

Article

SARIMA Model-Based Monte Carlo Simulation of Option Contract Design for Maize Seasonal Heavy Precipitation in Shenyang

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Abstract: Agricultural production is highly dependent on weather conditions such as temperature, light, water and heat. The huge loss caused by extreme disaster weather makes the global insurance and reinsurance market overwhelmed, and seriously affects the enthusiasm of agricultural investment and the development of agricultural economy. With unique topography and vast territory, China is vulnerable to complex and diverse climate disasters. In recent years, the annual average economic loss caused by extreme weather disasters has reached about 200-300 billion yuan, among which floods caused by extreme heavy rainfall are the main agricultural disasters in China. In order to enhance the "farmer - insurance company - government" interest association to resist the risk of flood disaster caused by extreme heavy rainfall, financial hedging derivatives of weather disaster risk have gradually become a new hedging tool besides traditional insurance and reinsurance. This paper takes Shenyang, the main grain producing area in northeast China, as the sample of the study area, and uses the SARIMA model to obtain the distribution characteristics of seasonal rainfall time series. Different seasonal rainfall index option products (call option and put option contracts) are designed respectively, and the final option pricing is obtained by Monte Carlo stochastic simulation. The seasonal rainfall call option and put option contracts have opened up a new hedging model of agricultural extreme weather catastrophe outside the insurance and reinsurance market, which has enriched the varieties of weather financial derivatives market in China, reduced the severe impact of extreme weather disasters on agriculture, and enhanced the ability of agricultural stakeholders to resist the risk of extreme weather disasters.

Keywords: Seasonal Rainfall Option; Weather Index Financial Derivatives; SARIMA Model; Monte Carlo Simulation

1. Introduction

Weather factor is an environmental economic problem of human survival and development. China is one of the countries most threatened by weather disasters in the world. There are many kinds of meteorological disasters with high frequency and heavy losses. According to the statistics of the past two decades (2000-2023), the average annual economic loss caused by weather is about 315.89 billion yuan, and the loss caused by weather alone has exceeded 70% of the loss caused by natural disasters, and the annual economic loss caused by natural disasters is also gradually increasing.

Rainfall is an indispensable factor in the production of agricultural products, which has a great impact on the final output of crops. In the face of economic risks caused by rainfall disasters, it is completely insufficient to use insurance as a coping tool. The effect of weather financial derivatives on weather risk management has gradually been recognized, especially in the agricultural field, where weather options, futures and other products have become a new choice for producers to avoid the risks brought by abnormal weather.

As a major agricultural country in the world, China's agricultural production is highly dependent on rainfall and other weather conditions. Due to the great uncertainty of weather factors and the high probability of abnormal weather phenomena, it is difficult to effectively solve the loss caused by weather disasters through traditional insurance and reinsurance tools. Encouraged by financial subsidies, China's agricultural insurance has become a global agricultural insurance country (2021). However, the protection level of agricultural insurance is only about 23.61%, and both the coverage breadth and the number of insurance products need to be improved. There are not many new varieties in the weather financial derivatives market, and the demand for weather management financial derivatives is high.

This paper designs the seasonal option contract of regional rainfall and uses SARIMA model to predict the seasonal characteristics of regional monthly rainfall, to design a complete seasonal option product of rainfall. Compared with insurance with more restrictions, seasonal rainfall option contract has a wider scope of application, and as an option, the risk diversification and transfer ability are very strong, which is convenient for agricultural producers to make investment choices. It is a new variety in the weather financial derivatives market.

2. Materials and Methods

The product design of seasonal rainfall option contract in this paper is mainly divided into two parts: weather derivative design and pricing, rainfall index prediction model. The following will introduce the relevant research of each sector in turn.

2.1. Weather Derivative Design and Pricing

Weather derivatives first appeared in the United States. At present, the market of weather derivatives is developing rapidly in foreign countries, and there have been in-depth studies abroad. A relatively mature model has been put forward for the pricing and weather prediction of weather derivatives, and there have been in-depth discussions and empirical studies on its applicability and risk hedging effect.

The most classic and traditional pricing model for options is the BS formula (Black-Scholes Option Pricing Model). The model prices the current value of options based on the principle of no arbitrage by constructing a risk-free investment portfolio. However, the model makes numerous assumptions about the underlying asset and market environment. However, due to the significant differences between weather options and conventional options, and the fact that the weather derivatives market is an incomplete market, the underlying assets of weather index options are nontradable and do not meet the assumptions of a complete market in the BS model pricing (Davis, 2001) [1].

Subsequently, research on the applicability of weather index options continued to emerge. For special derivatives such as weather options that cannot construct strong replication strategies, have regression characteristics in underlying asset volatility, and cannot be traded, many scholars have combined existing incomplete market option pricing models to propose models applicable to weather options. Currently, there are two main types of methods used: actuarial pricing based on probability measures, and market pricing based on utility.

For the pricing of weather derivatives, the actuarial value method under pure probability measure was widely used at the beginning. This method conducts actuarial pricing of asset value on the premise that there is no hedging strategy provided by financial market. After that, the market pricing method based on the utility of the buyer and the seller is proposed, considering the actual utility of the product to the two parties, combined with the principle of marginal utility, the market equilibrium pricing of weather derivatives is carried out.

