Coordinated change of PM2.5 and multiple landscapes based on spatial coupling model: a comparison between inland and waterfront cities

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Abstract

Context

Landscape heterogeneity is closely related to the spatial differentiation characteristics of PM$_{2.5}$ concentration in urbanized areas. Exploring the changing coordination of landscape evolution and PM$_{2.5}$ change provides robust support for mitigating urban pollution. Previous studies mainly focused on a single landscape in a specific area, lacking a quantitative comparison of multiple landscape evolution and PM$_{2.5}$ concentration changes in different types of cities.

Objectives

This study aims to quantify how multiple landscapes evolution could affect PM$_{2.5}$ and compare whether and what kind of differences exist among such effects across various regions.

Methods

Taking two typical inland and waterfront cities in China as examples, this study uses exploratory spatial data analysis and spatial coupling models to compare and analyze the distribution of PM$_{2.5}$ and its coordinated changes with the multiple landscapes (i.e., green, blue, and gray), with townships as the basic unit.

Results

The PM$_{2.5}$ Concentrations in Hohhot and Tianjin have evident differences in spatial concentration. Moreover, the coordinated changes of green landscape and PM$_{2.5}$ in the two regions show opposite trends owing to the effect of the natural background. The change of green landscape to other landscapes in Hohhot can increase PM$_{2.5}$ concentration, with a maximum increase of 2.04 µg/m$^3$. However, this landscape evolution in Tianjin may inhibit PM$_{2.5}$, particularly in the blue dominant, strong coupling area.

Conclusions

By comparing the changes in PM$_{2.5}$ concentration caused by multiple landscape evolutions, managers can take differentiated measures tailored to local conditions to provide information for urban planning strategies related to mitigating air pollution.

1. Introduction

PM$_{2.5}$, also known as "lung accessible particles," refers to particulate matter that is < 2.5 µm in aerodynamic diameter (Shi et al. 2022). Exposure to PM$_{2.5}$ may directly lead to skin allergies and eye-related diseases (Jung et al. 2018; Rouadi et al. 2020) and is considered to be associated with a range of health risks, such as respiratory damage, cardiovascular diseases, and cancer (Han et al. 2016). Hence, PM$_{2.5}$ has been regarded as one of the important indicators of air quality (Coker et al. 2022; Marangon et al. 2021). According to the United Nations Environment Programme, almost all areas with air pollution exceed the World Health Organization's (WHO) regulations on fine particle volume (Qi et al. 2023). Urban built-up areas where humans live together in production and living activities are more apparent for PM$_{2.5}$ concentration, considering that the population is more concentrated with a higher density of non-agricultural activities, such as industrial production and urban construction (Ou et al. 2020). Southerland et al. (2022) showed that approximately 86% of the global urban population (250 million people) lived in areas with excessive PM$_{2.5}$ exposure in 2019, contributing to nearly 1.8 million deaths. Driven by advances in technology and changes in the age structure of the population, countries in Europe and America have made remarkable achievements in PM$_{2.5}$ prevention and treatment by adopting integrated management strategies (Kelly et al. 2011; Jiang et al. 2020; Lim et al. 2020). However, the average number of deaths attributable to PM$_{2.5}$ among urban populations continues to increase in developing countries or regions where rapid urbanization and industrialization are undergoing (Tsurumi and Managi 2020; Yousefi et al. 2023; Xiao et al. 2023). Further measures in PM$_{2.5}$ prevention are necessary to weigh better the conflict between socio-economic development and pollution abatement (Bottalico et al. 2016; Hien et al. 2020; Li et
Green landscape, which refers to the non-construction space characterized by green vegetation, mainly includes forest parks and green facilities within the built-up areas, including forestland and cultivated land around the city (Korpilo et al. 2023). The blue landscape is a general term for surface water spaces, such as ponds, rivers, lakes, oceans, and artificial canals (Friess et al. 2023). Generally speaking, the existence of green and blue landscapes can offset the negative effects of human activities during urban construction (Xue et al. 2022), thereby playing a good role in promoting air purification and mitigating climate change. Nature-based green landscapes have been proven to have a positive mitigating effect on preventing the spread of fine particulate matter, which will contribute to improving environmental quality (Li et al. 2021). For example, Nowak et al. (2013) showed that green landscapes of urban forests in Atlanta can eliminate up to 64.5 tons of PM$_{2.5}$ per year. The spatial pattern and scale effects of different green landscapes also differ regarding the effectiveness in mitigating PM$_{2.5}$ concentrations (Wu et al. 2018; Bi et al. 2022). Comparing the differences in spatial morphological patterns on the spatially heterogeneous nature of PM$_{2.5}$ will provide a new framework for rationalizing the layout of urban green spaces and solving environmental pollution problems to promote sustainable urban development (Yang et al. 2022). In addition, Zhu and Zhou (2019) found that blue landscapes, such as water bodies, also make a difference in removing particulate matter by regulating local microclimatic factors. By contrast, gray landscapes are characterized by high articiality and predominantly formed by sealed, impermeable, hard surfaces built from concrete or tarmac (Suligowski et al. 2018). These gray landscapes tend to be areas with high concentrations of PM$_{2.5}$ (Shi et al. 2017). The concentration of PM$_{2.5}$ in built-up areas with a high concentration of industrial, commercial, and residential buildings is higher than that in other areas because of domestic and industrial emissions (Gao and Ji 2018). From another aspect, the obstruction of building form to air flow further leads to the difficulty of pollutant diffusion. In addition, the morphology, composition, and configuration of the urban gray landscape will affect the spatial and temporal distribution of PM$_{2.5}$ (Shi et al. 2019; Xu et al. 2021). On the contrary, research also showed that the presence of blue landscapes in urban centers hinders the infiltration and diffusion of PM$_{2.5}$, further exacerbating the accumulation of pollutants (Zhou et al. 2021).

