Remotely sensed modelling of urban spatial-environmental health across 32 major cities in China

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Abstract. The timely and effective evaluation of spatially-explicit urban PM2.5 concentrations is highly important for an improved understanding of urban environmental health and sustainability in China. However, recent studies examining the spatiotemporal patterns of PM2.5 concentrations has not been comprehensively clarified due to the absence of spatial-detailed urban landscape linkage. In this study, a general non-linear model was developed to depict the non-linear relationship between spatially explicit impervious surface area (ISA) fractions and associated PM2.5 concentrations gradient changes for individual cities from multi-source satellite-based dataset. The comparative results of environmental quality across 32 major cities in China showed that the spatial pattern of urban PM2.5 concentrations is correlated with geographical orientation and socio-economic clusters—high baseline and more balanced states of PM2.5 concentrations are prevalent in North China and the Yangtze delta agglomerations. Temporally, during the period of 2000-2018, most of cities have the path dependency, whereas high concentration of PM2.5 diffused from the original east of ‘Hu-Huanyong Line’ toward some cities in north-eastern, central and western regions. In addition, our study highlights the optimizing regional economic structure and promoting urban greening construction will be of great significance in sustainable urban environmental health management.

1. Introduction
The high speed of growth of urban areas is occurring worldwide, but especially in developing countries. Reports suggest urban population in China has increased by nearly 60% since the late 1970s, and an additional 255 million people are expected to reside in cities by 2030 [1]. Although it has promoted socio-economic development, the accompanied environmental pollution continues to threaten the quality life of urban residents, human health and well-beings, thus becoming the frontline for tackling global/local climate change and consideration for sustainable development goals (SDGs) [2]. It is necessary to understand the status and dynamics of key urbanization environmental challenges in a changing urbanization planet.

Fine particulate matter (PM2.5) as one of crucial air pollutant, is defined as any aerosol particles smaller than 2.5 μm in diameter that are suspended in the air [3], ranking first among numerous
environmental concerns. The report of the World Health Organization has proven the highest number of residents in China has exposed to serious air pollution [4]. This environmental challenge, in particular represented by PM2.5 has aroused the widespread concern of the government and academic researchers [5].

Previous studies have conducted extensive and depth research on PM2.5 concentrations, mainly including depicting multiple characteristics, source apportionment and health evaluation/estimation [6]. In particularly, recent literatures are emerging on the temporal and spatial changes of PM2.5 concentrations in China. However, most of them devoted to a single city, such as the megacities of Shanghai, Beijing etc. or hotspot regions like East China, the North China Plain etc [7]. Therefore, a comparative analysis for characterizing divergent trajectories of PM2.5 concentrations across different cities with different geographic background and economic development levels have great importance to provide the necessary scientific and effective decision-making. Furthermore, few studies focusing on multiple cities quantitatively measure PM2.5 distribution derived from statistical/monitoring dataset are limited at the macro city scale and lack spatial information for inter-urban variability [8]. In reality, the spatial process that considered micro urban landscape patterns provide valuable information for revealing spatial variability and mechanisms of PM2.5 pollution. A comparative and multi-scale understanding of spatially-explicit PM2.5 concentrations trajectories is urgently needed.

Advanced satellite images offer large-scale and cost-effective measurements for monitoring, assessing and predicting the urban landscape and environmental health status from a spatial perspective. For example, the extensive studies on urban land use/cover mapping and landscape structure detection have been achieved with broad-wave remote sensing images for enormous urban spatial details [9]. Besides, it has also been employed to identify and detect environmental characteristics and air quality in urban settings with high-accuracy predictions [10]. Such combined data could commonly explicitly link landscape pattern to underlying environmental impacts. However, this spatially-detailed environmental health monitoring has not been comprehensively clarified from hierarchical intra- and inter-city space due to the absence of spatial distributions.

Here, we tried to involve general non-linear models to depict the relationship between spatially explicit land cover and associated environmental gradient changes for individual cities from combined urban impervious surface (UIS) cover and gridded PM2.5 concentrations dataset. Furtherly, we conduct a comparative study to analyse the systematic environmental quality across 32 major cities in China. It is expected that our new fresh insights through this approach might help reveal the spatial gradient patterns of PM2.5 concentrations and its evolution dynamics from 2000-2018, therefore could contribute to effective urban environmental early-warning and management practices.

