Research on Agricultural Drought Risk Measurement Based on Bayes Hybrid Model

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The development of agricultural economy depends to a large extent on the drought. It is necessary to accurately analyze the current drought risk in order to formulate a more reliable drought risk management strategy and reduce the impact of disasters on the development of the agricultural economy. In order to improve the level of drought risk measurement, this paper selects VaR as the measurement tool, and proposes a mixed distribution model research. Use this model to fit the distribution of drought loss rate, and measure the drought risk by estimating VaR. Among them, the mixed distribution model is mainly composed of two parts, namely GPD and conventional distribution. The former is used to characterize the risk tail. Considering the difficulty of selecting the GPD distribution threshold, this paper introduces the Bayes calculation method to optimize, forming a Bayes hybrid model, including Norm-GDP model and Gamma-GPD model. The application results show that the fitting results generated by the Norm-GDP model application have a better distribution of drought loss rates, and the VaR estimation results are more reliable. Taking 10-year, 20-year, and 100-year disasters as examples, the estimated drought loss rate is 9.46%, 11.05%, and 30.22%. The generation of these metric values can provide a reference for my country's agricultural drought risk management.

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China is a large agricultural country, and the development of agricultural economy has a greater impact on the overall economic development of our country. How to improve the development of agricultural economy is an important task of China's current economic construction [1-2]. Through collecting a large amount of data, it can be seen that the main reason for the difficulty of China's agricultural economy is drought. The failure to analyze the risk of drought in depth has led to inadequate handling of drought problems and failed to effectively reduce the loss rate caused by drought [3-4]. Therefore, how to strengthen drought risk management and deal with drought problems scientifically and effectively is one of the long-term concerns of agricultural development. In the past, the research on drought risk was based on drought statistical data, and the evaluation accuracy was low. This paper introduces the Bayes method, proposes the Bayes hybrid model, and uses it as a risk measurement tool to conduct research [5].

BAYES HYBRID MODEL

Extreme Value Theory and POT Model

At present, extreme value theory is selected as the theoretical basis for risk management research in many fields such as insurance and finance [6]. Assuming loss variables, these variables are independent and identically distributed, the cumulative distribution function is internally distributed, and the maximum loss is recorded as converging to GEV. The corresponding function is as follows:

$$G(z)=\begin{cases} exp\left(1-\left(1+\xi\frac{z-u}{\sigma}\right)^{1/\xi}\right), \xi\neq 0,1+\xi z>0 \\ exp\left(-exp\left(\frac{z-u}{\sigma}\right)\right), \xi=0,-\infty<z<\infty \end{cases} \quad (1)$$

In formula (1), represents the shape parameter; represents the scale parameter; represents the position parameter. Considering the large data demand of this model, the scope of application of

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the model is limited. In order to make up for the shortcomings of the model, this paper proposes the POT model, which has a larger threshold, the GPD density function is shown in formula (2), and the distribution function is shown in formula (3).

$$g\left(\frac{y}{\xi},\sigma\right)=\begin{cases}\sigma^{-1}\left(1+\frac{\xi y}{\sigma}\right)^{-(1+\xi)/\xi}, 1+\frac{\xi y}{\sigma}>0\\ \sigma^{-1}exp\left(-\frac{1}{\sigma}\right), \xi=0\end{cases} \quad (2)$$

$$G\left(\frac{y}{\xi},\sigma\right)=\begin{cases}1-\left(1+\frac{\xi y}{\sigma}\right)^{-1/\xi}, \xi\neq 0\\ 1-exp\left(-\frac{1}{\sigma}\right), \xi=0\end{cases} \quad (3)$$

The threshold of this function is difficult to control, which makes it difficult to control the convergence of GPD. At present, no scientific guarantee has been given. Therefore, this paper attempts to propose a mixed distribution function [7].

Mixed Distribution Function

In the mixed model, the threshold is set, the higher part is characterized by GPD, and the lower part is characterized by the conventional loss distribution [8]. Assuming that the threshold is greater than the observed value and is independent and identically distributed, the corresponding function is recorded as, and GPD is used to record the over-threshold part. The distribution function corresponding to the random variable X is expressed by formula (4), and the density function is expressed by formula (5).

$$F(x|\eta,\xi,\sigma,u)=\begin{cases}H(x|\eta), x\le u\\ H(u|\eta)+\left(1-H(u|\eta)\right)G(x|\xi,\sigma,u), x>u\end{cases} \quad (4)$$

$$f(x|\eta,\xi,\sigma,u)=\begin{cases}h(x|\eta), x\le u\\ \left(1-H(u|\eta)\right)g(x|\xi,\sigma,u), x>u\end{cases} \quad (5)$$

In the formula 4 and formula 5 , it represents the GPD distribution density function.

