



ANALYSIS OF FACTORS AFFECTING RICE PRODUCTION AND ITS ASSOCIATED RISKS

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ARTICLE INFO

Keywords:

Rice production
Production risk
Risk management
Sustainable farming

Submitted:

15 January 2025

Revised:

21 July 2025

Accepted:

20 August 2025

ABSTRACT

Effective risk management is essential for rice farmers to achieve sustainable agriculture. Rice production is inherently influenced by uncertainties that can lead to yield declines or, in severe cases, complete crop failure. These uncertainties arise from various factors, including climate change, nutrient leaching, soil erosion, landslides, floods, pests, and droughts. Such risks not only threaten production but also have short-term impacts on food security at regional and national levels, potentially resulting in rice scarcity and rising prices. This study aims to analyze rice production and its associated risks in Purbalingga Regency, Central Java. Using multiple linear regression and multiplicative heteroscedasticity regression methods, the study incorporates novel elements such as agricultural inputs (land size, seeds, urea fertilizer, pesticides, and machinery), socio-demographic factors (planting season, education, farming experience), and government policies (ownership of farmer cards and extension service intensity). The findings indicate that land area, urea fertilizer, pesticides, agricultural tools, Farmer Card ownership, extension services, and planting seasons significantly affect rice production and its risks. These results underscore the importance of enhancing farmers' capabilities through improved agricultural inputs, education, and a deeper understanding of evolving planting processes, ultimately enabling more effective risk management strategies.

Cite as:

Purnomo, D. S., Sundari, S., Jati, D., Cahyo, H., Urip, C. R., Octisari, S. K., & Luhita, T. (2025). Analysis of Factors Affecting Rice Production and Its Associated Risks. *Jurnal AGRISEP: Kajian Masalah Sosial Ekonomi Pertanian dan Agribisnis*, 24(02), 849-870. <https://doi.org/10.31186/jagriseip.24.02.849-870>

INTRODUCTION

Climate change has been a threat for the past few decades, thus threatening the sustainability of farming (Tripathi et al., 2016; Dabi & Khanna, 2018; Dube et al., 2016; Anik et al., 2021; Nwankwoala, 2018). Threatening climate change such as temperature changes, varying rainfall, salinity, drought, and waterlogging affect

agricultural production around the world, including seasonal shifts and changes in rainfall distribution patterns that trigger floods and landslides in the rainy season and droughts in the dry season (Dabi & Khanna, 2018; Nwankwoala, 2018; Cahyo et al., 2023; Ray et al., 2019). The impact of climate change on the agricultural sector, such as a decrease in rice crop production due to climate change, which is not in accordance with the growing conditions of rice crops, can put crops at risk of failure (Dabi & Khanna, 2018; Ray et al., 2019).

Climate change in Indonesia, based on observations by the Meteorology, Climatology, and Geophysics Agency, has changed the average air temperature in 2023 by 27.20 degrees Celsius, so that the average air temperature anomaly in 2023 is 0.50 degrees Celsius compared to the average air temperature for the period 1991-2020 (Meteorology, Climatology, and Geophysics Agency, 2024). This is due to the burning of fossil fuels that produce heat-trapping gases, deforestation, and the greenhouse effect. The impact of climate change in Indonesia in 2023 has resulted in rice production falling by up to 1.89 million tons and harming 607,810 hectares of rice fields. In 2023, rice production will be 52.98 million tons, a decrease of 2.41 per cent from the previous year's production of 54.75 million tons. Central Java Province in 2023 experienced a significant decline in rice production, namely 3.15 per cent compared to the previous year (Meteorology, Climatology, and Geophysics Agency, 2024). Purbalingga Regency contributed only a small share to rice production in Central Java Province, amounting to 2.68 percent in 2023. In addition, rice production in Purbalingga Regency experienced a significant decline of 12.30 per cent during the period from 2020 to 2023. Rice production in Purbalingga Regency from 2020 to 2023 has decreased significantly (167,446 tons in 2020; 166,804 tons in 2021; 170,805.07 tons in 2022; 146,840.40 tons in 2023) (Central Statistics Agency of Purbalingga Regency, 2024). This indicates that the risk of production in Purbalingga Regency is quite high. Various things, such as climate change, can cause these production risks.

