

Loss Assessment and Response Strategies Based On ARIMA And TOPSIS Models Under Triple La Niña Events

Jiayu Liu *

Business School, Xi'an International Studies University, Xi'an, China, 710128

* Corresponding Author Email: 107242022001870@stu.xisu.edu.cn

Abstract. This study aims to develop forecasting and quantitative loss analysis models for potential triple La Niña events in different countries in order to assess and respond to potential La Niña disaster losses. First, to build the ARIMA model, this study collected data from 2011 to 2020 and selected five indicators including Sea Surface Temperature (SST), Precipitation (PRCP), Temperature (TEMP), Standard Temperature and Pressure (STP) and Sea Level Pressure (SLP) that were more significantly correlated with the La Niña phenomenon, and then conducted correlation analysis using Pearson coefficient. Based on this, the research conducted principal component analysis to obtain three characteristic factors SST, PRCP and TEMP, and based on them, building ARIMA model to predict the possibility of La Niña occurrence in the future. Then, the study used the ADF test to check the smoothness. Second, this study carried out a TOPSIS evaluation to analyse the multiple damages caused by the high temperature and drought brought by the La Niña event in a country, taking into account the entropy weighting method-TOPSIS evaluation model, and determined the ranking of the indicators: La Niña event has the greatest impact on agriculture, followed by ecology and environment. Finally, the results of the score ranking were used to provide solutions. This study predicts the probability of future La Niña events through the development of two models, ARIMA and TOPSIS, assesses and analyses multi-indicator losses, comprehensively evaluates and ranks loss targets, and makes policy recommendations. The results of these studies contribute to the prevention and mitigation of losses caused by La Niña events, ensuring human safety and minimising economic losses.

Keywords: Triple La Niña, SST, ARIMA model, TOPSIS model, Loss Assessment.

1. Introduction

In recent years, rare high temperatures, heavy precipitation and drought events have occurred in southern China, northern China and Europe, respectively, and such catastrophic weather extremes have seriously threatened people's lives and property, and such events have been attributed to triple La Niña events by meteorological authorities. With abnormal and cold sea surface temperatures in the eastern and central equatorial Pacific Ocean, areas around the world such as Southeast Asia, the southern United States, and the Pacific Ocean will be affected by multiple La Niña events. The La Niña event is expected to continue through the end of this year and beyond. The causes of La Niña events will vary from region to region and country to country due to the vast size of the globe and the combined effects of topographic and climatic factors. Therefore, it is necessary to establish prediction models and quantitative loss analysis models for potential triple La Niña events in different countries [1].

The ARIMA model is frequently used for time series prediction. It involves analyzing and fitting historical data of a time series to forecast future trends and developments. This method has been applied in various domains such as industrial production. Long Yu et al. utilized the ARIMA model to make preliminary predictions on China's railway freight volume. "Prediction of railway freight volume based on ARIMA-LSTM-XGBoost combination model" [2].

In the field of finance, ARIMA models are often combined with LSTM neural networks to predict financial time series [3].

Additionally, in meteorology, Wu Huihui et al. employed the ARIMA model to analyze and forecast global surface temperatures [4].

Therefore, this study utilizes the ARIMA model in conjunction with the TOPSIS comprehensive evaluation analysis model to analyze loss assessment under extreme climate conditions using SST data [5].

Based on the observations collected from the International Meteorological Data Platform(<https://www.ncei.noaa.gov/maps/daily/>), this paper uses a mathematical model to solve the following problems. The study performed correlation analysis on the collected data, and after data pre-processing, this study performed principal component analysis to obtain three eigenvalue factors and built an ARIMA model to predict the likelihood of future La Niña events. A TOPSIS evaluation model was developed to evaluate the disaster losses due to drought and high temperature associated with La Niña and to suggest ways to cope with them.

2. Acquisition and Preprocessing of Data.

This research retrieved meteorological observation data from 2011 to 2020 on the International Weather Data Platform website (<https://www.ncei.noaa.gov/maps/daily/>), including sea surface temperature, precipitation, and surface temperature. In order to transform the data of different magnitudes into the same dimension, the study standardized the data with Z-score and then measured the calculated values to ensure the accuracy of data analysis and model construction.

