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Article

Evaluation of the Influence between Local Meteorology and Air Quality in Beijing Using Generalized Additive Models

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Abstract: Previous studies have confirmed the inextricable connection between meteorological factors and air pollutants. This study presents the complex nonlinear relationship between meteorological variables and four major air pollutants under high-concentration air pollution in Beijing. The generalized additive model combined with marginal effects is used for quantitative analysis. After controlling the confounding factors such as long-term trends, seasonality and spatio-temporal deviation, the final fitting results exhibit that temperature, relative humidity and visibility are the most significant meteorological variables associating with $PM_{2.5}$ concentration, and the marginal effect reaches 80%, −23% and 270%, respectively. Temperature and relative humidity are the most significant variables for SO_2, and the marginal effect reaches 15% and 7%. The most significant variables for O_3 are temperature and solar radiation, with marginal effect of up to 70% and 8%. Atmospheric pressure and temperature results in a positive effect on CO, and the marginal effect can reach 18% and 80%. All these indicate that local meteorological variables are a significant driving factor for air quality in Beijing. Other variables, such as wind speed, visibility, and precipitation, display some influence on air pollutants, but have less explanatory power in the model. Overall, our study provides a better understanding of the relationship between local meteorological variables and air quality, as well as an insight into how climate change affects air quality.

Keywords: meteorological factors; air pollutants; marginal effect; generalized additive models

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1. Introduction

It is well known that air quality can be influenced by meteorological factor variables in the atmosphere [1–3]. Meteorological factors play an important role in air quality both in terms of chemical reactions and physical changes [1,4,5]. Various meteorological variables in the atmosphere have an inherent relationship with each other [6]. Previous studies have confirmed that the increase in CO_2 content has a promoting effect on the greenhouse effect, leading to a rise in temperature [7]. At the same time, high temperature and low wind speed will affect air pollutant in reverse [5,8]. The increase in solar irradiance will accelerate the production of photochemical smog, which in turn increases the ozone content in the air [4]. Therefore, when dealing with the outcome variables associated with meteorological factors, the internal connection between them is a factor that cannot be ignored. Limited by external objective experimental conditions, previous studies on air quality and meteorological variables have mainly focused on the stage of low air pollution concentration [1]. Research on air quality and meteorological variables under high pollution conditions has been insufficient. The increased scrutiny of air quality suggests that many aspects of the meteorological variables associated with air pollution remain difficult to understand, especially during periods of high pollution. One aspect is to estimate the sensitivity of air pollutants to individual meteorological parameters. This has been proved particularly challenging for several reasons. First, meteorological parameters are intrinsically linked, leading to strong interdependence. These linkages make the task of isolating the effects of individual parameters highly complex [1]. Secondly, meteorological variables affect pollutants through direct physical mechanisms [3]. To complicate matters further, these effects can be influenced by seasonal and long-term temporal trends [1,6]. Therefore, it is very important and necessary to adopt effective methods to understand the nature of the relationship between meteorological variables and air pollution. Beijing has a variable terrain and a wide range of air quality conditions across time and space scales, in addition to higher air pollution compared with developed countries [9,10]. Previous studies have shown that meteorological factors such as low temperature, atmospheric pressure, relative humidity and solar radiation are associated with the concentration of particulate matter [11–14], sulfur dioxide [15,16], and ozone [17]. The diversity of topography, spatial and temporal differences lead to great variations in air pollution in Beijing [9,18], which also provides the necessary conditions for this study. The influence of meteorological variables on high concentration air pollution is still unclear. To address this, we focused on air pollution data of Beijing in the past 6 years and conducted a series of investigations on the relationship with meteorological variables.

Statistical methods have proven to be effective in investigating the relationship between meteorological variables and air quality [19], especially in quantifying and visualizing the relationship between individual meteorological variables and air pollutants [20]. Generalized additive model (GAM) is a flexible and effective analytical method to evaluate the nonlinear regression of time series [21]. It can be used to identify and describe the nonlinear relationship between independent variables and covariates in the model [22]. Previous studies based on GAM exhibit how meteorological conditions such as relative humidity and wind speed affect air pollution levels [23].

This study aims to provide an observational study of meteorological variables and air pollutants under air pollution of high concentration. The study area is Beijing, the capital of China, located at 116°20′ E and 39°56′ N. Beijing has a warm temperate semi-humid and semi-arid monsoon climate, high temperature and rainy in summer, cold and dry in winter, with a short spring and autumn. The diversity of its meteorological environment provides the necessary objective conditions for this research. The city is famous for its extensive meteorological conditions and diverse climates [24,25]. In recent years, with the rapid development of the economy and the surge in vehicle ownership, Beijing's air pollution has been under severer pressure [26,27]. Therefore, the overall objective of this study is to investigate the characteristics of local meteorological variables in Beijing, and to quantitatively analyze the nonlinear relationship between meteorological variables and air pollutants in combination with the generalized additive model (GAM).

2. Data

2.1. Local Meteorological Data

The meteorological data of the Capital Airport weather station near Beijing's southwest Fourth Ring Road were obtained every 3 h from June 2014 to December 2020. Detailed characteristics of the data are shown in Table 1. These data were monitored and saved by the monitoring station of the China Meteorological Administration (CMA). The data of this station were reported to the World Meteorological Organization and were preserved by the National Environmental Information Center (NOAA NEIC) of the National Oceanic and Atmospheric Administration of the United States. The location of the meteorological station was shown in Figure 1. This site was located at 39.48° N, 116.28° E with an elevation of 31.3 m. Variables provided by CMA included: Atmospheric pressure (hPa), temperature (°C), relative humidity (%), precipitation (mm), visibility (km), solar irradiance (w/m^2), zonal (u) wind (km/h) and meridional (v) wind (km/h).

