forests

Article

Urban Forest Locations and Patch Characteristics Regulate $PM_{2.5}$ Mitigation Capacity

Chang Zhai [1], Guangdao Bao [2,*], Dan Zhang [1] and Yinghu Sha [1]

[1] College of Landscape Architecture, Changchun University, Changchun 130022, China
[2] Institute of Forest Management, Jilin Provincial Academy of Forestry Sciences, Changchun 130033, China
* Correspondence: bao-gd@126.com

Abstract: Atmospheric pollution caused by fine particulate matter ($PM_{2.5}$) seriously damages human health. Urban forests have the ecological function of purifying the atmosphere, which can effectively reduce the ambient $PM_{2.5}$ concentration. This paper analyzed the ability of different forest types to mitigate $PM_{2.5}$ pollution and explored the effects of forest quality and morphological parameters on $PM_{2.5}$ concentration on the forest patch level. The results concluded that the $PM_{2.5}$ concentration of the Landscape and Relaxation Forest (LF) was significantly lower than that of the Roadside Forest (RF) and Affiliated Forest (AF) due to the environmental quality of their location. The effective distance of LF on $PM_{2.5}$ reduction was 80 m, which was significantly higher than RF and AF. The Normalized Difference Vegetation Index (NDVI), which indicated forest growth status, was the most effective parameter for improving the urban forest $PM_{2.5}$ mitigation ability. The concentration of $PM_{2.5}$ decreased linearly with the increase in NDVI. The area and perimeter of the forest patches had a significant nonlinear negative correlation with $PM_{2.5}$ concentration. In addition, the more irregular the shape of the forest patch, the lower the $PM_{2.5}$ concentration of the forest. Moreover, the simpler shape of RF and AF helped to alleviate $PM_{2.5}$ pollution. The round shape of AF more efficiently reduced $PM_{2.5}$ concentration. Our study demonstrated that the surrounding environment, forest growth status, and patch forms determined the $PM_{2.5}$ reduction capacity of an urban forest. The corresponding management and adjustment methods should be implemented in future urban forest management.

Keywords: location; growth status; patch forms; $PM_{2.5}$ concentration; urban forest

Citation: Zhai, C.; Bao, G.; Zhang, D.; Sha, Y. Urban Forest Locations and Patch Characteristics Regulate $PM_{2.5}$ Mitigation Capacity. *Forests* **2022**, *13*, 1408. https://doi.org/10.3390/f13091408

Academic Editor: Jose Luis Santiago

Received: 30 July 2022
Accepted: 30 August 2022
Published: 1 September 2022

1. Introduction

Urbanization is an inevitable trend in the development of human society [1,2]. In 1950, 30% of the world's population lived in cities, while the number reached 55% in 2018. It has been estimated that by 2050, 68% of the world's population is expected to live in cities [3]. Since the reform and opening up, China's urbanization rate has soared from 17.92% in 1978 to 63.89% in 2020 [4], which has exceeded the global average level. The intensification of urbanization has caused a series of environmental problems, among which air pollution has become a major environmental and public health problem all over the world [5,6]. The World Health Organization's "Global Urban Environment" air pollution database shows that 98% of cities in low- and middle-income countries are exposed to air pollution far in excess of air quality guidelines [7]. Among numerous air pollutants, fine particulate matter ($PM_{2.5}$) with an aerodynamic equivalent diameter of less than 2.5 microns has been significantly associated with human health [8–10]. It may cause premature death, increase lung inflammation, accelerate atherosclerosis, and change the heart function of humans [11]. In 2013, 910,000 people died prematurely from air pollution in China, and 760,000 of them were directly related to $PM_{2.5}$ [12]. High concentrations of $PM_{2.5}$ in urban air pose a threat to the health of urban residents [13]. Furthermore, it has serious impacts on the living environment and will affect the balance of the entire ecosystem as well as climate change in the long run [14,15]. At present, $PM_{2.5}$ pollution matter has not only become a critical issue affecting national image, social harmony, and stability but has also become a worldwide problem [10].

Urban forests can directly or indirectly affect urban air quality by changing the urban atmospheric environment [16,17]. Previous studies on the relationship between urban forests and ambient particulate pollutants were mostly focused on PM_{10}. In the past two decades, with the continuous confirmation of the link between $PM_{2.5}$ and human health, $PM_{2.5}$ has gradually attracted extensive attention. Urban forests decrease ambient particulate matter content by trapping particulate matter, releasing particulate matter (such as pollen), and resuspending particulate matter on plant surfaces [17] so that the concentration of particulate matter inside the forest is much lower than the forest edge and outside [18]. Some of these particles were absorbed by trees, while most of the rest were trapped by the plant surface. The intercepted particles are usually released back into the atmosphere, washed away by rain, or dropped to the ground with leaves and branches. During drought periods, particulate matter is constantly intercepted and resuspended, but during precipitation, it is washed away, dissolved, or transferred to the soil [19]. In addition, trees can indirectly affect particulate concentrations by changing air temperature, releasing volatile organic compounds (VOCs), reducing energy use (i.e., shading buildings, changing wind speeds, lowering temperatures, etc.), and reducing the emissions from power plants [20,21].

Studies have shown that increasing vegetation coverage in cities [22,23], changing the tree species [13,24] or community structure [25,26], or adjusting the landscape indices [27–31] can significantly reduce the $PM_{2.5}$ concentration. However, except in the new planning area, it is not feasible to reduce air particulate pollution by substantially increasing the area of urban forests or large-scale changes in forest species, community structure, landscape composition, and configuration. Nevertheless, the growth status and spatial forms of existing urban forests can be moderately modified to improve the efficiency of $PM_{2.5}$ mitigation. The ecological services of urban forests are affected by many factors. The basic components of the urban landscape, changes in the forest patch characteristics in terms of the forest growth status, and the spatial forms of the patch strongly affect the stability of ecological forest services. However, most of the studies were focused on the size or degree of fragmentation in forest patches [27,28], and the quantitative relationship between key characteristic parameters of urban forest patches and $PM_{2.5}$ concentration remains unknown. How to optimize the shape configuration of the existing forests in the limited space and effectively improve the ecological services of the urban forest ecosystem is one of the key and difficult points in future urban ecology research. Moreover, the current concerns about the ability of urban forests to reduce $PM_{2.5}$ mainly include urban street trees [32–34], green belts [30,35] and park green spaces [36,37], and few studies have been conducted on different functional types of urban forests, which were the basis of further studies to promote the harmonious development of urban ecological services.

In this paper, Changchun city, which is undergoing rapid urbanization, was selected as the study area. We analyzed the $PM_{2.5}$ concentration differences in urban forests, compared their $PM_{2.5}$ reduction capacity, and revealed the relationship between $PM_{2.5}$ variation in forest patch growth status and form parameters with the help of plant ecology, spatial analysis, and statistical techniques. Moreover, this research attempted to provide some useful guidance and suggestions for urban forest management regarding $PM_{2.5}$ mitigation. These findings were suitable for the cities suffering from serious air pollution problems brought about by rapid urbanization. Specifically, the three objectives of this study are: (1) to determine the $PM_{2.5}$ concentration difference among different forest types, (2) to explore the $PM_{2.5}$ reduction ability by comparing their $PM_{2.5}$ reduction distance, and (3) to reveal the key factors of urban forest patches that affect $PM_{2.5}$ mitigation.

