SEASONAL VARIATION IN $PM_{2.5}$ AND PM_{10} CONCENTRATIONS AFFECTED BY DIFFERENT LAND USE COVERS AND PRECIPITATION IN GUANGZHOU, SOUTH CHINA

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Abstract. While the negative health impacts of long-term exposure to fine particulate matter (PM) have been well documented, effectively reducing PM pollution through urban land-use planning remains a complex challenge. Using continuous auto-monitoring air quality data from Guangzhou in south China, average $PM_{2.5}$ and PM_{10} concentrations in the dry season were clearly higher than those in the wet season. During the wet season, $PM_{2.5}$ and PM_{10} concentrations exhibited a nonlinear increase with distance from the coastline in Guangzhou. Annually, average $PM_{2.5}$ and PM_{10} concentrations showed a negative correlation with green space cover and NDVI (Normalized Difference Vegetation Index), but a positive correlation with the extent of construction land. Notably, these correlations between average PM concentrations and NDVI/construction land cover were stronger in the dry season than in the wet season. Green space cover in the wet season did not show a significant relationship with average PM concentrations, suggesting that different urban land use/cover types exert a greater influence on PM pollution during the dry season. Furthermore, seasonal and annual average PM concentrations exhibited stronger correlations with the Euclidean distance and Kernel density of vegetable markets than with those of industrial zones. This indicates that local pollution sources, such as vehicle emissions and cooking activities, contribute substantially to elevated PM levels. The proximity of residential areas and food service establishments to vegetable markets suggests that that both traffic-related emissions and cooking fumes from daily life influence the temporal and spatial distribution of particulate pollutants.
Keywords: *particulate matter, construction land cover, green land cover, industrial zone, vegetable market, precipitation*

Introduction

Fine particulate matter (PM) has become a primary pollutant affecting air quality in urban areas worldwide. Epidemiological studies have consistently demonstrated that long-term exposure to fine particulate matter (PM) can lead to adverse health effects exceeding regional air quality standards (Amin et al., 2024; Li et al., 2023; Luderer, 2025; Sosa et al., 2017). Recent research highlighted that $PM_{2.5}$ and PM_{10} pollutants often combine with various hazardous pollutants, including heavy metals, carcinogenic organic compounds, and pathogenic bacteria. These particles can easily enter human respiratory system and blood system through nose and mouth, increasing the risk of cardiovascular diseases and respiratory infections, thereby elevating morbidity and mortality rates (Kan et al., 2012; Kumar et al., 2024; Wang and Liu, 2024; Yu et al., 2021; Zhang et al., 2022). Consequently, urban atmospheric PM pollution is a major global health concern (Ghosh et al., 2023; Miao et al., 2019; Wu et al., 2018; Zhu et al.,

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2021). Rapid urbanization and industrialization in recent decades have driven a significant increase in global material and fossil energy consumption. This growth, coupled with rapid economic development, has led to severe air pollution issues in many Chinese cities (Jia et al., 2024; Wu et al., 2018; Yang et al., 2017; Zhang et al., 2021). Due to the implementation of Chinese national ambient air quality standards in 2016- setting annual average PM_{10} and $PM_{2.5}$ concentrations at less than 70 and 35 μg m^{-3}, respectively, according to the second-grade assessment standard, reducing PM concentrations to meet these criteria has become a critical environmental challenge in China.

Urbanization and industrialization result in obvious land use/cover changes, increasing energy and material consumption. This consumption results in high-density pollution discharge and raises the risk of air PM pollution. Recent studies have primarily focused on predicting spatial patterns of PM concentrations using land use regression (LUR) models (Das et al., 2023; Enkhjargal et al., 2023; Gianquintieri et al., 2024; He and Huang 2018; Huang et al., 2017; Zhou et al., 2024). Most LUR models have emphasized that construction land cover increases PM concentrations, while green land cover can improve air quality by mitigating PM pollution, offering both ecological and economic benefits. However, previous literature reviews demonstrate that the explanatory variables in different LUR models vary in spatial scale, primarily ranging from 50 to 3000 m in recent studies (Li et al., 2024; Liu et al., 2016a; Shi et al., 2024; Stafoggia et al., 2019). Therefore, uncertainties arise when simulating the interactions between land use cover and PM pollution at different spatial scales. Moreover, few studies have reported how seasonal variation in PM concentrations are affected or predicted by LUR models. Limited research has focused on the impact of the spatial distribution of points of interest (POI) for both industrial zones and vegetable markets on PM pollution. The POI distribution of industrial zones can partially indicate industrial pollution sources, as it correlates with industrial activity and significant fossil energy consumption. Similarly, the POI distribution of vegetable markets can partially indicate domestic pollution sources, correlating with population distribution and energy consumption, as well as cooking fumes from daily activities like food preparation and urban-resident traffic. Considering industrial zone and vegetable market as key inner land-use types within construction land use type, studying how PM concentrations are affected by their POI distributions can improve our understanding of PM pollution sources. This knowledge can help determine which PM pollution control strategies should be implemented.

Since China’s reform and opening-up policy in 1978, Guangzhou has become one of the fastest urbanizing and industrializing cities in China (Guo et al., 2022a; Li et al., 2021), with the fourth-highest gross domestic product, following Shanghai, Beijing, and Shenzhen. This rapid urbanization and industrialization have led to a substantial increase in Guangzhou’s urban land area, from 70.0 to 1558.5 km^2 between 1975 and 2015, with a corresponding decrease in natural land cover (Meng et al., 2020; Xu et al., 2016; Yao et al., 2022). This has resulted in a series of air quality issues in Guangzhou. Although Guangzhou’s ambient air quality is better than that of cities in northern China due to higher precipitation, the city still faces significant air pollution challenges, particularly from PM pollutants (Wang et al., 2006; Yang et al., 2023; Zhang et al., 2018b). In this study, it was aimed to (1) assess the seasonal variation in PM_{10} and $PM_{2.5}$ concentrations as affected by precipitation and distance from the coastline; (2) explore the correlation between PM concentrations and construction land cover/green

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land cover at different spatial scales in the wet and dry seasons; (3) investigate the correlation relationships between PM concentrations and the POI Euclidean distance/Kernel density of industrial zones and vegetable markets.

Materials and methods

Study area

Guangzhou, the capital of Guangdong Province in Southern China, is located between N22°26’ and N23°56’ and E112°57’ and E114°03’ (*Fig. 1*), encompassing seven urban districts and four surrounding suburban districts. The city has a total area of 7434.4 km^2 and a forest coverage rate of 42%. In a typical subtropical zone, Guangzhou experiences a marine monsoon climate with high temperature (avg. 23.1℃) and humidity (about 75%). The mean annual precipitation exceeds 1800 mm, with most rainfall occurring from April to September (Guangzhou Municipal Bureau of Statistics and Survey Office of the National Bureau of Statistics in Guangzhou, 2023). Guangzhou has undergone significant land use/cover change, with substantial areas of arable land, wetland and forest inevitably replaced by built-up areas (Lin and Wang, 2023; Liu et al., 2016a). The built-up area of Guangzhou exceeds1800 km^2 (Lin and Wang, 2023), and as of 2022, the city had over 18 million urban residents (Guangzhou Municipal Bureau of Statistics and Survey Office of the National Bureau of Statistics in Guangzhou, 2023). Urbanization and industrialization have driven increased consumption and demands for energy resources and other materials, leading to many ecological and environmental issues, including impacts on ecosystem structure and function, as well as water, soil and air pollution (Qin et al., 2025; Wang et al., 2022; Yao et al., 2022). In recent years, Guangzhou’s ecological and environmental quality has been steadily improved since China’s new ambient air quality standards and their assessment technical regulation were issued in 2012. However, Guangzhou often ranks near the bottom in air quality among 21 cities in Guangdong Province. Annual average $PM_{2.5}$ and PM_{10} concentrations of Guangzhou were 22 μg m^{-3} and 39 μg m^{-3}, respectively, in 2022 (Guangzhou Municipal Bureau of Statistics and Survey Office of the National Bureau of Statistics in Guangzhou, 2023), still exceeding the standards set by the World Health Organization (World Health Organization, 2021). The WHO recommends that annual average concentrations of $PM_{2.5}$ and PM_{10} should be lower than 5 μg m^{-3} and 15 μg m^{-3}, respectively. $PM_{2.5}$ and PM_{10} pollution control has become a major environmental concern for Guangzhou’s urban residents. The locations of PM and precipitation continuous-monitoring sites in Guangzhou are shown in *Figure 1.*

Ground-level $PM_{2.5}$ and PM_{10} monitoring data

Ground-level $PM_{2.5}$ and PM_{10} concentrations have been recorded hourly since Guangzhou Municipal Ecological Bureau began establishing its ambient PM air quality monitoring network in 2012. Twenty-four-hour average concentrations of $PM_{2.5}$ and PM_{10} were calculated from the hourly data, and the annual average concentrations of $PM_{2.5}$ and PM_{10} were estimated from their 24-h average concentrations. Due to the monitoring system issues, PM measurements were occasionally not recorded, resulting in the missing values for the whole calendar year of 2015. Overall, the missing values for $PM_{2.5}$ and PM_{10} account for 3.43% and 3.39% of the total data, respectively. These missing values were excluded from our analyses. Given that $PM_{2.5}$ and PM_{10} levels can

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be easily affected by regional precipitation, the average concentrations of $PM_{2.5}$ and PM_{10} in the wet and dry seasons were also estimated and compared, based on monthly precipitation accumulations in Guangzhou. Following the city's precipitation patterns, the six months from April to September were designated as the wet season, and the remaining six months assigned to the dry season. In this study, ground-level $PM_{2.5}$ and PM_{10} monitoring data were collected from 33 monitoring sites from January 1, 2015 to December 31, 2015. The locations of these monitoring sites are shown in *Figure 1*. Annual and seasonal average concentrations of $PM_{2.5}$ and PM_{10} exhibited highly spatial heterogeneity across these different monitoring sites, as illustrated in *Figures A1, A2* and *A3* in the *Appendix*.