In the formula, $\theta=(\theta_1,\theta_2,u),\theta_1=\eta,\theta_2=(\xi,\sigma)$,calculate the logarithm of the loss sample likelihood function in the formula 6 :

$$L(\theta;X)=\prod_{\{i;x_i<u\}}h(x_i|\theta_1)\prod_{\{i;x_i>u\}}\left(1-H(u|\theta_1)\right)g(x_i|\theta_2) \quad (6)$$

When $\xi<-0.5$,there is no likelihood estimation。To make up for the shortcomings of this function, this paper introduces the Bayes method [9].

Bayes Calculation and Judgment

The calculation under Bayes theory is as formula 7:

$$f_X(x/y)=\frac{f_X(x)f_Y(y/x)}{\int f_X(x)f(y/x)dx} \quad (7)$$

The model supports prior information, and the loss function is constructed in units of square loss.

(1)Bayes calculation judgment based on Gamma-GPD mixed distribution

Suppose that GPD describes the over-threshold part, and the overall description of the Gamma distribution is less than the threshold part. Combine these two parts together to optimize the Gamma function, modify the likelihood function, and combine the prior distribution to get the posterior distribution function of the vector as follows , Use this function to calculate Bayes inferred value [10].

$$\pi_0(\theta|x_1,\cdots,x_n)\propto \prod_{\{i;x_i<u\}}\frac{\beta^\alpha}{\Gamma(\alpha)}e^{-\beta\pi_i x^{\alpha-1}}\times\prod_{\{i;x_i>u\}}\left(1-F_g(u|\alpha,\beta)\right)^{-1}\frac{1}{\alpha}\left(1+\frac{\xi(x_i-u)}{\sigma}\right)^{-\frac{1+\xi}{\xi}}\times\frac{b^\alpha}{\Gamma(\alpha)}\alpha^{-\alpha-1}exp\left(-\frac{b}{\alpha}\right)\frac{d^c}{\Gamma(c)}\beta^{c-1}exp(-d\beta)\times\sigma^{-1}(1+\xi)^{-1}(1+2\xi)^{-1/2}\times\frac{1}{\sqrt{2\pi}\sigma}exp\left(\frac{(u-\mu_u)^2}{-2\sigma_u^2}\right) \quad (8)$$

In formula 8, the parameters a, b, c, and d are all hyperparameters, and all of them are functional prior distributions.

(2) Bayes calculation judgment based on Norm-GPD mixed distribution

In addition to the above inference methods, this article also proposes an inference method based on Norm-GPD.Assuming that the random variable X obeys a normal distribution$N(\mu_N,\sigma_N^2)$,calculate the cumulative distribution function and the corresponding density function. Take the conventional prior distribution and calculate the posterior distribution function on the parameters θ as formula 9:

$$ln\pi_3(\theta|X)=c+\sum_{\{i;x_i<u\}}\left(-ln\sigma_N-\frac{(x_i-\mu_N)^2}{2\sigma_N^2}\right)+\sum_{\{i;x_i>u\}}\left(ln\left(1-\Phi\left(\frac{x_i-\mu_N}{\sigma_N}\right)\right)-ln\sigma+ln\left(1+\xi\frac{x_i-u}{\sigma}\right)\right)-ln\sigma_N^2-ln\sigma-ln(1+\xi)-\frac{1}{2}ln(1+2\xi)-ln\sigma_u^2-\frac{(u-\mu_u)^2}{2\sigma_u^2}-ln\sigma_{\mu_1}^2-\frac{(u-\mu_{\mu_1})^2}{2\sigma_{\mu_1}^2} \quad (9)$$

At present, MCMC sampling methods are more commonly used, and the Metropolis-Hastings method in this study is used as a sampling tool.

BAYES HYBRID MODEL AND RISK MEASUREMENT

VaR is a maximum loss measurement tool, which is used in many fields. This study uses this tool to establish the variable distribution function [11].

$$VaR(p) = F^{-1}(p,\theta) \qquad (10)$$

Applying this tool to the mixed distribution function, the following calculation formula 11 is obtained:

$$VaR(p) = \begin{cases} H^{-1}(p), H(u) > p \\ u + \frac{((1-p)^{-\xi}-1)\sigma}{\xi}, , H(u) \le p \end{cases} \qquad (11)$$

THE APPLICATION OF BAYES HYBRID MODEL IN AGRICULTURAL DROUGHT RISK MEASUREMENT

Calculation and Analysis of Crop Loss Rate

The disaster risk measurement proposed in this article refers to the loss that may be caused by a certain period of time in the future. According to the loss measurement idea in the literature [12], the following loss rate measurement model is constructed:

$$R_t = S_{1t} - S_{2t}\alpha_1 + (S_{2t} - S_{3t}\alpha_2 + S_{3t}\alpha_3)/S_{0t} \qquad (12)$$

In formula (12), planting area, disaster area, disaster area, disaster area, disaster area, and no harvest area. Using formula (12), statistical loss rate, the results are shown in Table 1.

