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2018
MCM/ICM
Summary Sheet

Climate Change Influence on Regional Instability

Summary

A state can be stable, vulnerable or fragile. To determine the fragility of a country, we select metrics on four aspects: cohesion, economic, political, social. Moreover, each metric sub-divides into three secondary metrics. We also select four features of climate change: tempreture, drought, storm and desertification, to describe how climate change affects a country's fragility.

At first, we establish a logistic regression model(*LRM*) to evaluate the indicators of fragility. After important data have been acquired, we need to find an acceptable classifier to determine a country's fragility. It occurs to us that logistic regression is remarkable in binary classification. However, what we encounter is a three-classification problem which requires us to adjust logistic regression. To solve this problem, we convert the three-classification problem into a multiple binary classification one. We build three binary classifiers, each of which represents a situation of states. Now we need to train all these classifiers to perform well in discriminating a country's fragility. This step is the same as training ordinary logistic regression.

Next, to measure the impact of climate change on the fragility of a country, we combine *LRM* with a correlation coefficient matrix **C** to get a new model named as *LRCM*. **C** is obtained when analyzing the correlation coefficient between each indicator of fragility and feature of climate change. We then use different data from authorized organizations to adjust *LRCM* which finally does good in measuring the effects of climate change. Besides, we derive accuracy rate to validate the model.

By adjusting three changeable parameters including initial weights, sampling fraction and iteration number, we analyze the sensitivity of *LRCM*, find that it stays stable as long as iteration number is big enough.

We use our model to analyze two countries Sudan and Kenya, and determine their fragility and how climate change influences their stability. Besides, we establish a predicting model to see when Kenya will reach its tipping point.

Finally, we use our model to make state driven interventions that could mitigate the risk of climate change and prevent a country from becoming a fragile state. We also search online for some information to predict the total cost of intervention we make for a given country.

Keywords: measure fragility; logistic regression; climate change

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February 13, 2018

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Contents

1 Introduction

1.1 Background

It has been found that Climate Change such as increased droughts and sea level rise will alter the way humans live and may have the potential to weaken social and governmental structures, thus to result in fragile states.

1.2 Problem Restatement

According to the background, there are five tasks for this problem :

- Develop a model that determines a country's fragility and measures the impact of climate change.
- Select one of the top 10 most fragile states and determine how climate change may have increased its fragility. Indicate how the state may be less fragile without these effects by using the model in task 1.
- Select another state not in the top 10 list to measure its fragility and predict its future situation under the impact of climate change.
- Use our model to determine a state driven intervention which could mitigate the risk of climate change and prevent a country from being fragile, and predict the cost of the intervention.
- Test our model on cities or continents and see whether we should modify it.

2 Creating the Model

2.1 Reviewing

In order to create a reasonable and accurate model that determines a country's fragility and simultaneously measures the impact of climate change, we have carefully read some related articles and books. Though climate change is gradual, severe weather conditions may break out beacause of it.[1]. Theison said,"The world is generally becoming less violent, but the debate on climate change raises the specter of a new source of instability and conflict. In this field, the policy debate is running well ahead of its academic foundation dnd sometimes even contrary to the best evidence."[6]

2.2 Notations

Table 1: Notations and brief descriptions

Notation	Description
F	1indicates a certain situation while 0 indicates not in the situation
$\mathbf{X}$	indicators of state fragility
$\mathbf{W}_i$	weight of $\mathbf{X}$,$(w_{i1}...w_{i4})$
M	fragility mark, the lower it is, the less fragile the state is
Q	the same as F but unknown
$E_p(w,x)$	criterion function to judge the model accuracy
w_{ij}^l	weight from node j in layer l to node i in layer $l+1$
$\mathbf{P}$	features of climate change
$\mathbf{C}$	correlation coefficient weighted matrix (CCWM), a 4×4 matrix
a_{ij}	element of CCWM, representing the correlation coefficient between p_i and x_i

2.3 Indicator Determination

To better describe the fragility situation of a country and efficiently distinguish countries that vary in fragility, we carefully select 4 indicators from some authorized data[3].

