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RESEARCH ARTICLE

Spatial-temporal characteristics of urban air pollution in 337 Chinese cities and their influencing factors

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Abstract

Urban air pollution, especially in the form of haze events, has become a serious threat to socio-economic development and public health in most developing countries. It is of great importance to assess the frequency of urban air pollution occurrence and its influencing factors. The objective of our study is to develop consistent methodologies for constructing an index system and for assessing the influencing factors of the urban air pollution occurrence based on the Driver-Pressure-State-Impact-Response (DPSIR) framework by incorporating spatial analysis, geographical detector, and geographically weighted regression models. The 27 influencing factors were selected for assessing their influences on the urban air pollution occurrence in 337 Chinese cities. The results indicate that the spatial pattern of the urban air pollution in China was mostly consistent with the Chinese population-based Hu Line. Urban air pollution frequently occurred in North China, Central China, Northeast China, and East China, and displayed strong seasonality. The influencing factors of urban air pollution were complex and diverse, varying from season to season. Influencing factor analysis also shows that the explanatory power between any two influencing factors was greater than that of a single influencing factor of the urban air pollution. Furthermore, most influencing factors had both positive and negative effects and local effects on urban air pollution. Finally, we put forward five suggestions on reducing urban air pollution occurrence, which can provide the basis and reference for the government to make policies on urban air pollution control in China.

Keywords DPSIR framework · Geographical detector · Geographically weighted regression · Urban air pollution · Influencing factor · Risk management

Introduction

After rapid industrialization and urbanization for more than four decades, China, in recent years, is facing a series of ecological and environmental challenges, such as land/soil degradation (Zhou et al. 2013), landscape fragmentation (Cui et al. 2019), biodiversity losses (Hou et al. 2014), water eutrophication (Malekmohammadi and Jahanishakib 2017), and urban air pollution (Huang et al. 2014). Since 2013, severe urban air pollution has started to occur extensively in many Chinese cities, especially in the rapid urbanization areas (Fu and Chen 2017), such as the Beijing-Tianjin-Hebei urban agglomeration (Zhang et al. 2018), the Yangtze River Delta urban agglomerations (Han and Ma 2020), the Pearl River Delta urban agglomerations (Li et al. 2018), and the Yellow River Basin (Chen et al. 2020).

Urban air pollution in Chinese cities is mainly manifested in the form of haze event, which is a weather phenomenon with a visibility of less than 10 km resulting from the dense

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accumulation of fine aerosol particles (Huang et al. 2014; Tao et al. 2012), not only affects people's daily life and physical health, but also causes enormous economic losses and social instability. It contributes negatively to regional climate conditions (Fu and Chen 2017), visibility (Shen et al. 2015), agricultural production (Zhou et al. 2018b), and public health (Song et al. 2019). Currently, urban air pollution has become a great environmental hazard and caused widespread social concerns in China (Braithwaite et al. 2019; Liu et al. 2017a; Song et al. 2017; Wu et al. 2017; Wu et al. 2020; Wu et al. 2021; Zhang et al. 2015; Zhou et al. 2018a).

Previous studies on urban air pollution have mainly focused on sources and types of air pollutants (e.g., PM2.5, PM10, NO_2, SO_2.) (Fu and Chen 2017), temporal and spatial variation of pollutants (Song et al. 2017), factors and formation mechanism of air pollution (Zhan et al. 2018), the relationship between human activities and air pollution (Li et al. 2020), and health damage caused by urban air pollution (Song et al. 2019). Studies find that urban air pollution usually resulted from a combination of high levels of air pollutant emissions and adverse meteorological conditions at the same time (Fu and Chen 2017). In terms of the sources of air pollutants and the process of pollutants transmission, the factors contributing to the formation of urban air pollution can be divided into two categories: (1) emissions of air pollutants from human activities, such as industrial exhaust, vehicle exhaust, coal, and dust; and (2) adverse climatic conditions caused by special landforms and unreasonable spatial structure of land use. Furthermore, Fu and Chen (2017) suggested that over 70 particulate matter sources have been identified, ranging from natural to anthropogenic sources. Chen et al. (2015) explored the spatial variations of air pollutants and air quality of Beijing at multiple temporal scales such as daily, weekly, and monthly. Cheng et al. (2017) discovered that there was a spillover effect in the time and space dimensions of the urban air pollution in China. Other studies also suggested that urban air pollution in Chinese cities were mainly a result of the interactions between natural (e.g., climate, topography, etc.) and socio-economic (e.g., industry structure, population, urbanization, and ventilation corridors) factors (e.g., Dong et al. 2019; Hao and Liu 2016).

Although the existing studies have made considerable achievements on this topic, they are not without limitations. First, regarding the selection of influencing factors, the existing studies mainly relied on subjective judgment that usually does not consider the causal relationship between urban air pollution and its influencing factors (Lin and Zhu 2018). Niemeijer and de Groot (2007) eloquently stated that a conceptual framework should play an important role in the processes of selecting influencing factors and developing a consistent influencing factor set. This is especially true in the case of assessing the urban air pollution risks and identifying their key influencing factors ranging from natural to human dimensions. Second, the quantitative methods employed for analyzing the influencing factors of urban air pollution employed by the existing studies mainly included factor analysis (Zhang et al. 2018), dynamic factor analysis (DFA) (Yu et al. 2015), principal component analysis (Pandey et al. 2014), extreme boundary analysis (Wang and Chen 2016), spatial Durbin model (Liu et al. 2017a), spatial lag model and spatial error model (Hao and Liu 2016), and land use regression (Huang et al. 2017). These statistical tools were effective in identifying the influence of individual factors on urban air pollution; however, most of them were global models that ignored the local effects of the influencing factors and interactive effects of multiple factors (Zhan et al. 2018). The geographical detector model proposed by Wang et al. (2010) was intended to address these problems by dividing the study area into a few subareas to identify the spatially stratified heterogeneity and the factors that are responsible for such spatial heterogeneity. The geographical detector was used in Zhou et al. (2018a) and Ding et al. (2019) to examine the effects of socio-economic development on PM2.5 in China. Furthermore, the geographically weighted regression (GWR), a local form of spatial analysis tool, was also widely used to explore the local spatial relationship between the explanatory variables and the response variable (You et al. 2016) as the regression coefficients in the GWR vary with locations (Zeng et al. 2016).

Therefore, our study aims to develop an index for the urban air pollution occurrence and to employ spatial analysis tools to answer the following questions:

(1) What is the frequency and spatial pattern of urban air pollution occurrence in a certain period (a year, a season, or a month) in China?
(2) What are the influencing factors of urban air pollution and how do they interact with each other?
(3) What are the positive and negative effects and the local effects of the influencing factors on urban air pollution?
(4) What measures should we take to alleviate the occurrence of urban air pollution, given that it is impossible to completely eradicate the emissions of air pollutants in China in a short period?

The main innovations of this paper are: (1) developing a Driver-Pressure-State-Impact-Response (DPSIR) framework to *qualitatively* elucidate the complex causal relationship between urban air pollution and their influencing factors and to avoid the subjective judgment in the process of selecting the influencing factors, and (2) employing the geographical detector and the geographically weighted regression model to *quantitatively* detect the effect of the influencing factors' interactions on urban air pollution and the local effects of the influencing factors on urban air pollution, respectively.

The paper is organized as follows: the "Materials and methods" section describes the materials and methods; the "Results" section presents the findings of our study; the "Discussion" section discusses the complexity of the influencing factors of urban air pollution and proposes five paths to alleviating the occurrence of urban air pollution in China. Conclusions are given in the "Conclusions" section. The technical flowchart of this study is shown in Fig. 1.

Materials and methods

Developing the DPSIR-based framework for urban air pollution

Proposed by the European Environmental Agency (EEA), the DPSIR framework is an improvement over the Pressure-State-Response (PSR) framework. In recent years, the DPSIR framework has been widely applied in sustainability assessment (Maurya et al. 2020), eco-environmental quality assessment (Chen et al. 2019), soil quality risk assessment (Zhou et al. 2013), land use assessment (Potschin 2009), wetland resources assessment (Malekmohammadi and Jahanishakib 2017), ecological security assessment (Gari et al. 2015), biodiversity risk assessment (Hou et al. 2014), and industrial economic sustainability assessment (Liu et al. 2018). The DPSIR framework is mainly used for identifying and evaluating environmental problems that are generally complex.

The DPSIR framework describes that the natural factors and/or socio-economic factors act as the *driver* (underlying drivers) and underpin the *pressure* (direct or proximate drivers—for example, secondary industrial development in this study) to change the environment (*state*, e.g., urban air quality), which further affects the socio-economic condition of the region of interest (*impact*). Finally, this complex situation is responded by the government or society through different initiatives (*response*) to reduce the negative impacts or to encourage the positive impacts (Potschin 2009; Qu et al. 2020).

On the one hand, the DPSIR framework provides a systematic mechanism to monitor the status of an environment or system, to describe the system's dynamics, and to express the coupling relationship among various influencing factors (Rapport and Friend 1979). Within the DPSIR framework, feedback may be provided to policymakers based on environmental quality and/or the resulting impact of policies made or

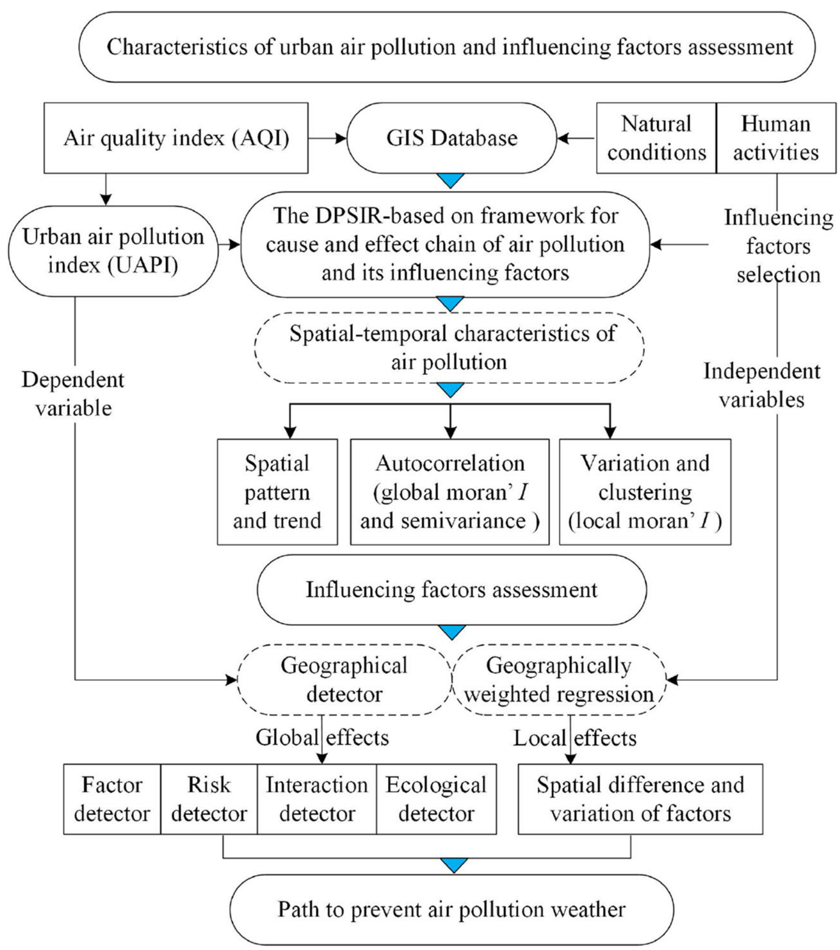

Fig. 1 The technical flowchart of this study. Note: DPSIR, Driver-Pressure-State-Impact-Response

to be made in the future (Bidone and Lacerda 2004). On the other hand, establishing the DPSIR framework under certain circumstances is a complex task because various cause-effect relationships must be carefully examined, and the environmental changes are rarely attributed to a single cause (Feld et al. 2010).

In this study, the DPSIR framework was used to elucidate the complex causal relationship between urban air pollution and its influencing factors by avoiding subjective factor selection. As illustrated in Fig. 2, by considering the complex relationship between urban air pollution and its influencing factors, we employed the DPSIR framework to construct an index system for assessing the influencing factors of urban air pollution (Table 1): (1) the "driver" factors include climate, topography, landform, and socio-economic activities that have positive or negative influences on urban air quality; (2) the "pressure" factors include urban spread, population growth, and energy consumption; (3) the driver and pressure factors contribute collectively to the change of urban air quality (i.e., "state"); (4) urban air pollution imposes negative "impacts" on a living quality, public health, social security, and economic development; and (5) the "response" factors include the actions taken by the government, society, and industrial sectors to mitigate the occurrence or risk of urban air pollution.

