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An Assessment Framework for Mapping the Air Purification Service of Vegetation at the Regional Scale

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Abstract: Efficiently mitigating the severe air pollution resulting from rapid progress is crucial for the sustainable development of the socio-ecological system. Recently, concerns about nature-based solutions have emerged in the research on the treatment of air pollution. Studies on the purification of $PM_{2.5}$ using vegetation currently concentrate on the individual scale of tree species or urban vegetation, ignoring the regional scale, which could better assist ecological governance. Therefore, taking the Fenwei Plain of China as the study area, an assessment framework of the air purification service's spatial distribution reflecting regional vegetation was constructed. The dry deposition model and GeoDetector were used to quantify the spatial-temporal pattern and explore natural driving factors on the removal of $PM_{2.5}$. The results showed that (1) the $PM_{2.5}$ purification services offered by various types of vegetation exhibit notable variations. The average removal rates of $PM_{2.5}$ by vegetation were 0.186%, 0.243%, and 0.435% in 2000, 2010, and 2021, respectively. (2) Meanwhile, a wide range of spatial mismatch exists between the $PM_{2.5}$ concentration and $PM_{2.5}$ removal. Insufficient supply regions of $PM_{2.5}$ purification services account for 50% of the Fenwei Plain. (3) $PM_{2.5}$ removal was strongly influenced by the types of vegetation and the Normalized Vegetation Index (NDVI), followed by the Digital Elevation Model (DEM), and less affected by meteorological factors; a strong joint effect was shown among the factors. The findings in this research provide a new perspective on regional air pollution management at the regional scale.

Keywords: dry deposition model; ecosystem services; Fenwei Plain; GeoDetector; $PM_{2.5}$ purification services; $PM_{2.5}$ removal

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1. Introduction

In recent years, sustained economic and social development has accelerated the urbanization process [1,2]. Air pollution has become a serious environmental problem that needs to be addressed across the world [2]. Goal 3 and Goal 11 of the United Nations Sustainable Development (SDG) emphasize the impact of air pollution on residents. This requires providing good health and well-being to residents and building sustainable cities and communities [3–5]. Fine particulate matter (particles with a diameter of less than 2.5 μm, $PM_{2.5}$) can be breathed deep into the lungs and, in some cases, enter the bloodstream. Epidemiological studies have confirmed that it has a direct negative impact on humans, especially respiratory and cardiovascular diseases. It threatens human health and well-being through complex interactions [6–8]. As a developing country, China has formulated and implemented the Air Pollution Prevention and Control Action Plan as well as the Three-year Action Plan to Fight Air Pollution [9]. Continuous improvements have been made to the ecological environment and air quality by updating industries and optimizing the energy structure [10]. These efforts have led to significant reductions in atmospheric $PM_{2.5}$ pollution levels in many areas [11]. However, the emission reduction potential of traditional treatment methods is gradually narrowing, especially when air pollution enters moderate and mild conditions, and landscape planning and optimization are considered effective ways to mitigate air pollution [12,13]. Nature-based solutions are beginning to receive attention from scholars, which can effectively mitigate $PM_{2.5}$ pollution by enhancing ecosystem services at the regional level [14]. The assessment of the dust retention capacity of vegetation has gradually become a hot research topic in this field.

Vegetation possesses a unique leaf structure that allows it to remove fine particulate matter from the atmosphere [15]. Current research suggests that ecosystems can help reduce $PM_{2.5}$ emissions in highly urbanized areas [16,17]. Green infrastructure such as urban trees plays a crucial role in providing ecosystem services such as air purification [18]. The government can effectively enhance regional air quality and promote sustainable urban growth by prioritizing the development of forest cities and strategically planning green spaces [19]. However, the existing research on vegetation dust retention primarily centers on assessing the dust-holding capacity of diverse tree species and investigating the removal effect of different urban vegetation on $PM_{2.5}$ [20]. In terms of this small scale, the assessment of the effects of tree species selection and vegetation structure on urban air purification focused on street trees and urban parks [21,22]. At the urban scale, they quantified the capacity of vegetation to remove air pollution in different cities. This can provide policy suggestions for optimizing urban green space construction [23–25]. Meanwhile, there are also comparative studies on the differences in air purification services of vegetation in multiple cities. Meanwhile, few studies have produced regional quantitative estimates of the capacity of vegetation to reduce $PM_{2.5}$ levels more effectively. Hence, it is imperative to merge high-resolution data from various sources and utilize mechanistic modeling to establish a framework. This could elucidate the connection between vegetation and the enhancement of air quality currently. The framework in this research will help us better understand how vegetation affects air quality and will be instrumental in developing a novel model for air pollution management.

Due to the complex topographic characteristics and industrial composition, Fen Wei Plain, where the accumulation of $PM_{2.5}$ has been elucidated, has now become a key area for air pollution control in China [26]. The $PM_{2.5}$ purification capacity of vegetation in this region is investigated based on high-resolution remote sensing data and spatial analyses. The objectives were to (1) quantify the spatial and temporal variability and spatial mismatch between regional $PM_{2.5}$ concentrations and $PM_{2.5}$ removal from air pollution amelioration by vegetation; (2) identify the natural factors that affect the $PM_{2.5}$ removal; and (3) incorporate nature-based air purification programs into regional-scale ecological construction. This research aims to provide nature-based solutions for air quality improvement and regional ecological environment optimization in key air pollution areas.

