ISSN 2502-5872 (Print)
ISSN 2622-3627 (Elektronik)

Volume 10 Nomor 4, November 2025, 1011-1028

INSURANCE PREMIUM DETERMINATION MODEL USING THE COBB-DOUGLAS REGRESSION METHOD ON SHALLOT PRODUCTION

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ABSTRACT
The production risk of shallots is very high due to their vulnerability to pest attacks, diseases, and climate change, which creates uncertainty that may cause significant losses for farmers. Insurance protection has therefore become a necessity as an effort to mitigate financial losses and maintain farmers' stability even in the event of crop failure. Accordingly, this study aims to analyze the production factors of shallots in determining agricultural insurance premiums. The study employs the Cobb-Douglas production function to analyze production factors and the pure premium model to calculate shallot insurance premiums. Data were collected through questionnaires distributed to shallot farmers in Tasikmalaya Regency, with 50 respondents included in the analysis. Based on the results, the determination of shallot insurance premiums using the expectation principle produces higher premium values compared to the standard deviation principle. Premiums under the expectation principle are more sensitive to risk variation, whereas the standard deviation principle tends to yield more conservative and relatively stable premiums. The analysis applies the Cobb-Douglas regression model, with shallot production (Y) as the dependent variable, and land area (X1), seeds (X2), fertilizer (X3), pesticide use (X4), and labor (X5) as independent variables, resulting in a coefficient of determination (R^2) of 96.2%. The findings imply that the expectation principle is more appropriate for calculating insurance premiums under conditions of high and fluctuating production risk, while the standard deviation principle is more suitable for relatively stable risk conditions. These results can serve as a basis for formulating agricultural insurance policies that are adaptive to risk variation, while simultaneously promoting more effective financial protection for shallot farmers.
Keywords: Cobb-Douglas Model, Insurance Premium, Production, Agriculture, Shallot.

How to Cite: Saudi, J. H., Kalfin, K., & Diantini, N. L. S. (2025). Insurance Premium Determination Model Using The Cobb-Douglas Regression Method On Shallot Production. *Mathline: Jurnal Matematika dan Pendidikan Matematika, 10*(4), 1011-1028. http://doi.org/10.31943/mathline.v10i4.1051

PRELIMINARY

Shallot farmers often face significant risks of losses due to various factors affecting harvest outcomes and income (Agustin, 2022; Ghozali & Wibowo, 2019). This is primarily caused by extreme weather changes, such as prolonged droughts or sudden floods, which can damage shallot crops that are highly sensitive to environmental conditions (Servina, 2019; Luluun et al., 2018). In addition, pest and disease attacks that are increasingly difficult to control, such as aphids or fungal infections, reduce crop quality and lead to substantial losses (Bawarta et al., 2022; Sari et al., 2022). Sharp fluctuations in market prices also frequently force farmers to sell shallots at prices far below production costs, thereby worsening their financial conditions (Adetya & Sidqi, 2024; Razzianto et al., 2021). Beyond natural and market challenges, farmers are burdened with high production costs, including the procurement of quality seeds, fertilizers, pesticides, and skilled labor. Therefore, it is crucial for shallot farmers to adopt comprehensive and effective risk mitigation strategies (Bawarta et al., 2022). One solution is to purchase insurance that provides financial protection in the event of crop failure or other unexpected losses (Prabowo, 2023; Kalfin et al., 2023; Purwandari et al., 2024; Rinardi et al., 2019). Moreover, government and institutional support including agricultural extension services, subsidies, and financial management training is also essential to strengthen farm resilience and improve farmers' welfare. This is supported by research conducted by Jiba et al. (2024) and Hazell & Varangis (2020), which argue that agricultural insurance protects farmers against crop failure risks, thereby enabling them to obtain capital to restart planting and cultivation. Furthermore, Alam et al. (2020) emphasize that in the era of climate change, agricultural insurance can serve as a solution to reduce farmers' economic losses. Agricultural production risks continue to increase, driven by climate-related disasters such as floods, droughts, and landslides. Collectively, production risks are closely linked to insurance premiums: the greater the risks faced, the higher the premiums that must be paid, and vice versa.

