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Evaluating the Association of Regional and City-Level Environmental Greenness and Land Over Patterns With $PM_{2.5}$ Pollution: Evidence From the Shanxi Province, China

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Ambient $PM_{2.5}$ (fine particulate matter with aerodynamic diameters ≤2.5 μm) is a major threat to human health. Environmental fates and human exposure to $PM_{2.5}$ can be affected by various factors, and environmental greenness have been documented to be significantly associated with the exposure disparities; however, the relationship between the greenness and ambient $PM_{2.5}$ on the region and city levels, and variations across different land cover types remain unclear. In this study, $PM_{2.5}$ changes from 2001 to 2020 varying over different land cover types and cities were analyzed, and discussed for the relationships with environmental greenness, by taking Shanxi province as an example. The results showed in the past 2 decades, the mean annual NDVI (normalized difference vegetation index) of the study area showed a significant increasing trend (p < 0.01), and the $PM_{2.5}$ concentration decreased as environmental greenness get better. The same trends were observed across different land cover types and cities. The negative correlation was stronger in the construction land with more frequent human activities, especially in the built-up areas with low vegetation coverage; but limited in the high green space coverage areas. These results provide quantitative decision-making references for the rational development, utilization and management of land resources, but also achieving regional coordinated controls of $PM_{2.5}$ pollution by optimizing land use.

Keywords: land cover, NDVI, fine particulate matter, spatiotemporal patterns, environmental greenness

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1 INTRODUCTION

Along with the fast development of urbanization and industrialization, environmental quality changes rapidly in most areas. Emissions from sources like industry sector, diesel or gasoline vehicles, coal and biomass burning in power plants and residential stoves lead to serious air pollution (Shi Y et al., 2020). In China, air pollution has been recognized as the 4th largest risk factor, following dietary risks, tobacco, and high blood pressure, and causing millions of premature deaths every year. Although efforts have been taken to fight against the serious air pollution issue and many countermeasures effectively reduced pollution levels, fine particulate matter ($PM_{2.5}$) remains a significant contributor to high burdens of disease (Liu et al., 2017). Several large-scale epidemiological studies highlighted significant correlations between exposure to air pollutants and premature mortality (Lu et al., 2015; Fang et al., 2016; Cohen et al., 2017; Huang et al., 2017). The Chinese Longitudinal Healthy Longevity Survey (CLHLS) showed that each 10 μg/m^3 increase in the past 3-years average $PM_{2.5}$ was associated with 8% higher mortality in adults aged 65 years or older, and extrapolated that more than 1.7 million premature deaths among Chinese older adults was associated with exposure to ambient air pollution (Li et al., 2018).

Characteristics, fates and influencing factors of $PM_{2.5}$ that can be affected by many factors have been widely discussed in literature studies. Natural meteorological conditions such as wind speed, temperature, humidity, etc., can affect transport and deposition of airborne particles, and meanwhile, factors associated with human activities, like combustion emissions and land use/cover change (LUCC), especially the deterioration of natural ecological environment such as grassland and woodland being caused by urban expansion and increase of cultivated land, influence $PM_{2.5}$ fates notably (Lin et al., 2014; Shi K et al., 2020). It has been realized that it is necessary to include the LUCC into researches of $PM_{2.5}$ influencing factors from the perspective of environmental geography (Fan et al., 2019). Usually, resident, road and industry lands in urban are associated with high $PM_{2.5}$ intensities as activities like biomass burning and coal combustions in these areas contribute obviously to increased $PM_{2.5}$ concentration (Huang et al., 2014; Zhang et al., 2016), while forest usually acts as the adsorption sink reducing ambient $PM_{2.5}$ concentration significantly (Dzierżanowski et al., 2011). She et al. found that PM concentration was proportional to patch area and patch number of LUCC (She et al., 2017). Different landscape patterns cam also affects the interaction between woodland, water and atmospheric PMs (Wu et al., 2015).

The relationship between land cover patterns and air pollution is complex and usually pattern-process relationships (Lam and Niemeier, 2005; Bandeira et al., 2011; Chen et al., 2013; Zhang et al., 2013). Results primarily focusing on urban land cover types (e.g., urban forests, built-up land) may be not generalized to settings where greenspace largely represents regional woodland, grassland, farmland, and open areas (Taylor and Hochuli, 2017). Vegetation was found to have potentially offsetting effects in increasing $PM_{2.5}$ levels driven by industrial structure and energy-related emissions (Wang et al., 2018). It was suggested that the response of PM pollution to LUCC had obvious differences across different regions, and the correlation between PM pollution and LUCC was weak in coastal areas but strong in inland areas (Sun et al., 2016). According to an investigation of spatial scale effect by Chen et al., the capability for a neighborhood green space to attenuate $PM_{2.5}$ pollution would be vanished when its size smaller than 200 m, and would be maximized when its size within 400–500 m (Chen et al., 2019). Impacts of land cover pattern changes on the spatial distribution of $PM_{2.5}$ from the view of different scales, i.e., regional, city and district levels, is still limited.

In China, Shanxi Province, as the country's main energy base, has vigorously developed the coal industry. Its industrial development, population growth, and urban expansion have caused significant changes in land use patterns and increasingly serious air pollution problems in the past several decades, which directly threaten the physical and mental health of local people and severely hinder its regional sustainability (Bandeira et al., 2011). Development and in-depth study of the relationship between land cover pattern and typical air pollutant $PM_{2.5}$ can enrich relevant research on the impact of land cover pattern caused by human activities on the ecological environment. Taking Shanxi Province as the research area, this study aims at analyzing 1) the land cover pattern and environment greenness characteristics, which has rapidly developed urbanization in the past 20 years; 2) characteristics of the spatiotemporal changes of $PM_{2.5}$ pollution in these 20 years under the background of air pollution prevention and control; 3) how does the environment greenness change affect $PM_{2.5}$ pollution. Carrying out researches on the impact of changes in land cover patterns on $PM_{2.5}$ can not only provide quantitative decision-making references for the rational development, utilization and management of land resources, but also achieve regional coordinated controls of $PM_{2.5}$ pollution by optimizing land use methods.

