survey was conducted in Wuhan with a 0.5% sample rate (Table 1). During the two-month period from October to December 2020, surveyors randomly selected a sample of every 10 households for face-to-face household interviews according to the principle of equidistant sampling, and used WeChat applets to fill in the questionnaire. Researchers conducted random household surveys using the WeChat app. A total of 43,660 people's travel information were collected over a two-month period. The data were further processed, missing information was removed, and 29,291 samples were obtained. Since the MGWR model requires minimizing the spatial overlap of samples, we de-duplicate the samples in terms of spatial location. The final selection of samples in the dataset, which were distributed as evenly as possible in space(Figure 1), totaled 2814.

Figure 2 reflects the proportion of the six travel modes. The proportion of fuel-fired motor vehicles reached 24%, transit share was 22%, metro was 5%, walking was 29%, and electric vehicles accounted for 17%, while cycling was only 3%. While transit and walking appear to have a higher share, the proportion of motorized trips was up 6% from 2019, while the proportion of transit trips had decreased by 5%. This indicates an upward trend in motor vehicle travel. In terms of the structure of motorization modes, the share of public transportation in Wuhan in 2020 was 50.3%, and the share of car trips was 45.1%. Compared with 2008, when public transportation in the main urban area accounted for 54.5%, car trips accounted for 25.9%, and other motorized trips such as cabs and motorcycles accounted for 20.0%, the share of public transportation decreased slightly, while the share of car trips and trips increased greatly. The number of private cars increased from 308,000 to

3.159 million from 2008 to 2020. The number of private cars increased about 9 times, which is the main reason for the significant growth of small cars and other modes of transportation. In terms of travel purpose, commuting trips account for the largest share, about 37.7%. The city's average travel distance also increased from 5.1 km in 2008 to 6.0 km. The city's average commuting travel distance reached 8.5 km in 2020, and the average motorized travel distance was 10.5 km.

Table 1. Basic information of data collection of four trips of residents in Wuhan.

Year	Zone	Resident Population and Scale	Survey Population and Household Size	Sample Rate
1987	Main urban area	330,000 people 940,000 households	—	—
1998	Main urban area	3,810,000 people 150,000 households	76,000 people 24,000 households	2.0%
2008	City area	870,000 people 200,000 households	120,000 people 38,000 households	1.5%
2020	City area	12,320,000 people 4,080,000 households	40,000 people 15,000 households	0.5%

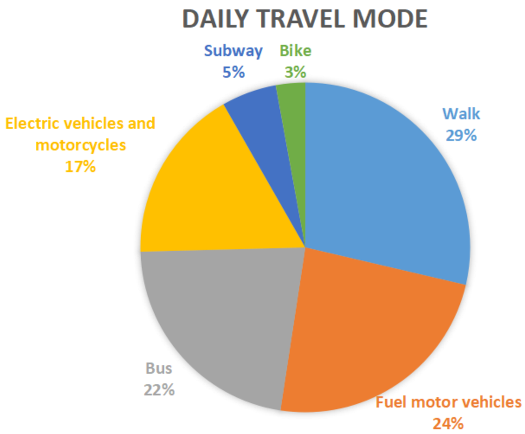


Figure 2. Travel mode proportion of Wuhan residents in 2020.

3.2. Variables

3.2.1. Residents' Daily Travel Carbon Emissions

The origin and destination (OD) points of residents' commuting trips obtained from the residents' travel survey were vectorized and the Baidu Map Path Planning API was used to calculate the actual commuting distance of a single sample and its commuting carbon emissions based on the individual commuting modes obtained from the survey. For the calculation, the following formulae were used:

$$C_i = \sum C_{ij} \tag{1}$$

$$C_{ij} = MTD_{ij} \times EF_m \tag{2}$$

$$MTD_{ij} = TD_{ij} - NTD_{ij} \tag{3}$$

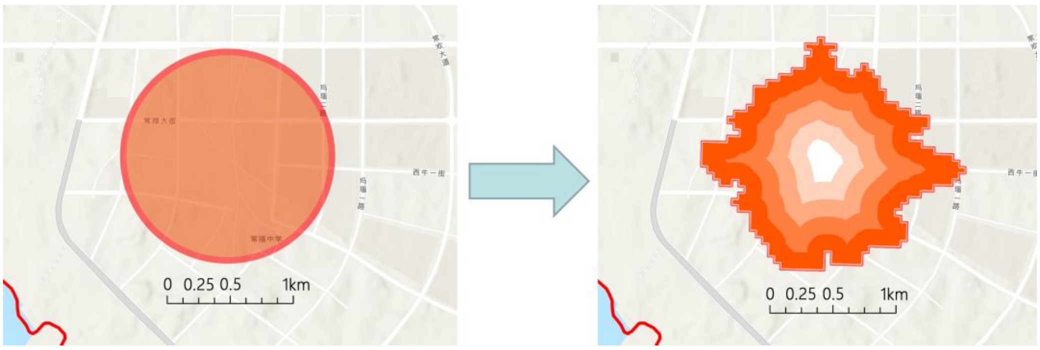
C_i is the daily carbon emissions from individual commuting, which is the total amount of carbon emissions generated by individual commuting in a day. C_{ij} is the carbon emissions from commuting trip j for sample i and EF_m is the carbon emission coefficient of residents' commuting vehicles. This study refers to the Carbon Emission Intensity Table for Mass Transportation in China. Xiao et al. [45] calculated the carbon emissions of the daily travel of Beijing citizens and compiled the carbon emission factors applicable to this study (Table 2). To estimate the carbon emissions of the commute as accurately as possible, it is necessary to compute the pure motorized distance of this regular Sample I trip. Consequently, when an M-class regular trip is used to complete trip J, the "Baidu Map Batch Road Calculation API" is used to calculate the travel distance (TD_{ij}) of the shortest travel scheme. This section of travel distance includes both motorized and non-motorized travel distances. NTD_{ij} represents the non-motorized travel distance in this section, and MTD_{ij} represents the pure motorized travel distance.

Table 2. Carbon emission coefficient of different commuting modes.

Traffic Category	Means of Transportation	Carbon Emission Coefficient (g/(km per Person))
Small cars	Private car, unit car, car rental	135
Bus class	Bus and unit shuttle bus	50
Rail transportation category	Subway	9.1
Personal assistance class	Electric bicycle/moped, light motorcycle	8
Others	Walking, cycling	0

3.2.2. Residents 15-min Pedestrian-Scale Neighborhood Built Environment

In order to calculate the built environment indicators within the actual 15-min pedestrian-scale neighborhoods of residents, we used the Baidu Maps API to calculate the actual reachable range of each respondent within a 15-min walk based on the actual paths taken by residents on foot. This range is no longer an ideal circle drawn with the respondent as the center and a specific distance as the radius(Figure 3a), but an actual reachable range calculated according to the actual walkable path of the residents, in an irregular shape (Figure 3b). The distribution of 15-min pedestrian-scale neighborhoods of all respondents is shown in the Figure 4.



(**a**) (**b**)

Figure 3. Calculation of residents' 15-min pedestrian-scale neighborhood. (**a**) Buffer area calculation. (**b**) 15-min pedestrian-scale neighborhoods calculation.

The Wuhan Urban GIS database provides measured data for built environment variables. We calculated built environment indicators within the respondents' 15-min pedestrian-scale neighborhood, including location, density, transit accessibility, land use diversity, and design. The mixed entropy index of land use considers six land types: residential, commercial, educational, industrial, public services, and green space. The supply of facilities in the 15-min pedestrian-scale neighborhood was divided into four categories, including educational facilities, medical facilities, shopping facilities and corporate/government departments. We used the POI density of these types of facilities to quantify the supply of facilities in the 15-min pedestrian-scale neighborhoods. The descriptive statistics of the variables are shown in Table 3.

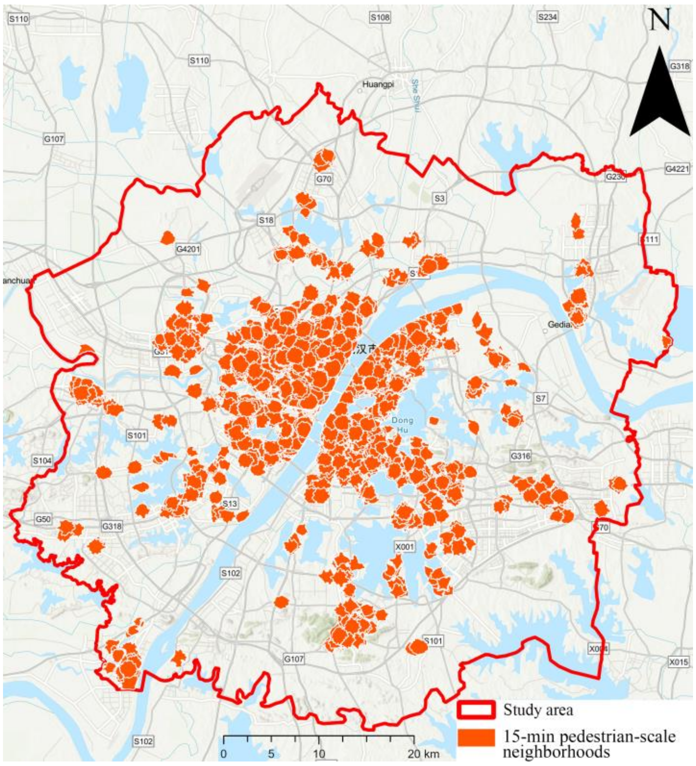


Figure 4. 15-min pedestrian-scale neighborhoods of all respondents.