Based on the application of the Cobb Douglas model in analyzing agricultural production risks, various methodological approaches have been employed, yielding important findings in research development. For instance, Saputra & Wicaksono (2023) applied a modified basic Cobb–Douglas model to horticultural commodities by incorporating a dummy risk variable, and found that although land area, fertilizer, and labor significantly increased production, the presence of climate and pest risks substantially suppressed productivity with negative coefficients. Meanwhile, Maulana et al. (2022), in their study on maize, adopted the more complex Just Pope approach, which separates the production function into an expected output function and a risk variance function. Their results showed that fertilizer and labor not only increased production but also simultaneously heightened production risks, while the use of superior seeds helped stabilize production by reducing variance. On the other hand, Subekti & Jati (2019) highlighted the complexity of location-specific risks, finding that in dryland areas, land area and labor variables were highly vulnerable to rainfall variability, where marginal productivity was strongly influenced by water conditions. Collectively, based on previous studies, the Cobb–Douglas model is appropriate for analyzing agricultural production risks because it realistically represents input–output relationships. The elasticity coefficients in this model indicate production sensitivity to changes in each input, thereby identifying the factors most vulnerable to risk.

Furthermore, recent studies on pure premium determination in agricultural insurance have advanced by utilizing both statistical and econometric approaches. Chen & Wang (2023) successfully developed a pure premium model for rice insurance based on rainfall index using the Generalized Gamma distribution to model losses and simulate more accurate premiums. Li & Liu (2021) further compared the performance of statistical distributions such as Weibull and Pareto in calculating Value at Risk (VaR) for determining pure premiums in maize insurance, finding that Weibull provided more stable estimates for tail risks. In Indonesia, Sari & Prasetyo (2020) applied a similar approach to soybean insurance by mapping historical losses into the Gamma distribution, while Park & Kim (2019) criticized traditional models by introducing soil moisture deficit as a new index variable that significantly influenced pure premium calculations for wheat crops.

Based on the problems and previous studies, this research generally aims to determine the agricultural insurance premium for shallots by considering collective risk factors such as land area, seed quantity, fertilizer, pesticides, and labor. The Cobb Douglas model is employed to assess collective risks in crop failure, which then serves as the basis for determining effective shallot insurance premiums. In addition, the general research problem is how the Cobb Douglas model can be applied to production risks and agricultural insurance premiums for shallot commodities with collective risk distribution. The implications of this study are expected to provide guidance for agricultural insurance companies in setting premiums that align with farmers' conditions, while also serving as a reference for the government in formulating insurance premium policies for shallot farmers.

METHODS

Research Location and Data

This study uses data obtained from questionnaires distributed to shallot farmers in Tasikmalaya Regency. The data employed in this research are quantitative in nature, covering various production factors in shallot farming. The variables examined include

Production (Y), representing the output of shallots in weight units; Land Area (X1), describing the size of land used for shallot cultivation; Seeds (X2), indicating the number of seeds used in planting; Fertilizer (X3), representing the amount of fertilizer applied in the farming process; Pesticides (X4), showing the use of pesticides to control pests; and Labor (X5), describing the number of workers involved in production activities. Fifty shallot farmers were selected using purposive sampling, with the criteria being that they owned a minimum of 0.3 hectares of land and had grown shallots for at least two growing seasons. This sample selection was conducted in a targeted manner to ensure the data collected was relevant to the research objectives and ensured transparency in the data collection process.

Cobb-Douglas Production Function

The method applied to estimate the Cobb-Douglas production function in this study is the stochastic frontier approach. The Cobb-Douglas production function itself is a mathematical model that links two or more variables, where the dependent variable (Y) represents output or production results, and the independent variables (X) represent inputs or production factors used in the process. This model assumes a specific functional relationship between inputs and outputs that reflects production efficiency. The Cobb-Douglas production function used in this study can be expressed in Equations (1) and (2) as follows (Vasyl'Yeva, 2021, p. 40).

$$Y_i = f(X_{1i}, X_{2i}, \dots, X_{ki}) \tag{1}$$

$$Y_i = a_0\, X_{1i}^{\beta 1} X_{2i}^{\beta 2} e^{\varepsilon_i} \tag{2}$$

To make the estimation process easier, the equation is changed into a multiple linear form by performing logarithms on both sides of the equation, so that Equation (3) is obtained (Vasyl'Yeva, 2021, p. 40).

