

Article

Dynamic Changes of Air Particle Pollutants and Scale Regulation of Forest Landscape in a Typical High-Latitude City

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Abstract: Particulate pollutants, particularly PM_{2.5} and PM₁₀, pose serious threats to human health and environmental quality. Therefore, effectively mitigating and reducing the concentrations of these pollutants is crucial for human survival and development. In this study, we analyzed the distribution characteristics of air particulate pollutants in a typical high-latitude city, extracted urban forest areas from high-resolution remote sensing images, and examined the changing characteristics of PM concentration and the relationship between landscape pattern indexes and PM at different scales. The results showed that the concentrations of PM_{2.5} and PM₁₀ were highest in winter and lowest in summer. At the small scales of 0.5 km × 0.5 km to 1.5 km × 1.5 km, PM concentration decreased with the decrease in PARA (Perimeter–Area Ratio). At the mesoscales of 2 km × 2 km to 2.5 km × 2.5 km, both PARA and CIRCLE (Related Circumscribing Circle) were highly significant ($p < 0.001$) correlated with PM concentration. At the large scales of 3 km × 3 km to 4 km × 4 km, PARA and PAFRAC (Perimeter–Area Fractal Dimension) were positively correlated with PM concentration. Our study indicates that reducing the complexity of forest patches in small-scale planning can help mitigate particulate air pollution. In the medium scale of urban forest planning, the more regular the forest patch shape and the more similar the patch shape to the strip, the better PM can be alleviated, while in large-scale planning, increasing the forest area and making the patches more normalized and simplified can reduce PM concentration. Moreover, reducing the complexity of forest patches can significantly mitigate PM pollution at all scales. The results of this research provide theoretical support and guidance for improving air quality in urban forest planning at different scales.

Keywords: particulate matter; urban forest; landscape parameters; scale effect



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1. Introduction

With the rapid development of global industrialization and urbanization, the scale of cities continues to expand [1], and there has been a significant increase in extreme weather, such as typhoons, droughts, and sandstorms [2–4], which has seriously affected air quality. Therefore, air pollution has become a global problem. As a developing country with a rapidly rising economy, China is undergoing a high-speed urbanization process [5] but at the expense of the quality of the urban atmospheric environment, which directly leads to a significant decline in environmental quality for human beings [6]. In 2022, the daily concentrations of airborne PM_{2.5} and PM₁₀ often exceeded standards, sometimes even tripling the limits [7]. PM can be divided into coarse particles (2.5–10 µm, PM₁₀), fine particles (0.1–2.5 µm, PM_{2.5}), and ultrafine particles (<0.1 µm, PM_{0.1}) according to the size of the aerodynamic equivalent diameter. PM_{2.5} refers to atmospheric particulate pollutants with a diameter of less than or equal to 2.5 µm, also known as Lung-enterable Particulate Matter

(LEPM) [8,9]. $PM_{2.5}$ has a small particle size, is rich in toxic and hazardous substances, and has a long residence time and transportation distance in the atmosphere; therefore, it is harmful to human health and air quality [10,11]. $PM_{2.5}$ can penetrate the respiratory tract and reach deep into the alveoli, potentially causing lung disease, cancer, heart disease, and other illnesses [12]. In 2016, more than 4 million people worldwide died due to prolonged exposure to excessive $PM_{2.5}$ [13,14], with nearly 50% of these deaths occurring in developing countries such as China and India. $PM_{2.5}$ is considered the most harmful substance to human health among all classes of atmospheric particulate pollutants [15–17]. Additionally, $PM_{2.5}$ significantly impacts climate change and atmospheric visibility [18]. $PM_{2.5}$ sources are both natural and anthropogenic [19], with anthropogenic sources having a greater impact, such as automobile exhaust emissions [20], fuel combustion, power generation, metallurgy, textile printing, and dyeing. Particulate pollutants are also found in soot and dust from coal and gas combustion and fuel oil used in heating and cooking, contributing to the heat island effect [21,22], making urban particulate pollution a prominent issue in urban development [23]. PM_{10} refers to respirable particulate pollutants with a particle size of 10 μm or less [24]. Such pollution typically comes from motor vehicles traveling on unpaved roads, material crushing and grinding processes, and dust raised by the wind [25,26]. When inhaled by humans, PM_{10} accumulates in the respiratory system, causing various diseases [27]. Peak and cumulative exposure to ambient airborne particulate pollutants pose significant health hazards to the public.

Studies have shown that numerous diseases with high morbidity rates are strongly associated with $PM_{2.5}$ and PM_{10} [28,29]. Furthermore, airborne particulate pollutants can increase surface albedo [30], raise surface temperature, trigger global warming [31], and influence the pH of precipitation, leading to the formation of acid rain [32]. At the beginning of 2020, the outbreak of COVID-19 posed a great threat to social activities and human health. One mode of transmission of the novel coronavirus is through aerosols. As types of aerosols, $PM_{2.5}$ and PM_{10} can carry toxic and harmful substances into the alveoli or bronchial tubes due to their fine particles [33] and pose health risks [34]. $PM_{0.1}$ can linger in the atmosphere for several years. Compared with $PM_{2.5}$ and PM_{10} , $PM_{0.1}$ has a stronger ability to penetrate body tissues and can be directly absorbed into the blood, so it is not easy to remove from the body to cause disease. Therefore, particulate pollutants have significant negative impacts on both the atmospheric environment and human health. As public health awareness increases, so does the demand for better environmental quality. Effectively reducing and controlling particulate pollutants has become an urgent issue.

To mitigate airborne particulate pollutants, three methods are commonly applied: source control, exhaust gas treatment, and natural resource abatement. Controlling automobile exhaust emissions, reducing thermal power generation, promoting energy conservation, encouraging low-carbon travel, and substituting natural gas for coal combustion can all help to alleviate particulate pollutant concentrations [35]. However, the production of particulate pollutants cannot be completely avoided in daily life, making it essential to properly treat the produced particulate pollutants. Particulate pollutants are commonly found in soot, and the process of separating particulate pollutants from exhaust gases and trapping and recovering them is called dedusting [36]. Existing exhaust gas treatment methods can be categorized based on the source of exhaust gas: fuel combustion exhaust treatment methods, process production exhaust treatment methods, and automobile exhaust treatment methods. Particulate pollutant treatment methods include gravity dedusting, inertial force dedusting, centrifugal force dedusting, wet dedusting, filtration dedusting, and electric dedusting [37,38]. All these methods effectively deal with particulate pollutants and reduce their harm. Additionally, natural ecosystems can reduce PM concentrations in the air through their powerful ecological service functions. Green plants, in particular, play a crucial role in particulate pollutant abatement. They can absorb particulate pollutants through the stomata on their leaves. Stomatal openings are generally much larger than the diameter of particulate pollutants, allowing the pollutants to enter plant leaf tissues,

where they undergo various biochemical reactions, becoming part of the plant's metabolic activities and, thus, playing a role in dust stagnation [39].

Given that vegetation can effectively reduce particulate pollutant concentrations in the atmosphere, the utilization of urban vegetation to mitigate PM concentrations has become a hot topic in ecology and environmental science research. Current research mainly focuses on vegetation selection [40,41], forest stands [42], forest community structure [43], and forest landscape structure [7,44]. When particulate pollutants approach tree leaves, they can pass through the air and leaf boundary layer and be adsorbed onto the leaf surface. Studies have shown that tree species such as *Taxus wallichiana* var. *chinensis* (Pilger) Florin, *Sabina chinensis* (L.) Ant. cv. *Kaizuca*, *Platycladus orientalis* (L.) Franco, and *Pinus tabulaeformis* Carrière can secrete mucilage due to the rough surface of their leaves, successfully retaining fine particulate objects on the surface and even absorbing some particulate pollutants into the interior of leaf stomata [45], making them excellent choices for urban tree species planning. Ji et al. noted that *Cupressus funebris* Endl. has a stronger ability to abate particulate pollutants than *Pinus* L. Higher planting densities are more effective in reducing PM concentrations than lower planting densities [46]. It has also been found that on roads with high traffic flow, as trees grow taller, they form “street canyons”, which may cause poor air circulation and trap airborne particulate pollutants [47], increasing localized pollutant concentrations [48,49]. The adsorption capacity of forest trees for airborne particulate pollutants depends on tree structural parameters such as canopy height, foliage density, tree height, and planting spacing, all of which directly or indirectly affect particulate pollutant concentrations. The combination of forest and other solid barriers has a combined benefit for urban air quality [50,51]. Additionally, air movement significantly affects the deposition of particulate pollutants [52]. Higher vegetation canopies can impede airflow and negatively affect air quality, whereas lower forest structures like hedgerows, which do not impede airflow, can improve air quality [53]. Forest stands also have different degrees of positive effects on particulate pollutant abatement. The rough surface of the stand canopy can play a direct role in the absorption of fine particulate matter, and the forest stand can also have an indirect effect on fine particulate matter in the air through the influence of the canopy on the microclimate in the forest [54].