2.1. Research methods

To develop the ARIMA model for studying the impact of La Niña events on the main affected countries, firstly this study selects several countries and regions that are more significantly affected by La Niña. Then, identifying five indicators that have a significant relationship with the La Niña phenomenon through relevant literature and surveys. These indicators are standardized uniformly. Subsequently, principal component analysis is applied to obtain three characteristic factors, namely SST, PRCP, and TEMP, which primarily describe the effects of La Niña on different countries and regions. These factors are used as core variables to build a time series model, enabling the prediction of future La Niña events.

ARIMA (Autoregressive Integrated Moving Average) is a time series forecasting model widely used in various fields such as economics, finance, and meteorology. It is designed to capture and predict the patterns and trends present in time series data.

The ARIMA model consists of three components: autoregression (AR), differencing (I), and moving average (MA). Let's break down each component:

Autoregression (AR): In this component, the future values of the time series are predicted based on its own past values. The "p" in ARIMA(p,d,q) represents the number of lagged observations used in the model. The AR component can be represented by the equation:

$$Y(t) = c + \varphi_1 Y(t-1) + \varphi_2 Y(t-2) + \dots + \varphi_p Y(t-p) + \varepsilon(t) \quad (1)$$

where $Y(t)$ denotes the value at time "t," φ_1 to φ_p are the autoregressive coefficients, c is a constant, and $\varepsilon(t)$ is the error term.

Differencing (I): The differencing component is used to make the time series stationary, which means removing any trend or seasonality present. The "d" in ARIMA(p,d,q) represents the order of differencing applied to the time series. Differencing can be represented by the equation:

$$\Delta Y(t) = Y(t) - Y(t-1) \quad (2)$$

where $\Delta Y(t)$ is the differenced series.

Moving Average (MA): The MA component helps to incorporate the error terms of previous observations into the model. The "q" in ARIMA(p,d,q) represents the number of lagged error terms included in the model. The MA component can be represented by the equation:

$$Y(t) = \mu + \theta_1 \varepsilon(t-1) + \theta_2 \varepsilon(t-2) + \dots + \theta_p \varepsilon(t-p) + \varepsilon(t) \quad (3)$$

Where μ is the mean of the series, θ_1 to θ_p are the moving average coefficients, and $\varepsilon(t)$ is the error term.

The overall ARIMA model can be defined as:

$$Y(t) = c + \varphi_1 Y(t-1) + \varphi_2 Y(t-2) + \dots + \varphi_p Y(t-p) + \varepsilon(t) - (\mu + \theta_1 \varepsilon(t-1) + \theta_2 \varepsilon(t-2) + \dots + \theta_p \varepsilon(t-p)) \quad (4)$$

In this model, the optimal values for p , d , and q are determined through diagnostic checks such as autocorrelation function (ACF) and partial autocorrelation function (PACF) plots, as well as analyzing the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) [5].

In order to evaluate and analyze the various losses resulting from the occurrence of a La Niña event, specifically those related to high temperatures and drought, the study propose the use of the entropy based TOPSIS evaluation model. This model employs normalization techniques for both benefit and cost indicators, followed by the determination of the weight assigned to each indicator in relation to the overall losses. By calculating the final scores, it yields a ranking indicator value, which serves as a comprehensive evaluation index for each scenario. The findings from this assessment indicate that the La Niña event exerts the most pronounced impact on agriculture, followed by livelihood. The obtained score rankings are then employed to formulate solution measures accordingly [6].

TOPSIS is a decision analysis method used to determine the optimal solution among multiple evaluation schemes. The basic principle is to compare all schemes with ideal and negative ideal solutions, calculate the distances between each scheme and these two extreme solutions, and determine the comprehensive evaluation index, which is then ranked based on the index value.

The TOPSIS model is an evaluation model that combines the objective weighting of each indicator based on the differences in information contained in the indicators and the approximation to the ideal solution. Prior to this, this research normalizes the attribute values by standardizing the efficiency-type and cost-type indicators.

Normalization of Cost-based Indicators:

$$x_j = \frac{x_{\max} - x}{x_{\max} - x_{\min}} \quad (5)$$

Normalization of Benefit-based Indicators:

$$x_j = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \quad (6)$$

Determining the ideal and negative ideal solution: The ideal solution refers to the solution that achieves the best performance in each indicator, while the negative ideal solution is the solution that performs the worst in each indicator. For benefit-type indicators, the ideal solution is the maximum value, while the negative ideal solution is the minimum value; for cost-type indicators, the ideal solution is the minimum value, while the negative ideal solution is the maximum value.

