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T1 ________________	**83836**	F1 ________________
T2 ________________		F2 ________________
T3 ________________	Problem Chosen	F3 ________________
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2018 MCM/ICM Summary Sheet

Will Climate Change Weaken a State?

Abstract

Bad climate change may greatly increase the fragility of the country. How to evaluate the impact of climate change and mitigate the impact of climate change has become an urgent problem.

With regard to task one, a **data envelopment analysis (DEA)** model is established to get the country's fragility. First of all, we selected 4 climate factors as input indicators and 5 output indicators. Then, we use the **entropy method** to determine the weight and then the national vulnerability is divided. At the same time, we get the conclusion that temperature affects GDP and the times of armed conflict directly and affects the fragility indirectly.

In view of task two, we choose Somalia as an object of study. First, all the indexes are divided into 5 levels by the method of **cluster analysis**. Second, we select 10 countries including Somalia, to solve the decision unit matrix. Then, using the model of the problem one, it is found that the increase in temperature and rainfall will cause the national vulnerability to rise and decrease, respectively. Finally, we assign 4 climate indicators to 0 of the decision units, and draw the conclusion that national vulnerability will be reduced without the impact of climate factors.

When it comes to task three, we use the **rough set theory** to reduce the output index to the number of armed conflicts. Then, we use the **BP neural network** model to predict the conclusion: There is a significant increase in fragility in cases of much more armed conflict and abnormal temperature. When the average annual armed conflict is certain, the national vulnerability index will face an increasing turning point at the temperature of 10.01 and the rainfall of 1823mm.

As to task four, three policies on energy reduction and emission reduction issued by the government have been selected, and a **model of carbon cycle** is established. Taking China as an example, we calculate the extent of the change of the average temperature by reducing the carbon dioxide emissions from the state, and calculate the change of the national vulnerability through the change of temperature. We conclude that when the temperature drops 1.9 degrees, the national vulnerability decreases by 0.1593 and the cost is 20.3 billion $.

Last but not least, due to the relative accuracy of the DEA model, the urban fragile performance is accurately predicted while the continent is not. In this paper, the **TOPSIS model of distance entropy of three parameter interval number** is used to modify the decision matrix of the DEA model. By increasing the upper and lower bounds of the interval, the value of the decision unit is more accurate, and then the weight of the index is modified based on the schedule. When we use the North American continent for test, the error was about 2.9%.

Keywords: DEA, entropy method, rough set, neural network, TOPSIS

Contents

I. Introduction

1.1 Problem Background

Fragileness is a pre-existing condition, disaster adjustment and coping capacity, and the degree of disaster in a specific location. The Fragile States refers to the extent to which the country is exposed to the potential disaster factors, the degree of damage and the ability to cope with the disaster. The current study of fragile states has become a central issue in the discussion of global security, development and poverty among western academics and policymakers.

According to the research of the Intergovernmental Panel on Climate Change, the Fragile States Index of countries is significantly affected by Climate Change. The effects of climate change not only the way people live, but also the weakening and disintegration of social and governmental structures. When the government's weak governance and social division are combined, it can lead to violent conflict and increase instability in the country.

1.2 Previous Research

Since 2005, the Fragile States Index has been published annually. In 2011, the index of economic, social, military and other indicators of 177 countries in the world was surveyed.

In 2008, the United States ranked Somalia as the world's most unstable country for the first time in an annual assessment of the world's most volatile countries, and Israel was among the 60 most fragile states. Since then, Somalia has topped the list of fragile states each year. It is reported that this is due to a combination of violent conflicts in the country, displacement of the population, low government effectiveness, lack of human rights and justice, and economic malaise.

1.3 Our Work

Climate change will affect the stability of the country, which in turn will affect the Fragile States Index. What we need to do is to show the impact of climate change on country’s fragility. Here are our tasks:

- Consider the impact of climate change and establish a model of a country’s fragility.
- Choose one of the top 10 fragile states and determine the impact of climate change.
- Use your model to measure the fragility of a non-top 10 country and predict when climate change will push the country's fragility to a tipping point.
- Give national interventions to mitigate the impact of climate change and predict the costs.
- How to modify the model can it be applied to the city or the mainland?

II. General Assumptions

We make the following assumptions to complete our model through this paper. Further improvements of these simplified assumptions will be achieved later with more reliable data.

- The assumption is that the national vulnerability ranking has absolute precision: error analysis is based on this ranking, and if it is not accurate, the error analysis results are inaccurate.

• Suppose that the war between states is not considered: Only the internal instability of the country is considered, and the influence of the war between countries is too large and uncertain.
• Assume that national leaders have the same governance capacity: The capacity of leaders has an enormous impact on national vulnerability.
• Ignoring the mutual aid between countries: The help of nations can ease the vulnerability and make it difficult to predict.

III. Notations and Symbol

Symbols	Definitions
x_{ij}	the input of DMU_j for the type i input
y_{k_j}	the output of DMU_j for the type k output
v_i	the weight of the type i input
u_k	the weight of the type k input
θ	comprehensive base scale efficiency index
x_{ij}	the extent to which the j country is affected by the i climate indicators
y_{ij}	the level of k output in the j country
W_{m_i}	the connection weight between input layer and hidden layer
Q_{ij}	the connection weight between hidden layer and output layer

IV. Impact of climate change on FSI

4.1 Data Envelopment Analysis Model

This task calls for the establishment of a relationship between climate change and national fragility. In fact, climate change will affect many other indirect factors. These will cause changes in national fragility, and these factors are linked to climate change at the same time. It is really too difficult to consider at the same time. Therefore, the task is considered by using the method of data envelopment analysis (DEA) to establish the model. The change of climate change and other factors caused the national economic downturn and turmoil to deepen. This process can be regarded as a "causal process", that is, the process of input and output.

The DEA model formally establishes multiple decision units to deal with this process. DEA uses mathematical programming models to compare the relative efficiency of decision making units (countries), and evaluates the decision units. Each decision making unit has the same "input" and "output". Through the comprehensive analysis of input and output data, DEA can get the quantitative index of the comprehensive efficiency of every decision unit, so as to measure the fragility of the country. Moreover, there are many internal relations between input and output.

4.1.1 Construction of DEA Model

Suppose there are n decision units $DMU_j\left(1\le j\le n\right)$, each DMU has m input and s output. As shown in the table, x_{ij} is the input of DMU_j for the type

i input; y_{k_j} is the output of DMU_j for the type k output; v_i is the weight of the type i input; u_k is the weight of the type k input. $(j=1,2,\cdots,n;i=1,2,\cdots,m;k=1,2,\cdots,s)$ and $x_{ij}>0,y_{kj}>0,v_i>0,u_k>0$. The input and output of the estimated system are respectively $X_j=(x_{1j},x_{2j},\cdots,x_{mj})^T>0,j=1,2,\cdots,n;Y_j=(y_{1j},y_{2j},\cdots,y_{sj})^T>0,j=1,2,\cdots,n$. Thus the efficiency value of all evaluation units can be obtained[1]:

$$h_j=\frac{u^TY_j}{v^TX_j}=\frac{\sum_r u_rY_{rj}}{\sum_i v_iy_{ij}}$$

Table 4.1: The input and output table of the DMU decision unit

		DMU_1	DMU_2	…	DMU_n	
V_1	$1\rightarrow$	x_{11}	x_{12}	…	x_{1n}	
V_2	$2\rightarrow$	x_{21}	x_{22}	…	x_{2n}	
		…	…	…	…	
V_m	$m\rightarrow$	x_{m1}	x_{m2}	…	x_{mn}	
		y_{11}	y_{12}	…	$y_{1n}\rightarrow 1$	u_1
		y_{21}	y_{22}	…	$y_{2n}\rightarrow 2$	u_2
		…	…	…	…	
		y_{s1}	y_{s2}	…	$y_{sn}\rightarrow s$	u_s

Here $U=(u_1,\ldots,u_s)^T,V=(v_1,\ldots,v_s)^T$ is the weight coefficient corresponding to the input and output elements and is subject to the following constraints:

$$\max_{u,v}\frac{\sum_r u_ry_{r0}}{\sum_i v_iy_{i0}}=\frac{u^TY_0}{v^TX_0}\leq 1$$