Regarding the influence of urban forest community structure on PM concentration, studies have shown that forest structure is the main reason for differences in PM concentration within different forests. Parameters such as forest canopy density, leaf area indexes, and diameter at breast height are significantly correlated with PM_{2.5} concentration [43]. The dominant factor in the urban forest community structure for PM_{2.5} abatement is the tree canopy. The complex structure of the forest canopy plays a major role in the adsorption of particulate pollutants. At the same time, the forest canopy greatly increases ground surface roughness, which promotes air turbulence, increasing the settling rate of airborne particulate pollutants and retaining particulate pollutants from the air more effectively [55]. Additionally, the surrounding environment of the urban forest, vegetation growth conditions, and patch form can affect the ability of urban forests to mitigate PM_{2.5}. Some studies have revealed the relationship between forest landscape structure and PM concentration. The area and perimeter of forest patches and PM_{2.5} concentration show a significant nonlinear negative correlation, with more irregularly shaped forest patches having a stronger ability to abate PM_{2.5} concentration [7,46]. However, most studies mainly focus on analyzing the relationship between basic parameters such as area and the number of forest patches and PM concentration [44]. Other landscape pattern indexes that may have important effects on PM concentration need to be further explored. Changes in forest patch characteristics have an impact on landscape structure, and different forest patch patterns may have different effects on the ecological service functions of forest landscape structure. Only by fully analyzing the coupling relationship between the characteristics of forest patches and particulate pollutants can we effectively reduce the level of air pollution. In addition, the scale effect of urban forests should also be fully taken into account. Bi et al. found that it was feasible to reduce PM_{2.5} by increasing the complexity of patch

shape and edge length but did not compare the correlation differences among multiple scales [56]. However, the relationship between landscape pattern and PM concentration can not only be analyzed from a macro perspective, and research results at different scales are completely different. Chen et al. showed that the buffer radius on the scale of 0.5 km is important to reduce PM pollution [57]. Recent studies have placed less emphasis on the coupling effect between multi-scale forest landscape patterns and PM_{2.5} and PM₁₀ concentrations, and the relationship between urban forests and PM concentration at spatial scales remains unclear. Therefore, it is necessary to conduct multi-scale studies on urban forests and refine important landscape indicators that can mitigate particulate pollutants at different scales. We assume that larger forest areas and more complex patches have a stronger effect on PM concentration abatement. Studying the relationship between the urban forest landscape pattern index and PM concentration lays the foundation for further promotion of the harmonious development of urban ecological service functions.

In this paper, Changchun City, a rapidly urbanizing city, was selected as the study area. Our previous studies focused on the effects of forest type and forest patch index on PM_{2.5} concentration [7], but the scale effect of urban vegetation was not considered. In this study, eight buffer zones were set up, which enabled the response of urban forest landscape pattern indexes to PM concentration at different scales to be explained. The relationships between various landscape pattern indexes and PM concentration under different scale conditions still need further exploration. The objectives of this paper are (1) to analyze the characteristics of PM_{2.5} and PM₁₀ concentration changes and differences, (2) to explore the relationship between landscape pattern indexes and particulate pollutant concentrations at different landscape scales, and (3) to identify the key indexes affecting the concentrations of airborne particulate pollutants. This study can provide a theoretical basis for urban forest planning at different spatial scales to abate airborne particulate pollutants. These findings are applicable to cities suffering from serious air pollution problems due to rapid urbanization.

2. Materials and Methods

2.1. Study Area

The study site of this research is Changchun City (43°05′–45°15′ N; 124°18′–127°05′ E), the capital of Jilin Province, located in the hinterland of the Northeastern Plain of China (Figure 1). Changchun is the natural geographic center of the Northeast region [58]. The climate in the study area is a temperate continental semi-humid monsoon climate characterized by a dry and windy spring, a warm and short summer, a sunny and warm autumn, and a long and bitterly cold winter. The area lies in the transition zone between the humid eastern mountains and the semi-arid western plains. Changchun has a forest area of 200,800 ha, with a forest coverage rate of 8.1% [59]. In 2022, the average annual concentration of inhalable particulate matter (PM₁₀) in Changchun was 48 µg/m³, and the average annual concentration of fine particulate matter (PM_{2.5}) was 28 µg/m³. The World Health Organization (WHO) recommends an annual average PM_{2.5} concentration of no more than 5 µg/m³. Therefore, the current PM_{2.5} concentration in Changchun is almost six times the level suggested by the WHO. The average annual temperature is 6.9 °C, and the annual precipitation is 732.5 mm [60]. The total population is 9,065,400 [58].

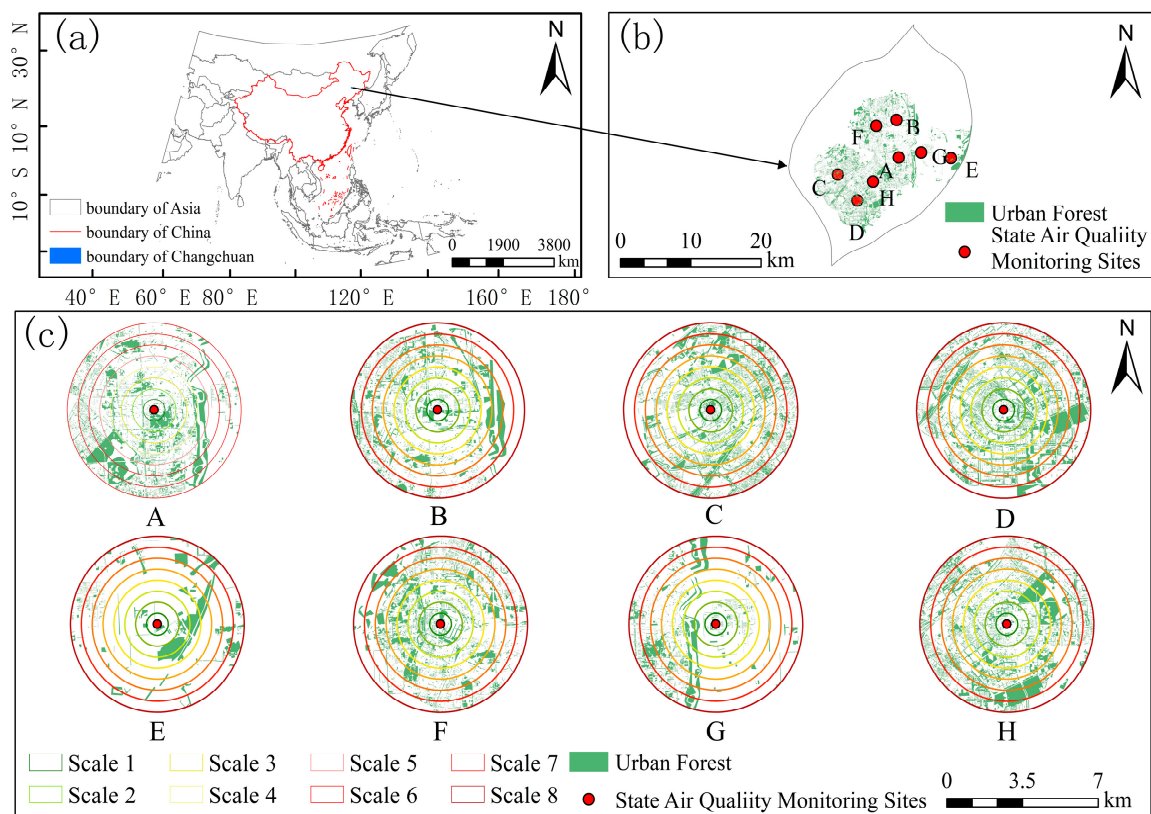


Figure 1. Map of 8 state air quality monitoring sites in Changchun, Jilin, China. (a) Map of Asia. (b) Map of Changchun City and the locations of state air quality monitoring sites. (c) 8 different scales around state air quality monitoring sites. The air quality monitoring sites were named by their locations. Point A, Gardening Department; Point B, Food Factory; Point C, Daishan Park; Point D, High-Tech District Committee; Point E, Environmental Sanitation Department; Point F, Bus Factory; Point G, Labor Park; Point H, Post and Telecommunication College. Scales of 1–8 represent buffer zones of $0.5\text{ km} \times 0.5\text{ km}$, $1\text{ km} \times 1\text{ km}$, $1.5\text{ km} \times 1.5\text{ km}$, $2\text{ km} \times 2\text{ km}$, $2.5\text{ km} \times 2.5\text{ km}$, $3\text{ km} \times 3\text{ km}$, $3.5\text{ km} \times 3.5\text{ km}$, and $4\text{ km} \times 4\text{ km}$, respectively.