However, both methods have their advantages and disadvantages:

Table 2. Summary of the strengths and weaknesses of the methods.

With the continuous development of technology, the method of combining market and Monte Carlo simulation with weather option pricing is now widely used by scholars, but it also puts forward higher requirements on the accuracy of the original model. Therefore, the prediction model of the price change of the underlying asset has become an important part of subsequent research. Monte Carlo simulation based on equilibrium pricing (Davis, 2001) [1], both refine Monte Carlo in different directions.

Year	Proposer	Method	Contents		
2000	Nelken	Monte Carlo simulation based on mean reverting.	A mean-reverting model of temperature change is proposed, based on which the derivative price is calculated by Monte Carlo simulation.		
2004	Fleege, Richards, Manfredo, Sanders	Monte Carlo simulations based on equilibrium pricing.	The principle of indifference utility maximization is used to establish a pricing model, which is combined with Monte Carlo simulation for pricing.		

Table 3. Summary table of Monte Carlo methods.

With the introduction of the concept of weather derivatives into China, the early literature mainly discussed the feasibility of weather index prediction or weather derivatives, and the pricing methods were relatively single. For example, this paper introduces the generation and development of weather derivatives and their impact on financial derivatives transactions (Liu, 2005) [2]. It emphasizes that due to the particularity of the underlying assets of weather derivatives and the difficulty of continuous hedging in the current market environment, actuarial pricing method and market pricing method should be applied comprehensively, and actuarial pricing method should be more relied on to price weather derivatives (Xie & Mei, 2011 [3]; Pan & Pu, 2009 [4]; Pan & Pu, 2015 [5]). With the continuous innovation of pricing methods, the impact factors of output are found to predict the loss caused by disasters, which are indexed to construct index insurance. For example, Monte Carlo pricing method is used to price option products related to temperature index (Wang et al., 2015) [6]. With the continuous emergence of weather disaster risk index insurance, the association between meteorological risk and risk loss and insurance compensation is used to index the loss assessment results. When the meteorological disaster index reaches a certain threshold, compensation can be paid (Chen, 2020) [7]. Flood disaster insurance meteorological claim index, corn drought index insurance (Dong, 2023) [8]. It is easy to see that weather index insurance significantly reduces moral hazard and high operating costs caused by adverse selection (Wang & Chen, 2023) [9], improves claim settlement efficiency (Chen, 2023) [10], and has incomparable advantages to traditional insurance (Li, 2023) [11]. Especially in recent years, with the popularization and application of satellite communication and network technology, digitalization and intelligence have become a new trend. The digital twin system formed by the combination of UAV with remote sensing and artificial intelligence has completely changed the traditional insurance business model and the behavioral preferences of all stakeholders (Huang, 2019 [12]; Li & Qu, 2022 [13]). It has significantly changed the ecology of agricultural insurance and has become a hot topic of concern for the industry and scholars.

If we only use domestic weather data to construct different option pricing models, and combine the production data of various industrial sectors, we discuss the corresponding advantages and limitations. Domestic scholars generally believe that the traditional pricing model is no longer applicable due to the non-tradability of the underlying asset, the incomplete market and the autoregressive nature of the underlying asset price when choosing the pricing model of weather index options.

DOI: https://doi.org/10.54560/jracr.v14i2.475 254 In general, although some scholars innovatively combined market asset prices to price weather options, the research results are not rich. The overall market of weather derivatives in China is not mature at present. How to combine the existing pricing methods to study a new type of weather derivatives with a wider applicability is the place that the follow-up research should pay attention to.

2.2. Prediction Model of Rainfall Index

Most of the research on weather index and fluctuation simulation at home and abroad focuses on temperature, and the model prediction of rainfall index is relatively few at present. In addition, in Monte Carlo simulation pricing, rainfall prediction is a difficult point in the pricing of rainfall index options, and its accuracy affects the judgment of the intrinsic value of options.

Table 4. Summary table of domestic research methods.

Since the seasonal and regional characteristics of rainfall conditions are relatively obvious, the model for its prediction should also conform to the local rainfall characteristics. At present, the methods of rainfall prediction mainly include SARIMA model, BP neural network technology, wavelet analysis, Ornstein Uhlenbeck mean reversion process model. In the practical application of option pricing, a variety of methods can be combined to design the corresponding price path based on the prediction method, and Monte Carlo simulation can be carried out by computer. To sum up, in the current research on option pricing based on prediction model combined with Monte Carlo simulation, most Chinese scholars focus on the establishment and test of prediction model, and most literature compares the differences of different prediction methods. Some scholars prefer to use empirical research to discuss the comparison of risk hedging effect of weather option product design. However, there is still a lack of research combining prediction, hedging effect and pricing model, and there is also a lack of specific analysis and discussion on the design of weather index option contract.

