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Original Paper

The Impact of Urban Green Patches on Air Pollutant Concentration: A Case Study of Hangzhou

Hao Tao[a], Rikun Wen[*,1a&b], Hexian Jin[2a], Liu Yang[a] & Chingaipe N'tani[a]

[a] School of Landscape Architecture, Zhejiang Agriculture and Forest University, Hangzhou, Zhejiang Province, PR of China

[b] Zhejiang Province Key Think Tank：Institute of Ecological Civilization，Zhejiang Agriculture and Forest University, Hangzhou, Zhejiang Province, PR of China

[*] Corresponding author: wenrk@zafu.edu.cn, Department of Landscape Architecture, Zhejiang Agriculture and Forest University, Hangzhou, Zhejiang Province, PR of China

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Abstract

To explore the impact of landscape pattern index on air pollutant, this study takes the annual average concentrations of $PM_{2.5}$, O_3, PM_{10}, and NO_2 at 14 national air quality monitoring stations in Hangzhou from 2014 to 2021 as the dependent variables, and selects five landscape pattern indices of green patches within 500m of the monitoring stations as independent variables. An enhanced regression tree model was used to study the influence of landscape patterns on the concentrations of the four air pollutants. The results show that the most significant influencing factors for the concentrations of $PM_{2.5}$, O_3, PM_{10}, and NO_2 are the aggregation index, Shannon's diversity index, aggregation index, and largest patch index respectively, with relative influence rates of 29.27%, 25.06%, 31.28%, and 28.58%, respectively. The aggregation index has a significant impact on all types of air pollutants and plays a good role in reducing air pollution. With higher regional patch aggregation index, the concentration of air particulate matter and nitrogen oxides is greatly alleviated. The largest patch index is significantly *negatively correlated with air particulate matter and ozone concentration, and an increase in green areas has a good mitigating effect on these two types of air pollutants. As the Shannon diversity index increases, there is a general trend of decreasing particulate matter concentration, while the concentrations of nitrogen dioxide and ozone show a decrease as well. This suggests that the complexity of landscape shape and boundaries is conducive to the reduction of nitrogen dioxide and ozone concentrations to a certain extent.*

Keywords

Concentrations of $PM_{2.5}$, O_3, PM_{10}, and NO_2, Landscape Pattern Index, Boosting Regression Tree, Threshold effect, Influence mechanism

1. Introduction

In many cities around the world, air pollution has become a serious problem. The accelerated industrialization process, vehicle emissions, and exhaust from coal-fired power plants continue to release pollutants into the atmosphere. Major pollutants include atmospheric particulate matter, nitrogen oxides, and ozone. Air pollution has become a significant challenge for cities worldwide. The European Environment Agency has identified air pollution as the largest environmental health threat in Europe (WHO, 2019). In 2018, between 168,000 and 346,000 premature deaths in EU countries were attributed to exposure to fine particulate matter (Laurent, 2022). Thirteen of the 20 cities with the highest annual average $PM_{2.5}$ concentrations are in India (Gordon et al., 2018). Severe air pollution has had a significant impact on the health of Indian residents. Although improved air quality is a common phenomenon, in some cities, air quality has not significantly improved and in some cases, has even worsened (Adam et al., 2021). For example, the U.S. Environmental Protection Agency provided monitoring data that contradicted expectations, showing slightly lower than expected levels of pollutants such as ozone, nitrogen oxides, and PM_{10} during this period, while the average concentration of $PM_{2.5}$ was slightly higher than expected (Bekbulat et al., 2021).

With the rapid advancement of urbanization in China in recent decades (Guan et al., 2018), the concentration of the urban population and the increasing number of urban vehicles have led to a series of ecological environmental issues for cities. Among them, urban air pollution, which is closely related to residents' lives, has increasingly attracted people's attention and gradually become a research hotspot (Gorai et al., 2014; Shi et al., 2013; Song et al., 2017). The main sources of air pollution are industrial production activities, residential activities, and transportation. Air particulate matter, nitrogen oxides, and ozone are among the main components of air pollution, which have a significant impact on human health (Karimi et al., 2019; Li et al., 2021; Li et al., 2021). Although China has made some progress in controlling air pollution, it still faces challenges. According to the 2021 China Ecological Environment Status Report, in 2021, 39.7% of the days in 339 Chinese cities were heavily polluted with $PM_{2.5}$ as the main pollutant, 34.7% with O_3, 25.2% with PM_{10}, and 0.6% with NO_2 as the main pollutants. In the Yangtze River Delta region, the proportions of days exceeding the standard for $PM_{2.5}$,

O_3, PM_{10}, and NO_2 were 55.4%, 30.7%, 12.3%, and 1.7% (MEEPRC, 2022), respectively. The control of air pollution remains a long and arduous task. This study will focus on the analysis of two types of air particulate matter, nitrogen dioxide, and ozone, which have been more severe in recent years.

Urban green spaces, as a natural part of the urban system, play an important role in adsorbing air pollutants and reducing environmental air particulates (Li et al., 2014; Wu & Wang, 2007; Wu et al., 2008; Zhu & Zhao, 2014). For example, investigated the impact of green space landscape pattern characteristics on $PM_{2.5}$ concentrations in Nanchang, Jiangxi Province, China, and conducted a preliminary analysis of the emission reduction effects of urban green spaces on $PM_{2.5}$. (Ventera et al., 2024) studied the relationship between vegetation and air quality, finding that while urban greening may improve air quality within certain areas, its effects are moderate and can even be detrimental at the street level, depending on the type of vegetation and urban morphology. (Ren et al., 2023) employed remote sensing and ArcGIS technologies to investigate the scale effects, spatial differentiation, and synergistic effects of green space landscape patterns on $PM_{2.5}$ and PM_{10} in Xi'an. They identified a significant gradient change in the green space landscape pattern of Xi'an and concluded that increasing the number and area of green space patches while reducing their overall dispersion can effectively lower particulate matter concentrations. This study selected five urban green space landscape pattern indices to investigate their relative impacts on four major air pollutants from both patch and landscape perspectives, whereas previous studies primarily focused on the effects on particulate matter. Moreover, delineating the key influencing factors of concentration variations in each air pollutant aids in optimizing the landscape pattern of green spaces tailored to specific pollutants. The research in this area can help understand the purification function of green patches on air pollutants and provide more scientific guidance for urban green space development.

