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Spatial and Temporal Evolution of Population-Weighted PM2.5 Concentration and Its Influencing Factors in China from 2000 to 2021

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Abstract: *The repeated occurrences of severe haze in China in recent years have drawn increased attention from the public and government departments to the impact of pollutants on public health. In order to investigate the spatial and temporal distribution patterns and risks of PM2.5 population exposure levels in various regions of China, based on population-weighted PM2.5 concentration data, spatial autocorrelation analysis and geographic detector methods are used to reveal its overall spatial and temporal evolution patterns and local variation characteristics. The specific influences and interactions of population-weighted PM2.5 concentrations in China are also studied in four dimensions: socio-economic, climatic, geographic environment and policy. Finally, projections of population-weighted PM2.5 concentrations in China from 2019 to 2021 are made based on the main influencing factors. The study shows that (1) China's population-weighted PM2.5 concentrations decreased year by year from 2000 to 2018. (2) Spatial clustering of population-weighted PM2.5 concentrations in China is evident. (3) The population-weighted PM2.5 concentration in China showed a spatially heterogeneous pattern between 2000 and 2018. (4) At the national scale, the factor with the greatest explanatory power of China's population-weighted PM2.5 concentration is the average temperature. The interactions between the factors mainly show two types of interactions: two-factor enhancement and non-linear enhancement. (5) A prediction model of China's population-weighted PM2.5 concentration was established to predict the population-weighted PM2.5 concentration from 2019 to 2021 with high accuracy.*

Keywords: *Population-Weighted, PM2.5, Spatial Autocorrelation, Geodetectors, GRNN*

1. Introduction

PM2.5 refers to dust, soot and smoke particles made up of hundreds of chemicals that are 2.5 microns or smaller in diameter.[1]. This paper uses population-weighted PM2.5 concentration data to reveal the spatial and temporal distribution characteristics and evolution patterns of PM2.5 concentrations in various regions of China. In studies on the spatio-temporal evolution analysis of PM2.5 concentrations in China, numerous scholars have studied the spatio-temporal evolution of PM2.5 concentrations and the analysis of influencing factors in local areas and specific time periods in China. As cities are important areas for air pollution control, studies on the spatial and temporal evolution of pollutants in a particular city, such as exploring the spatial and temporal variation characteristics of PM2.5 concentrations and their influencing factors in Beijing [2], have been conducted by scholars to evaluate regional and seasonal differences in PM2.5 concentrations based on long-term monitoring data. There are also studies on regions or cities such as Hubei [3] and Nanjing [4]. There are also studies on the spatial and temporal evolution of pollutants in urban agglomerations, which are important units in the current and even future construction of new urbanisation in China, including the Beijing-Tianjin-Hebei urban agglomeration [5] and the Yangtze River Delta urban agglomeration [6]; the time periods studied also vary [7, 8]. In recent years, scholars have increasingly focused on the study of population-weighted pollutants, and studies have found that population-weighted PM2.5 concentrations can better reflect the threat of air pollutants to human health [9, 10].

The studies mentioned above are not perfect for the following aspects. First, the PM2.5 concentrations used in most of the studies did not consider the effects of air pollution on exposed populations. Secondly, most of the studies on the influence of pollutants involve the analysis of influencing factors in terms of policy. Thirdly, the current studies have not adequately investigated the spatial and temporal evolution characteristics and influencing factors of PM2.5 concentrations at a national scale and over a long time span. Finally, most studies have neglected the influence and spatial heterogeneity of compound multifactor interactions on the spatial and temporal evolution of PM2.5 concentrations in China. Therefore, the construction of a systematic, comprehensive and region-specific comprehensive monitoring index system for population-weighted PM2.5 concentrations can provide a theoretical basis for improving regional environmental protection and reducing the risk of pollutants to human health.

2. Methodology

2.1 Study area

China is located in eastern Asia and on the west coast of the Pacific Ocean. The study area and the seven sub-regions of China in this paper are shown in Figure 1 and include the 31 mainland provincial cities of China except for the Hong Kong SAR, Macau SAR and Taiwan Province. Note: All maps of China in this paper are based on the standard map of the Ministry of Natural Resources with the review number GS (2020)4619, and the base map is unmodified.