Table 1. Detailed characteristics of the data used in the model.

Variable	Units	Mean	Median	SD	Min	Max	Definition
$PM_{2.5}$	$\mu g/m^3$	80.05	59.41	71.08	4.29	516.23	Daily Avg
SO_2	$\mu g/m^3$	13.8	8.25	15.03	1.98	97.87	Daily Avg
CO	mg/m^3	1.25	0.95	1.04	0.10	9.03	Daily Avg
O_3	$\mu g/m^3$	60.65	55.04	39.78	2.00	183.13	Daily Avg
Atmospheric pressure	hPa	1011.39	1012.5	29.24	142	1040.5	Daily Avg
Zonal (u) wind	km/h	−1.72	−3.03	13.35	−18.52	391.99	Daily Avg (N_+, S_-)
Meridional (v) wind	km/h	1.99	2.68	8.63	−20.37	214.61	Daily Avg (E_+, W_-)
Temperature	°C	55.8	56.24	19.91	9.17	97.43	Daily Avg
Relative humidity	%	13.62	15	11	−15.38	32.5	Daily Avg
Visibility	km	11.68	9.73	7.23	0.64	30	Daily Avg
Solar irradiance	w/m^2	249.6	246.07	79.42	80.52	392.77	Daily Avg
Precipitation	mm	17.8	12.39	14.6	0	68.18	Daily Avg

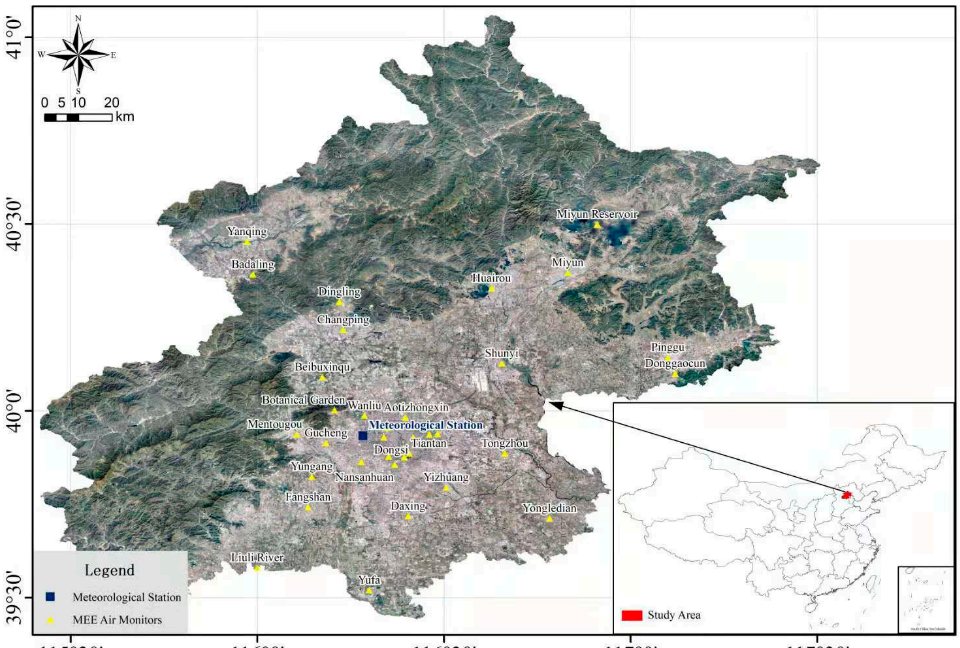

Figure 1. Distribution map of monitoring sites.

2.2. Air Pollutant Monitoring Data

Hourly air pollutant data from 34 air pollution monitoring stations in Beijing released by the Ministry of Ecology and Environment (MEE) were obtained from June 2014 to December 2020 (Table 1). The distribution of monitoring sites was shown in Figure 1. PM_{10}, $PM_{2.5}$, SO_2, CO, NO_2 and O_3 were included in the recorded observations. Due to the limitation of measurement method, NO_2 monitoring value was susceptible to interference by other nitrides, so NO_2 data were not involved in this study. Since there were numerous missing PM_{10} monitoring values, PM_{10} data were also excluded here.

Due to observation, record and other reasons, air pollution or meteorological data at a certain moment were missing. Therefore, in this study, three linear interpolation methods were used to interpolate the missing air pollution or meteorological data; a similar solution was found in our previous study [9]. In general, the interpolation for air pollution data and meteorological data did not exceed 6% and 3%, respectively.

3. Methods

3.1. General Form of Generalized Additive Models

Generalized additive models are a flexible and effective method for evaluating nonlinear regression analysis of time series related to air quality [21]. It can be used to identify and describe the nonlinear relationship between each individual independent variable and covariates in the model [15]. The general form of the model can be written as:

$$g(\mathrm{E}(\mathrm{Y})) = \beta_0 + \sum_{j=1}^{n} s_j(x_{ij}) + \varepsilon_i \tag{1}$$

where g is the link function, E(Y) is the mathematical expectation of Y, β_0 is the intercept, $s_j(x_{ij})$ is the smooth function of the ith value of the covariate j, n is the total number of covariates, and ε_i is the random error term. In this study, four air pollutants concentration approximately obeys the normal distribution, and the link function is an identity link [22].