Table 2: Indicators for a country's fragility

Indicator	**Sub-indicator**
Cohesion	Security Apparatus
	Factionalized Elites
	Group Grievance
Economic	Economic Decline
	Uneven Economic Development
	Human Flight and Brain Drain
Polictical	State Legitimacy
	Public Services
	Human Rights and Rule of Law
Social	Demographic Pressures
	Refugees and IDPs
	External Intervention

- Cohesion
  a. Security apparatus generally takes security threats such as bombings, attacks and battle-related deaths, rebel movements, mutinies, coups, or terrorism, and serious criminal factors, such as organized crime and homicides into account.

b. Factionalized Elites measures power struggles, political competition, political transitions, and where elections occur will factor in the credibility of an electoral processes.
c. Group Grievance indicator focuses on divisions and schisms between different groups in society-particularly divisions based on social or political characteristics-and their role in access to services or resources, and inclusion in the political process. It may also have a historical component.

- Economy
  a. Economic decline indicators considers factors related to economic decline within a country. It also takes into account sudden drops in commodity prices, trade revenue, or foreign investment, and any collapse or devaluation of the national currency.
  b. Uneven economic development indicator considers inequality within the economy, irrespective of the actual performance of an economy. It also takes perceptions of inequality, recognizing that perceptions of economic inequality can fuel grievance as much as real inequality into account.
  c. Human flight and brain drain indicator considers the economic impact of human displacement and the consequences this may have on a country's development.

- Political
  a. The State Legitimacy Indicator considers the representativeness of government and its relationship with its citizenry.
  b. Public Service Indicator refers to the presence of basic state functions that serve the people. On the other hand, this may include the provision of essential services, such as health, education, water and so on.
  c. Human Rights and Rule of Law Indicator considers the relationship between the state and its population insofar as fundamental human rights are protected and freedoms are observed and respect.

- Social
  a. Demographic Pressures Indicator consider pressure upon the state deriving from the population or the environment around it.
  b. Refuges and Internally Displayed Persons Indicator measures the pressure upon states caused by the forced displacement of large communities as a result of social, political environmental or other causes, measuring displacement within countries, as well as refugee flows into others.
  c. External Intervention Indicator considers the influence and impact of external actors in the functioning-particularly security and economic-of a state.

2.4 Model Establishment

Our first thought of Task 1 was adopt frequently used evaluation models such as *AHP* and *Fuzzy Mathematics*. Given that these models require much subjective factors, we started to look for a model based mostly on objective factors. After spending long time searching and debating, we attempted to adopt *Backpropagation Neural Network* (*BP*), so that we needn't personally determine the weights of indicators. These weights could be obtained from a *BP* model trained by authorized data concerning country fragility. However, we found it hard to explain both the result and the processing of a *BP* model. Since the result was crucial for later analysis of climate change effects, we finally give up *BP* model and use *Logistic Regression Model* (*LRM*) which is more intuitional. Besides, to further analyze the effects of climate change on country fragility, we adjust *LRM* via correlation to get another model named by us as *LRCM*.

2.4.1 *LRM* model

First, we establish a *LRM* to evaluate the fragility of a country. To further simplify our model, we use symbol $F = \{0, 1\}$, 1 indicating a certain situation and 0 indicating not in the situation. F of each analyzed country is accessible through authorized data. According to task 1, we classify fragility of states into three classifications: stable, vulnerable and fragile. In fact, distinguishing a country's fragility is a three-classification problem, so we search online for some materials [2] and adopt logistic regression for analysis. Generally logistics regression is only suitable for binary classification problems. Therefore, to realize a three-classification, we need to train three binary classifiers. Note that a classifier only divide given elements into two classifications. To classify an unknow x, classifiers work together as a voting machine. For example, if x belongs to classification j, classifier j gets a vote when the rest get none. If x does not belong to classifier j, other classifiers both get a vote when j gets none. Obviously, after the voting process, x belongs to the classifier which gets most votes. Here is a logistic regression function:

$$g(z) = \frac{1}{1 + e^{-z}} \tag{1}$$

The function's values range from 0 to 1, as is shown in Figure 1.

