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Application of Correlation Analysis Based on Principal Components in the Study of Global Temperature Changes

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A B S T R A C T

The current issue of global warming is prominent, and there are many factors that affect global temperature changes. Therefore, how to correctly judge the relationship between each influencing factor and global temperature changes and accurately find out the main reasons of global temperature rise which are the problems that must be considered and solved to alleviate global warming at present. According to previous official data, this paper proposed a correlation analysis method based on principal components to comprehensively analyze the relationship between natural disaster factors, human factors, and global temperature changes, and find out the main reasons that affect global temperature rise. Compared with traditional research methods, the new method provided in this paper can still remain scientific and accurate calculation results while reducing computational dimensions. The experimental results showed that in the relationship between natural disasters and global temperature changes, the average correlation coefficient of the principal component represented by biological disasters and geological disasters was the highest at 0.6097 and a test value of $p<0.05$, indicating a significant positive correlation between them and global temperature. However, the correlation coefficient of the principal component represented by floods and storms was negative, indicating a negative correlation between them and global temperature. In exploring the main factors affecting global temperature rise, both the total global population and the total global CO_2 emissions had a significant positive correlation with global temperature. Among them, the average correlation coefficient of the total global population was the highest at 0.9972, and its weight also was the highest at 26.42%. Therefore, this indicates that the total global population is the most important factor affecting global temperature rise. This study can provide reference for countries to make decisions in response to global warming.

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NOMENCLATURE

X_1	Forest and grassland fire	*TGP*	Total global population
X_2	Volcano	*TGCE*	Total global CO_2 emissions
X_3	Earthquake	*AT*	Global average temperature
X_4	Biological disaster	G_i	i principal components
X_5	Drought	*PCC*	Pearson correlation coefficient
X_6	Flood	*KCC*	Kendall correlation coefficient
X_7	Geological disaster	*SCC*	Spearman correlation coefficient
X_8	Storm	*MC*	Mean of correlation coefficient

INTRODUCTION

Currently, the issue of climate change has become one of the most serious challenges facing human society, especially the issue of global warming, which is a global threat. Similarly, global warming is also one of the major environmental issues affecting all living organisms, which has begun to put pressure on various sectors [1].

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Global warming refers to the climate change that causes temperature rise in the Earth's atmosphere and oceans over a period of time due to the greenhouse effect. Specifically, due to the continuous accumulation of the greenhouse effect, the energy absorbed and emitted by the Earth's atmosphere system is imbalanced, and energy continues to accumulate in the Earth's atmosphere system, leading to an increase in temperature and global warming [2]. The fifth assessment report prepared by the United Nations Intergovernmental Panel on Climate Change (IPCC) pointed out that global warming is continuing, and by 2100, the average temperature of the Earth will increase by 0.3-4.5° C compared to 1986-2005 [3]. In addition, in 2019 Nowak [4] explained that the accumulation of carbon dioxide in the atmosphere reached about 403 parts per million, while in 2015 this index was about 400 ppm. According to scientists, the earth has never experienced such a rate of increase in carbon dioxide production, so that its growth rate has been 100 times faster than during the last ice age.

Global warming can have a series of impacts on the natural environment and human society, such as extreme temperature or heavy precipitation, sea level rise, glacier melting, hurricanes, drought, loss of biodiversity and the threat to the physical health of people in various countries, etc [5-8]. Ashrafizadeh and Seifollahi [2] points out that global warming will cause polar ice sheets to melt, ocean water levels to rise, temperature gradients between the poles and the equator to disappear, precipitation and humidity from the Atlantic to the Green Continent to be disrupted, the Green Continent to dry up, and atmospheric changes caused by polar ice sheet melting will cause severe and destructive storms along the ocean coast. Besides, hurricanes bring rainstorm, causing devastating floods around the world. Some animal species are extinct, and many animal pests reproduce exponentially [9]. With this unfavorable climate change and the growth of plant and animal pests, the proliferation of pathogenic viruses and microorganisms poses serious risks to our human life and aquatic life in the ocean [10].

From this, it can be seen that if effective measures are not taken to control it, the continuous rise in global temperature will bring many devastating disasters to human society, cause the death of many animals and plants, and cause destructive changes to the environment, seriously affecting human normal life. However, before proposing solutions, we must clearly identify the main reasons that affect global warming.

