Evaluating the influence of land use and land cover change on fine particulate matter

Wei Yang1,2 & Xiaoli Jiang2

Fine particulate matter (i.e. particles with diameters smaller than 2.5 microns, PM$_{2.5}$) has become a critical environmental issue in China. Land use and land cover (LULC) is recognized as one of the most important influence factors, however very fewer investigations have focused on the impact of LULC on PM$_{2.5}$. The influences of different LULC types and different land use and land cover change (LULCC) types on PM$_{2.5}$ are discussed. A geographically weighted regression model is used for the general analysis, and a spatial analysis method based on the geographic information system is used for a detailed analysis. The results show that LULC has a stable influence on PM$_{2.5}$ concentration. For different LULC types, construction lands have the highest PM$_{2.5}$ concentration and woodlands have the lowest. The order of PM$_{2.5}$ concentration for the different LULC types is: construction lands > unused lands > water > farmlands > grasslands > woodlands. For different LULCC types, when high-grade land types are converted to low-grade types, the PM$_{2.5}$ concentration decreases; otherwise, the PM$_{2.5}$ concentration increases. The result of this study can provide a decision basis for regional environmental protection and regional ecological security agencies.

With the rapid development of China's economy and society, its rate of urbanization is accelerating. China's industrial scale is also expanding rapidly, and the problem of air pollution is becoming increasingly serious, which has a tremendous impact on the environment, economic development, and even people's health. Fine particulate matter (i.e. particles with diameters smaller than 2.5 microns, PM$_{2.5}$) is considered a crucial protagonist among the various air pollution factors. As a significant health hazard, PM$_{2.5}$ is highly associated with an increased probability of respiratory diseases, cardiorespiratory problems, mutagenic diseases and increased mortality. Therefore, it is of vital significance to understand PM$_{2.5}$ pollution clearly, especially its distribution characteristics and influence factors, which are helpful for reducing pollution and protecting human health.

As a severe air pollutant, the concentration of PM$_{2.5}$ is influenced by meteorological factors, human activities, and the surrounding environment. PM$_{2.5}$ is emitted mainly from anthropogenic sources, such as from traffic and industrial production. The spatial and temporal distributions of PM$_{2.5}$ are impacted by meteorological and environment factors. Previous research has revealed that PM$_{2.5}$ is severely affected by meteorological factors at the macro-scale in terms of temperature, precipitation, wind conditions, etc., while at the micro-scale, PM$_{2.5}$ is strongly associated with land use and land cover (LULC) type. Optimizing LULC type may reduce PM$_{2.5}$ pollution at the community or city level. Land use and land cover change (LULCC) is the embodiment of human activities, which also has an obvious effect on PM$_{2.5}$ distribution. To mitigate pollution, it is significant to explore the effects of LULC and LULCC on PM$_{2.5}$ pollution.

To conduct research on the relationship between LULCC and PM$_{2.5}$, relevant data are required. Remote sensing based LULCC research has a long history and is relatively mature, which has become an effective method to obtain LULCC data. Conventional methods of obtaining PM$_{2.5}$ data employ monitoring stations at fixed sites, whose effective monitoring distances range from 0.5 to 4 km, and which can provide accurate point-source data. The area among the monitoring sites can not be represented by this data. Due to the discontinuous spatial distribution of sites monitoring PM$_{2.5}$ data, several methods have been employed to solve this problem, including spatial interpolation, chemical transport models, land-use regression models and aerosol optical depth (AOD) based statistical models. However, as the use of a single approach leads to large uncertainties, some researchers have sought to integrate different methods to improve the PM$_{2.5}$ estimation accuracy, such as a combination of chemical transport models and satellite-derived AOD.
At present, researches on the relationship between PM$_{2.5}$ and land use mostly focus on city scale$^{36,37}$. Due to atmospheric transport, PM$_{2.5}$ distribution is not only affected by local emissions, but also regional transport$^{38}$. Regional land use changes can directly or indirectly affect PM$_{2.5}$ distribution. There is an insufficient amount on research at regional scale. Moreover, most of the existed researches focus on the influence of landscape patterns on PM$_{2.5}$ pollution but not LULCC types$^{39,40}$. And the PM$_{2.5}$ data used in these studies was station monitoring data which is spatially discontinuous and cannot reveal the spatial relationship between PM$_{2.5}$ and LULCC types. Therefore, in this paper we analyze the relationship between dynamic PM$_{2.5}$ and LULCC type. To avoid the spatial discontinuity of station monitoring PM$_{2.5}$ data, the spatially continuous PM$_{2.5}$ data from the Atmospheric Composition Analysis Group (ACAG) are used. A geographical weighted regression model and a spatial analysis method are employed to identify the response mechanism between dynamic PM$_{2.5}$ and LULCC type. The results of this study can provide a decision basis for regional environmental protection and regional ecological security agencies.

