Article

Spatio-Temporal Patterns of Global Population Exposure Risk of PM_{2.5} from 2000–2016

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Abstract: A high level of fine particulate matter (PM_{2.5}) has become one of the greatest threats to human health. Based on multi-source remote sensing data, the pollutant population exposure model, accompanied by the Theil–Sen Median and Mann–Kendall methods, was used to analyze the spatio-temporal patterns of global population exposure risk of PM_{2.5} from 2000 to 2016. The population distribution patterns of high-risk exposure areas have been accurately identified; the variation trend and stability of global population exposure risk of PM_{2.5} have also been analyzed. According to the results, the average concentration of PM_{2.5} is correlated with the total population. The average concentration of PM_{2.5} for countries from high to low are Asia (14.7 µg/m³), Africa (8.1 µg/m³), Europe (8.03 µg/m³), South America (5.69 µg/m³), North America (4.41 µg/m³), and Oceania (1.27 µg/m³). In addition, the global average population exposure risk of PM_{2.5} is decreasing annually. Specifically, China, India, Southeast Asia, and other regions have higher exposure risks. Less developed mountainous regions, cold regions, deserts and tropical rainforest regions have lower exposure risks. Moreover, Oceania, North America, South America and other regions have relatively stable exposure, whereas areas with relatively unstable exposure risk of PM_{2.5} are mainly concentrated in Asia, India, and eastern China, followed by Southeast Asia, Europe, and Africa. Furthermore, Asia has the largest population of all the continents, followed by Africa and Europe. Countries with increased populations are mainly distributed in Africa, whereas the countries with a declining population are mainly distributed in Europe. Based on this, it is important to identify the relationship between PM_{2.5} concentration and population exposure risk to improve human settlements and environmental risk assessment.

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1. Introduction

Due to the continuous growth of the global manufacturing scale and population, energy extraction, processing, and consumption are exponentially increasing. The contradiction between resources, environment, and development has intensified, leading to great difficulties in the governance of ecological environments. Air pollution has become a global challenge to human health, production, and life. The World Health Organization has emphasized that air pollution is one of the main environmental risks affecting human health. PM_{2.5} (or particulate matter with an aerodynamic diameter ≤2.5 µm) is a solid particulate matter with an equivalent diameter less than or equal to 2.5 µm in aerodynamics [1]. It is the main form of air pollution and the leading cause of global non-communicable diseases [2]. Air pollution exposure refers to the state or process in which individual residents are exposed to air pollution by direct contact with air pollutants [3]. Scientific and accurate exposure assessment is a prerequisite for the risk prevention and control of PM_{2.5}. Since the beginning of the 21st century, PM_{2.5} has not only become one of the main threats to human health but has also brought many challenges to the sustainable development of cities [4]. Scientifically identifying the changing characteristics and patterns of the spatial

distribution of PM_{2.5} concentration and revealing the patterns of population exposure risk of PM_{2.5} are of great significance to the coordinated development of regional environmental protection and economy.

European and American countries, as well as the WHO, have stipulated an international standard for PM_{2.5} monitoring based on the results of epidemiological research on PM_{2.5} [1]. The international standard has three transitional goals. The annual average concentration and daily average concentration standards of PM_{2.5} are 35 µg/m³ and 75 µg/m³ in the first transition period and 25 µg/m³ and 50 µg/m³ in the second transition period, and 15 µg/m³ and 37.5 µg/m³ in the third transition period. At present, this standard has been widely adopted in the world [5,6]. Previous studies have shown that long-term exposure to excessive PM_{2.5} increases the risk of lung diseases (such as lung cancer) [1,7], cardiovascular diseases [8], cerebrovascular diseases [9], etc., while also increasing the death rate [1,10,11]. Since the beginning of the 21st century, developed countries in Europe and North America, which were plagued by environmental pollution, have successfully dealt with pollution problems. The present environmental pollution is mainly distributed across developing countries. The report of State of Global Air 2019 released by the American Institute of Health Effects shows that the number of people who died of stroke, heart disease, lung cancer, diabetes, and chronic lung disease due to long-term exposure to outdoor and indoor air pollution in 2017 reached nearly 5 million worldwide, and 1.2 million in China.

At present, most research has been conducted on the spatial and temporal pattern and evolution of PM_{2.5} at different spatial scales [12–14]. Few have studied the exposure risk assessment for macro-level populations and the temporal and spatial changes of PM_{2.5}. Most research uses air quality monitoring data to widely study the temporal changes and spatial patterns of PM_{2.5} nationwide, in regions (such as the Yangtze River Delta, Pearl River Delta, Beijing-Tianjin-Hebei) [15,16], provinces [17], as well as cities [18]. Some scholars have put PM_{2.5} monitoring values into space through spatial interpolation methods such as the Kriging interpolation, inverse distance weighted interpolation, and spline function interpolation to obtain the spatial data of PM_{2.5} [19]. Using Zhao County in Shijiazhuang as an example, Li et al. [20] selected 100 monitoring sites of PM_{2.5} as sample points to compare and analyze the accuracy of different interpolation methods on the spatial results of PM_{2.5}. The aerosol optical depth (AOD) in satellite remote sensing data and the particle concentration observed on the ground are closely correlated [21]. Therefore, models such as the linear regression model [22], generalized additive model [23], geographic weighted model [24], BP neural network model [25], and support vector machines [26] can be used to construct the relationship between remote sensing retrieved AOD data and PM_{2.5}, and assess PM_{2.5} mass concentration. While exploring the temporal and spatial changes of PM_{2.5}, some scholars have also analyzed the composition of PM_{2.5} and its relationship with natural conditions such as meteorology [27], topography and vegetation, and social and economic activities such as population distribution, urbanization, energy utilization, to explain the source of PM_{2.5} and the reasons for its changes. With a deeper understanding of PM_{2.5} and its hazards, research on PM_{2.5} has gradually extended to the field of human health but mostly focuses on specific groups (such as the elderly and children) or microscopic assessment of individual exposure and health risks [28,29].

