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Seasonal Disparity in the Effect of Meteorological Conditions on Air Quality in China Based on Artificial Intelligence

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Abstract: Air contamination is identified with individuals' wellbeing and furthermore affects the sustainable development of economy and society. This paper gathered the time series data of seven meteorological conditions variables of Beijing city from 1 November 2013 to 31 October 2017 and utilized the generalized regression neural network optimized by the particle swarm optimization algorithm (PSO-GRNN) to explore seasonal disparity in the impacts of mean atmospheric humidity, maximum wind velocity, insolation duration, mean wind velocity and rain precipitation on air quality index (AQI). The results showed that in general, the most significant impacting factor on air quality in Beijing is insolation duration, mean atmospheric humidity, and maximum wind velocity. In spring and autumn, the meteorological diffusion conditions represented by insolation duration and mean atmospheric humidity had a significant effect on air quality. In summer, temperature and wind are the most significant variables influencing air quality in Beijing; the most important reason for air contamination in Beijing in winter is the increase in air humidity and the deterioration of air diffusion condition. This study investigates the seasonal effects of meteorological conditions on air contamination and suggests a new research method for air quality research. In future studies, the impacts of different variables other than meteorological conditions on air quality should be assessed.

Keywords: air quality index; meteorological condition; PSO; GRNN

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1. Introduction

Air contamination affects the sustainable and long-term development of both the economy and society. The majority of chronic, lethal and severe diseases are brought about by air contamination that has grown worse over time. Specialists have reported widely on these illnesses, which include bronchitis, heart attacks, and lung cancer, all of which result in premature death [1–4]. Eliminating air contamination will improve quality of life, which is a significant and timely issue of worldwide concern [5,6], especially in China, which has the most serious air contamination on the planet [7–9]. Consequently, improving air quality has attracted a great deal of interest and enthusiasm in China, both from the public, the media and from the Chinese government.

Air contamination is a combined effect of air pollution, atmosphere diffusion and diluting conditions, and objects emitting air pollutants. The degree of air contamination is related to the total amount of air pollutants discharged in the region; the total amount does not change with meteorological conditions. However, meteorological conditions determine the concentration, spatial and temporal distribution of air pollutants through diffusion and dilution effects [4–8]. The main factors affecting atmospheric diffusion and dilution capacity are meteorological dynamic factors and meteorological thermal factors. Meteorological dynamic factors mainly refer to wind and turbulence, which play a decisive role in the diffusion and dilution of air pollutants in the atmosphere. Wind can transport and dilute air pollutants; wind direction and speed determine the migration, direction, and speed of air pollutants, respectively. When pollutants are discharged into the atmosphere,

turbulent movement causes them to mix with the clean air and then at the same time disperses them in other directions. Air pollutants are therefore continuously diffused and diluted. Meteorological thermal factors mainly refer to temperature stratification, which determines atmospheric stability. Temperature stratification is closely related to air contamination. In general, the temperature decreases as the height increases, forming different temperature stratifications, but on some nights with no wind and little cloud, there will be a temperature inversion. In this case, the atmosphere is in a stable state, turbulence is inhibited, the diffusion and dilution capacity of the atmosphere to pollutants is weakened, and the dilution capacity of the atmosphere to pollutants is enhanced, which will lead to air pollution [10–15].

Therefore, the main cause of air pollution is enormously due to the restricted transport conditions of air pollutants, that is, the essential processes of air pollution diffusion, dilution and transformation are affected and confined by meteorological conditions. Many previous studies have shown that meteorological conditions significantly affect air contamination, but most research is carried out for specific air pollutants, the detailed mechanism regarding the impacts of meteorological factors such as rainfall, humidity and temperature, etc. on air quality is still unclear [10–30]. In 2012, the Ministry of Ecology and Environment of the People's Republic of China issued the Technical Provisions on Ambient Air Quality Index (AQI) (trial), which firstly uses the air quality index (AQI) as an indicator to measure air quality. At present, research concerning the relationship between AQI and meteorological elements is gradually being carried out, but there are few studies on the air quality index of Beijing city. As the capital of China, Beijing city is also one of the most polluted cities in China. Since 2013, Beijing repeatedly suffered air pollution, especially in winter. The terrible air contamination situation has attracted the attention of people all over the country and the world. Taking Beijing city for instance, this paper gathered the time series data of AQI and meteorological factors from 1 November 2016 to 31 October 2017, analyzed the variation characteristics of AQI of Beijing city and explored the dynamic impacts of 8 meteorological factors on air quality with an aim to deepen the understanding of air quality in Beijing city and provide a scientific basis for controlling air contamination and protecting the ecological environment.