$$\ln\ Y_i = \ln\ a_0 + \beta_1 lnX_{1i} + \beta_2 lnX_{2i} + \varepsilon_i \tag{3}$$

Correlation Coefficient

Correlation refers to a number that describes the direction and strength of the relationship between two or more variables simultaneously. Correlation analysis encompasses various techniques used to measure the relationship between two variables, with the primary goal of describing the extent of the relationship between the variables (Lind et al., 2008). The correlation between the dependent and independent variables can be calculated using the Pearson correlation method, as described in Equation (4) (Melantika et al., 2024, p.189).

$$r_{yx} = \frac{n\sum_{i=1}^{n} y_i x_i - (\sum_{i=1}^{n} y_i)(\sum_{i=1}^{n} x_i)}{\sqrt{n\sum_{i=1}^{n} y_i^2 - (\sum_{i=1}^{n} y_i)^2}\sqrt{n\sum_{i=1}^{n} x_i^2 - (\sum_{i=1}^{n} x_i)^2}} \tag{4}$$

Pure Premium

Pure premium is the fundamental component in insurance premium calculation, determined based on the insured risk. The amount of this premium covers the costs required to compensate for potential losses that may occur, without taking into account other charges such as administrative expenses or company profit. Thus, pure premium serves as a tool to measure risk exposure and to ensure the financial sustainability of insurance companies in addressing possible claims (Yulita et al., 2024). The calculation of premiums based on the principles of expected value and standard deviation is presented in Equations (5) and (6) (Simamora et al., 2024; Kalfin et al., 2024, p. 40; Sukono et al., 2022, p. 215).

$$\Pi_E = (1 + \theta)\, E[Y] \tag{5}$$

$$\Pi_{SD} = E[Y] + \theta\sqrt{Var[Y]} \tag{6}$$

RESULT AND DISCUSSION

Data Visualization

This study employs shallot production (Y) as the dependent variable, along with land area (X1), number of seeds (X2), amount of fertilizer (X3), pesticide use (X4), and labor (X5) as independent variables. All data were obtained from relevant secondary sources, and for regression analysis as well as to meet statistical assumptions, each variable was transformed into its natural logarithm (ln). This transformation was carried out to stabilize variance, reduce the influence of outliers, and improve the distribution of data so that it more closely approximates normality. Consequently, the estimation results of the regression model can be interpreted more accurately. The visualization of the transformed research data is presented in Figure 1.

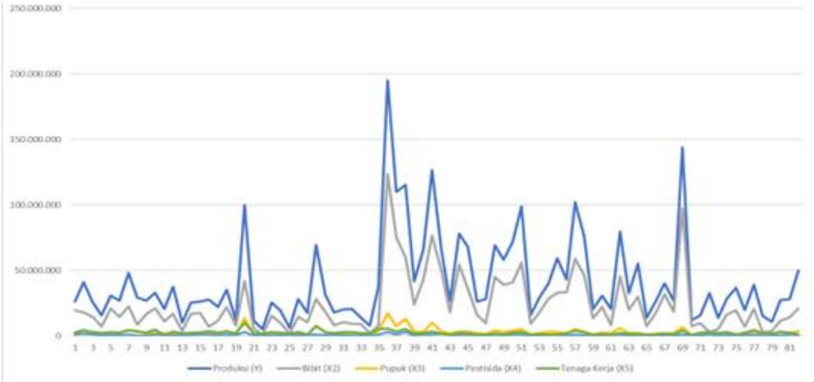

Figure 1. Visualization of Research Data

Correlation

Table1. Data Correlation

Correlations		Y	X1	X2	X3	X4	X5
Y	Pearson Correlation	1	-.384**	.950**	.937**	.815**	.426**
	Sig. (2-tailed)		.006	.000	.000	.000	.002
	N	50	50	50	50	50	50
X1	Pearson Correlation	-.384**	1	-.378**	-.345*	-.316*	-.070
	Sig. (2-tailed)	.006		.007	.014	.025	.631
	N	50	50	50	50	50	50
X2	Pearson Correlation	.950**	-.378**	1	.855**	.783**	.295*
	Sig. (2-tailed)	.000	.007		.000	.000	.038
	N	50	50	50	50	50	50
X3	Pearson Correlation	.937**	-.345*	.855**	1	.806**	.504**
	Sig. (2-tailed)	.000	.014	.000		.000	.000
	N	50	50	50	50	50	50
X4	Pearson Correlation	.815**	-.316*	.783**	.806**	1	.530**
	Sig. (2-tailed)	.000	.025	.000	.000		.000
	N	50	50	50	50	50	50
X5	Pearson Correlation	.426**	-.070	.295*	.504**	.530**	1
	Sig. (2-tailed)	.002	.631	.038	.000	.000	
	N	50	50	50	50	50	50