Regarding the issue of what causes global warming, Raj, et al. [11] points out that the release of greenhouse gases such as CO_2 has a significant impact on global warming. The allowable concentration of CO_2 in the atmosphere is 0.04%, and when the CO_2 concentration in the atmosphere exceeds the allowable range, it will lead to global warming. Zhong [12] points out that the gradual enhancement of the greenhouse effect will cause global warming, and the factors affecting global climate change include changes in the earth's orbit, solar radiation, volcanic activities, the intensity of the magnetic field, changes in the ocean, and human influence. Chen [13] points out that the main reason for climate change in the past century is the large amount of greenhouse gases emitted by humans. Fallah, et al. [14] points out that the large-scale emissions of greenhouse gas (GHG) are an important cause of climate change, and urban household waste (MSW) is an important source of greenhouse gas emissions [15]. Vilakazi Bonginkosi and Mukwada Geofrey [16] points out that population growth is an important factor leading to climate change activities. Kumar [17] points out that human activities mainly enhance the impact of greenhouse gases by emitting carbon dioxide, but humans also have a significant impact on other greenhouse gases, and the continuous accumulation of greenhouse gases promotes the intensification of global warming. Mella [18] points out that global warming depends on the greenhouse effect generated by the continuous emissions of greenhouse gases from human activities and natural events. Pandey [19] points out that human intervention through industrialization and deforestation has caused ecological and environmental imbalances, making survival difficult, and global warming is one of the main threats to human survival caused by this imbalance. Bian [20] suggests that waste heat dominates global warming. Wu and Jiang [21] points out that the destruction of the ozone layer, continental storms and Asian brown clouds are the causes of global warming.

In a word, there are many factors that affect the global temperature change, such as floods, hurricanes, droughts, volcanic eruptions, forest fires and other natural disasters, as well as the total global population and total global carbon dioxide emissions, etc. Thus, it is very necessary to adopt appropriate tools and means to accurately analyze the relationship between various influencing factors and global temperature change, and further find out the main reasons for the current global temperature rise, so that various countries can adopt targeted and effective policies to address the problem of global warming.

Therefore, based on the Global Disaster Data Platform, the World Meteorological Organization (WMO) and the National Aeronautics and Space Administration (NASA) of the United States [22-24]. This paper identified eight natural disaster factors and two human factors related to the global temperature changes, and collected the corresponding data of each index factor and the global average temperature data from 2012 to 2021. In order to solve the problem of data redundancy and high computational complexity caused by excessive index dimensions in traditional research methods, this paper proposed a correlation analysis method based on principal components to calculate and analyze the index data of various influencing factors. This method can not only solve the problem of redundant index data and reduce computational complexity, but also comprehensively consider the impact of various index factors without missing key influencing factors. Also, experimental results indicated that this method can scientifically and correctly identify the relationship between various factors and global temperature changes, as well as find out the main reasons of global warming.

METHODOLOGY

Principal component analysis

Principal component analysis is a multivariable technique for analyzing data tables, in which the observed values are described by several interrelated quantitative dependent variables, and the objective is to extract important feature information from literature [25]. It mainly converts multiple indexes into several comprehensive indexes, and usually refers to the comprehensive indexes generated by the transformation as the main components. From a mathematical point of view, this is a dimension reduction processing technology [26-28]. The algorithm flowchart is shown in Figure 1.

The specific steps of the principal component analysis algorithm are as follows:

Assuming there are n samples and p indexes, and the value of the j-th index in the i-th sample is $\mathrm{w_{ij}}$, and then the sample matrix W of size $n \times p$ can be formed:

$$\mathrm{W} = \begin{bmatrix} \mathrm{w}_{11} & \cdots & \mathrm{w}_{1p} \\ \vdots & \ddots & \vdots \\ \mathrm{w}_{n1} & \cdots & \mathrm{w}_{np} \end{bmatrix} = \begin{bmatrix} \mathrm{w}_1 \\ \vdots \\ \mathrm{w}_n \end{bmatrix} \quad (1)$$

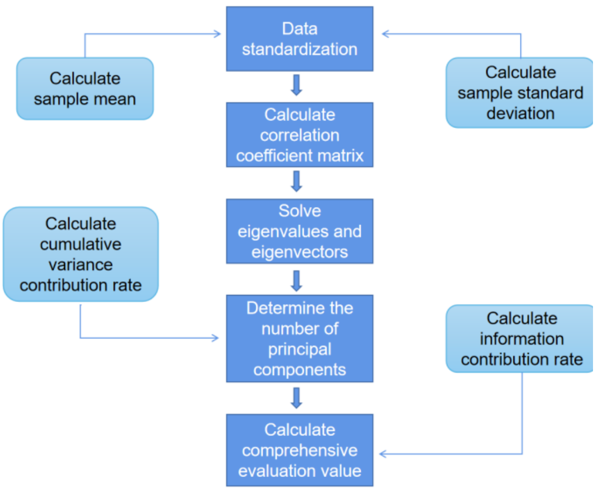

Figure 1. Principal component analysis flowchart

Data standardization

Because the units of each index data are different, in order to facilitate the subsequent quantitative analysis and the indexes need to be dimensionless processed, namely data standardization. So we need to convert the values of each index $\mathrm{w_{ij}}$ into standardized index $\widetilde{w}_{ij}$.