Figure 1: Schematic diagram of the study area

2.2 Variable selection and data description

Data on population-weighted PM2.5 concentrations in China [11, 12] were obtained from the University of Washington Atmospheric Composition Analysis Group website (https://sites.wustl.edu/acag/datasets/surface-pm2-5/). To provide a comprehensive picture of the influence of various aspects on population-weighted PM2.5 concentrations in China, 17 representative influencing factors from four aspects: socio-economic factors, climatic factors, geographical environmental factors and policy factors were selected as indicator variables for analysis based on literature analysis [2, 3, 7, 8]. Data on total population (X1), GDP per capita (X2), amount of foreign investment (X3), share of employment in secondary industries (X4), share of employment in tertiary industries (X5), investment in science and technology (X6), electricity consumption (X8) and per capita consumer spending (X9) were obtained from the China Statistical Yearbook. Data on industrial output value (X7) are from the China Industrial Statistics Yearbook. Data on greening coverage of built-up areas (X14), industrial wastewater emissions (X15) and industrial sulphur dioxide emissions (X16) are from the China Environment Statistical Yearbook. Environmental protection keyword search index (X17) data from the official website of Baidu Index. Precipitation (X10), average temperature (X11) and average wind speed (X12) were originally obtained from the National Centers for Environmental Information (NCEI) of the National Oceanic and Atmospheric Administration (NOAA). Topographic relief (X13) data were obtained by resampling the digital elevation model (SRTM 90 m) data to 1 km and applying the model calculations to obtain a kilometre grid dataset of terrain relief in China.

ISSN 2616-5805 Vol. 4, Issue 2: 1-9, DOI: 10.25236/AJMS.2023.040201

2.3 Methodology

1) Spatial autocorrelation analysis: Spatial autocorrelation analysis [13] was used to quantify the degree of spatial correlation of population-weighted PM2.5 concentrations. The global Moran index is a comprehensive evaluation index used to measure the degree of spatial autocorrelation. The local Moran's index is a statistical analysis of the correlation between each spatial unit and the surrounding spatial units. there are two main expressions: one is the Moran's I scatter plot and the other is the LISA aggregation plot. there are five types in the LISA aggregation plot, spatially insignificant areas of correlation, four similar areas of significant spatial correlation: High-High -local high peripheral high, Low-Low-local low peripheral low, Low-High-local low peripheral high, High-Low-local high peripheral low.

2) Geo-detector: Geo-detector [14] can effectively detect the geospatial heterogeneity of variables and identify the main explanatory factors and interactions between factors, which is often expressed by the q-statistic value, q-values range from [0,1], with larger q-values indicating that the influence factor explains more about the population-weighted PM2.5 concentration. The interaction between the influencing factors can also be explored using the geodetector.

3) Generalised regression neural network prediction: generalised regression neural networks [15] are built based on radial basis neurons and linear neurons. A GRNN consists of an input layer, a mode layer, a summation layer and an output layer. Each unit of the pattern layer corresponds to a training sample with a gaussian function as the activation kernel function. The summation layer has 2 cells, cell 1 calculates the weighted sum of the outputs of the cells in the pattern layer, called the numerator cell, and cell 2 calculates the sum of the outputs of the cells in the pattern layer, called the denominator cell. The output layer unit divides the outputs of the numerator and denominator units of the summation layer to calculate the estimated value.

