



# Analysis of the Impact of Climate Change on Countries' Fragility

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## Abstract:

"Fragility" is a comprehensive index that measures different indicators, which is used to assess the degree of instability of a country. Mathematical models such as evaluation, regression and prediction are comprehensively used to explore the relationship between climate change and national fragility in this paper. Based on the conditions given in each question, the impact of climate changes on each factor and the total index was analyzed in this paper, accordingly, giving the specific index system to define the national vulnerability. After verifying, the model of this paper is reasonable and has practical significance.

*Keywords: National fragility, Climate change, Integrated assessment, Regression modeling, GM (1,1) prediction*

## INTRODUCTION

### Problem Background

With the advent of the blooming economy, the government of different countries tends to neglect environmental preservations [1] and society harmony [2] to some degree. The increase impacts of climate changes namely droughts, famine do increasingly harm to people's livelihoods as well as the sustain abilities of country's development [3-6]. It is a global emergency and one of the greatest challenges facing humanity today. Nevertheless, so many elements have something to do with such a situation that barely have people could find an effective way to tackle it, if we feel like finding a significant method to mitigate the danger of climate changes and keep a country from becoming a fragile state, there is no denying that a model which could define and handle the fragility is inexorable.

### Restatement of the Problem

Climate change is dedicated to the totality of the problem of climatic variability and change. Meanwhile, climate change is the main factor to determine the degree of fragile state of the country. Given the background information and requirements in the problem description, we need to tackle the following problems step by step:

**Task1.** Build up a model system to identify factors which could affect fragility.

**Task2.** Use one of the top 10 the most fragile states whose datum we utilized to settle the model to experiment the flexibility of the model system.

**Task3.** Use the datum from other resources to figure out the Fitting degree of the model system.

**Task4.** Intervene human factors one by one to see the trend of the climate change risk, then making full use of those indicators to find out the country which could have the optimum with

interventions taking effect.

**Task5.** Decrease or increase the scope of space we used as a date to experiment whether the system works. If not, modify the model to prompt the universality.

### Our Work

On the whole, all the tasks require us to build relationships between climate change and countries' fragility from different perspectives in order to analyze the impacts by using mathematical model.

Firstly, task 1 requires us to build a comprehensive assessment model of national vulnerability. We should define which indicators would influence vulnerability including climate change and the weight of each indicator.

Next, we should continue to make research on how climate change influences regional instability based on the built model before. The impacts would be divided into two parts. For one thing, the temporal connection based on the time factor was explored. The grey prediction model is mainly used to predict Kenya's vulnerability by defining tipping points according to the actual situation.

For another, a regression model to explore the significance of the association between various indicators was built, human intervention for the salient indicators was proposed, taking Afghanistan as an example, and how to prevent the impact of climate change on national vulnerability was reasonably explained. The structure of our work is shown in Fig. 1.

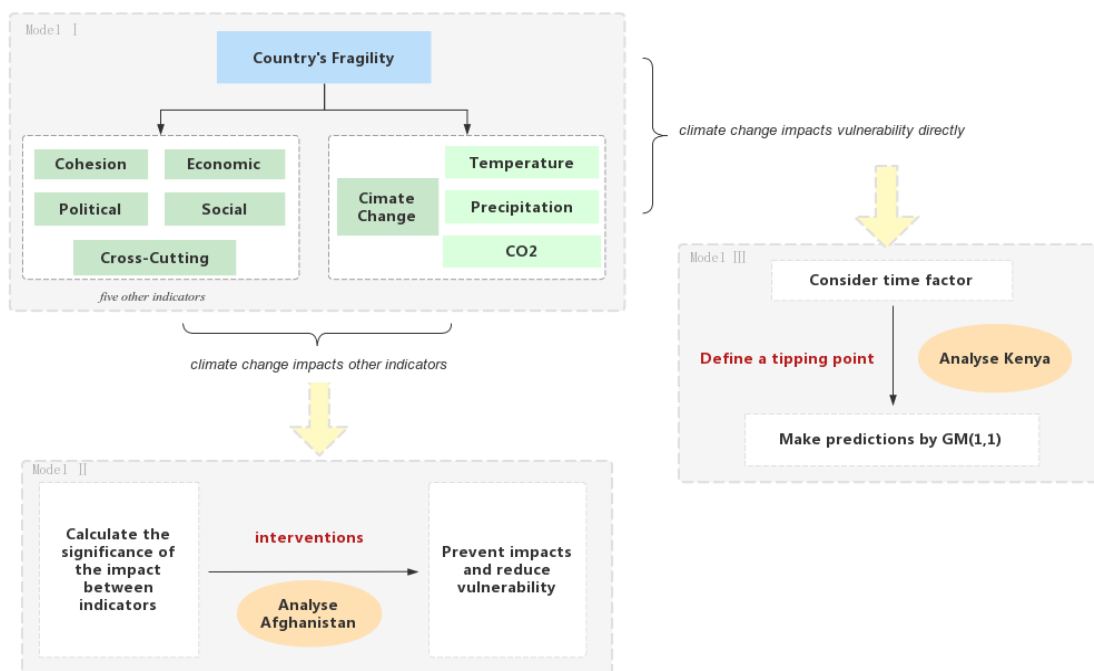


Fig. 1: The structure of our work.

### ASSUMPTIONS AND JUSTIFICATIONS

**We Assume That Only Temperature, Precipitation And Per Capita CO<sub>2</sub> Emissions Affect the Climate Change of Each Country**

The factors that affect the climate and environment are complex and profound, including latitude, atmospheric circulation, land and sea distribution, ocean current and topography. We select the

main characteristics of climate (i.e., temperature and water), and consider that carbon emissions have a serious impact on climate, which together determine the climate.

### We Assume That the Extreme Weather Only Occurs in The Six Months of Summer and Winter Include Extremely Hot or Severely Cold

Considering that the impact of temperature on vulnerability is often the higher the temperature or the lower the temperature, the higher the vulnerability, so these extreme temperatures are our key analysis objects.

