

## Research Article

# Spatiotemporal Relationships between Air Quality and Multiple Meteorological Parameters in 221 Chinese Cities

Mengyi Ji,<sup>1</sup> Yuying Jiang,<sup>1</sup> Xiping Han,<sup>1</sup> Luo Liu,<sup>2</sup> Xinliang Xu,<sup>3</sup> Zhi Qiao <sup>1</sup> and Wei Sun <sup>4</sup>

<sup>1</sup>Key Laboratory of Indoor Air Environment Quality Control, School of Environmental Science and Engineering, Tianjin University, Tianjin 300350, China

<sup>2</sup>Guangdong Province Key Laboratory for Land Use and Consolidation, South China Agricultural University, Guangzhou 510642, China

<sup>3</sup>State Key Laboratory of Resources and Environmental Information Systems, Institute of Geographical Sciences and Natural Resources Research, Chinese Academy of Sciences, Beijing 100101, China

<sup>4</sup>Nanjing Institute of Geography and Limnology, Key Laboratory of Watershed Geographic Sciences, Chinese Academy of Sciences, Nanjing 210008, China

Correspondence should be addressed to Zhi Qiao; qiaozhi@tju.edu.cn and Wei Sun; wsun@niglas.ac.cn

Received 7 March 2020; Accepted 9 May 2020; Published 14 June 2020

Guest Editor: Jianhong (Cecilia) Xia

Copyright © 2020 Mengyi Ji et al. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

Air quality in China is characterized by significant spatial and temporal differences, which are directly related to local meteorological conditions. This study used air quality monitoring data, namely, the air pollution index (API) and air quality index (AQI) between 2005 and 2018, together with meteorological data and identified key meteorological factors that affected the spatial and temporal variation of air quality using a random forest algorithm. The spatial and temporal differences in the threshold values of different meteorological factors affecting the concentrations of PM<sub>2.5</sub>, PM<sub>10</sub>, SO<sub>2</sub>, CO, NO<sub>2</sub>, and O<sub>3</sub> were identified. The AQI has the advantages of facilitating higher index values than the API. The air quality showed an improvement from 2005 to 2018. Wind direction and precipitation were the most important meteorological factors affecting the air quality in northern and southern China, respectively, which to some extent reflected the causes and degradation mechanisms of air pollution in the two regions. There were significant spatial and temporal differences in the effects of meteorological factors on the concentrations of different pollutants. The influence of atmospheric pressure on pollutant concentration differed between the east and west. Precipitation and relative humidity in most cities had significant impacts on PM<sub>2.5</sub> and PM<sub>10</sub>. The influence of relative humidity was most significant for SO<sub>2</sub> and it also had a great influence on O<sub>3</sub>, while wind speed had a great influence on NO<sub>2</sub>. The results of the study confirm the meteorological sensitivity of air quality and provide support for the implementation of regional air pollution prevention and control initiatives.

## 1. Introduction

In recent years, China has experienced large-scale industrialization and rapid urbanization, but has also paid the price of environmental pollution, especially air pollution, which is characterized by large-scale haze [1–4]. China's Ministry of Ecology and Environment has conducted long-term air quality monitoring. The air quality datasets are expressed as an air pollution index (API: before 2012) and air quality index (AQI: after 2013), which can intuitively evaluate the air quality status. At the same time, the formulation and implementation

of the “Air Pollution Prevention and Control Action Plan” and regional (e.g., Beijing-Tianjin-Hebei, Yangtze River Delta, and Pearl River Delta) joint prevention and control policies for air pollution also demonstrate the determination of the Chinese government to control air pollution.

Air quality depends not only on the concentration and quantity of pollutants emitted, but also on regional and local meteorological conditions, which determine whether air pollutants are concentrated, diluted, or transported [5, 6]. Researchers have investigated the spatiotemporal relationship between air pollution and meteorological conditions, including

the atmospheric processes and mechanisms affecting individual pollutants, and predictions of the effects of meteorological conditions on pollution levels [7–12]. Most of these studies have focused on cities and regions with severe air pollution issues and dense populations, such as Beijing [13–15], the Yangtze River Delta [16, 17], and California [18, 19], Iberia [20], Iran [21, 22], and Milan area [23, 24]. In addition, researchers have identified the large-scale spatiotemporal characteristics of atmospheric pollution and their relationships with key meteorological factors [25, 26]. The existing research has shown that meteorological conditions have temporal and spatial control on the impact of air pollution [27–29]. At the same time, European scholars also studied the influence of meteorological conditions on the pollutant concentration after forest fires [30–32]. However, the spatiotemporal characteristics of meteorological factors on the thresholds of typical atmospheric pollutants are not known. Additionally, the consistency of long-term sequences of data (such as the API and AQI) and their relationship with pollutant concentrations are uncertain.

The random forest model, as a classification and prediction model, has a high operating efficiency and accuracy for multidimensional feature dataset classification and is often used to select the importance of feature factors. The random forest model has been widely used in geography [33], environmental science [34], ecology [35, 36], and the social sciences [37]. The model has a strong tolerance of outliers and noise, and multiple influencing factors can be calculated by the model at the same time to obtain accurate and comprehensive information.

Therefore, the objectives of this study were to (1) compare the consistency of API and AQI data, (2) identify the key meteorological factors that affect air quality under different temporal and spatial conditions, and (3) measure the threshold of the influence of meteorological factors on the typical air pollutant concentrations through a random forest classification and a regression analysis between air quality and meteorological factors in 221 cities in China. The results can be used to improve regional air pollution prediction systems and develop joint prevention and control strategies.

## 2. Data and Methods

### 2.1. Data Collection

**2.1.1. Air Pollution Data.** The Ministry of Ecology and Environment of the People’s Republic of China (<http://www.mee.gov.cn/>) has provided air quality monitoring data for 371 cities since 2000. The API and AQI are used to quantify the state of air quality. The API was made public from 2000 to 2012 to evaluate the daily  $\text{SO}_2$ ,  $\text{NO}_2$ , and  $\text{PM}_{10}$  pollution levels of 120 cities. The AQI was then introduced in 2012. Initially, the index was used to convey information regarding the concentration of pollutants such as  $\text{O}_3$ , CO, and  $\text{PM}_{2.5}$ , which best reflect the characteristics of the overall composite air pollution. Then, the expression of the index classification levels was adjusted to better describe the impact of the corresponding level of air pollutants on human health. In addition, the temporal accuracy of the data was improved (hourly) and the calculation cycle was updated (0–24 h).

Finally, the scope of monitoring was expanded. The monitoring program now covers 371 cities in China. The API and AQI classification standards are aligned with the air quality standards (GB3095-1996 and GB3095-2012).

**2.1.2. Meteorological Data.** Meteorological data were obtained from the China National Meteorological Science Data Centre, which provides the Chinese ground climate standard dataset (<http://data.cma.cn/site/index.html>). This dataset contains daily values of air pressure, temperature, precipitation, evaporation, relative humidity, wind direction (WD) and speed, sunshine hours, and ground temperature (0 cm) at 699 reference stations and basic meteorological stations in China since January 1951. In this study, mean air temperature (T), mean air pressure (AP), mean relative humidity (RH), mean wind speed (WS), daily precipitation (P), and wind direction were selected as the six key meteorological factors to study their spatial and temporal effects on air quality. To compare the seasonal differences of meteorological factors on air quality, this study investigated the spring (March, April, and May), summer (June, July, and August), autumn (September, October, and November), and winter seasons (December, January, and February).

**2.1.3. Case City Selection.** To study the relationship between air quality and meteorology, air quality monitoring stations and meteorological monitoring stations were selected with precise spatial matching. We matched two datasets from the two types of station and selected a total of 221 case cities (Figure 1 and Supplemental Table 1). From these cities, we selected 84 with both an effective daily AQI and API as research objects to explore the similarities and differences between the two indexes, while 67 cities with both effective daily air quality (AQI and API) and meteorological monitoring data were selected to identify the key meteorological factors affecting air quality under different spatial and temporal conditions. A total of 209 cities with both effective daily pollutant concentration and meteorological monitoring data were selected as research objects to determine the influence threshold of meteorological factors on typical air pollutant concentrations.

**2.2. Random Forest.** The random forest (RF) algorithm integrates multiple trees through the concept of integrated learning. Its basic unit is the decision tree. By classifying the data, it can give the importance score of each variable according to out-of-bag (OOB) observations and evaluate the role of each variable in the classification. In this study, the importance of meteorological factors to API and AQI values and typical pollutant concentrations was quantified using a random forest model to explore the relationship between the API, AQI, and pollutant concentrations and six meteorological factors.

The number of original samples was  $N$  and the variables  $x_i$  were air pressure, temperature, relative humidity, precipitation, wind speed, and wind direction. The bootstrap method was applied to randomly select  $n$  new bootstrap samples by putting

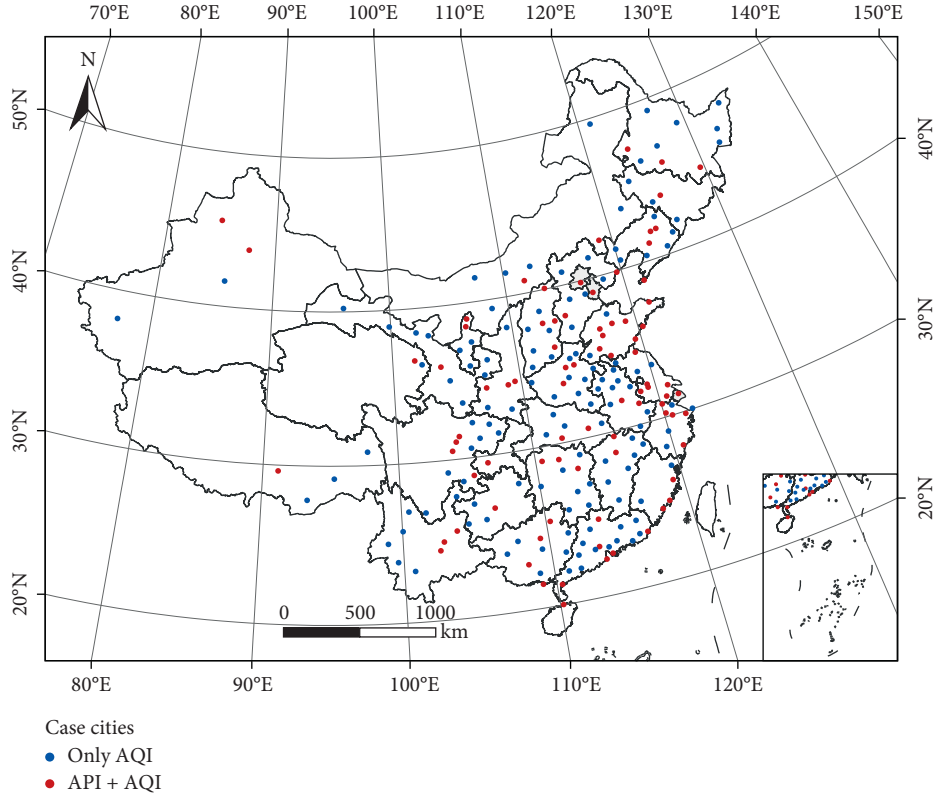


FIGURE 1: Locations of case cities.

them back, and the samples that were not selected each time constituted  $n$  OOB. The realization process was as follows:

- (1) The bootstrap samples formed each tree classifier. At the same time, the corresponding OOB classification obtained  $n$  bootstrap samples based on the OOB of the vote score, which was recorded as  $V_1, V_2, \dots, V_n$ .
- (2) Samples of variable  $x_i$  had an  $n$  OOB value of the order of the random change and formed new OOB test samples. They were then used to establish the random forest for classifying new OOB samples according to the correct discrete sample number of each sample as a vote score.
- (3) With  $n$  bootstrap samples, each sample had OOB scores  $V_1, V_2, \dots, V_n$ , minus the score of each variable after the random order change in  $n$  OOB samples. The importance score of variable  $x_i$  was determined after summing the average values. The importance score is defined as follows:

$$VIx_i = \frac{1}{n_{\text{tree}}} \sum_{t=1}^{n_{\text{tree}}} \left( \text{errOOB}_t^i - \text{errOOB}_t \right), \quad (1)$$

where  $n_{\text{tree}}$  is the number of trees in the random forest algorithm. In this study,  $n_{\text{tree}} = 500$ ,  $\text{errOOB}$  is the error out-of-bag, and  $\text{errOOB}^i$  is a new error out-of-bag [38].

The model parameters in this study were as follows: number of trees = 500; number of node variables = 2; minimum sample

size of leaf nodes = 5; independent variables were the six meteorological factors (AP, T, RH, P, WS, and WD); and the dependent variables were API, AQI, and pollutant concentrations. Taking the importance scoring of the six meteorological factors as an example, the importance scoring process for random forest variables is explained in Figure 2.

The importance score of the random forest classification was expressed by the number of fitting differences and was used to calculate the difference in the prediction accuracy between all trees. This was standardized with the standard deviation, and the mean square error was defined as follows:

$$\text{MSE} = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i), \quad (2)$$

where  $\hat{y}_i$  is the output of the observed value of the reaction quantity and the predicted value of  $y_i$  ( $i = 1, 2, \dots, n$ ).

**2.3. Threshold of the Influence of Meteorological Factors on Air Pollutant Concentrations.** In this study, the influence threshold of meteorological factors on the concentration of typical air pollutants was measured by calculating the partial dependence relationship between meteorological factors and pollutant concentration. The partial dependence relationship is the tendency of the dependent variable (pollutant concentration) to change the independent variable (meteorological factors), which is calculated by considering the average effect of other variables on the dependent variable.

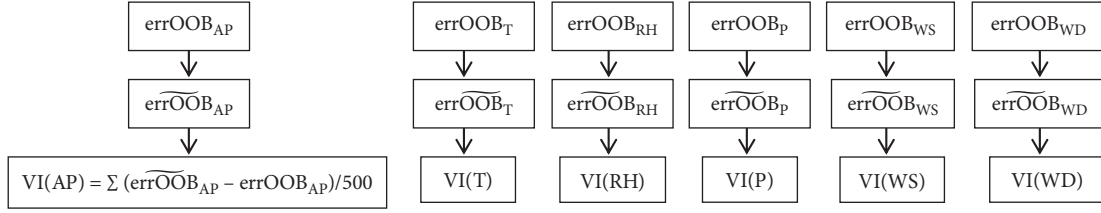


FIGURE 2: Importance scores of six meteorological factors.

The function plotted is defined as follows:

$$\bar{f}(x) = \frac{1}{n} \sum_{i=1}^n f(x, x_{iC}), \quad (3)$$

where  $x$  is the variable for which partial dependence is sought (a meteorological factor) and  $x_{iC}$  are the other variables in the data (other meteorological factors). The summand is the predicted regression function for the regression and logit (i.e., log of fraction of votes), for which the classification is as follows:

$$f(x) = \log p_k(x) - \frac{1}{K} \sum_{j=1}^K \log p_j(x), \quad (4)$$

where  $K$  is the number of classes,  $k$  is the class, and  $p_j$  is the proportion of votes for class  $j$  [39].

Taking the influence of winter meteorological factors on the  $PM_{2.5}$  concentration in Beijing from 2014 to 2018 as an example, the process of measuring the influence threshold of meteorological factors on typical air pollutant concentrations can be illustrated. The partial dependence relationship between meteorological factors and  $PM_{2.5}$  concentration was analyzed using daily data, and the partial dependence plot between meteorological factors and  $PM_{2.5}$  concentration was drawn (Figure 3). The  $PM_{2.5}$  concentration reached the maximum when the air pressure was 1011.47 hPa. In this study, the meteorological factors corresponding to the maximum pollutant concentrations in each season in 209 cities were calculated to determine the influence thresholds of the seasonal meteorological factors on the typical air pollutant concentrations, and the spatial differences were further analyzed.

**2.4. Technology Roadmap.** To provide a clear overview of the research process, we produced a detailed technology roadmap (Figure 4).