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Based on Table 1, which presents the results of the Pearson correlation test conducted on six variables, namely Y as the dependent variable and X1, X2, X3, X4, and X5 as independent variables, it was found that most variables have a significant relationship with Y. Variable X2 shows a very strong and positive correlation with Y, with a correlation coefficient of 0.950 and a significance level of 0.000 ($p < 0.01$), indicating that the higher the value of X2, the more Y tends to increase significantly. A similar pattern is observed in variable X3, which has a very strong positive correlation with Y ($r = 0.937$, $p = 0.000$), as well as variable X4, which demonstrates a strong positive correlation (r = 0.815, p = 0.000). In addition, variable X5 also exhibits a positive relationship with Y, with a moderate correlation strength (r = 0.426) and significance at the 1% level (p = 0.002). Meanwhile, variable X1 shows a different direction of relationship, namely a negative correlation with Y (r = -0.384, p = 0.006), meaning that an increase in X1 is significantly associated with a decrease in Y.

Furthermore, the relationships among the independent variables also reveal significant correlations, particularly between X2, X3, and X4. For instance, X2 and X3 have a correlation of 0.855 (p = 0.000), X3 and X4 of 0.806 (p = 0.000), and X2 and X4 of 0.783 (p = 0.000), indicating very strong inter-variable relationships. Such close associations may suggest potential multicollinearity if these three variables are used simultaneously in the regression model. Meanwhile, variable X1 shows negative correlations with most other independent variables, such as X2 (r = -0.378, p = 0.007), X3 (r = -0.345, p = 0.014), and X4 (r = -0.316, p = 0.025), although the correlation strengths range from weak to moderate. In contrast, the correlation between X1 and X5 is not significant (r = -0.070, p = 0.631), thus showing no meaningful relationship. Therefore, it can be concluded from the correlation test results that most independent variables have significant relationships with the dependent variable, with varying directions and strengths, and that potential multicollinearity should be considered in further analysis.

Estimating Cobb-Douglas Regression Parameters

This model was developed to analyze the factors influencing shallot productivity. The model employs the logarithmic form of the Cobb-Douglas function, which has been linearized, so that the regression model becomes:

$$\ln(Y) = \beta_0 + \beta_1 \ln(X_1) + \beta_2 \ln(X_2) + \beta_3 \ln(X_3) + \beta_4 \ln(X_4) + \beta_5 \ln(X_5) + \varepsilon \qquad (7)$$

With the following estimation results:

Table 2. Estimation Results of Multiple Linear Regression Parameters

Coefficient	Estimated	std. error	t-value	Pr(>|t|)
(constant)	0.620479	0.115342	5.379472	2.72897E-06
ln X1	-0.00094	0.001453	-0.64439	0.522667626
ln X2	0.442234	0.050683	8.725514	3.75619E-11
ln X3	0.312246	0.049946	6.251662	1.43912E-07
ln X4	-0.00276	0.055758	-0.04949	0.960753468
ln X5	0.057665	0.048508	1.188763	0.240909417

Residual Standard Error	0.009124			
R-Squared	0.962356			
Adjusted R-Squared	0.958078			
F-Statistics	224.9661703			
P-Value	3.69376E-30			

The construction of the shallot productivity model was carried out using multiple linear regression, aiming to estimate the parameters of variables that affect productivity. The variables used in this model include Y as shallot productivity, and the independent variables consisting of X1 (land area), X2 (number of seeds), X3 (amount of fertilizer), X4 (amount of pesticides), and X5 (labor). This model was built based on the Cobb-Douglas production function, which is nonlinear in form. Therefore, the function was first linearized using natural logarithm transformation to simplify parameter estimation through multiple linear regression.

