Analysis of response strategies for triple La Niña events based on fuzzy evaluation algorithm

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Abstract. The climate anomalies caused by La Niña events have caused some economic losses and human casualties in several regions around the world. In this paper, we first visualize and analyze the climate data of four representative countries to obtain the impact of La Niña on different countries. Then a BP neural network model is built to predict the probability of La Niña events in different regions. Finally, taking six different provinces in southern China as examples, an indicator system is established, a fuzzy comprehensive evaluation algorithm is used to summarize the impacts of different regions and indicators under a La Niña event, and practical response strategies are proposed.

Keywords: Fuzzy comprehensive evaluation; BP neural network; triple La Niña events.

1. Introduction

This summer, several regions around the world experienced climate anomalies, resulting in frequent precipitation and flooding in the north and high temperatures and low rainfall and frequent droughts in the south, leading to huge economic losses and some degree of human casualties. Meteorological authorities attribute these phenomena such as abnormally high temperatures and unusually heavy precipitation to triple La Niña events. Studies have shown that La Niña events may last until the end of this year or even longer, so it is important to predict the possibility of future La Niña events and suggest targeted strategies.

In this paper, we analyze the relevant index data of four representative countries located in different regions for the last three years and build a relevant model to predict the probability of future La Niña events in each region. Subsequently, six provinces and cities in southern China are selected for the study, and the corresponding index system is established to analyze the different disaster losses caused by floods during triple La Niña events and to propose targeted response strategies on this basis.

2. Occurrence probability prediction based on BP neural network model

2.1. Analysis of four representative countries

2.1.1 Selection of indexes

Many regions around the world are affected by triple La Niña events. In order to make the study representative, for the main countries involved in the global triple La Niña events, four countries located in different regions are selected for analysis in this paper, namely, the United States in central North America, Brazil in eastern South America, Malaysia in Southeast Asia, and Indonesia in southeastern Asia.

We selected the relevant index data for the last three years for these four countries: average monthly maximum and minimum temperature, average monthly precipitation rate, average monthly precipitation days, average monthly wind speed and average monthly water temperature.[1]

2.1.2 Specific analysis of the data

The data obtained were visualized and analyzed in a line graph to visualize the changes of the relevant indicators for each month in different countries.

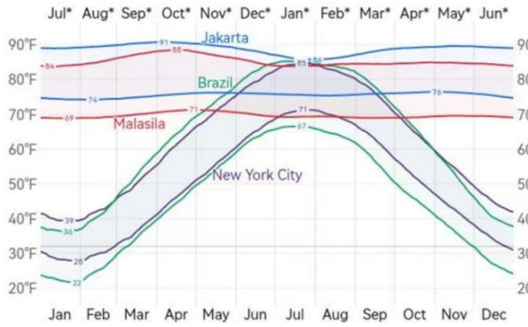
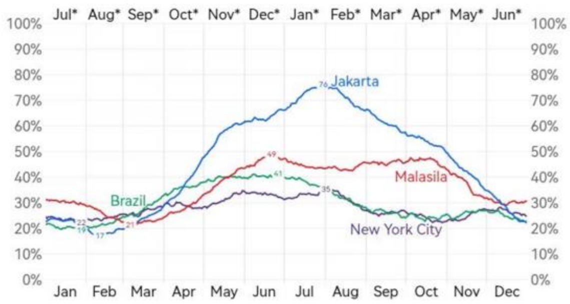


Fig.1 Average monthly maximum and minimum temperatures

As you can see from the graph above, the maximum and minimum temperatures as well as the maximum temperature difference occurred at basically the same time in New York City and Brazil, indicating that these two regions were affected by the triple La Niña event at the same time, while the minimum temperatures were also lower and the temperature fluctuations were larger, indicating that zhe3 two regions were affected by the triple La Niña to a higher degree. In contrast, the minimum temperature in both Malasila and Jakara is around 70°F, which is not much different from the maximum temperature, indicating that the temperature variation is stable and the temperature impact by the triple La Niña event is less.[2]



