For office use only	Team Control Number	For office use only
T1 ________________	**87094**	F1 ________________
T2 ________________		F2 ________________
T3 ________________	Problem Chosen	F3 ________________
T4 ________________	**E**	F4 ________________

2018
MCM/ICM
Summary Sheet

Evaluation and Prediction Model of Regional Instability Affected by Climate Change

Summary

Climate change affects a country's fragility, directly and indirectly. It is crucial to find out how climate change influences regional instability.

First, we use PCA to establish the comprehensive evaluation model. We choose eight indicators related economic, politics, society and climate change. We first calculate the comprehensive evaluation scores of all countries. Then we divide all countries into three parts according to the scores. Through the comprehensive evaluation formula, it can be seen that climate change has a direct impact on the country's fragility. The correlation coefficient matrix can reflect the indirect effect on the country's flagility.

Second, we remove the factors of climate change. Then use principal component analysis to calculate comprehensive evaluation scores as task 1. Finally, we compare the countries' rankings with task 1. We find that the rankings of the top 10 most fragile countries all drops. So the climate change has a directly effect on fragile country.

Third, we choose China as the research object. We assume that other factors do not change, considering only the impact of climate change. We first get the tipping point 0.9546 from task 1,which is the dividing line between fragility and vulnerable. Then we use grey prediction model to predict when China will be a fragile country. We calculate the result is 2030 or 2032. So if China does not take measures about climate, China may become a fragile country.

Fourth, we take China as example and start with the factors which can be controlled easily to reduce the fragility of a country. So we only consider scientific expenditures ($\% of GDP$) and health expenditures($\% of GDP$). We make a conclusion that the Chinese government need to increase scientific and health expenditures to prevent China from becoming a fragile state, and the Chinese goverment will spend 399.143 billion dollars.

Fifth, we use the model in task 1(PCA) and find out it does not work on larger "status". The reason is that the effect of normalization in food production index is very bad since the amount of data is too few. Thus we delete the food production index and create the new model which works better.

Finally, we analyze the performance of our model under various conditions, and modify our model to accommodate to those conditions.

Contents

1 Introduction

1.1 Problem Background

As we all know, climate change has a significant impact on production and enviromment.It also influences economy,health,and even politics and eduction. Many of these effects will alter the way humans live,and may have the potential to cause the weakening and breakdown of social and governmentalstructures. Consequently, destabilized governments could result in fragile states.

In another way, climate change combined with other factors could result in fragility of a country. There is evidence that, if a country has a weak social division, coupled with environmental pressures from climate change, it could lead to violent events.

In a word, it is crucial to study relationship between fragility and climate change of a country.

1.2 Assumptions

To simplify our problems, we make the following basic assumptions:

1. A country's fragility is only affected by four aspects:economic,politics,society,climate change.
2. Very few missing data is replaced by maximum value after normalization, as missing data basicaly represents highest fragility.
3. When predicting the impact of climate change on a country's fragility, we assume that other factors do not change.

1.3 Variable Description

Variable	Description
Z	Fragile state score
y_i	The i_{th} principal component in Principal component analysis
x_1	GDP per capita
x_2	climate change index (% of total population)
x_3	Food production index
x_4	Unemployment rate
x_5	scientific and technical expenditures($\% of GDP$)
x_6	Corruption Perception index
x_7	Health expenditures($\% of GDP$)
x_8	Environment index
$\bar{x}_i$	Normalized Variable
t	year

Table 1: Variables Description

2 Statement of Our Models

2.1 Task 1

2.1.1 Analysis of Task 1

We describe fragility of a country in four factors[1].As we want to study how climate change influences fragility, climate change factor should be included.Thus four factors are economic, politics,society,climate change. The logical relationship is shown in the relation diagram as follows:

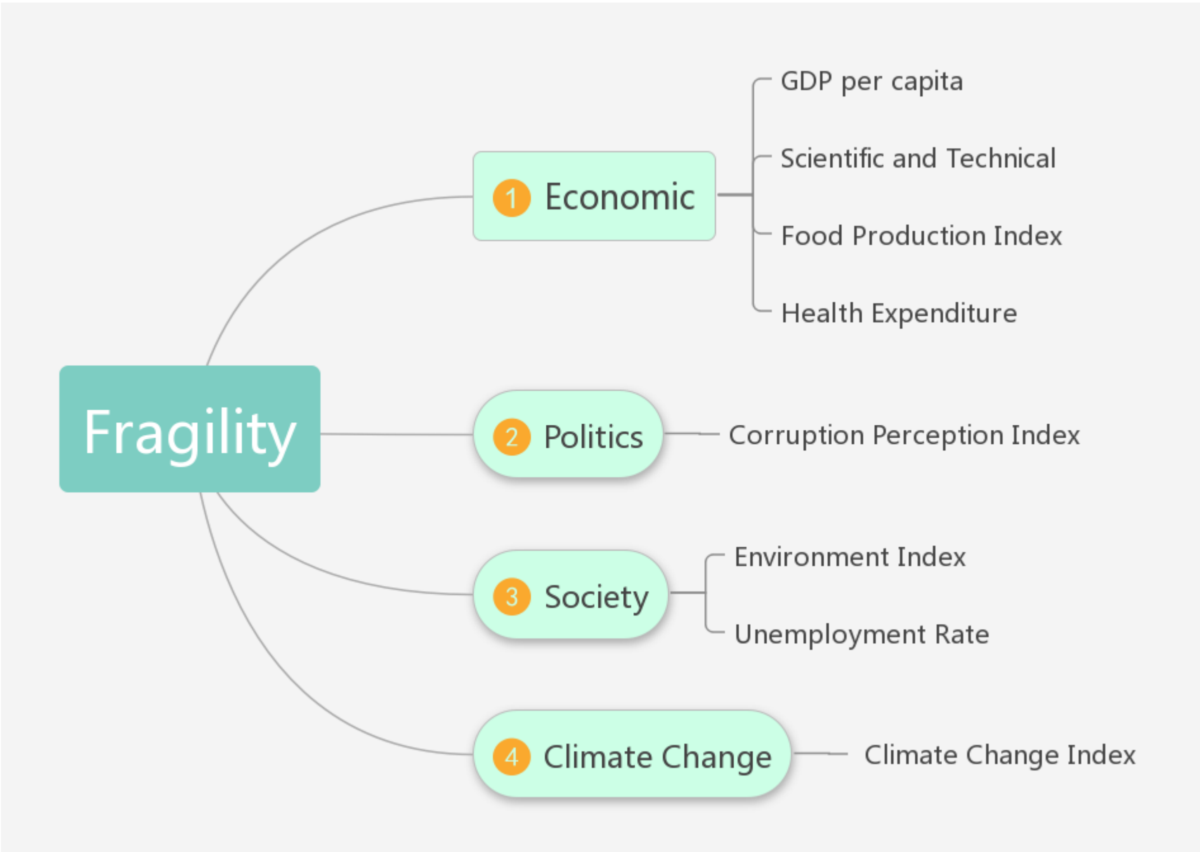

Figure 1: The Relationship between these factors

Next we collect data on these factors in 150 countries(see appendix B).Most of the data comes from the world bank website[2].Then we build a comprehensive evaluation model with these data to assess a country's fragility. And then we divide all countries into three parts: fragile, vulnerable,stable depending on the country's score. Finally, we discuss the impact of climate change with the model.

2.1.2 Model Implementation and Results

We regard eight factors as independent variables and fragile state score as dependent variables.First,We normalize 8 independent variables to facilitate comprehensive evaluation. Next,we calculate the correlation coefficients between eight independent variables,the correlation coefficient matrix is shown in Table 1.

	$\bar{x}_1$	$\bar{x}_2$	$\bar{x}_3$	$\bar{x}_4$	$\bar{x}_5$	$\bar{x}_6$	$\bar{x}_7$	$\bar{x}_8$
$\bar{x}_1$	1.0000	0.3725	0.3343	0.0993	0.8060	0.8170	0.5082	0.7215
$\bar{x}_2$	0.3725	1.0000	0.4060	0.0367	0.2018	0.2929	0.1629	0.3868
$\bar{x}_3$	0.3343	0.4060	1.0000	-0.1269	0.3287	0.3633	0.3116	0.3789
$\bar{x}_4$	0.0993	0.0367	-0.1269	1.0000	0.0761	0.0564	-0.1198	0.0265
$\bar{x}_5$	0.8060	0.2018	0.3287	0.0761	1.0000	0.7564	0.5279	0.6878
$\bar{x}_6$	0.8170	0.2929	0.3633	0.0564	0.7564	1.0000	0.5284	0.7377
$\bar{x}_7$	0.5082	0.1629	0.3116	-0.1198	0.5297	0.5284	1.0000	0.4962
$\bar{x}_8$	0.7215	0.3868	0.3798	0.0265	0.6878	0.7377	0.4962	1.0000

Table 2: The Correlation Coefficient Matrix($\bar{x}_i$ represents the normalized variable)

We can see that there is a strong correlation between some factors. If we use the factors directly for comprehensive evaluation, the overlap of information will inevitably influence the objectivity of the evaluation results. Principal component analysis can transform multiple factors into a few unrelated factors.Therefore, we use the principal component analysis method for comprehensive evaluation.

We use matlab for principal component analysis.First, we calculate the contribution rate and cumulative contribution rate of 8 eigenvalues , as shown in the Table 3:

indicator	1	2	3	4	5	6	7	8
Contribution	50.1655	14.1311	12.2259	8.0339	6.7382	3.7011	2.9214	2.0829
Cumulative	50.1655	64.2966	76.5225	84.556	91.2964	94.9957	97.9171	100

Table 3: Contribution Rate of 8 Eigenvalues

We can easily see that the cumulative contribution rate of the first 4 eigenvalues is over 80%, so the results of principal component analysis is good.We use the first four principal components for comprehensive evaluation. The eigenvectors corresponding to the first four eigenvalues are shown in the Table 4.

	$\bar{x}_1$	$\bar{x}_2$	$\bar{x}_3$	$\bar{x}_4$	$\bar{x}_5$	$\bar{x}_6$	$\bar{x}_7$	$\bar{x}_8$
1	0.4460	0.2133	0.4469	0.0159	0.4326	0.2609	0.3385	0.0279
2	-0.0463	-0.4656	-0.0565	0.3501	0.0186	0.7941	-0.0270	-0.1540
3	0.1680	-0.1392	-0.4356	0.8308	0.1485	0.1027	-0.1979	0.4311
4	-0.1152	0.8013	0.3276	0.3032	-0.2037	-0.0945	-0.3035	0.0540

Table 4: The First Four Eigenvalues

So we get the four principal component.

$$y_1 = 0.4460\bar{x}_1 + 0.2133\bar{x}_2 + ... + 0.0279\bar{x}_8 \tag{1}$$

$$y_2 = -0.0463\bar{x}_1 - 0.4656\bar{x}_2 + ... - 0.1540\bar{x}_8 \tag{2}$$

$$y_3 = 0.1680\bar{x}_1 - 0.1392\bar{x}_2 + ... + 0.4311\bar{x}_8 \tag{3}$$

$$y_4 = -0.1152\bar{x}_1 + 0.8013\bar{x}_2 + ... + 0.0540\bar{x}_8 \tag{4}$$

From the coefficient of the principal component, it can be seen that the first principal component reflects the economy(GDP per capita,scientific and technical,food production index,health expenditure), the second principal component reflects the politics(corruption perception index), the third principal component reflects the society(environment index,unemployment rate), and the fourth principal component reflects the climate change(climate change index).

Based on the contribution rate of four principal components, we construct the comprehensive evaluation model.

$$Z = 0.5017y_1 + 0.1413y_2 + 0.1223y_3 + 0.0803y_4 \tag{5}$$

Use the formula(1)(2)(3)(4)(5), we can calculate a comprehensive evaluation score with normalized independent variables.

$$Z = 0.2297\bar{x}_1 + 0.1479\bar{x}_2 + 0.1732\bar{x}_3 + 0.1906\bar{x}_4 + 0.2146\bar{x}_5 + 0.2226\bar{x}_6 + 0.1026\bar{x}_7 + 0.2144\bar{x}_8 \tag{6}$$

And by substituting the data of all the countries obtained from the website into formula (6),we get the fragile state score of all countries(see appendix B),also we can see clearly in Figure 2.