$$\widetilde{w}_{ij} = \frac{\mathrm{w_{ij}} - \bar{\mathrm{w}}_{\mathrm{j}}}{S_j} \quad (2)$$

where, $\bar{\mathrm{w}}_{\mathrm{j}} = \frac{1}{\mathrm{n}}\sum_{\mathrm{i=1}}^{\mathrm{n}} \mathrm{w_{ij}}$, $S_j = \sqrt{\frac{1}{n-1}(w_{ij} - \bar{\mathrm{w}}_{\mathrm{j}})^2}$, $(j = 1,2,3,\ldots.,p)$, namely $\bar{\mathrm{w}}_{\mathrm{j}}$ is the sample mean of the jth index, and S_j is the standard deviation of the jth index. Correspondingly, $\widetilde{w}_i = \frac{\mathrm{w_i} - \bar{\mathrm{w}}_{\mathrm{i}}}{S_i}, (i = 1,2,\cdots,p)$ is referred to as the standardized index variable [29, 30].

Calculate covariance matrix

The correlation coefficient matrix is:

$$A = \begin{bmatrix} a_{11} & \cdots & a_{1p} \\ \vdots & \ddots & \vdots \\ a_{p1} & \cdots & a_{pp} \end{bmatrix} = \begin{bmatrix} a_1 \\ \vdots \\ a_p \end{bmatrix} \quad (3)$$

where, $a_{ij} = \frac{\sum_{k=1}^{n} \widetilde{w}_{ki} \cdot \widetilde{w}_{kj}}{n-1}, (i,j = 1,2,\ldots.,p)$, $a_{ii} = 1, a_{ij} = a_{ji}$, and a_{ij} is the correlation coefficient between the i-th indicator and the j-th indicator [29, 30].

Solve eigenvalues and eigenvectors

Firstly, the eigenvalues need to be sorted in descending order. Then, calculate the eigenvalues $\varepsilon_1 \geq \varepsilon_2 \geq \cdots \geq \varepsilon_p \geq 0$ of the correlation coefficient matrix A, calculate its corresponding eigenvectors $u_1, u_2, \cdots, u_p$, where $u_j = (u_{1j}, u_{2j}, \cdots, u_{nj})^T$. Finally, the p new index variables composed of eigenvectors are as follows:

$$\begin{cases} y_1 = u_{11}\widetilde{w}_1 + u_{21}\widetilde{w}_2 + \cdots + u_{n1}\widetilde{w}_n \\ y_2 = u_{12}\widetilde{w}_1 + u_{22}\widetilde{w}_2 + \cdots + u_{n2}\widetilde{w}_n \\ \cdots\cdots \\ y_p = u_{1p}\widetilde{w}_1 + u_{2p}\widetilde{w}_2 + \cdots + u_{np}\widetilde{w}_n \end{cases} \quad (4)$$

where, y_1 is the first principal component, y_2 is the second principal component, and y_p is the p-th principal component [29, 30].

Determine the number of principal components

There are two algorithms: one is to sort the eigenvalues from the largest to the smallest, and select the largest h (usually the eigenvalue is greater than 1) to replace the original p index variables. The other is to count the corresponding h when the cumulative variance contribution rate reaches 85%, which represents the number of main components. In this experiment, we comprehensively considered these two algorithms and analyzed the h principal components obtained.

Calculate comprehensive evaluation value

$$Z = \sum_{j=1}^{h} b_j y_j \tag{5}$$

where, $b_j = \frac{\varepsilon_j}{\sum_{k=1}^{p} \varepsilon_k} (j = 1,2,\cdots,p)$, and it represents as the information contribution rate of the j-th principal component [29, 31].

Correlation analysis

Correlation analysis refers to the analysis of two or more variable elements with correlation, in order to analyze and measure the correlation and closeness between variables. Generally, correlation analysis can only be carried out if there is a certain relationship or probability between correlation elements [29, 31-35]. And common analysis methods include chart correlation analysis, covariance and covariance matrix, correlation coefficient analysis, univariate regression and multiple regression, information entropy and mutual information, etc. In this paper, we will use correlation coefficient analysis to carry out experiments.

