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Weather-Driven Loss Modeling for Rice Farmers' Losses Using Cobb–Douglas and VaR–ES

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ABSTRACT

Weather variability poses significant risks to rice production, leading to potential income losses for farmers and increased uncertainty in agricultural planning. This study integrates a Cobb–Douglas production function with Value at Risk (VaR) and Expected Shortfall (ES) measures to assess weather-driven production losses in Aceh Besar using secondary data on rainfall, temperature, and wind speed from 2010 to 2023. Rice production is first modeled to estimate output sensitivity to climatic factors, after which production losses are derived from forecast-based outcomes. Several candidate parametric probability distributions are fitted to the loss data, and the most suitable distribution is selected based on goodness-of-fit ranking. The results indicate that weather variables significantly reduce rice output and that the production process exhibits decreasing returns to scale. The selected distribution yields a potential loss of IDR 774,352 and an expected loss of IDR 940,160 per hectare at the 95% confidence level. These findings provide a quantitative basis for weather-based agricultural risk assessment and support evidence-based risk mitigation strategies for farmers and policymakers.

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1. INTRODUCTION

The agricultural sector plays a crucial role in achieving the second Sustainable Development Goal (SDG), Zero Hunger, which emphasizes food security, improved nutrition, and sustainable agriculture. In Indonesia, agriculture is the second-largest contributor to national Gross Domestic Product (GDP), highlighting its importance for economic stability and rural livelihoods [1]. Rice farming, as a strategic subsector, is central to food security due to rice being the primary staple food for the population [2]. Consequently, maintaining stable rice production is essential, particularly in the context of population growth and increasing food demand [3].

Despite its importance, rice production in Indonesia remains highly vulnerable to weather variability. In Aceh Province, rice production declined by 7.68% in 2023 compared to the previous year, with significant reductions occurring in several major rice-producing districts [4]. Extreme weather events such as floods and droughts are among the main drivers of crop failure, directly affecting farmers' productivity and income. Climate change is expected to intensify these risks by increasing temperature extremes, altering rainfall patterns, and raising the frequency of extreme events, all of which negatively affect crop growth and agricultural sustainability [5]–[8].

Previous studies have extensively examined the relationship between weather conditions and rice production. Research using production-function and stochastic approaches has shown that rainfall, temperature, and wind speed significantly influence rice yields [9] [11]. While these studies provide important insights into yield variability, they largely focus on biophysical production outcomes and do not explicitly quantify the financial losses faced by farmers under extreme weather conditions. As a result, the economic implications of weather-induced production shocks remain insufficiently explored. Previous studies have identified drought and flood events as the dominant causes of rice crop failure, with drought consistently ranked as the primary driver of production losses, while prolonged climate variability has been shown to reduce farmers' welfare and increase economic vulnerability [12] [13].

From a risk-management perspective, weather-induced crop failure represents a form of extreme loss that cannot be adequately captured by average yield analysis alone. Value at Risk (VaR) and Expected Shortfall (ES) are widely used risk measures designed to quantify tail risk, that is, the risk of rare but severe losses. Unlike VaR, which identifies a loss threshold at a given confidence level, ES measures the expected magnitude of losses exceeding that threshold and satisfies desirable mathematical properties such as subadditivity and convexity [14], [15]. However, applications of VaR–ES in agricultural contexts particularly those integrated with production-function modeling remain limited, especially in Indonesia.

This study addresses this gap by integrating a Cobb–Douglas production function with Value at Risk (VaR) and Expected Shortfall (ES) measures to quantify weather-driven rice production losses. Weather variables, including rainfall, temperature, and wind speed, are incorporated into the production function to capture output sensitivity to climatic conditions. To characterize the distribution of production losses and the associated financial risks, the study fits several candidate parametric probability distributions to forecast-based loss data and selects the most appropriate model based on goodness-of-fit criteria. By combining production modeling with distribution-based risk assessment, this study provides a quantitative framework for evaluating weather-related agricultural risk, offering insights that are directly relevant for farmers, policymakers, and agricultural risk management strategies.