2 MATERIALS AND METHODS

2.1 Study Area

Shanxi Province (ranging from 110°14′-114° 33′E, 34°34′ -40° 43′N) is in the hinterland of China, with an area of about 156,300 km^2 (**Figure 1**), relying on Taihang Mountain and neighboring Hebei in the east, acing Shaanxi across the Yellow River in the west, and adjoining the Inner Mongolia to the north and Henan Province to the south. There are 11 prefecture-level cities, namely Taiyuan, Datong, Yangquan, Changzhi, Jincheng, Shuozhou, Jinzhong, Xinzhou, Linfen, Yuncheng and Lvliang. Shanxi Province has a very complex topography, with mountains, hills, plateaus and basins widely distributed. With the acceleration of urbanization and industrial development, the emission of particulate pollutants is increasing, and the air pollution pressure is becoming more and more urgent, which has become an important constraint factor for the opening-up and sustainable economic development of Shanxi Province.

2.2 Data Source

The land cover data in this study (including 2000 and 2020) were obtained from the 30-m spatial resolution global land cover data (GlobeLand30, http://www.globallandcover.com/). The images used for classification in this dataset are mainly multi-spectral images of 30-m spatial resolution, including TM5 (Thematic Mapper), ETM+ (Enhanced Thematic Mapper), OLI (Operational Land Imager) multi-spectral images of Landsat and HJ-1 multi-spectral images. The selection principle of these images includes the multispectral image of vegetation growth season within ±2 years of the data production base year or the update year, under the premise of ensuring that the image is cloudless (less cloud). The confusion matrix was used to verify the accuracy of GlobeLand30 data, and its overall

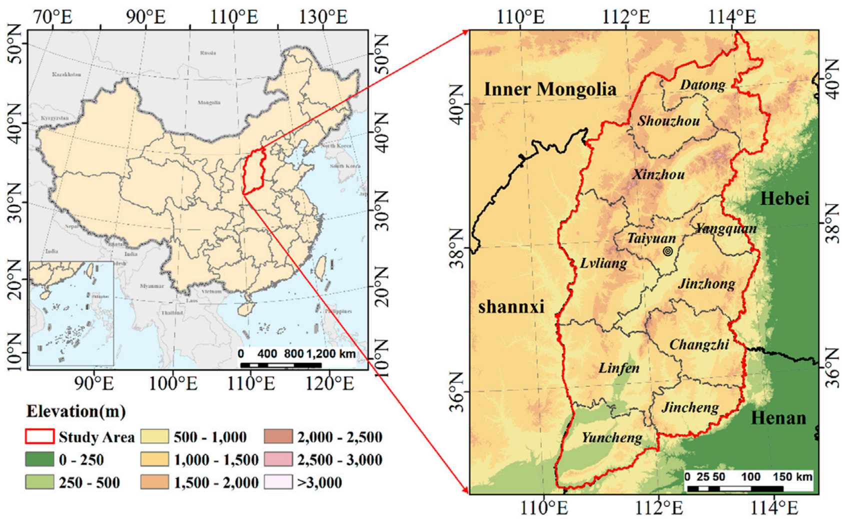

FIGURE 1 | Location of the study area (Shanxi Province).

accuracy reached over 80%. Based on the existing GlobeLand30 classification system, this study divides land cover types into seven categories: cropland, woodland, grassland, wetland, water body, built-up land, and barren land.

In this study, NDVI (normalized differential vegetation index), a symbolic index representing vegetation growth status and coverage, was selected to reflect environment greenness. NDVI is the ratio of the difference between the near-infrared region and red visible reflectance to the sum of these two measures, ranging from −1.0 to 1.0. Negative NDVI values are often thought of as blue space or water, whereas larger values indicate denser green vegetation (Tucker et al., 2020). We measured NDVI values from the Moderate-Resolution Imaging Spectro-Radiometer (MODIS) in the National Aeronautics and Space Administration's Terra Satellite (http://wist.echo.nasa.gov) from 1 January 2001 to 31 December 2020. MODIS has a temporal resolution of 16 days and varying spatial resolution up to 250 m. After the projection transformation, format conversion and splicing processing of the original data set, the annual average of NDVI was calculated for analysis. This calculation process was conducted using Google Earth Engine.

Estimates of ground-level concentrations of $PM_{2.5}$ were obtained from the ChinaHigh$PM_{2.5}$. It is generated from MODIS/Terra + Aqua MAIAC AOD products together with other auxiliary data (e.g., ground-based measurements, satellite remote sensing products, atmospheric reanalysis, and model simulations) using artificial intelligence by considering the spatiotemporal heterogeneity of air pollution. Hourly $PM_{2.5}$ were obtained from the China National Environmental Monitoring Center. Daily $PM_{2.5}$ values were then averaged from valid hourly observations at each monitoring station. Auxiliary data, including meteorological variables, surface conditions, pollutant emissions, and population distributions, that may potentially affect $PM_{2.5}$ concentrations, were collected to improve $PM_{2.5}$-AOD relationships in China. In this study, meteorological variables considered included temperature, relative humidity, precipitation, evaporation, surface pressure, wind speed, and wind direction, as described in detail elsewhere (Wei et al., 2021). Annual $PM_{2.5}$ estimates were calculated from 2000 to 2020, at 1 × 1 km spatial resolution, which was averaged from the Level 2 daily products. Since the data for the year 2000 is averaged from March 2000 to December 2000, we extract the annual PM2.5 data from 2001 to 2020 for analysis. The annual $PM_{2.5}$ estimates are highly related to ground-based measurements (R^2 = 0.94) with an average root-mean-square error (RMSE) of 5.07 μg/m^3, as described in detail elsewhere.

2.3 Data Analysis

2.3.1 Land Cover Change Rate

To analyze and assess the dynamic degree of land cover types objectively, the land change rate (LCR) of each land cover type was calculated, which is expressed as follows:

$$LCR = \frac{U_b - U_a}{U_a} \times 100\%$$

where Ua and Ub represent the area of each land cover type at the beginning year and ending year of the study period, respectively.