This study is based on air pollutant monitoring data from 2014 to 2021 at national control monitoring points in Hangzhou, established a 500-meter buffer zone around each monitoring point. Five green space landscape pattern indices were selected to analyze the distribution of $PM_{2.5}$, O_3, PM_{10}, and NO_2 concentrations. Using the Gradient Boosting Regression Tree model, the study quantitatively analyzed the relative influence and threshold effects of green space landscape patterns on air pollutant concentrations. It explored the impact of urban green patches on air pollutant concentrations and examined the effects of different green space landscape pattern indices on these concentrations. The objective is to provide a theoretical and methodological basis for optimizing urban landscape patterns, improving air quality, and reducing air pollution. The findings offer scientific evidence for urban planners and policymakers, supporting the rational layout and planning of urban green spaces.

2. Literature Review

2.1 Urban Landscape Pattern

From the perspective of urban landscape patterns, landscape is usually used to describe the inland terrain, landforms, and scenery, such as water systems, forests, etc., or to describe the geographic features of a certain area (Wu, 2007). It has clear boundaries and spatial divisions (Wen, 2013). The landscape is an embedded body composed of elements such as patches, corridors, and matrix, and can be classified into artificial landscapes, natural landscapes, and small and medium-sized landscapes according to different geographical types. An urban landscape is a typical artificial landscape. The landscape pattern index is a method that can quantitatively analyze landscape patterns, can highly condense landscape pattern information, and reflect the distribution and spatial changes of landscapes. The study of urban landscape pattern can more clearly and rationally address various ecological problems faced by the city through the quantitative analysis of the process of urban landscape pattern evolution (Luo & Cao, 2022). Currently, the landscape pattern index is widely used in the analysis of urban landscape patterns and the study of urban spatial forms. For example, Wang et al. (2022) analyzed the relationship between urban green space landscape patterns and atmospheric pollutant concentrations. The landscape pattern indices of urban green spaces (LSI, PD, PLAND) exhibit significant threshold effects on the mechanisms influencing the concentrations of atmospheric pollutants such as $PM_{2.5}$, NO_2, and SO_2. analyzed the impact of land use/cover on the Air Quality Index (AQI), $PM_{2.5}$ concentration, and PM_{10} concentration, finding that land use/cover types significantly influence variations in atmospheric particulate matter concentrations, at the scale of the 5000-meter buffer zone, the quantity and density of forest patches are positively correlated with the concentration of $PM_{2.5}$. Jaafari et al. (2020) assessed the impact pathways of green spaces on air pollution, revealing that maximizing green space area and cohesion while minimizing fragmentation and edge effects contribute to reducing air pollution, particularly with respect to the most critical indicator, $PM_{2.5}$. Urban green spaces, serving as pivotal constituents of urban ecology, wield significant influence upon it. This investigation endeavors to assess the relative impact of green patch landscape patterns on air pollutant concentration by employing five pertinent green indices, namely patch density, aggregation index, maximum patch index, area-weighted patch fractal dimension, and Shannon-Wiener index. When selecting landscape metrics, high correlation among indices can lead to information redundancy (Rafiee et al., 2009), complicating interpretation. Therefore, this study opted for five green indices with low inter-correlation, thereby enhancing the accuracy of predictive outcomes. These indices describe the structure and spatial distribution of green patches at both patch and landscape scales, providing a clearer depiction of the quantity and connectivity of green patches within the study area.

2.2 Research Progress on the Influence of Urban Landscape Patterns on Air Pollution

From the perspective of influence on air pollution by urban landscape patterns, changes in urban landscape patterns can affect the ecological environmental effects of surrounding areas (Schwarz et al., 2012). Previous studies have found that changes in land use types can have a certain impact on the concentration changes of major atmospheric pollutants such as $PM_{2.5}$ (Cui, 2013; Wang et al., 2014). For example, Xu et al. (2015) analyzed the coupling relationship between NO_2, PM_{10}, O_3, $PM_{2.5}$ concentrations, and landscape pattern, revealing a significant influence of land use/cover on the variation of atmospheric pollutant concentrations in the study area, along with seasonal effects. Li et al.

(2016) found that landscape patterns have a certain influence on the distribution of $PM_{2.5}$ concentrations, with landscape area, density, fragmentation, and aggregation-dispersion being the main factors affecting $PM_{2.5}$ concentrations. Wu et al. (2015) selected five landscape pattern indices, namely PLAND, PD, ED, SHEI, and CONTAG, to study their relative relationship with $PM_{2.5}$ concentration. They found that vegetation significantly reduces $PM_{2.5}$ concentration, while farmland has a particular impact on $PM_{2.5}$ concentration. At the landscape level, SHEI and CONTAG are closely related to $PM_{2.5}$ concentration.

2.3 Boosted Regression Tree Methods in Atmospheric Pollution Studies

The use of machine learning methods to predict the concentration of atmospheric pollutants has rich examples, such as the use of neural network models to predict the concentration of atmospheric pollutants at city locations on an urban scale (Kukkonen et al., 2003), and the use of gradient boosting regression trees within reasonable buffer zones to predict the impact of urban morphological factors on the concentration of atmospheric pollutants (Cui et al., 2022). The relationship between atmospheric pollutants and meteorological factors, the method of principal component analysis is often used in previous studies, which may ignore the correlation between independent variables, resulting in large errors in the generated results. The use of enhanced regression trees can effectively eliminate redundant information and improve the accuracy of model predictions. Current regression modeling is used as a predictive tool in many fields due to its applicability and efficiency, especially in the prediction of air pollution, and boosted regression tree modeling has recently been used in air pollution prediction due to its better adaptive ability. Ge et al. (2017) utilized boosted regression tree model to analyze the contributions of seven meteorological factors to the daily variations in $PM_{2.5}$. Zhang et al. (2021) employed boosted regression tree model to quantify the contributions of various land use types to PM2.5 concentrations across different seasons. Li et al. (2021) selected 10 two-dimensional and three-dimensional landscape pattern indices as independent variables and utilized a boosted regression tree model to investigate their effects on the concentrations of four atmospheric pollutants. They found that the proportion of impervious surfaces was the most significant factor influencing the concentrations of NO_2, SO_2, $PM_{2.5}$, and PM_{10}, with relative contribution rates of 40.7%, 36.3%, 51.0%, and 51.8%, respectively. Shaziayani et al. (2021) used Boosted Regression Trees (BRT) to predict PM10 concentrations in Klang, Alor Setar, and Kota Bharu, Malaysia. Their results indicated that quantile regression met the assumptions and served as a robust model for predicting maximum daily PM10 concentrations using BRT. Suleiman et al. (2016) also explored the application of Boosted Regression Trees (BRT) in air quality modeling. The study suggested that BRT models offer more advantages in model interpretation and feature selection. When prioritizing model interpretability, BRT can be used as an alternative to Artificial Neural Networks (ANN). This study uses enhanced regression trees to quantitatively analyze the contribution rate and marginal effects of green patches' landscape patterns to the annual average concentrations of $PM_{2.5}$, O_3, PM_{10}, and NO_2.