The research techniques utilized by prior scholars include chemical or physical experiments [11,20,25], mathematical simulation [12,18,23,28], multiple linear regression or statistical analysis [13,16,27], which cannot fit the non-linear nonlinear relationship between variables. As a new radial basis function (RBF) neural network, the generalized regression neural network (GRNN) model has powerful nonlinear approximation and mapping capacity, which is entirely appropriate for tackling nonlinear issues [31]. Additionally, the parameters needed to be adjusted by GRNN is only one (SPREAD) and it possesses a quicker learning speed and better fault tolerance [32,33]. In this paper, the generalized regression neural network optimized by the particle swarm optimization algorithm (PSO-GRNN) model with better robustness and precision is set up by searching for the best parameter SPREAD of GRNN via the particle swarm optimization (PSO) algorithm, then the PSO-GRNN model is applied to assess the impacts of meteorological conditions on air quality, which expands on the studies from this discipline and fills the research gap.

The following section provides a brief literature overview of the current research on the relationship between air contamination and meteorological conditions, together with current research deficiency before we discuss our constructed PSO-GRNN model in Section 3. Taking Beijing city as the case study, an empirical analysis of meteorological conditions variables affecting air quality is demonstrated in Section 4. The main conclusions of empirical analysis are discussed in Section 5, with policy implications on air contamination based on these results being proposed.

2. Literature Review

2.1. Meteorological Conditions and Air Quality

In previous studies, most scholars had simply analyzed and described the variation of air pollutant concentration [17,21,22,24,26], or focused on the effects of a particular meteorological condition or one specific pollutant source on air quality [10,14,15,19,29,30].

Wang et al. [17] utilized long-term air pollution data with high temporal and spatial resolutions to analyze the spatial and temporal changes of six air contaminations in China's 31 provincial capitals during 2013–2014, and revealed that secondary aerosol formation throughout the year, coal ignition and biomass consuming in winter, and long-range transport of windblown dust in spring all distinctly affected the degree of air contamination. He et al. [21] constructed an artificial neural network model to investigate the air contamination and their connection to multi-scale meteorological conditions in China's 31 provincial capitals during 2014–2015 and found that meteorological factors were the main variables determining everyday varieties of pollutant concentrations, clarifying over 70% of the change of daily average air contamination concentration in China. Wang et al. [22] monitored the concentrations of PM₁₀, PM_{2.5} and PM₁ at 24 CAWNET (China Atmosphere Watch Network) stations from 2006 to 2014, then explored the spatial and temporal varieties of the centralizations of PM₁₀, PM_{2.5} and PM₁ in China and uncovered that the meteorology and emission varieties determined the long-term trend of PM concentration, and meteorological variables mainly had a temporary effect. Wen et al. [24] combined observation data, emission reduction measures, and air quality simulations that were applied before, during, and after the emission control measure implement to analyze the chemical composition change and relationship between emissions and concentrations of pollutants in region. They proved that the Beijing-Tianjin-Hebei air quality can be improved by introducing integrated emission reduction measures. Zhang et al. [26] described the local variety of air contamination during and after the 2008 Olympics and found that air mass transport direction influenced the magnitude and properties of the pollutants in the measured region through back-trajectory analysis.

Chen et al. [10] found that an amazing two-contamination-layer structure was seen via airplane in Beijing on 18 August 2007 and concluded that the rapid increase in the surface concentrations of pollutants may be attributed to the vertical down-mixing of pollutants, based on an analysis from the Weather Research and Forecasting (WRF)-TRACER model and wind profile data. He et al. [14] developed an artificial neural network (ANN) model to investigate the relationships between winter air pollutant concentrations and local meteorological parameters, synoptic-scale circulations and precipitation based on observed pollutant concentrations, high-resolution meteorological data from the Weather Research and Forecast model and gridded reanalysis data. They found that local meteorological conditions are the main factor causing the day-to-day variations of pollutant concentrations, followed by synoptic-scale circulation type, emission variation, and wet removal process. Liu et al. [15] investigated statistics on air pollution events in northern China in the 2015 winter months of November and December and found that the worsening meteorology conditions are the main reason behind this unusual increase in air pollutant concentrations and the emission control measures taken during this period have contributed to mitigate the air pollution in the region. Zhang et al. [19] used an obliquely rotated T-mode principal component analysis (PCA) to identify nine weather circulation types (CTs) over the north China region during 2000–2009 and revealed that CTs are the primary drivers of day-to-day variations in pollutant concentrations over Beijing and its vicinity. Laña et al. [29] presented a data-based method to inspect the interplay among traffic, meteorological conditions and pollution in Madrid and found that air pollution in Madrid, Spain was mainly determined by stable meteorological conditions rather than vehicle emissions. Gualtieri et al. [30] assessed the importance of road traffic, residential heating and meteorological conditions as major drivers of urban PM₁₀ concentrations during air pollution critical episodes in the city of Florence (Italy) during the winter season and found that meteorological variables