Table 3. Descriptive statistics of variables.

Variables				Description	Mean.	Std.	Min	Max
Dependent variable	Commuting CO_2 emissions		Daily commute CO_2 emissions	Commuting carbon emissions per respondent per day (in grams)	808.666	895.367	0.000	11,043.740
Independent variable	Built environment	District Location	Distance from the city center	Distance to Hankou, the first-class urban center of Wuhan (in km)	9.135	7.400	0.134	38.805
		Public transport accessibility	Distance to nearest public transport stop	Distance (in km) from the respondent's residence to the nearest bus stop (both metro and surface bus)	0.240	0.334	0.002	9.461
			Number of public transport stations	Number of public transport stops within a 15-min pedestrian-scale neighborhood of the respondent	51.157	34.363	0.000	151.000
		Density	Population density	Residential density (persons/km^2) within a 15-min pedestrian-scale neighborhood of respondents	25,453.881	17,154.969	36.518	72,108.063
			Job density	Job density (persons/km^2) within a 15-min pedestrian-scale neighborhood of respondents	16,970.961	11,015.509	259.746	46,206.179
			Land use intensity	Floor area ratio of sites within a 15-min pedestrian-scale neighborhood of the respondent	3.108	1.428	0.010	5.972

Table 3. *Cont.*

Variables			Description	Mean.	Std.	Min	Max
	Design	Intersection density	Density of intersections of four or more roads within a 15-min pedestrian-scale neighborhood of respondents (pcs/km^2)	17.178	9.796	0.667	53.186
	Design	Road network density	Density of the road network within a 15-min pedestrian-scale neighborhood of the respondent (in km/km^2)	7.162	3.559	0.008	42.256
	Diversity	Land use mixed entropy index	Mixed entropy of land use within a 15-min pedestrian-scale neighborhood of respondents	0.695	0.097	0.000	0.967
Facility supply	Educational facilities	Density of schools and educational institutions	Density of schools and educational institutions POI points within a 15-min pedestrian-scale neighborhood of respondents	8.468	5.371	0.000	26.696
Facility supply	Medical facilities	Density of hospitals and other medical institutions	Density of hospitals and other medical institutions POI points within a 15-min pedestrian-scale neighborhood of respondents	7.739	5.735	0.000	25.280
Facility supply	Shopping facilities	Density of shopping malls and other shopping places	Density of shopping malls and other shopping places POI points within a 15-min pedestrian-scale neighborhood of respondents	7.677	5.000	0.000	26.691
Facility supply	Enterprise and government department	Density of enterprises and government departments	Density of enterprises and government departments POI points within a 15-min pedestrian-scale neighborhood of respondents	67.828	46.857	0.000	278.163
Economic characteristics		House price	Average of house prices within 15-min pedestrian-scale neighborhood (CNY)	17,130.571	5371.632	4881.000	44,688.000

3.3. Modeling Methods

3.3.1. Spatial Autocorrelation

1. Global spatial autocorrelation (Moran's I)

Moran's I is a widely used global index that measures the similarity for values in neighboring places from an overall mean value and reflects a spatially weighted form of Pearson's correlation coefficient [51–53]. Global spatial autocorrelation measures correlation based on the location and values of elements in the region [54,55]. For a given set of factors and their associated attributes, it determines whether they are clustered, discrete or randomly distributed. To explore the spatial autocorrelation of daily travel carbon emissions and the 15-min pedestrian-scale neighborhood built environment across the study area, we used the spatially autocorrelated Moran's I statistics. The formula is as follows:

$$I = \frac{n}{S_0} \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} W_{ij} Z_i Z_j}{\sum_{i=1}^{n} Z_i^2} \tag{4}$$

where Z_i is the deviation of the attribute of element i from its mean, w_{ij} is the spatial weight between elements i and j, we used the most common inverse distance weighting method to construct the spatial weight matrix, where both the spatial weights are the inverse of the ij Euclidean distance; n is equal to the total number of elements, and S_0 is the aggregation of all spatial weights. Moran's I values range from −1 to 1. When the value of Moran's I is greater than 0, this indicates that the variables are positively correlated in space. When the value is less than 0, this means that the variables are negatively correlated in space.

2. Local spatial autocorrelation (LISA)

In contrast to global spatial autocorrelation, local spatial autocorrelation calculates the spatial correlation between each spatial object and its neighbors in the analyzed area, calculates the differences of local characteristics in the distribution of spatial objects, and reflects the spatial heterogeneity and instability in the local area [55]. Since global autocorrelation assumes stationary spatial processes, it may obscure the properties of local autocorrelation of the data, so we further use the local spatial autocorrelation approach (LISA) to explore the local tethering features of the samples. The formula is as follows:

$$I_i = Z_i \sum_{i=1}^{n} W_{ij} Z_j \tag{5}$$

where Z_i and Z_j are the normalized values of the observations in spatial units i and j, respectively, and W_{ij} is the spatial weight. We also used the most common inverse distance weighting method to construct the spatial weight matrix.

3.3.2. Multi-Scale Geographically Weighted Regression (MGWR)

The GWR model can be adjusted to different parameters depending on the location, thus being able to clarify the spatially varying relationships between travel carbon emissions and the corresponding drivers [56]. A limitation of the GWR is that the bandwidth used in the model is constant across the study area and does not allow analysis of local relationships at different spatial scales [57]. The MGWR model solves this problem well. As an improvement to the GWR model, it selects smaller bandwidths for variables with large local variations and larger bandwidths for more stable variables, thus obtaining better fitting performance and more robust prediction results [57]. Considering that the relationship between carbon emissions and their influencing factors may vary with geographic location in different regions of the city, the MGWR model is further used based on OLS and ordinary GWR models. The model equation is as follows:

$$y_i = \beta_{bw0}(u_i,\ v_i) + \sum_{j=1}^{k} \beta_{bwj}\,(u_i, v_i) x_{ij} + \varepsilon_i \tag{6}$$

where x_{ij} is the jth predictor variable, (u_i, v_i) the coordinates of sample i, β_{bwj} represents the bandwidth of the regression coefficient of the jth variable, and ε_0 is the error term. $\beta_{bw0}(u_i,\ v_i)$ is the intercept.

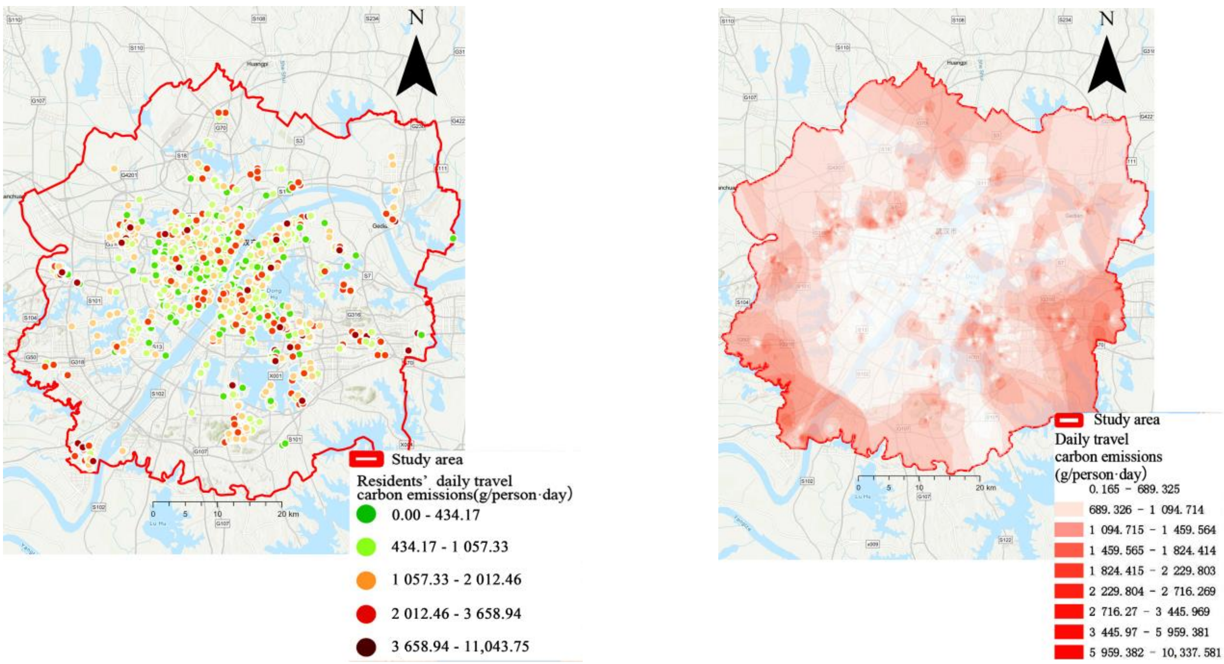
$$\omega_{ip} = \begin{cases} \left[1 - \left(\frac{d_{ip}}{b}\right)^2\right]^2, d_{ip} < d_{max} \\ 0,\ \ \text{otherwise} \end{cases} \tag{7}$$