**Methodology**

**Study area.** Shanxi Province is located in the middle of China (Fig. 1), which is the most important energy bases in the country and whose coal output was ranked first before 2016, and second thereafter. Due to the abundance of coal resources in Shanxi Province, its energy structure is focused on coal, which accounts for 72% of its total energy consumption. Shanxi Province is not only an important coal exporter, but also an important power exporter. The power plants in Shanxi Province are mainly coal-fired, which produce considerable amounts of emissions. Additionally, coking and steel industries are pillar industries in Shanxi Province, which also produce vast amounts of emissions. This economic structure based on energy consumption causes serious air pollution. Several cities in Shanxi Province, such as Taiyuan, Linfen, Jincheng, etc., contain the worst air pollution of all cities in China. Meanwhile, Shanxi Province had experienced obvious LULCCs, such as urban expansion caused by fast urbanization and an increase of green land owing to the growth of the ‘Grain for Green’ project. Therefore, Shanxi Province was selected as the study area to analyze the relationship between LULCC and PM$_{2.5}$.

**Data acquisition and preparation.** PM$_{2.5}$ data. The PM$_{2.5}$ data provided by ACAG were generated based on a combination of a chemical transport model, satellite observations and ground-based observations$^{41}$. The data have been validated in North America, which have been shown to have higher accuracy than purely geoscience-based estimates$^{35}$. However, the accuracy of the ACAG data of China has not been validated; therefore, in this work we estimated its accuracy (see Sect. 3.1).

Ground-based data from 58 state-controlled air quality monitoring stations from 2018 were used in the validation (Fig. 1). The ACAG PM$_{2.5}$ data from 2000 to 2018 were downloaded from (http://fizz.phys.dal.ca/...
Pearson's correlation coefficient and the root mean square error (RMSE) were calculated in the validation as:

\[
\text{Pearson correlation coefficient} = \frac{N \sum X_i Y_i - \sum X_i \sum Y_i}{\sqrt{N \sum X_i^2 - (\sum X_i)^2} \sqrt{N \sum Y_i^2 - (\sum Y_i)^2}}
\]

\[
\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (X_i - Y_i)^2}
\]

where \(X_i\) represents a PM_{2.5} value from the ACAG, and \(Y_i\) represents a PM_{2.5} value from monitoring stations.

**Land use and land cover data.** The China multi-period land use land cover data set (CNLUCC) was used. The CNLUCC data were generated with a visual interpretation method based on Landsat remote-sensing data. The data set was provided by the Data Center for Resources and Environmental Sciences, Chinese Academy of Science (http://www.resdc.cn). Data in 2000 and 2018 were used (Fig. 3). The data consist of six classes: farmlands, forests, grasslands, water, construction lands, and unused lands. The data were shown to have an accuracy of 88.95%, which meet the needs of this study.

**Geographical weighted regression model.** Geographical weighted regression (GWR) models are a powerful tool to explore the heterogeneity of spatial relations. As a local spatial regression model, GWR can effectively solve the nonstationarity of variable space, which has been widely used in the spatial analyses of different geographic elements. The essence of GWR is locally weighted least squares, where the ‘weight’ is a distance function of spatial position between the point to be estimated and other observation points. The expression of GWR is as follows:

\[
y_i = a_0(u_i, v_i) + \sum_k a_k(u_i, v_i)x_{ik} + \epsilon_i
\]

where \(y\) is the dependent variable, \(x\) is the explanatory variable, \((u_i, v_i)\) is the coordinates of the \(i\)th point in space, \(a_k(u, v)\) is a realization of the continuous function \(a_k(u, v)\) at point \(i\), and \(\epsilon_i\) is the error term.

To identify the spatial relationship between LULCC and PM_{2.5}, a 3 × 3 km grid map (Fig. 2) was generated of the study area. The variations of PM_{2.5} between 2000 and 2018 were calculated in each grid, where the results were considered as the dependent variable in Eq. (3). The changing area of each different land type in each grid was also calculated and considered as the explanatory variable. Four main land types, farmlands, woodlands, grasslands, water, construction lands, and unused lands.
and construction lands, were selected as the explanatory variables because their combined area accounted for nearly 99% of the total area.

**Analysis framework.** A GWR analysis was used to determine the overall characteristic between the LULCC and PM$_{2.5}$ dynamics. After that, based on the spatial analysis tools in ArcGIS 10.2, a detail analysis was conducted from two aspects: (1) PM$_{2.5}$ distributions for the different LULC types, and (2) PM$_{2.5}$ dynamics for the different LULCC types. The analysis process is shown in Fig. 4.

**Results**

**Validation of the PM$_{2.5}$ data.** As mentioned above, station monitoring data can represent a scope from 0.5 to 4 km. Thus, a 4-km buffer from each monitoring station was generated. In the buffer, the mean values of the PM$_{2.5}$ data from ACAG were calculated and validated according to the station monitoring data. The results (Table 1) show an RMSE of 7.05 and a Pearson’s correlation coefficient of 0.82, which show that the ACAG PM$_{2.5}$ data have high consistency with the ground-based observational data.