### 3. Results

#### 3.1. Spatiotemporal Comparative Analysis of the API and AQI

**3.1.1. Interannual Changes of the API and AQI.** In this study, API values in 2005–2012 and AQI values in 2014–2018 for 84 cities in China were calculated and their spatial and temporal differences were evaluated (Figure 5). The API and AQI values of northern cities were generally higher than those of southern cities, indicating that the air quality of southern cities was better than that of northern cities [40]. In particular, the API and AQI values of cities dominated by steel and coal were significantly higher [29]. The annual mean

API and AQI values in Lanzhou and Qinhuangdao were the highest of all cities at 102.61 and 134.26, respectively. This was closely related to topography and pollutant emissions [41, 42]. In contrast, Haikou had the smallest annual mean API and AQI values, which was mainly due to the orientation of its urban development and climatic conditions. Compared with the annual mean change in the API from 2005 to 2012, the API in most northern cities displayed a downward trend, with Datong having the largest decline, dropping from 108.03 to 63.47. In contrast, the API fluctuations in most cities in the south were relatively small. In 2014–2018, the AQI trend in cities in China was similar to that of the API, and the air quality showed an improvement. Shijiazhuang showed the greatest improvement in annual average AQI, which decreased from 158.73 to 119.5.

**3.1.2. Seasonal Changes of the API and AQI.** The API and AQI exhibited seasonal characteristics (Figure 6). The average API and AQI values in winter in the selected cities were significantly higher than those in other seasons, with maximum values of 78.99 and 103.51, respectively. The second highest values were recorded in spring, with average API and AQI values of 72.16 and 86.55, respectively. The best air quality was observed in summer, with average API and AQI values of 58.06 and 73.84, respectively. The seasonal trends were largely dependent on the winter heating period (coal dominated) and local climate characteristics [43]. In winter, the height of the mixed layer in most northern areas was relatively low, with stable weather resulting in the continuous accumulation of pollutants and less precipitation than in other seasons, which increases the frequency and severity of air pollution episodes [44]. These seasonal differences were extremely obvious from a spatial perspective. In winter, the API and AQI values in northern cities were much higher than those in southeastern coastal cities. In addition to the direct sources of pollutants, such as industrial emissions, water vapor is plentiful in the atmosphere of the southeastern coastal cities, and sea salt aerosols can act as condensation nuclei, increasing the frequency of wet deposition, and greatly reducing atmospheric pollutant levels [45].

**3.2. Relationship between the API/AQI and Meteorological Factors.** The importance of the influence of six meteorological factors on the API and AQI in different seasons was calculated using the random forest algorithm, and spatial clustering was conducted accordingly. The degree of influence of meteorological factors on the API and AQI had significant spatial differences.

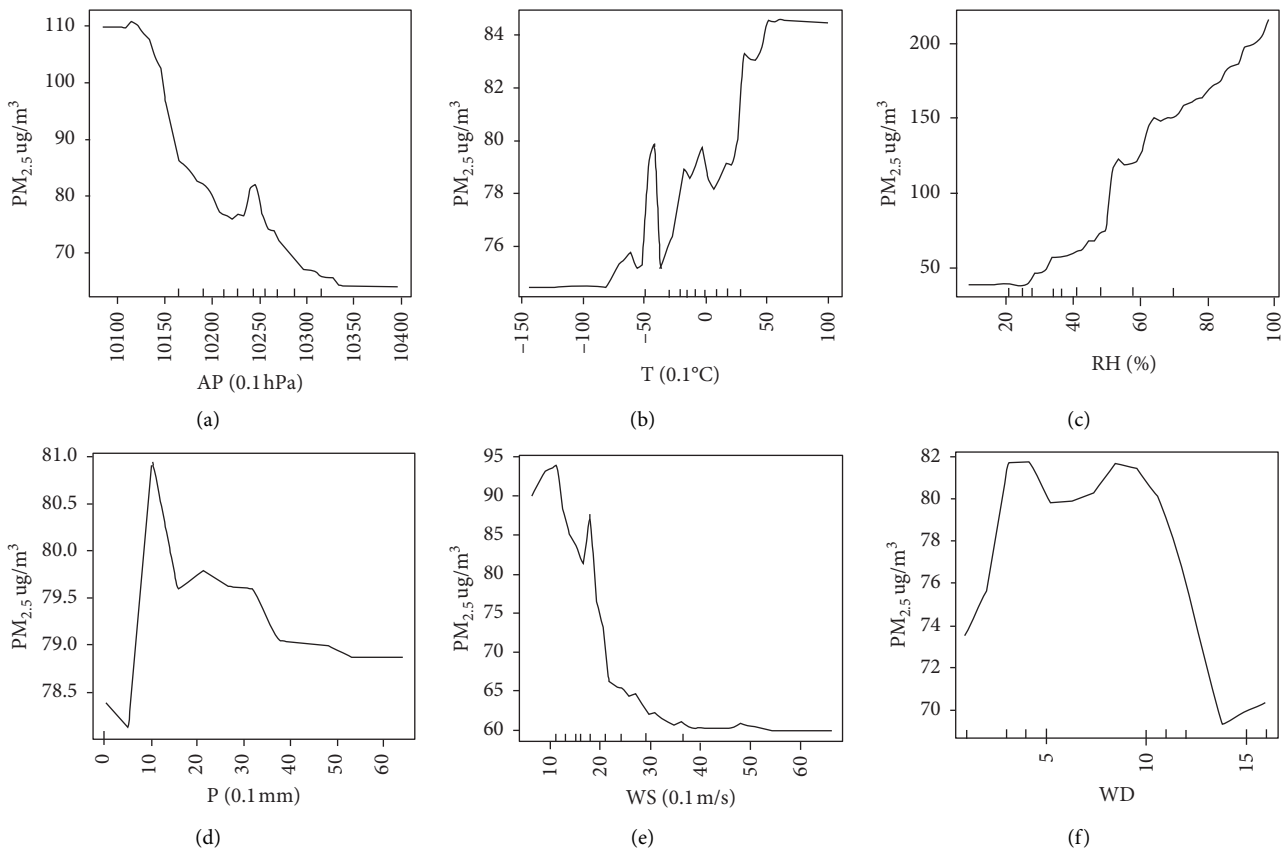


FIGURE 3: Partial dependence plots between meteorological factors and  $PM_{2.5}$  concentrations in Beijing in winter.

**3.2.1. Relationship between the API and Meteorological Factors.** The API was influenced most by wind direction and precipitation (Figure 7). However, there were significant spatial differences between northern and southern China. The most important meteorological factor affecting API values in northern cities was wind direction, followed by precipitation. For example, the importance score for the impact of wind direction on the API in Shizuishan was 0.28. Wind direction had a significant role in the accumulation or diffusion of pollutants in the north [46–48]. Precipitation had a large impact on the API of southern cities, followed by wind direction; for example, the importance score in Fuzhou was 0.34. This indicated that the wet deposition of pollutants was the dominant process in southern cities [49, 50].

There were significant local spatial differences in the influences of other meteorological factors among the seasons. Relative humidity influenced the API in all parts of the country. Under a high relative humidity, high  $PM_{10}$  and  $SO_2$  concentrations promote the formation of secondary particles and further aggravate air pollution [29]. In spring and summer, wind speed had the most significant impact on the API in southeastern coastal areas. In autumn, precipitation in some northern cities had a significant impact on the API; for instance, its importance score in Anshan was 0.26. In winter, the importance of wind speed in northern and northeastern cities increased significantly.

**3.2.2. Relationship between the AQI and Meteorological Factors.** The trend of the influences of meteorological factors on the AQI was consistent with that of the API for southern and northern cities, i.e., wind direction had the most significant influence on the AQI in northern cities, while precipitation was more significant in southern cities (Figure 8). However, the influences of the other meteorological factors on the AQI were only consistent with those on the API in autumn, and there were some spatial differences in the other seasons. In spring, wind direction had a far greater influence on the AQI than precipitation in northern and central cities, making it the most influential meteorological factor. In summer, wind speed was more important than relative humidity in most eastern cities. Precipitation was the most important meteorological factor in Beijing, Tianjin, and most cities in the middle and lower reaches of the Yangtze River. In winter, the importance of wind direction in some northern cities significantly increased, while the importance of wind speed in the middle and lower reaches of the Yangtze River was greater than that of relative humidity.

### 3.3. Relationship between Pollutant Concentration and Meteorological Factors

**3.3.1. Verification of Model Accuracy.** Before measuring the spatial effects of meteorological factors on the typical air pollutant concentration using the random forest algorithm, the accuracy of the model was verified. In this study, the

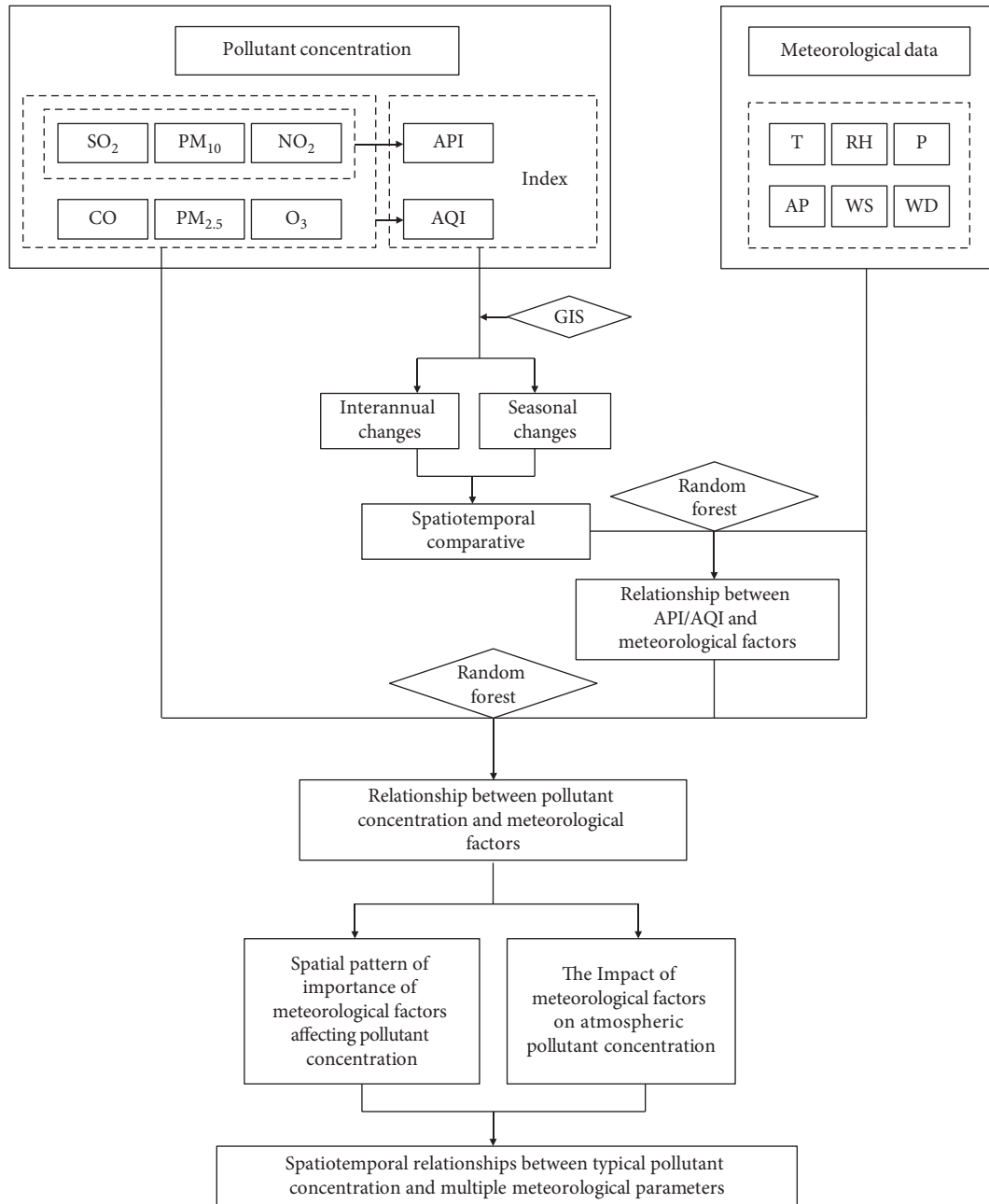


FIGURE 4: Technology roadmap.

meteorological monitoring data of 209 cities from January 1, 2014, to January 19, 2019, were used to predict the concentrations of six air pollutants and compare the estimates with the actual monitored concentrations. The simulation results showed that the coefficients of determination for the six pollutant concentrations were all over 0.79, with the value for  $\text{NO}_2$  being 0.88. The simulation showed that the random forest model was stable and the precision was reliable (Figure 9).

**3.3.2. Spatial Pattern of the Importance of the Impacts of Meteorological Factors on Pollutant Concentrations.** The

random forest algorithm was used to calculate the importance of the impacts of six meteorological factors on different pollutant concentrations in different seasons and to provide further spatial clustering:

(a) *Relationship between  $\text{PM}_{2.5}$  Concentration and Meteorological Factors.* At the national scale, the effects of relative humidity and temperature on the  $\text{PM}_{2.5}$  concentration were most significant in central and northern China (Figure 10). In Shanxi Province, temperature had the greatest influence on the  $\text{PM}_{2.5}$  concentration in autumn; for example, the importance score in Taiyuan was 0.41. In Henan Province, relative humidity had the greatest influence on the  $\text{PM}_{2.5}$  concentration in spring and winter. For

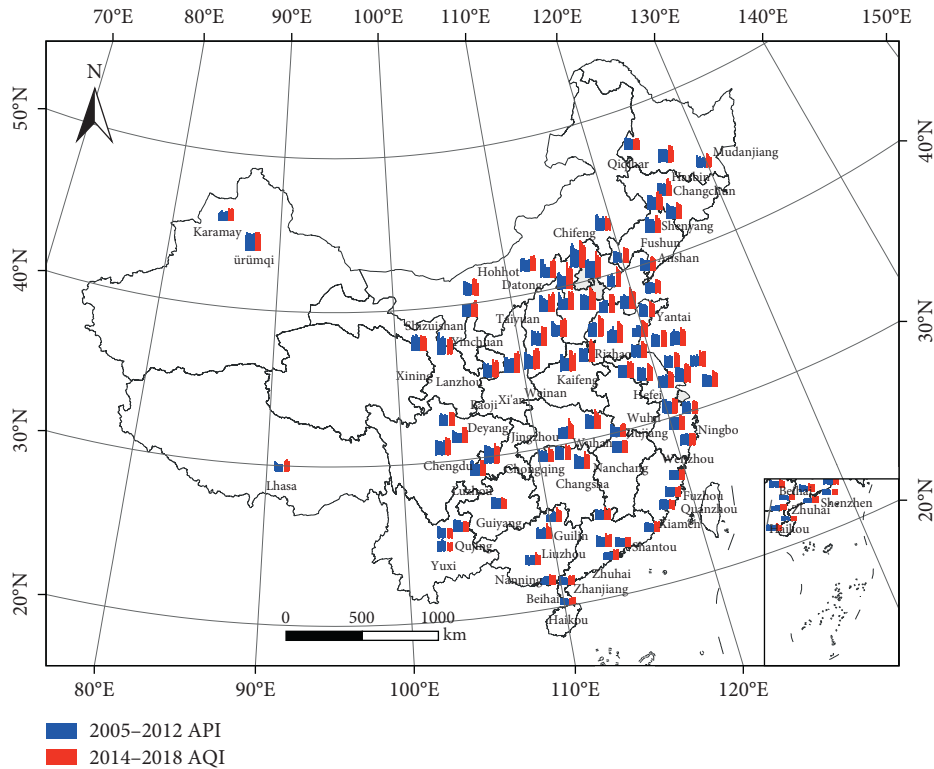


FIGURE 5: Interannual changes of the API and AQI.

example, the importance score of the impact of relative humidity in spring on the  $PM_{2.5}$  concentration in Zhengzhou was 0.42. High humidity is an important condition supporting the development of heavy fog and serious air pollution. This is because water vapor can absorb pollutants, which act as a condensation core to make small water droplets larger and simultaneously impede pollutant retention and nonproliferation [51, 52]. For southern and eastern China, wind speed had the most significant impact on the  $PM_{2.5}$  concentration in spring in most cities; for example, the importance score in Xiamen was 0.38. Temperature had a large impact on the  $PM_{2.5}$  concentration in summer; for example, the importance score in Wuzhou was 0.37. High temperatures in summer may affect the  $PM_{2.5}$  concentration in these areas, but in the coastal areas of Guangdong Province, relative humidity had the largest impact on the  $PM_{2.5}$  concentration; for example, the importance score in Zhanjiang was 0.41. In autumn and winter, relative humidity had a large impact on the  $PM_{2.5}$  concentration [52]. For example, the importance score for the impact of relative humidity on the  $PM_{2.5}$  concentration in autumn in Jiujiang was 0.39. For northeastern China, temperature had the most significant impact on the  $PM_{2.5}$  concentration in most cities in spring, summer, and autumn. For example, the importance score for the impact of temperature on the  $PM_{2.5}$  concentration in Huludao in spring was 0.4. Meanwhile, in winter, the influence of relative humidity was more significant; for example, the importance score in Dalian was 0.63. In northwestern China, temperature was the most important meteorological variable

influencing the  $PM_{2.5}$  concentration in spring and autumn. For example, the importance score of the impact of temperature on the  $PM_{2.5}$  concentration in Karamay in spring was 0.48. Relative humidity was the most important meteorological variable influencing the  $PM_{2.5}$  concentration in summer and winter. For example, the importance score of the impact of relative humidity on the  $PM_{2.5}$  concentration in summer in Xining was 0.37. In southwestern China, meteorological factors had no obvious impact on the  $PM_{2.5}$  concentration, while elsewhere, precipitation, temperature, and relative humidity had an influence. In the eastern part of Sichuan Province, in spring, autumn, and winter, precipitation had a large influence on the  $PM_{2.5}$  concentration. For example, the importance score of the impact of precipitation on the  $PM_{2.5}$  concentration in Mianyang in winter was 0.34.