where d_{ip} represents the distance between point i and p; b denotes the bandwidth describing the distance between regression point i and the j-th nearest neighbor. The magnitude of the bandwidth determines the decay rate of the distances in the weighting process. Thus, the bandwidth reflects the geographic spatial scale of the location being modeled, for the process considered [58].

4. Results

4.1. Spatial Pattern of Carbon Emissions from Daily Travel of Residents

The daily travel carbon emissions calculated in Section 3.2.1 were visualized and interpolated using the inverse distance weight method to obtain the spatial pattern of daily travel carbon emissions in Wuhan (Figure 5). The daily travel carbon emission value was classified into nine levels by the natural breaks method. The results show that the daily travel carbon emissions of Wuhan residents show a clear circle pattern of high periphery and low center. In other words, daily travel carbon emissions are like a "funnel" in space, the further away from the city center, the higher the daily travel carbon emissions (Figure 6). Obtaining this result is not surprising, as the daily travel distance for residents living in urban centers is likely to be shorter [8]. Because urban centers have better road systems and higher levels of public transportation services, residents are more likely to choose green travel modes, so they will have lower levels of daily travel carbon emissions. In addition, despite the recent trend of Wuhan developing in a multi-center mode, the occupation and residence functions of each cluster center have not yet been fully developed and cannot replace the top-level urban center. In the past two decades, due to the rapid urban expansion and the mismatch between public transportation development and excessive urbanization, many new districts have suffered from inadequate supply of public transportation facilities and poor service quality. At the same time, poor street conditions have caused unsafe and uncomfortable walking and cycling. Therefore, when people living in new areas want to reach the old city, many people prefer to drive. For example, the "Optics Valley High-tech District" in the eastern part of the city, a new high-tech district that the city has focused on in recent years, has relatively high carbon emissions for daily travel. This indicates that it has not yet been able to replace the old central city district as an independent center. This area still suffers from an imbalance in jobs and housing, inadequate public transport provision, and poor quality of street space, and people still need to drive further to the old city center for their daily activities. The high carbon emission levels of other peripheral group centers also support this argument.



(**a**) (**b**)

Figure 5. Spatial pattern of daily travel carbon emissions. (**a**) Distribution of respondents' daily travel carbon emissions. (**b**) Spatial pattern of respondents' daily travel carbon emissions.

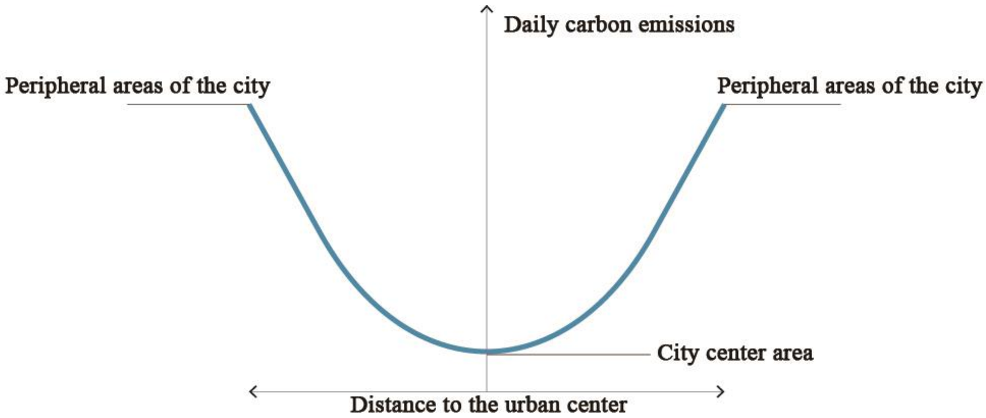


Figure 6. Spatial distribution of carbon emission values for daily travel.

4.2. Global Autocorrelation Analysis (Moran's I) of Daily Travel Carbon Emissions

Firstly, in order to investigate the spatial heterogeneity of different geographical location variables, the spatial distribution differences were tested for spatial effects before constructing the MGWR model. In this study, Moran's Index (I) test was introduced to determine whether daily travel carbon emissions are spatially autocorrelated. We also tested the spatial autocorrelation of other independent variables (Table 4). The global autocorrelation analysis was implemented with ArcGIS Pro 3.0 and the spatial weight matrix was constructed using the inverse distance weighting method.

Table 4. Moran 'I of variables.

Variables	Moran's I	Z Score	*p*-Value
Daily travel carbon emissions	0.236 *	53.253	0.000
Distance to the urban center	0.925 *	207.868	0.000
Distance to nearest public transport stop	0.326 *	76.697	0.000
Number of public transport stations	0.494 *	111.080	0.000
Population density	0.562 *	126.307	0.000
Job density	0.597 *	134.042	0.000
Land use intensity	0.595 *	133.728	0.000
Intersection density	0.518 *	116.371	0.000
Road network density	0.037 *	8.460	0.000
Land use mixed entropy index	0.212 *	47.604	0.000
Density of schools and educational institutions	0.445 *	99.883	0.000
Density of hospitals and other medical institutions	0.471 *	105.870	0.000
Density of shopping malls and other shopping places	0.447 *	100.412	0.000
Density of enterprises and government departments	0.453 *	101.702	0.000
House price	0.633 *	142.245	0.000

* The Z and *p* values used for spatial autocorrelation significance tests were obtained based on the assumption of normality.

The results of the spatial autocorrelation test show that the Moran's I of Wuhan daily travel carbon emissions is 0.236 and the Z Score is 53.253, with a p-value approximately equal to 0, passing the significance test (Table 4). It indicates that Wuhan residents' daily travel carbon emissions have significant spatial autocorrelation, and it is likely to be influenced by factors of different geographical locations to produce significant spatial divergence. Furthermore, similar spatial phenomena exist for other built environment variables. It is demonstrated that the use of regression models that consider spatial parameters is necessary for this study.

4.3. Local Autocorrelation Analysis (LISA) of Daily Travel Carbon Emissions

The local spatial autocorrelation of daily travel carbon emissions is shown in Figure 7. The local autocorrelation analysis was implemented with ArcGIS Pro 3.0 and the spatial weight matrix was constructed using the inverse distance weighting method. High daily travel carbon emission aggregation areas are mainly located in several clusters on the periphery of urban areas. These areas are late in development, with imperfect public facilities and a mismatch of job and housing. This creates more demand for long-distance daily travel, and due to the relative lack of public transportation facilities, people prefer to travel by private car [8,59,60], which in turn results in high levels of daily travel carbon emissions. Low-value carbon agglomerations are mainly located in the urban center, where the road system and public transportation facilities have been developed over a long period of time to a higher level, with better public services and a better balance of jobs and housing. As a result, people travel shorter distances on a daily basis and are more likely to choose public transportation or walk and ride [4,8]. In addition, the urban center contains a number of high emission areas surrounded by low carbon emission areas. These areas are mainly urban core business districts, or neighborhoods where high-income groups congregate. High incomes cause people living in these areas to be more likely to choose high-carbon emission daily travel modes [3,15,16]. The main reason is that high-income residents are more concerned about the efficiency and comfort of travel than the monetary cost of travel. Therefore, point-to-point driving can better meet the travel needs of high-income residents than public transportation that requires waiting for transfers and is congested. In addition, as mentioned above, in China, high-income people also consider traveling by car as a symbol of their social status, and thus their travel carbon emissions are higher.