Calculating the distance between each scheme and the ideal and negative ideal solutions: Use the Euclidean distance or other distance measurement methods to calculate the distance between each scheme and the ideal and negative ideal solutions. The formula is as follows:

The distance from the positive ideal solution to solution i :

$$s_i^* = \sqrt{\sum_{j=1}^n (c_{ij} - c_j^*)^2}, i = 1, 2, \dots, m \quad (7)$$

The distance from the negative ideal solution to solution i :

$$s_i^0 = \sqrt{\sum_{j=1}^n (c_{ij} - c_j^0)^2}, i = 1, 2, \dots, m \quad (8)$$

Ranking based on indicator values: Ranking various solutions based on the value of their comprehensive evaluation index, where a higher value indicates a better solution [7].

3. Results

3.1. Correlation analysis

Correlation is a non-deterministic relationship and Pearson's correlation coefficient is used to measure the linear relationship between two variables. In order to eliminate the unevenness between different attributes or sample squares, so that the variance between different attributes within the same square or the same attribute within different squares is reduced, this study performed correlation analysis on the data collected at the International Weather Data Platform for the 2011- -2020 decade data collected in the International Meteorological Data Platform for correlation analysis, and five indicators, PRCP, SST, TEMP, SLP and STP, were selected based on relevant literature and meteorological knowledge. The Correlation analysis as shown in Table.1. [7]

$$\rho_k = \frac{\sum (X - \bar{X})(Y - \bar{Y})}{\sqrt{\sum (X - \bar{X})^2 \sum (Y - \bar{Y})^2}} \quad (9)$$

Table.1. Correlation analysis table

	Item	TEMP	SLP	STP	SST	PRCP
Pearson correlation	TEMP	1	0.104**	-0.171**	0.922**	0.950**
	SLP	0.104**	1	-0.781**	-0.010	0.171**
	STP	-0.171**	-0.781**	1	-0.069**	-0.220**
	SST	0.922**	-0.010	-0.069**	1	0.791**
	PRCP	0.950**	0.171**	-0.220**	0.791**	1

** .At the 0.01 level (two-tailed),the correlation is significant

3.1.1 Principal component analysis

After performing correlation analysis, this paper study and analyze the data in more depth. In order to unify the data of different magnitudes into the same dimension, the article measured the values calculated after standardizing the data to ensure the quality and accuracy when analyzing and constructing models. Among them, Z-score normalization is a common method for processing data. Based on the analysis of relevant literature and considering multiple factors, including the explanatory power of principal components, their interpretability, practical application needs, and domain expert knowledge, the final selection for the feature factor as followed: SST, PRCP, and TEMP.

$$z = \frac{x - \mu}{\sigma} \quad (10)$$

$$Z_p = c_{p1}X_1 + c_{p2}X_2 + \dots + c_{pp}X_p \quad (11)$$

3.2. ARIMA

A search of the relevant literature shows that the occurrence of La Niña events follows a certain pattern over a longer period of time.

In order to predict the possibility of a triple La Niña event in the future, based on the three eigenvalue factors derived from PCA, the paper established a time series analysis model and conducted stability tests using the ARIMA model, concluding that La Niña events have a certain periodicity, which means that the possibility of a future La Niña event is high [8].

In addition, to check the smoothness of the data, this article utilized the ADF test to verify that the obtained goodness of fit was 0.859, i.e., the data fit the model and could be used.

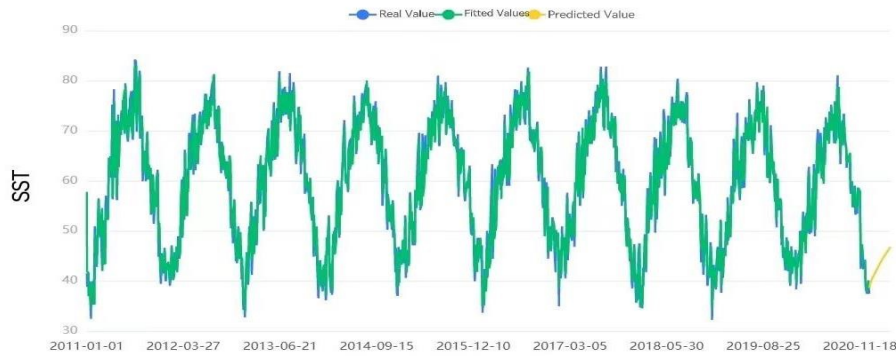


Figure. 1. SST forecast for China region

Based on the variable SST, the model results were established as an ARIMA model (1,0,5) test table and based on 0-difference data. The result as shown in Figure.1.