2. Datasets and methodologies

2.1. Multi-source spatial gridded datasets

2.1.1 China’s Urban impervious surface area (UISA) fraction dataset
A 30-meter resolution dataset of China’s urban impervious surface area (UISA) was obtained to characterize the spatially heterogeneous patterns of ISA and their expansion processes [11]. Using extracted the vector boundaries of urban areas from China’s Land Use/cover Dataset (CLUD), the ISA was retrieved using the logistic regression from the Landsat-derived annual maximum Normalized Difference Vegetation Index on Google Earth Engine platform. This product was provided with high-accuracy ISA fractional information across cities of China, as indicated by low root mean square errors of ISA estimates (0.10), thus can effectively delineate complex intra-urban land cover components in 30-m spatial resolution at national scale at five-year intervals between 2000 and 2018. Recent studies have proven this dataset can be adopted in the field of geospatial distribution of large-scale high-resolution impervious surface mapping [12] and impacts of rapid urban sprawl on the local environment [13]. Therefore, we used the urban vector boundaries from CLUD dataset and corresponding ISA
fractional images from UISA dataset in 2000 and 2018 to acquire the spatial extent of whole city and spatial distribution of intra-urban ISA components, respectively.

2.1.2 The gridded PM2.5 concentration dataset
PM2.5 concentrations were commonly regarded as an important variable to characterize the urban environment. The annual mean PM2.5 concentration dataset with a spatial resolution of $0.01^\circ \times 0.01^\circ$ were available from the Atmospheric Composition Analysis Group Web site (http://fizz.phys.dal.ca/~atmos/martin/?page_id=140). These products were estimated by combining the Aerosol Optical Depth from multiple satellite-based sources, and then applying a geographically weighted regression approach to calibrate them to regional ground-based observations [14]. The global scale validation proved that this satellite-based product was accurate and reliable to PM2.5 characterization. We thus collected the gridded global PM2.5 concentrations data of 2000 and 2018, and explored explicit spatial relationship between this environmental variable and urban ISA fractions.

2.2. Research methodologies

2.2.1 The Spatial environmental health index
We reconstructed spatial environmental health gradient curves with urban ISA density changes. For a given city in a specific year, all pixels derived from spatially-gridded PM2.5 concentration images within the geographical urbanized extent have been resampled to 500m and overlaid based upon a uniform geo-reference system (WGS-84). The average PM2.5 concentrations were therefore calculated at every 1% ISA interval using the following equations (1) and (2):

$$T_P = \sum_{j=1}^{n_i} P_{ij}$$ (1)

$$M_P = \frac{\sum_{j=1}^{n_i} P_{ij}}{N_i}$$ (2)

For all ISA pixels where the IS fractions is between i% and i+1% (i is the integer from 1 to 100), $M_P$ and $N_i$ indicates the average PM2.5 concentrations and total amounts of those pixels, respectively; where j is ranging from 1 to $n_i$, $P_{ij}$ represents the corresponding PM2.5 concentrations of pixel j that belongs to the specific ISA interval between i% and i+1%.

2.2.2 The developed urban spatial PM2.5 concentration curve
Different patterns of spatial gradient in PM2.5 concentrations may vary with increasing urban ISA fractions. We applied two best-performing non-linear models, that is, logistic model to fit the response of urbanization environmental variable to changes in urban ISA density extended from empirical relationship reported in published literature [15]. A logistic model with an “S-shaped” curve was utilized to quantify the complex spatial dynamics of PM2.5 concentrations to escalated ISA fractions over the entire urban area. The developed spatial gradient curve for urban PM2.5 concentration can, therefore, be expressed as follows:

$$MPC = \frac{a}{1 + e^{b + cISA}} + d$$ (3)

Where a, b, c, d in equation (3) are the coefficients of models, $MPC$ is the environmental dependent variable, and $ISA$ indicates the proportion of artificial IS of the grids.

The urban spatial PM2.5 concentration curves of 32 individual cities were quantified with our proposed logistic models. The fitted parameters of these models characterized different spatial patterns of urbanization variables, and they were also estimated using the Non-linear Least-fitting (LMFIT) package in python 2.7. The significance of all models’ curve fitting was tested using the coefficients of determination ($R^2$), a standard F-test (p-value), and the root mean square error (RMSE).
3. Results and Discussion

3.1. Performance of fitting Spatial Environmental health curve

The fitted spatial gradient curves of environmental health trajectories for 32 major cities in 1990 and 2018 are shown in Fig.1., and the estimated parameters of the models shown in Table 1. Overall, the models were fitted well for the gradient changes in PM2.5 concentrations of all cities. The averaged goodness of fit (that is, coefficient of determination $R^2$) for over 96% of city samples were above 0.6, with p-value lower than 0.01. The relative bad performances (accounting for only ~4%) were distributed in western cities of China, for example, Yinchuan and Urumqi, which are characterized by small and sparse urban spaces and low population densities.