3. Materials and Methods

3.1 Study Area

The city of Hangzhou is located in the eastern part of Zhejiang Province, China, with a diverse natural environment characterized by hills, plains, and mountains. According to the 2021 Ecological Environment Bulletin of Hangzhou, the city had 321 days of excellent air quality, a decrease of 13 days compared to 2020, with an excellent rate of 87.9%, representing a 3.4 percentage point drop (HZMEEB, 2022). The concentration of fine particulate matter $PM_{2.5}$ and nitrogen dioxide NO_2 decreased compared to 2020, while inhalable particulate matter PM_{10} remained stable, and ozone O_3 concentration showed an increasing trend.

The study area covers 14 national monitoring stations in Hangzhou, Zhejiang Province, China, with a 500-meter buffer zone established around each station (Figure 1 and Figure 2). This includes the QianDaoHu station, HeMuXiaoXue station, ZhejiangNongDa station, WoLongQiao station, XiaSha station, YunQi station, ChengXiangZhen station, LinPingZhen station, XiXi station, BinJiang station, ZhaoHuiWuQu station, XiaoFangDaDui station, ZhenErZhong station, and ShiFuDaLou station (hereinafter referred to by acronyms). Among these, the HMXX station, CXZ station, LPZ station, BJ station, ZHWQ station, XFDD station, and ZEZ station are located near urban residential areas with high building density and a high proportion of grey patches with scattered green spaces between buildings, resulting in fragmented landscapes. The QDH station, WLQ station, YQ station, and XX station are located in scenic areas, near large water bodies or surrounded by large-scale green spaces, with generally high vegetation coverage and good ecological environments. On the other hand, the ZJND station, XS station, and SFDL station are primarily located in areas designated for construction use, but due to their location within a university or near a park, they also have relatively high vegetation coverage.