**GWR analysis.** The GWR analysis showed that $R^2$ reached 0.94 which implies a good fitting effect. 93.56% of the standardized residuals were between −2 and 2, which demonstrates that the model fitting was stable.$^4$$^4$. The results show that there was a stable relationship between PM$_{2.5}$ and LULCC. As shown in Fig. 5, the local $R^2$ values were between 0.01 and 0.93. In contrast with the LULCC data, the high values of the local $R^2$ were distributed in places where the LULCC showed an obvious dynamic while the low local $R^2$ values were distributed in LULCC areas that did not change. The result indicated that dynamic PM$_{2.5}$ had a significant response to LULCC.

**Effect of the LULC type on PM$_{2.5}$.** To further investigate the relationship between the PM$_{2.5}$ dynamics and the different LULC types, a spatial analyze based on ArcGIS was conducted. The results (Table 2) show that, for all LULC types, the mean PM$_{2.5}$ concentrations significantly increased from 2000 to 2018. Among them, unused lands had the largest increase. Woodlands and grasslands had the largest increasing rates, 86.02% and 81.00%, respectively. Construction lands had the lowest increasing rate of 20.92%. The rates of increase of other the LULC types were relatively close, with a scope of 38.45% and 47.99%. The increasing trends indicate that the PM$_{2.5}$ pollution situation worsened during the study period. The standard deviations (SDs) all increased, meaning that the spatial difference of PM$_{2.5}$ pollution was increased. Indeed, the whole study area is faced with a seriously PM$_{2.5}$ polluted situation.

Furthermore, for the different LULC types, in 2000, woodlands had the lowest mean PM$_{2.5}$ concentration, although that of the grasslands was very similar. Construction lands had the highest mean PM$_{2.5}$ concentration. In 2018, the mean PM$_{2.5}$ concentrations of the woodlands and grasslands were still very close, and were

---

**Figure 3.** The land use and land cover data in 2000 and 2018.
still the lowest values. The PM$_{2.5}$ concentration of the construction lands was still the highest. In both 2 years, the order of PM$_{2.5}$ concentration for the different LULC types was the same: construction lands > unused lands > water > farmlands > grasslands > woodlands, meaning that the LULC type had an important influence on the PM$_{2.5}$ concentrations.

**Effect of the LULCC type on PM$_{2.5}$.**

As showed in Table 3, in 2000, the main land type in Shanxi Province was farmland, whose area was $6.12 \times 10^4$ km$^2$, accounting for 39.09% of the total area. Next in total area were grasslands and woodlands, accounting for 29.16% and 28.01% respectively. Construction lands covered $0.42 \times 10^4$ km$^2$, accounting for 2.67% of the total area. The areas of water and unused lands were very little, accounting for just 0.97% and 0.10% respectively. In 2018, although farmlands still covered the largest area, its area reduced to $5.78 \times 10^4$ km$^2$, accounting for 36.91% of the total area. The area of woodlands increased, accounting for 28.36% of the total area, and became the second largest land type. The area of grasslands decreased by $0.16 \times 10^4$ km$^2$ and became the third largest land type. The area of construction lands increased dramatically, and its proportion increased to 5.56%, which was two times greater than in 2000. Water and unused lands still covered very little area, accounting for 0.94% and 0.08% of the total, respectively.

From the perspective of land being converting from one type to another, there was a large conversion of farmlands to other land types, roughly $2.29 \times 10^4$ km$^2$. Grasslands, woodlands, and construction lands underwent the largest amounts of change, accounting for 53.47%, 23.07%, and 20.91% of the total converted area, respectively. On the other hand, the other land types that were converted to farmlands accounted for $1.95 \times 10^4$ km$^2$, which significant decreased the total area of farmlands. The main conversion types of woodlands to other land types were grasslands, farmlands and construction lands. The sources of woodlands were mainly grasslands and farmlands. It was seen that the amount of woodlands converted to other types, and those converted to woodlands, were nearly equivalent in total area. Grasslands showed a similar trend as seen for the woodlands, which also showed a relatively stable state. Construction lands were mainly converted to farmlands, which accounted for 82.51% of the total converted area. The total area of construction lands that were converted to other types was $0.22 \times 10^4$ km$^2$. The main conversion sources of construction lands were farmlands, grasslands, and woodlands, and the total conversion area was $0.67 \times 10^4$ km$^2$, which was caused by fast urbanization.

| PM$_{2.5}$ | Max   | Min   | Mean  | SD    | RMSE  | Pearson correlation |
|------------|-------|-------|-------|-------|-------|--------------------|
| Station monitoring | 84.03 | 30.42 | 58.18 | 12.01 | 7.05  | 0.82               |
| ACAG       | 74.40 | 32.20 | 59.78 | 11.19 |       |                    |

