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The Impact of PM10 and Other Airborne Particulate Matter on the Cardiopulmonary and Respiratory Systems of Sports Personnel under Atmospheric Exposure

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Abstract: Respirable particulate matter (PM10) is atmospheric particulate matter with a kinetic diameter of less than or equal to 10 μm in air. According to the definition of the World Health Organization, it is called thoracic-enterable particulate matter because it can enter the body through the respiratory tract and be deposited into the lungs or absorbed into the blood and lymphatic systems. The toxic substances in it can enter the bloodstream directly and cause serious harm to human health. In addition, PM10 has unique physiological and biological effects, making it an important area of atmospheric chemistry research. In this study, two urban neighborhoods and sports companies were selected for the purpose of investigating the effects of PM10 concentrations in the air of neighborhoods and workplaces on people living and working in these environments for a long period of time, as well as synergistic effects between PM10 concentrations and changes in temperature and the incidence of related diseases. By assessing the extent of PM10's impact on the respiratory system, this study provides basic data for assessing the health hazards of particulate matter in community environments. This study also analyzed the synergistic effects between air pollutant concentrations, temperature changes, and the incidence of related diseases in two cities to investigate the spatial and temporal distribution characteristics of air pollution and the meteorological causes of pollution in China. On this basis, we established a prediction model for related sensitivity diseases to provide theoretical and technical support for the prediction of related sensitivity diseases on a nationwide scale. Meanwhile, our study also provides support to relevant government departments to formulate a scientific basis and preventive and control measures for dealing with air pollution and its effects on human health.

Keywords: atmospheric environment; PM10; sports personnel; cardiopulmonary respiratory system

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1. Introduction

Geological and climatic conditions, human life, and the development of production activities all have an impact on the air. Once the impact exceeds the self-purification ability of the atmosphere itself, it will cause atmospheric pollution, and the polluted atmosphere will affect human survival [1]. The level of particulate matter in the ambient air is the most important indicator for evaluating air pollution. Particulate matter (PM) is a solid or liquid particulate matter dispersed in the air, and its aerodynamic diameter is between 0.001 μm and 100 μm [2]. Of these, particles $\leq$ 10 microns in size are called PM, or PM10 [3]. PM originates not only from nature (such as volcanoes or sandstorms), but also from man-made activities such as industrial production, agricultural production, automobile exhaust emissions, and urban construction. PM stays in the air for a long time, which not only leads to reduced visibility and an imbalance in the atmospheric radiation balance, but more importantly, some fine and ultra-fine particles can enter the body (such as the bronchus and blood) and directly (metabolic products) and indirectly (follow-up emergency) harm the human body [4]. Ambient air particles are the most important indicator of environmental pollution. Previous studies have shown PM10 exposure can lead to the occurrence and aggravation of respiratory diseases; PM10 can also induce airway defense responses, such as increased mucus secretion and increased bronchial hyper-responsiveness, that aggravate an incomplete reversible obstruction of the airway [5,6]. These changes in the respiratory system can be reflected by changes in lung function [7].

The current research focuses scientifically and quantitatively on the impact of different types of pollutants on the incidence and mortality of sensitive diseases related to different sports personnel under the new level of air pollution so that different sports personnel can take targeted protective measures based on the pollutant concentration changes, and, at the same time, provides a scientific basis for related toxicological studies [8]. In addition, the literature [9] found that the association between pollutants and disease morbidity and mortality varied by countries and regions. Researchers [10] used advanced statistical methods such as time series to study the impact of some air pollutants on the morbidity of sports personnel. Researchers [11] believe that the existing research results are still very limited and the research is still in its infancy. It is necessary to further carry out the quantitative evaluation of the impact of air pollutants in different regions of the country on the human health of local sports personnel, and the detection of this potential subtle relationship is a challenging task. The research results show that the causes of pollutants are complex, and there are many influencing factors that are not only related to pollution source emissions but also closely related to local meteorological conditions [12]. The researcher believes that for a certain urban area, because the local pollution source is relatively stable within a certain time frame, the quality of the atmospheric environment mainly depends on the diffusion and dilution capacity of the atmospheric boundary layer for the pollutants. It can be seen that the pollution of the pollutant's distribution and diffusion are closely related to meteorological conditions [13]. Researchers have found that, according to their analysis, coal in the national energy structure accounts for about 70% of the total energy structure, which shows that the national energy is still dominated by coal [14]. Researchers have found that, in the past 30 years, the number of motor vehicles has increased sharply year by year, and the main pollution sources have changed from coal burning and industry to coal burning, industry, motor vehicles, and dust. The type of air pollution in the country's urban agglomerations has become soot [15,16]. At this stage, motor vehicle exhaust pollution has gradually replaced coal smoke pollution and has gradually become the main source of national pollutants. Some large cities have even changed from coal smoke pollution to motor vehicle exhaust pollution [17]. Statistics from the environmental protection departments of some cities in the area show that the "contribution rate" of pollutants emitted by motor vehicles to urban air pollution is as high as 50%, and some cities even reach 70% [18,19]. At the same time, medical meteorologists have found that changes in weather, climate, and related meteorological elements also have an impact on human health. Among them, the hot and cold effects caused by drastic changes in temperature usually play a leading role, thereby affecting the physical health of sports personnel, which can produce adverse effects, induce the occurrence or deterioration of related sensitive diseases, and even cause death [20]. Existing studies generally only focus on the impact of pollutants or meteorological elements on the morbidity and mortality of related diseases. Changes in the concentration of pollutants and changes in meteorological elements will both have adverse effects on human health, and the two influence and restrict each other. Therefore, when studying related sensitive diseases, the synergistic interaction between pollutants and meteorological elements should be considered at the same time [21].