3.2. Model Construction

Based on model (1), we further constructed the following GAMs to evaluate the relationship between the concentration of each individual air pollutant and local meteorological variables.

$$g(u) = \beta_0 + s(TIME, df_1) + s(SEASON, df_2) + s(DOW, df_3) + s(long, lat) + \varepsilon_i \tag{2}$$

where is the mathematical expectation of the variables $x(x_1, x_2, \ldots, x_p)$. *TIME* is the long-term trend, *SEASON* is seasonality to account for the seasonal trend, *long* and *lat* are longitude and latitude longitude to represent the influence of spatial distribution and autocorrelation. *DOW* is the day of the week, represented by 1–7. *df* is the degree of freedom (*df*), which is used to control the influence of each variable in the model. We used Akaike's Information Criteria (AIC) [28] to evaluate each variable and its *df* in the model. When the AIC value was the lowest, it was the most appropriate fit and the corresponding *df* value was selected. Additionally, we substituted various meteorological variables into the model, and fitted the AIC value of the model. When the model yielded a lower AIC value, the variable was remained in the model, otherwise it was eliminated. The final fitting model can be written as

$$\begin{gathered} g(u) = \beta_0 + s(TIME, df_1) + s(SEASON, df_2) + \\ s(DOW, df_3) + s(T, df_4) + s(RH, df_5) \\ +s(VISIB, df_6) + s(IRRADI, df_7) + s(U, df_8) + \\ s(V, df_9) + s(P, df_{10}) \\ +s(PRCP, df_{11}) + s(long, lat) + \varepsilon_i \end{gathered} \tag{3}$$

where T is temperature, *RH* is relative humidity, *VISIB* is visibility, *IRRADI* is solar irradiance, U is the zonal wind component, V is the meridional wind component, P is atmospheric pressure, *PRCP* is precipitation. Other variables and symbols represent the same meanings as model (2). Subsequently, we assessed the relationship between each air pollutant and meteorological factors using model (3). The quantitative analysis results were visualized using partial residual plot and marginal effect [1]. The marginal effect *ME* can be written as

$$ME = 100 \times [\exp(\mathrm{s}(x)) - 1] \tag{4}$$

where x is the meteorological variable of interest, and s is the corresponding smooth function in model (3). The partial residual plots reflect the influence of each meteorological factor on different air pollutants [1,9]. The marginal effect is above 0, indicating that the meteorological variable has a positive effect on air pollutants, and the marginal effect is below 0, indicating that the meteorological variable has a negative effect on air pollutants.

4. Results and Discussion

4.1. $PM_{2.5}$

As shown in Figure 2, atmospheric pressure was found to have the maximum impact on $PM_{2.5}$ at 1040hpa with a 20% increase. When atmospheric pressure exceeds 1020 hPa, it has a significant and positive effect on $PM_{2.5}$. Temperature was found to have the greatest impact on $PM_{2.5}$ around 35 degrees, with an approximate increase of 80%. This result indicated that the relationship between temperature and $PM_{2.5}$ was positively correlated. The impact of zonal (u) wind on $PM_{2.5}$ generally showed a trend of gradually decreasing and then increasing, indicating that it could promote the elimination of particulate matter under strong winds. Similar results were obtained for meridional (v) wind. As the wind speed increased, the impact on $PM_{2.5}$ gradually decreased with a minimum effect of 10% at 26.4 km/h. This result was related to the decrease in particulate matter concentration due to higher wind speed. Relative humidity was found to have a relatively stable effect on $PM_{2.5}$ below 40%, which was a positive promoting effect. Above 45%, the marginal effect gradually decreased to the minimum of −23% with a relative humidity value of 97%. The main reason might be that higher relative humidity accelerated the secondary formation of the particulate matter of gas-phase chemical pollutants, and it is not conducive to the diffusion of fine particles simultaneously. The relationship between visibility and $PM_{2.5}$ showed a gradual downward trend, which was a negative correlation. Solar irradiance was found to promote an increase in $PM_{2.5}$ concentration. The marginal effect approached the maximum of 3% when it reached about 350 w/m^2. There was a negative correlation between precipitation and $PM_{2.5}$ in general with a decrease of −20% at 53 mm. This was because a greater degree of precipitation could promote the deposition of particulate matter, thereby reducing the concentration of particulate matter in the atmosphere.

4.2. SO_2

As shown in Figure 3, the influence of atmospheric pressure on SO_2 reached its maximum at 1040 hpa with an increase of 13%. Atmospheric pressure presented a promoting effect on SO_2 generally. This was related to higher pressure, which enhanced the increase in SO_2 concentration. The response of SO_2 to temperature exhibited that the effect gradually decreased and was a negative correlation with SO_2, reaching a minimum decrease of −10% at 32.5 °C. This might be related to the fact that high temperature could enhance the instability of SO_2. Zonal (u) wind and meridional (v) wind were found to have similar effects on SO_2. When the wind speed increased from a negative value to 0 km/h, the marginal effect increased slightly. As the wind speed exceeded 0 km/h, the marginal effect gradually decreased. This was mainly related to strong winds that could strengthen the dispersion of SO_2 in the atmosphere; it could be clearly seen that relative humidity had a negative effect on SO_2. As relative humidity increased, the SO_2 level gradually decreased. The increase in relative humidity meant the increase in water content in the air, which promoted the water solubility of SO_2. Visibility was found to have a negative correlation with SO_2, which was related to the fact that SO_2 could promote the formation of sulfate aerosols. Aerosols were considered to negatively correlated with atmospheric visibility. Therefore, as the visibility increased, the SO_2 concentration decreased. The response of SO_2 to solar irradiance exhibited a positive correlation with a maximum increase of 5% at 392.8 w/m^2. It was found that the impact of precipitation on SO_2 exhibited a decreasing trend, indicating a negative correlation. As the precipitation approached 54 mm, the marginal effect on SO_2 decreased to −5%, which was the minimum value. This result could be attributed to the fact that SO_2 was easily soluble in water. The increase in precipitation directly increased the water content in the air and thus reduced the concentration of SO_2 in the atmosphere.