3. Results

3.1 Descriptive analysis

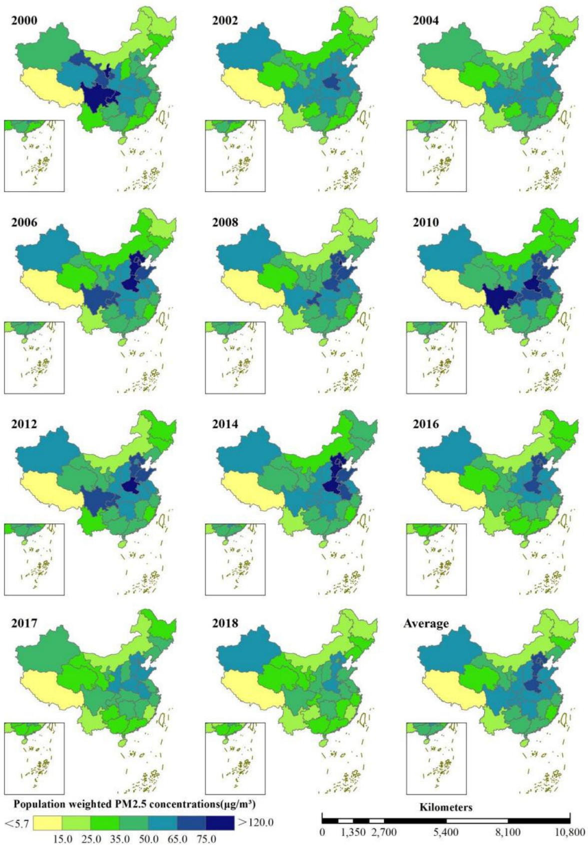

Figure 2: Interannual variation population-weighted PM2.5 concentrations in China, 2000 to 2018

ISSN 2616-5805 Vol. 4, Issue 2: 1-9, DOI: 10.25236/AJMS.2023.040201

Firstly, the population-weighted PM2.5 concentrations were divided into seven levels, from which the interannual variation of China's population-weighted PM2.5 concentrations from 2000 to 2018 was obtained as shown in Figure 2. During 2000~2018, the spatial pattern of population-weighted PM2.5 concentrations in China remained stable, and there were three main regions with low population-weighted PM2.5 concentrations, one located in Inner Mongolia Autonomous Region, another in Northeast China, and another in Tibet Autonomous Region and Qinghai Province. The regions with high population-weighted PM2.5 concentrations were mainly concentrated in the Beijing-Tianjin-Hebei Economic Zone, the Central Plains Region, the Yangtze River Delta Economic Zone and Shandong Province, followed by the Xinjiang Uyghur Autonomous Region and Sichuan Province. Among them, the population-weighted PM2.5 concentrations in the Beijing-Tianjin-Hebei region and Henan Province are both above 50 μg/m³. In addition, population-weighted PM2.5 concentrations have also been decreasing year on year in most regions of China since 2013.

3.2 Spatial autocorrelation analysis of population-weighted PM2.5 concentrations

Spatial autocorrelation analysis was performed using GeoDa and ArcGIS software to calculate the global Moran's I index of population-weighted PM2.5 concentrations in China from 2000 to 2018, and the results are shown in Figure 3. The Moran's I index was positive during the study period, and the Moran's I index was above 0.4 except for the years 2000 and 2004. In addition, it can be seen from Figure 3 that the Moran's I index showed an increasing trend from 2000 to 2003, and the Moran's I index from 2003 to 2012 Moran's I index generally tends to be stable, Moran's I index steadily increases from 2012 to 2015, and Moran's I index gradually decreases from 2015 to 2018.