explained 80.5–85.5% variation of PM_{10} concentration, while major emission sources had only minor effects.

2.2. Research Technique

The research methods used by contemporary scholars include physical or chemical experiments [11,20,25], numerical simulation [12,18,23,28], statistical analysis and multiple linear regression [13,16,27].

Crippa et al. [11] utilized an aerosol mass spectrometer (AMS) and a proton transfer reaction mass spectrometer (PTR-MS) to analyze the sources of secondary organic aerosol (SOA) and found that continental SOA was dominant during both seasons (24–50% of total OA), while contributions from photochemistry-driven SOA (9% of total OA) and marine emissions (13% of total OA) were also observed during summertime. Zhang et al. [20] quantified the source contributions to surface $PM_{2.5}$ (fine particulate matter) pollution over North China from January 2013 to 2015 using the GEOS-Chem chemical transport model and its adjoint with improved model horizontal resolution ($1/4^\circ \times 5/16^\circ$) and aqueous-phase chemistry for sulfate production. Han et al. [25] investigated the chemical and optical properties of aerosol particles during the 2014 Asia-Pacific Economic Cooperation (APEC) summit in Beijing, China, using the highly time-resolved measurements by a high-resolution aerosol mass spectrometer and a cavity attenuated phase shift extinction monitor and found that the extinction contributions of aerosol species varied greatly between different air masses but generally with ammonium nitrate, ammonium sulfate, and secondary organic aerosol being the three major contributors.

Gao et al. [12] conducted a series of numerical experiments over East Asia for the period of July to September 2008 using a coupled meteorology-chemistry model (WRF-Chem), found that meteorological conditions (e.g., wind direction and precipitation) were important in producing the low aerosol concentrations appearing during the Olympic period, and the transport from the regions surrounding Beijing determined the daily variation of aerosol concentrations in Beijing. Wu et al. [18] developed an online air pollutant tagged module in the Nested Air Quality Prediction Model System (NAQPMS) to investigate the impact of local and regional sources on the air pollutants in Beijing, the results indicated that the efforts to control the air pollutants in Beijing should focus on controlling both local and regional emissions. An, Zuo, Chen [23] used the numerical models and a linear programming model to estimate the atmospheric environmental capacities of SO_2 on representative days over Lanzhou, the result indicated the total emission control method based on atmospheric environmental capacity is the most effective in air pollution mitigation. Calkins et al. [28] used satellite data from the Ozone Monitoring Instrument (OMI), chemistry transport model (GEOS-Chem) simulations, and National Center for Environmental Prediction (NCEP) meteorological reanalysis to analyze the meteorology and weather conditions related to air pollution events in winter from 2006 to 2015, and found that the annual variation of the columnar SO_2 distribution in winter was largely due to the SO_2 emission, the surface SO_2 distribution was more dependent on the meteorology than the columnar SO_2 distribution.

He et al. [13] developed multiple linear regression models for estimating NO_2 and PM_{10} concentrations over urban Lanzhou, north-western China. They explored the connections between winter air contamination concentrations and ten meteorological factors and discovered that compared with other meteorological variables, air contamination concentration is more affected by potential temperature lapse rate and boundary layer height. Pearce et al. [16] applied the self-organizing diagram (SOM) and generalized additive model (GAM) to analyze regional synodic circulation patterns and the relationships with air quality; the result indicated that synoptic-scale circulation features were not the primary driver of day-to-day pollutant concentrations, while individual synoptic categories had differential effects on air pollutants. Jo and Park [27] explored the relationship between roadside air contamination and meteorological factors in Daegu, South Korea, through mul-

multiple regression equation and found that the quantity and type of meteorological conditions were diverse for different roadside air contamination, monitoring stations or seasons.