In Table 1, the state in the DPSIR framework for our study is the risk of urban air pollution represented by the urban air pollution index, which is the dependent variable in the following influencing factor assessment. The impact factors are the negative effects of urban air pollution on public health and social security, such as respiratory diseases, carcinogenesis, social panic, and psychological illness risk (Braithwaite et al. 2019; Song et al. 2019). Urban air pollution also reduces visibility and increases the number of traffic accidents (Shen et al. 2015). Unfortunately, due to limited data, these impact indicators were not included in the following case study. Therefore, a set of 27 individual indicators were selected to assess the influencing factors of urban air pollution in this study (Table 1).

Developing the urban air pollution index

Based on the air quality index (AQI) (Appendix A), we developed the urban air pollution index (UAPI) to represent the potential that may lead to haze events (urban air pollution) in Chinese cities in a certain period (e.g., annual, seasonal, or monthly) when AQI is at the 3 to 6 levels. The UAPI is defined as follows:

$$\mathrm{UAPI} = \frac{\sum_{k=3}^{6} D_k}{S_k} \tag{1}$$

where k is the level of AQI (k = 3,4,5, and 6); D_k is the number of days at the k level; S_k is the total number of days in

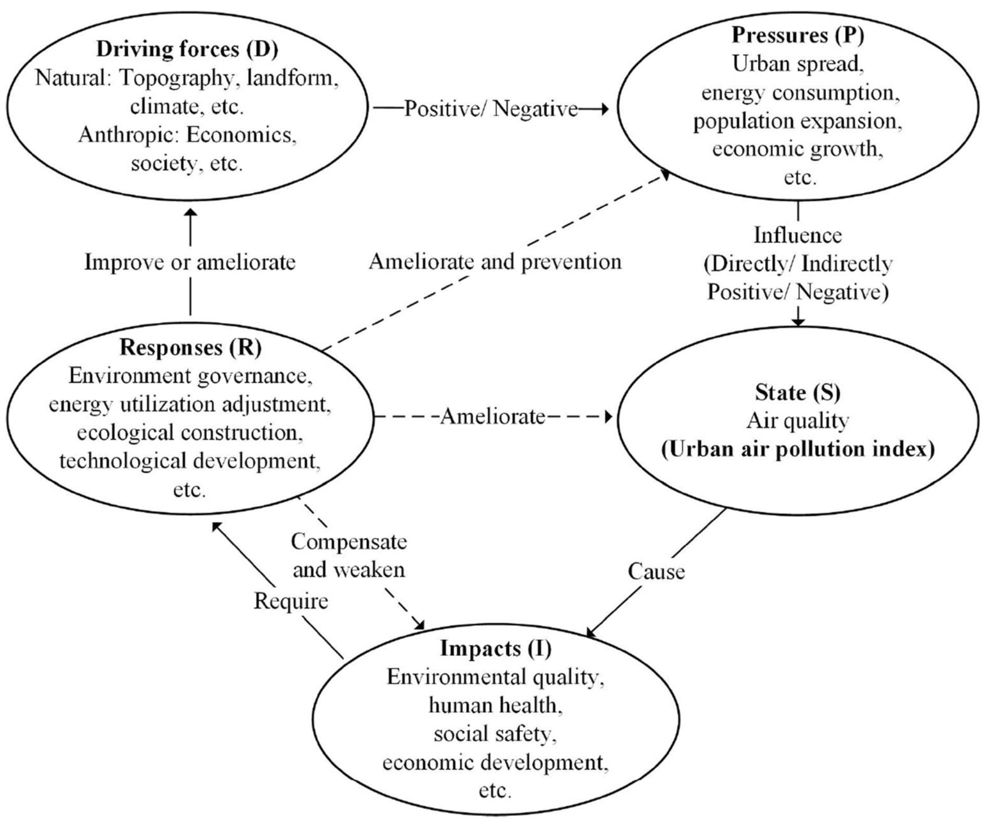

Fig. 2 The DPSIR framework for the cause-effect chain of urban air pollution and its influencing factors

Table 1 The selected influencing factors of urban air pollution based on the DPSIR framework

Criteria	Categories	First-level indicators	Basic-level indicators		Sources
Driver (D)	Natural factor	Landform	D1	Relative elevation (m)	Cao et al. (2015); Zhan et al. (2018); Zhou et al. (2017)
		Temperature	D2	Annual average temperature (°C)	
		Humidity	D3	Humidity index (-)	
		Air motion	D4	Wind speed (m/s)	
		Precipitation	D5	Annual average precipitation (mm)	
	Economy	Economic growth	D6	Regional GDP growth rate (%)	Hao and Liu (2016)
		Industrial structure	D7	Proportion of secondary industry in regional GDP (%)	Zhou et al. (2018a)
		Real estate development	D8	Investment in real estate development (10^8 Yuan)	Wang and Fang (2016)
		Foreign investment	D9	Actually utilized foreign capital (10^8 Yuan)	Liu et al. (2017b)
	Society	Population growth	D10	Natural population growth rate (‰)	Wang et al. 2015
Pressure (P)	Land use	Land development	P1	Proportion of construction land to the total area of the city (%)	Xu et al. (2015)
	Energy consumption	Energy structure	P2	Proportion of coal consumption (%)	Wang and Chen (2016)
	Economy	Industrial size	P3	Number of manufacturing enterprises (#)	Dong et al. (2019)
		Agricultural production	P4	Nitrogen fertilizer application rate (10^4 t)	Zhao et al. (2017)
	Society	Population size	P5	Population density (people/km^2)	Lin and Zhu (2018)
		Building construction	P6	Per unit construction building area (m^2/hm^2)	Wang and Fang (2016)
		Private car ownership	P7	Number of domestically made car ownership (10^4 #)	Song et al. (2017)
		Road network	P8	Highway density (10^4m/km^2)	Zhou et al. (2018a)
		Heat supply	P9	Ratio of the central heating (%)	Cheng et al. (2017)
State (S) *	Air quality	SO_2	S1	Annual average SO_2 concentration (μg/m^3)	Chen et al. (2015); Hao and Liu (2016); Zhan et al. 2018
		NO_2	S2	Annual average NO_2 concentration (μg/m^3)	
		PM2.5	S3	Annual average PM2.5 concentration (μg/m^3)	
		PM10	S4	Annual average PM10 concentration (μg/m^3)	
		CO	S5	Annual average CO concentration (mg/m^3)	
		O_3	S6	Annual average O_3 concentration (mg/m^3)	
Impact (I)	Human health	Tumor disease§	I1	Mortality rates in cancer diseases (‰)	Lin et al. (2016)
		Respiratory disease §	I2	Mortality rates in respiratory diseases (‰)	Zhang et al. (2015)
	Social safety	Traffic accident §	I3	Amount of traffic accident loss (10^4 Yuan)	Shen et al. (2015)
Response (R)	Ecological construction	Green land cover	R1	Rate of green land in built-up area (%)	Liu et al. (2017b)
		Environmental governance	R2	Proportion of energy conservation and environmental protection expenditures to local fiscal expenditure (%)	López et al. (2011)
	Economic readjustment	Industrial upgrading	R3	Ratio between the third industry and the second industry (-)	Wang and Chen (2016)
		Industrial agglomeration	R4	Per unit area industrial output (10^4 yuan/km^2)	Dong et al. (2015)
	Energy utilization adjustment	Energy price	R5	Ex-factory price index of industrial products (-)	Xu et al. (2018)
		Efficiency of energy utilization	R6	Per unit GDP in energy consumption (10^4 Yuan/t)	Hao and Liu (2016)
		Gas utilization	R7	Gas penetration rate (%)	Lin and Zhu (2018)
	Technical innovation	Research input	R8	Expenditure of research and experimental development funds (R&D) (10^4 Yuan)	López et al. (2011)

*The dependent (explained) variable

§ The factor that was excluded in this study due to limited data a certain period (annual, seasonal, or monthly). A higher UAPI value corresponds to more days with bad air quality.

Figure 3 compares the daily characteristics of AQI (Fig. 3a) and the monthly characteristics of UAPI (Fig. 3b) from 2015 to 2019 in China. It is evident that both AQI and UAPI display the U-shape periodic characteristics.

Spatial autocorrelation analysis

Spatial autocorrelation analysis, which reveals the degree of similarity of the attributes of neighboring geospatial units, includes calculations of the global Moran' I and the local indicators of spatial association (LISA). While the global Moran's I quantifies the spatial autocorrelation as a whole, the LISA measures the degree of spatial autocorrelation (spatial clustering) at each specific location by using local Moran's I (Anselin 1995). The global Moran' I can be expressed as (Moran 1948):

$$\text{Global Moran's } I = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}(x_i-\overline{x})(x_j-\overline{x})}{\left(n\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}\right)\sum_{i=1}^{n}(x_i-\overline{x})^2}, (i\neq j) \quad (2)$$

where x_i and x_j are the values of variables for evaluation units i and j respectively; $i = 1, 2, \ldots, n$; $j = 1, 2,\ldots, m$; n is the number of evaluation units; m represents the number of evaluation units which geographically adjacent to evaluation unit i; $\overline{x}$ is the average value of x; W_{ij} is a weight parameter for the pair of evaluation units i and j in proximity; when i and j are adjacent, $W_{ij} = 1$; otherwise, $W_{ij} = 0$. The Moran's I ranges from − 1 to 1. When $I > 0$, it indicates a positive spatial correlation with the spatial pattern being agglomeration distribution; when $I < 0$, it indicates a negative spatial correlation the spatial pattern being diffusion or uniform distribution; and when $I = 0$, it indicates no spatial autocorrelation with the spatial pattern being random distribution.

The local Moran's I is used to identify local spatial clustering and is defined as (Anselin 1995):

$$\text{Local Moran's } I = \frac{n(x_i-x)\sum_{j=1}^{m} W_{ij}(x_j-x)}{\sum_{i=1}^{n}(x_i-x)^2}, (i\neq j) \quad (3)$$

The LISA has four kinds of local spatial associations: High-high or low-low indicates a spatial positive association or clustering; high-low or low-high represents a spatial negative association or heterogeneity (Li et al. 2014).

Assessment of influencing factors

Geographical detector

The geographical detector, a spatial statistical tool newly proposed by Jinfeng Wang (Wang et al. 2010; Shi et al. 2018), is used to reveal the global effects of the influencing factors of urban air pollution *at the global scale* in this study. It examines whether the spatial distribution of the dependent variable Y (an event or a phenomenon) and that of the independent variable X (the influencing factors) are likely to be the same (Luo et al. 2019).

