

Article

Influence of Urban Landscape Patterns on PM_{2.5} Concentrations from the LCZ Perspective in Shanghai City

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Abstract

Under the fast development of urbanization, PM_{2.5} pollution has become a prominent issue affecting the urban ecological environment and residents' health. To investigate the impact of urban landscape patterns on PM_{2.5} concentrations, this study applies the Local Climate Zone (LCZ) classification to Shanghai using the World Urban Database and Access Portal Tools (WUDAPT). LCZ-derived landscape metrics are adopted as predictor variables to focus on how urban form and spatial configuration affect PM_{2.5} distribution and to identify the key landscape categories and types influencing PM_{2.5} levels. The results reveal notable seasonal and spatial differences in the effects of different LCZ types and landscape metrics on PM_{2.5} concentrations; on average, over 69% of the spatial variation in PM_{2.5} across the four seasons can be explained by the Multi-scale Geographically Weighted Regression (MGWR) model. This research demonstrates that the LCZ framework effectively uncovers the seasonal and spatial mechanisms by which urban landscape patterns influence PM_{2.5} concentrations in Shanghai. It offers a novel perspective for understanding the interplay between urban landscape and atmospheric pollution, and provides scientific guidance for sustainable urban planning and precise air pollution control strategies in other cities.

Keywords: landscape metrics; local climate zones (LCZ); PM_{2.5}; landscape pattern; land use

1. Introduction

The process of urbanization has been rapidly advancing worldwide, with cities gradually becoming the core hubs of economic, cultural, and political activities [1]. As a typical developing country, China has made remarkable achievements in urbanization: its urbanization rate surged from less than 20% in 1978 to over 60% today [2]. Notably, intensive urbanization has directly led to large-scale transformations of natural landforms and extensive deforestation for city construction, significantly exacerbating air pollution problems [3]. PM_{2.5}, one of the primary atmospheric pollutants, is known to cause respiratory and cardiovascular diseases [4–6], reduce visibility, alter climate patterns, and damage ecosystems [7,8]. Additionally, widespread use of concrete and asphalt in urban construction contributes to heat absorption, further deteriorating local climate conditions and indirectly intensifying pollutant retention [9]. Investigating the relationship between urban landscape patterns and PM_{2.5} is instrumental for rational city planning, improving atmospheric environmental quality, and promoting sustainable urban development.

At present, investigations into the correlation between urban landscape configurations and air quality predominantly rely on the traditional Land Use and Land Cover (LULC) classification framework. At the categorical level, vegetation and water bodies are



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considered significant landscape components in reducing $PM_{2.5}$ concentrations, whereas built-up areas tend to exacerbate $PM_{2.5}$ concentrations [10–12]; At the landscape level, overall landscape evenness (SHEI) and fragmentation (CONTAG) are strongly correlated with $PM_{2.5}$ concentrations [13]. In high-density and highly compact urban areas, variations in building height and building density lead to different urban functionalities, making the LULC classification insufficient to accurately characterize urban features [14]. Stewart and Oke proposed the Local Climate Zone (LCZ) classification framework [15], which enables a more effective explanation of the relationship between urban landscape patterns and atmospheric particulates than traditional land use change methods [16]. LCZ classification data can be mainly divided into three categories: those based on remote sensing, those based on geographic information systems (GIS), and methods that combine both [17,18]. Among these, classification methods based on remote sensing are used most frequently. The World Urban Database and Access Portal Tools (WUDAPT) is a global database that provides LCZ maps for cities worldwide [19]. The platform initially offered a standard, universal workflow that utilized random forest classification, using free data from the open-source community-such as Landsat imagery and free software like SAGA. Building on this foundation, WUDAPT introduced another major advancement: an online platform for generating urban LCZ maps. This platform can automatically map cities to LCZ types with only a valid training area file and some metadata as inputs [20]. This generator has simplified the process of creating LCZ maps, greatly facilitating urban climate research for researchers.

The LCZ framework is a classification system based on the physical properties of the surface and climatic functions. This system uses 12 core indicators-including building morphology parameters (such as height and density), surface cover attributes (such as impervious materials, vegetation density, and the distribution of water bodies)-to divide urban spaces into 17 standard types (comprising 10 built-up cluster types and 7 natural surface types). Urban morphological and climate studies have shown that the heterogeneity of different LCZ types is significantly spatially coupled with their historical evolutionary stages [21]. The LCZ scheme has been widely applied in studies analyzing the relationship between urban landscape patterns and atmospheric particulate concentrations [14,22]. Most research results indicate that, throughout the year, $PM_{2.5}$ concentrations in built types generally follow the patterns of “compact > open” and “high-rise > mid-rise > low-rise”. The $PM_{2.5}$ concentration in natural categories is always lower than that in built categories [22]. However, studies on the spatial correlation between LCZ type landscape metrics and seasonal urban $PM_{2.5}$ concentrations remain limited. In this study, the LCZ framework is used to characterize urban landscape patterns, with $PM_{2.5}$ as the representative atmospheric pollutant. The impacts of urban landscape patterns under the LCZ classification on the seasonal spatial variation in $PM_{2.5}$ are examined.

