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Meteorological Composite Index Prediction Based on WD-SSA-LSTM Modeling and Pricing Study of Weather Derivatives

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Abstract: *In recent years, global climate change has intensified, and extreme weather events have occurred frequently, especially in 2022, the world has suffered a 60-year extreme high temperature weather, water shortages in many places, power constraints, and extreme high temperature weather caused huge direct and indirect economic losses, resulting in a greater impact on agricultural production. The impact of weather risk on China's economy has become increasingly prominent and aroused widespread concern. The 14th Five-Year Plan points out that the innovation level of financial products should be improved to grasp the new opportunities of the growth of the rural industry. Weather derivatives, as a kind of meteorological financial derivatives, are priced on the basis of meteorological indicator data in a certain region, and have been widely used in mature markets and related industries abroad, however, the development history in China is relatively short, and the perfect meteorological financial market has not yet been established. In view of this, we select nine weather stations across the country according to the distribution of climate zones as the research object, and take Nanchang City as an example to model for detailed analysis. Firstly, this study uses the AHP-CRITIC combination method to assign weights to temperature, wind speed and humidity and constructs a weather composite indicator; secondly, the combination model is used to predict the weather composite indicator respectively, and the research results show that the WD-SSA-LSTM model constructed has the best prediction effect; thirdly, the pricing of weather derivatives for each city is realized through Monte Carlo simulation, and a weather financial market with strong flexibility and adaptability is established. option contracts with strong flexibility and adaptability; finally, according to the research conclusions, corresponding recommendations are put forward for traders, related parties and government departments, which provide a strong guarantee for the healthy development of weather-sensitive industries such as agriculture and help China's high-quality development.*

Keywords: *weather derivatives, weather composite index, AHP-CRITIC combined empowerment model, WD-SSA-LSTM model, Monte Carlo simulation*

1. Introduction

Agricultural production is vital to China's development, and with the promotion of rural revitalization, its impact on farmers' well-being and national food security has become increasingly significant. However, agricultural production is susceptible to adverse weather conditions, and in recent years China has experienced frequent meteorological disasters, affecting the supply of agricultural products and the profits of associated enterprises. As a result, the country has emphasized in the 14th Five-Year Plan the need to continuously strengthen the fundamental position of agriculture and promote the revitalization of rural industries in order to safeguard agricultural development and food security. To this end, weather derivatives, as an emerging financial derivative product, can better measure the fluctuation of general weather risks by using weather conditions as indicators, providing an effective way to avoid weather risks and promote the development of rural revitalization. By accurately predicting future weather conditions and customizing corresponding weather derivatives for each city, it can play an important role in practice.

A comprehensive analysis of the existing research results shows that most scholars tend to focus on single meteorological factors such as temperature [1-2], rainfall [3-4], and wind for research [5], and mainly rely on traditional models such as ARMA models for the prediction of meteorological data. However, given the significant differences in the climatic characteristics of various regions, it is obvious that a single prediction model is difficult to be applied to a wide geographical range. In addition, most of

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the current studies are based on the historical temperature data of a single city for prediction, with insufficient consideration of the geographical characteristics of the temperature and the potential impact of neighboring cities on it. Based on the background of rural revitalization, combined with the current agricultural production and food security issues in China, this paper comprehensively considers the advantages and shortcomings of the above methods, firstly, using the AHP-CRITIC coefficient of variation combination of weighting method, comprehensively considering the three typical meteorological indexes of temperature, wind speed and humidity, to establish a more complete meteorological index system, and construct a meteorological composite index (CCI), which is an extension of the back-end derivatives. Secondly, a CCI prediction model based on WD-SSA-LSTM neural network, which can accurately predict meteorological data and is applicable to multiple regions, is constructed from the aspects of time-frequency analysis, parameter optimization and prediction model. Finally, the market pricing is derived through distribution analysis and Monte Carlo method, so as to calculate the pricing of local weather derivatives for different cities in China, which is highly flexible and adaptable, and is conducive to filling the vacancies in the options market, promoting the establishment of a complete market system, and then contributing to the construction of an emerging meteorological financial derivatives trading market in China.