The principle of the geographical detector is to divide a spatial region into several subregions with spatially stratified heterogeneity based on influencing factors' subclasses. The geographical detector is similar to variance analysis

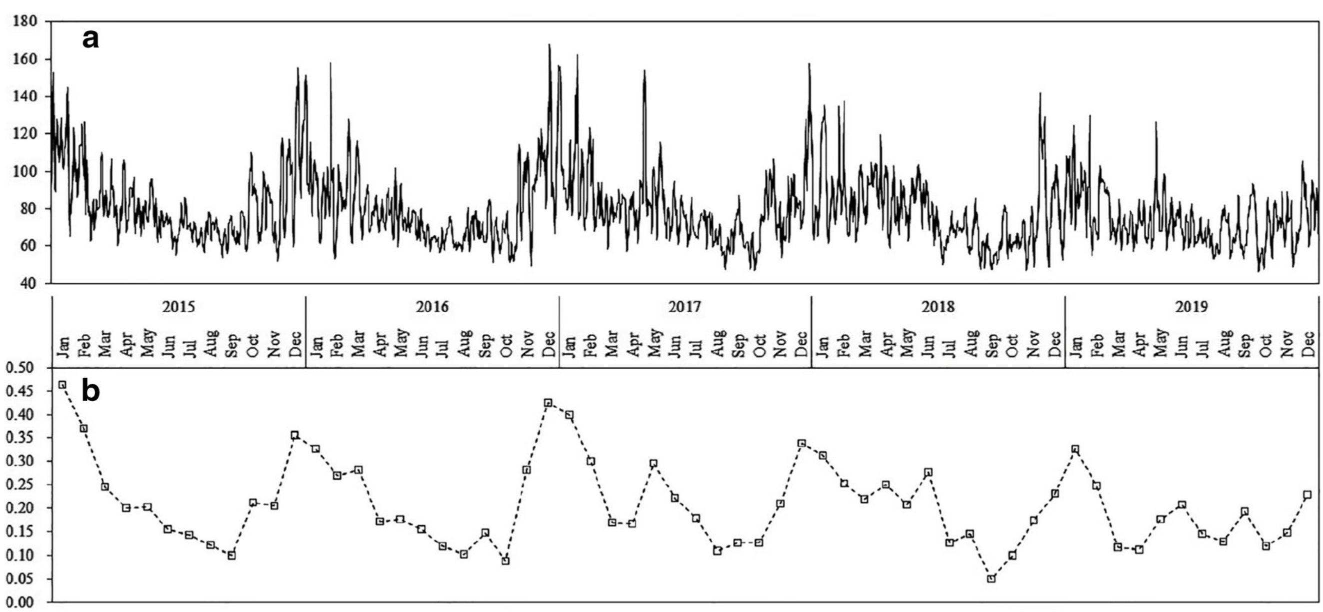

Fig. 3 The temporal characteristics of **a** the air quality index (AQI) and **b** the urban air pollution index (UAPI) from 2015 to 2019

(ANOVA) in that it provides feasible means to measure spatially (globally) stratified heterogeneity of the dependent variable Y between subregions (Ding et al. 2019; Peng et al. 2019; Liu et al. 2020). The hypothesis is that if the sum of the variances of the subareas, which are classified by the factor, is less than the variance of the whole region, spatially stratified heterogeneity exists (Wang and Xu 2017; Ding et al. 2019). The geographical detector has the following advantages over the classical statistical methods: (1) as a spatial analysis tool grounded in spatial statistics, it does not require the assumption that the independent or dependent variables must be independently and identically distributed (IID) as generally required by traditional classical statistics (Ding et al. 2019; Wang et al. 2017; Zhou et al. 2018a; Zhao et al. 2020); (2) the geographical detector does not require consideration of the collinearity of multiple independent variables so that any influencing factors can be included in the analysis (Zhou et al. 2018a; Ding et al. 2019; Duan and Tan 2020); (3) the geographical detector has also a unique advantage that can be used to explore the interactions of two influencing factors affecting the dependent variable and to reveal whether the interactions of the two factors are linear or nonlinear (Bai et al. 2019); and (4) the stratified independent variables in the geographical detector can enhance the representation of a sample unit to afford a greater level of statistical accuracy (Duan and Tan 2020).

Therefore, we used the geographical detector to further answer the following three questions (see also Qiao et al. 2019): (1) which influencing factors contribute to urban air pollution? (2) what is the level of contribution from each influencing factor? and (3) whether these factors work independently or interdependently to influence urban air pollution?

The geographical detector consists of four processes (Wang and Xu 2017): factor detection, risk detection, interaction detection, and ecological detection (see Appendix A for more about the geographical detector). The geographical detector employs the q-statistic to measure the explanatory power of the independent variables to the dependent variable. The q-statistic is defined as in Eq. (4).

$$q = 1 \frac{\sum_{h=1}^{1} N_h \sigma_h^2}{N\sigma^2} \tag{4}$$

where $h = 1, \ldots, l$ is the stratification of the independent variable; N_h and N are the sample size of the h ($h = 1, \ldots, l$) layer and across all subregions, respectively; $\sigma_h{}^2$ and σ^2 are the variances of the dependent variable of the h ($h = 1,\ldots, l$) layer and across all subregions, respectively. The values of q range from 0 to 1, meaning the independent variables could explain $100\times q\%$ of the dependent variable. The greater the value of q is, the stronger the explanatory power of the independent variable to the dependent variable, or vice versa. Because discrete variables are superior to continuous variables in the geographic detector (Wang et al. 2010), the continuous data of independent variables were discretized using the quantile and the natural breakpoint method.

Geographically weighted regression

The geographically weighted regression (GWR) was employed to assess the influencing factors of urban air pollution *at the local scale*. GWR is a locally weighted least squares linear regression model for spatial analysis (You et al. 2016). The spatial weighting function employed in a GWR model assumes that spatial locations close to each other have similar characteristics than those distant from each other. The GWR model can be expressed as follows:

$$y_i = \beta_{0(\mu_i v_i)} + \sum_{j=1}^{k} \beta_{j(\mu_i v_i)} x_{ij} + \varepsilon_i \tag{5}$$

where y_i and x_{ij} are the observed values of the response variable and the explanatory variables at the location (μ_i, v_i); (μ_i, v_i) is the x–y coordinate of the ith location; β_j (μ_i, v_i) is the regression coefficient associated with the jth explanatory variable at location i whose geographical coordinates are (μ_i, v_i); ε_i is the model error at location i.

For the GWR model defined in Eq. (5), the regression coefficient β_j (μ_i, v_i) varies from location to location, which can be estimated using

$$\widehat{\beta}_{(\mu_i v_i)} \left[\boldsymbol{X}^T \boldsymbol{W}(\mu_i, v_i)\boldsymbol{X}\right]^{-1} + \boldsymbol{X}^T \boldsymbol{W}\left(\mu_{i,} v_i\right)\boldsymbol{Y} \tag{6}$$

where $\boldsymbol{X}$ is the matrix of the observed explanatory variables; $\boldsymbol{Y}$ is the vector of observed values of the response variable; and $\boldsymbol{W}$ (μ_i, v_i), is the spatial weight matrix, which can be estimated using Gaussian distance function or chi-square distance function. In our study, the Gaussian distance function was used.

Data sources and pre-processing

Due to limitations in data availability, we only tested the assessment of the influencing factors of the urban air pollution in 337 Chinese cities in 2015. The data in this study include three categories: air quality, geographical and meteorological data, and socio-economic data. The air quality data was collected from the Ministry of Environmental Protection (http://www.mee.gov.cn/hjzl/), which mainly included the 24-h average values of six pollutants (PM10, NO_2, SO_2, PM2.5, O_3, and CO). The geographical data, including altitude, temperature, humidity, and precipitation, were collected from the Resource and Environment Data Cloud Platform (http://www.resdc.cn). The meteorological data, including annual mean temperature, annual mean precipitation, and humidity index, were retrieved from 1915 meteorological stations in China, and their spatial interpolation maps were produced in ArcMap 10.5 (ESRI Inc., CA) by using the inverse distance weighted method. Because more than 60% of China is mountainous and the meteorological conditions in mountainous areas are significantly affected by topography, we used the national digital elevation model (DEM) to adjust the temperatures at different elevations at the rate that temperature declines 0.6 °C per 100 m increase. The wind speed data was downloaded from the National Meteorological Information Center (https://data.cma.cn/en). The socio-economic data were obtained from China Urban Construction Statistical Yearbook (National Bureau of Statistics 2016), China Urban Statistical Yearbook (National Bureau of Statistics 2016), and local statistical yearbooks and annual reports. The four seasons are defined as follows: winter (January 1–March 20, December 24–December 31), spring (March 21–June 22), summer (June 23–September 22), and autumn (September 23–December 23).

Results

Spatial-temporal characteristics of UAPI

Annual characteristics Figure 4 shows that the average of the UAPI in the 337 Chinese cities in 2015 was 0.22. The 337 cities were classified into ten groups with their UAPI values falling into the following intervals [0, 0.1], (0.1, 0.2], …, (0.9, 1.0], respectively. In 2015, about 30 cities (8.9%) had UAPI greater than 0.5.

Interestingly, as shown in Fig. 4, the spatial pattern of the UAPI was largely consistent with the population-based Hu Line that generally divides China into east and west regions (Hu et al. 2016). The cities in the eastern region generally had higher UAPI values than the cities in the west region. Similarly, the Yangtze River divides China into north and south regions, and the cities in the north had higher UAPI than the cities in the south. The cities with annual average UAPI greater than 0.5 were mostly concentrated in North China, Central China, Northeast China, and East China, whereas the cities with lower UAPI (< 0.5) were mostly distributed in the west of the Hu Line and the south of the Yangtze River, except for the four cities in west-central Xinjiang and northern Tibet Autonomous Regions.

Seasonal characteristics Figures 5 and 6 present the seasonal characteristics and spatial patterns of the UAPI in 2015, respectively. Not surprisingly, the winter had the most frequent urban air pollution days in 2015, with an average UAPI of 0.42. In this winter, about 100 cities in North, Central, and Northwest China (Fig. 6d) had UAPI higher than 0.5. In contrast, the summer had the least urban air pollution days in 2015 (Fig. 5b), with an average UAPI of 0.11. Only 12 cities spread in South Xinjiang and North China had UAPI greater than 0.5 (Fig. 6b). In general, there were more urban air pollution days in the autumn (Fig. 6c) than in the spring (Fig. 6a). For example, there were 34 cities in the autumn and 30 cities in the spring that had UAPI higher than 0.5.

Monthly characteristics Figure 7 shows the monthly averages of UAPI at the spatial and temporal scales. The UAPI declined continuously from December/January to August, then increased continuously from August to November. In January when the UAPI's peaked for almost all cities, there were 162 cities with UAPI higher than 0.5. These cities were mainly concentrated in the east of the Hu Line, the north of the Yangtze River, the eastern coastal region, and Northwest China.

Spatial analysis

The global Moran's I analysis of UAPI shows that annual Moran's I was 0.7652 ($p < 0.05$) and the seasonal Moran's Is were as follows (in decreasing order): autumn (0.7098) > spring (0.7036) > winter (0.6646) > summer (0.5337). The results indicate that the UAPI had significant positive spatial autocorrelation at the global scale, which means the occurrence of urban air pollution events such as haze days in one area was positively affected by its adjacent areas.

On the other hand, the LISA analysis shows that the annual and seasonal UAPIs can basically be divided into four or five clusters (Fig. 8, see also Fig. A1 in Appendix A for monthly information). The H-H (hot spot) agglomeration areas were mainly concentrated in North China, Central China, and the southern Xinjiang, whereas the L-L (cold spot) agglomeration areas were mainly located in Southwest China, Southeast China, and the Great Xing-an Mountains of Northeast China. There were a few regions with high values of UAPI surrounded by the regions with low values (H-L, heterogeneity spot), and they were mainly distributed in the southeast of Qinghai and Guizhou provinces. The areas with a low value of UAPI that were surrounded by the high-value areas (L-H) were mainly distributed in northern Tibet, North China, and the Shandong Peninsula, scattered across mainland China.

Global effects of the UAPI influencing factors—geographical detector

Factor detection Table 2 presents the factor detection results for the UAPI at the annual and seasonal scales. The q values of the influencing factors were ranked for a better comparison of the contributions from individual influencing factors to the UAPI. First, the ranks of the influencing factors varied from season to season. For example, wind speed (D4) rose from 23rd place in the summer to 14th place in the winter at $\alpha = 0.05$, which indicated that wind might have played a more