### We Assume That All Data Comes from Authentic Sources

Most of the data in this paper come from online sources and literature, including countries' vulnerability indices, temperature, precipitation, and CO<sub>2</sub> emissions. Through this assumption, the results of our model can be more objective and authoritative, and the correctness of our model can be verified from a positive perspective.

### We Assume That the Value of Country Vulnerability Follows a Normal Distribution Globally as A Whole

Normal distributions are a very common type of data distribution and are relatively natural. With this assumption, we can better use models such as regression for analysis, and we can also classify data more objectively.

## NOTATIONS

The key mathematical notations used in this paper are listed in Table 1.

**Table 1: Notations used in this paper**

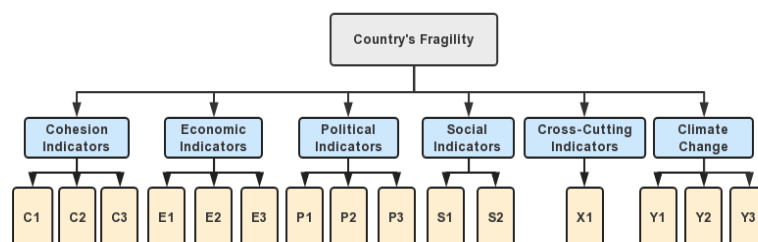
Symbol	Description	Unit
$a_{ij}$	Actual value of each indicator	1
$x_i$	Secondary indicators	1
$\omega_i$	Weight of factors	1
$\hat{x}_i$	Secondary indicator estimator	1
$\beta_i$	Constant corresponding to each indicator	1
$R^2$	Goodness of fit	1
$CF$	Representation of countries' fragility results	1

## MODEL I: NATIONAL FRAGILITY ASSESSMENT SYSTEM MODEL

### Modeling Ideas

#### **Determine Evaluation Indicators:**

A model to determine a country's fragility based on AHP has been established and evaluation indicators should be determined at first. The structure of AHP is shown in Fig. 2.



**Fig. 2: The structure of AHP.**

Evaluation indicators consist of primary indicators and secondary indicators. There are many influencing factors and we could not put all into consideration, so five main factors (*Cohesion, Economic, Political, Social and Cross-cutting*) as primary indicators according to the information online ([fragilestatesindex.org/](http://fragilestatesindex.org/)) were chosen. Meanwhile, task1 requires us to measure the impact of climate change simultaneously and we also define *Climate Change* as a primary indicator here. Next, we determine secondary indicators in the same way.

Description of Secondary Indicators in Table 2.

**Table 2: Description of secondary indicators**

Cohesion Indicators	C1	Security Apparatus	Political Indicators	P1	State Legitimacy
	C2	Factionalized Elites		P2	Public Services
	C3	Group Grievance		P3	Human Rights
Economic Indicators	E1	Economy	Climate Change	Y1	Temperature
	E2	Economic Inequality		Y2	Precipitation
	E3	Human Flight and Brain Drain		Y3	CO <sub>2</sub> Emission
Social Indicators	S1	Demographic Pressures	Cross-Cutting Indicators	X1	External Intervention
	S2	Refugees and IDPs			

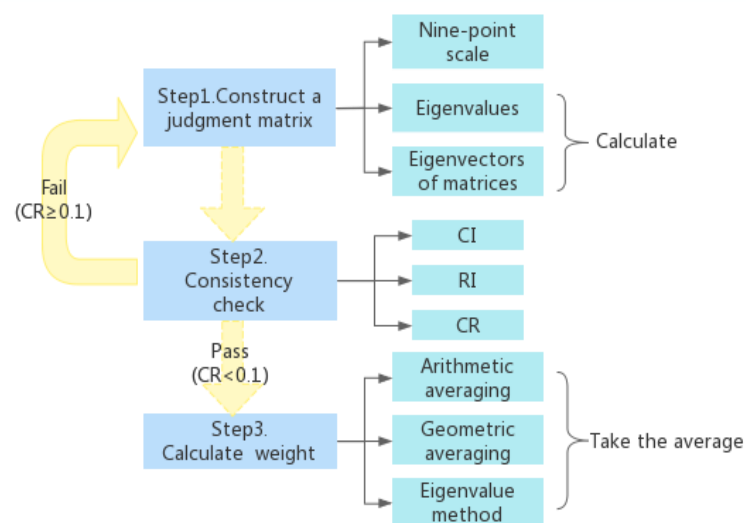
**Determine the Weight [7]:**

In order to analyze a country’s fragility, determining the weight of every indicator is significant in this model. **Entropy Weight Method combining subjective and objective** was used to determine the weight.

Entropy Weight Method combining subjective and objective means that we should combine the results both from Entropy Weight Method subjectively and Expert Scoring objectively.

**Expert Scoring:**

Through the form of expert scoring, the scale value of the comparison between the elements is determined by the nine-point scale method, and the judgment matrix is established, and the eigenvalues and eigenvectors of the matrix are solved by MATLAB software, and the consistency test of the matrix is carried out. The process of Expert Scoring is shown in Fig. 3.



**Fig. 3: The process of expert scoring.**

**Consistency Check:** Check whether the judgment matrix and the consensus matrix we construct are too different.

Step 1: Calculate consistency metrics (CI)

$$CI = \frac{\lambda_{\max} - n}{n - 1} \quad (1)$$

Step 2: Find the corresponding average random consistency indicator RI table

n	2	3	4	5	6	7	8	9	10	11
RI	0	0.58	0.9	1.12	1.24	1.32	1.41	1.45	1.49	1.51

Step3: Calculate the consistency scale CR

$$CR = \frac{CI}{RI} \quad (2)$$

If  $CR < 0.1$ , the consistency of the judgment matrix can be considered acceptable. Otherwise, the judgment matrix needs to be corrected.

### Entropy Weight Method:

The principle of entropy weight method is a method of quantifying and synthesizing the information of each unit to be evaluated in the evaluation. The use of entropy weights to empower each factor can simplify the evaluation process.

