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RESEARCH ARTICLE

# Investigating the factors underlying participation by the Chinese public in environmental management: an approach based on spatial heterogeneity

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**Abstract**
Public participation in environmental management (PPEM) in China has become increasingly prominent; thus, investigating the factors that underlie participation by the Chinese public in environmental management is important. To this end, we adopted unique data for PPEM, which was measured based on environmental complaints logged by the telephone hotline set up by the Ministry of Ecology and Environment of China. We observed that PPEM greatly varied from one city to another, indicating significant spatial heterogeneity. In addition, complaints were mainly concentrated in four large regions, namely, the North China Plain, the Yangtze River Delta, the Pearl River Delta, and the Chengdu-Chongqing urban agglomeration. Next, a newly developed spatial heterogeneity analysis method, namely, geographical detector, was applied to investigate the driving factors of PPEM. From the factor detector analysis results, we confirmed that the economic level, energy consumption, urban population, college-educated population, wastewater, environmental risk, $SO_2$ emissions, and $PM_{2.5}$ concentrations were the dominant factors that caused citizens to voice environmental complaints. In addition, we noticed that moderately developed cities were the leading risk areas, which indicated that these cities had serious environmental pollution problems and their citizens actively voiced complaints. As economies continue to grow, the populations in these cities are projected to become more aware of environmental quality and will implement stricter regulations to protect the environment and lower complaints. Moreover, the interaction detector analysis results revealed that the interaction of urban and college-educated populations with other factors played more important roles in affecting PPEM.

**Keywords** Public participation · Environmental management · Environmental protection · Spatial heterogeneity · Geographical detector

## Introduction

In recent years, the rapid economic development in China has led to various issues such as resource depletion and environmental pollution (Zhang et al. 2016a; Fang and Zeng 2007). This intensification has not only damaged sustainability but also aroused awareness among the Chinese public of the importance of implementing environmental protection and maintaining environmental rights; this awareness, in turn, has led to the expression of environmental interests and participation in environmental management through various channels, including supervision of the environmental aspects of manufacturers' economic activities (Li et al. 2012a; Johnson et al. 2018). In response to environmental pollution problems, the Chinese government is seeking methods of transforming the resource-intensive development model to achieve the goal of ecological and sustainable development (Du 2015) while also recognizing the important role of public participation in environmental management (Chen et al. 2015). In China, public participation represents an available channel for voicing concerns about the environment (Li et al. 2012b). Notably, PPEM has played an important role in promoting the improvements

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of China's ecological environment and reshaping its environmental governance systems. Moreover, it also offers a significant sustainable development direction for environmental regulation tools.

Traditional environmental regulation refers to the government's direct intervention through mandatory administrative measures to prevent and control environmental problems (Liu et al. 2018a). Usually, such regulation can be divided into two types of policy tools, namely, command-and-control-based and market-based regulatory tools (Zhang et al. 2018a; Blackman et al. 2018; Xie et al. 2017). The Organization for Economic Cooperation and Development (OECD) proposed the environmental regulation methods of direct control, economic means, and persuasion (OECD 1995). Subsequently, the implications of environmental regulation have been further enriched. For example, the World Bank extended the definition to include four environmental governance policy tools, namely, markets, market creation, environmental administration, and public participation (Hamilton 1998). In addition, some scholars in their empirical studies have divided environmental regulations into administrative-related, market-related, and public participation-related environmental regulations (Feng and Chen 2018). Thus, a transition has occurred from emphasizing the government's intervention to adopting new policy tools, including public participation in environmental issues, based on a better understanding of environmental regulations. Traditional command-and-control environmental management systems are far from effective and efficient due to insufficient involvement (OECD 2006); hence, PPEM, as an effective environmental regulation policy tool that promotes strong monitoring for resource regulation and environmental issues, has received extensive attention from the academic community (Nadeem and Fischer 2011). Therefore, PPEM has enhanced the effectiveness of environmental governance (Drazkiewicz et al. 2015) and contributed to a deep understanding of the pathway to building environmentally sustainable societies.

The main aim of this study is to explore the determinants of PPEM in China. To this end, we first employed a geovisualization technique to display the spatial distribution patterns of PPEM in Chinese cities. We noticed that the number of PPEM cases greatly varied among Chinese cities, indicating significant spatial heterogeneity. Notably, we found that PPEM cases were primarily concentrated in economically developed and highly polluted regions. Next, a novel spatial heterogeneity analysis method, i.e., geographical detector, was applied to investigate the driving factors of PPEM in Chinese cities. The geographical detector method, which was developed by Wang et al. (2010), applies a spatial variation analysis perspective to resolve several issues. First, it can be used to quantify the spatially stratified heterogeneity of a variable. Second, it is able to test the spatial association between pair variables under the assumption that their stratified heterogeneity tends to be consistent without the linearity assumption. Third, the interaction effects between two explanatory variables on the dependent variable can also be detected and quantified (Bai et al. 2019). Based on the geographical detector method, we confirmed that economic level, energy consumption, urban population, college-educated population, wastewater, environmental risk, $SO_2$ emissions, and $PM_{2.5}$ concentrations were the important driving factors of PPEM.

The motivation underlying this study is fourfold. (1) It helps to identify a new attempt to build a comprehensive environmental governance system in the wake of ever-growing public environmental awareness in a transitioning developing country, such as China. (2) This study develops a better understanding of how PPEM, as a type of informal environmental regulation tool, contributes to enriching the field of informal environmental regulation research. (3) We desire to put forward several important factors that can promote the development of PPEM and the construction of environmental governance systems in China. (4) There is a high possibility that the main findings of this study can be applied to developing countries that are attempting to arouse public interest in the construction of their environmental governance systems and effectively solve worsening environmental problems.

## Literature review

As an effective environmental regulation, PPEM has exhibited a positive impact on environmental protection (Wesselink et al. 2011). The Chinese government has also recognized that public participation has become an important voluntary tool (Zhang et al. 2017). Hence, the role of PPEM in effectively addressing environmental problems and building an environmentally sustainable society in China has been increasingly prominent in recent years. Since environmental pollution has been regarded as one of the primary barriers to achieving sustainable development goals (SDGs) in China, the topic of reducing environmental pollution and improving environmental quality has received widespread attention from researchers (Tao et al. 2017; Li et al. 2018).

A considerable number of empirical studies have focused on the effect of PPEM on reducing environmental pollution. For example, Zhang and Chen (2018) studied the impact of public environmental participation on atmospheric pollutant emissions in China and found that public environmental participation had a significant positive impact on the reduction of pollutants. Li et al. (2018) adopted a natural experimental approach to evaluate the effect of PPEM on industrial pollution emissions. They observed that joint participation among government policies, the public, and enterprises could more effectively reduce air pollution emissions and represented the only method by which SDGs be ultimately achieved. Wu et al. (2018) focused on the impact of PPEM on environmental performance and considered two PPEM indicators, namely, the number of environmental letters and visits by the public and the number of China's environmental nongovernmental organizations (ENGOs). They concluded that the development of ENGOs was beneficial to promoting environmental governance and sustainable development. The findings showed that public participation had different effects on environmental performance. Specifically, environmental letters were closely correlated with industrial wastewater discharge while ENGOs did not exhibit significant impacts on pollutant emissions. In addition, public concerns about environmental problems could improve the environmental performance of polluting firms or might encourage polluting firms to relocate to other regions or countries with low levels of PPEM, which has been evidenced in both developed and developing countries (see, among others, Cole et al. 2013; Féres and Reynaud 2012). Hence, Zheng and Shi (2017) reexamined the role of PPEM in the relocation of polluting industries in China based on a panel data set of 30 Chinese provinces from 2004 to 2013. They found that PPEM measured based on environmental letters and public protest cases played an important role in promoting industrial relocation. Most importantly, protest cases, as an increasingly prominent factor, determined industry location.