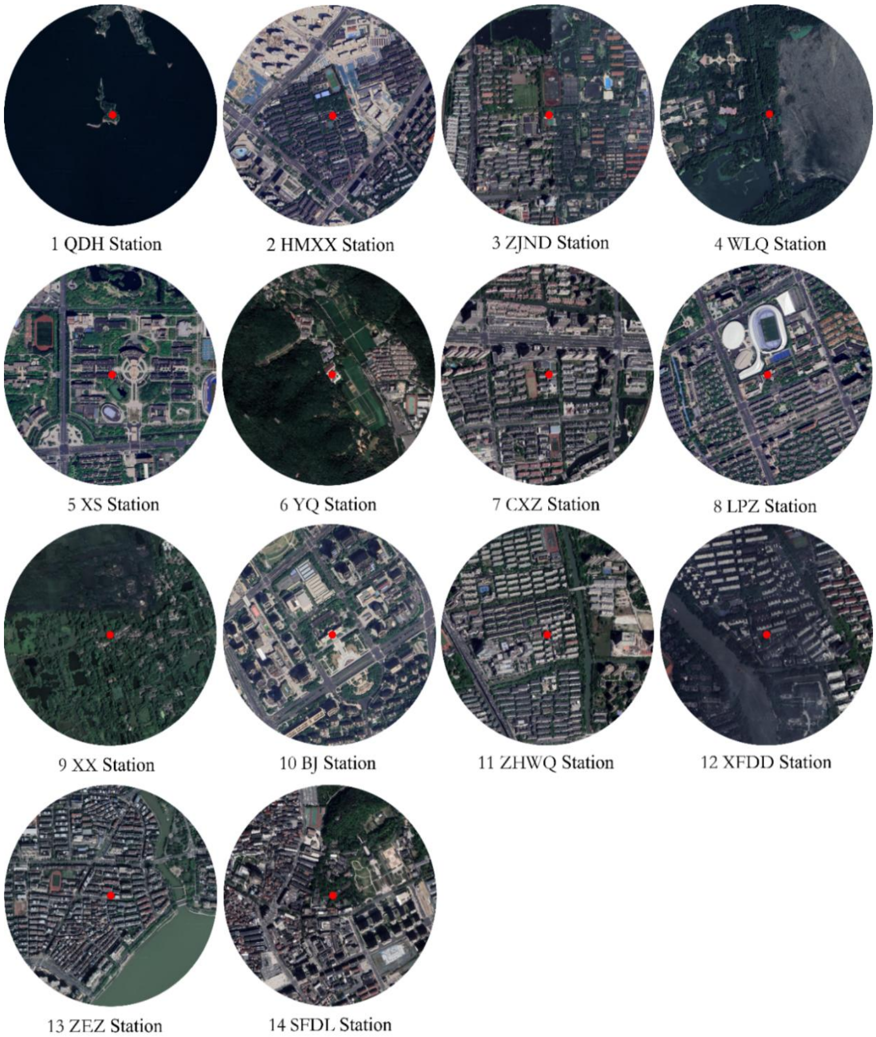

Figure 1. Satellite Image of the Study Area

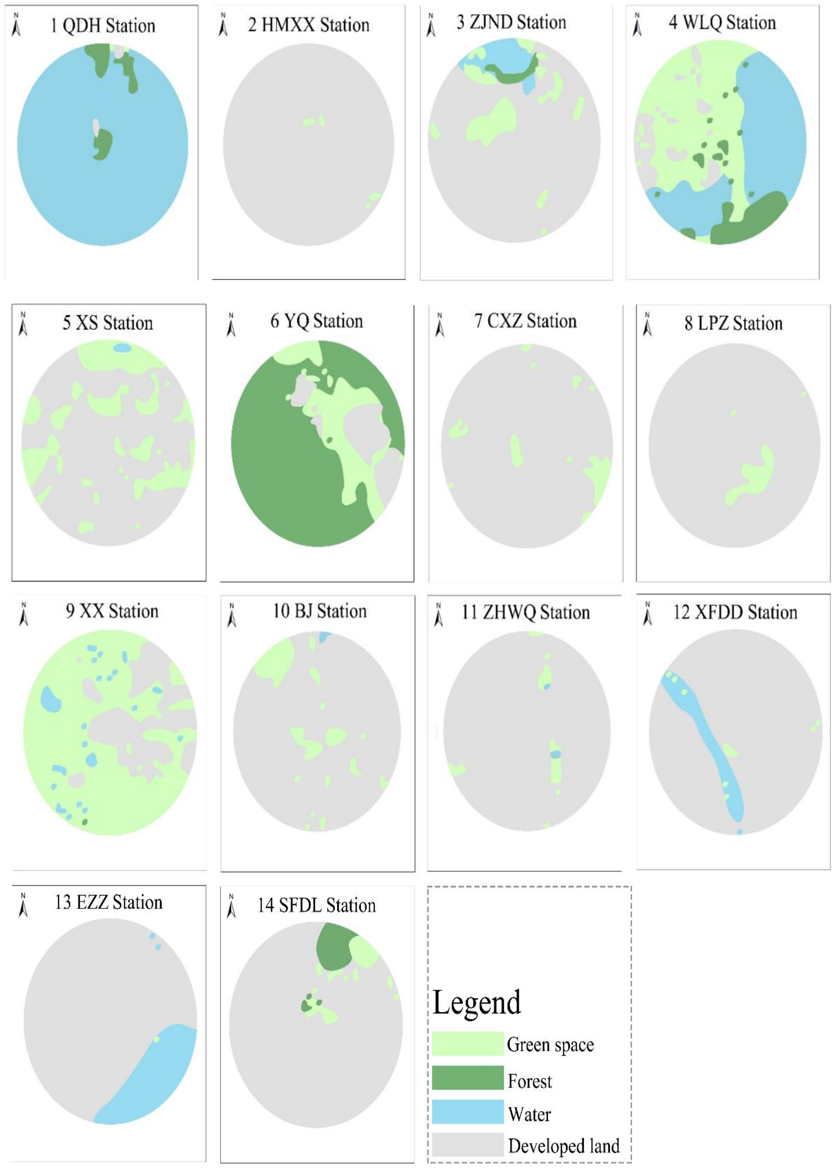

Figure 2. Map of Patches in the Study Area

3.2 Data Collection

The research data used in this study include the 2014-2021 China Land Use/Cover Dataset, covering the study area where 14 national monitoring stations are located. The land use data comes from the Earth System Science Data and is produced annually by the Landsat satellite and the China Land Use/Cover Dataset (CLUD), with a spatial resolution of 30m and an accuracy of 79.31%. Raster reclassification using ArcGIS divides land types into green space, forest land, construction land, and water bodies. Frastats is used to calculate the patch density (PD), aggregation index (AI), largest patch index (LPI), area-weighted fractal dimension (FRAC_AM), and Shannon diversity index (SHDI) of green patches. Air pollution concentration data for the study area from 2014 to 2021 is obtained from open source data at the national monitoring stations in Hangzhou, Zhejiang Province, China, including daily concentrations of $PM_{2.5}$, O_3, PM_{10}, and NO_2, with statistical time from January 1 to December 31 each year. The average concentrations of each station are extracted, totaling 75 sample data points over 8 years for the 14 stations.

4. Methodology

4.1 Landscape Pattern Index-Driven Method

The study selected 5 two-dimensional landscape indicators to investigate their correlation with urban air pollutant concentrations, namely: Patch Aggregation Index (AI), Patch Density (PD), Largest Patch Index (LPI), Area-Weighted Patch Fractal Dimension (FRAC_AM), and Shannon-Weiner Index (SHDI). The calculation formulas and explanations of the indicators are shown in Table 1. Landscape pattern indices of green patches within the buffer zone were calculated using Fragstats. The landscape pattern indices of green patches were used as the independent variable, and the annual average concentrations of atmospheric pollutants monitored at each site were used as the dependent variable to analyze the relationship between them.

Table 1. Landscape Pattern Index

Metrics	Formula	Parameter Description
Aggregation Index (AI)	$AI = \left[\sum_{i=1}^{m}\left(\frac{g_{ij}}{max\rightarrow g_{ij}}\right)\right] \times 100$	The degree of aggregation between various patches in the landscape reflects the connectivity between the patches. In the formula, represents the maximum number of similar adjacencies.
Patch density(PD)	$PD = \frac{N}{A}$	The number of patches per unit area in the landscape reflects the overall fragmentation of the landscape. In the formula, N represents the number of patches in the landscape, and A represents the total area of the landscape.
Largest Patch Index (LPI)	$LPI = \frac{a_{max}}{A} \times 100$	Reflecting the dominance species in the landscape, as well as the richness of internal species. Where: represents the maximum patch area within the landscape.
Area-weighted mean patch fractal dimension (FRAC_AM)	$F = \frac{2\ln\left(\frac{P}{K}\right)}{\ln A}$	This equation reflects the complexity of patch shapes in landscapes. Here, P represents the patch perimeter; K is a constant, and for general grid landscapes, K=4.

Shannon's Diversity Index (SHDI)	SHDI = $-\sum_{i=1}^{m}[P_i \ln P_i]$	The proportion of patch types in the landscape multiplied by the sum of that proportion, reflects the richness of landscape types. In the equation: represents the probability of patch type i appearing in the landscape.

4.2 Boosted Regression Tree Model

The boosted regression tree (BRT) modeling type is used to investigate the contribution and threshold effects of landscape patterns on urban air pollution. It uses recursive binary partitioning to remove interactions between independent variables, iteratively fitting the tree-based model in segments and identifying poorly modeled observations in the existing tree until minimal model bias is achieved. The BRT equation package was invoked in the R platform for enhanced regression tree operation analysis, the number of trees was set to 500, the shrinkage parameter was set to 0.01, 50% of the data were extracted for training analysis and 50% for testing each time, the interaction depth was set to 3, cross-validation was performed, and the final target results were presented visually.

5. Results

5.1 Contribution of Landscape Pattern Indices to Air Pollutant Concentrations

Table 2 present the historical landscape pattern indices for each research site. Figure 3 and Table 3 show the contribution of each landscape pattern index to the relative influence of annual average pollutant concentration. The simulation experiment using an augmented regression tree to explore the influence of landscape pattern index on $PM_{2.5}$ concentration in green patches shows that the contribution of each landscape pattern index is Aggregation Index AI (29.27%) > Patch Density PD (20.99%) > Shannon-Wiener Index SHDI (18.45%) > Area-weighted patch dimension FRAC_AM (17.59%) > Maximum patch index LPI (13.7%), which has a training set RMSE value of 7.347 and a test set RMSE value of 13.1298, with excellent model accuracy. Simulation experiments on the effect of landscape pattern indices on O_3 concentration showed that the contribution of each landscape pattern index was Shannon-Wiener index SHDI (25.06%) > Aggregation index AI (20.25%) > Area-weighted patch dimensionality FRAC_AM (20.22%) > Maximum patch index LPI (17.71%) > Patch density PD (16.76%), and its The RMSE value of the training set is 6.8904, and the RMSE value of the test set is 8.9523, the model accuracy is excellent; the simulation experiments of the influence of landscape pattern index on PM_{10} concentration show that the contribution of each landscape pattern index is Aggregation index AI (31.28%) > Area-weighted plaque subdimension FRAC_AM (21.01%) > Shannon - Wiener index SHDI (18.68%)>Patch Density PD (14.98%)>Maximum Plaque Index LPI (14.04%), with a training set RMSE value of 10.2132 and a test set RMSE value of 17.0765, which is an excellent model accuracy; the simulation experiments on the effect of landscape pattern indices on the concentration of NO_2 showed that the contribution of each landscape pattern index was Maximum

Plaque Index LPI (28.58%) > aggregation index AI (26.41%) > patch density PD (24.33%) > area-weighted patch dimension FRAC_AM (11.89%) > Shannon-Wiener index SHDI (8.78%), with a training set RMSE value of 4.3281 and a test set RMSE value of 5.5838, resulting in excellent model accuracy. The major and minor influencing factors are shown in Table 2.