**Table 1.** Validation of the PM$_{2.5}$ data (units: μg/m$^3$).
Figure 5. Local $R^2$ values from the GWR analysis.

| LULC type         | 2000       | 2018       |
|-------------------|------------|------------|
|                   | Min | Max | Mean | SD | Min | Max | Mean | SD |
| Farmlands         | 0   | 75.90 | 25.34 | 14.40 | 1.00 | 72.90 | 37.50 | 14.60 |
| Woodlands         | 0   | 62.10 | 10.87 | 9.45 | 0.40 | 65.70 | 20.22 | 11.71 |
| Grasslands        | 0   | 60.80 | 15.21 | 11.51 | 0.40 | 68.90 | 27.53 | 12.71 |
| Water             | 0   | 72.30 | 29.78 | 16.04 | 1.80 | 73.10 | 41.23 | 15.16 |
| Construction lands| 0   | 75.60 | 33.92 | 13.58 | 1.70 | 74.40 | 43.95 | 14.45 |
| Unused lands      | 0   | 68.50 | 30.21 | 14.92 | 2.50 | 63.80 | 43.45 | 14.11 |

Table 2. PM$_{2.5}$ concentrations of different the LULC types (units: μg/m$^3$).

| 2000                | 2018              |
|---------------------|-------------------|
|                     | Farmlands | Woodlands | Grasslands | Water | Construction lands | Unused lands | Total   |
| Farmlands           | 38,293     | 5281      | 12,243     | 542   | 4788               | 41           | 61,188  |
| Woodlands           | 4984       | 31,572    | 6572       | 118   | 584                | 8            | 43,838  |
| Grasslands          | 12,058     | 7341      | 24,791     | 260   | 1162               | 25           | 45,637  |
| Water               | 574        | 85        | 182        | 507   | 153                | 23           | 1524    |
| Construction lands  | 1798       | 98        | 253        | 26    | 2005               | 4            | 4184    |
| Unused lands        | 58         | 15        | 19         | 12    | 14                 | 31           | 149     |
| Total               | 57,765     | 44,392    | 44,060     | 1465  | 8706               | 132          | 156,520 |

Table 3. LULCC in Shanxi Province between 2000 and 2018 (units: km$^2$).
PM$_{2.5}$ dynamics. As water and unused lands covered only 1% of the total area, we only considered the other four land types (farmlands, woodlands, grasslands, and construction lands) to ascertain the influence of the LULCC types on the PM$_{2.5}$ dynamics. As discussed above, the PM$_{2.5}$ concentrations considerably increased from 2000 to 2018 for all land types, which indicated that there would be a PM$_{2.5}$ concentration increase for non-LULCC areas. The increase was mainly caused by increased pollution levels, not by LULCC. This would bring disturbance to our analysis. To avoid this disturbance, the range of PM$_{2.5}$ concentration variations in non-LULCC areas was calculated first (Table 4) and set as the reference variation range when analyzing the PM$_{2.5}$ concentration variations in the LULCC areas.

As showed in Table 4, the PM$_{2.5}$ dynamics in the different LULCC types showed two opposing trends, increasing and decreasing. The largest increase was for woodlands converted to construction lands, while the largest decline was for woodlands converted to farmlands. When farmlands were converted to woodlands and grasslands, the PM$_{2.5}$ concentrations declined, but when they were converted to construction lands, the PM$_{2.5}$ concentration increased. Increasing trends were seen when woodlands were converted to the other three land types. Conversely, declining trends were found when construction lands were converted to the other land types. When grasslands were converted to woodlands, a declining trend was witnessed, but when they were converted to the other two land types, increasing trends were seen.

As discussed above, the PM$_{2.5}$ concentrations for the four land types showed similar trends in both years: construction lands > farmlands > grasslands > woodlands. Therefore, according to the PM$_{2.5}$ concentrations, the four land types were divide into four grades: highest (construction lands), high (farmlands), medium (grasslands) and low (woodlands). As showed in Table 5, when high-grade land types are converted to low-grade types, the PM$_{2.5}$ concentrations decrease, and when low-grade land types are converted to high-grade types, the PM$_{2.5}$ concentrations increase.

**Table 4.** Dynamic PM$_{2.5}$ concentrations in the non-LULCC areas (units: μg/m$^3$).

| LULCC type                  | PM$_{2.5}$ concentration | Reference variation range |
|-----------------------------|--------------------------|---------------------------|
|                             | 2000         | 2018     |                |
| Farmland to farmland        | 27.98        | 40.46    | 12.48          |
| Woodland to woodland        | 10.16        | 18.79    | 8.63           |
| Grassland to grassland      | 14.85        | 27.33    | 12.48          |
| Construction land to construction land | 35.58    | 50.67    | 15.09          |