Another line of research includes the use of various indicators to measure PPEM activities. For example, compared with studies investigating the value of environmental letters and visits, Tu et al. (2019) adopted the Pollution Information Transparency Index (PITI) to evaluate public participation and analyzed the impact of PPEM on pollution emission reduction. They concluded that PITI information disclosure contributed to reducing pollution emissions. Zhang et al. (2019) introduced two PPEM indicators and analyzed the impacts on the public's living environment based on Chinese provincial data from 2004 to 2014, and they found that PPEM measured by the number of proposals from members of the Chinese People's Political Consultative Conference had a significant impact on the public's living environment while that measured by the number of environmental letters did not. Similarly, Wu et al. (2020) utilized environmental decentralization to denote environmental management and employed a data set of 30 Chinese provinces to conduct an empirical analysis of the effect on the improvement of regional environmental quality, which was an indicator for the assessment of the environmental sustainability of Chinese provinces. They found that PPEM helped improve environmental quality and contributed to sustainable development. Moreover, public participation and government environmental governance had positive coordinated effects on regional environmental quality.

In addition, the topic of how to build an effective PPEM system has also attracted considerable attention. For instance, Huang (2015) focused on a public environmental campaign in China that promoted the establishment of a national $PM_{2.5}$ monitoring network and pollution mitigation plan. They concluded that public participation in environmental governance could occur in centralized China and promote progressive social change. In contrast, Chen et al. (2015) noted that public participation had not been well institutionalized in China and the role of the public in environmental management was limited. In summary, these researchers proposed innovative models that would enable the public to effectively participate in China's environmental management and environmental protection.

A review of the existing literature showed that previous studies considered the enhancement of PPEM as a method of affecting environmental protection and achieving SDGs. Specifically, they mainly emphasized the impact of PPEM on pollution reduction or environmental performance and have drawn fruitful conclusions. However, few studies have paid attention to the driving factors underlying PPEM. One exception is Zhang et al.'s (2018b) study, which explored the factors underlying the development of environmental public participation in China using provincial-level data. The findings showed that the degree of openness to participation and level of economic development determined different participation styles. In addition, educational level and environmental pollution level were also important determinants. Similar to the aforementioned studies, Zhang et al.'s (2018b) adopted the data for "environmental letters and visits" as an indicator of PPEM in China since the "letters and visits" system was once considered the most commonly accepted channel of public participation in environmental management in China, thus offering citizens a method of expressing their concerns about environmental issues (Brettell 2003). However, only the data at provincial levels are available in China, which is primarily why the abovementioned studies adopted provincial-level data to conduct empirical studies. Overall, the data for this environmental complaint system are characterized by low availability, and certain provinces do not release data related to environmental complaints. Notably, data at the prefecture-city level are not available in China and are unable to describe the level of PPEM at the city level. Hence, in this study, we attempt to unravel the driving factors of PPEM from the perspective of Chinese cities. The main differences between the findings of our research and that of other studies are twofold. One difference is that we can quantify the spatial heterogeneity associations between PPEM and the driving factors and the interaction effects of paired factors on the PPEM of Chinese cities. The second difference is that the leading high-risk areas for different driving factors detected by the risk detector methods can be identified. The results indicate that the priority for different cities is to address the city-specific factors driving PPEM since it is an effective method of reducing PPEM cases. In other words, the determinants of PPEM substantially vary from one city to another. Hence, regionalized and precise policies cannot be overstated when addressing environmental pollution events.

The innovation and contribution of this research may be threefold. (1) We focus on PPEM at a smaller administrative scale, namely, the prefecture-city level, which can capture more refined factors of PPEM because provincial-level data could mask important information due to data merging, which leads to a failure to detect large variations in PPEM. Technically, since prefecture-city level data have a greater variance than provincial-level data, they help identify spatial heterogeneity. (2) The number of environmental complaints in Chinese cities logged through the telephone hotline "12369," which is collected by the Data Center of the Ministry of Ecology and Environment of China, is considered an adequate indicator to evaluate PPEM at the prefecture-city level in China; however, it has seldom been used in the existing literature. This indicator may contribute to enriching the literature on PPEM and help policy-makers better understand public PPEM activities and immediately and effectively solve environmental issues. (3) We emphasize the spatial heterogeneity of the PPEM of Chinese cities since PPEM cases greatly vary from one city to another because of city-specific characteristics. Technically, we applied the newly developed geographical detector method, which considers spatial heterogeneity, to unravel the driving factors of PPEM in China. Our study not only bridges the spatial heterogeneity analysis and PPEM activities but also extends the application of the new approach to the PPEM research field. (4) Last, this study is of great significance to enhance policy-makers' understanding of PPEM and even contributes to the improvements of environmental governance systems in China. Most importantly, the main findings of this research offer a few important practical implications and propose a pathway for effectively building environmentally sustainable Chinese cities in the long run through the enhancement of PPEM.

## Methods and data

### Kernel density estimation

After obtaining the geographic coordinates of environmental complaint cases from the Ministry of Ecology and Environment of China, we geovisualized these point features in maps. However, to further identify the spatial distribution characteristics and the details of the PPEM, we apply a kernel density estimation method to visualize the spatial clusters of point features because the approach can detect densities by summing all points around the focus point within a bandwidth. It is expressed as follows (Silverman 1986; Anderson 2009).

$$f(x) = \frac{1}{nb}\sum_{i=1}^{n} K\left(\frac{x - x_i}{b}\right) \quad (1)$$

where $f(x)$ is the value obtained by the sample point estimate at $x$; $b$ is the bandwidth; $(x - x_i)$ denotes the Euclidean distance from the sample point $x_i$ to the estimated point; and $K(x)$ is the kernel function. In this study, a Gaussian kernel function is used:

$$K\left(\frac{x - x_i}{b}\right) = \frac{1}{\sqrt{2\pi}} e^{-\frac{(x - x_i)^2}{2b^2}} \quad (2)$$

The bandwidth $b$ is the main determinant that affects the kernel density estimation results. In this study, it is set to 100 km based on a comprehensive consideration of the spatial scale of the study area and the recognition of hotspot areas.

### Geographical detector

Since the PPEM of Chinese cities exhibits significant spatial heterogeneity, we consider a novel spatial variation analysis method, namely, geographical detector, which was developed by Wang et al. (2010) to explore the socioeconomic factors that can determine PPEM in China. Compared with classical statistical methods, such as Pearson correlation coefficient analysis, multivariate regression, and geographically weighted regression (Fotheringham et al. 2003), the geographical detector presents four advantages. First, it enables the quantification and testing of the significance of spatial heterogeneity (Wang et al. 2010; Wang and Xu 2017). Spatial heterogeneity in this study refers to the uneven distribution of PPEM across China. Second, it can reveal the driving forces by quantifying the impacts of relevant factors without applying assumptions on the distribution. The basic principle is that if a driving factor is related to the dependent variable, then their spatial distributions may be similar. Third, the dependent variable allows either continuous or categorical (stratified) data (Polykretis and Alexakis 2021). Fourth, it has the ability to detect the interaction impact of two driving factors on the dependent variable (Xu et al. 2018). Due to the abovementioned advantages, geographical detector has gained popularity in many applications, such as built-up land expansion (Ju et al. 2016), housing prices (Wang et al. 2017), carbon emissions (Zhang and Zhao 2018), $PM_{2.5}$ pollution (Ding et al. 2019), urban forests (Duan and Tan 2020), and fertility (Polykretis and Alexakis 2021).

Overall, the geographical detector analysis process has three steps (Wang et al. 2016; Wang and Xu 2017). The first step is to discover and measure the spatial heterogeneity of a variable. Technically, a certain specific classification method is applied. The second step is to calculate the relationships between paired variables. In other words, the quantitative relationships between PPEM and socioeconomic driving factors are obtained. The last step is to examine the interaction effects between two factors on PPEM, and this step focuses on the joint impacts of paired factors on PPEM (Bai et al. 2019).