Second, we need to find mark lines that helps us discriminate stable, vulnerable and fragile countries. To get the mark line, we search *FRAGILE STATES INDEX 2017 – ANNUAL REPORT* for data to train our model. From that report, we obtain 12 sub-indicators of country fragility and fragility marks of 178 states all over the world. To better analyze these data and describe fragility, we classify these 12 sub-indicators into 4 indicators whose values are represented by a column vector $\mathbf{X} = (x_1, x_2, x_3, x_4)^T$. Each indicator contains 3 sub-indicators which are highly relevant.[2.4.1] Correspondently, each indicator has a weight to determine its contribution to fragility mark, so we get a column vector $\mathbf{W} = (w_1, w_2, w_3, w_4)^T$. Therefore, we get $M = \mathbf{W}^T\mathbf{X}$, M representing calculating

Figure 1: Logistic function

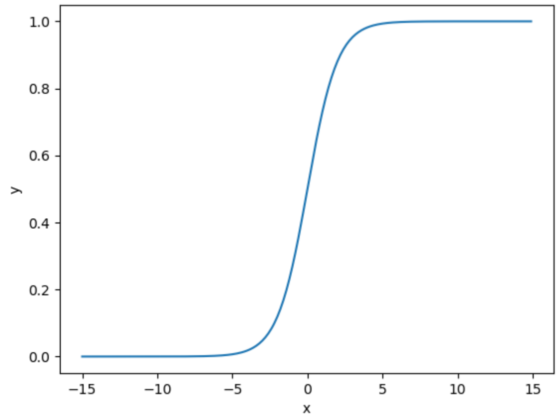
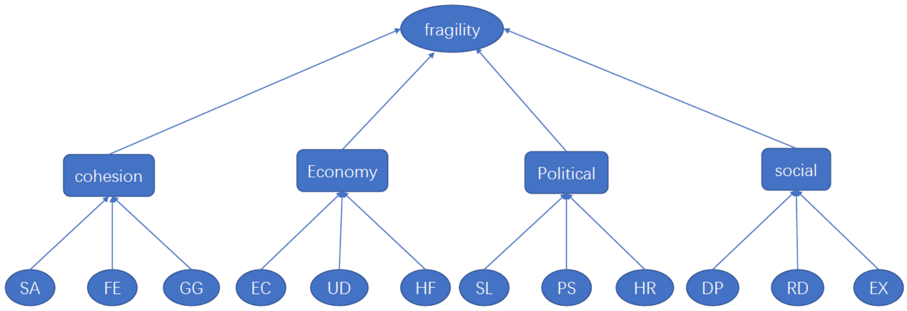


Figure 2: Indicators of Fragility



fragility mark of a country which considers all the indicators.To compare with F, we derive Q from a classification function $h_w(\mathbf{X})$ or $g(z)$:

$$Q = h_w(\mathbf{X}) = g(M) = \frac{1}{1+e^{-\mathbf{W}^T\mathbf{X}}} \tag{2}$$

To judge the reasonability of $h_w(\mathbf{X})$, we need to compare its output Q with known F. According to logistic regression theory, we define a new function used to judge the reasonability of $h_w(\mathbf{X})$:

$$\text{Cost}\big(h_w(\mathbf{X}), F\big) = \begin{cases} -\log\big(h_w(\mathbf{X})\big) & \text{if } F = 1 \\ -\log\big(1 - h_w(\mathbf{X})\big) & \text{if } F = 0 \end{cases} \tag{3}$$

$$\begin{aligned} J(\mathbf{W}) &= \frac{1}{m}\sum_{i=1}^{m} \text{Cost}\big(h_w(\mathbf{X}), F\big) \\ &= -\frac{1}{m}\left[\sum_{i=1}^{m} F^{(i)}\log(h_w(\mathbf{X}^{(i)})) + \big(1 - y^{(i)}\log(1 - h_w(\mathbf{X}^{(i)}))\big)\right] \end{aligned} \tag{4}$$