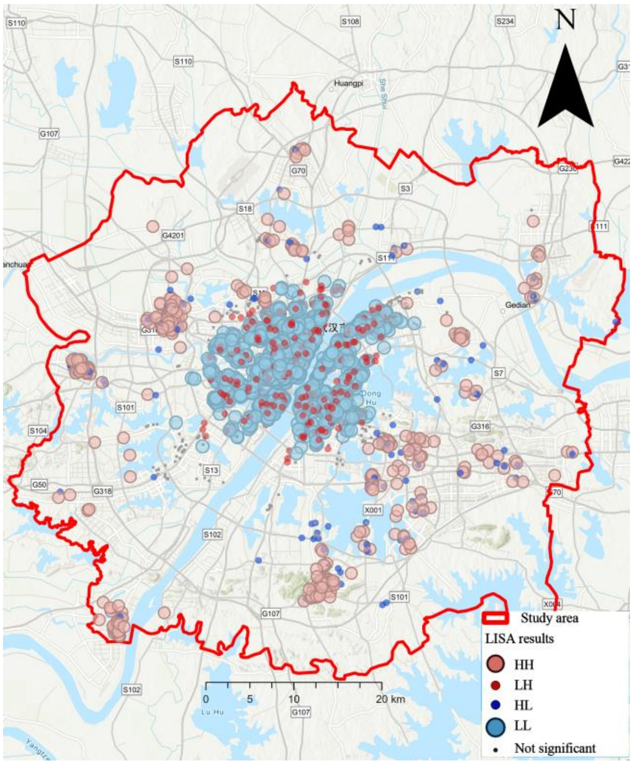


Figure 7. LISA cluster map of daily travel carbon emissions. HH = high-value concentration area; HL = high-value area surrounded by low-value areas; LH = low-value area surrounded by high-value areas; LL = low-value concentration area.

4.4. Heterogeneous Influence Mechanism of the 15-min Pedestrian-Scale Neighborhood Built Environment on Residents' Daily Travel Carbon Emission

The R^2 of the MGWR model is 0.310, which is better than the goodness of fit of the global linear regression model (0.232). This indicates that for this study, the MGWR model performs better. The results show that the effect of each independent variable on carbon emissions varies in different spatial locations. To reveal the spatial heterogeneity of the association between variables, we further interpolated the regression coefficients of each independent variable spatially using the IDW method. To test the significance of the results, we interpolated the t-values for each sample using the IDW method as well. In the interpolation results, regions with absolute values of t-values less than 1.96 are not significant at the 5% confidence level and we have marked these regions. The results are shown in Figures 8 and 9.

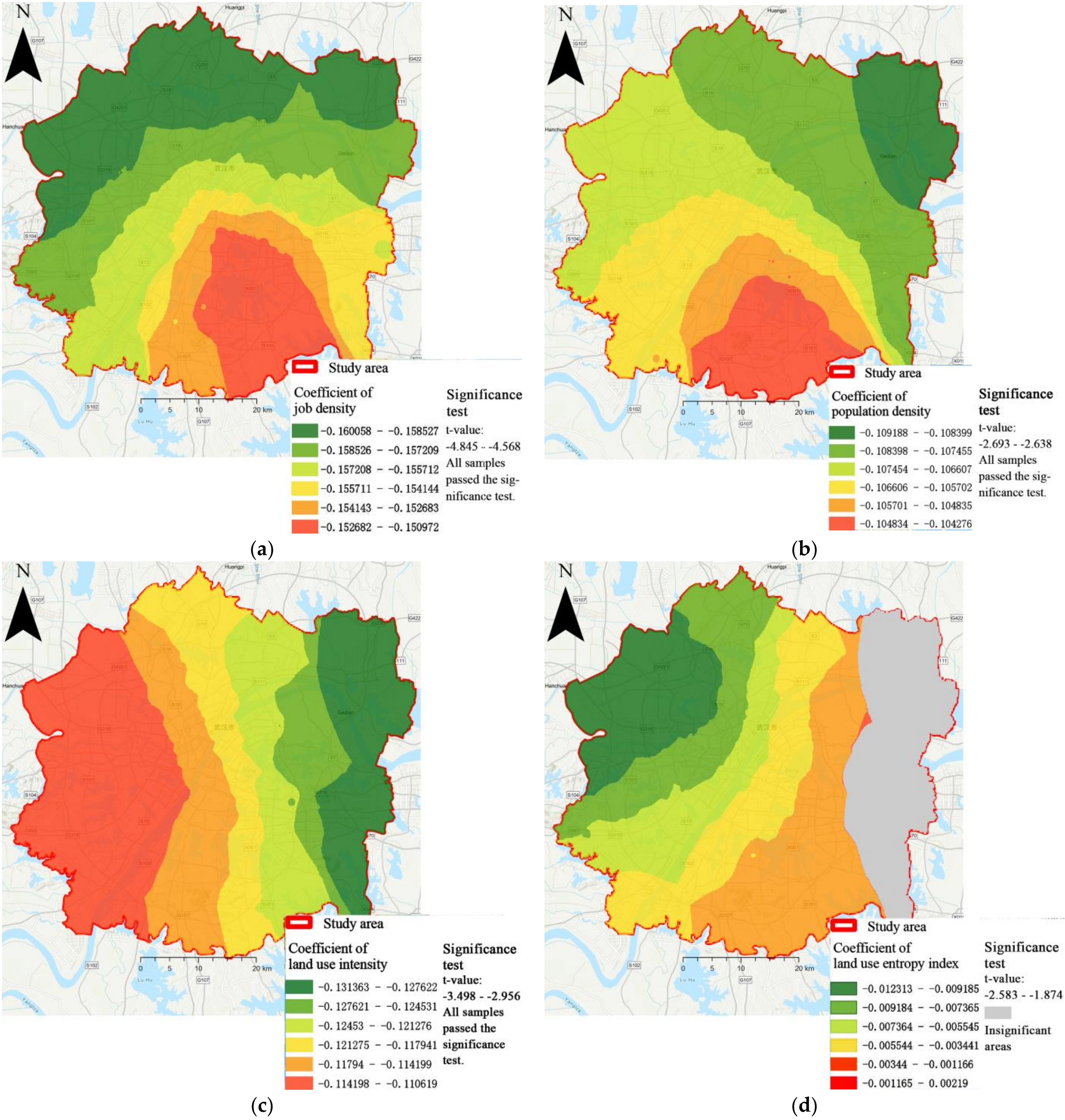
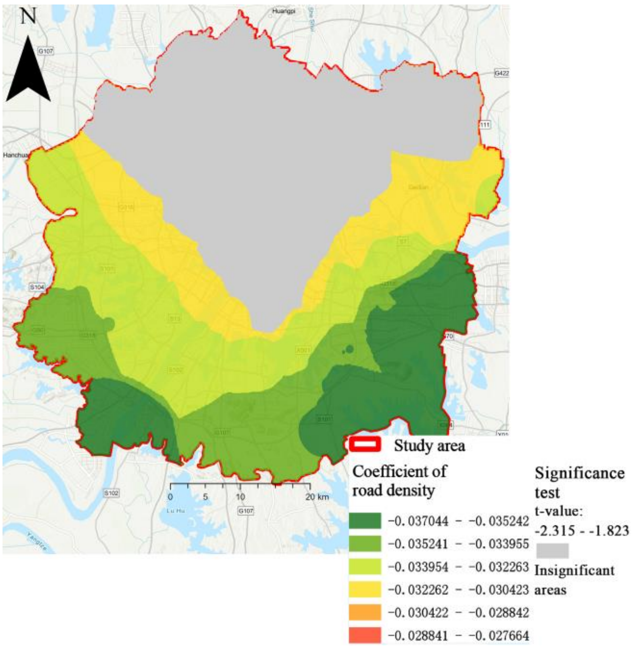
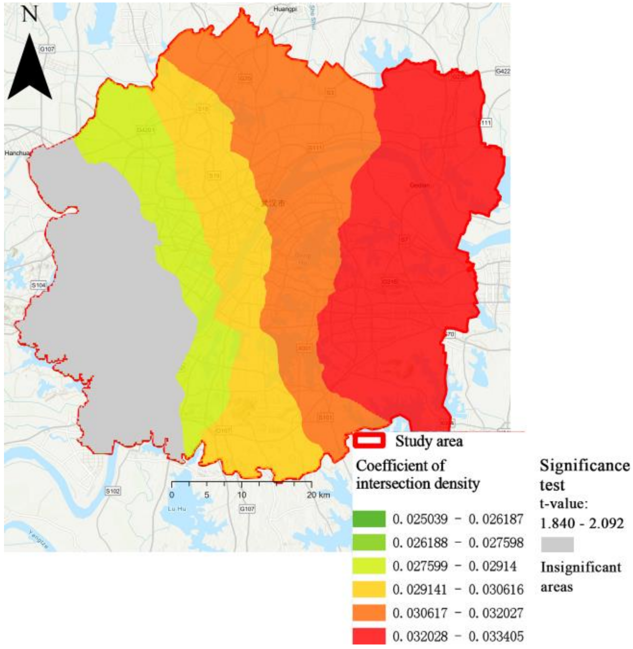