The correlation coefficient is a statistical index that reflects the close relationship between variables. Generally, the value range is [-1, 1]. And among them, the positive number indicates a positive correlation between two variables, the negative number indicates a negative correlation between two variables, 1 indicates a completely positive correlation between the two variables, -1 indicates a completely negative correlation between the two variables, and 0 indicates no relationship between the two variables [36]. Assuming there are two variables X and Y (which can also be considered as two sets), and their number of elements is n. $\bar{X}$ represents the mean of variable X, and $\bar{Y}$ represents the mean of variable Y. Therefore, the calculation formula of correlation coefficient is as follows:

$$r_{xy} = \frac{S_{xy}}{S_x S_y} \tag{6}$$

where, r_{xy} represents the sample correlation coefficient, S_{xy} represents the sample covariance, S_x represents the sample standard deviation of X, and S_y represents the sample standard deviation of Y.

The sample covariance S_{xy} is calculated as:

$$S_{xy} = \frac{\sum_{i=1}^{n}(X_i - \bar{X})(Y_i - \bar{Y})}{n-1} \tag{7}$$

The sample standard deviation S_x is calculated as:

$$S_x = \sqrt{\frac{\sum(X_i - \bar{X})^2}{n-1}} \tag{8}$$

The sample standard deviation S_y is calculated as:

$$S_y = \sqrt{\frac{\sum(Y_i - \bar{Y})^2}{n-1}} \tag{9}$$

Generally, there are three algorithms for calculating correlation coefficient, namely Pearson correlation coefficient (PCC) method, Kendall correlation coefficient (KCC) method and Spearman correlation coefficient (SCC) method [37-39]. In order to further prove the scientific and accuracy of the experimental results, this paper will synthesize these three algorithms to calculate the correlation coefficient for analysis. And the calculation formulas for the three correlation coefficient methods are as follows:

Assuming there are two variables X and Y (which can also be considered as two sets), and their number of elements is N.

Pearson correlation coefficient method

$$\rho_1 = \frac{\sum_{i=1}^{N}(X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^{N}(X_i - \bar{X})^2 \sum_{i=1}^{N}(Y_i - \bar{Y})^2}} \tag{10}$$

where, $\bar{X}$ represents the mean of variable X, $\bar{Y}$ represents the mean of variable Y, and ρ_1 represents the correlation coefficient of Pearson [31, 37].

Kendall correlation coefficient method

$$\rho_2 = \frac{C - D}{\frac{1}{2} N(N-1)} \tag{11}$$

where, C represents the logarithm of elements with consistency in XY (two elements are a pair), D represents the logarithm of elements with inconsistency in XY, and ρ_2 represents the correlation coefficient of Kendall [40].

Spearman correlation coefficient method

$$\rho_3 = \frac{\sum_{i=1}^{N}(R_i - \bar{R})(S_i - \bar{S})}{\sqrt{\sum_{i=1}^{N}(R_i - \bar{R})^2 \sum_{i=1}^{N}(S_i - \bar{S})^2}} = 1 - \frac{6\sum {d_i}^2}{N(N^2-1)} \tag{12}$$

where, R_i and S_i are the levels of values for variables X and Y, while $\bar{R}$ and $\bar{S}$ are the average levels of variables X and Y respectively, $d_i = R_i$ -S_i represents the level difference between two paired variables, and ρ_3 represents the correlation coefficient of Spearman [35].

RESULTS AND DISCUSSION

Data sources

The index data and global average temperature used in this experiment from 2012 to 2021 are from the Global Disaster Data Platform, the World Meteorological Organization (WMO) and the National Aeronautics and

Table 1. Data of each index

Year	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	TGP/100 million	TGCE/Mt	AT/°C
2012	6	1	27	25	18	136	14	91	70.89	32.46	14.87
2013	10	3	29	23	9	148	12	105	71.76	33.11	14.92
2014	4	6	26	24	20	137	15	99	72.62	33.19	15.02
2015	13	6	23	14	27	161	21	121	73.48	32.99	15.21
2016	10	0	30	25	14	159	13	86	74.34	33.01	15.36
2017	15	2	22	27	12	127	26	130	75.19	33.51	15.48
2018	10	9	20	16	17	128	13	96	76.03	34.28	15.58
2019	14	4	31	45	15	195	25	91	76.84	34.34	15.68
2020	8	4	16	9	10	202	19	129	77.64	33.35	15.73
2021	19	9	28	7	15	222	12	119	78.37	34.53	15.80

Space Administration (NASA) of the United States. And it is assumed that the data used are true and reliable. The specific data are shown in Table 1.