In addition, two modules in the geographical detector method, namely, the factor detector and interaction detector, are utilized in this study. We first introduce the factor detector, which is measured based on the following $q$ statistic:

$$q = 1 - \frac{\sum_{h=1}^{L} N_{\mathrm{h}} \sigma_{\mathrm{h}}^2}{N\sigma^2} \tag{3}$$

where $L$ represents the number of subregions of factor $X$; $N$ and $N_{\mathrm{h}}$ denote the number of cities over the entire area and the number of samples in subregions $h$, respectively; and $\sigma$ and $\sigma_{\mathrm{h}}^2$ are the total variance of the whole sample and the variance of samples in subregions, respectively.

Next, we describe the interaction detector. It can be employed to investigate the interaction impacts of different factors on PPEM. Technically, we utilize it to determine whether the interaction of paired factors, e.g., $X_1$ and $X_2$, enhances or weakens the impact on PPEM or whether they have independent effects on PPEM. Specifically, the $q$ values of factors $X_1$ and $X_2$ calculated using the factor detector mentioned in Eq. (3) can be denoted by $q(X_1)$ and $q(X_2)$. Then, by overlaying the factor strata $X_1$ and $X_2$, written as $X_1 \cap X_2$, where $\cap$ represents the interaction between factor strata $X_1$ and $X_2$, may generate new factor strata and subregions. Thus, we can obtain the $q$ value of the interaction of $X_1 \cap X_2$, written as $q(X_1 \cap X_2)$. Generally, five categories of interaction factor relationships are observed when comparing the $q$ value of the interaction of paired factors and the $q$ values of each of the two factors, which can be summarized in Table 1.

The impact of a driving factor on PPEM should vary in different regions, indicating spatial heterogeneity. The risk detector can determine whether a significant and different impact of a driving factor occurs on PPEM in two subregions through a $t$-test. This impact can be expressed as follows.

$$t_{\bar{y}_{h=1}-\bar{y}_{h=2}} = \frac{\bar{Y}_{h=1} - \bar{Y}_{h=2}}{\left[\frac{\mathrm{Var}\left(\bar{Y}_{h=1}\right)}{n_{h=1}} + \frac{\mathrm{Var}\left(\bar{Y}_{h=2}\right)}{n_{h=2}}\right]^{1/2}} \tag{4}$$

where $\bar{Y}_{\mathrm{h}}$ and $\mathrm{Var}\left(\bar{Y}_{h=1}\right)$ denote the average value and variance of $Y$ in subregion $h$, respectively, and $n_{\mathrm{h}}$ represents the size of cities in subregion $h$.

## Variable selection and description

Broadly, the Chinese public participates in environmental management mainly through the environmental proposals of the National People's Congress (NPC) and the Chinese People's Political Consultative Conference (CPPCC), environmental hearings, environmental questionnaires, environmental visits, and environmental complaints. However, the data obtained from environmental proposals, environmental hearings, environmental questionnaires, and environmental visits are not available at the prefecture-city level in China. An alternative feasible method of measuring PPEM at the prefecture-city level could be environmental complaints (Zhang et al. 2017). In 2001, the Ministry of Ecology and Environment of China opened the "12369" environmental complaint telephone hotline to respond to environmental complaints and cope with environmental emergencies. If people in Chinese have complaints and suggestions regarding the surrounding environment, they can directly dial the hotline number to require local administrative departments to deal with environmental problems that may affect their properties and health. Although these data reveal the records of environmental violations, they are also able to describe the extent to which the Chinese public participates in environmental management because Chinese citizens tend to be more aware of environmental issues that directly affect their properties or/and impair their health. Currently, environmental complaints represent the most popular and easiest method for the Chinese public to participate in environmental management, which contributes to reducing environmental problems and lowering potential negative environmental impacts.

**Table 1** Interaction categories of two factors and interactive relationship

| Description | Interaction effect |
|---|---|
| $q(X_1 \cap X_2) < \mathrm{Min}\ (q(X_1), q(X_2))$ | Weaken, univariate |
| $\mathrm{Min}\ (q(X_1), q(X_2)) < q(X_1 \cap X_2) < \mathrm{Max}(q(X_1), q(X_2))$ | Weaken, univariate |
| $q(X_1 \cap X_2) > \mathrm{Max}(q(X_1), q(X_2))$ | Enhance, bivariate |
| $q(X_1 \cap X_2) = q(X_1) + q(X_2)$ | Independent |
| $q(X_1 \cap X_2) > q(X_1) + q(X_2)$ | Nonlinearly enhance |

By reviewing the existing literature, we observed that PPEM was mainly attributed to a couple of socioeconomic factors and environmental issues (Zeng and Hu 2015). In this study, we consider eight driving factors, namely, gross urban product (*Econ*), urban population (*UrbPOP*), college-educated population (*EduPOP*), energy consumption (*Energy*), environmental risk (*Risk*), wastewater discharges (*Wastewater*), $SO_2$ emissions ($SO_2$), and $PM_{2.5}$ concentrations ($PM_{2.5}$).

Economic growth is an important indicator to evaluate the political performance of local governments (Jiang 2018). China's economic success is heavily dependent on the expansion of industrialization. In other words, industry has long been the main economic engine to stimulate both employment and economic development. However, it is also the primary contributor to environmental pollution in China since it is the largest pollutant emitter (Jiang et al. 2020). As a result, many local governments have paid attention to economic growth driven by the expansion of industrialization at the expense of the environment (Zhang and Chen 2018; Liu and Lin 2019). As a result, citizens tend to lodge complaints against local environmental pollution (Johnson et al. 2018). Hence, in this study, we hypothesize that economic level is closely related to PPEM.

In addition to industrialization, China's rapid economic growth has been accompanied by urbanization (Wang and Su 2019). In general, industrialization intertwines with urbanization. Specifically, industry is an engine that promotes economic growth and accelerates urbanization. Conversely, environmental problems frequently occur in Chinese cities where industrial parks are extensively established (Jiang and Ji 2016). Once environmental violations occur, urban citizens tend to resort to legitimate means or dial the telephone hotline to require administrators to deal with the problems because they have higher income levels and demand a quality environment (Xie et al. 2019). Hence, we hypothesize that the urbanized population is the main factor affecting PPEM.

In this study, we consider the college-educated population as an environmental awareness indicator. In general, education levels determine environmental awareness, with a higher education level corresponding to greater likelihood of reporting potential environmental issues using the telephone hotline. It has been verified that education levels can significantly affect the frequency of Chinese residents' environmental complaints (Dong et al. 2011) because well-educated populations usually have higher environmental awareness. In this study, education level is measured as the number of people with degrees at the undergraduate and higher levels.

China has become the world's largest fossil fuel energy consumer and is greatly responsible for various environmental problems (Jiang et al. 2018). Hence, one of the main aims of this study is to verify the relationship between energy consumption and PPEM. However, data on energy consumption at the prefecture-city level in China are not available. One possible solution is to use a proxy variable. In this study, the energy consumption data of Chinese cities are obtained by processing nighttime light data because an extensive number of previous studies have verified that there is a significant linear correlation between nighttime light data and energy consumption (see, among others, Xie and Weng 2016; de Miguel et al. 2014; Liu et al. 2018b). We follow the idea of linearly estimating energy consumption data. Technically, the sum of all gray grid values within a city is taken as the energy consumption index of the city.

Environmental factors are directly correlated with environmental complaints and cause the public to participate in environmental management. In China, highly polluting enterprises are unevenly distributed, which not only promotes local economic development but also impairs the environment (Liu et al. 2016). Hence, these highly polluting enterprises have been monitored by the Ministry of Ecology and Environment of China, which also refers to state-monitored key polluting enterprises (Wei et al. 2014; Zhang et al. 2016b; Hsu et al. 2021). Generally, the more state-monitored key polluting enterprises in a city, the higher the possibility of generating environmental violations and the greater likelihood that the Chinese public will be inspired to participate in environmental management. Hence, we expect that the variable is closely related to PPEM. In addition, PPEM is mainly driven by environmental pollutants. Generally, the more pollutants, the higher the PPEM. In this research, we consider three pollutants, namely, industrial wastewater discharges, industrial $SO_2$ emissions, and $PM_{2.5}$ concentrations, and hypothesize that they have close relationships with PPEM.