The urgency of this research is that climate change is an important factor in the sustainability of farming. High rainfall intensity in rural areas with agricultural land will have an impact on declining rice production, due to the occurrence of leaching processes (loss of nutrients), erosion, landslides and floods, pests (Huq et al., 2015; Asante et al., 2021; Tadele, 2017). The occurrence of a prolonged dry season will have an impact on drought, so that rice plants become dry, wilt and cause crop failure (Zaini et al., 2017). The impact of climate change will affect national or regional food security (Hammad et al., 2017; Hussain et al., 2020), so that it will cause a shortage of rice and an increase in rice prices in general.

Empirical studies on climate change on agricultural sustainability have been carried out extensively, especially in developing countries such as Cambodia (Mishra et al., 2018), Africa (Dube et al., 2016 and Coulibaly et al., 2020), Bangladesh (Anik et al., 2021), Ghana (Asante et al., 2021), South Asia (Aryal et al., 2020), and Kenya (Kogo et al., 2021), but similar studies related to cases in Indonesia are still limited. Empirical studies by Suharyanto et al (2015), Dewanti & Waluyati (2018), Yanamisra et al., (2023) and Wadu et al., (2019) analyzed production risk using the residual variance model or the Just and Pope model with independent variables on agricultural input elements (fertilizer, seeds, land area) without including elements of social/demographic capital and government policies. The novelty of this research lies in the measurement of production risk using the value of residual variance of rice

production. One of the models that can determine the residual variance of rice production is the Just and Pope model. The model is reduced to multiplicative heteroscedasticity regression by maximizing the likelihood function. Empirical studies by Suharyanto et al., (2015), Dewanti & Waluyati (2018), Yanamisra et al., (2023) and Wadu et al., (2019) using the model only tested agricultural production factors (organic fertilizers, seeds, pesticide fertilizers, land) against production risks. There are still limited studies that use the Just and Pope model by combining three elements, namely agricultural input elements (land area, seeds, urea fertilizers, pesticides, agricultural tools and machinery), demographic elements (planting season, education, and farming experience) and government policy elements (farmer card ownership and extension intensity) on rice production and rice production risks.

Theoretically, this study adopts the theory of production (Cobb & Douglas, 1928) and the theory of risk and uncertainty in agricultural production (Hardaker et al., 2015a and Hardaker et al., 2004b). Cobb & Douglas's (1928) theory of production describes the relationship between the inputs used in production and the outputs produced. In the context of rice production, this includes land use, seeds, fertilizers, water, labour, and technology. This theory seeks to determine the most efficient combination of inputs to maximize production output. In addition, Hardaker et al., (2015a, 2004b) explained the theory of risk and uncertainty in agricultural production as the variability of production results caused by the uncertainty of environmental factors such as weather, pest and disease attacks, and the variability of agricultural inputs. This risk has a direct impact on crop yields and farmers' incomes. Theory of risk and uncertainty in agricultural production, Hardaker et al., (2015a, 2004b), uses a probabilistic approach to analyze production risk. Hardaker uses probability distributions to describe crop yield uncertainty and develops simulation models to estimate the impact of various risk factors.

Based on above discussion, rice farming in Purbalingga Regency faces not only the challenge of increasing production but also the uncertainty of risks that threaten farmers' livelihoods. This study was designed to uncover two essential questions: what factors drive rice production in the region, and what forces create risks in the farming process. Beyond numbers and models, the research seeks to capture how farmers respond to these challenges, especially in adapting to climate change. The insights gained are expected to help the agricultural sector strengthen farmers' strategies in managing risks, paving the way toward more resilient and sustainable rice farming in Purbalingga.

RESEARCH METHOD

This study uses an ex-post facto approach, which is to analyze the causes of the symptoms or phenomena that occur. This study uses a quantitative approach. According to Creswell (2010), quantitative research is research that tests several previous theories using the relationship between certain variables. Then, from some of these variables, using several research instruments and the use of the data that has been obtained, the data is analyzed by statistical procedures. The form of quantitative research has the assumption of deductive theoretical testing. The location chosen as the research site was Toyareka Village, Kemangkon District, Purbalingga Regency. The research was conducted in May – June 2024. The population of this study is 70 active farmers in Toyareka Village, Kemangkon District, Purbalingga Regency. The

sampling technique used in this study is saturated sampling. Saturated sampling is a sampling technique in which all members of the population are sampled. This is done when the population is relatively small.

This study uses primary data. Primary data is data obtained directly from the research object. In obtaining research data, the researcher used a questionnaire instrument in data collection. The next step is to tabulate the data, process the data, interpret the results, and draw conclusions. This study analyzes rice production and rice production risks with independent variables including agricultural input elements (land area, seeds, urea fertilizers, pesticides, agricultural tools and machinery), democratic elements (planting season, education, and farming experience) and government policy elements (farmer card ownership and extension intensity).