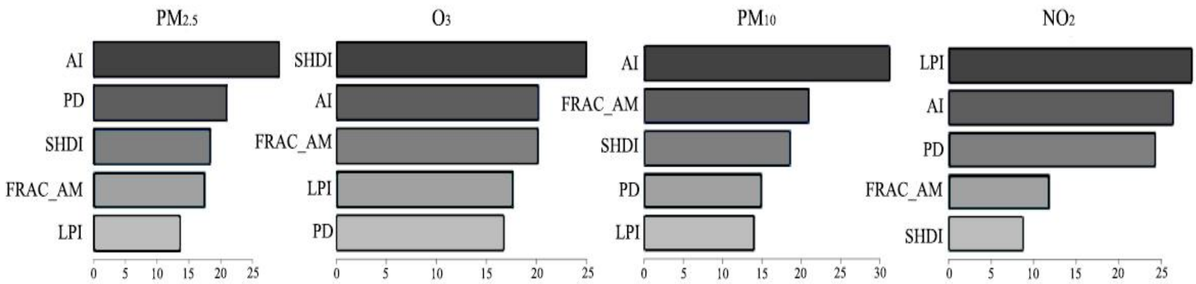

Figure 3. Contribution of Landscape Pattern Indices of the Green Patches on Air Pollutant Concentrations in the Study Area

Table 2. Study Area Landscape Pattern Index (2014 Study Area Landscape Pattern Index)

Station	PD	LPI	FRAC_AM	AI	SHDI
2014 ZHWQ	7.6422	0.4386	1.0390	38.8889	0.1540
2014 HMXX	3.8245	0.3512	1.0412	50.0000	0.0590
2014 WLQ	6.3853	52.2427	1.1693	90.6169	0.8950
2014 XS	21.6910	7.4692	1.1070	71.7117	0.6036
2014 YQ	2.5407	86.5267	1.1068	96.4044	0.3973
2014 ZJND	15.3653	6.7019	1.0908	73.7931	0.6499
2014 SFDL	10.1807	2.2787	1.0868	59.5238	0.4189

2015 Study Area Landscape Pattern Index

Station	PD	LPI	FRAC_AM	AI	SHDI
2015 ZHWQ	8.9159	0.5263	1.0394	37.5000	0.1548
2015 HMXX	3.8245	0.3512	1.0412	50.0000	0.0590
2015 WLQ	6.3853	52.6825	1.1675	90.8621	0.8937
2015 XS	21.6910	7.4692	1.1070	71.7117	0.6036
2015 YQ	2.5407	86.5267	1.1068	96.4044	0.3973
2015 ZJND	15.3653	6.3492	1.0937	72.7915	0.6437
2015 SFDL	10.1807	2.5416	1.0843	61.5385	0.4202

2016 Study Area Landscape Pattern Index

Station	PD	LPI	FRAC_AM	AI	SHDI
2016 ZHWQ	11.4633	0.5263	1.0466	40.0000	0.1514
2016 HMXX	3.8245	0.3512	1.0412	50.0000	0.0590
2016 WLQ	7.6624	52.9464	1.1646	90.9247	0.8926
2016 XS	21.6910	7.4692	1.1117	69.8502	0.5932
2016 YQ	2.5407	86.3517	1.1046	96.5013	0.4006
2016 ZJND	15.3653	6.3492	1.0933	72.6316	0.6432
2016 SFDL	10.1807	2.8046	1.0851	62.8866	0.4209

2017 Study Area Landscape Pattern Index

Station	PD	LPI	FRAC_AM	AI	SHDI
2017 ZHWQ	10.1896	0.7018	1.0472	48.7805	0.1415
2017 HMXX	3.8245	0.3512	1.0412	50.0000	0.0590
2017 WLQ	7.6624	52.9464	1.1646	90.9247	0.8926
2017 XS	21.6910	7.4692	1.1117	68.8502	0.5932
2017 YQ	2.5407	86.3517	1.1046	96.5013	0.4006
2017 ZJND	14.0849	6.3492	1.0982	72.8223	0.6426
2017 SFDL	10.1807	2.8046	1.0851	62.8866	0.4209

2018 Study Area Landscape Pattern Index

Station	PD	LPI	FRAC_AM	AI	SHDI
2018 BJ	20.3614	4.2945	1.0821	62.9834	0.3221
2018 XX	5.0726	61.3100	1.2401	83.3809	0.8659
2018 QDH	3.8211	2.3684	1.0695	79.4643	0.2618
2018 XS	22.9669	7.4692	1.1027	69.9248	0.5923
2018 WLQ	7.6624	52.9464	1.1646	90.9247	0.8926
2018 ZJND	14.0849	6.3492	1.0982	72.8223	0.6426
2018 ZHWQ	10.1896	0.8772	1.0290	55.5556	0.1385
2018 HMXX	3.8245	0.3512	1.0412	50.0000	0.0461
2018 LPZ	6.3853	4.3096	1.1143	76.8421	0.2065
2018 CXZ	15.2979	2.5461	1.1054	52.8926	0.2286
2018 YQ	2.5407	86.3517	1.1046	96.5013	0.4006

2019 Study Area Landscape Pattern Index

Station	PD	LPI	FRAC_AM	AI	SHDI
2019 BJ	20.3614	4.2945	1.0821	62.9834	0.3221
2019 ZHWQ	10.1896	0.8772	1.0365	55.1020	0.1345
2019 CXZ	14.0230	2.5461	1.1084	53.9130	0.2213
2019 HMXX	3.8245	0.3512	1.0412	50.0000	0.0461
2019 LPZ	5.1083	4.3096	1.1164	78.4946	0.2039
2019 QDH	3.8211	2.3684	1.0695	79.4643	0.2618
2019 WLQ	7.6624	52.9464	1.1646	90.9247	0.8926
2019 XX	5.0726	63.0568	1.2247	85.4268	0.8310
2019 XS	22.9669	7.4692	1.1027	69.9248	0.5923
2019 YQ	2.5407	86.3517	1.1046	96.5013	0.4006
2019 ZJND	14.0849	6.3492	1.0982	72.8223	0.6426