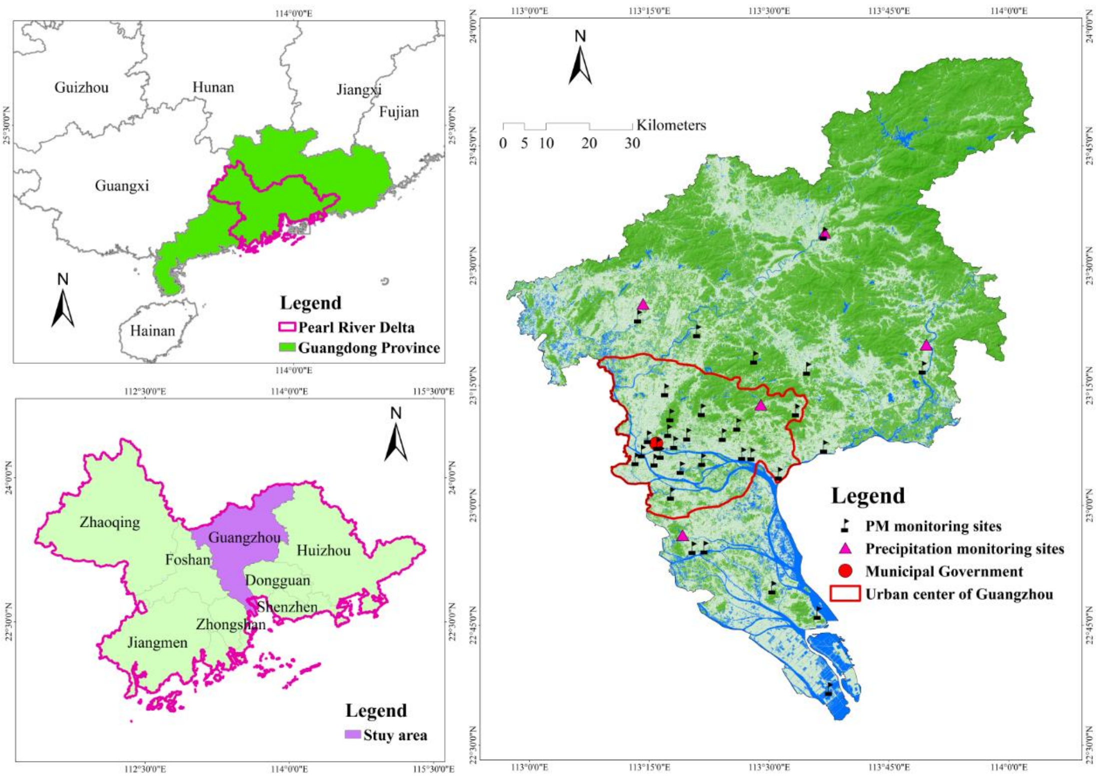

Figure 1. *Location of Guangzhou, Guangdong province of south China and the PM and precipitation continuous-monitoring sites around Guangzhou*

Land use types and normalized difference vegetation index (NDVI)

Land use types and NDVI were derived from multi-spectral Landsat-8 OLI images acquired on 18th October 2015. Landsat-8 images were freely downloaded from http://www.gscloud.cn/. The images of nine shortwave spectral bands (bands 1~7 and 9) have a spatial resolution of 30 m, whereas that of the thermal bands 10 and 11 was 100 m and the panchromatic band 8 offered a spatial resolution of 15 m. The study area was covered by a single scene, path 122, raw 44, with a cloud cover of 0% over Guangzhou. To minimize atmospheric scattering effects, dark object subtraction techniques within ENVI 5.1 Software were applied to the calibrated images. A land use/cover map with a 30 m resolution was then generated using a supervised classification method (i.e. Maximum Likelihood Classifier of ENVI 5.1) for the

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calibrated Landsat-8 images. Six land use/cover types are identified in Guangzhou: (1) green land, (2) construction land, (3) barren land, (4) arable land, (5) wetland, and (6) water. The overall accuracy of the land-use supervision classification is 92.56%, and Kappa coefficient is 0.79. Using the reflectance values of the near-infrared band (band 5) and visible red-light band (band 4), an NDVI map with 30 m resolution was produced using the following equation: NDVI = (band 5-band 4) / (band 5 + band 4) using the ENVI 5.1 Software. *Figure A4* illustrates the spatial distributions of land use types and NDVI.

Collection and pre-processing methods of POI (points of interest)

Points of interest (POI) are inherently linked to specific geographic locations. Each POI represents not only a simple geo-referenced position, but also a series of spatial coordinates defining a geographical area. Industrial production sites or vegetable market sites, for example, are closely related to industrial vitality and population density, respectively, reflecting urban development patterns. To a certain extent, POI can indicate ecological and environmental pressures resulting from substantial energy and material consumption that accompanies rapid industrialization and urbanization (Gao et al., 2021). Geographic POI locations of both industrial zones and vegetable markets were obtained from Baidu Map (https://map.baidu.com/) using Bazhuayu software (https://www.bazhuayu.com/). To maximize POI retrieval, searches were conducted using the Chinese keywords for “industrial zone” and “vegetable market,” combined with street and town names within Guangzhou. Duplicate POI entries were manually removed using Excel 2013 software. The resulting POI data, containing geo-location information, was imported into ArcGIS 10.2 software. Using ArcGIS 10.2, we calculated the Euclidean distance and Kernel density for both industrial zones and vegetable markets. The spatial distribution of Euclidean distance and Kernel density for both industrial zones and vegetable markets are presented in *Figures A5* and *A6*.

Coastline and precipitation analysis

The coastline was delineated in Google Earth and subsequently used to determine the distance of each PM monitoring site from the coastline in Guangzhou, using ArcGIS 10.2 software. Coastal distances were extracted from the Euclidean distance raster data generated from the coastline in Guangzhou. Due to the absence of meteorological data at the ambient air quality monitoring stations, daily precipitation data for 2015 in Guangzhou were obtained from four monitoring stations operated by the National Meteorological Bureau of China. Monthly precipitation totals were calculated from the daily data and used to assess the impact of precipitation on PM pollution, as well as to differentiate between wet and dry seasons.

Data integration and statistical analyses

Five different-scale fishnets of 1 × 1 km, 2 × 2 km, 3 × 3 km, 4 × 4 km, and 5 × 5 km were created using Arc GIS 10.2 software. These fishnets were used to integrate various independent variables at different spatial scales, including green land cover, construction land cover, average NDVI, average Euclidean distance to different industrial zones and vegetable markets, and average Kernel density of different industrial zones and vegetable markets. To analyze the potential influence of built-up areas, green land cover, and human activity on PM pollution control, this study first

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employed Pearson correlation analyses to identify potential correlations between these variables. If independent variables showed a significant correlation with $PM_{2.5}$/PM_{10} concentrations, this study then applied stepwise regression analysis to determine the key variables that potentially affected the deposition, absorption, and diffusion of $PM_{2.5}$ and PM_{10} pollutants. Pearson correlation and regression analyses were performed using SPSS software (Version 18.0, SPSS Inc., USA). Both linear and non-linear regressions were further conducted using the Origin 8.0 software package to determine the nature of the relationship between $PM_{2.5}$/PM_{10} concentrations and the various influencing factors. All statistical tests were conducted using a confidence level of 95%.

Results

Variations in $PM_{2.5}$ and PM_{10} and their correlations with precipitation

Average $PM_{2.5}$ and PM_{10} concentrations exhibited significant spatiotemporal variations across Guangzhou. In general, the average concentrations of $PM_{2.5}$ and PM_{10}, whether measured annually or during the wet and dry seasons, decreased from urban centers towards suburban areas, as illustrated in *Figures A1, A2*, and *A3*. Urban areas in Guangzhou faced higher PM pollution risks due to the greater daily energy and material consumption associated with city centers. These urban districts with elevated PM pollution risks primarily included Liwan, Yuexiu, Tianhe, and Haizhu. Due to the effective regulation of PM pollutants by precipitation, $PM_{2.5}$ and PM_{10} concentrations were notably higher during the dry season compared to the wet season (*Fig. 2a*). Across the different monitoring sites in Guangzhou, the average concentrations of $PM_{2.5}$ and PM_{10} in the dry season ranged from 40.50 and 50.10 μg m^{-3} to 56.67 and 101.11 μg m^{-3}, respectively. In contrast, average concentrations of $PM_{2.5}$ and PM_{10} in the wet season ranged from 19.34 and 28.84 μg m^{-3} to 35.27 and 68.28 μg m^{-3}. Annual average concentrations of $PM_{2.5}$ and PM_{10} for all monitoring stations ranged from 31.46 and 43.37 μg m^{-3} to 45.24 and 84.74 μg m^{-3} with average values of 38.54 and 60.57 μg m^{-3}. The linear relationship observed between annual average $PM_{2.5}$ and PM_{10} concentrations at different monitoring sites (*Fig. 2b*) suggests that these pollutants may share similar pollution sources. As shown in *Figure 2c, d*, monthly average $PM_{2.5}$ and PM_{10} concentrations were correlated with monthly precipitation. To some extent, PM concentration decreases with increasing monthly precipitation. This is likely due to the washing effect of precipitation, which enhances the deposition of PM pollutants during the wet season (Luan et al., 2021; Yu et al., 2018), leading to a much lower PM pollution frequency compared to the dry season.