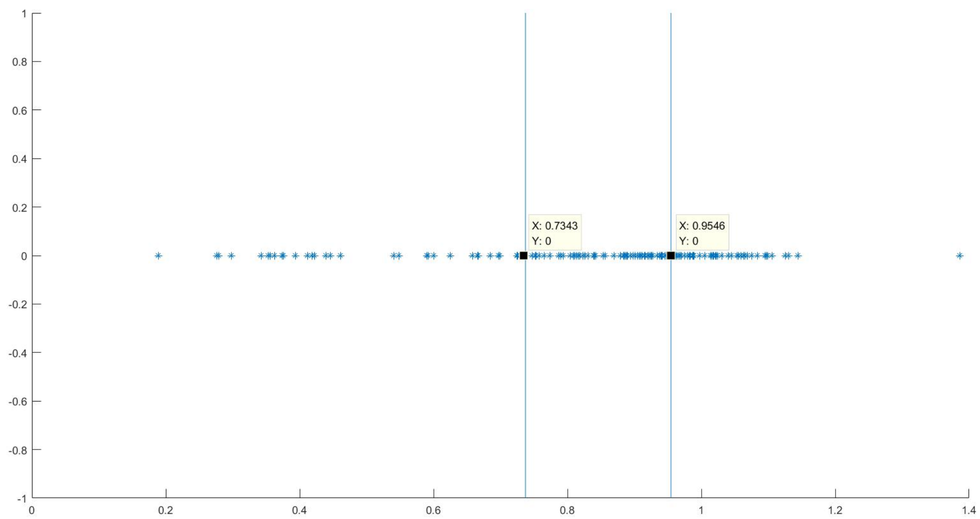

Figure 2: The vulnerability score of all the countries(x axis)

There are about 40 fragile countries on the world bank website[3], so we divide 40 states according to the national ranking we calculated above. And then we determine the boundary score between vulnerable vountries and stable countries combined with Figure 2. The result is shown in Table 5.

Fragile	Vulnerable	Stable
$score > 0.9546$	$0.7343 \leq score \leq 0.9546$	y$score < 0.7343$

Table 5: Boundary score

We also try to use cluster analysis to classify countries as fragile, vulnerable or stable, but not effective. Because we calculate the score gap between vulnerable countries and stable countries is not obvious, cluster analysis brings together the closest points. So the vulnerable countries and stable countries will be in the same class, therefore we cannot be use cluster analysis.

From the the correlation coefficient matrix(Table 2), we can see $\bar{x}_2$(climate change index) is related to $\bar{x}_1$ GDP per capita(correlation coefficient :0.3725), $\bar{x}_3$ food production index(correlation coefficient : 0.4060), $\bar{x}_8$ environment index(correlation coefficient : 0.3868). So we make a conclusion that the climate change indirectly affects national fragility because it does affect other independent variables.

From formula (5),we can get the contribution rate to the comprehensive evaluation score which is shown in Figure 3. We can find that climate change directly influences fragility of a country to a small extent, as it takes up nearly 8% of contribution rate.

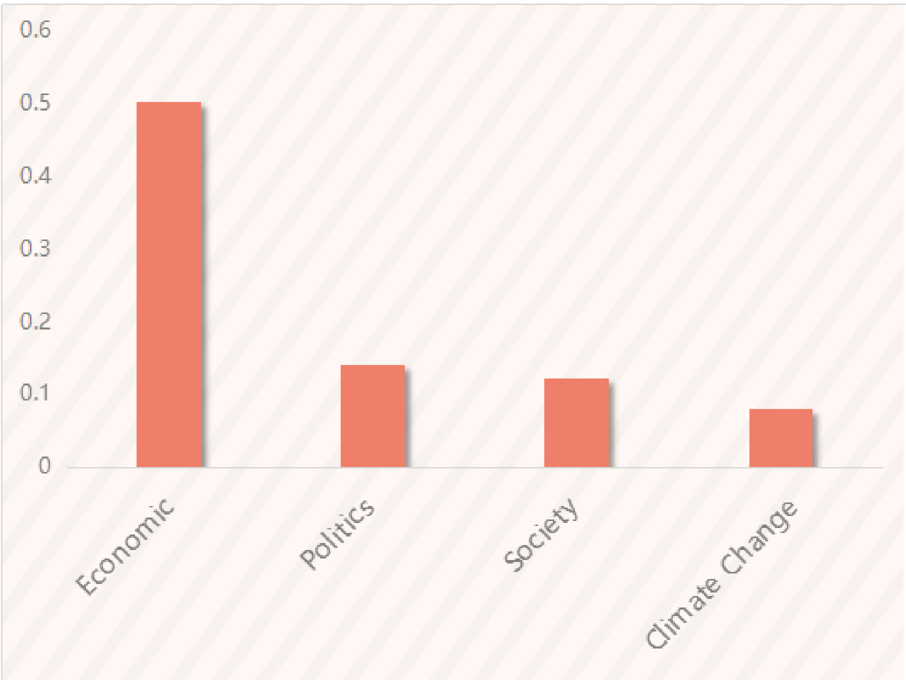

Figure 3: The contribution rate to the comprehensive evaluation score

From Figure 3,we can see the climate change affects national vulnerability but not significantly.

2.2 Task 2

2.2.1 Analysis of Task 2

In this task, we use principal component analysis to solve it as task 1, but remove the factors of climate change. We compare the rankings of comprehensive evaluation scores with task 1. We check to see if these countries'rankings increase, in order to find out how climate change affects the fragility of the state.

2.2.2 Model Implementation and Results

First,we select the top 10 most fragile states as determined by the Fragile State Index on the website[4].Since we removed the climate change factor , we choose three principal components, representing the economy, politics and society respectively.Use the same method as in task 1,we can calculate that the cumulative contribution rate of the first 3 eigenvalues is over 81%,so the results is acceptable. We can also get the comprehensive evaluation model as shown below.

$$Z = 0.5528y_1 + 0.1609y_2 + 0.1046y_3 \tag{7}$$

Where y_1, y_2, y_3 is shown in Table 1.

We can calculate the comprehensive evaluation scores and rankings, which is shown in Table 6 below(the country with the highest score is most fragile).

country	score1	rank1	score2	rank2
South Sudan	1.3858	1	1.4925	1
Somalia	1.1443	2	1.2310	3
Central African	1.0188	13	1.1686	16
Yemen	1.0405	9	1.1854	10
Sudan	0.9896	16	1.0803	33
Syria	1.0634	5	1.2172	7
Congo Democratic	0.9704	18	1.1231	25
Chad	1.0593	7	1.1627	18
Afghanistan	1.0227	10	1.1525	22
Irap	0.9678	20	1.1054	30

Table 6: Comparison of rankings and scores

From Table 6, by comparing rank1 with rank2, we can see that every of the top 10 most fragile countries' ranking drops. We make a conclusion that climate change has a direct impact on these fragile states[5], because if the climate change factor is removed, these countries' rankings have an decrease. Therefore, we can improve our fragility by reducing the impact of climate change[6].