2.3.2 Correlation Analysis Between Vegetation Dynamics and $PM_{2.5}$ Change

The Pearson correlation analysis model is used to calculate the correlation coefficient between NDVI and $PM_{2.5}$ from 2001 to 2020, and to study the relationships between environmental greenness and air pollution on the spatial scales and pixel scales. The equation is as follows:

$$r_{xy} = \frac{\sum_{i=1}^{n} (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n} (x_i - \bar{x})^2} \sqrt{\sum_{i=1}^{n} (y_i - \bar{y})^2}}$$

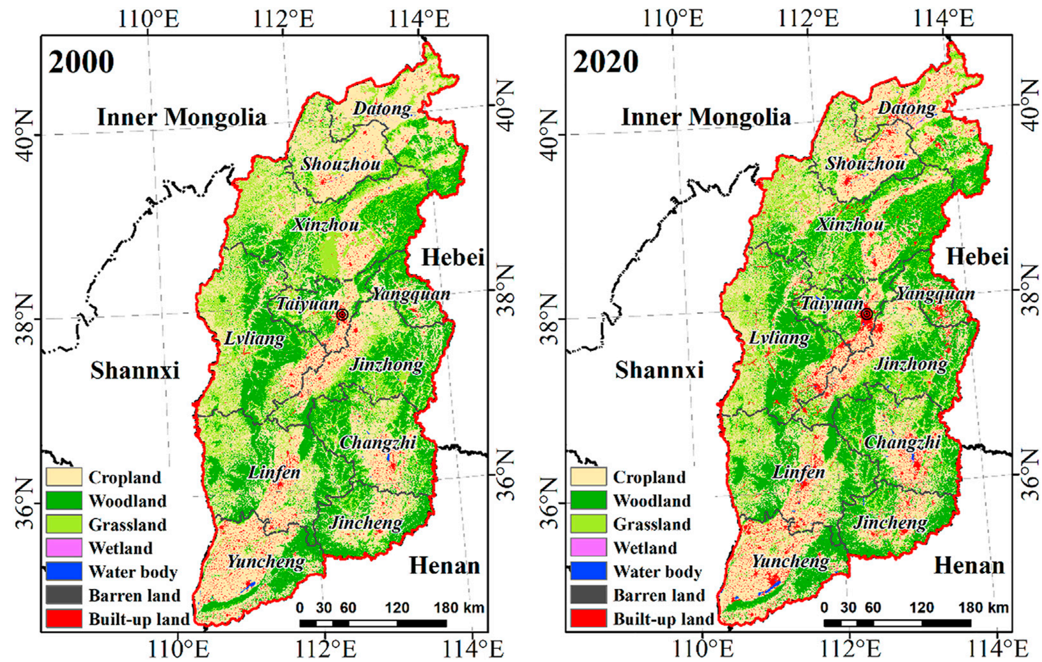

FIGURE 2 | The spatial distribution of land cover types in 2000 and 2020.

where n is the number of years, xi represents the value of variable x in the year i, and y_i represents the value of variable y in the year i. x and y represent means of the two variables, respectively. r_{xy} represents the correlation coefficient between x and y ranging from -1 to 1. If the $r_{xy} > 0$, it indicates variables x and y have a positive correlation. On the contrary, if the $r_{xy} < 0$, it indicates variables x and y have a negative correlation. In addition, if the absolute value of r_{xy} is closer to 1, the correlation between variable x and variable y is stronger. In this study, x and y refer to NDVI, which represents environmental greenness, and PM, which represents air pollution, respectively.

2.3.3 Trend Analysis of Normalized Difference Vegetation Index and $PM_{2.5}$

In this study, we applied a simple linear regression analysis method based on ordinary least squares (OLS) (Jiang et al., 2017) to detect the trend of mean annual NDVI, and $PM_{2.5}$ at the regional or pixel scale from 2001 to 2020. The expression of the slope is:

$$Slope = \frac{n\sum_{i=1}^{n} i \times N_i - \sum_{i=1}^{n} i \times \sum_{i=1}^{n} N_i}{n \times \sum_{i=1}^{n} i^2 - \left(\sum_{i=1}^{n} i\right)^2}$$

where Ni is the value of parameter (NDVI or $PM_{2.5}$) in the year i, and n represents the number of years. If the Slope >0, it means the parameter exhibits an upward trend. Otherwise, if the Slope <

Zero, it means the parameter exhibits a downward trend. In addition, the T-test method was operated to examine whether the trend of the parameter was significant at the basin or pixel scale.

TABLE 1 | Areas and changes of land cover types from 2000 to 2020 in study area.

Land cover type	2000	2020	2000–2020	
	Area/km^2	Area/km^2	Change Area/km^2	LCR
Cropland	70710.4 (44.97%)	65639.9 (41.91%)	−5070.5	−7.17%
Woodland	42747.2 (27.18%)	44295.2 (28.28%)	1548.0	3.62%
Grassland	39042.0 (24.83%)	37245.6 (23.78%)	−1796.4	−4.60%
Wetland	155.4 (0.10%)	234.3 (0.15%)	79.0	50.81%
Water body	386.0 (0.25%)	592.7 (0.38%)	206.7	53.53%
Built-up land	4153.3 (2.64%)	8515.9 (5.44%)	4362.7	105.04%
Barren land	51.3 (0.03%)	93.5 (0.06%)	42.2	82.30%

3 RESULTS

3.1 Land Cover Change Between 2000 and 2020

The distribution of land cover types showed significant spatial and temporal differences (**Figure 2**). Cropland is the most widely distributed type, accounting for more than 40% of the total area, mainly distributed in basin located in the central, northeast and southeast, and southwest in Shanxi Province. Woodland and grassland accounted for 28.28 and 23.78% of the total area in 2020, respectively, comprising two dominant natural land cover