Function $J(\mathbf{W})$ is used to judge the quality of $h_w(\mathbf{X})$. We need only change $\mathbf{W}$ constantly adjust $\mathbf{W}$ to minize the value of $J(\mathbf{W})$, so that we can get the nearly best methodology of classification. Now we transform this problem into a optimization problem, and we adopt the gradient descent method to derive the optimal point. According to gradient descent method, we update $\mathbf{W}$ by using the following equation:

$$\mathbf{W}_{t+1} = \mathbf{W}_t - \alpha \frac{\partial}{\partial \mathbf{W}_t} J(\mathbf{W}) \tag{5}$$

$$\mathbf{W}_{t+1} = \mathbf{W}_t - \alpha \frac{1}{m} \sum_{i=1}^{m} (h_w(x^{(i)} - y^{(i)}))x_j \quad j = 1, 2, \ldots, n \tag{6}$$

We use python code to realize the calculation above, and three welcome weight vector $\mathbf{W}$ is achieved. To strictly test our model, we follow Cross-validation to divide 178 states from data into two collections, named as testing collection and training collection respectively. We use the training collection to gain a series of weights which are subsequently used to determine the fragility of countries involved in the testing collection. By comparing determined fragility with authorized fragility, we derive an accuracy rate of the model to see whether $\mathbf{W}$ is practical. Now we define that the number of testing states divides sample number to be equal to sampling fraction. For different sampling fraction, we get the accuracy rate from 2008 to 2017:

Table 3: Accuracy Rate

Sampling Fraction	0.80	0.82	0.84	0.86	0.88
2007	0.53	0.87	0.96	1	1
2008	0.85	0.57	0.81	0.61	0.89
2009	0.94	0.87	0.96	0.87	1
2010	0.74	0.9	0.92	0.87	1
2011	0.79	0.9	0.73	0.91	0.95
2012	0.66	0.84	0.7	0.92	1
2013	0.54	0.87	0.89	0.88	0.95
2014	0.83	0.74	0.85	0.88	0.85
2015	0.8	0.87	0.89	0.96	1
2016	0.7	0.77	0.85	0.88	0.95
2017	0.77	0.87	0.85	0.96	0.95

2.4.2 *LRCM* model

According to some pertinent literature, climate change has an effect on the indicators we mentioned above and so the fragility of a country is changed. To make analysis feasible, we find 4 features of climate change as temperature, drought, storm and desertification.

Assumption

- We assume that a country is thought to be under climate change effects as long as it is entirely or partly affected. For example, we suppose Russia is affected by drought even when only a little fraction of its territory is affected. Though, this assumption is reasonable in some way because climate change affects the world at a large scale and most countries are tiny enough for most of its area to be affected simultaneously.

- We assume that any features of climate change has the same objective impact on states it affected. Therefore, if a state is affected by drought we record $p = 1$ and if it is unaffected we record $p = -1$, where p will be discussed later.

