Problem Chosen	2022	Team Control Number
D	ShuWei Cup Summary Sheet	2022101212848

Research on loss assessment and coping strategies of extreme climate disasters under Triple La Niña events

Summary

Under the influence of the first Triple La Niña in this century, different parts of the world are affected by extreme climate, such as hurricanes, floods, droughts, heavy rainfall, etc., which has attracted wide attention from countries all over the world. Therefore, it is of great practical significance to evaluate the loss of extreme climate disasters under Triple La Niña events and conduct in-depth research on its coping strategies.

In response to question 1, the years with weak influence of El Nino and La Niña (2004-2006) were determined based on Nino3.4 sea surface temperature anomaly (SSTA) and Southern Oscillation index (SOI). Reanalysis data provided by NCEP/NCAR were introduced and the nc grid data were visualized using python software. The global monthly mean temperature and precipitation in summer and winter during 2004-2006 and 2020-2022 were compared by meteorological filling-in charts, and the major countries and regions under the influence of Triple La Niña were analyzed according to the charts. In view of the question 2, Nino3.4 index, which defines El Nino and La Niña events internationally, is introduced to analyze its growth trend and stable fluctuation characteristics in the past 40 years from 1981 to now. The ARIMA model is used for fitting, and the change process of nino3.4 index over time is finally obtained as follows: Y (t) = 0.016 + 1.721 * y (t - 1) to 0.768 * y (t - 2) to 0.46 * epsilon (t - 1).

In response to the question 2, the author makes an overall analysis of the disaster conditions of various countries in recent years, selects China as the assessment object, introduces the disaster data provided by the National Bureau of Statistics, and selects 7 typical indicators to reflect the degree of national disaster of heat and drought. Starting with the evaluation results of EWM,GRA,TOPSIS,PCA and AHP, the AHP method was introduced to distribute weights of various evaluation methods, and a comprehensive evaluation model of drought and heat disaster with more comprehensive information and more practical information was established. The disaster situation of heat and drought in 2010-2011 was evaluated and analyzed in time scale and space scale, and corresponding suggestions were given.

In response to the question 3, similar to the question 2, we analyze the flood disaster situation of various countries in recent years, choose China as the assessment object, and use the flood data provided by the national water resources department to select 8 typical indicators to reflect the degree of flood disaster. We use the method in question 2 to establish a flood comprehensive evaluation model based on a variety of evaluation methods. Based on the comprehensive evaluation results, we evaluate and analyze 2010-2011 year flood disaster situation and give targeted advice.

In response to the question 4, we analyzed the La Nina event from five aspects: overview, cause, influence scope, influence degree and prediction method, and put forward a series of countermeasures.

Keywords: Data Visualization ,ARIMA ,AHP ,Disaster comprehensive evaluation model

Contents

1 Introduction

1.1 Problem Background

La Nina is a widespread and persistent abnormal cooling of sea surface temperatures in the eastern and central equatorial Pacific Ocean. It is also known as an anti-El Nino. It is the product of the combined action of the tropical ocean and atmosphere. La Nina is characterized by hurricanes, heavy rains and severe cold, which can cause severe weather anomalies around the world, including high temperatures, heavy rainfall and droughts. A Triple La Nina event is the occurrence of three consecutive La Nina winters in the region. From 2020 to 2022, the first triple La Nina event of this century occurred, causing economic losses and casualties in China, Australia, Europe and other countries and regions. Monitoring and forecasting La Nina is a global problem in climatology. For the rare Triple La Niña, it is more necessary to strengthen the prediction and research, analyze the possible impacts in different regions, and minimize losses to the greatest extent.

1.2 Our Work

1.This paper makes a statistical analysis of the major countries and regions affected by triple La Nina and predicts the future development trend of triple La Nina

2. A country was selected as an indicator to evaluate and analyze the losses of heat and drought disasters under the influence of triple La Nina events, and suggestions were put forward to deal with such losses.

3. This paper selects a country as an indicator to evaluate and analyze the flood disaster losses under the influence of triple La Nina events, and puts forward countermeasures for such losses.

4. Write a report to management about triple La Nina events.

2 Problem Analysis

2.1 Analysis of question one

This article divides the question one in the title into two parts:

Part I：On the basis of consulting a large number of data, this paper intends to find out the years that are weakly affected by El Nino and La Nina and the summer and winter of 2020-2022 for comparative statistical analysis of global monthly mean temperature and precipitation, and then find out the main countries and regions involved in the triple La Nina events.

Part II：The question asks to predict the likelihood of future triple occurrences. The first step is to find a representative index to judge La Nina events. Secondly, the growth trend and stable fluctuation characteristics of the index are analyzed, and then an appropriate prediction model is selected to predict the future value, which can reflect the possibility of triple La Nina events to some extent.

2.2 Analysis of question two

First of all, according to the disaster conditions of heat and drought in various countries in recent years, a heavily affected country is selected as the assessment object, so as to more directly reflect the extent of disaster losses caused by triple La Nina events to the country. Secondly, in order to evaluate the losses caused by various kinds of heat and drought disasters under the triple La Nina events, we need to find out the typical indicators to reflect the degree of disaster under the heat and drought disasters, establish the comprehensive evaluation model of heat and drought disasters according to the indicators with high correlation, and then summarize the targeted response strategies according to the evaluation results.

2.3 Analysis of question three

According to the flood disaster situation of each country in recent years, a country with severe disaster situation is selected as the assessment object. Then, the typical indicators that can reflect the flood disaster situation are selected, and the comprehensive evaluation model of flood disaster is established according to the correlation between the indicators and the disaster damage situation, and the targeted response strategies are summarized according to the evaluation results.

2.4 Analysis of question four

In order to submit a report on the triple La Nina event to the relevant management, we need to introduce the triple La Nina event in detail from the following aspects: the definition of triple La Nina, climate impact, disaster situation of various countries, and monitoring methods. It is hoped that the management should pay attention to the triple La Nina events and take countermeasures.

3 Symbol and Assumptions

3.1 Symbol Description

NO	Symbol	Symbol meaning
1	P	Statistical signficance
2	AIC	Akaike Information Criterion
3	BIC	Bayesian Information Criterion
4	y(t)	The t annual precipitation
5	ε(t-1)	Error value
6	R^2	Goodness of fit

3.2 Fundamental Assumptions

1. We assume that the data collected is true and valid

2. We assume there is no lag in the data in this article.

3. We assume that the effects of global warming on the years studied in this paper are negligible.

4 Model

4.1 Question one

4.1.1 ENSO years and intensity demarcation

In order to find years that are less affected by El Nino and La Nina, the Nino3.4 SSTA and SOI indexes are used to determine El Nino and La Nina years. The results are shown in Table 1.