2. Materials and Methods

2.1. Study Area

Changchun city (43°05′–45°15′ N; 124°18′–127°05′ E) is the capital of Jilin Province, located in the middle latitude of the Northern Hemisphere, the hinterland of the Northeastern Plain of China [38]. The built-up area is 543 km^2, and it had a population of 4.468 million at the end of 2020. Changchun is in the warm temperate zone, a continental monsoon climate area, with an annual average temperature of 7.1 °C, annual precipitation of 662 mm, and an annual sunshine duration of 2688 h in 2020. The altitude is 250–350 m in Changchun, and the main types of soil are black soil, meadow soil, and chernozem soil. The vegetation area was 228.65 km^2, and the coverage rate was 42.11% [39]. In 2020, 89.8% of days had good air quality in Jilin Province. Of the days with air quality exceeding the standard, 69.6% were caused by $PM_{2.5}$ [40]. From 2018 to 2020, the primary air pollutant in Changchun was $PM_{2.5}$, and the annual average concentrations were 33 $\mu g/m^3$,38 $\mu g/m^3$, and 42 $\mu g/m^3$ [40–42], respectively, with an annual growth rate of 27%. With the acceleration of industrialization and urbanization, atmospheric environmental quality presented a downward trend. This study takes the built-up area of Changchun city as the research area, and the real-time air pollutants data were collected by the 8 Chinese National air quality monitoring stations within the area (Figure 1).

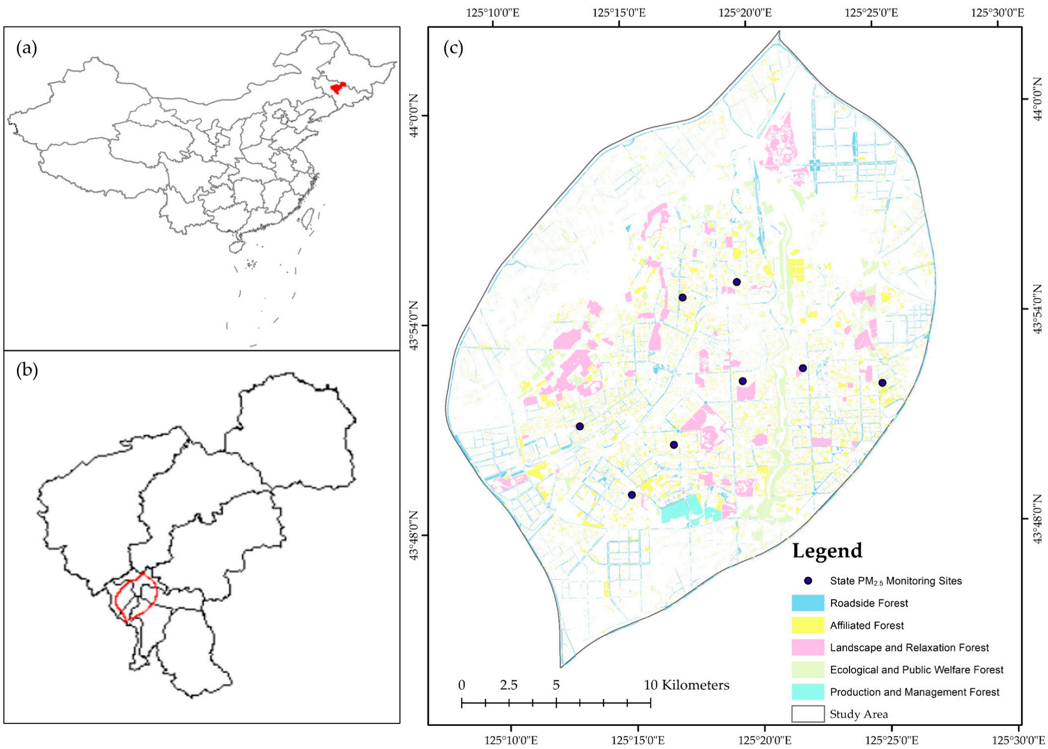

Figure 1. (**a**) The Administrative Map of China, with Changchun city displayed in red color. (**b**) The Administrative Map of Changchun city, with the red line indicated the built-up area. (**c**) Map of Changchun built-up area, different types of urban forest and the location of China State $PM_{2.5}$ Monitoring Sites.

2.2. Data Sources

The $PM_{2.5}$ concentration data of 8 monitoring stations in Changchun were provided by the China Environmental Monitoring Station (http://www.cnemc.cn/, accessed on 29 August 2022). The meteorological data were from the Daily Dataset of China Surface Climatic Data (V3.0) provided by the National Meteorological Science Data Center (https://data.cma.cn/dataService/cdcindex/datacode/A.0012.0001_220/show_value/normal.html, accessed on 29 August 2022), which mainly included precipitation, average air pressure, average wind speed, average temperature, and average relative humidity. The land-use data were from the Third National Land Resources Survey. Three Gaofen-2 images of different months in autumn were selected, with the dates of 23 August, 12 September, and 5 October 2020, respectively. The images had four multispectral bands (4 m resolution), namely a blue, green, red, and near-infrared spectrum, and one panchromatic band (1 m resolution), which were obtained from the High Resolution of the Earth Observation System Jilin Data and Application Center (http://gaofen.jlu.edu.cn/).

2.3. Methods

2.3.1. Urban Forest Classification and Extraction

The urban forests in Changchun were extracted from the Gaofen-2 images by ArcGIS10.8 (ESRI, Redlands, CA, USA) (Figure 1c). They were divided into 5 types [43] according to their location, function, and management method (Table S1), namely Roadside Forest (RF), Affiliated Forest (AF), Landscape and Relaxation Forest (LF), Ecological and Public Welfare Forest (EF), and Production and Management Forest (PF). The areas of the last two urban forest types in Changchun were relatively low; therefore, only RF, AF, and LF were analyzed in this study. In order to ensure visual interpretation accuracy, 50 of each forest type (about 1%) were randomly selected for site accuracy verification using a field survey. As all kinds of urban forests have clear shape, distribution, and tone characteristics, visual interpretation accuracy reaches 100%.

2.3.2. Forest Patch Characteristic Parameters

To measure the patch characteristics of the urban forests in terms of area, boundary, shape, complexity, and quality, we selected six indexes to represent the forest patch feature, which included patch area (AREA) and patch perimeter (PERIM) on the area and boundary level; shape index (SHAPE), fractal dimension index (FRAC), and related circumscribing circle (CIRCLE) on the patch shape scale level; in addition, the Normalized Difference Vegetation Index (NDVI) was used to indicate the growth status of the urban forests. The ecological significance of the six parameters is shown in Table 1.

Table 1. Name, meaning, and range of forest patch characteristic parameters.