Principle component analysis

Because the number of eight natural disaster factors selected is too large, it is not convenient for the subsequent model research, calculation and analysis. Therefore, in order to ensure the accuracy of the later correlation calculation, this paper used the principal component analysis method to reduce the dimension of multiple influencing factor indexes $X_i(i = 1,2,\dots,8)$ and extract the principal component.

It can be seen from the following gravel map (Figure 2) that the characteristic values of the first four factors are greater than 1, and they fall rapidly. Therefore, according to the previous theoretical introduction, we should select four principal components.

In addition, according to another rule for selecting the number of principal components, it can be seen from Table 2 that the cumulative contribution rate of the first four factors is 87.086%, which has exceeded 85%, which is enough to represent the original multiple indexes; so the first four factors are selected as principal components.

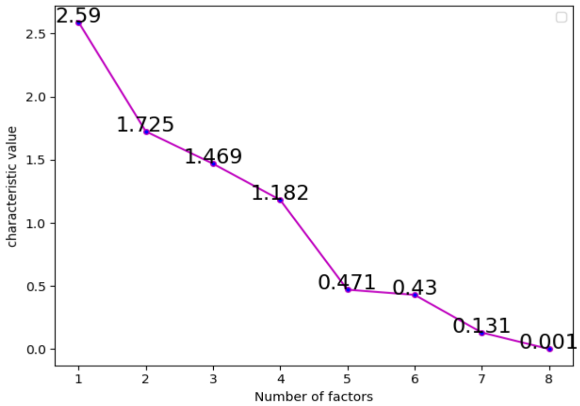

Figure 2. PCA gravel map

According to the factor load factor obtained from the experiment, it can be seen from Table 3 that the principal component G_1 reflects forest and grassland fire (X_1) and volcano (X_2); The principal component G_2 reflects the biological disaster (X_4) and geological disaster (X_7); The principal component G_3 reflects earthquake (X_3) and drought (X_5); The principal component G_4 reflects flood (X_6) and storm (X_8).

The values of the four selected principal components $G_i(i = 1,2,3,4)$ can be calculated according to the composition matrix table obtained from the experiment in Table 4. For example, the first principal component G_1 is:

$$G_1 = 0.386X_1 + 0.246X_2 - 0.252X_3 - 0.303X_4 + 0.017X_5 + 0.180X_6 + 0.036X_7 - 0.085X_8$$

The other three principal components are calculated according to this method.

Correlation analysis results

Relationship between natural disasters and global temperature changes

The four principal components $G_i(i = 1,2,3,4)$ obtained after dimensionality reduction by principal component analysis were used as new indexes. And then, these four

Table 2. Cumulative variance contribution rate

Component	Variance explained (%)	The Cumulative (%)
1	32.377	32.377
2	21.567	53.944
3	18.362	72.305
4	14.781	87.086

new indexes were combined with the global average temperature (AT) to perform three correlation coefficient analysis methods. The correlation coefficient matrix and test matrix of Pearson are shown in Figures 3 and 4, respectively. Finally, the results are as follows:

The correlation coefficient matrix and test matrix of Kendall are shown in Figures 5 and 6, respectively.

Table 3. Factor load factor

Factor load factor	G_1	G_2	G_3	G_4
X_1	0.666	0.468	0.368	0.157
X_2	0.636	-0.274	0.394	0.384
X_3	-0.652	0.309	0.622	0.094
X_4	-0.784	0.504	-0.125	0.216
X_5	0.043	-0.338	0.885	0.029
X_6	0.466	0.448	-0.162	0.540
X_7	0.094	0.698	-0.587	0.368
X_8	-0.100	0.238	-0.374	0.836

Table 4. Composition matrix

Composition matrix	G_1	G_2	G_3	G_4
X_1	0.386	0.181	0.251	0.133
X_2	0.246	-0.159	0.268	0.325
X_3	-0.252	0.179	0.424	0.08
X_4	-0.303	0.292	-0.085	0.183
X_5	0.017	-0.196	0.748	0.019
X_6	0.180	0.259	-0.137	0.367
X_7	0.036	0.405	-0.399	0.312
X_8	-0.085	0.138	-0.254	0.323