(b) *Relationship between  $PM_{10}$  Concentration and Meteorological Factors.* At the national scale, precipitation and temperature in most cities in central and northern China had the most significant impacts on  $PM_{10}$  concentration (Figure 11). In northern China, temperature had greatest impact on the  $PM_{10}$  concentration in spring; for example, the importance score in Yuncheng was 0.4. In central China, precipitation had the greatest impact on the  $PM_{10}$  concentration in autumn; for example, the importance score in Kaifeng was 0.44. For most cities in southern and eastern China, temperature and relative humidity had the most significant impacts on the  $PM_{10}$  concentration in spring and summer. For example, the importance scores of the impacts of temperature and relative humidity on the  $PM_{10}$  concentrations in Huainan in spring were 0.22 and 0.28,

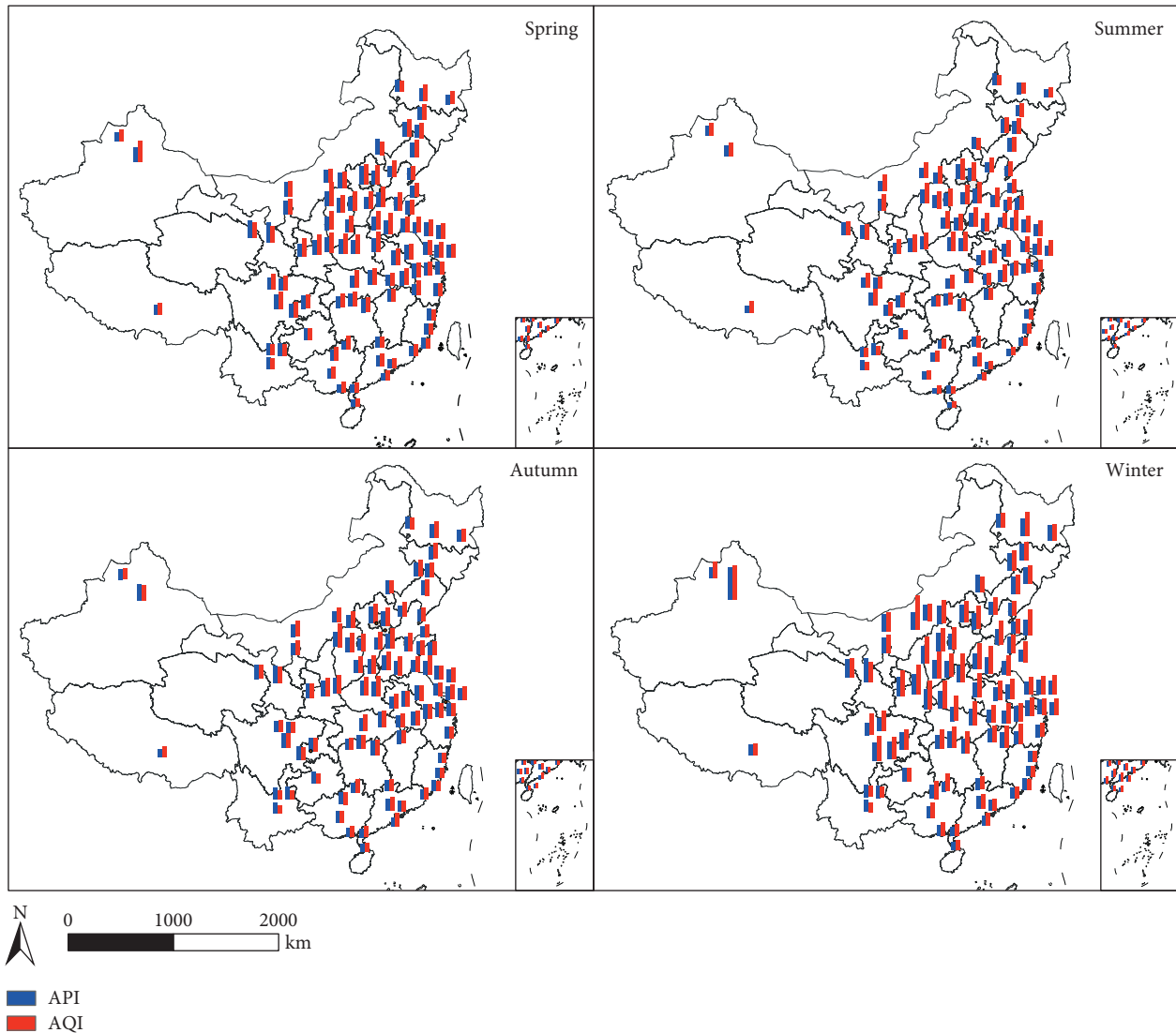


FIGURE 6: Seasonal changes of the API and AQI.

respectively. In autumn and winter, temperature and precipitation had large impacts on the  $PM_{10}$  concentration. For example, the importance scores of the impacts of temperature and precipitation on the  $PM_{10}$  concentrations in Nanjing in autumn were 0.22 and 0.35, respectively. Meanwhile, in coastal areas of Guangdong Province, relative humidity had a greater impact on  $PM_{10}$  concentrations; for example, the importance score in Zhanjiang was 0.72. In northeastern China, the relationships between meteorological factors and  $PM_{10}$  concentration were similar to those of  $PM_{2.5}$  concentration. In northwestern China, temperature and relative humidity had the most significant impacts on the  $PM_{10}$  concentration in spring, summer, and winter. For example, the importance scores of temperature and relative humidity on the  $PM_{10}$  concentration in Karamay in spring were 0.34 and 0.27, respectively. Precipitation had the most significant impact on the  $PM_{10}$  concentration in autumn; for example, the importance score in Hanzhong was 0.38. In southwestern China, precipitation had the most significant

impact on the  $PM_{10}$  concentration in autumn; for example, the importance score in Leshan was 0.55, although temperature, relative humidity, and precipitation in the other three seasons also influenced  $PM_{10}$ .

(c) *Relationship between  $SO_2$  Concentration and Meteorological Factors.* At the national scale, relative humidity and temperature had the most significant effects on the  $SO_2$  concentration in most parts of China (Figure 12). In northern China, temperature had a crucial influence on the  $SO_2$  concentration in spring and autumn; for example, the importance score in Changzhi was 0.4. Relative humidity influenced the  $SO_2$  concentration in summer and winter; for example, the importance score in Zhangjiakou was 0.44. In central and southern China, relative humidity had the most significant effect on the  $SO_2$  concentration, especially in Henan Province and central and southern China in winter. For example, the importance score of the impact of relative humidity on the  $SO_2$  concentration in Anyang in summer was 0.46. In eastern China, relative humidity had the most



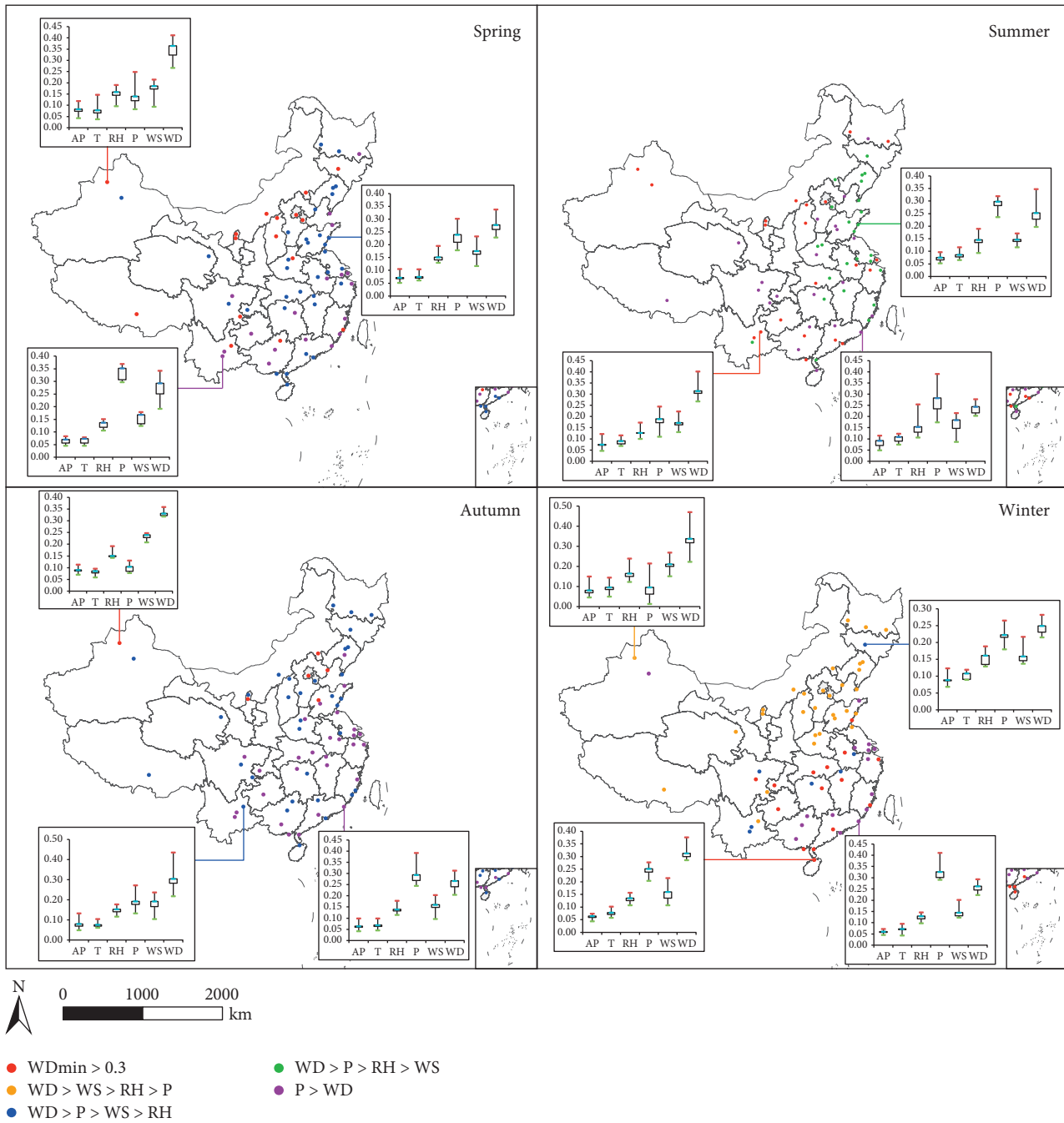


FIGURE 7: Spatial clustering of the importance of the influence of meteorological factors on the API.

significant effect on the  $SO_2$  concentration in most cities in winter; for example, the importance score in Nantong was 0.53. Seasonal temperature, relative humidity, and wind speed and direction all influenced  $SO_2$  concentration. In northeastern China, temperature had the most significant effect on the  $SO_2$  concentration in spring and autumn; for example, the importance score in Shenyang in spring was 0.6. However, relative humidity had a more significant influence on the  $SO_2$  concentration in summer and winter; for example, the importance score in Fushun was 0.6. The relationships between meteorological factors and the  $SO_2$  concentration in northwestern China were consistent with

those for  $PM_{2.5}$ . In southwestern China, temperature had the most significant effect on the  $SO_2$  concentration; for example, the importance score in Chengdu in spring was 0.36.

(d) *Relationship between CO Concentration and Meteorological Factors.* At the national scale, in most parts of the country, temperature had a significant impact on the CO concentration in spring and autumn, while temperature, relative humidity, and wind speed influenced the CO concentration in summer and winter (Figure 13). In northern China, relative humidity had a great influence on the CO concentration in summer and winter; for example,

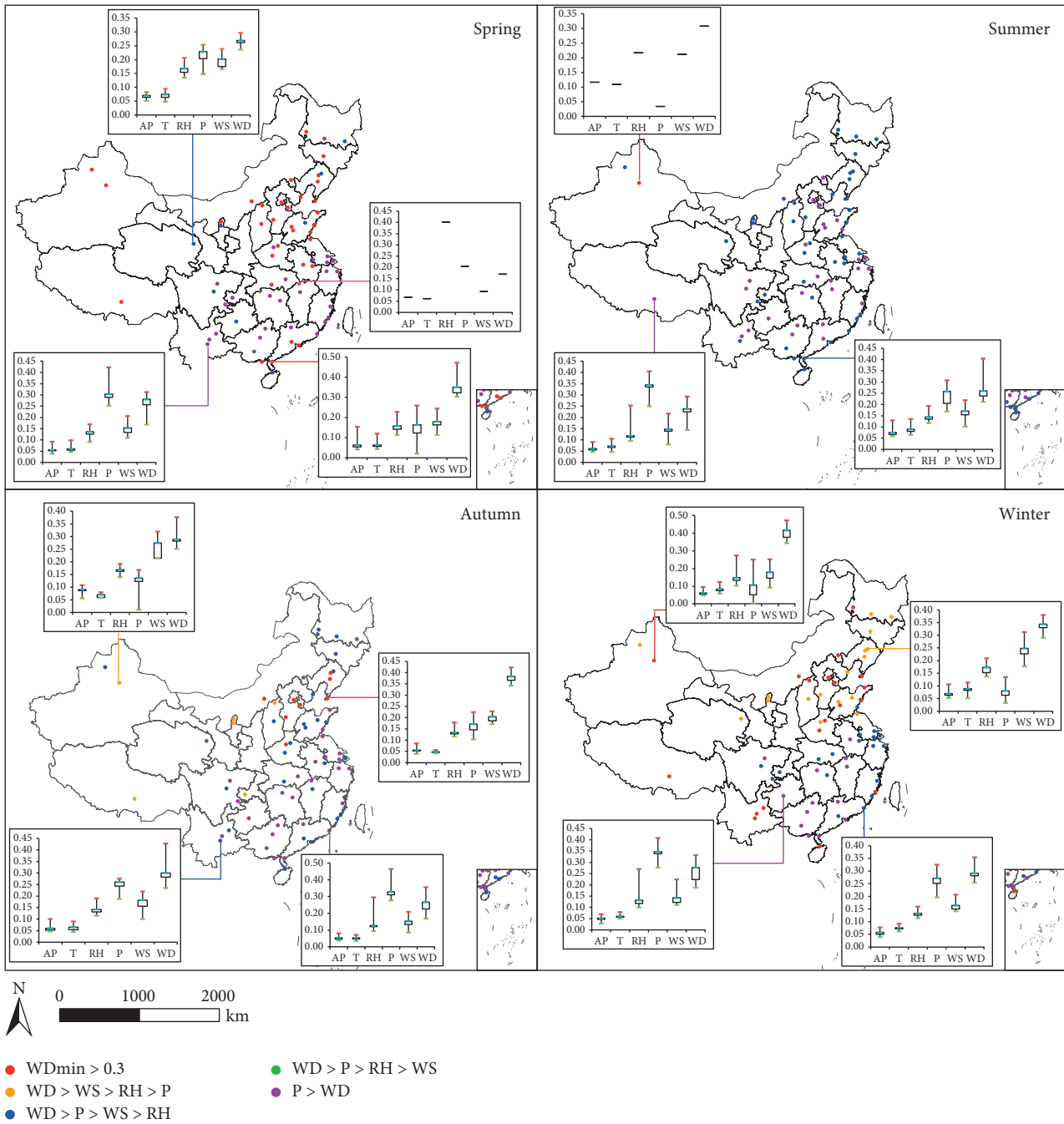


FIGURE 8: Spatial clustering of the importance of the impact of meteorological factors on the AQI.