The model equation is as follows:

$$y(t) = 57.745 + 0.995 * y(t-1) - 0.048 * \varepsilon(t-2) - 0.156 * \varepsilon(t-3) - 0.074 * \varepsilon(t-4) - 0.029 * \varepsilon(t-5) \quad (12)$$

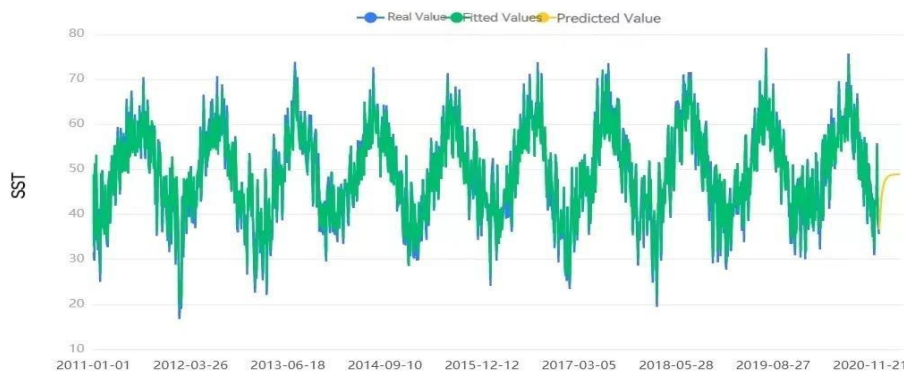


Figure. 2. SST forecast for the French region

Based on the variable SST, the model results were established as an ARIMA model (1,0,0) test table The result as shown in Figure.2 and based on 0-difference data. The model equation is as follows:

$$y(t) = 48.909 + 0.923 * y(t-1) \quad (13)$$

3.3. Establishment and solution of entropy method-TOPSIS evaluation model

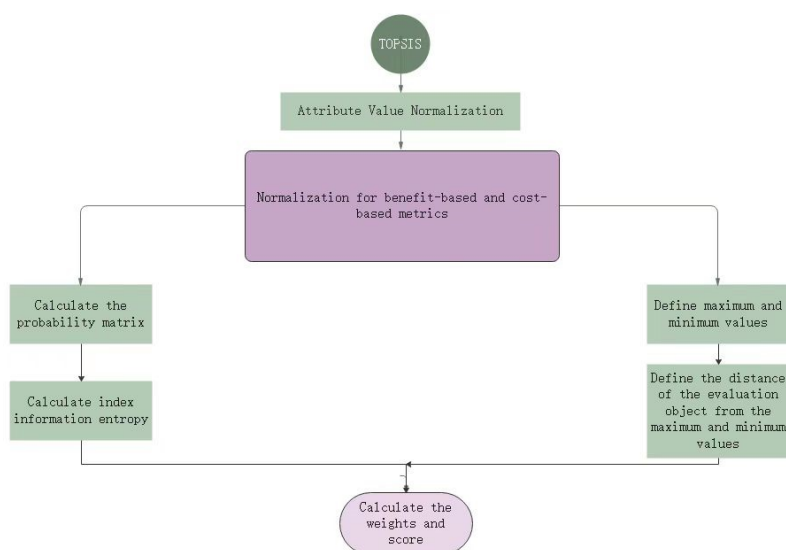


Figure. 3. Flow chart of entropy-TOPSIS method

In China, for example, to evaluate and analyze the disasters and losses caused by drought and high temperature in the context of La Niña, this article developed the TOPSIS evaluation model, the process is shown in Figure.3, which is an evaluation model that combines objective weighting of each indicator based on the variability of the information contained in each indicator and ranking that approximates the ideal solution. Before that, the paper normalizes the attribute values, i.e., normalize the benefit-based and cost-based indicators [9].

In this study, the most visually representative data caused by La Niña, i.e., temperature, was selected and refined to produce the China temperature map shown in Figure 4.