In conclusion, the heterogeneity of landscape is closely related to the spatial differentiation of the regional concentration of PM$_{2.5}$ (Xian 2007) as it is a direct reflection of the relationship between human beings and land use (Gordon 2009). Thus, exploring the relationship between landscape and PM$_{2.5}$ can provide a scientific basis for mitigating environmental pollution (de Groot et al. 2010). However, existing studies mainly focused on the role of a single landscape in mitigating or enhancing PM$_{2.5}$. Moreover, research on the coupling effect of multiple landscapes and their interactions with PM$_{2.5}$ is limited. Quantitative studies on the response of PM$_{2.5}$ concentration to landscape change are even rarer. Moreover, the heterogeneity of climatic characteristics and geography is an important factor contributing to the different changes in PM$_{2.5}$ (Du et al. 2013; Branis et al. 2005), with even diametrically opposite results in different regions. Proximity to the waterfront usually provides better ventilation for the dispersion of pollutants (Simpson 1994), whereas inland areas are generally less affected by the thermal circulation between land and sea (Tai et al. 2010). In previous cases, the relationship between landscape and PM$_{2.5}$ was often explored using correlation and regression methods for a single region rather a comparison between two regions. The coupling/driving mechanism of landscape evolution on the change of PM$_{2.5}$ concentration in different areas also needs to be explored.

Therefore, taking a typical waterfront city (Tianjin) and a typical inland city (Hohhot) in China as examples, this study aims to analyze how multiple landscapes change could affect PM$_{2.5}$. In addition, we compare whether and what kind of differences exist among such effects across various regions. We choose these two cities as the study area because of the following: (1) located in regions with rapid urbanization, the urban scale of the two areas is expanding, which results in frequent changes in land use types and significant changes in the landscape; (2) the large pollutant emissions are conducive to analyzing the spatial and temporal distribution of PM$_{2.5}$ and its variability over a long time series; and (3) Geographically, Hohhot is located in the inland area, whereas Tianjin is located in the coastal area. However, the similar latitudes of the two regions can not only ensure the comparability of the two regions but also make it possible to explore the differences in the effects of multiple landscape evolutions on PM$_{2.5}$ change under different climatic characteristics and geographical environment conditions. Exploring the coordinated relationship between multiple landscapes and PM$_{2.5}$ in different regions would provide information for mitigating air pollution and the differentiation strategies for landscape planning.

2. Methodology

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2.1 Study area

As one of the most rapidly developing countries in the world, China is experiencing significant urbanization and increasing energy consumption (Gao et al. 2022). Thus, particulate matter pollution, mainly composed of PM$_{2.5}$, has become one of the major problems of urban air pollution in China. According to Zhang and Crooks (2012), less than 1% of the 500 largest cities in China meet the WHO's recommended air quality standards. Particularly in northern China, the cold weather in winter urgently requires artificial heating to maintain the necessary temperature for living, resulting in more serious hazy weather with PM$_{2.5}$ as the main pollutant than in southern China (Wang et al. 2023).

Hohhot is (40° 51'–41° 8' N, 110° 46'–112° 10' E) located on the northern border of China, in the interior of Eurasia (Fig. 1), with a typical continental climate of the Mongolian Plateau. According to the monitoring data of the environmental monitoring stations, the excessive rates of pollutant emissions caused by electric power, chemical plants, and other activities have exceeded 10%. Hohhot has experienced rapid socio-economic development, noticeable urban expansion, and evident landscape evolution owing to its status as an important node city of the China–Mongolia–Russia Economic Corridor, making air pollution more serious in recent years (Fan et al. 2016). Notably, the special geographical location at the foot of Daqing Mountain in the middle of Inner Mongolia leads to diffusion conditions of air pollutants, causing a further spatial concentration of PM$_{2.5}$ (Ren et al. 2021). Specifically, in November 2015, most regions of Inner Mongolia suffered from the worst fog and haze weather in recent years. Among them, the concentration of PM$_{2.5}$ in Hohhot reached a severely polluted level at the end of November, which had a serious impact on the lives and health of residents.

Tianjin (38° 34'–40° 15' N, 116° 43'–118° 4' E) is located in North China, downstream of the Haihe River Basin and east of the Bohai Sea. It is situated in the sea-land connect belt, with a typical temperate continental monsoon climate. As one of the core cities of the Beijing–Tianjin–Hebei Metropolitan Region, Tianjin has gradually accelerated the urbanization process, in which the urbanization rate has exceeded 84.88% (Gao et al. 2022). The scale of petrochemical, chemical, metallurgical, and other industries has been expanding in Binhai New District. Although the economy is developing rapidly, the unreasonable patterns of energy consumption and economic growth have led to a sharp increase in emissions of pollutants, such as PM$_{2.5}$, resulting in serious haze problems (Wu et al. 2020). The unique characteristics of static weather conditions and boundary layer structure have made Tianjin one of the foggiest areas in China, which directly threatens the basic living conditions and well-being of the inhabitants.