Now we make the efficiency evaluation of the j decision unit. DMU_{j_0} is written as DMU_0, $X_0=X_{j_0},Y_0=Y_{j_0},Y_0=Y_{j_0},(1\leq j_0\leq n)$. Under the condition that the efficiency values of each decision unit are not more than 1, the weight coefficient u and v are selected to make h_0 reach the maximum. So the following fractional programming model is formed:

$$\max\frac{\sum_{i=1}^{s}u_iy_{ij_0}}{\sum_{i=1}^{m}v_ix_{ij_0}}$$

$$s.t.\frac{\sum_{i=1}^{s}u_iy_{ij}}{\sum v_ix_j}\leq 1,\ j=1,2,\ldots,n$$

Using Charnes-Cooper transform:

$$\theta=\frac{1}{v^TX_0},u^T=\theta u^T,w=\theta v^T$$

The optimal solution of the decision unit efficiency evaluation can be transformed into the following form:

$$\max_{u,v}\theta_0=\sum_r u_rv_{r0}=u^TY_0$$

It is also bound by the following conditions:

$$w^T X_0 = \sum_i w_i x_{i0} = 1, \sum_r u_r y_{rj} - \sum_i w_i x_{ij} \le 0, u_r, w_i \ge \varepsilon$$

Suppose that there are n national decision units $DMU_j\left(j = 1, 2, \cdots, n\right)$, any DMU_j has m input and s output, input vector is $X_j = \left(x_{1j}, x_{2j}, \cdots, x_{mj}\right)^T$, output vector is $Y_j = \left(y_{1j}, y_{2j}, \cdots, y_{sj}\right)^T$, the above formula is merged, and the national vulnerability DEA model is established as follows:

$$\min\left[\theta - \varepsilon\left(\hat{e}_1^{\,T} S^- + e_2^{\,T} S^+\right)\right]$$

$$s.t.\begin{cases} \sum_{j=1}^{n} X_j \lambda_j^* + S^- = \theta X_0 \\ \sum_{j=1}^{n} Y_j \lambda_j^* - S^+ = Y_0 \\ \lambda_j^* \ge 0;\ j = 1, 2, \cdots, n;\ S^- \ge 0, S^+ \ge 0 \\ \hat{e}_1^{\,T} = (1, 1, \cdots, 1) \in E_m, e_2^{\,T} = (1, 1, \cdots, 1) \in E_n \end{cases}$$

In order to discuss and calculate conveniently, we introduce a slack variable S^+ and the remaining variable S^-, making it a range of constraints in the formula: $\theta\left(0 < \theta \le 1\right)$ is the comprehensive technical scale efficiency index of DEA model, on behalf of the state fragility. If the θ of a country is closer to 1, according to the meaning of DEA model, it is explained that the country has higher input and output and higher level of national production. Under the background of this problem, it is considered that the country's fragility is greatly influenced by the level of climate change and the weak government's regulation capacity.

4.2 Selection of Input and Output Indicators

DEA method does not need to identify explicit expressions of input and output, excludes many subjective factors, and has a strong objectivity. Therefore, selection of input and output indexes is very important.

To consider the impact of climate change on national vulnerability, we choose 4 weather factors as input indicators and 5 countries as output indicators. Specific indicators are illustrated as follows:

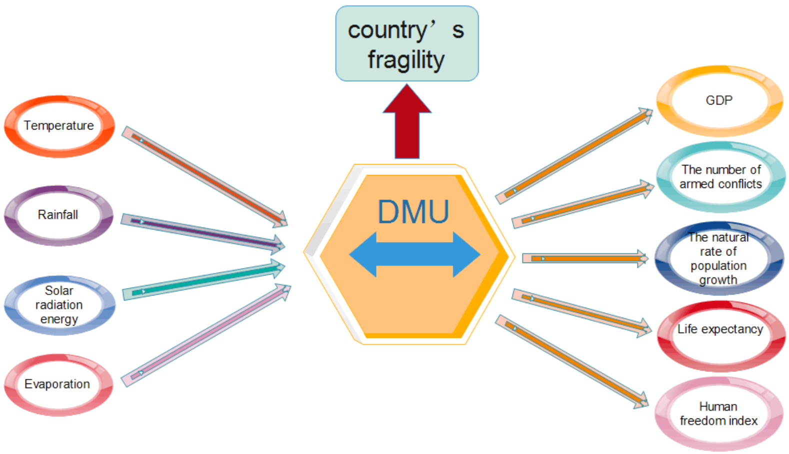


Figure4.1: DEA input and output index relation diagram

Input indicators:

1. Average temperature v_1

The annual mean temperature is the arithmetic mean of the daily average temperature of a year, which is directly influenced by the influence of solar radiation and geothermal energy, and it is an important factor of climate change.

2. Annual rainfall v_2

The average annual rainfall refers to the mean of the total annual rainfall divided by the year number, or the mean annual rainfall measured at multiple observation points. It has a direct impact on the level of drought and waterlogging in a certain area and the species of crops.

3. Annual solar radiation energy v_3

The sun emits electromagnetic waves and particle flows to the universe to produce solar radiation, and the energy transmitted by the solar radiation is called the solar radiation energy. Solar radiation is the main source of energy for the movement of the atmosphere, and also the main source of the earth's photothermal energy.

4. Annual average evaporation v_4

Annual evaporation refers to the amount of water emitted into the air through evaporation during a certain period of time, usually expressed in millimeters of the thickness of the evaporated water layer. Evaporation is very important in agricultural production and hydrology. Too little evaporation is easy to flood, too much evaporation is prone to drought.

Output indicators:

1. National GDP u_1

National GDP refers to the sum of all the final products and service value produced by a country's all permanent units within a certain time. It is often considered as an index to measure the economic status of a country.

2. Frequency of armed conflict u_2

First, armed conflict is the most direct reflection of the improper governance of the state. When people's living standard is not high, it will be more prone to turmoil. Secondly, armed conflict indirectly reflects the weakness of the government's deterrence and the ability to suppress it, which is an important index to measure the fragility of the country.

3. Natural population growth rate u_3

The natural growth rate of population reflects the speed of population development. It is an important index for making population plan, indicating the degree and trend of natural growth of population, and it is a comprehensive index reflecting population reproduction activity.

4. Life expectancy u_4

Social economic conditions and health care level limit people's life span. Therefore, in different societies and different periods, the life span of human beings is quite different, reflecting the quality of a social life.

5. Human rights freedom index u_5

The human rights freedom index reflects the state of human rights in a country. Its evaluation is based on life expectancy, literacy rate, registered student number and GDP per capita.

4.3 Calculation of index weight

Since the proportional relationship between the factors is not given in the question, we adopt the entropy method to determine the weight of the evaluation index. When there is a large difference in the index value of each evaluation object, the entropy value is small. It is indicated that this index provides a large amount of effective information and its weight should be larger. On the contrary, if there is a small difference in the index value, the entropy value is larger, indicating that the information provided by this index is small, and its weight should be smaller. When the index value of each evaluation object is completely identical, the entropy value reaches the maximum, which means that the index has no useful information and can be removed from the evaluation index system.

There are three steps to determine the weight using entropy weight method:

(1)The original data matrix is normalized. The original data matrix of the m evaluation index n evaluation objects is $A=\left(a_{ij}\right)_{m\times n}$, and after normalization, $R=\left(r_{ij}\right)_{m\times n}$ is obtained.

For profitability indicators (supplied by optimal), normalized formula is:

$$r_{ij}=\frac{a_{ij}-\max_{j}\left\{a_{ij}\right\}}{\max_{j}\left\{a_{ij}\right\}-\min_{j}\left\{a_{ij}\right\}}$$

For index (outsiders for optimal) into nature, normalization formula is:

$$r_{ij}=\frac{\max_{j}\left\{a_{ij}\right\}-a_{ij}}{\max_{j}\left\{a_{ij}\right\}-\min_{j}\left\{a_{ij}\right\}}$$

(2) The definition of entropy

In the evaluation of m indicators and n evaluated objects, the entropy of the j th index is:

$$h_i=-k\sum_{j=1}^{n} f_{ij}\ln f_{ij}$$

Where $f_{ij}=\dfrac{r_{ij}}{\sum_{j=1}^{n} r_{ij}}$ and $k=\dfrac{1}{\ln n}$.