The parameter estimation process was conducted using IBM SPSS Statistics 25 software. In the initial stage, all research variables were included in the model to examine the extent to which each variable contributes to shallot productivity. Based on Table 2, the R-Squared value obtained was 96.24%, indicating that the model is able to explain 96.24% of the variation in shallot productivity. The model also passed the classical assumption tests and is considered valid for drawing conclusions. The regression model obtained is as follows:

$$\ln(Y) = 0.62 - 0.00094\ln(X_1) + 0.44\ \ln(X_2) + 0.31\ln(X_3) - 0.00276\ln(X_4) + 0.058\ln(X_5) \tag{8}$$

Based on the model in Table 2, it can be observed that the variable land area ln(X1) has a negative effect, as larger land areas are associated with higher risks, which in turn reduce productivity ln(Y). Similarly, pesticide use ln(X4) has a negative effect on shallot productivity, as higher pesticide application increases the risk of crop failure due to its adverse effects. In contrast, seeds ln(X2), fertilizer ln(X3), and labor ln(X5) show positive effects, indicating that increases in these inputs contribute positively to shallot productivity.

Based on Equation (8), the negative coefficient for land area (X1) reflects managerial inefficiency at larger scales of farming operations. Referring to Birthal et al. (2015) in Agricultural Economics, it is confirmed that economies of scale are not achieved on large land areas without adequate management. Theoretically, the negative phenomenon in land area (X1) represents a manifestation of the Law of Diminishing Returns, where input optimization is not attained at larger scales, as supported by the study of Koirala et al. (2019) in Food Policy on small-scale vegetable farming. In addition, the speculative nature of pesticide use (X4) indicates excessive spraying practices as a form of “chemical insurance” driven by fear of pest risks, a behavioral pattern explained by the risk-aversion theory of Ullah et al. (2021) in the Journal of Cleaner Production. Empirical justification for speculative pesticide use (X4) is evidenced by the study of Nurmayasari et al. (2020) in the Indonesian Journal of Horticulture, which found no significant correlation between spraying intensity and increased shallot yields.

Simultaneous Hypothesis Testing (F-Test)

The F-test was conducted to evaluate whether the overall regression model, which uses five predictor variables Land Area (X1), Seeds (X2), Fertilizer (X3), Pesticides (X4), and Labor (X5) simultaneously has a significant effect on shallot production (Y) after ln transformation.

Table 3. Results of the F-Test

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	.094	5	.019	224.966	.000[b]
	Residual	.004	44	.000		
	Total	.097	49			

a. Dependent Variable: Y

b. Predictors: (Constant), X5, X1, X2, X4, X3

From the Table 3, the Sum of Squares Regression was obtained at 0.094 with 5 degrees of freedom (representing the number of predictors), and the Sum of Squares Residual was 0.004 with 44 degrees of freedom (derived from 50 observations minus the number of predictors and the constant). This calculation produced an F-statistic of 224.966 and a significance value (Sig.) of 0.000. By comparing the model’s significance value (0.000) with the predetermined significance level ($\alpha = 0.05$), it is evident that $0.000 \leq 0.05$, thus rejecting the null hypothesis (H_0), which states that there is no simultaneous effect of the five predictor variables on shallot production.

Conclusion: The F-test results clearly indicate that, simultaneously, Land Area (X1), Seeds (X2), Fertilizer (X3), Pesticides (X4), and Labor (X5) have a highly significant effect on shallot production (Y). In addition, the results of the F-test confirm that the Cobb–Douglas model is suitable as a framework for analyzing production risks and determining insurance premiums, as it effectively represents the collective relationship among production factors with a very high level of significance.