2.2 Data source and processing

2.2.1 PM$_{2.5}$ concentration dataset

The PM$_{2.5}$ concentration dataset is based on the daily 1-km PM$_{2.5}$ data from 2000 to 2018 in China, released by He et al. (2021). The dataset is a long-term, full-coverage, and high-quality ground-based air pollutant dataset with a high spatial resolution of a 1-km grid in China. Adopting a new statistical strategy, this dataset incorporates seasonal-GTWR models with adaptive model structures. Then, the dataset uses the Multi-Angle Implementation of Atmospheric Correction 1-km aerosol optical depth dataset, the observed meteorological data (including surface temperature, relative humidity, wind speed, surface pressure, and planetary boundary layer height), and surface conditions (including NDVI and DEM data) as model inputs to predict the temporal and spatial distribution of daily, monthly, and annual average PM$_{2.5}$ concentrations throughout mainland China in recent 19 years, respectively (He et al. 2020). The resultant annual PM$_{2.5}$ of this dataset has been validated to be highly correlated with ground measurements ($R^2 = 0.77$). For each verification year, 62–84% of the observations are within the deviation range of ±10 µg/m$^3$. Our research used the annual average PM$_{2.5}$ concentration data of 2000, 2005, 2010, and 2015.

2.2.2 Landscape mapping

The base map of landscape pattern adopts the land use/cover data for the years 1995, 2000, 2005, 2010, and 2015 from the Resource and Environment Data Cloud Platform (http://www.resdc.cn/). We defined and classified different landscapes as green, blue, and gray landscapes from Dan et al. (2022). Among them, the blue landscape includes lakes, reservoirs, rivers, and perennially waterlogged swamps. The green landscape includes arable land, forestland, grassland, and other vegetation. Furthermore, the gray landscape refers to urban and rural areas, industrial and mining, residential land, and other construction land not covered by vegetation or water bodies.

2.3 Exploratory spatial data analysis
According to the first law of geography, geographic objects or attributes are mutually related in spatial distribution, with clustering, random, and regular distribution (Vivaldini et al. 2019; Tobler 1970). Spatial autocorrelation is a phenomenon that near things are more related to each other (Pranzo et al. 2022). Spatial autocorrelation statistics can characterize the potential interdependence or closeness of connections between the observation data of variables in the same distribution area (Chen 2021). It is often used to analyze the spatial agglomeration and change trend of geographical and atmospheric elements, providing a basis for exploring the laws of spatiotemporal concentration and evolution between them (Soares and Clements 2011). Affected by the spatial correlation characteristics of atmospheric activities, the PM$_{2.5}$ concentrations in the adjacent regions within a specific area will be statistically closer, showing a certain concentration or dispersion law (Wu et al. 2015; Qi et al. 2023). We introduce global spatial autocorrelation and local spatial autocorrelation to explore their spatial patterns and changes in hot zones to analyze the spatial agglomeration law and characteristics of PM$_{2.5}$ concentration in the study area.

2.3.1 Global spatial autocorrelation

Moran’s $I$ index is a commonly used indicator for measuring global spatial autocorrelation (Kumari et al. 2019). This index comprehensively represents the average spatial correlation degree, spatial distribution pattern, and significance of specific variables or attributes of each unit in the entire regional space according to the location and value of an element (Wang et al. 2015). The calculation formula is as follows:

$$I = \frac{n}{S_0} \sum_{i=1}^{n} \sum_{j=1}^{n} W_{ij} Z_i Z_j / \sum_{i=1}^{n} Z_i^2,$$

$$S_0 = \sum_{i=1}^{n} \sum_{j=1}^{n} W_{ij},$$

where $I$ is the statistic of Moran’s $I$, $n$ is the total number of elements; $Z_i$ is the deviation of the value of element $i$ from the average value of all elements; $W_{ij}$ is the spatial weights matrix, and $S_0$ is the aggregation of all spatial weights. The significance of spatial autocorrelation is tested by the statistic $Z$, which follows a normal distribution. The value range of Moran’s $I$ is $[-1,1]$. When $0 <$ Moran’s $I < 1$, a positive spatial correlation exists. Areas with higher or lower PM$_{2.5}$ pollution tend to converge in space. When $-1 <$ Moran’s $I < 0$, a negative spatial correlation exists. Areas with higher or lower PM$_{2.5}$ pollution tend to disperse spatially. When Moran’s $I = 0$, the area with a similar PM$_{2.5}$ pollution degree is randomly distributed.

2.3.2 Local spatial autocorrelation

Local spatial autocorrelation characterizes the ideology and local instability of any two adjacent units within a regional unit (Guo et al. 2014). We use it to describe the differentiated characteristics of each regional unit within the regional space and determine the specific location of PM$_{2.5}$ spatial agglomeration, which can be simplified as Eqs. (3)–(4).

$$I_i = \frac{X_i - X}{S_i^2} \sum_{j=1, j\neq i}^{n} W_{ij} (X_i - X),$$

$$S_i^2 = \frac{\sum_{j=1, j\neq i}^{n} W_{ij}}{n - 1} - X^2,$$

where $X_i$ is the value of element $i$ and $X$ is the average value. Eqs. (1)–(2) show the meaning of the remaining variables. The significance is also tested by $Z$ statistic, which follows a normal distribution. At a significant level of 0.01, if $Z > 2.58$ and the PM$_{2.5}$ concentration of a unit and other neighboring units is higher than the average, it is called a “hotspot.” If $Z > 2.58$ and the PM$_{2.5}$
concentration of this cell and other neighboring units is lower than the average, it is a “cold spot.” \( Z < -2.58 \) indicates a negative spatial correlation, which means that units with high PM\(_{2.5}\) concentration are surrounded by those with low PM\(_{2.5}\) concentration (“High Low Correlation”) or units with low PM\(_{2.5}\) concentration are surrounded by those with high PM\(_{2.5}\) concentration (“Low High Correlation”). However, when \( Z = 0 \), the observations present independent random distribution. Generally speaking, \( Z > 1.96 \) is significant, and \( Z > 2.58 \) is extremely significant.