Table1：El Nion year and La Nina year

El Niño year	Lasts for months	Event intensity	La Niña year	Lasts for months	Event intensity
1963	9	strong	1962	8	weak
1965	12	moderate	1964	11	weak
1969	17	weak	1970-1971	19	moderate
1972	11	strong	1973-1974	15	strong
1976	6	weak	1975	7	strong
1982-1983	14	strong	1985	12	weak
1986-1987	7	strong	1988	12	strong
1991	13	moderate	1995	7	weak
1994	7	moderate	1998-2000	21	strong
1997	12	strong	2007	11	strong
2002	10	weak	2010	10	moderate
2004	19	weak	2011	8	moderate
2006	20	weak			
2009	10	strong			

The years from 2004 to 2006 were identified as the weak years affected by El Nino and La Nina. The global monthly mean temperature and precipitation data in summer and winter during 2004-2006 and 2020-2022 were downloaded from the data website of the National Oceanic and Atmospheric Administration of the United States. The distribution maps of global mean temperature and precipitation in summer and winter during the two periods and the difference maps of mean temperature and precipitation in summer and winter during the two periods were drawn using Python. Through statistical comparative analysis of the average temperature and precipitation in summer and winter of the two periods, the distribution of the major countries and regions involved in the triple La Nina events is obtained. Considering the influence of global warming, climate change cycles in the tropics and other complex factors on the temperature in Antarctica, the temperature change in Antarctica is not analyzed in this question.

(1) Global mean summer temperature for 2004-2006 and 2020-2022

By referring to the data and comparing and analyzing Figure 2, it can be found that the major countries and regions where the triple La Nina events make the summer temperature rise significantly are: western South America, North America, northern Greenland, most of Europe, Australia, central and northern Africa, Southeast Asia (Thailand, Indonesia, etc.), India, and southern China. The temperature rise range is basically stable between 0.0 and 2.5K, which accords with the characteristics that the triple La Nina makes the subtropical high stronger in summer, and then makes the summer temperature rise.

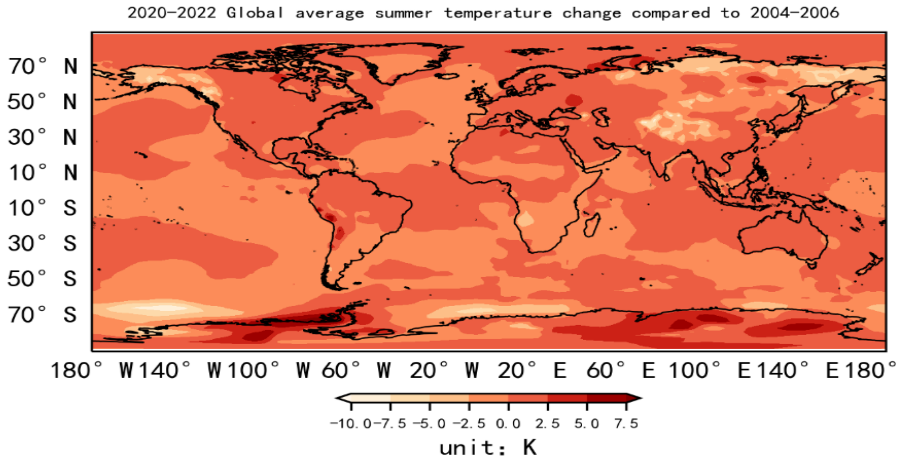


Figure1: Global average summer temperature change comparison

(2) Global mean winter temperature during 2004-2006 and 2020-2021

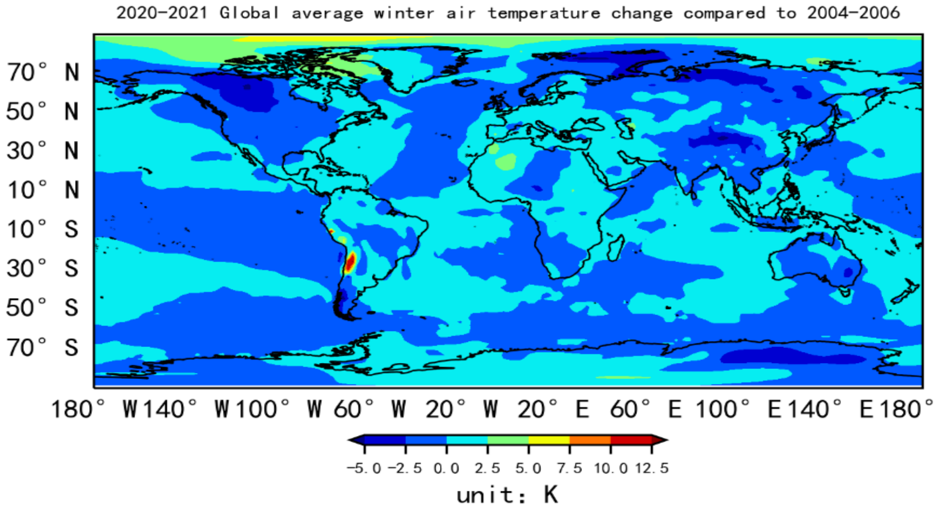


Figure2: Global average winter air temperature change comparison

(3) Global mean summer precipitation during 2004-2006 and 2020-2022

By referring to the data and comparing figures 4 and 5, it can be seen that the precipitation of the Pacific Ocean will increase significantly from 2020 to 2022. Major countries and regions with significant increase in summer precipitation due to triple La Nina events include southern South America, Southeast Asia (Thailand, Indonesia, etc.), southern China, and Japan. La Nina alters atmospheric circulation through the exchange of energy between the ocean and the atmosphere, bringing heavy rainfall to these areas.