$PM_{2.5}$ and PM_{10} correlated with coastal distance and land use cover

The frequency and intensity of the landward-to-seaward wind patterns typically decrease with distance from the coastline. Consequently, PM pollutants are less effectively dispersed by the regional wind circulation in more landward zones. This conclusion is supported by our finding that $PM_{2.5}$ and PM_{10} concentrations were positively correlated with coastal distance (*Table 1*). Specifically, $PM_{2.5}$ concentration alone showed a positively correlation with Sea-D (the coastal distance of different monitoring sites) in 2015. During the wet season, both $PM_{2.5}$ and PM_{10} concentrations exhibited a positive correlation with Sea-D. Notably, $PM_{2.5}$ concentration tended to be more strongly correlated with Sea-D compared to PM_{10} concentration. However, no

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significant correlation was found between $PM_{2.5}/PM_{10}$ concentration and Sea-D during the dry season. This result can be attributed to the higher frequency of atmospheric circulation during the wet season in the study area.

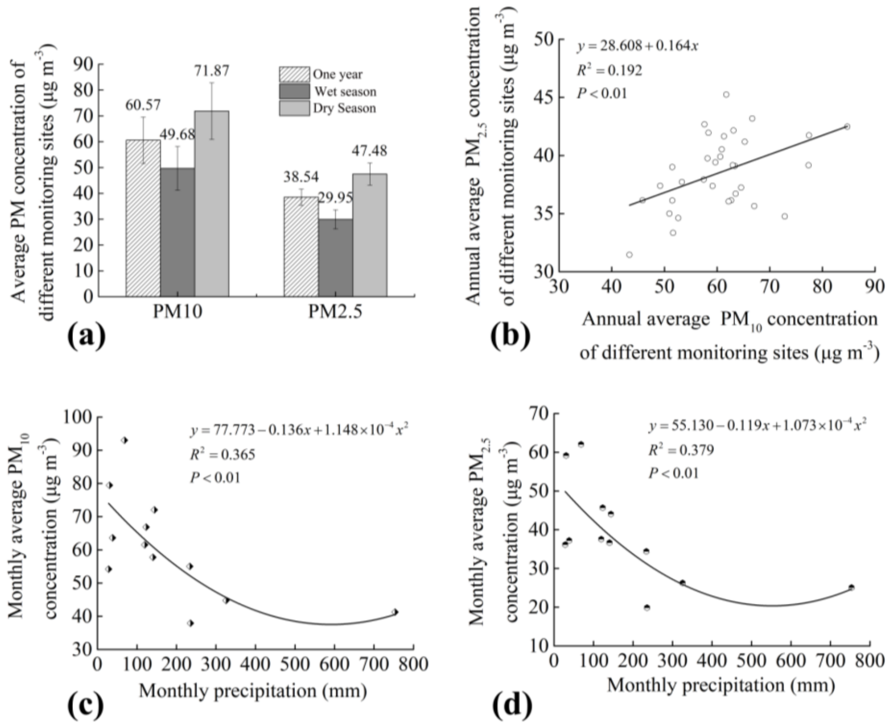

Figure 2. *(a) Annual/seasonal average $PM_{2.5}$ and PM_{10} concentrations around Guangzhou in 2015; (b) The relationships between annual average $PM_{2.5}$ and PM_{10} concentrations of different monitoring sites; (c) The relationship between monthly average PM_{10} concentration and precipitation around Guangzhou; (d) The relationship between monthly average $PM_{2.5}$ concentration and precipitation around Guangzhou*

As shown in *Tables 1* and *2*, regional construction land cover was positively correlated with $PM_{2.5}$ and PM_{10} concentrations, while the green land cover was negatively correlated with $PM_{2.5}$ and PM_{10} concentrations. In other words, increased construction of land cover would likely increase PM pollution levels, whereas increased green land cover is likely to mitigate PM pollution levels. However, the regulatory function of land use/cover change depends on the spatial scales considered. The strongest correlation coefficients between $PM_{2.5}/PM_{10}$ concentrations and construction land cover were observed at the 4 × 4 km spatial scale for the one-year period and the dry season (*Table 1*). During the wet season, the strongest correlation coefficient between $PM_{2.5}$ concentration and construction land cover was found at the 5 × 5 km spatial scale, while the strongest correlation coefficient between PM_{10} concentration and construction land cover was found at the 3 × 3 km spatial scale. The strongest correlation coefficients between $PM_{2.5}/PM_{10}$ concentrations and green land cover were observed at the 4 × 4 km spatial scale during the dry season (*Table 2*). For the one-year period, the strongest correlation coefficient between $PM_{2.5}$ concentration and green space cover was found at the 3 × 3 km spatial scale, while the strongest correlation coefficient between PM_{10} concentration and green space cover was found at the 2 × 2 km spatial scale. However, no significant correlation between $PM_{2.5}/PM_{10}$

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concentrations and green land cover was observed at any spatial scale during the wet season. These findings indicate that the seasonal regulatory functions of land use/cover change are dependent on regional landscape scale effects.

Table 1. *Annual/seasonal average $PM_{2.5}$ and PM_{10} concentrations of different PM monitoring sites in Guangzhou, were correlated with the seaward distance of different PM monitoring sites and the construction land cover surrounding different PM monitoring sites*

Factors		**Sea-D**	**Const1**	**Const2**	**Const3**	**Const4**	**Const5**
One year	$PM_{2.5}$	**0.371***	**0.581****	**0.555****	**0.583****	**0.726****	**0.675****
	PM_{10}	0.140	**0.548****	**0.627****	**0.649****	**0.668****	**0.527****
Wet season	$PM_{2.5}$	**0.707****	0.293	0.290	**0.348***	**0.424***	**0.483****
	PM_{10}	**0.386***	**0.467****	**0.532****	**0.590****	**0.557****	**0.472****
Dry season	$PM_{2.5}$	-0.067	**0.605****	**0.568****	**0.562****	**0.700****	**0.584****
	PM_{10}	-0.073	**0.537****	**0.617****	**0.609****	**0.664****	**0.501****

*P < 0.05. **P < 0.01. [a] Sea-D stands for the seaward distance of different PM monitoring sites. Const1, Const2, Const3, Const4 and Const5 signify the construction land cover surrounding these different PM monitoring sites at five different spatial scales such as the fishnets of 1 × 1 km, 2 × 2 km, 3 × 3 km, 4 × 4 km and 5 × 5 km

Table 2. *Annual/seasonal average $PM_{2.5}$ and PM_{10} concentrations of different PM monitoring sites in Guangzhou, were correlated with the green land cover and NDVI surrounding these different PM monitoring sites[a]*

Factors	**One year**		**Wet season**		**Dry season**	
	$PM_{2.5}$	**PM_{10}**	**$PM_{2.5}$**	**PM_{10}**	**$PM_{2.5}$**	**PM_{10}**
Green1	-0.325	**-0.346***	0.063	-0.174	**-0.539****	**-0.437***
Green2	-0.335	**-0.429***	0.07	-0.239	**-0.564****	**-0.524****
Green3	**-0.373***	**-0.425***	0.014	-0.241	**-0.564****	**-0.512****
Green4	**-0.369***	**-0.415***	0.062	-0.185	**-0.604****	**-0.544****
Green5	**-0.357***	-0.281	-0.04	-0.117	**-0.506****	**-0.381***
NDVI1	**-0.492****	**-0.524****	-0.14	**-0.399***	**-0.609****	**-0.553****
NDVI2	**-0.435***	**-0.572****	-0.059	**-0.415***	**-0.598****	**-0.620****
NDVI3	**-0.465****	**-0.516****	-0.136	**-0.387***	**-0.569****	**-0.547****
NDVI4	**-0.482****	**-0.551****	-0.103	**-0.359***	**-0.626****	**-0.631****
NDVI5	**-0.455****	**-0.391***	-0.17	-0.261	**-0.537****	**-0.448****

*P < 0.05. **P < 0.01. [a] Green1, Green2, Green3, Green4 and Green5 signify the green land cover surrounding these different PM monitoring sites at five different spatial scales such as the fishnets of 1 × 1 km, 2 × 2 km, 3 × 3 km, 4 × 4 km and 5 × 5 km. NDVI1, NDVI2, NDVI3, NDVI4 and NDVI5 stand for the average NDVI surrounding these different PM monitoring sites at five different spatial scales such as the fishnets of 1 × 1 km, 2 × 2 km, 3 × 3 km, 4 × 4 km and 5 × 5 km

Compared to the quantity of green land cover, the quality of green land cover, as indicated by NDVI, can be more effective in reducing PM pollution levels, given the stronger negative correlation coefficients between $PM_{2.5}$/PM_{10} concentrations and NDVI (*Table 2*). The strongest correlation coefficient between $PM_{2.5}$ concentration and NDVI was observed at the 1 × 1 km spatial scale for the one-year period, while the strongest correlation coefficient between PM_{10} concentration and NDVI was found at

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the 2 × 2 km spatial scale. During the wet season, the strongest correlation coefficient between PM_{10} concentration and NDVI was also found at the 2 × 2 km spatial scale. During the dry season, the strongest correlation coefficients between $PM_{2.5}$/PM_{10} concentrations and NDVI were found at the 4 × 4 km spatial scale. Similar to green space cover, we observed stronger correlation coefficients between $PM_{2.5}$/PM_{10} concentrations and NDVI during the dry season compared to the wet season. This result partially supports the idea that green space cover primarily affects spatial patterns of PM pollution at a regional scale during the dry season, while climatic factors primarily control seasonal variations in PM pollution.