Focusing on Shanghai, we generated the LCZ classification map following the WUDAPT Level 0 protocol. To rigorously examine the coupling effects between urban landscape configurations and $PM_{2.5}$, a hierarchical analytical framework was employed. This included Pearson’s correlation for preliminary screening, multiple linear regression for global assessment, and Multi-scale Geographically Weighted Regression (MGWR) for capturing local non-stationarity, thereby offering deep insights ranging from general statistical associations to complex spatial heterogeneity. The results of this multi-scale analysis reveal the mechanisms linking LCZ landscape patterns with urban air pollution across different spatial scales, offering empirical evidence to guide the refinement of urban spatial configurations and the development of precision air quality management policies. The main workflow of this study is illustrated in Figure 1.

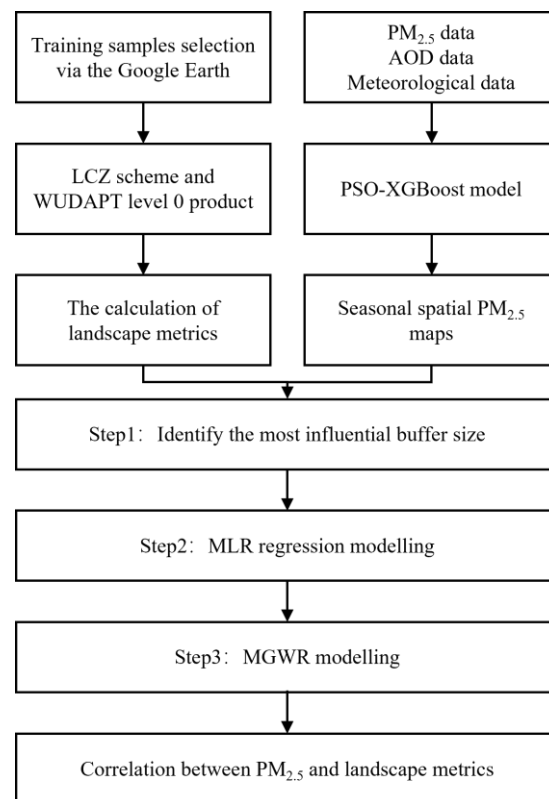


Figure 1. The main workflow of this study.

2. Materials and Methods

2.1. Study Area

Shanghai (120°52' E–122°12' E, 30°40' N–31°53' N) is located in East China, with a total area of 6340.5 km². In recent years, the atmospheric environmental quality in Shanghai has improved significantly, with a downward trend in the concentrations of major pollutants. However, the annual average concentration of fine particulate matter (PM_{2.5}) was 35 µg/m³ in 2022, ranking at a medium-to-low level nationally. This is mainly due to the rapid increase in the number of motor vehicles, intensive urban construction, and the fast growth of population and economy, which continue to pose substantial challenges to air quality.

2.2. Seasonal Spatial PM_{2.5} Concentration Estimation

2.2.1. PM_{2.5} Estimation Data

The PM_{2.5} data used were sourced from national air quality monitoring stations, specifically from the China National Environmental Monitoring Center (<http://www.cnemc.cn/> (accessed on 15 November 2023)) and the historical PM_{2.5} data website (<https://www.aqistudy.cn/> (accessed on 15 November 2023)). Data from 19 national air quality monitoring stations in Shanghai in 2022 were selected, and hourly PM_{2.5} concentration monitoring data for each day throughout the year were obtained and used to calculate daily averages [23]. The distribution of the monitoring sites is shown in Figure 2. The Aerosol Optical Depth (AOD) data product is MODIS MCD19A2 V6 aerosol data (<https://earthexplorer.usgs.gov/> (accessed on 24 April 2024)). MODIS satellite sensors were used to acquire daily AOD data, and the MCD19A2 V6 product is a grid-based Level 2 aerosol optical depth (AOD) product from the joint Multi-Angle Implementation of Atmospheric Correction (MAIAC) algorithm for MODIS Terra and Aqua, generated daily at a spatial resolution of 1 km [24]. Meteorological data were obtained from the ERA5 reanalysis dataset (hourly) provided by the European Centre for

Medium-Range Weather Forecasts (ECMWF) (<https://www.ecmwf.int/en/forecasts/datasets> (accessed on 19 June 2024)) [25]. Variables selected include 2 m air temperature, surface temperature, relative humidity, wind speed, wind direction, precipitation, and atmospheric pressure, all at a daily time resolution.