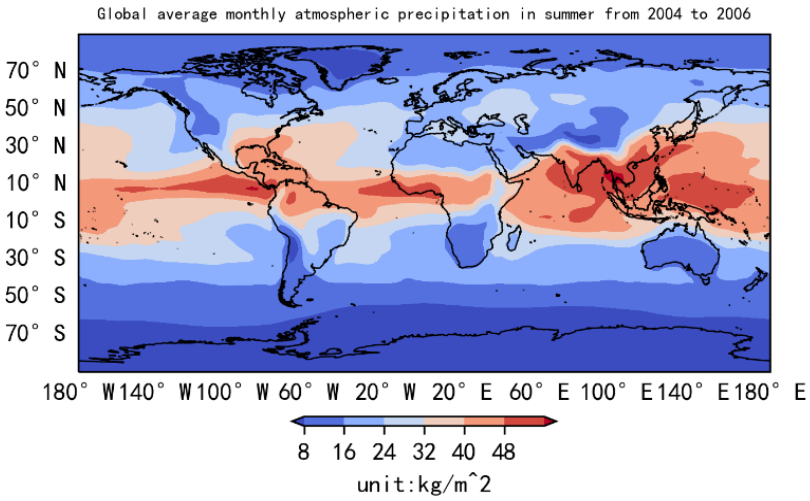


Figure3：Global average monthly atmosphere precipitation in summer-1

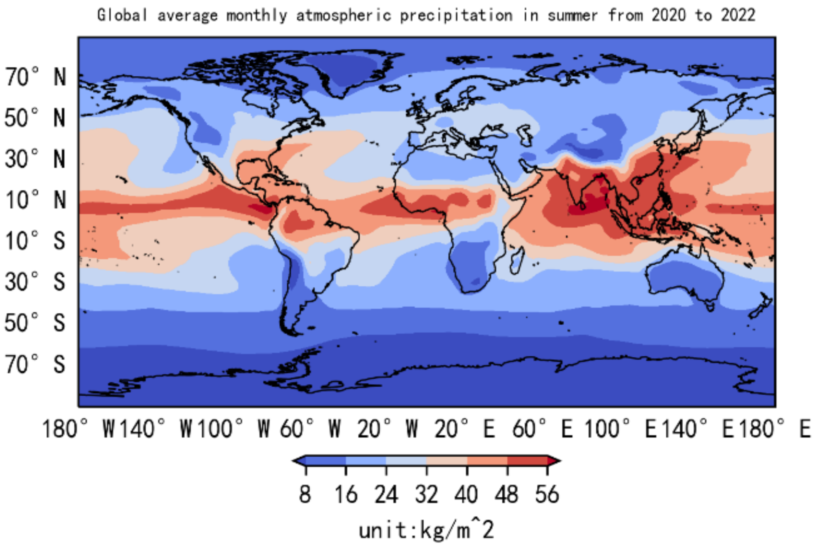


Figure 4 Global average monthly atmosphere precipitation in summer-2

(4) Global mean winter precipitation in 2004-2006 and 2020-2021

As winter precipitation data for 2022 has not yet been released, we conducted a statistical analysis of the global average winter precipitation for 2020-2021. By referring to the data and comparing figures 7 and 8, it can be seen that the precipitation of the Pacific Ocean decreased significantly during 2020-2021. Major countries and regions with significant decreases in winter precipitation due to triple La Nina events include western and northern South America, southern Africa, northern Australia, and Southeast Asia (Thailand, Indonesia, etc.). La Nina events lead to abnormal cyclonic circulation, which obstructs water vapor transport and reduces precipitation.

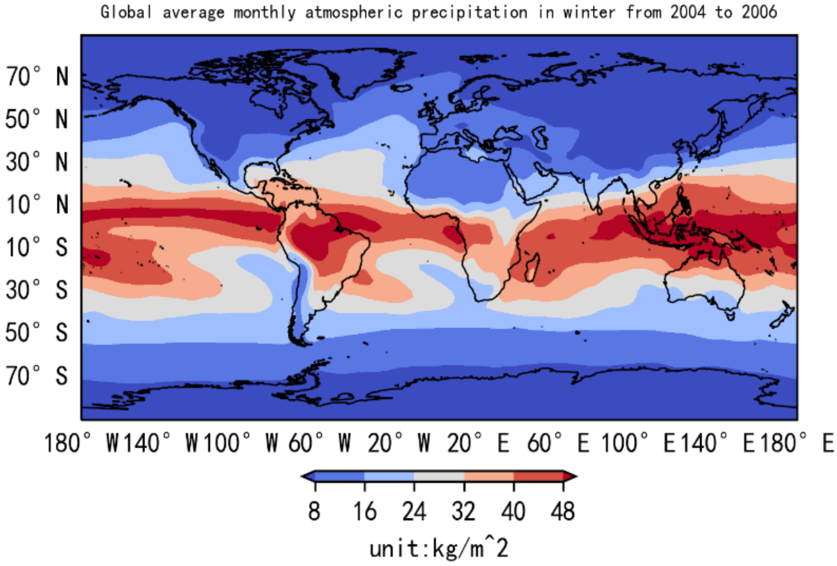


Figure5 : Global average monthly atmosphere precipitation in winter-1

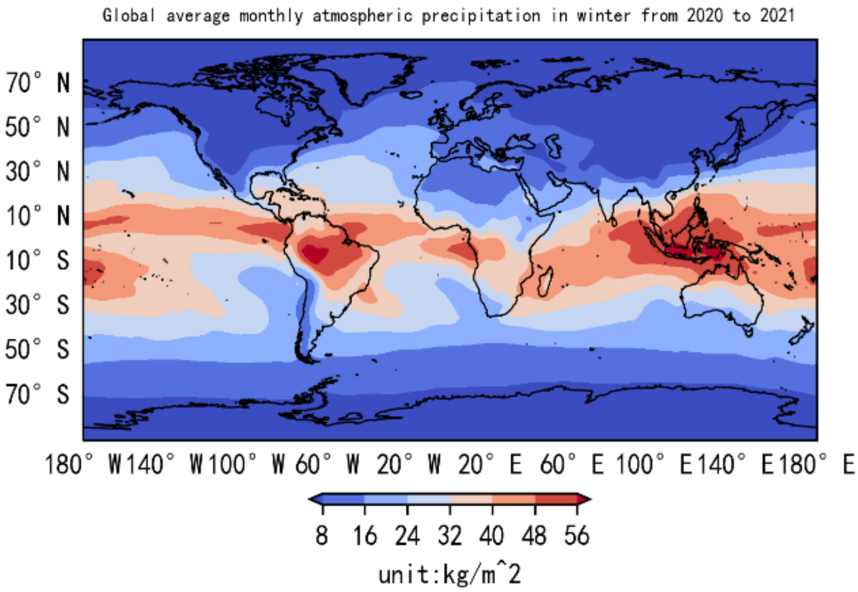


Figure6: Global average monthly atmosphere precipitation in winter-2

4.1.2 The establishment of prediction model

The Nino3.4 index data from January 1981 to September 2022 is selected and the time sequence diagram is drawn as follows：

