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Impact of land-cover layout on particulate matter 2.5 in urban areas of China

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ABSTRACT

Urbanization in China is closely connected with ambient particulate matter 2.5 ($PM_{2.5}$). However, the potential for altering $PM_{2.5}$ through the urban landscape characteristics is uncertain. In this study, we analyzed the urban $PM_{2.5}$ pollution situation for 2014–2016 and investigated the impact of landscape factors on urban $PM_{2.5}$ in China at the city level. All the prefecture-level cities were stratified by urban population size into *small* (<500,000), *medium* (500,000–1,000,000), and *large* (>1,000,000), and the other second-level administrative cities were assigned as '*other*' cities. The multivariate regression model including both urban landscape factors and social-economic variables explained 70.0%, 32.8%, 19.2%, and 12.4% of the arithmetic mean $PM_{2.5}$ concentration (AMC-$PM_{2.5}$) for the *other*, *small*, *medium*, and *large* cities, respectively. With regard to the configuration of land cover, agricultural activity is a major contributor of $PM_{2.5}$ pollution, for which the explanatory power ranged from 7.6% (for the *large* cities) to 64% (for the *other* cities). In addition, grassland aggregation also has a limited but negative effect on urban $PM_{2.5}$ pollution, despite the negligible effect on dry deposition. Overall, these findings likely reflect the interaction between urban air quality and urbanization, and will have implications for air quality control strategies.

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$PM_{2.5}$; China; urban landscape; urbanization; land cover

1. Introduction

Air pollution, in which ambient fine particulate matter ($PM_{2.5}$) acts as a vital protagonist, has aroused widespread public concern. Numerous studies have indicated that even short-term human exposure to $PM_{2.5}$ is associated with increased cardiovascular and respiratory morbidity and mortality (Zhou et al. 2011; Wang et al. 2014), especially for the elderly (Zeng et al. 2010). As the world's second-largest economy and the most populous nation, more than 56% of the population of China, which is higher than the global average level (54%) (Marchand and Siegel 2015), live in urban areas, and this number is projected to reach 73% by 2050 (United Nations 2012). For China, as one of the hardest-hit areas and a rapidly developing country, it has been documented that more than 500 million urban residents are at risk of severe $PM_{2.5}$ pollution (He, Han, and Zhang 2016). However, to date, the mechanisms leading to urban $PM_{2.5}$ formation in China remain highly

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Supplemental data for this article can be accessed here https://doi.org/10.1080/17538947.2018.1530310 uncertain, in part because of the capricious climate, complex chemical components (Zhang et al. 2015), and diverse sources of urban $PM_{2.5}$ in different regions (Hu et al. 2017).

Sustainable economic and social development is essential to eradicate poverty while ensuring environmental protection (McCarty and Kaza 2015). A number of studies have focused on the relationships between urban form characteristics and $PM_{2.5}$ exposure. For instance, Clark, Millet, and Marshall (2011) investigated the effects of population form (including density and centrality) and transit supply on $PM_{2.5}$ in 111 U.S. urban areas, and McCarty and Kaza (2015) focused on the correlation between urban area form and $PM_{2.5}$ in metropolitan areas of America. It is noted that these studies have limited applicability with regard to China, as a result of the large differences between China and the other study areas. Meanwhile, several studies have attempted to explore the interaction between the $PM_{2.5}$ of China and urban characteristics, mainly at the individual city level (e.g. Beijing [Han et al. 2015b; Fan et al. 2017] and Wuhan [Xu et al. 2016]) or the urban agglomeration level (e.g. Jing-Jin-Ji, Yangtze River Delta, Pearl River Delta, Chang-Zhu-Tan, Chengdu-Chongqing, and Guanzhong [Feng, Zou, and Tang 2017]). Nonetheless, experts have called for a more thorough consideration of China's urbanization at the national scale (Han, Zhou, and Li 2015a; Li et al. 2016; Wang et al. 2017). However, there are still three main research gaps with regard to these national-scale studies. Firstly, the study periods of most of the studies are pre-2015 (e.g. 246 prefecture-level cities during 1999–2011 [Li et al. 2016], 190 cities in 2013 [Zhang and Cao 2015], and 190 cities in 2014 [Wang et al. 2017]), while both the general public and the authorities are more concerned with the current pollution situation, especially since the most recent revision of the environmental protection laws in China (2014). Secondly, limited by the relatively low urbanization level and the sparsely distributed $PM_{2.5}$ monitoring stations, some autonomous prefectures (i.e. cities at the second administrative level,) have attracted much less concern than the prefecture-level cities, as mentioned before. Thirdly, composition-related landscape factors (e.g. built-up proportion, ecological land proportion [Han et al. 2015b]), nighttime light intensity (Larkin et al. 2016), and population data (e.g. population density [Han, Zhou, and Li 2015a] and urbanization-induced population migration [Shen et al. 2017]) have been the major focus in recent studies, in addition to statistical data (Li et al. 2016) and gross domestic product (Wang et al. 2017). Meanwhile, the effect of each land-cover type on $PM_{2.5}$ pollution concentration is less well understood and requires further study. For instance, in 2015, Suzhou and Wuhu, two large cities in Anhui province, experienced AMC-$PM_{2.5}$ concentrations that were significantly different (71.75 μg/m^3 in Suzhou and 49.09 μg/m^3 in Wuhu), despite the cities being mainly affected by similar pollution sources, including dust and vehicle emissions. It is of interest to note that these two cities are comparable in built-up proportion and numbers of residents (31.4/32.2% for built-up proportion and 1.47/1.67 million urban residents), but there is a large discrepancy in the average size of the built-up parcels within the urban areas (4.29 ha. for Suzhou and 6.68 ha. for Wuhu, it is mentioned that all these parameters are calculated in this research, the below is same). That is to say, it is of value to analyze the associations between spatial layout (i.e. both composition and configuration) of land cover and $PM_{2.5}$ in the different urban levels of China, as cities of different sizes may suffer from specific problems.