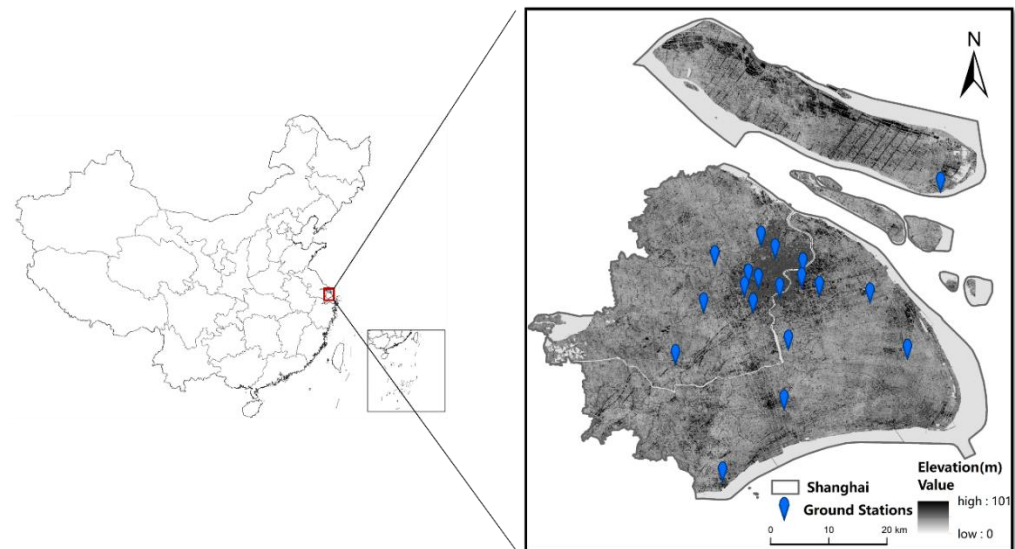


Figure 2. Geographical location and corresponding air pollution monitoring stations in Shanghai.

2.2.2. Construction of Inversion Models

To accurately capture the spatial variation in seasonal $PM_{2.5}$, this study employs the PSO-XGBoost model for $PM_{2.5}$ estimation. Extreme Gradient Boosting (XGBoost) is an efficient and widely used machine learning algorithm that demonstrates remarkable scientific rigor and practical value in $PM_{2.5}$ estimation. It is capable of efficiently and accurately modeling the complex relationships among environmental variables [26,27]. Based on the gradient boosting framework, XGBoost iteratively minimizes model residuals for optimization, and incorporates multiple innovations that significantly enhance its accuracy, efficiency, and scalability. The model is represented as follows:

$$\hat{y}_l = \sum_{k=1}^k f_k(x_i), f_k \in F (i = 1, 2, 3, \dots, n) \quad (1)$$

where $\hat{y}_l$ represents the predicted value for the i th sample, k denotes the number of trees, and F represents the space of regression tree ensembles; x_i denotes the feature vector of the i th data point. To further enhance the performance and generalization ability of the XGBoost model, as well as to improve the accuracy and effectiveness of $PM_{2.5}$ inversion, the Particle Swarm Optimization (PSO) algorithm is incorporated.

$$x^{k+1} = x^k + v^{k+1} \quad (2)$$

$$v^{k+1} = \omega \times x^k + c_1 \times r_1 \times (p_{pbest}^k - x^k) + c_2 \times r_2 \times (p_{pbest}^k - x^k) \quad (3)$$

As a global optimization algorithm, Particle Swarm Optimization (PSO) can quickly search for optimal combinations of hyperparameters by simulating the collaborative behavior of particles in the search space. Compared to traditional methods such as Grid Search or Random Search, PSO offers higher optimization efficiency and stronger global search capabilities [28]. During the model construction process, a PSO algorithm framework tailored to the characteristics of the experimental data and the requirements of the XGBoost model was designed based on the core principles of PSO optimization. By integrating the PSO algorithm with the XGBoost model, a PSO-optimized XGBoost model was suc-

successfully developed, laying a solid foundation for achieving more efficient and accurate model performance.

PM_{2.5} station data, Aerosol Optical Depth (AOD) data, and meteorological data were utilized for seasonal PM_{2.5} estimation. The study period was stratified into four standard seasons: spring (March to May), summer (June to August), autumn (September to November), and winter (December to February), and the PSO-XGBoost model was established for each period. The dataset was randomly partitioned into a training set (75%) and a validation set (25%). An in-depth evaluation and analysis of the results were performed. Model performance was assessed using the coefficient of determination (R^2), mean absolute error (MAE), and root mean square error (RMSE). To avoid prior partitioning bias of the samples, the modeling process was repeated three times, and the optimal model was selected as the final best model. Finally, the PM_{2.5} concentrations predicted by the final PSO-XGB model were mapped onto a 100 m spatial resolution grid.

2.3. Quantifying the Land Use and Landscape Spatial Pattern

2.3.1. Construction of LCZ Classification Map

The Local Climate Zone (LCZ) scheme provides a more detailed description of urban morphology compared to traditional land-use classification, highlighting the response of compact and high-density urban forms to environmental factors. The LCZ system divides urban areas into 10 types of built-up zones and 7 types of natural land zones (Figure 3). For the urban spatial morphology of Shanghai, LCZ7 (lightweight low-rise buildings) and LCZF (bare soil or sand), which do not exist in this area, were excluded to achieve a more accurate representation of the city's morphology.

