A Model for Evaluating Climate Change on Fragile States

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Abstract. In our paper, we find data of 178 states and then establish a series of models to identify and predict the influences of climate change on states’ fragility. First, we select representative indexes. Then we employ K-means Clustering Analysis method to classify the state’s fragility. Next we conducted collinearity test and parallelism test. Lastly, we made improvements to the model to enhance the impact of climate change on vulnerability.

1. Introduction
Nowadays, climate change has drawn more and more attention. The influences of climate change mainly include drought, increased greenhouse gas, sea level rise and more [1]. However, the impact of climate change is not only limited to the environment aspect, it will change people’s life. Specifically, the environmental problems caused by climate change will lead to the decline of environmental carrying capacity. These problems will inevitably lead to a series of international disputes, thus increasing the state fragility [2].

Research on fragile states began in the 1990s, when the fragile states, especially in the area of development assistance, received widespread attention. Fragility refers to structural weakness or failure, that is to say, due to the inability or unwillingness of the state to fulfill its basic functions, including the application of law to protect human rights and fundamental freedoms, ensure the safety of the population and provide service for poverty reduction and so on, thus leading to the breakdown of the social contract [3].

Although there is a great deal of research on state fragility, few studies have examined the impact of climate change on fragile states. Therefore, it is necessary to establish the connection between climate change and state fragility. In our paper, we improve the traditional two-category Logistic model and establish a three-category Logistic model that is more accurate and adaptable [4].

2. Assumptions and index selection

2.1 Research Assumptions
To simplify the problems, we make the following basic assumptions:

Assumption 1: We don’t consider the interactions of other irrelevant factors. Since we mainly study the influences of climate changes, the others factors such as war or turmoil can be neglected.

Assumption 2: We assume there are no extreme weather conditions. We only consider the influences of normal climate changes, because the probability of extreme weather is small and it is also difficult to predict.

Assumption 3: The fragilities of states are irrelevant. In order to identify the influences of climate change, we assume the fragility of each country is independent.
2.2 Data Normalization

In order to establish the relationship between climate change and state fragility, we need to normalize the data. Here we use the min-max normalization and do linear transformation of the raw data. The normalization formula is shown as follow:

\[ x' = \frac{x - x_{\text{min}}}{x_{\text{max}} - x_{\text{min}}} \]

Where \( x \) and \( x' \) respectively means the original value and normalized value. The data are collected from the World Bank.

2.3 Index Screening

2.3.1 The correlation test of initial index

According to the fragile state index released by the U.S. Fund for Peace and Foreign Policy Magazine, the twelve indexes can be divided into three categories. The specific classification is shown in the following table:

| Classification of Indexes | Initial Fragile Indexes |
|---------------------------|-------------------------|
| E: Economic Indexes       | E1: Economic Decline    |
|                           | E2: Uneven Economic Development |
|                           | C3: Group Grievance     |
| S: Social Indexes         | E3: Human Flight and Brain Drain |
|                           | S1: Demographic Pressures |
|                           | S2: Refugees and IDPs   |
| P: Political and military Indexes | C1: Security Apparatus |
|                           | C2: Factionalized Elites |
|                           | P1: State Legitimacy     |
|                           | P2: Public Services      |
|                           | P3: Human Rights and Rule of Law |
|                           | X1: External Intervention |

Among them, Economic Indexes (\( E \)) are indicators of a state’s economic development, specifically including Economic Decline and Uneven Economic Development; Social Indexes (\( S \)) refer to a series of indicators that reflect the conditions of public order and human resources, specifically including Group Grievance, Human Flight and Brain Drain, Demographic Pressures, Refugees and IDPs; Political and military Indexes (\( P \)) are indicators that reflect the state of politics and security in the country, which specifically include Security Apparatus, Factionalized Elites, State Legitimacy, Public Services, Human Rights and Rule of Law, External Intervention.

