Essay

Exploring the Joint Impacts of Natural and Built Environments on PM_{2.5} Concentrations and Their Spatial Heterogeneity in the Context of High-Density Chinese Cities

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Abstract: Air pollution in China has attracted wide interest from the public and academic communities. PM_{2.5} is the primary air pollutant across China. PM_{2.5} mainly comes from human activities, and the natural environment and urban built environment affect its distribution and diffusion. In contrast to American and European cities, Chinese cities are much denser, and studies on the relationships between urban form and air quality in high-density Chinese cities are still limited. In this paper, we used the ordinary least square (OLS) and geographical weighted regression (GWR) models, selected an already high-density city, Shenzhen, as the study area, and explored the effects of the natural and built environments on air pollution. The results showed that temperature always had a positive influence on PM_{2.5} and wind speed had a varied impact on PM_{2.5} within the city. Based on the natural factors analysis, the paper found that an increase in the floor area ratio (FAR) and road density may have caused the increase in the PM_{2.5} concentration in the central city. In terms of land use mix, land use policies should be adopted separately in the central city and suburban areas. Finally, in terms of spatial heterogeneity, the GWR models achieved much better performances than the global multivariate regression models, with lower AICc and RMSE values and higher adjusted *R*² values, ultimately explaining 60% of the variance across different city areas. The results indicated that policies and interventions should be more targeted to improve the air environment and reduce personal exposure according to the spatial geographical context.

Keywords: natural and built environment; PM_{2.5} concentrations; spatial heterogeneity

1. Introduction

In China, rapid urbanization and motorization in recent decades have not only brought about economic development but also caused serious urban environmental problems. The early 2010s was the most severe and persistent period of haze pollution nationwide. Since then, PM_{2.5} has become the main pollutant of interest in atmospheric pollution control in China. Several studies concerning the characteristics and sources of PM_{2.5} have been conducted in recent years. How to effectively reduce the distribution of air pollution and minimize its adverse exposure to citizens has therefore been one of the key issues for researchers and policy makers. Many scholars have conducted useful explorations and accumulated a large number of experiences, including different research scales (e.g., national scale, regional and urban scales and microscale of blocks) and research perspectives (e.g., the causes, prediction, and simulation of PM_{2.5} and its relationship with socioeconomic factors, urbanization, urban form and built environment). Meanwhile, with economic transformation and air pollution control, the national air environment quality has improved significantly. According to the new Ambient Air Quality Standards (GB 3095-2012) published in March 2012, the number of cities that failed to meet the standards decreased from 265 (2015) to 135 (2020), and the number of cities that met the standards

increased from 73 (2015) to 202 (2020) (Ministry of Ecology and Environment of the People's Republic of China released Bulletin on the Status of Ecological Environment in China 2015 and Bulletin on the Status of Ecological Environment in China 2020).

Although the overall environmental situation in the country is continuously improving, the factors affecting air pollution are different in each region/city, and there are case-specific sensitivities. To further examine the strong yet inconsistent meteorological influences on $PM_{2.5}$ concentrations, many studies have been conducted and suggest that multiple factors, including temperature, wind, humidity, precipitation, and atmospheric pressure, are closely related to $PM_{2.5}$ concentrations. Their results show universal spatiotemporal variation and variance, not only at a regional level but also within a city. Additionally, some studies have shown that the built environment can affect the concentrations of air pollutants in urban areas. Previous studies have explored the relationship between urban form (e.g., street accessibility, degree of centering, land use mix, residential density, sprawl index, urban continuity, and shape complexity) and air pollution. However, many previous studies considered natural factors and built-up environmental factors separately, but the influencing factors of $PM_{2.5}$ are comprehensive and complex, and a single consideration of either factor cannot be used to fully understand the real influencing mechanism of the distribution or diffusion of $PM_{2.5}$ in different regions/cities. Additionally, several built environments have been built in major Chinese cities, and the natural conditions of each city are relatively stable. We are interested in addressing the following question: how is $PM_{2.5}$ affected after a large amount of construction and expansion? Therefore, this paper takes natural factors as control variables to explore the influence of the built environment on $PM_{2.5}$ under the condition of stable natural factors.