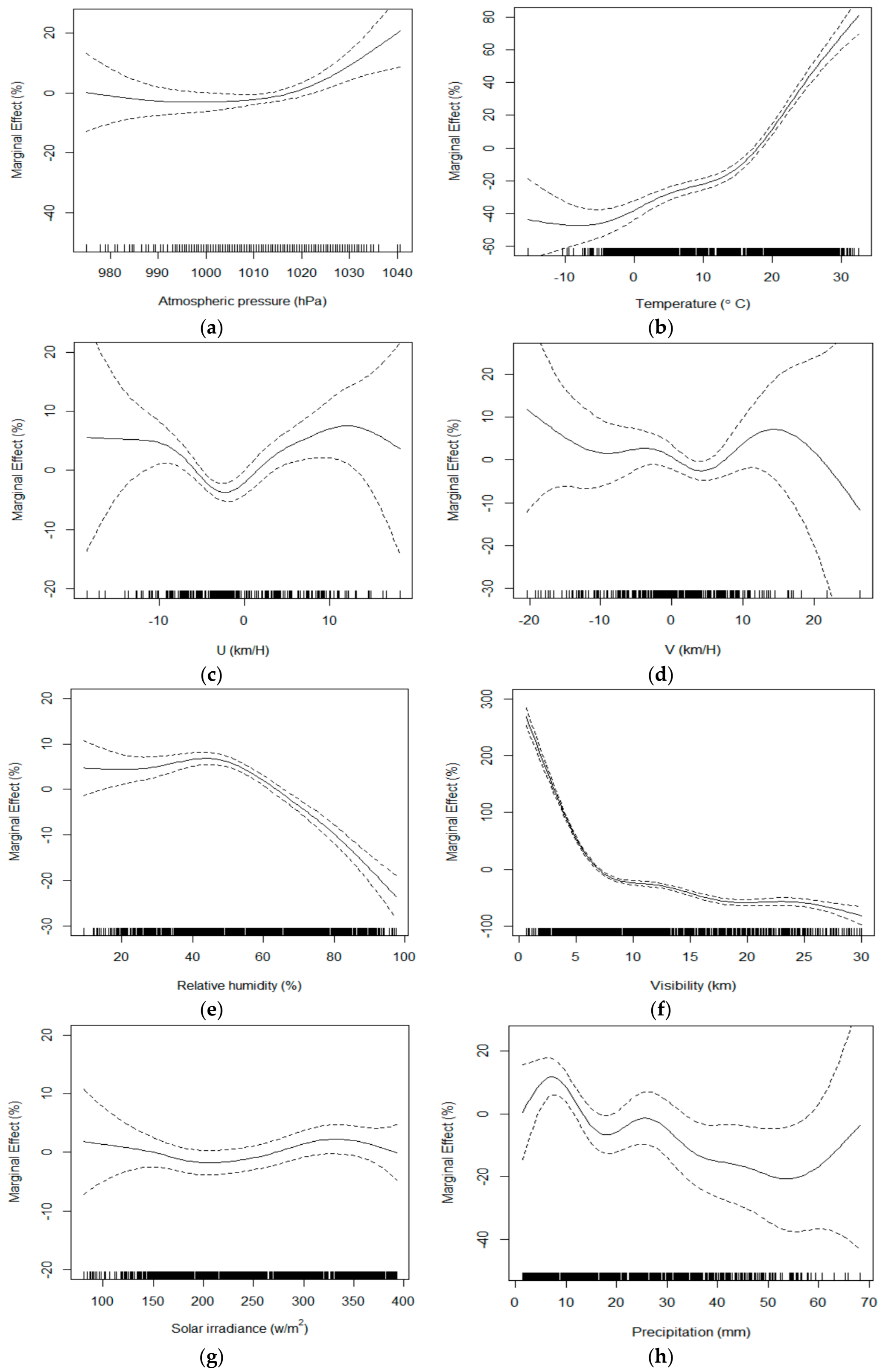

Figure 2. Partial residual plot for $PM_{2.5}$. (**a**) atmospheric pressure; (**b**) temperature; (**c**) zonal (*u*) wind; (**d**) meridional (*v*) wind; (**e**) relative humidity; (**f**) visibility; (**g**) solar irradiance; (**h**) precipitation. The abscissa represents the magnitude of each meteorological variable. The ordinate represents the marginal effect, which is the impact of various meteorological variables on air pollutants. The dashed line is the 95% confidence interval and the short line perpendicular to the abscissa represents the distribution frequency of each meteorological variable.