According to Spearman rank correlation coefficient test, we conduct a correlation test of the 12 indexes, the formula of the coefficient test is

\[ r_i = \frac{1}{n-1} \sum_{t=1}^{n} \left( \frac{X_t - \bar{X}}{S_X} \right) \left( \frac{Y_t - \bar{Y}}{S_Y} \right) \]

Where \( r_i \) is the simple correlation coefficient,
\( n \) is the sample size,
\( X_t, Y_t \) are respectively indicate the observation values of variables,
\( \bar{X}, \bar{Y} \) are respectively indicate the mean values of variables.

The correlation coefficient \( r \) represents the linear correlation between two variables, which is constrained to \([-1, 1]\) interval. The specific criterion is

a) If \( r \) is greater than 0, it indicates that the two variables are positively correlated;
b) If \( r \) is less than 0, it indicates that the two variables are negatively correlated.
In this problem, Y is the state fragility, \( X_i \) (i=1, 2, …, 12) are 12 indexes. We do the Spearman rank correlation coefficient test by SPSS, and we can get the following results:

| Index | Coefficient \( r_i \) |
|-------|----------------------|
| C1    | 0.8807               |
| C2    | 0.8673               |
| C3    | 0.6842               |
| E1    | 0.8197               |
| E2    | 0.8367               |
| E3    | 0.7336               |
| P1    | 0.8380               |
| P2    | 0.9128               |
| P3    | 0.8138               |
| S1    | 0.8880               |
| S2    | 0.8215               |
| X1    | 0.8270               |

In our model, six indexes are selected, so \( n \) is equal to six. The significance level \( r \) we choose is 0.05, so the threshold \( r \) is 0.829. When the significance level \( r_i \) we calculated is larger than \( r \), we think the correlation is significant, when \( r_i \) is less than \( r \), we think the correlation is not significant.

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According to the results we get, these six indexes pass the significance test, which are respectively Security Apparatus (C1), Factionalized Elites (C2), Uneven Economic Development (E2), State Legitimacy (P1), Public Services (P2), Demographic Pressures (S1). The six indexes are more relevant to state fragility, while the others are less relevant.

These indexes are independent of each other and they have the same representation of the same type of fragile states indexes. For example, in terms of the Economic Indexes (E), Economic Decline (E1) and Uneven Economic Development (E2) have the same representative, that is to say any one of the indexes can independently represent the state’s economic conditions. Therefore, we separately select one from three types of indexes, which are listed as follows:

| Classification of Index | The selected index |
|-------------------------|--------------------|
| Economic Index (E)      | Uneven Economic Development (E2) |
| Social Index (S)        | Demographic Pressures (S1) |
| Political and military Index (P) | Public Services (P2) |

2.3.2 The selection of climate change index

We select five of the more representative indexes of climate change, they are Rain Fall (R), Temperature (T), CO\(_2\) Emission (CE), Arable Land Area (A) and Forest Area (F). In order to facilitate the follow-up analysis, we carried out a correlation test of each index. When screening the indexes, we conduct two types of tests, one for each index and the state fragility test, and the other is for each index and the selected indexes (E2), (S1), (P2) in the first step.

In the first type of test, after Spearman correlation analysis, we get the following results:
Table 5. The coefficient of climate change indexes

| Index | Coefficient $r_j$ |
|-------|------------------|
| R     | 0.9051           |
| T     | 0.9123           |
| CE    | 0.9333           |
| A     | 0.8721           |
| F     | 0.8501           |

In this process, five indexes are selected, so $n$ is equal to five. Like the first step for screening indexes, the significance level we choose is also 0.05, so the threshold $r$ is 0.900. When the significance level $r_j$ we calculated is larger than $r$, we think the correlation is significant, when $r_j$ is smaller than $r$, we think the correlation is not significant.