Table 1. Parameters of the fitted logistic models for 32 major cities of China in 2000 and 2018.

| City         | Year_2000 a | b | c | d | R2 | P | RMSE | Year_2018 a | b | c | d | R2 | P | RMSE |
|--------------|-------------|---|---|---|----|---|------|-------------|---|---|---|----|---|------|
| Beijing      | 18.6        | 9.8 | -5.8 | 53.6 | 0.9 | 0.001 | 0.3 | 17.8 | -0.1 | -8.0 | 64.9 | 0.9 | 0.004 | 1.3 |
| Tianjin      | 1.4         | 1.6 | 5.7 | 65.0 | 0.6 | 0.008 | 1.7 | 1.4 | -0.5 | -21.8 | 77.4 | 0.7 | 0.006 | 1.8 |
| Shijiazhuang | 15.0        | 12.2 | -7.9 | 59.3 | 0.8 | 0.006 | 1.2 | 20.8 | -0.1 | -7.7 | 72.6 | 0.8 | 0.004 | 2.0 |
| Taiyuan      | 22.4        | 11.2 | -10.1 | 38.4 | 0.7 | 0.006 | 1.9 | 15.7 | -0.1 | -10.4 | 33.6 | 0.6 | 0.007 | 1.1 |
| Hohhot       | 11.0        | 11.8 | -8.0 | 17.8 | 0.8 | 0.006 | 1.1 | 11.3 | -0.1 | -10.9 | 23.8 | 0.7 | 0.005 | 2.0 |
| Shenyang     | 4.5         | 7.3 | -3.5 | 26.5 | 0.8 | 0.006 | 0.9 | 7.8 | 0.0 | -6.1 | 61.9 | 0.7 | 0.005 | 1.3 |
| Changchun    | 0.3         | 1.6 | -5.8 | 27.5 | 0.6 | 0.007 | 0.5 | 1.8 | 0.0 | -1.1 | 69.6 | 0.6 | 0.008 | 1.9 |
| Harbin       | 2.0         | 0.3 | -1.7 | 26.6 | 0.7 | 0.005 | 0.3 | 4.1 | 0.0 | -9.7 | 26.1 | 0.7 | 0.008 | 2.3 |
| The parameters of the fitted models showed the difference in urban spatial patterns of PM2.5 concentrations (Table 1). The coefficient $d$ of logistic curves that characterized spatial PM2.5 concentrations curve indicated the baseline value of urban pollutant corresponding to lowest ISA fractions. The overall average baseline of pollution levels exhibited an increasing trend, ranging from 32.12 μg·m⁻³ in 2000 to 40.67 μg·m⁻³ in 2018 across 32 cities. Besides, the magnitude of urban pollutant concentration along the impervious surface gradient (coefficient $a$) identified the variability of the spatial distribution of urban pollutant concentrations and indicated the aggregation degree of pollution generated by human economic activities during urbanization and industrialization. The results showed that the spatial magnitude of PM2.5 concentrations in all cities exhibited great disparities in 2000 with an average PM2.5 concentration of 12.25 μg·m⁻³. In 2018, the average coefficient $a$ showed a slight decrease to 11.91 μg·m⁻³, representing an overall mitigated spatial imbalance of urban PM2.5 concentrations for all the cities in China.
3.2. Comparing urban spatial environmental health status across cities and over time

Spatially, as shown in Fig.1. and Fig.2. the majority of the cities (20/32, about 62.5 % of the total amounts) in the study area exhibited a relatively balanced state of spatial distribution of PM2.5 concentrations in response to the increase of ISA fractions. Eight cities, for example, Tianjin, Shanghai et al. that were identified as this balanced state with high PM2.5 concentrations, mainly distributed in the northern heavy industry zone and around the Yangtze River Basin. This might be related to severe environmental pollution derived from high density transportation network and strong regional industrial development. In comparison, small cities with low population density in the Northwest, such as Xining, Lhasa and Yinchuan, were experiencing slow process of urbanization and have less pressure on the urban environment, thus locating in relatively low air pollution states. The spatial differentiation of PM2.5 concentration of Shenzhen and Guangzhou was also small between the suburban and core regions with relatively low PM2.5 concentration baseline. Moreover, the remaining 37.5% of the cities showed significant spatial gradient difference in terms of the distribution of PM2.5 concentrations along the ISA fractions. Due to the rapid development of industrialization and urbanization, cities in Beijing-Tianjin-Hebei region, Shandong Province, Henan Province and Yangtze River Basin have generated serious environmental pollution problems. A high PM2.5 baseline (>35 μg m⁻³) appeared in cities, such as Shijiazhuang, Beijing, and Zhengzhou with a great concentration of PM2.5 pollutant in the areas with high ISA, therefore exposed the residents in these cities a higher risk of environmental health. In general, the spatial pattern of high pollution and strong diffusion of PM2.5 is closely correlated with the distribution of population density and economic activity intensity.