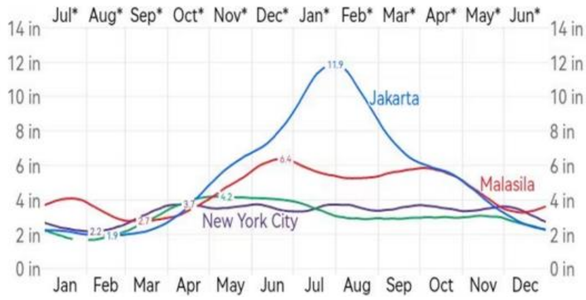
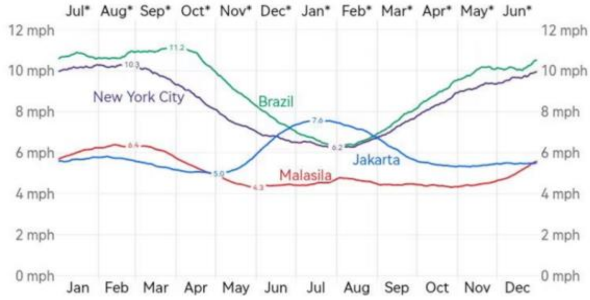


Fig.2 Average monthly precipitation rate **Fig 3** .number of precipitation days per month

The figure 2 shows that Jakara has the highest precipitation rate, followed by Malasila, and New York City has the lowest rate.

As you can see from the figure 3: Jakarta's monthly precipitation starts to drop from January, reaches its lowest in August, and then starts to increase; Malasila's precipitation reaches its highest in June; Brazil and New York City's monthly precipitation is relatively stable.



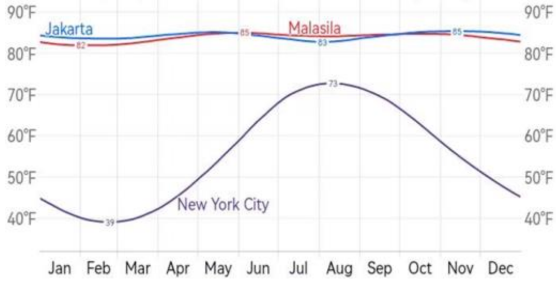


Fig.4 Monthly average wind speed **Fig.5** Monthly average water temperature

As can be seen from the figure 4: under the influence of triple La Niña events, the monthly average wind speed of the four countries in the selected area fluctuates from month to month, with Brazil and New York City fluctuating more, indicating that these two countries are more affected by triple La Niña events.

As you can see from the figure 5: New York City's average water temperature varies widely from month to month, reaching a maximum in August and a minimum in February, while the other three countries' monthly average water temperatures do not vary significantly.

2.2. Establishment and analysis of BP neural network model

2.2.1 Model building

BP neural network is a multi-layer feed-forward neural network with error correction by error back propagation algorithm, which contains an input layer, a hidden layer and an output layer. In this paper, a single hidden layer BP neural network is used.

From the above figure, we can see that in this paper, three variables of pressure, temperature and salinity are selected as input layers, an implicit layer is selected which contains 10 nodes, and the final output layer is a 0-1 variable representing whether a La Niña event occurs or not, and the sum of squares method is selected to calculate the error function.

After repeatedly training and adjusting the network parameters, we determine the structure of the hidden layer activation function as tansig and the output layer activation function as purelin.

Based on the parameter estimates given in the software, we can obtain the final results of the established BP neural network model as:

$$y = 0.476 * tansig(-0.244 * x_1 - 0.340 * x_2 + 0.089 * x_3 + 0.328) + \cdots + 0.908 * tansig(-0.220 * x_1 - 0.663 * x_2 + 0.073 * x_3 + 0.257 + 0.524 * tansig(-0.244 * x_1 - 0.340 * x_2 + 0.089 * x_3 + 0.328) + \cdots + 0.092 * tansig(-0.220 * x_1 - 0.663 * x_2 + 0.073 * x_3 + 0.257 \quad (1)$$