2. Materials and Methods

2.1. Study Area

Fenwei Plain is a general term for the Fen River Plain, Wei River Plain, and its surrounding terraces. It is located in the middle reaches of the Yellow River, with the Loess Plateau in the northwest and the Qinling Mountains in the south, making it the fourth-largest plain in China [27]. The geographical distribution of the study area in a northeast-southwest band is not conducive to the dispersal of pollutants. The climate of this region is mainly affected by the East Asian monsoon, with annual precipitation of less than 600 mm in most areas [28], and the prevailing winds throughout the year are northeasterly and usually around 2 m/s [26]. The interaction of pollution emissions between cities is significant. In addition, the energy structure of the region is heavy, and the coal industry is relatively developed. The river valley is densely populated and has severe air pollution. The availability of clean air for the inhabitants of the region is not guaranteed. At present, the FenWei Plain is a key area in China's air pollution control. As defined in the "Three-Year Action Plan to Fight Air Pollution", it includes 11 cities and 1 district. Among them, five cities and one district are in Shaanxi Province, including Xi'an (XA), Tongchuan (TC), Baoji (TC), Xianyang (XY), Weinan (WN), and the Yangling Demonstration Area; four cities are in Shanxi Province: Jinzhong (JZ), Yuncheng (YC), Linfen (LF), and Lvliang (LL); and it also includes Luoyang (LY) and Sanmenxia (SMX) in Henan Province. This study focuses on a region with 11 prefecture-level cities (Figure 1).

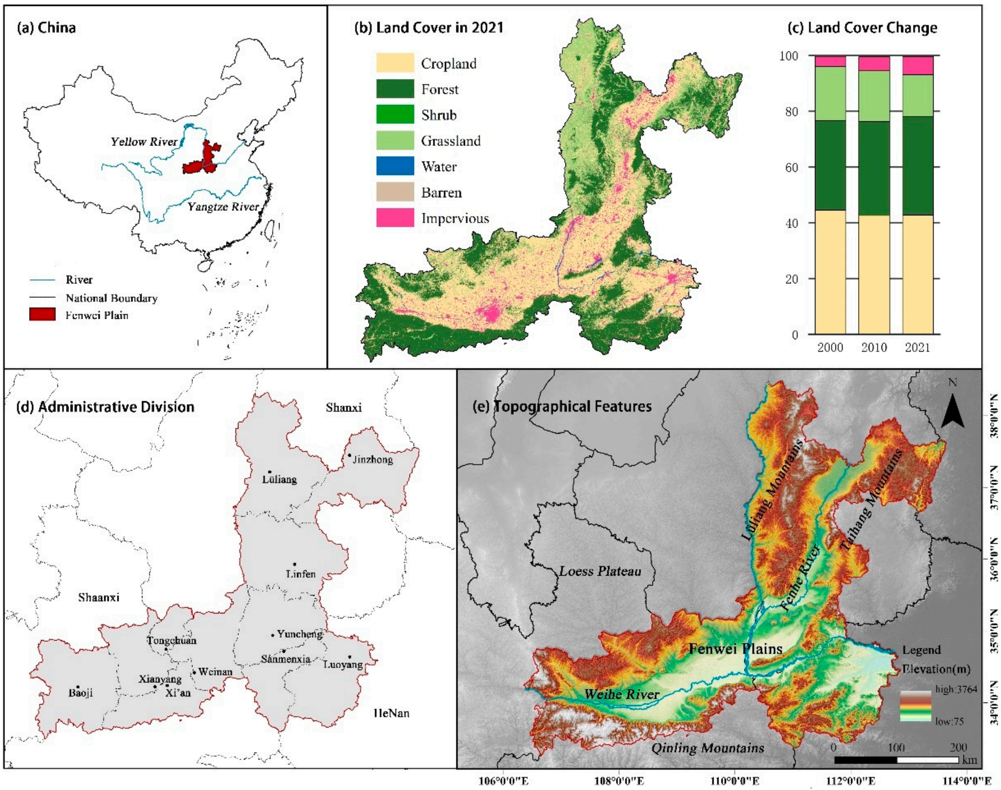

Figure 1. Overview of the Fenwei Plain. The spatial location (**a**); land cover in 2021 (**b**); land cover changes in 2000, 2010, and 2021 (**c**); administrative divisions (**d**); and topographical features (**e**).

2.2. Research Framework

The research framework includes five main stages (Figure 2), which mainly include (1) index selection and parameter calculation; (2) the quantification of vegetation $PM_{2.5}$ purification services; (3) analysis of influencing factors for $PM_{2.5}$ removal; and (4) proposal of measures to improve regional air quality.

In the first stage, natural indicators related to $PM_{2.5}$ pollution and vegetation dust retention were selected, followed by the collection of $PM_{2.5}$ spatial distribution data, the Normalized Vegetation Index (NDVI), the China Land Cover Dataset (CLCD), the Digital Elevation Model (DEM), meteorological data, and other basic data. Secondly, based on the retention effect of vegetation leaves on particulate matter, the dry deposition model [24] was used to quantify the $PM_{2.5}$ purification service, which was used to visualize the effect of vegetation on $PM_{2.5}$ removal and the temporal and spatial distribution characteristics. Thirdly, spatial matching relationships between $PM_{2.5}$ concentration and $PM_{2.5}$ removal were determined. These can be used to identify areas at risk of $PM_{2.5}$ pollution. In the fourth stage, natural drivers of $PM_{2.5}$ removal were revealed using GeoDetector [23]. The main influencing factors of $PM_{2.5}$ removal can be determined. Finally, combined with the above content, it can provide scientific support for the formulation of air quality improvement measures and regional ecological construction decision-making in key areas of national air pollution.