Forest Patch Metrics	Definition	Ecological Meaning	Data Range
Patch Area (AREA)	The extent of urban forest patch.	The larger the number, the larger the area, and richer the species diversity.	AREA > 0
Patch Perimeter (PERIM)	The length of urban forest patch edge.	The larger the number, the larger the perimeter. It also reflects the complexity of the forest edge.	PERIM > 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 spatial scale.	The larger the value, the more complex the shape and the greater the ecological complexity.	$1 \leq$ FRAC ≤ 2
Related Circumscribing Circle (CIRCLE)	The degree of near-circular or near-strip shape of forest patch.	The smaller value means the shape tends to be round, while the larger value indicates the patch shape tends to be strip.	0 < CIRCLE < 1
Normalized Difference Vegetation Index (NDVI)	The degree of forest coverage and health condition.	The positive value indicates vegetation exist, and the larger the value, the greater the vegetation coverage.	−1 < NDVI < 1

2.3.3. $PM_{2.5}$ Concentration Data

A Land Use Regression (LUR) model was used to simulate the concentration of $PM_{2.5}$ [31,44,45] in Changchun, as it can accurately reflect the spatial distribution characteristics of air pollutants with a simple model structure and less computing resources than non-linear models [31]. There were mainly two or more independent variables and one dependent variable in the LUR model, as follows:

$$y = \lambda_0 + \lambda_1 X_1 + \lambda_2 X_2 + \ldots + \lambda_n X_n + \delta \quad (1)$$

where the dependent variable y was the $PM_{2.5}$ concentration of the monitoring sites, the independent variables X_1, $X_2 \ldots X_n$ were the environmental factors that influence the $PM_{2.5}$ variation, λ_1, $\lambda_2 \ldots \lambda_n$ were the associated coefficients, and σ was the random variable.

Considering the city size and the research scale, we selected five categories as the independent variables, which included the traffic factor, land use factor, population factor, meteorological factor, and vegetation factor, respectively. Buffer zones of 300 m, 600 m, 900 m, 1200 m, and 1500 m radius were established at the 8 state-controlled monitoring points in Changchun, and a total number of 55 factors were calculated to establish the LUR model. The environmental factors of each category and their relationships with the $PM_{2.5}$ concentration can be seen in Table S2. The variables with a correlation coefficient less than 0.4 with $PM_{2.5}$ concentration were removed, and the remaining variables were analyzed by multiple linear regression. The optimal LUR model is listed in Equation (2). Then, ArcGIS 10.8 was used to grid the study area (the grid size was 1 km × 1 km), and the relevant environmental variables of each grid center point were calculated. After standardized processing, the $PM_{2.5}$ concentration of each point in autumn was calculated according to the optimal LUR model. Finally, the ordinary kriging interpolation method was used to obtain the spatial distribution of the $PM_{2.5}$ concentrations (Figure S1). The mean $PM_{2.5}$ concentration was 52.70 μg/m^3 in Changchun.

$$y = 42.54 + 0.152x_{ILP900} + 3.314x_{TROAD600} + 2.801x_{MROAD600} - 17.953x_{NDVI300} - 19.315x_{PRE300} \quad (2)$$

The adjusted R^2 was 0.852, and the p value was 0.018. Where y was the $PM_{2.5}$ concertation calculated by LUR, x_{ILP900} was the industrial land area of the 900 m buffer zone radius; $x_{TROAD600}$ was the total road density of the 600 m buffer zone radius (km·km^{-2}); $x_{MROAD600}$ was the first-level road density of the 600 m buffer zone radius (km·km^{-2}); $x_{NDVI300}$ was the NDVI value of the 300m buffer zone radius, and x_{PRE300} was the precipitation (mm) of the 300m buffer zone radius.

2.3.4. Data Analysis

The number of patches included in the analysis was determined by a stratified random sampling method. The forest patch metrics were obtained by FRAGSTATS 4.2 after being converted to a raster format in ArcGIS 10.8 (ESRI, Redlands, CA, USA). NDVI was calculated from the Gaofen-2 images through band calculation as Equation (3) in ENVI 5.3 (ITT Visual Information Solutions, Boulder, CO, USA). The $PM_{2.5}$ data from the different forest types and buffer zones were extracted by spatial analysis in ArcGIS 10.8. One-Way ANOVA was applied to find the $PM_{2.5}$ concentration differences among the different forest types, and Pearson correlation analysis and regression analysis between the patch characteristic parameters and $PM_{2.5}$ concentrations were conducted in R (CRAN project). The $PM_{2.5}$ mitigation distance was calculated by comparing the $PM_{2.5}$ concentration of different buffer zones from the forest patches. In this study, the seasonal mean concentration of $PM_{2.5}$ was used, and similar meteorological conditions were assumed in the same season. In this way, the influence of the urban forest landscape on the $PM_{2.5}$ concentration can be highlighted under the premise of relatively consistent meteorological conditions.

$$\mathrm{NDVI} = (\mathrm{NIR} - \mathrm{R})/(\mathrm{NIR} + \mathrm{R}) \quad (3)$$

where NIR was the near-infrared spectrum, and R was the red spectrum of the Gaofen-2 images.

3. Results

3.1. Spatial Forms, NDVI and $PM_{2.5}$ Concentration of Different Urban Forest Types

As shown in Table 2, the AREA and PERIM of LF were 10.29 km^2 and 2380.94 m, respectively, and were much bigger than RF and AF, while FRAC and CIRCLE were the least in LF among the three forest types. Moreover, AREA and PERIM were more discrete in LF than RF and AF. The SHAPE index appeared to be very different among the different forest types, which presented as RF > LF > AF. In addition, the mean values of NDVI in RF, LF, and LF were not too different, but the maximum and minimum values varied greatly. RF had the lowest NDVI value of 0.43, and AF had the largest value of 0.89. The $PM_{2.5}$ concentration was significantly different among the different urban forest types. RF had the highest $PM_{2.5}$ concentration (52.23 μg/m^3) and was significantly higher than AF (46.74 μg/m^3) and LF (44.07 μg/m^3), and LF was significantly lower than RF and AF. However, the standard deviation (SD) of LF was much lower than RF and AF.

Table 2. Descriptive statistic of forest patch characteristic parameters and $PM_{2.5}$ concentration of three forest types.