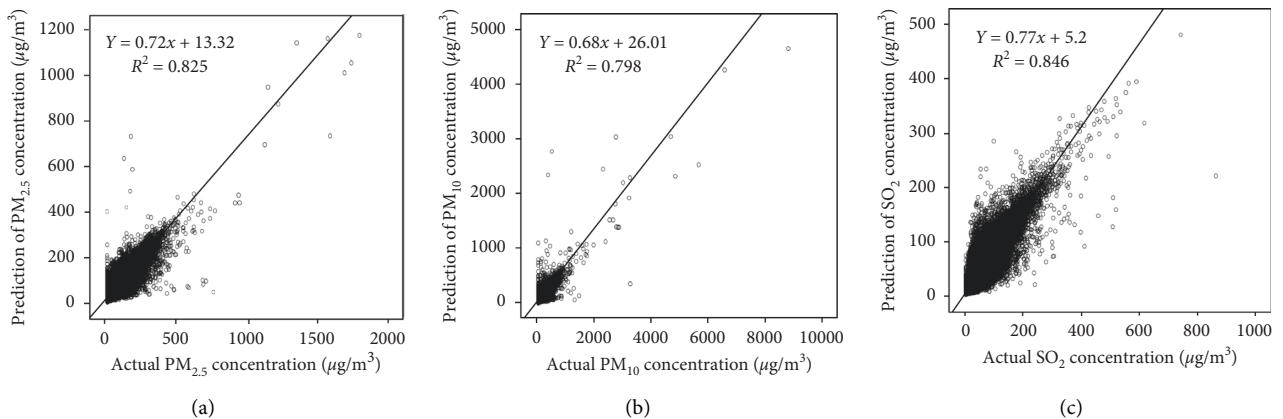


FIGURE 9: Continued.

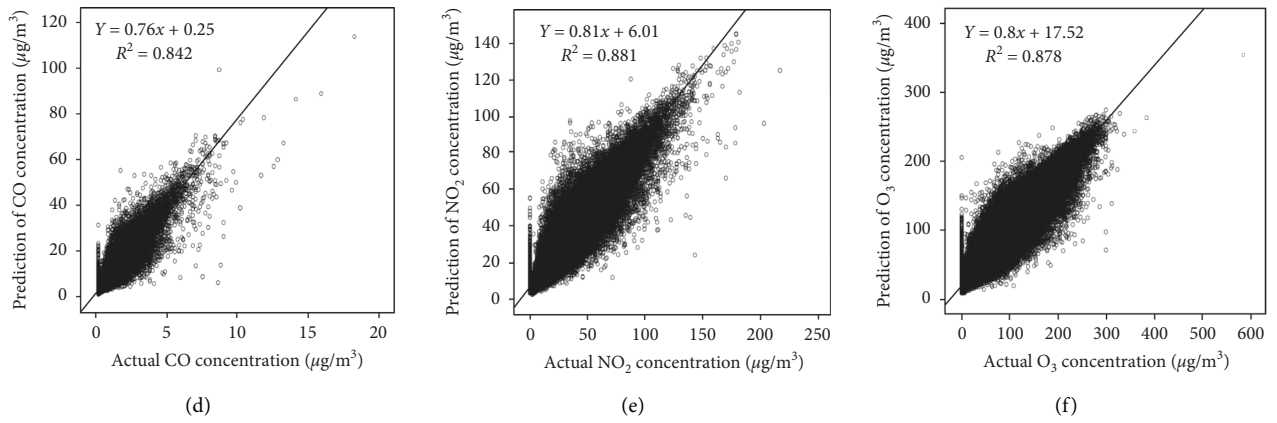


FIGURE 9: Verification of pollutant concentrations obtained from the random forest model.

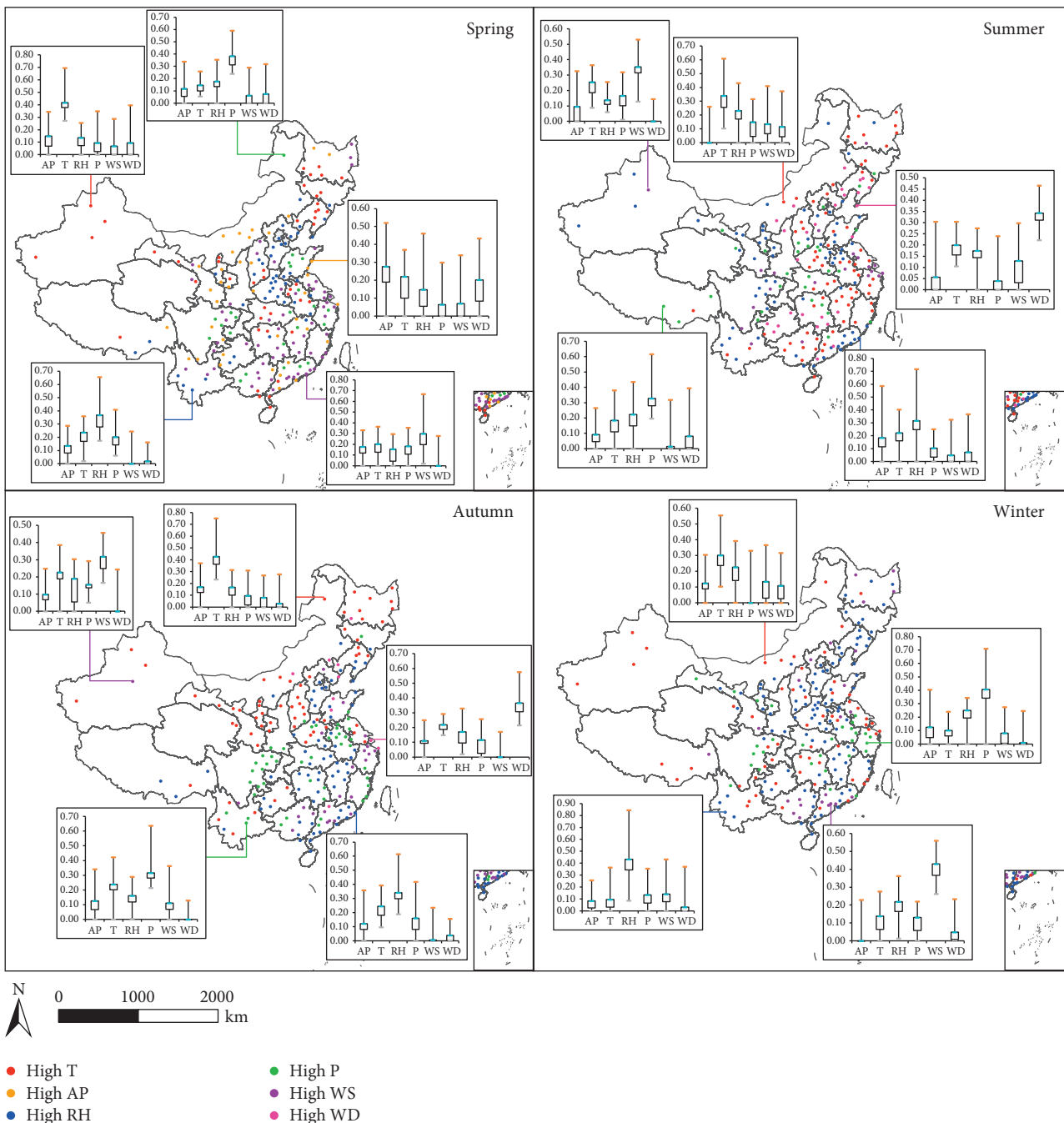


FIGURE 10: Relationship between  $\text{PM}_{2.5}$  concentration and meteorological factors.

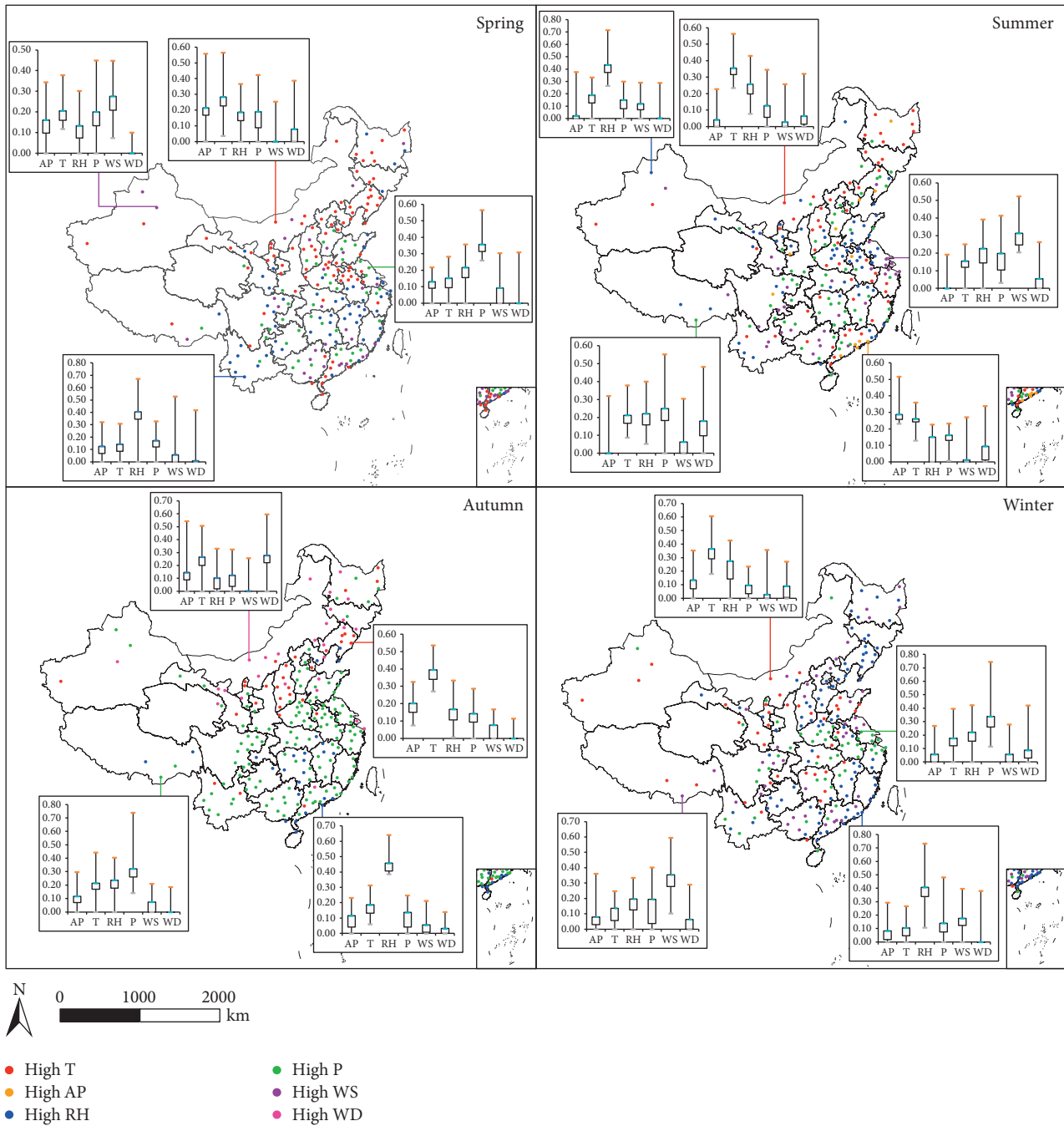


FIGURE 11: Relationship between  $PM_{10}$  concentration and meteorological factors.

the importance score in Beijing in summer was 0.38. In central and southern China, temperature had a great influence on the CO concentration in winter; for example, the importance score in Zhangjiajie was 0.33. Atmospheric pressure and wind speed affected the CO concentration in summer. In eastern China, wind speed had the most significant effect on the CO concentration in summer; for example, the importance score in Shanghai was 0.4. Temperature, wind speed, and precipitation all affected the CO concentration in winter. In northeastern China, temperature and wind speed had the most significant effects on the CO concentration in summer. For example, the importance

scores of the impacts of temperature and wind speed on the CO concentration in Jiamusi were 0.54 and 0.25, respectively. Relative humidity and wind speed had the most significant effects on the CO concentration in winter. For example, the importance scores of the impacts of relative humidity and wind speed on the CO concentration in Dandong were 0.5 and 0.3, respectively. In northwestern and southwestern China, wind speed, temperature, and relative humidity influenced the CO concentration in summer and winter.

(e) Relationship between  $NO_2$  Concentration and Meteorological Factors. At the national scale, temperature and

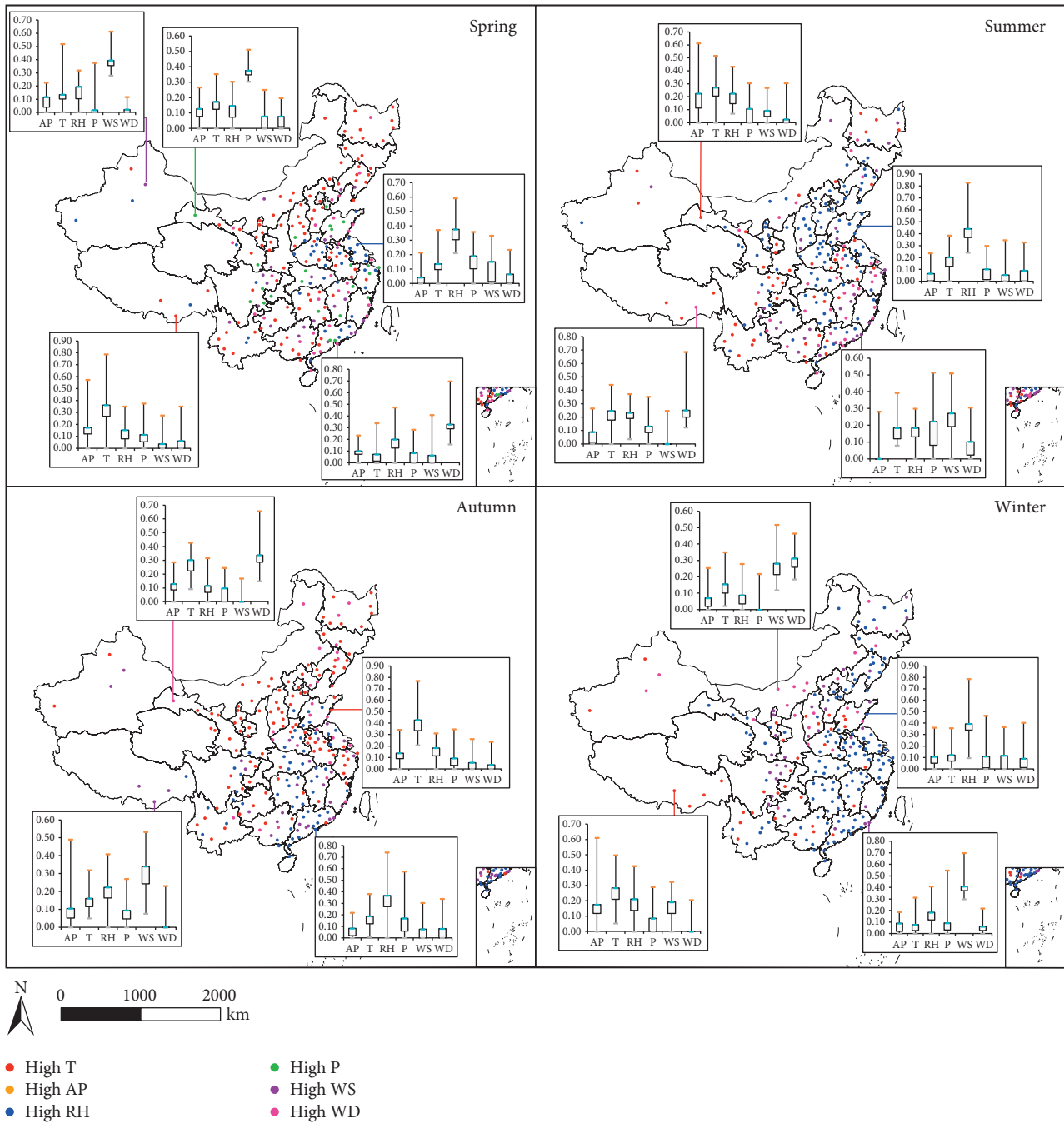


FIGURE 12: Relationship between SO<sub>2</sub> concentration and meteorological factors.

wind speed had significant impacts on the NO<sub>2</sub> concentration in most parts of the country (Figure 14). In northern China, relative humidity also influenced the NO<sub>2</sub> concentration in summer; for example, the importance score in Beijing was 0.49. In spring and summer in southwestern China and autumn in northeastern China, temperature also had a great influence on the NO<sub>2</sub> concentration. For example, the importance score of the impact of temperature on the NO<sub>2</sub> concentration in spring in Chengdu was 0.35. The rest of the region was significantly affected by wind speed.