**Table 5.** Dynamic PM$_{2.5}$ concentrations in the LULCC areas (units: μg/m$^3$).

| LULCC type                  | PM$_{2.5}$ concentration | Variation range | Reference variation range | Variation trend |
|-----------------------------|--------------------------|-----------------|---------------------------|----------------|
| Farmland to woodland        | 15.58                    | 26.11           | 10.53                     | 12.48          | −1.94↓         |
| Farmland to grassland       | 18.73                    | 30.74           | 12.01                     | 12.48          | −0.47↓         |
| Farmland to construction land| 31.30                   | 45.52           | 14.22                     | 12.48          | 1.74↑          |
| Farmland to farmland        | 16.00                    | 26.57           | 10.57                     | 8.63           | 1.95↑          |
| Woodland to woodland        | 9.69                     | 21.99           | 12.30                     | 8.63           | 3.68↑          |
| Woodland to construction land| 16.28                   | 28.81           | 12.53                     | 8.63           | 3.90↑          |
| Woodland to farmland        | 18.76                    | 31.48           | 12.26                     | 12.48          | 0.24↓          |
| Woodland to grassland       | 9.77                     | 21.87           | 12.09                     | 12.48          | −0.39↓         |
| Grassland to farmland       | 18.82                    | 33.82           | 15.01                     | 12.48          | 2.52↑          |
| Grassland to construction land| 33.71                   | 47.32           | 13.61                     | 15.09          | −1.47↑         |
| Grassland to woodland       | 20.31                    | 34.48           | 14.18                     | 15.09          | −0.91↓         |
| Grassland to construction land| 20.69                   | 35.25           | 14.56                     | 15.09          | −0.53↓         |

**Discussion**

As an important energy base, the economic development of Shanxi Province has been mainly based on energy consumption, which continues to generate large quantities of harmful emissions. Therefore, human activities were considered as the most important influence factor of PM$_{2.5}$ pollution. However, LULC types were also representative of different human activities. Different to previous studies, which mainly focused on discussing the relationship between land use type and PM$_{2.5}$ concentrations at urban scales, in this study we discussed the impact of land use on PM$_{2.5}$ concentrations from two aspects: different LULC and LULCC types at regional scales.

The different LULC types indicated the different intensities of human activities. Construction lands represented the highest intensity because of the high population density, traffic flow, industrial and commercial activities, etc., therein. All of these generate large quantities of air pollutants and caused the highest PM$_{2.5}$
concentrations\(^{48}\). Farmlands were also intensively affected by human activities, which caused relatively high PM\(_{2.5}\) concentrations. Firstly, straw burning in farmlands can result in a sharp increase of PM\(_{2.5}\) concentration within a short time\(^{49}\). Secondly, as a great agricultural country, the use of fertilizer in China is pervasive, and emissions arising from the manufacturing and use of fertilizer have a strong relationship with PM\(_{2.5}\)\(^{50}\). For example, fertilizer liberated from the soil can be converted into a precursor of PM\(_{2.5}\)\(^{51}\). Thirdly, heating activities in rural areas in winter mainly consist of burning coal, which generates large quantities of air pollutants and has an important impact on the PM\(_{2.5}\) concentration in farmlands\(^{52,53}\). Vegetation covered area, including woodlands and grasslands, had relatively low PM\(_{2.5}\) concentrations. These areas were less influenced by human activities, as indicated by the lower pollutant emissions therein. Meanwhile, it has been suggested that vegetation coverage has a negative regulating effect on PM\(_{2.5}\) concentration\(^{54,55}\). Thus, woodlands have the lowest PM\(_{2.5}\) concentrations because of their highest vegetation coverage.

The different LULCC types represented transitions among the different intensities of human activities, which caused dynamic changes of the PM\(_{2.5}\) concentrations. When other land types were converted to construction lands, the intensity of human activities increased, which caused an increase of PM\(_{2.5}\) concentration. A similar conclusion was found in another study, which showed that when natural land cover is replaced by manmade areas PM\(_{2.5}\) concentrations increase\(^{58}\). Furthermore, other LULCC types were also discussed in our study. Farmlands may also contain intense human activities that can increase the PM\(_{2.5}\) concentration, such as agricultural activities\(^{57,58}\). This was demonstrated by the increasing trend of PM\(_{2.5}\) concentration when woodlands and grasslands were converted to farmlands. As vegetation coverage had a negative effect on PM\(_{2.5}\) concentration\(^{55}\), the PM\(_{2.5}\) concentration also changed when the vegetation type changed; i.e., an increase trend was seen when woodlands were converted to grasslands.

Due to the limited LULC data, this study illustrated the influence of LULC and LULCC on PM\(_{2.5}\) at the regional scale where human activities were considered as the most important influence factor. However, PM\(_{2.5}\) pollution is both affected by human and natural factors\(^{59}\). In desert areas, natural factors including dust and wind could be the most important factors\(^{46}\), while in coastal areas, climatic elements had the most important influence on PM\(_{2.5}\) pollution\(^{57}\). These situations were not discussed in the present study. Future studies at larger scales are required to demonstrate the influence of LULC on PM\(_{2.5}\) more comprehensively. The relationship between PM\(_{2.5}\) pollution and its influence factors is complex and non-linear\(^{61}\). Traditional linear analysis methods have certain limitations and new non-linear analysis methods should be employed. Moreover, higher spatial and temporal resolution PM\(_{2.5}\) data and LULC data are also required to better understand the response mechanism of PM\(_{2.5}\) pollution to LULCC.