(3) Definition of entropy

After the entropy of the j^{th} index is defined, the entropy weight of the i^{th} index can be obtained:

$$w_i=\frac{1-h_i}{m-\sum_{i=1}^{m} h_i}\left(0\le w_i\le 1,\sum_{1}^{m} w_i=1\right)$$

Using MATLAB R2017a to calculate. The weight of our input index is $W_i=\begin{pmatrix}0.224 & 0.482 & 0.155 & 0.140\end{pmatrix}$ and the weight of our output index is $W_o=\begin{pmatrix}2.145 & 3.292 & 1.532 & 1.778 & 1.253\end{pmatrix}$.

4.4 Impact of climate change on fragility

According to the weight of the above mentioned index, combined with the data, we can get the comprehensive base scale efficiency index θ of each decision unit. The size of the θ reflects the vulnerability of the country, and we have made the following provisions for the value of θ:

Table 4.2: The division of state fragility

θ	0 ~ 0.4	0.4 ~ 0.7	0.7 ~ 1.0
State	stable	vulnerable	fragile

In the DEA model, X_{ij} indicates the input of DMU_j to the i input. y_{kj} is the output of DMU to the k output. In this task, X_{ij} is the worst degree of the i climate condition of the j country. y_{kj} indicates the level of the output of the k species in the j country. Observing changes in θ and y_{k_j} by changing X_{ij}, that is, to observe the effects of climate change on other non-climatic factors and fragilities.

We have identified 4 input factors and 5 output factors, so there are 20 cases in all. We change the X_{ij} and observe the change of the curve and find that the following 4 trends are most obvious.

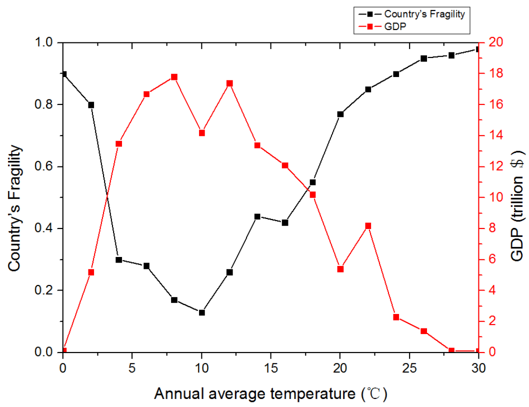


Figure 4.2: Temperature and GDP

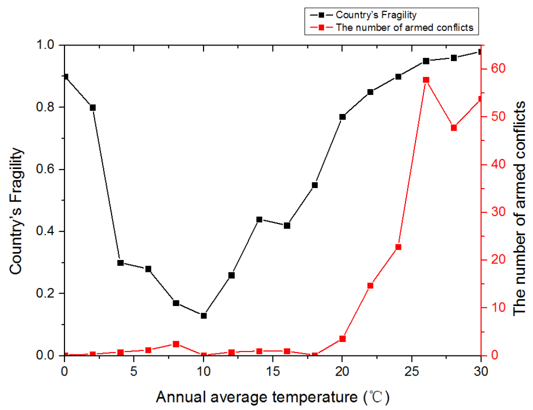


Figure 4.3: Temperature and times of armed conflict

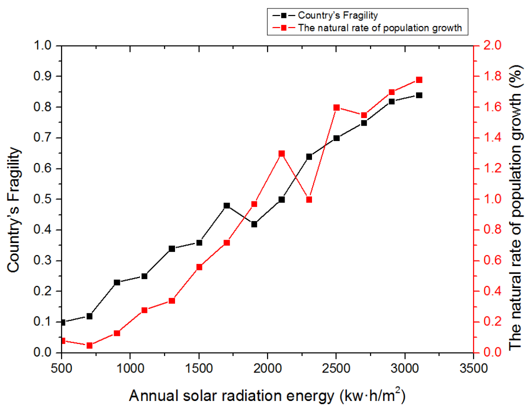


Figure 4.4: Solar energy and the natural growth rate of population

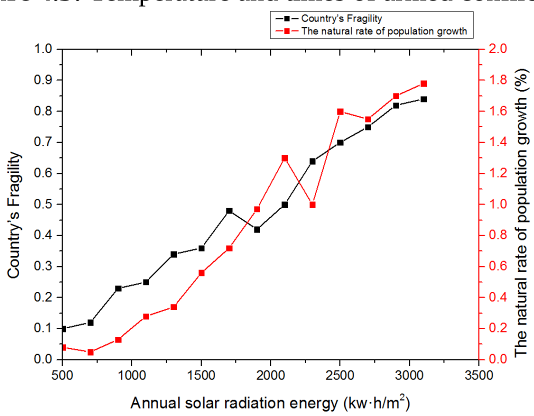


Figure 4.5: Solar energy and GDP

From Figure 4.2, we can see that as the temperature increases, the national vulnerability decreases first and then increases, while the GDP increases first and then decreases. In some extreme cold regions, the population is scarce and the country has a high fragility. The high temperature region is located in the tropics, and most of the countries are in Central Africa. In the middle of Africa, the economy is poor, the comprehensive national strength is not strong, and the country has a large number of countries, so it has a large proportion and high fragility. For the GDP curve, according to the 2016 global GDP report, the United States accounts for 24% of the world's GDP value, and China accounts for 14%. Therefore, there are two obvious peaks in the middle of the curve.

For Figure 4.3, it reflects the change of state fragility caused by the influence of temperature on the number of armed conflicts. The number of armed conflicts remains unchanged, and in the case of high temperature, the country's vulnerability is growing in a straight line. Because of the smooth economic development in China, Japan, Australia and other countries. While North America and other places, although advocating freedom, but the government has strong control ability, the rule of law is strict, so the probability of armed conflict is low. In contrast, people in Africa, the Middle East, and other places are living in poverty, the gap between the rich and the poor is serious and lack of education, and the government's ability to control is poor. As a result, the number of armed conflicts occurs.

For Figure 4.4 and Figure 4.5, the natural growth rate of the population reflects the living standard of the people. In general, the natural growth rate per capita in developing countries is about 1.7%, and the developed countries are about 0.5%. As can be seen from the map, the places where the rainfall is low are very dry, lack of water resources, the country's fragility and the natural growth rate of the population are high. In contrast, the countries with moderate rainfall are low in fragility and low in natural growth rates. The average annual solar radiation energy is lower mainly in northern Asia and northern North America. These countries, based on the analysis of fragile states index, show that the country is low in fragility. Too high solar radiation and easy to bring drought, resulting in the lack of water resources and reduce the fragility of the country. In general, the national fragility and the natural growth rate of the population are in a functional distribution.

V. Impact of Climate Change on Somalia

5.1 Application of model

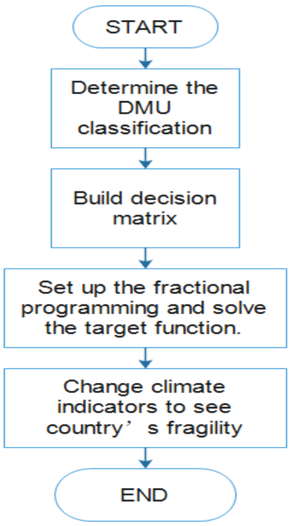


Figure 5.1: Flow chart

We choose the Somali of ten most vulnerable countries as a demonstration object and use the DEA model to analyze the impact of climate change on it. The following steps are as follows:

Step1: Determining the classification of the value of the decision unit

In decision table, x_{ij} indicates the extent to which the j country is affected by the i climate indicators. y_{kj} shows the level of k output in the j country. Since each index is between different classes, and the state is not necessarily to have a positive and negative relationship (mostly normal distribution), so we adopt a classification method (with temperature for example).