Forest Type	Index	Max.	Min.	Mean	SD
RF	AREA (km^2)	6.85	0.04	0.88	1.03
	PERIM (m)	3880	140	825.42	521.19
	SHAPE	3.96	1.57	2.31	0.43
	FRAC	1.26	1.08	1.20	0.04
	CIRCLE	0.97	0.57	0.88	0.07
	NDVI	0.79	0.43	0.65	0.07
	$PM_{2.5}$ (μg/m^3)	60.10	47.52	52.23 ^{a}	2.22
LF	AREA (km^2)	123.71	0.01	10.29	19.09
	PERIM (m)	30,800	64.00	2380.94	4331.54
	SHAPE	10.58	1.03	2.00	1.47
	FRAC	1.36	1.01	1.11	0.83
	CIRCLE	0.95	0.09	0.61	0.18
	NDVI	0.85	0.55	0.67	0.07
	$PM_{2.5}$ (μg/m^3)	58.01	31.00	44.07^c	7.57
AF	AREA (km^2)	5.64	0.04	0.40	0.62
	PERIM (m)	1940	140	380.23	245.20
	SHAPE	2.57	1.03	1.63	0.25
	FRAC	1.20	1.01	1.14	0.37
	CIRCLE	0.91	0.30	0.73	0.11
	NDVI	0.89	0.53	0.67	0.09
	$PM_{2.5}$ (μg/m^3)	55.61	36.32	46.74 ^{b}	3.00

Notes: Different letters indicated significant differences. Refer to Table S1 for the meaning of the abbreviated forest types, and Table 1 for the meaning of the abbreviated forest patch characteristic parameters, respectively.

3.2. $PM_{2.5}$ Reduction Capacity of Different Forest Types

As shown in Figure 2, LF had the longest $PM_{2.5}$ reduction distance (80 m), and it was 5.3 times that of RF (15 m). The $PM_{2.5}$ reduction distance of AF was 35 m, which was bigger than RF but much smaller than LF. The $PM_{2.5}$ concentration of LF and AF fluctuated wildly within the 100 m buffer zone around the forest patch, while RF had a relatively stable variation. Moreover, the $PM_{2.5}$ concentration of RF on each distance point was larger than AF and LF.

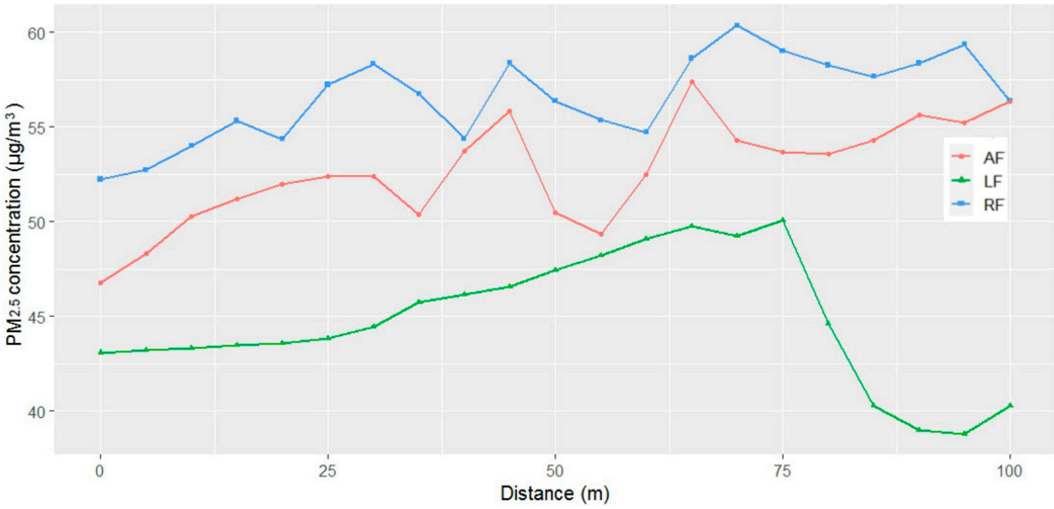

Figure 2. The $PM_{2.5}$ reduction distance of RF, LF, and AF. Note: Refer to Table S1 for the meaning of the abbreviated forest types.

3.3. Relations of Forest Patch Characteristics Parameters and $PM_{2.5}$ Concentration

3.3.1. Correlations of Forest Patch Characteristics and $PM_{2.5}$ Concentration

The correlation of the patch characteristic parameters and $PM_{2.5}$ concentration appeared to be different among the three forest types (Table 3). The AREA, PERIM, and NDVI of RF, LF, and AF had a high negative significance with the $PM_{2.5}$ concentration. Moreover, NDVI had the biggest correlation coefficient, larger than AREA and PERIM. The SHAPE index had a negative significance in relation to the $PM_{2.5}$ concentration of RF and LF at a 0.01 level but with AF at a 0.05 level. In addition, the relationship was negative between FRAC and $PM_{2.5}$ concentration in LF, but it displayed a significant positive correlation in RF and AF. Moreover, the relationship between CIRCLE and the $PM_{2.5}$ concentration was also inconsistent, as RF represented the negative correlation and LF and AF appeared to have a positive correlation.

Table 3. Correlations of forest patch characteristic parameters and $PM_{2.5}$ concentration.

Forest Type	AREA	PERIM	SHAPE	FRAC	CIRCLE	NDVI
RF	−0.447 **	−0.475 **	−0.206 **	0.137 **	−0.035	−0.751 **
LF	−0.648 **	−0.542 **	−0.354 **	−0.102	0.035	−0.715 **
AF	−0.530 **	−0.479 **	−0.088 *	0.136 **	0.127 **	−0.716 **

Notes: * Correlation is significant at 0.05 level; ** Correlation is significant at 0.01 level. Refer to Table S1 for the meaning of the abbreviated forest types, and Table 1 for the meaning of the abbreviated forest patch characteristic parameters, respectively.

3.3.2. Effects of Forest Patch Characteristics Parameters on $PM_{2.5}$ Concentration

Figure 3 reveals the $PM_{2.5}$ concentration variation with the urban forest patch parameters. AREA and PERI had a logarithmic relationship with the $PM_{2.5}$ concentration in RF (Figure 3a,b), and LF (Figure 3f,g), but changed linearly in AF (Figure 3j,k). SHAPE had a negative linear relationship with $PM_{2.5}$ concentration in all three forest types, but only 4.26%, 12.53%, and 0.77% of the variation of the $PM_{2.5}$ concentration in RF, LF, and AF was associated with it (Figure 3c,h,l). Figure 3d,m show that a positive correlation existed between the $PM_{2.5}$ concentration and FRAC in RF and AF, in which 1.87% and 1.85% of the $PM_{2.5}$ concentration variation was caused by FRAC, respectively. CIRCLE appeared to have a positive relationship with the $PM_{2.5}$ concentration in AF (Figure 3n). NDVI had the most associations with $PM_{2.5}$ concentration, and it can explain 56.46%, 51.06%, and 51.27% of the $PM_{2.5}$ concentration variation of RF, LF, and AF, respectively, by the linear regression models (Figure 3e,i,o).