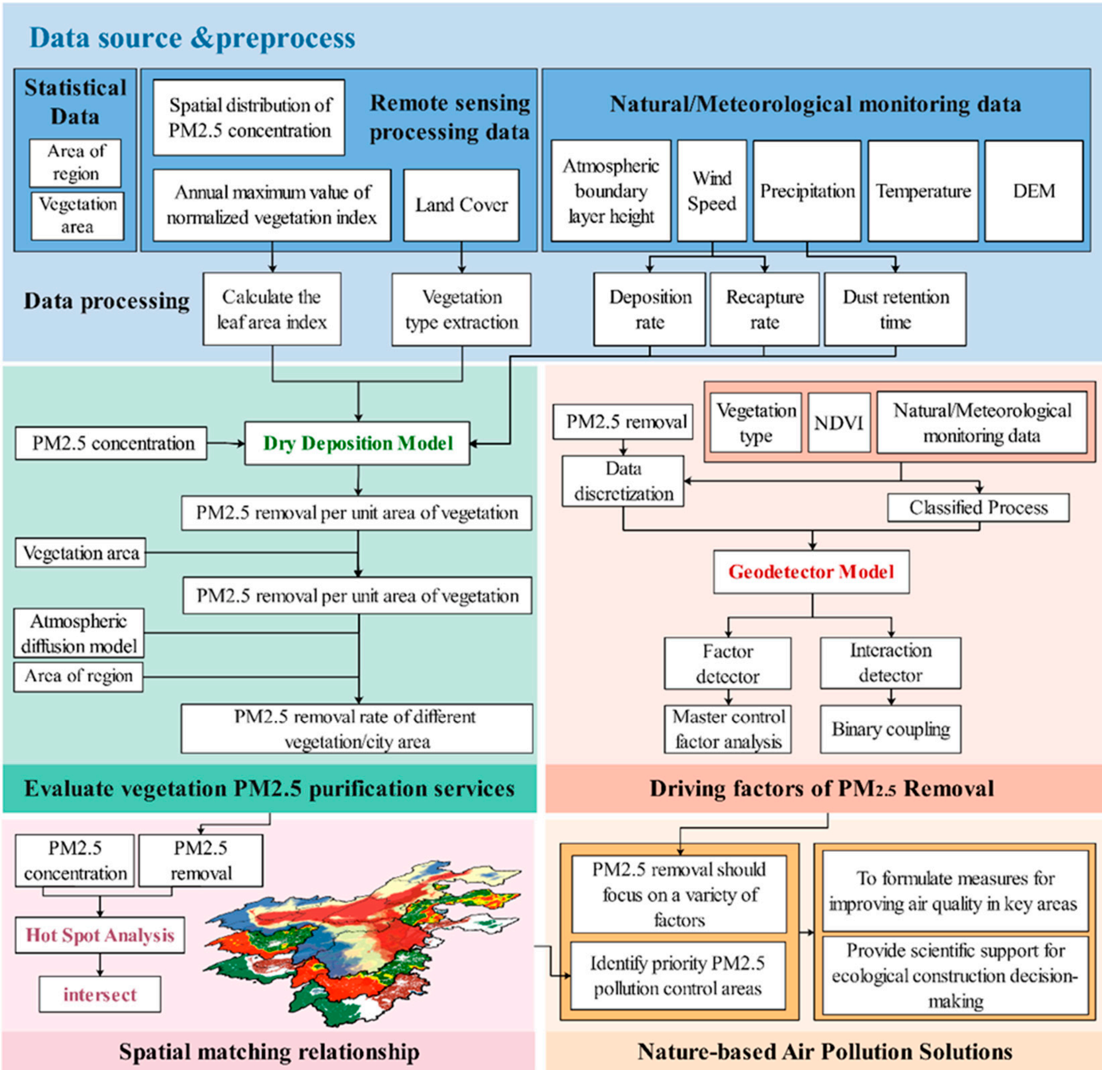

Figure 2. A framework for the study of $PM_{2.5}$ purification services for regional vegetation and their natural influence factors.

2.3. Data Sources and Processing

The multi-source data used in the study include land-use classification, DEM data, meteorological elements, NDVI, and $PM_{2.5}$ spatial distribution data. The CLCD dataset published by Yang et al. [29] was adopted as the land-use classification data from Wuhan University. The $PM_{2.5}$ spatial distribution data were from the Chinese high-resolution and high-quality near-surface air pollutant (CHAP) dataset published by Wei et al. [30,31]. The dataset of a 30 m annual maximum NDVI in China was from the Resource and environmental science data registration and publication system (https://www.resdc.cn/DOI/DOI.aspx?DOIID=68, accessed on 26 January 2024). The datasets of precipitation, wind speed, and temperature came from the NOAA's National Centers for Environmental Information (https://www.ncei.noaa.gov, accessed on 26 January 2024) through sorting, computation, and spatial interpolation generation. The atmospheric boundary layer height data are from the ECMFW European Center, the fifth-generation atmospheric reanalysis dataset (https://cds.climate.copernicus.eu, accessed on 26 January 2024) for the global climate of the ERA5 meteorological data. DEM data were obtained from the National Earth System Science Data Center (http://www.geodata.cn, accessed on 26 January 2024). The NDVI data were from the Resource and Environmental Science Data Center of the Chinese Academy of Sciences with a resolution of 30 m (Table 1).

Table 1. Datasets, sources, and calculated parameter data sources used to analyze $PM_{2.5}$ purification services of vegetation in the Fenwei Plain.

Data Classification	Data Name	Spatial Resolution
CLCD	2000, 2010, 2021 Land use data	30 m
Vegetation data	2000, 2010, 2021 NDVI	30 m
$PM_{2.5}$ data	2000, 2010, 2021 Annual average concentration of $PM_{2.5}$	1000 m
Meteorological data	Average annual wind speed Average daily precipitation Average annual temperature	- - -
	Atmospheric boundary layer height	0.1°
Terrain data	DEM data (ASTER DEM v3)	30 m

2.4. Methods

2.4.1. Simulating $PM_{2.5}$ Removal

Vegetation possesses a unique leaf structure that allows it to remove fine particulate matter from the atmosphere [15]. $PM_{2.5}$ removal per unit area can be estimated as [12]:

$$Q_d = C \times V \times LAI \times T \times (1 - r) \tag{1}$$

where Q_d (μg/m^2) is the $PM_{2.5}$ removal per unit area of vegetation; C (μg/m^3) is the concentration of $PM_{2.5}$, which is resampled to 30 m; V (cm/s) is the rate at which $PM_{2.5}$ settles onto the surface of vegetation leaves; LAI is the leaf area index of the vegetation (m^2/m^2); T is the dust retention time; and r is the resuspension rate (%) [32]. Annual mean $PM_{2.5}$ concentration raster data were used in this research. The $PM_{2.5}$ deposition rate and resuspension rate were determined from the annual average wind speed (Table 2). The dust retention time was calculated from the continuous non-precipitation time (less than 15 mm daily precipitation) [33]. LAI was calculated based on the NDVI using the formula found in a literature review (Table 3).