In recent decades, the exposure risk assessment of PM_{2.5} pays less attention to the exposure risk of large-scale groups. In addition, a common research paradigm and approach have not been established on this topic. Most of the existing studies only analyze the impact of PM_{2.5} exposure on human health from a micro perspective and lack a macro perspective and long-term evaluation of the temporal and spatial patterns of PM_{2.5} population exposure risk [30]. In the past, the population exposure risk of PM_{2.5} was mostly based on the analysis of an administrative unit scale, although social and economic factors such as population, gender, education level, and income can also be considered administrative regions. The research based on this type of data treats the population of each census block as a homogeneous entity and does not study the spatial heterogeneity in depth.

Research on the exposure risk of the environmental population in previous years was mainly conducted in the disciplines of epidemiology and environmental chemistry, and the research content developed from single pollutant to mixed pollutants, from individuals to groups, from statistical methods to model improvements. Traditional research on the population exposure risk of PM_{2.5} is based on administrative regions, which has defects in the continuity of time and space [31,32]. Some research relying on the census data and the data of PM_{2.5} from environmental monitoring sites ignore the internal spatial heterogeneity and splits the spatial units, which is not conducive to pollutant prevention and control from a macro perspective [33]. For the census data, the credibility is high, but the time resolution updated every decade or more meets neither the real-time change of exposure risk nor matches the data of PM_{2.5}. In recent years, with the wide application of the pattern-scale-driving force paradigm in the fields of geoscience and environmental science, as well as the rapid progress in the spatial and temporal resolution of remote sensing data, better data sources are provided to conduct environmental monitoring, pollution distribution, and exposure risk assessment on different temporal and spatial scales. Research objects include administrative regions, cities (groups), watersheds [34–36], and others. The research content mainly focuses on factor research, source analysis, migration paths, health risks, and policy governance of environmental exposure [37,38].

Mankind has only one earth, and all countries live in one world. It is the responsibility of everyone to build a community of shared future for mankind, protect the ecological environment, and resolve climate change issues. Based on the remote sensing data of global PM_{2.5} and population from 2000 to 2016, this article uses the pollutant population exposure risk model and the approaches of Theil–Sen Median and Mann–Kendall to analyze the temporal and spatial evolution patterns of PM_{2.5} in long-term time series and the evolution characteristics of global population exposure risk of PM_{2.5} on the pixel scale. This article also analyzes the stability of PM_{2.5} population exposure and explores the temporal and spatial evolution patterns of exposure risk. By showing spatial results of regional differences in the population exposure risk of PM_{2.5} globally, this article proposes differentiated and targeted response measures to PM_{2.5}. Long-term quantitative studies of PM_{2.5} population exposure risk are helpful to analyze global exposure risk changes of PM_{2.5}. They not only provide a reliable and detailed data basis for research on health effects and exposure risk of PM_{2.5}, environmental management, and epidemiology, but also provide scientific references for the governance of the global atmospheric environment.

2. Materials and Methods

2.1. Data Source

The concentration data of PM_{2.5} used in this article comes from the Global Annual PM_{2.5} Grids from Moderate Resolution Imaging Spectroradiometer (MODIS), Multi-angle Imaging SpectroRadiometer (MISR), Sea-Viewing Wide Field-of-View Sensor (SeaWiFS) and Aerosol Optical Depth (AOD) with geographically weighted regression (GWR). The data was downloaded from NASA (National Aeronautics and Space Administration). The time series was from 2000 to 2016, and the spatial resolution was $0.01^\circ \times 0.01^\circ$ (<http://earthdata.nasa.gov>, accessed on 10 October 2020). The PM_{2.5} grid data used GWR, which was retrieved from AOD data from MODIS, MISR and SeaWiFS. In order to determine whether the accuracy of the data met the research needs, this article collected accessible PM_{2.5} data monitored on the ground in three regions (Europe, Canada, and China). The data was matched with the remote sensing data, and three selected indicators including Coefficient of Determination (R^2), Mean Prediction Error (MPE), and Root Mean Squared Prediction Error (RMSE), to verify the accuracy of the remote sensing data of PM_{2.5} mass concentration.