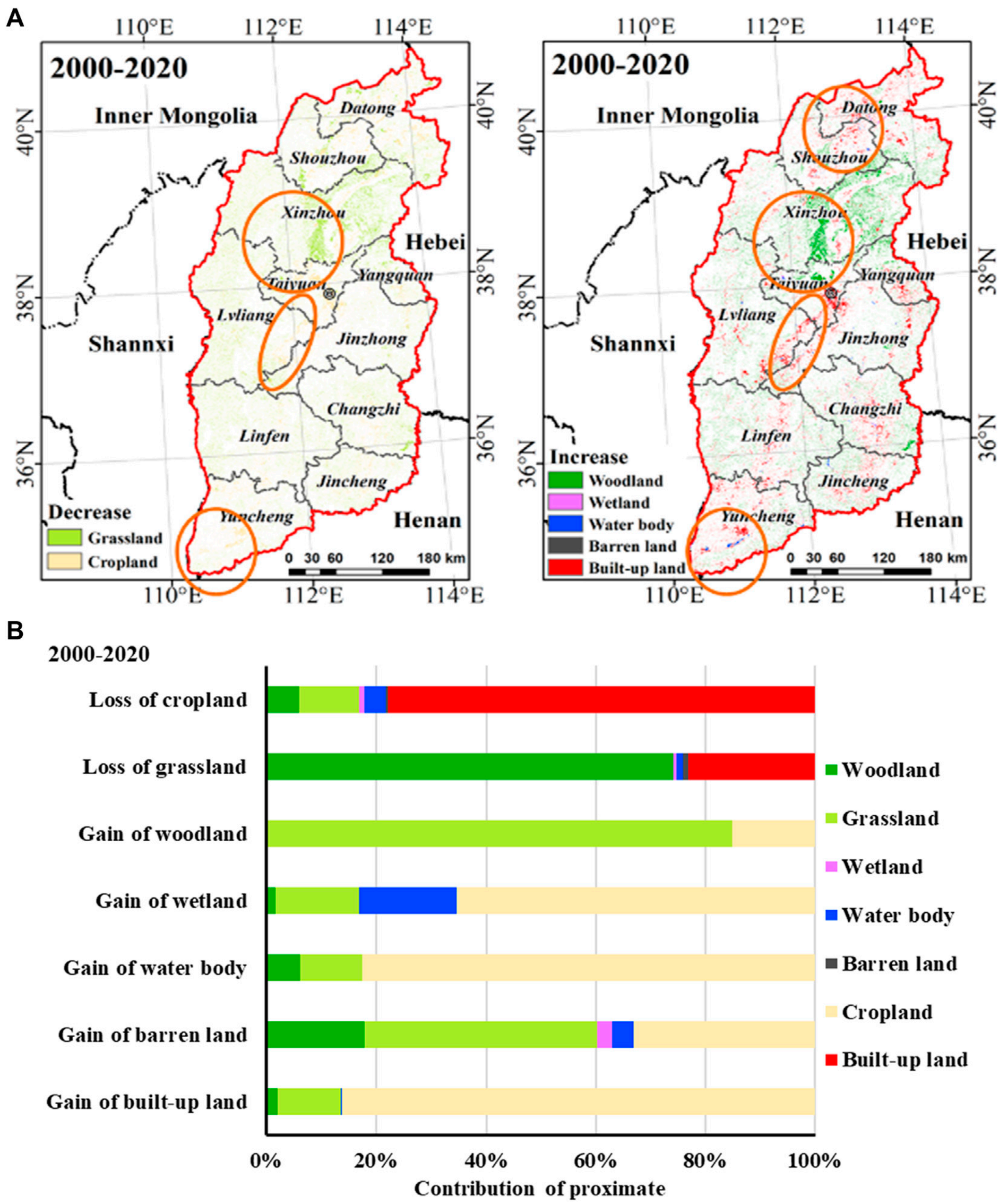

FIGURE 3 | The spatial location **(A)** and contribution of proximate driver **(B)** of decreasing and increasing land cover type.

types. Woodland is distributed mainly along mountain ranges, such as Taihang Mountain, Lvliang Mountain and other mountains. Grassland is mainly distributed in the west and center part. Built-up land is mainly distributed in the central and southeastern basin, accounting for 5.44% of land cover types. The proportions of wetland, water body and barren land in the study area are few, accounting for ~0.15, 0.38, and 0.06%, respectively. The area statistics of different land cover types are shown in **Table 1**.

The statistical area change of land cover types results are shown that areas of cropland and grassland had a decrease rate of 7.17 and 4.60%, respectively. Our estimates showed a 5070.5 km^2 and 1796.4 km^2 net loss areas of cropland and grassland, respectively (**Table 1**). Grassland loss occurred mainly in the forest-grass ecotone of the northern and central parts, with woodland (contribution to 74.13%) and built-up land (contribution to 23.25%) expansion being the main proximate driver. While cropland decrease was also extensive in these regions, decreased croplands occurred mainly in the central and southwestern basins. As can be seen from **Figure 3**, the main proximate driver of cropland reduction is built-up extension (contribution to 77.94%), followed by conversion of

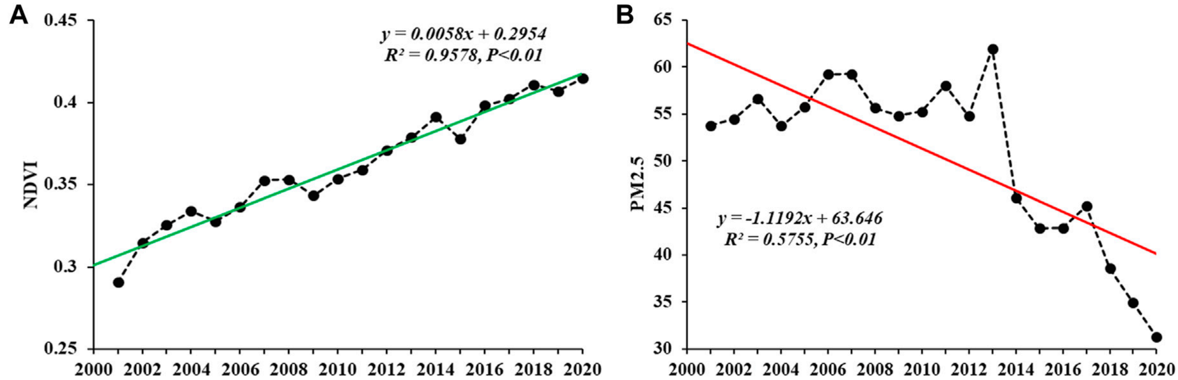

FIGURE 4 | Change trend of NDVI **(A)** and $PM_{2.5}$ **(B)** in the Shanxi Province from 2001 to 2020.

farmland to woodland and grassland (contribution to 16.73%). The area of built-up land increased the most (4362.7 km^2) and the increase rate was the highest (105.04%), followed by the area of woodland, the increase area was 1548.0 km^2. The increase rates of wetland, water body and barren land were high, but the increase areas were very small due to the low distribution area. Expanded built-up lands were mainly due to the occupation of cropland (contribution to 86.34%) and grassland (contribution to 11.5%), with Taiyuan, Datong and Yuncheng as the center, and other cities also expanded. Woodland expansions were mainly distributed in the central part, and returning grassland (contribution to 84.89%) or cropland (contribution to 15.11%) to forest were the main proximate driver.