① On the basis of the national vulnerability index on national ranking[8]

Table 5.1: 2006 national vulnerability index and annual average temperature statistics

Country	Norway	Sweden	Finland	…	Congo	Sudan
Fragile index	16.8	18.2	18.2	…	110.1	112.3
Temperature(℃)	3.2	4.0	2.0	…	28.9	27.4

② Cluster and classification of 146 countries

We have to use quantitative methods to classify things, so we use distance to measure the similarity between sample points. Here we use the Euclidean distance (Euclid).

$$d(x,y)=\left[\sum_{k=1}^{n}\left|x_k-y_k\right|^2\right]^{\frac{1}{2}}$$

Then, we use the class averaging method to calculate the inter class distance.

$$D(G_1,G_2)=\frac{1}{n_1 n_2}\sum_{x_i\in G_1}\sum_{x_j\in G_2} d\left(x_i,x_j\right)$$

It equals the average of the distance between two sample points in G_1, G_2, and n_1, n_2 is the number of sample points in G_1, G_2, respectively.

SPSS22.0 is used to cluster analysis, and the clustering classification is shown as shown in Table 5.2.

Table 5.2: National classification based on temperature

Level	1	2	3	4	5
Temperature(℃)	0-12	12-17	17-23	23-27	27-40 or -20-0

Other indicators are also classified, specifically in the Appendix.

Step2: Based on the above criteria, the decision matrix of 10 countries, such as Somalia, is established.

Table 5.3: Decision judgment matrix

	Somalia	Niger	…	France	
V_1	5	4	…	1	
V_2	4	4	…	2	
V_3	3	3	…	1	
V_4	4	2	…	1	
	3	4	…	2	U_1
	4	3	…	1	U_2
	5	2	…	1	U_3
	5	3	…	2	U_4
	4	3	…	1	U_5

Step3: Establishment of fractional programming

$$\sum_{j=1}^{n} X_j \lambda_j + S^- = \theta X_0$$

$$\sum_{j=1}^{n} Y_j \lambda_j - S^+ = Y_0$$

Step4: Objective function

Step5: 4 input indexes were changed to observe the changes of θ, that is, the impact of climate change on national vulnerability. The change is shown in Figure 5.2.

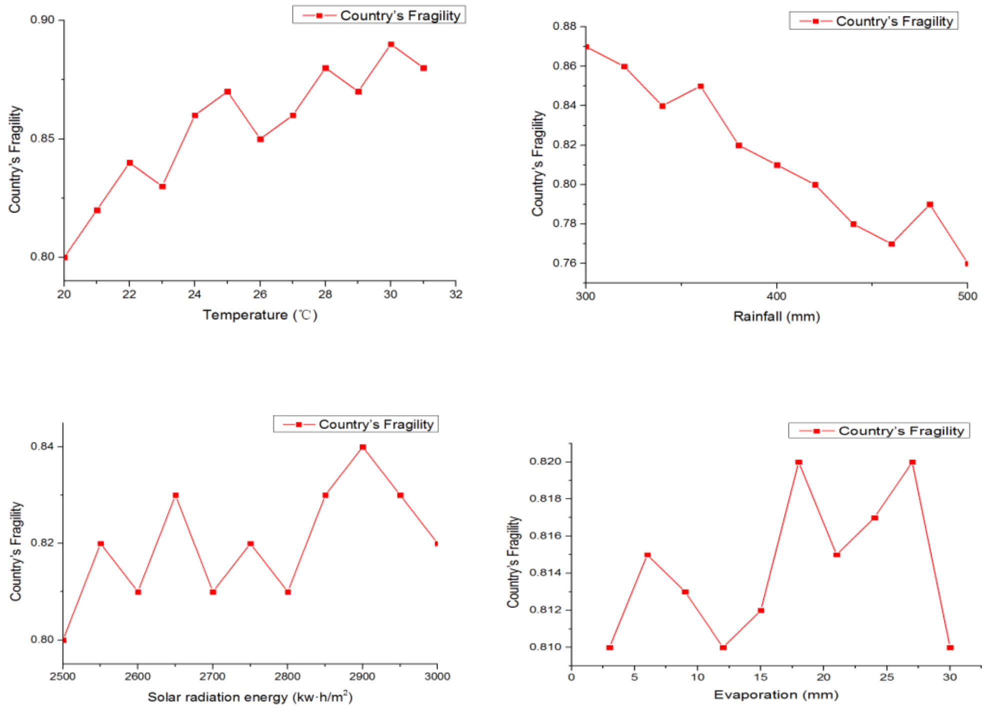


Figure 5.2: the impact of climate change on national vulnerability

5.2 How Fragile State Index changes without the impact of climate

All values of x_{ij} are set to 0, that is, the country's fragility changes are shown in Table 5.4 as the state is not affected by climate change.

Table 5.4: Changes on country's fragility

	normal	ignore the temperature	ignore the rainfall	ignore the Solar radiation energy	ignore the evaporation
Country's Fragility	0.85	0.64	0.68	0.72	0.78

As shown in Figure 5.1, temperature and rainfall have a significant impact on national fragility, while the effects of solar radiation and evaporation are not very obvious. When the temperature rises and rainfall decreases, Somalia countries tend to be dry, and crop growth is slow. This will lead to a food shortage in the country and easily lead to civil upheaval and high fragility. Therefore, when the temperature and rainfall are ignored, the country's fragility is reduced most and the state security is relatively stable.

VI. How and When can the Climate Change the FSI

6.1 Rough set theory

The question is to measure when and to what extent climate change will make the country more fragile. According to the background and reference 3, we can see that the combination of weak governance and social fragmentation is likely to greatly increase social vulnerability, that is, the number of armed conflicts in the model. This output indicator is obviously important for other output indicators, but the vulnerability prediction should not completely abandon other indicators. The attribute reduction of the index is considered here by the rough set theory[5].

• **Definition 1:** To a given decision table $\Omega=(v_1,v_2,\cdots,v_4 \vee u_1,u_2,\cdots,u_5),\forall B\subseteq v_2$, the decision attribute u_1 is $POS_B(u_1)=\underset{x\in U/d}{U}\underline{R_B}(x)$ relative to the conditional attribute B, and is recorded as $POS_B(B)$.

• **Definition 2:** Set up $\Omega=(v_1,v_2,\cdots,v_4 \vee u_1,u_2,\cdots,u_5,O,f)$ is a decision table. Suppose that $b\in B\subseteq v_3,v_4$ or $POS_B(u_1)=POS_{B-\{b\}}(u_1)$, we called b_0 is not necessary in B, otherwise, b is the u_1 necessity in the B. If every attribute in B is necessary, then B is called u_1 independent.

• **Definition 3:** In a decision system $\Omega=(v_1,v_2,\cdots,v_4 \vee u_1,u_2,\cdots,u_5)$, for any $H\subseteq B$, if H is satisfied at the same time: ① H is u_1 independent ② $POS_H(u_1)=POS_B(u_1)$, then H is a u_1 reduction of B.

6.2 Prediction model of BP neural network based on Rough Set Theory

First, we use the definition of rough set theory 1,2,3, select an output index to replace all indicators in an overall way, and change the value of its index, that is, $POS_H(u_1^*)=\{POS_B(u_1),POS_B(u_2), POS_B(u_3), POS_B(u_4), POS_B(u_5)\}$, and then build a neural network model with only one output[2].

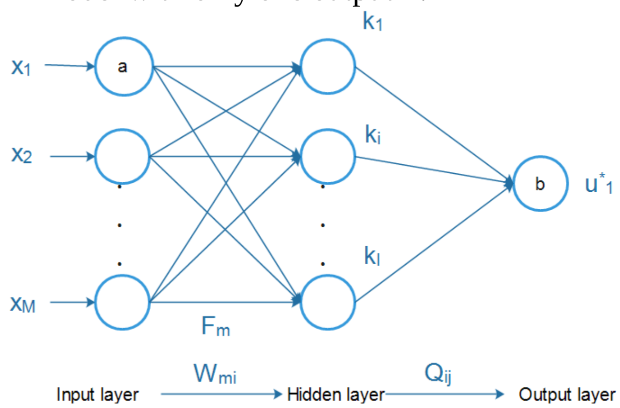


Figure 6.1: BP neural network schematic diagram

In Figure 6.1, $x_m(i=1,2,\cdots,M)$ is input data, u_1^* is the only output data, W_{m_i} is the connection weight between input layer and hidden layer, Q_{ij} is the connection weight between hidden layer and output layer, a is the hidden layer threshold, and b is the output layer threshold.