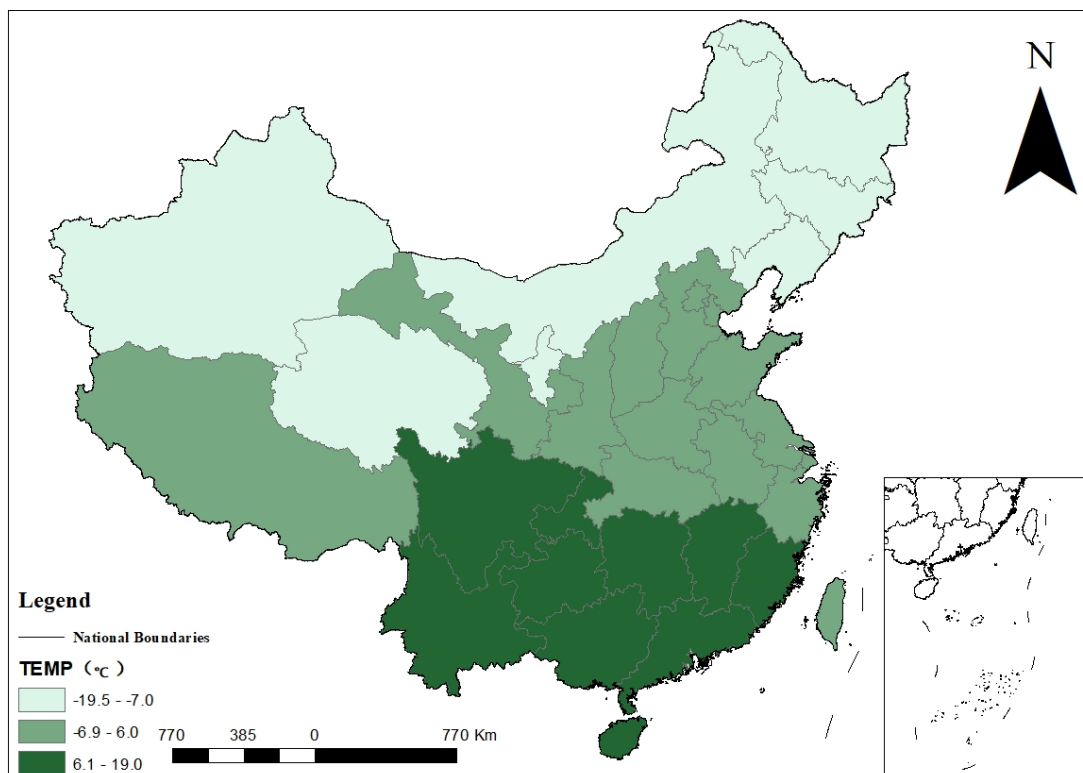


Figure. 4. Temperature map of China under the influence of La Niña

3.3.1 Determination of weights.

The weights for the 11 indicators affected by La Niña were determined using formulas (5) to (8). The specific results are provided in Table 2, which includes indicators such as GDP, hydropower capacity, grain production, total area of fire impact, fire damage, drought-affected area, affected population, death toll, economic losses caused, affected forest area, and area of drought-induced crop failure.

Table.2. The results of calculating the weights of relevant variables

Comparison	Weight (%)
GDP	11.253
Hydropower	8.746
Grain Production	6.192
Total area of the fire site	7.526
Fire Damage	10.666
Drought affected area	6.618
Affected population	10.029
Death	10.001
Economic losses caused	9.996
Area of affect forest	12.789
Drought crop failure area	6.184

3.3.2 Score ranking.

Combining the formulas, the final scores were obtained and ranked as shown in the Table 3 below.

Table.3. The results of calculating the weights of relevant variables

Item	Positive ideal solution distance(D+)	Negative ideal solution distance(D-)	Overall Score Index	Ranking
1	0.40278651	0.1100405	0.21457625	11
2	0.34246171	0.19463328	0.36238149	9
3	0.3597904	0.1862641	0.341109	10
4	0.35466239	0.20342093	0.36449921	8
5	0.26477806	0.27070689	0.50553594	7
6	0.26431273	0.30547624	0.53612171	6
7	0.13684532	0.38026659	0.73536615	2
8	0.18144328	0.38287713	0.67847471	3
9	0.22531665	0.33662494	0.59903902	4
10	0.12445697	0.40368379	0.76434887	1
11	0.25315734	0.3680712	0.5924892	5