2.3 Task 3

2.3.1 Analysis of Task 3

In this task, we choose China as the research object. We assume that other factors do not change, considering only the impact of climate change. From formula (6), the coefficient of climate factor is 0.1479, we can think the climate change has an direct effect on fragility. And from the correlation coefficient matrix(Table 2),we can see the climate change has an indirect effect on fragility.

From Table 5(Boundary score), we get the tipping point 0.9546. So we only need to predict when China's comprehensive evaluation score is greater than 0.9546.

2.3.2 Model Implementation and Results

We assume that other factors do not change, China's vulnerability is a function of the climate change. That is

$$Z = 0.8009 + 0.2144\bar{x}_2 \tag{8}$$

Through formula (8), we forecast China's vulnerability score indirectly by predicting China's climate change index. It's equivalent to predict when China's climate change index is smaller than 0.2971. We have found China's data on climate change for nearly six years.

year	2006	2008	2010	2012	2014	2016
data	0.567	0.271	0.4059	0.393	0.43	0.651

Table 7: Climate data for nearly 6 years

Because the vulnerability score has upper and lower bounds, we use the Verhulst model for prediction[4]. Set $x^{(1)}$ as the initial data sequence and $x^{(1)}$ as the 1-AGO sequence.The differential equation of Verhulst model is

$$\frac{\mathrm{d}x^{(1)}}{\mathrm{d}t} + ax^{(1)} = b(x^{(1)})^2 \tag{9}$$

Solve the above differential equation, and then we can get the sequence solution

$$\hat{x}^{(1)}(k+1) = \frac{ax^{(0)}(1)}{bx^{(0)}(1) + (a - bx^{(0)}(1))e^{ak}} \tag{10}$$

We get the recurrence sequence solution

$$\hat{x}^{(0)}(k+1) = \hat{x}^{(1)}(k+1) - \hat{x}^{(1)}(k) \tag{11}$$

For discrete data, we use least square method to calculate the parameter a and b, and $a = -0.3743$, $b = -0.0005$, substituted in equation(10), we get

$$\hat{x}^{(1)}(k+1) = \frac{-0.3743x^{(0)}(1)}{-0.0005x^{(0)}(1) + (-0.3743 - -0.0005x^{(0)}(1))e^{-0.3743k}} \tag{12}$$

year	2006	2008	2010	2012	2014	2016
data	0.5670	0.2710	0.4059	0.3930	0.4300	0.6510
predictive value	0.5670	0.2292	0.3067	0.3975	0.4945	0.5847
relative error	0	0.1541	0.2444	0.0114	0.1499	0.1018

Table 8: Predictive value and relative error

We use matlab to calculate the predictive value and estimate error.

We can see the relative error is no more than 30%, so the predictive value is acceptable. Now let's give the prediction.

2018	2020	2022	2024	2026	2028	2030	2032	2034
0.6513	0.6790	0.6607	0.6011	0.5143	0.4175	0.3246	0.2441	0.1789

Table 9: Predictive value and relative error

From Table 9, China's climate change index will reach 0.2441 in 2032, which is smaller than 0.2971. So if China does not take relevant measures, China will be fragile in 2030 or 2032.

2.4 Task 4

2.4.1 Analysis of Task 4

No matter how powerful the country is, it is impossible to control climate change. So we start with what we can control to reduce the fragility of a country. To improve GDP,food production index,corruption perception is very slow and difficult[7]. Therefore, in order to reduce the fragility of a country, we might start with factors which can be controlled easily. This model reduces the fragility of the state by increasing x_5 (the proportion of technology input to GDP) and x_7 (the proportion of health expenditure as a share of GDP).

2.4.2 Model Implementation and Results

Taking China as example, previously Chinese's fragile score is:

$$Z = 0.8009 + 0.2144\bar{x}_2$$

From Table 5(Boundary score), we know that when z>0.9546, China becomes a fragile state. As $\bar{x}_2$ is not larger than 1, when constant term is smaller than 0.7402, China can't be fragile. Because,

$$Z = const + 0.2144x_2 < 0.7402 + 0.2144x_2 \leq 0.7402 + 0.2144 = 0.9546$$

x_5, x_7 should be increased so as to changes constant term from 0.8009 to 0.7402, and we have the following formula.

$$0.2146 \bigtriangleup \bar{x}_5 + 0.1025 \bigtriangleup \bar{x}_7 = 0.8009 - 0.7402 = 0.0607$$

The data 0.2146, 0.1026 come from Formula (6) and the factors except x_5, x_7 can't be changed in the assumption. Theoretically, the coefficient of x_5 is larger than x_7, which means x_5 can be changed easier. But in fact, x_5 is related to GDP, and it is more difficult to be improved. So we can assume that x_5, x_7 take up half of the increasement respectively,

$$0.2146 \bigtriangleup \bar{x}_5 = 0.0303, 0.1026 \bigtriangleup \bar{x}_7 = 0.0303$$

$$increment = (maximum - minimum) * coefficient$$

So the expenditures of x_5 (scientific and technical) should be increased by 0.60% and x_7 (expenditures of health) should be increased by 2.96%. The GDP of China in 2018 is 11200 billion dollars, thus the expense of scientific and technical is 67.623 billion dollars, the expense of health is 331.520 billion dollars and the total expense is 399.143 billion dollars.

It means that in order to prevent China from becoming a fragile state, Chinese goverment need to spend 399.143 billion dollars.

	scientific and technical	expense of health
Should be increased ($\%GDP$)	0.60%	2.96%
GDP(2018)	11200 billion dollars	11200 billion dollars
Spending	67.623 billion dollars	331.520 billion dollars

Table 10: Result of Task 4

2.5 Task 5

2.5.1 Analysis of Task 5

In this task, we choose larger "states" to study. We use the model in task 1 to calculate the score and rankings of these larger "states".The we compare the result with reality, we can find whether our model still work on larger "states". Next, we will modify the model by lefting out some factors to make the model more reasonable.

2.5.2 Model Implementation and Results

By substituting the data of all the continents(Table 11) into formula (6),we get the fragility score of all continents(Table 11).