Table 2. $PM_{2.5}$ deposition rate (cm/s) of different vegetation types [24,34].

Vegetation Types \ Wind Speed (m/s)	1	2	3	4	5	6	7	8
Mixed Forest	0.02	0.285	0.545	0.64	0.735	0.83	0.925	1.02
Shrub	0.03	0.24	0.45	0.55	0.66	0.76	0.86	0.96
Grassland	0.006	0.012	0.018	0.022	0.025	0.029	0.056	0.082
Cropland	0.006	0.012	0.018	0.022	0.025	0.029	0.056	0.082
Resuspension rate	0.025	0.029	0.032	0.036	0.039	0.059	0.079	0.099

Table 3. Calculation formula of LAI for different vegetation types [35,36].

Vegetation Types	Regression Equation
Forest	LAI = 4.689NDVI/(1.818 − NDVI)
Shrub	LAI = 6.211NDVI − 1.088
Grassland	LAI = 3.227NDVI/$NDVI_{avg}$
Cropland	LAI = 8.547NDVI − 0.932

P Total vegetation $PM_{2.5}$ removal can be estimated as [34]:

$$Q_z = Q_d \times S \tag{2}$$

where Q_z (µg) is the total amount of $PM_{2.5}$ removed by each type of vegetation and S (m^2) is the area of each type of vegetation, which was extracted and counted by CLCD.

2.4.2. Simulating of $PM_{2.5}$ Removal Rate

The removal rate (P_i) of $PM_{2.5}$ from vegetation foliage was calculated as [24]:

$$P = \frac{Q_z}{Q_z + E} \tag{3}$$

E (µg) was the total amount of $PM_{2.5}$ in the atmosphere calculated as [37]:

$$E = C \times BLH \times A \times 365 \times 24 \tag{4}$$

where BLH (m) is the height of the atmospheric boundary layer. The average value was calculated using the spatial distribution. A (m^2) is the area of the region.

2.4.3. Identification of Coldspots and Hotspots

The spatial distribution of $PM_{2.5}$ concentration in this region is uneven. $PM_{2.5}$ removal in spatial heterogeneity due to different regional vegetation types. To accurately identify the risk areas of air pollution, Gi*statistics was employed to spatially identify the coldspots and hotspots of $PM_{2.5}$ concentration and $PM_{2.5}$ removal. Meanwhile, this study explored the spatial match between $PM_{2.5}$ concentration and $PM_{2.5}$ removal based on intersect analysis. Gi* is an indicator of local autocorrelation, which incorporated each adjacent raster into the calculation. This approach could visualize the spatial clustering patterns of hotspots and coldspots. Features with high z-scores and low p-values indicated statistically significant hotspots. Conversely, features with low negative z-scores and small p-values indicated statistically significant coldspots [38,39].

2.4.4. GeoDetector

Seven indexes including the NDVI, Vegetation Type (VT), the Digital Elevation Model (DEM), Precipitation (Pre), Wind Speed (WS), Temperature (Tem), and Atmospheric Boundary Layer Height (BLH) were involved in quantifying $PM_{2.5}$ removal. Based on the vegetation type data, each indicator was classified into 4 categories using the natural breakpoint method, and the natural meteorological drivers of $PM_{2.5}$ removal were analyzed using the GeoDetector model.

The GeoDetector model is a new statistical method proposed by Wang Jinfeng et al. [40]. It can fully consider the degree of spatial dissimilarity between the dependent and independent variables, and it was widely used in driving factor analysis. The core of the method assumed that there is a certain similarity in the spatial distribution between variables if the change in the independent variable has an important effect on the dependent variable. GeoDetector can detect both numerical and qualitative data, and they can also detect the interaction of two factors on the dependent variable. This paper used two detectors of the software (http://www.geodetector.cn/, accessed on 26 January 2024):

Factor_detector: This was employed to investigate the existence of spatial heterogeneity and identify the factors causing such differences using the q-value, which ranges from 0 to 1. The q-value represents the extent to which X explains 100 × q% of Y. A higher q-value indicates more pronounced spatial heterogeneity.

Interaction_detector: This was used to detect the relationship between the independent variables of the risk factors. First, the q-values of the two factors and the q-values of the combined polygon were calculated. Then the three values are compared and analyzed, and finally, we can determine if the independent variables are truly independent or if there are broader interactions at play.

3. Results

3.1. Quantification of $PM_{2.5}$ Removal and Identification of Risk Areas

3.1.1. Spatial and Temporal Distribution of $PM_{2.5}$ Concentration and Removal

The annual $PM_{2.5}$ concentration showed an overall increasing and then decreasing trend from 2000 to 2021. The area with a relatively high $PM_{2.5}$ concentration was distributed in the center of the Fenwei Plain (Figure 3a–c), perhaps due to its low topographic conditions, sparse vegetation, and large numbers of artificial surfaces. In comparison, the mountainous region southwest of Baoji and the central mountainous area of Lüliang have relatively low $PM_{2.5}$ concentrations, meaning they have relatively better air quality. This is likely related to the presence of large vegetation areas in these regions. The average of the three-year $PM_{2.5}$ concentration far exceeded the $PM_{2.5}$ concentration limits (5 $\mu g/m^3$) set by the World Health Organization (WHO). The maximum $PM_{2.5}$ values in 2000 and 2010 were mildly polluted according to China's $PM_{2.5}$ pollution standards (35 $\mu g/m^3$) [41] (Figure 3g).