The population grid data comes from LandScan Global Population Grids (<https://landscan.ornl.gov>, accessed on 10 October 2020), and the spatial resolution is about 1km. LandScan collects high-precision census data and data on roads, slopes, land cover, night lights and city density in various countries using GIS technology and high-resolution remote sensing

images to simulate the spatial distribution of a population. LandScan uses population-related indicative factors such as building areas and residential areas to check and verify the simulation results, thereby ensuring the accuracy of the data. Many scholars use LandScan to conduct research in different regions of China, verifying its applicability and accuracy [39,40]. This article uses the population data of various countries published by the World Bank (<https://www.worldbank.org/en/home>, accessed on 10 October 2020) to verify the LandScan population grid data. It uses GIS spatial zoning statistical tools to count the total population of each country in LandScan and compares it with the total population published by the World Bank for verification.

The vector base map of the world's boundaries comes from standard maps on the website of the Department of Natural Resources of China (<http://bzdt.ch.mnr.gov.cn/>, accessed on 10 October 2020). It was drawn based on a world map with the approval number GS (2016) No. 1665. The base map was not modified.

2.2. Research Methodology

2.2.1. Accuracy Test of Remote Sensing Data

To comprehensively and objectively evaluate the estimation accuracy of the GWR spatial downscaling method used in this article, predicted values and observed values from the ground observation stations of R^2 , MPE and RMSE are used to evaluate the accuracy of the remote sensing data of $PM_{2.5}$. The formula and specific definitions are as follows:

$$MPE = \frac{\sum_{i=1}^n |P_{PM_{2.5}} - PM_{2.5}|}{n} \quad (1)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (P_{PM_{2.5}} - PM_{2.5})^2}{n}} \quad (2)$$

where $P_{PM_{2.5}}$ indicates remote sensing value; $PM_{2.5}$ represents station observations; n represents the total number of modeling dataset records.

2.2.2. Calculation of Global Population Exposure Risk of $PM_{2.5}$

The $PM_{2.5}$ population exposure risk index can evaluate the exposure status in each pixel of raster [41,42]. The formula is as follows:

$$R_i = \frac{POP_i \times C_i}{\sum_{i=1}^n POP_i \times \frac{C_i}{n}} \quad (3)$$

where i denotes the grid number; R_i represents the $PM_{2.5}$ population exposure risk index in grid i ; POP_i denotes the number of populations within grid i ; C_i denotes the $PM_{2.5}$ concentration value within grid i ; n is the sum of the number of grid nets in the study area.

2.2.3. Trend Analysis

Theil–Sen Median trend analysis can simulate the changing trend of each grid. It does not require samples to form a certain distribution and is not interfered with by abnormal values. It has strong resistance to data errors and can objectively reflect the changing trend of $PM_{2.5}$ population exposure risk in a long-term time series. The formula is as follows [43]:

$$S_R = Median\left(\frac{R_j - R_i}{j - i}\right) \quad 2000 \leq i \leq j \leq 2016 \quad (4)$$

where S_R is the slope of the fitted equation; R_i is the exposure risk index value in year i ; R_j is the exposure risk index value in year j . $S_R > 0$ indicates an increasing trend in the population exposure risk to $PM_{2.5}$, and $S_R < 0$ indicates population exposure risk to $PM_{2.5}$ showing a decreasing trend.

The Mann–Kendall test is a non-parametric statistical test used to determine the significance of trends. The formula is as follows [44].

Setting the time series data i and j , $2000 \leq i \leq j \leq 2016$.

$$Z = \begin{cases} \frac{S-1}{\sqrt{s(S)}}, & S > 0 \\ 0, & S = 0 \\ \frac{S+1}{\sqrt{s(S)}}, & S < 0 \end{cases} \quad (5)$$

$$S = \sum_{j=1}^{n-1} \sum_{i=j+1}^n \operatorname{sgn}(R_j - R_i) \quad (6)$$

$$\operatorname{sgn}(R_j - R_i) = \begin{cases} 1, & R_j - R_i > 0 \\ 0, & R_j - R_i = 0 \\ -1, & R_j - R_i < 0 \end{cases} \quad (7)$$

$$s(S) = \frac{n(n-1)(2n+5)}{18} \quad (8)$$

where R_i and R_j denote the $\text{PM}_{2.5}$ population exposure risk values in years i and j of the cell, respectively; n indicates time series; $\operatorname{sgn}(R)$ represents notation function. When $|Z| \geq Z_{1-\alpha/2}$, the null hypothesis is rejected. $Z_{1-\alpha/2}$ is the standard normal variance, and α is the significance test level. When $|Z_c|$ is greater than or equal to 1.28, 1.64, and 2.32, it means that the significance test passed the 90%, 95%, and 99% confidence levels, respectively. It judges the significance of exposure risk over time series in $\alpha = 0.05$ [45].

3. Results

3.1. Spatial Distribution Pattern of Global $\text{PM}_{2.5}$ and Population

3.1.1. Spatial Distribution Pattern of Global $\text{PM}_{2.5}$

The article ensures the reliability of the remote sensing data of $\text{PM}_{2.5}$ by selecting China, Canada, and Europe as the verification regions and matching the data with annual averages of $\text{PM}_{2.5}$ in the three regions until 2016. Since 2016, there have been 1542 environmental monitoring sites in China. This article ensured that the verification points were distributed as evenly as possible in space by selecting 230 verification points randomly in space. There are 1327 $\text{PM}_{2.5}$ monitoring sites in Europe, from which 180 verification points were selected randomly. There are 30 monitoring sites in Canada, located mainly in the south, from which 12 verification points were randomly selected. Finally, a total of 442 sets of valid data were obtained. The spatial distribution is shown in Figure 1. This study conducts the accuracy test to it.