2.2. Data Sources

$\text{PM}_{2.5}$ and PM_{10} concentration data were obtained using real-time air pollutant data from 8 Chinese National Air Quality Monitoring Stations (Figure 1; Post and Telecommunication College in Chaoyang District, Daishan Park in Lvyuan District, High-Tech District Committee, Environmental Sanitation Department in Jingkai District, Bus Factory in Lvyuan District, Labor Park, Food Factory, and Gardening Department). The hourly air quality data ($\text{PM}_{2.5}$ and PM_{10} concentrations) for these 8 Chinese National Air Quality Monitoring Stations from 1 January 2022 to 31 December 2022 were obtained from the China National Environmental Monitoring Centre “<https://www.cnemc.cn> (accessed on 10 January 2023)”. These data were used to calculate the monthly mean, seasonal mean, maximum, minimum, and standard deviation of $\text{PM}_{2.5}$ and PM_{10} concentrations. The year was divided into four seasons: spring (March to May), summer (June to August), autumn (September to November), and winter (December to February). Monthly and seasonal averages of $\text{PM}_{2.5}$ and PM_{10} concentrations at 8 Chinese National Air Quality Monitoring Stations were used to calculate monthly and seasonal variations and differences in the concentrations of air particle pollutants. The correlation analysis and redundancy analysis between PM concentration and landscape pattern indexes were carried out using the average PM concentration detected at 8 Chinese National Air Quality Monitoring Stations.

2.3. Methods

2.3.1. Extraction of Urban Forest Areas and Establishment of Landscape Scale Buffer Zone

The urban forest in Changchun City was extracted from Gaofen-2 images using ArcGIS 10.8 (ESRI, Redlands, CA, USA) in our previous study [7]. To explore the influence of urban forest landscape patterns on PM concentration at different scales, eight buffer zones with radii of $0.5 \text{ km} \times 0.5 \text{ km}$, $1 \text{ km} \times 1 \text{ km}$, $1.5 \text{ km} \times 1.5 \text{ km}$, $2 \text{ km} \times 2 \text{ km}$, $2.5 \text{ km} \times 2.5 \text{ km}$, $3 \text{ km} \times 3 \text{ km}$, $3.5 \text{ km} \times 3.5 \text{ km}$, and $4 \text{ km} \times 4 \text{ km}$ were established, centering on the eight Chinese National Air Quality Monitoring Stations (Figure 1). These buffer zones were used to analyze the characteristics of urban forest landscape pattern indexes and the coupling relationship between landscape pattern indexes and PM concentration.

2.3.2. Selection of Landscape Pattern Indexes

In this study, we characterized the landscape pattern indexes of urban forest in terms of patch size, shape, number of fractal dimensions, and complexity. Seven indexes were selected to measure the spatial pattern of urban forest, including Class Area (CA), Patch Area (AREA), Shape Index (SHAPE), Fractal Dimensionality Index (FRAC), Perimeter–Area Ratio (PARA), Related Circumscribing (CIRCLE), and Perimeter–Area Fractal Dimension (PAFRAC) (Table 1). The equations of these landscape pattern indexes are shown in the Appendix A at the end of the manuscript. These indexes can clearly and accurately show the relationship between urban forest landscape pattern indexes and PM concentration [61]. The principles of index selection are as follows: (1) The selected variables can reflect changes in the entire landscape or each type as much as possible, (2) they are easy to calculate and analyze, (3) they have a small amount of redundancy [44,62,63], and (4) the selected indexes can characterize the composition or structure of the landscape.

Table 1. Introduction to the landscape pattern indexes.

Landscape Index	Definition	Ecological Meaning	Data Range
Class Area (CA)	The area of the plaque type.	CA is the basis for measuring landscape components and calculating other indexes, and its value restricts the species abundance, quantity, food chain, and reproduction of secondary species, with a certain landscape type patch as the gathering place.	$CA > 0$
Patch Area (AREA)	The extent of urban forest patch.	AREA is an ‘area and edge metric’ that summarizes the landscape as the mean of all patches in the landscape. It is a simple way to describe the composition of the landscape.	$AREA > 0$
Shape Index (SHAPE)	Degree of regularity of patch shape.	The larger the value, the more complex the patch shape. When the value approaches 1, it indicates that the patches are aggregated to the maximum extent (such as square or near square).	$SHAPE \geq 1$
Fractal Dimension Index (FRAC)	The complexity of patch shape on a spatial scale.	The larger the value, the more complex the shape and the greater the ecological complexity.	$1 \leq FRAC \leq 2$
Perimeter–Area Ratio (PARA)	Average circumference-to-area ratio.	PARA is used to indicate the complexity of plaque shape	$PARA > 0$
Related Circumscribing Circle (CIRCLE)	The degree of near-circular or near-strip shape of the forest patch.	A smaller value means the shape tends to be round, while a larger value indicates the patch tends to be strip-shaped.	$0 < CIRCLE < 1$
Perimeter–Area Fractal Dimension (PAFRAC)	The number of dimensions of the perimeter area.	The closer the value is to 1, the more regular the shape of the plaque or the simpler the plaque, indicating a greater degree of human disturbance.	$1 < PAFRAC < 2$

2.3.3. Data Analysis

First, ArcGIS was applied to set up the buffer zones; then, mask extraction was performed. Landscape pattern index data were calculated by Fragstats 4.2. A one-way ANOVA was conducted to determine the differences in $PM_{2.5}$ and PM_{10} concentrations among the seasons, and a Pearson correlation analysis was performed to explore the relationship between $PM_{2.5}/PM_{10}$ concentrations and urban forest landscape parameters at different scales using R (CRAN project). In this study, redundancy analysis was conducted using Canoco 5 (Microcomputer Power, Ithaca, NY, USA). The results of this analysis were used to identify the key factors affecting changes in particulate pollutant concentrations and to determine the magnitude of the influence of landscape pattern indexes on $PM_{2.5}$ and PM_{10} concentrations [64].

3. Results

3.1. Differences in $PM_{2.5}$ and PM_{10} Concentrations

Figure 2 shows the monthly changes and seasonal variations in $PM_{2.5}$ and PM_{10} concentrations. As the months progressed, the concentration of $PM_{2.5}$ initially decreased, then increased, decreased again, reached its lowest values in August, then increased and decreased once more. The concentration of $PM_{2.5}$ remained stable from June to September. The $PM_{2.5}$ concentration was highest in January, at $59.49 \mu\text{g}/\text{m}^3$, and lowest in August, at $12.15 \mu\text{g}/\text{m}^3$ (Figure 2a). As for PM_{10} , the concentration initially decreased, then increased, decreased again, and finally increased steadily. It reached a maximum of $82.73 \mu\text{g}/\text{m}^3$ in April and a minimum of $27.65 \mu\text{g}/\text{m}^3$ in July (Figure 2b). The $PM_{2.5}$ and PM_{10} concentrations showed the greatest differences in April and May, at $23.35 \mu\text{g}/\text{m}^3$ and $38.04 \mu\text{g}/\text{m}^3$, respectively.