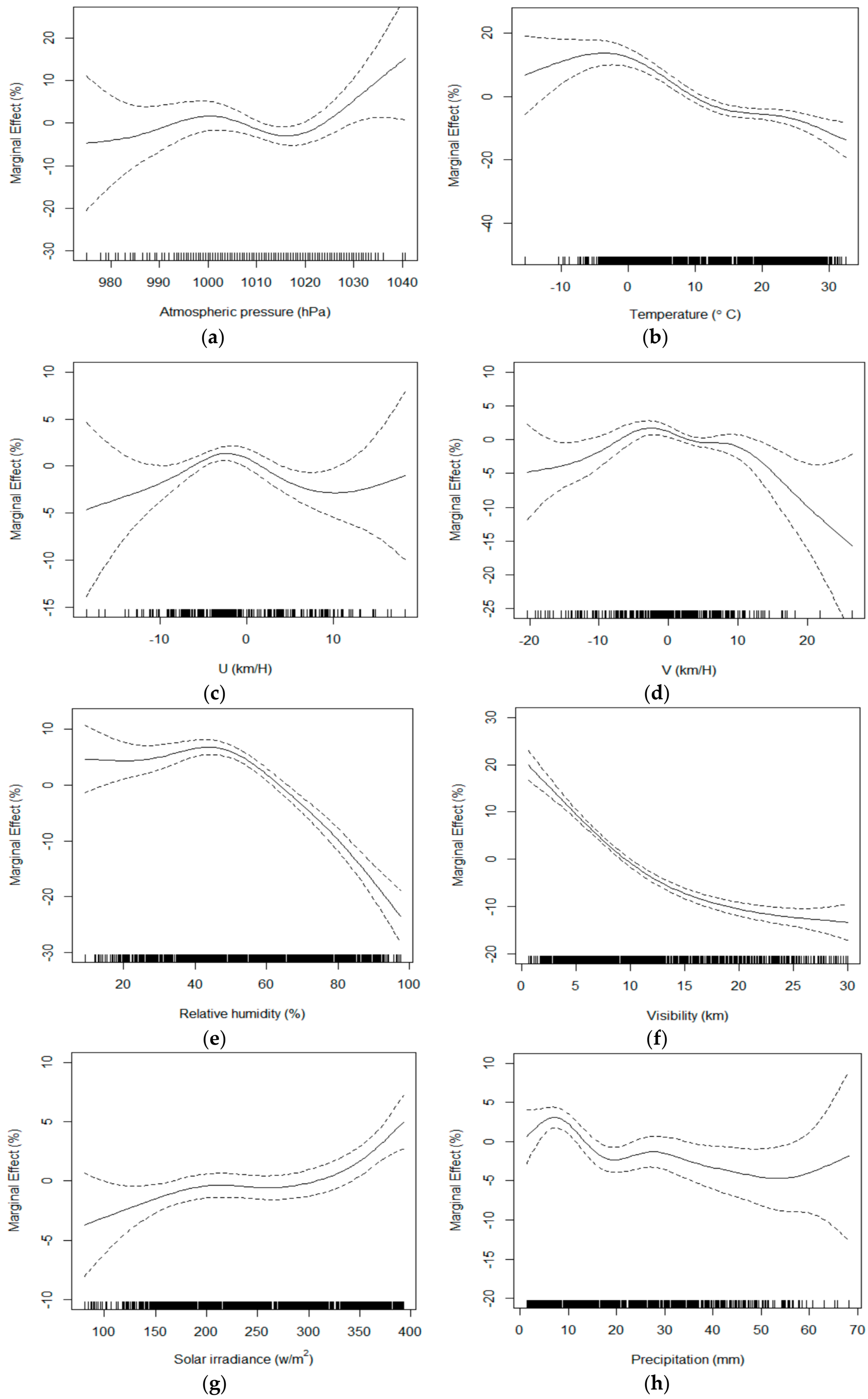

Figure 3. Partial residual plot for SO_2. (**a**) atmospheric pressure; (**b**) temperature; (**c**) zonal (*u*) wind; (**d**) meridional (*v*) wind; (**e**) relative humidity; (**f**) visibility; (**g**) solar irradiance; (**h**) precipitation. The abscissa represents the magnitude of each meteorological variable. The ordinate represents the marginal effect, which is the impact of various meteorological variables on air pollutants. The dashed line is the 95% confidence interval and the short line perpendicular to the abscissa represents the distribution frequency of each meteorological variable.

4.3. O_3

As shown in Figure 4, the influence of atmospheric pressure on ozone appeared to increase first and then decrease. The overall performance was a downward trend, indicating a negative correlation. With the increase in atmospheric pressure to 1040.5 hPa, the marginal effect decreases to the minimum value of −27%. This result was related to the fact that the influence of atmospheric pressure on ozone is a relatively negative effect. Temperature was found to exert a promotional effect on ozone, indicating a positive correlation with a maximum increase of 75% at 32.5 °C. Temperature could be involved in the physical process of ozone formation, and high temperatures contributed to the accumulation of ozone concentrations. The response of ozone to zonal (u) wind and meridional (v) wind exhibited a similar variation pattern. The wind speed in the middle had less effect, while lower or higher than the middle part had more obvious effect on ozone. Slight winds were found to associate with the increase in ozone concentration elsewhere. Relative humidity was found to have a negative weakening effect on ozone with a decrease of −17% when it approached 97.4%. The response of ozone to visibility showed a negative correlation with a decrease of −3% at 30 km. Photochemical smog could reduce atmospheric visibility and enhance the increase in ozone concentration, which explained the negative correlation between ozone and visibility. Solar radiation was found to be positively correlated with ozone, reaching the maximum effect of 8% when it increased to 392.8 w/m^2. This result represented that solar irradiance exerted a positive effect on ozone. The influence of precipitation on ozone fluctuated greatly, and it could be seen that the influence of slight rainfall on ozone was different from that of heavy rainfall. This had been reported in other studies, implying that wet deposition during heavy rainfall reduced ozone concentration, and a certain degree of moisture in the atmosphere was conducive to the formation of ozone [8].