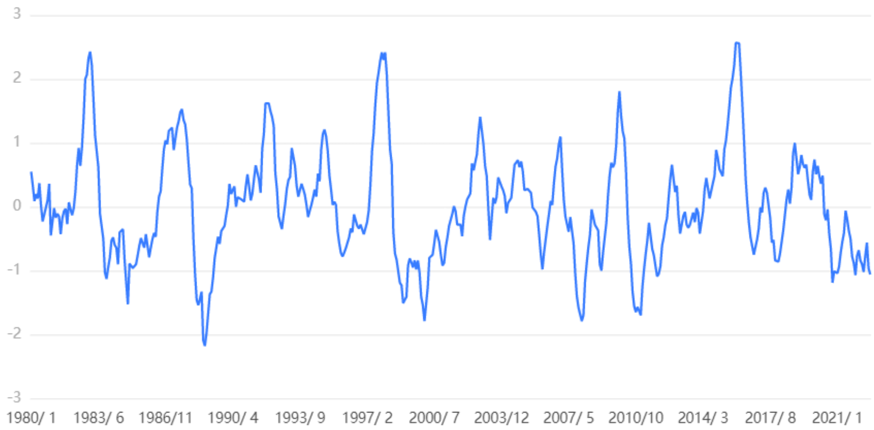


Figure7: Niño3.4 index

Then the ADF test was conducted on the time series, and the results were as follows：

Table2：ADF inspection

variable	difference order	T	P	AIC	critical value 1%	5%	10%
data	0	-6.589	0.000***	-46.462	-3.444	-2.867	-2.57
	1	-9.669	0.000***	-23.14	-3.444	-2.867	-2.57
	2	-8.986	0.000***	20.763	-3.444	-2.868	-2.57

By analyzing the test results, the ARIMA model requires stationary time series data, and P values of the three groups of data all meet $P<0.05$, showing significant level. The hypothesis of series instability can be significantly rejected, that is, the series is a stationary time series. At the same time, the critical values of 1%, 5% and 10% reject the comparison between the statistics of the original hypothesis and the ADF Test result to different degrees. If the ADF Test result is less than 1%, 5% and 10% at the same time, it indicates that the hypothesis is very well rejected. Based on AIC value, 0 order difference is selected, and then the autocorrelation graph (ACF) and partial autocorrelation graph (PACF) under 0 order difference are made.

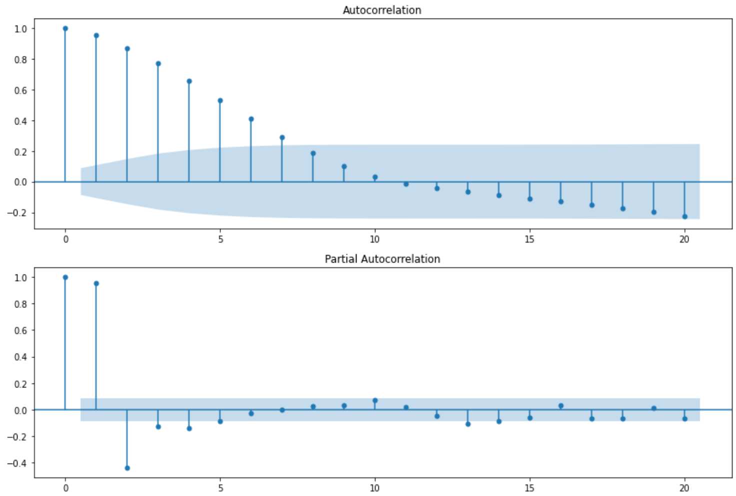


Figure8:ACF PACF

p and q were traversed, and the optimal parameters were found based on AIC criterion and BIC criterion, and the model result was finally determined as ARIMA(2,0,1). The resulting residual autocorrelation (ACF) and residual partial autocorrelation (PACF) of the model are shown in FIG. 12 and FIG. 13: blue represents the correlation coefficient, and the green and yellow lines are the upper and lower bounds of the 95% confidence intervals of ACF and PACF respectively.

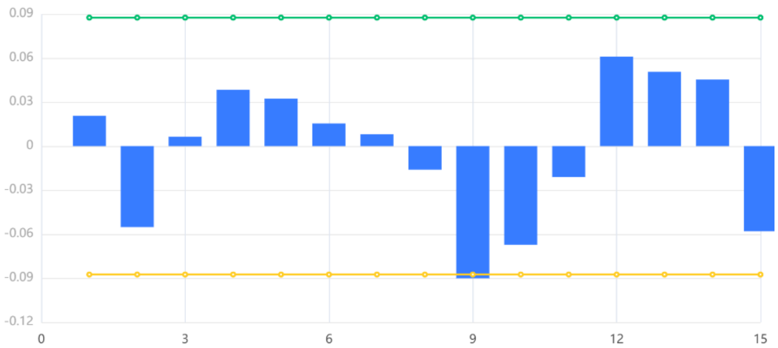


Figure9: residual error ACF

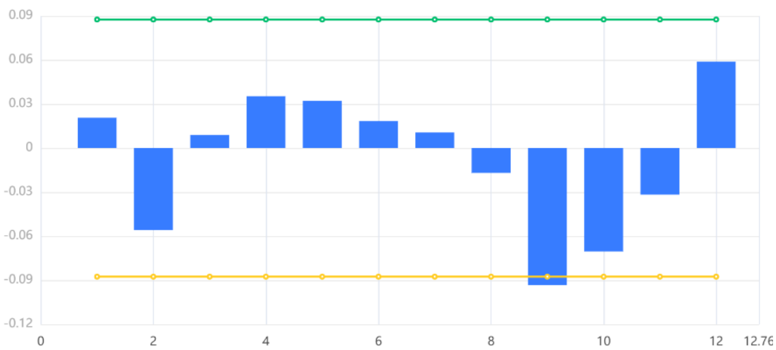


Figure 10：idual error PACF

As can be seen from the figure above, the correlation coefficient and partial correlation coefficient of the residual are both within the confidence interval, indicating that the residual of the autoregressive model (AR) and the moving average model (MA) are both white noise sequences.