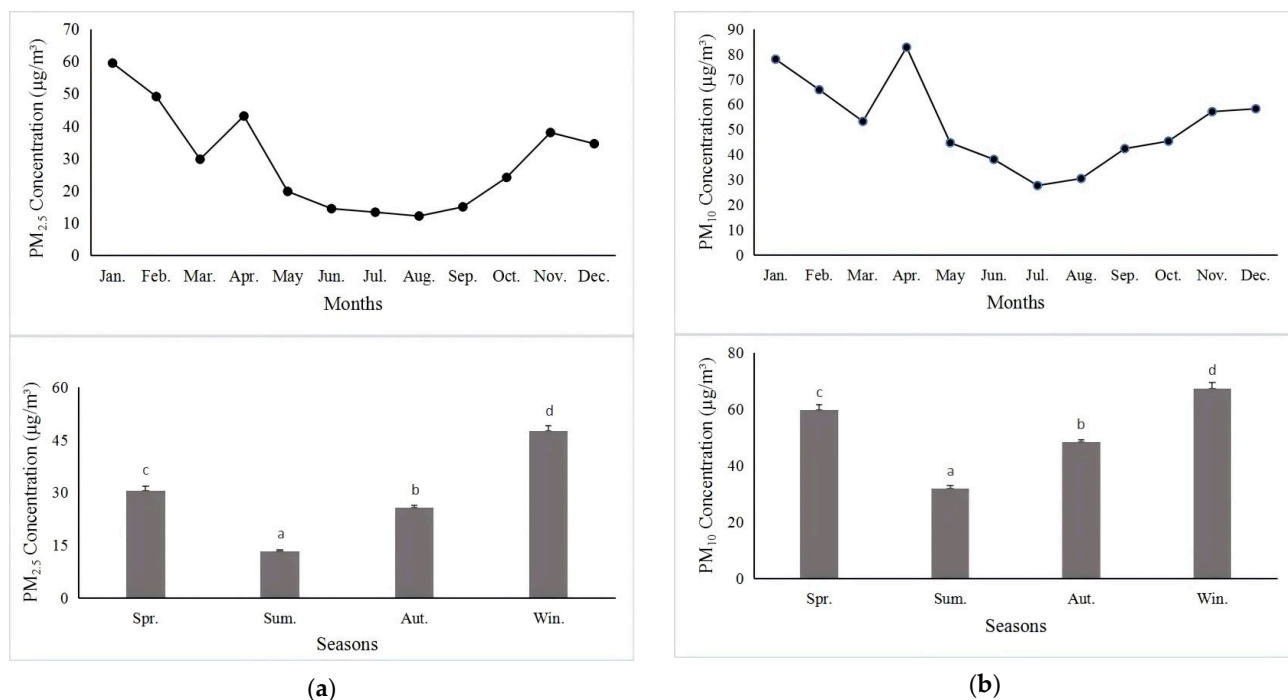


Figure 2. (a) Seasonal and monthly concentrations of $PM_{2.5}$ in Changchun. (b) Seasonal and monthly concentration of PM_{10} in Changchun. Note: Different letters indicate that PM concentrations vary significantly in different seasons ($p < 0.05$).

The concentrations of $PM_{2.5}$ and PM_{10} both decreased, then increased with seasonal changes; and overall, the PM_{10} concentration was higher than the $PM_{2.5}$ concentration across all four seasons. Both $PM_{2.5}$ and PM_{10} concentrations followed the trend of summer < autumn < spring < winter. The $PM_{2.5}$ concentration was $13.27 \mu\text{g}/\text{m}^3$ in sum-

mer and 3.6 times higher in winter than in summer (Figure 2a). The PM₁₀ concentration in summer was significantly lower than in the other three seasons, corresponding to 47.36% of the winter value. However, there was not much difference between the spring and winter concentrations, which were 59.64 µg/m³ and 67.35 µg/m³, respectively (Figure 2b).

3.2. Characteristics of Urban Forest Landscape Parameters at Different Landscape Scales

As the buffer zones gradually increased, the mean value of CA also increased (Table 2). The mean value of CA was smallest (17.47 ha) in the 0.5 km buffer zone and largest (1031.86 ha) in the 4 km buffer zone. The mean values of FRAC and PAFRAC showed the same trend. AREA initially decreased (0.39 at scale 1), then increased to its highest value (0.99 at scale 2) and gradually became smaller (0.50 at scale 4). As the scales increased, SHAPE increased to a maximum value (1.72 at scale 2.5), then slightly decreased and stabilized. PARA initially increased (2752.07 at scale 1), then decreased (2713.96 at scale 2) and increased again (2851.95 at scale 4). CIRCLE initially decreased, then increased and, finally, tended to stabilize.

Table 2. Characteristics of each parameter at different scales.

Scale (km)	Parameter	Max.	Min.	Mean	SD
0.5	CA (ha)	23.49	10.33	17.47	6.34
	AREA	1.48	0.13	0.42	0.41
	SHAPE	2.03	1.35	1.64	0.18
	FRAC	1.16	1.09	1.13	0.02
	PARA	3513.36	1688.23	2696.44	606.76
	CIRCLE	0.76	0.62	0.69	0.04
	PAFRAC	1.41	1.18	1.34	0.07
1	CA (ha)	92.75	25.87	69.13	23.27
	AREA	0.99	0.16	0.39	0.24
	SHAPE	2.04	1.49	1.66	0.17
	FRAC	1.16	1.11	1.13	0.02
	PARA	3595.56	2174.32	2752.07	450.92
	CIRCLE	0.73	0.64	0.68	0.03
	PAFRAC	1.41	1.24	1.35	0.06
1.5	CA (ha)	210.69	99.39	151.09	34.65
	AREA	3.59	0.18	0.70	1.09
	SHAPE	2.01	1.52	1.67	0.15
	FRAC	1.15	1.12	1.13	0.01
	PARA	3486.94	2035.08	2733.69	416.84
	CIRCLE	0.75	0.65	0.69	0.03
	PAFRAC	1.42	1.20	1.35	0.07
2	CA (ha)	372.41	155.10	269.44	68.49
	AREA	5.83	0.21	0.99	1.83
	SHAPE	2.13	1.54	1.71	0.17
	FRAC	1.15	1.13	1.14	0.01
	PARA	3375.29	1706.59	2713.96	454.14
	CIRCLE	0.75	0.67	0.69	0.03
	PAFRAC	1.42	1.20	1.36	0.07
2.5	CA (ha)	589.43	207.79	423.88	127.70
	AREA	5.61	0.22	0.99	1.74
	SHAPE	2.04	1.58	1.72	0.13
	FRAC	1.15	1.13	1.14	0.01
	PARA	3351.15	1722.03	2751.48	437.68
	CIRCLE	0.73	0.67	0.69	0.02
	PAFRAC	1.41	1.20	1.36	0.07

Table 2. Cont.

Scale (km)	Parameter	Max.	Min.	Mean	SD
3	CA (ha)	880.11	313.73	624.08	196.02
	AREA	2.27	0.26	0.61	0.63
	SHAPE	1.82	1.61	1.70	0.06
	FRAC	1.15	1.13	1.14	0.01
	PARA	3285.24	2300.10	2820.48	258.09
	CIRCLE	0.74	0.67	0.69	0.02
	PAFRAC	1.42	1.22	1.36	0.06
3.5	CA (ha)	1180.46	418.67	839.13	256.09
	AREA	1.79	0.29	0.56	0.47
	SHAPE	1.81	1.64	1.71	0.06
	FRAC	1.15	1.13	1.14	0.01
	PARA	3195.88	2200.43	2837.10	266.79
	CIRCLE	0.74	0.67	0.69	0.02
	PAFRAC	1.41	1.25	1.37	0.05
4	CA (ha)	1424.97	538.65	1031.86	298.54
	AREA	1.39	0.31	0.50	0.34
	SHAPE	1.78	1.64	1.71	0.05
	FRAC	1.15	1.14	1.14	0.01
	PARA	3127.27	2250.73	2851.95	245.68
	CIRCLE	0.73	0.68	0.69	0.02
	PAFRAC	1.42	1.28	1.37	0.04

3.3. Correlation Between Landscape Pattern Indexes and Particulate Pollutants

3.3.1. Correlation Between Landscape Pattern Indexes and PM_{2.5} and PM₁₀ Concentrations

Figure 3a–h show that PAFRAC and PARA were positively correlated with PM_{2.5} concentration. PAFRAC was correlated with PM_{2.5} concentration at 3 km × 3 km, 3.5 km × 3.5 km, and 4 km × 4 km buffers. The correlation coefficient at the 4 km × 4 km radius was 0.34 ($p < 0.01$). PARA was significantly positively correlated with PM_{2.5} concentration in all study areas, with the correlation coefficient reaching 0.79 ($p < 0.001$) at the 1.5 km × 1.5 km and 2 km × 2 km scales. As shown in Figure 3b–h, AREA and CIRCLE were negatively correlated with PM_{2.5} concentration at the scales of 1 km × 1 km, 1.5 km × 1.5 km, 2 km × 2 km, 2.5 km × 2.5 km, 3 km × 3 km, 3.5 km × 3.5 km, and 4 km × 4 km. According to Figure 3h, the correlation coefficient of AREA was -0.41 ($p < 0.001$) at the 4 km × 4 km scale, showing a significant negative correlation with PM_{2.5} concentration. Figure 3d–h show that the correlation coefficients of CIRCLE were -0.61 , -0.61 , -0.62 , -0.62 , and -0.62 ($p < 0.001$) at scales of 2 km × 2 km, 2.5 km × 2.5 km, 3 km × 3 km, 3.5 km × 3.5 km, and 4 km × 4 km, respectively, showing a significant negative correlation with PM_{2.5} concentration. As the buffer zones increased, AREA and CIRCLE had stronger negative correlations with PM_{2.5} concentration. Figure 3c–h show that SHAPE was also negatively correlated with PM_{2.5} concentration starting from the 1.5 km × 1.5 km scale, with a correlation coefficient of -0.41 ($p < 0.01$) at the 2.5 km × 2.5 km scale (Figure 3e).