4.4. CO

As shown in Figure 5, atmospheric pressure was found to have a positive effect on CO, especially at high pressure above 1020 hPa. The marginal effect approached the maximum value of 20% at 1040.5 hPa. This might be related to the enhancement of CO stability under high pressure. The response of CO to temperature exhibited a gradually ascending trend with an increase of 80% at 32.5 °C. This was consistent with our knowledge that a higher temperature suggested that more carbon compounds were converted or formed into CO. Zonal (u) wind and meridional (v) wind were found to have a similar influence on CO, exhibiting that high wind speed could reduce CO concentration. This might associate with strong wind contributing to the diffusion of traffic-related CO in city, which reduced CO concentration to a low extent. The response of CO to relative humidity exhibited a relatively stable curve, and the marginal effect hovered around 0. This agreed with our understanding that CO was less soluble in water and less susceptible to the effect of moisture in the air. Visibility was found to be negatively correlated with CO in general. As visibility approached 30 km, the marginal effect reached the minimum value of −7%. The increase in atmospheric visibility reflected a significant improvement of air quality, implying that CO concentration had decreased in the air. This led to a negative correlation between visibility and CO. Solar radiation was found to have various effects on CO with respect to different intensities of radiation. The marginal effect increased slightly to 5% at 140 w/m^2 and then decreased with a fluctuation. The response of precipitation to CO exhibited that the effect was not significant with a maximum increase of 0.3% at 8mm and a minimum decrease of −0.6% at 56 mm, respectively. This might be caused by the reason that CO was insoluble in water.

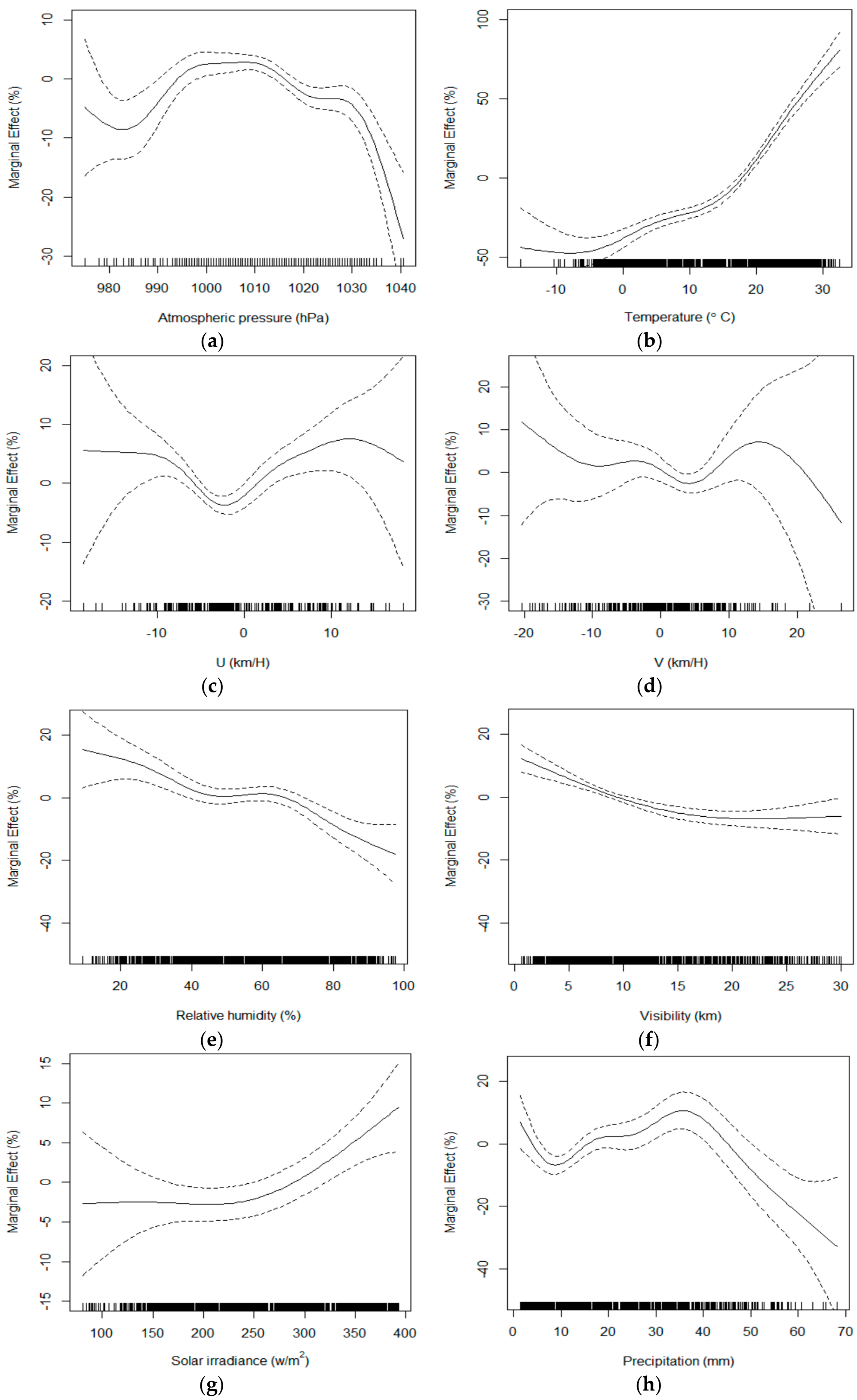

Figure 4. Partial residual plot for O_3. (**a**) atmospheric pressure; (**b**) temperature; (**c**) zonal (u) wind; (**d**) meridional (v) wind; (**e**) relative humidity; (**f**) visibility; (**g**) solar irradiance; (**h**) precipitation. The abscissa represents the magnitude of each meteorological variable. The ordinate represents the marginal effect, which is the impact of various meteorological variables on air pollutants. The dashed line is the 95% confidence interval and the short line perpendicular to the abscissa represents the distribution frequency of each meteorological variable.