$PM_{2.5}$ and PM_{10} correlated with POI Kernel density and Euclidean distance of industrial zones and vegetable markets

Urbanization and industrialization intensify population aggregation and increase energy and material consumption, subsequently elevating the risks of air pollution. In this study, neither $PM_{2.5}$ nor PM_{10} concentrations showed a significant correlation with the Kernel density of POIs representing industrial zones (*Table 3*). However, $PM_{2.5}$ and PM_{10} concentrations did exhibit significant correlations with the Euclidean distance of POIs representing industrial zones at certain spatial scales, as shown in *Table 3*. For the year 2015, PM_{10} concentration was negatively correlated with the Euclidean distance of POIs representing industrial zones at the 2 × 2 km and 4 × 4 km fishnet scales, while $PM_{2.5}$ concentration did not correlate with the Euclidean distance of POIs representing industrial zones at any of the fishnet scales. During the wet season, $PM_{2.5}$ and PM_{10} concentrations were not significantly related to the Euclidean distance of POIs representing industrial zones. However, they were negatively correlated with the Euclidean distance of POIs representing industrial zones at some spatial scales during the dry season (*Table 3*). $PM_{2.5}$ concentration was negatively correlated with the Euclidean distance of industrial zones at the 4 × 4 km fishnet scale. Notably, PM_{10} concentration was negatively correlated with the Euclidean distance of industrial zones at different fishnet scales, except for the 5 × 5 km fishnet scale.

$PM_{2.5}$ and PM_{10} concentrations were significantly influenced by the POI Kernel density and Euclidean distance of vegetable markets (*Table 4*). $PM_{2.5}$ concentrations of the one-year period, wet season, and dry season in Guangzhou were positively related to the POI Kernel density of vegetable markets in five spatial fishnet scales (*Table 4*). The highest correlation coefficients of the one-year period, wet season, and dry season were found in the 4 × 4 km spatial scale, 4 × 4 km spatial scale, and 1 × 1 km spatial scale. For the one-year period and the wet season in Guangzhou, significantly positive correlation relationships were observed between PM_{10} concentration and POI Kernel density of vegetable markets in all the analysis scales except for the 4 × 4 km spatial scale, and the highest correlation coefficients between PM_{10} concentration and POI Kernel density of vegetable markets were found in the 1 × 1 km spatial scale. Compared to the POI Kernel density of the vegetable markets, $PM_{2.5}$ and PM_{10} concentrations appeared to be more strongly correlated with the Euclidean distance of vegetable market POIs, as evidenced by the higher correlation coefficients observed in Guangzhou (*Table 4*). Although $PM_{2.5}$ concentration was not correlated with the POI Euclidean distance of vegetable markets at the 2 × 2 km and 3 × 3 km spatial scales, $PM_{2.5}$ and PM_{10} concentrations were significantly negatively correlated with POI Euclidean distance of vegetable markets at various spatial scales. For the one-year period, the highest correlation coefficients for $PM_{2.5}$ and PM_{10} were found in the 4 × 4 km spatial scales. For the wet season, the highest

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correlation coefficients for $PM_{2.5}$ and PM_{10} were found in the 4 × 4 km and 3 × 3 km spatial scales, respectively. For the dry season, the highest correlation coefficients for both $PM_{2.5}$ and PM_{10} were found at the 1 × 1 km spatial scales.

Table 3. *Annual/seasonal average $PM_{2.5}$ and PM_{10} concentrations of different PM monitoring sites in Guangzhou, were correlated with POI Kernel density and Euclidean distance of the industry zones surrounding these different PM monitoring sites*[a]

Factors	One year		Wet season		Dry season	
	$PM_{2.5}$	**PM_{10}**	**$PM_{2.5}$**	**PM_{10}**	**$PM_{2.5}$**	**PM_{10}**
I-DEN1	0.153	0.12	0.002	-0.011	0.227	0.209
I-DEN2	0.179	0.15	0.033	0.037	0.239	0.221
I-DEN3	0.2	0.159	0.05	0.036	0.253	0.236
I-DEN4	0.194	0.199	0.046	0.092	0.247	0.258
I-DEN5	0.197	0.138	0.123	0.047	0.182	0.192
I-DIS1	-0.163	-0.333	0.074	-0.183	-0.315	**-0.410***
I-DIS2	-0.169	**-0.371***	0.08	-0.208	-0.333	**-0.454****
I-DIS3	-0.149	-0.29	0.067	-0.142	-0.293	**-0.372***
I-DIS4	-0.195	**-0.366***	0.074	-0.189	**-0.368***	**-0.462****
I-DIS5	-0.178	-0.263	0.025	-0.134	-0.298	-0.333

*$P < 0.05$. **$P < 0.01$. [a] I-DEN1, I-DEN2, I-DEN3, I-DEN4 and I-DEN5 signify the POI Kernel density of industry zones surrounding these different PM monitoring sites at five different spatial scales such as the fishnets of 1 × 1 km, 2 × 2 km, 3 × 3 km, 4 × 4 km and 5 × 5 km. I-DIS1, I-DIS2, I-DIS3, I-DIS4 and I-DIS5 stand for the POI Euclidean distance of industry zones surrounding these different PM monitoring sites at five different spatial scales such as the fishnets of 1 × 1 km, 2 × 2 km, 3 × 3 km, 4 × 4 km and 5 × 5 km

Table 4. *Annual/seasonal average $PM_{2.5}$ and PM_{10} concentrations of different PM monitoring sites in Guangzhou, were correlated with POI Euclidean distance and Kernel density of the vegetable markets surrounding these different PM monitoring sites*[a]

Factors	One year		Wet season		Dry season	
	$PM_{2.5}$	**PM_{10}**	**$PM_{2.5}$**	**PM_{10}**	**$PM_{2.5}$**	**PM_{10}**
V-DEN1	**0.577****	**0.412***	**0.489****	**0.442***	**0.430***	0.336
V-DEN2	**0.521****	**0.362***	**0.479****	**0.387***	**0.354***	0.296
V-DEN3	**0.560****	**0.399***	**0.479****	**0.427***	**0.416***	0.325
V-DEN4	**0.619****	0.333	**0.570****	0.328	**0.418***	0.291
V-DEN5	**0.614****	**0.348***	**0.489****	**0.378***	**0.497****	0.283
V-DIS1	**-0.588****	**-0.559****	**-0.381***	**-0.472****	**-0.545****	**-0.556****
V-DIS2	**-0.474****	**-0.567****	-0.316	**-0.512****	**-0.436***	**-0.539****
V-DIS3	**-0.448****	**-0.577****	-0.295	**-0.545****	**-0.414***	**-0.527****
V-DIS4	**-0.651****	**-0.584****	**-0.543****	**-0.537****	**-0.489****	**-0.540****
V-DIS5	**-0.527****	**-0.430***	**-0.444****	**-0.434***	**-0.410***	**-0.374***

*$P < 0.05$. **$P < 0.01$. [a] V-DEN1, V-DEN2, V-DEN3, V-DEN4 and V-DEN5 signify the POI Kernel density of vegetable markets surrounding these different PM monitoring sites at five different spatial scales such as the fishnets of 1 × 1 km, 2 × 2 km, 3 × 3 km, 4 × 4 km and 5 × 5 km. V-DIS1, V-DIS2, V-DIS3, V-DIS4 and V-DIS5 stand for the POI Euclidean distance of vegetable markets surrounding these different PM monitoring sites at five different spatial scales such as the fishnets of 1 × 1 km, 2 × 2 km, 3 × 3 km, 4 × 4 km and 5 × 5 km

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Key factors influencing $PM_{2.5}$ and PM_{10} determined by stepwise regression analysis

Stepwise regression analysis revealed that PM pollution is influenced by various factors across different periods with diverse climatic characteristics (*Table 5*). over the one-year period, regression analysis indicated that $PM_{2.5}$ concentration was primarily influenced by construction land cover at the 4 × 4 km spatial scale and coastal distance, while the PM_{10} concentration was mainly regulated by vegetation quality (NDVI in the 2 × 2 km spatial scale). During the wet season, regression analysis found that the factors influencing PM pollution were more complex. $PM_{2.5}$ concentration was primarily determined by coastal distance, construction land cover in the 5 × 5 km spatial scale and POI Euclidean distance and Kernel density of vegetable markets in the 4 × 4 km spatial scale. Meanwhile, PM_{10} concentration during the wet season was primarily controlled by coastal distance and construction land cover in the 3 × 3 km spatial scale. During the dry season, $PM_{2.5}$ concentration was regulated by the construction land cover in the 5 × 5 km spatial scale, while PM_{10} concentration was primarily regulated by vegetation quality (NDVI in the 4 × 4 km spatial scale). However, these selected key factors did not linearly affect PM pollution. PM concentrations increased nonlinearly with construction land cover (*Fig. 3a, d, e*) and seaward distance (*Fig. 3c*) and decreased nonlinearly with NDVI (*Fig. 3b*) over the one-year period, while PM_{10} concentration during the dry season decreased linearly with NDVI (*Fig. 3f*). Based on the analysis of the above results, PM pollution will be mainly influenced by the regulation function of vegetation cover and pollutant emission associated with the construction land cover.