(f) Relationship between O<sub>3</sub> Concentration and Meteorological Factors. At the national scale, temperature and relative humidity had significant impacts on the O<sub>3</sub> concentration in most parts of the country (Figure 15). Relative humidity had the most significant effect on the O<sub>3</sub> concentration in southern China; for example, the importance score in Haikou in winter was 0.45. Temperature had the most significant effect on the O<sub>3</sub> concentration in northern China in spring and autumn; for example, the importance score in Baotou in spring was 0.6. There was no obvious

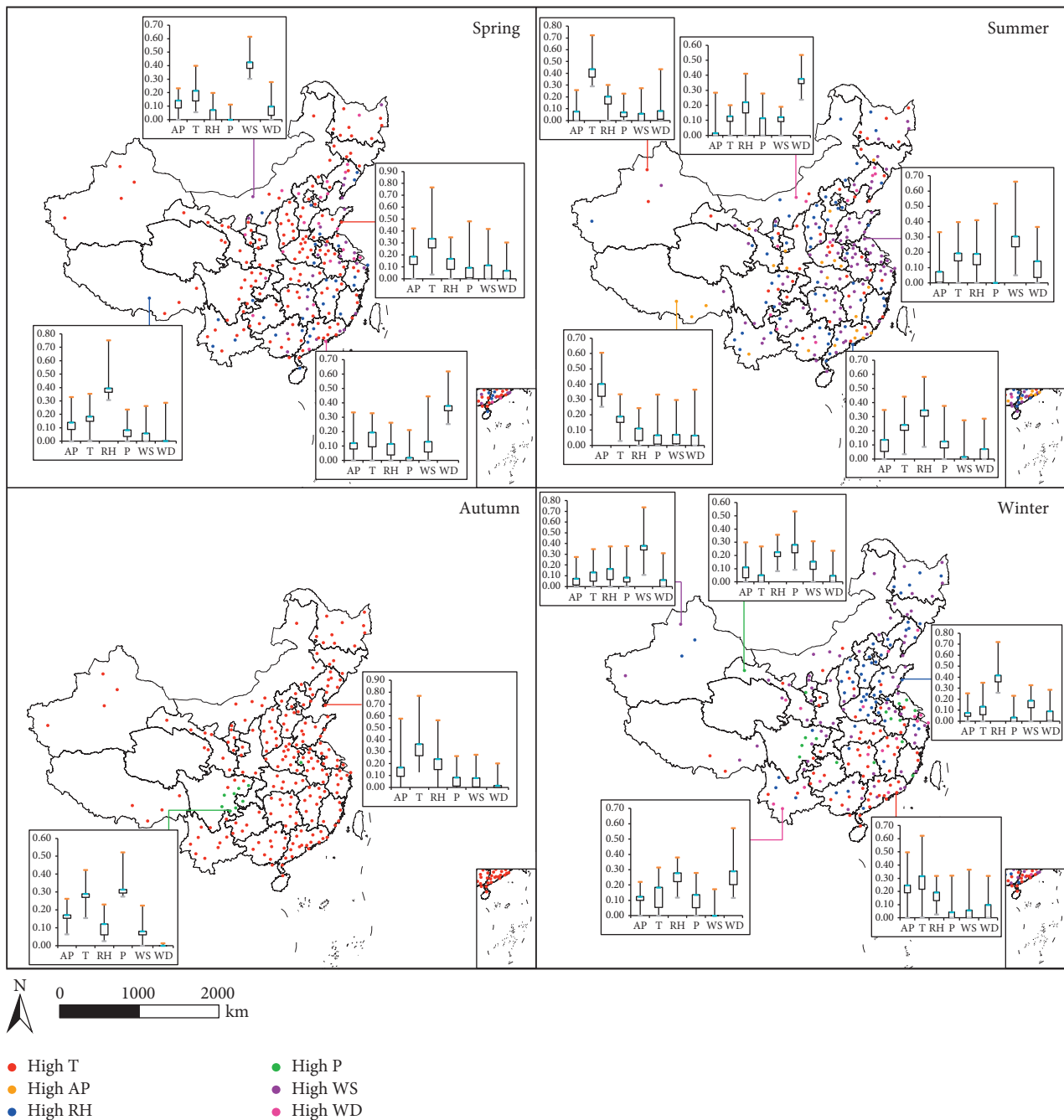


FIGURE 13: Relationship between CO concentration and meteorological factors.

aggregation in winter, but  $O_3$  concentration was affected by temperature, wind speed, and relative humidity. In northern and northeastern China, temperature had a large influence on the  $O_3$  concentration in summer; for example, the importance score in Hohhot was 0.61.

**3.3.3. Analysis of the Impact of Meteorological Factors on Atmospheric Pollutant Concentrations.** In this study, the partial dependence of the concentrations of pollutants in different seasons on six meteorological factors was determined for various cities. The magnitudes of different

meteorological factors corresponding to the maximum concentrations of various pollutants were calculated, and this value was taken as the impact threshold of the meteorological factors on air pollutant concentrations. A classification and spatial mapping exercise was conducted, and the temporal and spatial differences of the influence of meteorological factors on atmospheric pollutant concentrations were further analyzed.

*(a) Spatial Pattern of the Impact of Meteorological Factors on  $PM_{2.5}$  Concentration.* There were significant spatial and temporal differences in the influence of different meteorological factors on the  $PM_{2.5}$  concentration (Figure 16). The

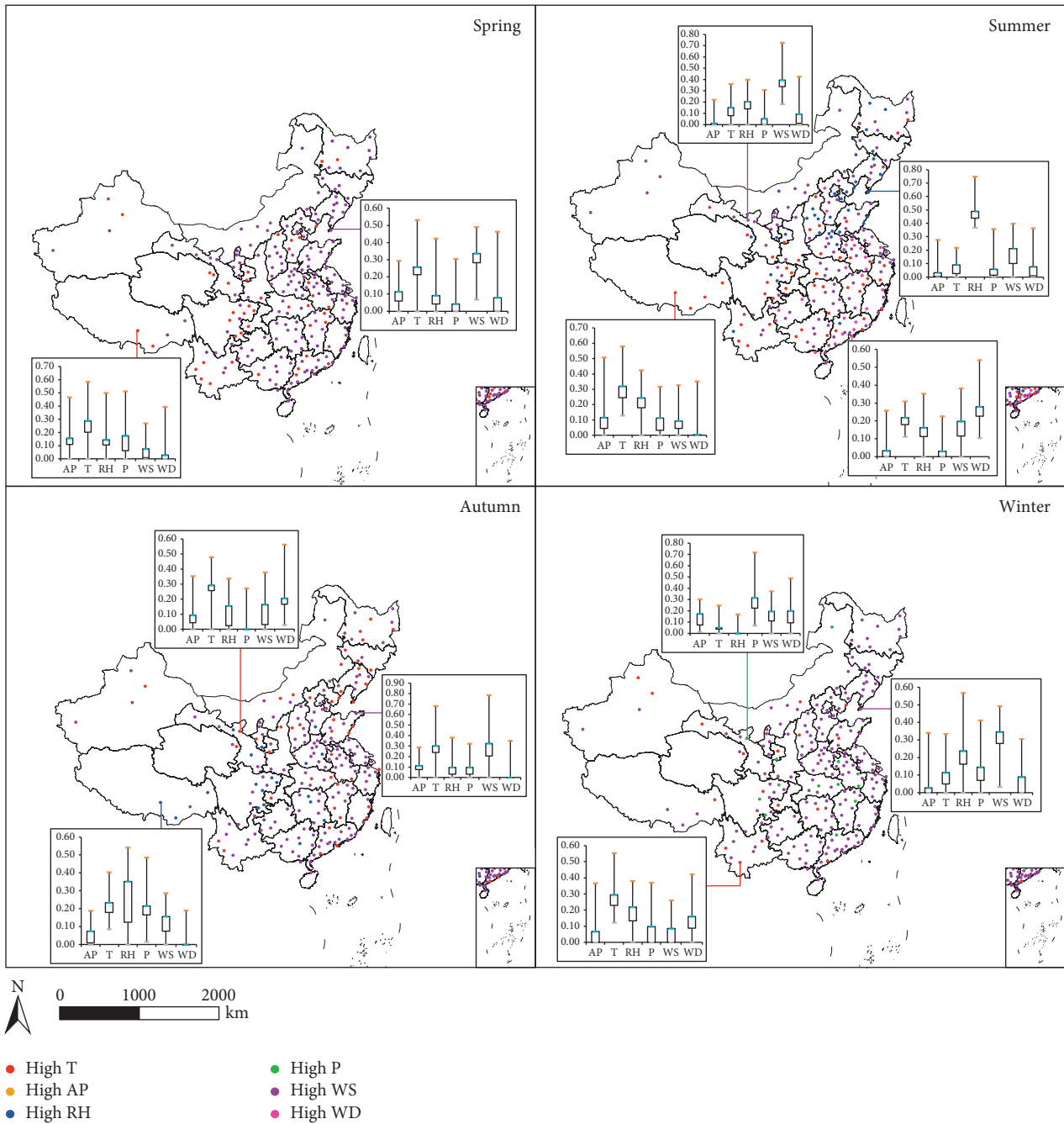


FIGURE 14: Relationship between  $\text{NO}_2$  concentration and meteorological factors.

spatial distribution of the threshold value of the influence of atmospheric pressure on the  $\text{PM}_{2.5}$  concentration differed significantly between eastern and western China, especially in spring, autumn, and winter. In summer, air pollution was more serious in the southeastern coastal areas when the atmospheric pressure exceeded 900 hPa. The impact of relative humidity differed markedly between northern and southern China, with the Qinling-Huaihe Line as the boundary. The threshold value of the influence of relative humidity on the  $\text{PM}_{2.5}$  concentration south of the Qinling-Huaihe Line was between 40% and 80%; for example, that in

Baoshan was only 41%, but the corresponding value north of the Yangtze River generally exceeded 80%. In spring, the threshold value of the influence of relative humidity on the  $\text{PM}_{2.5}$  concentration in Yinchuan was 96%. Precipitation had a direct spatial impact on the  $\text{PM}_{2.5}$  concentration. The  $\text{PM}_{2.5}$  concentration reached a maximum under conditions with little-to-no precipitation. The spatial influence of wind speed on the  $\text{PM}_{2.5}$  concentration was mainly reflected in the east-west difference. The southeastern coastal areas were prone to  $\text{PM}_{2.5}$  pollution when the wind speed was relatively low, whereas the  $\text{PM}_{2.5}$  concentration usually reached a

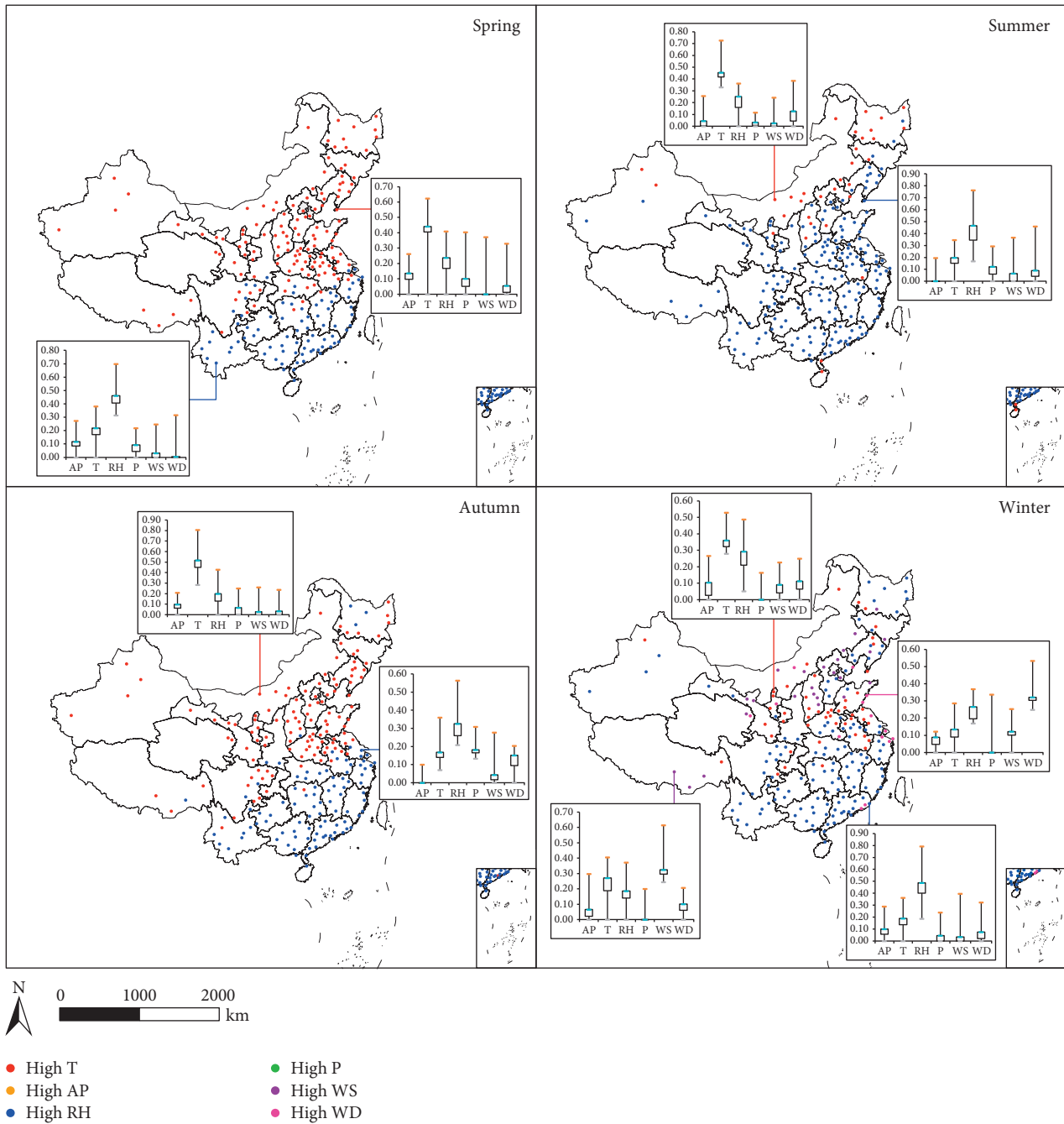


FIGURE 15: Relationship between  $O_3$  concentration and meteorological factors.

maximum in northwest inland areas when the wind speed was usually high. For example, in summer when the wind speed in Inner Mongolia and its surrounding areas exceeded 2 m/s, the  $PM_{2.5}$  concentration reached a maximum. In summer, the maximum wind speed in Baotou was 7 m/s. Thus, these areas were mostly affected by exogenous pollution [53]. In northeastern and northern China, the wind direction was typically from the southeast to southwest, and this region had the highest  $PM_{2.5}$  concentrations in the country. In most other areas, the wind direction at the time

of the maximum  $PM_{2.5}$  concentration was usually from the northwest to the northeast.

(b) *Spatial Pattern of the Impact of Meteorological Factors on  $PM_{10}$  Concentration.* The spatial patterns of the meteorological factors affecting the  $PM_{10}$  concentration were similar to those affecting the  $PM_{2.5}$  concentration (Figure 17). However, when the  $PM_{10}$  concentration was highest in spring and summer, the threshold of relative humidity in northern China was significantly reduced. For example, the relative humidity of Datong in spring was only 14%.