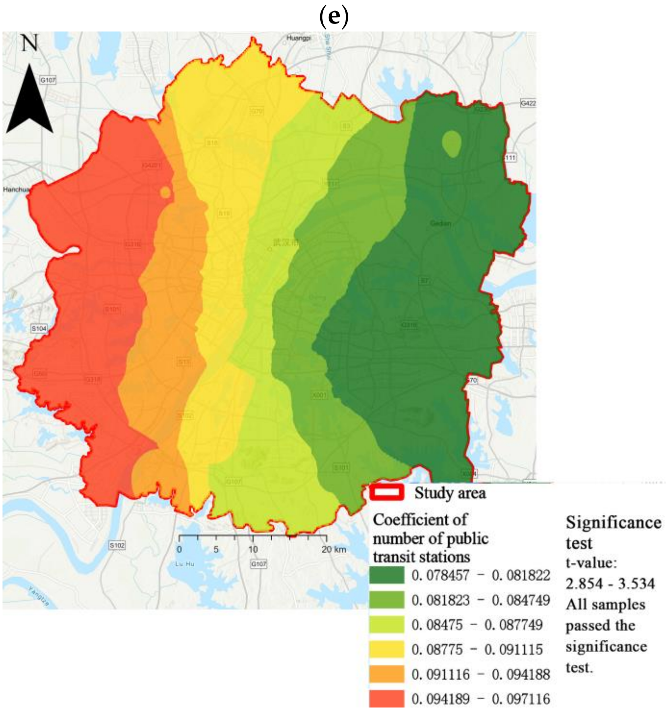
Figure 8. *Cont*.



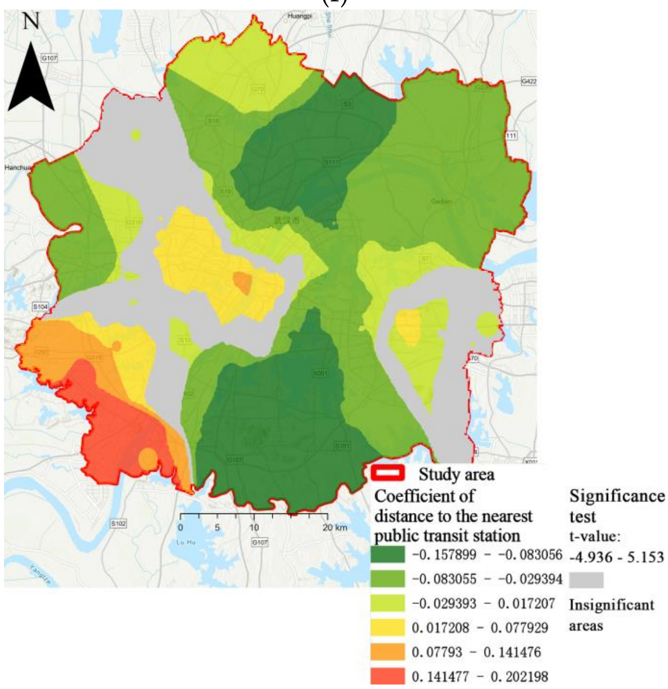
(**e**)



(**f**)

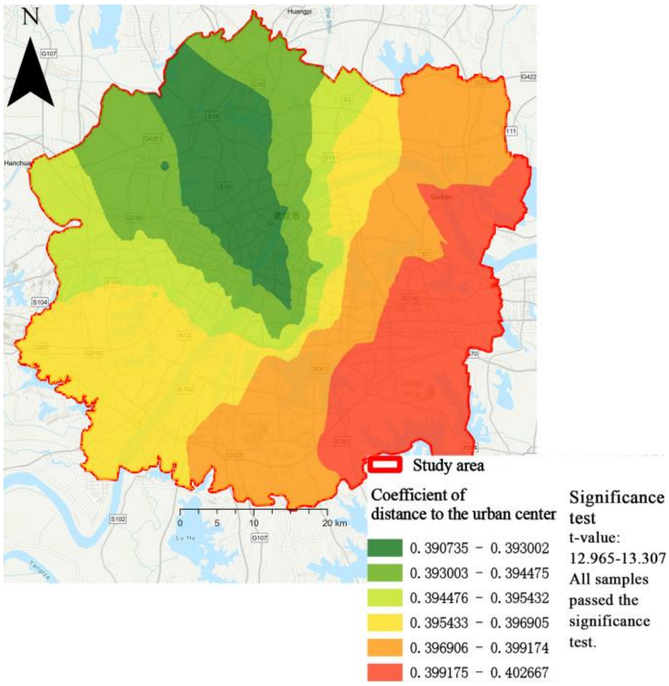


(**g**)



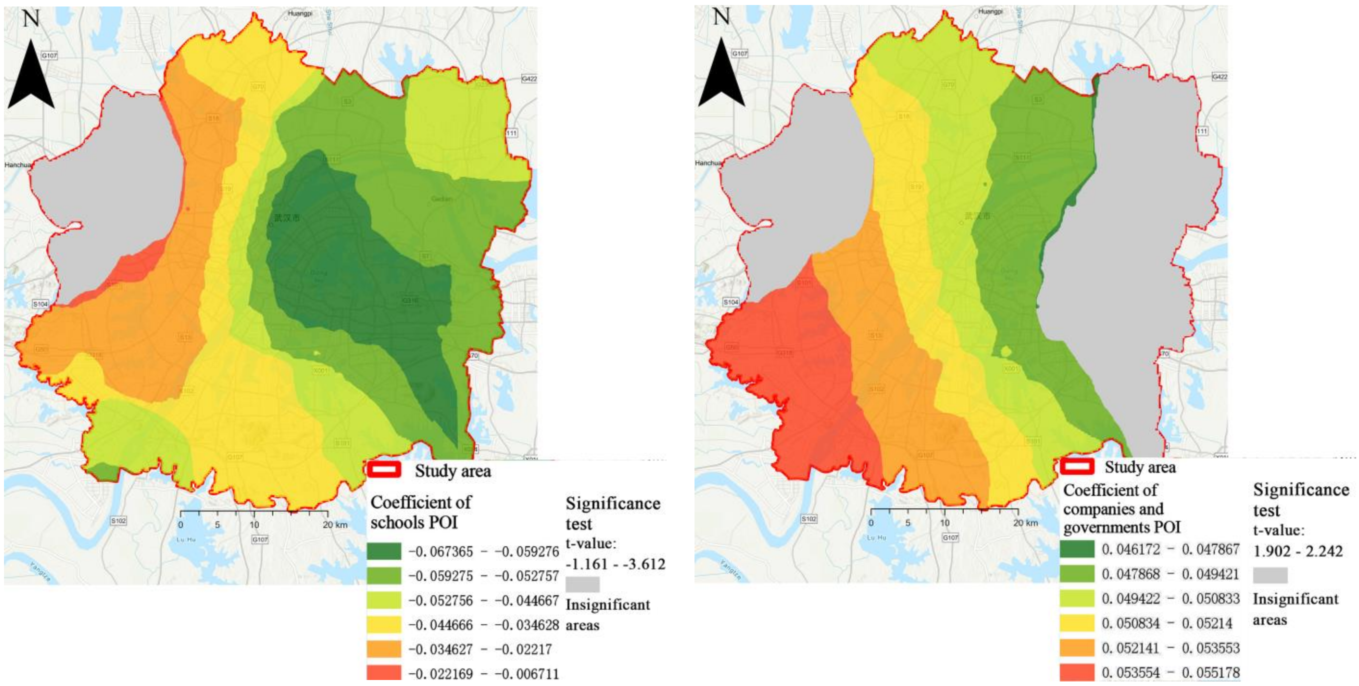
(**h**)

Figure 8. *Cont*.