Partial Hypothesis Testing (t-Test)

Table 4. Results of the t-Test on the Data

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	.620	.115		5.379	.000
	X1	-.001	.001	-.020	-.644	.523
	X2	.442	.051	.571	8.726	.000
	X3	.312	.050	.421	6.252	.000
	X4	-.003	.056	-.003	-.049	.961
	X5	.058	.049	.046	1.189	.241

a. Dependent Variable: Y

Based on the t-test results of the multiple linear regression model in Table 4, it was found that, partially, the variables Seeds (X2) and Fertilizer (X3) significantly affect shallot production (Y). This is indicated by their significance values being smaller than 0.05, specifically 0.000. The regression coefficient for Seeds is 0.442, which implies that each one-unit increase in seeds increases shallot production by 0.442 units. Meanwhile, Fertilizer has a coefficient of 0.312, also contributing positively and significantly to production. The finding that seeds have a significant effect is consistent with the study of Satriagasa et al. (2020), which demonstrated that the use of high-quality shallot seeds increases productivity by 25–30% through genetic improvement and enhanced plant vigor. This positive coefficient confirms the production function theory, which positions seeds as the initial input in determining the potential for maximum yield (Hayashi, 2019). Meanwhile, fertilizer (X3) shows a significant effect in line with Wijayanto et al. (2021), who stated that precision farming with the appropriate NPK dosage can increase yields by 18.5% on marginal land. This finding is consistent with the concept of the law of the minimum, which posits that crop production is constrained by the most critical factor, such as nutrient availability (Van Ittersum et al., 2020).

Conversely, Land Area (X1), Pesticides (X4), and Labor (X5) do not significantly affect shallot production, as their significance values are greater than 0.05, namely 0.523, 0.961, and 0.241, respectively. Thus, it can be concluded that in this model, only Seeds and Fertilizer have significant partial effects on shallot production, while the other variables do not provide meaningful influence. However, this model is maintained because in theory, these three variables influence the risk of shallot production. According to Wooldridge (2019), statistically insignificant variables should be retained in the model if they have a strong theoretical foundation. Eliminating variables solely based on statistical significance may lead to model specification bias (omitted variable bias). Based on agricultural production theory, land area (X1) is a fundamental variable in the Cobb–Douglas function because it determines the scale of farming and production capacity, as emphasized in the theoretical framework of production by Coelli et al. (2005), who identified land as a primary input that cannot be disregarded. Furthermore, pesticides (X4) conceptually serve as a protective input that secures potential yields from pest disturbances, and their inclusion in the model reflects the reality of risk management in farming practices, as outlined in the study of Fuglie & Rada (2014) on production function construction. Labor (X5) must also be retained, as it acts as a proxy for cultivation intensity; given that shallot farming is labor-intensive, this variable theoretically determines technical efficiency, consistent with empirical findings in horticultural commodities reported by Rahman (2010).

Residual Normality Testing of the Cobb-Douglas Model

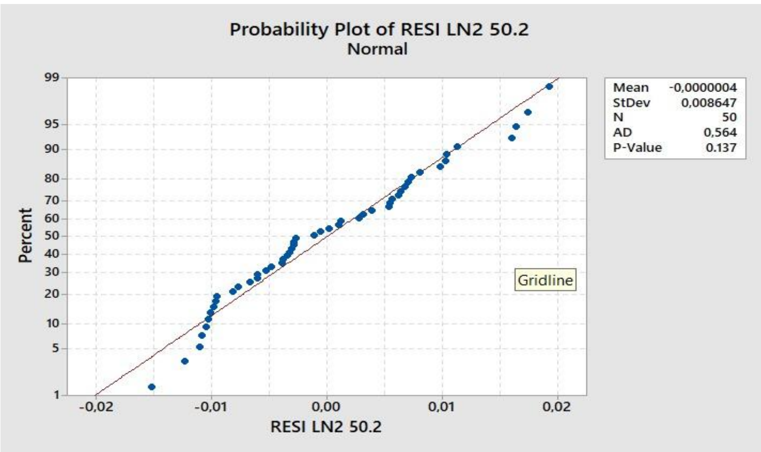

Figure 2. Results of Residual Normality Testing

The probability plot in Figure 2 shows the results of the normality test on the residuals of the second linear regression model used to analyze shallot production data from 50 observations. This model represents Production (Y) as a function of several independent variables, namely Land Area (X1), Seeds (X2), Fertilizer (X3), Pesticides (X4), and Labor (X5). The purpose of the probability plot is to evaluate whether the residuals of the regression model are normally distributed, which is one of the key assumptions in classical linear regression analysis.