The data is not reasonable. For example, the difference of fragile state score between Latin America & Caribbean and East Asia & Pacific is too large.(the GDP of Latin America & Caribbean and East Asia & Pacific is 15027 and 17023. The difference of GDP between two of them is quite small and it partly reflects fragility.)

Some factors in task 1 may not suitable in task 5. After normalize 8 independent variables to facilitate comprehensive evaluation, food production index of all continents are shown in Table 12 as follow.

As shown above, the effect of normalization in food production index is very bad. So we delete the factor food production index, and calculate a new comprehensive evalua-

Continent	x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8	Score
World	16167	1.164	123.3	5.4	2.23	43.15	9.9	56.24	1.291
East Asia & Pacifici	17023	1.544	127.4	4.6	2.46	48.55	6.9	54.56	1.250
Europe & Central Asia	30825	0.3935	111.9	8.1	1.93i	54.57	9.5	66.87	1.016
Latin America & Caribbean	15027	0.8259	128.2	7	0.77	40.54	7.2	58.24	0.9718
Middle East & North Africa	19619	0.74	114.2	8.9	0.94	38	5.3	58.14	0.7995
North America	57163	0.1	113.8	5.3l	2.79	78	16.5	71.69	0.7894
South Asia	6063	1.7625	136.5	3.5	0.58	34.86	4.4	40.85	0.5836
Sub-Saharan Africa	3613	2.088	125.6	6.4	0.55	31.14	5.5	45.18	0.0769

Table 11: Data and Score of Continents

Continent	Food Production Index
Sub-Saharan Africa	0.6301
South Asia	0.0000
Latin America and Caribbean	0.6626
Middle East and North Africa	0.0935
East Asia and Pacific	0.0772
World	1.0000
Europe and Central Asia	0.5569
North America	0.0000

Table 12: Food Production Index of Contients

tion score with normalized independent variables. We get

$$Z = 0.2465\bar{x}_1 + 0.2596\bar{x}_2 + 0.1293\bar{x}_4 + 0.2196\bar{x}_5 + 0.2446\bar{x}_6 + 0.1199\bar{x}_7 + 0.2575\bar{x}_8 \quad (13)$$

By substituting the data of all the continent(Table 11) into formula (13),we get the fragility score of all continents as follow(Table 13).

Continent	Score
Sub-Saharan Africa	1.3701
South Asia	1.2715
Latin America & Caribbean	0.9706
Middle East & North Africa	1.0000
East Asia & Pacific	0.8239
World	0.8044
Europe & Central Asia	0.5859
North America	0.0431

Table 13: Score of Improved Model

In this new model, the difference of fragile state score between Latin America & Caribbean and East Asia & Pacific becomes smaller. The new model lefts out a factor and does better than the previous model.

3 Evaluation of the model

3.1 Strengths

- Our model can be applied in various situations with slight changes. For example, we can predict the fragility and , determine how climate change affects the fragility and so on.
- Our model has theoretical support from books and papers. Our model use mathematicall algorithms which can be executed by computer to get the result.
- The results calculated by our models are reasonable.
- Our model erases the mutual impact among eight factors. More importantly, we also analysis the relation among eight factors.

3.2 Weakness

- Since few of data is missing, we have to fill in the missing data, which is not precise in a way. And the source of some data is different, which may lead to errors when they are used together.
- To simplify our problems, we make some basic assumptions which may affect the result of our model.
- In principal component analysis, there are eight factors in our model, it is not enough.

4 Conclusions and Future work

4.1 conclusions

In this paper, we have considered the indicators of the country's fragility and established the comprehensive evaluation model. First, we choose eight factors which belong to four parts:economic, politics, society and climate change. Then we use PCA to established the comprehensive evaluation model. Nest we calculate the comprehensive evaluation scores and the correlation coefficient matrix. Using the results, we can determine a country whether is fragile and divied all countries into three parts: fragile, vulnerable and stable. And we get two boundary score:0.9546,0.7343.

Then, we remove the factors of climate change. We calculate the comprehensive evaluation scores used the same method as task 1. Next, we compare the countries' rankings with task 1. We find that the rankings of the top 10 most fragile countries' drops. So we get a conclusion that the climate change has a directly effect on these fragile countries.

In terms of the prediction of the country's fragility, we use the grey prediction to predict when China will be fragile. But we assume that other factors do not change. We predict that China will be a fragile country in 2030 or 2032if Chinese goverment does not take measures.

Finally, we consider two facors: scientific expenditures and health expenditures($\% of GDP$) to calculate that Chinese goverment need to spend 399.143 billion dallars to prevent China from becoming fragile.

However, our model can't work well on the "larger states". As we can't get enough data and the data of food production index we get is not very reasonable.

4.2 Future Work

Unfortunately, there are many drawbacks in our model, We have to do a lot more to improve our work.

Lack of Data
As we can't get enough data, the results of our model may be not very reasonable. Next,we should find more data for study.

Using Model on Continents
Our model can't work well on the "larger states", so we need to find more reasons and solve it.

More Factors
We use PCA with only eight factors, so the results may be not in accordance with the actual situation.

References

[1] LIU, Tianxu, WU, Tao. Evaluation Criteria of Fragile States[J]. LILUN TANTAO, 2016, (04): 20-25

[2] http://www.worldbank.org/table

[3] http://www.worldbank.org/en/topic/fragilityconflictviolence/brief/harmonized-list-of-fragile-situations

[4] http://fundforpeace.org/fsi/data/

[5] http://www.xzbu.com/8/view-7168155.htm

[6] Zhang, Qian, Meng, Huixin. Social Fragility and Poverty Under the Influence of Climate Change: A Review of Foreign Research[J]. China Agricultural University Journal of Social Sciences Edition, 2014, 31(2): 55-62

[7] Michael A. Williams,Grace Baek,Yiyang Li,Leslie Y. Park,Wei Zhao. Global evidence on the distribution of GDP growth rates[J]. Physica A: Statistical Mechanics and its Applications,2017,468.