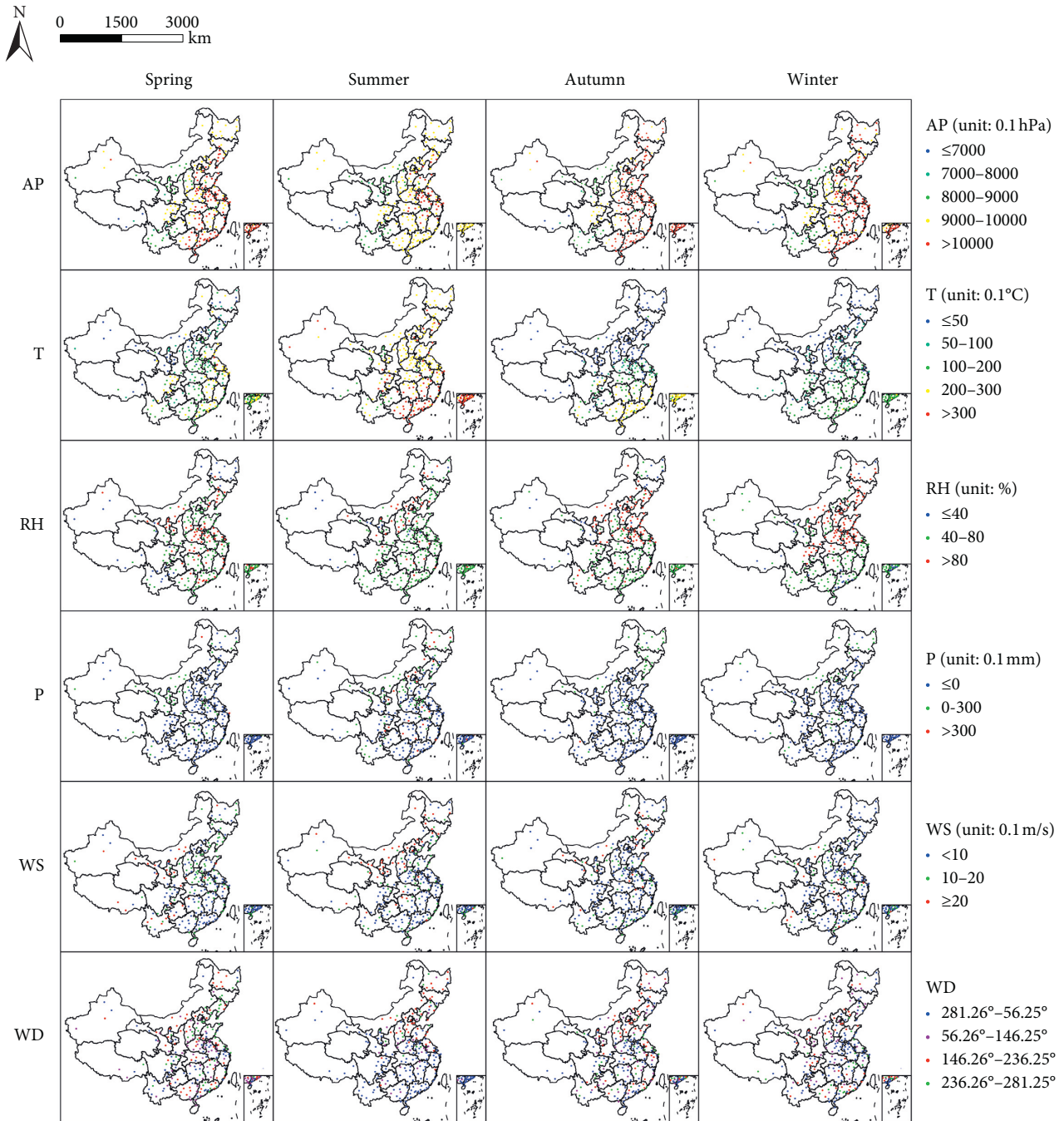


FIGURE 16: Spatial pattern of the impact of meteorological factors on  $PM_{2.5}$  concentration.

(c) *Spatial Pattern of the Impact of Meteorological Factors on  $SO_2$  Concentration.* The spatial patterns of the influences of meteorological factors on the  $SO_2$  concentration were similar to those for  $PM_{10}$  (Figure 18). However, in summer, when the temperature in the south exceeded  $20^\circ\text{C}$ , the  $SO_2$  concentration reached a maximum, while the maximum  $PM_{10}$  concentration only occurred when the temperature exceeded  $30^\circ\text{C}$ . In Huainan, temperatures of  $20.4^\circ\text{C}$  and  $32^\circ\text{C}$  had the greatest influence on  $SO_2$  and  $PM_{10}$  concentrations in summer, respectively. When the  $SO_2$  concentration was highest in autumn and winter, the influence threshold of

relative humidity in northern China decreased. For example, the influence thresholds of the relative humidity of the  $SO_2$  and  $PM_{10}$  concentrations in autumn in Tianjin were 51.8% and 97%, respectively. In the inland area of northwestern China,  $SO_2$  pollution usually occurred when the wind speed was low.

(d) *Spatial Pattern of the Impact of Meteorological Factors on CO Concentration.* The spatial pattern of CO concentration was affected by various meteorological factors, but was similar to that of  $SO_2$  (Figure 19). However, in southern

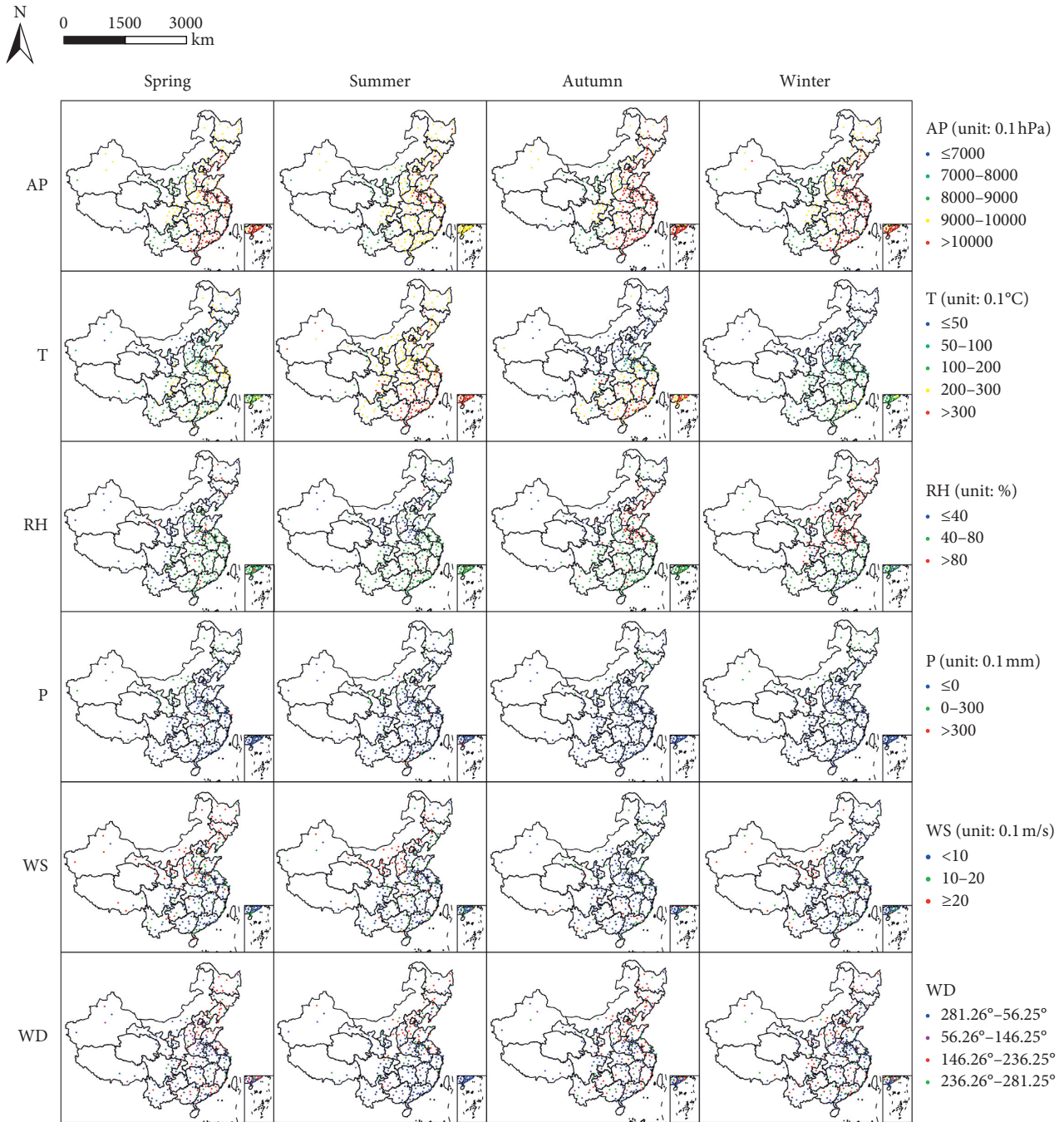


FIGURE 17: Spatial pattern of the impact of meteorological factors on  $PM_{10}$  concentration.

China, when the CO concentration was highest, the threshold of relative humidity was also high. For example, the relative humidity in Heyuan in summer was 99%. In winter, the CO concentration was largest when precipitation in the southeastern coastal area exceeded 30 mm.

(e) *Spatial Pattern of the Impact of Meteorological Factors on  $NO_2$  Concentration.* The spatial pattern of  $NO_2$  concentration was affected by relative humidity and was similar to that of  $PM_{10}$ . Although the spatial pattern of  $NO_2$  concentration was affected by other meteorological factors, the influences of the meteorological factors were similar to those

for CO (Figure 20). However, in autumn, the  $NO_2$  concentration reached a maximum in the southeastern coastal area under conditions with little-to-no precipitation.

(f) *Spatial Pattern of the Impact of Meteorological Factors on  $O_3$  Concentration.* The spatial patterns of the influences of meteorological factors on  $O_3$  concentration were similar to those for  $NO_2$  (Figure 21). However, in spring and autumn, the  $O_3$  concentration reached a maximum when the temperature exceeded  $20^\circ C$ . In summer, the temperature influence threshold in eastern China increased significantly; for example, in summer, in Chengdu, it was  $36.5^\circ C$ . When

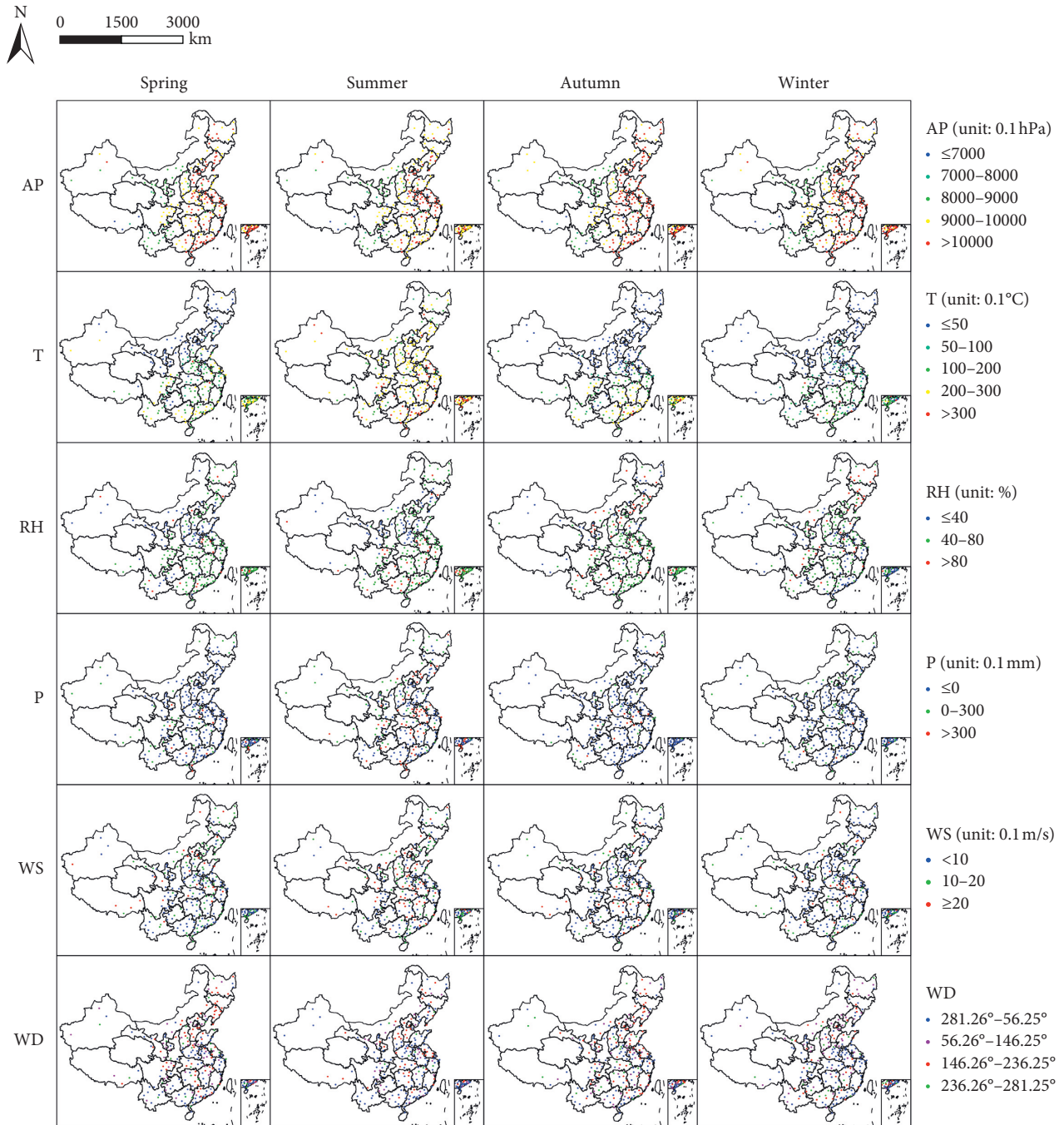


FIGURE 18: Spatial pattern of the impact of meteorological factors on  $\text{SO}_2$  concentration.

the highest  $\text{O}_3$  concentration occurred, the influence threshold of relative humidity in northern China in autumn and winter was low; for example, the relative humidity in Shenyang was 22% in winter. In winter, the  $\text{O}_3$  concentration was highest in northern China, which received very little precipitation; for example, the precipitation in Tianjin was just 12.3 mm in winter. The  $\text{O}_3$  concentration reached a maximum in the north during periods with high wind speeds, for example, when the wind speed in Hohhot in winter reached 9.3 m/s. In winter, the  $\text{O}_3$  concentration

reached a maximum in Beijing-Tianjin-Hebei when the wind direction was from the northwest to the northeast.