The research in this article shows that lung function is affected by factors such as race, gender, height, weight, etc. The impact of the exposure level and time of production-environment air particles on lung function has also received attention, but the impact of community-environment air particles on lung function has been rarely reported. In order to compare the effects of different types of ambient air particles on lung function, we selected two communities and a sports company. Based on the monitoring of ambient air particles and the pulmonary function tests of the subjects' sports personnel, we discussed the level and time of exposure to environmental particles. The degree of impact on lung function provides basic data for evaluating the respiratory system hazards of particulate matter in the community environment. The research results using the AQI (Air Quality Index) data of 366 cities in the mainland country show that the overall AQI of northern cities is higher than that of southern cities over the whole year, and the region and the southern basin are the high-value centers of national pollution.

2. Methods and Materials

This thesis research uses multiple linear regression theory and the buffer method to establish a multiple linear regression model and input independent variables (weather, traffic, land type) to estimate the concentration of airborne particulate matter in the region. The model uses a combination of multiple seasons and multiple buffers to evaluate the fit of the four buffers in the four seasons of spring, summer, autumn, and winter, and select a well-fitted model to estimate the concentration of inhalable particulate matter; using GIS theory, we apply the multiple linear regression model equation to the geographic information of the region and city, and output the distribution map of PMl0 concentration in the four seasons of the region and city. Finally, we use cross-validation to evaluate the accuracy of the experimental model, check the closeness of the estimated concentration value of the model to the actual observed concentration value, and evaluate the rationality of the model. The concentration of particulate matter in the ambient air is determined using the filter quality method. Dust-laden air is collected using a dust-testing filter of known quality, and the concentration of particulate matter in the air is calculated according to the increase in the filter membrane after sampling and the amount of air collected. The collection of PM10 and PM2.5 uses the pre-separator on the sampler, and the separated dust particles of the corresponding size are collected using a dust-measuring filter of known quality.

In this study, in order to improve analytical accuracy, an XYZ-type mass spectrometer was used to measure the amount of solid particles in the atmosphere. This instrument has high precision mass measurement and particle counting with a detection accuracy of ±0.001 micrograms (ng).

The SPSS 11.5 and Epidat 4.2 statistical analysis software used in this study can be used for analysis to the nearest thousandth of a percentile.

2.1. Calibration of Air Pollution Index

The Air Pollution Index (API) is a dimensionless number that is used to reflect and evaluate air quality. It simplifies the concentrations of several air pollutants that are routinely monitored into a single conceptual index value form, and characterizes the air into grades of pollution degree and air quality status. Figure 1 shows the hierarchical distribution of the air pollution index.

The API ranges from 0 to 500 and is divided into 5 levels. An API value less than or equal to 50 indicates that the air quality is excellent. An API value greater than 50 and less than or equal to 100 indicates that the air quality is good, which is equivalent to reaching the national air quality class II standard. An API value greater than 100 and less than or equal to 200 indicates that the air quality is slightly polluted, which is equivalent to reaching the national air quality class III standard; after long-term exposure, the symptoms of susceptible people are slightly aggravated, and healthy people have irritation symptoms. An API value greater than 200 indicates that the air quality is poor, exceeding the national air quality level III standard. After a certain period of exposure, it will cause great harm to the human body.