**Step 1:** Data collection and processing according to the relevant data obtained by the survey, the data is collected, summarized and sorted out, special test data, etc., and the original data  $a_{ij}$  is first normalized, and the proportion  $p_{ij}$  is calculated:

$$p_{ij} = \frac{a_{ij}}{\sum_{i=1}^n a_{ij}}, i = 1, 2, \dots, n, j = 1, 2, \dots, m \quad (3)$$

**Step 2:** Entropy calculation: For the  $j$ th influencing factor, the data column under the influencing factor is used to calculate the entropy value  $e_j$  of the influencing factor, that is

$$e_j = -\frac{1}{\ln n} \sum_{i=1}^n p_{ij} \ln p_{ij}, j = 1, 2, \dots, m \quad (4)$$

**Tips:**  $k > 0, k = 1/\ln m, 0 \leq E_j \leq 1$

**Step 3:** Calculate the degree of bias: calculate the deviation degree  $g_j$  of the  $j$ th influencing factor, for the  $j$ th influencing factor determined, if the degree of influence of this factor on the comprehensive evaluation of the entire data sample index is smaller, the closer the data column under the influencing factor is to the completely disordered state, the larger the  $e_j$ , the smaller the deviation degree of the influencing factor should be, hence the definition

$$g_j = 1 - e_j, j = 1, 2, \dots, m \tag{5}$$

**Step 4:** After calculating the weights to normalize the deviation degree calculated above, the weights of each influencing factor are obtained, which reflects the degree of influence of the influencing factors on the comprehensive evaluation of the entire data sample index. Among them, the weight calculation formula of the *j*th influencing factor is

$$w_j = \frac{g_j}{\sum_{i=1}^m g_j}, j = 1, 2, \dots, m \tag{6}$$

**Combination of the Both:**

Finally, we combine the two methods by means of the averaging method.

$$w_i = \frac{w_{1i} + w_{2i}}{2} \tag{7}$$

Table 3 lists the weight diagram of each indicator.

**Table 3: The weight of each indicator**

Cohesion Indicators	C1	0.0452	Political Indicators	P1	0.0805
	C2	0.0452		P2	0.0403
	C3	0.0452		P3	0.0805
	total	0.1357		total	0.2013
Economic Indicators	E1	0.1148	Climate Change	Y1	0.0087
	E2	0.1148		Y2	0.0288
	E3	0.1148		Y3	0.0159
	total	0.3443		total	0.0534
Social Indicators	S1	0.0671	Cross-Cutting Indicators	X1	0.0640
	S2	0.1342			
	total	0.2013		total	0.0640

**Establishment and Explanation of Comprehensive Evaluation System:**

We weighted the indicators based on the above weights to obtain the vulnerability of each country.

$$CF = \sum w_i * x_i \tag{8}$$

**Among them,**

- *CF*: Representation of countries' fragility results;
- *w<sub>i</sub>*: weight of each secondary indicators, *i*=1,2...15;
- *x<sub>i</sub>*: secondary indicators, *i*=1,2...15.

According to Task<sub>1</sub>, our model should meet some requirements and standards:

**When a State is Fragile, Vulnerable, or Stable:**

In our model, the higher the value of CF is, the higher the vulnerability is. A country's CF changes according to the year and the value of each indicator, so we can determine the status of a country by determining the threshold value.

### **How Climate Change Increases Fragility:**

On one hand, climate change directly affects vulnerability as an indicator. Our model can give a diagram which shows the direct relationship between climate change and vulnerability based on data for each indicator.

On the other, it also affects ultimately vulnerability by indirectly or directly affecting other indicators. Our model can explain the functional relationship between other indicators and climate change indicators through a regression model, and use the significance of the relationship between model indicators.

Specific instructions are explained in the following questions.

### **Calculation of a Specific Country and Result Analysis**

In order to meet Task2's requirements, we select Afghanistan (ranked 8<sup>th</sup> in 2022) to determine how climate change may have increased fragility of that country. We should search for concerned data and make necessary calculation based the evaluation system model.

### ***Data Collection and Quantification of Indicators:***

Based on the secondary indicators, the data of those influencing factors expect *Climate Change* come from the global vulnerability index of the website ([fragilestatesindex.org/](http://fragilestatesindex.org/)). On this website, each indicator is scored out of 10, and the higher the score, the worse the indicator scores, increasing the country's vulnerability.

About the indicators of *Climate Change*, we quantify Temperature, Precipitation and CO<sub>2</sub> Emission.

- **Temperature:** Considering the influence of hypothetical extreme weather, we select the average temperature in summer from June ~ August and winter in December ~ February, and take the average of these six months after assigning a ten-point value with 15~18 degrees Celsius as the best range.
- **Precipitation:** We take the annual precipitation of the country and also take 1000~1800mm per year as the best interval for assignment.
- **CO<sub>2</sub> Emission:** The higher the annual per capita carbon emissions were, the higher the country's vulnerability was.

The temperature each year comes from the weather spark website. The average annual precipitation and carbon emissions per capita of each country come from the World Bank Organization.

### ***Data Normalization [8]:***

We found that most of the indicators were minimal data, with temperature and precipitation being ranged, so we needed to standardize the data.

Transform interval data into extremely small:

$$x' = \begin{cases} 1 - \frac{a-x}{c}, & x < a \\ 1, & a \leq x \leq b \\ 1 - \frac{x-b}{c}, & x > b \end{cases} \quad (9)$$

Among them,

- $[a, b]$ : the best stable interval for  $x$ .
- $c = \max\{a-m, M-b\}$
- $M$ : the maximum values of  $x$ 's possible values.
- $m$ : the minimum values of  $x$ 's possible values.

**Presentation of the Results:**

The vulnerability of the final country is derived from the weighted formula in the model. Table 4 shows the vulnerability of Afghanistan.

**Table 4: Vulnerability of Afghanistan**

Time	Temperature	Precipitation	CO <sub>2</sub>	Fragility
2022	6.94	9.74	4.35	8.69
2021	7.64	9.48	3.78	8.36
2020	6.92	9.87	3.31	8.41
2019	6.67	9.61	4.08	8.59
2018	6.33	9.22	3.97	8.71
2017	6.78	10.00	2.73	8.74
2016	6.48	9.48	2.76	8.77
2015	5.78	9.09	2.89	8.70

**Sensitive Analysis-How Climate Change Increases Fragility**

Task 2 requires us to determine how climate change may have increased fragility of a country. Therefore, we use sensitive analysis based on model I by adjusting data of climate change indicators in order to find some connections between climate change and fragility.