2. Data and indicators

The meteorological data used in this paper were obtained from the National Weather Data Center (NCDC)[1] and the China Meteorological Data Network[2] ,nine typical meteorological belts in China were selected as the scope of the study, and one meteorological representative station from each of these belts (9 in total) was finally selected as the object of this study.In this paper, the time-degree data of temperature, wind speed, and barometric pressure for the period of 2014-2022 were obtained from the NCDC, the daily data of average humidity for the period of 2014-2022 were obtained from the China Meteorological Data Network (CMDN) to obtain the daily data of average humidity during 2014-2022. In this paper, the three indicators of temperature, humidity and wind speed are selected to establish a comprehensive indicator model to measure the weather risk.

3. Modeling and solving

3.1 AHP-CRITIC Combined Empowerment Modeling

(1) Modeling Portfolio Empowerment

$$w_j = \alpha w'_j + \beta w''_j \tag{1}$$

Where α is the subjective evaluation weight, β is the objective evaluation weight, and the conditions are met $\alpha, \beta > 0, \alpha + \beta = 1$

(2) Tectonic target planning:

$$\begin{cases} \max J_j = \alpha \sum_{j=1}^{n} w' A' + \beta \sum_{j=1}^{n} w'' S' \\ st \quad \alpha, \beta > 0, \alpha + \beta = 1 \end{cases} \tag{2}$$

Using Lagrange's method, the extreme values are obtained as, α β, normalized to , α^* β^* , and hence:

$$w_j = \alpha^* w'_j + \beta^* w''_j \tag{3}$$

(3) The final value of the combined weights of the indicators is $w^* = \left[w_1^*, w_2^*, \ldots, w_n^* \right]$.

[1] https://www.library.ucsb.edu/research/db/1027
[2] http://data.cma.cn/

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(4) Weather Composite Index (CCI) values are calculated using the formula: $CCI = WS$

3.2 Empirical analysis

Using the above combined assignment model, this paper can obtain the weights of each indicator, and the coefficients in the formula are the weights of the corresponding indicators in the CCI.

3.3 Meteorological composite index prediction model based on WD-SSA-LSTM neural network

3.3.1 Modeling framework

Based on the data characteristics of CCI, which is the object of study in this paper, this paper constructs a prediction model of WD-SSA-LSTM neural network. The two main sections of this model are: the time-frequency analysis section of wavelet decomposition and the SSA-LSTM neural network prediction section. The model is based on the original sequence of CCI, which is firstly decomposed using wavelet decomposition; then the LSTM neural network based on SSA algorithm is used to predict each sub-sequence; finally the predicted values are fused and rearranged to get the final predicted values.

3.3.2 Empirical analysis

(1) Wavelet decomposition

According to the characteristics of the data and the results of the comparison and analysis of several parameters, this paper finally chooses sym function for wavelet decomposition. sym function has orthogonality, bi-orthogonality, tight support, which is suitable for both discrete and continuous data. In the model of this paper, sym is set as sym2 and level is set as 5.

(2) SSA-LSTM

The five subsequences obtained from the decomposition and the optimal parameters derived from the SSA algorithm are brought into the LSTM model respectively, and the five predictive models obtained are evaluated as follows table 1:

Table 1: Evaluation table for each subsequence parameter

Evaluation parameters	A5	D1	D2	D3	D4
MSE	0.3882	2.8726	0.6866	0.7281	0.4903
MAE	0.2510	2.1931	0.4938	0.5066	0.3379
R2	0.9930	0.7567	0.8490	0.8690	0.9258

Collectively, LSTM predicts the subsequences more accurately.

3.3.3 Model application

In order to verify the practicability of the WD-SSA-LSTM model, the data from other eight urban meteorological stations are substituted in turn for fitting, and the WD-SSA-LSTM model fits the data of each city well in general, while the fits of Coral Island and Haikou are relatively poor, which may be due to the fact that these two cities are close to the seashore, and the change of wind speed is unstable, which leads to the random error becoming larger in the fitting of the model.