Conclusions
In this study, high-accuracy PM\(_{2.5}\) data from ACAG and LULC data were employed to explore the relationship between PM\(_{2.5}\) and LULCC. A GWR method was used for the general analysis, and a spatial analysis method based on the geographic information system was used for the detailed analysis. The main conclusions can be drawn as follows:

1. The GWR analysis showed that R\(^2\) reached 0.92, which represented a stable relationship between PM\(_{2.5}\) and LULCC. High local R\(^2\) values located in highly dynamic LULCC areas indicated that the dynamic PM\(_{2.5}\) had a significant response to LULCC.
2. In both considered years, 2000 and 2018, the order of PM\(_{2.5}\) concentration in the different LULC types was the same: construction lands > unused lands > water > farmlands > grasslands > woodlands, meaning that the LULC type had an important influence on the PM\(_{2.5}\) concentration.
3. LULCC can also impact the dynamics of PM\(_{2.5}\) concentration. When low-grade land types are converted to high-grade types, the PM\(_{2.5}\) concentration increases; otherwise, it decreases. From another angle, when natural lands are converted to human-related lands, the PM\(_{2.5}\) concentration increase; otherwise, the PM\(_{2.5}\) concentrations decrease.

Received: 13 February 2021; Accepted: 17 August 2021
Published online: 02 September 2021

References
1. Ru-Jin, H. et al. High secondary aerosol contribution to particulate pollution during haze events in China. *Nature* **514**, 218–222 (2014).
2. Bilal, M., Nichol, J. E. & Spak, S. N. A new approach for estimation of fine particulate concentrations using satellite aerosol optical depth and binning of meteorological variables. *Aerosol Air Quality Res.* **17**, 356–367. [https://doi.org/10.4209/aaqr.2016.03.0097](https://doi.org/10.4209/aaqr.2016.03.0097) (2017).
3. Götschi, T., Heinrich, J., Sunyer, J. & Künzli, N. J. E. Long-term effects of ambient air pollution on lung function: A review. *Epidemiology* **19**, 690–701 (2008).
4. Jiang, Z., Kaukoaho, I., Ramona, L., Morton, L. & George, T. J. E. H. P. Time-series analysis of mortality effects of fine particulate matter components in Detroit and Seattle. *Environ. Health Perspect.* **119**, 461–466 (2011).
5. Weichenthal, et al. PM2.5, oxidant defence and cardiorespiratory health: a review. *Environ. Health. 12*, 40–40 (2013).
6. Calmaik, S. et al. Metal composition of fine particulate air pollution and acute changes in cardiorespiratory physiology. *Environ. Pollut.* **189**, 208–214 (2014).
7. Zha, Y. et al. Indoor/Outdoor relationships and diurnal/nocturnal variations in water-soluble ion and PAH concentrations in the atmospheric PM 2.5 of a business office area in Jinan, a heavily polluted city in China. *Atmos. Res.* **153**, 276–285 (2015).
8. Zhao, C. X., Wang, Y. Q., Wang, Y. J., Zhang, H. L. & Zhao, B. Q. J. E. S. Temporal and spatial distribution of PM_{2.5} and PM_{10} pollution status and the correlation of particulate matters and meteorological factors during Winter and Spring in Beijing. Environ. Sci. Technol. 35, 418–427 (2014).

9. Guo, J. et al. Impact of diurnal variability and meteorological factors on the PM2.5—AOD relationship: Implications for PM2.5 remote sensing. Environ. Pollut. 221, 94 (2017).

10. Hajiloo, F., Hamzeh, S. & Ghayarsi, M. Impact assessment of meteorological and environmental parameters on PM 2.5 concentrations using remote sensing data and GWR analysis (case study of Tehran). Environ. Sci. Pollut. Res. 26, 24331–24345 (2018).

11. Bao, C. et al. Association of PM2.5 pollution with the pattern of human activity: A case study of a developed city in eastern China. J. Air Waste Manag. Assoc. 66, 1202–1213 (2016).

12. Chan, C. K. & Yao, X. Air pollution in megacities in China. Atmos. Environ. 42, 1–42 (2008).

13. Kinney, P. L. et al. Traffic impacts on PM2.5 air quality in Nairobi. Kenya. Environ. Sci. Policy 14, 369–378 (2011).

14. Jing, M., Liu, J., Yuan, X. & Shu, T. Tracing primary PM2.5 emissions via Chinese supply chains. Environ. Res. Lett. 10, 054005 (2015).

15. Tao, C., He, J., Lu, X., She, J. & Guan, Z. Spatial and temporal variations of PM2.5 and its relation to meteorological factors in the urban area of Nanjing, China. Int. J. Environ. Res. Public Health 13, 921 (2016).

16. Wang, Y., Qi, Y., Hu, J. & Zhang, H. Spatial and temporal variations of six criteria air pollutants in 31 provincial capital cities in China during 2013–2014. Environ. Int. 73, 413–422 (2014).

17. Zhang, H., Wang, Z. & Zhang, W. Exploring spatiotemporal patterns of PM 2.5 in China based on ground-level observations for 190 cities. Environ. Pollut. 216, 559–567 (2016).

18. Li, X. et al. The application of semicircular-buffer-based land use regression models incorporating wind direction in predicting quarterly NO2 and PM 10 concentrations. Atmos. Environ. 103, 18–24 (2015).