We build a row vector $\mathbf{P} = (p_1, p_2, p_3, p_4)$, where the elements represent the logic outputs of temperature, drought, storm and desertification respectively. In fact, features of climate change and indicators of fragility are not necessarily highly related, so we need to analyze their correlation. According to statics, correlation coefficient can well describe the correlation of two variables. However, we possesses two columns of variables, each column consisting of four relatively independent variables, which causes trouble in analyzing in traditional ways. To solve this problem, we derive the correlation coefficients of all features and indicators, through which we get a 4×4 correlation matrix $\mathbf{C}$:

$$\mathbf{C} = \begin{pmatrix} a_{11} & a_{12} & a_{13} & a_{14} \\ a_{21} & a_{22} & a_{23} & a_{24} \\ a_{31} & a_{32} & a_{33} & a_{34} \\ a_{41} & a_{42} & a_{43} & a_{4} \end{pmatrix} \tag{7}$$

where a_{ij} represents the correlation coefficient of $p_i(i = 1, 2, 3, 4)$ and $x_j(j = 1, 2, 3, 4)$. From matrix $\mathbf{C}$ we can see how climate change influences indicators of fragility. Then we adjust *LRM* by combining $\mathbf{C}$, so we get:

$$\mathbf{W}^{(2)} = \mathbf{C}\mathbf{W}^{(1)T} \tag{8}$$

$$M^{(2)} = \mathbf{W}^{(2)T}\mathbf{X} \tag{9}$$

2.4.3 Predicting model

According to task 3, we are required to predict a country's fragility. To do that, we can use a simple a N-order polynomial $f(x) = a_0x^N + a_1x^{N-1} + \ldots + a_N$ for fitting operation then subsequently predict a country's fragility in near future. However, fitting operation is known to be easily overfitting or underfitting, so we adopt the following algorithm:

Assumption and Descriptions

- We assume that the order of the fitting function is no over than 10, so $N = 1, 2, \ldots, 10$.

- We build a vector $\mathbf{Y} = (y_1, y_2 ... y_{10})$, where the elements indicate a certain country's fragility of 10 years.
- Every N is correspondent to a fitting function $f_N(x)$, where x represent year.
- $\mathbf{error} = \sum_{i=1}^{m} (f_N(i) - y_i)^2$.

Running the codes above provides $f_p(x)$ which has the least error. This function can be used to predict a country's fragility based on its previous data. We use this model to predict the fragility mark of Kenya in the later discussion.

2.5 Strengths and Weaknesses

- **Strengths**

  Model *LRCM* combines logistic function and correlation analysis, and therefore well describe the relation between country fragility and climate change.

- **Weaknesses**

  The logistic function we use is excellent when analyzing linearly separable data but helpless when encounters with opposite data. In reality, the indicators we use to determine a state's fragility are not likely to be linear as we simply expect. Therefore, the calculating results from the model are not accurate enough.

  Besides, to simply our model, we do a lot of approximate treatment on climate change situations of each country based on data which are vague or unspecific, which is a major disadvantage.

3 Sensitivty Analysis

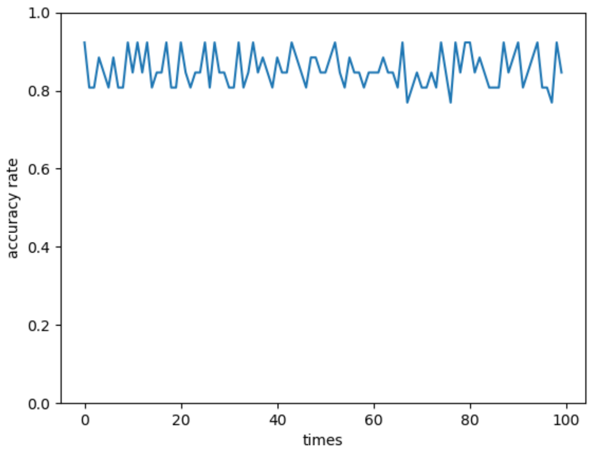
According to the training process, at first we need to find an original weight vector $\mathbf{W}_{init}$, divide data into training collection and testing collection, then $\mathbf{W}_{init}$ iterates on the training collection to adjust itself and outputs a final $\mathbf{W}$ to be tested by the testing collection, and finally we can use $\mathbf{W}$ to evaluate country fragility. Three significant parameters, original weight $\mathbf{W}_{init}$, iteration number and sampling fraction α respectively, are selected for sensitivity analysis. We will see how these parameters influence the accuracy of model *LRCM*.