3. Methods

3.1. Sensitivity Analysis Based on Artificial Neural Network

Sensitivity analysis assumes that the model is $y = f(x_1, x_2, \dots, x_n)$ (x_i is the i th attribute of the model), each attribute changes within the possible value range to study and predict the effect on the output value. The effect size is called the sensitivity coefficient. The greater the sensitivity coefficient, the higher the influence of the attribute on the model output.

Since the sensitivity analysis is operated on the basis of the modeling approaches, according to the modeling approaches, sensitivity analysis can be divided into two categories: modeled sensitivity analysis and modelless sensitivity analysis. In the early studies, scholars used statistical methods to establish the model, and the most common model was the multiple linear regression. With the emergence of various problems in different research fields, the statistical modeling approach gradually exposes its limitations, scholars begin to adopt an artificial neural network to establish the sensitivity analysis model. The artificial neural network model does not require a priori knowledge, only need to know the input variable and output data. It is self-organizing and self-learning, has strong mapping ability and robustness, and can fit arbitrary nonlinear function between input variables and the output variable without precise mathematical model [34,35].

However, the shortcomings of the artificial neural network model is poor interpretation or explanation and black-box problem, therefore, how to illuminate the “black box” is the key to use the sensitivity analysis based on an artificial neural network. The mechanics of an artificial neural network is revealed by the description of average impact value (MIV) in this study.

Mean impact Value (MIV), as one of the best indicators to evaluate the correlation of variables, was proposed by Dombi et al., an American scholar, in 1995 [36]. The calculation process of MIV value is as follows: the artificial neural network model is established, trained and tested through historical data, then, other independent variables remain unchanged, one certain independent variable is selected to increase and decrease by 10%, respectively, to form two new samples P_1 and P_2 . New samples P_1 and P_2 are entered into the artificial neural network model to obtain two simulation results A_1 and A_2 . The difference between the simulation results A_1 and A_2 is called impact value (IV), and the mean of the impact value is called mean impact value (MIV) of the independent variable. It can be seen that the symbol of MIV indicator represents the positive and negative influences of independent variables on dependent variables, and the absolute value represents the influence size. Therefore, in recent years, MIV indicator has been increasingly used in sensitivity analysis to measure the effect of independent variables on dependent variables.

By applying MIV to the artificial neural network model, the “black box” mechanism of the artificial neural network model can be well revealed. Furthermore, when the new explanatory ability of the neural network is combined with its strong predictive ability, the neural network model is expected to become a valuable quantitative tool for understanding, evaluating and predicting economic and management phenomena.

3.2. Generalized Regression Neural Network Model

Generalized regression neural network (GRNN) is a completely new radial basis function (RBF) neural network, proposed by American scholar Specht in 1991. GRNN does not need a pre-exist function and converges to the optimized regression surface through accumulating more samples. Therefore, it has strong capability of nonlinear mapping and approximation, very suitable for solving nonlinear problems. In addition, GRNN has faster learning speed and higher fault tolerance, because it has only one parameter SPREAD to be adjusted. In addition, it also has strong adaptability to small sample data and unstable data [37].

Similar to the RBF neural network, the GRNN network structure is composed of an input layer, pattern layer, summation layer and output layer, as shown in Figure 1, wherein $X = [x_1, x_2, \dots, x_n]^T$ represents the network input vector, $Y = [y_1, y_2, \dots, y_k]^T$ represents the network out vector.

Figure 1. The topological structure of GRNN.

(1) Input layer

The input layer is responsible for transmitting a learning sample to the pattern layer. The input layer neurons are simply distributed, and their number is equal to the input vector dimension.

(2) Pattern layer

The pattern layer neurons are associated with the learning samples, equal in number. Assuming that X is input vector, X_i is the one learning sample corresponding to pattern layer neuron i . The output value of pattern layer neuron i is equal to the exponentiation of the squared Euclidean distance between input vector X and learning sample X_i . The computation formula is shown below.

$$D_i^2 = (X - X_i)^T (X - X_i) \quad (1)$$

The transfer function of pattern layer neuron i is shown in Formula (2).

$$p_i = \exp\left[-\frac{(X - X_i)^T (X - X_i)}{2\sigma^2}\right], i = 1, 2, \dots, n \quad (2)$$

(3) Summation layer

The summation layer neuron is used for the calculation of the outputs of pattern layer neurons. The summation calculation is classed into the arithmetic summation method and weighted summation method. If using the arithmetic summation method, the sum of the connection weights between the pattern layer neurons and the summation layer neurons is 1. The output value of the summation layer neuron i is computed by Formula (3).