Figure 1. Spatial Distribution of Verification Points of $\text{PM}_{2.5}$ Data.

After comparing the verification results of PM_{2.5} data in the three regions, this article finds that the EU has the highest R², followed by Canada and China; Canada has the highest MPE and RMSE, followed by the EU and China. It can be concluded that PM_{2.5} data from the EU and Canada have high accuracy and good inversion results, whereas that of China is low. The average R² of these three regions is 0.755, MPE is 3.512%, and RMSE is 4.739 µg/m³. On the whole, the accuracy of PM_{2.5} remote sensing data met the research needs and accuracy was ensured. The data has also been widely used in related research [12,46–48].

The spatial distribution of global and various continents average PM_{2.5} concentration from 2000 to 2016 is shown in Figure 2a. It can be seen that Asia has the highest concentration, followed by Africa, Europe and other continents. The average concentration of PM_{2.5} per unit is 14.7 µg/m³ in Asia, 8.1 µg/m³ in Africa, 8.03 µg/m³ in Europe, 5.69 µg/m³ in South America, 4.41 µg/m³ in North America, and 1.27 µg/m³ in Oceania. The current value of PM_{2.5} (2016) is 16.6 µg/m³ in Asia, 9.15 µg/m³ in Africa, 8.9 µg/m³ in Europe, 5.66 µg/m³ in South America, 3.6 µg/m³ in North America, and 1.34 µg/m³ in Oceania.

Figure 2. Global average PM_{2.5} concentration of spatial distribution from 2000 to 2016 (a); changes in PM_{2.5} concentration of in various continents (b).

Figure 2b shows the PM_{2.5} concentration of various continents. It can be directly concluded that the PM_{2.5} pollution in Asia is much higher than in other continents; the average concentration of PM_{2.5} in 17 years is about 30 µg/m³, especially that in India and China. The areas with high PM_{2.5} concentrations in China are mainly distributed in the central part of the Northeast Plain and the triangle, an area surrounded by Beijing–Shanghai–Changde. The highly polluted areas of PM_{2.5} in South Asia are mainly distributed in India and Bangladesh, and the PM_{2.5} concentration in India shows a gradually increasing trend, with a 17-year annual average value of 33.36 µg/m³. The PM_{2.5} value in Europe is also relatively high, showing an increasing then decreasing trend. Highly polluted areas of PM_{2.5} are distributed in Poland, Czech Republic, Bulgaria, and Italy. The third highest is in Africa, where the PM_{2.5} concentration is spatially high in the middle, low in the north and south, high in the west and low in the east. The 17-year PM_{2.5} concentration in Africa shows a slowly increasing trend. The areas with increases are mainly distributed in the central and southern regions of Africa. The Sahara Desert in the northern region is inaccessible, so the PM_{2.5} concentration remains extremely low throughout the year.

The annual average PM_{2.5} value of North America and Oceania remained at a relatively low level; the average PM_{2.5} concentration in 2017 was 4.4 µg/m³ and 1.34 µg/m³, respectively. The two continents have a low population density with high industrial output value but low pollution due to the developed tourism industry in Oceania and the surrounding ocean so it is not affected by the diffusion of PM_{2.5} from other areas; therefore, the air quality is good. The economic development of South America is much lower than that of North America; it is an important agricultural product and the export regions of mineral resources have underdeveloped industries. The annual average concentration of PM_{2.5} is 5.69 µg/m³, which is slightly higher than that of North America.

3.1.2. Spatial Distribution Pattern of Global Population

LandScan Global Population Grid data is the basic data for research on $PM_{2.5}$ population exposure risk in this article, so it is necessary to ensure the accuracy of the population grid data. This article obtains the total population data of various countries in 2016 from the World Bank database, including 97 sets of valid data. Using the regional statistical tool of ArcGIS software, the total population of each country under the remote sensing data was counted. Through comparison with statistical data from the World Bank, this article verifies these 97 sets of data. It was found that the data is accurate, with $0.99 R^2$ ($p < 0.001$). The average deviation was only 2.43%.

In Figure 3, which shows the spatial distribution of the global population from 2000 to 2016, it can be seen that Asia has the largest population, followed by Africa, Europe, North and South America, and Oceania. Asia has the largest population base and land mass than that of other continents. In particular, the countries of China, India, Indonesia, and Japan account for about 40% of the global population. This massive population consumes a lot of resources and energy, and the processing and production of resources and energy have caused a large amount of $PM_{2.5}$ emissions. On the contrary, serious $PM_{2.5}$ pollution has a counterproductive effect on humans and affects human health. Countries where the population continues to grow are mainly distributed in Africa, and countries where the population continues to decrease are mainly distributed in Europe. The population growth rate of Africa is fast, and regions with the highest population densities are distributed in three regions, namely, the Nile River Basin, the Gulf of Guinea coast, and the Mediterranean coast. The population density in Europe is 20–50 persons/ km^2 . The population density of North and South America is 0–25 persons/ km^2 with densely populated areas mainly distributed in the United States, Brazil, and Mexico. The population of Oceania is mainly distributed in the coastal areas of southeastern Australia and New Zealand.

Figure 3. Global population average spatial distribution from 2000 to 2016.