## Data sources

The data for environmental complaints can be obtained from the Data Center of the Ministry of Ecology and Environment of China (https://datacenter.mee.gov.cn/websjzx/dataproduct/resourceproduct/queryDataToReport.vm?id=43&url=/websjzx/report!list.vm?xmlname=1462866483032&ftype=zyml), but they are only available for 3 years, namely, 2013, 2014, and 2015. Detailed information is recorded on each environmental complaint, for example, year, month, province, company involved, the content of the complaint, and the handling of the complaint. In addition, to measure the PPEM of each Chinese city, the geographical coordinates of enterprises involved in environmental complaints are recorded as the spatial attributes of environmental complaints. Next, the number of environmental complaints of each city can be calculated using the spatial join function of the ArcGIS 10.2 software (shown in Fig. 1). Last, to eliminate the fluctuations for a single year, we took the average of the PPEM cases for the 3 years, which also applies to the driving factors.

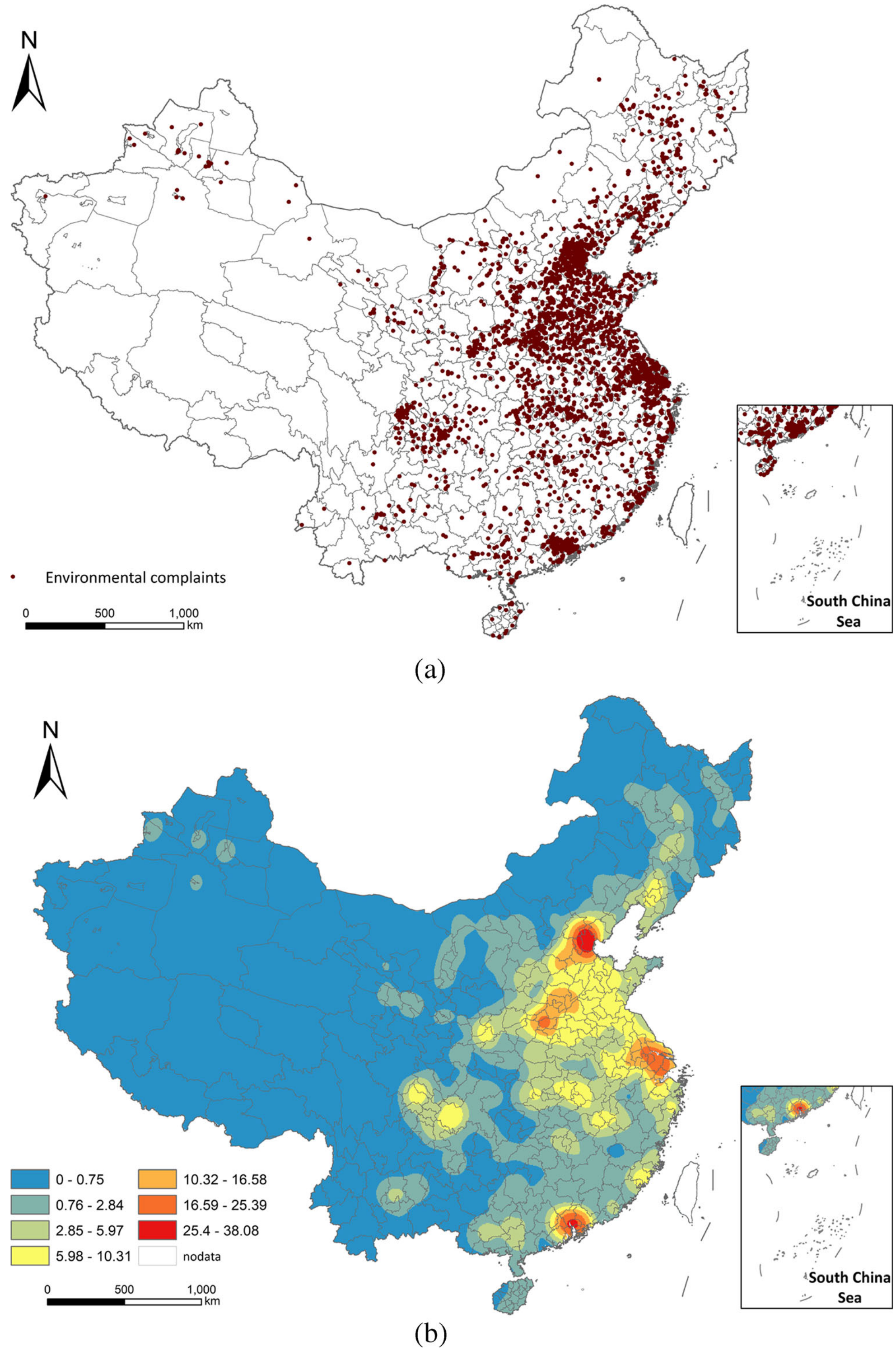


**Fig. 1** Spatial distributions of environmental complaints. **a** Spatial distribution of environmental complaint cases. **b** Kernel density estimates

Regarding the data sources of the driving factors, the data for economic level, industrial wastewater discharges, and industrial $SO_2$ emissions are available from the China City Statistical Yearbooks. The urban population and college-educated population are collected from the 6th National Population Census of China. Nighttime light data for China are obtained from the Resource and Environmental Science Data Center of the Chinese Academy of Sciences (http://www.resdc.cn/data.aspx?DATAID=213). The data for the state-monitored key polluting enterprises can be obtained from the Data Center of the Ministry of Environmental Protection of China. $PM_{2.5}$ data were obtained from the

Atmospheric Composition Analysis Organization (https://sites.wustl.edu/acag/datasets/surface-pm2-5/).

The definitions, descriptions, and data sources of the variables involved in this study are summarized in Table 2.

## Empirical results

In this section, we first present the spatial distribution of PPEM and the driving factors of 275 Chinese cities and then discuss the results of the factor detector analysis and the interaction detector analysis.

### Spatial distribution of PPEM and driving factors

We use a geovisualization technique to present the spatial distribution of environmental complaints (Fig. 1**)**. Figure 1a displays the geographic coordinates of environmental complaints in China. We converted them into the number of environmental complaints within Chinese cities using the ArcGIS software package. Additionally, for a robustness check, we applied the kernel density estimation method to visualize the spatial distribution of point features. It is presented in Fig. 1b.

Figure 1 shows that most of them were primarily concentrated on the North China Plain, which presents several of the most polluted cities in China (Jiang and Bai 2018) because the economy of these cities is mainly characterized by highly polluting heavy industries, such as steel and cement industries. It has long been plagued with various environmental pollutants, such as $SO_2$ and $PM_{2.5}$. Hence, environmental complaints in this region have notably emerged in recent years.

In addition, the other three largest urban agglomerations in China, namely, the Yangtze River Delta, the Pearl River Delta, and the Chengdu-Chongqing urban agglomeration, also had a large number of environmental complaints, indicating that they not only experienced rapid economic growth but also had serious environmental pollution. Hence, environmental complaints in the three regions have rapidly risen recently.

In addition, many environmental complaints have also been made in the eastern Shandong Peninsula, the western Guanzhong Plain, and the northeastern Jilin Province. In contrast, southwestern and northwestern cities usually had a small number of environmental complaints, which is primarily because these underdeveloped southwestern and northwestern cities are characterized by lower levels of industrialization, fewer pollutant emissions, and a better-quality environment.

Next, we present the spatial distribution of the driving factors of PPEM. They are plotted in Fig. 2**.**

Figure 2 shows that PPEM is closely related to the economic level, potential environmental risk, and environmental pollutants since they had similar spatial patterns to that of PPEM. Hence, we applied the geographical detector method to quantify the relationships between PPEM and these driving factors.