Table3:ARIMA Inspection

ARIMA（2,0,1）List of inspection		
Q	Q6(P)	0.214(0.643)
	Q12(P)	3.17(0.787)
	Q18(P)	11.976(0.448)
	Q24(P)	18.889(0.399)
	Q30(P)	22.022(0.578)
Criterion of information	AIC	-43.759
	BIC	-22.676
Goodness of Fit	R^2	0.931

Based on variables, it can be concluded from the analysis of Q statistic results that Q6 does not show significance horizontally, and the hypothesis that the residual of the model is white noise sequence cannot be rejected. Meanwhile, the goodness of fit R^2 of the model is 0.931, which indicates that the model performs well and basically meets the requirements. The model formula is as follows:

$$y(t)=-0.016+1.721*y(t-1)-0.768*y(t-2)-0.46*\varepsilon(t-1) \tag{1}$$

4.1.3Forcasting based on ARIMA Time Series

This model is used to predict nino3.4 index in the future months, and the final result is shown in Figure 14:

(Blue is the true value, green is the fitting value, and yellow is the predicted value)

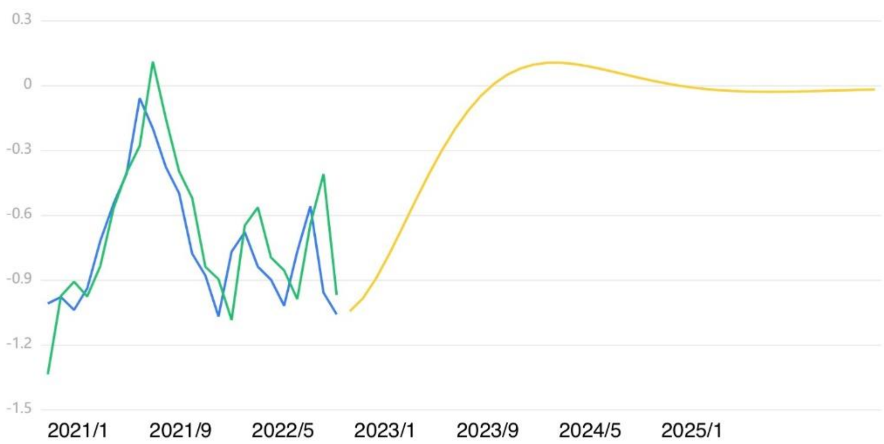


Figure 11： Forcast

It can be seen from the figure that nino3.4 index is on the rise in the future, but considering the limitations of ARIMA model, we take the predicted value of the next 12 months for analysis:

Figure4: Forcast Niño3.4 Index

Niño3.4 Index					
Oct-22	Nov-22	Dec-22	Jan-23	Feb-23	Mar-23
-1.05	-0.99	-0.89	-0.78	-0.66	-0.53
Apr-23	May-23	Jun-23	Jul-23	Aug-23	Sep-23
-0.41	-0.30	-0.20	-0.12	-0.05	0.01

Forecast results: At the end of 2022, Nino3.4 Index will still be below -0.5℃, and the index will show an upward trend in 2023. After 2024, the index will be flat, so there will be no La Nina phenomenon in the next three years. Generally speaking, as the cold and warm phases of SST anomalies in the tropical Pacific, La Nina and El Nino appear alternately in an interval of 2-4 years, while La Nina and El Nino rarely occur in consecutive years, which is consistent with our prediction results, and the prediction model we established has excellent performance.

4.2 Question two

4.2.1 Establishment of model

Based on the existing research results, there are many evaluation methods to study the severity of the disaster, such as analytic hierarchy process, entropy weight method, etc., which are mainly different in the way to determine the weight, roughly divided into subjective weighting method and objective weighting method. In order to take into account the advantages of various methods, on the basis of the results of various evaluation methods, AHP method is used to allocate weights to various evaluation methods, and finally, comprehensive indicators are calculated by using the weights. The flow chart is shown in Figure 14:

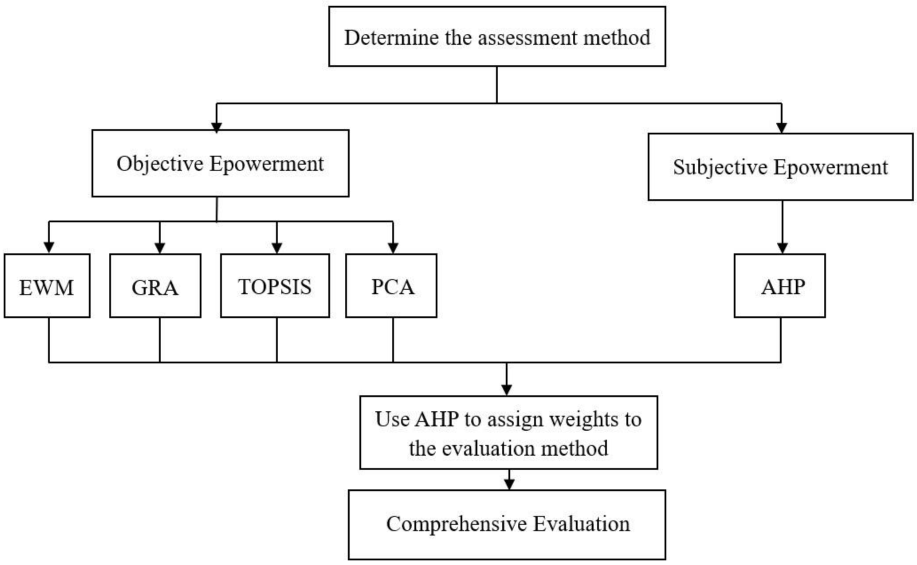


Figure12: Evaluate the result model calculation process

Considering the finiteness of the data index and its correlation with the degree of heat exposure and drought, seven analysis indexes were finally adopted: damage area,disaster area,harvest area, Direct economic loss, Livestock with difficulty drinking water, People with difficulty drinking water, Food loss

Five evaluation methods were selected from different perspectives of mathematical statistics, systems engineering and intelligence, including EWM,GRA,TOPSIS,PCA and AHP.