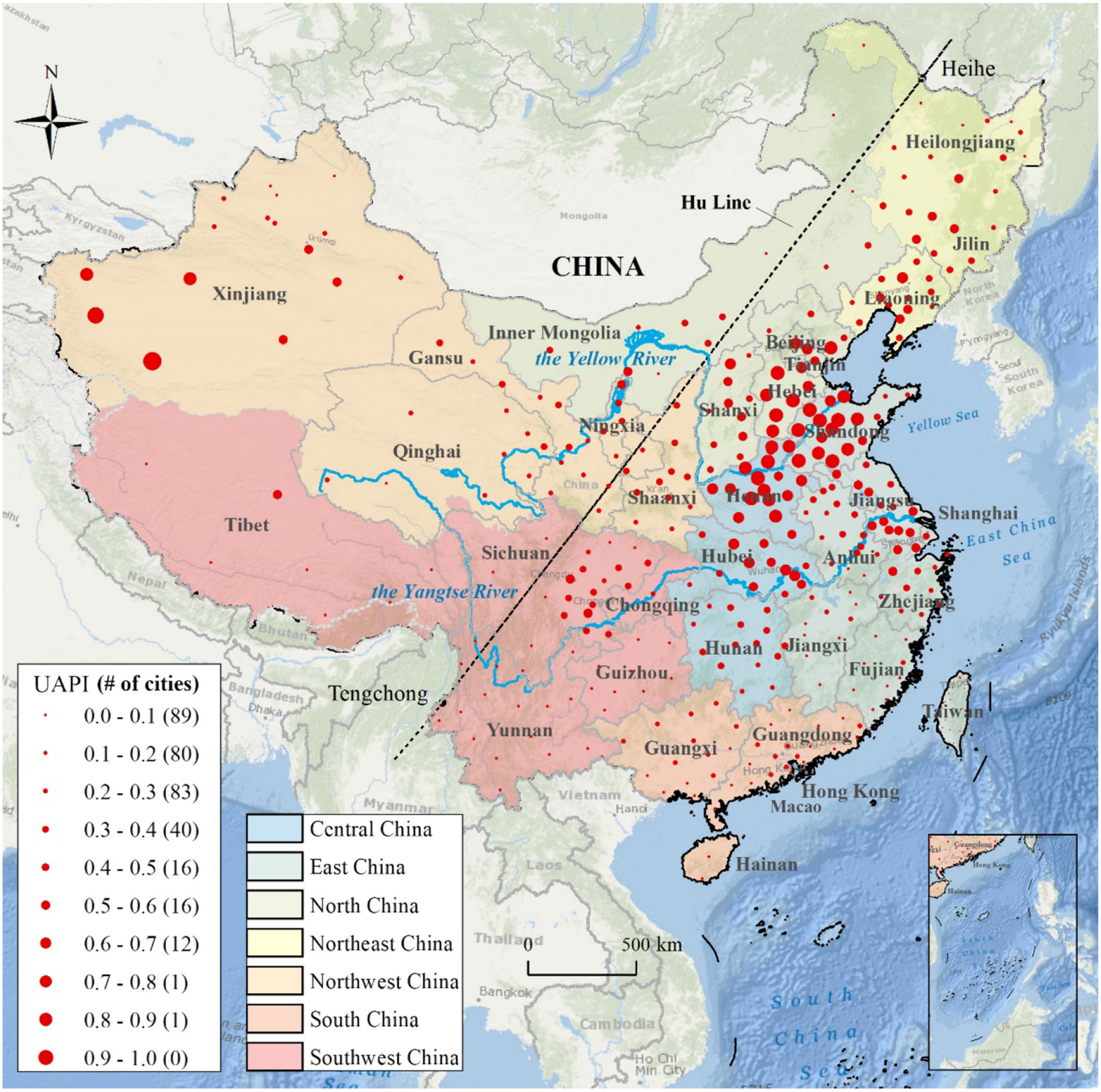

Fig. 4 The urban air pollution index (UAPI) in 337 Chinese cities in 2015

important role in the formation of the air pollution events in the winter than in the summer. Second, annual average temperature (D2), humidity index (D3), and annual average precipitation (D5) were the biggest contributors among natural factors to urban air pollution in 2015. Third, the socio-economic factors in the pressure group, such as the proportion of the construction land to the total area of the city (P1), number of manufacturing enterprises (P3), nitrogen fertilizer application rate (P4), number of domestically made car ownership (P7), highway density (P8), and the ratio of the central heating (P9), had larger contributions than the factors in the driver's group. Fourth, the responses to urban air pollution need to be strengthened because the contribution from the response factors was generally low, although some measures (such as industrial upgrading and energy efficiency) had already played an active role in alleviating urban air pollution. The complex, interactive relationships between the influencing factors were further explored by using risk detection and interaction detection as shown in the following paragraphs.

Risk detection The risk detector was used to further identify the direction and magnitude of the influencing factors' effect

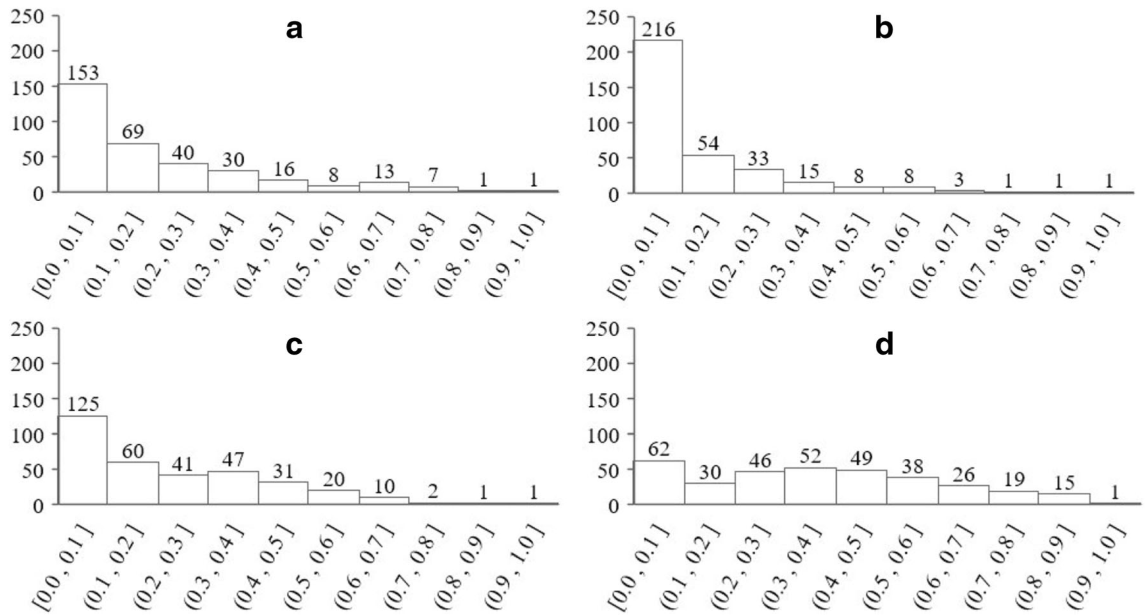

Fig. 5 Seasonal characteristics of the urban air pollution index in 2015. **a** Spring. **b** Summer. **c** Autumn. **d** Winter

on urban air pollution. As shown in Fig. 9 and Table 3, the influence of natural factors on urban air pollution is more complicated than that of socio-economic factors when comparing the difference between the subregions of influencing factors.

First, the natural factors such as annual average temperature (D2), humidity index (D3), and annual average precipitation (D5) had apparently nonlinear effects on the urban air pollution at the subregion level, whereas the effects of the relative elevation (D1) and the wind speed (D4) on the urban air pollution were monotonically decreasing with the subregion level. Second, in terms of the anthropogenic factors, the relationships between most influencing factors and urban air pollution were close to monotonically increasing or decreasing (Fig. 9 and Table 3). In general, the relationships between urban air pollution and its influencing factors at the subregion level may be categorized into six types of linear or nonlinear relationship as defined in Table 3.

Interaction detection and ecological detection Table 4 lists the q values of interaction detection. It shows that the explanatory power (interactive effect) between any two influencing factors (i.e., the q values in the off-diagonal cells) was always greater than that of a single individual influencing factor to the urban air pollution (i.e., the q value in the diagonal cells). Furthermore, the interaction relationship was mainly expressed as nonlinear enhance (287 pairs, accounting for 81.77%) and bi-enhance (64 pairs, accounting for 18.23%) (refer to Table A2 for more details). First, in terms of nonlinear enhance, the explanatory power had a maximum value of 0.664 (D5∩P3) and a minimum value of 0.050 (R2∩R6). The explanatory powers for 16 pairs were greater than 0.5, of which 13 pairs were interactions between a natural factor and a socio-economic factor. Second, in terms of bi-enhance, the maximum value of the explanatory power was 0.4748 (D2∩P8), whereas the minimum value was 0.1172 (D1∩R8). These results show that, to some extent, the interactions between the natural factors and the socio-economic factors can enhance the explanatory ability of the influencing factors to the urban air pollution in China.

Table 5 further explores whether the influences from different influencing factors on urban air pollution were significantly different from each other. For example, the natural factors, including relative elevation (D1), annual average temperature (D2), humidity index (D3), and annual average precipitation (D5), had a significant effect on urban air pollution, compared with the effect of wind speed (D4). In terms of socio-economic factors, the effects of the factors D10, P5, P8, P9, R1, R2, R3, R4, and R6 on urban air pollution were significantly different from each other. These results show that these influencing factors dominated the temporal and spatial evolutions of urban air pollution and urban air pollution was a result of the interactions among multiple influencing factors.

Local effects of the UAPI influencing factors—geographically weighted regression

Since the q statistic of the geographical detector can only describe the explanatory power of the influencing factors on urban air pollution, we also used the GWR model to further

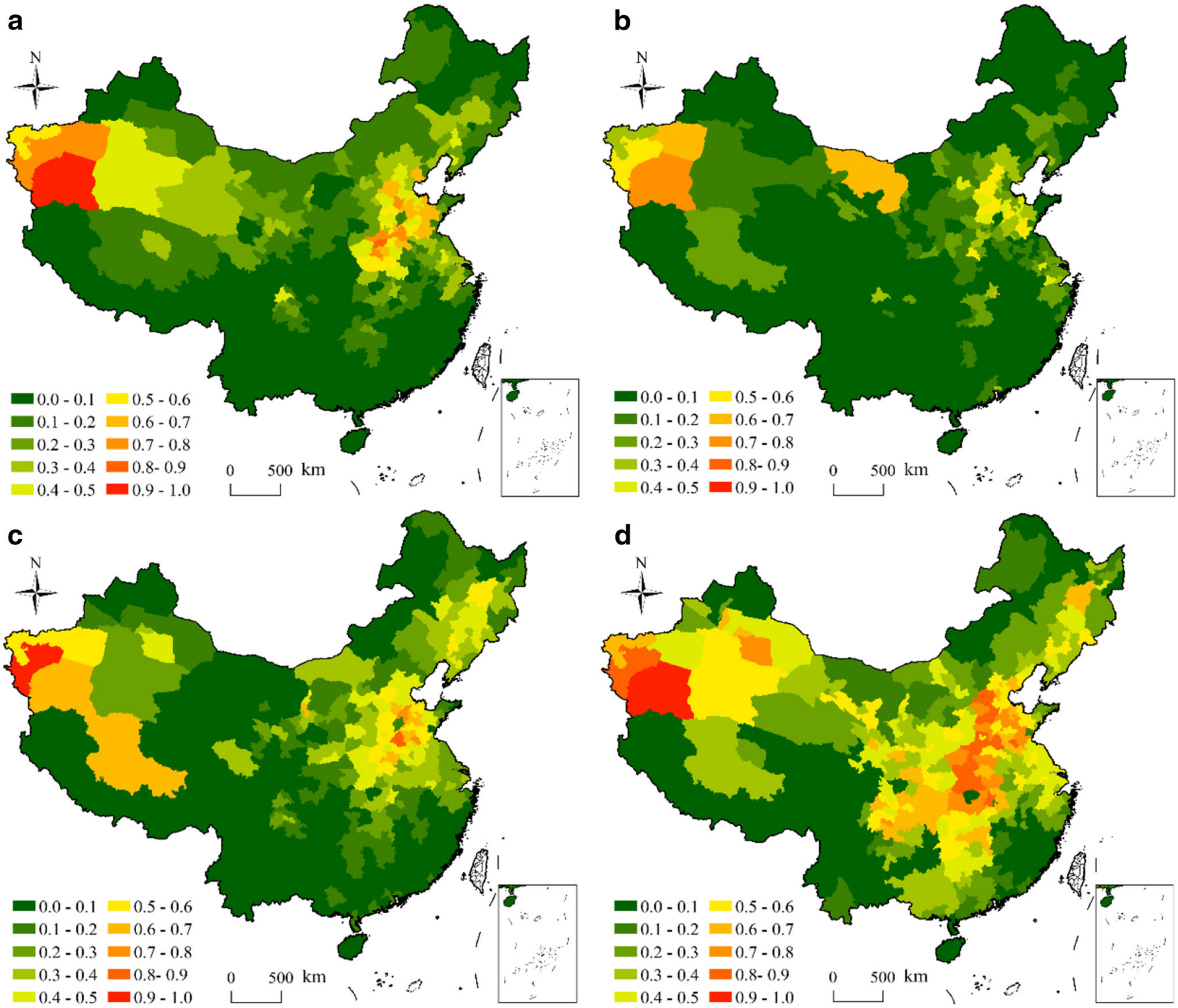

Fig. 6 Spatial patterns of the urban air pollution index in four seasons in 2015. **a** Spring. **b** Summer. **c** Autumn. **d** Winter

quantify the local positive and negative effects of the influencing factors, which were to be represented by the signs and magnitudes of the estimated regression coefficients of the GWR. As compared in Table 6, the GWR model is clearly a better model than the ordinary least squares (OLS) linear regression model to explain the relationships between urban air pollution and its influencing factors. This is because the OLS model ignored the potential spatial effects of the independent and dependent variables (Wang et al. 2017).