The operational definitions for the independent variables were as follows: Land area was measured in square meters (m²). Seeds were defined as the average seed in Rupiah per square meter. Urea fertilizers and pesticides were both measured based on their prices per square meter. Agricultural tools and machinery refer to the number of tools and machines used up to the harvest period. The planting season was represented as a dummy variable. Education was measured by the number of years of formal schooling completed. Farming experience was defined in terms of the number of years the farmer had been engaged in farming activities. Farmer card ownership was also represented as a dummy variable. Lastly, extension intensity referred to the number of times the farmer received agricultural extension services.

The magnitude of the effect of input use on production risk was analyzed using multiple linear regression using the heteroscedastic method. The heteroscedastic model used is a multiplicative heteroscedasticity model by maximizing the likelihood function (Just & Pope in Roumasset, 1976; Greene, 2003). The regression model for the effect of agricultural input elements (land area, seeds, urea fertilizers, pesticides, agricultural tools and machinery), democratic elements (planting season, education, and farming experience) and government policy elements (farmer card ownership and extension intensity) on production and on production risks in general is written as follows:

Production function:

$$Y = a_0 + a_1LL_{1i} + a_2B_{2i} + a_3PU_{3i} + a_4PT_{4i} + a_5DMT_{5i} + a_6AMP_{6i} + a_7PDK_{7i} + a_8PUT_{8i} + a_9DKT_{9i} + a_{10}IP_{10i} + \varepsilon \dots \dots \dots (1),$$

Production risk function:

$$\varepsilon_i^2 = \beta_0 + \beta_1LL_{1i} + \beta_2B_{2i} + \beta_3PU_{3i} + \beta_4PT_{4i} + \beta_5DMT_{5i} + \beta_6AMP_{6i} + \beta_7AMP_{7i} + \beta_8PUT_{8i} + \beta_9DKT_{9i} + \beta_{10}IP_{10i} + \varepsilon \dots \dots \dots (2),$$

Note:

Y = Rice Production (Kg); ε_i^2 = Rice production risks (Residual); $\alpha_1 - \alpha_{13}$ = Regression coefficient (presumptive production parameter); $\beta_1 - \beta_{13}$ = Regression coefficient (a parameter of presumptive production risk); i = Cross section; LL = Land Area (m²); B = Seeds (IDR/m²); PU = Urea Fertilizer (Rupiah/m²); PT = Pesticides (IDR); DMT = Planting Season Dummy (1=Rainy Season, 0=Dry Season); AMP = Agricultural Tools and Machinery (Quantity); PDK = Education (Year); PUT =

Farming Experience (Year); DKT = Farmer Card Dummy (1=Own, 0=Don't Own); IP = Extension Intensity (times) ; ε = error.

The statistical test on the regression model consists of three types of tests, namely the determination coefficient test (R^2), the likelihood ratio test and the Individual test (t-test). The value of the determination coefficient (R^2) is used to see the proportion of variation of the dependent variable that can be explained by the variation of the independent variables.

RESULT AND DISCUSSION

After determining the regression model, the next step is to test the assumptions required for multiple linear regression testing. The necessary tests are multicollinearity, normality, heteroskedasticity, and autocorrelation tests. The normality test is intended to find out if the residual follows the normal distribution. A residual value must have a normal distribution; if this assumption is violated, then the statistical test becomes invalid for a small sample size. To detect whether the residue is normally distributed or not, it can be seen through the statistics of the Jarque-Bera test. Residual is declared to be normally distributed if the resulting normality probability \geq level of significance ($\alpha=5\%$), as presented in Table 1.

Table 1. Normality Test Output

Number	Model	Jarque Berra	Probability
1	Production Model	0.593479	0.743238
2	Production Risk Model	1.963293	0.374694

Table 1 shows that the Jarque Bera test on all models produces a probability value greater than the level of significance ($\alpha=5\%$). It can be stated that the residuals in all models are declared to be normally distributed. Accordingly, the assumption of normality is fulfilled.

Multicollinearity testing is intended to determine whether there is a relationship between independent variables. In linear regression analysis, no relationship between independent variables is allowed. The multicollinearity test was carried out by looking at the Variance Inflation Factor (VIF) value of each independent variable. The test criteria stated that if the VIF value was less than 10, there were no symptoms of multicollinearity. The summary of the results of the multicollinearity test is presented in Table 2.