According to the results we get, these three indexes pass the significance test, which are respectively Rain Fall ($R$), Temperature ($T$), CO$_2$ emission ($CE$). The three indexes are more relevant to state fragility, while the others are less relevant. We regard the influences of the three indexes as **direct influence**.

In the second type of test, the results show that the other two climate change indexes have some relevance. Thus we define the influences of the other two indexes as **indirect influence**.

The direct influence and indirect influence are illustrated in Fig.1.

![Fig.1. The direct and indirect indexes](image)

2.3.3 The classification of fragile state degree

Many methods are available for massive data processing. Here we use K-means clustering method. Based on the indexes of state fragility, we classify the 178 states into three categories.

Table 6. Three categories of fragile degree

| Fragile state Index | Fragile Degree   |
|---------------------|------------------|
| 1-57                | Stable           |
| 58-132              | Vulnerable       |
| 133-178             | Fragile          |
According to Table 6, we can see that the states with fragile index of 1-57 are classified as Stable, the states with fragile index of 58-132 are classified as Vulnerable, the states with fragile index of 133-178 are classified as Fragile.

2.3.4 Collinearity and parallelism test

We establish an ordinal three-category logistics model for the division of state fragility levels. First of all, we need to introduce the basic principle of ordinal polytomous logistics. It can be represented by the following formula:

\[ y^* = \alpha + \sum_{i=1}^{m} \beta_i x_i + \varepsilon \]

Where \( y^* \) represents the inherent tendency of a predictor, which cannot be directly measured, \( \alpha \) represents a constant, \( \beta_i \) represents coefficient term, \( \varepsilon \) represents error term.

Let the result variable \( y \) be an ordered variable of \( k \) levels, the \( k \) levels are respectively represented by 1, 2, ..., \( k \), \( x^T = (x_1, x_2, ..., x_p) \) is the independent variable. The probability of level \( j \) is

\[ P(y = j | x) \]

The probability that the level is less or equal to \( j \) is

\[ P(y \leq j | x) = P(y = 1 | x) + \cdots + P(y = j | x) \]

The logit transformation for the cumulative probability of rank less than or equal to \( j \) can be represented as follow:

\[ \logit P_j = \logit [P(y > j | x)] = \ln \frac{P(y > j | x)}{1 - P(y > j | x)} \]

\[ j = 1, 2, ..., k - 1 \]

The Logistic regression of ordered classification results can be defined as

\[ \logit P_j = \logit [P(y > j | x)] = -\alpha_j + \sum_{i=1}^{p} \beta_i x_i \]

\[ j = 1, 2, ..., k - 1 \]

which is equal to

\[ P(Y \leq j | x) = \frac{1}{1 + \exp (-\alpha_j + \sum_{i=1}^{p} \beta_i x_i)} \]

According to the following formula

\[ P(y \leq 1 | x) < P(y \leq 2 | x) < \cdots < P(y \leq k | x) \]

We can get

\[ \alpha_1 < \alpha_2 < \cdots < \alpha_k \]

Among which is called division factor, it splits the distribution.

For parameter estimation, we adopt the maximum likelihood estimation method, which is listed as follows:

\[ P(y = j | x) = P(y \leq j | x) - P(y \leq j - 1 | x) \]

\[ = P(-\alpha_j + \sum_{i=1}^{p} \beta_i x_i < u < -\alpha_{j-1} + \sum_{i=1}^{p} \beta_i x_i) \]

\[ = \frac{1}{1 + \exp (-\alpha_j + \sum_{i=1}^{p} \beta_i x_i)} - \frac{1}{1 + \exp (-\alpha_{j-1} + \sum_{i=1}^{p} \beta_i x_i)} \]

Before the ordinal three-category logistics regression, we need to conduct Collinearity and parallelism test. We select 10 countries from 57 states that are Fragile, 15 countries from 75 states that
are Vulnerable, 10 countries from 46 states that are Stable. And then we conduct Collinearity and parallelism test of the 35 samples. The formula is

\[ P(Y < m \mid x) = F(\alpha_m - x\beta_m) \quad m = 1,2, \ldots, j - 1 \]

In the collinearity test results, if the Tolerance is less than 0.1 or Variance Inflation Factor (VIF) is larger than 10, we think there is a collinear existence. In our problem, the Tolerances are much larger than 0.1, the VIFs are less than 10, so there is no multicollinearity. The collinearity test is passed.