2. RESEARCH METHOD

2.1 Data Source and Variables

Data collected in this study are secondary data obtained from Aceh Besar Agricultural service and Climatology Station. The scope of this research is risk management of rice farming losses, especially in Aceh Besar, Aceh, Indonesia. it can be used for other regions that have similar weather. The variables of this study are the amount of rice production per growing season, rainfall, temperature, and wind speed. The data used are data from 2010 to 2023. Considering the weather data in Indonesia, especially Aceh Besar, is different every month, the presentation of the data is grouped by month, and calculated the average per growing season of rice. After data aggregation and preprocessing, the final dataset consists of 22 observations, representing seasonal rice production outcomes over the study period. The recorded data consist of rice productivity, wind speed, temperature, and rainfall data. The processed data were obtained over a period of approximately 13 years. In this paper, data analysis of weather variables on rice production (Y) is carried out as the dependent variable. Weather variables, which consist of wind speed (X_1), average temperature (X_2), and rainfall (X_3), then act as independent variables. These variables will be modeled using a linear regression model, followed by classical assumption tests, namely normality, multicollinearity, heteroscedasticity, and autocorrelation tests.

2.2 Cobb–Douglas Production Function

To analyze the relationship between weather variability and rice production, a Cobb–Douglas production function is employed. The Cobb–Douglas specification is appropriate because rice production depends multiplicatively on weather inputs, and output is assumed to approach zero when any essential climatic factor is absent [11],[16]. The Cobb–Douglas production function is estimated in its log-linear form, which allows the model to be expressed as a linear regression with respect to the transformed variables and enables the application of standard classical assumption tests. The production function is expressed as equation (1)

$$Y = \beta_0 X_1^{\beta_1} X_2^{\beta_2} X_3^{\beta_3} \quad (1)$$

Where Y denotes rice production, X_1, X_2 and X_3 represent rainfall, temperature, and wind speed, respectively β_0 is a scale parameter, β_i are output elasticities, and μ is a stochastic error term.
Taking natural logarithms yields the estimable linear form in equation (2).

$$\ln \hat{Y} = \ln \beta_0 + \beta_1 \ln X_1 + \beta_2 \ln X_2 + \beta_3 \ln X_3 + \mu \quad (2)$$

The parameters are estimated using ordinary least squares (OLS). Classical assumption tests, including normality, multicollinearity, heteroskedasticity, and autocorrelation tests, are conducted to ensure the validity of the regression model. In this study, production loss is defined as the deviation of observed output from its estimated expected level, such that losses occur when realized production falls below the model-implied baseline due to adverse weather conditions. It should be noted that non-climatic production factors, such as land area, fertilizer use, and technological inputs, are not explicitly included in the model due to data limitations, which may introduce omitted variable bias into the estimated production relationships. The parameters β_1, β_2 and β_3 as represent the elasticities of the input factors X_1, X_2, and X_3, respectively. The sum of these elasticity parameters reflects the production response to proportional changes in all inputs, which can be interpreted as returns to scale. The following conditions apply [11]:

a. Constant returns to scale occur when $\sum_{i=1}^{3} \alpha_i = 1$. Under this condition, a proportional increase in all input factors results in an equivalent proportional increase in output. For example, doubling all inputs leads to a doubling of output.
b. Increasing returns to scale occur when $\sum_{i=1}^{3} \alpha_i > 1$. In this case, a proportional increase in inputs results in a more than proportional increase in output. For instance, doubling the input factors may lead to output increasing by more than two times, such as tripling or quadrupling.
c. Decreasing returns to scale occur when $\sum_{i=1}^{3} \alpha_i < 1$. Under this condition, a proportional increase in inputs results in a less than proportional increase in output. Thus, when all inputs are doubled, the resulting increase in output is smaller than double.

2.3 Risk Analysis

Production risk is analyzed by focusing on downside losses associated with adverse weather conditions. Rice production returns are defined as the logarithmic difference between observed production and its fitted value from the Cobb–Douglas model, capturing deviations attributable to extreme weather shocks. Negative returns correspond to production losses and are used for tail risk modeling.