In view of this, by controlling the natural environmental, population, and economic factors, this study was aimed at quantifying the effects of the urban land-cover landscape on the arithmetic mean $PM_{2.5}$ levels (AMC-$PM_{2.5}$) in China for 2014–2016, using a multivariate regression model. We used the available long-term datasets in relation to AMC-$PM_{2.5}$ levels to analyze the large-scale spatial (Figure 1) and temporal (i.e. seasonal and monthly) variations (Figure 2). In the meantime, the availability of remote sensing data enabled the analyses to be undertaken at a larger spatial extent (including all the cities at the second administrative level in mainland China) and finer resolution (e.g. 30 m for land cover) than had previously been possible. It is noted that cities of different levels may suffer from specific $PM_{2.5}$ problems. For instance, cropland landscapes are more important for small cities with agriculture-based economies, while

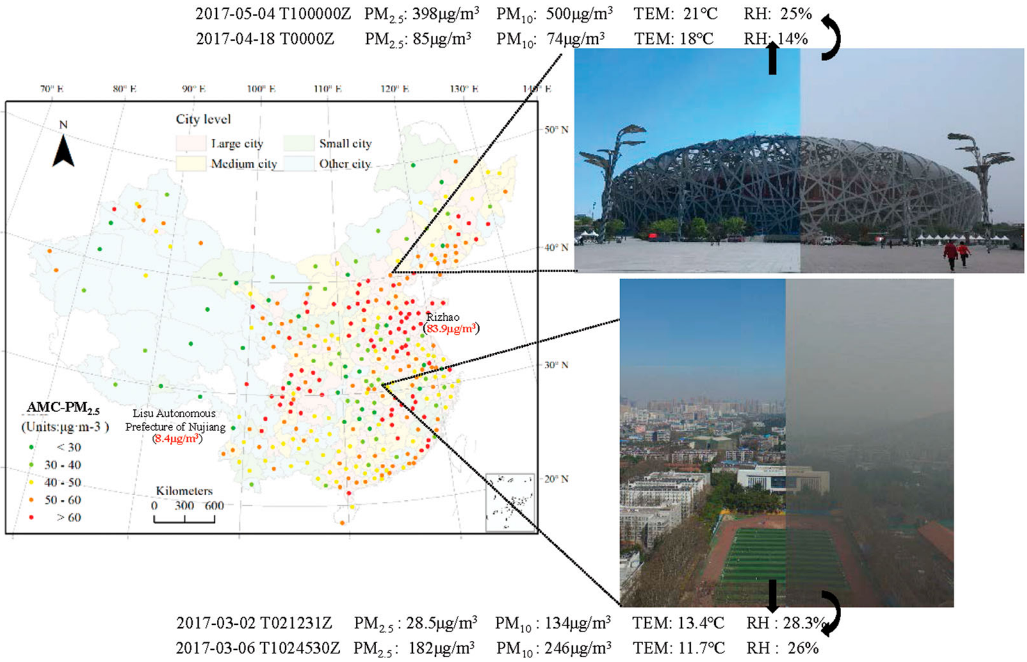

Figure 1. The current AMC-$PM_{2.5}$ state of China. Left: long-term two-year arithmetic mean concentrations of $PM_{2.5}$ for each of the 325 cities evaluated from 01 June 2014 to 31 May 2016. Top right: two digital photos (taken on a high air quality day and a foggy day, respectively, where TEM and RH are short for temperature and relative humidity, respectively) from the Bird's Nest Stadium, Beijing. Bottom right: similar photos from the campus of Wuhan University, Wuhan.

built-up/population-related factors are more important for metropolises such as Wuhan. In view of this, by controlling for all the confounding factors, we addressed the effects of the urban landscape at each city level, according to the urban scale division of the State Council of China. Finding strategies to balance urban air pollution, development levels, and land-cover functions in these areas, including a more sustainable management of urban planning, will be essential for China to achieve the goals of the Action Plan on Prevention and Control of Air Pollution (available at: http://www.gov.cn/zwgk/2013-09/12/content_2486773.htm).