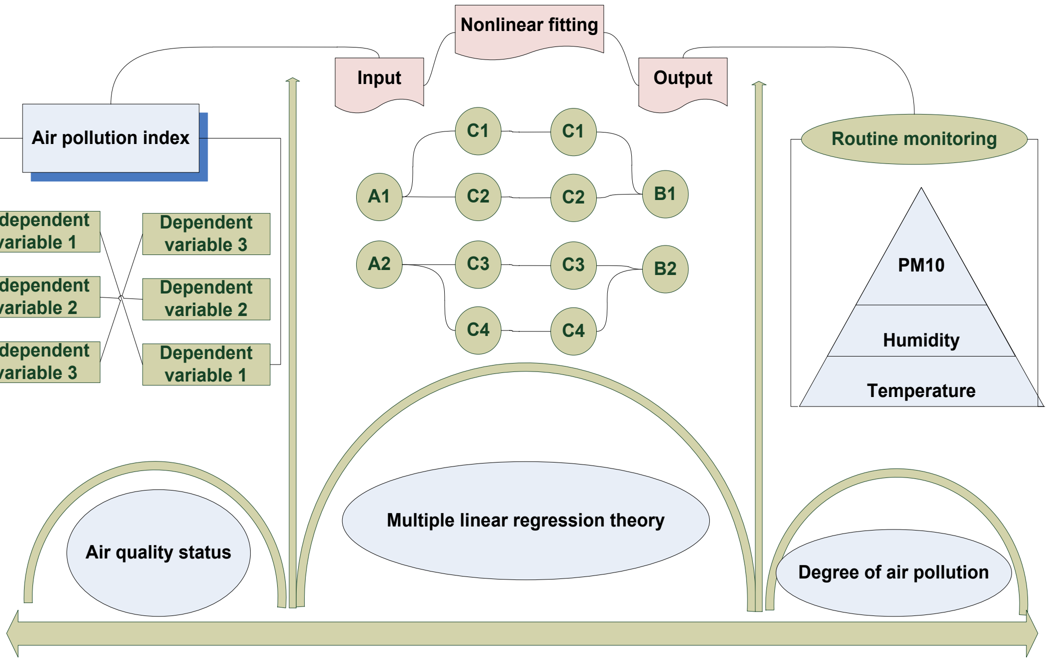

Figure 1. Hierarchical distribution of air pollution index using intelligent algorithms and big data analytics.

$$X[n] = \{x(1), x(2), \ldots, x(i)\}, i = 1, 2, \ldots, n, n \in R \tag{1}$$

The sub-index of a pollutant has a piecewise linear function relationship with the actual measured concentration. The specific calculation formula is as follows:

$$T[x] = \frac{x(i) - x(i-1)}{i} \times x(i), i = 1, 2, \ldots, n \tag{2}$$

$$D(x) = \sum_{i=1}^{n} (x(i) - \overline{x})^2, i = 1, 2, \ldots, n \tag{3}$$

Using the above formula, the sub-index of each pollutant can be obtained, API = max (1, 2, 3,..., *n*) is the value of the city's API, and the primary air pollutant of the city can be determined at the same time. According to the calculated API value and the air quality level table, the air quality pollution level and its impact on human health can be judged.

$$Y[x] = \begin{bmatrix} x(1) & 1 & 1 \\ 1 & \ldots & 1 \\ 1 & 1 & x(i) \end{bmatrix} \times \begin{bmatrix} 1 & 0 & 0 \\ 0 & \ldots & 0 \\ 0 & 0 & 1 \end{bmatrix} \tag{4}$$

$$\sum_{i=1}^{n} a(i) \times x(i) = a(1) \times x(1) + a(2) \times x(2) + \ldots + a(i) \times x(i) = 0 \tag{5}$$

The Air Quality Index (AQI) is a further improvement on the API. It monitors the average concentration of 6 pollutants including PM2.5, PM10, SO_2, NO_2, CO, and O_3 over a certain period of time, the API solution process is similar to that for obtaining the corresponding AQI sub-index values of these 6 pollutants, and the maximum value of AQI is the air quality situation at that time.

$$z = \begin{cases} \frac{\sqrt{x-1+i^2}}{x-1}, x > 1 \\ \frac{x}{\sqrt{x-1+i^2}}, 0 < x < 1 \end{cases} \tag{6}$$