3.3.3 Analysis of experimental results

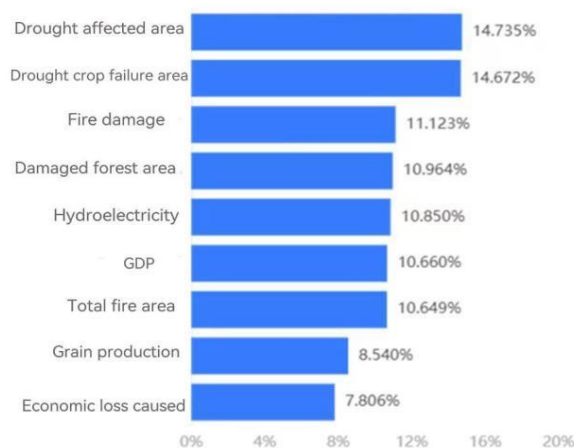


Figure. 5. Calculation of the percentage of the weight of relevant variables

Displaying the table content in the form of a histogram as shown in Figure 5, the weighted calculation results of the 11 indicators mentioned above indicate that La Niña has the most significant impact on agriculture. This means that the climate changes and extreme weather events triggered by La Niña, such as droughts and wildfires, have a severe impact on crop production and agricultural systems.

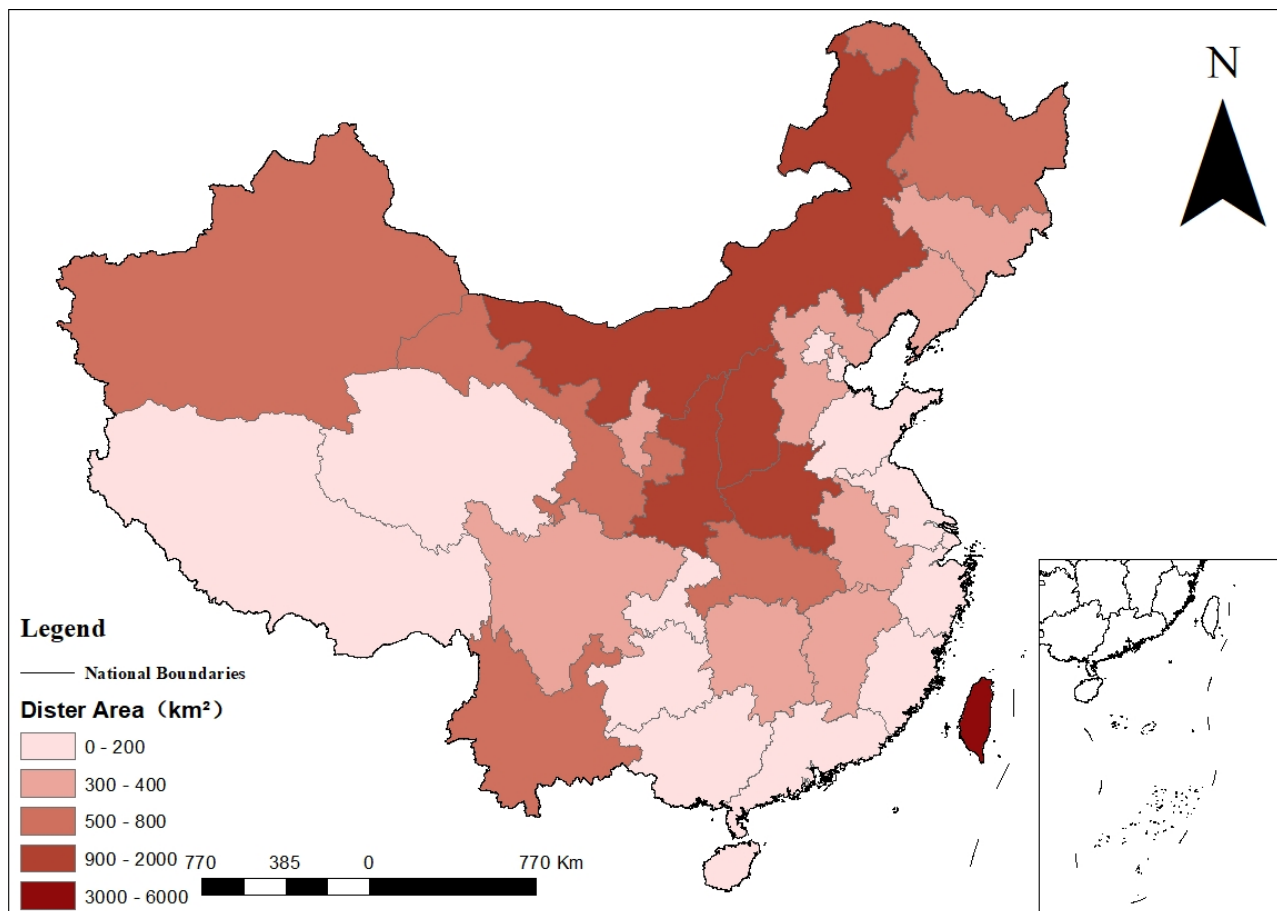


Figure 6. Map of the extent of disasters in China under the influence of La Niña

Based on the aforementioned study, this research has selected the agricultural sector most significantly impacted by La Niña events and depicted it in Figure 6. By focusing on the affected agricultural areas and visually illustrating the extent of its impact on China, this study provides a crucial basis for the relevant departments to formulate disaster response strategies.

Firstly, the impact of La Niña on agriculture is significant. Drought and high temperatures lead to water shortages, soil dryness, and crop reduction. This not only causes significant losses in farmers' income but also potentially leads to food supply shortages. Agriculture is a vital foundational industry for many countries, so the La Niña event poses a threat to global food security and market stability.

Secondly, the environment is greatly affected by the La Niña event. Water shortages, caused by drought and high temperatures, result in the drying up of lakes and shrinking of rivers, as well as degradation of wetlands and forests, leading to ecosystem damage. This poses challenges to biodiversity preservation and the maintenance of ecological balance and climate regulation functions.

Thirdly, the livelihoods of communities are directly and indirectly impacted by the La Niña event. People relying on natural resources such as farmers and fishermen may face crop failures, loss of income, and food shortages. Additionally, frequent disasters caused by La Niña, such as floods and storms, may damage housing and infrastructure, affecting the livelihoods and capabilities of individuals.

Lastly, the La Niña event has economic implications. Reduced agricultural output can lead to increases in food prices, subsequently affecting the cost of living for residents. Moreover, the need for resources to repair and rebuild after frequent disasters presents challenges to the fiscal conditions of countries and regions. The tourism industry may also be affected by extreme weather, resulting in income losses [10].

4. Conclusions