3.2 Spatiotemporal Patterns of Normalized Difference Vegetation Index and $PM_{2.5}$

At the regional scale, the mean annual NDVI of the study area is 0.36 from 2001 to 2020, which showed significant increasing trends, and the increased rate is 0.0058/year ($p < 0.01$, **Figure 4A**). Of the total pixels, 93.67% of the entire area had significant increase detected, while only 0.97% experienced significant NDVI decreases in the study area, which were detected mainly in the central construction area (**Figure 5**). It indicates that the environmental greenness of Shanxi Province has been improved in the last 20 years. We analyzed the mean annual NDVI changes of four main land cover types (**Table 2**) and found that the mean annual NDVI of Woodland is 0.49, which is the highest value of four main land cover types. The mean annual NDVI of Built-up land had lowest value. Significant increase in mean annual NDVI was found in woodland (0.0064/year, $p < 0.01$), grassland (0.0065/year, $p < 0.01$), cropland (0.0055/year, $p < 0.01$), and built-up land (0.0029/year, $p < 0.01$). The analysis of the mean annual NDVI in different cities shows that the mean annual NDVI of different cities in Shanxi Province is significantly increased, but the change trends are different (**Table 2**). The mean annual NDVI value of Jincheng from 2001 to 2020 is the highest among different cities in Shanxi Province, with an increased trend of 0.005/year. Shuozhou has the lowest mean annual NDVI from 2001 to 2020, which is 0.27, lower than the mean annual NDVI of the entire region. The city with the slowest increase of the mean annual NDVI is Jincheng, with an increase rate of 0.005/year, and the city with the fastest increase of the mean annual NDVI is Lvliang (0.0073/year).

The annual average of $PM_{2.5}$ concentration in Shanxi Province was 50.77 μg/m^3 from 2001 to 2020, showing a significant decrease trend (over 99% of the entire area), especially in the central and southern regions, whose decrease trend was faster than that of other regions, indicating that the atmospheric environment in Shanxi Province was getting better during these 2 decades (**Figure 4B**, and **Figure 5**). Different decrease trends were observed in four main land cover types (**Table 2**). The annual average of $PM_{2.5}$ concentration of Woodland is 46.59 μg/m^3, which is the lowest value of four main land cover types, and the annual average of $PM_{2.5}$ concentration of the Built-up land had highest value (62.10 μg/m^3). The most significant decrease was found in the built-up land (1.388 μg/m^3year^{-1}) from 2001 to 2020, followed by the cropland and grassland, and the lowest in the woodland. According to the regional statistics of the annual average of $PM_{2.5}$ concentration in different cities, the annual average of $PM_{2.5}$ concentration of different cities in Shanxi Province showed a significant decrease trend from 2001 to 2020 (**Table 2**). More than half of the cities have higher annual average of $PM_{2.5}$ concentration than the average value in Shanxi Province, with Yuncheng having the highest annual average of $PM_{2.5}$ concentration at 69.33 μg/m^3. The city with the slowest decrease of the annual average of $PM_{2.5}$ concentration is Datong, with a decrease rate of 0.882 μg/m^3year^{-1}, and the city with the fastest decrease of the annual average of $PM_{2.5}$ concentration is Yuncheng (1.680 μg/m^3year^{-1}).

3.3 Spatially Different Correlation Between Normalized Difference Vegetation Index Dynamics and $PM_{2.5}$ Variations

The relationship between the NDVI dynamics and $PM_{2.5}$ variations over the period 2001–2020 was analyzed by using the Pearson correlation method in the overall region at Shanxi Province (**Figure 6**). The annual average of $PM_{2.5}$ concentration had significant negative correlation with the

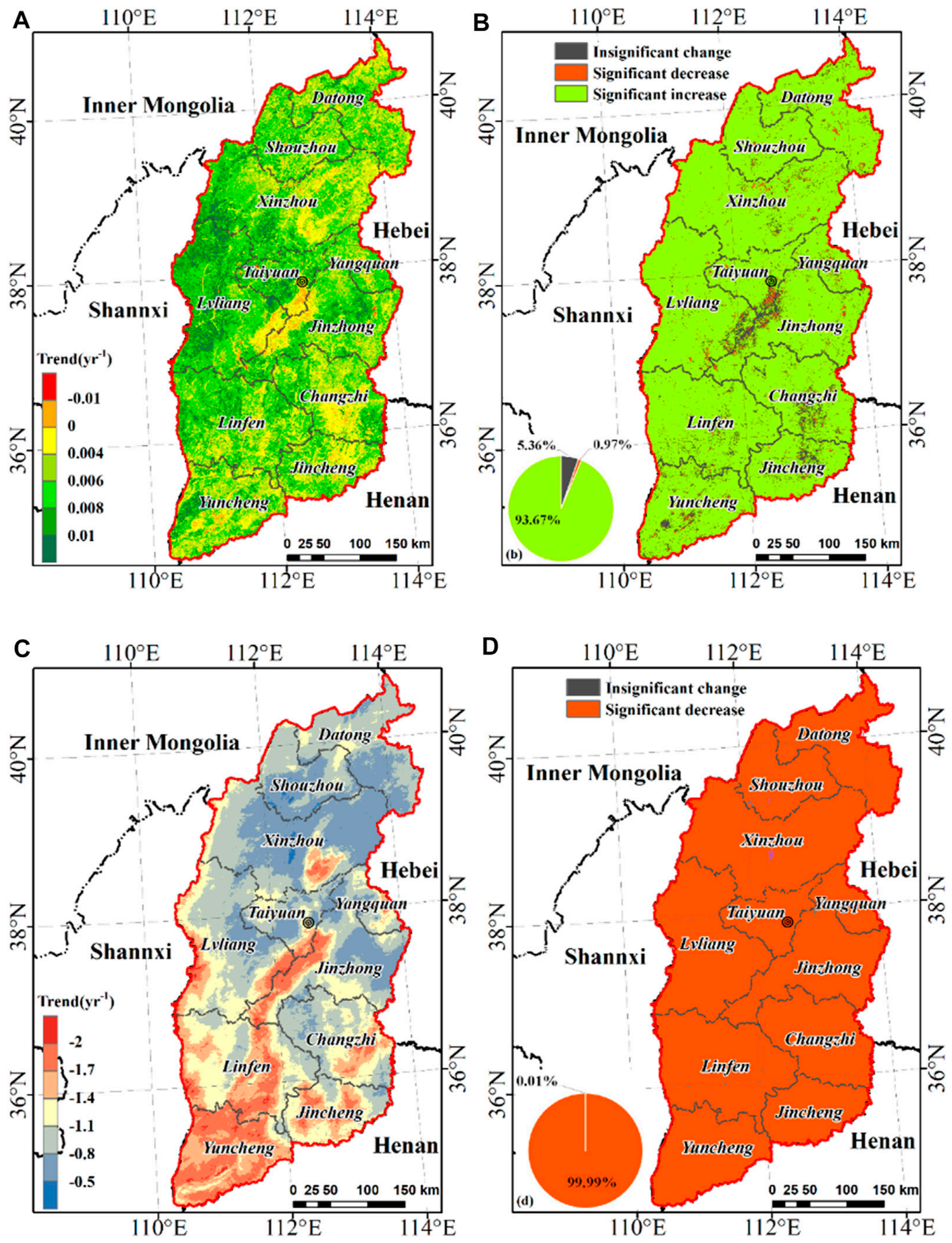

FIGURE 5 | Difference in the NDVI change trend **(A,B)** and $PM_{2.5}$ trend **(C,D)** in Shanxi Province from 2001 to 2020.