Following are the specific measures. We select the data of Afghanistan’s fragility in 2022 as sample and then the three indicators of climate change will be increased by 0.1, 0.2 and 0.3 in turn, and decreased by 0.1, 0.2 and 0.3, respectively, to compare the changes of the results before and after. We use Excel to analyze the sensitivity of each indicator and the results are as follows. Table 5 shows the results of the sensitive analysis.

**Table 5: Results of sensitive analysis**

Adjustment	Temperature	Precipitation	CO <sub>2</sub> Emission
+0.3	8.6889	8.6950	8.6911
+0.2	8.6881	8.6921	8.6895
+0.1	8.6872	8.6892	8.6879
previous	8.6863		
-0.1	8.6854	8.6834	8.6847
-0.2	8.6846	8.6805	8.6831
-0.3	8.6837	8.6777	8.6816



From the results of sensitive analysis, we can clear see:

1. **Precipitation impacts fragility the most** since with its value larger, the more value of vulnerability changes. *Practically speaking*, the greater the distance between the precipitation and the ideal value in the current year, that is, the possibility of experiencing a long period of drought and flood, will increase the country's vulnerability.
2. Apart from precipitation, **temperature and CO<sub>2</sub> emission also have some effects**. With their value larger, the greater the vulnerability of the country. *Practically speaking*, on the one hand, some extreme weather like severe cold and hot or unpredictable weather will make it difficult for the country to cope with, on the other hand, the increase in CO<sub>2</sub> emissions will affect the role of the greenhouse effect, so that Eldono effect caused by global warming affects the country's development. But none of their effects are as pronounced as precipitation.

To conclude, if the state of a country like Afghanistan would not be so fragile as before, without the impacts of those three indicators.

## MODEL II: PREDICTIONS BY YEAR ABOUT A COUNTRY'S FRAGILITY

### Modeling Ideas

We have obtained some countries' fragility by year. In order to predict fragility by year for a country and we have considered that there are 15 secondary indicators of which data is hard to define or predict in the next few years. These indicators also have little connection with time. So, we would like to use the **Grey Prediction GM (1,1) model** [9] to make predictions about a country's fragility by year.

The grey prediction model GM (1,1) uses the original discrete data column to generate a new regular discrete data column that weakens the randomness by one accumulation, and then obtains the approximate estimate of the original data generated by the accumulation of the solution at the discrete point by establishing a differential equation model, so as to predict the continuous development of the original data.

Following is the process of GM (1,1).

### Step 1: Generate Discrete Sequences

Suppose  $x^{(0)} = \{x^{(0)}(1), x^{(0)}(2), \dots, x^{(0)}(n)\}$  is the original data column is the original one, and we can accumulate it once to get the new generated data column as

$$\begin{cases} x^{(1)} = \{x^{(1)}(1), x^{(1)}(2), \dots, x^{(1)}(n)\} \\ x^{(1)}(k) = \sum_{i=1}^k x^{(0)}(i) \end{cases} \quad (10)$$

### Step 2: Least Squares Estimation

We introduce the matrix form :

$$B = \begin{bmatrix} -\frac{1}{2}(x^{(1)}(1) + x^{(1)}(2)) & 1 \\ -\frac{1}{2}(x^{(1)}(2) + x^{(1)}(3)) & 1 \\ \vdots & \vdots \\ -\frac{1}{2}(x^{(1)}(5) + x^{(1)}(6)) & 1 \end{bmatrix}, Y = \begin{bmatrix} x^{(0)}(2) \\ x^{(0)}(3) \\ \vdots \\ x^{(0)}(5) \end{bmatrix} \quad (11)$$

Therefore, we can use the least square method to obtain the estimated values of parameters a and b

$$\hat{u} = \begin{bmatrix} \hat{a} \\ \hat{b} \end{bmatrix} = (B^T B)^{-1} B^T Y \quad (12)$$

**Step 3: Solving the Results**

Solve the corresponding solution of the following equation

$$\frac{dx^{(1)}(t)}{dt} + \hat{a} x^{(1)}(t) = \hat{b} \quad (13)$$

The answer is:

$$\hat{x}^{(1)}(k+1) = (x^{(0)}(1) - \frac{\hat{b}}{\hat{a}})e^{-\hat{a}k} + \frac{\hat{b}}{\hat{a}} \quad (14)$$

From the above formula, the analog value of the original data column x (o) is

$$\hat{x}^{(0)}(k+1) = \hat{x}^{(1)}(k+1) - \hat{x}^{(1)}(k) = (1 - e^{-\hat{a}})[x^{(0)}(1) - \frac{\hat{b}}{\hat{a}}]e^{-\hat{a}m}, m = 1, 2, \dots, n-1 \quad (15)$$

We want to predict the original data, so we only need to take  $m \geq n$  in the above formula

**Model Calculation of Kenya**

Task3 requires us to predict a country’s fragility and we select Kenya as the sample country which is not in the top 10 list.

**Preparation of the Model:**

We calculate Kenya's vulnerability and some data about climate change by year by collecting data based on Model I (Table 6).

**Table 6: Kenya's vulnerability**

Time	Temperature	Precipitation	CO <sub>2</sub>	Fragility
2022	5.00	7.45	3.12	7.11
2021	4.52	7.36	3.38	7.19
2020	3.70	7.23	3.29	7.27
2019	4.17	7.36	2.97	7.51

2018	4.17	7.53	3.71	7.81
2017	4.58	7.32	3.72	7.79
2016	5.00	7.36	3.89	7.93
2015	4.91	7.62	4.07	7.91

**Calculation and Presentation of Prediction Results:**

Through screening and analyzing the data, we calculate the annual vulnerability of Kenya, and then use MATLAB to carry out grey prediction on the indicator data. The calculation results are shown in the table below (Table 7).