Table 5. *The stepwise regression analysis indicated that annual/seasonal average $PM_{2.5}$ and PM_{10} concentrations of different PM monitoring sites in Guangzhou, could be profoundly influenced by the land use/cover types and NDVI surrounding these different PM monitoring sites and the seaward distance of these different PM monitoring sites*[a]

Different period		Key factor	Standardized coefficients	R^2
One year	$PM_{2.5}$	Const4	0.7118	0.6434
		Sea-D	0.3418	
	PM_{10}	NDVI2	-0.6525	0.4258
Wet season	$PM_{2.5}$	Sea-D	0.5948	0.6896
		Const5	0.0375	
		V-DEN4	0.2314	
		V-DIS4	-0.2200	
	PM_{10}	Const3	0.5579	0.4571
		Sea-D	0.3322	
Dry season	$PM_{2.5}$	Const4	0.7058	0.4981
	PM_{10}	NDVI4	-0.6771	0.4585

[a]Const3, Const4 and Const5 signify the construction land cover surrounding these different PM monitoring sites at three spatial scales such as the fishnets of 3 × 3 km, 4 × 4 km and 5 × 5 km; Sea-D stands for the seaward distance of different PM monitoring sites; NDVI2 and NDVI4 stand for the average NDVI surrounding these different PM monitoring sites at two different spatial scales such as the fishnets of 2 × 2 km and 4 × 4 km; V-DEN4 and V-DIS4 stand for the POI Kernel density and Euclidean distance of vegetable markets surrounding these different PM monitoring sites at a 4 × 4 km fishnet scale

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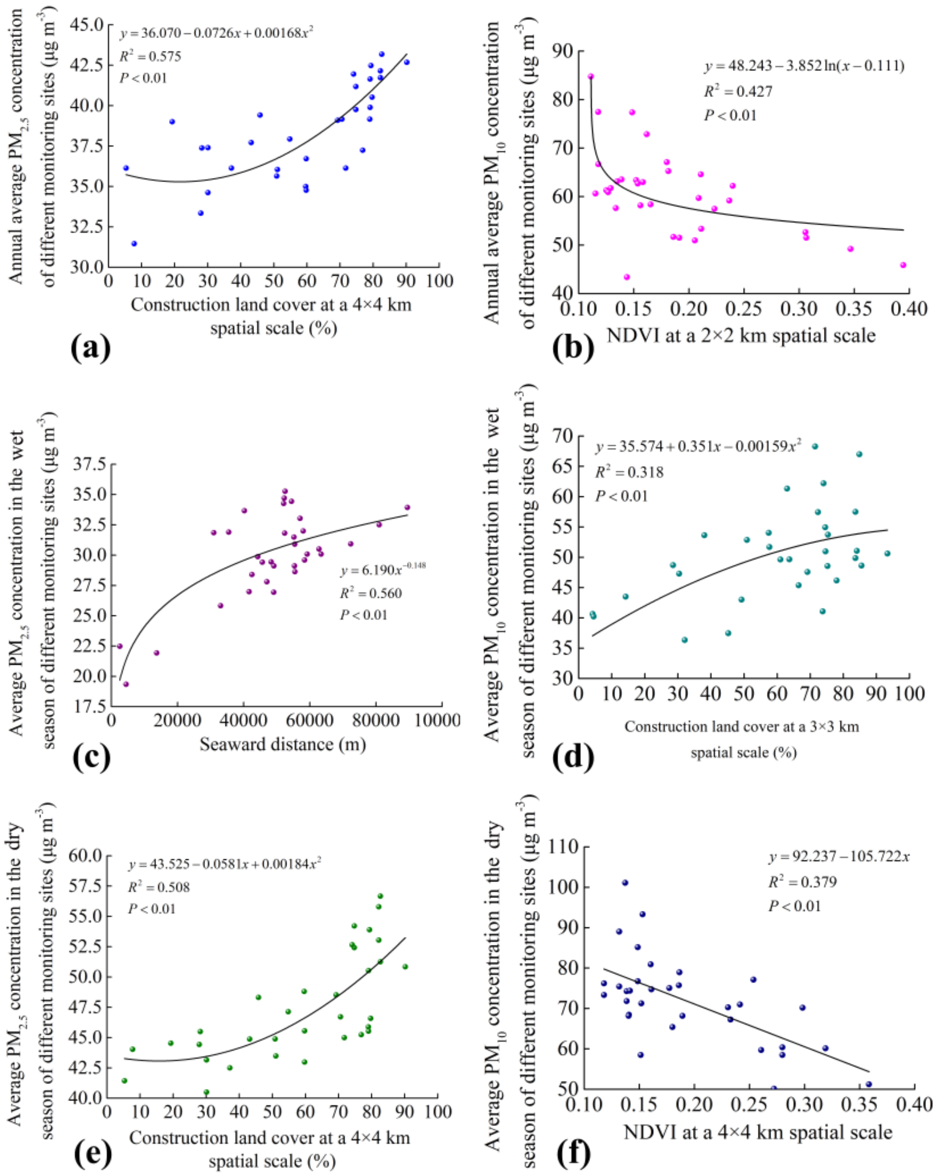

Figure 3. *(a) annual average $PM_{2.5}$ concentration correlated with construction land cover; (b) annual average PM_{10} concentration correlated with NDVI; (c) average $PM_{2.5}$ concentration correlated with seaward distance in the wet season; (d) average PM_{10} concentration correlated with construction land cover in the wet season; (e) average $PM_{2.5}$ concentration correlated with construction land cover in the dry season; (f) average PM_{10} concentration correlated with NDVI in the dry season*

Discussion

Annual/seasonal $PM_{2.5}$ and PM_{10} concentrations affected by construction land cover and green land cover

Urbanization and industrialization, characterized by high level of energy and material consumption, contribute to various ecological and environmental problems, including air PM pollution (Jia et al., 2024; Kim and Hong, 2022; Wu et al., 2018; Yang et al., 2017; Zhang et al., 2021). In this study, Pearson analysis and regression analysis indicated that construction land cover was a key factor influencing PM concentrations

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(*Tables 1* and *5*; *Fig. 3a, d, e*). In general, PM concentrations increased with increasing construction land cover. Similar results have been reported, showing that PM concentrations are positively correlated with construction land cover in Shenzhen (Zeng et al., 2022), Beijing-Tianjin-Hebei Region (Yang et al., 2020), Yangtze River Delta Region (Zhou et al., 2022) and urban agglomerations in the middle reaches of the Yangtze River (He et al., 2023). Many other previous studies have also reported that PM concentrations can be influenced/predicted by different typical land-use indicators related with the construction land cover, such as residential land cover (de Hoogh et al., 2016), industrial land cover (Liu et al., 2016a), artificial land cover (Yang et al., 2017) and land cover of inner different-construction land use types such as the residential, commercial, industrial and governmental land use types (Shi et al., 2016). These studies suggest that spatial differences in land-use types within construction land use cover can affect spatial patterns of PM pollutants. However, they often neglect the differences in how seasonal PM concentrations are influenced by construction land cover at different spatial pattern. In this study, higher correlation coefficients were found between PM concentrations and construction land cover in the dry season than in the wet season (*Table 1*). Moreover, the influences of construction land cover on the seasonal PM concentrations exhibited obvious spatial-scale effects. For example, the average $PM_{2.5}$ concentration during the wet season could be best predicted by construction land cover at a 5 × 5 km spatial scale, while the average $PM_{2.5}$ concentration during the dry season could be best predicted by construction land cover at a 4 × 4 km spatial scale (*Table 1*). Our research suggested that the spatial-scale effects of construction land cover for seasonal PM predictions should be taken into consideration.