The input signal for the entire network is:

$$F_M^m(n) = x(n)$$

The error signal after n iteration is defined as $e_j(n)$, and the total error of the network is[3]:

$$e(n) = \frac{1}{2}\sum_{j=1}^{J} e_j^2(n)$$

Adjust the weight between the hidden layer and the output layer Q_{ij}

$$\Delta Q_{ij}(n) = \eta e_j(n) F_J^j(n)$$

Adjust the input layer and the hidden layer weight

$$\Delta W_{m_i} = \eta \delta_I^i F_M^m(n)$$

In the form, δ_I^i is a local gradient, which is $\delta_I^i = \frac{\partial e_j(n)}{\partial F_I^i(n)} f\left(F_I^i(n)\right)$

Where $f(\ )$ is a Sigmoid transfer function

After multi wheel weight adjustment, the result of prediction is obtained.

6.3 Model solution and result analysis

Step1: Simplifying the output index of decision matrix based on Rough Set Theory.

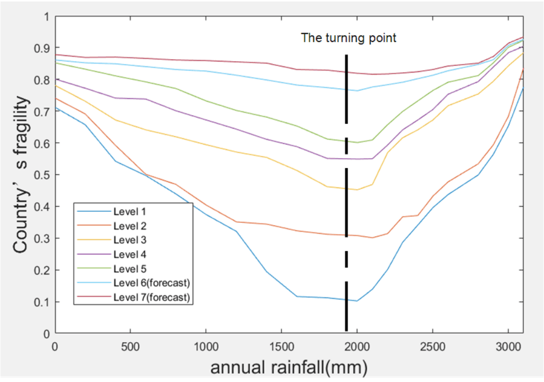
Table 6.1: Simplified decision matrix

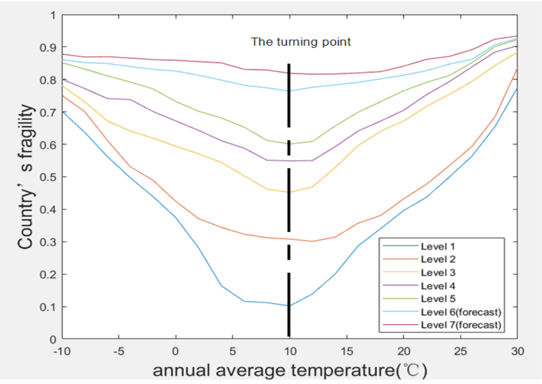
	Liberia	Cuba	Kenya	…	India	
V_1	5	3	4	…	1	
V_2	4	3	4	…	3	
V_3	3	2	3	…	4	
V_4	4	3	2	…	3	
	5	4	4	…	2	U_1

Step2: Using the model one model to change 4 climate change indicators to observe the impact of 4 climate variables on national vulnerability in Libya.

Step3: Change the armed conflict from level 1 to level 5, and observe the changes of 4 climate change indicators under the number of armed conflicts of level 5.

Step4: A BP neural network is used to predict the number of more armed conflicts, and the following results are obtained.





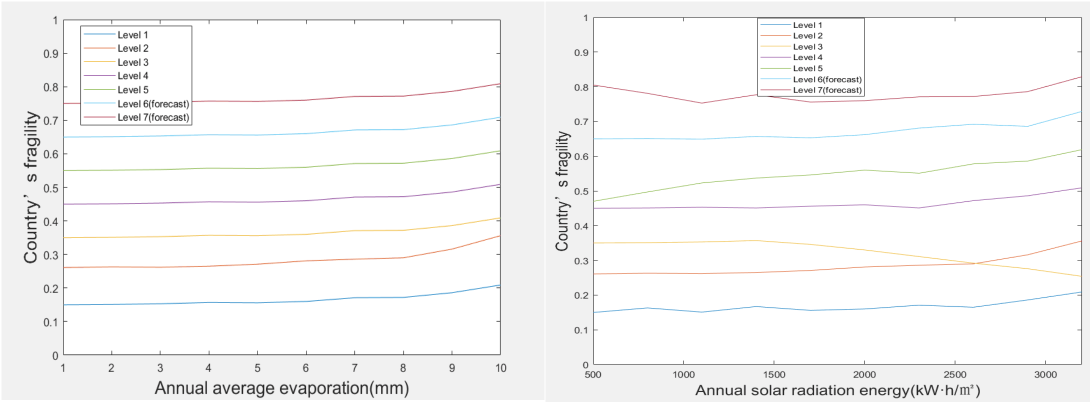


Figure 6.2: The predicted fragility curve

In the Figure 6.2, we can easily find that there is a significant turning point in the first two graphs. The specific data is shown in the following table.

Table 6.1: Turning point data

	Temperature(℃)	Rainfall(mm)
The turning point	10.01	1823

The above results are similar to that of task 2. Temperature and rainfall have great influence on fragility. And with the increase of the number of armed conflicts, the fragility of the country will increase at various levels in various stages. And the fragility curves of the 6 and 7 levels of the armed conflict based on the neural network are also consistent with the previous changes. The overall turning point is at the temperature of 10.01 ^{o}C and the rainfall of 1823mm. The temperature about 10 degrees centigrade is more suitable for the growth of crops. Excessive temperature can cause the surface drought, and the low temperature will freeze the soil. Most areas where rainfall is too high is mostly unsuitable for human habitation in tropical rainforests, and water resources are too low. Therefore, when the rainfall is about 1823mm, the country runs steadily. The perennial war in Libya has been greatly affected by the number of armed conflicts. When the number of armed conflicts reaches 7 levels (about 90 times a year), most countries maintain high fragility, which is almost independent of climate factors.

VII. Intervention measures to mitigate the risk of climate change

7.1 Current measures in the world

As climate change is closely related to the carbon emissions in people's lives, we have looked for some measures that have been introduced to control carbon emissions in some countries in the world.

Policy one: the US government introduced measures to control the total emissions and carbon emissions, set targets annually, and finally reduced greenhouse gas emissions to the level of 1990 in 2020, and then reduced 80% by 2050.

Policy two: the European Union invested and developed "green economy" in 2013, increasing the fuel consumption for traffic by at least 10%, and reducing the consumption of coal, oil and natural gas by 20%.

Policy three: Portugal builds the world's most powerful solar photovoltaic power plant, which can reduce nearly 90 thousand tons per year compared to coal powered power plants with equal power.

7.2 Carbon cycle model

• Total carbon dioxide (industry and site):

$$E(t) = E_{Ind}(t) + E_{Land}(t)$$

CO_2 from land use changes is exogenous, and FAO statistics are generally 1.57 billion tons of CO_2 a year in the world.

• Carbon cycle simulation system[7]:

① $M_{AT}(t) = E(t) + \phi_{11} M_{AT}(t-1) + \phi_{21} M_{UP}(t-1)$

② $M_{UP}(t) = \phi_{12} M_{AT}(t-1) + \phi_{22} M_{UP}(t-1) + \phi_{32} M_{LO}(t-1)$

③ $M_{LO}(t) = \phi_{23} M_{UP}(t-1) + \phi_{33} M_{LO}(t-1)$

$M_{AT}(t), M_{UP}(t), M_{LO}(t)$ represent carbon in the atmosphere, carbon in the upper ocean and in the biosphere, and carbon in the deep sea. Carbon flows in two directions between two adjacent reservoirs. Parameter ϕ_{ij} represents the flow parameters between the reservoirs.

$$F(t) = \eta\left\{\log_2\left[M_{AT}(t) / M_{AT}(1750)\right]\right\} + F_{EX}(t)$$

$F_{EX}(t)$ is a non CO_2 produced by external forces.

$$T_{AT}(t) = T_{AT}(t-1) + \xi_1\left\{F(t) - \xi_2 T_{AT}(t-1) - \xi_3\left[T_{AT}(t-1) - T_{LO}(t-1)\right]\right\}$$

$$T_{LO}(t) = T_{LO}(t-1) + \xi_4\left[T_{AT}(t-1) - T_{LO}(t-1)\right]$$

$T_{AT}(t)$ and $T_{LO}(t)$ represent surface and deep sea temperatures.