**Table 7: Vulnerability of Kenya in 2023 • 2026**

Country	2015	2016	2017	2018	2019	2020
Kenya	7.91	7.93	7.79	7.81	7.51	7.27
Country	2021	2022	<b>2023</b>	<b>2024</b>	<b>2025</b>	<b>2026</b>
			Estimate	Estimate	Estimate	Estimate
Kenya	7.19	7.11	<b>6.93</b>	<b>6.78</b>	<b>6.62</b>	<b>6.52</b>

**Result Analysis About When a State is Fragile, Vulnerable, or Stable**

**Define a Tipping Point:**

Considering the characteristics of the data of the indicators, we divide 10 into 3 parts to define tipping points based on the assumption that the data follows a normal distribution as following (Table 8).

**Table 8: Status score classification**

<b>score</b>	<b>state</b>
0–3	stable
3–7	vulnerable
7–10	fragile



**Result Analysis:**

The result analysis of GM (1,1) is shown in Fig. 4.

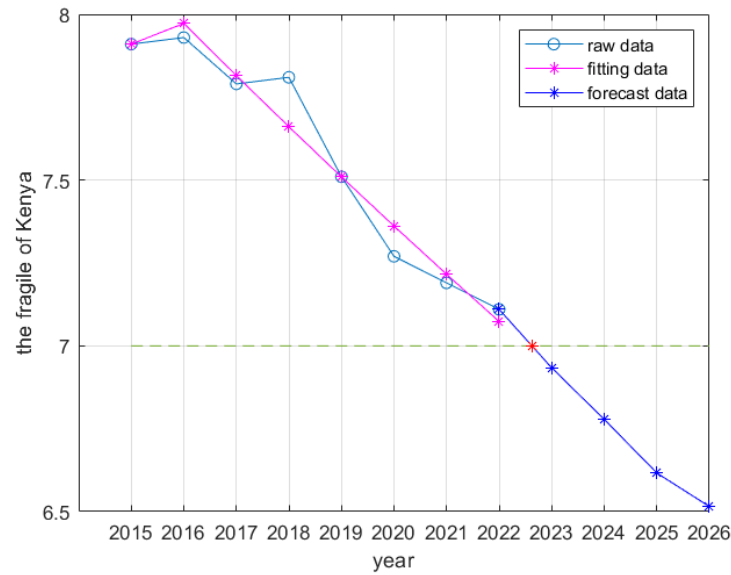


Fig. 4: Result analysis of GM (1,1)

**The Residual Test:**

We have done the Residual Test for this prediction results of the model and it shows that the result meets the requirements.

- The average relative residual is 0.0070074

The result of residual test shows that the model fits the original data very well.

- The average grade ratio deviation is 0.013741

The result of grade ratio deviation test shows that the model fits the original data very well.

**Result Analysis**

The fragility of Kenya is always above 7.0 and it is fragile according to the tipping point we have made before. The trend of Kenya's vulnerability decreasing over time is clear, so we can determine when Kenya reaches a state of vulnerability.

From the picture above, we can clearly see that in the second half of 2022 Kenya will reach a state of vulnerability.

**MODEL III: REGRESSION MODEL ABOUT CLIMATE CHANGE'S IMPACTS**

**Nonlinear Regression-How Climate Change Impacts Fragility Directly**

**Modeling Ideas:**

It is a common way to the scatter plot to see the trend of the model (Fig. 5), through the trend of the model we can fit the model by comparing its functional form:

From the scatter chart :

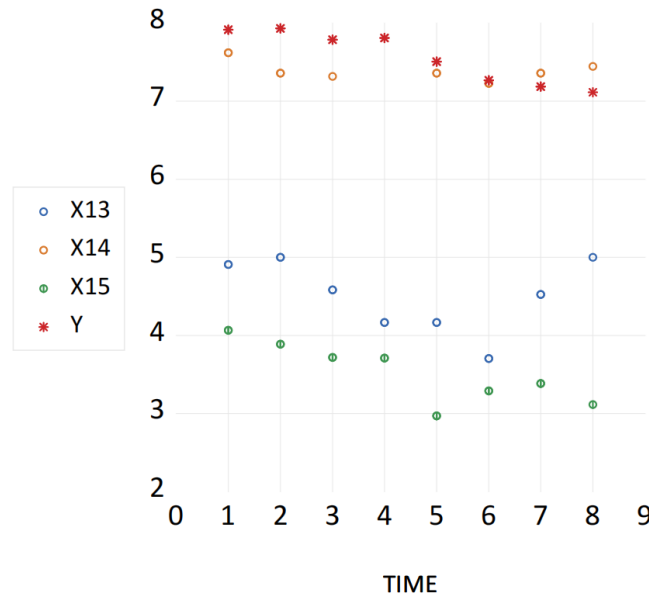


Fig. 5: (1) We could find the date of X15(Precipitation) in 2019 is out of track, we get off it for further study. (2) The trend of Y is similar to Index as well as X14; the trend of X15 is a liner model which is in a decrease; the trend of X13 has a peak in 2020, so we can define it as a quadratic function.

As a result, we would like to build a nonlinear regression [10] in order to find the relationships.

#### Model Calculation and Result Analysis:

$$e^{\hat{y}} = c + \beta_1 \hat{x}_{13}^2 + \beta_2 e^{\hat{x}_{14}} + \beta_3 \hat{x}_{15} + \beta_4 \text{Time} \quad (16)$$

$$c = 1066.6, \beta_1 = 3.99817, \beta_2 = 0.09212, \beta_3 = 446.3415, \beta_4 = -192.9375$$

$$R^2 = 0.93$$

#### Among them,

- c: Constant
- $\beta_i$ : Constant coefficient,  $i=1,2,3,4$ .
- $R^2$ : Goodness of fit
- $\hat{x}_{13}$  change a percentage,  $\hat{y}$  would relative change 3.99817 percentage;
- $\hat{x}_{14}$  change a percentage,  $\hat{y}$  would relative change 0.09212 percentage;
- $\hat{x}_{15}$  change a unit,  $\hat{y}$  would increase 446.34 units;

Given 'Time' is a variable based on time, it can be said that if other things being equal, vulnerability decreases 192.9375 each year over time.

#### Sensitive Analysis-How Climate Change Impacts Fragility:

Choose four parameters of the original data as the basic parameters of the control variables (see Table 9).