Based on the plot, the residual points are closely aligned with the red diagonal line representing the theoretical normal distribution. This indicates that the residuals tend to follow a normal distribution. The Anderson-Darling test produced an AD value of 0.564 and a p-value of 0.137, which is greater than the common significance level of 0.05. Therefore, it can be concluded that there is insufficient evidence to reject the null hypothesis that the residuals are normally distributed. With the normality assumption satisfied, the regression model can be considered statistically valid for inference. These results support the reliability of the model in explaining the effects of input variables such as land area, seeds, fertilizer, pesticides, and labor on shallot production.

Coefficient of Determination

Based on Table 2, the coefficient of determination (R^2) was found to be 0.962, meaning that 96.2% of the variation in shallot productivity can be explained by the five independent variables in the model, namely land area, seeds, fertilizer, pesticides, and labor. Meanwhile, the remaining 3.8% is influenced by other factors not included in this model.

Determining the Expected Value and Variance of Production Risk

The determination of the expected value and variance aims to estimate the mean and variance of production risk (Y) based on the regression model obtained in Equation (7). These expected and variance values can be used as references in decision-making for determining insurance premiums. Based on Equation (7), the formulas for the expected value and variance of shallot production are presented in Equations (9) and (10).

$$E[\ln(Y)] = \beta_0 + \beta_1 E[\ln(X_1)] + \beta_2 E[\ln(X_2)] + \beta_3 E[\ln(X_3)] + \beta_4 E[\ln(X_4)] + \beta_5 E[\ln(X_5)] \tag{9}$$

$$Var[\ln(Y)] = \beta_0 + \beta_1 Var[\ln(X_1)] + \beta_2 Var[\ln(X_2)] + \beta_3 Var[\ln(X_3)] + \beta_4 Var[\ln(X_4)] + \beta_5 Var[\ln(X_5)] \tag{10}$$

Subsequently, the expected values of each independent variable are calculated from the sample data as follows:

- E[ln(X1)]= 0.465985027

- E[ln(X2)]= 16.56277984
- E[ln(X3)]= 14.59148936
- E[ln(X4)]= 13.53063678
- E[ln(X5)]= 14.74944221

By substituting the coefficient values and the expected values of the independent variables into Equation (9), the expected production value is obtained as follows:

$$[\ln(Y)] = \beta_0 + \beta_1 E[\ln(X_1)] + \beta_2 E[\ln(X_2)] + \beta_3 E[\ln(X_3)] + \beta_4 E[\ln(X_4)] + \beta_5 E[\ln(X_5)]$$

$$E\,[\ln(Y)] = 0.620479 - 0.00094\,E[\ln(X_1)] + 0.442234\ E[\ln(X_2)] + 0.312246\,E[\ln(X_3)] - 0.00276\,E[\ln(X_4)] + 0.057665\,E[\ln(X_5)]$$

$$E\,[\ln(Y)] = 0.620479 - 0.00094\,(0.465985027) + 0.442234\,(16.56277984) + 0.312246(14.59148936) - 0.00276(13.53063678) + 0.057665(14.74944221)]$$

$$E\,[\ln(Y)] = 13.31398157$$

Meanwhile, the variance of each independent variable is calculated from the sample data as follows:

- Var[ln(X1)]= 2.583852266
- Var[ln(X2)]= 1.003312121
- Var [ln(X3)]= 1.003624838
- Var[ln(X4)]= 1.002002916
- Var[ln(X5)]= 1.001246808

By substituting the coefficient values and the variance values of the independent variables into Equation (10), the variance of production is obtained as follows:

$$Var[\ln(Y)] = \beta_0 + \beta_1 Var[\ln(X_1)] + \beta_2 Var[\ln(X_2)] + \beta_3 Var[\ln(X_3)] + \beta_4 Var[\ln(X_4)] + \beta_5 Var[\ln(X_5)]$$

$$Var\,[\ln(Y)] = 0.620479 - 0.00094\,Var\,[\ln(X_1)] + 0.442234\ Var\,[\ln(X_2)] + 0.312246\,Var\,[\ln(X_3)] - 0.00276\,Var\,[\ln(X_4)] + 0.057665\,Var\,[\ln(X_5)]$$

$$Var\,[\ln(Y)] = 0.620479 - 0.00094\,(2.583852266) + 0.442234\,(1.003312121) + 0.312246(1.003624838) - 0.00276(1.002002916) + 0.057665(1.001246808)$$

$$Var\,[\ln(Y)] = 1.430098122$$

These results indicate that the expected value and variance of production, based on the data and regression model, are **13.31398157** and **1.430098122** production units, respectively. The expected value and variance is important to be used as a reference in the analysis of pure premium calculations for agricultural insurance.