### Results of classical statistical methods

However, before performing the geographical detector analysis, the Pearson correlation coefficients between PPEM and the driving factors are given as a benchmark. This information is presented in Fig. 3.

Figure 3 shows the Pearson coefficient values in descending order. All coefficients were significant and positive, indicating that they were the main contributors to PPEM. In addition, we also observed from Fig. 3 that the socioeconomic factors, namely, economic level, urban population, and college-educated population, had higher values, indicating

**Table 2** Definitions, descriptions, and data sources of the variables

| Variable | Definition | Description | Data source | Unit |
|---|---|---|---|---|
| *PPEM* | Public participation in environmental management | Number of environmental complaints | Ministry of Ecology and Environment of China | Piece |
| *Econ* | Economic level | Gross urban product | China City Statistical Yearbook | Billion Yuan |
| *UrbPOP* | Urban population | Urban population | 6th National Population Census of China | Capita |
| *EduPOP* | College-educated population | Population with an undergraduate or higher degree | 6th National Population Census of China | Capita |
| *Energy* | Energy consumption | Summation of gray grid values within cities | Resource and Environmental Science Data Center of the Chinese Academy of Sciences | Index |
| *Risk* | Environmental risk | Number of enterprises monitored by the Ministry of Environmental Protection | Ministry of Ecology and Environment of China | Enterprise |
| *Wastewater* | Industrial wastewater | Industrial wastewater discharges | China City Statistical Yearbook | Ton |
| $SO_2$ | Industrial $SO_2$ emissions | Industrial $SO_2$ emissions | China City Statistical Yearbook | Ton |
| $PM_{2.5}$ | $PM_{2.5}$ concentrations | $PM_{2.5}$ concentrations | Atmospheric composition analysis organization | μg/m$^3$ |

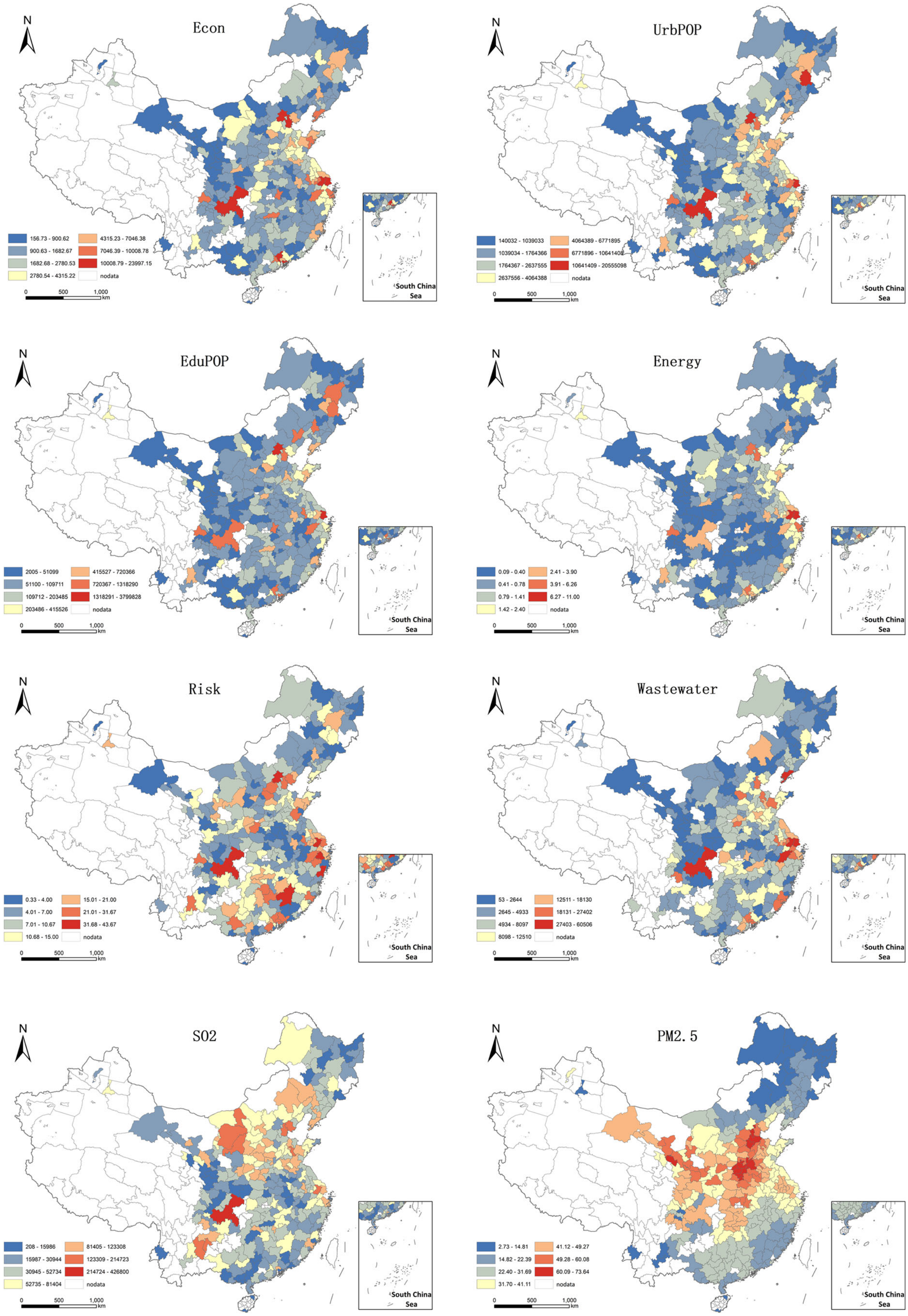


**Fig. 2** Spatial distribution of each driving factor of PPEM

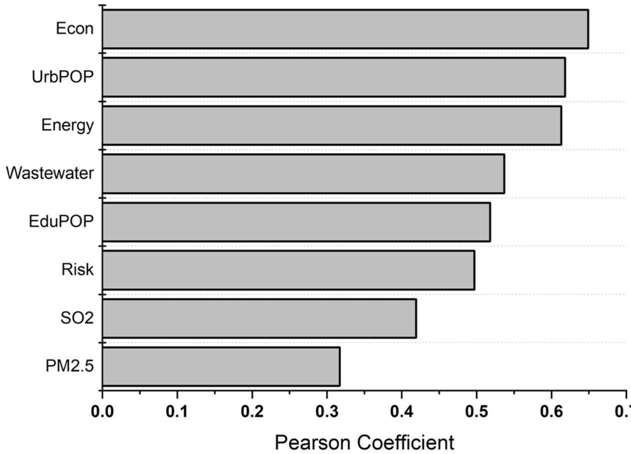


**Fig. 3** Pearson correlation coefficients

that they were more closely related to PPEM than environmental pollutants.

Although the Pearson correlation coefficients can measure how closely the driving factors are correlated to PPEM, they still suffer from a few shortcomings. For example, these coefficients merely quantify the pairwise correlation and ignore the joint impacts of the driving factors on PPEM. For a robustness check, we estimate an OLS model. Specifically, PPEM is considered a function of the abovementioned driving factors. It should be noted that to eliminate possible heterogeneity, we applied a logarithm transformation (Ln for short) for the variables. In addition, to avoid possible multicollinearity issues, we calculated the variance inflation factor of each driving factor. The estimation results of the OLS model and the VIF scores are summarized in Table 3.

As shown in Table 3, we observed that the variables *Energy*, *Risk*, *Wastewater*, and $SO_2$ in the OLS model were highly insignificant, indicating that they did not have a significant impact on PPEM, which is inconsistent with the Pearson correlation coefficients. One primary reason is that the OLS method is unable to determine the spatial heterogeneity of PPEM of Chinese cities. The huge spatial differences over China cannot be ignored because biased conclusions may be generated. In addition, from the VIF results, we concluded that the OLS model showed the multicollinearity issue, which was also the main reason that led to biased estimates. Thus, to overcome these shortcomings, we applied the geographical detector method to quantify the spatial heterogeneity correlations between PPEM and the driving factors.