mean annual NDVI (R = −0.723, p < 0.01). Thus, environmental greenness was influential in the decrease of $PM_{2.5}$ concentration in this region. Of the total pixels, $PM_{2.5}$ concentration showed significant negative correlation with NDVI in most areas of Shanxi Province, with proportion of 83.77%, which were mainly distributed in vegetated areas. While 15.56% of the entire area showed insignificant correlation between $PM_{2.5}$ concentration and NDVI, and only 0.67% showed significant positive correlation, which mainly occurred in the areas with expansion of built-up land.

The correlations of $PM_{2.5}$ concentration with NDVI by the main land cover types and different cities were also calculated, and listed in **Table 3**. $PM_{2.5}$ concentration of four main land cover types was significantly negative correlated with NDVI. It is important to note that $PM_{2.5}$ concentration had the

TABLE 2 | The changes of mean annual NDVI and $PM_{2.5}$ in main land cover types and different cities.

Main Land cover types	Mean NDVI	Trend NDVI	Mean $PM_{2.5}$	Trend $PM_{2.5}$
Woodland	0.49	0.0064*	46.59	−1.012**
Grassland	0.34	0.0065*	47.28	−1.033**
Cropland	0.31	0.0055*	54.51	−1.218**
Built-up land	0.24	0.0029*	62.10	−1.388**
Different cities				
Datong	0.28	0.0052*	40.53	−0.882**
Shuozhou	0.27	0.0058*	42.65	−0.833**
Xinzhou	0.33	0.0059*	42.24	−0.859**
Taiyuan	0.35	0.0063*	48.99	−0.992**
Yangquan	0.38	0.0055*	51.57	−1.027**
Lvliang	0.35	0.0073*	48.30	−1.128**
Jinzhong	0.39	0.0056*	50.91	−1.092**
Linfen	0.40	0.006*	57.66	−1.370**
Changzhi	0.41	0.0051*	54.28	−1.118**
Jincheng	0.45	0.005*	58.85	−1.350**
Yuncheng	0.40	0.0052*	69.33	−1.680**

*The symbol * meant that the trend NDVI of the four land cover types and different cities had significant increase and the value of p is below 0.01. The symbol ** meant that the annual mean decrease value of $PM_{2.5}$ concentration of the four land cover types and different cities and the decrease trends were all significant and the value of p is below 0.01.*

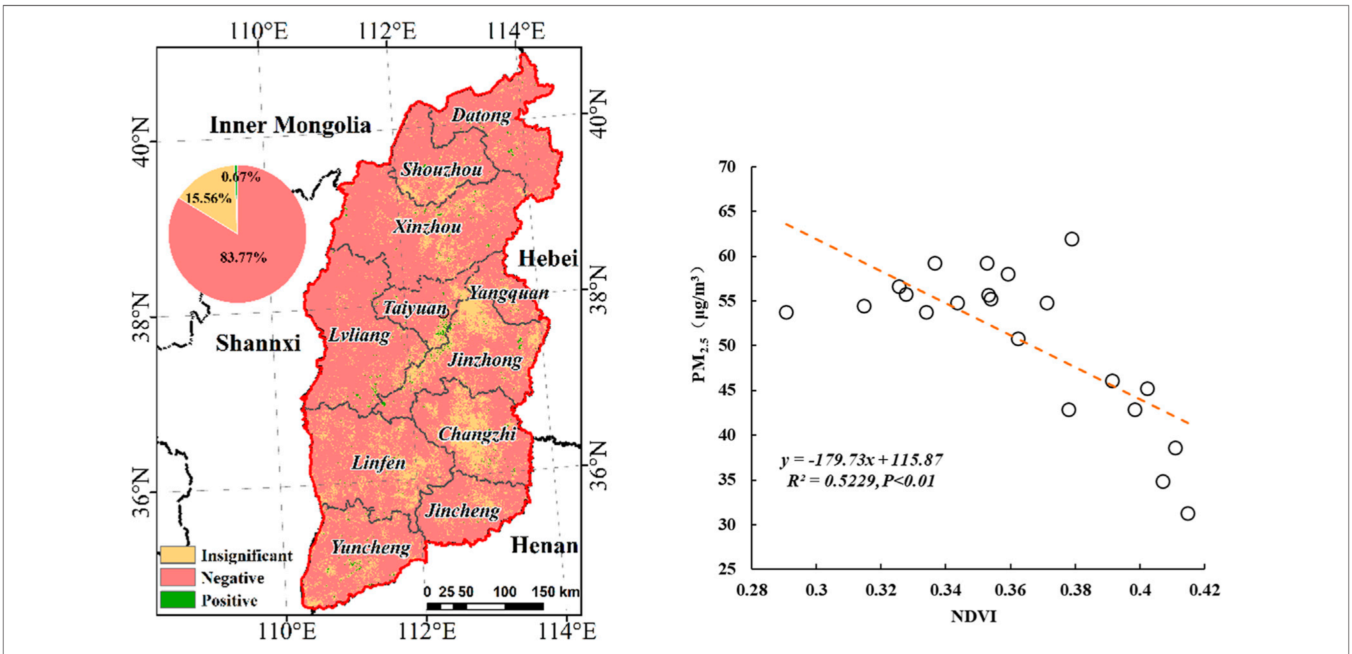

FIGURE 6 | The correlation between NDVI and $PM_{2.5}$. The pie charts illustrate the area percentage of different spatial patterns of the correlations.

strongest negative correlation with NDVI (R = −0.827, $p < 0.01$) in the built-up land, followed by the cropland (R = -0.726, $p < 0.01$) and then the woodland (R = −0.710, $p < 0.01$), and grassland has the weakest negative correlation with NDVI. The relationship between $PM_{2.5}$ concentrations with NDVI in different cities showed similar results (**Table 3**), and the trend of correlation coefficient was different among different cities. $PM_{2.5}$ concentrations were negatively correlated with NDVI for all cities, and the correlation coefficient ranged from −0.626 to −0.817, with Datong showing the strongest significant correlation (R = −0.817, $p < 0.01$), following by Yuncheng (R = −0.772, $p < 0.01$) and then Lvliang (R = −0.743, $p < 0.01$). The weakest negative correlation between $PM_{2.5}$ concentration and NDVI was occurred in Jinzhong.