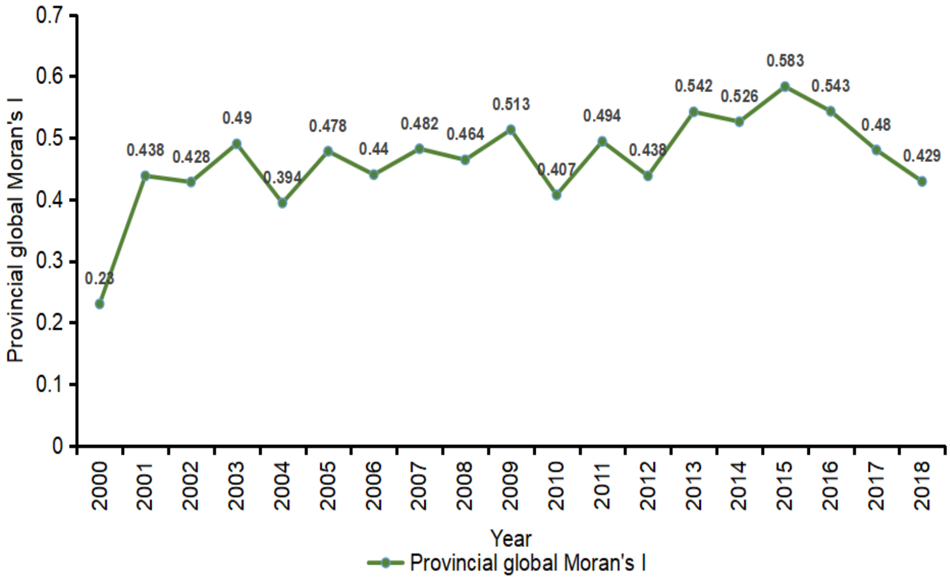

Figure 3: Interannual variation of the global Moran's I index of population-weighted PM2.5 concentrations in China, 2000 to 2018

In order to conduct a long time span study, the spatial clustering types of population-weighted PM2.5 concentrations within each provincial region of China and its adjacent areas were analysed, and the results are shown in Figure 4. 2000-2018 population-weighted PM2.5 concentrations in China mainly show three spatial clustering types: "high-high ", "high-low" and "low-low". The distribution of the "high-high" type is relatively concentrated, but there is a tendency to shift from central China to the east, mainly including Beijing-Tianjin-Hebei region, Shandong, Henan, Jiangsu, Anhui, Shanghai, Chongqing, Gansu, Hubei and Shaanxi; the "high -low" type areas are more scattered, mainly in the Sichuan Basin and the Tarim Basin in Xinjiang; "low-low" type areas are concentrated in Northeast China, especially in Jilin Province, until 2012, and in Yunnan Province after 2012. The 'low-low' type area was concentrated in northeastern China, particularly in Jilin Province, until 2012 and in Yunnan Province after 2012.

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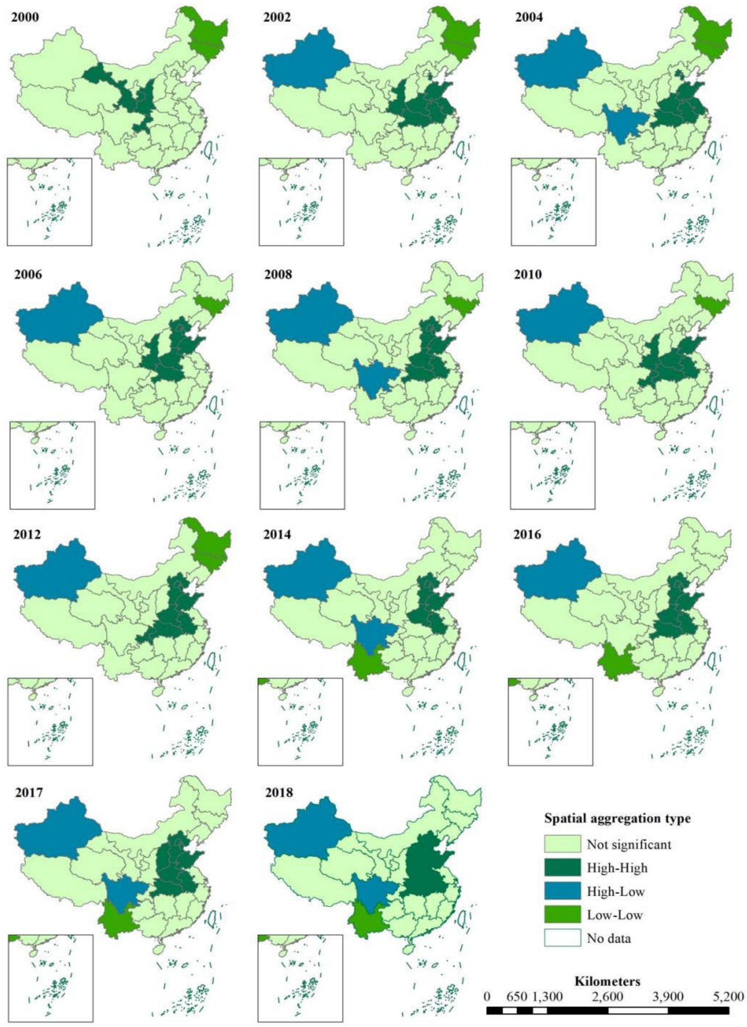