**Table 3** Results of the OLS model and VIF scores

| Variable | Coefficient | Standard Error | *P* value | VIF |
|---|---|---|---|---|
| Ln*Econ* | 0.3807 | 0.1644 | 0.0210 | 6.6578 |
| Ln*UrbPOP* | 0.7381 | 0.1895 | 0.0000 | 9.9404 |
| Ln*EduPOP* | −0.4062 | 0.1544 | 0.0090 | 9.9800 |
| Ln*Energy* | 0.1132 | 0.1237 | 0.3610 | 4.4623 |
| Ln*Risk* | −0.0186 | 0.0748 | 0.8040 | 1.7995 |
| Ln*Wastewater* | 0.0551 | 0.0733 | 0.4530 | 2.9138 |
| Ln$PM_{2.5}$ | 0.4291 | 0.0742 | 0.0000 | 1.1096 |
| Ln$SO_2$ | 0.0741 | 0.0628 | 0.2390 | 1.5755 |
| Constant | −9.8352 | 1.4679 | 0.0000 | |
| $R^2$ | 0.5522 | | | |
| *F* statistic | 55.44 | | | |
| *P* (*F* statistic) | 0.000 | | | |

## Results of factor detector analysis

The geographical detector method requires that continuous spatial processes be classified into discrete strata (Wang et al. 2016; Wang and Xu 2017). To satisfy the requirement, these driving factors of PPEM were discretized using an optimal discretization process according to the criterion that the classification may have the highest explanatory power, namely, the highest $q$ value. The optimal classification of each driving factor is shown in Fig. 4.

Then, the $q$ values of the eight driving factors of the PPEM can be calculated via the factor detector method, and they are plotted in Fig. 5.

In Fig. 5, the $q$ values are displayed in descending order. The $q$ values of these driving factors were smaller than the Pearson correlation coefficients. We concluded that the correlations between PPEM and the driving factors using the Pearson correlation coefficient could be overestimated since spatial heterogeneity is ignored. On the other hand, we noticed that the magnitude of the correlations between PPEM and driving factors using the two methods hardly varied, which also indicated that the factor detector could be appropriate for evaluating spatial heterogeneity correlations between pair variables.

In addition, we observed that economic level had the highest $q$ value, implying that it was the dominant contributor to PPEM, which was consistent with our expectations. In nature, the true driving force determining PPEM is economic growth because the primary engine driving local economic development in most Chinese cities is industrialization, which not only stimulates rapid economic growth but also causes environmental pollution.

Next, we utilized the risk detector analysis method to classify 275 cities into subregions for each driving factor. It is worth noting that the subregion with the highest value can be identified as the leading impact area, which indicates a high-risk area. In other words, high PPEM in a subregion is driven by the factor with the highest value.

As shown in Fig. 6, we found that the subregion showing gross urban product within an interval from 12 to 16 trillion yuan was the leading impact area in terms of the economic level factor (*Econ*). In other words, the cities of the subregion

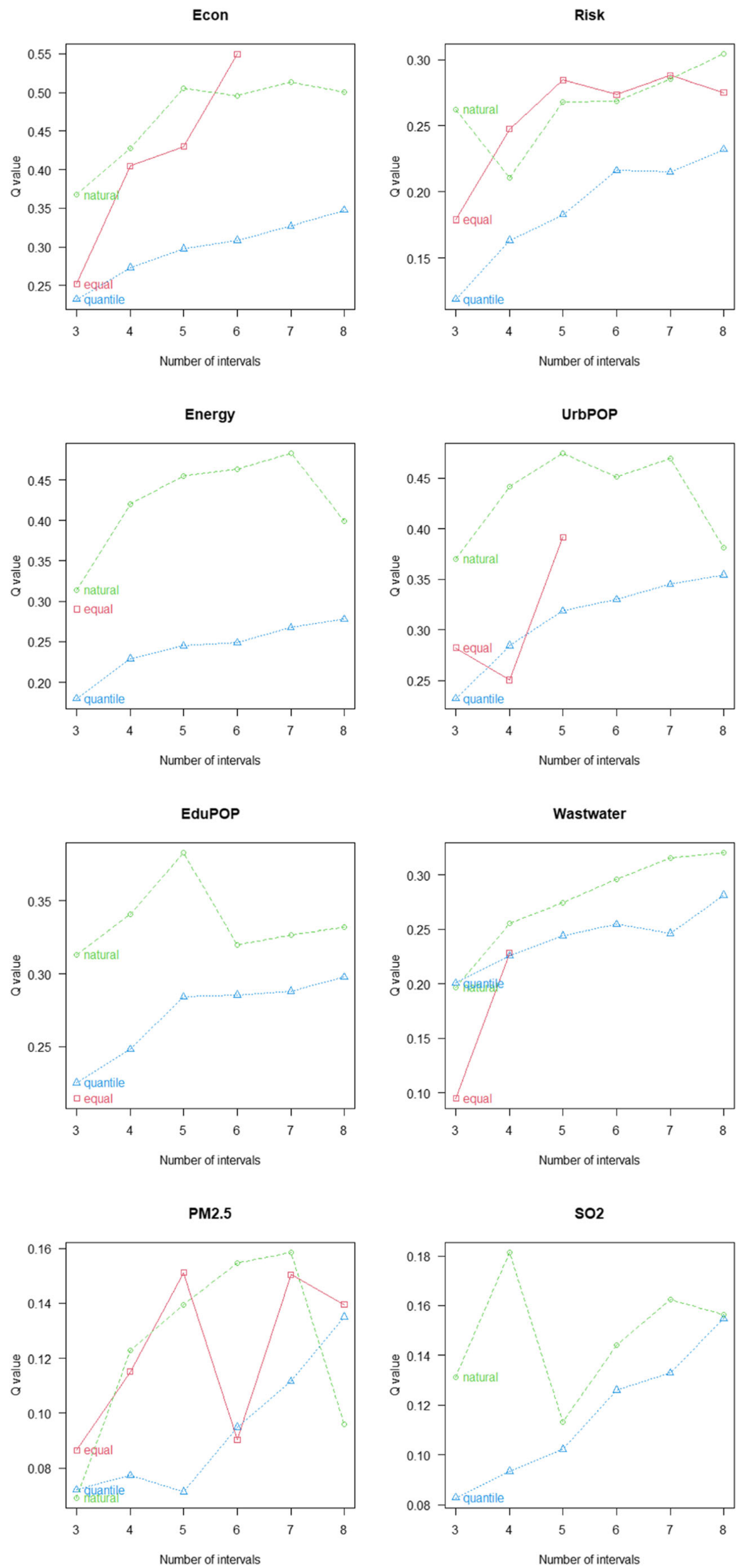


**Fig. 4** Optimal classification of driving factors

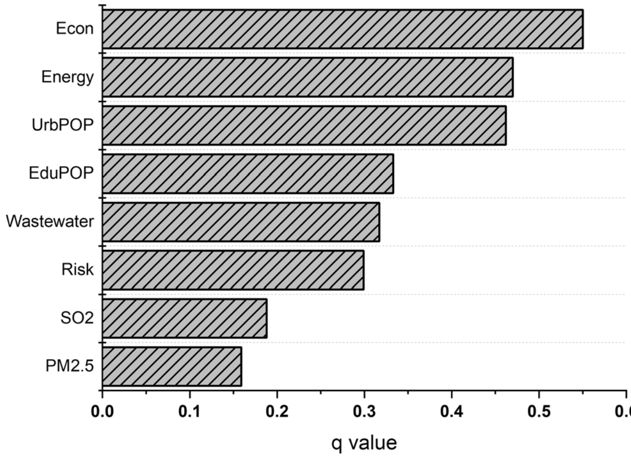


**Fig. 5** Driving factors of $q$ values

were sensitive to environmental impacts and tended to actively participate in environmental management through the telephone hotline. In contrast, the risk detector confirmed that the subregions with low and high urban product levels were low-risk areas for different reasons. The main reason is that cities with low urban products do not establish industrial systems well, which leads to the emission of fewer environmental pollutants. In addition, citizens in the area usually have lower environmental awareness but pay more attention to incomes and possibly ignore surrounding environmental quality. These cities are mainly found in southwestern and northwestern China. On the other hand, cities with high urban products are often aware of environmental quality because people with higher economic levels demand a better environment. In response to ever-growing environmental awareness, local governments have already enacted strict environmental regulations to restrain industrial emissions in case of environmental degradation. However, once potential environmental impacts occur, citizens in these cities tend to immediate voice their environmental complaints.