Station	PD	LPI	FRAC_AM	AI	SHDI
2020 BJ	20.3614	4.2945	1.0821	62.7778	0.3200
2020 XX	5.0726	65.2402	1.2082	87.3826	0.7810
2020 QDH	3.8211	2.3684	1.0695	79.4643	0.2576
2020 XS	22.9669	7.4692	1.1027	69.9248	0.5923
2020 WLQ	7.6624	53.1223	1.1644	90.9556	0.8921
2020 ZJND	14.0849	6.3492	1.0982	72.8223	0.6426
2020 ZHWQ	10.1896	0.8772	1.0365	55.1020	0.1345
2020 HMXX	3.8245	0.3512	1.0412	50.0000	0.0461
2020 LPZ	3.8312	4.2216	1.1205	79.7753	0.1986
2020 CXZ	14.0230	2.5461	1.1084	53.9130	0.2213
2020 YQ	2.5407	86.3517	1.1046	96.5013	0.4006
2020 ZEZ	1.2715	0.0876	1.0000	N/A	0.4598
2020 SFDL	8.9081	2.7169	1.0801	65.9794	0.4209

2021 Study Area Landscape Pattern Index

Station	PD	LPI	FRAC_AM	AI	SHDI
2021 BJ	17.9005	4.0276	1.0889	57.9710	0.3247
2021 XX	6.3565	67.3913	1.1984	86.6838	0.7465
2021 XS	25.3678	7.7626	1.1058	64.1148	0.6020
2021 WLQ	5.0852	52.6316	1.1715	88.8764	0.9099
2021 ZJND	11.4811	5.2813	1.1164	66.3366	0.6043
2021 HMXX	3.8358	0.3452	1.0488	37.5000	0.0469

2021 LPZ	3.8139	4.1190	1.1106	79.3651	0.1788
2021 CXZ	12.7714	2.6437	1.0912	54.1176	0.2200
2021 YQ	6.3638	14.0893	1.1861	73.1034	0.8284
2021 ZEZ	1.2728	0.1145	1.0000	N/A	0.4583
2021 SFDL	8.8991	2.5172	1.0862	60.8108	0.4188
2021 XFDD	7.6278	0.4577	1.0534	20.0000	0.3538

Table 3. Relative Influence of Landscape Pattern Indices on Air Pollutants in the Study Area

Atmospheric pollutants	Main impact factors	Secondary impact factor			
$PM_{2.5}$	AI 29.27%	PD 20.99%	SHDI 18.45%	FRAC_AM 17.59%	LPI 13.7%
O_3	SHDI 25.06%	AI 20.25%	FRAC_AM 20.22%	LPI 17.71%	PD 16.76%
PM_{10}	AI 31.28%	FRAC_AM 21.01%	SHDI 18.68%	PD 14.98%	LPI 14.04%
NO_2	LPI 28.58%	AI 26.41%	PD 24.33%	FRAC_AM 11.89%	SHDI 8.78%

5.2 Threshold Effects on the Contribution of Landscape Pattern Indices to Air Pollutant Concentrations

Figure 4 shows the threshold effects of the factors affecting the annual average concentrations of the four pollutants in order of contribution, i.e., how each factor affects the model regression. When the plaque aggregation index is in the range of 50%-75%, an increase in the value of the plaque aggregation index negatively affects the annual mean concentration of $PM_{2.5}$, decreasing it from 43 μg/m^3 to 33 μg/m^3; whereas, when the aggregation index is in the ranges of 0-50% and 75%-90%, its effect on the annual mean concentration of $PM_{2.5}$ becomes flat. When the patch density was <5/100ha, the annual mean $PM_{2.5}$ concentration decreased sharply from 40 μg/m^3 to 35.5 μg/m^3, and when the patch density was in the interval of 5-15/100ha, the increase in patch density had a positive effect on the increase in $PM_{2.5}$ concentration, with an increase in the concentration from 35.5 μg/m^3 to 39.5 μg/m^3, and then the relationship between the two tended to flatten out. Excluding the idiosyncratic points caused by the source data, when the Shannon-Wiener index was in the interval of 0.1-0.7, it had a negative effect on the annual mean O_3 concentration, and the pollutant concentration decreased from 92.3 μg/m^3 to 90.3 μg/m^3 with the increase in the value of the Shannon-Wiener index, whereas there was no significant change in the relationship between the patch aggregation index and the annual mean O_3 concentration. When the area-weighted patch dimension value is in the range of 1.08-1.11, the index value and the annual average concentration of PM_{10} show a positive correlation, and the pollutant concentration increases from 64.5 μg/m^3 to 71 μg/m^3; after reaching the threshold value of 1.11, the green space's ability of PM_{10} abatement is enhanced, and the two show a negative correlation, and the pollutant concentration decreases from 71 μg/m^3 to 67.5 μg/m^3; when the agglomeration index value increases from 92.3 μg/m^3 to 90.3 μg/m^3; and there is no significant change in the relationship between patch aggregation index and O_3 annual average concentration; when the aggregation index value is in the range of 60%-80%, the stronger the green space's ability to reduce PM_{10}, and the lower the annual average PM_{10} concentration, from 74 μg/m^3 to 59 μg/m^3; and when the value of the Shannon-Wiener index is in the range of 0.25-0.7, it is significantly positively correlated with PM_{10}. When the maximum plaque index value was >10%, its effect on the annual mean NO_2 concentration was moderate; when the aggregation index value was in the range of 50-80, the plaque aggregation index had a negative effect on the pollutant concentration, which reduced the concentration from 43 μg/m^3 to 34 μg/m^3. The above analysis generally indicates that the patch aggregation index, patch density, and area-weighted patch subdimension number play a greater role in influencing the air pollution particulate matter $PM_{2.5}$, PM_{10}, and NO_2, but have a lesser effect on O_3 pollutants.