3.2. Distribution Pattern of Global Population Exposure Risk of $PM_{2.5}$

This article divides the population exposure risk value (R_i) of $PM_{2.5}$ into seven levels: extremely low risk, low risk, relatively low risk, general risk, relatively high risk, high risk, and extremely high risk [34,49]. Table 1 shows the detailed descriptions.

3.2.1. Interannual Change of $PM_{2.5}$ Population Exposure Risk

The annual average population exposure risk of $PM_{2.5}$ globally is decreasing annually on a macro-scale. However, due to significant differences in industrialization and consumption levels in various regions, differences show within the regions (Figure 4). Areas with high $PM_{2.5}$ exposure risk are distributed in regions and countries with high population

density and rapid economic growth, including China, India, Southeast Asia, the Nile River, the Gulf of Guinea, Western Europe, and other places. Areas with low PM_{2.5} exposure risk are mainly distributed in plateaus, deserts, tropical rainforests, and other places, such as the Qinghai-Tibet Plateau, Greenland Island, Siberian Plain, Sahara Desert, and Amazon River. Asia (5.94) has the highest PM_{2.5} exposure risk, followed by Africa (0.62), Europe (0.45), South America (0.32), North America (0.27), and Oceania (0.01).

Table 1. Division of Population Exposure Risk Value of PM_{2.5}.

Population Exposure Risk Value	Population Exposure Risk Levels
$R_i = 0$	extremely low risk
$0 < R_i \leq 1$	low risk
$1 < R_i \leq 2$	relatively low risk
$2 < R_i \leq 3$	general risk
$3 < R_i \leq 4$	relatively high risk
$4 < R_i \leq 5$	high risk
$R_i > 5$	extremely high risk

With every 5 $\mu\text{g}/\text{m}^3$ indicating a level, the cumulative percentage of populations exceeding the limit of each level was counted by the average PM_{2.5} concentration every 4 years from 2000 to 2016 from 10 to 45 $\mu\text{g}/\text{m}^3$ (Figure 5). The results show that from 2000 to 2008, the proportion of people over 20 $\mu\text{g}/\text{m}^3$ had a significant upward trend; in 2012, it shows a significant downward trend, and in 2016, it shows a trend of recovery. In 2000, 73.82% of the global population were exposed to an environment with PM_{2.5} concentration over 10 $\mu\text{g}/\text{m}^3$, 12.59% were exposed to an environment with PM_{2.5} concentration over 35 $\mu\text{g}/\text{m}^3$, and 6.26% were exposed to an environment with PM_{2.5} concentration over 45 $\mu\text{g}/\text{m}^3$. In 2004, 76.51% of the global population were exposed to an environment with PM_{2.5} concentration over 10 $\mu\text{g}/\text{m}^3$, and 22.06% were exposed to an environment with PM_{2.5} concentration over 35 $\mu\text{g}/\text{m}^3$. In 2008, 74.09% of the global population were exposed to an environment with PM_{2.5} concentration over 10 $\mu\text{g}/\text{m}^3$, 28.77% were exposed to an environment with PM_{2.5} concentration over 35 $\mu\text{g}/\text{m}^3$, and 18.99% were exposed to an environment with PM_{2.5} concentration over 45 $\mu\text{g}/\text{m}^3$. In 2012, 75.17% of the global population were exposed to an environment with PM_{2.5} concentration over 10 $\mu\text{g}/\text{m}^3$, 25.07% were exposed to an environment with PM_{2.5} concentration over 35 $\mu\text{g}/\text{m}^3$. In 2016, 75.72% of the global population were exposed to an environment with PM_{2.5} concentration over 10 $\mu\text{g}/\text{m}^3$, 27.51% were exposed to an environment with PM_{2.5} concentration over 35 $\mu\text{g}/\text{m}^3$, and 18.8% were exposed to an environment with PM_{2.5} concentration over 45 $\mu\text{g}/\text{m}^3$.

Figure 4. Cont.

Figure 4. Cont.

Figure 4. The spatial distribution of annual average $PM_{2.5}$ population exposure risk globally from 2000 to 2016.

Figure 5. Population percentage of exposure exceeding the $5 \mu\text{g}/\text{m}^3$ limit of each level.

3.2.2. Distribution Pattern of Population Exposure Risk of PM_{2.5} in Various Continents

The average population exposure risk of PM_{2.5} in all continents from 2000 to 2016 are shown in Figure 6. The average exposure risk in Asia in the past 17 years was 5.94, much higher than that of other continents. Exposure is an extremely high risk. Due to flat terrain, frequent human activity, high levels of industrialization and consumption, northern India and eastern China, which are the two major regions with the highest PM_{2.5} concentration in the world, have serious air pollution. Exposure risk is determined by both PM_{2.5} and population; those two regions not only have high PM_{2.5} concentration but also an extremely high population density. China and India are the most populous countries in the world, so the exposure is at an extremely high-risk level. The population exposure risk of PM_{2.5} is also high in Japan, with an average value of 4.48 in the past 17 years, which is at a high-risk level. India, Bangladesh, and eastern Pakistan in South Asia are areas with extremely high risk of population exposure to PM_{2.5}, and the risk is increasing annually with the highest value in 2016. Southeast Asia is another region with high PM_{2.5} population exposure risk, including Vietnam, Thailand, Cambodia, Myanmar, and Indonesia. The average exposure risk in the past 17 years was 8.44, 5.89, 2.03, 2.25, and 2.76, respectively, among which Vietnam and Thailand have extremely high exposure risk.