**Table 9: Sensitivity analysis samples**

Model	X13	X14	X15	Time	Fragility
A1	4.9090	7.6190	4.0664	2015	7.9972
A2	5	7.3593	3.8876	2016	7.8863
A3	4.5833	7.3160	3.7167	2017	7.7703
A4	4.1666	7.5324	3.7083	2018	7.6923

The problem requires a sensitivity analysis of the results, we adjust the variables of the numerical value up and down, increase the perturbation rate, compare the results before and after the change. Table 10 gives the Results of the sensitivity analysis.

**Table 10: Results of sensitivity analysis**

Fragility	Number	Pre-adjustment vulnerability of each variable	X13 increase by 10%	X14 increase by 10%	X15 increase by 10%
	A1	7.9972	8.0040	8.0668	8.0565
A2	7.8863	7.8942	7.9438	7.9495	
A3	7.7703	7.7777	7.8315	7.8380	
A4	7.6923	7.6990	7.7769	7.7651	
Number	Pre-adjustment vulnerability of each variable	X13 decrease by 10%	X14 decrease by 10%	X15 decrease by 10%	
	A1	7.9972	7.9910	7.9630	7.9342
A2	7.8863	7.8791	7.8576	7.8189	
A3	7.7703	7.7636	7.7395	7.6977	
A4	7.6923	7.6863	7.6499	7.6138	

Based on the above results, we can see that vulnerability has decreased over time, such a situation has something to do with Kenyan policies and international support. On the basement of the fixing values of the other parameters, changing the values of X13, X14 one by one to observe the changes in vulnerability can be seen a slight increase in X13, X14's 10% decreased vulnerability and a relative decrease in X13, X14's 10% decreased in vulnerability, however, the magnitude of the changes is very small, indicating that the impact of temperature on vulnerability is very small. The contribution of CO<sub>2</sub> to the vulnerability change in Kenya can be seen from the observation of vulnerability changes by changing the values of X15 alone while fixing the values of other parameters, this relates with Kenya's status as a developing country and a populous nation [11].

**Linear Regression--How Climate Change Impacts Other Indicators**

**Modeling Ideas:**

**Step 1: Build multiple linear regression models [12]**

A multiple linear regression model involving p independent variables can be expressed as

$$\begin{cases} y = \beta_0 + \beta_1x_1 + \dots + \beta_px_p + \varepsilon \\ \varepsilon \sim N(0, \sigma^2) \end{cases} \tag{17}$$

**Among them,  $\varepsilon$ :** error

For the convenience, we introduce matrix notation by actual observing data through n groups:

$$Y = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{bmatrix}, X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1p} \\ x_{21} & x_{22} & \cdots & x_{2p} \\ \vdots & \vdots & \ddots & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{np} \end{bmatrix}, \beta = \begin{bmatrix} \beta_1 \\ \beta_2 \\ \vdots \\ \beta_n \end{bmatrix}, \varepsilon = \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_n \end{bmatrix} \quad (18)$$

Inside that,  $X$  is the model design matrix, which is a constant matrix,  $Y$  and  $\varepsilon$  are random vectors  
 $Y \sim N_n(X\beta, \sigma^2 I), \varepsilon \sim N_n(0, \sigma^2 I)$  (19)

is an unobservable random error vector,  $\beta$  is a vector composed of regression coefficients, which also is a constant vector that is unknown and undetermined.

### Step 2: Least squares estimate of the regression coefficient $\beta$

Take an estimate of the  $\beta$  and denote it as  $\hat{\beta}$  and make the sum of squares of the random error  $\varepsilon$  is the minimum

$$\begin{aligned} \min_{\beta} \varepsilon^T \cdot \varepsilon &= \min_{\beta} (Y - X\beta)^T (Y - X\beta) \\ &= (Y - X\hat{\beta})^T (Y - X\hat{\beta}) \stackrel{def}{=} Q(\hat{\beta}) \end{aligned} \quad (20)$$

Due to the requirements of the least square's method, and the must conditions for obtaining extreme values from multivariate functions, the standard equation for solving the regression parameters is as follows:

$$\begin{cases} \left. \frac{\partial Q}{\partial \beta_0} \right|_{\beta_0 = \hat{\beta}_0} = 0 \\ \left. \frac{\partial Q}{\partial \beta_1} \right|_{\beta_1 = \hat{\beta}_1} = 0 \end{cases} \quad (21)$$

### Step 3: the verify of *Multicollinearity*

Due to the numerous number of variables in the system, it is necessary to have the view that the climate changes do indirect affect economy, policy and human behaviors and everything, which would cause a *Multicollinearity* case in the established regression model to influence its accuracy and fitness<sup>13</sup>.

#### *Model Calculation and Result Analysis:*

##### **Define A Model That Included All Kinds of Variables:**

$$\begin{aligned} y &= c + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \beta_5 x_5 + \beta_6 x_6 + \beta_7 x_7 + \beta_8 x_8 + \beta_9 x_9 + \beta_{11} x_{11} + \beta_{12} x_{12} + \beta_{13} x_{13} + \beta_{14} x_{14} + \beta_{15} x_{15} \\ R^2 &= 0.998, P > 0.05, F_{test} < F_{\alpha/2} \end{aligned} \quad (22)$$

#### *Tips:*

- $\beta_i$ : Constant corresponding to each indicator,  $i=1,2,\dots,15$ .
- $x_i$ : secondary indicators,  $i=1,2,\dots,15$ .

From E views, it is not difficult to find that the coefficient of determination R2 of the model is close to 1, However, there are individual explanatory variables whose coefficients are not significant, suggesting that there may be *Multicollinearity* in our mode [13].

**Choose Variables Whose Coefficients Are Not Significant and Separate Them to Compare and Combinate with Variables of Climate Change:**

From the table, it is easy to point that climate changes can change fragility via other factors albeit to varying degrees. X3: Group Grievance, X5: Economic Inequality, X6: Human Flight and Brain Drain, X7: State Legitimacy, and X12: External Intervention are all highly correlated with one of variables in climate change (X13: Temperature, X15: level of CO<sub>2</sub>). Table 11 shows the linear regression results.