2.2.2 Analysis of the prediction accuracy of BP neural network model

(1) ROC curve

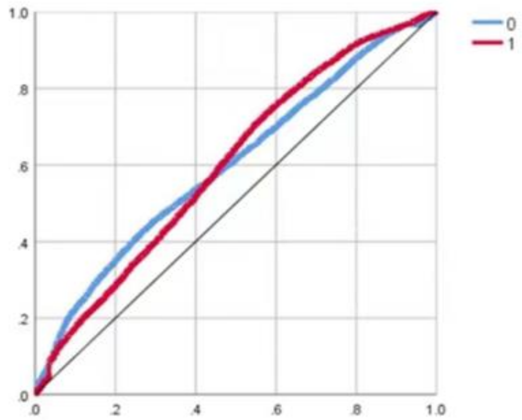


Fig.6 ROC curve

Table 1. Area under the curve

		area
Whether the La Nina incident occurred	0	0.602
	1	0.602

Regarding the ROC curve, we focus on the area under the curve (also called the area under the curve) with a total area of 1. The areas of 0 and 1 in the model are both greater than 0.6, indicating that the model has good predictive power.

Predicted results

Table 2. Partial forecast results

north	east	pressure	temp	psal	present	RBF_PredictedValue	RBF_PseudoProbability_1	RBF_PseudoProbability_2
60.4165	4.3142	575.00	6.08	35.032	0	1	0.427	0.573
60.4165	4.3142	600.00	5.15	35.009	0	1	0.429	0.571
60.4165	4.3142	625.00	4.74	35.000	0	1	0.443	0.557
60.4165	4.3142	643.00	4.52	35.003	0	1	0.451	0.549
61.1550	2.2847	550.00	5.08	35.020	0	1	0.453	0.547

The last three columns of the table show the predicted probability of whether a La Niña event will occur in the future in some regions, where the first group is not going to occur, indicated by "0", and the second group is going to occur, indicated by "1". The results show that a total of 110 regions will experience a La Niña event in the future, with a general probability of 55%-60%.

3. Disaster loss analysis based on fuzzy comprehensive evaluation algorithm

3.1. Model building

Since there are many missing values in the data for 2022, the years 2017-2018, when the same La Niña event occurred, were selected for the study. [3] Through reviewing the literature, it can be seen that the impact of high temperature and drought caused by the La Niña event in China is mainly concentrated in the southern region, so this paper selected six provinces and cities in southern China for the study and established a seven-indicator composition including gross regional product, year-end resident population, total water supply, the gross output value of agriculture, forestry, animal husbandry and fishery, drought-affected areas, flood-affected areas, and plantation production price index, etc. Indicator system. The data of each indicator were standardized by subtracting the data before and after the impact and then finding the inverse to indicate the impact of the event on each indicator.

On this basis, a fuzzy comprehensive evaluation algorithm is used, which is divided into the following steps:

STEP1. Determine the evaluation index and the set of comments, where the evaluation index is the row index name and the set of comments is the column name.

STEP2. Confirm the index weights, which can be determined by entropy weight method or AHP. In this paper, the entropy weight method is used.

STEP3. Calculate the weights and perform decision evaluation.

STEP4. Calculate the overall score distribution.

Table 3. Entropy method values

NO.	Information entropy e	Information utility value d	weight (%)
Shanghai	0.743	0.257	31.853
Jiangsu	0.911	0.089	10.975
Fujian	0.835	0.165	20.428
Guizhou	0.898	0.102	12.592
Yunnan	0.893	0.107	13.217
Sichuan	0.912	0.088	10.934

The calculation of the weight of entropy method shows that the weight of Shanghai is 41.996%, the weight of Jiangsu is 14.47%, the weight of Fujian is 26.932%, and the weight of Guizhou is 16.602%, where the maximum value of indicator weight is Shanghai (41.996%) and the minimum value is Jiangsu (14.47%), which indicates that Shanghai is the most influenced among these cities.[4]

The following table shows the composite scores of the fuzzy comprehensive evaluation, which can be used to assess the overall evaluation situation.[5] From the score results, it can be seen that gross regional product, year-end resident population, total output value of agriculture, forestry, animal husbandry and fishery, and drought-affected area coefficients are the largest, followed by total water supply and producer price index of plantation industry, respectively, and flood-affected area coefficients are the smallest, which coincides with the above analysis and indicates that gross regional product is most affected by La Niña event, followed by year-end resident population, [6]total output value of agriculture, forestry, animal husbandry and fishery, drought-affected area, and total water supply and the producer price index of the plantation industry are the next most affected.