Empirically, an inverted U-shaped environmental Kuznets curve may occur. Specifically, in the early stage of the economic level, economies grow and environmental pollution increases. As income levels continue to rise, citizens become more aware of the environment and express their strong concerns about environmental quality. As a result, environmental complaints have rapidly emerged. This is the main reason that moderately developed cities are the leading high-risk areas. However, when these cities enter developed stages, citizens' demand for a better environment will increase and their environmental complaints include requests for stricter enforcement of environmental regulations. Consequently, the environmental quality has been greatly improved and complaints have been substantially reduced in these areas.

We observed that the energy consumption factor had the second-largest $q$ value, as shown in Fig. 5, indicating that it was also a leading contributor to PPEM. Combined with Fig. 6, we found that the subregion with high energy consumption was taken as the high-risk area. In other words, the more energy used, the higher the PPEM, which is because the overuse of various fossil fuel energies, notably coal, is essentially responsible for environmental pollution in China. In 2009, based on rapid economic growth, China became the world's largest energy consumer and one of the most polluted countries in the world.

Regarding the factors of urban population and college-educated population, they played important roles in affecting PPEM because of their high $q$ values (0.462 and 0.333, respectively). In general, urban populations and citizens with high education levels have high environmental awareness and are more sensitive to environmental quality. Figure 6 shows that the two factors were proportionally related to PPEM. In other words, a more urban population and a higher number of college-educated individuals in a city correspond to higher PPEM and a greater likelihood of the public participating in environmental management.

Last, four environmental factors were also found to have significant $q$ values, indicating that they were the main factors of PPEM in China. Specifically, among the four factors, industrial wastewater has the highest $q$ value (0.317), followed by environmental risk (0.299), $SO_2$ emissions (0.188), and $PM_{2.5}$ (0.159). Additionally, from Fig. 6, we observed that the subregions with high values of environmental factors were identified as high-risk areas. Technically, high PPEM is closely correlated with highly polluted cities. On the other hand, we also noticed that environmental factors had lower $q$ values than economic and demographic factors. One possible interpretation is that we used the number of environmental complaints as a proxy variable of PPEM, which could be primarily attributed to environmental pollution events; however, these events were weakly correlated with the environmental factors involved in this research. However, we could still conclude that citizens in cities with high environmental pollutants were likely to participate in environmental management because environmental pollution events and even environmental conflicts between polluters and citizens tended to occur in these cities.

## Results of interaction factor detector analysis

Since the $q$ values of the eight driving factors are statistically significant, we can calculate the interaction effects of paired factors on PPEM. As a result, a total of 28 pairs of interaction effects can be obtained using the interaction factor detector analysis method. Moreover, they are all statistically significant. The results are summarized in Table 4.

As displayed in Table 4, we observed that the $q$ values of most of the paired factors were larger than that of each factor and smaller than the sum of the two factors' $q$ values, indicating that the interaction effects of most of the paired factors on

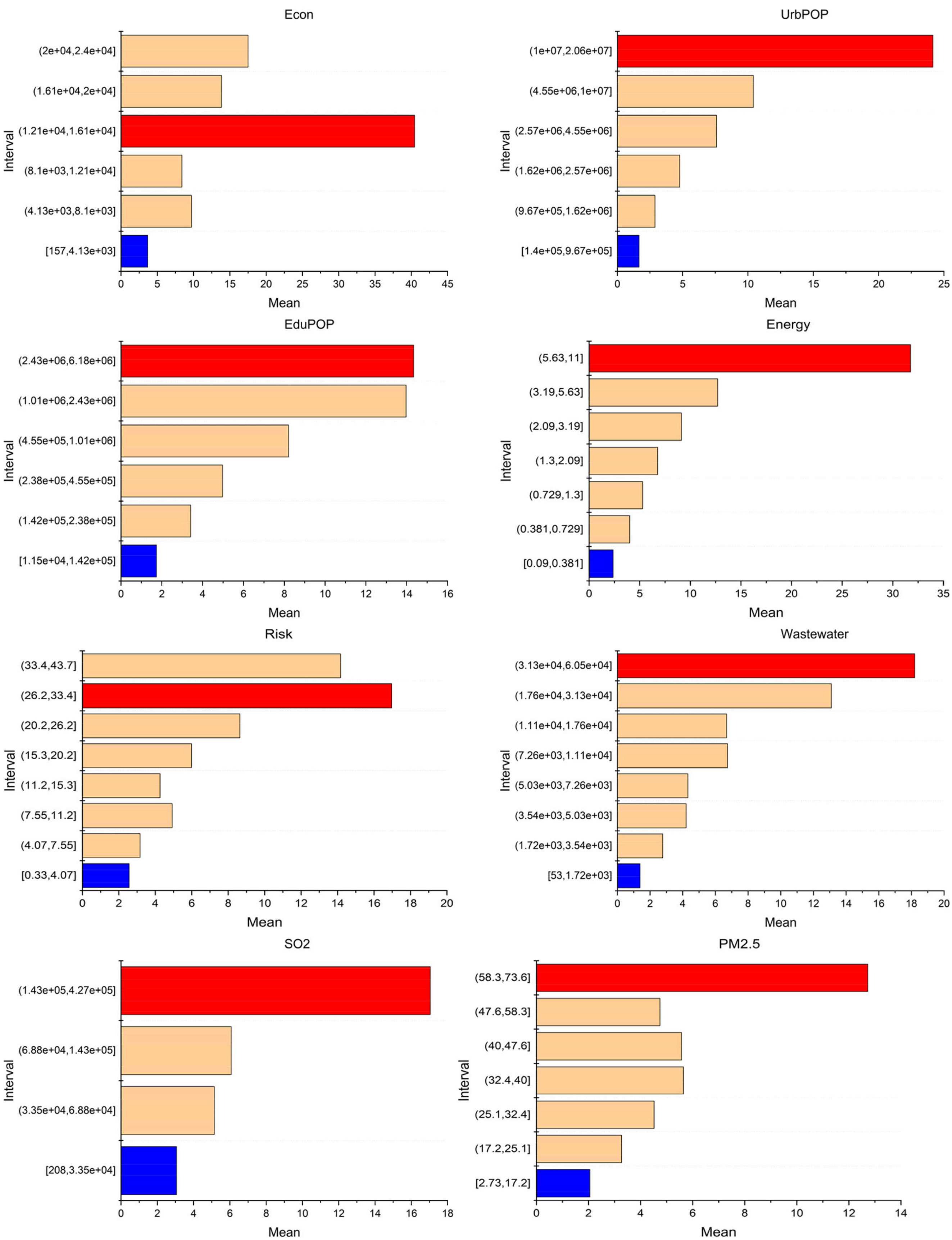


**Fig. 6** Subregions of the risk detector analysis for each driving factor

**Table 4** Interaction factor detector analysis results

| Variable | *Econ* | *Risk* | *Energy* | *UrbPOP* | *EduPOP* | *Wastewater* | $PM_{2.5}$ |
|---|---|---|---|---|---|---|---|
| *Risk* | 0.4755† | | | | | | |
| *Energy* | 0.5769* | 0.4570† | | | | | |
| *UrbPOP* | 0.6823* | 0.5890* | 0.5527* | | | | |
| *EduPOP* | 0.6099* | 0.4929* | 0.6039* | 0.5904* | | | |
| *Wastewater* | 0.5311† | 0.4965* | 0.5479* | 0.5708* | 0.5286* | | |
| $PM_{2.5}$ | 0.5153† | 0.5767# | 0.5960* | 0.6415# | 0.6566# | 0.6535# | |
| $SO_2$ | 0.5537* | 0.5416# | 0.5773* | 0.6812# | 0.5875# | 0.4913* | 0.3706# |

Note: *, #, and † denote that the interaction effect is bivariately enhanced, nonlinearly enhanced, and univariately weakened, respectively

PPEM were bivariately enhanced (represented as *). In addition, the interaction effects of a few paired factors are nonlinearly enhanced (represented as #). Last, four paired factors represent weakened interaction effects on PPEM (represented as †).