$$s_i = \sum_{i=1}^n \exp\left[-\frac{(X - X_i)^T (X - X_i)}{2\sigma^2}\right] \quad (3)$$

The transfer function of the summation layer neuron i is shown in Formula (4).

$$S_D = \sum_{i=1}^n P_i \quad (4)$$

When the weighted summation method is adopted, the element j in the output sample Y_i is the connection weight between pattern layer neuron i and summation layer neuron j . The output value of summation layer neuron i is computed by Formula (5).

$$s_i = \sum_{i=1}^n Y_i \exp\left[-\frac{(X - X_i)^T (X - X_i)}{2\sigma^2}\right] \quad (5)$$

The transfer function of summation layer neuron i is shown in Formula (6).

$$S_{Nj} = \sum_{i=1}^n y_{ij} P_i, j = 1, 2, \dots, k \quad (6)$$

(4) Output layer

The outputs of output layer neurons are obtained through division operation of the summation layer neurons. The output layer neurons correspond to the output variables, and the number of output layer neurons is equal to the output vector dimension k . The output value of output layer neuron j is computed by Formula (7).

$$y_j = \frac{S_{Nj}}{S_D}, j = 1, 2, \dots, k \quad (7)$$

3.3. PSO-GRNN Model

The parameter SPREAD determines the prediction performance of the GRNN model. Previous scholars [32,37–39] proposed many intelligent algorithms to search for the best parameters, such as particle swarm optimization (PSO), ant colony optimization (ACO), fruit fly optimization algorithm (FOA). In order to further improve the prediction accuracy and robustness of the GRNN model, particle swarm optimization was employed to search the parameter SPREAD of GRNN, a hybrid PSO-GRNN model was established in this study, which is a new model combining particle swarm optimization algorithm with generalized regression neural network.

Particle swarm optimization (PSO) is an effective global optimization algorithm developed by simulating the foraging process of birds. It searches for the best solution in complex space through cooperation and competition among individuals. It has the characteristics of evolutionary computation and swarm intelligence. It was first proposed by American scholars Kenedy and Eberhart in 1995 [40].

The effect size and direction of factors that influence technological innovation are calculated by using MIV and PSO-GRNN model, the calculation process is shown in Figure 2.

The main calculation steps are as follows:

Step 1: Initializing particles and velocities

Each SPREAD parameter of GRNN is encoded as one particle to form the initial particle swarm $X = \{X_1, X_2, \dots, X_N\}$, each particle has a velocity, the velocity is expressed as $V_i = \{v_{i1}, v_{i2}, \dots, v_{in}\}$.

Step 2: Calculating the particle fitness

After the PSO-GRNN model is trained and tested, the total absolute error between predicted and observed value of test sample is taken as the fitness value of each particle. The calculation equation is shown as follows.

$$F = \sum_{i=1}^n \text{abs}(y_i - o_i) \quad (8)$$

In Equation (8), n is the sample size, y_i and o_i , respectively represent the observed and predicted values of sample i .

Step 3: Determining the individual-extremum and global-extremum

Figure 2. The calculation process of PSO-GRNN model.

The fitness value for each particle position is calculated according to the fitness function. Assuming that $P_i = [P_{i1}, P_{i2}, \dots, P_{iD}]$ is the individual-extremum of particle i , $P_g = [P_{g1}, P_{g2}, \dots, P_{gD}]$ is the global-extremum.

Step 4: Updating the position and velocity

The position and velocity of each particle are constantly updated through individual and global extremum, the calculation equations are shown in Equations (9) and (10).

$$v_{id}(t+1) = \omega v_{id}(t) + \eta_1 \text{rand}() (p_{id} - x_{id}(t)) + \eta_2 \text{rand}() (p_{gd} - x_{id}(t)) \quad (9)$$

$$x_{id}(t+1) = x_{id}(t) + v_{id}(t+1) \quad (10)$$

Step 5: Establishing the PSO-GRNN model.

After decoding the optimal population particle searched by particle swarm optimization (PSO), the optimal SPREAD parameter of the GRNN network is obtained, then the PSO-GRNN model is established.

Step 6: Calculating the MIV of each variable

Increasing and decreasing the original value of one independent variable to form two new data samples, while the original value of other independent variables remains unchanged. Two new samples were input into the PSO-GRNN model for simulation and prediction, the average difference between the predicted values of the two new samples is the MIV of the variable. The positive or negative of MIV represents the direction of the influence of independent variable on dependent variable, and the absolute value represents the influence size.