Figure 6. Average population exposure risk of PM_{2.5} in all continents of the world from 2000 to 2016.

The average exposure risk of PM_{2.5} in the past 17 years in Africa was 0.62, and the exposure risk level is relatively low, showing a spatial distribution pattern of high in the south and low in the north. The areas with high population exposure risk of PM_{2.5} are mainly concentrated in five areas along the northern coast of the Gulf of Guinea, the Nile River and the deltas in Egypt, Ethiopia, Lake Victoria, and Pretoria in South Africa. The common denominator of these countries is the relatively slow economic development. However, they have abundant mineral resources and a large amount of cheap labor, so the economy will grow rapidly, and exposure risks will gradually increase. The Pretoria region of South Africa has the most developed economy and the largest population in Africa, so the exposure risk is also higher. The population exposure risk of PM_{2.5} in other regions and countries in Africa is mainly at low levels.

The average exposure risk of PM_{2.5} in the past 17 years in Europe was 0.45, second only to Asia and Africa. Europe borders the Arctic Ocean to the north, the Atlantic Ocean to the west, and the Mediterranean to the south. The climate is mainly a temperate marine and Mediterranean climate, which is suitable for human production and life. The population is mainly concentrated in megacities, and the urbanization rate is extremely high. Europe is also one of the most economically developed regions in the world. Belgium, Italy, Germany, the United Kingdom, Poland, France, and Ukraine have higher population exposure risks of PM_{2.5}. The average values in 2017 were 5.35, 3.63, 3.42, 2.81, 2.76, 1.58, and 1.29, respectively. Exposure risks in urban areas are mainly at extremely high levels.

The population exposure risk of $PM_{2.5}$ first increases then decreases. It gradually increased from 2000 to 2006, and then decreased slowly after 2006. The health standard of $PM_{2.5}$ stipulated by the EU is $25 \mu g/m^3$. In 2014, only 8% of the urban population was exposed to an environment where $PM_{2.5}$ exceeds the standard [50]. In summary, the European air pollution control effect is significant, and its air pollution control measures and experience have important reference value for other regions [51].

The population exposure risk of $PM_{2.5}$ in North America is relatively low, mainly with extremely low risk and low risk levels. The average population exposure risks of $PM_{2.5}$ in Mexico, the United States, and Canada are 1.27, 0.41, and 0.03, respectively, and the current exposure risk values are 0.98, 0.3, and 0.02. Both the 17-year average and current exposure values are relatively low. Although industry in South America is underdeveloped, this region is rich in natural resources and reserves, especially oil, iron ore, and coal. Economic development depends mainly on the export of primary products and singularized products [52]. Areas with the highest population exposure risk of $PM_{2.5}$ in North America are distributed in clusters of megacities. The population exposure risk of $PM_{2.5}$ in Oceania remains at extremely low and low risk levels. In recent years, the exposure risk of $PM_{2.5}$ in central Australia, southern Australia, and New Zealand has been gradually increasing; this is due to the arid climate and minimal rainfall in central and western Australia, which is affected by the subtropical high pressure and the great watershed. As the global climate becomes warmer, the temperature in Oceania is rising and has become more arid, so deserts are more widespread, causing a high concentration of $PM_{2.5}$.

3.3. Temporal and Spatial Changing Characteristics of Global Population Exposure Risk of $PM_{2.5}$

3.3.1. Temporal Changing Characteristics of Global Population Exposure Risk of $PM_{2.5}$

Figure 7 shows the time changing trend of population exposure risk of $PM_{2.5}$ in each continent from 2000 to 2016. It can be directly concluded that the changes in each continent are significantly different. The exposure risk value in Asia is significantly higher than other continents (the ordinate is on the right). The lowest value is in the year 2000, when the exposure risk value was 3.55. The highest value was in 2008, when the exposure risk value was 3.87. The exposure risk value of other continents was relatively low (the ordinate is on the left). The exposure risk value of Africa has been increasing, with the lowest value being 0.33 in 2009 and the highest value being 0.45. Europe and North America show a decreasing trend. The highest values of exposure risk in Europe and North America were 0.39 and 0.24 in 2000, and the lowest values were 0.23 in 2008 and 0.13 in 2016, respectively. The exposure risk values in Oceania and South America are relatively low and the changes are also small. In particular, the exposure risk values in Oceania have always remained extremely low.

Figure 7. Temporal changes of average global population exposure risk of $PM_{2.5}$ from 2000 to 2016.

3.3.2. Linear Change Trend of Global Population Exposure Risk of PM_{2.5}

The approaches of Theil–Sen Median and Mann–Kendall were used to characterize significant changes in the time series of global population exposure to PM_{2.5}. When $S > 0$, it indicates that the population exposure to PM_{2.5} has an increasing trend in the time series. When $S < 0$, population exposure to PM_{2.5} shows a decreasing trend. The Z value of the test result is graded separately, and the absolute value of the Z value is divided into four levels [45]: high reliability change ($|Z| > 2.58$), reliability change ($1.96 < |Z| \leq 2.58$), less reliability change (1.65), and no reliability change ($0 < |Z| \leq 1.65$). The S value and the $|Z|$ value are reclassified and then superimposed on the same pixel to obtain the linear change trend of global population exposure to PM_{2.5} (Figure 8).