3. Results

3.1. Study Area

As for the weather factor of rainfall, there are great regional differences in China, so this paper takes the city level as the minimum unit to select the study area. Considering that the option contract designed in this paper is mainly aimed at the agricultural field in China, the selection scope is divided into the northeast of the main agricultural producing areas in China.

3.2. SARIMA Model Construction

To accurately grasp the change of rainfall from month to month in the future, many mature forecasting methods can be applied to rainfall prediction. At present, rainfall prediction methods are mainly divided into two categories: one is the theoretical model based on mathematical statistics, including live partial least squares (PLS) regression algorithm (Niu et al., 2016) [18], time series model, Markov prediction model, etc. (Ma et al., 2010) [19]. The other category is modern machine learning methods, such as support vector machine (Ni, 2014) [20], random forest (Zhen et al., 2015) [21], LSTM neural network prediction model, etc. (Liu et al., 2020) [22]. Among them, time series models are widely used. The differential integrated moving average Autoregressive (ARIMA) model was proposed by Box and Jenkins in 1970 and is now widely used in various fields such as finance, disease and transportation (Ulrich, 1996) [23]. Domestic scholars such as Yi Yanfei predicted the epidemic trend of hepatitis B and tuberculosis in class B infectious diseases and influenza in class C infectious diseases. Pan Dianya took the GDP of Jilin Province as a time series to establish an ARIMA model and conduct an empirical analysis on the economic development of Jilin Province (Pan, 2021) [24].

SARIMA model is an improvement of ARIMA model, which can predict seasonal time series more scientifically and reasonably. In this paper, rainfall has obvious seasonal characteristics. Therefore, based on the accumulated rainfall data in Shenyang from 20 to 20 o 'clock provided by the National Meteorological Administration, this paper conducts statistical analysis and research on the rainfall in Shenyang region in monthly units, and uses R language to conduct modeling analysis and prediction based on SARIMA model for the monthly rainfall data from January 2000 to April 2021.

From the SARIMA (p, d, q) (P, D, Q) _S forecasting model principle, the time series model has the following structure:

$$
\begin{cases}\n\phi(B)\Phi_s(B)\nabla^d \nabla^D_s x_t = \theta(B)\Theta_s(B)\varepsilon_t \\
E(\varepsilon_t) = 0, \quad \text{Var}(\varepsilon_t) = \sigma_t^2, \quad E(\varepsilon_s, \varepsilon_t) = 0, s \neq t\n\end{cases}
$$

Where x_t is the time series data, ε_t is the zero-mean white noise sequence, p represents the autoregressive order, q represents the moving average order, d represents the difference order, P、D、Q respectively represents the autoregressive order, moving average order and difference order of the seasonal part, S represents the length of the seasonal cycle, B represents the delay operator, and is

$$
x_{t-p} = B^p x_t
$$

The delay operator is used to represent the difference operation, then the d-order difference can be expressed as:

$$
\nabla^{\mathbf{d}}\mathbf{x}_{t} = (1 - \mathbf{B})^{\mathbf{d}}\mathbf{x}_{t}
$$

And the polynomials related to B in the formula can be expressed as:

$$
\Phi(B) = 1 - \Phi_1 B - \Phi_2 B^2 \dots - \Phi_p B^p
$$

$$
\theta(B) = 1 - \theta_1 B - \theta_2 B^2 \dots - \theta_q B^q
$$

$$
\Phi_S(B) = 1 - \Phi_1 B^S - \Phi_2 B^{2S} \dots - \Phi_p B^{PS}
$$

$$
\Theta_S(B) = 1 - \Theta_1 B^S - \Theta_2 B^{2S} \dots - \Theta_Q B^{QS}
$$

When the series is not stationary, the difference method can be used to make the series stationary, and the time series modeling through stationarity test is meaningful. There are three common

difference methods: when the series has a significant linear trend, the first-order difference can achieve trend stationarity; When the series contains the curve trend, usually the low-order difference (2 or 3 order) can extract the influence of the curve trend; For a series containing a fixed trend, a difference operation with a step size of the period length can be performed (Wang, 2022) [25].

3.3. Prediction Using SARIMA Model

(1) Stationarity test and white noise test

Firstly, the rainfall data of Shenyang is read, and the data is converted into time series data of numerical type. The time series line chart, ACF chart and PACF chart of the original data are drawn as follows:

Figure 1. Picture of the original data.

It can be seen from the figure above that the observed values of the time series have obvious periodicity, and the seasonality, trend and irregular components of the series are obtained by using the moving average method. The conclusion that the series has obvious periodicity can be further verified by combining ACF and PACF and the figure below.

Figure 2. Periodogram.

Considering the influence of periodic fluctuations, the original time series is differenced with lag = 12, and the differenced series is shown in the figure:

Figure 3. Difference sequence diagram.

The Augmented Dickey-Fuller Test (ADF) method is used to test the stationarity of the differenced series. The null hypothesis of this method is that the series is not stationery and unit root exist. The alternative hypothesis is that the series is stationary, and Dickey-Fuller = -5.5199, P < 0.01 is calculated, so the null hypothesis is rejected, indicating that the series after difference is stationary.