2. Literature Review

It is generally acknowledged that $PM_{2.5}$ concentrations are affected by both natural and built environment characteristics [1]. Meteorological conditions affect the accumulation and diffusion of $PM_{2.5}$ through multiple mechanisms. Meteorological factors, usually including temperature [2,3], relative humidity [4,5], wind speed [4,6] and precipitation [7], can diffuse, dilute, and accumulate pollutants, thus causing spatiotemporal variation in particulate matter concentrations [6,7]. Due to the complex behavior of airborne aerosols, the meteorological influences on $PM_{2.5}$ concentrations vary significantly both spatially and temporally. Many studies have examined the spatiotemporal relationship at both the macro and the micro levels. At the national scale, seasonal variations have a large influence on $PM_{2.5}$ concentrations. In general, $PM_{2.5}$ concentrations are lowest in summer and highest in winter [8] and are ordered as follows: summer < spring < autumn < winter [9]. For specific regions, meteorological influences on $PM_{2.5}$ concentrations can vary across seasons. Meanwhile, different regions have various dominant meteorological factors affecting $PM_{2.5}$ concentrations. Yang [5] revealed that wind, humidity and planetary layer height exerted major influences on $PM_{2.5}$ concentrations in eastern China, southern China and northern China. Chen [10] summarized the inconsistent evidence underlying the mechanisms of $PM_{2.5}$ meteorological interactions across different regions/cities in China. For the developed Pearl River Delta, the dominant meteorological factors included wind [11,12], humidity [13], temperature [12], and precipitation [14]. Within a city, spatiotemporal variations in meteorological influences still exist. Particularly, when the combined effects of natural and built environment characteristics are considered, the influence of these variations is more uncertain and complex. These variables can be roughly divided into two categories: natural environment and human activities. In general, the natural environment includes temperature, relative humidity, and wind speed, etc. For example, temperature has been observed to have positive influences on $PM_{2.5}$ concentrations in built-up areas [5,15] but negative influences in wetland areas in Beijing [16]. For the same city (e.g., Beijing), temperature can either negatively or positively influence $PM_{2.5}$ concentrations, indicating that the overall influence of temperature on $PM_{2.5}$ concentrations may vary notably through different periods. Wind speed is a major influencing factor across China that can disturb

stagnant haze environments. However, under some special geographical conditions and wind directions, an increase in wind speed may conversely cause the accumulation of $PM_{2.5}$. For instance, mountains that surrounded Beijing stopped the $PM_{2.5}$ transported by increasing southerly winds, causing enhanced $PM_{2.5}$ concentrations in Beijing [17]. The influence of relative humidity on $PM_{2.5}$ varies with increasing humidity. When the relative humidity is lower than the threshold, humidity exerts a positive influence on $PM_{2.5}$. When the relative humidity is higher than the threshold, increasing humidity makes suspended particles coalesce, resulting in dry deposition or wet deposition [6,18].

When the interactions between natural meteorological factors and human activities occur, the variability and uncertainty of the influences greatly increase. Human activities change the characteristics of the urban environment. In general, urbanization (economic urbanization) has a strong influence on air quality [19–21]. The secondary industrial layout and secondary industrial structure/proportion were key factors affecting the $PM_{2.5}$ concentration [3,6,22]. Then, the built environment characteristics, including urban form and urban density, influence travel behavior and air pollution emissions [23,24]. On the one hand, the built environment influences the choice of travel [25]. On the other hand, the built environment affects the path of traffic pollutant emissions [26]. Hence, the built environment is an important factor influencing $PM_{2.5}$ concentrations. Researchers usually use quantifiable indicators to represent the characteristics of the urban built environment. For example, the floor area ratio (FAR) and building density are positively associated with $PM_{2.5}$ pollution, and different types of road densities have different effects on air pollution [23,27]. The FAR value indicates a level of population density and building density and may lead to different levels of traffic emissions. Road density for all types of roads is significantly correlated with $PM_{2.5}$ concentrations. Song [23] found that the densities of arterial roads and sub-arterial roads had a significant influence on $PM_{2.5}$ concentrations. However, congestion will cause more exhaust emissions from motor vehicles [28,29]. Hence, the driving conditions of vehicles (i.e., the level of congestion) also have a strong influence on $PM_{2.5}$ concentrations [30,31]. Bus station density has a negative influence on $PM_{2.5}$ concentrations, which may decrease the share of private cars and improve public transportation [32,33]. In terms of land use, a higher land mix may be more convenient and efficient. Some studies thought that the mix of land use was conducive to reducing the use of motor vehicles and reducing the generation of $PM_{2.5}$ indirectly [34–37]. The secondary industry may be an important source of $PM_{2.5}$ pollution and have a positive influence on $PM_{2.5}$ concentrations [38]. Green space has been deemed to be effective in mitigating $PM_{2.5}$ pollution. Chen [39] investigated the contributions from different landscape components in green space. The results showed that neighborhood green space greatly contributed to the spatial variation in $PM_{2.5}$ when its size was within 400–500 m.