Appendices

Appendix A Our Code

Task 1:

```
%Task 1

clc
clear
data=xlsread('data.xlsx','Sheet1');
data_max=max(data);
data_min=min(data);
data(:,1)=(data_max(1)-data(:,1))/(data_max(1)-data_min(1));
data(:,2)=(data(:,2)-data_min(2))/(data_max(2)-data_min(2));
data(:,3)=(data(:,3)-data_min(3))/(data_max(3)-data_min(3));
data(:,4)=(data(:,4)-data_min(4))/(data_max(4)-data_min(4));
data(:,5)=(data_max(5)-data(:,5))/(data_max(5)-data_min(5));
data(:,6)=(data_max(6)-data(:,6))/(data_max(6)-data_min(6));
data(:,7)=(data_max(7)-data(:,7))/(data_max(7)-data_min(7));
data(:,8)=(data_max(8)-data(:,8))/(data_max(8)-data_min(8));

data(isnan(data))=1;

r=corrcoef(data);
[vec1,lamda,rate]=pcacov(r);
contr=cumsum(rate);
f=repmat(sign(sum(vec1)),size(vec1,1),1);
vec2=vec1.*f;
num=4; % >80%
df=data*vec2(:,1:num);
tf=df*rate(1:num)/100;
[stf,ind]=sort(tf,'descend');
coefficient=zeros(size(data,2),1);
for i=1:num
    coefficient=coefficient+vec2(:,i)*rate(i);
end

[stf,ind]
rate
vec2
r
coefficient

point_y=zeros(size(tf,1),1);scatter(tf,point_y,'*');
y=[-1:0.1:1]; x=ones(size(y,2))*(0.7343+0.003);
hold on
plot(x,y,'-')
x=ones(size(y,2))*(0.9576-0.003);
hold on
plot(x,y,'-')
```

Task 2 :

```
%Task 2
clc
clear
data=xlsread('data.xlsx','Sheet1');
```

```
data_max=max(data);
data_min=min(data);
data(:,1)=(data_max(1)-data(:,1))/(data_max(1)-data_min(1));
data(:,2)=(data(:,2)-data_min(2))/(data_max(2)-data_min(2));
data(:,3)=(data(:,3)-data_min(3))/(data_max(3)-data_min(3));
data(:,4)=(data(:,4)-data_min(4))/(data_max(4)-data_min(4));
data(:,5)=(data_max(5)-data(:,5))/(data_max(5)-data_min(5));
data(:,6)=(data_max(6)-data(:,6))/(data_max(6)-data_min(6));
data(:,7)=(data_max(7)-data(:,7))/(data_max(7)-data_min(7));
data(:,8)=(data_max(8)-data(:,8))/(data_max(8)-data_min(8));

data(isnan(data))=1;

data(:,2)=[]; %delete Population affected by climate %%

r=corrcoef(data);
[vec1,lamda,rate]=pcacov(r);
contr=cumsum(rate);
f=repmat(sign(sum(vec1)),size(vec1,1),1);
vec2=vec1.*f;
num=3; % >80% %%
df=data*vec2(:,1:num);
tf=df*rate(1:num)/100;
[stf,ind]=sort(tf,'descend');
coefficient=zeros(size(data,2),1);
for i=1:num
    coefficient=coefficient+vec2(:,i)*rate(i);
end

[stf,ind]
rate
vec2
r
coefficient
point_y=zeros(size(tf,1),1);
scatter(tf,point_y,'*');
```

Task 3 :

```
% Task 3
clc
clear
x0=[56.7000,22.9231,30.6683,39.7477,49.4471,58.4712];
x1=cumsum(x0);
n=length(x0);
z=0.5*(x1(2:n)+x1(1:n-1));
b=[-z',z'.^2];
y=x0(2:end)';
u=b\y;


syms x(t)
x=dsolve(diff(x)+u(1)*x==u(2)*x^2,x(0)==x0(1));
xt=vpa(x,6);
yuce=subs(x,'t',[0:16]);
yuce=subs(x,'t',[0:n-1]);
yuce=double(yuce);
x0_hat=[yuce(1),diff(yuce)];
epsilon=x0-x0_hat;
delta=abs(epsilon./x0);
yuce=subs(x,'t',[0:14]);
```

```
yuce=double(yuce);
x0_hat=[yuce(1),diff(yuce)]
```

Task 5 :

```
% Task 5
clc
clear
data=xlsread('data(continent).xlsx','Sheet1');
data_max=max(data);
data_min=min(data);
data(:,1)=(data_max(1)-data(:,1))/(data_max(1)-data_min(1)); %GDP
data(:,2)=(data(:,2)-data_min(2))/(data_max(2)-data_min(2)); %Population affected by climate
data(:,3)=(data(:,3)-data_min(3))/(data_max(3)-data_min(3)); %Food production index
data(:,4)=(data(:,4)-data_min(4))/(data_max(4)-data_min(4)); %Unemployment rate
data(:,5)=(data_max(5)-data(:,5))/(data_max(5)-data_min(5)); %Scientific and technical
data(:,6)=(data_max(6)-data(:,6))/(data_max(6)-data_min(6)); %Corruption perception
data(:,7)=(data_max(7)-data(:,7))/(data_max(7)-data_min(7)); %Health expenditure
data(:,8)=(data_max(8)-data(:,8))/(data_max(8)-data_min(8)); %Environment performance index
%One
% coefficient=[22.9691,14.7901,17.3161,19.0581,21.4569,22.2607,10.2573,21.4416];
%Two
data(:,3)=[]; %Food production index
coefficient=[24.6492,25.9596,12.9314,21.9634,24.4563,11.9915,25.7527];
coefficient=coefficient./100;
for i=1:size(data,1)
    score(i)=sum(data(i,:).*coefficient);
end
score'
coefficient
```

Appendix B The Data and Score

The $x_1, x_2, ..., x_8$ is the same as the assumption in Table 1.