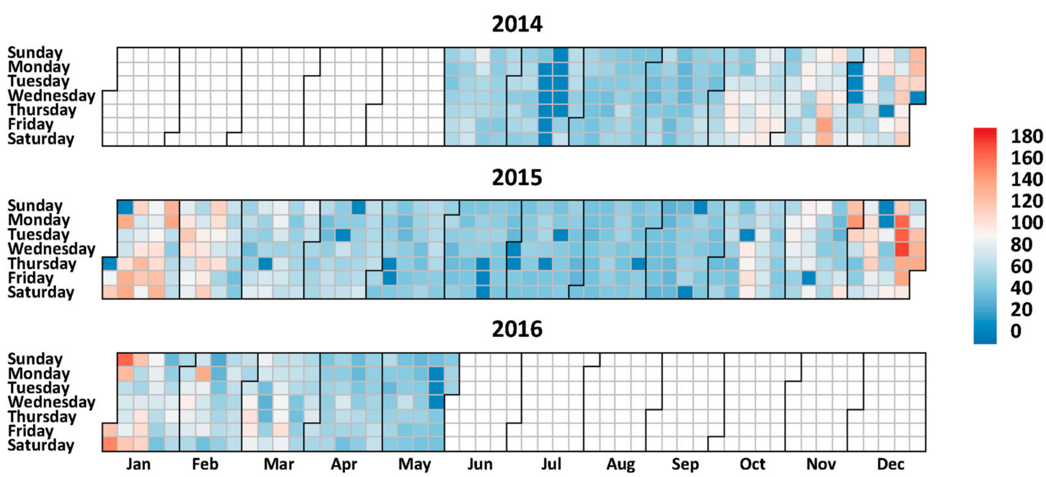

Figure 2. Average arithmetic mean $PM_{2.5}$ levels of the 325 cities in China, from 01 June 2014 to 31 May 2016.

2. Materials and methods

2.1. Urban area extraction

The materials used for the urban area extraction were the China Land Use/Cover Dataset (CLUD), including a 30 m summary of built-up land for the year circa 2015 (Liu et al. 2014), an elevation dataset (website: http://earthexplorer.usgs.gov/), and the administrative boundaries (website: http://www.gadm.org). The producer's accuracies and user's accuracies of all the thematic categories of the CLUD data have been reported to be higher than 90% (Liu et al. 2014). The urban area boundary delineation was based on the following three steps (Zhou et al. 2014): 1) a built-up intensity map was produced for each city by a 1 km × 1 km moving window method based on the CLUD data; 2) the built-up intensity map was split into high- and low-intensity land according to a 50% threshold; and 3) the built-up parcels were gathered in the high-intensity land by an aggregation distance of 2 km. Given the urban boundary for each city, the pollution data and the urban landscape factors were then both averaged at the city level.

2.2. Urban $PM_{2.5}$ estimation

The severe PM pollution status in China has forced the government to act. On 29 February 2012, the third revision of the National Ambient Air Quality Standards (NAAQS) (GB 3095–2012) (Chinese Ministry of Environmental Protection (MEP) 2012) was published, in which $PM_{2.5}$ was included in the NAAQS for the first time. Since then, a national network of real-time hourly $PM_{2.5}$ monitoring stations (made up of 1,510 monitoring stations, see: http://www.cnemc.cn/) has been gradually established. The values from the monitoring stations at each city are automatically reported to the MEP, and are published after being validated through the Technical Guideline on Environmental Monitoring Quality Management (HJ 630–2011) (Chinese MEP 2011).

The study period ranges from 01 June 2014 to 31 May 2016 (data are missing or invalid for 15–23 July, 28 July, and 04 October 2014; 01 January 2015; and 09 January 2016, and were thus removed, see Figure 2). In this study, to produce long-term pollution data for the individual sites, a quality check was first conducted on the hourly data to remove problematic data points (e.g. nonnumeric recordings), and the available daily average was calculated only when there were valid data for more than 20 h during the day. The inclusion criteria for the monitoring stations were: 1) available observations for at least 75% of the days in the study period; 2) designated as non-source oriented (i.e. 'ambient'); and 3) located in urban areas. In this way, data from 738 stations in 325 cities were used in this research.