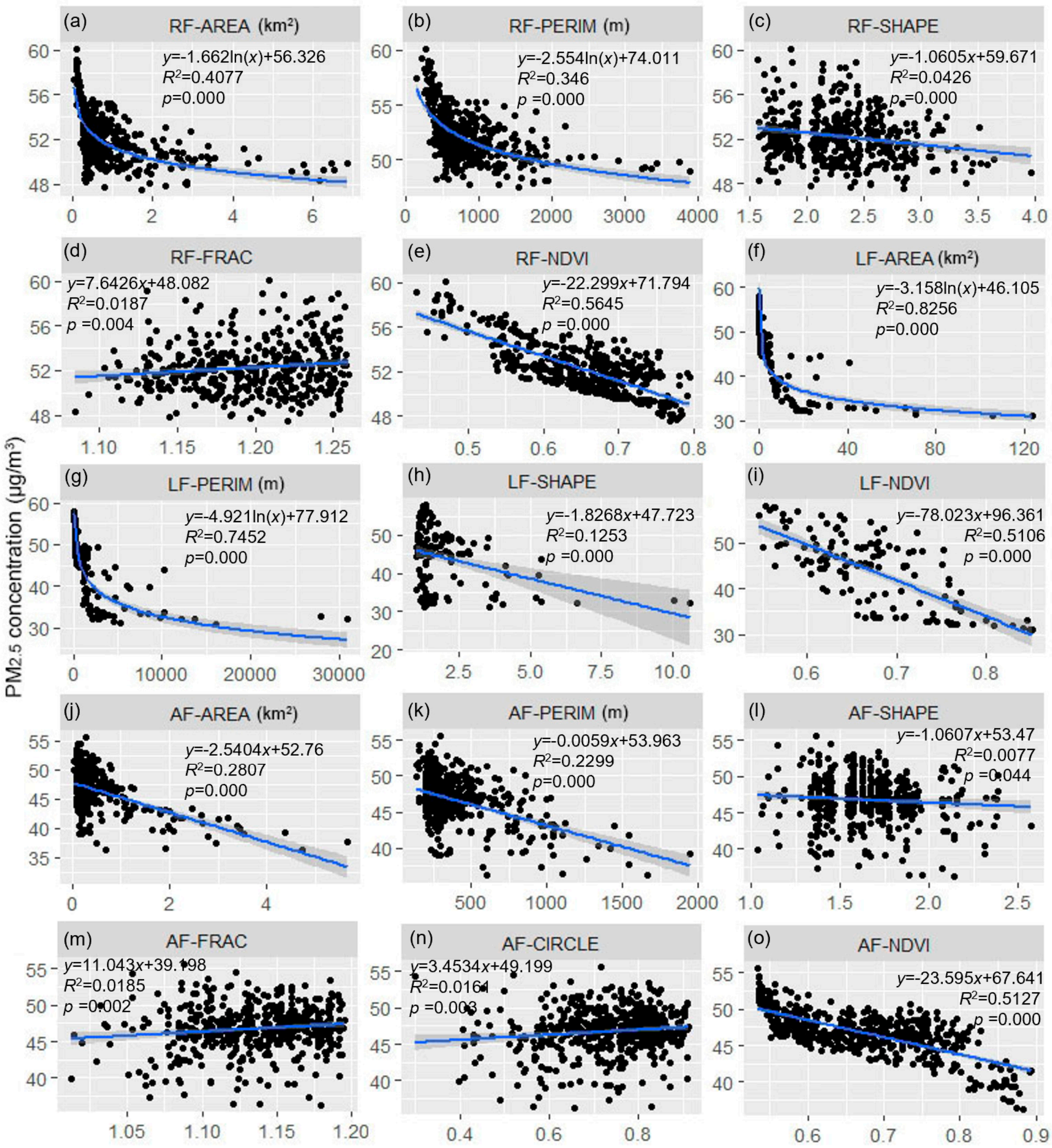

Figure 3. Regression analysis of $PM_{2.5}$ concentration and forest patch characteristics parameters. Notes: Refer to Table S1 for the meaning of the abbreviated forest types, and Table 1 for the meaning of the abbreviated forest patch characteristic parameters, respectively. Figures (**a**–**e**) were the regression model between $PM_{2.5}$ concentration and AREA, PERIM, SHAPE, FRAC and NDVI respectively in RF, Figures (**f**–**i**) were the regression model between $PM_{2.5}$ concentration and AREA, PERIM, SHAPE and NDVI respectively in LF, and Figures (**j**–**o**) were the regression model between $PM_{2.5}$ concentration and AREA, PERIM, SHAPE, FRAC, CIRCLE and NDVI respectively in AF.

4. Discussion

4.1. $PM_{2.5}$ Mitigation Capability of Urban Forest

Urban forests can help to mitigate $PM_{2.5}$ pollution, and according to Table 2, it was concluded that the $PM_{2.5}$ concentrations of RF, LF, and AF were 0.89%, 16.38%, and 11.31% lower than the mean value of Changchun, respectively. The main reason that RF had a higher $PM_{2.5}$ concentration than LF and AF may be due to the growth environment of their locations. RF planted by the roadside may suffer more gaseous pollutants from traffic transportation [32,35,46] than AF and LF. AF is usually located in the community or campus, and the distance from the road was further than RF, and the buildings around AF could help block pollutants. LF is usually located in favorable environments, such as parks or gardens [43]. Furthermore, apart from the advantage of its location, it also has a bigger size in the urban environment, which encourage forest ecological services to purify the atmosphere, similar to a natural forest. Moreover, the low species biodiversity of RF hindered the air pollution capacity. For the convenience of management and a trim appearance, unique species were selected for RF. Not only $PM_{2.5}$ mitigation, other services such as carbon sequestration, oxygen release, as well as soil and water conservation could not reach their potential in low biodiversity [47,48]. In addition, most of the RF species had a good adaption to urban environments. However, the species in RF were not the best choice for $PM_{2.5}$ removal. It was reported that conifer species ranked high in $PM_{2.5}$ removal efficiency [13]. However, broad-leaf species are always selected for RF in Northern Chinese cities [49], which reduced the $PM_{2.5}$ reduction capacity of RF.

The effective decreasing range of $PM_{2.5}$ concertation was also a criterion for the $PM_{2.5}$ reduction ability of urban forests. Generally, the further from the urban forest, the higher the $PM_{2.5}$ concentration. Therefore, the breakpoints of the curve from rising to declining (Figure 2) was regarded as the maximum distance of $PM_{2.5}$ reduction in urban forests. As illustrated in Figure 2, the $PM_{2.5}$ mitigation distance of LF was significantly greater than RF and AF. In addition, the fluctuation ranges of RF, AF, and LF were 8.13 $\mu g/m^3$, 10.64 $\mu g/m^3$, and 9.81 $\mu g/m^3$, respectively, in the 100m buffer zone radius. Although the fluctuation value was large in LF, all of the $PM_{2.5}$ concentrations in the buffer zone radius were smaller than the average $PM_{2.5}$ concentration in Changchun. Moreover, 4.76% and 57.14% of the $PM_{2.5}$ concentrations were lower than the average value of RF and AF. LF had fewer ups and downs than RF and AF, which indicated its stable $PM_{2.5}$ reduction capacity.

4.2. Forest Growth Status and Shape Regulated $PM_{2.5}$ Concentration

NDVI had the strongest relationship with $PM_{2.5}$ concentration than the other patch characteristic parameters in all of the forest types (Table 3). Healthy ecosystems provide stronger ecological services. As an important indicator reflecting plant growth and health [50,51], NDVI plays a critical role in $PM_{2.5}$ reduction. Our study demonstrated that the $PM_{2.5}$ concentration would decrease by more than 2.2 $\mu g/m^3$ with an NDVI increasing by 0.1 (Figure 3). In addition, a negative linear correlation appeared between NDVI and the $PM_{2.5}$ concentration of a forest patch, which meant that the $PM_{2.5}$ concentration changed monotonously with NDVI.