Natural and built environments are both responsible for $PM_{2.5}$ concentrations, and they tend to have stronger joint effects within a city. The influencing mechanisms of $PM_{2.5}$ -meteorological interactions have been extensively investigated, accumulating a large amount of empirical evidence. However, this evidence is very complicated and mixed. Whether considering the impact of the built environment alone or considering the interaction between the built environment and natural environmental factors, the empirical evidence is obviously case-sensitive. Therefore, although there are many related studies, the study has the significant objective of exploring the mechanisms that spread air pollution and control the emission of air pollution in a specific city.

3. Data and Methodology

3.1. Study Area and Data

The special interest in $PM_{2.5}$ -meteorological interactions in megacities (e.g., Beijing, Shanghai, Guangzhou, and Shenzhen) is mainly attributed to the fact that high concentrations of $PM_{2.5}$ in developed cities and air pollution pose major threats to public health in cities with a large population density. As a metropolis in southeastern China, Shenzhen

is a coastal city and a typical polycentric-structure city, which covers a total area of approximately 1953 km² and has a population of approximately 15 million. The central city consists of four districts (Yantian, Luohu, Futian, and Nanshan) from west to east, bordering Hong Kong. The peripheral area and suburban area include five districts (Dapeng, Pingshan, Longgang, Longhua, Guangming, and Baoan) from west to east, adjacent to Dongguan city and Huizhou city, Guangdong Province (Figure 1). Shenzhen is already a high-density developed city and has had abundant and various built environments since China's reform and opening up. Although Shenzhen's air quality has improved in recent years, automobile exhaust and industrial pollution are two important sources of PM_{2.5} pollutants in Shenzhen [40,41].

Figure 1. Map of the study area.

To more effectively analyze the natural/built environment and PM_{2.5} concentration in Shenzhen, a km grid was selected as the fundamental analysis unit in this paper. We excluded areas with no built-up environments, such as mountains, lakes, and forests.

The data used in our model comprise three components: natural data (temperature, relative humidity, wind speed), built environment data (FAR, road density, land use mix, industrial building density, bus station density, travel time index, green space rate), and air pollution-related data (PM_{2.5} concentration). The global annual PM_{2.5} grids from NASA Moderate Resolution Imaging Spectroradiometer (MODIS), Multiangle Imaging Spectro Radiometer (MISR) and the Sea-Viewing Wide Field-of-View Sensor (SeaWiFS) and aerosol optical depth (AOD) with geographically weighted regression (GWR) for 1998–2016 consist of annual concentrations (micrograms per cubic meter) of ground-level fine particulate matter (PM_{2.5}), with dust and sea-salt removed. The paper used the PM_{2.5} concentration data in 2016 because of its more obvious distribution characteristics and better match with other data. Natural factor data (temperature (TEM), relative humidity (RH), wind speed (WS)) came from the data released by the Meteorological Bureau of Shenzhen Municipality in 2020. Building data and land use data for FAR and industrial building data from Shenzhen Government Data Open Platform (<https://opendata.sz.gov.cn/>, accessed on 1 May 2021) include building area, building functions, floor area, and main land use function. The public transport data from the Shenzhen Urban Planning & Land Resource Research Center include road types and lengths and the distribution of bus stations. The travel time index was published by the Transport Bureau of Shenzhen Municipality. The

travel time index (TTI) can reflect the level of road operation and congestion. Green space data came from Shenzhen remote sensing satellite data for 2015 (Table 1).