(1) Since the five indicators are positive indicators that the greater the index value is, the higher the degree of disaster is, the standardization of cost-type indicators is carried out for grey prediction:

$$y_{ij}=\frac{x_{ij}-\min\limits_{1\le i\le n}\{x_{ij}\}}{\max\limits_{1\le i\le n}\{x_{ij}\}-\min\limits_{1\le i\le n}\{x_{ij}\}} \tag{2}$$

The other four methods are normalized by normalization method.

$$y_{ij}=\frac{x_{ij}-\overline{x_i}}{s} \tag{3}$$

Among them: $\overline{x_i}=\frac{1}{n}\sum_{i=1}^{n}x_{ij}$ $\quad s=\sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(x_{ij}-\overline{x_i})^2}$

In Formula (2) and (3), xij is the value of the original matrix, yij is the standardized value, and i and j are the ith row and JTH column of the matrix respectively.

(2) According to the principle of pairwise comparison, the final pairwise comparison result of each index is as follows:

Table5: Pairwise comparison matrix-1

Indicator	1	2	3	4	5	6	7
1	1	1	1	1	2	2	1
2	1	1	1	1	2	2	1
3	1	1	1	1	2	2	1
4	1	1	1	1	2	2	1
5	0.5	0.5	0.5	0.5	1	1	0.5
6	0.5	0.5	0.5	0.5	1	1	0.5
7	1	1	1	1	2	2	1

The final consistency test results are as follows:

Table6: consistency checking-1

一致性检验结果				
Maximum feature root	CI	RI	CR	consistency checking
7	0	1.341	0	pass

(3) Establishment of comprehensive index model weight of drought and heat disasters

The following principles are adopted in this paper for pare comparison of evaluation schemes: Subjective empowerment is slightly better than objective empowerment, because it is believed that empowerment can more flexibly reflect the importance of different indicators and has a higher degree of authenticity. TOPSIS and PCA were between equally important and slightly important. TOPSIS integrated the weight given in GRA in its analysis, making it more comprehensive. PCA can select the principal component according to the information contribution rate and cumulative contribution rate when facing the interrelated indicators, which is reasonable.

When comprehensive analysis is used, the comparison matrix of each evaluation index is:

Table7: Pairwise comparison matrix-2

Indicator	EWM	GRA	TOPSIS	PCA	AHP
EWM	1	1	0.5	0.5	0.333
GRA	1	1	0.5	0.5	0.333
TOPSIS	2	2	1	1	0.333
PCA	2	2	1	1	0.333
AHP	3	3	3	3	1

The consistency test result is

Table 8: consistency checking-2

Consistency test result				
Maximum characteristic root	CI	RI	CR	Consistency test result
5.078	0.019	1.11	0.017	pass

Finally, a comprehensive evaluation model of heat and drought is established which can evaluate the disaster situation of heat and drought.

4.2.2 Model solution

(1) Data preprocessing

We selected data from eight aspects that reflect the degree of disaster in China from 2011 to 2021.

The missing values in 2021 were predicted by using the exponential smoothing method.

Due to China's social development, scientific and technological progress, the level of heat and drought disaster prevention is constantly enhanced, and the disaster extent is affected by external factors, so the data are de-trended.

(2) Model solution

After processing the disaster data into the model, the calculation results of the heat and drought comprehensive evaluation model are finally obtained, as shown in Table 9:

Table9: Sort Ranking-1

Time	EWM	GRA	TOPSOS	PCA	AHP	Dggregative Indicator
2011	1	1	1	1	1	1
2012	11	11	11	11	11	11
2013	2	2	2	7	4	4
2014	4	3	4	4	3	3
2015	10	8	10	8	7	9
2016	7	6	7	6	6	6
2017	9	9	9	5	8	7
2018	8	10	8	9	9	8
2019	3	4	3	3	5	5
2020	5	5	5	2	2	2
2021	6	7	6	10	10	10

(3) Model test

Spearman's correlation coefficient is used to calculate the correlation between the evaluation results of comprehensive indicators and various evaluation results. Table 9 shows that the correlation coefficients in the table are all greater than 0.8, indicating that the comprehensive evaluation model has good representativeness.

表 10:Spearman Correlation Coefficient-1

Method	EWM	GRA	TOPSIS	PCA	AHP
Spearman Correlation Coefficient	0.818	0.855	0.818	0.909	0.973

4.2.3Result analysis

The worst drought years were 2011 and 2020, both La Nina years. The drought disaster in 2012 ranked the lowest, and the drought disaster in 2018 and 2019 was also relatively low, indicating that La Nina events had a significant impact on hot and drought disasters.

In 2020, there was a triple La Nina phenomenon, which theoretically caused the greatest damage to drought. However, due to the frequent occurrence of regional and phased meteorological disasters in 2011, the temperature in many places broke the historical high temperature record. Agriculture and fisheries in the middle and lower reaches of the Yangtze River were hit hard, with direct economic losses reaching 14.9 billion yuan. The main reasons for the severe drought are as follows: abnormally low rainfall in the middle and lower reaches of the Yangtze River, the national average precipitation was the lowest in nearly 60 years; In the south, the drought was aggravated by the increase of water use and the rise of temperature and evaporation. Super - strength utilization of river channel and lake resources, aging of drought-resistant irrigation equipment, etc. As a result, 2011 was more drought-stricken than 2020, when a triple La Nina event hit.

In 2021, the drought in China was relatively light on the whole, with periodic drought occurring in local areas. Although there was drought in South China and Northwest China, there was more precipitation in the late period and the drought was relieved. In December, Typhoon Rey brought rain again, alleviating the drought in Guangdong and other places to some extent. Therefore, in 2021, although affected by triple La Nina events, the national drought was significantly lighter, ranking 10th in the degree of drought.

4.2.4Targeted suggestions

1. Make full use of the flood disaster monitoring and early warning system and the group detection and mass prevention system, strengthen the release of early warning information, constantly improve the early warning mechanism, expand the release channels of early warning information, expand the coverage of early warning information, and eliminate the blind area of early warning information release.

2. Strengthening river regulation, dike construction and reservoir engineering facilities are direct measures to avoid flood disasters. Long-term and persistent implementation of water and timber conservation can fundamentally reduce the chance of flood disasters.

3, do a good job of scientific forecast of flood, weather and ground and reasonable planning of flood detention areas, establish flood prevention and rescue emergency system, these measures can greatly reduce the losses caused by flood disasters.

4. All departments of the state should strengthen the monitoring, early warning and forecast of the climate caused by La Nina, especially the medium and long term forecast, especially the meteorological and Marine departments.