Recent studies supported that green land cover in the urban zones can effectively and economically reduce PM pollutants at a regional scale, by combining the aerodynamic dispersive effect of trees and the deposition capabilities of trees and grass (He et al., 2023; Jeanjean et al., 2016; Nguyen et al., 2015; Zhou et al., 2022). In this study, average PM concentrations over one-year period and during the dry season were negatively correlated with green land cover (*Table 2*). Similar results were reported in Shijiazhuang (Zhao et al., 2020) and Shenyang (Kong et al., 2024). Other modeling and monitoring studies have also confirmed that PM pollution can be effectively mitigated by green land cover (Pugh et al., 2012). At a field sampling scale in Beijing, $PM_{2.5}$ concentration tended to decrease with increasing forest canopy density and leaf area index during the daytime (Liu et al., 2015). However, PM_{10} and $PM_{2.5}$ concentrations were not correlated with green land cover in the wet season (*Table 2*). This finding can be attributed to the high frequency and intensity of precipitation that dominantly affected PM scavenging and wet deposition. Furthermore, the removal efficiency of PM pollutants was affected not only by the quantity, but also the quality of the urban forest cover. In this study, NDVI, partially indicating the status and quality of green cover, was significantly negatively correlated with both PM_{10} and $PM_{2.5}$ concentrations. Jiang et al. (2017) and Fang et al. (2024) also reported that PM concentrations were negatively correlated with NDVI in the coastal domains of China and Central China. Other previous studies also emphasized that the structure and species of urban green cover disproportionally affect PM removal efficiency (Blanusa et al., 2015; Li et al., 2023; Sæbø et al., 2012). Urban green cover is known to be unevenly distributed across a city due to ecological, cultural, and social factors. As a result, PM pollution removal function by urban green land cover should vary because of the spatial heterogeneity in species and structure (Escobedo and Nowak, 2009). Future research should pay more

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attention to determining how PM removal efficiency is affected by these forest characteristics at a regional scale. This study also revealed that the maximum correlation coefficients between green land cover/NDVI and PM concentrations were often found in the 4 × 4 km spatial scale (*Table 2*). This finding suggests that urban green land cover has a greater effect locally than on a larger scale and agrees with recent studies that have demonstrated a reduction in PM close to green spaces (Chen et al., 2021; Irga et al., 2015).

Of particular note, literature reviews have explained that variables of different LUR models have very different spatial scales. The spatial scales of most recent studies ranged from 50 to 3000 m (Li et al., 2024; Liu et al., 2016a; Shi et al., 2024; Stafoggia et al., 2019). Nevertheless, this study indicated that the best spatial scales of predicting factors (including construction land cover, green land cover, and NDVI) for the LUR models may often reach 4000 m. In addition, the influences of different predicting factors on the seasonal PM concentrations exibited obvious spatial-scale effects and seasonal differences. Thus, future LUR model studies for PM pollution prediction should take these spatial-scale effects and seasonal differences into consideration.

Annual/seasonal $PM_{2.5}$ and PM_{10} concentrations correlated with the POI density and distance of industrial zone and vegetable market

Industrial zones and vegetable markets are two important inner land-use types of the construction land-use. In urban areas, spatial patterns of vegetable markets and industry zones are important factors reflecting the intensity of land-use and human activities. In Guangzhou, PM concentrations were significantly negatively correlated with the POI Euclidean distance of industrial zones during the dry season, although they were not associated with the POI Kernel density of industrial zones during the wet season. Unlike industrial zones, PM concentrations were significantly negatively correlated with the POI Euclidean distance of vegetable markets in both the wet and dry seasons. Furthermore, PM concentrations were significantly positively correlated with the POI Kernel density of vegetable markets in both the wet and dry seasons. These results supported that PM concentrations increased with vegetable market density but decreased with the distance from both the industrial zone and vegetable markets. However, it was noted that much higher correlation coefficients were observed between PM concentrations and POI Euclidean distance/Kernel density of the vegetable markets compared to those of industry zones. This result indicates that domestic pollution sources, such as vehicle emissions and food preparation, are partially responsible for increasing PM pollutants. Residential settlements and catering services are typically located near vegetable markets. Traffic emissions and cooking fumes from residents' daily activities will affect the temporal and spatial distribution of particulate pollutants. Recent studies have confirmed that vehicle emission and cooking two dominant sources of PM pollutants (Ma et al., 2015; Wang et al., 2006; Zhang et al., 2018b). Ma et al. (2015) reported that both vehicle emissions and cooking in Guangzhou accounted for 26.8% of the organic carbon content in $PM_{2.5}$. The contribution rate of Chinese catering sources to $PM_{2.5}$ is slightly higher than that of Western catering sources, which is related to the differences between Chinese and Western catering cultures and the frequent use of cooking methods such as stir frying in Chinese catering (Li et al., 2018). The contribution rate of catering sources in Beijing, Shenzhen and Wuhan to urban atmospheric $PM_{2.5}$ exceeded 14% (Li et al., 2018). Wang et al. (2006) found that vehicle emission accounted for 38.4% of ambient particulate aerosols in Guangzhou. Bayesian model calculations suggested that the main carbon sources of aerosols were vehicle emissions and biomass combustion in Guangzhou, with contributions of 62.30% and 18.10% in winter and 52.40% and 36.30% in autumn, respectively (Zhai et al., 2024).

Monthly average $PM_{2.5}$ and PM_{10} concentrations affected by monthly precipitation

Meteorological variables are known to directly affect the diffusion, accumulation, and transport of air pollutants (Deng et al., 2022; Huang, 2024; McMullen et al., 2021; Wang et al., 2014). Recent studies have underlined that among various meteorological variables, precipitation scavenging is one of the most important natural processes for reducing PM pollutants (Gao and Liu, 2023; Liu et al., 2016b; McMullen et al., 2021; Ouyang et al., 2015; Xu et al., 2017). This study further confirmed that monthly average $PM_{2.5}$ and PM_{10} concentrations decreased with precipitation (*Fig. 2c, d*). Average $PM_{2.5}$ and PM_{10} concentrations during the wet season were 62.32% and 53.96% higher than those during the dry season in Guangzhou. This finding can be largely explained by the much higher precipitation frequency and intensity that occur during the wet season compared to the dry season. According to meteorological monitoring data in Guangzhou, the precipitation frequencies during the wet and dry seasons were 11.33% and 7.19%, respectively, and their total precipitations were 1808.46 mm and 433.32 mm. The average precipitation intensity during the wet season was much higher than that during the dry season in Guangzhou, which subsequently resulted in much stronger precipitation scavenging effects on $PM_{2.5}$ and PM_{10} during the wet season. This can be partially supported by the research result of Liu et al. (2016b), who showed that moderate daily precipitation (>10 mm) had an obvious scavenging effect on $PM_{2.5}$ and PM_{10}. The precipitation scavenging effects on PM are generally manifested by wet removal and wet deposition. Furthermore, wind, which affects the PM dispersion process, is another key factor that effectively mitigates PM pollution. Previous studies have indicated that low-speed winds or calm conditions facilitate the PM accumulation (Sun et al., 2022; Zhang et al., 2018a). Low-speed winds or calm conditions were much more common during the dry season than the wet season (Guo et al., 2022b; Luo et al., 2006). Especially in comparison with the dry season, the higher frequency and intensity of typhoons during the wet season also contribute to decreasing PM pollution (Liu et al., 2017).

Annual/seasonal $PM_{2.5}$ and PM_{10} concentrations affected by coastal distance

Regression analysis and correlation analysis indicated that coastal distance also directly and indirectly affected PM concentrations in Guangzhou. In general, wind circulation between sea and land helps to remove PM pollutants in neighboring coastal zones. However, both $PM_{2.5}$ and PM_{10} concentrations are potentially affected only by coastal distance during the wet season due to the significant positive correlation found between $PM_{2.5}$/PM_{10} concentration and coastal distance during the wet season, which was not found during the dry season (*Table 1*). This finding can be primarily attributed to the higher frequency and intensity of typhoons during the wet season, which aid in PM dispersal and transmission (Liu et al., 2019; Sun et al., 2022). Furthermore, a higher correlation coefficient occurred between $PM_{2.5}$ concentration and coastal distance, indicating that $PM_{2.5}$ could be more easily regulated by the wind circulation between sea and land compared to PM_{10}. Similar results were found in Wuhan and Shanghai, where wind has a stronger negative impact on fine PM than coarse PM (Sun et al., 2022; Zhang et al., 2018a).

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Conclusions

Seasonal variations in average PM_{10} and $PM_{2.5}$ concentrations are primarily regulated by regional precipitation patterns in Guangzhou. Monthly average PM_{10} and $PM_{2.5}$ concentrations significantly decreased as precipitation increased. Due to substantial differences in precipitation frequency and intensity, PM pollution was considerably more pronounced during the dry season compared to the wet season. Influenced by distance from the coast and variations in land use, annual/seasonal average PM_{10} and $PM_{2.5}$ concentrations exhibited highly spatial heterogeneities. Areas closer to urban centers, characterized by extensive construction land and limited green space, experienced higher PM pollution risks. Correlation and regression analyses revealed that annual and seasonal average PM_{10} and $PM_{2.5}$ concentrations generally increased with construction land cover but decreased with green land cover and NDVI. Urban green cover has demonstrated the ability to mitigate urban PM pollution ecologically and economically on a regional scale. However, the regulatory functions of green land cover may vary significantly between the wet and dry seasons. During the wet season, no significant correlation was observed between average PM concentrations and green land cover. The correlation coefficients between NDVI/construction land cover and average PM concentrations were higher in the dry season compared to the wet season, indicating that PM pollutants are disproportionately affected by land use/cover changes across different seasons. Furthermore, stronger correlations were observed between annual and seasonal average PM concentrations and the Euclidean distance to and kernel density of vegetable markets compared to those of industrial zones. This suggests that local pollution sources, such as vehicle emissions and cooking activities, contribute to increased PM pollutant levels. However, this requires more quantitative testing through further empirical research in the future.