Table 7 lists the descriptive statistics of the regression coefficients of the GWR model (see also Fig. A2 for the percentages of the positive and negative values of the grid-level regression coefficients). As shown in Table 7, all influencing factors had both positive and negative effects on urban air pollution at the local scale. The four factors that had the largest positive average local effects were the proportion of secondary industry in regional GDP (D7), the ratio between the third industry and the second industry (R3), number of domestically made car ownership (P7), and highway density (P8). The four factors that had the largest average negative local effects were relative elevation (D1), annual average precipitation (D5), actually utilized foreign capital (D9), and annual average temperature (D2). Figure 10 further depicts the spatial characteristics of the regression coefficients of the GWR model. Apparently, the effects of the influencing factors on UAPI were different in different regions. For example, most natural driving factors (D1–D5) contributed positively to UAPI in western China, but not in

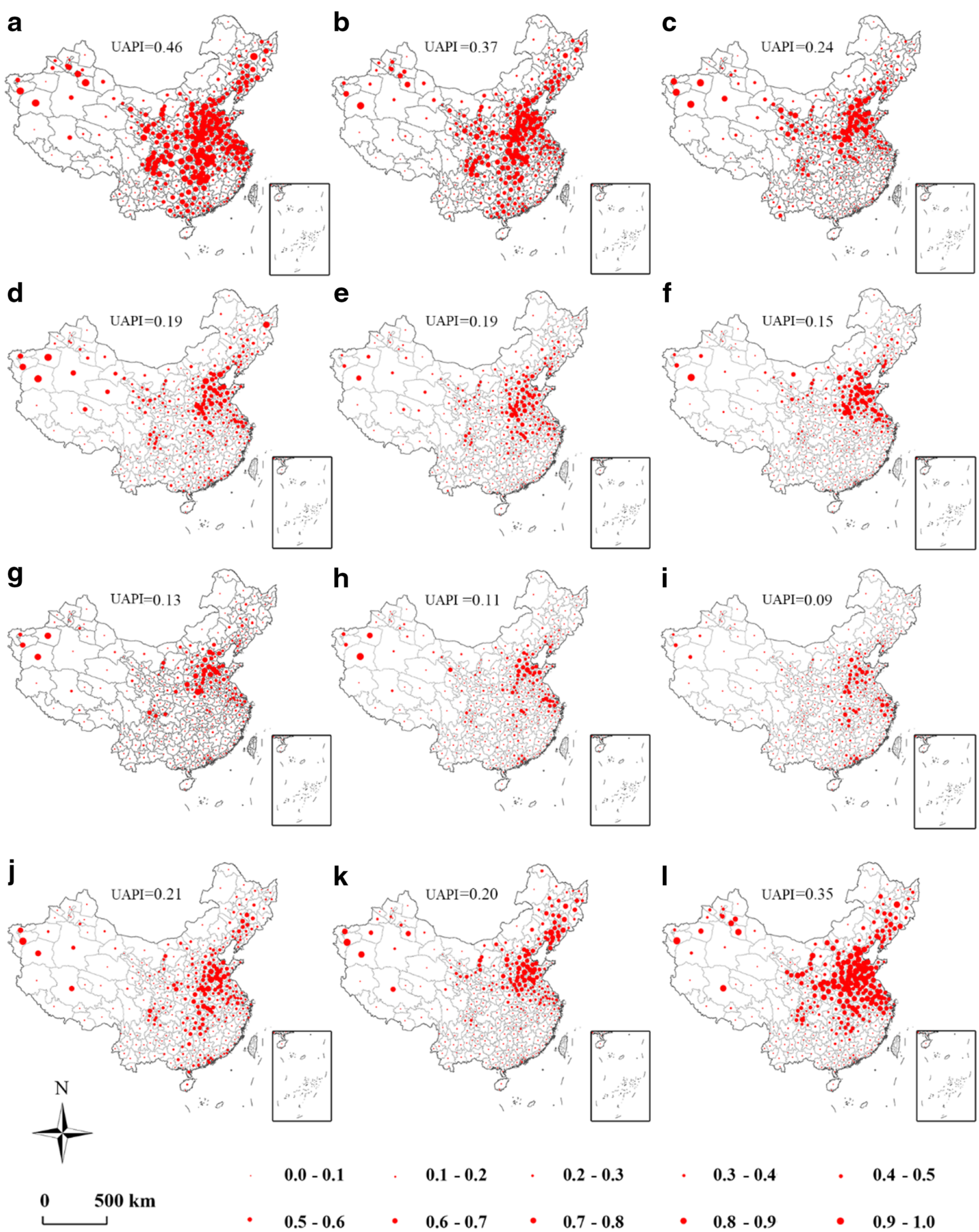

Fig. 7 Spatial variation of monthly average urban air pollution index (UAPI) in 2015. **a** January. **b** February. **c** March. **d** April. **e** May. **f** June. **g** July. **h** August. **i** September. **j** October. **k** November. **l** December

other regions. Some influencing factors such as the number of manufacturing enterprises (P3), number of domestically made car ownership (P7), and highway density (P8) contributed positively to urban air pollution in central China. The response factors such as the rate of green land in built-up area (R1) and per unit GDP in energy consumption (R6) had greater mitigation effects on urban air pollution in most areas from northwestern to southeastern China.

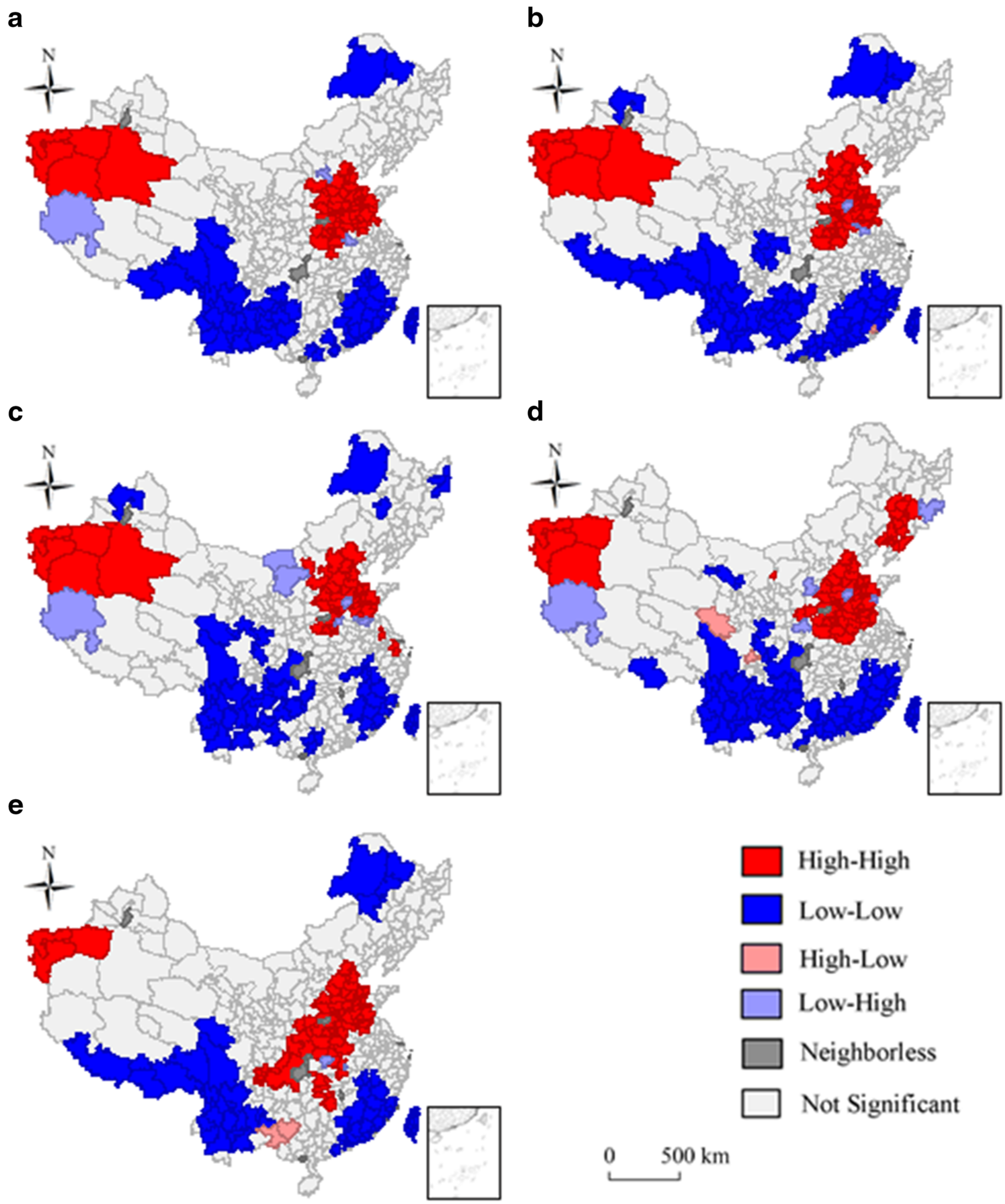

Fig. 8 Annual and seasonal spatial clustering of the urban air pollution index in 2015. **a** Annual. **b** Spring. **c** Summer. **d** Autumn. **e** Winter

Discussion

Complexity of the influencing factors of urban air pollution

Driver

The drivers, natural or socio-economic, have an indirect (potential) positive or negative contribution to urban air pollution (Tables 1, 2, and 3). In this study, the explanatory power of the natural drivers (such as temperature, precipitation, and humidity) on the urban air pollution is slightly higher than that of the socio-economic drivers (Table 2), which is consistent with the findings of Zhou et al. (2017) and Zhan et al. (2018). Our analysis shows that urban air pollution is closely related to natural factors. For example, meteorology is the main factor that affects the self-purification ability of the air environment and indirectly affects the formation of air pollution events in

Table 2 The results of the factor detection for the influencing factors of urban air pollution in 2015

Criteria	Basic-level indicators		Annual		Spring		Summer		Autumn		Winter	
			q	Rank	*q*	Rank	*q*	Rank	*q*	Rank	*q*	Rank
Driver (D)	D1	Relative elevation	0.0675**	16	0.0242	19	0.0231	21	0.0631**	17	0.0937**	12
	D2	Annual average temperature	0.3028**	1	0.3012**	1	0.1564**	3	0.2612**	2	0.2679**	1
	D3	Humidity index	0.2190**	4	0.2237**	4	0.1410**	6	0.2162**	4	0.1208**	6
	D4	Wind speed	0.0237	22	0.0214	21	0.0173	23	0.0184	23	0.0773**	14
	D5	Annual average precipitation	0.2579**	2	0.2682**	2	0.1827**	1	0.2533**	3	0.1802**	2
	D6	Regional GDP growth rate	0.0221	23	0.0210	22	0.0438**	16	0.0347*	20	0.0106	24
	D7	Proportion of secondary industry in regional GDP	0.0561**	18	0.0382**	18	0.0279*	19	0.0455**	19	0.0469**	16
	D8	Investment to real estate development	0.1004**	13	0.0764**	14	0.0960**	13	0.0817**	15	0.0967**	11
	D9	Actually utilized foreign capital	0.0646**	17	0.0638**	16	0.0617**	14	0.0682**	16	0.0385**	18
	D10	Natural population growth rate	0.0038	27	0.0045	27	0.0139	25	0.0143	26	0.0054	26
Pressure (P)	P1	Proportion of construction land to the total area of the city	0.1421**	9	0.1255**	6	0.1131**	11	0.1495**	6	0.0974**	10
	P2	Proportion of coal consumption	0.0454**	19	0.0646**	15	0.0204	22	0.1028**	12	0.0286*	21
	P3	Number of manufacturing enterprises	0.1453**	8	0.1190**	8	0.1145**	10	0.1097**	8	0.1200**	7
	P4	Nitrogen fertilizer application rate	0.1338**	11	0.1056**	11	0.0470**	15	0.1159**	7	0.1381**	4
	P5	Population density	0.0266*	20	0.0129	24	0.0264*	20	0.0177	24	0.0100	25
	P6	Per unit construction building area	0.1455**	7	0.1058**	10	0.1388**	7	0.0945**	14	0.1540**	3
	P7	Number of domestically made car ownership	0.1418**	10	0.1008**	12	0.1806**	2	0.1086**	10	0.0921**	13
	P8	Highway density	0.1767**	5	0.1448**	5	0.1226**	9	0.1710**	5	0.1138**	8
	P9	Ratio of the central heating	0.2514**	3	0.2612**	3	0.1335**	8	0.3073**	1	0.1316**	5
Response (R)	R1	Rate of green land in built-up area	0.0159	24	0.0125	25	0.0166	24	0.0229	21	0.0203	22
	R2	Proportion of energy conservation and environmental protection expenditures to local fiscal expenditure	0.0128	25	0.0151	23	0.0392**	18	0.0148	25	0.0018	27
	R3	Ratio between the third industry and the second industry	0.0262*	21	0.0238	20	0.0135	26	0.0222	22	0.0313**	20
	R4	Per unit area industrial output	0.1551**	6	0.1248**	7	0.1473**	4	0.1094**	9	0.1001**	9
	R5	Ex-factory price index of industrial products	0.0846**	14	0.1187**	9	0.0425**	17	0.1083**	11	0.0365**	19
	R6	Per unit GDP in energy consumption	0.0090	26	0.0075	26	0.0106	27	0.0104	27	0.0167	23
	R7	Gas penetration rate	0.1207**	12	0.0830**	13	0.1413**	5	0.0978**	13	0.0685**	15
	R8	Expenditure of research and experimental development funds (R&D)	0.0728**	15	0.0504**	17	0.1075**	12	0.0589**	18	0.0427**	17