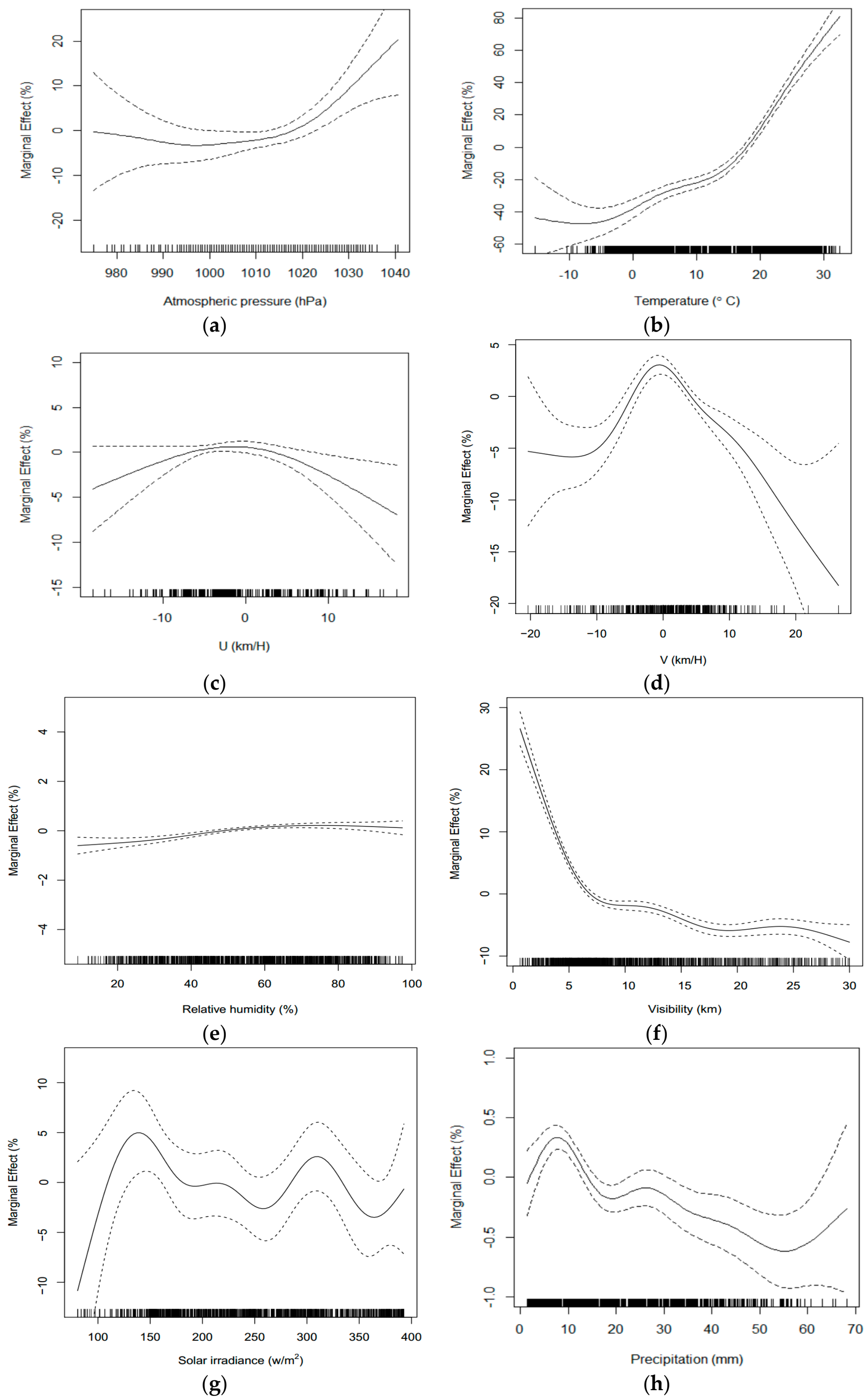

Figure 5. Partial residual plot for CO. (**a**) atmospheric pressure; (**b**) temperature; (**c**) zonal (*u*) wind; (**d**) meridional (*v*) wind; (**e**) relative humidity; (**f**) visibility; (**g**) solar irradiance; (**h**) precipitation. The abscissa represents the magnitude of each meteorological variable. The ordinate represents the marginal effect, which is the impact of various meteorological variables on air pollutants. The dashed line is the 95% confidence interval and the short line perpendicular to the abscissa represents the distribution frequency of each meteorological variable.

4.5. Discussion

The generalized additive models (GAMs) proved to be effective in quantifying the complex nonlinear relationship between multiple independent variables and covariates. In this study, we combined GAMs with marginal effect to assess the impact of individual meteorological variables on four major air pollutants in Beijing. This provided us with a visual and intuitive way to better understand the relationship between local meteorological variables and air pollutants. In the process of GAMs establishment, Akaike Information Criterion (AIC) was used to control the individual meteorological variables and confounding factors in the model, which could minimize the model deviation and improve the prediction accuracy to a greatest extent. Although our method did not take into account the chemical reaction and physical change process of meteorological factor variables, our results were reliable compared with other studies [1]. At the same time, the modeling and prediction analysis based on observed values proved to be reliable according to previous studies [1]. Beijing, with its adjacent areas, has a high level of air pollution compared to developed countries and regions [9,18]. The high concentration in Beijing provided a fruitful insight into the relationship between air pollution and meteorological variables, which could be seen as a reference and supplement to the research in other regions of the world.