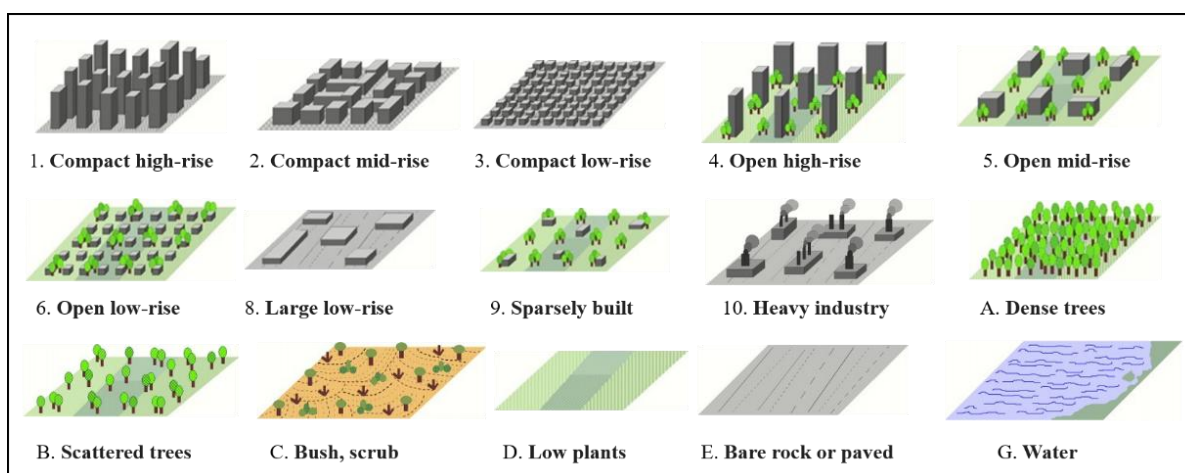


Figure 3. LCZ schematic diagram [15].

The WUDAPT workflow was utilized to generate the LCZ zoning map, referencing established models from previous studies [29] and following these steps: (1) Representative areas of each LCZ class were identified and delineated as training samples using polygons in Google Earth, supplemented by Baidu Street View imagery. For each LCZ class, 40–50 training samples were selected. (2) Pre-processed Landsat satellite images and the selected training areas were loaded into the LCZ Generator. Using the online random forest classification method, the local climate zone classification for the study area was performed, resulting in a preliminary zoning map. (3) The KML file generated in step (2) was loaded into Google Earth for verification. For areas where inconsistencies existed, new training samples were delineated and step (2) was repeated until the generated map accurately reflected real-world conditions.

2.3.2. Calculation of Landscape Metrics

This study selects landscape metrics from both the class level and the landscape level. At the class level, four metrics are used: Patch Area Percentage (PLAND), which indicates the composition characteristics of landscape patches; Largest Patch Index (LPI), reflecting the dominant patch types; Landscape Shape Index (LSI), representing the proportional composition of patch shapes; and Aggregation Index (AI), which measures the degree of spatial clustering of specific landscape types within the study area. At the landscape level, two metrics are employed: the Shannon Equability Index (SHEI), which represents the overall evenness of different landscape categories and identifies dominant classes; and the Contagion Index (CONTAG), which reflects the overall fragmentation degree of the urban landscape pattern. Fragstats was used to calculate all landscape metrics.

To quantify the dominance of specific land cover types, we calculated the PLAND, which measures the proportional area of each LCZ class relative to the total study extent. The calculation method is as follows:

$$PLAND = \frac{\sum_{j=1}^n a_{ij}}{A} * 100 \quad (4)$$

where n is the total number of patches of a specified landscape type within the study area, and a_{ij} is the area of patch j of the landscape type i . A represents the total landscape area.

The dominance of the single most extensive patch within a class was assessed using the LPI, serving as an indicator of fragmentation or continuity. The calculation method is as follows:

$$LPI = \frac{a_{max}}{A} \times 100 \quad (5)$$

where a_{max} is the area of the largest patch within the patch type.

LSI represents the proportion of a specific patch type within the landscape. Its value ranges from 0 to 100; the fewer the number of patches, the smaller the LSI value. The calculation method is as follows:

$$LSI = \frac{0.25 \sum_{k=1}^m e_{ik}}{\sqrt{A}} \quad (6)$$

where e_{ik} denotes the cumulative length of edges shared by patch types i and k , encompassing the entire landscape boundary and the partial or full background edge segments associated with class i .

The AI is the percentage value of the spatial adjacency frequency between raster cells of a particular landscape type. The spatial adjacency index AI is chosen to evaluate the degree of clustering of patches within each landscape type. When all patches of a given landscape type are completely dispersed, AI equals 0. The calculation method is as follows:

$$AI = \frac{g_{ii}}{\max_g_{ii}} \quad (7)$$

where g_{ii} represents the number of similar neighboring pixel pairs of class i based on the single-count method. $\max_g_{ii}$ indicates the maximum number of similar neighboring pixel pairs between pixels of class i based on the single-count method.

SHEI is used to measure whether the area distribution of different patch types in the landscape is uniform. Its value ranges from 0 (only one patch type exists in the landscape, indicating the lowest evenness) to 1 (high diversity, all patch types have equal area, indicating the highest evenness). The calculation method is as follows:

$$SHEI = \frac{-\sum_{i=1}^m (P_i \ln P_i)}{\ln m} \quad (8)$$

where P_i is the area proportion of class i . m is the total number of landscape types in the study area.

CONTAG is an index that measures whether patches of the same type are spatially adjacent and form continuous patches. It primarily reflects the spatial connectivity of the landscape, rather than the area distribution. The calculation method is as follows:

$$CONTAG = \left[1 + \frac{\sum_{i=1}^m \sum_{k=1}^m P_{ik} \ln P_{ik}}{2 \ln m} \right] \times 100\% \quad (9)$$

where P_{ik} is the probability that patches of type i are adjacent to patches of type j . m is the total number of landscape types in the study area.