Table 1. Variable specifications and descriptive statistics.

	Variables	Unit	Year	Average	Min	Max	St.Dev	Specifications
Dependent Variables	PM _{2.5} concentration	µg/m ³	2016	25.99	20.2	32.2	2.50	PM _{2.5} concentration data were from NASA; resolution: 0.01 longitude (1 km × 1 km)
	FAR	M ² /m ²	2018	0.90	0.00	7.30	0.97	Data source: Shenzhen Government Data Open Platform published building census data in 2018. FAR is the ratio of the total building area to the land area in each research unit, and it is an important index to measure the intensity of land development.
	Road density	km/km ²	2018	8.49	0.00	33.51	6.50	Summarize and calculate the total length of various urban roads on each square kilometer of urban land and calculate the length density of the road network of each grid.
	Land use mix degree	%	2018	0.39	0.00	0.83	0.22	Land use mixing degree refers to the overall situation of mixed use of different land use types in the research unit. Using Entropy method to calculate the mixing degree of land in each grid. Entropy index (ENT) = $-\left[\sum_{j=1}^k p_j \ln p_j\right] / \ln k$, let p_j be the percentage of each land use type j in the area, and let $k \geq 2$ be the number of land use types j .
	Industrial building ratio	%	2018	0.27	0.00	1.00	0.27	Count the total area of industrial buildings per square kilometer and calculate the ratio of industrial building area.
	Bus station density	number/km ²	2015	4.49	1.00	21.00	3.82	According to the distribution data of bus stations in Shenzhen, calculate the number of bus stations per square kilometer.
Independent Variables	Travel time index	-	2016	2.81	0.70	4.88	0.82	Traffic index is a comprehensive index that uses GPS floating car technology and fuses multisource data to quantitatively evaluate the overall operation status of road network traffic. TTI: in the same link in a time slice, $TTI = \text{free stream speed} / \text{actual speed}$. $S = \{link_1, link_2, link_3, link_4, \dots, link_N\}$, $TTI = \frac{\sum_{i=1}^N \frac{L_i}{V_i} \times W_i}{\sum_{i=1}^N \frac{L_i}{V_{free,i}} \times W_i} \times \text{speed} = \frac{\sum_{i=1}^N L_i \times W_i}{\sum_{i=1}^N \frac{L_i}{V_i} \times W_i}$, The total number of link is N , L_i is the length of links W_i is the weight of links $V_{free,i}$ is the free flow speed of links and V_i is the real time road speed of links.
	Green space rate	%	2015	2.81	0.70	4.88	0.82	Based on the remote sensing data of Shenzhen, the green space area per square kilometer of land is screened out, and the proportion of green space is calculated.
	TEM	°C	2020	23.13	21.35	23.83	0.49	Calculate the average temperature during the peak travel hours every day in 2020. The more solar radiation there is, the higher the temperature is. Generally, it refers to the temperature in the louver at a height of approximately 1.5 m on the ground.
	RH	°	2020	60.50	43.40	83.18	6.58	Data source: the data released by Meteorological Bureau of Shenzhen Municipality in 2020. Temporal interval: 7:00 AM–9:00 AM and 17:30 PM–19:30 PM Mass of water vapor per unit volume of air using relative humidity.
	WS	m/s	2020	1.71	1.10	2.74	0.33	Wind speed is the movement rate of air relative to a fixed place on the Earth and the wind speed in various regions of Shenzhen during peak hours.