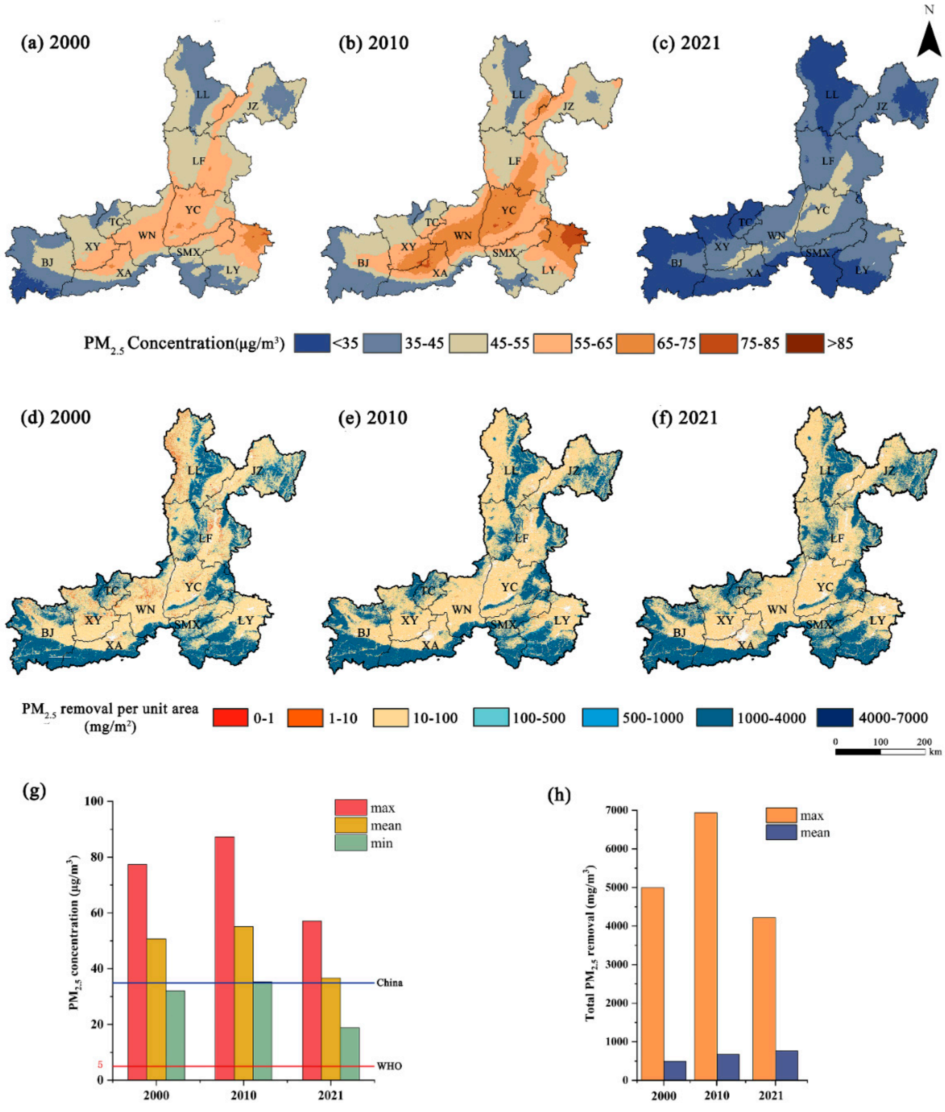

Figure 3. Spatial distribution of $PM_{2.5}$ concentration (**a**–**c**) and $PM_{2.5}$ removal per unit area (**d**–**f**) in 2000, 2010, and 2021 (LY: Luoyang; SMX: Sanmenxia; JZ: Jinzhong; LF: Linfen; LL: Lüliang; YC: Yuncheng; BJ: Baoji; TC: Tongchuan; WN: Weinan; XA: Xi'an; XY: Xianyang). Comparison of statistical values of $PM_{2.5}$ concentration (**g**) and comparison of statistical values of $PM_{2.5}$ removal per unit area (**h**) in 2000, 2010, and 2021.

3.1.2. Effect of Different Vegetation Types on $PM_{2.5}$ Removal

The level of $PM_{2.5}$ removal per unit area of vegetation had a high consistency with the vegetation types (Figure 3d–f). The removal of each vegetation type in order of magnitude is forest > shrub > grassland > cropland (Table 4). Both the maximum and average values of $PM_{2.5}$ removal per unit area increased in the given time (Figure 3h). The increase in 2010 compared with 2000 was mainly due to the larger concentration of $PM_{2.5}$, and the significant increase in 2021 was mainly due to the increased wind speed and precipitation. The total amount of $PM_{2.5}$ removed by different vegetation types was different from the amount removed per unit area. Forests remain the vegetation type that removes the most $PM_{2.5}$. Due to the large proportion of cultivated land, the total removal of $PM_{2.5}$ in the FenWei Plain is higher than that of shrubs and grasslands. The highest capacity for the removal of $PM_{2.5}$ was in forests, followed by cropland (Table 4).

Table 4. Annual $PM_{2.5}$ removal of different vegetation types in the Fenwei Plain.

Year / Vegetation Type	2000		2010		2021	
	Removal (t)	**Removal Rate (%)**	**Removal (t)**	**Removal Rate (%)**	**Removal (t)**	**Removal Rate (%)**
Cropland	1375.80	0.004	1731.02	0.004	1763.43	0.007
Forest	68,287.13	0.179	93,504.70	0.236	106,175.11	0.424
Shrub	846.92	0.002	617.02	0.002	421.54	0.002
Grassland	677.17	0.002	718.15	0.002	613.40	0.002
Sum	71,187.01	0.186	96,570.89	0.243	108,973.47	0.435

3.1.3. Comparison of $PM_{2.5}$ Removal Effect in Different Cities

The removal rate of $PM_{2.5}$ in the Fenwei Plain was 0%~0.634% in 2000, 0%~0.899% in 2010, and 0%~0.919% in 2021, totaling 71,187.01 t, 96,570.89 t, and 108,973.47 t, respectively. The removal rate of $PM_{2.5}$ in forest land accounted for the largest proportion, up to more than 90%, and the year average removal rate was 0.288% (Figure 4). Since there are large forest area in Baoji, its total annual $PM_{2.5}$ removal and removal rate was the largest, followed by Luoyang. The lowest total amount of $PM_{2.5}$ removed in 2000 and 2010 was in Xianyang, and in 2021, it was in Tongchuan.