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APPENDIX

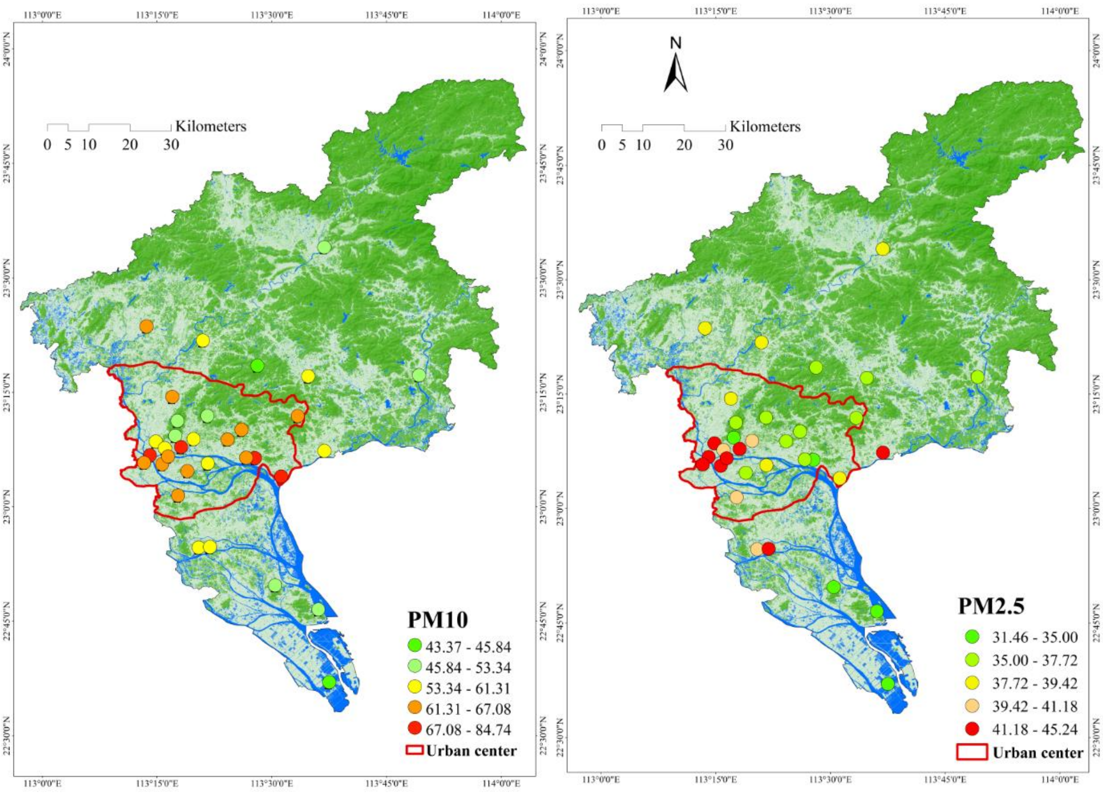

Figure A1. *Average concentrations of $PM2_{.5}$ and PM_{10} for one year (2015) in Guangzhou*

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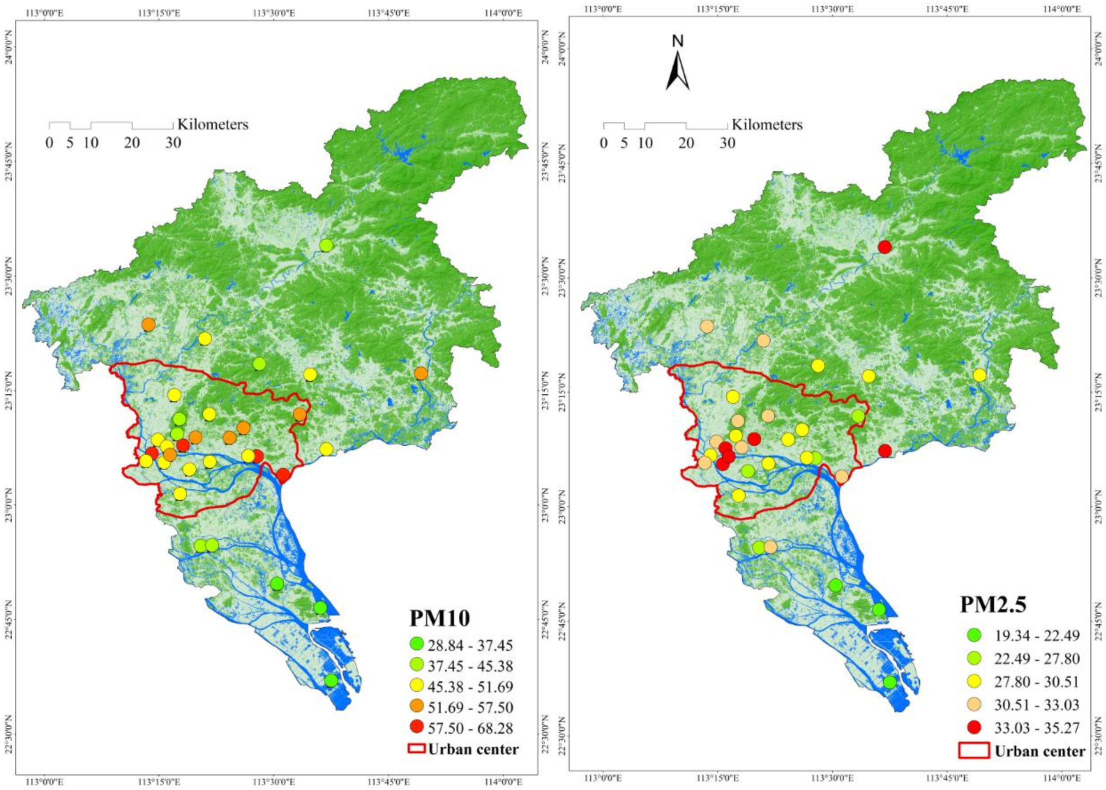

Figure A2. *Average concentrations of $PM_{2.5}$ and PM_{10} for wet seasons (2015) in Guangzhou*

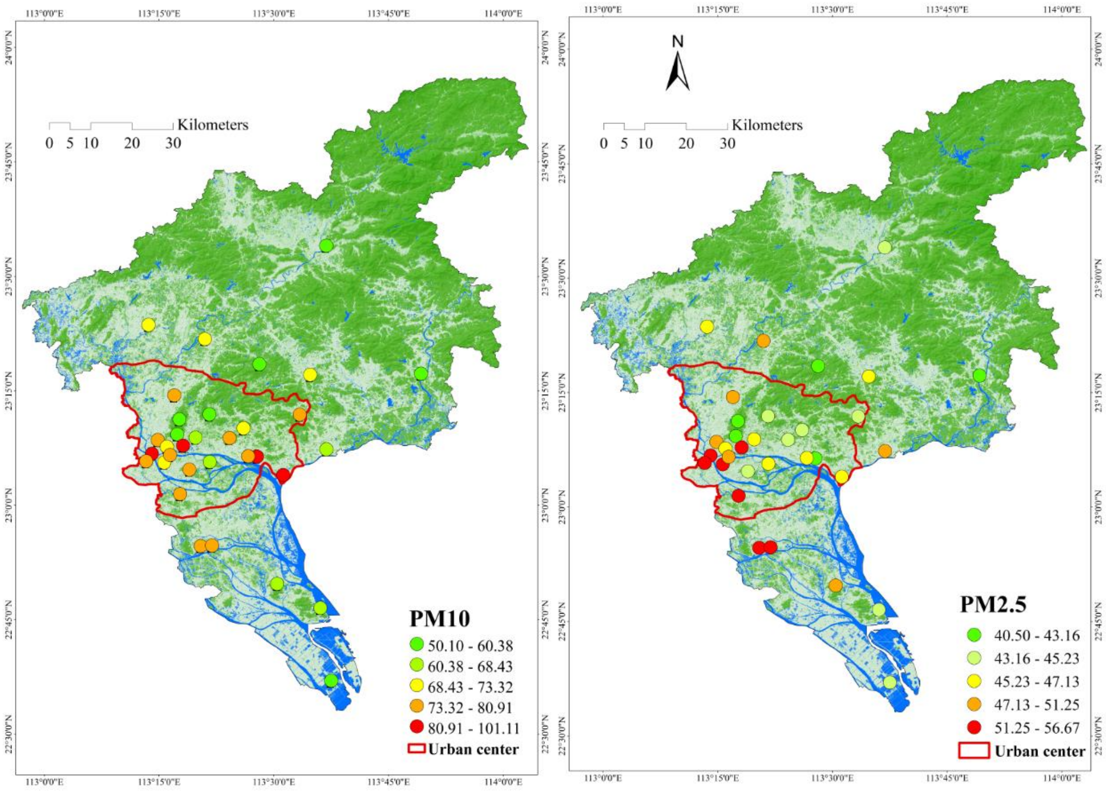

Figure A3. *Average concentrations of $PM_{2.5}$ and PM_{10} for dry seasons (2015) in Guangzhou*