*Statistically significant at the 0.1 level

**Statistically significant at the 0.05 level

Chinese cities. In terms of air temperature, high temperature promotes air photochemical reactions, which are conducive to the formation of air pollutants such as O_3 (Song et al. 2017). On the other hand, cities with lower average annual temperatures tend to burn more coals or other fuels for heating in the winter, emitting a large number of air pollutants. Moreover, the altitude of a city has an important effect on the dispersion and concentration of air pollutants. Han et al. (2016) also found that urban air pollution events occurred more frequently in the low-altitude areas than in the high-altitude areas. Wind can transport air pollutants and dilute the concentration of air pollutants, thus reducing the possibility of the formation and persistence of urban air pollution events. Precipitation can remove the suspended particles and gaseous pollutants from the air and clean the atmosphere to reduce the possibility of urban air pollution events.

Fig. 9 The risk detection of the influencing factors to urban air pollution. ▶ Notes: the x-axis is the subregion of influencing factors; the y-axis is the urban air pollution index. (a) D1, relative elevation; (b) D2, annual average temperature; (c) D3, humidity index; (d) D4, wind speed; (e) D5, annual average precipitation; (f) D6, regional GDP growth rate; (g) D7, proportion of secondary industry in regional GDP; (h) D8, investment to real estate development; (i) D9, actually utilized foreign capital; (j) D10, natural population growth rate; (k) P1, proportion of construction land to the total area of the city; (l) P2, proportion of coal consumption; (m) P3, number of manufacturing enterprises; (n) P4, nitrogen fertilizer application rate; (o) P5, population density; (p) P6, per unit construction building area; (q) P7, number of domestically made car ownership; (r) P8, highway density; (s) P9, ratio of the central heating; (t) R1, rate of green land in built-up area; (u) R2, proportion of energy conservation and environmental protection expenditures to local fiscal expenditure; (v) R3, ratio between the third industry and the second industry; (w) R4, per unit area industrial output; (x) R5, ex-factory price index of industrial products; (y) R6, per unit GDP in energy consumption; (z) R7, gas penetration rate; (aa) R8, expenditure of research and experimental development funds

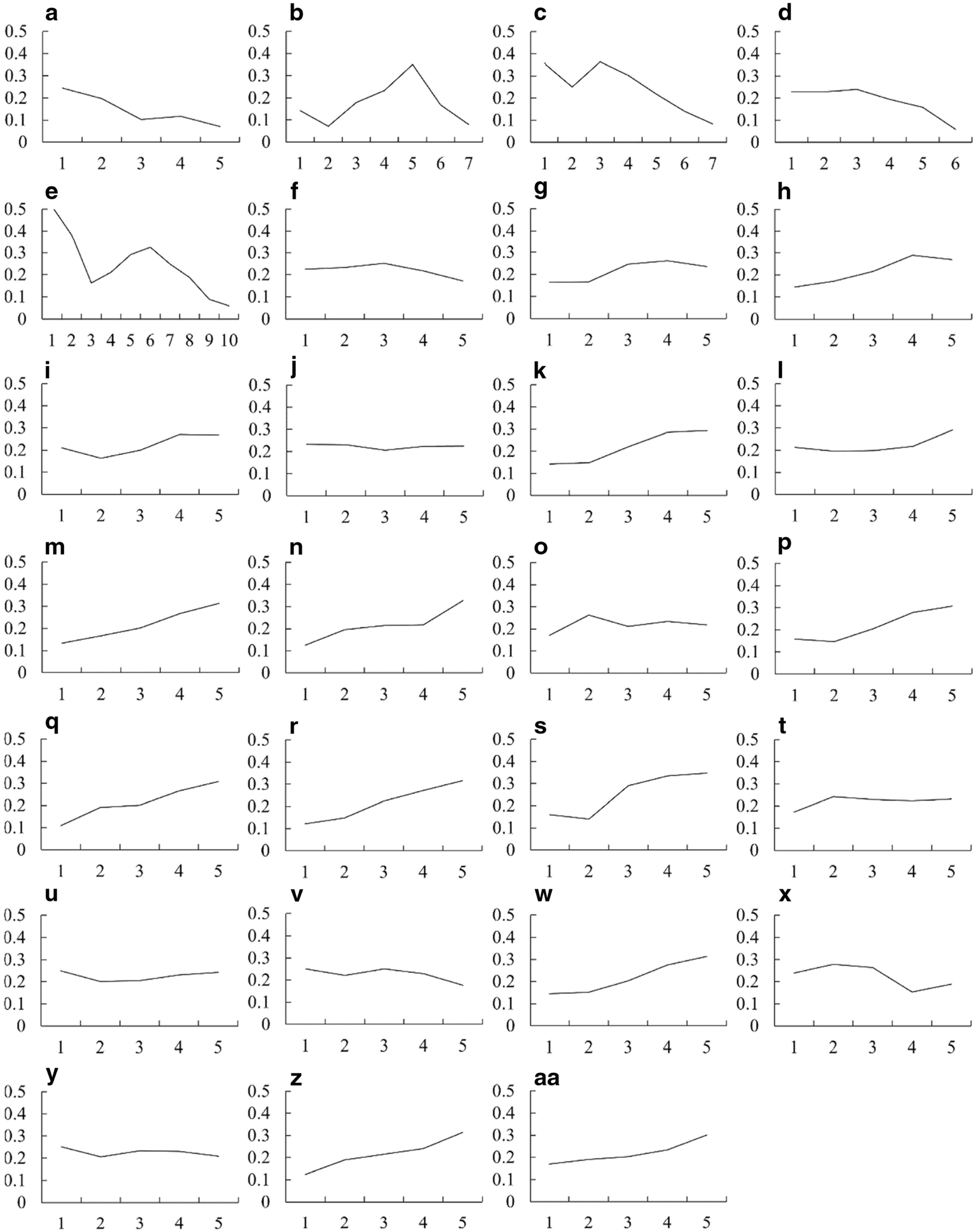
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Table 3 The complex relationship between urban air pollution and its influencing factors

Criteria	Basic-level indicators		Relations
Driver (D)	D1	Relative elevation	−
	D2	Annual average temperature	±
	D3	Humidity index	±
	D4	Wind speed	−
	D5	Annual average precipitation	±
	D6	Regional GDP growth rate	±
	D7	Proportion of secondary industry in regional GDP	+
	D8	Investment to real estate development	+
	D9	Actually utilized foreign capital	−/+
	D10	Natural population growth rate	−/+
Pressure (P)	P1	Proportion of construction land to the total area of the city	+
	P2	Proportion of coal consumption	+
	P3	Number of manufacturing enterprises	+
	P4	Nitrogen fertilizer application rate	+
	P5	Population density	±
	P6	Per unit construction building area	+
	P7	Number of domestically made car ownership	+
	P8	Highway density	+
	P9	Ratio of the central heating	+
Response (R)	R1	Rate of green land in built-up area	+/−
	R2	Proportion of energy conservation and environmental protection expenditures to local fiscal expenditure	−/+
	R3	Ratio between the third industry and the second industry	−
	R4	Per unit area industrial output	+
	R5	Ex-factory price index of industrial products	±
	R6	Per unit GDP in energy consumption	±
	R7	Gas penetration rate	+
	R8	Expenditure of research and experimental development funds (R&D)	×

"+" means a positive effect. "−" means a negative effect. "±" means the relationship between urban air pollution and its influencing factors is complex. "−/+" means the effect of the influencing factor on air pollution changes from negative to positive from subregion 1 to subregion 5, whereas "+/−" means the change of the effect is reversed from positive to negative. "×" means the relationship between air pollution and its influencing factors cannot be defined

Since its opening up to foreign trade and investment and implementing free-market reforms in 1979, China has been among the world's fastest-growing economies. Social and economic drivers also resulted in various environmental problems. First, an unsound industrial structure led to considerable pollution emission. For example, Hao and Liu (2016) reported that the secondary industry had contributed most to pollutant emissions and the formation of urban air pollution events. Second, the real estate industry has driven the rapid development of the relevant industries. Cheng et al. (2017) found that once the real estate industry had exceeded a reasonable scale, it would be an important driving factor to aggravate urban air pollution indirectly. Third, as shown in Fig. 9 and Table 3, our findings simultaneously support the two popular views about the effect of the foreign direct investment (D9) on the environment of China. One is the "pollution haven" hypothesis (Bakirtas and Cetin 2017), namely, foreign enterprises carry out industrial migration through investment abroad, transferring environmental pollution to China. The opposing view is the "pollution halo" hypothesis (Wang et al. 2019a), i.e., foreign companies can bring efficient production and clean technologies, promoting the efficiency of energy utilization in China, reducing pollutant emissions, and improving environmental quality. Fourth, studies found that population growth made the slope of the environmental Kuznets curve steeper; that is, the increment of GDP per capita led to higher natural resource consumption and pollution accumulation (Wang et al. 2015).

Pressure

In this study, the pressure factors include four aspects: land use, energy consumption, economy, and society. First, the land use pressure mainly comes from construction land sprawl. Unreasonable land use structure is not conducive to

Table 4 The explanatory power between any two influencing factors

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	P1	P2	P3	P4	P5	P6	P7	P8	P9	R1	R2	R3	R4	R5	R6	R7	R8
D1	0.067																										
D2	0.434	0.303																									
D3	0.376	0.571	0.219																								
D4	0.119	0.367	0.321	0.024																							
D5	0.483	0.604	0.415	0.389	0.258																						
D6	0.104	0.410	0.310	0.071	0.395	0.022																					
D7	0.145	0.368	0.338	0.122	0.462	0.129	0.056																				
D8	0.147	0.382	0.516	0.190	0.581	0.173	0.167	0.100																			
D9	0.149	0.368	0.357	0.135	0.433	0.197	0.193	0.193	0.065																		
D10	0.118	0.352	0.411	0.108	0.421	0.119	0.169	0.167	0.179	0.004																	
P1	0.209	0.448	0.418	0.228	0.511	0.217	0.194	0.234	0.236	0.227	0.142																
P2	0.145	0.388	0.322	0.142	0.375	0.134	0.163	0.205	0.154	0.151	0.236	0.045															
P3	0.182	0.463	0.533	0.226	0.664	0.231	0.195	0.218	0.211	0.259	0.253	0.300	0.145														
P4	0.220	0.354	0.383	0.221	0.488	0.195	0.226	0.237	0.210	0.226	0.282	0.220	0.263	0.134													
P5	0.110	0.329	0.273	0.084	0.378	0.078	0.131	0.139	0.160	0.133	0.206	0.115	0.206	0.180	0.027												
P6	0.210	0.489	0.501	0.227	0.597	0.237	0.196	0.268	0.228	0.312	0.233	0.254	0.215	0.309	0.207	0.145											
P7	0.203	0.409	0.401	0.212	0.525	0.229	0.239	0.189	0.221	0.176	0.265	0.238	0.221	0.264	0.195	0.241	0.142										
P8	0.225	0.475	0.462	0.258	0.562	0.244	0.214	0.243	0.268	0.261	0.200	0.258	0.234	0.313	0.215	0.237	0.262	0.177									
P9	0.335	0.572	0.331	0.376	0.446	0.329	0.330	0.472	0.351	0.464	0.439	0.391	0.509	0.379	0.337	0.431	0.391	0.465	0.251								
R1	0.099	0.341	0.326	0.092	0.419	0.081	0.113	0.148	0.135	0.096	0.205	0.122	0.184	0.185	0.098	0.206	0.204	0.233	0.308	0.016							
R2	0.128	0.349	0.277	0.073	0.361	0.100	0.118	0.193	0.136	0.183	0.184	0.133	0.219	0.164	0.078	0.228	0.212	0.234	0.308	0.099	0.013						
R3	0.114	0.332	0.322	0.076	0.411	0.085	0.109	0.159	0.190	0.160	0.191	0.124	0.190	0.207	0.095	0.211	0.237	0.228	0.318	0.098	0.120	0.026					
R4	0.191	0.586	0.542	0.245	0.638	0.227	0.197	0.263	0.251	0.344	0.274	0.281	0.241	0.344	0.215	0.218	0.264	0.252	0.456	0.205	0.230	0.194	0.155				
R5	0.204	0.448	0.322	0.146	0.393	0.154	0.166	0.285	0.205	0.186	0.281	0.222	0.307	0.247	0.167	0.294	0.316	0.287	0.325	0.152	0.121	0.132	0.292	0.085			
R6	0.122	0.356	0.288	0.076	0.355	0.079	0.135	0.198	0.116	0.130	0.252	0.106	0.270	0.198	0.090	0.258	0.234	0.292	0.331	0.092	0.050	0.114	0.281	0.147	0.009		
R7	0.174	0.457	0.370	0.182	0.493	0.228	0.218	0.190	0.233	0.168	0.243	0.257	0.250	0.259	0.206	0.290	0.227	0.317	0.369	0.209	0.193	0.184	0.285	0.238	0.227	0.121	
R8	0.117	0.416	0.342	0.145	0.418	0.177	0.176	0.172	0.153	0.222	0.237	0.210	0.190	0.231	0.135	0.218	0.174	0.229	0.337	0.118	0.148	0.173	0.214	0.213	0.157	0.210	0.073