When the pollution index of each pollutant is calculated, and when the AQI is greater than 50, the pollutant with the largest IAQI is the primary pollutant. If the IAQI is two or more, it is listed as the primary pollutant; pollutants with an IAQI greater than 100 are pollutants exceeding the standard.

$$s(x) - \frac{\frac{1}{n} \times \sum (x(i) - x) \times (y(i) - y)}{\frac{1}{n} \times \sqrt{\sum (x(i) - x)^2 \times (y(i) - y)^2}} = 0 \tag{7}$$

$$\begin{bmatrix} 1 & x^T \\ x & t + x^{-1} \end{bmatrix} \times \begin{bmatrix} a \\ b \end{bmatrix} = \begin{bmatrix} 1 \\ s(x) \end{bmatrix} \tag{8}$$

According to the range of AQI and the corresponding air quality level, we judge the air quality level of the city, the description of air quality, and the impact on human health. If the AQI value is less than 50, the air quality is class I (excellent); if the AQI value is between 51 and 100, the air quality is class II (good); if the AQI value is between 101 and 150, the air quality is class III (slight pollution); if the AQI value is between 151 and 200, the air quality is grade IV (moderate pollution); if the AQI value is between 201 and 300, the air quality is grade 5 (heavy pollution); and if the AQI value exceeds 300, the air quality is grade 6 (serious pollution).

2.2. Feature Extraction of Environmental Factors using Intelligent Algorithms and Big Data Analytics

Both the daily average values of atmospheric pollutant concentration data and meteorological data come from the automatic atmospheric detection system of a laboratory that has passed the National Metrology Certification (NMC), and there are special personnel responsible for inspection, discrimination, and management. The final data is without missing values. The respiratory (circulatory) system disease data of the regional cities used in this study are stored by a special person (SQL server database), summarized and sorted out, and the quality of the information excludes incomplete information and non-local population information. The Empirical Orthogonal Function (EOF) was first proposed by Pearson; it is a method for analyzing the structural features in matrix data and extracting the main data features. Table 1 shows the overall situation of the comprehensive environmental variable PM10. The principle of EOF is to find a comprehensive variable that can collectively reflect the information of the original variable from various linear combinations of the original variable, that is, to recombine the original multiple indicators into a few new uncorrelated comprehensive variables, and these integrated variables reflect as much information of the original variables as possible.

Table 1. Overall situation of the comprehensive environmental variable PM10 using intelligent algorithms and big data analytics.

Area Code	PM10 Mean	PM10 Min	PM10 Max
A	0.045	0.032	0.175
B	0.047	0.041	0.173
C	0.038	0.034	0.172

The API can only provide the daily average grading concentration standard of each pollutant, so the annual average concentration limit of each pollutant in this article is mainly based on the national air environmental quality standard and also refers to the corresponding foreign air environmental quality standard. The SO_2 annual average concentration limits for the first, second, and third levels are taken as 0.02, 0.06, and 0.10 mg/m^3, respectively (according to China's national standard "Atmospheric Environmental Quality Standard"). Figure 2 shows the statistical distribution of PM10 concentration limits at various levels. This article uses the index method to determine the monthly and quarterly average concentration limits of PM10.

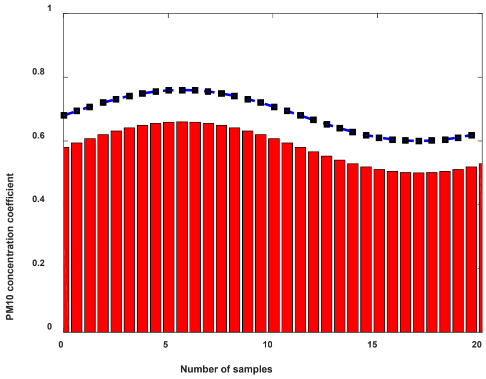

Figure 2. Statistical distribution of PM10 concentration limits at various levels. The red bars represent the number of examples, the black line represents the concentration of PM, and the black block just highlights the black line and has no real meaning.