Table 1
Statistics of agricultural drought loss rates from 2007 to 2020

Years	2007	2008	2009	2010	2011	2012	2013
Loss rate/%	8.17	3.82	7.41	4.35	3.96	2.06	3.42
Years	2014	2015	2016	2017	2018	2019	2020
Loss rate/%	3.35	3.11	3.00	2.86	2.74	2.64	2.53

From the statistical results in Table 1, there is no linear change in the loss rate, so the drought loss in the previous year will not affect the drought loss in the next year. In addition, from the statistics of qq distribution, it can be known that the drought loss rate has a thick tail.

Evaluation and Analysis of Agricultural Drought Loss Rate

In this study, A-D test and K-S test were used to test the normal distribution of the two models. The results are shown in Table 2.

Table 2
Non-parametric goodness of fit test results

Regular distribution	A-D inspection		K-S inspection	
	P value	Statistics	P value	Statistics
Normal	0.8740	0.37436	0.6925	0.11095
Gamma	0.9156	0.32906	0.9035	0.08822

In Table 2, the P values of the two models are both greater than 0.05, so the two models obey the normal distribution. Among them, the Gamma model is more dependent on sample data. Therefore, this study chooses these two models to construct a mixed model, and uses the MCMC sampling method to count the Norm-GPD mixed distribution function and Gamma-GPD mixed distribution function sampling results, as shown in Table 3. DIC comprehensive statistical results, the smaller the value, the better the sampling result.

Table 3
Parameters MCMC sampling results

Model	parameter	Sampling mean	G-R statistics	Standard deviation	0.975 points	0.025 分 points	DIC
Norm-GPDMixed distribution	σ_1	2.531	1.003	0.354	3.361	1.951	-87.188
	μ_1	6.282	1.002	0.393	7.086	5.542	
	σ	1.316	1.003	1.701	6.570	0.070	
	ξ	1.024	1.004	1.855	5.624	-1.679	
	u	9.174	1.000	0.749	11.025	8.043	
Gamma-GPDMixed distribution	β	0.566	1.012	0.124	0.843	0.351	-86.931
	α	3.684	1.013	0.693	5.181	2.469	
	σ	1.320	1.005	1.320	4.911	0.084	
	ξ	1.411	1.003	1.411	3.951	-1.595	

	u	8.841	1.006	0.755	11.119	7.962	

The statistical results in Table 3 show that the DIC comprehensive sampling result of the Norm-GPD mixed distribution model is -87.188, which is less than -86.931. Therefore, the advantages of this model are greater.

Measurement and Analysis of Agricultural Drought Risk

The two mixed distribution models proposed in this paper are applied to the drought risk measurement, and the loss value VaR and dispersion are counted. The results are shown in Table 4.Among them, p=0.99 is defined as a drought in 100 years, p=0.95 is defined as a drought in 20, and p=0.90 is defined as a drought in 10.

Table 4
Agricultural drought loss value VaR and accuracy statistics results

Statistical indicators	0.75		0.80		0.85		0.90		0.95		0.99		Mean absolute deviation
	Deviation	VaR	Deviation	VaR	Deviation	VaR	Deviation	VaR	Deviation	VaR	Deviation	VaR	
Gammadistributed	0.065	7.35	0.115	7.83	0.088	8.40	-0.022	9.15	0.004	10.35	0.015	13.0	0.049
Gamma-GPD Mixed distribution	-0.012	8.36	-0.067	8.95	-0.069	9.45	-0.046	10.71	-0.06	15.04	-0.01	68.41	0.045
Normdistributed	0.040	7.99	0.036	8.5	0.007	0.036	-0.019	9.49	0.004	10.44	0.015	12.14	0.022
Norm-GPDMixed distribution	0.040	8.00	0.036	8.39	0.007	8.89	-0.019	9.46	0.004	11.05	-0.01	30.22	0.019

Combining actual experience and analyzing the statistical results in Table 4, the risk measurement results generated by the Norm-GPD mixed distribution model are closer to actual experience, while the Gamma-GPD mixed distribution measurement results have a serious overestimation problem.

CONCLUSION

This paper explores the problem of agricultural drought risk measurement. By constructing a drought loss rate model and introducing Bayes algorithm, it proposes the creation of two hybrid models. Use the VaR tool to calculate the drought loss rate, compare the VaR statistical results of the two models, and combine actual experience to select a model that is more suitable for the measurement of the drought loss rate. The application results show that the Norm-GPD mixed distribution model measures the drought loss rate more closely with actual experience, and the results are more helpful for agricultural drought risk management. In the follow-up agricultural drought prevention work, you can try to use this article to propose a risk measurement plan to measure the drought risk in the next 1, 3, 5, and 10 years, and based on the measurement results, do a good job of preventing drought against drought. Lay the foundation for agricultural development. In addition, with the update of the measurement algorithm, it is also necessary to optimize the drought risk measurement model to continuously improve the accuracy of risk measurement and meet the measurement requirements under different conditions.

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