### 2.4 Regression analysis

In this study, the simple linear regression analysis is used to calculate the correlation coefficient between the proportion of blue, green, and gray landscapes and the average concentration of PM\(_{2.5}\) at the township scale. We apply the interaction multiple linear regression (Ngabirea et al. 2022) to explore the relationship between various landscapes and PM\(_{2.5}\), particularly the interaction of each two landscapes and PM\(_{2.5}\). The model constructed is as follows:

\[
Y = \beta_i X_i + \beta_j X_j + \beta_k X_i X_j,
\]

where \( Y \) represents PM\(_{2.5}\) concentration at the township scale, \( X_i \) represents the proportion of landscape \( i \), \( X_j \) represents the proportion of landscape \( j \), \( X_i X_j \) represents the interaction between landscape \( i \) and landscape \( j \), and \( \beta \) is the regression coefficient.

### 2.5 Spatial coupling model

The construction of the coordination index between various landscapes and PM\(_{2.5}\) can quantitatively measure the relationship between them. Coordination refers to the proportional and balanced development of several variables (Lai et al. 2020). Moreover, the degree of coordination is to measure the level of harmony between the system or the internal elements of the system in the development process (Yang et al. 2020). In this study, a spatial coupling model of multiple landscapes and PM\(_{2.5}\) was constructed by the geometric weighted averaging method to analyze the degree of interaction and coordination between the two types of indicators in each township (Wu et al. 2020):

\[
C_{LP} = \frac{|L_i - P_i|}{\sqrt{L_i^2 + P_i^2}},
\]

where \( C_{LP} \) is the coordination index of regional landscape (including green, blue, and gray landscapes) evolution and PM\(_{2.5}\) changes, \( L_i \) is the rate of change of landscape in the \( i^{th} \) township, and \( P_i \) is the rate of change of PM\(_{2.5}\) in the \( i^{th} \) township.

According to Eq. (6), the coordination index ranges from 0 to 1. If the rates of changes in landscape and PM\(_{2.5}\) are equal, the value of the coordination coefficient is 1, indicating that the coupling relationship is the strongest. Conversely, if the absolute values of the two indicators are equal, whereas the actual values are opposite, the value of the coordination coefficient will be 1, which means that the coupling relationship is the weakest (Yang et al. 2019). Table 1 presents the detailed division to further determine the degree of coordination index between different landscapes and PM\(_{2.5}\).

<table>
<thead>
<tr>
<th>( C_{LP} )</th>
<th>Coupling category</th>
</tr>
</thead>
<tbody>
<tr>
<td>[0, 0.8)</td>
<td>Weak</td>
</tr>
<tr>
<td>[0.8, 0.9)</td>
<td>Moderate</td>
</tr>
<tr>
<td>[0.9, 1]</td>
<td>Strong</td>
</tr>
</tbody>
</table>

### 3. Results
3.1 Analysis of PM$_{2.5}$ change

3.1.1 Agglomeration of PM$_{2.5}$

For the objects targeted in the field of geography, the process or pattern, spatiotemporal distribution, mutual coupling, and other characteristics are scale-dependent and will change with the change of research scale. Considering the original data and the actual area of the study area, we construct a spatial weight matrix with a distance threshold of 10–100 km to compare the spatial autocorrelation patterns of PM$_{2.5}$ concentrations in Hohhot and Tianjin.

As shown in Fig. 2, within different distance thresholds, Moran's $I$ index of PM$_{2.5}$ concentration in the two cities from 2000 to 2015 is positive, and the results of the Z test are significant. This case indicates that the spatial distribution of PM$_{2.5}$ concentration in both cities shows a strong spatial positive correlation. In other words, the high-value and low-value areas of PM$_{2.5}$ tend to converge in space. In general, the spatial agglomeration degree of PM$_{2.5}$ concentration in Hohhot is higher than that in Tianjin. In terms of the time scale, the concentration level of PM$_{2.5}$ tends to fall after rising in Hohhot, whereas that in Tianjin displays the tendency to decline at the beginning and then increase late, which is inseparable from the local economic development and industrial agglomeration (Jin et al. 2020; Yan et al. 2018). Our results show consistency with other research (Wang et al. 2015), that is, whether in Hohhot or Tianjin, the spatial autocorrelation of PM$_{2.5}$ concentration gradually decreases with the increase of distance threshold.

Analysis of local spatial autocorrelation shows that the high–high cluster area of PM$_{2.5}$ concentration is mainly distributed in urban areas (Fig. 3a). Regardless of Hohhot or Tianjin, the urban areas are still heavily polluted, which is the dilemma faced by many major cities worldwide because of the concentration of population and the development of industries. Specifically, the emissions from the industry and daily life jointly promote the accumulation of pollutants. In addition to the heat-island effect, the existence of high-rise buildings slows down air convection and further accumulates pollution (Buyantuyev et al. 2015). The difference is that apart from the hot spots of pollution in the urban area, PM$_{2.5}$ of the townships in western Tianjin is characterized by the high–high cluster.