The maximum mixed-layer thickness reflects the maximum atmospheric volume at which pollutants can be diluted. It represents the maximum range of pollutants being diluted and diffused in the vertical direction, and is one of the indicators of pollution prediction. This study uses the dry adiabatic curve graphical method. Is thisto calculate the maximum mixed-layer thickness. This study uses a stable energy calculation method, which is developed from an energetics point of view, and proposes a parameter that describes the stability of atmospheric stratification from the ground to a specific height-stabilized energy. In this study, the stable energy levels are 15 levels from the ground. Things that are close in space are more similar, and things that are far away are less similar. The value of the point to be interpolated is determined by the weight of several points closer to it. The closer the distance is, the greater is the weight of the interpolation point to determine the interpolation point, which is the reciprocal of the distance. On the contrary, the longer the distance is, the smaller the weight of the point is. The weight plays an important role in the interpolation process. When the weight is one, the inverse distance interpolation function becomes a linear function, and the interpolation result decreases as the distance increases. When the weight is greater than one, the inverse distance function becomes a nonlinear function, and the interpolation result can be optimized by adjusting the weight.

2.3. Pollution Parameter Weight Optimization

Correlation coefficients measure the degree of correlation and trends between variables and inform data analysis and modeling. But when several correlation coefficients are put together and their sample lengths are different, it is difficult to compare which correlation is better. Table 2 shows the results of correlation analysis between PM10 and meteorological factors. In order to unify the period, they need to be converted into correlation coefficients under the same sample for comparison. Methods using time series regression models (case crossover model, cohort method, generalized addition model, etc.) have been widely used in research on the adverse effects of atmospheric pollutants and meteorological elements on sports personnel’s health, and these are relatively mature and applied.

The structure of the model is determined by the internal connection of the data used in the research. The method is simple and the modeling form is very flexible. It can realize the addition and sum of different forms of functions. The model can be fitted using dependent variables. Independent variables with linear relationships can also be fitted to independent variables that have complex nonlinear relationships with dependent variables. It has more advantages in exploring the correlation between the dependent variable and the independent variable, the size of the correlation and the shape of the correlation curve, and it can better explain the essential relationship between the expectations of the reflected variable and the explanatory variable. Figure 3 shows a schematic diagram of confounding factors in the pollution model.

Table 2. Correlation analysis results of PM10 and meteorological factors using intelligent algorithms and big data analytics.

Index	PM10	Regional Sampling Point	Temperature	Humidity
PM10	1	0.010	0.213	0.342
Regional sampling point	0.010	1	0.183	0.235
Temperature	0.213	0.183	1	0.127
Humidity	0.342	0.235	0.127	1

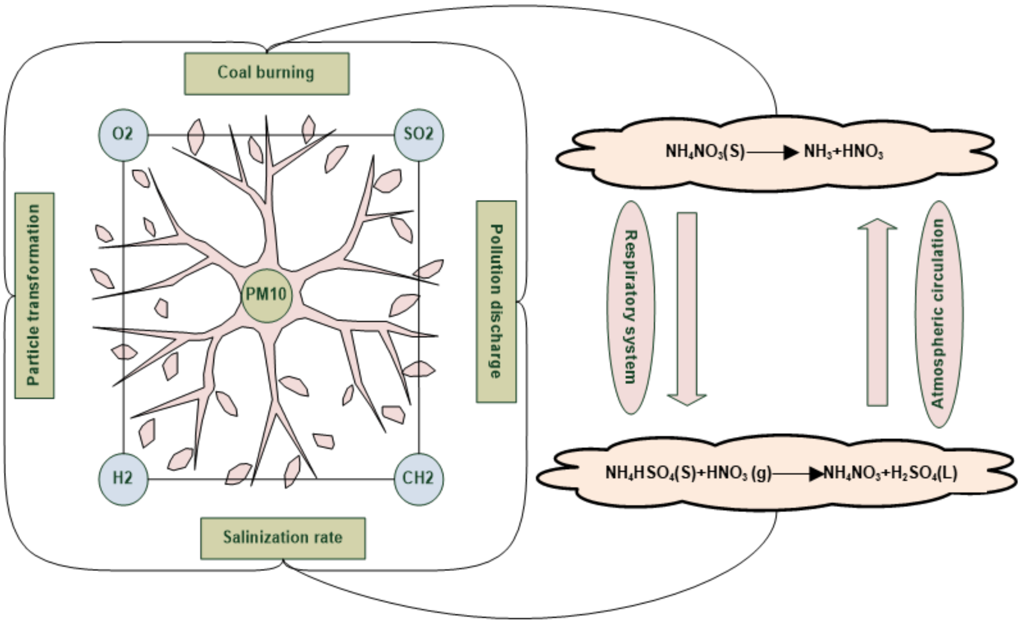

Figure 3. Schematic diagram of confounding factors in pollution model using intelligent algorithms and big data analytics.