As shown in Figure 4a–h, PARA and PAFRAC were positively correlated with PM₁₀ concentration. The landscape pattern indexes that were negatively correlated with PM₁₀ concentration were AREA, SHAPE, and CIRCLE. PARA was positively correlated with PM₁₀ concentration at all scales. PARA had the greatest effect on PM₁₀ concentration at the 2 km × 2 km scale, with a correlation coefficient of 0.81 ($p < 0.001$), while PAFRAC was only correlated with PM₁₀ concentration with the 3 km × 3 km, 3.5 km × 3.5 km, and 4 km × 4 km buffer zones, with correlation coefficients of 0.31 ($p < 0.05$), 0.35 ($p < 0.01$), and 0.38 ($p < 0.01$), respectively. CIRCLE was negatively correlated with PM₁₀ concentration at all study scales, and the correlation increased with increasing buffer zones. According to Figure 4b–h, AREA was negatively correlated with PM₁₀ concentration at all scales except the 0.5 km × 0.5 km scale. The correlation coefficients at the 3 km × 3 km, 3.5 km × 3.5 km, and 4 km × 4 km scales were -0.47 , -0.46 , and -0.45 ($p < 0.001$), respectively, showing a significant negative correlation with PM₁₀ concentration. Figure 4c–h show that

SHAPE was negatively correlated with PM_{10} concentration from the $1.5\text{ km} \times 1.5\text{ km}$ to $4\text{ km} \times 4\text{ km}$ scales, with the most significant correlation coefficient being -0.44 ($p < 0.01$) at the $2\text{ km} \times 2\text{ km}$ scale.

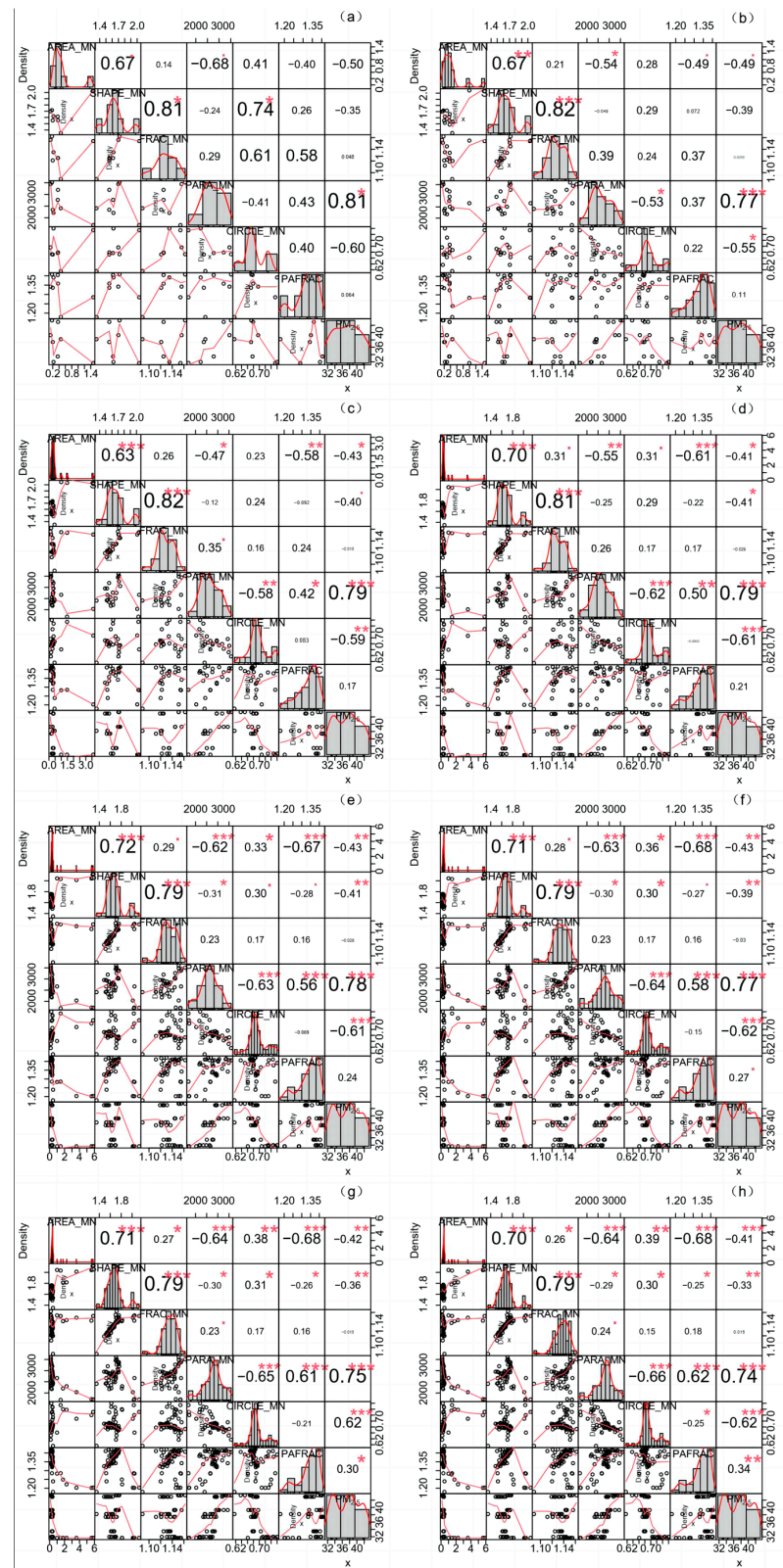


Figure 3. Correlation of landscape parameters and $PM_{2.5}$ concentration. Note: (a–h) show the correlations between $PM_{2.5}$ concentration and the 6 landscape patterns indexes at scales of 0.5 km,

1 km, 1.5 km, 2 km, 2.5 km, 3 km, 3.5 km, and 4 km, respectively. * Correlation is significant at the 0.05 level; ** correlation is significant at the 0.01 level; *** correlation is significant at the 0.001 level.

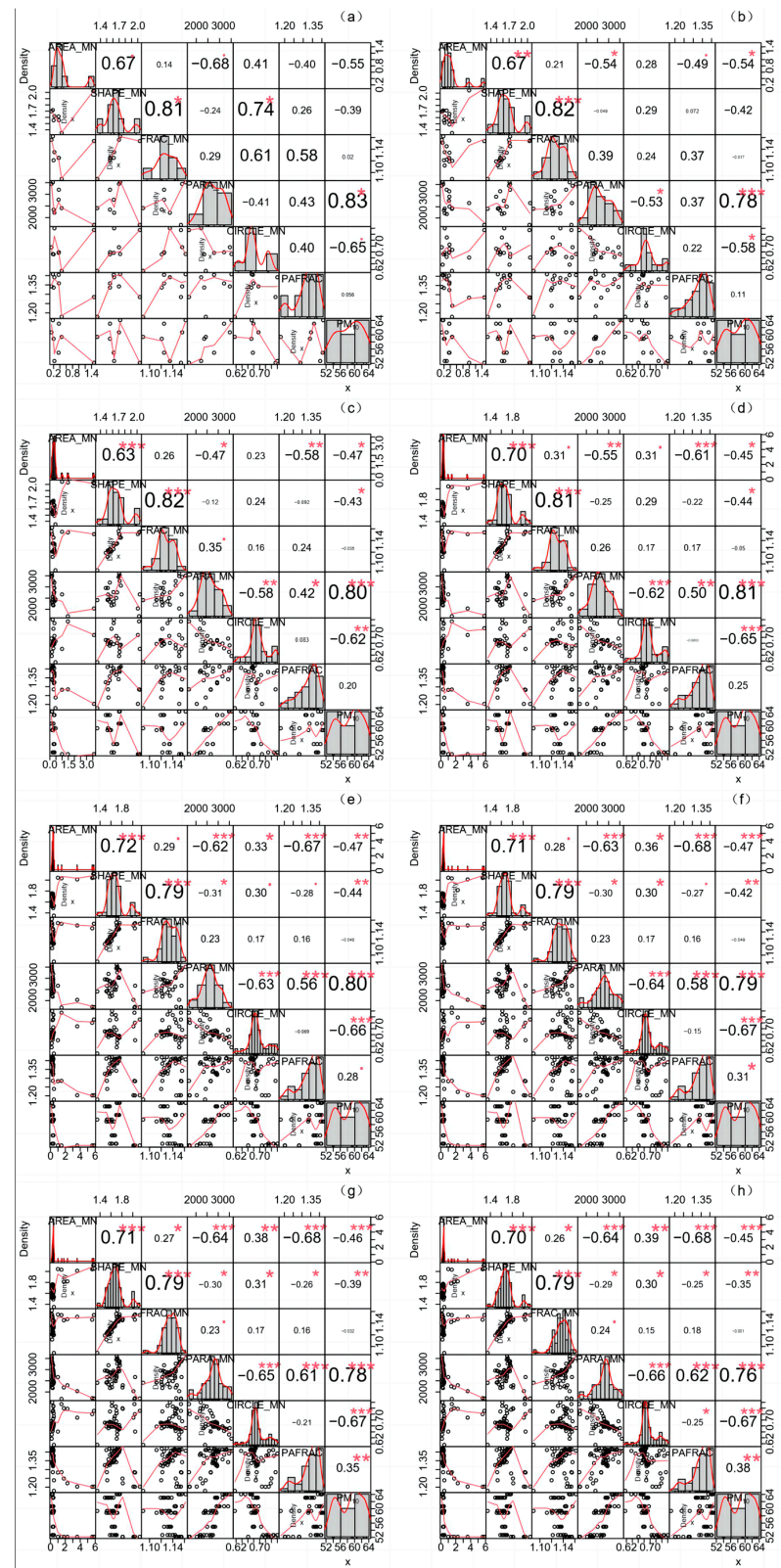


Figure 4. Correlation of landscape parameters and PM₁₀ concentration. Note: (a–h) show the correlations between PM₁₀ concentration and the 6 landscape patterns indexes at scales of 0.5 km,

1 km, 1.5 km, 2 km, 2.5 km, 3 km, 3.5 km, and 4 km, respectively. * Correlation is significant at the 0.05 level; ** correlation is significant at the 0.01 level; *** correlation is significant at the 0.001 level.