The diagonal q values represent the explanatory power of the single factor, whereas the off-diagonal q values represent the interactions between the influencing factors. D1, relative elevation; D2, annual average temperature; D3, humidity index; D4, wind speed; D5, annual average precipitation; D6, regional GDP growth rate; D7, proportion of secondary industry in regional GDP; D8, investment to real estate development; D9, actually utilized foreign capital; D10, natural population growth rate; P1, proportion of construction land to the total area of the city; P2, proportion of coal consumption; P3, number of manufacturing enterprises; P4, nitrogen fertilizer application rate; P5, population density; P6, per unit construction building area; P7, number of domestically made car ownership; P8, highway density; P9, ratio of the central heating; R1, rate of green land in built-up area; R2, proportion of energy conservation and environmental protection expenditures to local fiscal expenditure; R3, ratio between the third industry and the second industry; R4, per unit area industrial output; R5, ex-factory price index of industrial products; R6, per unit GDP in energy consumption; R7, gas penetration rate; R8, expenditure of research and experimental development funds

Table 5 The results of the ecological detection

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	P1	P2	P3	P4	P5	P6	P7	P8	P9	R1	R2	R3	R4	R5	R6	R7	R8
D1																											
D2	***Y***																										
D3	***Y***	N																									
D4	N	***Y***	***Y***																								
D5	***Y***	N	N	***Y***																							
D6	N	***Y***	***Y***	N	***Y***																						
D7	N	***Y***	***Y***	N	***Y***	N																					
D8	N	***Y***	***Y***	N	***Y***	N	N																				
D9	N	***Y***	***Y***	N	***Y***	N	N	N																			
D10	N	***Y***	***Y***	N	***Y***	N	N	N	N																		
P1	N	***Y***	N	N	***Y***	N	N	N	N	***Y***																	
P2	N	***Y***	***Y***	N	***Y***	N	N	N	N	N	N																
P3	N	***Y***	N	N	***Y***	N	N	N	N	***Y***	N	N															
P4	N	***Y***	N	N	***Y***	N	N	N	N	N	N	N	N														
P5	N	***Y***	***Y***	N	***Y***	N	N	N	N	N	N	N	N	N													
P6	N	***Y***	N	N	***Y***	N	N	N	N	***Y***	N	N	N	N	N												
P7	N	***Y***	N	N	***Y***	N	N	N	N	***Y***	N	N	N	N	N	N											
P8	N	***Y***	N	***Y***	N	***Y***	N	N	N	***Y***	N	***Y***	N	N	***Y***	N	N										
P9	***Y***	N	N	***Y***	N	***Y***	***Y***	***Y***	***Y***	***Y***	N	***Y***	N	***Y***	***Y***	N	N	N									
R1	N	***Y***	***Y***	N	***Y***	N	N	N	N	N	N	N	***Y***	N	N	***Y***	N	***Y***	***Y***								
R2	N	***Y***	***Y***	N	***Y***	N	N	N	N	N	***Y***	N	***Y***	N	N	***Y***	***Y***	***Y***	***Y***	N							
R3	N	***Y***	***Y***	N	***Y***	N	N	N	N	N	N	N	N	N	N	N	N	***Y***	***Y***	N	N						
R4	N	***Y***	N	***Y***	N	***Y***	N	N	N	***Y***	N	N	N	N	***Y***	N	N	N	N	***Y***	***Y***	***Y***					
R5	N	***Y***	***Y***	N	***Y***	N	N	N	N	N	N	N	N	N	N	N	N	N	***Y***	N	N	N	N				
R6	N	***Y***	***Y***	N	***Y***	N	N	N	N	N	***Y***	N	***Y***	N	N	***Y***	***Y***	***Y***	***Y***	N	N	N	***Y***	N			
R7	N	***Y***	N	N	***Y***	N	N	N	N	N	N	N	N	N	N	N	N	N	***Y***	N	N	N	N	N	N		
R8	N	***Y***	***Y***	N	***Y***	N	N	N	N	N	N	N	N	N	N	N	N	N	***Y***	N	N	N	N	N	N	N	

Y means there is a significant difference in the influence between two influencing factors on urban air pollution, N means there is no difference. D1, relative elevation; D2, annual average temperature; D3, humidity index; D4, wind speed; D5, annual average precipitation; D6, regional GDP growth rate; D7, proportion of secondary industry in regional GDP; D8, investment to real estate development; D9, actually utilized foreign capital; D10, natural population growth rate; P1, proportion of construction land to the total area of the city; P2, proportion of coal consumption; P3, number of manufacturing enterprises; P4, nitrogen fertilizer application rate; P5, population density; P6, per unit construction building area; P7, number of domestically made car ownership; P8, highway density; P9, ratio of the central heating; R1, rate of green land in built-up area; R2, proportion of energy conservation and environmental protection expenditures to local fiscal expenditure; R3, ratio between the third industry and the second industry; R4, per unit area industrial output; R5, ex-factory price index of industrial products; R6, per unit GDP in energy consumption; R7, gas penetration rate; R8, expenditure of research and experimental development funds

the overall ventilation capacity of a city, resulting accumulation of air pollutants in a certain area. Second, energy consumption is the primary source of air pollutants. The pollutant emission coefficients vary among different energy sources, especially the air pollutant emission coefficient of coal combustion is significantly higher than other energy production sources (Hao and Liu 2016). Third, although the emission from industries is the primary source of many air pollutants, the excessive use of nitrogen fertilizer in agriculture is the main cause of ammonia pollution, which plays an important role in increasing the concentration of PM2.5 (Zhao et al. 2019). During the process of industrialization in China, the additive effect of industrial pollution and soil and water pollutions in the vast rural areas also formed a mechanism of severe rural air pollution (Gu 2014). Unfortunately, few

Table 6 Comparisons of regression models

Model	R^2	AIC	RSS
OLS	0.5670	734.47	136.59
GWR	0.7603	536.16	56.48

(1) R^2 is the coefficient of determination; *AIC*, Akaike information criteria; *RSS*, residual sum of squares in the model. (2) *OLS*, ordinary least squares; *GWR*, geographically weighted regression

Table 7 Descriptive statistics of the regression coefficients of the geographically weighted regression model

Variable	Min	Max	Mean	Q1	Median	Q3	SD
Constant	− 3.39	0.87	0.07	0.04	0.08	0.10	0.26
Relative elevation (D1)	− 1.24	0.79	− 0.75	− 1.00	− 0.77	− 0.65	0.37
Annual average temperature (D2)	− 0.65	1.37	− 0.20	− 0.57	− 0.37	0.14	0.44
Wind speed (D4)	− 0.28	1.33	− 0.15	− 0.21	− 0.19	− 0.15	0.16
Annual average precipitation (D5)	− 0.99	1.81	− 0.50	− 0.72	− 0.51	− 0.32	0.31
Regional GDP growth rate (D6)	− 0.18	0.16	− 0.08	− 0.11	− 0.08	− 0.05	0.05
Proportion of secondary industry in regional GDP (D7)	0.03	0.52	0.28	0.18	0.28	0.38	0.12
Investment to real estate development (D8)	− 0.35	5.77	0.08	− 0.07	− 0.01	0.07	0.54
Actually utilized foreign capital (D9)	− 2.25	0.20	− 0.22	− 0.22	− 0.17	− 0.08	0.33
Natural population growth rate (D10)	− 0.05	0.82	0.07	0.02	0.06	0.07	0.13
Proportion of construction land to the total area of the city (P1)	− 2.20	0.85	− 0.02	− 0.05	− 0.02	0.00	0.19
Proportion of coal consumption (P2)	− 0.39	0.97	0.03	− 0.01	0.02	0.06	0.11
Number of manufacturing enterprises (P3)	− 12.39	0.79	0.09	0.11	0.19	0.26	0.94
Nitrogen fertilizer application rate (P4)	− 0.01	1.26	0.08	0.05	0.06	0.07	0.11
Population density (P5)	− 0.31	0.26	− 0.01	− 0.02	− 0.01	0.00	0.04
Per unit construction building area (P6)	− 2.04	1.48	0.07	0.01	0.03	0.10	0.22
Number of domestically made car ownership (P7)	− 0.37	3.52	0.16	0.09	0.12	0.15	0.28
Highway density (P8)	− 1.76	0.62	0.13	0.12	0.15	0.18	0.15
Ratio of the central heating (P9)	− 0.59	0.63	0.00	-0.01	0.00	0.02	0.09
Rate of green land in built-up area (R1)	− 0.29	0.15	− 0.09	− 0.12	− 0.11	− 0.08	0.05
Proportion of energy conservation and environmental protection expenditures to local fiscal expenditure (R2)	− 0.17	0.28	− 0.03	− 0.08	− 0.02	0.02	0.07
Ratio between the third industry and the second industry (R3)	− 0.02	0.80	0.21	0.09	0.21	0.30	0.14
Per unit area industrial output (R4)	− 0.24	2.70	0.06	0.00	0.02	0.07	0.24
Ex-factory price index of industrial products (R5)	− 0.51	0.15	0.04	0.03	0.07	0.08	0.10
Per unit GDP in energy consumption (R6)	− 0.57	0.17	− 0.13	− 0.17	− 0.14	− 0.11	0.11
Gas penetration rate (R7)	− 0.32	0.13	− 0.04	− 0.08	− 0.04	0.00	0.05
Expenditure of research and experimental development funds (R8)	− 3.33	0.27	− 0.07	− 0.11	− 0.06	0.02	0.27

Q1, lower quartile; *Q3*, upper quartile; *SD*, standard deviation

studies explored the relationship between agricultural production and air pollution in rural China (Zhou et al. 2018b). Fourth, additional pressures also come from population growth, building construction, vehicle holdings, and road density. Increasing the residential density in urban areas stimulates private consumption, which, in turn, may result in more industrial pollutions. Lin et al. (2016) found that the dusts from construction activities were important sources of urban air particles in China. Chen et al. (2015) and Lin and Zhu (2018) also found that the emissions from the vehicles would gradually become a key driving force of urban air pollution in China. Also, the winter heating in North China promoted harmful gas emission, which was one of the important causes of urban air pollution at the regional scale.