For white noise sequence, SARIMA model cannot be used for effective prediction. Therefore, the Ljung-Box Q statistic is used to check whether there is autocorrelation in the time series, and if there is autocorrelation, the model can be considered to fit the series. Therefore, the Ljung-Box test statistics and P values are calculated when the sequence order is 12 and 24 after difference, and the results are shown in the following table, which can be used to judge that the sequence is not a white noise sequence.

Table 5. Statistical scale.

(2) Model identification and order determination

The auto correlogram and partial auto correlogram are drawn for the differenced series in order to determine the situation of the model:

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The AIC criterion considers the simplicity and accuracy of the model, and the preferred model should be the one with the lowest AIC value. According to the AIC criterion, the optimal model is determined as sparse SARIMA (10,0,0) (1,1,2) with seasonal period 12 after repeated tests and combined with the residual situation, in which AR10 and SMA2 are sparse parts. Compared with the sparse SARIMA $(0,0,0)$ $(1,1,2)$ with a seasonal period of 12 (in which SMA2 is the sparse part), the AIC of the former is 2579.59, and the AIC of the latter is 2582.86. The parameters of the model are all significant, and the specific parameter estimation results are shown in the following table:

Index	ar10	sar1	sma2
coef	-0.1497	-0.7689	-0.8701
s.e.	0.0648	0.0674	0.1010
t ratio	-2.3107	-11.4107	-8.6172
p-value	0.0208	0.0000	0.0000

Table 6. Parameter estimation results.

The model is expressed as:

$$
(1+0.1497B^{10})(1+0.7689B^{12})\nabla^{12}x_t = (1-0.8701B^{24})\epsilon_t
$$

(3) Model test

To test the correlation of residual errors, draw the residual error diagram, ACF diagram of residual errors and PACF diagram of residual errors of the model, as shown below:

Figure 5. Related case plot of the residuals.

We continue to use Ljung-Box to test the order of lags, and the p values are all greater than 0.05, indicating that there is no significant correlation between the residuals, the series is stationary, and it is a white noise series, and the model basically meets the requirements.

(4) Model prediction and analysis

According to the above model, the rainfall data in Shenyang from May 2021 to April 2022 are predicted, and the predicted results and standard deviations are shown in the following table:

Time	2021.5	2021.6	2021.7	2021.8	2021.9	2021.10
Predicted value	113.433	72.538	147.963	163.15	50.026	40.995
Standard deviation	44.905	44.905	44.905	44.905	44.905	44.905
Time	2021.11	2021.12	2022.1	2022.2	2022.3	2022.4
Predicted value	27.456	15.838	10.177	10.702	12.477	40.636
Standard deviation	44.903	44.903	44.9	44.9	45.399	45.399

Table 7. Table of forecast results.

The forecast and its confidence interval are shown in the figure:

ARIMA(10,0,0)xSARIMA(1,1,2)Prediction and prediction interval

Figure 6. Forecast and confidence interval plot.

4. Discussion

In the design of weather derivatives, a crucial step is to set the underlying index. According to different market demands, the underlying index of different derivatives varies greatly. Therefore, we will first design the underlying index, then determine the price multiplier, and finally design the specific content of the contract.

Figure 7. Contract Design Section Flowchart.

4.1. Underlying Index

This paper is mainly a rainfall option product designed for the market demand of crops affected by rainfall. Considering that the impact of rainfall on crops is extreme, that is, the higher the rainfall is and the lower the rainfall is, the lower the rainfall will have a certain negative impact on the yield of crops, we set our target index as the monthly accumulative rainfall within the target period of the contract. It is named Cumulative Rainfall Index (CRI).

The cumulative rainfall index from the initial time point to the contract expiration date is calculated as follows:

$$
CRI_{t_0:T} = \sum_{i=t_0}^{T} R_i
$$

4.2. Contract Price Multiplier

The contract price multiplier is an intermediary index that connects the underlying index of the option with the currency in circulation. If the contract price index is higher, the buyer of the option will bear more risk in each unit of the contract. Therefore, if we fix the variation range of the underlying index and keep it as balanced as possible, a reasonable contract price multiplier can keep the risk of the unit option contract within a reasonable range, which is an important factor for the sale of options and the risk of investors.

By referring to the contract multipliers of some stock index futures in the world and considering the nature of rainfall option itself and market demand, this paper sets a relatively moderate price multiplier. At present, the contract multipliers of stock index indexes in some countries are as follows:

Table 8. Types of Contracts.

According to the above f table, most contract multipliers are in the range of 200 to 1000, so our contract multiplier will also be determined in this range.

In addition, the choice of contract multiplier is also closely related to the liquidity and transaction cost of the product in the market: that is, if the value of contract price multiplier is relatively large, the value of a single contract will be higher, and the higher contract value will lead to a higher investment threshold, making many small and medium-sized investors and speculators give up the product, thus affecting the liquidity of the product. Product liquidity is a necessary condition for the hedging function of options and futures. Conversely, if the price multiplier is at a small level, the value of the unit contract is correspondingly small, which will lead to an increase in transaction costs.