Country	x1	x2	x3	x4	x5	x6	x7	x8	score
Afghanistan	570	0.3774	120.1	7.7	0	15	8.2	1.1	1.0227
Albania	4180	0.6546	133.3	15	0.15	39	5.9	5.3	0.9869
Algeria	4220	0.5718	163.8	9.9	0.07	34	7.2	0	0.941
Angola	3450	0.3744	207.4	5.7	0	18	3.3	1	1.1299
Argentina	11970	0.593	117.9	7.8	0.59	36	4.8	0.2	0.8309
Armenia	3770	0.6207	142.7	16.6	0.25	33	4.5	0.5	0.9618
Australia	54420	0.7412	116.7	5.7	2.2	79	9.4	3	0.4608
Austria	45790	0.7897	104.4	6.4	3.07	75	11.2	0	0.3624
Azerbaijan	4760	0.6233	142.2	4.2	0.22	30	6	1.1	0.8891
Bangladesh	1330	0.2956	135.8	3.5	0	26	2.8	4.6	1.1057
Belarus	5590	0.6498	135.9	0.5	0.52	40	5.7	0	0.7869
Belgium	41820	0.7738	104.3	8.1	2.46	77	10.6	0	0.4189
Benin	820	0.3817	148.6	1.1	0	36	4.6	0.9	0.9747
Bhutan	2510	0.4722	95.5	1.9	0	65	3.6	0	0.7898
Bolivia	3070	0.5598	137.8	2.8	0.16	33	6.3	1.3	0.8984
Bosnia and	4940	0.4184	116.7	28.2	0.22	39	9.6	0.5	1.0244
Botswana	6750	0.517	127.7	14.9	0.54	60	5.4	0.7	0.8695
Brazil	8840	0.607	136.6	10.1	1.17	40	8.3	0.5	0.8134
Bulgaria	7580	0.6785	133.4	8.1	0.96	41	8.4	0	0.7736
Burkina Faso	620	0.4283	126.9	3.9	0.2	42	5	1.3	0.9277
Burundi	280	0.2743	144.7	1.2	0.12	20	7.5	2.4	1.0552
Cabo Verde	2970	0.5694	118.8	7.7	0.07	59	10.4	0	0.7869
Cambodia	1140	0.4323	98	9	0.12	21	4.8	6.6	1.0753
Cameroon	1400	0.4081	175.4	0.2	0	26	5.7	0.1	0.9972
Canada	43660	0.7218	159.5	3.6	1.62	82	4.1	0	0.541
Central	370	0.3642	123.7	6	0	20	4.2	0.2	1.0188
Chad	720	0.4534	153.4	4.7	0	20	3.6	2.7	1.0593
Chile	13540	0.5749	112.1	6.3	0.38	66	7.8	0.3	0.7255
China	8250	0.5074	129.5	5.1	2.07	40	5.5	8	0.9097
Colombia	6310	0.6522	116.3	6.5	0.24	37	7.2	0.7	0.8228
Comoros	770	0.4424	106.3	18.3	0	24	6.7	0	1.0158
Congo, Dem.	430	0.3756	110	2.9	0.08	20	4.3	0	0.9704
Costa Rica	10840	0.6785	123.3	7.3	0.58	58	9.3	0.7	0.7249
Croatia	12140	0.6545	102.6	12.5	0.85	49	7.8	0	0.7475
Cyprus	23680	0.726	77.7	12.6	0.46	55	7.4	0	0.666
Czech	17540	0.6768	95.5	3.4	1.95	55	7.4	0.2	0.5923
Denmark	56990	0.816	102	5.8	3.01	90	10.8	0	0.2789
Dominican	6390	0.6471	135.5	9.1	0	31	4.4	0.1	0.901
Ecuador	5800	0.5742	112.8	3.9	0.44	31	9.2	0.3	0.8182
Egypt, Arab	3410	0.6121	115.3	8.5	0.72	34	5.6	0	0.8397
El Salvador	3920	0.5391	117.8	8.4	0.13	36	6.8	0.4	0.8897
Estonia	17750	0.6431	133.1	7.4	1.5	70	6.4	0	0.6583
Ethiopia	660	0.4478	151.3	2.9	0.6	34	4.9	3.3	0.9799
Finland	45050	0.7864	99.1	9.1	2.9	89	9.7	0	0.3558
France	38720	0.8395	99.3	10.2	2.23	69	11.5	0	0.4392
Gambia, The	430	0.4242	97.7	21.7	0.13	26	7.3	0.2	1.0218
Georgia	3830	0.5569	87	13	0.32	57	7.4	0.8	0.8105

Germany	43850	0.7837	107	4.4	2.88	81	11.3	0	0.3526
Ghana	1380	0.4966	143.6	5.2	0.38	43	3.6	1	0.9217
Greece	19090	0.736	86.3	20	0.96	44	8.1	0	0.7333
Guatemala	3790	0.5233	153.6	2.2	0.04	28	6.2	1.3	0.9452
Guinea	670	0.4662	133.6	5.8	0	27	5.6	0.2	0.9634
Guinea-Bissau	600	0.4467	140.6	5.6	0	16	5.6	0.5	1.0133
Guyana	4240	0.4793	130.3	9.4	0	34	5.2	7.2	1.0684
Haiti	780	0.3374	160.8	11.9	0	20	7.6	0.8	1.0968
Honduras	2150	0.5151	121.8	4.3	0	30	8.7	1.3	0.9079
Hungary	12570	0.6501	90.1	5.1	1.38	48	7.4	0.1	0.6665
India	1670	0.3057	139	3.3	0.63	40	4.7	4.4	1.0173
Indonesia	3400	0.4692	137.2	5.2	0.08	37	2.8	0.2	0.9418
Iraq	5420	0.5816	126	12.9	0.04	17	5.5	0	0.9678
Ireland	51760	0.432	99.3	9	1.51	73	7.8	0	0.5902
Israel	36240	0.7501	111.8	4.7	4.27	64	7.8	0	0.394
Italy	31730	0.7696	91.5	10.9	1.33	47	9.2	0	0.6004
Jamaica	4630	0.5858	101.4	9.7	0	39	5.4	1.1	0.8787
Japan	37930	0.7469	97	3.3	3.28	72	10.2	0	0.3755
Jordan	3920	0.622	136	12.7	0.43	48	7.5	0.4	0.856
Kazakhstan	8810	0.5456	123.8	4.1	0.17	29	4.4	0.2	0.8835
Kenya	1380	0.4725	125.8	9.3	0.79	26	5.7	6.5	1.0403
Kuwait	34890	0.6228	176.3	2.9	0.3	41	3	0	0.8043
Kyrgyz	1100	0.5486	107.2	6.8	0.12	28	6.5	2.1	0.9246
Lao PDR	2150	0.4294	156.4	1.6	0	30	1.9	2.7	1.0312
Latvia	14570	0.6612	139.6	10.9	0.63	57	5.9	0	0.7739
Lebanon	7980	0.6108	92.6	5	0	28	6.4	0	0.8256
Lesotho	1270	0.3378	111.7	24.4	0.05	39	10.6	3.4	1.0841
Liberia	370	0.4162	130.6	3.8	0	37	10	1.9	0.9377
Lithuania	14750	0.6933	122	9.1	1.04	59	6.6	0	0.6986
Luxembourg	71470	0.7912	91.7	6.1	1.29	81	6.9	0	0.374
Macedonia,	4980	0.6106	114.4	24	0.44	37	6.5	0.3	0.9378
Madagascar	400	0.3373	119.7	1.6	0.02	26	3	0.9	0.9976
Malawi	320	0.4921	193.4	6.3	0	31	11.4	8.8	1.1253
Malaysia	9860	0.5922	128.8	3.3	1.3	49	4.2	0.1	0.7521
Maldives	10630	0.5214	63	3.4	0	36	13.7	0	0.7343
Mali	770	0.4371	147.1	8	0.58	32	6.9	0.7	0.9604
Mauritania	1130	0.3924	120.5	9	0	27	3.8	3.1	1.0536
Mauritius	9770	0.5663	93.2	4.9	0.18	54	4.8	0	0.7658
Mexico	9040	0.5969	115.3	3.8	0.55	30	6.3	0.1	0.8164
Moldova	2120	0.5197	99.7	5.3	0.37	30	10.3	0.3	0.8402
Montenegro	7120	0.6133	64.4	18.2	0.38	45	6.4	0	0.8105
Morocco	2850	0.6347	127.9	10.6	0.71	37	5.9	0.1	0.8535
Mozambique	480	0.4637	127.3	22.8	0.34	27	7	3.7	1.0974
Myanmar	1190	0.4532	124.7	0.8	0	28	2.3	0.1	0.9415
Namibia	4640	0.5846	89.3	22	0.34	52	8.9	3.4	0.9049
Nepal	730	0.3144	130.7	3.8	0.3	29	5.8	0.7	0.9878
Netherlands	46640	0.7546	113.6	5.6	2.01	83	10.9	0	0.4115
New Zealand	38750	0.7596	111.2	4.7	1.15	90	11	0	0.4463