19. Li, L. et al. Spatial and temporal analysis of Air Pollution Index and its timescale-dependent relationship with meteorological factors in Guangzhou, China, 2001–2011. Environ. Pollut. 190, 75–81 (2014).

20. Mazeikis, A. Urbanization influence on meteorological parameters of air pollution: Vilnius case study. Baltic Int. J. Geosci. 26, 51–57 (2013).

21. Zhang, Y. L. & Cao, F. Fine particulate matter (PM 2.5) in China at a city level. Sci. Rep. 5, 14884 (2015).

22. Wang, X., Wang, K. & Su, L. Contribution of atmospheric diffusion conditions to the recent improvement in air quality in China. Sci. Rep. 6, 36404 (2016).

23. Bandeira, J. M., Coelho, M. C., Maria Elisa, S., Richard, T. & Carlos, B. Impact of land use on urban mobility patterns, emissions and air quality in a Portuguese medium-sized city. Sci. Total Environ. 409, 1154–1163 (2011).

24. De, H. C. A regression-based method for mapping traffic-related air pollution: Application and testing in four contrasting urban environments. Sci. Total Environ. 253, 151–167 (2000).

25. Lu, C., Henderson, B. H., Wang, D., Yang, X. & Peng, Z. R. A land use regression application into assessing spatial variation of intra-urban fine particulate matter (PM 2.5) and nitrogen dioxide (NO2) concentrations in City of Shanghai. China. Sci. Total Environ. 565, 607–615 (2016).

26. Yang, W. & Jiang, X. Interannual characteristics of fine particulate matter in North China and its relationship with land use and land cover change. Environ. Sci. 41, 2995–3003 (2020).

27. Petit, C. C. & Lambin, E. F. Impact of data integration technique on historical land-use/land-cover change: Comparing historical maps with remote sensing data in the Belgian Ardennes. Landsc. Ecol. 17, 117–132 (2002).

28. Zadbagher, E., Becce, K. & Berberoglu, S. Modeling land use/land cover change using remote sensing and geographic information systems: Case study of the Seyhan Basin, Turkey. Environ. Monitor. Assess. 190, 494 (2018).

29. Sun, S. et al. Regulation of pollution change and correlation analysis with vegetation index in Beijing–Tianjin–Hebei. Environ. Sci. Technol. https://doi.org/10.1021/acs.est.8b03170 (2018).

30. Smith, R. L., Kolenikov, S. & Cox, L. H. Spatiotemporal modeling of PM2.5 data with missing values. J. Geophys. Res. Atmos. 108, D24 (2003).

31. Chemel, C. et al. Application of chemical transport model CMAQ to policy decisions regarding PM2.5 in the UK. Atmos. Environ. 82, 410–417 (2014).

32. Shi, Y., Lau, K. L. & Ng, E. Developing street-level PM2.5 and PM10 land use regression models in high-density Hong Kong with urban morphological factors. Environ. Sci. Technol. 50, 8178–8187 (2016).

33. Xuefei, H. U. et al. Estimating ground-level PM2.5 concentrations in the Southeastern United States using MAIAC AOD retrievals and a two-stage model. Remote Sens. Envir. 140, 220–232 (2014).

34. Van, D. A. et al. Global estimates of fine particulate matter using a combined geophysical–statistical method with information from satellites, models, and monitors. Environ. Sci. Technol. 50, 3762 (2016).

35. Van Donkelaar, A., Martin, R. V., Li, C. & Burnett, R. T. Regional estimates of chemical composition of fine particulate matter using a combined geosciences-statistical method with information from satellites, models, and monitors. Environ. Sci. Technol. 53, 2595–2611 (2019).

36. Yang, H., Chen, W., Liang, Z. J., J. O. E. R. & Health, P. Impact of land use on PM25 pollution in a representative city of middle China. Int. J. Environ. Res. Public Health 14, 462 (2017).

37. Sun, L. et al. Impact of Land-Use and Land-Cover Change on urban air quality in representative cities of China. J. Atmos. Solar-Terrest. Phys. 142, 43–54 (2016).

38. Yang, D. et al. Global distribution and evolvement of urbanization and PM2.5 (1998–2015). Atmos. Environ. 182, 171–178 (2018).

39. Zheng, S. et al. The spatiotemporal distribution of air pollutants and their relationship with land-use patterns in Hangzhou city, China. Atmosphere 8, 110 (2017).

40. Wu, J., Xie, W., Li, W. & Li, J. Effects of urban landscape pattern on PM2.5 pollution—a Beijing case study. PloS one 10, e0142449 (2015).

41. Hammer, M. S., Donkelaar, A. V., Li, C., Lyapustin, A. & Martin, R. V. Global estimates and long-term trends of fine particulate matter concentrations (1998–2018). Environ. Sci. Technol. 54, 7879–7890 (2020).

42. Propastin, P. Modifying geographically weighted regression for estimating aboveground biomass in tropical rainforests by multi-spectral remote sensing data. Int. J. Appl. Earth Observ. Geoinform. 18, 82–90 (2012).