3.2. The Global and Local Regression Models

The modeling analysis employs both ordinary least square (OLS) and GWR modeling approaches to detect the factors that affect PM_{2.5} concentration variation. The study adopted OLS for global regression simulation. OLS is a common method used to quantify the influence of independent variables on dependent variables, but it may lead to bias estimation because it does not consider spatial correlation.

$$y = \beta_0 + \sum_{i=1}^p \beta_i x_i + \varepsilon \quad (1)$$

where y is the dependent variable, β_0 is the intercept, β_i is the parameter estimate (coefficient) for independent variable x_i , p is the number of independent variables, and ε is the error term.

To comprehensively consider the influence of geographical locations on the spatial distribution and variations in individual variables, the study also adopted the GWR model, which presents variations in the influence of independent variables on dependent variables according to location changes [42]. GWR is a useful tool for quantifying comprehensive meteorological influences on PM_{2.5} concentrations [10]. Additionally, the GWR approach is better at addressing spatially varying parameters than is OLS. The GWR method can allow spatially unstable data to be directly simulated and used to perform local parameter estimation. A conventional GWR is described by the following equation:

$$y_i = \sum_{j=0}^{j=n} \beta_{ij} * X_{ij} + \varepsilon_i \quad (2)$$

where y_j , X_{ij} , and ε_i are the dependent variable, independent variable, and error term at location i , respectively, and β_{ij} is the local coefficient for the i th location and the j th independent variable, based on the varying conditions of the location.

4. Modeling Results and Discussion

4.1. OLS Results

Table 2 shows a summary of the OLS results. The OLS results indicate some general tendencies regarding the PM_{2.5} concentration distribution and its relationships with the natural/built environments. First, RH, bus station density, and the TTI had no significant relationship with PM_{2.5} concentration (p -value > 0.01). Second, WS and TEM had a positive influence on the PM_{2.5} concentration. We can infer that when the TEM is high, PM_{2.5} is more likely to be suspended in the air, and when the upstream clean airflow encounters a large number of street-level pollutants, the upstream clean airflow will also be rapidly polluted, which will increase the scope of pollution. Third, the FAR, land use mix, green space rate, industrial building ratio, and road density had significant relationships with PM_{2.5} concentration (p -value < 0.01).

The OLS diagnostics showed that the adjusted R^2 was 0.682, which was an acceptable result. The four statistics (joint F-statistic, joint Wald statistic, Koenker statistic, and Jarque-Bera statistic) in the model were significant ($p = 0$), which indicated that the residuals were spatially correlated. The global Moran's I of the PM_{2.5} data was tested. The results showed that Moran's I indicator for PM_{2.5} was 0.000 (p -value < 0.001). The PM_{2.5} data actually had a significant agglomerated distribution and significant spatial autocorrelation (z-score = 102.020). Based on these diagnostics, the OLS approach was not the best approach for analyzing the relationships between the PM_{2.5} concentration and the natural/built environment factors in this study. Thus, GWR models were utilized to solve the issue of spatial heterogeneity. The FAR, land use mix, and green space rate were negatively correlated with PM_{2.5}. When the industrial building ratio and road density increased, the PM_{2.5} concentration may also increase. Bus station density had an insignificant influence

on PM_{2.5} concentration. This paper infers that green energy buses are used in Shenzhen, so the pollutant emissions of bus stations are greatly reduced.

Table 2. Summary of the ordinary least square (OLS) results, diagnostics, and global Moran's test.

Variables	Normalization Coefficient	Nonnormalization Coefficient	t-Value	p-Value	VIF
Intercept	0.000	−62.609	−26.368	0.000 *	-
Wind speed	0.244	1.877	14.100	0.000 *	1.163
Temperature	0.734	3.728	39.186	0.000 *	1.359
Relative humidity	−0.014	−0.005	−0.831	0.406	1.132
FAR	−0.055	−0.141	−1.996	0.046 *	2.956
Land use mix	−0.077	−0.876	−3.302	0.001 *	2.089
Bus station density	0.026	0.017	1.056	0.291	2.417
Industrial building ratio	0.060	0.562	3.348	0.001 *	1.256
Green space rate	−0.195	−1.583	−7.244	0.000 *	2.816
Road density	0.056	0.021	1.778	0.076 *	3.802
TTI	0.025	0.77	1.339	0.181	1.381
Number of observations		1235			
AICc		4367.374			
Joint F-statistic		265.412			
Joint Wald statistic		22702.541			
Koenker (BP) statistic		247.000			
Jarque-Bera statistic		107.572			
R ²		0.684			
Adjusted R ²		0.682			
		Moran's I summary			
Moran's Index		0.654			
Expected Index		−0.000			
Variance		0.000			
z-score		102.020			
p-value		0.000			

* $p < 0.01$.