3.3.2. Redundancy Analysis of Particulate Matter Concentrations and Landscape Pattern Indexes

The ability of landscape pattern indexes to explain changes in particulate pollutants is shown in Table 3. The total interpretation rates of landscape pattern indexes at 0.5 km × 0.5 km, 1 km × 1 km, 1.5 km × 1.5 km, 2 km × 2 km, 2.5 km × 2.5 km, 3 km × 3 km, 3.5 km × 3.5 km, and 4 km × 4 km were 57.56%, 48.36%, 55.82%, 52.61%, 50.64%, 54.04%, 56.06%, and 59.75%, respectively. The spatial scale dependence of the impact of landscape pattern indexes on particulate pollutants was 4 km > 0.5 km > 3.5 km > 1.5 km > 3 km > 2 km > 2.5 km > 1 km. The results show that the impact of landscape pattern indexes on particulate pollutants was most significant within the 4 km × 4 km buffer zone. In the 1 km × 1 km buffer zone, the influence of landscape pattern indexes on particulate pollutants was the least.

Table 3. Interpretation rate for each ordering axis of redundancy analysis.

Scale (km)	Parameter	Axis 1	Axis 2	Total Explanation Rate
0.5	Eigenvalue	0.5442	0.0314	57.56
	Cumulative percentage of relevance	81.31%	48.35%	
1	Eigenvalue	0.4214	0.0622	48.36
	Cumulative percentage of relevance	86.15%	40.59%	
1.5	Eigenvalue	0.5448	0.0134	55.82
	Cumulative percentage of relevance	76.56%	47.91%	
2	Eigenvalue	0.5227	0.0033	52.61
	Cumulative percentage of relevance	73.21%	40.76%	
2.5	Eigenvalue	0.5047	0.0017	50.64
	Cumulative percentage of relevance	71.64%	38.00%	
3	Eigenvalue	0.5364	0.0040	54.04
	Cumulative percentage of relevance	74.52%	41.37%	
3.5	Eigenvalue	0.5571	0.0035	56.06
	Cumulative percentage of relevance	75.37%	56.28%	
4	Eigenvalue	0.5973	0.0003	59.75
	Cumulative percentage of relevance	78.20%	14.06%	

As shown in Figure 5a–h, PM concentration was positively correlated with PARA across the study range. In the 0.5 km × 0.5 km buffer zone, PM₁₀ was negatively correlated with CIRCLE (Figure 5a), but the correlation was weak. According to Figure 5b,c, PM concentration was negatively correlated with AREA and CIRCLE in the 1 km × 1 km buffer zone. In the 1.5 km × 1.5 km buffer zone, PM_{2.5} concentration was negatively correlated with AREA and CIRCLE, while PM₁₀ concentration was negatively correlated with AREA, SHAPE, and CIRCLE (Figure 5c). PM concentration was negatively correlated with AREA, SHAPE, and CIRCLE, with a strong correlation in the 2 km × 2 km, 2.5 km × 2.5 km, 3 km × 3 km, 3.5 km × 3.5 km, and 4 km × 4 km buffer zones. In the 3 km × 3 km, 3.5 km × 3.5 km, and 4 km × 4 km buffer zones, PM concentration was positively correlated with PAFRAC (Figure 5f–h), and the correlation between PM concentration and PAFRAC was strongest at the 4 km × 4 km scale (Figure 5d–h).

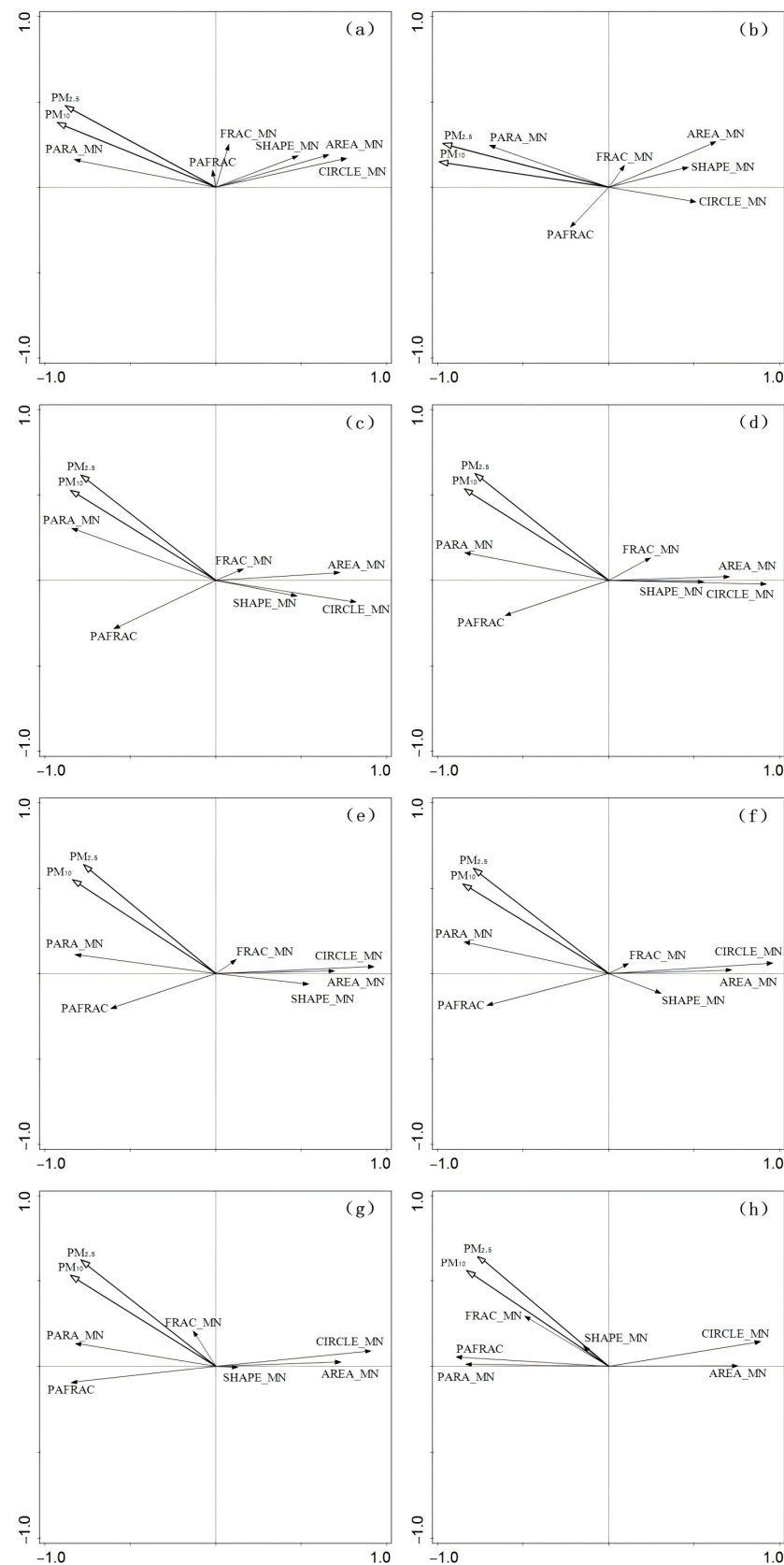


Figure 5. Redundancy analysis of landscape pattern indexes and particulate pollutant concentrations in different buffer zones. Note: (a–h) show the redundancy analysis of PM_{2.5} and PM₁₀ and landscape pattern indexes at scales of 0.5 km, 1 km, 1.5 km, 2 km, 2.5 km, 3 km, 3.5 km, and 4 km, respectively.