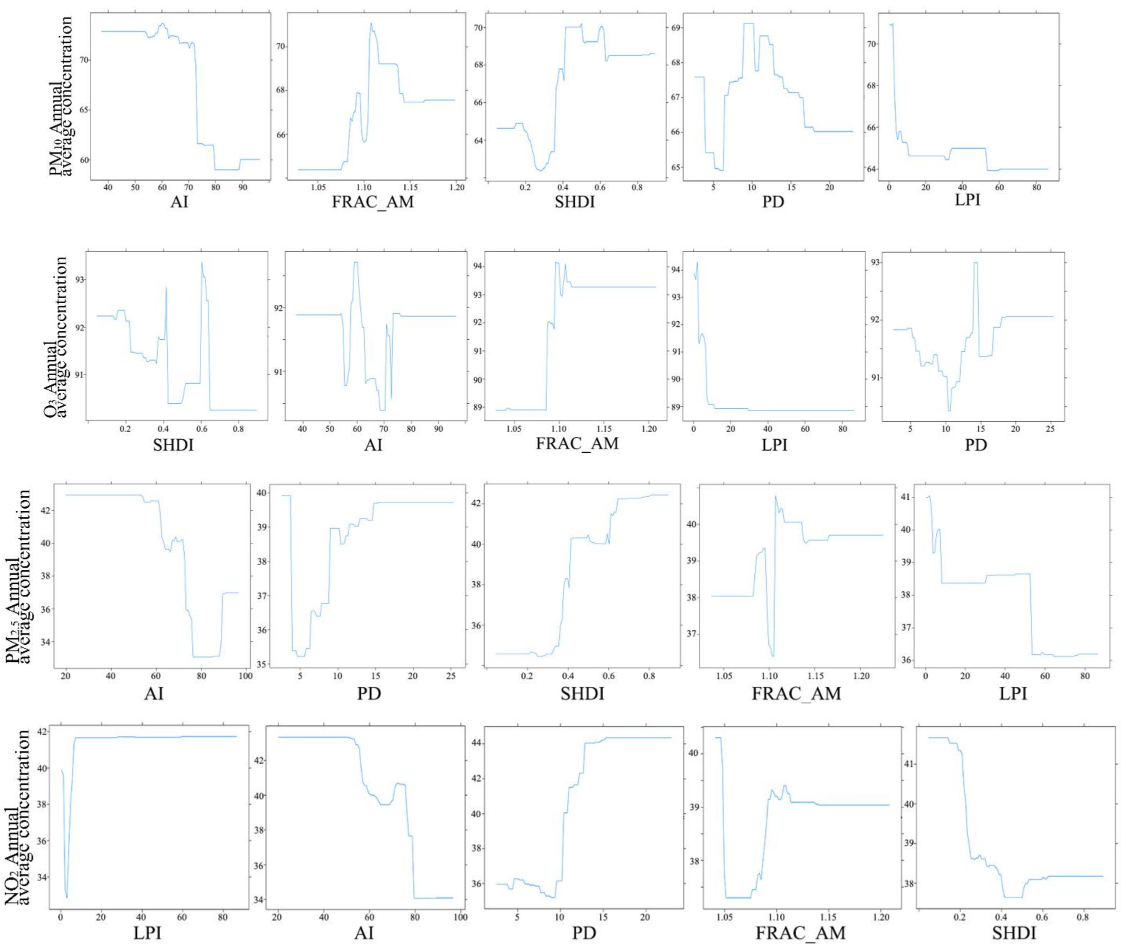

Figure 4. Threshold Effects of Green Patch Landscape Patterns on Annual Average Concentrations of Air Pollutants

5.3 Influence Mechanism of Landscape Pattern Index on Air Pollutant Concentration

In terms of the influence mechanism of landscape pattern index, the lower the aggregation index, the more discrete the green patches are, and the weaker their adsorption and purification effect on $PM_{2.5}$; and with the increase of aggregation, the stronger their adsorption and purification effect on $PM_{2.5}$, and the lower the concentration of $PM_{2.5}$; the increase of the density of the patches implies that the fragmentation of the regional landscape is aggravated, and the purification ability of the overall landscape for $PM_{2.5}$ is reduced, so the annual average concentration of $PM_{2.5}$ increases with the increase of patch density. Therefore, the annual average concentration of $PM_{2.5}$ increases with the increase of patch density, and it is also pointed out in the study of (Li et al., 2022) that the fragmented regional landscape will inhibit the dust stagnation played by various types of green patches in the study area, and therefore the fragmentation of the landscape will lead to the reduction of $PM_{2.5}$ concentration by various types of landscapes; the maximal patch index represents the proportion of the largest green patches to the total area, and it has a significant effect on the particulate matter, which is the largest green patch in terms of the proportion of the total area. The maximum patch index represents the proportion of the largest area of green patches to the total area, which has a mitigating effect on particulate matter, and when the value of the maximum patch index is <90%, the stronger the dominance of green patches is, the stronger the mitigating effect on $PM_{2.5}$ is, and in the study of (Wang, 2021), etc., it was found that the maximum patch index was negatively correlated with the concentrations of $PM_{2.5}$ and PM_{10}, and it was pointed out that the bigger the area of the green area is, the better the coupling between green area and the concentration of particulate matter is, and the more obvious the mitigating effect is on the particulate matter, and the fragmentation of landscape will lead to the reduction of $PM_{2.5}$ concentration by all types of landscapes. The Shannon-Wiener index reflects the size of landscape type diversity, and to a certain extent also reflects the landscape fragmentation, the higher its value, the richer the land use type, the greater the degree of fragmentation. For example, in urban areas with rich land use types, the degree of landscape pattern fragmentation is higher, and the $PM_{2.5}$ concentration is correspondingly higher; the area-weighted patch dimension number has no obvious effect on the $PM_{2.5}$ concentration.

The reasons for the influence of the patch aggregation index AI and the maximum patch index LPI on the annual mean PM_{10} concentration are similar to those of $PM_{2.5}$. Based on the mitigating effect of green space patches on particulate matter, urban areas with small green space patch aggregation have relatively high PM_{10} concentrations; as the maximum patch index increases, the PM_{10} annual mean concentration decreases accordingly; the patch density PD and the area-weighted patch subdimension number FRAC_AM have no significant effect on the PM_{10} annual mean concentration.

Patch density PD, patch aggregation index AI, area-weighted patch sub dimensionality number FRAC_AM, and Shannon-Wiener index did not have a significant effect on ozone concentration, while ozone concentration decreased significantly when the maximum patch index of green patches increased.

The change of the maximum patch index value was not significantly correlated with the change in annual average NO_2 concentration; the aggregation index AI was negatively correlated with NO_2 concentration, while the patch density was positively correlated with it. (Huang et al., 2022) and others pointed out that the fragmentation of the landscape affects the NO_2 concentration, and the more fragmented it is, the weaker the effect of NO_2 concentration reduction; the increase of the area-weighted plaque dimension value will lead to the increase of the annual average NO_2 concentration within a certain range, and with the increase of the index leading to the increase of the spatial complexity within the landscape, the circulation of the air has been affected, which makes the accumulation of NO_2 in some areas lead to the increase of concentration; the Shannon-Wiener index showed no significant correlation with the change of maximum plaque index; the aggregation index AI showed a negative correlation with the NO_2 concentration, while the density of plaques showed a positive relationship with it. The Shannon-Wiener index is negatively correlated with the annual average concentration of NO_2. (Feng & Chu, 2017) et al., found that convective winds and turbulence are generated between urban green spaces and buildings due to heat exchange, and the wind speed is faster at the patch intersection coupling, and the mutual coupling between buildings and green spaces is more conducive to the reduction of pollutant aggregation, which can alleviate the NO_2 pollution to a certain degree, while (Zeng & Kong, 2002) suggested that the fragmentation of the landscape as a whole can lead to the increase of the NO_2 concentration. The fragmentation of the landscape as a whole leads to an increase in edge density, which in turn leads to an expansion of patch boundary coupling, i.e., enhanced airflow between patches, thus leading to a decrease in NO_2 concentration.