3. Results

3.1. The Seasonal Spatial Characteristic of $PM_{2.5}$ and LCZ Classification

The estimation results of $PM_{2.5}$ using the PSO-XGBoost model are shown in Figure 4. Model performance metrics for seasonal $PM_{2.5}$ estimation indicate R^2 values of 0.778, 0.777, 0.885, and 0.822 across four seasons, respectively. Corresponding root mean square error (RMSE) values are 7.216, 3.99, 4.43, and 5.41, while mean absolute errors (MAE) are 4.723, 2.921, 3.310, and 5.412. Overall, the $PM_{2.5}$ concentrations in Shanghai are at a favorable level, remaining below the Chinese air quality threshold of $75 \mu\text{g}/\text{m}^3$. Seasonal variation shows that $PM_{2.5}$ concentrations are highest in autumn and winter, followed by spring, and lowest in summer. Apart from the significant influence of water bodies at urban boundaries on $PM_{2.5}$ levels, the central urban built-up areas exhibit higher $PM_{2.5}$ concentrations, whereas regions with dense vegetation cover at the outskirts show comparatively lower concentrations.

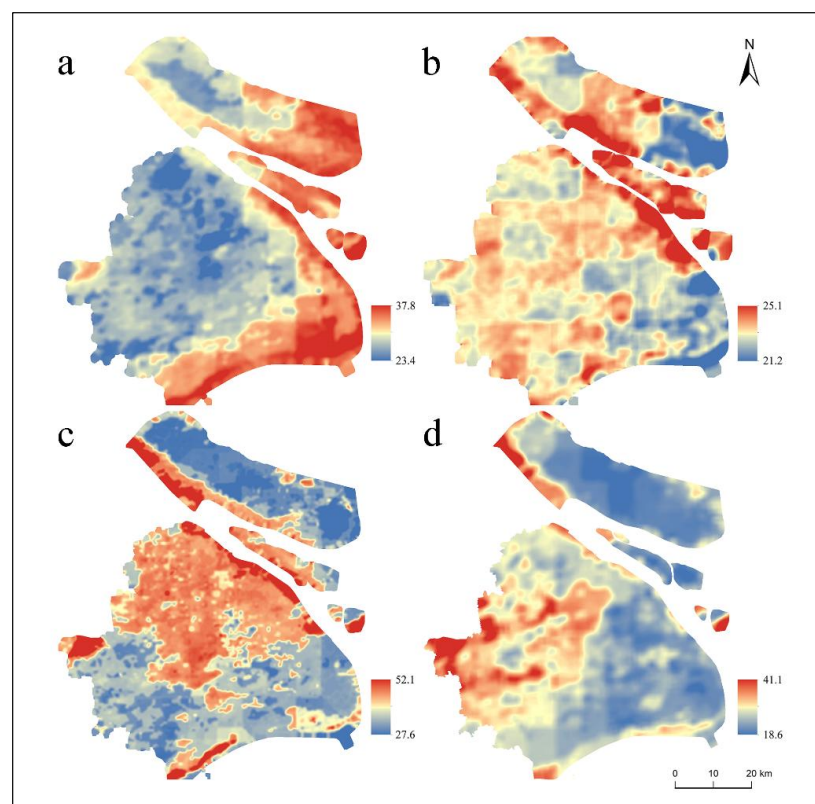


Figure 4. $PM_{2.5}$ maps of Shanghai in difference seasons in the year of 2022 ((a) spring; (b) summer; (c) autumn; (d) winter).

According to the LCZ map (Figure 5), it is apparent that building types—primarily indicated by red areas—are predominantly concentrated in the central urban region. High-density built-up zones, including LCZ1 (approximately 0.7%), LCZ2 (approximately 1.87%), and LCZ3 (approximately 3.62%), are mainly clustered around the Lujiazui area and its surroundings. In contrast, LCZ4 (about 7.2%), LCZ5 (about 5.71%), and LCZ6 (about 9.28%) are primarily distributed in districts such as Yangpu, Hongkou, Putuo, and Xuhui. Most natural landscape types, except for LCZG, are found in the peripheral areas of the city, with LCZE accounting for the largest proportion at approximately 22.4%. The overall classification accuracy is 77%, with a Kappa coefficient of 72.54%.