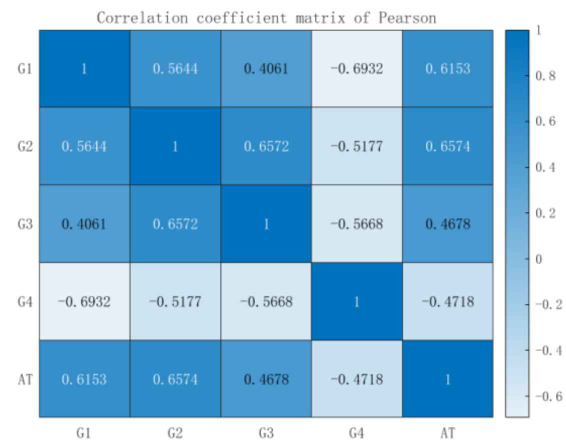

Figure 3. Correlation coefficient matrix of Pearson

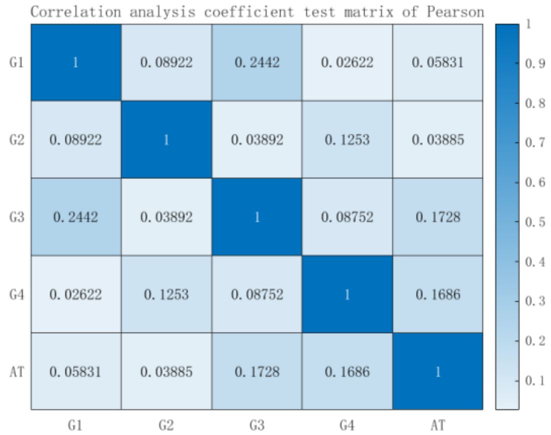

Figure 4. Test matrix of Pearson

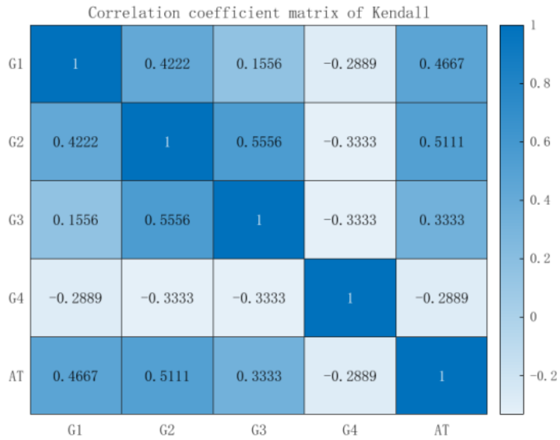

Figure 5. Correlation coefficient matrix of Kendall

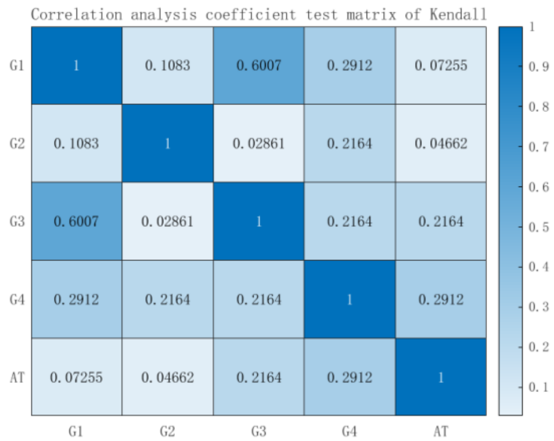

Figure 6. Test matrix of Kendall

The correlation coefficient matrix and test matrix of Spearman are shown in Figures 7 and 8, respectively. The comprehensive analysis results in Table 5 show that in the calculation of the three correlation coefficients, the correlation coefficients of the principal component G_2 are the largest, with an average correlation coefficient of 0.6097, and the p values are less than 0.05, which further indicates that its positive correlation is significant. And the experimental results also show that in the exploration of the relationship between natural disasters and global temperature changes, the principal component G_1, principal component G_2 and principal component G_3 have a positive impact on global temperature, but the positive impact of principal component G_2 is the most obvious, which indicates that forest and grassland fire (X_1), volcanic (X_2), earthquake (X_3), biological disaster (X_4), drought (X_5) and geological disaster (X_7) have a positive correlation with global temperature, namely with the occurrence of such natural disasters, the global temperature will rise. But the correlation coefficients of the principal component G_4 are all negative, with an average correlation coefficient of -0.4132, indicating that it has a negative impact on global temperature. At the same time, this indicates a negative correlation between flood (X_6) and storm (X_8) and global temperature, namely with the occurrence of such natural disasters, the global temperature will drop.