Based on the results in the table 2, it can be seen that all independent variables used in this study produce VIF values less than 10. Thus, all models are stated to be free of symptoms of multicollinearity. So that the assumption of multicollinearity is fulfilled. Table 2 shows that the results of the VIF estimation in the two models show the same estimation results. This is very possible, as stated by (Gujarati & Porter, 2009). They say that two different regression models can have the same Variance Inflation Factor (VIF) because the VIF only reflects the degree of multicollinearity between independent variables, not on the relationship of independent variables to dependent variables. In other words, VIF measures how much the variance of the regression coefficient increases due to the correlation between independent variables, regardless of the bound variable used in the model.

Table 2. Multicollinearity Testing Using VIF

No.	Variable	Variance Inflation Factor (VIF)	
		Production	Production Risk
1	Land	2.591257	2.591257
2	Seed	1.200583	1.200583
3	Urea fertilizer	2.267684	2.267684
4	Pesticides	2.088031	2.088031
5	Planting season	1.116047	1.116047
6	Agricultural Tools and Machinery	1.674069	1.674069
7	Education	1.614827	1.614827
8	Farming experience	1.087687	1.087687
9	Farmer card	1.364275	1.364275
10	Extension Intensity	1.362712	1.362712

The second assumption is the absence of heteroskedasticity. Heteroscedasticity assumption testing is used to find out whether residuals have a homogeneous variance or not. The assumption testing in this study was seen through the Harvey Test. The test criteria state that if the probability resulting from the Harvey Test \geq level of significance ($\alpha=5\%$), then the residual is stated to have a homogeneous variety. Table 3 presents the results of the heteroscedasticity assumption test.

Table 3. Heteroscedasticity Test Table

No.	Model	Obs*R-squared	Prob.
1	Production Model	17.53910	0.0633
2	Production Risk Model	17.17003	0.0707

Testing of heteroscedasticity assumptions shows that the probability in all models produces values greater than the level of significance ($\alpha=5\%$ or 0.05). This means that the residual is stated to have a homogeneous variety. Thus, the assumption of the absence of heteroscedasticity in the model is fulfilled.

After testing heteroscedasticity assumptions, autocorrelation assumption testing is carried out. To determine the existence of autocorrelation with the Breusch-Godfrey Serial Correlation test, the test criteria are that if the probability value of the Breusch-Godfrey Serial Correlation test results is more than a significant alpha of 5% or 0.05, then the absence of autocorrelation can be stated. The following are the results of the autocorrelation test using the Breusch-Godfrey Serial Correlation.

Table 4. Autocorrelation Test Table

Number	Model	Obs*R-squared	Prob.
1	Production Model	1.475244	0.4782
2	Production Risk Model	0.912705	0.6336

The autocorrelation assumption test shows that the probability in all models produces a value greater than the level of significance ($\alpha=5\%$ or 0.05). This means that residual is stated to have no correlation problems. Thus, the assumption of no correlation in the model is fulfilled. The signification of this finding is that If in a regression model there is no autocorrelation in the error term, then the model can be said to meet one of the important assumptions of the classical linear regression model (CLRM). This condition makes Ordinary Least Squares (OLS) the Best Linear Unbiased Estimator (BLUE), so that the estimation of the resulting parameters is more efficient and reliable (Gujarati & Porter, 2009). The absence of autocorrelation also ensures that the standard value of error is not biased, so that hypothesis tests using t-statistics and F-statistics can be trusted (Wooldridge, 2016). In addition, the absence of autocorrelation suggests that the model is sufficiently capable of capturing the dynamics of explanatory variables, while the rest is purely in the form of random disturbances or white noise (Stock & Watson, 2015). Thus, the predictions generated from the model are more accurate, and the results of the analysis can be used as a basis for more valid decision-making in research and policy practice (Greene, 2018).

Testing using regression analysis is used to determine whether there is an effect of independent variables on dependent variables. The results of the panel regression analysis included simultaneous and partial testing of the hypothesis and the determination coefficient. The test criteria state that if the coefficient value is marked with an asterisk, there is a significant effect. The results of the hypothesis test can be seen through the table 5.