Considering the influence of the above two aspects, and the demander of rainfall option is mainly farmers, who do not have a great demand for speculation, we choose to imitate the CSI 300 stock index futures and set the price multiplier of this product to 300.

4.3. Contract Term

In addition, according to the data graph predicted by the SARIMA model above, the months with the largest rainfall change are concentrated from March to October, which is used as the basic range for the selection of contract term.

Figure 8. Forecast rainfall changes.

According to the statistical yearbook of Shenyang in 2019, the total grain output of Shenyang in 2019 is mainly divided into the following categories, and its distribution ratio is as follows:

Figure 9. Crop distribution in Shenyang.

As can be seen from the figure above, the crops with the highest yield in Shenyang are mainly corn and rice. These two crops are divided into early, medium and late maturity, and the full maturity of different qualities is shown in the following table:

Based on the above table, which combines the whole growth period of each variety, the seasonal characteristics of the predicted rainfall, and the demand coverage of the contract, we set the contract term to be from the beginning of May to the end of September, i.e. [5.1, 9.30].

4.4. Exercise Price

We set our contract price, the exercise points, using the Shenyang crop as an example. Since agricultural products are greatly affected by rainfall, both excessive rainfall and low rainfall will lead to crop production and thus bring the risk of loss to farmers. According to the investigation of historical rainfall in Shenyang since 2000, the average accumulative rainfall in Shenyang from May to September is about 491. The specific changes of rainfall over the years are as follows:

Figure 10. Plot of changes in cumulative rainfall.

According to the accumulated rainfall from May to September over the years and the average, we take 490 as the reference, set 550 as the strike price of the call option, and 450 as the strike price of the put option, namely: $K_c = 550$; $K_p = 450$.

4.5. Contract Contents

Table 11. Contract Content.

Contract name: Seasonal Rainfall Option Product				
Subject matter of contract	Cumulative rainfall index (CRI)			
City	Shenyang			
Type of contract	Call options; Put options			
Term of contract	[5.1, 9.30]			
Contract multiplier	$M = 300$			

4.6. Pricing Model Selection

Considering the non-tradability of the weather index itself, the particularity of the fluctuation and the difficulty of measuring the economic impact, the traditional B-S option pricing model and binary tree pricing are not suitable for the pricing of the weather index option.

The basic formula can be expressed as:

$$
V_t = e^{-r(T-t)} * E_T(payment)
$$

Where V_t is the embedded value of the option at time t, T is the option expiration date, $e^{-r(T-t)}$ is the discounted value of the risk-free interest rate under continuous compounding, and E_T (payment) is the expected payment value of the option at maturity.

4.7. Pricing Formula

Now based on the Monte Carlo simulation method, the cumulative rainfall index option product is priced, recorded at time t, the value of the call option is C_t , the value of the put option is P_t . A rainfall option with a contract multiplier of C, a strike price of K, and a contract maturity of t_0 -T is priced as follows:

If time t is not in the period of the option contract, then:

$$
C_t = e^{-r(T-t)} * E\{C * \max(CRI_{t_0:T} - K, 0)\};
$$

$$
P_t = e^{-r(T-t)} * E\{C * \max(K - CRI_{t_0:T}, 0)\};
$$

If time t is during the option contract, then:

$$
C_t = e^{-r(T-t)} * E\{C * \max[(CRI_{t_0:t} + CRI_{t:T}) - K, 0]\};
$$

$$
P_t = e^{-r(T-t)} * E\{C * \max[K - (CRI_{t_0:t} + CRI_{t:T}), 0]\};
$$

where $CRI_{t_0:t}$ is the realized CRI calculated based on real rainfall data, $CRI_{t_0:T}$ and $CRI_{t:T}$ is the stochastic simulation predicted value calculated by Monte Carlo simulation method after regression analysis of rainfall according to SARIMA model based on historical rainfall information.

The steps for calculating the expected payoff by Monte Carlo simulation method are as follows:

The output of the simulation error term (here denoted as the error between the estimated monthly rainfall forecast and the actual rainfall value) is calculated by setting the path to calculate the final payment value.

In addition, the extreme value of the payment here has too much influence on the mean value, which will make the expected payment value calculated by directly taking the mean value be too large due to the influence of the outlier value with extremely small possibility and extremely large payment value. Here, the outlier is defined as the point outside the specified percentile.

In the calculation of the call option, we choose the point deviating from the quantile of (10, 90) as the outlier, that is, we eliminate the payment value with a probability of less than 10% due to the large value; For the put option, the monthly rainfall itself has non-negative constraints and is less affected by extreme values than for the call option. Therefore, the quantile interval is appropriately enlarged, and (5, 95) is selected as the critical quantile of its extreme value.

5. Conclusions

5.1. Value of Various Option Products at the Beginning of the Year

The rainfall forecast value from May to September 2021 obtained by SARIMA model is (113.433; 72.538; 147.962; 163.149; 50.026), and the total is about 547.108. The residuals of monthly rainfall obtained by the prediction model follow the normal distribution with the mean of 0 and the standard deviation of 44.905. Therefore, we use the option pricing model to conduct 5 million simulations under the condition that the risk-free interest rate is set at 4%, and obtain various situations as follows: (1) K=550, call option

Figure 11. CDF plot of call options.