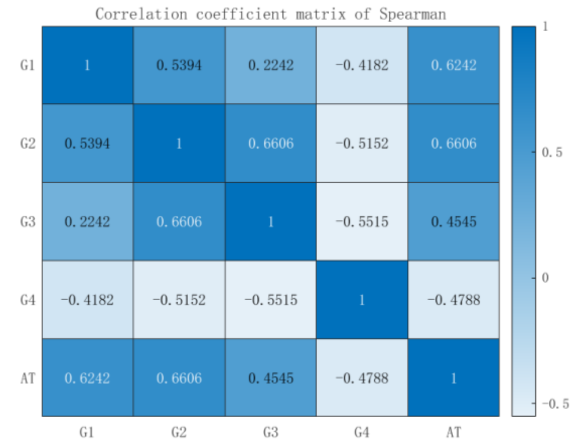

Figure 7. Correlation coefficient matrix of Spearman

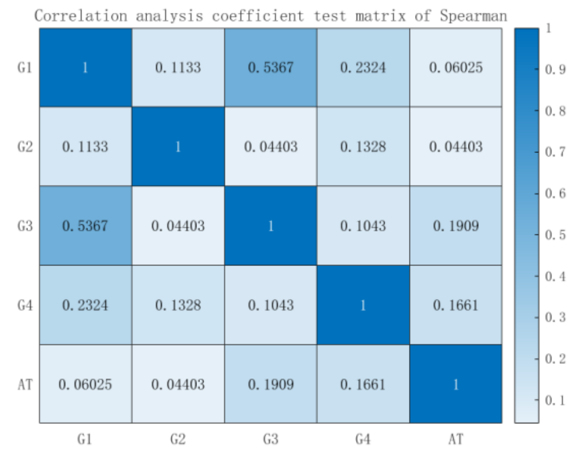

Figure 8. Test matrix of Spearman

Explore the main factors affecting global temperature rise

In this part, two additional human factors were introduced, namely the total global population (TGP) and the total global CO_2 emissions (TGCE). By introducing these two indexes and combining the four principal components $G_i(i = 1,2,3,4)$ obtained from experiments, we can analyze the main factors affecting the global temperature changes more comprehensively. After calculation of three correlation coefficients, Table 6 can be obtained as follows.

According to the experimental results, we also compared the weight proportions of each index factor. And the weight calculation formula is as follows:

$$T = \frac{|MC_i|}{|\sum_{i=1}^{n} MC_i|}(i = 1,2,\dots,n) \quad (13)$$

where, MC_i is the average correlation coefficient value obtained after calculation for the corresponding index,

Table 5. Comprehensive analysis of correlation between average temperature and principal components

	G_1	G_2	G_3	G_4
PCC	0.6153 /0.05831	0.6574 /0.03885	0.4678 /0.1728	-0.4718 /0.1686
KCC	0.4467 /0.07255	0.5111 /0.04662	0.3333 /0.2164	-0.2889 /0.2912
SCC	0.6242 /0.06025	0.6606 /0.04403	0.4545 /0.1909	-0.4788 /0.1661
MC	0.5621	0.6097	0.4185	-0.4132

(Note: the value in the table means "correlation coefficient r / test value p" and the correlation is significant if p<0.05)

Table 6. Comprehensive analysis of correlation between average temperature and index factors

	G_1	G_2	G_3	G_4	TGP	TGCE
PCC	0.6153	0.6574	0.4678	-0.4718	0.9916 /2.106e-08	0.8025 /0.005204
KCC	0.4467	0.5111	0.3333	-0.2889	1 /5.511e-07	0.6889 /0.004687
SCC	0.6242	0.6606	0.4545	-0.4788	1/0	0.8303 /0.005557
MC	0.5621	0.6097	0.4185	-0.4132	0.9972	0.7739

(Note: the last two columns in the table mean "correlation coefficient r / test value p" and the correlation is significant when p<0.05) and the values need to be taken as their corresponding absolute values.

The calculated results showed that the principal component G_1 accounted for 14.89%, the principal component G_2 accounted for 16.15%, the principal component G_3 accounted for 11.09%, the principal component G_4 accounted for 10.95%, TGP accounted for 26.42%, and TGCE accounted for 20.50%. And the results are shown in Figure 9.

Based on the results of comprehensive analysis of correlation in Table 6 and the analysis of weight proportion in Figure 9, it can be seen that the two human factors of total global population (TGP) and total global CO_2 emissions (TGCE) are significantly positively correlated with the global temperature, with their average correlation coefficients of 0.9972 and 0.7739 respectively, and their weight proportions are the two largest of all indexes, with 26.42% and 20.50% respectively. Meanwhile, this can also indicate that human factors are the main causes of global temperature rise. However, compared with the TGCE, the weight of TGP is higher, 5.92% higher than TGCE, indicating that TGP has a more significant impact on global temperature rise. Therefore, this shows that the main reason for the global temperature rise is the TGP (namely total global population).