3.1 Original Weight

We use codes to generate $\mathbf{W}_{init}$ randomly. It turn out that the accuracy is highly related to the original weight, which is shown in Figure 3. Random generated

$\mathbf{W}_{init}$ could be very different from the adjacent one, which accounts for fluctuation of the curve.

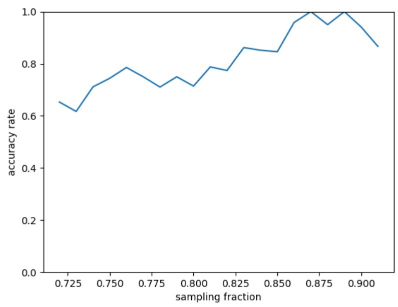
Figure 3: The influence of $\mathbf{W}_{init}$



3.2 Sampling Fraction

Figure 4 shows that with the increasing sampling fraction, the accuracy of the model increase unstably at first and decline after it reaches its maximum where the correspondent sampling fraction is 0.875.

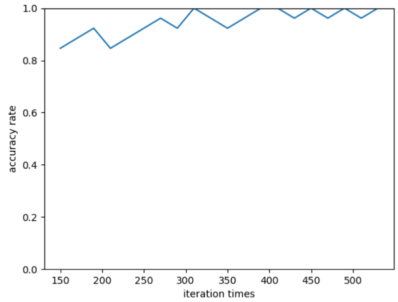
Figure 4: The Influence of Sampling Fraction



3.3 Iteration Number

Figure 5 illustrate that the model's accuracy is improved with the increase of the iteration number, but the trend is fairly fluctuating.

Figure 5: The Influence of Iteration Number



4 Cases Studies

4.1 Sudan

According to task 2, we are required to select one of the top 10 most fragile states as determined by the Fragile State Index and determine how climate change may have increased fragility of that country. Use your model to show in what way(s) the state may be less fragile without these effects. After discussion, we select Sudan to be analyzed. It is bordered by Egypt to the north, the Red Sea, Eritrea and Ethiopia to the east, South Sudan to the south, the Central African Republic to the southwest, Chad to the west and Libya to the northwest.[4]

4.1.1 How climate change impacts Sudan's fragility

At first we use *LRM* to measure all indicators and fragility of Sudan from 2008 to 2017, and we get the trend of them by drawing them into Figure 6 and Figure 7.

Figure 6: Fragility trend without climate change

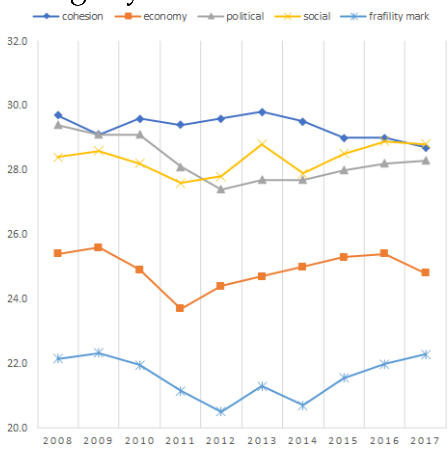
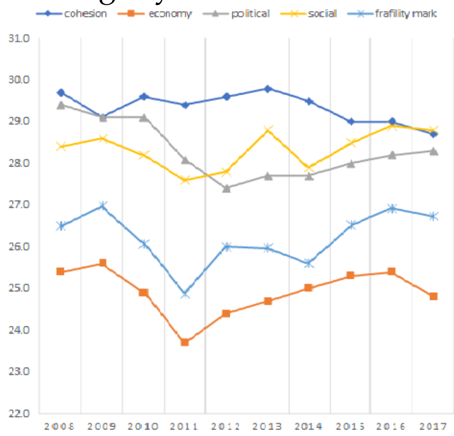


Figure 7: Fragility trend with climate change



4.1.2 How can Sudan be less fragile

Now we put aside the effects of climate change and determine Sudan's fragility by directly assessing its four indicators based on authorized data. From Table 4, we find that Sudan's indicator values are all much higher than world average, indicating that Sudan is in an alert situation. Since we have ignored climate change, the government of Sudan should take the following suggestions into account to be less fragile:

- Increase security measures, improve national security and enhance national cohesion of the people.
- Develop the economy, reduce the rate of poverty.
- Improve the laws and regulations of the country, protect the legitimate rights and interests of the citizens.
- Improve the social public service and increase the social welfare.