Figure 12. Plot of expected call option returns.

The figure can be seen from the cumulative probability distribution function of the future payment of the option. On this basis, after excluding outliers, the average value is calculated to be 7254 yuan. After discounting it under continuous compound interest to the beginning of the year, the intrinsic price should be 7134 yuan. The change in return of the value of this option with the accumulated rainfall at maturity is thus obtained.

(2) K=450, put option

Similarly, the cumulative probability distribution of option payment at maturity obtained by simulation is calculated as 771 yuan on the basis of excluding outliers, and its intrinsic price should be 758 yuan after discounting it to the beginning of the year under continuous compound interest. The change in return of the value of this option with the accumulated rainfall at maturity is thus obtained.

Figure 13. CDF plot of put options.

Figure 14. Plot of expected return of put option.

5.2. Time Variation of Option Prices

Since rainfall data are updated as the time approaches expiration, the value of the option also changes as the weather data is updated. As the expiration date approaches, the amount of rainfall during the contract is gradually determined, and the value of the option is eventually equal to its strike price.

In the figure, the call option with K=550 is taken as an example. At the beginning of the year, the present value of the expected value calculated by the rainfall forecast is 7,125 yuan. With the change of the actual rainfall in Shenyang in 2021, the option price also fluctuates greatly. When rainfall is higher than expected in each month, the option price will rise; When rainfall is lower than expected, the option price will decrease.

In June 2021, Shenyang suffered the most rainfall in the same period since 1951, so the option value also rose sharply after the end of June, and its price exceeded 13,000 yuan. The actual rainfall in the following month was lower than expected, resulting in a slight decrease in the option price. However, since the peak of the accumulative rainfall in August was not expected in time and was postponed to September, after the end of August, the rainfall situation much lower than expected led to the option value dropping to 0 yuan. However, with the unexpected over rainfall in September, the option value gradually increased. Finally, after the end of September, the accumulative rainfall from May to September is 579.3mm, and the minimum unit of variation of CRI index is 1mm. Therefore, the value is 597, which is higher than the execution value of 550. The buyer chooses to exercise the option and gets a cash inflow of 8700 yuan for each one. If an option buyer buys at the beginning of the year and holds it until the end of September, the income from each option after expiration not only covers the option fee expense of \$7,125 at the beginning of the period, but also brings a net income of \$1,575.

Figure 15. Trend and characteristics of time variation in option prices.

5.3. Feasibility Analysis of Transactions

5.3.1. Traders

(1) Buyer

This product sets up call options with high strike value and put options with low strike value, which can be used to deal with weather risks of insufficient rainfall and excessive rainfall respectively. Therefore, option buyers are mainly groups that will suffer losses due to extreme rainfall, among which agricultural producers and agriculture-related industries are the main parts. At present, agricultural producers generally deal with weather risks by risk retention or purchasing agricultural insurance. Here are the advantages of this rainfall index option product over agricultural insurance products:

At present, there are many types of agricultural insurance, mainly including the protection of production facilities and agricultural products. The insurance for agricultural products can be divided into two types: cost insurance and income insurance. The coverage of different insurance products is different. This product is designed for rainfall, and producers only need to judge the sensitivity of future income to rainfall, so they can buy a call or put option on rainfall according to their own needs. Assuming that there are other types of weather index products in the market, the same producer can buy a call or put option on rainfall according to the sensitivity of each factor in its production process. Independently select the type, quantity and trading point of weather index option products.

In addition, the compensation conditions in the insurance clauses are strict, and there are certain technical quality requirements for each process of its production. Moreover, the compensatory insurance is based on the actual loss amount, and the loss rate also needs to reach a certain index to be paid. In addition, the underwriting and claim settlement procedures are complex and highly technical, and the verification results lack unified standards. Moreover, insurance companies need to spend a lot of manpower, material and financial resources for this part of the process, resulting in high operating costs and management costs. However, the maturity price of this product is only related to the actual rainfall in the region, which is calculated based on the data published by the Meteorological Bureau. It is objective, unified and low-cost. There is no provision on whether the trader has insurance interest, and its final income is not limited according to its actual profit and loss.

(2) Seller

The seller of this option is mainly the subject that can benefit when the rainfall deviates significantly from the expectation, which can be divided into two categories: one is the direct benefit through the increase of the profit of its production products, and the other is the benefit through the change of the price of related assets.

The first category of sellers, such as rain gear manufacturers, dehumidifier manufacturers, agricultural water-retaining agents or water-absorbing agents' manufacturers, will generally bring more than expected profits due to market factors such as increased sales or higher prices of their products when there is unusually high or low rainfall. A rain gear manufacturer, for example, can choose to sell a call option on rainfall at the beginning of the year to obtain a current cash inflow, which can be used to start a production line or make production investments. If there is less rainfall in the rainy season this year, the demand for its products is also less, and the manufacturer cannot obtain the expected profit. However, since the capital used in production is the income from the put option, the strike price is not triggered at this time, and there is no cash outflow, the capital integrated into the product is a compensation for the decline in its product profit. When the rainfall exceeds expectations this year, the seller is required to pay a cash payment at the end of the option period. However, as a rain gear manufacturer, its profit during the corresponding period also increases due to the increase of rain, and the option payment can be regarded as the repayment of the funds it has integrated at the beginning of the year.