4. Discussion

4.1. Seasonal and Monthly Differences in Particle Pollutant Concentrations and Influencing Factors

This research showed significant seasonal differences in particulate pollutant concentrations (Figure 2). Both $PM_{2.5}$ and PM_{10} concentrations followed the trend of summer < autumn < spring < winter, consistent with studies on PM pollution in northern China [65]. The $PM_{2.5}$ and PM_{10} concentrations showed a trough in summer and a peak in winter, which aligns with a large body of literature. For example, Hua et al. [66] studied the seasonal and monthly variation of $PM_{2.5}$ concentration in Beijing's road shelter forest and found that the $PM_{2.5}$ concentration was highest in winter, followed by autumn and summer, with significantly lower levels in summer, especially in August and October. Changchun is located in the hinterland of the Northeastern Plain of China, and its climate is characterized by hot summers and cold winters. Summer features abundant forest plants, high vegetation cover, robust growth, and a strong particulate retention capacity of tree leaves, all of which effectively reduce particulate pollutant concentrations. Additionally, the relatively low consumption of fossil energy in summer was one of the reasons for the lowest PM concentration in the four seasons [67]. Particulate pollutant levels are comparable in spring and fall. Changchun's higher latitude results in lower winter temperatures, necessitating measures to keep buildings warm, thereby ensuring normal life for citizens. Although natural gas is increasingly used, coal remains the primary fuel for winter heating in northern China. Consequently, winter is the coal-burning season, requiring large amounts of fossil energy to be burned for heating. The fly ash produced during combustion increases dust, raising particulate pollutant concentrations. Fly ash stockpiles also pose pollution risks to air, groundwater, and soil [68]. Furthermore, coal combustion produces more $PM_{2.5}$ precursors (suspended matter capable of generating $PM_{2.5}$ particles through chemical reactions) than natural gas [69], exacerbating particulate pollution in winter. At the end of fall and the beginning of winter, Abscissic Acid (ABA) is produced in the petiole area of plants, prompting leaves to detach from branches and wither, leading to a sharp decrease in the number of leaves. This reduces the ability of leaves to retain particulate pollutants, causing an increase in their concentrations. In fall and winter, the edges of urban forests are generally unshaded, the climate is dry, and increased wind speeds can carry more soil and road dust into the air, raising particulate pollutant concentrations [70]. Relevant literature shows that particulate pollutant concentrations in northern China are generally higher than in southern China, closely related to industrial structure, climate characteristics, and urban size [71]. We also considered that meteorological factors may influence PM concentration changes, so we collected meteorological data [59] and analyzed monthly changes in temperature, precipitation, and wind speed. We found that precipitation was related to PM concentration. The annual precipitation in the study area was 678.5 mm, and the precipitation from June to August (summer) was as high as 514.3 mm. As can be seen from Figure 2, the PM concentration was lowest in summer, indicating that precipitation effectively washed away particulate matter pollutants. Additionally, the presence or absence of leaves on vegetation and changes in fossil energy consumption patterns may contribute to the large fluctuations in $PM_{2.5}$ and PM_{10} concentrations across the four seasons [72,73].

PM_{10} contains $PM_{2.5}$ [8,24], which means that the $PM_{2.5}$ concentration will always be less than the PM_{10} concentration detected at the same time and location. Thus, the ratio of $PM_{2.5}$ to PM_{10} should be less than 100%. As shown in Figure 6, the ratio of $PM_{2.5}$ to PM_{10} showed a decreasing trend over the months, with a brief upward trend in June, followed by a decrease to a minimum value of 35.4% in September. The data indicate that the ratio of $PM_{2.5}$ to PM_{10} from January to April and from October to December exceeded 50%, but all ratios were less than 100%, confirming that the results of this study are consistent with the expected rule. To some extent, the ratio of $PM_{2.5}$ to PM_{10} concentrations can indicate the types of pollution and possible sources of pollutants. The primary sources of $PM_{2.5}$ include motor vehicle exhaust, soot emissions from power plants and chemical plants, and straw

burning [74]. In contrast, PM_{10} is mainly derived from motor vehicle dust, construction dust, and other inorganic dust particles [75]. According to Figure 2, the concentrations of $PM_{2.5}$ and PM_{10} showed the greatest difference between April and May. In China, 5 April 2022 was the Tomb-sweeping Day, when people set off firecrackers and burned paper products to pay tribute to their lost loved ones, contributing great harm and hidden dangers to air quality. In addition, although most areas stopped heating in April, there was still a demand for heating in the countryside, with firewood burned for heating. The climate was dry, and the soil was easily turned to dust. In addition, construction projects around the country had started one after another, and construction, sludge transportation, and ground exposure caused increases in dust emission, resulting in an increase in PM concentration in the study area. Although the dust was mainly composed of coarse particles, it also contributed to the formation of $PM_{2.5}$. In addition, in the process of repeated settling, rolling, and re-raising, the coarse particles in the dust may be broken into fine particles. The dusty weather in Changchun City was concentrated in March to May, with the most in April, including sandstorms. These were the reasons for the high PM concentration in April. Article 31 of the Regulations on the Administration of Urban Heating in Changchun states that the heating period in Changchun City is from 0:00 on October 20 to 24:00 on April 6 of the following year. This indicates that heating stops over a large area in May, greatly reducing the amount of coal burned and, thereby, significantly lowering particulate pollutant concentrations in May. Moreover, with the development of modern agriculture, mechanized crop harvesting methods have gradually replaced traditional methods, and crop straw has gradually lost its role as an energy material and livestock feed. Consequently, large-scale straw burning has been on the rise in recent years [76–78]. Changchun is rich in crop straw resources, and straw burning during the farming season significantly impacts atmospheric environmental quality, leading to serious air quality deterioration [79].

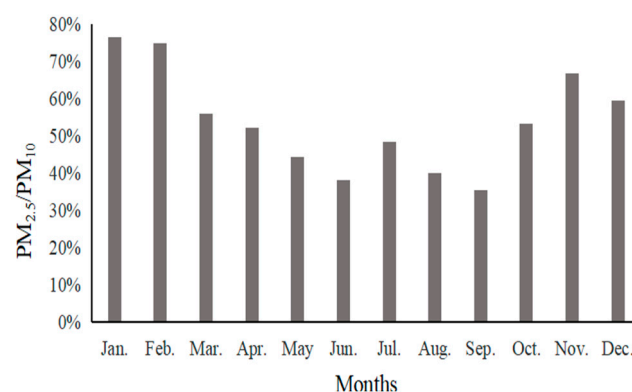


Figure 6. The ratio of $PM_{2.5}$ to PM_{10} from January to December.

4.2. Optimization Measures for Regulating Air Particle Pollutants in Forest Landscapes at Different Scales

Urban forests are a natural component of urban ecosystems [80], and their main form is green vegetation, which plays an irreplaceable role in reducing particulate pollutants. Theoretically, pollution levels can be reduced by increasing the proportion of urban forest footprint in the urban landscape. However, it is almost impossible to reduce urban land to increase urban forest in the context of urbanization. Therefore, changes in forest landscape patterns are particularly important in addressing today's air pollution problems. This study showed that PARA had a significant positive correlation with PM concentration at the landscape-type level within the study area. As seen in Table 1, PARA represents the mean value of the perimeter–area ratio of each patch, a rough measure of the complexity of each forest-patch type. The more complex the shape of the patch at the spatial scale, the higher the PM concentration. These results suggest that simplifying and regularizing the shape of forest patches can reduce the PM concentration. When the buffer zones reached $1\text{ km} \times 1\text{ km}$ and above, increases in AREA and CIRCLE significantly reduced the $PM_{2.5}$