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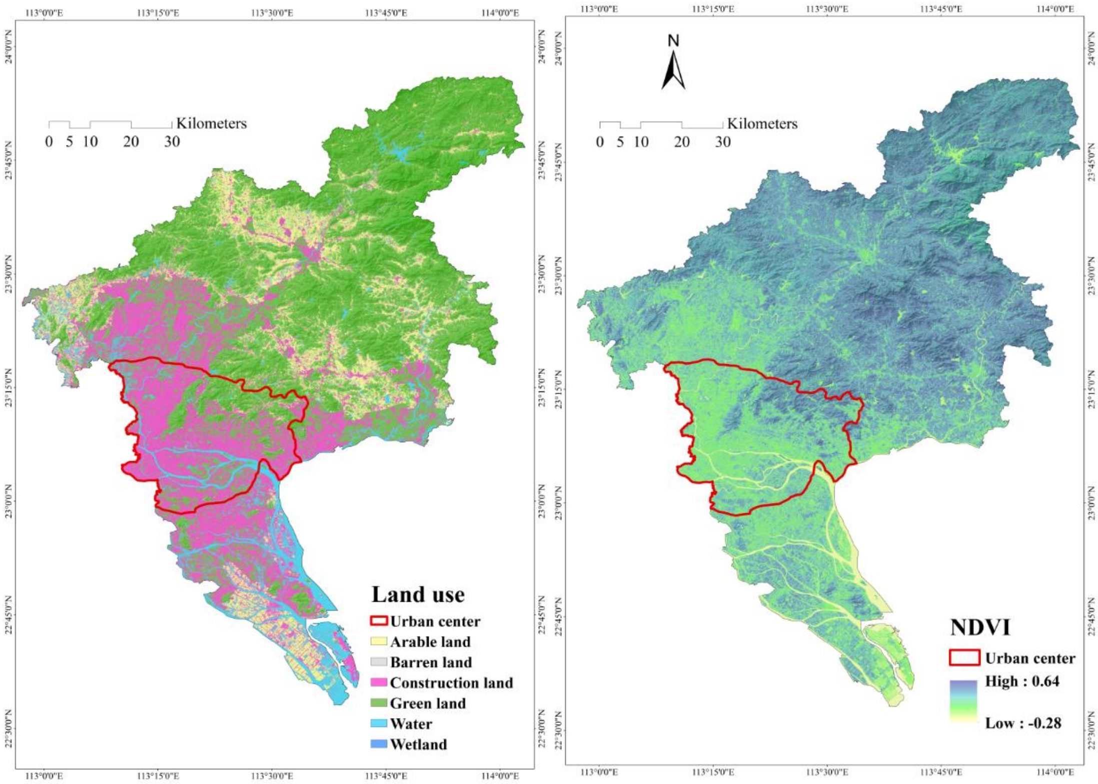

Figure A4. *Land use types and normalized difference vegetation index (NDVI) of 2015 in Guangzhou*

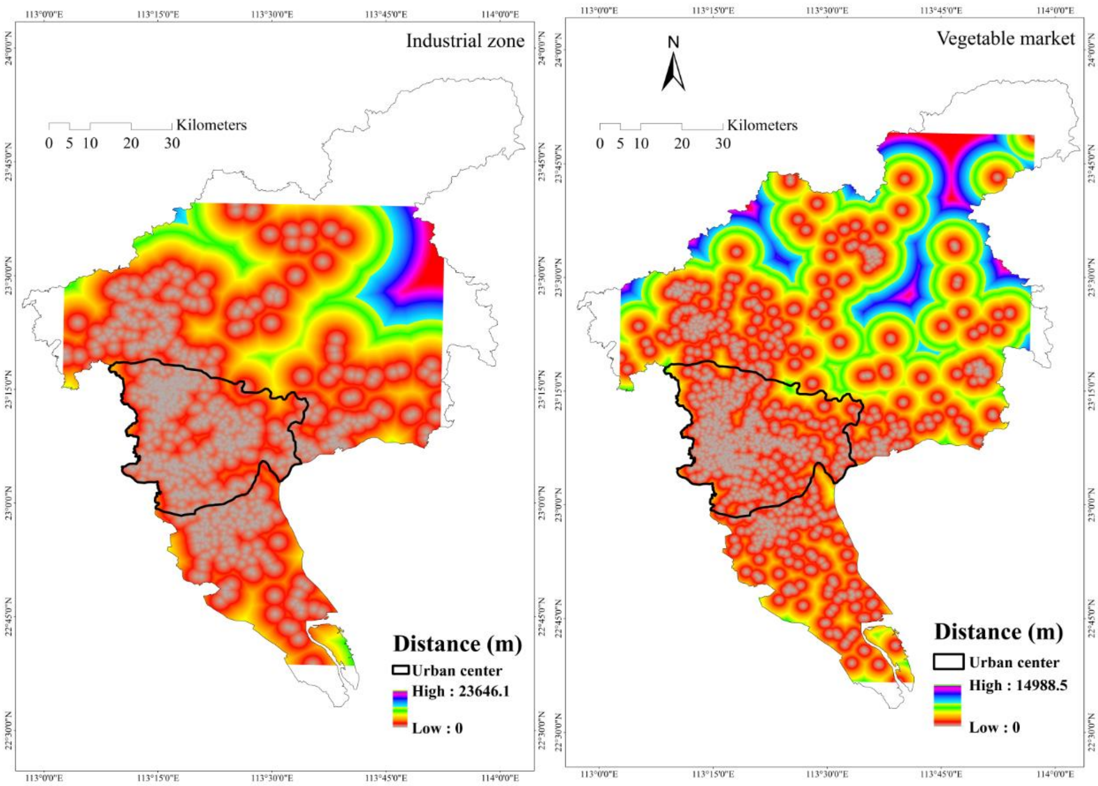

Figure A5. *Euclidean distance for industrial zones and vegetable markets in Guangzhou*

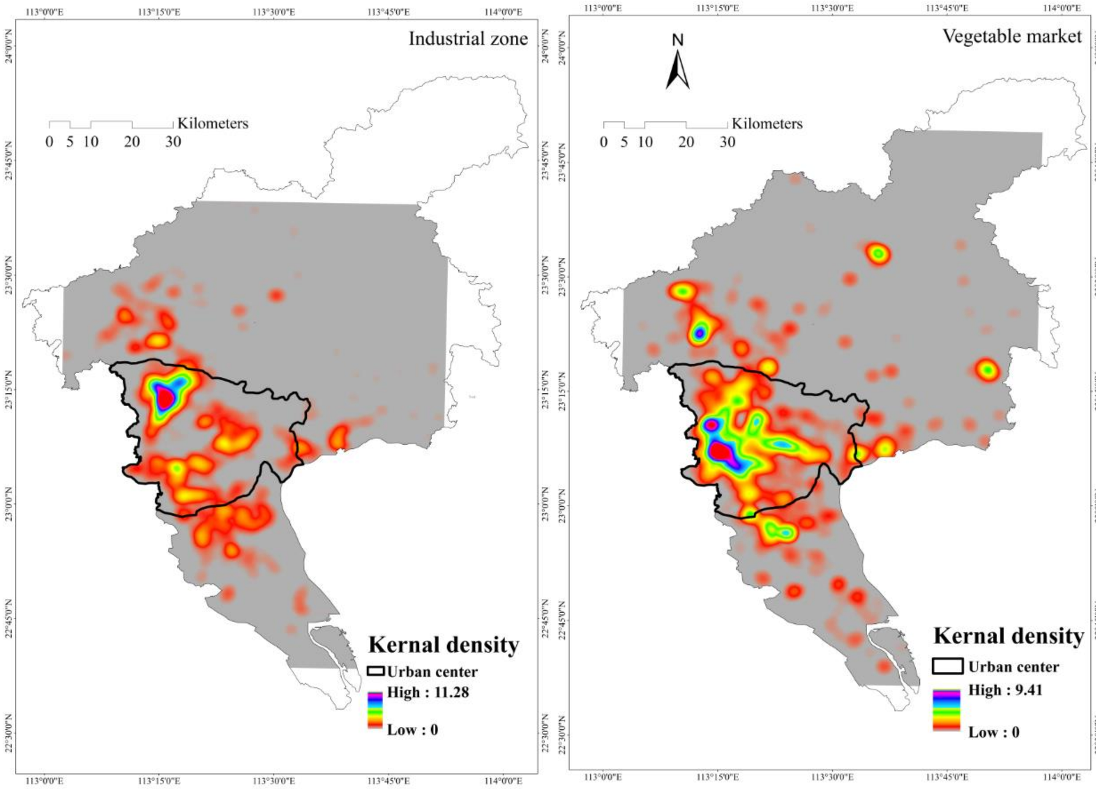

Figure A6. *Kernel density for industrial zones and vegetable markets in Guangzhou*

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