This study proposes recommendations and measures to cope with the "Triple La Niña" event. Firstly, it suggests strengthening monitoring and research by closely collaborating with meteorological, emergency affairs, and water conservancy departments to timely understand major weather changes, rainfall, water conditions, and disaster dynamics. It also emphasizes regional and international cooperation, organizing experts to conduct scientific analysis and develop targeted disaster avoidance and prevention techniques during critical agricultural periods and high-risk periods, as well as issuing timely warning information and taking proactive defensive measures.

Secondly, it calls for soil erosion control and enhanced ecological environmental protection. Special funds should be established, and scientific planning of water and soil management should be implemented based on local conditions to carry out comprehensive ecological environment governance. Relevant departments should implement forest closure, prohibit logging and deforestation, reduce irrational development, actively engage in afforestation, increase vegetation coverage, improve soil erosion issues, promote ecological environment enhancement, reduce economic losses, and maintain social stability and harmony.

Thirdly, it suggests conducting risk analysis of the disaster situation from both natural and social attributes. Regarding natural attributes, attention should be focused on the frequency of natural disasters (mainly droughts and floods caused by La Niña) to conduct disaster and vulnerability assessments. From a social attribute perspective, factors such as the population, housing facilities, and resource environment that may be affected by natural disasters should be assessed. Meanwhile, the local disaster prevention and mitigation capabilities and residents' awareness of natural disaster risks should be considered, and a systematic risk analysis system should be established.

Finally, it emphasizes the importance of strengthening publicity and guidance by utilizing new media and means to enhance the response speed and effective coping abilities of residents and farmers under extreme weather conditions. The government should pay special attention to people's livelihood issues and promote disaster response measures in major grain-producing provinces. Relevant departments should provide positive guidance, actively promote agricultural disaster prevention and reduction work, popularize the impacts of major agricultural meteorological disasters and scientific techniques for avoidance, prevention, and disaster resistance, enhance farmers' abilities to respond to disasters, combine self-rescue efforts with government assistance, and vigorously publicize significant measures, important initiatives, as well as good experiences, practices, and cases in agricultural disaster prevention and reduction, creating a favorable public opinion atmosphere.

Through these measures and recommendations, it is hoped that government departments can better cope with the upcoming "Triple La Niña" event, protect people's food security and property safety, improve disaster prevention and control mechanisms, and enhance the level of disaster response.

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