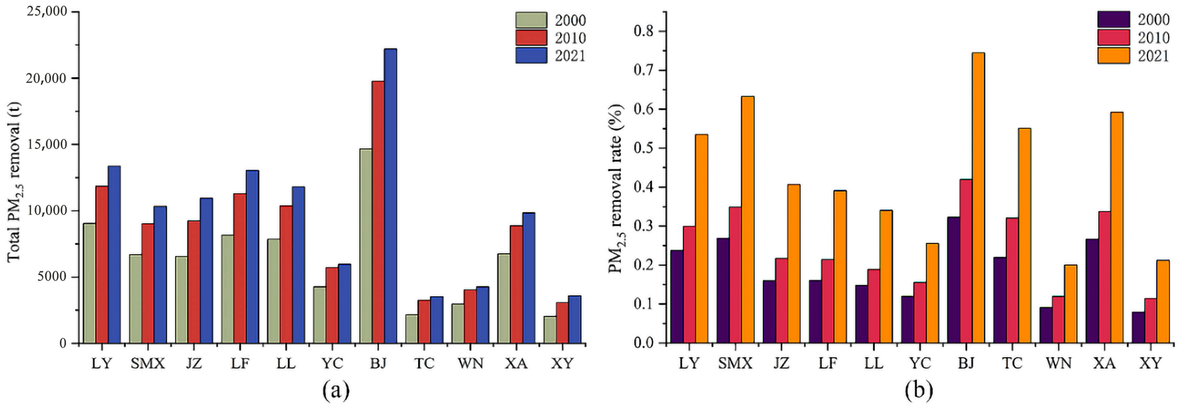

Figure 4. Annual total $PM_{2.5}$ removal (**a**) and $PM_{2.5}$ removal rate (**b**) in 11 cities.

3.1.4. Identification of Risk Areas

A certain spatial mismatch between $PM_{2.5}$ concentration and $PM_{2.5}$ removal was shown in the study area (Figure 5). The high $PM_{2.5}$ concentration combined with low $PM_{2.5}$ removal (high pollution with low $PM_{2.5}$ removal) accounted for the largest proportion (approximately 50%), mainly distributed in the plains area. In the eastern middle part of the study area, there are some areas with $PM_{2.5}$ hotspots superimposed on $PM_{2.5}$ removal hotspots (high pollution with high $PM_{2.5}$ removal). Areas with $PM_{2.5}$ concentration coldspots were superimposed on $PM_{2.5}$ removal coldspots (low pollution with low $PM_{2.5}$ removal), mainly in the western mountainous areas, with a significant decrease in the proportion in 2021 compared with the previous two years. The $PM_{2.5}$ concentration coldspots combined with $PM_{2.5}$ removal hotspots are mainly distributed in mountainous areas (low pollution with high $PM_{2.5}$ removal).

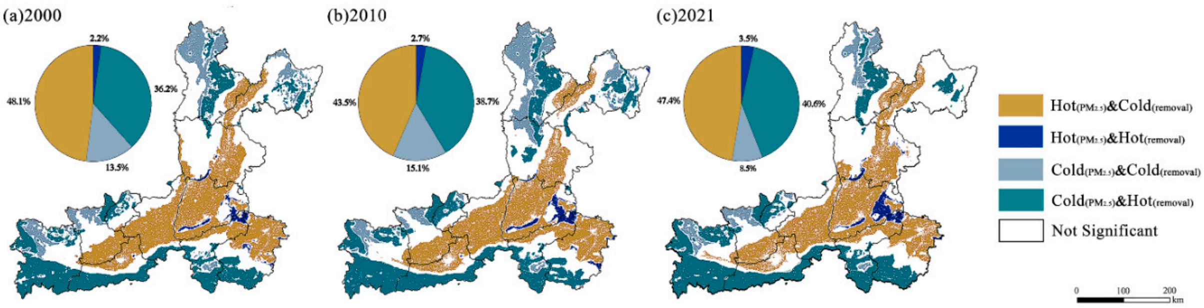

Figure 5. Spatial matching relationship between $PM_{2.5}$ concentration and $PM_{2.5}$ removal in 2000, 2010, and 2021.

3.2. Influencing Factors of $PM_{2.5}$ Removal Services in the Fenwei Plain

All factors passed statistical significance tests ($p < 0.01$). The order of explanatory power of each factor for $PM_{2.5}$ removal in order from strong to weak in 2000, 2010, and 2021 was Vegetation Types, NDVI, DEM, Precipitation, Temperature, Wind Speed, and Boundary Layer Height. Among them, vegetation type and NDVI had explanatory power for $PM_{2.5}$ removal greater than 60%. The others showed slightly lower explanatory power, and the explanatory power of the annual mean wind speed decreased to 0.001 in 2021. This indicated that the spatial distribution of annual mean wind speed and $PM_{2.5}$ removal in that year had low similarity, so the effect was small, whereas the similarity of the distributions in 2000 and 2010 was relatively high (Figure 6). Overall, vegetation has a significant effect on $PM_{2.5}$ removal services, followed by elevation as $PM_{2.5}$ and vegetation cover in the Fenwei Plain region were strongly influenced by topographic conditions.

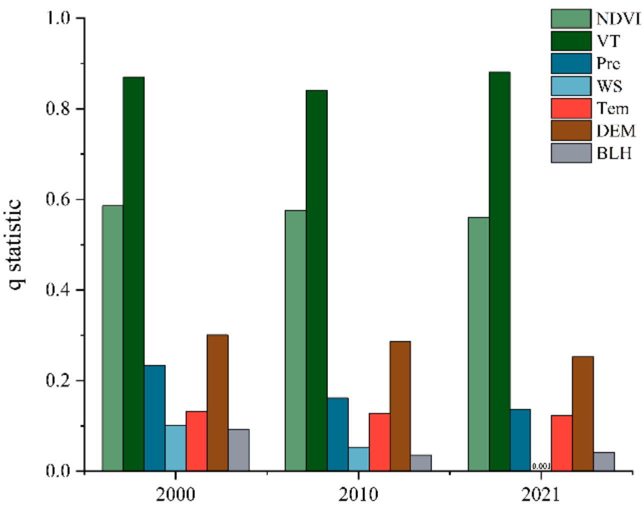

Figure 6. Analysis of the impact of natural factors on $PM_{2.5}$ removal.