5. Regular maintenance and overhaul of water conservancy facilities

6. After the occurrence of the flood disaster, the relevant departments shall timely report the flood disaster to the flood control and drought relief headquarters. The flood control and drought relief headquarters shall collect the dynamic disaster situation, fully grasp the disaster situation, and provide accurate basis for disaster relief.

4.3 Question three

4.3.1Establishment of model

This question requires the assessment of disaster losses caused by floods. Based on the model in question two, we select 8 indicators that can reflect the degree of flood damage: Number of people affected,Number of missing deaths,Crop damage area,Harvested area,Direct economic loss,The number of rivers that exceed the alert level,Number of collapsed houses,The number of rivers exceeding the guaranteed water level.

The paired comparison results of the 8 indicators are as follows:

Table 11: Pairwise comparison matrix-3

指标	1	2	3	4	5	6	7	8
1	1	1	1	1	1	2	2	2
2	1	1	1	1	1	2	2	2
3	1	1	1	1	1	2	2	2
4	1	1	1	1	1	2	2	2
5	1	1	1	1	1	2	2	2
6	0.5	0.5	0.5	0.5	0.5	1	1	1
7	0.5	0.5	0.5	0.5	0.5	1	1	1
8	0.5	0.5	0.5	0.5	0.5	1	1	1

The consistency test results are:

Figure 12: consistency checking-3

Consistency test result				
root	CI	RI	CR	Consistency test result
8	0	1.404	0	Pass

The weight of different analysis methods is still consistent with the comprehensive evaluation model of drought and heat disaster. Finally, we establish a comprehensive evaluation model of flood disaster based on different flood disaster indicators.

4.3.2Solving the model

Table13: Sort -ranking-2

Time	EWM	GRA	TOPSIS	PCA	AHP	Dggregative Indicator
2011	6	5	6	7	7	7
2012	3	2	4	3	3	3
2013	1	1	1	1	1	1
2014	8	8	8	8	8	8
2015	10	10	10	10	9	9
2016	2	3	2	2	2	2
2017	9	9	9	9	10	10
2018	11	11	11	11	11	11
2019	7	7	7	6	6	6
2020	4	4	3	4	4	4
2021	5	6	5	5	5	5

We still adopt trend processing for the obtained data, and the final model results are shown in Table 13

Spearman's correlation coefficient is:

Table14: Spearman Correlation Coefficient-2

Method	EWM	GRA	TOPSIS	PCA	AHP
Spearman Correlation Coefficient	0.982	0.955	0.973	0.991	1

The correlation between the evaluation results of comprehensive indicators calculated by Spearman correlation coefficient and various evaluation results is shown in Table 12. The correlation coefficients in the table are all greater than 0.9, indicating that the comprehensive evaluation model has good representativeness.

4.3.3 Result analysis

According to the results of model solving, 2013 was the year with the most severe flood disaster, followed by 2016, 2012, and the two years affected by triple La Nina ranked the 4th and 5th.

After consulting the data, it was found that 2012, 2011, and 2016 were all affected by La Nina events. Compared with the years without the impact of La Nina events, the losses caused by flood disasters were generally higher, ranking relatively higher. It is concluded that La Nina is closely related to the degree of flood damage in China. Years affected by La Nina generally have higher levels of flooding. In theory, the year 2020,2021, which is affected by a triple La Nina, is the year with the most flooding. The possible reason for the flood disaster in 2013 ranking the first is the influence of external factors such as the development of Chinese society, the gradual progress of science and technology, and the gradual improvement of a series of flood control measures. Although this paper detrended the data, this method could not completely eliminate its influence.

4.3.4 Targeted suggestions

1. Scientifically designate irrigation schemes to ensure agricultural irrigation by storing, transferring and replenishing water, and provide strong support for maintaining national food security in special years.

2. Strengthen the construction of small drought-resistant water source projects, organize social forces to take emergency measures such as pulling water and delivering water, adopt measures in centralized water supply areas, limit water supply at different peaks, and disperse water supply to organize pulling water and delivering water to ensure the water demand of the people in drought.

3. Establish emergency response systems of different levels according to different disaster situations

4. Strengthen the forecasting, monitoring and prevention of the drought caused by La Nina, scientific water management, increase engineering construction, ensure the safety of irrigation, and prepare enough drought-resistant materials

5. The government should strengthen the publicity on the hazards of triple La Nina events, coordinate the work among relevant departments, and reduce disaster losses as much as possible.

4.4 Question four

The report on the triple La Nina incident

Management of Triple La Nina events:

Three La Nina events, from summer 2020 to spring 2021, autumn 2021 to early summer 2022 and again from autumn 2022, are known as "triple" La Nina events. La Nina event refers to a cold water event with abnormally cold sea surface temperature in the central and eastern equatorial Pacific Ocean, which is a typical event of sea-air interaction. In terms of business, the sliding average SST anomaly index in the monitoring area (Nino3.4 area) is lower than -0.5℃ for more than five consecutive months as the criterion. La Nina causes global climate anomalies and has profound effects on climate in many parts of the world through teleconnections.

Under the triple La Nina events, climate anomalies occur in many places around the world. Such as Indonesia, eastern Australia precipitation increase; Places such as northeastern Brazil, India and southern Africa are prone to flooding; South American coastal areas near the precipitation decreased, central Africa, the southern United States and other places often occur drought; Active typhoons in the South China Sea and the West Pacific. China, Australia, the

United States, Japan and other countries and regions are greatly affected by the triple La Nina events. Drought in the south and flood in the north have greatly reduced crop production in China. Around 18,000 people have been forced to move in Australia due to the "worst flooding in a century"; The United States is suffering from widespread drought, reducing food production. An unusually cold winter and the peak of the epidemic in Japan...

The statistical prediction methods of La Nina are mainly divided into statistical model and dynamic model. The commonly used methods include typical correlation analysis (CCA), singular spectrum analysis (SSA), main oscillation analysis (POP), Markov chain, regression analysis and neural network. Although many countries have begun to release La Nina trend forecasts for the next 12 to 24 months using complex climate models, no national model can accurately predict every detail of La Nina events. Therefore, the study of statistical forecasting method of La Nina will have indispensable development space and important application value in a long time. At present, a consensus has been reached on the prediction methods of La Nina at home and abroad, that is, relying on the climate model system with complex ocean-air coupling ability, and combining the technical means of ensemble prediction, improving the model, improving the quality of observation data, and further improving the prediction skills of climate models for La Nina.