Due to the spatially uneven distribution of the stations, we needed to interpolate the ground site data into surface data. In a similar way to the calculation approach presented in Clark, Millet, and Marshall (2011), Equations (1) and (2) were used to calculate the daily population-weighted (PW) and arithmetic mean (AM) $PM_{2.5}$ concentrations for each urban area:

$$\mathrm{PWC} = \frac{\sum_{i=1}^{n}(p_i \cdot c_i)}{\sum_{i=1}^{n} p_i} \tag{1}$$

$$\mathrm{AMC} = \frac{\sum_{i=1}^{n} c_i}{n} \tag{2}$$

where c_i, p_i are the interpolated concentration (using inverse distance weighting of the daily available observations from the three nearest monitoring stations within 50 km) and estimated population (from the latest gridded population dataset for the year 2010, relative error: 4.5–13.6%, Fu, Jiang, and Huang [2014]) in each 1 km grid cell i within the urban area; and n is the number of 1 km grid cells within the urban area. Given the daily $PM_{2.5}$ pollution level, two annual averages (01 June 2014 to 31 May 2015; and 01 June 2015 to 31 May 2016, to average the mean concentration levels of each day in a civil year) and the two-year average concentration were then estimated.

2.3. Spatial metrics of urban land cover

In landscape ecology, land-cover map patterns represent the data of interest as a mosaic of discrete patches. Each patch is a continuous parcel in a free-form shape, where each pixel in a patch belongs to the same land-cover type. Table 1 summarizes the urban land-cover layout factors utilized in this study, which were estimated from the CLUD, which is a ∼30 m gridded summary of national land cover (including cropland (CL), grassland (GL), water bodies, forest, and built-up land (BL)). We used FRAGSTATS (McGarigal et al. 2002), which is a spatial pattern analysis package, to quantify the spatial composition and configuration. In this study, proportion, elongation, aggregation, and isolation for each land-cover type were calculated. The abbreviation of the metric is prefixed with the short name of the land-cover type. For instance, CL_PLAND refers to the proportion of cropland within the urban area. Table A.1 summarizes the independent variables considered in each city group.

2.4. Stratified statistical analysis

According to the urban scale division of the State Council of China (available at: http://www.gov.cn/zhengce/content/2014-11/20/content_9225.htm) and the sixth national census (the latest and most detailed, available at: http://www.stats.gov.cn/ztjc/zdtjgz/zgrkpc/dlcrkpc/dlcrkpczl/), the prefecture-level cities were grouped as, *small*, *medium*, and *large* (Table 2). In addition to these prefecture-level cities, there were 48 secondary administrative cities, including 27 minority-nationality autonomous prefectures, 11 minority-nationality autonomous municipalities, and some county-level cities. Although accounting for a considerable proportion of the urban areas in China, these cities have attracted much less concern, due to the lack of measurements of the factors of interest. In this study, we classified these cities as the '*other*' city group (Table 2). We first evaluated the daily, annual, and two-year average $PM_{2.5}$ pollution levels in the 325 cites of China. The four city groups were compared by ANOVA analysis, including a summary of AMC-$PM_{2.5}$ and its difference with PWC-$PM_{2.5}$. Finally, to investigate the relationship between the spatial metrics of land cover and AMC-$PM_{2.5}$, a multivariate linear regression model (Broman and Speed 2002) for each city group was applied, with the model structures consisting of a subset of variables selected via forward and backward stepwise regression. A univariate association analysis (including zero-order and partial Pearson correlations) was also conducted to endorse the correlations between the selected factor and AMC-$PM_{2.5}$. The adjusted factors used in the regression model included both natural environmental and socio-

Table 1. Landscape pattern metrics used in the study.

Metric (abbreviation)	Equation	Description
Proportion of the urban area occupied by one land-cover type (PLAND)	$sum_{i,j=1}^{n_i} a_{i,j}/A$	A measure of the proportion of the total area occupied by one land-cover type.
Largest patch index of one land-cover type (LPI)	$\max_{i,j=1}^{n_i} a_{i,j}/A$	The percentage of the urban area comprised by the largest land-cover type.
Area-weighted mean of the related circumscribing circle of one land-cover type (CIRCLE_AM)	$\sum_{i,j=1}^{n_i}\left(1-\frac{a_{i,j}}{a_{i,j}^s}\right)\frac{a_{i,j}}{\sum_{i,j=1}^{n_i} a_{i,j}}$	An elongation measure, i.e. more highly convoluted but long, narrow land-cover patches will have a high value, and vice versa.
Normalized landscape shape index of one land-cover type (NLSI)	$\frac{e_i - \min e_i}{\max e_i - \min e_i}$	Isolates the aggregation effect from the landscape composition effect.
Area-weighted mean of the nearest neighboring patches for one land-cover type (ENN_AM)	$\frac{\sum_{i,j=1}^{n_i} a_{i,j}h_{i,j}}{\sum_{i,j=1}^{n_i} a_{i,j}}$	Increases as the patches with a larger size become more isolated.