$PM_{2.5}$ removal was affected by multiple external factors, which have interactions with each other. In this study, the joint effect of any two factors would increase the effect on the removal of $PM_{2.5}$, mainly manifested as two-factor enhancement and nonlinear enhancement of two types, and the joint effect made the explanatory power significantly larger. As shown in Figure 7, the green circle was the nonlinear enhancement factor. Because vegetation type and NDVI have stronger explanatory ability for $PM_{2.5}$ removal, the explanatory ability of the combination with other factors is also larger. In conclusion, the removal of $PM_{2.5}$ is a combination of many factors, rather than a single factor that plays a decisive role.

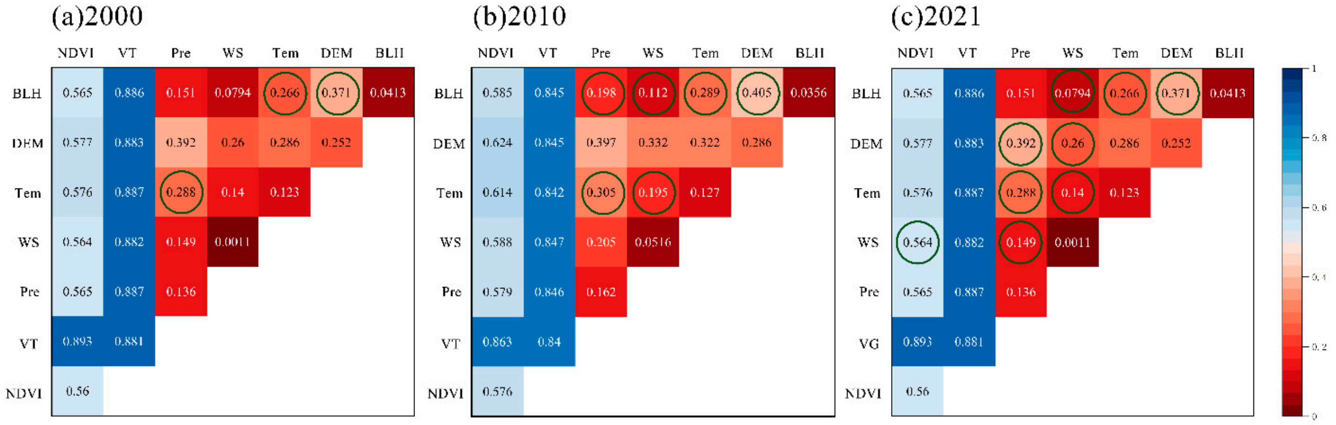

Figure 7. Effect of natural factor interactions on $PM_{2.5}$ removal (green circles indicate that the two factors acting together exhibit nonlinear enhancement, and the absence of circles indicates two-factor enhancement).

4. Discussion

4.1. Effect Analysis of Vegetation $PM_{2.5}$ Purification Services

The vegetation in the Fenwei Plain possesses distinct abilities to purify $PM_{2.5}$. Forests possess the highest removal capacity for $PM_{2.5}$ due to their higher deposition rate and larger distribution area, accounting for over 96% of the total removal. Among the 11 cities in the Fenwei Plain, the removal rates ranged from 0 to 0.63%. The $PM_{2.5}$ removal rates in this region align closely with the findings of similar studies in the world. The forest in Jiangsu Province has an average $PM_{2.5}$ removal rate of approximately 0.03% [37]. In Beijing, urban green spaces have a $PM_{2.5}$ removal rate ranging from 0.07% to 0.19% [42]. Additionally, research conducted abroad also demonstrated that San Francisco experienced an average annual air quality improvement of 0.05%, while Atlanta saw a larger improvement of 0.24% [24]. $PM_{2.5}$ deposition rates vary across vegetation types, with trees generally having a greater effect. Existing research suggests that coniferous forests, in particular, play a significant role in retaining $PM_{2.5}$ due to their higher deposition rate [43]. In Taipei City in 2016, the contribution of vegetation to $PM_{2.5}$ removal was found to be highest in mixed forests, followed by broadleaf forests, coniferous forests, greenfield trees, and street trees [34]. Few researchers are focusing on the deposition rate of grassland and cropland, although some studies have indicated that they have a certain level of retention effect on particulate matter [44].

Various factors influence the dispersion and accumulation of air pollutants in the Fenwei Plain, particularly $PM_{2.5}$. The findings showed that vegetation and NDVI exert the most significant influence on $PM_{2.5}$ removal. The type and amount of vegetation play a significant role in the rate at which vegetation captures and removes $PM_{2.5}$ particles. Previous studies have shown a connection between Net Primary Productivity (NPP) and the concentration of $PM_{2.5}$. This includes selecting tree species with higher sedimentation rates or net productivity, optimizing the layout of urban green spaces, and implementing effective vegetation management practices. These measures contribute greatly to enhancing regional air quality and maintaining ecological balance, and nature-based air purification services hold great potential for future air pollution management [37]. In addition, the spatial distribution of $PM_{2.5}$ concentrations and $PM_{2.5}$ removal cold hotspots in the Fenwei Plain show obvious spatial mismatch patterns. Purification of $PM_{2.5}$ is lower in vegetation at lower elevations, where $PM_{2.5}$ pollution is more severe and the vegetation distribution is smaller. Undeniably, the key to effectively solving air pollution still remains controlling the emission of $PM_{2.5}$ or minimizing the $PM_{2.5}$ pollution by treating it through physical and chemical methods. However, the emission reduction capacity of traditional solutions is gradually reduced, and upgrading the industrial structure and energy transformation are arduous tasks. However, nature-based solutions to air pollution are also a direction that could be explored in depth in the future [13].