4.2. GWR Results

GWR 4.09 software was used in this study. Given that the GWR model estimates coefficients for each observed point with a certain number of neighboring points, the outcomes are significantly influenced by the chosen kernel function and bandwidth. The golden section search method in GWR 4.09 is used to efficiently identify the optimal bandwidth size. We used the Akaike information criterion (AICc) as a criterion to choose the best model. The optimal bandwidth size was 54, and the smallest AICc value was 2463.943.

Table 3 lists the performances of the OLS and GWR models. The GWR outperformed the OLS approach. The reduction in the AICc values and the improvement of the R^2 /adjusted R^2 also implied the marked effectiveness of the GWR models. Furthermore, the GWR model better performed in terms of the Moran's test (z -score = 4.862), which indicated that the GWR models managed the issue of spatial autocorrelation that occurred in the previous OLS analysis.

As the t -value statistics and maps in Table 4 and Figure 2 show, the significance level of each independent variable varied over space. In certain areas, an independent variable may have significant relationships with PM_{2.5} concentration. To better understand the spatial non-stationarity of the relationships, Table 4 summarizes the percentage of coefficients that were negatively or positively significant at the 90% and 95% levels and the percentage of coefficients that were not significant. The effect of important explanatory variables on PM_{2.5} concentration can be spatially investigated, as shown in Figures 2 and 3.

Table 3. Comparison of OLS and GWR model performance and summary of the GWR results, diagnostics and global Moran's I test.

Comparison		R^2		Adjusted R^2		AICc
OLS		0.684		0.682		4367.374
GWR		0.967		0.950		2463.943
Variables	Min	Median	Mean	Max	Positive	Negative
Wind speed	−23.459	0.796	0.856	16.552	33.85%	16.60%
TEM	0.002	1.047	1.078	2.941	98.22%	0.00%
FAR	−2.872	0.004	0.072	2.334	18.54%	6.32%
Land use mix	−5.646	−0.154	−0.034	5.251	12.15%	10.53%
Industrial building density	−7.644	−0.144	−0.330	12.230	3.00%	18.30%
Green space rate	−11.565	−0.458	−0.665	2.472	3.00%	21.70%
Road density	−0.195	0.010	0.019	0.168	17.57%	1.94%
Diagnostic information						
Degree of freedom (residual:n-2trace(S)+trace(S'S))				815.626		
ML ¹ based sigma estimate				0.456		
Unbiased sigma estimate				0.561		
Classic AIC ²				2223.134		
AICc				2463.943		
BIC/MDL ³				3909.828		
CV ⁴				0.406		
R^2				0.967		
Adjusted R^2				0.950		
Moran's I summary						
Moran's Index				0.030		
Expected Index				−0.001		
Variance				0.000		
z-score				4.862		
p-value				0.000		

Note: ¹ ML: maximum likelihood; ² AIC: Akaike information criterion; ³ BIC/MDL: Bayesian Information Criterion/minimum description length; ⁴ CV: cross-validation

Table 4. Descriptive statistics for the geographical weighted regression (GWR) *t*-value.

Independent Variables	Negatively Significant at 95%	Negatively Significant at 90%	Not Significant	Positively Significant at 90%	Positively Significant at 95%
Wind speed	15.30%	1.30%	49.55%	3.81%	30.04%
TEM	0.00%	0.00%	1.78%	0.40%	97.81%
FAR	4.13%	2.19%	75.14%	2.35%	16.19%
Land use mix	6.72%	3.81%	77.33%	2.19%	9.96%
Industrial building density	13.36%	4.96%	78.70%	1.30%	1.70%
Green space rate	17.41%	4.29%	75.30%	0.57%	2.43%
Road density	1.46%	0.49%	80.49%	3.32%	14.25%

Figure 2. Spatial relationships between $PM_{2.5}$ concentration and natural factors (the control variables). (A) GWR results for the independent variable: Coefficients (wind speed). (B) GWR results for the independent variable: t -values (wind speed). (C) GWR results for the independent variable: Coefficients (TEM). (D) GWR results for the independent variable: t -values (TEM). (note: (A) shows each district and some typical locations).