4. Results

4.1. Statistic Analysis

The air quality index (AQI) is a dimensionless index that quantitatively describes the state of air quality, the degree of air cleanliness or pollution, as well as the impact on health. AQI is a new air quality assessment standard, issued by China in March 2012. The

main pollutants involved in air quality assessment include fine particulate matter PM_{10} , fine particulate matter $PM_{2.5}$, sulfur dioxide (SO_2), nitrogen dioxide (NO_2), ozone (O_3), carbon monoxide (CO). AQI combines six pollutants and presents air pollution levels using uniform values. The higher the AQI value, the more serious the air contamination, and the greater the harm to human health. The air quality index is generally divided into six levels. When AQI value is 0–50, it represents excellent air quality; when AQI value is 51–100, it represents good air quality; when AQI value is 101–150, it represents mild pollution; when AQI value is 151–200, it represents moderate pollution; when AQI value is 200–300, it represents heavy pollution; when AQI value is above 300, it represents severe pollution.

The data source of this paper is the China National Environmental Monitoring Center (<http://www.cnemc.cn/>, accessed on 31 October 2020). Taking Beijing city (Figure 3) as an example [41], the time series of air quality index and seven meteorological condition variables on 1 November 2013 and 31 October 2017 were collected. The AQI time series data of Beijing is shown as Figure 4. Meteorological condition variables include mean atmospheric pressure, mean atmospheric temperature, mean atmospheric humidity, rain precipitation, mean wind velocity, insolation duration, mean land surface temperature and maximum wind velocity. The seasonal statistical data are shown in Table 1.

Figure 3. Geographical locations of Beijing city in China. The maps were drawn by the software of ArcGIS version 10.2, <http://www.esri.com/software/arcgis/arcgis-for-desktop>, accessed on 31 October 2020.

4.2. Impact Size Analysis

Seven meteorological condition factors were taken as input variables and air quality index (AQI) as output variables, the PSO-GRNN model was constructed, trained and tested. Then, each input variable increased and decreased by 10%, respectively, while other input variables remained unchanged. MIV value of each meteorological condition variable is calculated via trained PSO-GRNN model. The results are shown in Table 2.

Figure 4. Time series data about AQI of Beijing city.

Table 1. Statistics about meteorological factors affecting AQI of Beijing city.

Meteorological Factors	Spring	Summer	Autumn	Winter
Mean Atmospheric Temperature	9.2347	25.0109	20.7122	1.1011
Mean Atmospheric Humidity	39.1625	54.1359	64.7609	50.1250
Rain Precipitation	0.3120	3.0413	2.4307	0.1095
Mean Wind Velocity	2.3933	2.2326	1.7606	1.9902
Insolation Duration	7.5810	7.5022	6.1688	5.6957
Mean Land Surface Temperature	10.8468	29.1016	22.4008	−0.3644
Maximum Wind Velocity	9.1300	9.0997	7.1155	7.6190

Table 2. The MIV of factor affecting air quality index.

Mean Atmospheric Temperature	Mean Atmospheric Humidity	Rain Precipitation	Mean Wind Velocity	Insolation Duration	Mean Land Surface Temperature	Maximum Wind Velocity
0.2870	5.1158	−0.0806	−0.3482	−6.7892	1.3489	−2.3340

As shown in Table 2, the meteorological variable that has the highest influence on the air quality of Beijing is insolation duration ($MIV = -6.7892$), followed by mean atmospheric humidity ($MIV = 5.1158$), maximum wind velocity ($MIV = -2.3340$), mean land surface temperature ($MIV = 1.3489$), mean wind velocity ($MIV = -0.3482$), mean atmospheric temperature ($MIV = 0.2870$) and rain precipitation ($MIV = -0.0806$). Among the seven influencing factors, mean atmospheric humidity, mean land surface temperature and mean atmospheric temperature are positively correlated with AQI; insolation duration, maximum wind velocity, mean wind velocity and rain precipitation are negatively correlated with AQI.

4.3. Seasonal Disparity Analysis

Beijing has four distinct seasons, with hot and rainy summer and cold and dry winter, which is a typical continental monsoon climate. The meteorological conditions and AQI in Beijing city vary greatly from season to season, therefore, the study period of AQI is divided into spring, summer, autumn and winter. The MIV of meteorological factors affecting air quality index are compiled and calculated, respectively (Table 3 and Figure 5).