At the pixel scale, the correlation analysis between $PM_{2.5}$ concentrations and NDVI in the main land cover types and different cities revealed that $PM_{2.5}$ concentrations had

TABLE 3 | Correlations between NDVI and $PM_{2.5}$ in different land cover types and cities.

		Correlation of $PM_{2.5}$ and NDVI		
Main Land cover types	Trend	Negative (%)pixels, $p < 0.05$)	Positive (%)pixels, $p < 0.05$)	Insignificant (%)pixels, $p > 0.05$)
Woodland	−0.710**	91.12	0.26	8.62
Grassland	−0.700**	87.15	0.29	12.56
Cropland	−0.726**	79.57	0.51	19.91
Built-up land	−0.827**	72.58	1.14	26.28
Different cities				
Datong	−0.817**	92.58	0.69	6.73
Shuozhou	−0.705**	86.47	0.45	13.09
Xinzhou	−0.704**	87.24	0.56	12.21
Taiyuan	−0.737**	81.64	1.75	16.60
Yangquan	−0.656**	83.29	0.64	16.07
Lvliang	−0.743**	92.59	0.64	6.77
Jinzhong	−0.626**	71.85	1.21	26.95
Linfen	−0.664**	81.03	0.26	18.71
Changzhi	−0.631**	70.09	0.49	29.42
Jincheng	−0.727**	87.22	0.31	12.47
Yuncheng	−0.772**	83.20	0.92	15.88

*The second column of table meant that the annual mean decrease values of $PM_{2.5}$ concentration of the four land cover types and different cities. The symbol ** meant that the decrease trends were all significant and the value of p is below 0.01.*

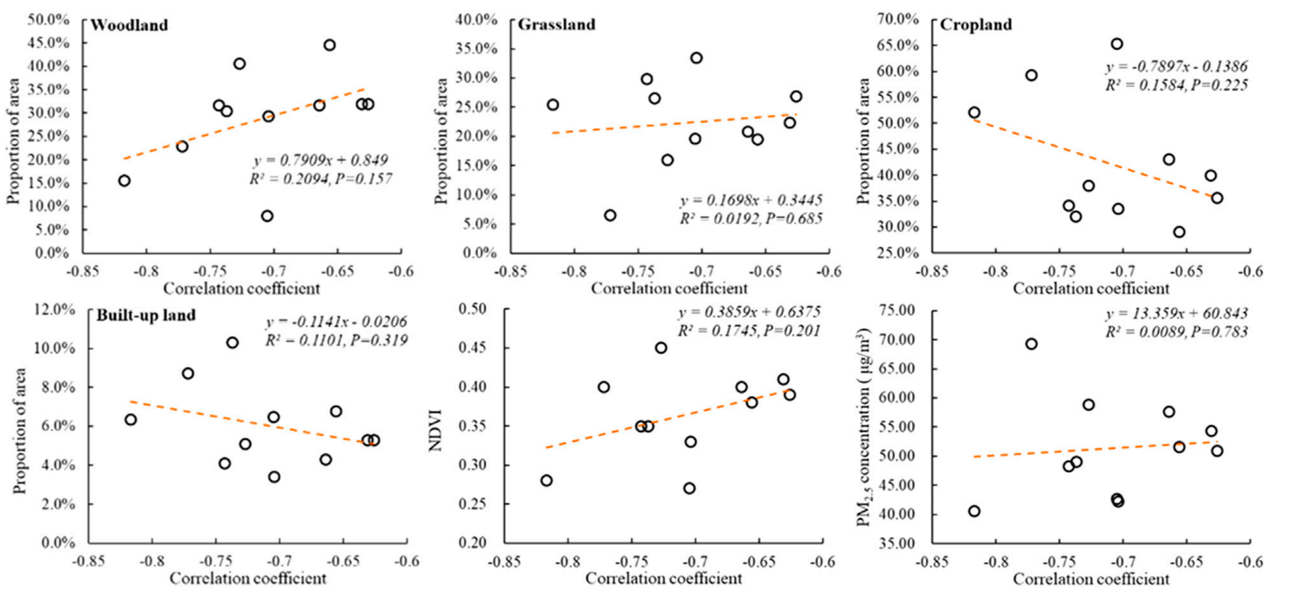

FIGURE 7 | The trends of the correlation coefficient between $PM_{2.5}$ concentration and NDVI with the change of NDVI, $PM_{2.5}$ concentration, and area of land cover types.

significantly negative correlations with NDVI in most areas of woodland, grassland, cropland and built-up land, with proportion of 91.12, 87.15, 79.57 and 72.58%, respectively (see **Table 3**). The insignificant correlation areas are relatively few, mainly in the built-up land (26.28%), followed by cropland (19.91%). Among different cities, Lvliang has the highest proportion of significant negative correlation between $PM_{2.5}$ concentrations and NDVI (92.59%), and almost the same result was showed in Datong (92.58%). The areas that $PM_{2.5}$ concentrations showed insignificant correlation with NDVI mainly occurred in Changzhi and Jinzhong, with proportion of 29.42 and 26.95%, respectively. There are few areas with significant positive correlation between $PM_{2.5}$ concentrations and NDVI in all cities, and the highest proportion occurs in Taiyuan, accounting for only 1.75%. The trends of the correlation coefficient between $PM_{2.5}$ concentration and NDVI were different with the change of NDVI, $PM_{2.5}$ concentration, and area of land cover type (**Figure 7**). The correlation coefficient becomes stronger with the decrease of NDVI. At the same time, the smaller ratios of woodland and grassland area were, the higher the negative correlation coefficient between $PM_{2.5}$ concentration and NDVI is, while the larger the built-up land area is, the higher the negative correlation coefficient between $PM_{2.5}$ concentration and NDVI is. These indicate that in the region with lower vegetation coverage, the increase of environmental greenness has a stronger reduction effect on $PM_{2.5}$ concentration. Thus, increasing environmental greenness has a stronger effect on $PM_{2.5}$ concentration reduction in low-vegetation areas than that in high-vegetation areas.