We suggest that relevant management should pay more attention to La Nina events, establish a perfect monitoring, forecasting, evaluation and countermeasure service system for La Nina, minimize the casualties and economic losses caused by La Nina, and provide guarantees for people's life and property safety, stable economic operation and social stability.

Competition team
2022/11/20

5 Strengths and Weakness

5.1 advantages

(1) in this paper, from the Angle of the high degree of approximation, error and minimum optimization model is established the calculation method of the optimal solution is given.

(2) Based on the past trend of temperature and precipitation, the ARMA model is used to predict the possibility of triple La Nina events in the future, and the influence of seasonal and cyclical changes on specific time points is emphasized to make the prediction more accurate.

(3) in a variety of evaluation results for the analysis of the evaluation object , indirect includes direct assessment and indirect assessment, the advantages of subjective assignment and objective value assignment

(4) the evaluation results as the analysis object of optimization model, credible and representative, for triple la Nina provides a powerful tool for monitoring and evaluation.

5.2 disadvantage

(1) Heat, drought and flood lack key data, and the time span is small, the sample size is small, although the detrending process, but still limited by social development and other factors, not accurate enough.

(2) The use of entropy weight method has limitations. It ignores the importance of the

index itself, and sometimes the weight of the index determined is far from the expected result

6 References

[1] Li Xiaoyan, Zhai Panmao. Study on ENSO event index and index [J]. Acta Meteorologica Sinica,2000(01):102-109. (in Chinese)

[2] Zhang Qiang, Sun Peng, et al. Spatial and temporal changes of drought and flood disasters and agricultural production losses in Anhui Province under the influence of ENSO [J]. Water Resources Protection,2016,32(06):6-18.

[3] Ding Xianfa, Li Qiaoyuan, et al. Fractal study on time series of drought and flood disasters in Yunnan Province in recent 500 years [J]. Journal of Catastrophology,2010,25(02):76-80.

[4] Shi Neng, Zhou Jiade. Statistical analysis of the relationship between typhoon activity and ENSO in the Northwest Pacific [J]. Journal of Nanjing Institute of Meteorology,1990(03):402-409.

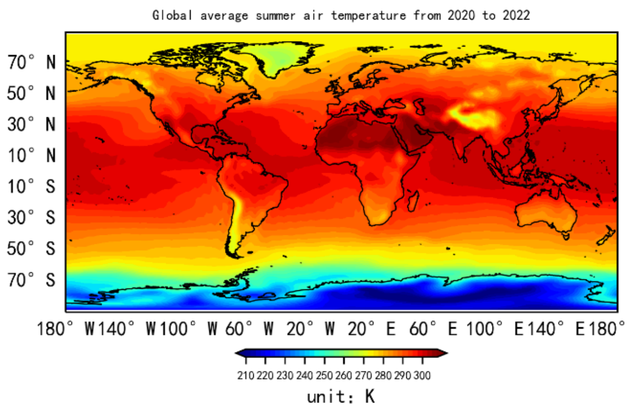
[5] Jiang Guorong, Zhang Ren, et al. Prediction of ENSO using EOF expansion and Artificial neural network [J]. Marine Forecasting,2001(03):1-11. (in Chinese)

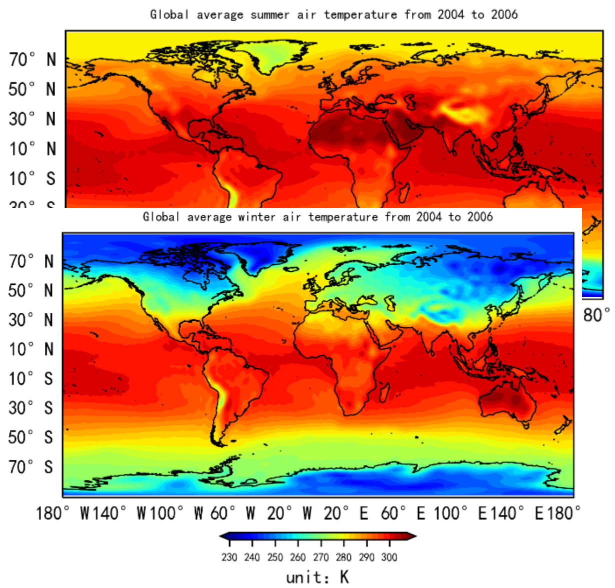
[6] Ren Fumin, Yuan Yuan, et al. Review on research progress of ENSO in recent 30 years [J]. Advances in Meteorological Science and Technology,2012,2(03):17-24. (in Chinese)

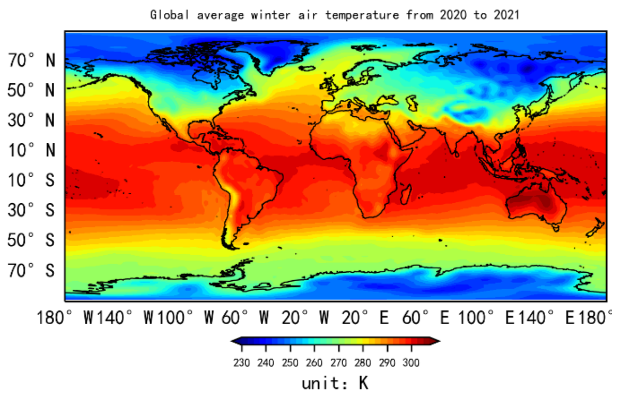
[7] Zhang Yongjin, Yue Xinli, et al. Application of comprehensive optimization model in flood assessment [J]. Systems Engineering Theory & Practice,2008(09):112-116. (in Chinese)

[8] Zheng Dongxiao, Yang Xiaoguang. Effects of ENSO on agro-meteorological disasters and grain yield in China and the World [J]. Meteorological and Environmental Sciences,2014,37(04):90-101.

7 Appendix




Global average summer air temperature from 2004 to 2006
Global average winter air temperature from 2004 to 2006
70° N
50° N
30° N
10° N
10° S
30° S
50° S
70° S
180° W140° W100° W 60° W 20° W 20° E 60° E 100° E140° E180°
230 240 250 260 270 280 290 300
unit: K


Global average winter air temperature from 2020 to 2021
70° N
50° N
30° N
10° N
10° S
30° S
50° S
70° S
180° W140° W100° W 60° W 20° W 20° E 60° E 100° E140° E180°
230 240 250 260 270 280 290 300
unit: K