**Table 11: From the table, it is easy to point that climate changes can change fragility via other factors albeit to varying degrees. X3: Group Grievance, X5: Economic Inequality**

Dependent variable	Independent variable	Equation	R-squared
X2	X13	$x_2 = c + \beta x_{13}$ $c = 13.9355, \beta = -0.873647$	0.685
X5	X13	$x_5 = c + \beta_1 x_{13} + \beta_2 x_{15}$ $c = 4.3956, \beta_1 = 0.35748, \beta_2 = 0.258069$	0.783
	X15		
X6	X13	$x_6 = c + \beta x_{13}$ $c = 12.0309, \beta = -0.619$	0.549
X7	X13	$x_7 = c + \beta x_{13}$ $c = 12.15958, \beta = -0.455$	0.762
X12	X15	$x_{12} = c + \beta x_{15}$ $c = 11.96814, \beta = -0.823$	0.540

**Use a Variable-Elimination Method, Implementing High Fit of The Model**

$$\alpha_1 x_{13} + \alpha_2 x_{15} = x_2 + x_5 + x_6 + x_7 + x_{12} \tag{23}$$

$$y = c + (\beta_1 + \alpha_1)x_{13} + \beta_2 x_{14} + (\beta_3 + \alpha_2)x_{15}$$

By imposing the datum, we could get the specific number of coefficients:

$$y = 5.148539 - 0.025675x_{13} + 0.170954x_{14} + 1.059128x_{15} \tag{24}$$

$$R^2 = 0.76$$

Based on the above conclusions we could define that some factors related with economy and policy are somewhat reliance on the climate change which tells us the importance to protect the environment and the fragility is highly related to climate changes:

1. **Factionalized Elites’s negative effect will be ease off due to the climate change** [14]  
Factionalized Elites means the policy [15] changes of upper-class to the society, and as the degree of vulnerability to climate impacts increases, there will be a political tendency to mitigate this, then neutralize the increase in vulnerability.
2. **Temperature and precipitation increase the influence of economic inequality**



When vulnerability indicators of temperature and precipitation rise, natural diseases can accelerate to the point where they become a drag on Economic development, thus contributing to Economic Inequality.

3. **Brain drain becomes the vice influence** [16]  
As the impact of climate change increases, the focus of the state is on keeping the country running, so the impact of the brain drains on national vulnerability declines.
4. **State Legitimacy is a regional problem in comparison of the climate diseases** [17]  
Climate impacts are national, so the political nature of State Legitimacy is of less importance for a country when natural diseases are sweeping the globe.
5. **External interventions maintain country's stability**  
Extreme weather and CO<sub>2</sub> emissions both cause external interventions to maintain social stability, so external intervention under the influence of climate will decrease the overall vulnerability to maintain this value.

### ***Considering Human Interventions and Its Cost [18,19]:***

Due to the specific situation of Afghanistan which is the most developing country in the world [20], namely the constant wars, geography location as well as the survivals that reliance on financial assistances. All variables seem make a big difference on the fragility; we choose to **take Afghanistan as an example** for further study.

Our team believes that ***the state power should establish a comprehensive civil defense system.***

From our view as outsiders, intervening in the factor 'national legitimacy' is a good choice. Given the situation of Afghanistan, countless parades and armed rebellions sway such a country which could highlight the influence of state legitimacy (X<sub>7</sub>) among all variables.

It is widely acknowledged that building a comprehensive civil defense system is a good way to prompt the legitimacy of the country. If a comprehensive civil defense system is built, it would help to reduce the natural disasters impacts on people's survival as well as strengthen the status of government.

In 2022, Afghanistan has lost more than 2 billion dollars in its economy due to climate changes, but if human interventions on national legitimacy take effect, it is highly expected that the cost will retain in 2.5-3 billion dollars.

## **MODEL EVALUATION AND FURTHER DISCUSSION**

**Task 5 needs us to discuss whether the model we have built can be used in small or large areas.** We will analyze the advantages and disadvantages of the model to see whether our model can adapt well when the scope of the region changes. The vulnerability results will be analyzed, and give the corresponding modification plan.

### **Strengths**

We adopt a combination of subjective and objective methods to calculate the weight. When assessing the fragile, this scheme considers a variety of human and natural factors. meanwhile, the analysis and decision-making of complex systems are more in line with the decision-making process and the psychology of decision makers. This scheme is not only practical but also scientific.

Grey prediction with high fitting accuracy was adopted. In the case of a small number of samples, the fitting value with high accuracy can be obtained directly according to the change trend.

The influence of *multicollinearity* was firstly eliminated. After eliminating this influence; it will be easy to consider the influence of climate as an independent variable on various factors, so that the regression equation can be obtained with high goodness of fit.

### **Weaknesses**

The amount of data referred to when establishing the model is small, and the adaptability of the model will decline when the scope of the problem becomes larger.

It is difficult to find suitable and public data, so we can only select Afghanistan, a fragile country, and Kenya, a country that has gradually improved its vulnerability. We can only use climate impact assessment and prediction models in small areas.

### **Analysis**

The model we have built is highly scientific and highly predictive. When it is necessary to study the vulnerability of a smaller area, the reference value can be obtained by using the local distinct climatic conditions. The numerical values are brought into the assessment model we built earlier, and then we can use our prediction model to accurately and completely see the vulnerability of the next few years, and at the same time, we can see the impact of climate on various indicators in the regression model, it is convenient for regional managers to take corresponding measures.

However, for a large area (such as the mainland), its climate conditions will be greatly affected by the dimension, so it is difficult to uniformly select a suitable value to bring into our model.

### **Further Discussion**

**In order to make our model more suitable for large regions**, the assumptions and the definition of the data being used should be changed. For example, we need to expand the scope of the assumptions and define a new continental vulnerability. For example, the mainland GDP, population density, and currency devaluation, etc. might be used. After carefully defining the new indicators to evaluate the continental vulnerability, we can substitute it into the equation according to our method to make it applicable to larger regions.