Response

The response includes various countermeasures implemented by policymakers and environmental managers. The responses to mitigate the urban air pollution included ecological construction, economic adjustment, energy utilization adjustment, and technology innovation (Table 1). First, ecological construction, such as forest coverage and urban green space, played an important role in absorbing air pollutants and purifying the air. Second, López et al. (2011) reported that increasing investment in environmental protection helped to reduce the emission of air pollutants. Economic adjustment such as industrial upgrading promoted the transformation of industrial structures that might have potentially contributed to alleviating the haze air pollution risks. For example, Zeng and Zhao (2009) deemed that industrial agglomeration led to cleaner production due to the efficient utilization of capital and labor resources. Zhao et al. (2019) suggested that economic agglomeration was convenient for cities to deal with industrial pollution and air quality control by optimizing the industrial structure and improving business innovation. Third, energy utilization adjustment included energy price adjustment and energy efficiency improvement. Through adjusting

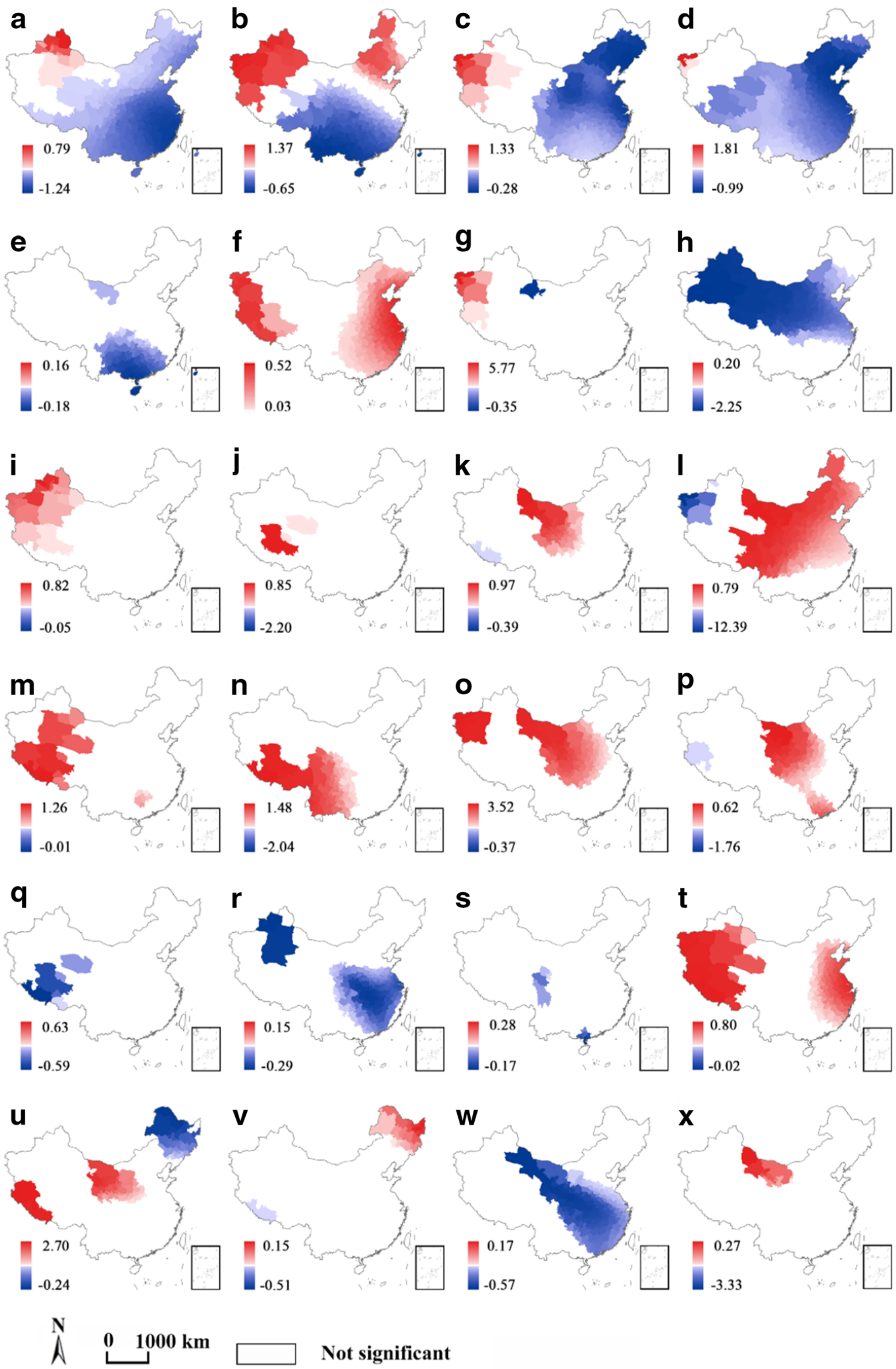

Fig. 10 Spatial patterns of the estimated regression coefficients of the geographically weighted regression (GWR) model. (a) D1, relative elevation; (b) D2, annual average temperature; (c) D4, wind speed; (d) D5, annual average precipitation; (e) D6, regional GDP growth rate; (f) D7, proportion of secondary industry in regional GDP; (g) D8, investment to real estate development; (h) D9, actually utilized foreign capital; (i) D10, natural population growth rate; (j) P1, proportion of construction land to the total area of the city; (k) P2, proportion of coal consumption; (l) P3, number of manufacturing enterprises; (m) P4, nitrogen fertilizer application rate; (n) P6, per unit construction building area; (o) P7, number of domestically made car ownership; (p) P8, highway density; (q) P9, ratio of the central heating; (r) R1, rate of green land in built-up area; (s) R2, proportion of energy conservation and environmental protection expenditures to local fiscal expenditure; (t) R3, ratio between the third industry and the second industry; (u) R4, per unit area industrial output; (v) R5, ex-factory price index of industrial products; (w) R6, per unit GDP in energy consumption; (x) R8, expenditure of research and experimental development funds

energy prices, the government can control the total consumption of coal and optimize the composition of energy sources. Also, air quality may be improved by increasing energy efficiency. The development of clean energy technology is an important way to reduce the occurrence of urban air pollution events (Zhan et al. 2018).

Path to mitigating the urban air pollution in China

Based on the above analysis of spatial and temporal characteristics of urban air pollution in China and the influencing factors, we attempt to propose a specific path to reducing the occurrence of urban air pollution events in China. The proposed path includes the following five themes.

The first theme is multi-sectoral, multi-regional, and collaborative legislation and governance. The spatial pattern and variation analysis in this study show that the urban air pollution days in a city is not only related to local influencing factors but also related to the urban air quality in the neighboring cities. These results indicate that urban air pollutants have strong spatial diffusion or spatial spillover effects. Consequently, we suggest that local governments should strengthen regional cooperation on scientific research, promote the unification of regional environmental standards on energy conservation and emission reduction, and improve the mechanism for industry entry and exit. Moreover, it is important to establish a cooperation and law enforcement system for regional information sharing on air quality and emergency response.

The second theme is industrial upgrading and reconstruction. On the one hand, the industrial upgrade should be oriented toward raising the standards for environmental protection and energy consumption, increasing the penalties for environmental protection violations, and shutting down backward and excessive production capacities. On the other hand, China needs additional industrial upgrades, which will be driven by the new-type urbanization development and ecological civilization construction (Zhou et al. 2015). Chinese cities should strengthen structural adjustment in heavily polluting industries, strengthen source control, and reduce pollutant emissions by increasing technological innovation and upgrading heavily polluting industries, so as to change the pattern of economic growth and alleviate the increasing pressure on the environment.

The third theme is to upgrade the energy consumption structure. Economic development is not only a process of goods production and city infrastructure construction, but also a process of material and energy consumption (Lin and Zhu 2018). In the future, China should limit the use of low-grade coals, promote central heating, and combine heat and power supplies, so as to minimize fuel consumption and pollutant emissions. China should also increase the supply and consumption of clean energy such as natural gas, liquefied petroleum gas, and solar energy in the cities. In addition, China should promote the use of new energy vehicles and speed up the construction of supporting facilities and transportation networks for new energy vehicles in the cities.

The fourth theme is to optimize the "spatial distribution" of the population. China's rapid urbanization has resulted in a series of population issues, such as population overgrowth, rural population moving to urban areas, and spatial imbalance between population and economy (Wang et al. 2015). Currently, the population's spatial distribution and changes are becoming more and more important for regional socioeconomic development in China. China's urbanization needs to transform from the "land-based urbanization" to the "population-based urbanization" (Chen et al. 2013). Therefore, China should put a limit on megacity' population and form the "new-type" urbanization (Chen et al. 2016) development plans that take into account the sustainability of the environment and resources in a region for balanced economic, social, and resource allocations.

The fifth theme is the reconstruction of the multi-level air duct systems. In recent years, spatial layout and structure change driven by urban expansion and land use have been among the main research areas on air pollution control (Xu et al. 2015; Yuan et al. 2017; Zhao et al. 2019). For example, Xu et al. (2015) found that unreasonable urban expansion would lead to the obstruction of the urban ventilation corridors, further reducing the speed and intensity of wind flowing through the city and increasing the frequency of stagnant air. The urban heat island effect and the temperature inversion effect may weaken the convection and diffusion of air pollutants (Fu and Chen 2017), which may lead to the microclimate conditions that favor the formation of urban air pollution events. Furthermore, Wang et al. (2019b) reported that the Chinese Academy of Sciences proposed a new low-cost charge-coupled device (CCD) Lidar detection system to measure the near-ground (< 500 m) aerosol profiles in haze days. Unfortunately, urban ventilation corridors have often been disregarded in the process of rapid urbanization development and land utilization in China in the past. Our results indicate that (Table 2) topographic and climate conditions are important factors of urban air pollution on a global scale. As shown in Fig. 4, urban air pollution events frequently occurred in the Northwest and North China. From summer to winter, air pollution mainly centered in North China and gradually expanded from there. Under the influence of the northwest monsoon, northwestern China has also become a "hotspot" of urban air pollution events and has gradually spread from Kashi in South Xinjiang to the northwest and the southeast Xinjiang. With the arrival of the southeast monsoon and the increase of precipitation in summer and autumn, the air pollutants are dissipated in the southeastern region of China. Therefore, we propose two measures for the reconstruction of air duct systems. One is to understand the importance of regional air duct systems based on regional climate, terrain, and wind conditions, making good use of the natural air duct in a region (such as green open space, ecological space, and ecological corridor). The other is to reduce near-ground (< 500 m) urban air pollution by combining urban planning, land use planning, and spatial planning, by designing the height and density of urban buildings reasonably at the city level, and by developing computer models to improve the urban air pollution forecasting based on urban air duct optimization and reconstruction.

Conclusions

In this study, we integrated the DPSIR framework, the geographical detector, and the geographically weighted regression model to understand the spatial and temporal characteristics of urban air pollution in China and to study the individual and interactive effects of the 27 influencing factors on the urban air pollution. Our empirical study in the 337 Chinese cities demonstrates that the proposed urban air pollution assessment framework is an effective tool to examine the important links among nature, society, and economic systems.

On the one hand, the DPSIR framework assumes a chain of causal links starting with the *drivers* (natural conditions and human activities) through the *pressures* (production, living, and emissions) to the *states* (air environment and quality) and the *impacts* on the nature-society-economy complex systems (public health and functions), finally leading to the "responses" (legal, economic, and administrative). The DPSIR framework is able to capture the cause-effect relationships among social, economic, environmental, and other systems, to simplify the complex human-environmental integrated system, and to contribute to the formulation of policies. On the other hand, the geographical detector is used to explore the influencing factors of urban air pollution and how they interact with each other *at the global scale*, while the geographically weighted regression model is used to detect the positive/negative effects of the influencing factors on the urban air pollution *at the local scale*.

Our findings suggest that the influencing factors of urban air pollution are complex and diverse, varying from season to season. Urban air pollution is the result of the interactions of multiple influencing factors, while the explanatory power between any two influencing factors is greater than that of a single influencing factor to the urban air pollution. Furthermore, the interaction of natural factors and socioeconomic factors can enhance the explanatory ability of the influencing factors to urban air pollution.

Nevertheless, our study is not without limitations. The main limitation is that the cross-section dataset of the UAPI in the Chinese 337 cities is from a single year (2015). It is necessary to use multiple years of data over a long period for trend analysis of the urban air pollution in China. Another limitation is that urban air pollution is a systemic global or local problem, reflecting the complex relationship between human activities and the environment. It is also necessary to adopt a multidisciplinary approach to reveal the deep-rooted causes of urban air pollution. We plan to integrate process-based simulation and risk assessment to study the long-term dynamics of the urban air pollution in China and to recommend science-based mitigation strategies. In addition, data precision mismatch and partially missing data caused by compiling multiple data sources are also important factors that may affect the reliability of the results.

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Data availability The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

Declarations

Ethics approval and consent to participate Not applicable.

Consent for publication Not applicable.

Competing interests The authors declare no competing interests.

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