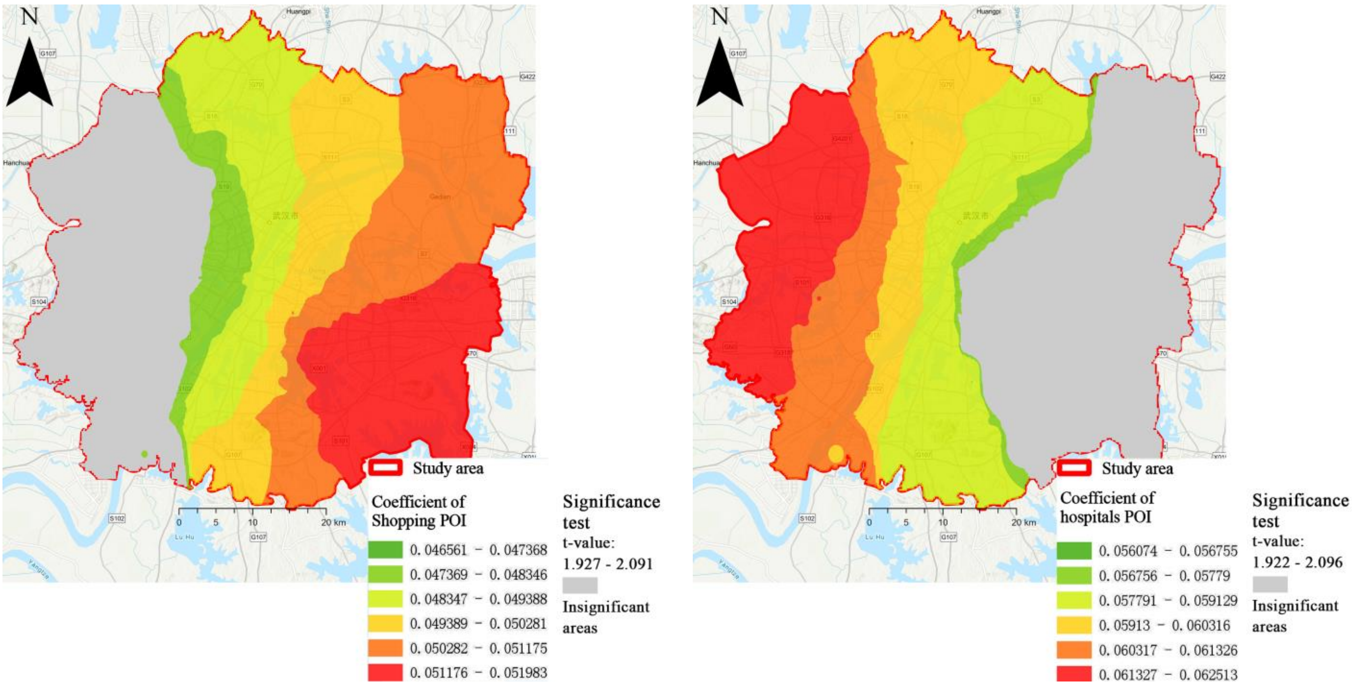
(**i**) (**j**)

Figure 8. Spatial distribution of coefficients for the effects of 15-min pedestrian-scale neighborhood built environment and house prices on daily travel carbon emissions. (**a**) Coefficient of job density; (**b**) Coefficient of population density; (**c**) Coefficient of land use entropy index; (**d**) Coefficient of land use intensity; (**e**) Coefficient of road density; (**f**) Coefficient of intersection density; (**g**) Coefficient of number of public transit stations; (**h**) Coefficient of distance to the nearest public transit station; (**i**) Coefficient of distance to the urban center; (**j**) Coefficient of house prices.



(**a**) (**b**)

Figure 9. *Cont*.



(**c**) (**d**)

Figure 9. Spatial distribution of coefficients for the effects of 15-min pedestrian-scale neighborhood facilities supply on daily travel carbon emissions. (**a**) Coefficient of schools density; (**b**) Coefficient of companies and governments density; (**c**) Coefficient of shopping facility density; (**d**) Coefficient of medical facility density.

4.4.1. Spatial Heterogeneity of the 15-min Pedestrian-Scale Neighborhood Built Environment on the Impact of Daily Travel Carbon Emissions

In terms of population and job density, in general, they were negatively correlated with daily travel carbon emissions, similar to the findings of established studies [37,38]. All samples passed the significance test. However, their impact on carbon emissions differs in space (Figure 8a,b). Specifically, the degree of negative effect of job density on daily travel carbon emissions decreased from northwest to southeast, while the negative effect of population density decreased from northeast to south. The magnitude of the elasticity coefficients of the two was close.

Figure 8c,d shows the spatial distribution of the effects of two important land use indicators, land use mix and intensity, on the carbon emissions of daily travel. Land use intensity was more influential than land use mix. Overall, these two variables were also negatively correlated with daily travel carbon emissions. However, the spatial distribution of the two effects was opposite, with the negative effect of land use intensity decreasing from east to west and the negative effect of land use mixture decreasing from west to east, with a weak local positive correlation. However, for land use intensity, all samples passed the significance test. For land use mix, the sample from a small area in the east did not pass the significance test.

The effects of two elements of the urban design dimension, road network density and intersection density, are shown in Figure 8e,f. Road density was negatively correlated with daily travel carbon emissions overall, and the degree of negative correlation increases from north to south. Intersection density was positively correlated with daily travel carbon emissions, which was different to the findings of existing studies [39]. The positive effect of intersection density increases from west to east. For road density, an area in the north did not pass the significance test. A small area in the west did not pass the significance test for intersection density.

In terms of public transportation (Figure 8g,h), unlike the findings of studies in developed countries [38], the number of bus stations within the 15-min pedestrian-scale neighborhood was weakly positively correlated with daily travel carbon emissions this finding is similar to that of Xiao et al. [45] in Beijing and differs from those of Western countries. We found that with more transit stops, the expected reduction in travel carbon emissions did not occur, but rather a small increase. This may be attributed to the fact that although the unit carbon emissions of buses (50 g/km·person) are lower compared to cars (135 g/km·person), they are higher than rail (9.1 g/km·person) and electric vehicles (8 g/km·person). This relatively high emission coefficient results in a weak positive marginal effect of the number of bus stops and travel carbon emissions. Although buses are undergoing an "electrification revolution" in China, a large number of buses are still fuel-powered, and our empirical study illustrates the necessity of promoting the use of clean energy in buses for carbon reduction. The distance to the nearest bus stop was also positively correlated with daily travel carbon emissions overall, because the further away from the bus stop, the less likely people are to choose public transportation due to inconvenience, resulting in an increase in carbon emissions. The degree of influence of bus stations within the 15-min pedestrian-scale neighborhood increases from east to west, and the degree of influence of the distance to the nearest bus stop was spatially scattered. For the number of public transit stations, all samples passed the significance test. For distance to the nearest transit station, several small patches in the west, center and east did not pass the significance test.

The distance to the city center was positively correlated with daily travel carbon emissions, and as many established studies have found the same pattern, the closer to the city center, the shorter the distance residents are likely to travel on a daily basis, and the degree of its effect increases from northwest to southeast (Figure 8i). For distance to the urban center, all samples passed the significance test. The impact of house prices was also positive, with the degree of positive impact increasing from west to east (Figure 8j). For house prices, all samples passed the significance test. House prices are to some extent indicative of the economic level of the residents. The highest impact values were found in the eastern part of the city, in the high-tech zone, where residents have higher income levels, are mostly full-time employees, have longer commuting distances and prefer to travel by car.

4.4.2. Spatial Heterogeneity of the 15-min Pedestrian-Scale Neighborhood Facilities Supply on the Impact of Daily Travel Carbon Emissions

Figure 9 illustrates the spatial differentiation of the impact of four types of public service facilities within a 15-min pedestrian-scale neighborhood on daily travel carbon emissions. Overall, except for schools, all three types of public facilities within the 15-min pedestrian-scale neighborhood showed a weak positive correlation with daily carbon emissions. The negative correlation between school facilities and daily travel carbon emissions emerges as a core in the eastern part of the city, with the negative correlation decreasing from east to west in the other regions (Figure 9a). However, there is a small area in the west that did not pass the significance test. The degree of influence of companies and government departments on the daily travel carbon emissions increases from east to west (Figure 9b). One area in the east and one area in the west did not pass the significance test. The degree of impact of medical facilities also increases from east to west (Figure 9d). There is an area in the east that did not pass the significance test. Conversely, the degree of influence of shopping facilities on daily travel carbon emissions increases from west to east (Figure 9c). There is an area in the west that did not pass the significance test. These results suggest that the spatial differentiation of the impact of different types of facilities on the daily travel carbon emissions varies.

5. Conclusions and Discussion

This study used a disaggregate dataset of 2814 samples covering the entire Wuhan metropolitan area and employed the spatial autocorrelation and MGWR methods to investigate spatial heterogeneity of daily travel carbon emissions. The results showed that there is a significant spatial dependence of residents' daily travel carbon emissions. This study also explored the spatial variation of the effect of the built environment on the daily travel carbon emissions in 15-min pedestrian-scale neighborhoods. It specifically contributes to the literature in three ways: (1) Examined the spatial heterogeneity of daily travel carbon emissions in metropolitan areas and described its spatial pattern in detail. (2) Measured the built environment elements that affect the residents' daily travel carbon emissions based on the 15-min pedestrian-scale neighborhood where they actually traveled. (3) Quantified the spatial heterogeneity in the extent and direction of the impact of the built environment on the daily travel carbon emissions in the 15-min pedestrian-scale neighborhood. In general, it fills the gap in the literature on the spatial heterogeneity of carbon emissions from residents' daily travels and the spatial heterogeneity of the association between the 15-min pedestrian-scale neighborhood built environment and the daily travel carbon emissions.