(a)

(b)

(c)

(d)

(e)

(f)

Figure 3. Cont.

Figure 3. Spatial relationships between $PM_{2.5}$ concentration and the built environment. (a) GWR results for the independent variable: Coefficients (FAR). (b) GWR results for the independent variable: t -values (FAR). (c) GWR results for the independent variable: Coefficients (land use mix). (d) GWR results for the independent variable: t -values (land use mix). (e) GWR results for the independent variable: Coefficients (industrial building density). (f) GWR results for the independent variable: T -values (industrial building density). (g) GWR results for the independent variable: Coefficients (green space ratio). (h) GWR results for the independent variable: t -values (green space ratio). (i) GWR results for the independent variable: Coefficients (road network density). (j) GWR results for the independent variable: c -values (road network density). (note: (a) shows each district and some typical locations).

5. Discussion

The GWR results showed that there were close relationships between built environment factors and $PM_{2.5}$ concentrations. These factors included WS, TEM, FAR, land use mix, industrial building density, green space rate, and road density. However, the variables were different, and spatial heterogeneity appeared. The two natural environmental variables, the WS and TEM, had different influences on $PM_{2.5}$ concentrations. TEM was significantly and positively related to $PM_{2.5}$ concentrations in most areas (approximately 85%). This outcome was consistent with our OLS models (Figure 2C,D). Meanwhile, WS had a strong spatial variability that affected $PM_{2.5}$. As shown in Figure 2A,B, WS had a positive influence on $PM_{2.5}$ in most areas of the central city. The negative relationships between WS and $PM_{2.5}$ occurred merely in Shekou Peninsular among the central city. We speculated that the relatively high FAR and building density in the central city, particularly in Nanshan and Futian CBD, obstructed air circulation. The lack of ventilation corridor weakened the role of WS in reducing the concentration of $PM_{2.5}$. Contrarily, there existed a negative correlation in Shekou Peninsula of Nanshan District, probably resulting from its proximity to Shenzhen Bay. We inferred that the ventilation corridor is unblocked for the most areas of Shekou Peninsula where is adjacent to the Pearl River Estuary. Therefore,

the increase of WS significantly improved the diffusion of PM_{2.5} pollutants, suggesting the importance of creating ventilation corridor in high-dense urban areas for better air quality.

Under similar natural environments, the FAR was significantly and positively related to the PM_{2.5} concentrations in most downtown areas (Figure 3). Then, the FAR had a negative influence on the suburban areas (Pingshan District). In terms of the land use mix, with the increase in the land use mix, the PM_{2.5} concentrations in the Futian CBD and Qianhai CBD obviously decreased. We may infer that CBD was built at the beginning of the 21st century, and the layout of mixed functions was adopted, which effectively reduced the travel distance and increased the use of public transportation. The relationship between industrial building density was inconsistent with the OLS model in the central city. We infer that most industrial buildings in the central city belong to a new type of pollution-free industry, so they have little impact on PM_{2.5}. The green space rate had a negative influence on PM_{2.5} concentrations, and this result was consistent with previous studies. In most of our study area, road density was significantly and positively related to PM_{2.5} concentrations. With the increase in road density, the PM_{2.5} concentrations also increased.

The GWR model with PM_{2.5} concentrations as the dependent variable performed much better than the OLS model. The GWR results indicated that the PM_{2.5} concentration was influenced by the natural environment and built environment at different locations. This result may contribute to developing a new model to further simulate PM_{2.5} concentrations based on unique city characteristics.