Additionally, topography plays a substantial role in air purification. However, meteorological factors have a comparatively small direct impact on $PM_{2.5}$ removal but are intricately connected to the rate of $PM_{2.5}$ reduction. In northwest China, wind speed and temperature have a more pronounced effect on $PM_{2.5}$ levels [45,46]. Typically, elevated wind speeds under normal conditions promote pollutant dispersion, resulting in a gradual decline in $PM_{2.5}$ concentration [47]. However, within the Fenwei Plain, distinctive topographical features give rise to diminished wind speeds, impeding pollutant dispersion and potentially exacerbating pollutant aggregation. Additionally, wind speed affects the deposition rate of $PM_{2.5}$ by vegetation, with higher wind speeds leading to a higher relative deposition rate. There are generally two types of $PM_{2.5}$ removal in the natural environment, one is dry deposition selected in this study and the other is wet deposition. Notably, it is only intense precipitation that exerts a potent scouring effect on $PM_{2.5}$ concentrations, leading to a substantial reduction in $PM_{2.5}$ levels. For the meteorological conditions of the Fenwei Plain, dry deposition assumes a more prominent role. Vegetation loses its trapping capacity after a certain duration of the dry deposition and precipitation is needed to purify the vegetation for recovery.

4.2. Policy Recommendations

Currently, certain success has been achieved in air pollution control in China. But when urban air quality reaches moderate or low pollution levels, landscape regulation and optimization have been recognized as an effective way to mitigate air pollution [48]. In areas with high population densities, there is a growing demand for air improvement. Hence, it is necessary to implement more effective air purification measures to protect public health in the future [49].

In the long term, the services provided by ecosystems have a significant positive impact on the removal of $PM_{2.5}$ particles from the air [17]. Nature-based solutions have the potential to enhance ecosystem services, resulting in significant economic and social advantages when compared to traditional solutions. It helps in conserving natural resources and managing intangible assets in China [37]. Increasing the area of green space is also an effective way to achieve collaborative control of various air pollutants [50] and the significant removal capacity of forests for $PM_{2.5}$. It also has a good temperature regulation effect. The proper allocation of forests and green spaces can potentially reduce energy consumption, thereby delaying climate change [51,52]. Therefore, in areas with high pollution and high vegetation coverage, priority should be given to energy transformation and industrial structure optimization. In areas with high pollution and low vegetation coverage, while considering energy emission reductions, it is also necessary to consider the reasonable allocation of natural resources [53]. These could give full play to the air purification role of vegetation. In the process of urban expansion, the rational design of green space layout needs to be considered. Planning policies should also be based on natural laws, taking into account local geographical conditions and dominant tree species. In addition, urban construction should focus on strengthening green infrastructure, such as the rational use of shrubs and hedges for vertical greening and the construction of green roofs [54]. In mountainous areas with high vegetation cover, forests and grasslands need to be restored and protected. Those can further consolidate the results of governance [55].

Above all, nature-based solutions to air pollution are of great significance to developing countries. In future air pollution control, policymakers need to break away from traditional thinking and entrenched patterns and implement diversified and innovative measures. In particular, regionally coordinated development should be integrated into urban planning and management, which is crucial to jointly promote regional pollution prevention and control precise pollution management.

4.3. Limitations

Nonetheless, there are still some uncertainties that need to be addressed in further research. Firstly, the deposition rate of forests and shrubs, as well as the resuspension rate, were derived from the existing study. The sedimentation rates of grassland and cropland were determined using the minimum value of the vegetation $PM_{2.5}$ sedimentation rate. Additionally, LAI was calculated using an empirical function. These factors could have an effect on the variability of the outcomes; given this, the subsequent stage would be focusing on the setting of the parameters. In addition, the spatial resolution of NDVI and vegetation distribution is 30 m, which could not accurately depict the distribution of green areas in spaces that are smaller than 600 m^2. Higher-resolution data should be explored in future studies to parse the $PM_{2.5}$ removal status of vegetation within the city in a more in-depth manner. Secondly, the impact of vegetation and its natural and ecological factors on $PM_{2.5}$ purification services was taken as the focus. Socio-economic factors such as industrial emissions, transportation, energy, population, and GDP were not taken into account, to explore the socio-ecological effects of vegetation air purification services. Nevertheless, nature-based solutions for mitigating air pollution represent a promising avenue of progress due to their substantial socio-economic benefits. A primary benefit lies in the augmentation of ecosystem services, which can positively influence the environment. Moreover, these solutions can inspire novel research on air purification services and foster a deeper understanding of how ecosystems can retain and absorb air pollutants.

5. Conclusions

The framework in this research was constructed to quantify the $PM_{2.5}$ purification services of vegetation and explore the natural drivers of $PM_{2.5}$ removal at the regional scale. The expression of the degree of spatial matching between the $PM_{2.5}$ concentration and $PM_{2.5}$ removal has also been visualized. The results showed that spatial heterogeneity of $PM_{2.5}$ purification services provided by vegetation exists in the Fenwei Plain due to the uneven distribution of vegetation. Meanwhile, vegetation type and NDVI significantly affected the $PM_{2.5}$ removal in the Fenwei Plain. $PM_{2.5}$ removal is high in mountainous areas with high vegetation coverage. $PM_{2.5}$ removal is low in plains and urban areas with high emissions. The air-purifying capacity of vegetation in densely populated areas is limited, resulting in a spatial mismatch between $PM_{2.5}$ concentration and $PM_{2.5}$ removal. The under-supply of $PM_{2.5}$ purification services from vegetation in areas with high pollution concentrations is close to 50%, indicating the critical role of vegetation in regional air pollution management. The implementation of regional air pollution control measures needs to be accompanied by the prioritization of improving green infrastructure and optimizing the layout of green spaces in urban development. This is a potential future means of addressing air pollution and a scientific basis for regional ecological construction.

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