This study reached a similar conclusion as the existing studies, that the built environment is closely related to travel carbon emissions, and the results further confirm that the built environment of the 15-min pedestrian-scale neighborhood is also significant for travel carbon emissions. Specifically, among the 5D built environment elements of the 15-min pedestrian-scale neighborhood, density, diversity, road network and intersection density are all negatively associated with daily travel carbon emissions. However, for public transportation, two key indicators, the number of bus stops and transit accessibility, are positively correlated with carbon emissions. This result is in line with the findings of another study conducted in China [45] and contrary to the findings of most studies [6,38]. In the future, promoting changes in the electrification of public transportation may be a good way to reduce carbon emissions from travel. Furthermore, as many established studies have concluded, moderately increasing land use density and mix, improving road networks and street connectivity, and improving the quality of pedestrian and cycling space are critical to promote green travel.

In addition, except for school facilities, all other facility densities in the 15-min pedestrian-scale neighborhood have a weak positive correlation with daily travel carbon emissions. This is due to the fact that these public facilities serve as daily travel destinations and schools mainly contribute to students' travel behavior. In China, schools are allocated as a basic unit of 15-min pedestrian-scale neighborhood, and students mostly go to school by walking or cycling nearby, and these activities are low-carbon travel behaviors, thus causing a negative correlation between schools and daily travel carbon emissions. It is commonly believed that the denser the public facility, the lower the carbon emissions, and our empirical study proves that this negative correlation may not be definitive. This study shows that facility density is positively correlated with carbon emissions in a significant portion of the area; therefore, an unlimited increase in public service facilities in the 15-min pedestrian-scale neighborhood is not the best choice. Of course, as mentioned above, none of these effects are global, but rather there is significant spatial differentiation, and the present study examines these phenomena in detail.

This study also contributes to the theory of low carbon 15-min pedestrian-scale neighborhood planning in China. On the one hand, it demonstrates the spatial dependence of residents' daily travel carbon emissions, and it further confirms the applicability of the "residential self-selection" theory in Chinese cities. On the other hand, it demonstrates that the effect of the built environment on travel carbon emissions is not spatially homogeneous but spatially heterogeneous. It is necessary to consider the spatial parameters of the elements in the method of studying similar scientific problems.

The empirical results of this study have important implications for megacity planning in China. The study showed that due to spatial effects, different planning policies should be applied in different regions to achieve carbon reduction more efficiently. In recent years, Wuhan has been committed to improving the built environment of 15-min pedestrian-scale neighborhoods and promoting green travel for residents to reduce their carbon emissions from daily trips, and the results of our empirical study can provide precise guidance for specific planning efforts.

In addition, the empirical methodology of this study can be applied to other developing countries with similar urban conditions as China. This study, however, has several limitations: (1) Because the study uses cross-sectional data from a residential travel survey, the findings of this study are closer to an "association" than to a causal "effect." This is similar to most current studies and should be further explored in the future using data over time. (2) Since there is a hierarchy of public facilities, there may be some city-level public facilities in the 15-min pedestrian-scale neighborhood besides those just meeting daily activities, which may cause some interference to the study, but due to the difficulty of data acquisition, this study cannot investigate the impact of these POIs on carbon emissions in a hierarchical manner. (3) As the sample collection is based on the actual population distribution, the sample is larger in the central city and smaller in the peripheral areas, and the distribution of the sample does not cover the whole study area, which may lead to less accurate results of the MGWR model in the peripheral areas.

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References

1. IEA. *CO_2 Emissions from Fuel Combustion Highlights*; IEA: Paris, France, 2019.
2. Yang, S.; He, L.Y. Fuel demand, road transport pollution emissions and residents' health losses in the transitional China. *Transp. Res. Part D Transp. Environ.* **2016**, *42*, 45–59. [CrossRef]
3. Cao, X.; Yang, W. Examining the effects of the built environment and residential self-selection on commuting trips and the related CO_2 emissions: An empirical study in Guangzhou, China. *Transp. Res. Part D Transp. Environ.* **2017**, *52*, 480–494. [CrossRef]
4. Wu, X.; Tao, T.; Cao, J.; Fan, Y.; Ramaswami, A. Examining threshold effects of built environment elements on travel-related carbon-dioxide emissions. *Transp. Res. Part D Transp. Environ.* **2019**, *75*, 1–12. [CrossRef]
5. Ao, Y.; Zhou, Z.; Wang, Y. Progress of research on the impacts of built environment on travel carbon emissions. *Sci. Technol. Rev.* **2022**, *40*, 94–105.
6. Ewing, R.; Cervero, R. Travel and the Built Environment. *J. Am. Plan. Assoc.* **2010**, *76*, 265–294. [CrossRef]
7. Stevens, M.R. Does Compact Development Make People Drive Less? *J. Am. Plan. Assoc.* **2016**, *83*, 7–18.
8. Zhang, W.; Lu, D.; Zhao, Y.; Luo, X.; Yin, J. Incorporating polycentric development and neighborhood life-circle planning for reducing driving in Beijing: Nonlinear and threshold analysis. *Cities* **2022**, *121*, 103488. [CrossRef]
9. Allam, Z.; Nieuwenhuijsen, M.; Chabaud, D.; Moreno, C. The 15-minute city offers a new framework for sustainability, liveability, and health. *Lancet Planet. Health* **2022**, *6*, E181–E183. [CrossRef]
10. Moreno, C.; Allam, Z.; Chabaud, D.; Gall, C.; Pratlong, F. Introducing the "15-Minute City": Sustainability, Resilience and Place Identity in Future Post-Pandemic Cities. *Smart Cities* **2021**, *4*, 93–111. [CrossRef]