Considering that the west of Tianjin is adjacent to Langfang City, one of the cities with the gravest air pollution in China, the diffusion of pollution is bound to affect the adjacent areas because of the spatial correlation of atmospheric activities. As the capital of Inner Mongolia, Hohhot has a higher level of economic development than the surrounding areas, which has often spread to the surrounding areas as a "source" of pollution, rather than a gathering place for the diffusion of pollution. The low–low cluster areas in Hohhot are mainly distributed in the Daqingshan Nature Reserve and on the northern side, whereas those in Tianjin are distributed in the north and coastal areas. We also conducted a standard deviation elliptic analysis in the high–high cluster area of PM$_{2.5}$ from 2000 to 2015 to understand the spatial-temporal variation characteristics of high pollution caused by PM$_{2.5}$ (Fig. 3b-Fig. 3c). In Hohhot, the center of the standard deviation ellipse moved to the southwest, and the elliptical area gradually increased. This case indicates that the high value of the polluted areas showed a gradual expansion trend to the southwest, but its distribution direction remained unchanged. By contrast, the high value of the polluted areas in Tianjin showed an irregular change but generally displayed a tendency of concentration in the southwest of the city center.

3.1.2 Evolution trend analysis of PM$_{2.5}$

We calculated the change slope of PM$_{2.5}$ concentration in each township to explore the evolution trend of PM$_{2.5}$ pollution. According to the actual value of the change slope of PM$_{2.5}$ in the study period, the changing trend is divided into enhancement and mitigation. Moreover, the absolute value of the slope is divided into two levels with the help of the natural breakpoint classification method, namely high and low speeds. The final trend is divided into four categories, namely the high-speed enhancement area, low-speed enhancement area, high-speed mitigation area, and low-speed mitigation area (Fig. 4). Combined with the spatial distribution and change trend of PM$_{2.5}$, the Daqingshan Nature Reserve and the area to the north are still the pollution mitigation areas in Hohhot, which is consistent with the spatial distribution of low-value areas of PM$_{2.5}$ concentration. However, the changing trends of PM$_{2.5}$ concentration in the high–high cluster areas are different, showing a trend of low-speed enhancement within the Second Ring Road. Outside the Second Ring Road, there is a trend of high-speed enhancement in the east and low-speed enhancement in the west. In addition, we found that the townships in central and western Hohhot are generally increasing at high speed. The reason is that these regions are the concentrated areas of coal production, and the dust and radioactive aerosols caused by open-pit mining have greatly increased the content of PM$_{2.5}$ in the air. With regard to Tianjin, the PM$_{2.5}$ concentration in coastal areas has decreased, whereas that in other areas has generally increased.
3.2 Analysis of landscape change

The results of landscape classification and change (Fig. 5) show that green landscape has an absolute quantitative advantage in both places, with Hohhot remaining at approximately 90% and Tianjin at approximately 60%. However, the proportion of the green landscape is declining year by year. The grey landscape of Hohhot increased from 7.86% in 2000 to 9.05% in 2015, and that of Tianjin increased from 16.54% in 2000 to 26.78%. The difference is that the blue landscape in Hohhot first increases and then decreases, whereas that in Tianjin first decreases and then increases with a slight variation.

3.3 Spatial coupling relationship between PM$_{2.5}$ and multiple landscapes

Taking townships as the basic unit, we calculated the proportion of green, blue, and gray landscapes and the average concentration of PM$_{2.5}$ in each unit. The correlation coefficient between multiple-landscape proportion and PM$_{2.5}$ concentration was calculated based on $R$ (Table 2). The results showed that a significant positive correlation exists between the proportion of gray landscape and PM$_{2.5}$ concentration in the two cities. A significant negative correlation exists between green landscape and PM$_{2.5}$ concentration in Hohhot, which is in contrast to that in Tianjin and is contrary to cognition. The existence of the blue landscape in Tianjin has a good inhibitory effect on PM$_{2.5}$, but no such effect has been found in Hohhot. The results of the two-factor regression analysis showed that the interaction between green and gray landscapes in Hohhot was related to PM$_{2.5}$, whereas the interaction between blue and green landscapes in Tianjin was significantly related to PM$_{2.5}$.

Table 2
Correlation analysis of multiple landscapes and their interaction with PM$_{2.5}$ concentration.

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<tbody>
<tr>
<td></td>
<td>Coef</td>
<td>Coef</td>
<td>Coef</td>
<td>Coef</td>
</tr>
<tr>
<td>Hohhot</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Green</td>
<td>-11.6637</td>
<td>3.01e-13</td>
<td>-13.522</td>
<td>3.61e-12</td>
</tr>
<tr>
<td>Blue</td>
<td>-46.2686</td>
<td>0.105</td>
<td>0.0462*</td>
<td>0.0785</td>
</tr>
<tr>
<td>Grey</td>
<td>11.6274</td>
<td>1.88e-13</td>
<td>2.3e-14</td>
<td>5.09e-12</td>
</tr>
<tr>
<td>Green*Blue</td>
<td>-22.102</td>
<td>0.811</td>
<td>-281.926</td>
<td>0.0280*</td>
</tr>
<tr>
<td>Green*Grey</td>
<td>16.763</td>
<td>0.0195*</td>
<td>19.6745</td>
<td>0.00165*</td>
</tr>
<tr>
<td>Blue*Grey</td>
<td>130.996</td>
<td>0.0513</td>
<td>422.101</td>
<td>0.0179*</td>
</tr>
<tr>
<td>Tianjin</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Green</td>
<td>6.992</td>
<td>5.38e-05</td>
<td>7.1164</td>
<td>9.11e-09</td>
</tr>
<tr>
<td>Blue</td>
<td>-9.4297</td>
<td>0.00417**</td>
<td>-15.5393</td>
<td>0.00026**</td>
</tr>
<tr>
<td>Grey</td>
<td>3.6784</td>
<td>0.0293*</td>
<td>3.8768</td>
<td>0.0162*</td>
</tr>
<tr>
<td>Green*Blue</td>
<td>35.594</td>
<td>0.004663**</td>
<td>42.806</td>
<td>0.000143**</td>
</tr>
<tr>
<td>Green*Grey</td>
<td>-3.405</td>
<td>0.709</td>
<td>2.961</td>
<td>-0.3132*</td>
</tr>
<tr>
<td>Blue*Grey</td>
<td>9.952</td>
<td>0.6367</td>
<td>-54.786</td>
<td>0.0151*</td>
</tr>
</tbody>
</table>

*, **, and *** indicate that the correlation is significant at the 0.05, 0.01, and 0.001 levels, respectively.