Figure 8. Linear change trend of global population exposure to PM_{2.5}.

As shown in Figure 8, regions with high reliability increases in global population exposure risk of PM_{2.5} are mainly distributed in Asia and Africa. Regions with less reliability increases are distributed around the areas of high reliability increases, and regions with high reliability decreases are mainly distributed in Western Europe and the United States.

The regions with significant increases in Asia are mainly distributed in the South Asia, Northeast China, the Qinghai-Tibet Plateau, the Pamirs Plateau, the Caspian Sea, and Southeast Asia. The Indo-China Peninsula also shows a significant increase, including Vietnam, Laos, Cambodia, Myanmar, eastern Thailand, and Java Island, the northwestern Sumatra Island in Indonesia. Their changing trends all increased significantly. In particular, the Qinghai Tibet Plateau is sparsely populated; however, there is also an increasing trend of exposure risk with high reliability. With the increase of global temperature, the frozen soil becomes degraded, and even freeze-thaw desertification occurs; the climate of Qinghai Tibet Plateau is cold and dry, and the effect of freezing and weathering is strong. The freezing and thawing process of surface rock and soil is also intensified due to the degradation of frozen soil; it will lead to vegetation decline with bare and broken soil, leading to desertification. The PM_{2.5} concentration formed an increasing trend in this area.

The changing characteristics in Africa are mainly high reliability increases, caused by the rapidly growing economy and population. The proportion of secondary industry in Africa continues to rise, leading to a significant increase in industrial waste gas, which has deteriorated the natural environment and continuously destroyed ground vegetation. Therefore, many areas see a significant increase in population exposure to PM_{2.5}. Areas with high reliability increases include Congo, Zambia, Angola, Tanzania, Zambia, South Africa, Madagascar, southern Niger, northern Nigeria, Burkina Faso, western Chad, and central Algeria. Areas with reliability increases and less reliability increases surround areas with high reliability increases. Areas with significant decreases in Africa are distributed in the northern Gulf of Guinea, Western Sahara, Egypt, and Libya.

The changing trends in North America are polarized. The United States sees high reliability decreases, and only southern Alaska has a small area with high reliability increases. The western and central regions of Canada show a large area with high reliability increases. The changing characteristics in South America are mainly increasing, and the areas with significant increases include the Amazon delta, eastern Brazil, and the Negro and Colorado river basins in Argentina.

Oceania is the region with the best air quality in the world, except for Antarctica. Central and southwestern parts of Australia have seen high reliability increases of PM_{2.5} exposure risk due to the influence of the natural environment. The central and western areas of Australia are affected by the subtropical ridge, so the climate is arid. In addition, the Great Dividing Range blocks the warm and wet flow brought by southeast monsoons, rendering the climate more arid. Moreover, there are many eucalyptus trees in Australia prone to large fires, thus increasing the exposure risk of PM_{2.5}.

3.3.3. Stability of Global Population Exposure Risk of PM_{2.5}

The stability of the population exposure risk of PM_{2.5} from 2000 to 2016 was analyzed by the standard deviation method, and the stability of population exposure changes is divided into five levels: stable, relatively stable, mildly stable, relatively unstable, and unstable. It can be seen in Figure 9 that there are apparent spatial differences in the changes in population exposure to PM_{2.5}. Asia, India and eastern China see the significant changes in exposure risk, followed by Southeast Asia, Europe and Africa. The two regions of India and eastern China are among the fastest growing regions in the world in terms of GDP. The material and capital flow are extremely fast, the population density is high, the PM_{2.5} concentration is high, and the fluctuation is dramatic; therefore, the exposure risk is unstable.

Figure 9. Stability of global population exposure risk of PM_{2.5}.

The regions with unstable exposure risk in Africa are mainly distributed in the Congo, South Africa, the Gulf of Guinea, Lake Victoria, and Ethiopia. These regions are rich in natural resources and abundant in labor, attracting a large amount of foreign capital for development and investment, especially for mine development and the manufacturing industry, which have continuously increased the concentration of fine particles; the stability of population exposure to PM_{2.5} has also continued to decrease. Europe is one of the most economically developed regions in the world. Most countries have entered the post-industrial era. In recent years, low-risk atmospheric control has been improved, and the air quality has become increasingly excellent. Most areas of North America show good stability. Only the eastern part of the United States, Guatemala, and Mexico City, the capital of Mexico, show unstable population exposure to PM_{2.5}. These three regions are areas where population exposure to PM_{2.5} has significantly decreased.

3.4. Population Distribution Characteristics under High Exposure Risk of $PM_{2.5}$

For 2016, the total population distribution under high exposure risk of $PM_{2.5}$ (including high risk and very high risk of exposure) is shown in Figure 10. The total population distribution of all countries under high exposure risk shows a high spatial distribution in Asia and the Americas and a low spatial distribution in Europe, Africa, and Oceania. Countries with a total population exceeding 100 million with high exposure risk include China, India, the United States, Indonesia, Brazil, Pakistan, Nigeria, and Bangladesh, which are among the top ten countries in terms of population. Countries with a population between 50 million and 100 million with high exposure risk include Russia, Mexico, Japan, and Egypt. The actual populations of these countries also rank among the highest in the world. The total population under high exposure risk is consistent with the actual population.