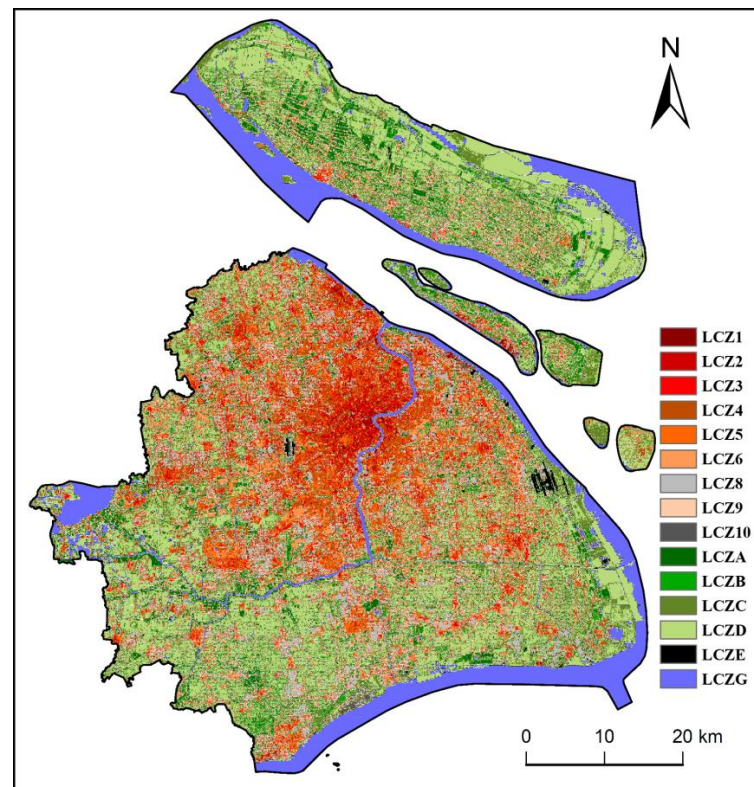


Figure 5. LCZ map of Shanghai.

3.2. The Relationship Between $PM_{2.5}$ and Landscape

To investigate the relationship between $PM_{2.5}$ distribution and landscape characteristics, this study employs a spatial analysis method based on a moving window technique. Initially, the study area is divided into uniform grids measuring 6 km by 6 km. The average $PM_{2.5}$ concentration within a 6 km buffer zone centered on the geometric centroid of each grid is calculated. Circular buffers with radii of 300 m, 500 m, 1000 m, 2000 m, 3000 m, and 5000 m are set around the grid centers, serving as the analysis scope of the moving window. The sizes of the buffers are determined based on previous research and the urban morphology of the study area [30,31]. Within each buffer zone, landscape metrics are computed using LCZ classification data. By systematically moving the grid centers in space, the spatial distribution of landscape metrics across the region is obtained. For each buffer radius, the same landscape index is considered as different variables, denoted as $LCZ(i)_y_x$, where i indicates the LCZ category, y indicates the landscape type, and x represents the buffer radius.

To investigate the impacts of urban form and landscape patterns on $PM_{2.5}$ concentrations, a three-stage screening process was employed to select predictor variables:

① Pearson's correlation coefficients were calculated to preliminarily assess the relationships between the landscape metrics of different LCZ types and PM_{2.5} concentration data. Prior to further analysis, variables undergo collinearity diagnosis: by comparing the Pearson's correlation coefficients of variables across different buffer zones, the buffer with the highest absolute correlation coefficient is selected as the subcategory for screening. Subsequent collinearity diagnostics are performed to eliminate multi-collinearity among model variables.

② To further refine variable selection, this study employs multiple linear regression analysis on the preliminarily screened variables. Both the remaining independent variables and the dependent variable are included in the multiple linear regression analysis. During model development, variables that do not meet the significance level ($\alpha = 0.05$), such as those with failing *t*-tests (regression coefficient *p*-value > 0.05), variables that fail the overall F-test, or variables inconsistent with the model's prior assumptions, are iteratively removed. Additionally, the contribution of each variable to the model's coefficient of determination (R^2) is evaluated, and variables contributing less than 1% to R^2 are discarded. This process is repeated until the model converges, resulting in an optimized regression model where all variables are significant and contribute meaningfully to the explanation of the model, as shown in the table.

③ The selected predictor variables from multiple linear regression are used to build a Multi-scale Geographically Weighted Regression (MGWR) model, which describes the spatial heterogeneity of relationships among variables in spatial data. In contrast to conventional GWR models that enforce a uniform spatial scale across all predictors, MGWR assigns distinct bandwidths to individual variables. This flexibility allows the model to differentiate between local and regional effects, thereby providing a more precise representation of spatial heterogeneity [32,33].

The adjusted R^2 values of the four seasonal models are 0.999, 0.999, 0.993, and 0.995, indicating strong explanatory power. The Variance Inflation Factor (VIF) for all variables is within reasonable ranges, demonstrating that the independent variables have significant impacts on the dependent variable and are not highly correlated with each other (Table 1). In the spring model, the LPI of LCZ3 within the 1000 m buffer is negatively correlated with PM_{2.5} concentrations. Additionally, the AI value of LCZ6 within the 5000 m buffer also shows a negative correlation with PM_{2.5}. These results suggest that dispersed, low-rise open buildings effectively reduce pollution levels. The LSI value of LCZB shows a significant positive correlation with PM_{2.5}, and its Beta value is the highest among all variables, indicating that large areas of vegetation and woodland have a notable impact on PM_{2.5} concentrations. In the summer model, LCZ3, LCZ6, and LCZB again appear as significant factors, with natural landscape type LCZB exerting the strongest influence on PM_{2.5}. Furthermore, the PLAND value of LCZ8 within the 500 m buffer shows a significant positive correlation with PM_{2.5}, implying that large structures and factories influence local pollution levels. In the autumn model, the PLAND value of LCZ9 is significantly negatively correlated with PM_{2.5}, suggesting that sparse medium- and small-sized buildings can reduce pollution levels. Meanwhile, LCZ8 reappears as a significant positive factor at a larger buffer of 1000 m, indicating that large constructions and factories impact PM_{2.5} pollution over broader areas. In the winter model, the AI values of LCZ1 and LCZ4 are negatively correlated with PM_{2.5}, whereas the AI of LCZ3 shows a positive correlation. This suggests that compact mid- to high-rise buildings and human activities might promote PM_{2.5} pollution. Notably, SHEI_3000 appears across all four models, showing a positive relationship with PM_{2.5} during spring and autumn, and a negative relationship during summer and winter.