1) n_i is the numbers of patches belonging to the i-th land-cover type; A is the area of the current urban area.
2) $a_{i,j}$ is the size of the j-th patch belonging to the i-th land-cover type; $a_{i,j}^s$ is the area of the smallest circumscribing circle around the j-th patch of the i-th land-cover type.
3) e_i is the total length of the edges of the i-th land-cover type in terms of the number of cell surfaces; min e_i (max e_i) is the minimum (maximum) value.
4) $h_{i,j}$ is the distance from the j-th patch of the i-th land-cover type to the nearest neighboring patch of the same type.

Table 2. Descriptive statistics of the city groups of China.

City group by State Council of China	Urban population size (Unit: million)	Num. of cities	City group in this study
Super-large city	>10	6	
Megacity	[5, 10)	10	*Large* city
Large-sized city	[1, 5)	117	
Medium-sized city	[0.5, 1)	97	*Medium* city
Small city	<0.5	47	*Small* city
Other city	-	48	*Other* city

economic factors. The natural environmental variables were two-year average temperature (Tem.), two-year average precipitation (Pre.), and two-year average dilution rate (Dil.), as well as distance to coast (Coast). The socio-economic factors were urban population per square kilometer (POPD) and total value of nighttime light per square kilometer (NTLD). Details of the production processes for these adjusted factors can be found in Appendix Notes A1–A3. Variable selection was processed using the corrected Akaike Information Criterion (AIC) (Burnham and Anderson 2002), which is an information-theoretic approach. By this means, variables with the greatest explanatory power and least multicollinearity were retained to establish the final model. In the reduced regression models, the highly auto-correlated independent factors were eliminated.

3. Results

3.1. General $PM_{2.5}$ pollution situation

During the two study years, taking all 325 cities as a whole, although the annual average showed a decreasing tendency (by 4.8 ± 4.4 μg/m^3 for AMC-$PM_{2.5}$) over the study period, there were still 115.5 ± 81.9 days where pollution exceeded Grade II of the NAAQS of China. According to the NAAQS of China (Grade II), as many as 282 and 260 cities did not meet the annual standard for AMC-$PM_{2.5}$ during the two study years, respectively. The two-year average 24 h AMC-$PM_{2.5}$ concentrations ranged from 8.45 μg/m^3 (Lisu Autonomous Prefecture of Nujiang, an *other* city in Yunnan province) to 83.89 μg/m^3 (Rizhao, in Shandong province), with a general average of 50.21 ± 15.31 μg/m^3. Specifically, the northern regions (Figure 1) and the inland regions contain the severely affected cities, where the top two hardest-hit areas—the North China Plain and the northwest desert area—are a result of anthropogenic activity/interaction between wind circulation and terrain and Asian dust, respectively. As can be seen in Figure 1, except for the cities suffering from Asian dust, the rest of the *other* cities located in the Yunnan-Guizhou Plateau and Tibetan Plateau are less affected by AMC-$PM_{2.5}$ pollution as they benefit from the low level of human activities and the large areas of ecological land cover. $PM_{2.5}$ shows remarkable seasonable variability, with the highest levels seen during the winter and the lowest during the summer (Figure 2). We can attribute the former situation to the enhanced anthropogenic emission in the cold temperature period, the temperature inversion, and the weak wind. In contrast, the latter situation can be attributed to the Asian summer monsoon and increased precipitation (Zhang and Cao 2015).

3.2. Group comparison

The pollution levels and the differences of all the cities in the four urban divisions are listed and compared in Table 3 and Table 4, respectively. Overall, the AMC-$PM_{2.5}$ pollution level increases with the city level. By the use of a one-way ANOVA analysis, it was found that the differences between the four city groups are significant. In detail, the *other* cities present significantly lower $PM_{2.5}$ pollution levels than the *large* and the *medium* divisions (Table 3). At the same time, with regard to AMC-$PM_{2.5}$, there is no significant difference between the *large* cities and the *medium* cities, and between the *small* cities and the *other* cities (Table 4). The AMC-$PM_{2.5}$ levels in the *other* cities (with less than 0.5 million urban residents) are significantly lower than in the *large* and the *medium* cities, with large

Table 3. Descriptive statistics of AMC-$PM_{2.5}$ and its difference with PWC-$PM_{2.5}$ in the four urban divisions.