In summary, when establishing the core model of pollutants on the number of emergency department visits for respiratory diseases, other factors such as meteorological factors, time series, week effects, holiday effects, and flu days were introduced as confounding factors to correct their effects on pollutants. Taking into account that the trend of the number of daily emergency room visits for respiratory diseases is nonlinear over time, the natural Cubie Spline Functions in the model are used to control the mid-to-long-term trend. Taking into account the effects of the above-mentioned confounding effects, a core model of regional and municipal respiratory diseases was established. After that, the residual graph and partial autocorrelation function graph are used to judge whether the residual of the model has a random and stable white-noise distribution. If the residual independence requirement is not met, the model is further adjusted.

2.4. PM10 Particulate Matter Level Detection

Cities A and B in China are Nanjing and Xiamen, respectively, with annual average PM10 values of 0.174 and 0.13, representing moderately polluted and mildly polluted PM10. Xiamen is a coastal city located on the southeastern coast of Fujian Province, China, and Nanjing is the capital city of Jiangsu Province, China, located in the eastern part of Jiangsu Province on the southern bank of the lower reaches of the Yangtze River (Figure 4).

Figure 4. Map of China.

Neighborhoods and sports companies in the two cities were selected to conduct medical examinations of people who had lived or worked there for more than five years. Table 3 shows the comparison of the PM10 concentration interpolation models. According to the results of physical examination, 345 sports personnel who have no occupational exposure, no bad habits, and no chronic liver, kidney, and immune system diseases are selected for the questionnaire survey. The surveyed persons were between 18 and 60 years old, with 199 males and 146 females; all of them had graduated from junior high school or above; the living area was between 50 and 200 square meters. All rooms are central-heating unit-style suites, and household fuels are all natural gas.

Table 3. Comparison of PM10 concentration interpolation models.

Index	Input Parameter	Mean Square Error	Standard Deviation	Mean Standard Deviation
1	65	0.013	0.23	1.002
2	59	0.021	0.18	1.251
3	83	0.037	0.75	1.341
4	97	0.038	0.28	1.021
5	72	0.051	0.41	1.251

We used questionnaires to learn about respiratory symptoms such as fever, cough, sputum, and other respiratory symptoms of sports personnel over the past two weeks, respiratory system diseases and respiratory system chronic diseases over the past six months, and to calculate the positive rate of respiratory symptoms over two weeks and the two-week prevalence of disease and six-month prevalence of chronic respiratory disease. Similarly, GIS is used to calculate the area ratio of land-use types in the entire region, and the proportions of various types of land data in a buffer zone of 5, 10, 20, and 50 m are obtained, respectively. The data has been saved in a raster format to obtain the area data on land-use types covered by the city.

In order to study the effects of pollutants on the health of sports personnel of different genders, ages, and in different seasons, this paper analyzes gender (male and female), age (0~15, 15~64, ≥65 years old), and cold and warm season (April to September is the warm season, October to March is the cold season) stratification, and stratifies analysis of the health effects of pollutants. In addition, the multi-pollutant model is fitted on the basis of the single-pollutant model to test the robustness of the single-pollutant model. At the same time, it analyzes the adverse effects of PM 10 on the health of sports personnel and evaluates other pollutants on the pollution of concern for the impact of the material effect estimate. Figure 5 shows the environmental pollution assessment matches in different regions. Pollutants have a certain impact on the number of emergency department visits for respiratory diseases. At the same time, considering that temperature also has a certain effect on the number of emergency department visits for respiratory diseases, there is a certain relationship between average temperature and pollutants. Therefore, this study uses a generalized additive model to explore the effects of PM 10 under the condition of different meteorological factor stratification.

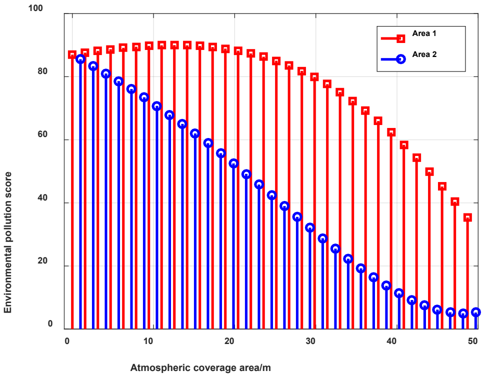

Figure 5. Matchsticks of environmental pollution assessment in different regions.