Value at Risk (VaR) and Expected Shortfall (ES) are employed to quantify the magnitude of extreme losses. The lower tail of the return distribution is modeled, as it represents unfavorable production outcomes. Let X denote the loss variable derived from negative production returns with cumulative distribution function $F_X(x)$. The Value at Risk at confidence level α is defined as equation (3)

$$VaR_\alpha(X) = F_X^{-1}(\alpha) = x_\alpha \quad (3)$$

ES means the amount of loss value that will be borne if there is a loss whose value exceeds *VaR*. *ES* can be written with the following mathematical equation (4):

$$ES_{1-\alpha}(X) = \frac{1}{\alpha}\int_{VaR_{1-\alpha}}^{1} x f(x)dx = \frac{1}{\alpha}\int_{1-\alpha}^{1} VaR_\mu(X)d\mu \quad (4)$$

Several candidate distributions, including the Generalized Extreme Value (GEV), Generalized Pareto, and Normal distributions, are fitted to the loss data. Distribution selection is based on goodness-of-fit statistics, namely the Kolmogorov–Smirnov, Anderson–Darling, and Chi-square tests, with priority given to tail-sensitive criteria. The selected distribution is subsequently used to estimate VaR and ES values and to compute potential financial losses faced by rice farmers.

3. RESULT AND ANALYSIS

In this paper, the risk value of rice is calculated based on changes in crop productivity results, with the Cobb-Douglas concept modified with the natural logarithm function by comparing the current production amount with the production amount of one previous period. To clarify the interpretation of production sensitivity, the logarithmic transformation allows the estimated coefficients to be interpreted as elasticities, capturing proportional changes in rice production associated with weather variability. Deviations between observed and fitted production values are later used to quantify downside risk attributable to adverse weather conditions, rather than to evaluate predictive accuracy alone. The variable used is the amount of production Y. Based on the results of data analysis, the production function model is obtained with the equation:

$$Ln\,\widehat{Y} = 12.98938 - 0.080527\,ln\,X_1 - 0.263015\,ln\,X_2 - 0.097326\,ln\,X_3$$

$$\hat{Y} = exp\,[12.98938 - 0.080527\,ln\,X_1 - 0.263015\,ln\,X_2 - 0.097326\,ln\,X_3]$$

The value of $\ln\beta = 12.98938$ or $\beta = exp\,(12.98938) = 437739.82$, meanwhile the value of $\alpha_1 = 0.080527$, $\alpha_2 = -0.263015$ and $\alpha_3 = -0.097326$, then rice production function based on weather variability can be written as:

$$\hat{Y} = exp\,[ln\,437{,}739.82\,X_1^{-0.080527} X_2^{-0.263015}\,X_3^{-0.097326}]$$

$$\hat{Y} = 437739.82\,X_1^{-0.080527} X_2^{-0.263015}\,X_3^{-0.097326}$$

In this case $\sum_{i=1}^{3}\alpha_i = -0.080527 - 0.263015\ - 0.097326 = -0.440868 < 1$, the function shows decreasing returns to scale, which means that an increase in input results in a disproportionate increase in output. In the context of weather variables, decreasing returns to scale indicate that unfavorable changes in climatic conditions can generate amplified negative effects on production. The negative elasticities should therefore be interpreted as reflecting production sensitivity to deviations from optimal weather conditions, rather than as linear marginal effects of increasing rainfall, temperature, or wind speed. In other words, if all inputs in the production process increase by a certain percentage, the output produced increases by a smaller percentage. Prob (F-statistic) = 0.004534 means simultaneously, weather variables affect rice production with a significance level of 0.05.

From the regression model obtained, the forecasting value of rice production influenced by weather factors will be calculated. The comparison of forecasting results and actual data can be seen in Figure 1.

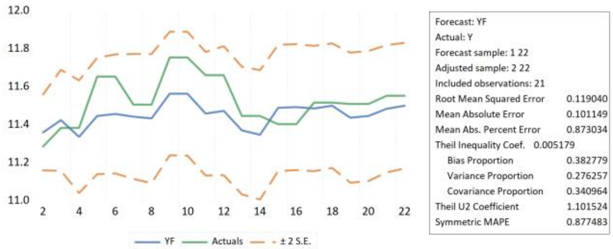

Figure 1. Comparison of Forecasting Results and Actual Data

Based on Figure 1, it can be seen that the MAPE value obtained is 0.873%, which means that the average error of the forecasting model against the actual data is only 0.87%. Although this low MAPE value suggests a strong in-sample fit, it should be interpreted with caution. The result may partly reflect the limited sample size and the use of in-sample estimation rather than out-of-sample validation; therefore, the MAPE is better viewed as an indicator of explanatory accuracy rather than predictive robustness.