Table 1. MLR model for PM_{2.5} concentration.

Predictor Variables	Predictor Variables	Predictor Variables	Beta	VIF	R ²
Spring regression model	Intercept	20.838			0.999
	LCZ3_LPI_1000	−0.044	−0.111	1.062	
	LCZ6_AI_5000	−0.0159	−0.617	1.033	
	LCZB_LSI_3000	0.803	0.663	1.043	
	SHEI_3000	8.415	0.338	1.039	
Summer regression model	Intercept	22.953			0.999
	LCZ3_LSI_500	0.195	0.583	1.244	
	LCZ6_PLAND_5000	0.004	0.046	1.124	
	LCZ8_PLAND_500	0.007	0.194	1.076	
	LCZB_LPI_3000	0.545	0.63	1.119	
	SHEI_3000	−0.739	−0.117	1.016	
Autumn regression mode	Intercept	7.524			0.993
	LCZ8_LSI_1000	2.436	0.373	1.029	
	LCZ9_PLAND_3000	−0.981	−0.58	1.038	
	LCZ15_LSI_5000	−0.125	−0.023	1.111	
	SHEI_3000	30.978	0.647	1.101	
Winter regression model	Intercept	63.725	-	-	0.995
	LCZ1_AI_5000	−0.051	−0.372	1.156	
	LCZ3_AI_5000	0.201	0.355	1.322	
	LCZ4_AI_5000	−0.228	−0.303	1.095	
	SHEI_3000	−45.941	−0.986	1.274	

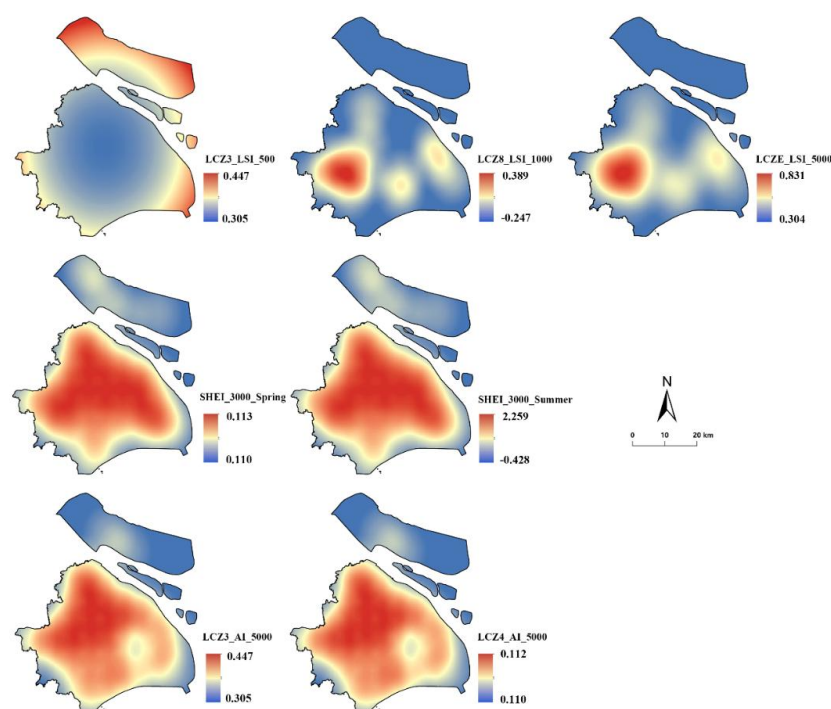
The results indicate that the R² values for the seasonal models are 0.804, 0.745, 0.885, and 0.804, with corresponding AICc values of 80.664, 99.240, 107.774, and 92.680 (Table 2). The summarized statistics—including mean, standard deviation, median, minimum, and maximum—enable comparison of coefficient values for each independent variable and reveal the spatial variation in these coefficients within the study area (Figure 6). In the spring model, SHEI_3000 shows a significant positive influence. During summer, LCZ3_LSI_500 and SHEI_3000 exhibit both positive and negative effects, respectively. In autumn, LCZ8_LSI_1000 and LCZE_LSI_5000 have a significant positive influence. In winter, LCZ3_AI_5000 and LCZ4_AI_5000 are the variables with the most influence. The coefficient of LCZ8_LSI_1000 exhibited a decreasing trend from west to east; it was higher in the western inland region and gradually transitioned to negative values along the eastern coast. In contrast, LCZE_LSI_5000 demonstrated a stronger positive driving effect on PM_{2.5} concentrations in the northern region. Notably, the influence of SHEI revealed substantial seasonal heterogeneity. During spring, its positive impact was predominantly concentrated in the central urban area and its periphery. However, in summer, the high-value zone shifted to the eastern coastal belt, while coefficients in the western region became negative.

Table 2. Summary of PM_{2.5} concentration MGWR model statistics.