We further calculated the correlation among cropland, forest and grassland, and PM$_{2.5}$ to further compare why the green landscapes of the two research sites have different impacts on PM$_{2.5}$ (Table 3). A significant negative correlation was found between the proportion of forest and PM$_{2.5}$ concentration in both Hohhot and Tianjin, as was the case for grassland. However, the difference is that the
The proportion of cropland in Hohhot shows a significant negative correlation with PM$_{2.5}$, whereas the proportion of cropland in Tianjin shows a significant positive correlation with PM$_{2.5}$, which is the main reason for the different coordinated changes between green landscape and PM$_{2.5}$ in the two regions.

**Table 3**

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<tbody>
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<td>Hohhot</td>
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*, **, and *** indicate that the correlation is significant at the 0.05, 0.01, and 0.001 levels, respectively.

The results of spatial coupling (Fig. 6) show that a large spatial overlap exists between the changes in various landscapes and PM$_{2.5}$. We also analyzed the coupling relationship between landscape evolution and the change in PM$_{2.5}$ concentration from 2000 to 2015 using the spatial coupling model. In general, the coupling distribution patterns of green, blue, and gray landscapes in the two regions are quite different, particularly the strong coupling. For example, those townships with a strong coupling relationship between green landscape evolution and PM$_{2.5}$ change tend to have weak coupling relationships between the other two landscapes and PM$_{2.5}$. As the coupling relationship between grey landscape evolution and PM$_{2.5}$ change is stronger than the other two landscapes, the importance of grey landscape for air pollution control must be emphasized in urban planning. In addition, we further analyzed the coupling relationship that has been confirmed, that is, there is a significant correlation at each stage (Fig. S1). From 2000 to 2015, the coupling between the green landscape and PM$_{2.5}$ in the two study areas decreased first and then increased, whereas the coupling between the gray landscape and PM$_{2.5}$ gradually increased. The coupling between the blue landscape of Tianjin and PM$_{2.5}$ also weakened first and then strengthened.

### 3.4 Response of PM$_{2.5}$ concentration change to multiple landscape evolution

Considering that PM$_{2.5}$ is comprehensively affected by climate, terrain, spatial pattern, and other factors, we need to exclude the interference of other factors on PM$_{2.5}$ changes to explore the response of PM$_{2.5}$ to various landscape evolution. We calculated the average PM$_{2.5}$ concentration of grid cells that have changed and remained unchanged in each coupling region. Then, the change value of the average PM$_{2.5}$ concentration in the landscape change area was subtracted from that in the unchanged area. The difference was used to represent the response of the PM$_{2.5}$ concentration change to the landscape evolution in each coupling area during the study period. Specifically, taking the green-gray landscape change from 2010 to 2015 (i.e., the green landscape in 2010 evolved into the gray landscape in 2015) as an example, we first extracted all the green landscape grids that did not evolve from 2010 to 2015 and calculated the average PM$_{2.5}$ concentrations of these grids in 2010 and 2015, which were recorded as $A$ and $C$, respectively. The difference between $C$ and $A$ ($C-A$) refers to the change in PM$_{2.5}$ concentration caused by other factors except for landscape evolution. Second, we extracted all grid cell changes from the green landscape to the gray landscape during 2010–2015. We also calculated the average PM$_{2.5}$ concentrations of these grids in 2010 and 2015, which were recorded as $B$ and $D$, respectively. The difference between $D$ and $B$ ($D-B$) refers to the change in PM$_{2.5}$ concentration caused by all factors. Finally, the difference obtained in the first two steps is the impact of green-gray landscape evolution on PM$_{2.5}$ concentration change during the study period (Fig. 7).
The change of PM$_{2.5}$ concentration in different coupling areas of inland and waterfront cities showed different responses to multiple landscape evolution (Fig. 8-Fig. 9). In inland arid areas, such as Hohhot, the change from the green landscape to other landscapes will lead to an increase in PM$_{2.5}$ concentration, with a maximum increase of 2.04 µg/m$^3$. However, in waterfront cities such as Tianjin, the kinds of landscape changes have a dampening effect on the spread of PM$_{2.5}$, which is more evident in areas dominated by blue space. During the transition from the blue landscape to the gray landscape in Hohhot, we only found a slight upward trend of PM$_{2.5}$ in the blue dominant strong coupling area. This result indicates that this change will not have a significant impact on air pollution in this kind of coupling area. On the contrary, the change from the blue landscape to the gray landscape in Tianjin led to the common increase of PM$_{2.5}$, particularly in the gray dominant strong coupling area, with a maximum value of 4.42 µg/m$^3$. Undoubtedly, the changes in the gray landscape to other landscapes in coastal areas have reduced the concentration of PM$_{2.5}$. However, the research results of Hohhot showed that during the transition from the gray landscape to the green landscape, we only found a decrease in PM$_{2.5}$ concentration in the gray dominant strong coupling area. Moreover, during the transition from the gray landscape to the blue landscape, we only observed a decrease in PM$_{2.5}$ concentration in the green dominant strong coupling area. The pollutant mitigation effect of different landscape evolution provides a reference for future urban pollution control planning.