Nicaragua	2100	0.5504	138.1	5.9	0.11	26	9	0.8	0.9203
Niger	370	0.3574	145	3.1	0	35	5.8	7.5	1.0988
Nigeria	2450	0.5476	111.1	4.2	0.22	28	3.7	0.1	0.8892
Norway	82440	0.7749	104	5.4	1.93	85	9.7	0	0.2977
Pakistan	1500	0.375	124.4	4.6	0.25	32	2.6	1.1	0.9834
Panama	12140	0.6271	115.6	3.4	0.06	38	8	0.2	0.7876
Papua New	2680	0.3935	119	2.2	0	28	4.3	0.7	0.9576
Paraguay	4060	0.5393	176.6	4.9	0.13	30	9.8	0.7	0.9396
Peru	5950	0.6192	147.2	6.1	0.12	35	5.5	2	0.9148
Philippines	3580	0.5765	120.8	5.5	0.14	35	4.7	0.8	0.8853
Poland	12690	0.6411	110.5	6.1	1	62	6.4	0	0.6852
Portugal	19880	0.7191	104	10.9	1.28	62	9.5	0	0.6254
Romania	9480	0.6478	103.2	6.6	0.49	48	5.6	0.1	0.7577
Russian	9720	0.6379	123.3	5.8	1.13	29	7.1	0.1	0.7905
Rwanda	700	0.4368	168.3	2.6	0	54	7.5	1.3	0.926
Samoa	4120	0.545	105.1	7.1	0	60	7.2	0	0.7939
Senegal	950	0.4952	123.3	7.6	0.54	45	4.7	0.6	0.8867
Serbia	5310	0.5749	101.9	14.6	0.87	42	10.4	0	0.8089
Sierra Leone	490	0.4254	172.2	3.6	0	30	11.1	0.2	0.9663
Slovenia	21620	0.6757	84.2	7.5	2.21	61	9.2	0	0.5488
Solomon	1880	0.4322	115.3	30.3	0	42	5.1	0.1	1.0652
South Africa	5490	0.4473	123.7	24.4	0.72	45	8.8	1.8	0.9822
Spain	27600	0.7839	113.7	18.1	1.22	58	9	0.7	0.6671
Sri Lanka	3780	0.6061	139.8	3	0.1	36	3.5	2.2	0.9118
Sudan	2140	0.5149	106.7	11.1	0.3	14	8.4	2.8	0.9896
Suriname	6990	0.542	156.1	5.4	0	45	5.7	0.3	0.894
Sweden	54590	0.8051	94.9	7.3	3.26	88	11.9	0	0.2763
Switzerland	81240	0.8742	102.6	4.4	2.97	86	11.7	0	0.1894
Tajikistan	1110	0.4785	152.1	11.5	0.11	25	6.9	5.4	1.0949
Tanzania	900	0.5083	168.6	1.8	0.53	32	5.6	1.5	0.9457
Thailand	5640	0.4988	130.4	0.9	0.63	35	4.1	3.8	0.9194
Timor-Leste	2060	0.4954	118.4	3.1	0	35	1.5	0	0.9151
Togo	540	0.4178	125.8	5.7	0.27	32	5.2	0.5	0.9513
Trinidad and	16240	0.6736	96.5	3.3	0.09	35	5.9	0	0.7533
Tunisia	3690	0.6235	118.3	12.6	0.63	41	7	0.1	0.8419
Turkey	11230	0.5296	129.8	9.6	1.01	41	5.4	0.1	0.8406
Turkmenistan	6670	0.661	122.5	8.8	0	22	2.1	0	0.9162
Uganda	630	0.4428	100.7	2.5	0.48	25	7.2	0.9	0.8942
Ukraine	2310	0.5287	156.2	10.3	0.62	29	7.1	0.3	0.9472
United	42330	0.7989	101.8	4.9	1.7	81	9.1	0	0.4221
United States	56810	0.7119	113.2	5	2.79	74	17.1	0.2	0.3425
Uruguay	15230	0.6465	127	6.5	0.34	71	8.6	0.3	0.6972
Uzbekistan	2220	0.4588	150.7	8.9	0.21	21	5.8	0.1	1.005
Yemen, Rep.	1040	0.4696	139.3	11.8	0	14	5.6	0.1	1.0405
Zambia	1360	0.5097	185.6	7.4	0.28	38	5	4.2	1.0449
Zimbabwe	890	0.4341	96.8	5.6	0	22	6.4	0	0.9341
Somalia	6217	..	117.1	5.7	0	10	..	4.6	1.1443
South Sudan	820	..	..	..	0	11	2.7	3	1.3858