The second type of seller generally holds assets whose prices are affected by rainfall. For example, investors with long positions in agricultural futures can choose to sell call or put options. When rainfall leads to production reduction of agricultural products, the price of agricultural products rises, and the long position of agricultural products futures gains profits, while the option seller pays a certain amount. When the rainfall is in the normal range, the agricultural products produce normally, and the long position of the futures cannot or less gain income, while the normal rainfall does not trigger the strike price, the option fee earned by the selling option increases the return, and the volatility of the return is reduced in general.

To sum up, compared with traditional risk management means, this rainfall index option product has the advantages of high flexibility, objective maturity value, few restrictions on participants and low internal cost, which reduces the volatility of future returns of trading subjects and hedges rainfall risk well. As a result, the option market has a wide range of participants and reduces the price risk caused by market speculators.

5.3.2. Trading Platform

During the operation of the product, the trading platform only needs to obtain rainfall information from the meteorological bureau of the specified area of the product and publish the accumulated rainfall up to the trading day. Market participants can independently buy and sell and bid according to the published information and judgment of the future. During the whole period of option trading, due to its large number of participants, the trading platform can obtain a large amount of commission fees from it, and the cost of running the product is very low, so the product can bring considerable profits to the trading platform.

In addition, as mentioned above, the holder of the relevant asset can manage the risk by buying and selling the option. Therefore, the launch of the option product can also become part of the portfolio investment strategy of some assets, which also has a positive effect on the buying and selling of the relevant asset. If the trading platform also provides services for this part of the asset, the option can also increase the profit of the trading platform by affecting the trading volume of the related asset.

5.3.3. Government

Due to the characteristics of agricultural insurance, such as high risk, high operating cost and widespread information asymmetry, there are failures in the agricultural insurance market. Therefore, to guarantee farmers' income, stabilize the enthusiasm of agricultural production and promote agricultural industrialization, the government will choose to borrow from the agricultural insurance market to provide a series of relevant support for agricultural producers to participate in agricultural insurance. For example, the establishment of state-owned agricultural insurance companies, the establishment of corresponding systems to manage the agricultural insurance market, agricultural insurance companies and cooperative insurance organizations to provide financial subsidies, etc. Therefore, many current agricultural insurances are policy-based insurance, in which the government needs to invest financial subsidies to ensure both agricultural production and insurance company operation.

If agricultural producers can hedge rainfall risk through option products, it will not only solve the dilemma of insurance companies, but also reduce the financial pressure of the government in stabilizing agriculture and ensuring income. Introducing participants with opposite exposures in the market redistributes funds from extreme weather losses to farmers to other economies that may benefit from them. In the whole process, risk transfer and loss compensation are completed spontaneously through the market, which greatly reduces the direct intervention of the government and plays the role of the "invisible hand", which not only protects the interests of farmers, but also improves the marketization degree of risks.

5.3.4. Research Conclusions and Suggestions

As one of the big agricultural countries in the world, agriculture has a profound impact on the economy of our country. As the basic sector of the three major economic sectors, how to alleviate the current situation that agriculture is vulnerable to extreme weather and cause heavy economic losses is a problem that China must face in the continuous development. Rainfall has a significant impact on China's economy and agriculture, and the rainfall index option contract can be used to hedge the loss risk caused by extreme rainfall. However, the rainfall itself fluctuates greatly, and because of the vast territory of our country, the characteristics of rainfall in different regions are not all the same, and the regional difference is obvious.

In this paper, the less studied rainfall is selected as the research target, and Shenyang is taken as the research area. Based on the historical rainfall data from 2000 to 2020, the SARIMA model is used to do time series fitting, and the rainfall of Shenyang is analyzed and predicted. After considering the obvious seasonal characteristics of rainfall, a seasonal option contract is set according to the crop characteristics of Shenyang, and the option price is calculated by Monte Carlo model. Finally, a complete option contract is formulated, which provides a reference for the development of weather option in China and a new way for agricultural producers to avoid the risk of abnormal rainfall.

5.3.5. Countermeasures and Suggestions

In addition, we give the following suggestions for different subjects:

Farmers: Most agricultural insurance has the disadvantages of high insurance threshold, harsh compensation conditions and poor compensation, while new weather derivatives such as rainfall options have the characteristics of low purchase threshold, objective and uniform compensation conditions, small limit on compensation amount, and are not based on their actual profit and loss. Farmers can reasonably choose financial products according to their own risk preference and demand for compensation, and appropriate selection of new weather derivatives can greatly increase their ability to resist extreme risks.

Financial institutions: Compared with traditional risk diversification tools such as agricultural insurance, weather derivatives not only have low operating costs and management costs, but also have a much larger scope of trading subjects, not only limited to agricultural producers. The demand for products is large, and the benefits brought by weather derivatives will also increase. So various financial institutions can deal in more such weather derivatives. In addition, operating a wealth of financial products is of great benefit to the development of China's financial market.