Next, distribution fitting will be done from the forecasting data. The purpose of this step is to identify a probability distribution capable of adequately capturing extreme deviations in production outcomes associated with adverse weather conditions. Since the analysis focuses on tail risk, particular attention is given to distributions that provide a good fit in the tails rather than only around the mean. The pattern of return data is plotted and fitted with a distribution from the exponential family using Easy Fit 5.5. the results are presented in table 1.

Table 1. Plotting the results of rice yield return data.

	Distribution	Kolmogorov Smirnov		Anderson Darling		Chi-Squared	
		Statistic	Rank	Statistic	Rank	Statistic	Rank
1	Beta	0.28109	4	5.2675	4	N/A	
2	Exponential (2P)	0.31718	5	3.3216	3	14.768	3
3	Gen. Extreme Value	0.16779	1	0.57512	1	9.2542	2
4	Gen. Pareto	0.18255	2	7.973	5	N/A	
5	Normal	0.19151	3	0.58641	2	4.0238	1
6	Exponential	No fit					
7	Pareto	No fit					

Table 1 shows that the General Extreme Value distribution was the first rank, General Pareto was the second rank, and the Normal distribution was the third rank. The selection of the Generalized Extreme Value (GEV) distribution is primarily justified by its superior performance under tail-sensitive goodness-of-fit tests, especially the Anderson–Darling statistic. Distributions categorized as "no fit" indicate that the corresponding goodness-of-fit tests failed to satisfy acceptable significance thresholds and were therefore excluded from subsequent risk estimation. The complete results of parameter estimation for each data distribution are presented in Table 2.

Table 2. Parameter estimation results

#	Distribution	Parameters
1	Beta	$\alpha_1 = 0.83908$ $\alpha_2 = 0.77047$ $a = -0.10552$ $b = 0.14165$
2	Exponential (2P)	$\lambda = 8.9813$ $\gamma = -0.10427$
3	Gen. Extreme Value	$k = -0.18035$ $\sigma = 0.06346$ $\mu = -0.0198$
4	Gen. Pareto	$k = -0.77671$ $\sigma = 0.18842$ $\mu = -0.09897$
5	Normal	$\sigma = 0.06823$ $\mu = 0.00708$
6	Exponential	No fit
7	Pareto	No fit

Next, based on Table 2, we will calculate the VaR and ES values of the three distributions: the General Extreme Value, General Pareto, and Normal distribution presented in table 3.

Table 3. The values of VaR and ES

Distribution	α	VaR	ES
	0.95	0.096794	0.11752
General Extreme Value	0.99	0.13138	0.1451
	0.999	0.16654	0.15805
	0.95	0.11994	0.1741
General Pareto	0.99	0.13683	0.15235
	0.999	0.14248	0.14508
	0.95	0.11931	0.14782
Normal	0.99	0.16581	0.18893
	0.999	0.21793	0.23682

From Table 3, the *VaR* value increases as the α value increases; the same thing happens to the *ES* value. This pattern reflects increasing exposure to extreme losses under higher confidence levels. Differences in VaR magnitude across distributions highlight the sensitivity of risk estimates to distributional assumptions, with the GEV distribution providing a tail-consistent representation of extreme production losses.

Estimates of losses that can be suffered by rice farmers involving weather change factors can be calculated concerning the size of the risk of loss and the amount of capital spent. Based on BPS Aceh, farmers' average production cost per hectare per growing season is IDR 6,000,000 to IDR 8,000,000. Therefore, when referring to the average cost of rice production per hectare and planting period incurred by farmers of IDR 8,000,000 and the average income of farmers from production of IDR 15,000,000, the net profit is around IDR 7,000,000.

Furthermore, the possibility of farmers' losses on production capital will be calculated based on the VaR and *ES* values in Table 10. If it is assumed that the fixed capital for rice production per hectare per planting period is IDR 8,000,000, the potential losses that may occur in capital can be seen in Table 4.

Table 4. Value of risk of loss on capital.