4 DISCUSSION

Results here are expected to be informative for regional land use planning and ecological environment construction to improve air quality, especially to control $PM_{2.5}$ pollution. With the construction of the *Beautiful China* in recent years, China's ecological environment has improved and air pollution has been effectively controlled. With the implementation of the Air Pollution Prevention and Control Action Plan (APPCAP) since 2013, significant declines in pollutants concentrations have achieved in nationwide of China (Bai et al., 2021); however, there are significant differences in $PM_{2.5}$ concentrations across different regions (Huang et al., 2018). Previous studies revealed that more than 70% of Chinese cities were found to exceed Grade II of the Chinese National Ambient Air Quality Standard, with the highest levels in the North China (Wang et al., 2018). This study found that $PM_{2.5}$ pollution in Shanxi province has decreased significantly since 2013, which is consistent with the overall pollution trend in China.

As an important energy base in China, the economic development of Shanxi Province has been dominated by the energy consumption, which produces large amounts of harmful emissions (Wei et al., 2018). Different from previous studies that mainly discussed the relationship between urban green space and $PM_{2.5}$ concentration, this study explored the impact of environmental greenness on $PM_{2.5}$ concentration from multiple perspectives of different land cover types and different cities at the regional scale (Feng et al., 2017; Chen et al., 2019). The results showed that less vegetation cover has limited ability to deal with high $PM_{2.5}$ concentration, which was consistent with a previous observation showing that higher green space coverage the site had, the lower the $PM_{2.5}$ concentration were there (Yang and Jiang, 2021). It has been recognized that vegetation may play an important role in reducing air pollution and improving air quality. For example, Sun et al. found that the concentrations of pollutants including SO_2, NO_2, CO, $PM_{2.5}$, and PM_{10} all have a negative correlation with the NDVI value (Sun et al., 2019). Some studies pointed out that the vegetation cover and $PM_{2.5}$ concentration correlated negatively (Jin et al., 2020; Kulsum and Moniruzzaman, 2021). The results of this study further confirmed the importance of environmental greenness in mitigating air pollution.

Some scholars studied the mechanism of green vegetation reducing air particulate pollution, and found that plants absorb pollutants through root absorption and leaf absorption pathways, as well as three mitigation mechanisms of green space on particulate matter: deposition, dispersion and modification (Diener and Mudu, 2021). Greenness, on the contrary, can effectively reduce the amount of fine particulate matter in the air. However, in the present study, we found that although environmental greenness has a significant reduction effect on $PM_{2.5}$ concentration, the reduction effect of NDVI on $PM_{2.5}$ is affected by green space coverage and $PM_{2.5}$ concentration level. With the increase of woodland and grassland area, the reduction effect of NDVI on $PM_{2.5}$ is weakened, and with the expansion of built-up area (that is, the area of green space decreases), the reduction effect of NDVI on $PM_{2.5}$ is enhanced. Woodlands may be more effective than grasslands in removing particulate matter, but the ability of green space to reduce $PM_{2.5}$ also has its limitations (Qiu et al., 2018). In high-density urban areas with low vegetation coverage, $PM_{2.5}$ concentration is high and pollution is serious. Improving environment greenness can more effectively control particulate pollution, while in high-density vegetation areas, air particulate concentration is relatively low, and continuously increases of environment greenness will reduce $PM_{2.5}$ reduction efficiency (Chen et al., 2019). In addition, as the concentration of $PM_{2.5}$ in the environment continues to increase, the reduction effect of NDVI on $PM_{2.5}$ is weakened. In the environment with high concentration of $PM_{2.5}$, the absorption of particulate matter by leaves will eventually reach saturation, and then the protection efficiency of particulate pollution is reduced (Hui et al., 2020). This suggests that, in densely populated residential or commercial areas, increasing environmental greenness may offer greater opportunities to improve air quality.

However, the mechanism, process, and outcome of PM mitigation by green space are complex and subjected to various influencing factors. Because of limited sample sites, evidence to quantitatively define the level of influence of green space on PM reduction is insufficient in this study. In addition to the land cover types and environmental greenness, researchers found that the landscape pattern (e.g., Patch area, degree of urban cluster, etc.), can also strongly affect $PM_{2.5}$ concentration (Wu et al., 2015), which was not addressed here due to limited information available. It is also necessary to note that the study did not consider possible time-lag effect, as it was found that the LUCC caused by natural disasters or human activities may have smaller impacts on air pollution in a short period of time, but stronger impacts over a few years (Sun et al., 2016). The time-lag effect is an interesting issue to be investigated in future.

5 CONCLUSION

Based on GlobeLand30, MODIS NDVI and ChinaHigh$PM_{2.5}$ data, this study investigated the spatiotemporal patterns of land cover types and environmental greenness in Shanxi province, and their relationships with ambient $PM_{2.5}$ over a period from 2001 to. This study found that although the vegetation area in Shanxi Province decreased since 2000, the environment greenness did show an upward trend. The $PM_{2.5}$ concentration fluctuated before 2013, and then started to decline continuously. Through the multi-scale analysis, it is found that there is a significant negative correlation between the $PM_{2.5}$ concentration and environment greenness, confirming the important role of regional greenness on $PM_{2.5}$ reduction. The study further demonstrates the multiscale effects of the relationship between $PM_{2.5}$ concentration and environment greenness, that is, $PM_{2.5}$ concentration is negatively correlated with environmental greenness, and the reduction effect of greenness on $PM_{2.5}$ was stronger with the low green space coverage areas than in high green space coverage areas, and higher in the low $PM_{2.5}$ concentration area than in high concentration area. This indicates that the reduction effect of environmental greenness on air particulate pollution is limited, but in construction land with frequent human activities, especially in built-up areas with low vegetation coverage, improving environmental greenness can effectively reduce PM pollution. The results of this study provide a theoretical basis for regional environmental planning and prevention and control of regional $PM_{2.5}$ pollution.

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/Supplementary Material, further inquiries can be directed to the corresponding author.

AUTHOR CONTRIBUTIONS

GG and YD designed the study. GG and LL analyzed and interpreted the results of the data. GG drafted the manuscript. YD revised the manuscript.

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