#### 4. Discussion

This study evaluated daily air quality monitoring data and meteorological monitoring data from 2005 to 2018 for 221 Chinese cities. The random forest algorithm was applied, and the key meteorological factors affecting air quality under different spatiotemporal conditions were identified. The

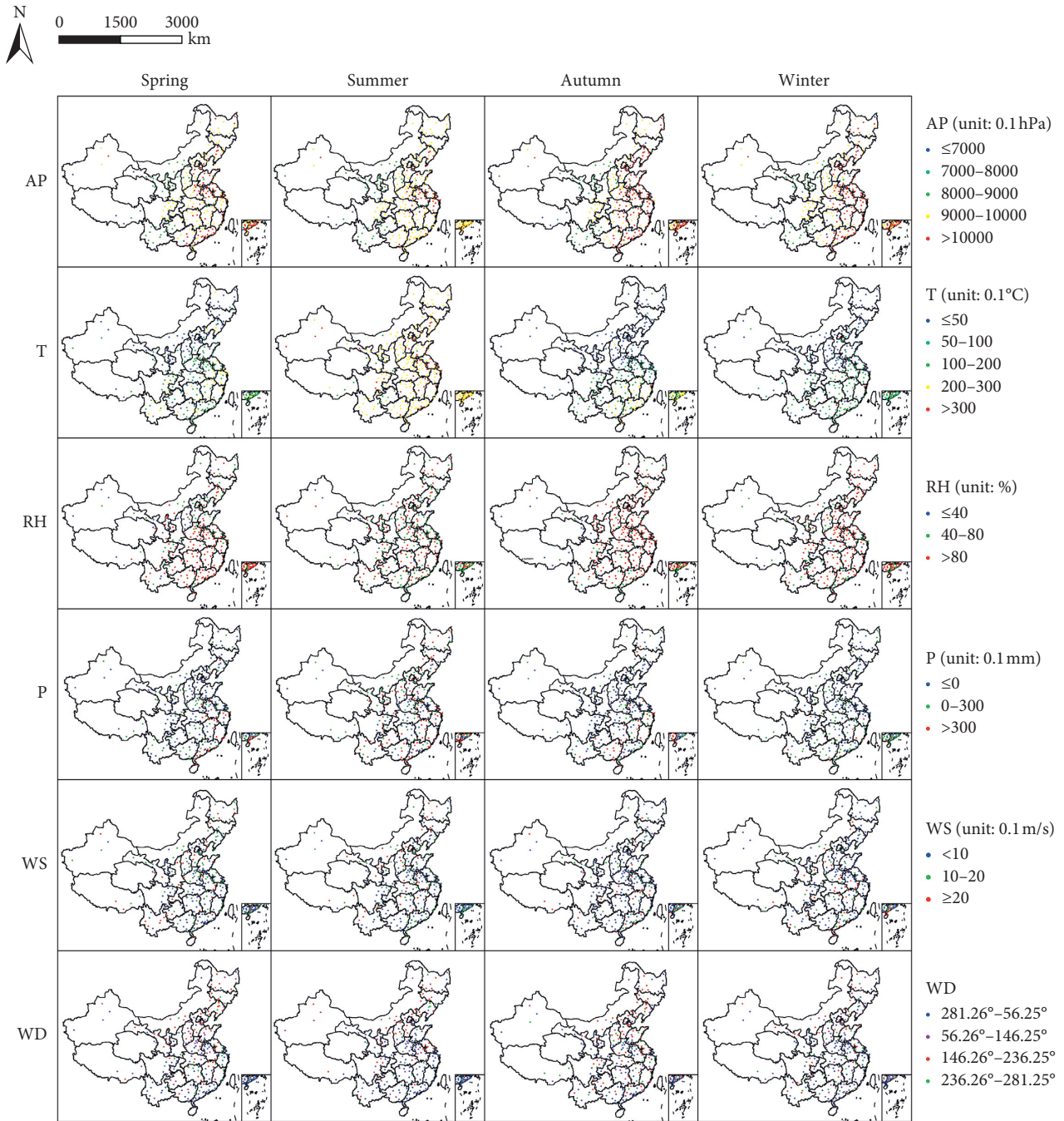


FIGURE 19: Spatial pattern of the impact of meteorological factors on CO concentration.

temporal and spatial differences of the threshold values of different meteorological factors on typical air pollutants ( $PM_{2.5}$ ,  $PM_{10}$ ,  $SO_2$ , CO,  $NO_2$ , and  $O_3$ ) were then identified.

The data consistency characteristics were studied by comparing the spatiotemporal variation characteristics of the API and AQI. Temporally, the API and AQI were significantly higher in winter than in other seasons, with the second highest values in spring and the lowest in summer [46]. Spatially, the API and AQI values of northern cities were generally higher than those of southern cities [40, 54]. From the perspective of the spatial and temporal trends, the AQI and API values were basically consistent, indicating a

gradual improvement of air quality in China. The AQI values were slightly higher than the API values. This is because the AQI is based on more stringent standards than the API, and there are some differences in their calculation. In addition, the AQI has the advantages of facilitating higher index values than the API, and data have been released at a greater frequency; this also confirms that the AQI is an appropriate replacement for the API.

We considered the relationship between AQI values and pollutant concentrations. Wind direction and precipitation were important meteorological factors affecting air quality in most cities in China, with wind direction being the most

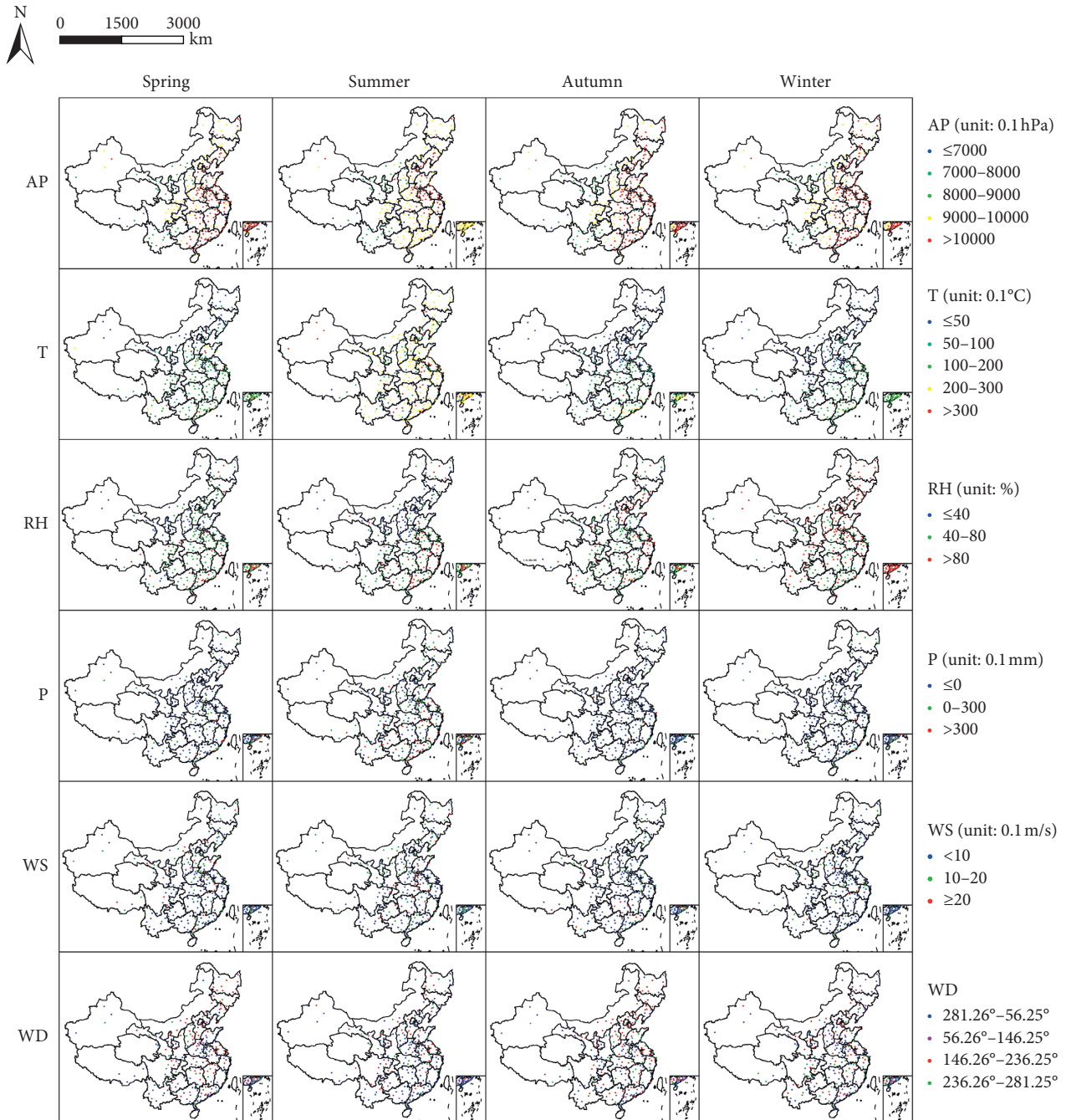


FIGURE 20: Spatial pattern of the impact of meteorological factors on  $\text{NO}_2$  concentration.

important meteorological factor affecting API and AQI values in northern cities. Precipitation was the most important meteorological factor affecting API and AQI values in southern cities, which was consistent with other studies [29, 55]. To some extent, this reflects the mechanisms of the release and degradation of air pollutants in northern and southern China. There were major local spatial differences in the other meteorological factors in the different seasons. Temperature had the main influences on the concentrations of the different pollutants. Temperature is closely related to pollutant concentrations because it regulates atmospheric

turbulence and chemical reactions [52, 56]. This phenomenon has also been observed in the United States [57]. In addition to temperature, precipitation and relative humidity significantly affected  $\text{PM}_{2.5}$  and  $\text{PM}_{10}$  concentrations in most cities, indicating the importance of the hygroscopic growth of aerosol particles in China [52]. In addition, wind speed and relative humidity had great influences on  $\text{NO}_2$  and  $\text{O}_3$  concentrations, respectively. In the presence of sunlight and water vapor,  $\text{O}_3$  can form the hydroxyl radical, which is conducive to the consumption of  $\text{O}_3$  [58, 59]. These results were consistent with those of other studies [60, 61].

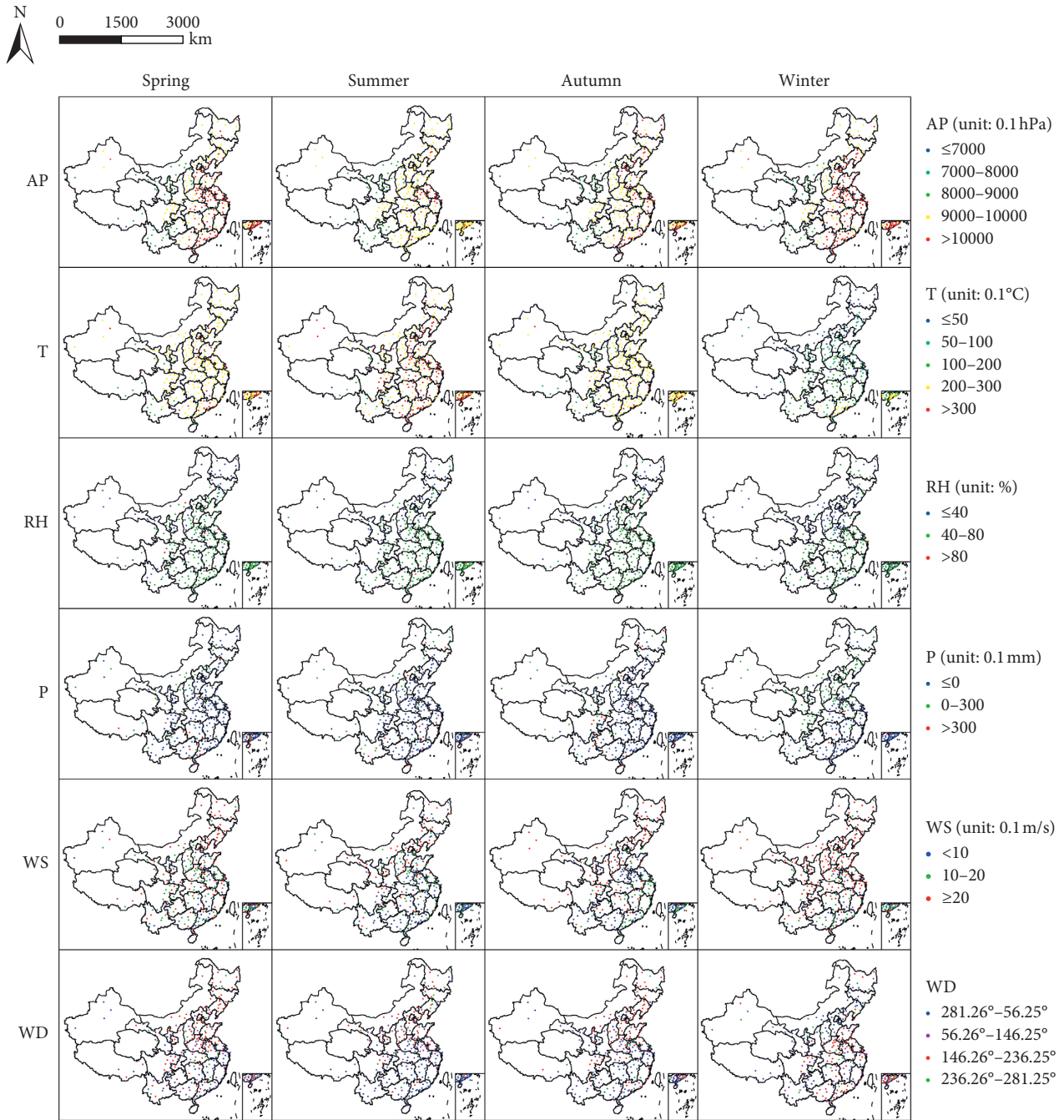


FIGURE 21: Spatial pattern of the impact of meteorological factors on  $O_3$  concentration.

We also found an interesting phenomenon regarding the relationship between the concentrations of various pollutants and meteorological factors. The relationship between  $PM_{10}$  and meteorological factors differed from those of the other pollutants, although the relationships of the concentrations of the other five pollutants and meteorological factors were similar. This is because the API and AQI calculations use the primary pollutant as the air quality measure, ignoring the levels of other pollutants.  $PM_{10}$  accounted for 89.4% of the primary pollutants considered in the API and AQI, with  $SO_2$  being the next most abundant pollutant. Therefore, if only the API and AQI values are used

to evaluate the relationship between meteorological factors and air quality, the conclusions obtained will only reflect the primary pollutant used in the calculation of the indexes. Such conclusions may also be detrimental to the prediction of specific pollutant concentrations and the management of regional pollution prevention and control.

## 5. Conclusions

This study used daily API, AQI, and meteorological monitoring data from 221 cities in China to compare the consistency of the API and AQI values. The random forest

algorithm was used to identify the key meteorological factors that affected air quality under different spatiotemporal conditions, and the thresholds of meteorological factors at which typical air pollutant concentrations were affected and their spatial differences were determined. The results can be used to determine the meteorological sensitivity of air quality and provide quantitative support for the implementation of joint air pollution prevention and control initiatives.

However, the study was limited by the uneven distribution of monitoring stations. During the process of comparing air quality monitoring data with meteorological data, to retain as much air quality monitoring data as possible for cities without meteorological monitoring data, we used the nearest meteorological station, which may have introduced errors. In addition, when the random forest algorithm was used to analyze the impact of meteorological factors on atmospheric pollution, the value obtained only represented the degree of importance, but not its positive or negative impact. One further point was not considered in this study. Except for the impact of meteorological conditions, the volume of local pollutant emissions is a direct factor affecting air quality. In addition to meteorological conditions, future research should also consider pollutant emission inventory data. The Weather Research and Forecasting mesoscale meteorological model and air quality model (such as CALPUFF, CAMx, and CMAQ) could then be used to simulate different weather and air quality conditions by setting varying amounts of pollutant discharge in each grid. Further studies should introduce other possible influence parameters and conduct longer time series data analysis [3, 4, 62–64].

### Data Availability

The air quality and meteorological data used to support this study were supplied by the Department of Ecology and Environment and China National Meteorological Science Data Centre under license and they are not available. Requests for access to these data should be done through contacting the Department of Ecology and Environment (<http://www.mee.gov.cn>) and China National Meteorological Science Data Centre (<http://data.cma.cn/site/index.html>), respectively.

### Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

### Authors' Contributions

All the authors have made a significant contribution to the conception, design, execution, or interpretation of the reported study. Z.Q. conceptualized the study; M.J. and Z.Q. contributed to methodology; X.X. is responsible for resources and software; M.J., Y.J., and X.H. performed data curation; M.J. involved in visualization; M.J., L.L., and Z.Q. prepared the original draft; Z.Q. and W.S. reviewed and edited the manuscript.

### Acknowledgments

This work was supported by the National Natural Science Foundation of China (Grant no. 41871211), the Natural Science Foundation of Tianjin City (Grants no. 16JCQNJC08900), and the National Key Research and Development Program of China (Grants no. 2018YFC0213600).