Determining Insurance Premiums

In determining insurance premiums for the expected value $E[\ln(Y)]$ and variance $Var[\ln(Y)]$ of shallot production, it is necessary to transform the natural logarithm (ln) back into its original state (actual values) using the exponential function (exp), which is the inverse of ln.

Expected Production (E(Y))

$$E(Y) = EXP(E\,[\ln(Y)] = EXP(13.31398157)$$
$$E(Y) = 605604$$

Variance of Production (Var(Y))

$$Var(Y) = EXP(Var\,[\ln(Y)] = EXP(1.430098122)$$
$$Var(Y) = 4.179109233$$

Based on the expected value and variance of shallot production, the insurance premium is determined using the principles of expectation and standard deviation as follows:

Premium Model	Premium Yield (IDR/hectare/year)
Expectation Principle: $\Pi_E = (1+\ \theta)\ E[Y]$	$\theta_1 =\ 1\% : \Pi_Y = (1+0{,}01) \times 605604 = 611{,}660.03$
Standard Deviation Principle: $\Pi_{SD}\ = E[Y]\ + \theta\sqrt{Var[Y]}$	$\theta_1 = 1\% : \ \Pi_Y = (605604 \quad + 0{,}01 \times \sqrt{4{,}179}) = 605{,}604.01$

Table 5. Results of insurance premium calculations

θ	Π_Y**(E) [IDR]**	Π_Y**(SD) [IDR]**
1%	611,660.03	605,604.01
2%	617,716.07	605,604.03
3%	623,772.11	605,604.05
4%	629,828.15	605,604.07
5%	635,884.19	605,604.09
6%	641,940.23	605,604.11
7%	647,996.27	605,604.13
8%	654,052.31	605,604.15
9%	660,108.35	605,604.17
10%	666,164.39	605,604.19

Table 5 shows that the calculation of insurance premiums using the expected value principle yields higher values compared to the standard deviation principle. As the loading factor (θ) increases from 1% to 10%, the premium values exhibit a consistent upward trend in line with the magnitude of the applied loading factor. Under the expected value principle, the lowest premium is recorded at IDR 611,660.03 when (θ) is 1%, while the highest premium reaches IDR 666,164.39 when (θ) is raised to 10%. Meanwhile, under the standard deviation principle, the smallest and largest premiums are IDR 605,604.01 and IDR 605,604.19, respectively, which also occur when the loading factor is at the 1% and 10% levels.

CONCLUSION

This study successfully achieved its objective by developing a shallot insurance premium model based on the Cobb–Douglas production function, while simultaneously addressing a gap in the literature on high-value horticultural commodities in Indonesia. The identification of production risks, particularly the insignificance of land area and pesticide variables, highlights managerial inefficiencies that directly affect farmers' vulnerability and insurers' risk assessments. Despite limitations in geographic coverage and sample size, the model provides a robust theoretical framework grounded in neoclassical production theory and actuarial principles.

The findings demonstrate that the expectation principle produces premiums that are more sensitive to risk, whereas the standard deviation principle offers more stable premiums, making both viable alternatives to the flat premium scheme currently applied in Indonesia. Future research should expand geographic coverage and integrate climate variables and machine learning techniques to enhance predictive accuracy. From a policy perspective, the government should consider implementing differentiated premium schemes based on risk clusters and providing targeted subsidies, while insurance companies may adopt this parametric model to develop microinsurance products with flexible payment structures.

The novelty of this study lies in the integration of stochastic production modeling with actuarial pricing for Indonesian agribusiness, surpassing traditional approaches focused on staple commodities. Critically, the findings on negative elasticity of land area and the ineffectiveness of pesticide use provide relevant intervention points for improving production efficiency. Ultimately, this model serves not only as a premium calculation tool but also as a diagnostic framework for identifying systemic vulnerabilities, thereby contributing significantly to the development of more resilient and personalized agricultural insurance solutions in developing countries.

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