In addition to NDVI, which indicated the forest growth status, the forest shape parameters also played a vital role in $PM_{2.5}$ mitigation. Usually, AREA reflected the forest size. As is known, the ecological services provided by the small-sized forest were limited, and large-sized forests have stable ecological services [52], including $PM_{2.5}$ reduction. However, the relationships between AREA and the $PM_{2.5}$ concentration in RF and LF were non-linear; that is, the $PM_{2.5}$ concentration would decrease gradually when the urban forest size increased with a forest size larger than a certain threshold. However, the AREA of AF displayed a linear variation with $PM_{2.5}$ concentration. This may be caused by the AREA distribution differences among the different urban forest types. The mean AREA of RF and LF were bigger than AF (Table 2), and 96.62% of the AF patches AREA were smaller than 2 km^2 (Figure 3), which did not reach the curves' breakpoint of AF and LF. Similar to AREA, PERIM was another parameter that denoted forest size. Therefore, the relationship between PERIM and the $PM_{2.5}$ concentration showed the same trend as the AREA in RF, LF, and AF. However, PERIM also signified forest patch boundary complexity. A large PERIM with the same AREA meant a longer border and more contact opportunities with the outside environment. When PERIM was bigger than the threshold, the $PM_{2.5}$ reduction efficiency would decline, and atmospheric purification could not keep pace with the increasing rate of $PM_{2.5}$ concentration. SHAPE signifies the regularity of the forest patch [30], the larger the value, the more irregular the forest patch (Table 1), and the bigger the ecologic ecotone area. As the results in Table 3 suggest, the $PM_{2.5}$ concentrations in RF and LF were highly negatively correlated with SHAPE. It suggested that the irregular shape of the forest patch could help to mitigate $PM_{2.5}$ concentration. On the other hand, the relationship between SHAPE and the $PM_{2.5}$ concentration of AF was relatively low, as well as the explanation degree in the regression model (Table 3 and Figure 3). The mean SHAPE of AF was much smaller than RF and LF, and 92.29% were less than 2. For aesthetic purposes, green community spaces are usually designed in a square shape, and as such, the square or near-square shape of AF had fewer opportunities than the complicated shape for gas flow and exchange. Therefore, the SHAPE of AF had a lower significance level regarding the $PM_{2.5}$ concentration compared with RF and LF. The variations in the FARC and $PM_{2.5}$ concentration were not consistent in different urban forest types. With an increase in FARC, the $PM_{2.5}$ concentration increased accordingly in RF and AF. However, there existed a weak negative relationship in LF. Unlike SHAPE, FARC represented the shape complexity of the forest patch on a spatial scale. Despite the FARC in RF, LF and AF had few differences; the SDs of LF were 12 times that of RF and two times that of AF. Therefore, there was no significant connection between FARC and the $PM_{2.5}$ concentration of LF due to the large variation. CIRCLE reflected the shape of the patches, which either tend to be round or in strips (Table 1). The smaller the value, the closer the shape was to a circle. On the other hand, the closer the value was to 1, the closer the shape was to a strip. As shown in Table 2, RF had the biggest CIRCLE, which indicated that the RF patches were more stripped than LF and AF. The strip shape of the patches had more chances to contact and exchange with external materials, including particulate matter. Therefore, the CIRCLE of RF had an opposite relationship with the $PM_{2.5}$ concentration than LF and AF.

5. Conclusions and Implications

This study extracted urban forest patches from remote sensing images and calculated patch quality and shape parameters with the help of image processing and landscape ecology methods. By using the LUR model, a $PM_{2.5}$ concentration distribution map was simulated to compare the difference in the ecological services regarding the $PM_{2.5}$ reduction in three urban forest types. Then the decisive factors influencing $PM_{2.5}$ concentration were obtained by correlation analysis and a regression model. It was concluded that urban forests play an important role in $PM_{2.5}$ mitigation. The $PM_{2.5}$ concentration of the urban forests varied due to their locations and the opportunity of contact with contaminants. Furthermore, LF had the strongest $PM_{2.5}$ reduction capacity, larger than RF and AF, for it had the biggest $PM_{2.5}$ reduction distance when compared to RF and AF. NDVI was the most important factor for mitigating the $PM_{2.5}$ concentration than the other patch shape indexes. The AREA, PERIM, and SHAPE parameters also significantly affected $PM_{2.5}$ concentration. The $PM_{2.5}$ concentration decreased rapidly when the AREA and PERIM of the forest patch were small and then declined slowly when AREA and PERIM increased. In addition, the $PM_{2.5}$ variation of RF and LF cannot be regulated by FRAC, and CIRCLE only has a positive relation with AF.

Urban air quality suffers enormous pressure under intensive urbanization and global change. Urban forest ecosystems have huge potential for atmosphere purification, including $PM_{2.5}$ mitigation. Reasonable forest management measures can help to sustain the stability of ecological services. The exact connections between $PM_{2.5}$ concentration and urban forest characteristics are critical to establishing such practices. The following recommendations should be considered to decrease $PM_{2.5}$ pollution.

(1) Improve urban forest growth status or health condition. Growth status represented by NDVI had the greatest influence on $PM_{2.5}$ reduction. LF and AF were far away from road traffic pollution and usually received more maintenance than RF. Therefore, the focus for RF should be their conservation in terms of water, fertilizer, and pest and disease management in urban management.

(2) Increase the forest patch area, perimeter, and irregularity. As we know, it is difficult to increase the forest size in the limited urban environment. Nevertheless, the amount of forest can be increased through roof greening, vertical greening, and building metope greening, etc. On the other hand, when the forest size is fixed, the $PM_{2.5}$ concentration can be effectively reduced by increasing the length of its boundary and creating a

more irregular spatial shape of the boundary, which helps to maximize the reduction ability of the urban forest. In addition, to improve the $PM_{2.5}$ mitigation capacity of AF, an irregular round boundary should be considered for landscape planning.

(3) The regression model between the patch parameters of the urban forests and $PM_{2.5}$ concentrations should be used to evaluate the reduction effect of the forest. Low $PM_{2.5}$ concentration patches should be selected as the optimal urban forest planning and design scheme. Through assessing the $PM_{2.5}$ reduction capacity of different forest types, related transformation and optimization measures could be implemented.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/f13091408/s1, Figure S1: Spatial distribution of $PM_{2.5}$ concentration in Changchun; Table S1: Urban forest classification; Table S2: Correlations between environmental factors and $PM_{2.5}$ concentration for LUR model.

Author Contributions: C.Z., G.B. and D.Z. lead to collect and analyze the data. Forest patches were extracted by Y.S. The manuscript was written by C.Z. and G.B. The article was revised by D.Z. and G.B. All authors have read and agreed to the published version of the manuscript.