11. Xiao, Z.; Chai, Y.; Yan, Z. Overseas Life Circle Planning and Practice. *Planners* **2014**, *10*, 93–94.
12. Yifan, Y.U. From Traditional Residential Area Planning to Neighborhood Life Circle Planning. *City Plan. Rev.* **2019**, *43*, 17–22.
13. Wu, H.; Wang, L.; Zhang, Z.; Gao, J. Analysis and optimization of 15-minute community life circle based on supply and demand matching: A case study of Shanghai. *PLoS ONE* **2021**, *16*, e0256904. [CrossRef]
14. Luo, X.; Zhang, W.; Chai, Y. Research on threshold effects of built environment settings in 15-minute life-circles. *Geogr. Res.* **2022**, *41*, 2155–2170.
15. Yang, W.; Cao, X. Examining the effects of the neighborhood built environment on CO_2 emissions from different residential trip purposes: A case study in Guangzhou, China. *Cities* **2018**, *81*, 24–34. [CrossRef]
16. Ma, J.; Liu, Z.; Chai, Y. The impact of urban form on CO_2 emission from work and non-work trips: The case of Beijing, China. *Habitat Int.* **2015**, *47*, 1–10. [CrossRef]
17. Zhou, M.; Wang, D.; Guan, X. Co-evolution of the built environment and travel behaviour in Shenzhen, China. *Transp. Res. Part D Transp. Environ.* **2022**, *107*, 103291. [CrossRef]
18. Cao, J. Examining the Relationship between Neighborhood Built Environment and Travel Behavior: A Review from the US Perspective. *Urban Plan. Int.* **2015**, *30*, 46–52.
19. Wang, D.; Lin, T. Residential self-selection, built environment, and travel behavior in the Chinese context. *J. Transp. Land Use* **2014**, *7*, 5–14. [CrossRef]
20. Guan, X.D.; Wang, D.G. Residential self-selection in the built environment-travel behavior connection: Whose self-selection? *Transp. Res. Part D-Transp. Environ.* **2019**, *67*, 16–32. [CrossRef]
21. Wolday, F.; Næss, P.; Cao, X.Y. Travel-based residential self-selection: A qualitatively improved understanding from Norway. *Cities* **2019**, *87*, 87–102. [CrossRef]
22. Ding, C.; Cao, X.; Yu, B.; Ju, Y. Non-linear associations between zonal built environment attributes and transit commuting mode choice accounting for spatial heterogeneity. *Transp. Res. Part A Policy Pract.* **2021**, *148*, 22–35. [CrossRef]
23. Rong, P.; Zhang, L.; Qin, Y.; Xie, Z.; Li, Y. Spatial differentiation of daily travel carbon emissions in small- and medium-sized cities: An empirical study in Kaifeng, China. *J. Clean. Prod.* **2018**, *197*, 1365–1373. [CrossRef]
24. Liu, T.B.; Chai, Y.W. Daily life circle reconstruction: A scheme for sustainable development in urban China. *Habitat Int.* **2015**, *50*, 250–260. [CrossRef]
25. Gower, A.; Grodach, C. Planning Innovation or City Branding? Exploring How Cities Operationalise the 20-Minute Neighbourhood Concept. *Urban Policy Res.* **2022**, *40*, 36–52.
26. Balletto, G.; Ladu, M.; Milesi, A.; Borruso, G. A Methodological Approach on Disused Public Properties in the 15-Minute City Perspective. *Sustainability* **2021**, *13*, 593. [CrossRef]
27. Abdelfattah, L.; Deponte, D.; Fossa, G. The 15-minute city: Interpreting the model to bring out urban resiliencies. *Transp. Res. Procedia* **2022**, *60*, 330–337.
28. Sisson. How the '15-Minute City' Could Help Post-Pandemic Recovery. *Bloom. CityLab* **2020**, *16*, 2020.
29. *GB50180-2018*; Standard for Urban Residential Area Planning and Design. National standards of the People's Republic of China, Ministry of Housing and Urban-Rural Development: Beijing, China, 2018.
30. Shen, Z.; Lin, X.; Yan, M. On the Combination of Japanese Urban Master Plan and "Life Circle" Concept in Recent Years. *Urban Rural. Plan.* **2018**, *6*, 74–87.
31. Huang, J.; Zhang, R.; Gangyu, H. A Research of the Elderly's Daily Life Circle Based on Spatial-Temporal Behavior—Analysis of Place Recognition and Spatial Features. *Urban Plan. Forum* **2019**, *3*, 87–95. [CrossRef]
32. Zhao, P.; Luo, J.; Hu, H. Character of the Elderly's Life Circle and Public Service Facilities Configuration by Using Big Data: A Case of Beijing. *Sci. Geogr. Sin.* **2022**, *42*, 1176–1186.
33. Ewing, R.; Cervero, R. Travel and the built environment—A synthesis. *Transp. Res. Rec.* **2001**, *1780*, 87–114. [CrossRef]
34. Cao, X.; Mokhtarian, P.L.; Handy, S.L. The relationship between the built environment and nonwork travel: A case study of Northern California. *Transp. Res. Part A Policy Pract.* **2009**, *43*, 548–559. [CrossRef]
35. Handy, S.L.; Boarnet, M.G.; Ewing, R.; Killingsworth, R.E. How the built environment affects physical activity: Views from urban planning. *Am. J. Prev. Med.* **2002**, *23*, 64–73. [CrossRef]
36. Cervero, R.; Kockelman, K. Travel Demand and the 3Ds: Density, Design And Diversity. *Transp. Res. Part D Transp. Environ.* **1997**, *2*, 199–219. [CrossRef]
37. Brownstone, D.; Golob, T.F. The impact of residential density on vehicle usage and energy consumption. *J. Urban Econ.* **2009**, *65*, 91–98. [CrossRef]
38. Barla, P.; Miranda-Moreno, L.F.; Lee-Gosselin, M. Urban travel CO_2 emissions and land use: A case study for Quebec City. *Transp. Res. Part D Transp. Environ.* **2011**, *16*, 423–428. [CrossRef]
39. Xin, W.; Khattak, A.; Zhang, Y. Is Smart Growth Associated with Reductions in Carbon Dioxide Emissions? *Transp. Res. Rec. J. Transp. Res. Board* **2013**, *2375*, 62–70.
40. Zahabi, S.A.H.; Miranda-Moreno, L.; Patterson, Z.; Barla, P. Transportation Greenhouse Gas Emissions and its Relationship with Urban Form, Transit Accessibility and Emerging Green Technologies: A Montreal case study. In Proceedings of the 15th Meeting of the Euro-Working-Group-on-Transportation (EWGT), Cite Descartes, Paris, France, 10–13 September 2012.
41. Hong, J.; Goodchild, A. Land use policies and transport emissions: Modeling the impact of trip speed, vehicle characteristics and residential location. *Transp. Res. Part D Transp. Environ.* **2014**, *26*, 47–51. [CrossRef]

42. Yang, W.Y.; Li, T.; Cao, X. Examining the impacts of socio-economic factors, urban form and transportation development on CO_2 emissions from transportation in China: A panel data analysis of China's provinces. *Habitat Int.* **2015**, *49*, 212–220. [CrossRef]
43. Cervero, R.B. Linking urban transport and land use in developing countries. *J. Transp. Land Use* **2013**, *6*, 7–24. [CrossRef]
44. Yang, J.; He, D.-Q.; Christopher, Z. Impact of Neighborhood Land Use on Residents Travel Energy Consumption Urban Transp. *China* **2011**, *9*, 21–29.
45. Xiao, Z.P.; Chai, Y.; Liu, Z. Quantitative Distribution and Related Factors for Household Daily Travel CO_2 Emissions in Beijing. *Urban Stud.* **2011**, *18*, 104–112.
46. Wang, Y.; Chen, W.; Kang, Y.; Li, W.; Guo, F. Spatial correlation of factors affecting CO_2 emission at provincial level in China: A geographically weighted regression approach. *J. Clean. Prod.* **2018**, *184*, 929–937. [CrossRef]
47. Li, C.; Li, H.; Qin, X. Spatial Heterogeneity of Carbon Emissions and Its Influencing Factors in China: Evidence from 286 Prefecture-Level Cities. *Int. J. Environ. Res. Public Health* **2022**, *19*, 1226. [CrossRef] [PubMed]
48. Ding, C.; Cao, X.; Næss, P. Applying gradient boosting decision trees to examine non-linear effects of the built environment on driving distance in Oslo. *Transp. Res. Part A Policy Pract.* **2018**, *110*, 107–117. [CrossRef]
49. Ding, C.; Cao, X.; Wang, Y. Synergistic effects of the built environment and commuting programs on commute mode choice. *Transp. Res. Part A Policy Pract.* **2018**, *118*, 104–118. [CrossRef]
50. World Resources Institute. *Wuhan Transport Sector Carbon Emissions Roadmap Study*; World Resources Institute: Washington, DC, USA, 2019.
51. Rogerson, P.A. The Detection of Clusters Using a Spatial Version of the Chi-Square Goodness-of-Fit Statistic. *Geogr. Anal.* **1999**, *31*, 130–147. [CrossRef]
52. Jackson, M.C.; Waller, L. Exploring goodness-of-fit and spatial correlation using components of Tango's index of spatial clustering. *Geogr. Anal.* **2005**, *37*, 371–382. [CrossRef]
53. Jackson, M.; Huang, L.; Xie, Q.; Tiwari, R. A modified version of Moran's I. *Int. J. Health Geogr.* **2010**, *9*, 33. [CrossRef]
54. Ord, J.K.; Getis, A. Testing for Local Spatial Autocorrelation in the Presence of Global Autocorrelation. *J. Reg. Sci.* **2001**, *41*, 411–432. [CrossRef]
55. Fan, C.; Myint, S. A comparison of spatial autocorrelation indices and landscape metrics in measuring urban landscape fragmentation. *Landsc. Urban Plan.* **2014**, *121*, 117–128. [CrossRef]
56. Brunsdon, C.; Fotheringham, A.S.; Charlton, M.E. Geographically Weighted Regression: A Method for Exploring Spatial Nonstationarity. *Geogr. Anal.* **1996**, *28*, 281–298. [CrossRef]
57. Yu, H.; Fotheringham, A.S.; Li, Z.; Oshan, T.; Kang, W.; Wolf, L.J. Inference in Multiscale Geographically Weighted Regression. *Geogr. Anal.* **2019**, *52*, 87–106. [CrossRef]
58. Yang, W.; Fotheringham, A.; Harris, P. An Extension of Geographically Weighted Regression with Flexible Bandwidths. In Proceedings of the GISRUK 2012, Lancaster, UK, 11–13 April 2012.
59. Zang, P.; Qiu, H.; Xian, F.; Yang, L.; Qiu, Y.; Guo, H. Nonlinear Effects of the Built Environment on Light Physical Activity among Older Adults: The Case of Lanzhou, China. *Int. J. Environ. Res. Public Health* **2022**, *19*, 8848. [CrossRef]
60. Hu, Y.; Sobhani, A.; Ettema, D. Exploring commute mode choice in dual-earner households in a small Chinese city. *Transp. Res. Part D Transp. Environ.* **2021**, *102*, 103148. [CrossRef]