Table 4: Data of 2017

indicators	Sudan	world average	units
cohesion	28.7	18.4	1
economic	24.8	17.2	1
political	28.3	17.4	1
social	28.8	16.9	1

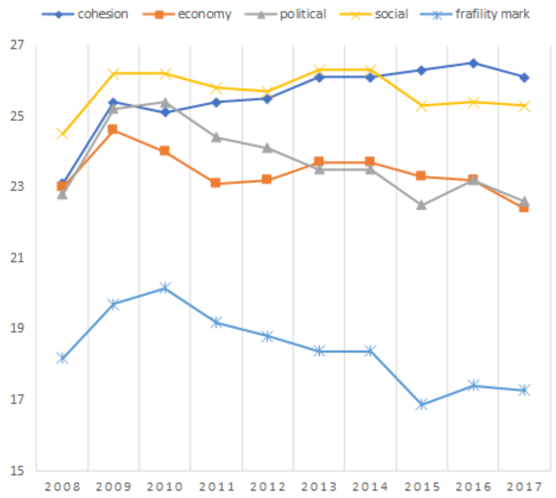
4.2 Kenya

According to task 3, we should use our model on another state not in the top 10 list to measure its fragility, and see in what way and when climate change may push it to become more fragile. We select Kenya for analysis. Located in the eastern Africa[5], Kenya is not a top-10 country, ranking the 22th, a little way from top-10 countries.

4.2.1 Fragility Analysis

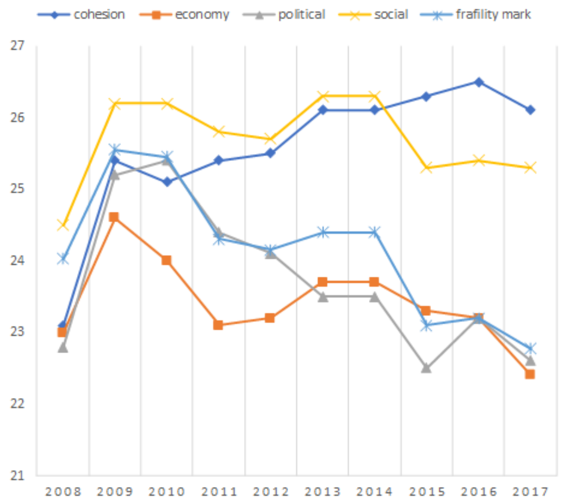
We first use the former model *LRM* to evaluate all indicators and fragility of Kenya from 2008 to 2017:

Figure 8: Trend of mark of indicators and fragility without climate change



We then use the model *LRCM* to evaluate all indicators and fragility of Kenya under climate change from 2008 to 2017:

Figure 9: Trend of mark of indicators and fragility with climate change



$$\mathbf{C} = \begin{pmatrix} -0.15713412 & -0.11253383 & -0.18310954 & -0.23512443 \\ 0.4174407 & 0.51861573 & 0.57119768 & 0.51138573 \\ 0.17743893 & 0.57374765 & 0.24303604 & 0.52174132 \\ 0.55235765 & 0.56916228 & 0.70088346 & 0.64734183 \end{pmatrix}$$