## **CONCLUSIONS**

A framework to measure national fragile based on data processing analysis was constructed in this paper and Cohesion, Economic, Political, Social, Cross-cutting and climate change into account were considered. In our method, comprehensive measurement and weight assessment of the main indicators have been carried out, and the rationality and sensitivity of the data results were tested. Also, the changes in Kenya's vulnerability in the next few years using the GM (1,1) model were successfully predicted. The *multiple* regression model to solve the impact of climate change on other indicators was also used. The results still followed the latest ranking of the fragile country index.

1. A comprehensive assessment model for national fragility based on AHP was established. First, other indicators and secondary indicators of temperature, precipitation and CO<sub>2</sub> emissions in the climate change through information online were identified, and the indicators were totally quantified. Then, the weight of each indicator was determined by the entropy weight method combining subjectivity and objectivity, and then the

- vulnerability of the country was determined by weighting.
2. Afghanistan as a sample for specific analysis was selected. Afghanistan's vulnerability from 2020 to 2022 is: 8.41, 8.36, and 8.69, respectively. Sensitivity analysis based on the model of Task 1 was conducted, and the size of temperature, precipitation, and CO<sub>2</sub> emissions up and down, respectively, were adjusted in order to conclude that droughts and floods, extreme weather, and the increase of greenhouse gases made countries more vulnerable. If the climate and environment were good, the country would not be so fragile.
  3. Kenya as a sample for specific analysis was selected. First, a nonlinear regression model is constructed considering the time factor, and then a sensitivity analysis is carried out, and the size of each indicator is adjusted up and down. It was found that the effect of CO<sub>2</sub> emissions over time was more significant, which means that the impact of the greenhouse effect is increasing year by year, making the country more vulnerable. Later, we determined the tipping points: 0~3 is stable; 3~7 is vulnerable; 7~10 is fragile. Finally, GM (1,1) to make predictions by year was built, and the result is that Kenya will move from a fragile state to a fragile state in the second half of 2022.
  4. The relationship between temperature change and other factors based on linear regression model was explored, and conclude that temperature and politics-related national legitimacy are the most significant. Through the analysis of the Afghan state, an intervention was proposed: a comprehensive civil defense system was established, its impact process was analyzed, and finally the approximate cost of 2.5~3 billion dollars was predicted.
  5. The advantages and disadvantages of the model to conclude that the model was suitable for smaller countries were analyzed and we hope to adjust the type of indicators in the comprehensive evaluation: considering GDP, population density and other factors, so that the model can be applied to larger countries.

## REFERENCES

- [1]. Couldrey M, Herson M. States of fragility. *Forced Migration Review*. 2013; 43.
- [2]. Huda M, Muhamad NHN, Isyanto P, et al. Building harmony in diverse society: insights from practical wisdom, 2020.
- [3]. Duijndam SJ, van Beukering P. Understanding public concern about climate change in Europe, 2008–2017: the influence of economic factors and right-wing populism. *Climate Policy*. 2020; 21: 353–367.
- [4]. Zhuang Y, Yang S, Razzaq A, Khan Z. Environmental impact of infrastructure-led Chinese outward FDI, tourism development and technology innovation: a regional country analysis. *Journal of Environmental Planning and Management*. 2021; 66: 367–399.
- [5]. Bangalore MR. Shock Waves: Managing the Impacts of Climate Change on Poverty, 2015.
- [6]. Stukalo N, Lytvyn MV, Petrushenko Y, Omelchenko Y. The achievement of the country's sustainable development in the conditions of global threats. *E3S Web of Conferences*. 2020.
- [7]. Mohtadi SS, Payan A, Kord A. Ranking Alternatives in Multi-Criteria Decision Analysis using Common Weights Based on Ideal and Anti-ideal Frontiers. *World Academy of Science, Engineering and Technology, International Journal of Mathematical, Computational, Physical, Electrical and Computer Engineering*. 2012; 6: 881–885.
- [8]. Amorim LBVd, Cavalcanti GDC, Cruz RMO. The choice of scaling technique matters for classification performance. *ArXiv*. 2022; abs/2212.12343.

- [9]. Hu Y-C, Jiang P, Tsai J-F, Yu C-Y. An Optimized Fractional Grey Prediction Model for Carbon Dioxide Emissions Forecasting. *International Journal of Environmental Research and Public Health*. 2021; 18.
- [10]. Bates DM, Watts DG. *Nonlinear Regression Analysis and Its Applications*, 1988.
- [11]. Hallegatte S, Ghil M. Natural disasters impacting a macroeconomic model with endogenous dynamics. *Ecological Economics*. Dec 2008; 68(1-2): 582–592.
- [12]. Seber GAF. *Linear regression analysis*, 1977.
- [13]. Kim JH. Multicollinearity and misleading statistical results. *Korean Journal of Anesthesiology*. 2019; 72: 558–569.
- [14]. Albuquerque PH, Rajhi W. Banking stability, natural disasters, and state fragility: Panel VAR evidence from developing countries. *Research in International Business and Finance*. Dec 2019; 50: 430–443.
- [15]. Anand R, Mishra S, Peiris SJ. Inclusive Growth: Measurement and Determinants. *ERN: Other Emerging Markets Economics: Macroeconomic Issues & Challenges (Topic)*. 2013.
- [16]. He X, Iop. Research on the Impact of Climate Change on the Fragility of a Country Based on Analytic Hierarchy Process. Paper presented at: International Conference on Air Pollution and Environmental Engineering (APEE); Oct 26–28, 2018; Hong Kong, HONG KONG.
- [17]. Grant A, Ison RL, Faggian R, Sposito V. Enabling Political Legitimacy and Conceptual Integration for Climate Change Adaptation Research within an Agricultural Bureaucracy: A Systemic Inquiry. *Systemic Practice and Action Research*. 2018: 1-28.
- [18]. Whajah J, Bokpin GA, Kuttu S. Government size, public debt and inclusive growth in Africa. *Research in International Business and Finance*. 2019.
- [19]. Gregory JM, Stouffer RJ, Molina MJ, et al. Climate Change 2021—The Physical Science Basis. *Chemistry International*. 2021.
- [20]. Fowowe B, Folarin EO. The Effects of Fragility and Financial Inequalities on Inclusive Growth in African Countries. *Wiley-Blackwell: Review of Development Economics*. 2019.