Table 3. The MIV of meteorological factors affecting air quality index.

Meteorological Factors	Spring	Summer	Autumn	Winter
Mean Atmospheric Temperature	−0.1103	1.4782	0.3445	−0.5761
Mean Atmospheric Humidity	4.4602	0.8380	2.0914	13.0540
Rain Precipitation	−0.0164	−0.1264	−0.1708	−0.0068
Mean Wind Velocity	−0.0243	1.3392	−0.2062	−2.4918
Insolation Duration	−7.0758	−6.6482	−7.6961	−5.7453
Mean Land Surface Temperature	0.0787	3.9839	1.7917	−0.4966
Maximum Wind Velocity	−1.6598	−0.9452	−2.9479	−3.7631

Figure 5. Seasonal disparity of meteorological factors affecting air quality index.

(1) Spring Season

Sorted by the MIV absolute value, the meteorological variables that have highest influences on air quality of Beijing city in spring are insolation duration ($MIV = -7.0758$), mean atmospheric humidity ($MIV = 4.4602$) and maximum wind velocity ($MIV = -1.6598$), followed by mean atmospheric temperature ($MIV = -0.1103$), mean land surface temperature ($MIV = 0.0787$), mean wind velocity ($MIV = -0.0243$), rain precipitation ($MIV = -0.0164$).

The meteorological factors with a positive influence on air quality are mean atmospheric humidity and mean land surface temperature. Other meteorological factors include insolation duration, maximum wind velocity, mean atmospheric temperature, mean wind velocity and rain precipitation, all of which have a negative influence (Table 3 and Figure 6).

The results indicate that the meteorological diffusion conditions represented by insolation duration and mean atmospheric humidity have an important influence on air quality. The maximum wind velocity, rather than mean wind velocity, is the important meteorological factor affecting the AQI change of Beijing city, which has a great direct and indirect influence on air quality through reducing mean atmospheric humidity, improving insolation duration and air contamination diffusion conditions.

(2) Summer Season

Sorted by the MIV absolute value, the meteorological variables with the highest influences on air quality of Beijing city in summer are insolation duration ($MIV = -6.6482$), mean land surface temperature ($MIV = 3.9839$), mean atmospheric temperature ($MIV = 1.4782$) and mean wind velocity ($MIV = 1.3392$), followed by maximum wind velocity ($MIV = -0.9452$), mean atmospheric humidity ($MIV = 0.838$) and rain precipitation ($MIV = -0.1264$).

Figure 6. The effect comparison of different meteorological conditions of Beijing in spring.

The meteorological factors with a positive influence on air quality are mean land surface temperature, mean atmospheric temperature, mean wind velocity and mean atmospheric humidity. Other meteorological factors include insolation duration, maximum wind velocity and rain precipitation, all of which have negative influence (Table 3 and Figure 7).

Figure 7. The effect comparison of different meteorological conditions of Beijing in summer.

The results indicate that besides insolation duration, temperature and wind are the important factors affecting air quality of Beijing in summer. The higher the temperature, the more water vapor the air can hold, combined with the low wind speed, that creates adverse conditions for the accumulation of air contamination.

(3) Autumn Season

Sorted by the MIV absolute value, the meteorological variables that have highest influences on air quality of Beijing city in autumn are insolation duration (MIV = -7.6961), maximum wind velocity (MIV = -2.9479), mean atmospheric humidity (MIV = 2.0914) and mean land surface temperature (MIV = 1.7917), followed by mean atmospheric tem-

perature ($MIV = 0.3445$), mean wind velocity ($MIV = -0.2062$) and rain precipitation ($MIV = -0.1708$).

The meteorological factors with a positive influence on air quality are mean atmospheric humidity, mean land surface temperature and mean atmospheric temperature, other meteorological factors include insolation duration, maximum wind velocity, mean wind velocity and rain precipitation, all of which have a negative influence (Table 3 and Figure 8).

Figure 8. The effect comparison of different meteorological conditions of Beijing in autumn.

All the results above show that the meteorological diffusion conditions represented by insolation duration and mean atmospheric humidity have important influence on air quality. At the same time, the increase in air humidity and mean land surface temperature will lead to more haze and air pollution.