					95% CI for mean		AMC-$PM_{2.5}$ value		Kolmogorov-Smirnov (KS) Test	
	City rank	Mean	Std. dev.	Std. error	Lower bound	Upper bound	Min.	Max.	Z value	Sig.
AMC-$PM_{2.5}$	Large	53.192	13.541	1.179	50.860	55.523	15.239	83.886	1.026	0.243*
	Medium	51.166	15.261	1.566	48.057	54.275	20.977	77.280	0.687	0.733*
	Small	48.145	16.408	2.532	43.032	53.258	10.553	75.918	0.584	0.884*
	Other	43.090	16.330	2.182	38.717	47.463	8.455	76.173	0.706	0.702*
	Total	50.207	15.305	0.849	48.537	51.877	8.455	83.886	0.868	0.439*
					95% CI for mean		PWC-$PM_{2.5}$ − AMC-$PM_{2.5}$		Kolmogorov-Smirnov (KS) Test	
	City rank	Mean	Std. dev.	Std. error	Lower bound	Upper bound	Min.	Max.	Z value	Sig.
PWC-$PM_{2.5}$ − AMC-$PM_{2.5}$	Large	4.685	7.029	0.612	3.475	5.896	−8.839	38.436	1.743	0.005
	Medium	8.374	12.461	1.278	5.835	10.912	−5.717	62.001	2.028	0.001
	Small	12.068	14.257	2.200	7.625	16.511	−8.992	48.021	0.877	0.425*
	Other	16.463	19.108	2.553	11.346	21.581	−2.157	82.349	1.539	0.018
	Total	8.747	13.085	0.726	7.319	10.175	−8.992	82.349	3.430	<0.001

*KS test as normal distribution

Table 4. Games-Howell multiple comparisons between the pairwise city groups.

(I) City rank	(J) City rank	Mean difference (I–J)	Std. error	Sig.	95% CI Lower bound	95% CI Upper bound
Medium city	Large city	−2.026	1.960	0.730	−7.106	3.054
Small city	Medium city	−3.021	2.977	0.741	−10.846	4.804
	Large city	−5.047	2.793	0.280	−12.427	2.333
Other city	Small city	−5.055	3.342	0.435	−13.807	3.698
	Medium city	−8.076*	2.686	0.017	−15.083	−1.069
	Large city	−10.102*	2.480	0.001	−16.596	−3.608

*The mean difference is significant at the 0.05 level.

intra-class variation. On the one hand, the harsh natural environment (i.e. Asian dust) is partly responsible for the severe $PM_{2.5}$ pollution in some of the *other* cities (for instance, Haidong prefecture in Qinghai province, with 71.84 μg/m^3, see Figure 1). On the other hand, due to the reduced human emissions as well as the large amount of ecological land cover, some *other* cities are relatively free from $PM_{2.5}$ pollution. For instance, the two-year average AMC-$PM_{2.5}$ in Enshi Tujia and Miao Autonomous Prefecture in Hubei province, where the forest coverage rate reaches 70%, is 13.19 μg/m^3. We further recorded the concentration difference between PWC-$PM_{2.5}$ and AMC-$PM_{2.5}$ for each city group (Table 3). From the mean value, this indicates that, within the urban areas, the densely populated regions are more polluted, but this phenomenon is only significant in the *small* city group. Moreover, it is of interest to note that the differences increase with the decrease of the city level.

3.3. Association with urban landscape factors

The last two columns of each group in Table 5 represent the correlation analysis results, which are consistent with the results from the corresponding stepwise regression. The stepwise multivariate models of $PM_{2.5}$ are shown in the first three columns of Table 5, where the multicollinearity in

Table 5. Multivariate association between AMC-$PM_{2.5}$ and urban landscape factors.

	Stepwise regression			Pearson correlations	
Large cities	Std. coef.	R^2	Sig.	Zero-order	Partial
CL_LPI	0.283	0.076	0.001	0.276	0.282
GL_NLSI	0.192	0.035	0.023	0.122	0.198
POPD	−0.184	0.033	0.028	−0.229	−0.191
Full model R^2	0.144	Adjusted R^2	0.124		
Medium cities	Stepwise regression		Sig.	Pearson correlations	
	Std. coef.	R2		Zero-order	Partial
CL_PLAND	0.441	0.157	<0.001	0.397	0.437
GL_NLSI	0.231	0.052	<0.001	0.146	0.247
Full model R^2	0.209	Adjusted R^2	0.192		
Small cities	Stepwise regression		Sig.	Pearson correlations	
	Std. coef.	R2		Zero-order	Partial
CL_PLAND	0.441	0.244	0.001	0.493	0.478
GL_NLSI	0.341	0.113	0.008	0.409	0.387
Full model R^2	0.357	Adjusted R^2	0.328		
Other cities	Stepwise regression		Sig.	Pearson correlations	
	Std. coef.	R2		Zero-order	Partial
CL_PLAND	0.776	0.643	<0.001	0.802	0.812
CL_CIRCLE_AM	0.176	0.030	0.040	0.318	0.301
GL_ENN_AM	−0.167	0.028	0.047	−0.134	−0.291
Full model R^2	0.700	Adjusted R^2	0.680		

Table 6. Univariate association (partial Pearson correlation) between cropland composition metrics and AMC-$PM_{2.5}$ concentration.