3. Results and Analysis

3.1. Analysis of the Effects of the Atmospheric Environment

By analyzing the distribution of and changes in PM10 pollution meteorological parameters and their relationship with API in two typical representative cities in China, it is found that the annual change in the thickness of the inversion layer is significantly positively correlated with the PM10 concentration, and the annual average value is thick in winter and thin in summer; the maximum thickness of the mixing layer is negatively correlated with the PM10, and its intra-annual change is contrary to the thickness of the inversion layer, which is thick in summer and thin in winter; the stabilizing energy is similarly positively correlated with PM10, and the maximum value appears in early summer, and the stabilizing energy in northern cities is larger than that in southern cities. The maximum value occurs in winter and the minimum value occurs in early summer, and the stabilization energy of the northern cities is larger than that of the southern cities. Therefore, the heavy pollution in northern cities in winter is caused by the double effect of the increase in pollution emissions due to heating and the decrease in diffusion capacity of the atmospheric boundary layer reflected by the pollution meteorological parameters. In this study, it is clarified that the nonparametric function estimation method is generalized cross-validation (GCV) with unrestricted degrees of freedom.

The cumulative values of PM10 heavy pollution impacts in each region and city had the maximum lag effect on the increase in the number of respiratory (circulatory) emergency room patients. After the significance test (significance level of 0.01), for every 10 $\mu g/m^3$ increase in PM10 concentration at a cumulative lag time of 6 days, the number of daily outpatient and emergency department visits for respiratory (circulatory) diseases in the corresponding regions and cities increased by 1.72% (1.39%).

3.2. Example Application and Analysis

The data was input into the computer using Epidat A3.1, and SPSS 11.5 was used for analysis. Statistical analysis was performed using a chi-square test, etc., and the significance level was 0.05. The impact of pollutants on the incidence of respiratory diseases in young ($\leq$30 years old) and elderly sports personnel ($\geq$65 years) is higher than that in adults; the impact on the incidence of circulatory diseases in elderly sports personnel is higher than adults. The impact of pollutants in regions and cities on the number of children and elderly sports personnel hospitalized with respiratory diseases is higher than that on the number of adults, with the most significant impact affecting children. In short, as far as respiratory diseases are concerned, pollution has the most significant impact on vulnerable elderly and child sports personnel; as far as circulatory system diseases are concerned, pollution affects elderly sports personnel the most significantly. At the same time, the results of studies in the two cities both show that women are more sensitive to pollutants than men. During the study period, the annual average concentration of pm10 was 73.305 $\pm$ 30.539 $\mu g/m^3$, which was higher than the WHO's annual average quality guideline value of PM10 (20 $\mu g/m^3$) and the national secondary standard annual average concentration (70 $\mu g/m^3$). The maximum monitoring average value reached 193.179 $\mu g/m^3$. The annual average concentration of PM2.5 in the main urban area is 49.200 $\pm$ 23.848 $\mu g/m^3$, which is higher than the World Health Organization (WHO) air fine particulate matter PM2.5 annual average quality guideline value (10 $\mu g/m^3$) and the national secondary annual standard. The average concentration is 35 $\mu g/m^3$, and the maximum daily monitoring average value reaches 156.115 $\mu g/m^3$.

The basic meteorological elements, pollutant concentrations, and pollution meteorological parameters were comprehensively considered, relevant forecasting factors were selected, and the respiratory system test results of personnel in regional cities were established, respectively. The trial prediction results showed that the model trial prediction accuracy rates of the number of emergency department visits for respiratory and circulatory diseases in the region and city were 66.73% and 72.16%, respectively, and the trial prediction accuracy rates were 79.73% and 85.09%, respectively. The accuracy rates of the network model for the respiratory system and circulatory system disease inpatients were 44.12% and 51.54%, respectively, and the test prediction accuracy rates were 54.45% and 63.20%, respectively.

Figure 6 shows the trapezoidal graph of air pollution rank correlation analysis. Spearman rank correlation analysis showed that respiratory visits for children in the main urban area were positively correlated with PM10 ($r = 0.1260$, $p = 0.0159$) and negatively correlated with mean temperature ($r = -0.4189$, $p < 0.0001$). We controlled for meteorological factors, weekly effects, seasonal variations, and other confounders with temporal effects. PM10 had a lagged effect on daily respiratory visits for sports personnel. The differences in the two-week positive rate, two-week prevalence, and six-month prevalence of respiratory symptoms among sports personnel in the two cities with different pollution levels were statistically significant ($p < 0.05$), indicating that PM10 infection increased the prevalence of respiratory diseases among personnel significantly. Based on the different sources of ambient air production, two neighborhoods and a sports company were selected for this part of the study. Based on the selection of representative sampling sites, ambient air particulate samplers were used to measure particulate concentrations in the ambient air of the communities and the workplace of the stadium. Via continuous sampling and measurement of the atmospheric environment, basic data on ambient air particulate levels in different areas were obtained, and ambient air particulate levels in the communities and workplaces were analyzed.