From table 5, simultaneous effect testing on all models resulted in a probability value $<$ level of significance ($\alpha=5\%$ or 0.05). This means that there is a significant effect on land area, seeds, urea fertilizers, pesticides, planting season, agricultural tools and machinery, education, farming experience, farmer cards, and the intensity of extension simultaneously or together on production and production risks. The result of the coefficient of determination in the production model is 0.7879. This means that the contribution of the effect of land area, seed, urea fertilizer, pesticides, planting season, agricultural tools and machinery, education, farming experience, farmer cards, and extension intensity to production is 78.79%. The remaining 21.21% was influenced by other variables outside this study. The result of the coefficient of determination in the production risk model is 0.3965. This means that the contribution of the effect of land area, seed, urea fertilizer, pesticides, planting season, agricultural tools and machinery, education, farming experience, farmer cards, and extension intensity to production risk is 39.65%. Other variables outside this study influenced the remaining 60.35%.

Table 5. Multiple Regression Analysis Output

Variable	Production		Production Risk	
	Coefficient	t-Statistics	Coefficient	t-Statistics
Land	0.584377***	2.843524	-2171.837***	-2.742854
Seed	0.006530 ^{ns}	1.034423	20.86956 ^{ns}	0.858021
Urea	0.009938*	1.745760	-60.27106***	-2.747828
Pesticides	0.051304***	3.588255	-92.84813*	-1.685443
Planting season	-1635.816 ^{ns}	-1.172931	-13470459**	-2.506870
Agricultural Tools & Machinery	1833.261***	3.020247	-3180031. ^{ns}	-1.359757
Education	-26.91185 ^{ns}	-0.145639	158526.8 ^{ns}	0.222664
Farming experience	-31.52702 ^{ns}	-0.536144	-765977.1***	-3.380852
Farmer card	2606.665*	1.822818	956885.8 ^{ns}	0.173672
Extension Intensity	1359.771**	2.500892	-4145143*	-1.978701
Constant	36995.50***	5.972754	24290415 ^{ns}	1.017823
R Squared	0.822147		0.493912	
Adjusted R Squared	0.787945		0.396587	
F Statistic	24.03766***		5.074889***	

Note: * significant 10%, ** significant 5%, ***significant 1%, ns: insignificant

The Effect of Land Area on Production and Production Risk

Land use in rice production is a positive and significant sign for rice production. These findings are in line with an empirical study by Zhang et al., (2019), which found that an increase in land area correlates with an increase in the efficiency and productivity of rice production. The study was conducted in China, which found that increasing land area reduced production costs per kilogram of rice, improving overall economic efficiency. In addition, research in Vietnam also supports these findings, showing that larger land sizes and the use of organic fertilizers can improve the technical efficiency of rice production (Chau & Ahamed, 2022). In the Philippines, decades of rice production data show that land area has a significant effect on crop yields, with higher production on larger areas despite significant climate variation (Stuecker et al., 2018). This finding is in line with Cobb & Douglas's theory of production (1928), describing the relationship between the inputs used in production and the outputs produced. In the context of rice production, this includes the use of a large land area that will increase its production. Stuecker et al., (2018) explained that the increase in land area contributes significantly to rice production, especially in the irrigated rice system, which accounts for 60% of the total rice production in the country.

The results of the analysis of the risk function of rice production showed that the land area had a significant negative effect on the risk of rice production. Farmers with a large area of arable land/the larger the rice farming business, will be careful in managing their farming business so that there is no loss, so that the higher the area

of cultivated land, the smaller the production risk. In addition, the findings of the study show that farmers with a larger land area plant types of superior rice varieties. This superior rice seed reduces the risk because not all crops will be affected by the same disease or severe weather conditions, this is in line with the opinion of Chen et al., (2012) that farmers who have a large area of land will allow farmers to plant different types of crops or varieties of rice, which reduces the overall risk because not all crops will be negatively affected by diseases or bad weather conditions. Lobell & Burke (2010) explained that large areas of land usually have greater variation in microclimate. This means that some parts of the land may be more resistant to extreme weather conditions, such as drought or flooding, than others. Farmers with large plots of land typically have better access to resources such as water, fertilizers, and labour, allowing for more effective and responsive land management (Ray et al., 2019). In line with the findings of research in Uganda, it is shown that increasing the area of agricultural land can help reduce risks associated with rice production. In Uganda, farmers who have more land are likely to be better able to manage production risk because they have more resources to apply more advanced agricultural technologies and better management practices (Kijima, 2019).