The equilibrium temperature is as follows:

$$\Delta T_{AT} = \Delta F(t) / \xi_2$$

7.3 Model solution and result analysis

Step1: Suppose that three policies are used in China to observe the temperature changes in China, the results are as follows[9]:

Table7.1: The changes brought about by the three policies

	Policy 1	Policy 2	Policy 3
Reduced CO_2 emissions(t)	178560	234562	90000

Step2: Find the atmosphere, biosphere and deep-sea carbon

Table7.2: Carbon displacement

	M_{AT}	M_{UP}	M_{LO}
Carbon content(t)	$2*10^{12}$	$2.7*10^{16}$	$4.82*10^{11}$

Step3: Observing the temperature of the deep sea around China and finding the amount of temperature change.

$$\Delta T = \frac{3.732}{1.88} = 1.98$$

Step:4: The parameters of China including the annual temperature, including the annual temperature, are replaced in the model and the θ is solved. And then compare it with the θ after the change of ΔT for the change of temperature.

Table7.3: Comparison of θ before and after changes

	before implementing the policy	after implementing the policy
θ	5.8736	5.7143

Step5: Solving the cost.

Table7.4: Various cost

	Biofuels	Coal	Oil	Natural gas
Average annual use in China(10 thousand t)	138965	189923	156782	78567
Change of the amount	13896	37985	31356	15713
The cost per t($)	90.1	118.7	172.1	57.2
Total cost(billion $)	20.12			

The cost of the power station is 0.2088 billion $, with a total of 20.3288 billion $.

result analysis:

These policies have indeed reduced the temperature, alleviated the trend of global warming in recent years, and reduced the national vulnerability index by 0.1593 by calculation. In comparison, it consumes 20 billion US dollars, but if these policies continue to continue, they will result in a benign cycle growth for the country. After years of policy implementation, the vulnerability of the country can be significantly reduced.

VIII. How to make the model more applicable

8.1 Model improvement

The comparison of the data envelopment analysis model is the relative attribute between the decision units. The DEA model specifies that the number of DMU needs to be greater than the number of input and output indicators, that is, the more the number of DMU is more accurate, the more the model can be embodied. Smaller "states" (cities) are more accurate because of a wide range of levels, and this model is more practical. But the larger "state" (continental), because of the less factors, the DEA results are very inaccurate.

In this paper, a modified TOPSIS model of distance entropy of three parameter interval number is used to transform the DEA model. By increasing the interval upper and lower bounds of input output in decision matrix, the most probable value of grey number is increased, which makes up for the shortage of decision information and provides more accurate results.

8.2 Model establishment

Suppose that there are $m+s$ decision plans (Input index v_i and output index u_k). n decision making unit DMU_j unified input and output indexes to

$v_i, m \leftarrow m+s, i=1,2,\cdots,m$, v_i is expressed by three parameter interval numbers, and it is $x_{ij}(\otimes)=\left[x_{ij}^l, x_{ij}^a, x_{ij}^b\right](i=1,2,\cdots,n; j=1,2,\cdots,m)$.

① Establishing decision matrix[4]

$$X=\left(x_{ij}(\otimes)\right)_{m\times n}=\left(\left[x_{ij}^l, x_{ij}^a, x_{ij}^b\right]\right)_{m\times n}\left(i=1,2,\cdots,n; j=1,2,\cdots,m\right)$$

Where $x_{ij}^b > x_{ij}^a > x_{ij}^l \geq 0$.

② Determine the weight of v_i

The weight of each input and output index determined here with the task one model.

③ Selection of positive and negative ideal solutions

For the positive index, we use the positive ideal scheme $X^+=\left(x_1^+, x_2^+, \cdots, x_m^+\right)$ for each index established by formula (3); For the anti-index, we use the positive ideal scheme $X^+=\left(x_1^+, x_2^+, \cdots, x_m^+\right)$ and the negative $X^-=\left(x_1^-, x_2^-, \cdots, x_m^-\right)$ for each index established by formula (4).

$$\begin{cases} X_j^+=\left(x_{ij}^{l+}, x_{ij}^{a+}, x_{ij}^{b+}\right)=\left[\max\limits_i x_{ij}^l, \max\limits_i x_{ij}^a, \max\limits_i x_{ij}^b\right] \\ X_j^-=\left(x_{ij}^{l-}, x_{ij}^{a-}, x_{ij}^{b-}\right)=\left[\min\limits_i x_{ij}^l, \min\limits_i x_{ij}^a, \min\limits_i x_{ij}^b\right] \end{cases} \quad (3)$$

$$\begin{cases} X_j^+=\left(x_{ij}^{l+}, x_{ij}^{a+}, x_{ij}^{b+}\right)=\left[\min\limits_i x_{ij}^l, \min\limits_i x_{ij}^a, \min\limits_i x_{ij}^b\right] \\ X_j^-=\left(x_{ij}^{l-}, x_{ij}^{a-}, x_{ij}^{b-}\right)=\left[\max\limits_i x_{ij}^l, \max\limits_i x_{ij}^a, \max\limits_i x_{ij}^b\right] \end{cases} \quad (4)$$

④ Calculating the positive ideal scheme and the distance entropy of each scheme H_i^+

$$H_i^+=\sum_{j=1}^{n} H\left(d_{ij}^+\right)$$

Where:

$$\begin{aligned} H\left(d_{ij}^+\right)=&\beta\times\left[\left(-\frac{x_{ij}^l}{x_{ij}^l+x_{ij}^{l+}}\log_2^{\frac{x_{ij}^l}{x_{ij}^l+x_{ij}^{l+}}}\right)+\left(-\frac{x_{ij}^{l+}}{x_{ij}^l+x_{ij}^{l+}}\log_2^{\frac{x_{ij}^{l+}}{x_{ij}^l+x_{ij}^{l+}}}\right)\right] \\ &+\alpha\times\left[\left(-\frac{x_{ij}^a}{x_{ij}^a+x_{ij}^{a+}}\log_2^{\frac{x_{ij}^a}{x_{ij}^a+x_{ij}^{a+}}}\right)+\left(-\frac{x_{ij}^{a+}}{x_{ij}^a+x_{ij}^{a+}}\log_2^{\frac{x_{ij}^{a+}}{x_{ij}^a+x_{ij}^{a+}}}\right)\right] \\ &+\gamma\times\left[\left(-\frac{x_{ij}^b}{x_{ij}^b+x_{ij}^{b+}}\log_2^{\frac{x_{ij}^b}{x_{ij}^b+x_{ij}^{b+}}}\right)+\left(-\frac{x_{ij}^{b+}}{x_{ij}^b+x_{ij}^{b+}}\log_2^{\frac{x_{ij}^{b+}}{x_{ij}^b+x_{ij}^{b+}}}\right)\right] \end{aligned}$$

⑤ Calculating the negative ideal scheme and the distance entropy of each scheme H_i^-

$$H_i^-=\sum_{j=1}^{n} H\left(d_{ij}^-\right)$$

Where:

$$H\left(d_{ij}^{-}\right)=\beta\times\left[\left(-\frac{x_{ij}^{l}}{x_{ij}^{l}+x_{ij}^{l-}}\log_2^{\frac{x_{ij}^{l}}{x_{ij}^{l}+x_{ij}^{l-}}}\right)+\left(-\frac{x_{ij}^{l-}}{x_{ij}^{l}+x_{ij}^{l-}}\log_2^{\frac{x_{ij}^{l-}}{x_{ij}^{l}+x_{ij}^{l-}}}\right)\right]$$
$$+\alpha\times\left[\left(-\frac{x_{ij}^{a}}{x_{ij}^{a}+x_{ij}^{a-}}\log_2^{\frac{x_{ij}^{a}}{x_{ij}^{a}+x_{ij}^{a-}}}\right)+\left(-\frac{x_{ij}^{a-}}{x_{ij}^{a}+x_{ij}^{a-}}\log_2^{\frac{x_{ij}^{a-}}{x_{ij}^{a}+x_{ij}^{a-}}}\right)\right]$$
$$+\gamma\times\left[\left(-\frac{x_{ij}^{b}}{x_{ij}^{b}+x_{ij}^{b-}}\log_2^{\frac{x_{ij}^{b}}{x_{ij}^{b}+x_{ij}^{b-}}}\right)+\left(-\frac{x_{ij}^{b-}}{x_{ij}^{b}+x_{ij}^{b-}}\log_2^{\frac{x_{ij}^{b-}}{x_{ij}^{b}+x_{ij}^{b-}}}\right)\right]$$

⑥ Calculating the positive ideal scheme and the closeness of each scheme C_i

$$C_i=\frac{H_i^{+}}{H_i^{+}+H_i^{-}}$$

⑦ Considering the weight v_i and the closeness degree C_i, the new weight is set up to be:

$$G_i=C_i^2\cdot v_i$$

The new weight matrix is recorded as λ_i^{*}

⑧ The modified DEA model is as follows:

$$\min\left[\theta-\varepsilon\left(\hat{e}_1^{\,T}S^{-}+e_2^{\,T}S^{+}\right)\right]$$
$$s.t.\begin{cases}\sum_{j=1}^{n}X_j\lambda_j^{*}+S^{-}=\theta X_0\\ \sum_{j=1}^{n}Y_j\lambda_j^{*}-S^{+}=Y_0\\ \lambda_j^{*}\ge 0,X_j\ge 0,Y_j\ge 0,\ j=1,2,\cdots,n\\ S^{-}\ge 0,S^{+}\ge 0\\ \hat{e}_1^{\,T}=(1,1,\cdots,1)\in E_m,e_2^{\,T}=(1,1,\cdots,1)\in E_n\end{cases}$$

8.3 Model solution and result analysis

We take the North American continent as an example to solve and test the model.