Figure 4: Spatial clustering of population-weighted PM2.5 concentrations in China, 2000 to 2018

3.3 Spatial heterogeneity analysis

In this section, the population-weighted PM2.5 concentrations in provincial areas of China were stratified into seven layers according to the geographic subdivisions shown in Figure 1 using the GeoProbe software to detect the spatial heterogeneity of population-weighted PM2.5 concentrations in China, and the detection results are shown in Figure 5. The results show that the spatial heterogeneity measures were all greater than 0.3 during the study period, and the spatial heterogeneity measures were all greater than 0.4 from 2014 to 2018. The values of spatial heterogeneity measures tend to be stable from 2014 to 2018.

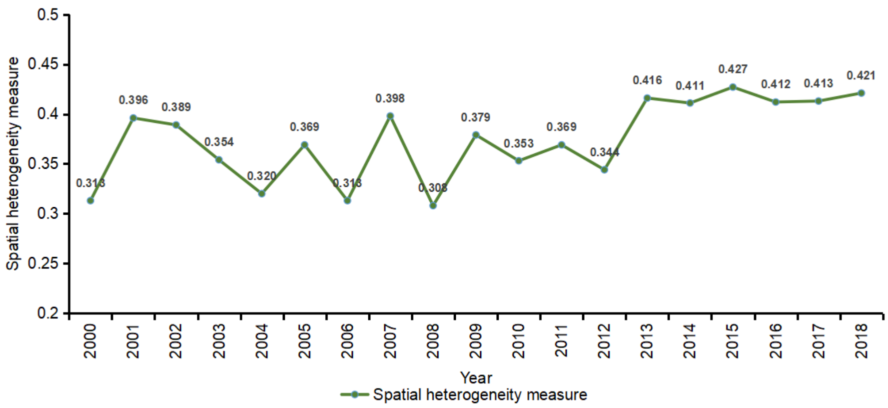


Figure 5: Spatial Heterogeneity Analysis of Population-Weighted PM2.5 Concentrations in China