Figure 10. Population distribution under high exposure risk of $PM_{2.5}$.

Figure 11 shows the spatial distribution of population density under high exposure risk of $PM_{2.5}$ globally in 2016. The population density of continents with high exposure risk are Asia and Europe in terms of spatial distribution, and low in other continents. Countries with a population density over 200 persons/ km^2 with high exposure risk include India, Japan, South Korea, Bangladesh, the Netherlands, Rwanda, and Burundi. There are 13 countries with a population density between 100 and 200 persons/ km^2 , namely, the United Kingdom, Germany, Switzerland, Belgium, Italy, Pakistan, Nepal, North Korea, Vietnam, the Philippines, Dominica, El Salvador, and Nigeria. Countries with a population density between 50 and 100 persons/ km^2 include China, Thailand, Malaysia, Indonesia, Sri Lanka, France, Spain, Poland, Czech Republic, Hungary, Croatia, Turkey, Iraq, Jordan, and Egypt.

Figure 11. Population density distribution under high exposure risk of $PM_{2.5}$.

4. Discussion

This article focuses on the current situation of population exposure of PM_{2.5} from a global macro perspective by identifying high exposure risk areas and analyzing the temporal and spatial changes of areas with high exposure risk of PM_{2.5}. By combining previous research results, this article explores the reasons for high exposure risk in various countries in order to reduce exposure risks and provide continuous basic data in continuous time and space for cross-border and inter-regional air pollution prevention and control. The analysis of the population exposure risk of PM_{2.5} in the long-term time series from 2000 to 2016 has compensated for missing data in some countries.

This article finds that from 2000 to 2016, the global population exposure risk of PM_{2.5} showed a gradually decreasing trend on a macro-scale, with the highest spatial distribution in Asia, followed by Africa, Europe, and other continents. Among them, the PM_{2.5} pollution in Asia is the most serious, with the exposure risk value far higher than that of other continents. In particular, India and China, which are also the two most populous countries in the world, have a high exposure risk of PM_{2.5} as a result of their high population density. In these areas of high exposure risk, it is necessary to establish atmospheric quality standards and reduce emissions simultaneously [53]; a series of environmental action plans should be continuously formulated, adjusted and implemented. The effectiveness of economic activities should be emphasized, and a convergence of environmental protection and economic development should be established [54,55]. Under unchangeable natural conditions such as terrain and climate, adjusting and optimizing the industrial structure, energy consumption structure, and transportation structure are the main means to eradicate air pollution [56].

Considering the low level of economic development in some countries and regions, the imperfect industrial structure, the complexity of air pollutants and the long-term governance of air pollutants, it is important to think about solutions for treating both symptoms and root causes in order to mitigate air pollution when a radical cure cannot be achieved. While mitigating air pollution, reducing population exposure risks and protecting public health are also issues that must be considered. In addition to source prevention and control, this article's authors believe that areas with high population exposure risk of PM_{2.5}, public awareness of air pollution, health risk assessment, health warning on heavy pollution, the emergency response of medical systems, and health protection of special groups should also be considered, and corresponding countermeasures should be formulated.

Due to limited data acquisition, this article lacks daily, monthly and seasonal average data of PM_{2.5} and population data. Therefore, it does not analyze the daily, monthly and seasonal differences of population exposure to PM_{2.5}. Future research is expected to obtain such data with a higher temporal and spatial resolution to further refine the dynamic population exposure risk analysis of PM_{2.5}. In addition, this article's authors think that the driving mechanism of the evolution of temporal and spatial patterns of population exposure of PM_{2.5} require further in-depth and quantitative research.

5. Conclusions

In general, based on multi-source remote sensing data, the pollutant population exposure model, accompanied by the Theil–Sen Median and Mann–Kendall methods were used to analyze the spatio-temporal patterns of global population exposure risk of PM_{2.5} from 2000 to 2016. The population distribution patterns of high-risk exposure areas were accurately identified, the variation trend and stability of global population exposure risk of PM_{2.5} were also analyzed. It was found that the total population has a certain relationship with PM_{2.5} concentration and exposure risk. The average annual population exposure risk of PM_{2.5} globally is decreasing annually on a macro-scale but there are differences within various regions. Specifically, areas with a higher population exposure risk of PM_{2.5} are China, India, Southeast Asia, and other areas with rapid economic development and a dense population. Eight countries among the most populated ten countries are under

high exposure risk of PM_{2.5}. On the contrary, exposure risk of PM_{2.5} is relatively low in mountainous areas, cold regions, deserts, tropical rainforests, and other areas with poor transportation and underdevelopment. Areas with a relatively stable population exposure risk of PM_{2.5} are mainly concentrated in Oceania, North America and South America; in contrast, areas with relatively unstable population exposure risk of PM_{2.5} are mainly concentrated in Asia, India and eastern China, followed by Southeast Asia, Europe and Africa. Therefore, by exploring the relationship between PM_{2.5} concentration and population exposure risk, we not only clarify the impact of spatial heterogeneity on PM_{2.5} concentration and population exposure risk but also provide a theoretical basis for global environmental risk assessment.

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