4. Discussion

4.1 Reasons for differences in sources and agglomeration of PM$_{2.5}$

The generation of PM$_{2.5}$ is the result of the joint promotion of a variety of reasons, which is mainly attributed to two aspects, namely natural and artificial sources (Xu et al. 2021). The objective existence of soil dust, plant pollen, spores, and bacteria in nature is one of the sources of PM$_{2.5}$ (Fadel et al. 2023). Natural disaster events in nature also produce considerable pollutants. For example, volcanic eruptions discharge a large amount of volcanic ash into the surrounding environment (Tang et al. 2020), and forest fires will also transport several fine particles into the atmosphere, causing serious air pollution. For example, the continuous mountain fire in Australia has made the air quality pollution index in most regions of the country exceed the normal values by more than 26 times. What's worse, it also puts cities with beautiful scenery and pleasant climates, such as Sydney, Melbourne, and Canberra, on the list of the world's worst air quality. The emissions of PM$_{2.5}$ from forest fires in Siberia will even increase to 5.4 Mt/yr during 2016–2021 (Romanov et al. 2022). By contrast, the impact of anthropogenic sources on air quality is more severe. For example, open-pit mining generates a series of dust, harmful toxic gases, and radioactive aerosols in the surrounding air, which leads to a significant increase in the content of PM$_{2.5}$ in the air and threatens the health of surrounding residents (Huertas et al. 2012). Thus, the rapid growth area of PM$_{2.5}$ is located in the central and western Hohhot rather than in urban areas in Section 3.1. The exhaust gas emitted by various vehicles during operation is the main source of human movement that causes PM$_{2.5}$, and the urban built-up areas are often the places with the most concentrated number of vehicles. Therefore, as shown in Fig. 3, one of the common points of the inland and waterfront cities is that high–high cluster areas are distributed in urban areas.

However, the distribution of low–low cluster areas in the two cities is evidently different. For Hohhot, we observed that no significant correlation exists between the blue landscape and PM$_{2.5}$ (Table 2), whereas the green landscape was negatively correlated with it. In particular, among the primary green landscapes, the forest has the strongest negative correlation with PM$_{2.5}$. Correspondingly, we found that PM$_{2.5}$ of townships located in northern Hohhot is in a low concentration state, which is clearly bounded by the Daqingshan Nature Reserve (Fig. 3). The reason is that the nature reserve is a high-value area of habitat quality in Hohhot (Liu et al. 2022) and also the zone with the largest contiguous area and the most widely distributed forests. According to Lin et al. (2020), the annual average concentration of PM$_{2.5}$ will decrease by 2.53% for every 1% increase in the forest area. The reason is that forest leaves are generally believed to adsorb PM$_{2.5}$ and other fine particles in the atmosphere (Fig. 10), thereby reducing the environmental pollution level (Rasanen et al. 2013). Large-scale forests can also reduce or change the wind speed to prevent the inflow of PM$_{2.5}$ (Wuyts et al. 2008). The low-high cluster area in the north of the central urban area and the south of Daqingshan Mountain is caused by the sudden increase in altitude. The vertical motion plays an important role in forming a good atmospheric circulation, which is conducive to the diffusion of pollution (Tham et al. 2019). For Tianjin, the evaporation of seawater will absorb some impurities in the air, and the resulting role in purifying the air makes the low–low cluster areas mainly in coastal townships. In addition, as these areas are close to water, the increased air humidity at night promotes the accumulation and sedimentation of PM$_{2.5}$ and other particles (Gunawardena et al. 2017; He and Lin 2017). More importantly, owing to the role of thermal circulation between sea and land, the acceleration of airflow has further played an effective role in guiding the transport of atmospheric pollutants (Banks and Baldasano 2016).
4.2 Enlightenment for the prevention and control of atmospheric pollution: based on the landscape layout perspective

Since the detection standard of PM$_{2.5}$ was proposed by the United States in 1997, it has become an important index to measure and control the degree of air pollution. Particularly in China, PM$_{2.5}$ has been considered one of the most familiar air pollutants in reports related to urban air quality. Clarifying the spatial-temporal distribution and change of PM$_{2.5}$ has become one of the critical contents in air pollution control. Previous studies considered the impact of landscape, meteorology, topography, and other factors on PM$_{2.5}$. However, few studies linked multiple landscape evolution with changes in PM$_{2.5}$. Clarifying the coordination among green, blue, and gray landscapes and their interaction and PM$_{2.5}$, particularly the latter’s response to the former, will help support mitigating urban air pollution by controlling the sources and adjusting the landscape layout (Fig. 10).