Partial correlation*	Spring	Summer	Autumn	Annual
CL_PLAND	0.473[c]	0.429[c]	0.424[c]	0.457[c]
CL_LPI	0.361[c]	0.333[c]	0.355[c]	0.360[c]

[a]*P*-value <0.05. [b]*P*-value <0.01. [c]*P*-value <0.001.

*FRP, natural environmental variables (temperature, precipitation, distance to coast, and dilution rate) and socio-economic terms (total number of urban residents, urban residents per kilometer, total radiation value of nighttime light [NTL] as a proxy of economic activity, and radiation value of NTL per square kilometer) are taken as controlled variables for the partial correlation estimation.

each model has been avoided (see Appendix Table A3). The reduced models incorporating integrated urban landscape factors explain 70.0%, 32.8%, 19.2%, and 12.4% of the concentration of AMC-$PM_{2.5}$ for the *other*, *small*, *medium*, and *large* cities, respectively. When taking the socio-economic factors as controlling factors, the built-up related metrics present only limited effects. The grassland aggregation level works in favor of the aggravation of $PM_{2.5}$ pollution in all the prefecture-level cities, and the isolation of grassland patches with a larger size results in a small drop in the concentration of $PM_{2.5}$ in the *other* cities. Cropland plays a significant role in every city group. Compared to the *medium* and *large* cities, agricultural activity in the *small* and *other* cities acts as an important pollution source (i.e. CL_PLAND for the *small* and *other* cities is $R^2 = 24.4\%$ and $R^2 = 64.3\%$, respectively). With regard to the elongation level of cropland, it is associated with an increase in AMC-$PM_{2.5}$ in the *other* cities ($R^2 = 3\%$). It should be noted that, in the stepwise regression model, more informative independent variables have been picked out from the clusters of highly correlated variables, to avoid the multicollinearity problem (Appendix Table A4).

When further focusing on agricultural activity, it is well known that straw burning in autumn in China has an unignorable impact on $PM_{2.5}$ (Zhang, Liu, and Hao 2016). However, this effect may be confused with the effect of fertilizer, which is mostly applied in spring and early summer, as the stepwise regression was conducted for the annual AMC-$PM_{2.5}$. To investigate this issue, the relationships between the cropland composition metrics (both proportion [CL_PLAND] and the size of the largest cropland patch within the urban area) and seasonal/annual AMC-$PM_{2.5}$ are presented in Table 6. Due to the lack of a straw burning metric, we added fire radiative power (FRP) acquired from the Visible Infrared Imaging Radiometer Suite (VIIRS) Active Fire Data (see Appendix Note A3) as an additional proxy to control the partial correlation process. The suitability of this data was confirmed in Zhang et al. (2015). As nitrogen fertilizer is applied mostly in spring and early summer, the largest correlation value in Table 6 confirms the impact of fertilizer on $PM_{2.5}$ in the urban areas in China.

4. Discussion

The environmental protection laws in China were revamped in 2014 by the Chinese government. However, after two years of intense effort, $PM_{2.5}$ concentration still often fails to meet the standard criteria. Despite the awakening of public awareness, there is a lack of awareness of the impact of anthropogenic activities on AMC-$PM_{2.5}$ pollution. An important message is the need for greater understanding of how the layout of the urban land cover of cities impacts the air quality of China. Our results will have some important implications for China, revealing a conflict between urbanization, the environment, and economic growth.

In contrast to the recent studies that have mainly focused on developed regions (Xu et al. 2016), this paper has reported on the $PM_{2.5}$ status in the urban areas of different city levels. As an addition to the survey of city-average $PM_{2.5}$ of 190 cities in 2013 (Zhang and Cao 2015), this research further reports on the most recent two-year situation in all the second-level administrative urban areas of China and the associated non-attainment rates. During the study period, the national two-year average was $50.21 \pm 15.31\ \mu g/m^3$ for daily $PM_{2.5}$, and around 15.8%±11.2% of the days were non-attainment days that exceeded the new NAAQS standard of China. In view of the spatial distribution, the results obtained in this study are consistent with the measurements for 2013 (Zhang and Cao 2015). However, the two-year average for 2014–2016 is below that for 2013 (i.e. 61 μg/m^3 in Zhang and Cao [2015]), for the following reasons. 1) Our result represents an average status for 325 cities across multiple city levels (including both *small* and *other* cities), whereas the previous study mainly focused on cities at the *medium* level (and above). Considering that pollution status generally gets worse with the increase of city level, a national average that does not consider the smaller cities may lead to some overestimation. 2) In accordance with the view that ambient $PM_{2.5}$ pollution has improved significantly between 2014 and 2016 (Song et al. 2017), our result can be considered as reasonable. 3) Compared to the hourly data from all the monitoring sites used in Zhang and Cao (2015), in this study, we calculated the distance-weighted ambient concentration of all the valid urban areas, which is a more consistent approach for measuring the status of urban $PM_{2.5}$ pollution. In addition, the increased number of $PM_{2.5}$ monitoring stations in recent years enables more accurate $PM_{2.5}$ concentration estimation.