ISSN 2616-5805 Vol. 4, Issue 2: 1-9, DOI: 10.25236/AJMS.2023.040201

3.4 Study of factors influencing population-weighted PM2.5 concentrations

1) Analysis of the factors influencing population-weighted PM2.5 concentrations

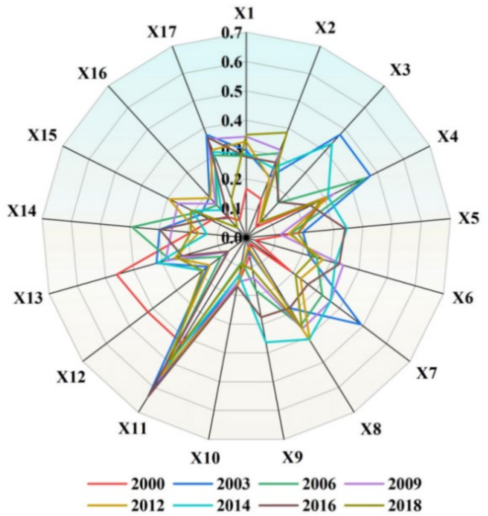


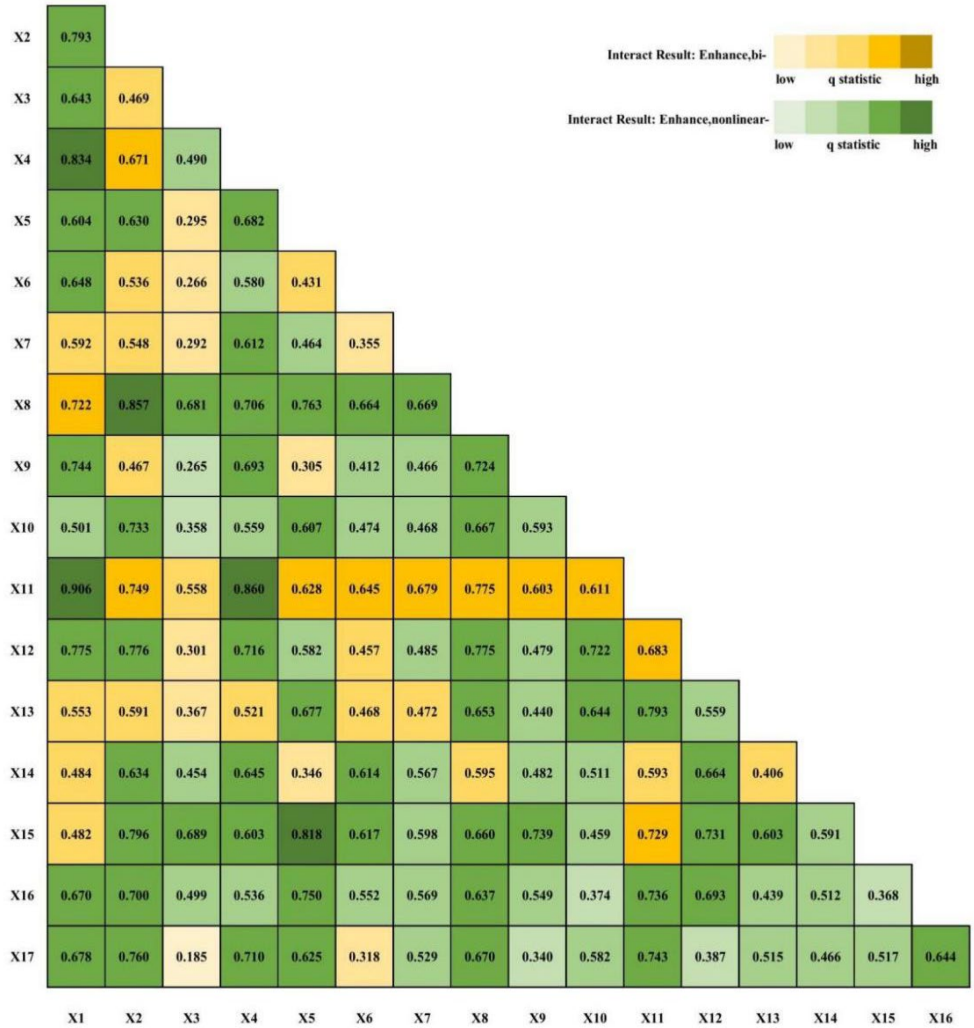
Figure 6: Radar plot of the results of the detection of factors influencing population-weighted PM2.5 concentrations in China

This section explores the factors influencing population-weighted PM2.5 concentrations in China. The influencing factors were first classified into six categories using K-means clustering, and the influencing factors of population-weighted PM2.5 concentration were analysed using the geodetector method, and the results obtained are shown in Figure 6. The factors affecting population-weighted PM2.5 concentrations in China are complex, and each factor has some explanatory power for population-weighted PM2.5 concentrations in most years. The factor with the greatest explanatory power for population-weighted PM2.5 concentrations is the average temperature, which has a q-value greater than 0.4 in all years, followed by the share of employment in the secondary sector, which has a q-statistic value in the range of 0.245 to 0.473. Electricity consumption and industrial output also have a greater degree of influence on population-weighted PM2.5 concentrations, and the former has a higher influence than the latter. In addition, topographic relief and total population also have a certain degree of influence on population-weighted PM2.5 concentrations, and the overall influence of total population on population-weighted PM2.5 concentrations tends to increase gradually.