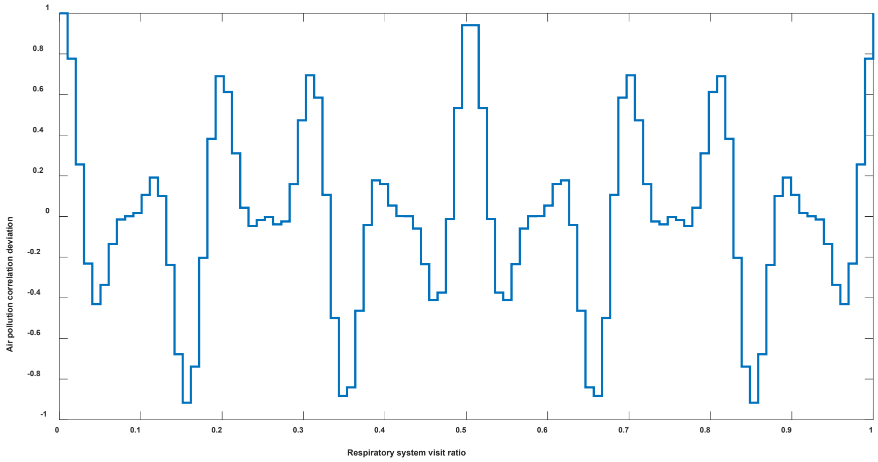

Figure 6. Air pollution rank correlation analysis ladder diagram.

4. Conclusions

The concentration of particulate matter generated by the sports company during production is much higher than the atmospheric particulate matter concentration in the community. Even using various measures to reduce the dust concentration in the stadium, the concentration of particulate matter in the workplace was more than 15 times that of the community. Lung function tests were performed in 345 sports personnel of the community and stadium with age and gender matching. The results showed that the main indicators of physical lung function of sports personnel were less than those of the community sports personnel, and the proportion of lung dysfunction was 85.5%. It is above that of the community at 51.5%. The most restrictive pulmonary ventilation disorder is a restricted ventilation barrier, which is suspected to be associated with respiratory disease or fibrosis caused by particulate dust exposure, resulting in decreased pulmonary compliance. As a result, the percentage of the damage of the sports company (76.5%) was higher than that of the neighborhoods (26.9%), and the difference was statistically significant. It shows that high levels of particles cause more damage to lung function.

(1) This study informs the impact of PM10 on respiratory health. The effects of airborne particulate pollutants on respiratory disease clinic visits for athletes varied from season to season with different lag periods. Meanwhile, the study revealed the temperature threshold that leads to heavy air pollution. In the vicinity of this threshold, the atmospheric stratification tends to stabilize. At this time, it is easy to reach the minimum value, and the stabilization energy easily approaches the maximum value, showing the most unfavorable horizontal transport and vertical diffusion of pollutants. Meteorological conditions can be used as an important indicator for forecasting air pollution potential.

(2) The degree of PMl0 pollution varies in different seasons in the region, and there is a certain change law; according to the contour map under different concentration gradients to qualitatively analyze the exposed population, it is found that most of the sports personnel in the region are exposed to the heavily polluted area of PMl0. This paper uses the cross-validation method to evaluate the reliability of the model and calculates the value of the regression model, which indicates that the existing data is better for fitting the model. This paper collects meteorological data such as the monitoring concentrations of daily inhalable particulate matter PM10. Spearman rank correlation was used to analyze the correlation between the number of athletes' respiratory system outpatient visits in the main urban area, meteorological factors, and various pollutants. Based on possible confounding factors such as seasonal trends and other time random effects, the lag effect is included to quantitatively analyze the effects of PM10 on athletes' daily respiratory outpatient clinic visits.

(3) The trial prediction results showed that the model trial prediction accuracy rates of the number of emergency department visits for respiratory and circulatory diseases in the region and city were 66.73% and 72.16%, respectively, and the trial prediction accuracy rates were 79.73% and 85.09%, respectively. The accuracy rates of the network model for the respiratory system and circulatory system disease inpatients were 44.12% and 51.54%, respectively, and the test prediction accuracy rates were 54.45% and 63.20%, respectively.

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