Funding: The research article was supported by the Natural Science Foundation of Jilin Province (20220101315JC), the Scientific Research Cultivation Project of Changchun University (ZKC202005; ZKQ201913), and the "Climbing" Program of Changchun University (ZKP202015).

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

References

1. She, Q.; Cao, S.; Zhang, S.; Zhang, J.; Zhu, H.; Bao, J.; Meng, X.; Liu, M.; Liu, Y. The impacts of comprehensive urbanization on $PM_{2.5}$ concentrations in the Yangtze River Delta, China. *Ecol. Indic.* **2021**, *132*, 108337. [CrossRef]
2. Li, J.; Lei, J.; Li, S.; Yang, Z.; Tong, Y.; Zhang, S.; Duan, Z. Spatiotemporal analysis of the relationship between urbanization and the eco-environment in the Kashgar metropolitan area, China. *Ecol. Indic.* **2022**, *135*, 108524. [CrossRef]
3. *World Urbanization Prospects: The 2018 Revision*; United Nations: New York, NY, USA, 2018.
4. *2020 China Statistical Yearbook*; China National Bureau of Statistic: Beijing, China, 2021.
5. Ren, M.; Fang, X.; Li, M.; Sun, S.; Pei, L.; Xu, Q.; Ye, X.; Cao, Y. Concentration-Response Relationship between $PM_{2.5}$ and Daily Respiratory Deaths in China: A Systematic Review and Metaregression Analysis of Time-Series Studies. *Biomed. Res. Int.* **2017**, *2017*, 5806185. [CrossRef] [PubMed]
6. Liang, Z.; Wang, W.; Wang, Y.; Ma, L.; Liang, C.; Li, P.; Yang, C.; Wei, F.; Li, S.; Zhang, L. Urbanization, ambient air pollution, and prevalence of chronic kidney disease: A nationwide cross-sectional study. *Environ. Int.* **2021**, *156*, 106752. [CrossRef] [PubMed]
7. Ambient Air Pollution; World Health Organization: Geneva, Switzerland. 2020. Available online: www.who.int/multi-media/details/ambient-air-pollution (accessed on 29 August 2022).
8. Lu, C.W.; Fu, J.; Liu, X.F.; Chen, W.W.; Hao, J.L.; Li, X.L.; Pant, O.P. Air pollution and meteorological conditions significantly contribute to the worsening of allergic conjunctivitis: A regional 20-city, 5-year study in Northeast China. *Light Sci. Appl.* **2021**, *10*, 190. [CrossRef]
9. Liu, Y.; Tong, D.; Cheng, J.; Davis, S.J.; Yu, S.; Yarlagadda, B.; Clarke, L.E.; Brauer, M.; Cohen, A.J.; Kan, H.; et al. Role of climate goals and clean-air policies on reducing future air pollution deaths in China: A modelling study. *Lancet Planet. Health* **2022**, *6*, e92–e99. [CrossRef]
10. Shao, Y.; Ma, Z.; Wang, J.; Bi, J. Estimating daily ground-level $PM_{2.5}$ in China with random-forest-based spatiotemporal kriging. *Sci. Total Environ.* **2020**, *740*, 139761. [CrossRef] [PubMed]
11. Pope, C.A., 3rd; Burnett, R.T.; Thurston, G.D.; Thun, M.J.; Calle, E.E.; Krewski, D.; Godleski, J.J. Cardiovascular mortality and long-term exposure to particulate air pollution: Epidemiological evidence of general pathophysiological pathways of disease. *Circulation* **2004**, *109*, 71–77. [CrossRef]
12. Song, Y.; Wang, X.; Maher, B.A.; Li, F.; Xu, C.; Liu, X.; Sun, X.; Zhang, Z. The spatial-temporal characteristics and health impacts of ambient fine particulate matter in China. *J. Clean. Prod.* **2016**, *112*, 1312–1318. [CrossRef]
13. Yang, J.; Chang, Y.; Yan, P. Ranking the suitability of common urban tree species for controlling $PM_{2.5}$ pollution. *Atmos. Pollut. Res.* **2015**, *6*, 267–277. [CrossRef]
14. Cheng, Z.; Wang, S.; Jiang, J.; Fu, Q.; Chen, C.; Xu, B.; Yu, J.; Fu, X.; Hao, J. Long-term trend of haze pollution and impact of particulate matter in the Yangtze River Delta, China. *Enviton. Pollut.* **2013**, *182*, 101–110. [CrossRef] [PubMed]
15. Pratichi Singh, D.Y.; Pandian, E. Link between air pollution and global climate change. *Glob. Clim. Change* **2021**, *5*, 79–108.
16. Nowak, D.J.; Crane, D.E.; Stevens, J.C. Air pollution removal by urban trees and shrubs in the United States. *Urban For. Urban Green.* **2006**, *4*, 115–123. [CrossRef]