![Fig. 1. The fitted spatial gradient curves of PM2.5 concentrations for 32 major cities of China in 1990 and 2018.](image)

Temporally, during the study period of 2000-2018, Fig.3. showed that the baseline values of spatial PM2.5 concentrations in cities in Northeast China (e.g., Shenyang, Changchun and Harbin) presented relatively great increase due to the industrial development and economic prosperity. This aggravated trend was also prevalent in some cities along the Yangtze River, such as Hefei, Wuhan and Changsha and Northwest China (Urumqi). Overall, in summary, this high concentration of PM2.5 diffused from the original east of ‘Hu Huanyong Line’ toward the central and western regions, which may be affected
by the industrial expansion in these newly-degraded cities along with the policies of Western Development and the rise of central China. In terms of spatial imbalance of urban PM2.5 pollutants, due to ring-shaped urban distribution, the spatial distribution of PM2.5 concentrations in Beijing, Shijiazhuang, Xi’an, Taiyuan and other cities showed continued gradient transition along the changes of ISA fractions in both 2000 and 2018, which indicates the temporal stability over the time. Conversely, the construction of urban green space and the weakening of industrial activities played an important role in the improvement of urban environment. In comparison, the baseline values and overall spatial imbalance of urban PM2.5 concentrations in Lanzhou, Xining, Yinchuan and Kunming showed a downward trend. Besides, Fuzhou, Shenzhen, Guangzhou and other southern cities maintained a low baseline and a balanced state during the study period, which indicated that these cities attached great importance to urban sustainable and green development mode, economic structure adjustment and ecological construction.

![Fig. 2. The spatial distribution of coefficients (d and a) of the fitted urban PM2.5 concentration curve in 2000 and 2018.](image)

![Fig. 3. The fitting coefficients of urban PM2.5 concentration curve in 2000 (a) and 2018 (b), and changes of model coefficients of d (c) and a (d) between 2000 and 2018 for 32 major cities in China.](image)
Therefore, our results implied the relationship between ISA and PM2.5 over China agreed with the theory of environmental Kuznets curve. Increase of impervious surface, industrial activities and population density may significantly increase the pollution levels of PM2.5 concentrations, and lead to the highly exposed risks of air pollution (e.g., the North-eastern cities of China). In particular, the PM2.5 concentration of some northern cities in China tend to continue the spatial gradients in the direction of increasing ISA fractions. With the diffusion and accumulation of air pollutant, the environmental space of some cities in North China and the Yangtze delta metropolis agglomerations are dominated by high baseline and more balanced states of PM2.5 concentrations, which is consistent with the previous research results [9]. As the continuous development of social economy and structural optimization, PM2.5 concentrations in some southern cities of China show the trend toward spatial equalization with low pollution concentration. This can be supported by the fact that a fine air quality condition with balanced spatial distribution clustering in Pearl River Delta urban agglomeration. Hence, optimizing regional economic structure and promoting urban greening construction are of great significance and role in controlling pollutant emissions, improving atmospheric quality and enhancing urban environmental health.

4. Conclusions
This study illustrates a comparative analysis of urban environmental health status and dynamic from a spatial-explicit view in major 32 cities of China during the period of 2000-2018. With the multi-resource satellite image dataset of urban ISA fractions and gridded PM2.5 concentration, we firstly developed non-linear models and thus constructed the divergent spatial-environmental urban PM2.5 concentration trajectories. The developed model performed well and guaranteed the calculation accuracy of urban cover and environmental variables. And the spatial structure, distribution and patterns, as well as the evolution dynamics of urban PM2.5 concentrations were evaluated from the both inter- and intra-city scale.

Our results highlight the spatial pattern of high pollution and strong diffusion of urban PM2.5 concentration is closely correlated with the distribution of population density and economic activity intensity. High baseline and more balanced states of PM2.5 concentrations are mainly dominated in North China and the Yangtze delta agglomerations Temporally, the spatial trajectories of PM2.5 concentration of most of cities have the path dependency and are generally suitable with urban socio-economic development stages, however, the high concentration of PM2.5 diffused from the original east of ‘Hu Huanyong Line’ toward the central and western regions. The developed analysis framework for monitoring urban environmental health is applicable to analyse a single city with a long-term assessment or multiple cities. The refined insights also contribute to help provide a priori basis for future urban sustainable development planning and management.

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