4. Empirical Pricing Study of Weather Derivatives

Weather derivatives, as a type of European-style option, settle the option contract as soon as the option contract reaches its execution date and the value of the weather indicator is released. Under a risk-neutral measure, the option price is able to be expressed as the expected value of its discounted return to maturity. Distributional analysis yields that the distribution of the CCI indicator is more suitable for a uniform distribution, and the Monte Carlo methodology achieves the pricing of call options by simulating the price paths of the underlying assets of the CCIs as described above as a means of estimating the expected value. Currently the market commonly used weather derivatives based on the HDD and CDD index, this paper will CCI index analogous to the HDD index, respectively, to calculate the pricing formula for January call options for different observation locations.

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4.1 Pricing under distributional analysis method and Monte Carlo simulation

(1) Distributional analysis approach

Using the quantitative distribution analysis method for the 8-year day-by-day index, it was concluded that a uniform distribution simulated the best results, so a uniform distribution was used to generate a day-by-day CCI index for January 2023, and a normal perturbation term was added to better simulate stochastic conditions.

(2) Monte Carlo method

Use the Monte Carlo method to generate a randomized path under which to compute the price according to the formula in the corresponding call option contract above. Repeat this step to obtain a large number of randomly selected data by varying the choice of N, for which the sample mean is obtained and the Monte Carlo simulation of the option price is obtained by Kolmgorov's strong law of numbers. Explanation of the selection of indicator symbols are shown in table 2.

$$\mathrm{C_{CCI}} = e^{-rT} \frac{1}{\mathrm{N}} \sum_{\mathrm{i}=1}^{\mathrm{N}} \mathrm{N_p E\{max(CCIs(0, T) - K，0)\}} \tag{4}$$

Table 2: Explanation of the selection of indicator symbols

notation	norm
$\mathrm{C_{CCI}}$	Returns at maturity of options
r	risk-free rate
T	Expiry time of the option
$\mathrm{C_{base}}$	Baseline value of composite indicator CCI
K	Implementation price
Np	Contract Specifications
N	Number of simulations

4.2 Baseline value selection

On the basis of uniform distribution, for the purpose of calculating the call option, the baseline values of CCI for each site are selected and the following results are obtained in table 3:

Table 3: Baseline CCI indicators by site

Site name	CCI indicator baseline selection
Tuli River, flowing from Xizang inMyanmar	9.631
Hohhot prefecture level city in Shaanxi	13.265
Ji'nan, subprovincial city and capital of Shandong province in northeast China	21.460
Wuhan city on Changjiang, subprovincial city and capital of Hubei province	28.097
also Nanchang county	29.222
Guangzhou subprovincial city and capital of Guangdong	36.490
estuary	38.316
Sanya prefecture level city, Hainan	39.229
coral island	39.129

4.3 Call Option Contract Design

The experimental design options products for the December 31, 2022 offering, January 31, 2023 expiration of the CCI call options, ignoring the small differences in the number of days between the months, T take the value of 1/12, the risk-free interest rate selected in January 2023 term of one month Shanghai Interbank Offered Rate (SHIBOR) average, after searching can be obtained as 2.09%, the design of the The table is as follows Table 4:

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Table 4: Call Option Contract Design

Observation sites	Type of climate zone	Implementation price	Contract Specifications	risk-free rate
Tuli River, flowing from Xizang inMyanmar	cold temperate zone	30	100	2.09%
Hohhot prefecture level city in Shaanxi	middle temperate zone	40	100	2.09%
Ji'nan, subprovincial city and capital of Shandong province in northeast China	warm belt (e.g. of northeast China)	55	100	2.09%
Wuhan city on Changjiang, subprovincial city and capital of Hubei province	subtropical (zone or climate)	45	100	2.09%
also Nanchang county	subtropical (zone or climate)	50	100	2.09%
Guangzhou subprovincial city and capital of Guangdong	subtropical (zone or climate)	30	100	2.09%
estuary	Marginal Tropics	30	100	2.09%
Sanya prefecture level city, Hainan	the middle tropics	30	100	2.09%
coral island	equatorial tropics	20	100	2.09%