The final results showed that temperature, relative humidity and visibility were the most significant meteorological variables associated with $PM_{2.5}$ concentration, which was consistent with the results of previous studies [1,29–31]. Temperature influence for particulate matter was mainly related to stagnation and fronts, excluding the effect caused by chemical reaction [32]. Higher wind speeds were also shown to be associated with lower $PM_{2.5}$ and CO concentrations [33–35]. Solar irradiance was found to promote an increase in $PM_{2.5}$ concentration, which was similar to the study of [36] that solar radiation could increase the photolysis of aerosol-like particulate matter [37]. Precipitation was found to reduce the concentration of particulate matter in the atmosphere, which was related to its promotion of particulate matter deposition [38]. Temperature and relative humidity were found to be the most significant variables of SO_2, which were caused by its water-soluble properties and instability at high temperatures [15,16]. Visibility was negatively correlated with SO_2, which is mainly caused by SO_2 promoting the formation of sulfate aerosols [39,40]. Temperature and solar radiation were found to have the most significant effects on ozone, which was caused by the promotion of ozone production in the atmosphere under high temperature and solar radiation [6,41]. The effect of atmospheric pressure on ozone was consistent with previous studies [42], indicating a relatively negative effect. Relative humidity was found to have a negative weakening effect on ozone, which was consistent with previous studies that high relative humidity would promote the opening of the stomata of trees to absorb ozone and reduce the concentration [43]. Solar radiation was found to be positively correlated with ozone [44]. Atmospheric pressure and temperature resulted in a positive effect on CO, which was caused by the increased stability of CO under high pressure [1]. In order to further reduce the interaction between various meteorological variables and the model fitting deviation, variance inflation factor was used to control the multicollinearity effect of each variable. The final results showed that our research was relatively reliable.

There were still some limitations in our study. We used the average pollution data of 34 air quality monitoring stations in Beijing and the meteorological data of the capital airport to establish the connection. Air pollution data were bound to be slightly different due to the geographical distribution of monitoring stations, which might have led to a deviation in the averaging process [1]. In this study, we collected various meteorological factors and air pollution data from the ground monitoring sites and interpolated the missing data. Missing data affected the fitting and assessment of the model. The inclusion of more sophisticated emission data would improve the fitting accuracy of the model. High-precision air pollution data near the meteorological monitoring station could be inversed from satellite remote sensing image data, which could further improve the accuracy of the fitting results [25]. The dynamics of concentrations of substances variations in the atmospheric boundary layer of the atmosphere are largely determined by the energy of air currents and thermal stratification. The stratification of the atmosphere and the energy of the airflow determine the spectral composition of the turbulence and the structure of the small-scale turbulence, thereby affecting the impurities in the atmosphere, which is also the source of the deviation of the influence of meteorological factors on air pollutants.

As a responsible developing country, the Chinese government has adopted a series of policies and measures based on its national conditions and made positive contributions to the mitigation of global climate change. The air pollution level in Beijing had alleviated significantly compared with previous years [18]. Previous studies have confirmed that there is a certain connection between air pollution and meteorological variables. The global surface temperature is rising at an unprecedented rate, especially in China [25]. The rising temperature has made an indelible contribution to the deterioration of air quality in Beijing, based on our research. The variations of temperature can affect the wind speed. The wind speed has a significant effect on the diffusion of air pollutants. At the same time, the global sea level rises due to rising temperatures, which will have an impact on atmospheric pressure and the concentration of air pollutants. According to the results of our study, the increase in atmospheric pressure will aggravate the severity of air pollution. Changes in precipitation and relative humidity will also affect the level of air pollutants with the expansion and intensification of arid regions around the world. This directly reflects the potential impact of global climate change on air quality.

5. Conclusions

In this study, we found that local meteorological factors could affect the variation of $PM_{2.5}$, SO_2, O_3 and CO concentrations, and the influence was different in Beijing. The final fitting results exhibit that temperature, relative humidity and visibility are the most significant meteorological variables associated with $PM_{2.5}$ concentration, and the marginal effect reaches 80%, −23% and 270%, respectively. Temperature and relative humidity are the most significant variables for SO_2, and the marginal effect reaches 15% and 7%, respectively. The most significant variables for O_3 are temperature and solar radiation, with marginal effect of up to 70% and 8%, respectively. Atmospheric pressure and temperature results in a positive effect on CO, and the marginal effect can reach 18% and 80%, respectively. The remaining meteorological variables also demonstrated the impact on air pollutants, and the effects were relatively weak. The global climate is changing under the influence of human activities and other factors, and meteorological factors such as temperature and atmospheric pressure are also affected simultaneously. This study provides a deep insight into the analysis of local meteorological factors and four main air pollutants in Beijing and provides a supplement to the study of the relationship between high concentration air pollution and local meteorological factors. It holds significance for other regions of the world. In addition, by presenting percentage changes in air pollutant responses across a range of meteorological variables, it provides a clear window into how potential climate change may affect air quality. This window suggests that necessary climate adjustment measures should be developed and implemented by policymakers in order to achieve future air quality goals.

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