When linking urban $PM_{2.5}$ concentration with land-cover factors, the most obvious correlation is that agricultural activity has an impact on urban $PM_{2.5}$ in multiple city levels. China is a great agrarian country, and is also the biggest user of fertilizer in the world (Food and Agricultural Organization of the United Nations 2016). To balance the trade-off between achieving crop production targets and the environmental bearing capacity, efficient allocation of nitrogen should be ensured (Mueller et al. 2014). In this study, it was found that allocating cropland layout has a non-negligible role in diluting the $PM_{2.5}$, as the fertilizer released from the soil can be transformed into a precursor of $PM_{2.5}$ (Han et al. 2015b). Consistent with the conclusion that even small fertilizer emission decreases can have a strong and absolute impact on $PM_{2.5}$ reduction in East Asia (Pozzer et al. 2017), we have further identified the specific impacts across multiple city levels. In addition to the model mainly addressing fertilizer emission, which reported that East Asia would benefit from a large relative change, reducing the number of deaths by ~8% (Pozzer et al. 2017), it is suggested that taking the spatial configuration of cropland into consideration would further reduce the ambient pollution concentration and the mortality attributable to air pollution. It is of interest to see that the proportion of cropland increases with the city level (Table A.1), which will sound alarm bells for the different city groups in China, rather than only the *small* and *other* cities. Thus, agricultural industrialization, efficient agriculture waste management, slashing fertilizer losses to the environment, and keeping compactness and avoiding connectivity and sprawl in the spatial allocation of cropland are noteworthy suggestions for urban planning. Furthermore, it is of interest to see the limited but negative function of grassland aggregation on urban $PM_{2.5}$ pollution, despite the negligible effect on dry deposition (Chen et al. 2016). Therefore, it is suggested that the design of green spaces in the urban environment should also consider this issue.

Limited data availability and incomplete integration of landscape-related causes have hampered the understanding of the associations with $PM_{2.5}$ pollution in China. The high-resolution remote sensing data used in this study strengthen the statistical power in analyzing the $PM_{2.5}$ at the city scale, as the results we captured are based on a cross-sectional analysis by the use of the most recent empirical evidence. It is also noted that the current high spatial density of ground pollution monitoring stations can support studies at the city level. The ubiquity of air pollution during China's urbanization highlights the enormous challenges involved in achieving continued socio-economic growth without environmental degradation. To date, the focus in the discussions of the impact of air pollution has been on anthropogenic aspects. Future actions should be aimed at sustainable development with mitigated $PM_{2.5}$ pollution.

5. Conclusion

China, the world's second-largest economy and the most populous nation, which is experiencing an unprecedented urbanization rate, is among the countries with the most severe ambient $PM_{2.5}$

pollution. In this study, we utilized a unique and high-resolution geo-spatial dataset to fully investigate the interactions at the city level. Based on the stratified statistical analysis of all the second-level administrative cities in the Chinese mainland, we found that: 1) During the last two years, more than 90% of the cities did not reach the annual Grade II standard of the NAAQS of China. Among these cities, there were 158.6 ± 74.2 days where AMC-$PM_{2.5}$ exceeded the daily Grade II standard of the NAAQS of China. As stratified by urban population size, the *large* cities suffered from the most severe $PM_{2.5}$ pollution, while the *other* cities and the *small* cites suffered from less $PM_{2.5}$ exposure. 2) Comparing PWC-$PM_{2.5}$ with AMC-$PM_{2.5}$ in each city group, it can be seen that the densely populated areas suffer from more severe air pollution. Thus, it can be stated that urban residents, who are not only the victims of $PM_{2.5}$ pollution but also the source of the pollutant, have a great effect on urban $PM_{2.5}$ concentration. 3) Agricultural activity is a major contributor of $PM_{2.5}$ pollution, which is severe in the *small* and *other* cities. The ubiquity of air pollution during China's urbanization highlights the enormous challenges involved in achieving continued socio-economic growth without environmental degradation. It is therefore of great significance to analyze the urban landscape relationship with $PM_{2.5}$ in present-day China and provide suggestions for urban planning.

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