2) Study on the interaction effect of influencing factors on population-weighted PM2.5 concentration

Since the spatial divergence of population-weighted PM2.5 concentrations in China is usually not determined by a single influencing factor, a geographical detector was used to quantify the linkage effect on the influencing factors of population-weighted PM2.5 concentrations after the two-factor interaction, and the results of the interaction detector in 2018 are shown in Figure 7. The results of the interaction detector show that the interaction between factors shows two main types of interactions: two-factor enhancement and non-linear enhancement. The interaction factors with strong explanatory power for population-weighted PM2.5 concentrations also differed for each year, with the higher interactions of the tertiary employment share and industrial SO_2 emissions factor in 2000, the higher interactions of average temperature with secondary employment share, tertiary employment share and industrial output value in 2003, and the higher interactions of secondary employment share and industrial output value in both 2006 and 2009. The interaction of the factor of the proportion of employment in the secondary sector and the factor of average temperature was larger in 2006 and 2009, the interaction of the factor of GDP per capita and industrial sulphur dioxide emissions was larger in 2012, the interaction of the factor of consumption expenditure per inhabitant and environmental protection keyword search index was larger in 2014, and the interaction of the factor of average temperature and industrial sulphur dioxide emissions was larger in 2016. The interaction between total population and average temperature was the largest in 2018, and most of the two-factor enhanced interaction types existed when science and technology input, industrial output value, average temperature, topographic relief, and built-up area greenery coverage interacted with other factors, with non-linear enhanced interaction types accounting for most of the interaction types.

ISSN 2616-5805 Vol. 4, Issue 2: 1-9, DOI: 10.25236/AJMS.2023.040201



Note: The interactions between the factors show two main types of interactions: two-factor enhancement and non-linear enhancement.

Figure 7: Interaction of factors influencing population-weighted PM2.5 concentrations in China in 2018

3.5 Population-weighted PM2.5 concentration prediction based on generalized regression neural networks

A high-precision prediction model is established to predict regional population-weighted PM2.5 concentrations based on the influencing factors, which is conducive to the coordinated allocation of various influencing factors. Based on the results of the detection of the influencing factors of population-weighted PM2.5 concentration in provincial areas of China, nine index factors, namely total population, GDP per capita, the proportion of people employed in secondary industries, scientific and technological investment, industrial output value, electricity consumption, average temperature, topographic relief and environmental protection keyword search index, which have greater explanatory power for the population-weighted PM2.5 concentration in provincial areas of China, are selected as network inputs, and the index factor of population-weighted PM2.5 concentration, an indicator factor, is used as the network output. In order to improve the accuracy of the whole prediction system and its stability, this paper adopts the cross-validation method to train the GRNN neural network and cycle through to find the best SPREAD, using Matlab software to build the GRNN neural network to predict the population-weighted PM2.5 concentration. Cross-validation by the leave-one-out method can be obtained when the SPREAD value is set to 0.05, at which time the value of the root mean square error is 6.1611 μg/m³ and the value of R^2 is 0.9661, and the training data is predicted well using this model. The model was used to predict the population-weighted PM2.5 concentrations in provincial areas of China from 2019 to 2021, and the prediction results are shown in Table.1.

ISSN 2616-5805 Vol. 4, Issue 2: 1-9, DOI: 10.25236/AJMS.2023.040201

Table 1: Projected population-weighted PM2.5 concentrations in China from 2019 to 2021

ProvName	2019	2020	2021	ProvName	2019	2020	2021
Beijing	58.69	54.40	50.00	**Hubei**	53.33	55.22	50.45
Tianjin	85.68	85.64	84.60	**Hunan**	57.14	62.84	52.07
Hebei	76.40	76.62	77.79	**Guangdong**	27.00	28.60	28.60
Shanxi	58.56	63.46	51.06	**Guangxi**	43.62	44.56	41.03
InnerMongolia	24.56	23.72	22.36	**Hainan**	18.99	20.46	19.56
Liaoning	31.61	39.91	36.91	**Chongqing**	54.92	55.92	45.53
Jilin	34.57	34.53	37.74	**Sichuan**	43.88	45.30	36.79
Heilongjiang	31.26	28.04	28.95	**Guizhou**	52.96	40.65	33.98
Shanghai	35.70	43.78	40.07	**Yunnan**	24.55	24.06	21.92
Jiangsu	58.60	51.56	46.20	**Tibet**	7.57	7.59	7.58
Zhejiang	41.28	41.49	31.41	**Shaanxi**	60.91	59.93	51.61
Anhui	52.99	52.88	50.18	**Gansu**	48.39	48.32	48.95
Fujian	26.72	25.50	24.27	**Qinghai**	38.57	38.93	39.57
Jiangxi	30.82	39.07	36.40	**Ningxia**	50.04	48.37	45.06
Shandong	61.24	47.70	47.70	**Xinjiang**	52.27	52.92	53.20
Henan	57.61	86.31	82.37				