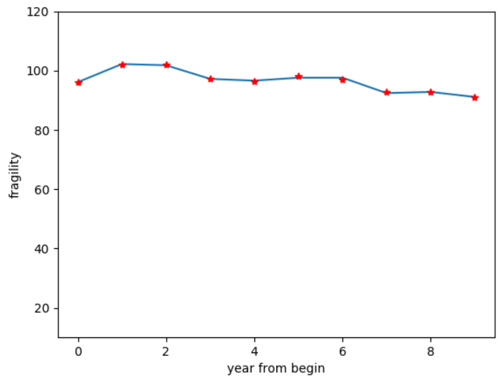
Note that x_1, x_2, x_3, x_4 represent the values of cohesion, economic, political, social respectively. **C** is the correlation coefficient weighted matrix. It illustrates that climate change correlates relatively little with x_1 or climate change has less impact on cohesion than others. Therefore, we conclude that climate change influence a country's fragility mainly through x_2, x_3 and x_4.

4.2.2 Fragility Predicting

The two figures above illustrate that as time goes by the fragility trend of Kenya shows a fluctuating decline. Besides, climate change does not necessarily mean countries affected tend to be more fragile. As for fragile countries, they have to take more methods to prevent themselves from worsening. To predict the future fragility of Kenya, we adopt the predicting model mentioned previously. We derive $N = 7$ for the fitting function via data of the latest 10 years:

$$\begin{aligned} f_7(x) &= -0.002827x^7 + 0.08722x^6 - 1.042x^5 + 6.002x^4 \\ &\quad -16.64x^3 + 17.84x^2 - 0.1974x + 96.11 \end{aligned} \tag{10}$$

Figure 10: Fragility Trend of Kenya



According to the figure above, we can predict when Kenya will reach a tipping point.

4.2.3 Defining Tipping Points

According to an authorized report [3], we divide fragility in four classifications: sustainable$(0 < M < 40)$, stable$(40 < M < 70)$, warning$(70 < M < 100)$, alert $(100 < M < 120)$. Then we define two tipping points : $M = 10$, below which means least fragile and $M = 110$, above which means most fragile.

5 Intervention Analysis

In the previous work, we have established *LRM* to determine the fragility of a country and *LRCM* to measure the impact of climate change on a country. We have also proved by calculating matrix **C** that climate change have little influence on cohesion compared with other indicators. We also get a lot of information on the relation between other features and indicators. Therefore, we make state driven interventions based on matrix **C**.

The actual impacts would vary greatly depending on the nuances of the weather conditions, the adaptability of humanity, and decisions by policymakers.[1] To mitigate the risk of climate change and prevent a country from becoming a fragile state, we suggest that governments think over the following interventions:

- Improve predictive climate models to allow investigation of a wider range of scenarios and to anticipate how and where climate changes could occur so that governments can better prepare for climate change and extreme weather as well.
- Develop a system to deal with problems brought by climate change. A good system will efficiently prevent the country from being too much impact as it would be for a unprepared country.
- Support circular economy and make policies to strictly reduce greenhouse gas emissions. The effort will significantly reduce the effect of climate change.

To calculate the cost of the interventions, we adopt life circle cost analysis. We get cost of each intervention plan via the following function:

$$totalcost = maintainmentcost + managementcost + operationscost$$

6 Model Modification

According to task 5, our model should be tested on smaller states or lager ones to see if it still fits. Through carefully analyzing, our model need some adjustment before being used to determine smaller or larger states.

First, it is obvious that a smaller or larger state has different indicators of fragility from a country. As for smaller states, we should adopt more detailed indicators to determine fragility more accurately. By contrast, a larger state has fewer indicators.

Second, a smaller state has fewer features of climate change than larger states, so improper number of features may provide unreasonable results which will apparently mislead us. Therefore, features of climate change should be selected based on the reality and sub-divided if needed.

Above all, basing on the original model, we replace the features of climate change. Still we can get a correlation matrix C and subsequently derive

$$M^{(3)} = \mathbf{W}^{(3)T}\mathbf{X}$$

, which is likely to fit smaller or larger states.

References

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