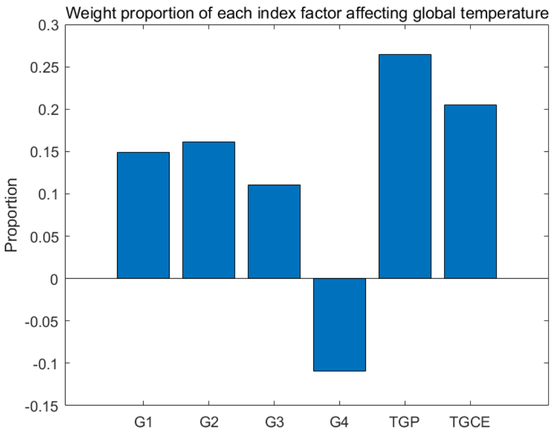

Figure 9. Proportion of weight

CONCLUSIONS

This study first used principal component analysis to reduce the dimensionality of index data, and then combined three correlation coefficient methods for comprehensive analysis. This not only solves the redundancy problem of index data in traditional research methods, but also comprehensively considers the influence of various index factors to avoid missing key influencing factors. Therefore, the new method proposed in this paper can maintain the scientific and accurate calculation results while reducing computational dimensions. According to the experimental results, volcanoes, forest and grassland fires, biological disasters, geological disasters, earthquakes, and droughts are all positively correlated with global temperature among natural disaster factors. Among them, biological disasters and geological disasters have the most significant positive correlation, with an average correlation coefficient of 0.6097 and $p<0.05$, while floods and storms have a negative correlation with global temperature, with an average correlation coefficient of -0.4132. Meanwhile, in the analysis combining human factors, it was found that human factors are the main causes of global temperature rise, with the total global population being the most significant factor, accounting for 26.42%. The research results of this paper can greatly assist countries in making decisions to address the current global warming problem and provide reference.

The performance of this research method in application scenarios with numerous data indicators will be more obvious. Therefore, in the future, we will collect more data on relevant indexes for experimental analysis, in order to continuously improve the scientific and accurate results of the experiment. At the same time, we will still explore and try to combine other methods to continuously simplify the calculation processes and improve the accuracy of the results.

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CONFLICT OF INTEREST

The authors confirm that there is no conflict of interest in this research.

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Persian Abstract

چکیده

مسئله کنونی گرم شدن کره زمین برجسته است و عوامل زیادی وجود دارد که بر تغییرات دمای کره زمین تأثیر می گذارد. بنابراین، چگونه می توان به درستی در مورد رابطه بین هر یک از عوامل تأثیرگذار و تغییرات دمای کره زمین قضاوت کرد و بهرطور دقیق به دلایل اصلی افزایش دمای کره زمین که مشکلاتی هستند که برای کاهش گرمایش جهانی در حال حاضر باید مد نظر قرار گیرد و حل شود. با توجه به داده‌های رسمی قبلی، این مقاله یک روش تحلیل همبستگی مبتنی بر مؤلفه‌های اصلی را برای تجزیه و تحلیل جامع رابطه بین عوامل بلایای طبیعی، عوامل انسانی و تغییرات دمای جهانی و یافتن دلایل اصلی تأثیرگذار بر افزایش دمای جهانی پیشنهاد می‌کند. در مقایسه با روش های تحقیق سنتی، روش جدید ارائه شده در این مقاله همچنان می تواند نتایج محاسباتی علمی و دقیق و در عین حال کاهش ابعاد محاسباتی باقی بماند. نتایج تجربی نشان داد که در رابطه بین بلایای طبیعی و تغییرات دمای کره زمین، میانگین ضریب همبستگی مؤلفه اصلی نشان‌دهنده بلایای بیولوژیکی و بلایای زمین‌شناسی با ۰/۶۰۹۷ بالاترین میزان و مقدار آزمون p <۰/۰۵ بود که نشان‌دهنده همبستگی مثبت معنی‌دار است. بین آنها و دمای جهانی با این حال، ضریب همبستگی مولفه اصلی نشان‌دهنده سیل و طوفان منفی بود که نشان‌دهنده همبستگی منفی بین آنها و دمای جهانی است. در بررسی عوامل اصلی مؤثر بر افزایش دمای جهانی، هم کل جمعیت جهان و هم کل انتشار CO_2 جهانی همبستگی مثبت و معناداری با دمای جهانی داشتند. در این میان، میانگین ضریب همبستگی کل جمعیت جهان با ۰/۹۹۷۲ بالاترین و وزن آن نیز با ۲۶/۴۲ درصد بالاترین میزان بود. بنابراین، این نشان می دهد که کل جمعیت جهان مهمترین عامل تأثیرگذار بر افزایش دمای جهانی است. این مطالعه می تواند مرجعی برای تصمیم گیری کشورها در واکنش به گرمایش جهانی باشد.