Spring regression model	R ²	0.804				
	Adj. R ²	0.729				
	n	32.872				
	AICc	80.664				
	Predictor Variables	Mean	STD	Min	Median	Max
	Intercept	−0.029	0.77	−1.053	−0.118	2.009
	LCZ3_LPI_1000	−0.007	0	−0.008	−0.007	−0.007
	LCZ6_AI_5000	−0.07	0.017	−0.095	−0.072	−0.032
	LCZB_LSI_3000	−0.357	0.204	−0.821	−0.368	0.09
	SHEI_3000	0.112	0.001	0.11	0.112	0.113

Table 2. Cont.

Summer regression model	R ²	0.745				
	Adj. R ²	0.562				
	n	19.086				
	AICc	99.240				
	Predictor Variables	Mean	STD	Min	Median	Max
	Intercept	−0.102	0.13	−0.515	−0.075	0.078
	LCZ3_LSI_500	0.374	0.034	0.305	0.372	0.447
	LCZ6_PLAND_5000	0.069	0.001	0.066	0.069	0.071
Autumn regression mode	R ²	0.863				
	Adj. R ²	0.774				
	n	38.031				
	AICc	138.652				
	Predictor Variables	Mean	STD	Min	Median	Max
	Intercept	−0.039	0.548	−0.905	−0.158	0.819
	LCZ8_LSI_1000	0.065	0.145	−0.247	0.083	0.389
	LCZ9_PLAND_3000	0.046	0.001	0.044	0.046	0.047
Winter regression model	R ²	0.804				
	Adj. R ²	0.729				
	n	32.872				
	AICc	92.680				
	Predictor Variables	Mean	STD	Min	Median	Max
	Intercept	0.013	0.699	−1.131	0.031	1.683
	LCZ1_AI_5000	0.015	0.001	0.013	0.015	0.017
	LCZ3_AI_5000	0.097	0.001	0.095	0.097	0.098
	LCZ4_AI_5000	0.111	0.001	0.11	0.111	0.112
	SHEI_3000	−0.076	0.001	−0.078	−0.076	−0.074

Figure 6. Estimation of predictive variable coefficients for PM_{2.5} concentration MGWR model.

4. Discussion

The influence buffers for LCZ1 and LCZ4 are larger, indicating that high-rise building environments have a broader spatial impact. These tall buildings alter wind flow, suppress dispersion, and aggregate pollution sources, thereby significantly expanding the influence range of $PM_{2.5}$. This observation aligns with previous studies which report that variations in building height under different wind directions differently affect $PM_{2.5}$ diffusion [34]. The influence range of LCZ8 extends from 500 m to 1000 m, suggesting that large low-rise structures, through mechanisms such as physical barriers and low-height emissions, markedly broaden the impact zone of $PM_{2.5}$. The repeated inclusion of LCZB in the models, with substantial buffer zones, confirms that vegetation effectively reduces air pollution—consistent with prior research indicating that vegetation improves air quality through interception, adsorption of particulate matter, and absorption of gaseous pollutants [35,36]. The SHEI variable appears across models in all four seasons, with influence buffers consistently set at 3000 m but exhibiting seasonal differences in effect direction. This may be due to increased biological emissions and agricultural activities during spring and autumn, exacerbating $PM_{2.5}$ pollution, while vegetation's purifying effects dominate in summer, and anthropogenic emissions mask ecological impacts in winter.

Although the research results are promising, several limitations remain unresolved. Due to constraints in monitoring site locations and numbers, as well as limitations of meteorological data, the accuracy of $PM_{2.5}$ distribution still needs improvement. In this study, the selection and layout of control points were relatively balanced, and the analysis reflected the spatial differences in landscape patterns and $PM_{2.5}$ concentrations. However, it only confirmed the relationship between landscape patterns and $PM_{2.5}$ concentrations under the LCZ framework. This study did not clearly explain the underlying mechanisms and processes, which require further investigation.

5. Conclusions

This study utilized WUDAPT Level 0 products and introduced landscape metrics, through the application of mathematical statistics, multiple regression, MGWR, and other methods, to investigate the impact of urban landscape patterns on $PM_{2.5}$ concentrations, ranging from direct quantitative correlations to analyses of spatial variation differences. The result is as follows:

- (1) The regression analyses of landscape metrics and $PM_{2.5}$ showed that LCZ3 and LCZ6 entered the regression equations in both spring and summer with different buffer sizes, indicating that dispersed low-rise open buildings can effectively mitigate $PM_{2.5}$ pollution. In the winter model, LCZ1 and LCZ4 exhibited negative correlations with $PM_{2.5}$, while the aggregation index of LCZ3 was positively correlated, suggesting that compact mid-/high-rise buildings and intensified human activities contribute to elevated $PM_{2.5}$ levels. The LCZB factor appeared repeatedly in the models with larger buffer ranges and substantial effects, confirming the effectiveness of vegetation in reducing air pollution.
- (2) Factors selected through multiple linear regression were subsequently included in the MGWR model, where they collectively explained on average over 69% of the spatial variation in $PM_{2.5}$, highlighting the significant impact of urban landscape configuration on the spatial distribution of pollution, as well as the utility of the LCZ framework in elucidating urban $PM_{2.5}$ variation.

The findings demonstrate the scientific value of employing the LCZ classification system to analyze urban land use and $PM_{2.5}$ pollution linkages. This study not only provides a novel perspective for understanding the mechanisms underlying the interaction between

urban landscape structure and airborne pollutants, but it also offers a scientific foundation for sustainable planning and air quality improvement strategies in other urban areas.

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