Table 4. Overall Score

variable	coefficient
GDP	0.181
Permanent population at the end of the year	0.180
total water supply	0.117
Total output value of agriculture, forestry, animal husbandry and fishery	0.180
Area affected by drought	0.180
Flood affected area	0.061
Planting production price index	0.101

3.2. Conclusions of the analysis

1. In the southern region, the gross regional product is most affected by the hot and dry weather conditions caused by the La Niña event, followed by the year-end resident population, the gross output value of agriculture, forestry, animal husbandry and fishery, the area affected by the drought, and finally the total water supply and the producer price index of the plantation industry.

2. Among all the southern regions, Shanghai was the most affected, probably due to its more developed economy and higher living standard of its people, resulting in a high consumption and demand for necessities.

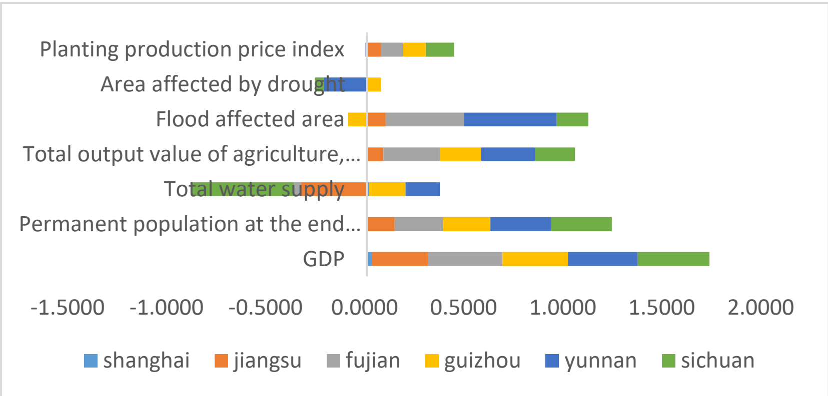


Fig.7 Summary of the impacted city

3.3. Coping strategies

From the available data, we can see that under the influence of La Niña phenomenon, the growth rate of regional GDP in Shanghai continuously shows a decreasing trend, the total water supply relatively decreases, and the price index of plantation production rapidly increases;[7] the influence of regional GDP in Fujian and Yunnan has a lagging effect; all indicators in Guizhou except the price index decrease, and the area affected by drought is doubled; the plantation industry in Yunnan has a large impact; Jiangsu In Jiangsu, water supply decreased and the drought-affected area increased significantly, but the economic change was stable.

After analysis, it is found that: the gross regional product is affected the most, while the area affected by floods has the least weight, indicating that compared to the floods in the south under normal conditions, the La Niña event makes the south drier, with a significant decrease in precipitation and droughts.

As a result, we should carry out water transfer projects in drought-prone areas, and we should make sure to reserve water in advance to prevent problems before they occur; for areas with slightly backward economy, we should give appropriate economic support, while the impact in some areas will have a lagging effect, and we should increase resource input, resource balance and optimization, and proper coordination.

In the southern region, the gross regional product is most affected by the high temperature and dry weather situation caused by La Niña event, followed by the year-end resident population, the total output value of agriculture, forestry, animal husbandry and fishery, the drought affected area, and finally the total water supply and the producer price index of planting industry. We should make relevant initiatives in advance to reduce losses according to different regions.

4. Summary

This paper uses interval prediction for the probability of La Niña time in different regions with higher accuracy. For six different provinces in southern China, an indicator system consisting of seven indicators, such as regional gross domestic product, year-end resident population, total water supply, and total output value of agriculture, forestry, animal husbandry and fishery, is established, and the entropy weighting method is used to determine the weights, which fully takes into account the differences between different regions and indicators and is in line with reality.

In predicting the probability of La Niña, our BP neural network model did not consider the influence of other causes on each indicator, which may overestimate or underestimate the actual impact of La Niña. Fewer countries and regions were selected in the selection of the study population, which may lead to representativeness errors.

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