Step1: Establish a three parameter interval decision table for Eurasian continent, African continent, North American continent and South American continent. (Shown in the appendix) The relative probability of three parameter interval's most probable value is $\alpha=\frac{2}{3},\beta=\gamma=\frac{1}{6}$.

Step2: The positive and negative distance entropy table is calculated according to the formula of distance entropy of positive and negative ideal scheme (Shown in the appendix).

Step3: After calculating the closeness according to the C_i formula, a new weight G_i is calculated. Calculate the above two sheets into the formula ,

$C_1 = \frac{0.9714}{0.9714+0.9510} = 0.5053$ .Similarly, $C_2 = 0.4931$， $C_3 = 0.5123$， $C_4 = 0.4957$， $C_5 = 0.4934$， $C_6 = 0.5001$， $C_7 = 0.5078$， $C_8 = 0.4998$， $C_9 = 0.5015$。

Step4： Replace G_i into task one's model, calculate the θ of the North American continent and make a verification by using it on the states shown in the data sheet.

Table 8.1: Error analysis

Country	American	Canada	…	Cuba	Average	Estimate value	Fractional error
θ	1.3	1.6	…	7.8	4.675	4.538	2.9%

The vulnerability index of 28 countries in the North American continent is averaged by using the problem model, and then the vulnerability index of the North American continent is directly counted by the improved model. We find that the difference between the two is 2.9% and the error is very small. It is proved that the TOPSIS model using three parameter interval number distance entropy can effectively improve the representativeness and accuracy of decision units in decision matrix, and the model is correct.

IX. Testing the Model

9.1 Error analysis of DEA model

In order to prove the accuracy of our model, we compare the θ with the FSI in 2017. Since the value of A is 0-1, and the value of FSI is 0-120. So, we standardize the FSI divided by 120.

Table 9.1: Error analysis

Country	Fragile State Index	θ	Absolute error	Relative error
South Sudan	0.949	0.932	0.017	1.81%
Syria	0.922	0.937	0.015	1.66%
Libya	0.803	0.912	0.110	13.64%
Zambia	0.732	0.724	0.008	1.05%
Turkey	0.673	0.648	0.025	3.76%
Russia	0.660	0.674	0.014	2.12%
China	0.623	0.621	0.002	0.24%
Armenia	0.592	0.581	0.011	1.80%
Japan	0.312	0.324	0.012	3.96%
Finland	0.156	0.151	0.005	3.10%

Looking at the above table, we can find that the relative error of Libya is larger while others are all below 4%.This is mainly because Libya is in the war perennial. Therefore, the 9 indicators can not be accurately judged on their vulnerability.

9.2 Sensitivity Analysis

For the number of passengers waiting on the regular platform, the other parameters remain unchanged. We changed the value of 4 input index, and the change in the number of passengers is shown in the figure below:

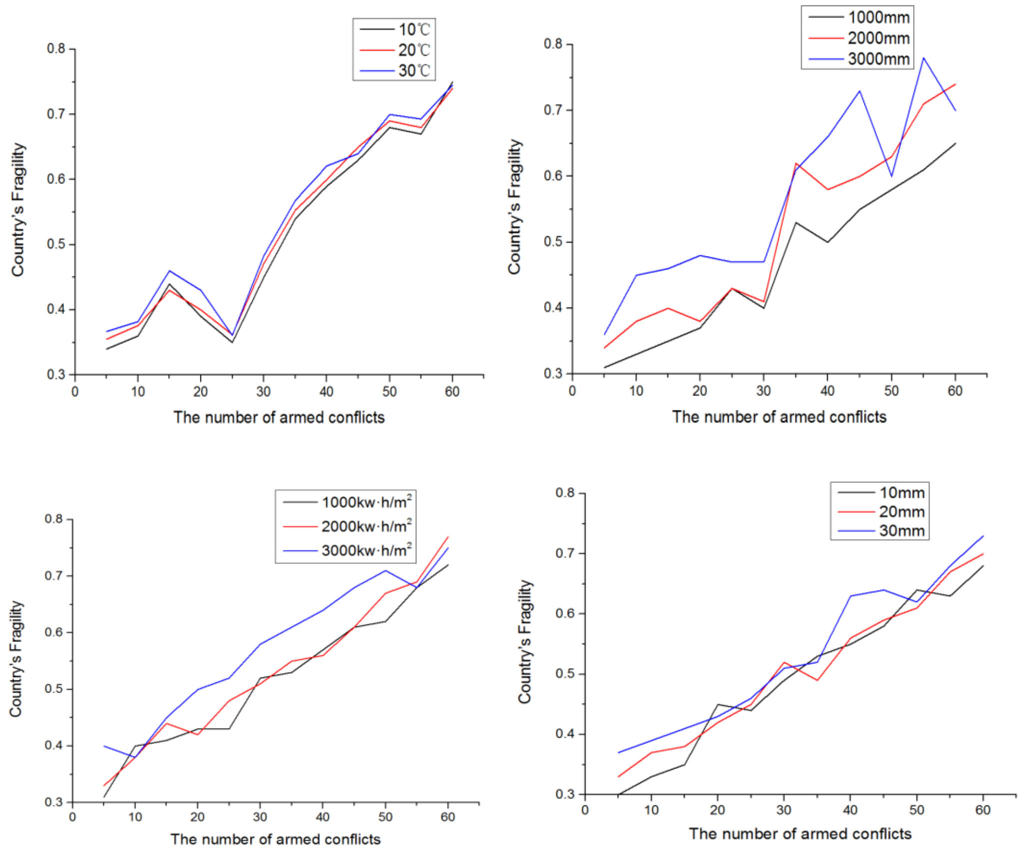


Figure 9.1: Sensitivity analysis

As shown in the sensitivity analysis, for the country's fragility, the changes in fragility can be found little by changing the values of 4 input indexes respectively. Therefore, the stability of the model is high.

X. Future Work

In this paper, the method of time distance entropy, when combining TOPSIS and DEA models, is relatively objectivity. But if in some special circumstances, such as during World War the vulnerability evaluation index, strong comprehensive power not fragile index is low, this method can put distance entropy fuzzy comprehensive evaluation method to add some subjective factors (such as whether the war is to distinguish between country), this model should be compared to now more accurate.

XI. Strengths and Weaknesses

11.1 Strengths

• The DEA model compares the relative efficiency between decision units, the more the decision making units are, the higher the accuracy is, so if we compare the urban or the housing area, the error will be smaller.

• The DEA model does not take into account the inherent relationship between the input and output indicators, and has a strong objectivity.

11.2 Weaknesses

• For a single DEA model, the smaller the decision making unit is, the lower the accuracy of the DEA model. When the number of decision making units is less than the total number of input and output indicators, the DEA model is no longer effective.

• For the binding model of TOPSIS and DEA, although there is still a high accuracy under the condition of fewer decision units, when the decision making unit is 1, such as the whole earth, it will lose the ability of decision evaluation.