4. Discussion

This study shows that the population-weighted PM2.5 concentrations in most regions of China decreased significantly in 2012, a decrease that is not only related to the energy conservation policies implemented by the state during the 11th Five-Year Plan, but also to the increased policy formulation and investment in the environmental protection industry in the opening year of the 12th Five-Year Plan. This reduction is not only related to the energy saving policies implemented by the State during the 11th Five-Year Plan, but also to the increased policy and investment in the environmental protection industry in the beginning of the 12th Five-Year Plan. According to Figure 4, the population-weighted PM2.5 concentration concentrations are concentrated in the Yangtze River Delta city cluster, the Central Plains city cluster, the Shandong Peninsula city cluster and the Beijing-Tianjin-Hebei city cluster, and it is important to strengthen pollution control in these city clusters in the future, balancing economic development with environmental protection. In addition, there are currently few clusters of low population-weighted PM2.5 concentrations within each of China's provincial regions, and there is a need to further strengthen the pollution control cooperation mechanism among China's provincial cities to enhance the diffusion effect and spatial clustering effect of low population-weighted PM2.5 concentrations in the region, thereby improving the overall pollution control level of China's provincial cities. Based on the results in Figure 5, there is a greater need to tailor pollution management policies and responses to the actual situation of pollution management in each region.

On a national scale, the results in Figure 6 are mainly related to global warming and China's vigorous industrial development. Inspired by the results in Figure 7, in reducing China's population-weighted PM2.5 concentrations to combat pollution in the future, the individual effects and interactive forces of multiple influencing factors need to be taken into account, and on the one hand, the importance of individual major influencing factors should be continuously strengthened, for example, the factor that has the greatest influence on the population-weighted PM2.5 concentrations in China's provincial areas in 2018 is the average temperature, and the natural environment should be continuously strengthened. On the other hand, factors that interactively enhance the effect should be controlled in order to reduce the population-weighted PM2.5 concentrations in provincial areas of China.

The population-weighted PM2.5 concentrations in China are influenced by a variety of factors. The prediction results show that GRNN has a strong non-linear fitting ability and the proposed GRNN model has excellent forecasting capability, which effectively solves the problem of predicting future population-weighted PM2.5 concentrations in China. The establishment of a high-precision prediction model can predict regional population-weighted PM2.5 concentrations in advance according to the influencing factors, thus facilitating the coordination of the development of various influencing factors.

5. Conclusions

The main findings of the study are as follows. (1) This study comprehensively describes the spatial and temporal variation characteristics of population-weighted PM2.5 concentrations in China from 2000 to 2018, in particular, the population-weighted PM2.5 concentrations have been decreasing year by year, which is to some extent attributed to the implementation of environmental protection policies. (2) China's population-weighted PM2.5 concentrations showed a spatially heterogeneous pattern between 2000 and 2018. (3) The factor with the greatest explanatory power for population-weighted PM2.5 concentrations at the national level is the average temperature. The interaction between the proportion of employment in the tertiary sector and the factor of industrial SO2 emissions is greater in 2000, the interaction between the proportion of employment in the secondary sector and the factor of average temperature is greater in 2009, and the interaction between total population and average temperature is greatest in 2018. (4) A prediction model of population-weighted PM2.5 concentration in China was established to predict the population-weighted PM2.5 concentration from 2019 to 2021. In the future, the distribution of population should be adjusted, investment in science and technology should be increased, high-quality foreign investment should be introduced, the importance of the natural environment should be continuously strengthened, industrial development should be planned and adjusted, the proportion of employment in each industry should be adjusted, strict laws and regulations for air pollution control should be set and financial investment for air pollution control should be increased, and the focus should be on linking ecological and economic benefits together for synergistic development in the future.

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