Government: as a new tool of financial derivatives to resist extreme weather, it can help farmers protect their own interests and ultimately improve our country's ability to resist weather risks. It can not only reduce the direct intervention of the government, but also reduce the national agricultural risk loss, which greatly improves the marketization degree of risks.

Therefore, the government should vigorously promote the popularity of weather derivatives and guide financial institutions to develop more derivatives like those designed in this paper through active policies.

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References

- [1] Davis, M. (2001). Pricing weather derivatives by marginal value. Quantitative Finance, 1(3), 305-308. DOI: 10.1080/713665730
- [2] Liu Yuanyuan. (2005). Re understanding of the functions of weather derivatives and financial derivatives. International Finance Research, (08), 53-56.
- [3] Xie Shiqing, Mei Yunyun. (2011). The operational mechanism and actuarial pricing of weather derivatives. Financial Theory and Practice, 32(06), 39-43.
- [4] Pan Xiaojun, Pu Chengyi. (2009). Design and constraints of risk bonds for tobacco and hail disasters. 2009 China Disaster Prevention Association, conference proceedings.
- [5] Pan Xiaojun, Pu Chengyi. (2015). Risk of sugarcane meteorological disasters and risk bond design under global climate anomalies. Insurance Research, (5), 11-18.
- [6] Wang Mingliang, He Jianmin, Cao Jie. (2015). Research on Pricing of Weather Derivatives in China Based on Temperature Index. Mathematical Statistics and Management, 34(02), 217-227.
- [7] Chen Mingshu. (2020). Pricing of weather derivatives in agricultural risk management. Overseas Chinese University. DOI: 10.27155/d.cnki Ghqiu.2020.000549
- [8] Dong Jianshe. (2023). Agricultural insurance design based on the summer maize drought weather index model in Puyang City. Zhongnan Agricultural Science and Technology. No.9.
- [9] Wang Xiaoli, Chen Shengwei. (2023). Path Analysis of Policy based "Meteorological Index Income Insurance" Supporting the Development of New Agricultural Business Entities. Lanzhou Academic Journal, No.10.
- [10] Chen Yanshui. (2023). Weather Index Insurance Supports Agricultural Protection Umbrella. Rural Financial Accounting. No.10.
- [11] Li Zhixing. (2023). Development Status and Reflection on Meteorological Index Insurance. Fujian Finance, (08), 53-60.
- [12] Huang Bo. (2019). Research on the Application of Drone Technology in Crop Insurance. Professional Master's Thesis, Kunming University of Technology.
- [13] Li Jianping, Qu Yao. (2022). Risk analysis and insurance transfer dilemma of intelligent drones. Science and Technology Innovation, (34).
- [14] Jiang Huiqin. (2013). Development and Pricing of Weather Derivatives Based on Rainfall Index. Nanjing University of Information Technology.
- [15] Huang Feng, Wang Baoqian. (2017). Research on precipitation option pricing based on precipitation data in Fuzhou. Water Resources Economics, 35(06), 44-49+81.
- [16] Huang Haonan, Zheng Xiang, Wei Yongfeng. (2018). Valuation of meteorological element prediction and weather multi factor options based on BP neural network-SARIMA combination model. Investment Research, 37(05), 82-97.
- [17] He Lijun. (2021). Research on pricing derivatives of rainfall index based on SARIMA Model. Journal of Jingdezhen University, No.3, 17-20.
- [18] Niu Zhijuan, Hu Hongping, Bai Yanping, Li Qiang. (2016). Prediction of Urban Precipitation Based on BP, PCA-BP, and PLS Algorithms. Journal of North Central University (Natural Science Edition), 37(02), 181- 186
- [19] Ma Zhanqing, Xu Mingxian, Yu Weiyang, Wen Shuyao. (2010). Markov prediction model for annual precipitation statistics and its application. Journal of Natural Resources, 25(06), 1033-1041.
- [20] Ni Yuanchen. (2014). Research on precipitation prediction model in Donggang City based on support vector machine. Shaanxi Water Resources, (02), 134-135.
- [21] Zhen Yiwei, Hao Min, Lu Baohong, Zuo Jian, Liu Huan. (2015). Research on Medium- and Long-Term Precipitation Prediction Model Based on Random Forests. Hydroelectric Energy Science, 33(06), 6-10.
- [22] Liu Xin, Zhao Ning, Guo Jinyun, Guo Bin. (2020). Monthly precipitation prediction on the Qinghai Tibet Plateau based on LSTM neural network. Journal of Earth Information Science, 22(08), 1617-1629.
- [23] Ulrich H. (1996). Box Jenkins modeling in medical research. Statistical Methods in Medical Research, 5(1), 3-22.
- [24] Pan Dianya. (2021). GDP Analysis and Prediction of Jilin Province Based on ARIMA Model. China Collective Economy, (27), 15-16.
- [25] Wang Yan. (2022). Time Series Analysis Based on R 2nd Edition. Renmin University of China Press.

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