4.4 Monte Carlo Pricing

Using the average of the prices of the generated paths to represent the price of the expected derivatives, pricing was simulated for each of the nine observed locations, varying the number of times N. The results are shown in the Table 5:

Table 5: Monte Carlo Pricing of Call Options

N	Tuli River, flowing from Xizang inMyanmar	Hohhot prefecture level city in Shaanxi	Ji'nan, subprovincial city and capital of Shandong province in northeast China	Wuhan city on Changjiang, subprovincial city and capital of Hubei province	also Nanchang county	Guangzhou subprovincial city and capital of Guangdong	estuary	Sanya prefecture level city, Hainan	coral island
100	1372.61	1406.07	1754.67	1638.21	1260.4	1426.34	1423.96	1364.09	1682.37
500	1360.27	1379.45	1732.43	1624.45	1250.95	1416.97	1400.12	1345.71	1677.79
1000	1356.15	1374.03	1722.77	1610.32	1242.66	1407.79	1389.97	1337.46	1674.22
5000	1354.34	1372.65	1716.84	1593.31	1239.57	1400.79	1380.16	1326.78	1672.98
10000	1351.83	1370.28	1716.29	1587.21	1236.01	1388.99	1377.02	1321.11	1671.01
50000	1346.88	1368.94	1712.10	1583.64	1234.79	1386.31	1375.25	1318.6	1670.53
100000	1343.95	1367.79	1710.01	1580.81	1232.96	1385.01	1373.99	1316.43	1667.01
500000	1343.06	1366.06	1709.97	1579.01	1231.84	1384.25	1372.01	1315.99	1665.28
1,000,000.	1342.68	1365.01	1709.77	1578.22	1230.04	1383.77	1371.50	1315.35	1665.20

4.5 Comparison of accuracy

Comparing the values from Monte Carlo simulation with the pricing of the predicted values obtained using the neural network, it can be seen that the relative error rate is around 3% and most of them are below 3%, so the prediction accuracy is higher using the WD-SSA-LSTM neural network model. Comparison of prediction accuracy is shown in Table 6.

Table 6: Comparison of prediction accuracy

Observation sites	projected value	actual value	relative error
Tuli River, flowing from Xizang inMyanmar	1342.68	1311.66	2.31%
Hohhot prefecture level city in Shaanxi	1365.01	1323.92	3.01%
Ji'nan, subprovincial city and capital of Shandong province in northeast China	1709.77	1664.34	2.65%
Wuhan city on Changjiang, subprovincial city and capital of Hubei province	1578.22	1610.10	2.02%
also Nanchang county	1230.04	1263.99	2.76%
Guangzhou subprovincial city and capital of Guangdong	1383.77	1344.33	2.85%
estuary	1371.50	1331.59	2.91%
Sanya prefecture level city, Hainan	1315.35	1281.94	2.54%
coral island	1665.20	1624.57	2.44%

5. Conclusions and recommendations

This study has made important progress and findings in weather risk measurement and weather derivatives market construction. Through multivariate measurement and combined empowerment modeling, we improved the robustness of weather risk models and provided more accurate risk assessment tools for agricultural production and related enterprises. In addition, we adopted a combined neural network prediction model based on seasonal temporal characteristics, which improves the prediction accuracy and utility of weather composite indicators and provides important support for the development of the weather derivatives market. Finally, in the design of call option contracts, we emphasize the principle of local adaptation and combine distribution analysis and Monte Carlo simulation methods, which provide effective reference opinions for contract pricing and market stability. Taken together, this study provides theoretical guidance and practical suggestions for weather risk management and the healthy development of the weather derivatives market. Our findings not only help agricultural producers, weather-related enterprises and traders to better manage weather risks, but also provide useful references for governmental departments in the regulation and policy support of the weather derivatives market, and promote the innovation and sound development of the financial market.

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