In the parallelism test results, the results show that the Chi-Square \( \chi^2 \) is 8.321, the significance \( p \) is 0.363, which mean the parallelism test is passed. After passing these two tests, we can do ordinal three-category regression analysis.

3. Model establishment and test

At first, we give number to the state fragility level. The stable states are numbered as 1, the vulnerable states are numbered as 2, and the fragile states are numbered as 3. And then we use the maximum likelihood estimation method for parameter estimation, the following model is established:

\[
\begin{align*}
P(y \leq 1) &= \frac{1}{1 + e^{x(0.62 - 0.96x_1 + 0.53x_2 + 0.19x_3 + 0.72x_4 - 0.38x_5 + 0.53x_6)}} \\
P(y \leq 2) &= \frac{1}{1 + e^{x(-0.83 - 0.96x_1 + 0.53x_2 + 0.19x_3 + 0.72x_4 - 0.38x_5 + 0.53x_6)}} \\
P(1) &= P(y \leq 1) \\
P(2) &= P(y \leq 2) - P(y \leq 1) \\
P(3) &= 1 - P(1) - P(2) = 1 - P(y \leq 2)
\end{align*}
\]

Where \( x_1 \) represents the index of Rain Fall (R), \( x_2 \) represents the index of Temperature (T), \( x_3 \) represents the index of CO2 Emission (CE), \( x_4 \) represents the index of Uneven Economic Development (E2), \( x_5 \) represents the index of Public Services (P2), \( x_6 \) represents the index of Demographic Pressures (S1).

\( P(1), P(2), P(3) \) are the probability that a state is Stable, Vulnerable and fragile. The state’s fragility is the level represented by the maximum probability.

According to the Table of Model Fitting Information, the significance of the last column is less than 0.05, indicating that the model pass the test; in the table of Goodness- of-Fit, the last column of Pearson Chi-Square significance of 0.964, which means the probability is great. Our model can fit the original data properly, so it passes the test. In the table of Pseudo R-Square, the three pseudo R-Square values are low, indicating that the model needs to be improved.

We compare the results obtained from our model with the fragile grades obtained by the K-means clustering analysis. In order to reflect the accuracy of the model, we randomly select Somalia, Central Africa Republic, Bulgaria and China these four countries to test our model. The following table shows our results:

| State                        | P(1)  | P(2)  | P(3)  |
|------------------------------|-------|-------|-------|
| Somalia                      | 0.0354| 0.1000| 0.8646|
| Central Africa Republic      | 0.1678| 0.2944| 0.5378|
| Bulgaria                     | 0.5598| 0.2845| 0.1557|
| China                        | 0.3153| 0.3153| 0.3374|

As we can see from the Table 7, the values of P(3) of Somalia and Central Africa Republic are relatively large, which means that they are both fragile countries; the value of P(1) of Bulgaria is the largest, indicating that it belongs to the stable country; the P(2) of China is the largest, which means it is a vulnerable country.
Next we verify the results of our model. In the state fragile index, Somalia and Central Africa Republic respectively rank the second and the third, which fall into [1,57] interval; Bulgaria ranks the 132th, belongs to stable country; China ranks the 85th, belonging to [58,132] interval. In conclusion, our model is reliable.

4. Summary
In our paper, we have done lots of data processing work, establish a basic model and improve it. However, just like other models, our model cannot avoid some weaknesses, such as lack of data, neglect of extreme conditions, some assumptions are not very adaptable in real world and so on.

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