17. Nowak, D.J.; Hirabayashi, S.; Bodine, A.; Hoehn, R. Modeled $PM_{2.5}$ removal by trees in ten U.S. cities and associated health effects. *Environ. Pollut.* **2013**, *178*, 395–402. [CrossRef] [PubMed]
18. Cavanagh, J.-A.E.; Zawar-Reza, P.; Wilson, J.G. Spatial attenuation of ambient particulate matter air pollution within an urbanised native forest patch. *Urban For. Urban Green.* **2009**, *8*, 21–30. [CrossRef]
19. Nowak, D.J.; Hirabayashi, S.; Bodine, A.; Greenfield, E. Tree and forest effects on air quality and human health in the United States. *Environ. Pollut.* **2014**, *193*, 119–129. [CrossRef] [PubMed]
20. Ren, Z.; He, X.; Pu, R.; Zheng, H. The impact of urban forest structure and its spatial location on urban cool island intensity. *Urban Ecosyst.* **2018**, *21*, 863–874. [CrossRef]
21. Zhou, W.; Cao, F. Effects of changing spatial extent on the relationship between urban forest patterns and land surface temperature. *Ecol. Indic.* **2020**, *109*, 105778.1–105778.8. [CrossRef]
22. Wu, J.; Wang, Y.; Qiu, S.; Peng, J. Using the modified i-Tree Eco model to quantify air pollution removal by urban vegetation. *Sci. Total Environ.* **2019**, *688*, 673–683. [CrossRef] [PubMed]
23. Tallis, M.; Taylor, G.; Sinnett, D.; Freer-Smith, P. Estimating the removal of atmospheric particulate pollution by the urban tree canopy of London, under current and future environments. *Landsc. Urban Plan.* **2011**, *103*, 129–138. [CrossRef]
24. Beckett, K.P.; Freer Smith, P.H.; Taylor, G. Effective tree species for local air quality management. *J. Arboric.* **2000**, *26*, 12–19.
25. Liu, X.; Yu, X.; Zhang, Z. $PM_{2.5}$ Concentration Differences between Various Forest Types and Its Correlation with Forest Structure. *Atmosphere* **2015**, *6*, 1801–1815. [CrossRef]
26. Nguyen, T.; Yu, X.; Zhang, Z.; Liu, M.; Liu, X. Relationship between types of urban forest and $PM_{2.5}$ capture at three growth stages of leaves. *J Environ. Sci.* **2015**, *27*, 33–41. [CrossRef] [PubMed]
27. Łowicki, D. Landscape pattern as an indicator of urban air pollution of particulate matter in Poland. *Ecol. Indic.* **2019**, *97*, 17–24. [CrossRef]
28. Wu, J.; Xie, W.; Li, W.; Li, J. Effects of Urban Landscape Pattern on $PM_{2.5}$ Pollution—A Beijing Case Study. *PLoS ONE* **2015**, *10*, e0142449. [CrossRef]
29. Bagheri, Z.; Nadoushan, M.A.; Abari, M.F. Evaluation the Effect of Green Space on Air Pollution Dispersion using landscape metrics: A case study of Isfahan city. *Fresenius Environ. Bull.* **2017**, *26*, 8135–8145.
30. Lei, Y.; Duan, Y.; He, D.; Zhang, X.; Chen, L.; Li, Y.; Gao, Y.; Tian, G.; Zheng, J. Effects of Urban Greenspace Patterns on Particulate Matter Pollution in Metropolitan Zhengzhou in Henan, China. *Atmosphere* **2018**, *9*, 199. [CrossRef]
31. Feng, H.; Zou, B.; Tang, Y. Scale- and Region-Dependence in Landscape-$PM_{2.5}$ Correlation: Implications for Urban Planning. *Remote Sens.* **2017**, *9*, 918. [CrossRef]
32. Kim, S.; Lee, S.; Hwang, K.; An, K. Exploring Sustainable Street Tree Planting Patterns to Be Resistant against Fine Particles ($PM_{2.5}$). *Sustainability* **2017**, *9*, 1709. [CrossRef]
33. Jin, S.; Guo, J.; Wheeler, S.; Kan, L.; Che, S. Evaluation of impacts of trees on $PM_{2.5}$ dispersion in urban streets. *Atmos. Environ.* **2014**, *99*, 277–287. [CrossRef]
34. Islam, M.N.; Rahman, K.-S.; Bahar, M.M.; Habib, M.A.; Ando, K.; Hattori, N. Pollution attenuation by roadside greenbelt in and around urban areas. *Urban For. Urban Green.* **2012**, *11*, 460–464. [CrossRef]
35. Chen, J.; Yu, X.; Sun, F.; Lun, X.; Fu, Y.; Jia, G.; Zhang, Z.; Liu, X.; Mo, L.; Bi, H. The Concentrations and Reduction of Airborne Particulate Matter (PM_{10}, $PM_{2.5}$, PM1) at Shelterbelt Site in Beijing. *Atmosphere* **2015**, *6*, 650–676. [CrossRef]
36. Sun, F.; Yin, Z.; Lun, X.; Zhao, Y.; Li, R.; Shi, F.; Yu, X. Deposition velocity of $PM_{2.5}$ in the winter and spring above deciduous and coniferous forests in Beijing, China. *PLoS ONE* **2014**, *9*, e97723. [CrossRef] [PubMed]
37. Liu, J.; Zhai, J.; Zhu, L.; Yang, Y.; Liu, J.; Zhang, Z. Particle removal by vegetation: Comparison in a forest and a wetland. *Environ. Sci. Pollut. Res. Int.* **2017**, *24*, 1597–1607. [CrossRef]
38. *2020 Jilin Statistical Yearbook*; Statistic Bureau of Jilin: Changchun, China, 2021.
39. *2020 Changchun Statistical Yearbook*; Changchun Bureau of Statistics: Changchun, China, 2021.
40. *2020 State of the Environment Bulletin of Jilin Province*; Ecology and Environment Department of Jilin Province: Changchun, China, 2021.
41. *2018 State of the Environment Bulletin of Jilin Province*; Ecology and Environment Department of Jilin Province: Changchun, China, 2019.
42. *2019 State of the Environment Bulletin of Jilin Province*; Ecology and Environment Department of Jilin Province: Changchun, China, 2020.
43. Zhai, C.; Wang, W.; He, X.; Zhou, W.; Xiao, L.; Zhang, B. Urbanization Drives SOC Accumulation, Its Temperature Stability and Turnover in Forests, Northeastern China. *Forests* **2017**, *8*, 130. [CrossRef]
44. Pitiranggon, M.; Johnson, S.; Haney, J.; Eisl, H.; Ito, K. Long-term trends in local and transported $PM_{2.5}$ pollution in New York City. *Atmos. Environ.* **2021**, *248*, 118238. [CrossRef]
45. Xu, X.; Qin, N.; Yang, Z.; Liu, Y.; Cao, S.; Zou, B.; Jin, L.; Zhang, Y.; Duan, X. Potential for developing independent daytime/nighttime LUR models based on short-term mobile monitoring to improve model performance. *Environ. Pollut.* **2021**, *268 Pt. B*, 115951. [CrossRef]
46. Zhao, M.; Liu, Q.; Xu, F.; Cheng, C. Effects of greenbelt plant configuration on atmospheric $PM_{2.5}$ in Beijing. *Int. J. Sustain. Dev. World Ecol.* **2017**, *25*, 176–183. [CrossRef]

47. Sebastiani, A.; Buonocore, E.; Franzese, P.P.; Riccio, A.; Chianese, E.; Nardella, L.; Manes, F. Modeling air quality regulation by green infrastructure in a Mediterranean coastal urban area: The removal of PM_{10} in the Metropolitan City of Naples (Italy). *Ecol. Model.* **2021**, *440*, 109383. [CrossRef]
48. Ohsawa, T. Idea paper: How are ecosystem services related to biodiversity and ecological integrity in each site under climate change? *Ecol. Res.* **2022**, *37*, 461–465. [CrossRef]
49. Zhang, D.; Zheng, H.; He, X.; Ren, Z.; Zhai, C.; Yu, X.; Mao, Z.; Wang, P. Effects of forest type and urbanization on species composition and diversity of urban forest in Changchun, Northeast China. *Urban Ecosyst.* **2015**, *19*, 455–473. [CrossRef]
50. Jin, H.; Chen, X.; Wang, Y.; Zhong, R.; Zhao, T.; Liu, Z.; Tu, X. Spatio-temporal distribution of NDVI and its influencing factors in China. *J. Hydrol.* **2021**, *603*, 127129. [CrossRef]
51. Ma, Y.; Zhang, Q.; Yi, X.; Ma, L.; Zhang, L.; Huang, C.; Zhang, Z.; Lv, X. Estimation of Cotton Leaf Area Index (LAI) Based on Spectral Transformation and Vegetation Index. *Remote Sens.* **2021**, *14*, 136. [CrossRef]
52. Liu, J.; Xiao, B.; Jiao, J.; Li, Y.; Wang, X. Modeling the response of ecological service value to land use change through deep learning simulation in Lanzhou, China. *Sci. Total Environ.* **2021**, *796*, 148981. [CrossRef]