concentration (Figure 3b–h), while CIRCLE began to affect the PM_{10} concentration at the $0.5 \text{ km} \times 0.5 \text{ km}$ scale, showing the same negative correlation. This result regarding AREA is consistent with the results of previous studies. For example, Lei et al. concluded that the average size of the patches reduced PM_{10} concentrations on some scales [44]. This suggests that smaller, more fragmented, and dispersed forest areas are less effective in mitigating particulate matter concentrations. In contrast, larger forest areas with aggregated landscapes, closer to natural forests, are better at performing forest ecosystem services, effectively mitigating particulate pollutants [46]. The larger the forest patch and the larger the area in contact with particulate pollutants, the more obvious the reduction effect on PM concentration. In addition, larger forest patches were more clustered, which may reduce wind speed and increase humidity, and the combined effect can reduce the production of soil dust and increase the wet settlement of PM. The smaller the CIRCLE value, the closer the patch is to a circle; otherwise, it is closer to a bar shape. Less circular forest patches have a larger and deeper contact area with the external environment, enhancing the ability of branches and leaves to trap particles. Therefore, shaping patches more like strips can reduce the $PM_{2.5}$ concentration. Among the factors affecting particle pollutant concentrations, the reduction in PARA had the most significant effect in terms of mitigating $PM_{2.5}$. When the buffer zones reached $2 \text{ km} \times 2 \text{ km}$ and above, SHAPE was negatively correlated with $PM_{2.5}$ concentration. However, at the $1.5 \text{ km} \times 1.5 \text{ km}$ scale and above, SHAPE began to affect the PM_{10} concentration negatively, indicating a stronger effect on PM_{10} . A greater SHAPE value indicates more complex patch shapes, which can improve the diffusion of organisms, intensify the exchange of matter and energy with the surrounding landscape, and enable the forest to absorb more particles from different sources, thereby reducing the PM concentration. Figures 3f–h and 4f–h showed that PAFRAC was positively correlated with $PM_{2.5}$ and PM_{10} concentrations at the scales of $3 \text{ km} \times 3 \text{ km}$, $3.5 \text{ km} \times 3.5 \text{ km}$, and $4 \text{ km} \times 4 \text{ km}$. As shown in Table 1, the closer the PAFRAC value is to 1, the more regular the patch shape and the more effective it is in reducing $PM_{2.5}$ concentration. Therefore, when planning and designing large-scale forests, PAFRAC should be taken into account. The results indicate that PARA and CIRCLE were the main factors affecting particulate pollutant concentrations, followed by AREA, SHAPE, and PAFRAC. This is not consistent with our assumption of the main factors affecting PM concentration. In urban forest planning, we can focus on optimizing PARA and CIRCLE to strengthen the connection between the green landscape and the outside area and play a greater role in dust retention. Our results are slightly different from those reported in a previous study [7] showing that the more complex the patches, the stronger the PM adsorption. However, the results of this study show that the more regular the urban forest patches, the better the effect in terms of reducing PM concentration. We thought the reasons may be due to the differences in the research perspectives between the two studies. The previous study took Roadside Forest (RF), Affiliated Forest (AF), and Landscape and Relaxation Forest (LF) as research targets to explore the reduction effect of different forest types on $PM_{2.5}$ concentration, and urban forest patches were not segmented by different scales. However, this paper mainly studied the scale effect of urban forest landscape pattern in reducing PM concentration, aiming to explore the relationship between landscape pattern indexes and PM concentrations at different scales. The former studied the whole forest landscape of one city, which was divided according to different forest types, and the forest patches were the true form of forests, while this paper analyzed the relations of forest landscape indexes and PM under different landscape pattern scales; therefore, some forest patches were cut by the buffers, and the calculation of the indexes might have been influenced by the buffer-zone boundaries. Therefore, index values such as PARA were affected.

The relationship between landscape pattern and PM concentration varies at different buffer scales, so achieving an effective balance of landscape patterns is crucial. To reduce $PM_{2.5}$ pollution, both scale and landscape pattern should be considered in urban planning and design. PARA should be reduced to decrease particulate pollutant concentrations within the study area. At the scales of $1 \text{ km} \times 1 \text{ km}$, $1.5 \text{ km} \times 1.5 \text{ km}$, $2 \text{ km} \times 2 \text{ km}$,

2.5 km × 2.5 km, 3 km × 3 km, 3.5 km × 3.5 km, and 4 km × 4 km, we should expand patch areas and make them closer to bar shapes. The complexity of patch shapes should be adjusted within the 2 km × 2 km, 2.5 km × 2.5 km, 3 km × 3 km, 3.5 km × 3.5 km, and 4 km × 4 km buffer zones. We should reduce PAFRAC and make urban forest patch levels more regular within the 3 km × 3 km, 3.5 km × 3.5 km, and 4 km × 4 km buffer zones. To reduce PM₁₀ pollution, PARA should also be reduced at all scales. SHAPE should be adjusted at the 2 km × 2 km and 2.5 km × 2.5 km scales. Within the 3 km × 3 km, 3.5 km × 3.5 km, and 4 km × 4 km buffer zones, we should increase forest area and CIRCLE, shaping patches more like bars and making urban forest patches more regular and simplified to mitigate PM₁₀ concentrations. Additionally, we should focus on strengthening the management of urban forests and consider planting more evergreen coniferous species such as *Acer truncatum* Bunge in winter and early spring. These species have small leaves and a large number of branches and leaves distributed in the canopy, increasing the area available for absorbing particulate pollutants and enhancing the adsorption capacity of urban forests [44].

Although this study clarified the effect of urban forest spatial patterns on PM concentrations and the relationship between them, the correlation does not represent causation. In this study, only eight Chinese National Air Quality Monitoring Stations were used, and the scope of the study also had some limitations. In future studies, it is necessary to expand the study scope, increase the number of monitoring stations, obtain more accurate and reliable results, and clarify the scale effect of urban forests on PM concentrations so as to better explain the relationship between landscape patterns and PM pollution. In addition, there are many factors affecting PM concentration, and studies have shown that the interaction between urban forests and land cover types also has certain effects on PM concentrations [81]. The use of land, emissions from transportation gases, changes in climate, and human activity may have influenced the research results. Also, land use variables should be considered to explore the effects of landscape patterns on PM concentrations.

5. Conclusions

This study extracted urban forest patches from remote sensing images and centered the study area around eight Chinese National Air Quality Monitoring Stations. We set up eight scales of 0.5 km × 0.5 km, 1 km × 1 km, 1.5 km × 1.5 km, 2 km × 2 km, 2.5 km × 2.5 km, 3 km × 3 km, 3.5 km × 3.5 km, and 4 km × 4 km. The landscape pattern indexes were calculated by Fragstats 4.2, and the scale effect of landscape pattern indexes on particulate matter concentration in urban forest was discussed. Then, the relationship between landscape pattern indexes and PM concentrations was obtained by correlation analysis and redundancy analysis.

The results showed that (1) the concentrations of PM_{2.5} and PM₁₀ showed significant differences between four seasons ($p < 0.05$), and the concentrations of PM_{2.5} and PM₁₀ showed a trend of summer < autumn < spring < winter. The PM_{2.5} concentration was highest in January, at 59.49 µg/m³, and lowest in August, at 12.15 µg/m³ (Figure 2a). The PM₁₀ concentration was highest in April, at 82.73 µg/m³, and lowest in July, at 27.65 µg/m³ (Figure 2b). The concentrations of PM_{2.5} and PM₁₀ showed the largest differences between April and May. (2) At small scales from 0.5 km × 0.5 km to 1.5 km × 1.5 km, PARA had the most significant effect on PM concentrations. Reducing the complexity of forest patches helped to reduce atmospheric particulate pollution. In urban forest planning at the medium scale of 2 km × 2 km to 2.5 km × 2.5 km, PARA and CIRCLE ($p < 0.001$) had obvious effects in terms of reducing PM concentrations, followed by SHAPE and AREA. The more regular the forest patch shape and the more similar the patch shape to a strip, the better the PM mitigation effect. In planning at large scales of 3 km × 3 km to 4 km × 4 km, the landscape pattern indexes affecting PM concentrations include AREA, SHAPE, PARA, CIRCLE, and PAFRAC. Among them, PARA and CIRCLE had significant effects on PM concentrations. At the scale of 4 km × 4 km, the inhibition effect of AREA on PM concentration was also very significant ($p < 0.001$). These results show that increasing the forest area and making

forest patches more regular had the strongest effects in terms of reducing PM concentrations in large-scale planning. In conclusion, urban forests play an important role in mitigating particulate pollutants, and our results can be used to formulate specific guidelines for urban forest planning.

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Data Availability Statement: The original contributions presented in the study are included in the article. Further inquiries can be directed to the corresponding author.

Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

Landscape Index	Equation (Unit)
Class Area (CA)	$\sum_{j=1}^n a_{ij} \times \frac{1}{10000} \text{ (ha)}$
Patch Area (AREA)	$a_i \text{ (m}^2\text{)}$
Shape Index (SHAPE)	$\frac{p_{ij}}{\min p_{ij}}$
Fractal Dimension Index (FRAC)	$\frac{2 \ln(0.25 p_{ij})}{\ln(a_{ij})}$
Perimeter–Area Ratio (PARA)	$\frac{p_{ij}}{a_{ij}}$
Related Circumscribing Circle (CIRCLE)	$1 - \left[\frac{a_{ij}}{a_{ij}^2} \right]$
Perimeter–Area Fractal Dimension (PAFRAC)	$\frac{\left[n_i \sum_{j=1}^n (\ln p_{ij} \cdot \ln a_{ij}) \right] - \left[\left(\sum_{j=1}^n \ln p_{ij} \right) \left(\sum_{j=1}^n \ln a_{ij} \right) \right]}{\left(n_i \sum_{j=1}^n \ln p_{ij}^2 \right) - \left(\sum_{j=1}^n \ln p_{ij} \right)^2}$

a_i , area of patch i ; p_{ij} , perimeter of patch ij ; $\min p_{ij}$, the lowest possible value for p_{ij} ; a_{ij} , area of patch ij ; n , number of patches; n_i , the number of patches contained in patch type i within the landscape.

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