Owing to the unique regional advantages and the impact of policies, Hohhot and Tianjin have both experienced rapid economic and urban development, including the expansion of the industrial scale and the transformation of consumption patterns, making the air pollution problems in the two regions prominent. However, the difference in geographical location and natural background makes the response of PM$_{2.5}$ change to landscape evolution different in the two cities, which is also a common phenomenon in other countries and regions. Therefore, policymakers should implement different air pollution control measures regionally and differently. For the arid and semi-arid areas represented by Hohhot, the correlation between the blue landscape and PM$_{2.5}$ is not significant because of the small distribution of water bodies. From our research results, the increase in the blue landscape may not have an evident effect on urban pollution control in such areas. However, we have observed the correlation between multiple landscapes and PM$_{2.5}$, particularly the correlation between the interaction of green–gray landscapes and PM$_{2.5}$, which is scarce in previous studies. What we could obtain is that in the typical cities represented by Hohhot, the planning of the green landscape is very necessary for urban pollution control, particularly the unique landscape, such as urban forests. The cropland of Tianjin, particularly the dry farm, has an absolute quantitative advantage in the green landscape. Thus, we observed a positive correlation between the green landscape and PM$_{2.5}$. As the vegetation covers only the season suitable for crop planting in northern China, this type of land often does not remain green all year round. We speculate that activities, such as straw burning among farmlands in non-farming seasons, may be one of the main reasons for the coordinated change of green landscape and PM$_{2.5}$ (Zhang et al. 2020). Nevertheless, a significant negative correlation between forest and PM2.5 in Tianjin will still provide an important reference for urban pollution control. More importantly, the existence of the blue landscape in waterfront cities has the most significant effect on reducing PM$_{2.5}$. Particularly during the transition from the grey landscape to the blue landscape, we have observed the effect of pollution mitigation in each strong coupling area. Therefore, given the quantity advantage of the blue landscape in waterfront cities represented by Tianjin, the water body should be reasonably rearranged, particularly within the urban growth boundary with the dense gray landscape.

4.3 Limitations and prospects

Analyzing the spatial-temporal distribution and change of PM$_{2.5}$ and determining the factors affecting PM$_{2.5}$ are crucial for haze control and pollution prevention. Our research adopts the spatial coupling model to measure the changing spatial coupling relationship between multiple landscapes and PM$_{2.5}$. The study also explores the increase and decrease of PM$_{2.5}$ concentration caused by multiple landscape evolution in different strong coupling areas. This notion is of great significance for describing the correlation between landscape layout and pollution control. However, one of the limitations of this study is that we only explored the changes in PM$_{2.5}$ concentration caused by changes in green–blue–gray landscapes at different stages, which does not deeply explain the causal relationship among them. The specific physical and chemical process and internal mechanism behind the appearance that the cropland landscape causes the increase of PM$_{2.5}$ concentration may need to be further clarified. Moreover, meteorological conditions, such as temperature and precipitation, inevitably affect the distribution and change of PM$_{2.5}$. When we analyze the response of PM$_{2.5}$ to landscape evolution in this study, homogenizing other factors in the same strong coupling area except landscape change may have an impact on the actual results. Future research could consider the climate factors of different geographical locations to analyze more practical coupling changes.

5. Conclusion

Landscape heterogeneity directly or indirectly affects the spatial differentiation of PM$_{2.5}$, and landscape evolution plays an important role in solving environmental pollution problems and promoting sustainable urban development. Taking an inland city and a waterfront
city as the study area, this study explores the spatial concentration and evolution trend of PM$_{2.5}$ in two cities with different geographical locations but affected by air pollution, with townships as the basic unit. Then, we analyzed the relationship between green–blue–gray landscapes and PM$_{2.5}$ and compared the coupling effect and the coordinated change between multiple landscape evolution and PM$_{2.5}$ change. The correlation between PM$_{2.5}$ and green, blue, and gray landscapes in inland semi-arid and coastal areas is different, which is reflected in the correlation between green landscape and PM$_{2.5}$. The blue landscape of Tianjin has a significant negative correlation with PM$_{2.5}$. By analyzing and comparing the differences in PM$_{2.5}$ changes caused by landscape evolution in various strong coupling areas under different time series, the results provide information for air pollution mitigation and differentiated landscape planning strategies in different cities.

Declarations

Author contributions


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Conflicts of interest

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

References


43. Pranzo A, Dai P E, Besana A (2022) Epidemiological geography at work: An exploratory review about the overall findings of spatial analysis applied to the study of CoViD-19 propagation along the first pandemic year. GeoJournal 1-23


60. Tsurumi T, Managi S (2020) Health-related and non-health-related effects of PM$_{2.5}$ on life satisfaction: Evidence from India, China and Japan. Econ Anal Policy 67: 114-123


Figures

Figure 1

Geographical location and land use types of the study area.
Figure 2

Global Moran's I index for PM$_{2.5}$ distribution at different scales.
Figure 3

Agglomeration analysis of PM$_{2.5}$ concentration: 3a: cluster analysis of average PM$_{2.5}$ concentration from 2000 to 2015 in Hohhot and Tianjin; 3b: analysis of standard deviation ellipse of high-high cluster areas in Hohhot; 3c: analysis of standard deviation ellipse of high-high cluster areas in Tianjin (Notes: HH stands for high-high cluster areas).
Figure 4

The changing trend of PM$_{2.5}$ concentration in Hohhot and Tianjin.
Figure 5

The proportion and change of multiple landscapes in Hohhot and Tianjin.
Figure 6

Spatial distribution of the coupling relationship between multiple landscapes and PM$_{2.5}$ concentration (Note: S stands for strong, W stands for weak, and M stands for moderate).
Figure 7

Schematic diagram of the response of PM$_{2.5}$ concentration changes to the evolution of green–gray landscapes.
Figure 8

Comparison of PM$_{2.5}$ responses to landscape evolution in different coupling areas in Hohhot (Notes:  represents the period from 2000 to 2005,  represents the period from 2005 to 2010, and  represents the period from 2010 to 2015).
Figure 9

Comparison of PM$_{2.5}$ responses to landscape evolution in different coupling areas in Tianjin (Notes:  represents the period from 2000 to 2005,  represents the period from 2005 to 2010, and  represents the period from 2010 to 2015).
Figure 10

Analysis of the sources, influencing factors and response mechanism of PM$_{2.5}$.

**Supplementary Files**

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