6. Conclusions and Policy Implications

Focusing on the spatial heterogeneity, this paper considered the combined effects of built environment and natural environment factors on PM_{2.5} concentration in Shenzhen, a typically high-dense metropolis of Southern China. To better understand the determinants of PM_{2.5} concentrations, this study applied OLS and GWR models to identify the potential influencing factors. In terms of modeling diagnostics and Moran's test analysis, the GWR approach performed better than the OLS approach, suggesting the superiority of local regression in alleviating the problems of spatial autocorrelation.

The modeling results of this paper provided insights into a better understanding of the joint impacts of natural and built environment on PM_{2.5} Concentrations. We concluded that the impacts of natural environment characteristics are generally stronger than those of built environments on PM_{2.5}. The spatial heterogeneity among these effects and its policy implications deserve further attention.

First, the coefficients of FAR in the GWR model are significantly positive in Nanshan and Bao'an central areas, which are however insignificant in most other areas. This suggested that the concentration of PM_{2.5} increases with the raise of FAR in these areas. The possible explanation is that FAR in these areas exceeds the ideal threshold, so that further increasing FAR aggravates rather than mitigates air pollution. For most Chinese metropolises, where the general density is already high enough, a reasonable upper limit towards FAR and building density could be thus essential for achieving sustainable development goals.

Second, the OLS model found that the land use mix had negative effects on the PM_{2.5} concentration in the whole city. However, as shown in the GWR model, the negative correlations between the land use mix and PM_{2.5} concentration were significant only in the central city, probably because the land use mix is conducive to shortening job-housing distances. However, these relationships become positive in some peripheral and suburban areas. We inferred that there are a large number of factories and land use in the peripheral and suburban areas, and mixed land is not conducive to the centralized treatment and discharge of industrial production. Therefore, mixed and diversified development of land use functions should be emphasized in downtown construction.

Third, in the suburban areas where traditional industries (M2) are mainly distributed, there was a significant positive correlation between industrial building density and PM_{2.5} concentration. However, in the city center, traditional industrial land (M2) was upgraded to M1 (high-tech, science and technology, modern industry, etc.), which showed a negative

correlation with the $PM_{2.5}$ concentration. Therefore, promoting industrial upgrading and improving the pollution discharge standards of traditional industries are effective measures to reduce $PM_{2.5}$ and improve the environment.

Fourth, there was a significant negative correlation between the green ratio and $PM_{2.5}$ concentration in both the OLS and the GWR models. The results showed that green space construction and wetland park protection had positive significance in terms of improving the urban environment.

Fifth, based on new urbanism and smart city theories, road density is an important index of sustainable cities, and increasing road density is an important way to promote sustainable transportation. However, in this paper, we found that an increase in road density would lead to an increase in $PM_{2.5}$. We inferred that when the density of the road network reaches a certain threshold, a further increase in road density would lead to an increase in motor vehicle quantity and a large amount of vehicle exhaust emissions. For example, a denser road network in downtown areas will improve accessibility and increase walking, but in suburban areas, the road network density should be controlled to the extent that it can limit the development of cars and promote the use of public transportation. However, the most suitable density threshold for each region needs further exploration and actual measurement, which is what we will continue to do in the next step of our research.

These findings are sufficient to answer our research questions: (1) The interaction between the natural environment and built environment makes the distribution of $PM_{2.5}$ spatially variable. Both natural and built environment factors should be adopted in future analyses of $PM_{2.5}$ concentrations within cities. (2) Targeted improvement and design of different areas will be better than a one-size-fits-all planning standard. Diversified planning strategies should be provided for urban centers and suburbs. (3) The distribution and diffusion of $PM_{2.5}$ will be affected by natural environmental factors. However, in high-density metropolises, the natural environmental elements are relatively stable, and livability is further improved. The air environment should be further improved, and the generation of $PM_{2.5}$ should be reduced from its own built environment.

There are some limitations in this study. First, we should consider a wider range of influencing factors, such as the proportion of various levels of roads and the impact of building forms on the diffusion of $PM_{2.5}$. Second, the distribution of $PM_{2.5}$ and the influence of natural factors have temporal variations, so temporal variations need to be considered to increase the accuracy of the study. Finally, the measurements and simulations should be carried out in some additional typical areas.

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