XII. Conclusion

Through the study of this paper, it is found that the index of temperature change and rainfall has a great influence on the national vulnerability. The more the times of armed conflict occur in the same climate conditions, the greater the vulnerability. The energy saving and emission reduction policy of the country can alleviate the problem of excessive vulnerability, and the change will become obvious over time. The combination model of TOPSIS and DEA can accurately measure the vulnerability of the mainland.

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Appendix

Table

A three parameter interval decision table

	North America continent	South American continent	African continent	Eurasian continent
Temperature(℃)	[15,17,19]	[16,18,20]	[26,27,29]	[12,14,15]
Rainfall(mm)	[1750,1850,1910]	[1540,1590,1670]	[2560,2650,2740]	[1870,1940,2010]
Solar radiation energy($kw \cdot h/m^2$)	[1200,1310,1400]	[1010,1100,1210]	[2180,2460,2790]	[1550,1610,1690]
Evaporation(mm)	[7,9,11]	[14,15,16]	[28,30,32]	[17,19,21]
GDP(trillion $)	[13,15,18]	[12,14,15]	[1,2,3]	[5,7,8]
The number of armed conflicts	[5,7,9]	[9,10,11]	[38,42,47]	[16,20,24]
The natural rate of population growth	[0.1,0.2,0.4]	[0.3,0.5,0.6]	[1.5,1.7,1.9]	[0.9,1.0,1.1]
Life expectancy(year)	[75,80,83]	[76,680,85]	[48,52,60]	[68,72,78]
Human freedom index	[6.7,7.0,7.8]	[6.5,6.7,7.0]	[2.3,3.0,3.5]	[5.1,5.9,6.8]

The positive distance entropy table

	$H(d^+_{i1})$	$H(d^+_{i2})$	$H(d^+_{i3})$	$H(d^+_{i4})$	H_i^+
Temperature(℃)	0.9856	0.9438	1.0000	0.9562	0.9714
Rainfall(mm)	0.8541	0.8794	0.9132	0.9756	0.9056
Solar radiation energy($kw \cdot h/m^2$)	1.0000	0.9341	0.9452	0.8564	0.9339
Evaporation(mm)	0.7568	0.8563	0.9061	0.8945	0.8534
GDP(trillion $)	0.9415	0.9236	0.9871	0.8755	0.9319
The number of armed conflicts	1.0000	0.8965	0.8923	0.8875	0.9191
The natural rate of population growth	0.9345	0.9561	0.8943	0.7954	0.8951
Life expectancy(year)	0.9534	1.0000	0.8547	0.8956	0.9259
Human freedom index	0.9134	0.8675	0.8976	0.9561	0.9087

The negative distance entropy table

	$H(d^-_{i1})$	$H(d^-_{i2})$	$H(d^-_{i3})$	$H(d^-_{i4})$	H^-_i
Temperature(℃)	0.9634	0.8534	0.9873	1.0000	0.9510
Rainfall(mm)	0.8997	0.9876	0.9347	0.8876	0.9274
Solar radiation energy($kw \cdot h/m^2$)	0.8769	1.0000	0.9567	0.9386	0.9431
Evaporation(mm)	0.7856	0.9768	0.7089	0.9876	0.8647
GDP(trillion $)	0.8847	0.9427	0.9678	0.8756	0.9177
The number of armed conflicts	0.9465	0.7986	1.0000	0.9326	0.9194
The natural rate of population growth	0.7546	0.9126	0.9621	0.8638	0.8733
Life expectancy(year)	0.9127	1.0000	0.9562	0.8674	0.9341
Human freedom index	0.9427	0.8070	0.9826	0.9532	0.9214

Programs and codes

① Matlab program of Entropy value method

```
clc
clear
a=xlsread('C:\Users\LY\Desktop\2018t1.xlsx')
sum=zeros(1,4)
for i=1:4
    for j=1:10
        sum(1,i)=a(j,i)+sum(1,i)
    end
end
a1=zeros(10,4)
for i=1:10
    for j=1:4
        a1(i,j)=a(i,j)/sum(1,j)
    end
end
a2=zeros(10,4)
for i=1:10
    for j=1:4
        a2(i,j)=a1(i,j)*log(a1(i,j))
    end
end
```

```
sum1=zeros(1,4)
for i=1:4
        for j=1:10
              sum1(1,i)=a2(j,i)+sum1(1,i)
        end
end
k=1/log(10)
Ej=zeros(1,4)
for i=1:4
        Ej(i)=sum1(1,i)*(-k)
end
Dj=zeros(1,4)
Dj=1-Ej
sum2=0
for i=1:4
        sum2=Dj(i)+sum2;
end
Wj=zeros(1,4)
Wj=Dj/sum2
```

② Lingo program of DEA model

```
model:
sets:
dmu/1..10/:s,t,p;
inw/1..3/:omega;
outw/1..2/:mu;
inv(inw,dmu):x;
outv(outw,dmu):y;
endsets
data:
ctr=?;
x=@OLE('C:\Users\LY\Desktop\2018t2.xlsx')
enddata
max=@sum(dmu:p*t);
p(ctr)=1;
@for(dmu(i)|i#ne#ctr:p(i)=0);
@for(dmu(j):s(j)=@sum(inw(i):omega(i)*x(i,j));
t(j)=@sum(outw(i):mu(i)*y(i,j));s(j)>t(j));
@sum(dmu:p*s)=1;
end
```

③ Matlab program of the neural network

```
clc, clear
a=load('C:\Users\LY\Desktop\2018t3.xlsx');
a=a';
P=a([1:4],[1:end-1]); [PN,PS1]=mapminmax(P);
T=a(5,[1:end-1]);    [TN,PS2]=mapminmax(T);
net1=newrb(PN,TN)
x=a([1:4],end); xn=mapminmax('apply',x,PS1);
yn1=sim(net1,xn); y1=mapminmax('reverse',yn1,PS2)
delta1=abs(a(5,20)-y1)/a(5,20)
net2=feedforwardnet(4);
net2 = train(net2,PN,TN);
yn2= net2(xn); y2=mapminmax('reverse',yn2,PS2)
```

④ Matlab program of the carbon cycle

```
clc
clear
a=xlsread('C:\Users\LY\Desktop\2018t4.xlsx')
M=a(1,:)
E=a(2,:)
for i=1:10
M(i)=E(i)+(i-1)M(i)
T=F(i)/u1
end
for k=1:length(M)
M(k)=(Tau(visited(end),E(k))^Alpha)*(Eta(visited(end),E(k))^Beta);
end
P=P/(sum(P));
Pcum=cumsum(P);
Select=find(Pcum>=rand);
tot=J(Select(1));
Mup(i,j)=Mat;
end
end
if NC>=2
Mlo(1,:)=Mup(NC-1,:);
end
L=zeros(m,1);
for i=1:m

F(i)=log10(Mat(i,:));
```

```
for j=1:(n-1)

Mlo(i)=Mup(i)+(Mat(j),Mlo(j+1));
end
L(i)=L(i)+D(R(1),R(n));
end
L_best(NC)=min(L);
pos=find(L==L_best(NC));
R_best(NC,:)=Tabu(pos(1),:);
L_ave(NC)=mean(L);
NC=NC+1
Delta_Tau=zeros(n,n);
for i=1:m
for j=1:(n-1)
Delta_Tau(Tabu(i,j),Tabu(i,j+1))=Delta_Tau(Tabu(i,j),Tabu(i,j+1))+Q/L(i);
end
Delta_Tau(Tabu(i,n),Tabu(i,1))=Delta_Tau(Tabu(i,n),Tabu(i,1))+Q/L(i);
end
```

⑤ Lingo program of TOPSIS

```
model:
sets:
dmu/1..10/:s,t,p;
inw/1..4/:omega;
outw/1..2/:mu;
inv(inw,dmu):x;
outv(outw,dmu):y;
endsets
data:
ctr=?;
x=@OLE('C:\Users\LY\Desktop\2018t5.xlsx')
enddata
max=@sum(dmu:p*t);
p(ctr)=1;
@for(dmu(i)|i#ne#ctr:p(i)=0);
@for(dmu(j):s(j)=@sum(inw(i):omega(i)*x(i,j));
t(j)=@sum(outw(i):mu(i)*y(i,j));s(j)>t(j));
@sum(dmu:p*s)=1;
end
```