Specifically, we observed that the $q$ value between the interaction of urban population and economic level ($UrbPOP \cap Econ$) was the maximum (0.6823), indicating that these factors had the strongest interaction effect on PPEM, followed by urban population and $SO_2$ emissions ($UrbPOP \cap SO_2 = 0.6812$), college-educated population and $PM_{2.5}$ ($EduPOP \cap PM_{2.5} = 0.6566$), and $PM_{2.5}$ and wastewater ($PM_{2.5} \cap Wastewater = 0.6535$). Notably, it should be noted that the interactions among the urban population and college-educated population and other factors exhibited stronger interaction effects than each factor separately, which indicated that these factors were the leading contributors to PPEM. In other words, once the environmental awareness of Chinese citizens was enhanced, they tended to actively participate in environmental management. Hence, we concluded that the interaction of paired factors played a more important role in affecting PPEM than each factor individually.

Last, we noticed that the interactions between economic level and environmental risk, wastewater, and $PM_{2.5}$ presented weakened effects. The main reason is that the interaction effects of the two factors on PPEM were smaller than that of economic level (the highest $q$ value in the factor detector analysis) but greater than those of environmental factors. This finding implies that there may be a trade-off between economic development and environmental worsening, which is notable for underdeveloped cities. In other words, citizens may tend to stimulate local economic growth at the expense of the environment. Hence, the interaction is impaired. In fact, we found that state-monitored key polluting enterprises were not distributed in economically developed cities due to strict environmental standards and regulations. In addition, the citizens of these rich cities tended to be more aware of surrounding environmental quality. Once polluters violate environmental standards, the citizens tend to request punishment for the polluters through the telephone hotline.

## Conclusions and policy implications

The main aim of this research is to explore what factors determine Chinese public participation in environmental management. To this end, we collected the data for environmental complaints via the telephone hotline "12369" from the Data Center of the Ministry of Ecology and Environment of China to measure the PPEM of 275 Chinese cities. Then, we geovisualized these factors in maps to display the spatial distribution. Finally, a novel spatial heterogeneity analysis method, namely, geographical detector, was applied to investigate the determinants of PPEM. The main findings and relevant policy implications are given as follows.

We observed that most environmental complaint cases were found on the North China Plain, which is home to several of the world's most polluted cities. Most cities in this region have had serious environmental pollution since local economies are typically characterized by highly polluting heavy industries, notably steel. In other words, the economic growth of these cities is heavily dependent on industrialization at the expense of the environment. In addition, three densely populated and economically developed urban agglomerations in China, namely, the Yangtze River Delta region, the Pearl River Delta region, and the Chengdu-Chongqing urban agglomeration, also witnessed high PPEM. From the factor detector analysis, PPEM was closely correlated with economic levels, indicating that PPEM was mainly driven by economic growth for the following reasons. Industrialization is not only an important economic engine to develop local economies but also should be mainly responsible for environmental pollution. As income levels increase, Chinese citizens become more aware of surrounding environmental quality and tend to participate in environmental management through environmental complaints once environmental violations occur. Hence, an important policy implication is that resource-intensive development is not considered a feasible method of sustaining economic growth in the long run and should transition towards a cleaner development pattern. To achieve the goal of sustainable development, optimizing the industrial structure and upgrading the industrial systems, especially in highly polluted regions, are urgently needed.

The risk detector analysis results showed that the moderately developed cities were the leading high-risk areas, indicating that they accounted for most environmental violations in China. One possible reason is that these cities are heavily dependent on resource-intensive industrial development patterns and local governments tend to lower environmental standards and regulations to attract industries. As a result, highly polluting industries migrate to these cities, which not only stimulates economic growth but also brings environmental degradation. In fact, these cities might become pollution havens. The environmental awareness of the citizens of these cities has already been enhanced since income levels continue to increase, which makes it possible that the public demands the rights to participate in environmental decisions and the cessation of environmental pollution that can directly affect the surrounding environment and pose a huge threat to their health. Hence, local governments should better address the trade-off between economic growth and the environment by reinforcing environmental regulations and implementing preferential industrial policies.

Two demographic factors, namely, urban population and college-educated population, were found to be more related to PPEM, indicating that they played important roles in affecting environmental management through environmental complaints. The main reason is that compared with rural citizens, urban citizens with higher income levels usually have higher environmental awareness and actively participate in environmental management through the telephone hotline once environmental violations or potential negative environmental impacts occur. On the other hand, we also noticed that the interaction of the urban population, college-educated population, and other factors had stronger impacts on PPEM than each individual factor, indicating that PPEM was mainly influenced by multiple factors. China has been experiencing rapid urbanization and an ever-growing college-educated population, implying that they increasingly pay attention to environmental justice. As income and education levels increase, citizens advocate that they possess an opportunity to participate in environmental decisions about economic activities that may generate negative impacts on the surrounding environment and citizen health. Hence, to lower the environmental complaints of citizens and protect the environment, environmental policy-makers should carry out a series of strict and active measures to ensure the enforcement of environmental protection laws and regulations and even severely punish polluters. Additionally, effective actions and policies to encourage the public to easily access participation in environmental management should also be needed, e.g., widening channels of complaints through the Internet.

Recently, China has been experiencing a transition of environmental governance intuitions. Over the past decade, it has heavily depended on “command-and-control” environmental policies to address environmental problems in China. However, the policy faced a major challenge because of the extensiveness of environmental problems. In response to the ever-growing pollution issues, the Chinese central government has increasingly emphasized the importance of public participation in environmental management because it may promote the effective implementation of environmental regulations. Even so, it has taken active measures to encourage citizens to report environmental violations. In most Chinese cities, responding to environmental complaints from local citizens has become one of the top priorities of local environmental protection bureaus. Moreover, PPEM has been verified to be an effective way to supplement the promulgation of environmental laws and regulations that are not always fully implemented. It has been shown that channels and institutions for public participation in addressing environmental issues have played an important role. Hence, widening channels to encourage the public to participate in environmental management and entitling citizens to access environmental information are urgently needed in China.

Last, our research has two limitations that may indicate future research directions. One is that this study only used a single indicator to measure PPEM, namely, 12369 telephone environmental complaints. In the mobile Internet era, a considerable number of citizens voiced environmental complaints through online channels, e.g., government websites, Sina Weibo (Chinese version of Twitter), and WeChat Official Accounts (equivalent of a Facebook page). Hence, one possible research direction could be that we employ a web crawler technique to obtain such data sets and investigate the PPEM issue from the perspective of the Internet. Second, due to data availability, we ignored the dynamic analysis of the PPEM of Chinese cities and had to analyze the driving factors of PPEM based on cross-sectional data. In the future, we will attempt to collect and accumulate a wide range of PPEM data, notably through the Internet, analyze the spatiotemporal variations in the PPEM of Chinese cities, and conduct an in-depth discussion about the mechanism of PPEM on the environment.

**Author contribution** Yun Tong: conceptualization, methodology, and visualization. Haifeng Zhou: data curation, software, and validation. Lei Jiang: methodology, formal analysis, and writing—original draft. Biao He: investigation and supervision.

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**Availability of data and materials** The data sets used during the current study are available from the corresponding author on reasonable request.

## Declarations

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