(4) Winter Season

Determined by the MIV absolute value, the meteorological variables that have highest influences on air quality of Beijing city in winter are mean atmospheric humidity ($MIV = 13.054$), insolation duration ($MIV = -5.7453$), maximum wind velocity ($MIV = -3.7631$) and mean wind velocity ($MIV = -2.4918$), followed by mean atmospheric temperature ($MIV = -0.5761$), mean land surface temperature ($MIV = -0.4966$) and rain precipitation ($MIV = -0.0068$).

The meteorological factors with a positive influence on air quality are mean atmospheric humidity. Other meteorological factors include insolation duration, maximum wind velocity, mean wind velocity, mean atmospheric temperature, mean land surface temperature and rain precipitation, all of which have negative influence (Table 3 and Figure 9).

The results indicated that the most important cause of winter air contamination in Beijing city is the increase in air humidity and the deterioration of air diffusion conditions, meanwhile, the improvement of air diffusion conditions, such as the increase in insolation duration, maximum wind velocity and mean wind velocity, are beneficial to the improvement of air quality.

Figure 9. The effect comparison of different meteorological conditions of Beijing in winter.

5. Conclusions

Taking Beijing as an example, this paper collects the time series data of AQI and meteorological factors from 1 November 2013 to 31 October 2017 and studies the influence of meteorological conditions on air quality by constructing a new PSO-GRNN model with stronger fitting capacity for nonlinear relations, and draws conclusions different from previous studies, which are summarized as follows.

On the whole, the most important influencing factor on air quality in Beijing is insolation duration, followed by mean atmospheric humidity, maximum wind velocity, mean land surface temperature, mean wind velocity, mean atmospheric temperature and rain precipitation. Mean atmospheric humidity, mean land surface temperature and mean atmospheric temperature are positively correlated with AQI; insolation duration, maximum wind velocity, mean wind velocity and rain precipitation are negatively correlated with AQI.

In spring, the meteorological diffusion conditions represented by insolation duration and mean atmospheric humidity had an important influence on air quality. Maximum wind velocity rather than mean wind velocity was the important meteorological factor affecting the AQI change of Beijing city.

In summer, temperature and wind are the important factors influencing air quality of Beijing city.

In autumn, insolation duration and mean atmospheric humidity had important influence on air quality. At the same time, the increase in air humidity and mean land surface temperature will lead to more haze and air pollution.

In winter, the most important cause of winter air contamination in Beijing is the increase in air humidity and the deterioration of air diffusion conditions, meanwhile, the improvement of air diffusion conditions, such as the increase in insolation duration, maximum wind velocity and mean wind velocity, are beneficial to the improvement of air quality.

The above conclusions confirm the research findings of some scholars [10–15], who argued that deteriorating meteorological conditions are important causes of air contamination; meteorological conditions could dilute, diffuse and transfer air pollutants through dynamic factors and thermal factors, thereby affecting air quality. At the same time, some scholars [11,12,17,20,25] attribute air pollution to primary aerosol or secondary aerosol, which is still related to meteorological conditions and is consistent with the above conclusions. Haze is a large number of very fine dry dust particles floating evenly in the air, making the air with horizontal visibility less than 10 km generally turbid. The dry

dust particles here refer to dry aerosol particles. Under normal circumstances, when the visibility is 1~10 km, it may not only have the influence of dry aerosol (that is, the influence of haze), but also the contribution of water droplets (that is, the contribution of light fog), and it is not easy to distinguish, so it is called “Fog-Haze” phenomenon. Since there are no aerosol particles in the actual atmosphere as condensation nuclei (or ice nuclei) of clouds and fog, fog cannot be formed, so the fog and haze are both related to aerosol particles.

Nevertheless, air contamination is caused by pollution sources discharging air pollutants, meteorological conditions that diffuse and dilute air pollutants, and objects that bear air pollution. The degree of air contamination in one region depends on the total amount of air pollutants discharged in this region. Meteorological conditions only play the role of diluting and dispersing air pollutants. Therefore, air pollution is an economic problem in nature. To combat air contamination, local governments must transform and upgrade traditional industries and vigorously support and develop industries with high added value, low energy consumption and low emissions. Meanwhile, understanding and mastering the law of meteorological change can help people avoid and reduce the social harm and economic loss caused by air contamination.

Although this paper contributes to the study about air quality, it still ignores some important influencing factors on air quality, such as topographic features, regional pollution residential heating, transportation and conversion, industrial pollution and automobile exhaust emission. The effects of these factors on air quality need to be further validated in future studies. Besides, the PSO-GRNN model needs to be further developed and tested in the application of other ecological or environmental fields.

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