Distribution	α	VaR (IDR)	ES (IDR)
	0.95	774,352	940,160
General Extreme Value	0.99	1,051,040	1,160,800
	0.999	1,332,320	1,264,400
	0.95	959,520	1,392,800
General Pareto	0.99	1,094,640	1,218,800
	0.999	1,139,840	1,160,640
	0.95	954,480	1,182,560
Normal	0.99	1,326,480	1,511,440
	0.999	1,743,440	1,894,560

Table 4 shows that if we look at the General Extreme Value distribution approach for α = 95% the potential loss experienced by farmers is IDR 774,352 if the capital spent is IDR 8,000,000. In other words, in 95 out of 100 growing seasons, farmers will experience a maximum loss of IDR 774,400 is the maximum value of losses that usually occur under normal conditions. While there is a 5% chance that the farmer's loss could be greater than IDR 774,400 means that in 5 out of 100 growing seasons the farmer is likely to be hit by a loss greater than IDR 774,400 due to adverse conditions such as natural disasters that cause greater losses. Meanwhile, the ES value of IDR 940,160 indicates the average loss that farmers may experience if losses exceed the VaR value. If the VaR value of IDR 774,400 is the maximum possible loss with a 95% confidence level, then the ES value of IDR 940,160 means that if there is a loss of more than IDR 774,400, the average loss that farmers face will be IDR 940,160. The ES value can help farmers who are exposed to risk in preparing themselves for the worst event. So, if a loss occurs that exceeds the *VaR* prediction, farmers should be prepared to face an average loss of IDR 940,160. These results translate statistical tail risk into economically meaningful measures, while also highlighting that estimated losses are conditional on model assumptions and may vary under alternative distributional or structural specifications.

The results of this study indicate that weather variability has a substantial impact on rice production and causes measurable financial risks for farmers. These findings are consistent with broader patterns observed in related studies. For instance, Impact of Historical Climate Variability on Rice Production in Mainland Southeast Asia [19] reported that fluctuations in rainfall and temperature significantly affect rice yields across Southeast Asia. While that study focused on multi-scale climate impacts on productivity, the present research extends the analysis by translating weather-induced variability into quantified financial losses using the VaR–ES framework, thereby providing a risk-oriented perspective not explored in earlier work.

Similarly, the study How Rice Responds to Temperature Changes and Defeats Heat Stress [20] found that temperature extremes contribute to reductions in rice productivity. However, unlike the [20] research which concentrates on physiological responses of rice to heat stress, this study incorporates climatic effects into a production-function model and evaluates the resulting economic risks faced by farmers. This offers a broader socioeconomic interpretation of how climate variability threatens farming livelihoods.

In addition, findings from the [21] meta-analysis on future climate-change impacts on rice yield indicated consistent yield reductions under increased temperature and rainfall anomalies. Although the meta-analysis focuses on projecting biophysical yield changes, the present study advances the literature by providing a practical assessment of current loss distributions under observed weather patterns. This novel combination of Cobb–Douglas modeling with VaR and ES strengthens the robustness of the analysis and contributes a methodological perspective that is increasingly relevant in agricultural risk studies.

Overall, the consistency of this study's findings with prior research supports the validity of the analysis. At the same time, the introduction of extreme-value-based financial risk measures offers new insights into how weather fluctuations translate into economic losses for rice farmers, which is essential for developing targeted risk-mitigation strategies and informing agricultural policy.

4. CONCLUSION

This study proposes a quantitative framework for assessing weather-related risk in rice production by integrating a Cobb–Douglas production function with Value at Risk (VaR) and Expected Shortfall (ES) measures. Weather variables are incorporated into the production model to estimate output sensitivity, after which forecast-based production outcomes are used to derive loss measures. Extreme production losses are characterized through parametric distribution fitting, with the most suitable probability distribution selected based on goodness-of-fit criteria. The empirical results indicate that adverse weather conditions significantly reduce rice output, while the estimated VaR and ES values highlight the magnitude of potential downside risk faced by farmers. Although the analysis demonstrates strong in-sample explanatory performance, the findings should be interpreted with caution due to data limitations and distributional assumptions. Overall, the proposed framework offers a transparent and flexible approach for translating weather-induced production variability into economically meaningful risk measures, providing a methodological basis for agricultural risk assessment and supporting informed risk management and policy decisions.

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