43. Jiang, M., Sun, W., Yang, G. & Zhang, D. Modelling seasonal GWR of daily PM2.5 with proper auxiliary variables for the Yangtze River Delta. Remote Sens. 9, 346 (2017).

44. Xiya, Z. & Haibo, H. Spatio-temporal characteristics of aerosol optical depth and their relationship with urbanization over Beijing–Tianjin–Hebei Region. Chin. J. Atmos. Sci. 41, 797–810 (2017).

45. Yang, W. & Jiang, X. Evaluating sustainable urbanization of resource-based cities based on the Mckinsey matrix: Case study in China. J. Urban Plan. Dev. 144, 05017020 (2018).

46. Li, X. et al. A new global land-use and land-cover change product at a 1-km resolution for 2010 to 2100 based on human–environment interactions. Ann. Am. Assoc. Geogr. 107, 1–20 (2017).

47. Li, J. & Huang, X. Impact of land-cover layout on particulate matter 2.5 in urban areas of China. Int. J. Digit. Earth 13, 474–486 (2018).

48. Bismarck-Osten, C. V. et al. Characterization of parameters influencing the spatio-temporal variability of urban particle number size distributions in four European cities. Atmos. Environ. 77, 415–429 (2013).
49. Zhang, L., Liu, Y. & Hao, L. J. E. R. L. Contributions of open crop straw burning emissions to PM2.5 concentrations in China. *Environ. Res. Lett.* **11**, 014014 (2016).
50. Pozzer, A. *et al.* Impact of agricultural emission reductions on fine-particle matter and public health. *Atmos. Chem. Phys.* **17**, 1–19 (2017).
51. Han, L. *et al.* Meteorological and urban landscape factors on severe air pollution in Beijing. *J. Air Waste Manag. Assoc.* **65**, 782–787 (2015).
52. Fan, M., He, G. & Zhou, M. The winter choke: Coal-fired heating, air pollution, and mortality in China. *J. Health Econ.* **71**, 102316 (2020).
53. Xiao, Q., Ma, Z., Li, S. & Liu, Y. The impact of winter heating on air pollution in China. *PloS One* **10**, e0117311 (2015).
54. Yanan, L., Zhenming, D., Yuanjie, D., Mengyang, H. & Shunbo, Y. Relationship between urban industrialization and PM2.5 in China: Also discussing the internal mechanism of EKC. *Environ. Sci.** **41**, 1987–1996 (2020).
55. Tong, Z., Whillow, T. H., Macrae, P. E., Landers, A. J. & Harada, Y. Quantifying the effect of vegetation on near-road air quality using brief campaigns. *Environ. Pollut.* **201**, 141–149 (2015).
56. Superczynski, S. D. & Christopher, S. A. Exploring land use and land cover effects on air quality in Central Alabama using GIS and remote sensing. *Remote Sens.* **3**, 2552–2567 (2011).
57. Zhang, H. *et al.* Emission characterization, environmental impact, and control measure of PM2.5 emitted from agricultural crop residue burning in China. *J. Clean. Prod.* **149**, 629–635 (2017).
58. Li, J. *et al.* Chemical characteristics and source apportionment of PM2.5 during the harvest season in eastern China's agricultural regions. *Atmos. Environ.* **92**, 442–448 (2014).
59. Yang, D. *et al.* Quantifying the influence of natural and socioeconomic factors and their interactive impact on PM2.5 pollution in China. *Environ. Pollut.* **241**, 475–483 (2018).
60. Xu, J., Zhou, G., Xu, Z. & De Zhou, S. Urban haze governance: Land use spatial conflict and governance urban air duct. *China Land Sci.* **29**, 49–56 (2015).
61. Lu, D., Mao, W., Xiao, W. & Zhang, L. Non-linear response of PM2.5 pollution to land use change in China. *Remote Sens.* **13**, 1612 (2021).

**Acknowledgements**

Funding for this study was obtained through the National Natural Science Foundation of China (No. 41701191), the Applied Basic Research Plan of Shanxi Province, China (No. 201701D221226) and the Science and Technology Innovation Project of Universities in Shanxi Province, China (No. 2019L0815). We are grateful to ACAG for providing the PM2.5 data used in this study. The authors also thank the reviewers for their valuable comments and suggestions.

**Author contributions**

W.Y. wrote the paper, X.J. processed the data.

**Competing interests**

The authors declare no competing interests.

**Additional information**

**Correspondence** and requests for materials should be addressed to W.Y.

**Reprints and permissions information** is available at www.nature.com/reprints.

**Publisher's note** Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

**Open Access** This article is licensed under a Creative Commons Attribution 4.0 International License, which permits use, sharing, adaptation, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons licence, and indicate if changes were made. The images or other third party material in this article are included in the article's Creative Commons licence, unless indicated otherwise in a credit line to the material. If material is not included in the article's Creative Commons licence and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder. To view a copy of this licence, visit http://creativecommons.org/licenses/by/4.0/.

© The Author(s) 2021