6. Discussion

6.1 Effect of Landscape Pattern Index on Air Particulate Matter

The analysis of the augmented regression tree regression model (Figure 5) shows that the air particulate matter concentration and the spatial morphology distribution of green patches in the study area where the monitoring stations are located show different degrees of negative correlation, in which the patch aggregation index and the maximum patch index are significantly negatively correlated with both particulate matters, while the Shannon-Wiener index is significantly positively correlated with the concentration of particulate matter in a certain range, and the correlation of the density of patches with the concentration of $PM_{2.5}$ is higher than that of PM_{10}, and it shows a positive effect on the increase of $PM_{2.5}$ concentration under the same change of patch density. concentration was higher than that of PM_{10}, which showed a positive effect on the increase of $PM_{2.5}$ concentration under the same change of patch density, while it did not have a typical pattern for the change of PM_{10} concentration. Landscape green space is an important factor affecting the $PM_{2.5}$ concentration reduction ability, within a certain range, the larger the green space area, the stronger the $PM_{2.5}$ reduction ability (Lei et al., 2018), the lusher the vegetation in the landscape, the more significant the reduction of airborne particulate matter concentration (Wang et al., 2021), while the fragmented regional landscape will inhibit the study area woodland, green space and other green patches of particulate matter dust retention effect, which will lead to the increase of airborne particulate matter concentration. This will lead to the increase of airborne particulate matter concentration and a decrease of air quality (Li et al., 2022).

6.2 Effects of landscape pattern indices on NO_2

The influence of spatial pattern distribution of green patches on NO_2 concentration is similar to that of airborne particulate matter, the size of green space and the degree of landscape fragmentation will affect the absorption and abatement of NO_2 in the landscape, and the increase in the degree of discrete green patches will obviously lead to an increase in the concentration of NO_2, whereas the increase in the density of patches will lead to the fragmentation of the landscape and make the concentration of NO_2 increase accordingly. Unlike particulate matter, the Shannon-Wiener index in the study area is significantly negatively correlated with NO_2 concentration, and the Shannon-Wiener index shows the richness of regional landscape types, and the increase in the richness of landscape types in the study area can increase the degree of coupling of various types of landscape boundaries (Zeng & Kong, 2002), and the coupling of plaque boundaries can produce strong air convection (Feng & Chu, 2017), which is more conducive to the diffusion of NO_2, and makes the concentration of its decreased.

6.3 Effects of Landscape Pattern Indices on Ozone

At the study scale of 500m radius of buffer size, the Shannon-Wiener index SHDI, patch aggregation index AI and patch density PD did not show a significant correlation with annual average ozone concentration, while the area-weighted patch dimension number was significantly positively correlated with ozone concentration, and the increase of the area-weighted patch dimension value showed the complexity of the shape of the patches, and the higher the complexity of the edge of the patch, the better coupling degree between green and gray patches, and the better air exchange at the edge. The higher the complexity of patch edges, the better the coupling between green patches and gray patches, the better the air exchange is strengthened at the edges, and then ozone is not easy to be retained in the built-up area; the maximum patch index is significantly negatively correlated with ozone concentration; near-surface ozone comes from a series of photochemical reactions of nitrogen oxides and volatile organic compounds in the atmosphere under the action of high temperature and strong light radiation (Peng et al., 2023), and urban ozone concentration is positively correlated with the temperature (Ma et al., 2019), and the increase in the size of the green space can effectively reduce summer air pollution (Li, 2023), which has an inhibitory effect on the increase of ozone concentration.

7. Conclusion

Based on using GIS technology and Fragstats to obtain land use data and landscape pattern indices in the study area, combined with the results of the analysis of the annual average concentration of air pollutants, this study explores and analyzes the relationship between the landscape pattern of urban green patches and the concentration of air pollutants from a spatial and temporal point of view and in combination with the augmented regression tree. The main conclusions are as follows:

(1) The distribution of urban green patches can influence the spatial distribution of air pollutant concentrations. Study areas with a higher percentage of gray patch areas tend to have higher annual average concentrations of air particulate matter and nitrogen oxides, and study areas with a higher percentage of forested and cultivated land tend to have lower annual average concentrations of air pollutants. The relationship between annual average ozone concentrations and the two is relatively unstable.

(2) The landscape pattern of urban green patches indicates the spatial distribution characteristics of air pollutants to a certain extent. The larger the values of the patch aggregation index and maximum patch index, the lower the annual average concentrations of $PM_{2.5}$ and PM_{10}. The changes in the annual average concentration of O_3 had little correlation with the landscape pattern of green patches.

(3) The fragmentation of green patches will weaken the abatement effect of green space for atmospheric particulate matter, resulting in the increase of regional $PM_{2.5}$ and PM_{10} concentrations, while when the green space is the dominant species in the landscape, the increase of its patch area can effectively improve the dust retention effect of green space, reduce the concentration of atmospheric particulate matter, and improve the connectivity between the green patches, which can play a better role in the "negative effect" of green space for atmospheric particulate matter. "Negative effect"; and green space for nitrogen oxides also play a role in abatement, but the landscape in a certain degree of fragmentation can strengthen the air circulation between the regions, so that nitrogen oxides are not easy to be deposited in the gray patches. Green patches, as an important part of the urban landscape, play an important role in mitigating the urban heat island effect, regulating the urban microclimate, and adsorbing atmospheric pollutants, but increasing the proportion of green space and striving to reduce the fragmentation of the landscape may lead to the deposition of certain pollutants.

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Authors Contributions

All authors contributed to the study conception and design. Material preparation, data collection and analysis were performed by [Hao Tao]. The first draft of the manuscript was written by [Hao Tao]. Liu Yang & Chingaipe N’tani edited the English of the paper and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

Declarations

Conflict of Interests The authors have no relevant financial or non-financial interests to disclose.

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Fig. 3 Contribution of landscape pattern indices of the green patches on air pollutant concentrations in the study area

Fig. 4 Threshold effects of green patch landscape patterns on annual average concentrations of air pollutants

Table 1. Landscape Pattern Index

Table 2 Study Area Landscape Pattern Index

Table 3 Relative influence of landscape pattern indices on air pollutants in the study area