### Supplementary Materials

Supplemental Table 1: description of air quality data and meteorological monitoring data in case cities. (*Supplementary Materials*)

### References

- [1] R.-J. Huang, Y. Zhang, C. Bozzetti et al., "High secondary aerosol contribution to particulate pollution during haze events in China," *Nature*, vol. 514, no. 7521, pp. 218–222, 2014.
- [2] L. Bai, L. Jiang, D.-y. Yang, and Y.-b. Liu, "Quantifying the spatial heterogeneity influences of natural and socioeconomic factors and their interactions on air pollution using the geographical detector method: a case study of the Yangtze river economic belt, China," *Journal of Cleaner Production*, vol. 232, pp. 692–704, 2019.
- [3] J. Yang, Y. C. Wang, X. M. Xiao, C. Jin, J. H. Xia, and X. M. Li, "Spatial differentiation of urban wind and thermal environment in different grid sizes," *Urban Climate*, vol. 28, pp. 1–13, 2019.
- [4] A. Guo, J. Yang, X. Xiao, J. Xia, C. Jin, and X. Li, "Influences of urban spatial form on urban heat island effects at the community level in China," *Sustainable Cities and Society*, vol. 53, 2020.
- [5] Z. H. Chen, S. Y. Cheng, J. B. Li, X. R. Guo, W. H. Wang, and D. S. Chen, "Relationship between atmospheric pollution processes and synoptic pressure patterns in northern China," *Atmospheric Environment*, vol. 42, no. 24, pp. 6078–6087, 2008.
- [6] S. Buchholz, J. Junk, A. Krein, G. Heinemann, and L. Hoffmann, "Air pollution characteristics associated with mesoscale atmospheric patterns in northwest continental Europe," *Atmospheric Environment*, vol. 44, no. 39, pp. 5183–5190, 2010.
- [7] K. Chen, Y. Yin, Z. H. Hu, F. F. Wu, and Q. H. Liu, "Analysis on the causes of the heaviest pollution episode of Nanjing in 2007," in *Proceeding of the 2008 International Workshop on Education Technology and Training & 2008 International Workshop on Geoscience and Remote Sensing*, December 2008.
- [8] R. M. Banta, C. J. Senff, R. J. Alvarez et al., "Dependence of daily peak O<sub>3</sub> concentrations near Houston, Texas on environmental factors: wind speed, temperature, and boundary-layer depth," *Atmospheric Environment*, vol. 45, no. 1, pp. 162–173, 2011.
- [9] I. Barmpadimos, C. Hueglin, J. Keller, S. Henne, and A. S. H. Prévôt, "Influence of meteorology on PM<sub>10</sub> trends and variability in Switzerland from 1991 to 2008," *Atmospheric Chemistry And Physics*, vol. 11, no. 4, pp. 1813–1835, 2011.
- [10] G. Tian, Z. Qiao, and X. Xu, "Characteristics of particulate matter (PM<sub>10</sub>) and its relationship with meteorological

- factors during 2001–2012 in Beijing,” *Environmental Pollution*, vol. 192, pp. 266–274, 2014.
- [11] J. A. Adame, A. Notario, C. A. Cuevas, A. Lozano, M. Yela, and A. Saiz-Lopez, “Recent increase in NO<sub>2</sub> levels in the southeast of the Iberian Peninsula,” *Science Of the Total Environment*, vol. 693, p. 12, 2019.
  - [12] J. A. Adame, L. Lope, M. Sorribas, A. Notario, and M. Yela, “SO<sub>2</sub> measurements in a clean coastal environment of the southwestern Europe: sources, transport and influence in the formation of secondary aerosols,” *Science Of the Total Environment*, vol. 716, p. 13, 2020.
  - [13] W. J. Zhang, D. Q. Xu, G. S. Zhuang, W. Wang, and L. L. Guo, “Characteristics of ambient 1-min PM<sub>2.5</sub> variation in Beijing,” *Environmental Monitoring and Assessment*, vol. 165, no. 1–4, pp. 137–146, 2010.
  - [14] L. Han, W. Zhou, W. Li, D. T. Meshesha, L. Li, and M. Zheng, “Meteorological and urban landscape factors on severe air pollution in Beijing,” *Journal of the Air & Waste Management Association*, vol. 65, no. 7, pp. 782–787, 2015.
  - [15] D. Hu, J. Wu, K. Tian, L. Liao, M. Xu, and Y. Du, “Urban air quality, meteorology and traffic linkages: evidence from a sixteen-day particulate matter pollution event in December 2015, Beijing,” *Journal of Environmental Sciences*, vol. 59, pp. 30–38, 2017.
  - [16] T. Chen, S. Deng, Y. Gao, L. Qu, M. Li, and D. Chen, “Characterization of air pollution in urban areas of Yangtze River Delta, China,” *Chinese Geographical Science*, vol. 27, no. 5, pp. 836–846, 2017.
  - [17] C. Shi, R. Yuan, B. Wu et al., “Meteorological conditions conducive to PM<sub>2.5</sub> pollution in winter 2016/2017 in the western Yangtze River Delta, China,” *Science Of the Total Environment*, vol. 642, pp. 1221–1232, 2018.
  - [18] A. Mahmud, M. Hixson, J. Hu, Z. Zhao, S.-H. Chen, and M. J. Kleeman, “Climate impact on airborne particulate matter concentrations in California using seven year analysis periods,” *Atmospheric Chemistry and Physics*, vol. 10, no. 22, pp. 11097–11114, 2010.
  - [19] A. Chauhan, S. C. de Azevedo, and R. P. Singh, “Pronounced changes in air quality, atmospheric and meteorological parameters, and strong mixing of smoke associated with a dust event over Bakersfield, California,” *Environmental Earth Sciences*, vol. 77, no. 4, p. 12, 2018.
  - [20] J. A. Adame, A. Notario, F. Villanueva, and J. Albaladejo, “Application of cluster analysis to surface ozone, NO<sub>2</sub> and SO<sub>2</sub> daily patterns in an industrial area in Central-Southern Spain measured with a DOAS system,” *Science of the Total Environment*, vol. 429, pp. 281–291, 2012.
  - [21] F. B. Asl, M. Leili, Y. Vaziri et al., “Health impacts quantification of ambient air pollutants using AirQ model approach in Hamadan, Iran,” *Environmental Research*, vol. 161, pp. 114–121, 2018.
  - [22] M. Ansari and M. H. Ehrampoush, “Meteorological correlates and AirQ+ health risk assessment of ambient fine particulate matter in Tehran, Iran,” *Environmental Research*, vol. 170, pp. 141–150, 2019.
  - [23] N. Baertsch-Ritter, J. Keller, J. Dommen, and A. S. H. Prevot, “Effects of various meteorological conditions and spatial emission resolutions on the ozone concentration and ROG/NO,” *Atmospheric Chemistry And Physics*, vol. 4, no. 2, pp. 423–438, 2004.
  - [24] A. Bigi, F. Bianchi, G. De Gennaro et al., “Hourly composition of gas and particle phase pollutants at a central urban background site in Milan, Italy,” *Atmospheric Research*, vol. 186, pp. 83–94, 2017.
  - [25] M. Athanassiadou, J. Baker, D. Carruthers et al., “An assessment of the impact of climate change on air quality at two UK sites,” *Atmospheric Environment*, vol. 44, no. 15, pp. 1877–1886, 2010.
  - [26] T. Banerjee, S. B. Singh, and R. K. Srivastava, “Development and performance evaluation of statistical models correlating air pollutants and meteorological variables at Pantnagar, India,” *Atmospheric Research*, vol. 99, no. 3–4, pp. 505–517, 2011.
  - [27] Y. Chen and S.-D. Xie, “Long-term trends and characteristics of visibility in two megacities in southwest China: Chengdu and Chongqing,” *Journal of the Air & Waste Management Association*, vol. 63, no. 9, pp. 1058–1069, 2013.
  - [28] W. Chen, S. Zhang, Q. Tong et al., “Regional characteristics and causes of haze events in northeast China,” *Chinese Geographical Science*, vol. 28, no. 5, pp. 836–850, 2018.
  - [29] Z. Qiao, F. Wu, X. Xu, J. Yang, and L. Liu, “Mechanism of spatiotemporal air quality response to meteorological parameters: a national-scale Analysis in China,” *Sustainability*, vol. 11, no. 14, p. 3957, 2019.
  - [30] J. A. Adame, M. A. Hernández-Ceballos, J. P. Bolívar, and B. De la Morena, “Assessment of an air pollution event in the southwestern Iberian Peninsula,” *Atmospheric Environment*, vol. 55, pp. 245–256, 2012.
  - [31] J. A. Adame, L. Lope, P. J. Hidalgo et al., “Study of the exceptional meteorological conditions, trace gases and particulate matter measured during the 2017 forest fire in Doñana Natural Park, Spain,” *Science of the Total Environment*, vol. 645, pp. 710–720, 2018.
  - [32] E. Alonso-Blanco, A. Castro, A. I. Calvo, V. Pont, M. Mallet, and R. Fraile, “Wildfire smoke plumes transport under a subsidence inversion: climate and health implications in a distant urban area,” *Science of the Total Environment*, vol. 619–620, pp. 988–1002, 2018.
  - [33] B. Yu, F. Chen, and H. Chen, “NPP estimation using random forest and impact feature variable importance analysis,” *Journal of Spatial Science*, vol. 64, no. 1, pp. 173–192, 2019.
  - [34] H. Sun, D. Gui, B. Yan et al., “Assessing the potential of random forest method for estimating solar radiation using air pollution index,” *Energy Conversion and Management*, vol. 119, pp. 121–129, 2016.
  - [35] D. R. Cutler, T. C. Edwards Jr., K. H. Beard et al., “Random forests for classification in ecology,” *Ecology*, vol. 88, no. 11, pp. 2783–2792, 2007.
  - [36] H. Wang, C. Lin, Y. Peng, and X. Hu, “Application of improved random forest variables importance measure to traditional Chinese chronic gastritis diagnosis,” in *Proceedings of the 2008 IEEE International Symposium on IT in Medicine and Education*, December 2008.
  - [37] M. Abdel-Aty, A. Pande, A. Das, and W. J. Knibbe, “Assessing safety on Dutch freeways with data from infrastructure-based intelligent transportation systems,” *Transportation Research Record: Journal of the Transportation Research Board*, vol. 2083, no. 1, pp. 153–161, 2008.
  - [38] R. Genuer, J.-M. Poggi, and C. Tuleau-Malot, “Variable selection using random forests,” *Pattern Recognition Letters*, vol. 31, no. 14, pp. 2225–2236, 2010.
  - [39] J. H. Friedman, “Machine,” *The Annals of Statistics*, vol. 29, no. 5, pp. 1189–1232, 2001.
  - [40] L. J. Xu, J. X. Zhou, Y. Guo et al., “Spatiotemporal pattern of air quality index and its associated factors in 31 Chinese provincial capital cities,” *Air Quality, Atmosphere & Health*, vol. 10, no. 5, pp. 601–609, 2017.



- [41] P. C. Chu, Y. Chen, and S. Lu, "Atmospheric effects on winter SO<sub>2</sub> pollution in Lanzhou, China," *Atmospheric Research*, vol. 89, no. 4, pp. 365–373, 2008.
- [42] J. Y. Tian, Z. X. Fan, and L. H. Sun, *Qinghuangdao City as Example: The Correlation Analysis for Air Quality and Meteorological Factors in an Urban City*, CRC Press-Taylor & Francis Group, Boca Raton, FL, USA, 2015.
- [43] D. T. Zhao, H. Chen, E. Yu, and T. Luo, "PM<sub>2.5</sub>/PM<sub>10</sub> ratios in eight economic regions and their relationship with meteorology in China," *Advances In Meteorology*, vol. 2019, Article ID 5295726, 15 pages, 2019.
- [44] B. Chen, S. Lu, S. Li, and B. Wang, "Impact of fine particulate fluctuation and other variables on Beijing's air quality index," *Environmental Science And Pollution Research*, vol. 22, no. 7, pp. 5139–5151, 2015.
- [45] F. Kong, L. Lu, J. Fang, and H. H. Xu, "Spatiotemporal pattern of the air pollution index and its trend in China from 2001," *Journal of Catastrophology*, vol. 32, no. 2, pp. 117–123, 2017.
- [46] H. Zhou, Y. Li, H. Liu et al., "Temporal distribution, influencing factors and pollution sources of urban ambient air quality in Nanchong, China," *Environmental Engineering Research*, vol. 20, no. 3, pp. 260–267, 2015.
- [47] M. S. Jassim and G. Coskuner, "Assessment of spatial variations of particulate matter (PM<sub>10</sub> and PM<sub>2.5</sub>) in Bahrain identified by air quality index (AQI)," *Arabian Journal of Geosciences*, vol. 10, no. 1, p. 14, 2017.
- [48] Y. Zhang, "Dynamic effect analysis of meteorological conditions on air pollution: a case study from Beijing," *Science of the Total Environment*, vol. 684, pp. 178–185, 2019.
- [49] X. Li, X. Chen, X. Yuan et al., "Characteristics of particulate pollution (PM<sub>2.5</sub> and PM<sub>10</sub>) and their spacescale-dependent relationships with meteorological elements in China," *Sustainability*, vol. 9, no. 12, p. 2330, 2017.
- [50] X. Zhang and Z. Gong, "Spatiotemporal characteristics of urban air quality in China and geographic detection of their determinants," *Journal of Geographical Sciences*, vol. 28, no. 5, pp. 563–578, 2018.
- [51] Y. Zhang, J. Wang, and L. Bu, "Analysis of a haze event over nanjing, China based on multi-source data," *Atmosphere*, vol. 10, no. 6, p. 338, 2019.
- [52] R. Li, Z. Wang, L. Cui et al., "Air pollution characteristics in China during 2015-2016: spatiotemporal variations and key meteorological factors," *Science of The Total Environment*, vol. 648, pp. 902–915, 2019.
- [53] Y. Wang, Y. Li, Z. Qiao, and Y. Lu, "Inter-city air pollutant transport in the Beijing-Tianjin-Hebei urban agglomeration: comparison between the winters of 2012 and 2016," *Journal Of Environmental Management*, vol. 250, p. 109520, 2019.
- [54] J. Bao, X. Yang, Z. Zhao, Z. Wang, C. Yu, and X. Li, "The spatial-temporal characteristics of air pollution in China from 2001-2014," *International Journal of Environmental Research and Public Health*, vol. 12, no. 12, pp. 15875–15887, 2015.
- [55] L. Zhang, Y. Liu, and F. Zhao, "Singular value decomposition analysis of spatial relationships between monthly weather and air pollution index in China," *Stochastic Environmental Research And Risk Assessment*, vol. 32, no. 3, pp. 733–748, 2018.
- [56] P. Li, R. Yan, S. Yu, S. Wang, W. Liu, and H. Bao, "Reinstate regional transport of PM<sub>2.5</sub> as a major cause of severe haze in Beijing," *Proceedings of the National Academy of Sciences*, vol. 112, no. 21, pp. E2739–E2740, 2015.
- [57] A. P. K. Tai, L. J. Mickley, and D. J. Jacob, "Correlations between fine particulate matter (PM<sub>2.5</sub>) and meteorological variables in the United States: implications for the sensitivity of PM<sub>2.5</sub> to climate change," *Atmospheric Environment*, vol. 44, no. 32, pp. 3976–3984, 2010.
- [58] F. Costabile and I. Allegrini, "Measurements and analyses of nitrogen oxides and ozone in the yard and on the roof of a street-canyon in Suzhou," *Atmospheric Environment*, vol. 41, no. 31, pp. 6637–6647, 2007.
- [59] E. Uherek, T. Halenka, J. Borken-Kleefeld et al., "Transport impacts on atmosphere and climate: land transport," *Atmospheric Environment*, vol. 44, no. 37, pp. 4772–4816, 2010.
- [60] M. Aldrin and I. Haff, "Generalised additive modelling of air pollution, traffic volume and meteorology," *Atmospheric Environment*, vol. 39, no. 11, pp. 2145–2155, 2005.
- [61] D. M. Agudelo-Castañeda, E. C. Teixeira, S. B. A. Rolim, F. N. Pereira, and F. Wiegand, "Measurement of particle number and related pollutant concentrations in an urban area in South Brazil," *Atmospheric Environment*, vol. 70, pp. 254–262, 2013.
- [62] J. Yang, J. Sun, Q. Ge, and X. Li, "Assessing the impacts of urbanization-associated green space on urban land surface temperature: a case study of Dalian, China," *Urban Forestry & Urban Greening*, vol. 22, pp. 1–10, 2017.
- [63] J. Liu, H. Cheng, D. Jiang, and L. Huang, "Impact of climate-related changes to the timing of autumn foliage colouration on tourism in Japan," *Tourism Management*, vol. 70, pp. 262–272, 2019.
- [64] J. Yang, S. Jin, X. Xiao et al., "Local climate zone ventilation and urban land surface temperatures: towards a performance-based and wind-sensitive planning proposal in megacities," *Sustainable Cities and Society*, vol. 47, 2019.