The Effect of Seeds on Production and Production Risks

The results of the analysis showed that seeds did not affect rice production and rice production risks. In this study, the seeds were measured with the seed price per m². The assumption built by the researcher is that the higher the seed price, the better the quality of the seeds, so that it will increase production and reduce production risks. However, in the field, some farmers use subsidized seeds and seeds from rice production in the previous harvest season. This indicates that the quality of the seeds is good, so it does not affect rice production or production risks. This finding is not in line with Cobb & Douglas (1928), who described the relationship between the inputs used (seeds) and the production yield. This is supported by an empirical study Assaye et al., (2023) explaining that although the adoption of high-quality seeds is an important component, rice production is more influenced by agronomic practices and technologies used by farmers. The use of irrigation technology and efficient land management plays a greater role in determining crop yields. In addition, the storage of seeds from previous production, if not in accordance with good storage methods, will reduce the quality of the seeds. In line with the findings of Assaye & Alemayehu (2023), it is explained that the quality of seeds can be affected by storage and packaging methods. Even high-quality seeds can lose their potential if they are not stored properly. Therefore, post-harvest storage and handling practices also play an important role in determining the effectiveness of seeds in rice production. In addition, climate variability also has an effect on rice production, suggesting that production risks are often caused by climate change and extreme weather conditions, which cannot be fully addressed by using high-quality seeds alone. Adaptation through changes in planting time and the use of efficient irrigation technology is more effective in reducing production risks (Hussain et al., 2022).

The Effect of Fertilizer on Production and Production Risk

The application of fertilizers in rice farming had a significant and positive impact on rice production. Fertilizers provided essential nutrients such as nitrogen,

phosphorus, and potassium, which played a crucial role in supporting various physiological processes in plants, including root development, photosynthesis, and grain formation. When applied in appropriate types and quantities, fertilizers contributed to healthier plant growth, stronger stems, and better grain filling—leading to increased yields. Efficient fertilizer management ensured that nutrient uptake was optimized, reducing nutrient loss and improving overall crop performance. Moreover, consistent and balanced fertilization helped maintain soil fertility and supported long-term agricultural productivity.

Building on this, empirical research supported these observations. For example, Wahab et al. (2024), in a study conducted in Punjab, Pakistan, demonstrated that optimal nitrogen application and the use of high-performing cultivars significantly increased rice yields. Their findings indicated that precise nitrogen fertilizer use enhanced nitrogen and water use efficiency, as well as the cost-benefit ratio in rice production systems. Similarly, Krein et al. (2023) emphasized that adopting more efficient and targeted fertilizer strategies not only boosted crop yields but also minimized environmental harm. This approach was critical for achieving sustainable rice production, particularly in the face of climate change and increasing global demand.

These results aligned with the Cobb-Douglas production theory (1928), which explains the relationship between production inputs and outputs, suggesting that appropriate fertilizer use is essential for maximizing rice yields. The combination of organic and inorganic fertilizers was found to significantly improve rice yield and quality, enhance nutrient absorption, and increase soil productivity (Krein et al., 2023; Amenyogbe & Dzomeku, 2023).

Fertilizer use also had a notable effect in reducing the risks associated with rice production. When applied appropriately, fertilizers supply essential nutrients vital for plant development throughout the growth cycle. Adequate nutrient availability improved plant vigour, increasing resilience against pests, diseases, and extreme weather. This contributed to more stable yields across growing seasons and reduced the likelihood of production failure. Supporting evidence from empirical studies confirmed that fertilizer use improved plant health and reduced vulnerability to biotic stressors (Amenyogbe & Dzomeku, 2023), while minimizing yield variability and enhancing predictability in harvest outcomes (Wahab et al., 2024; Mumtahina et al., 2024).

Furthermore, integrated water and fertilizer management systems contributed to increased yields while reducing the quantity of inputs required, thus lowering environmental risks and enhancing sustainability. Krein et al. (2023) noted that such integrated approaches improved resource use efficiency and reduced the risk of yield losses caused by drought or waterlogging. Studies in China further demonstrated that these systems optimized resource utilization, reduced greenhouse gas emissions, and promoted sustainable rice production practices.

The Effect of Pesticides on Production and Production Risks

The use of pesticides had a positive and significant effect on rice production, as they played a critical role in managing pests and diseases that could reduce crop yields. By eliminating or controlling harmful organisms, pesticides helped protect plant health, leading to increased productivity. However, despite these benefits, the

use of pesticides also had a significant negative effect on production risk. This paradox can be explained by the fact that excessive or improper pesticide use may lead to several unintended consequences that increase uncertainty in production.

One of the main concerns is the development of pest resistance due to repeated use of the same types of pesticides. Over time, pests can adapt and become resistant, rendering the pesticides less effective and increasing the likelihood of severe infestations in the future. Additionally, misuse or overapplication of pesticides may lead to phytotoxicity, damage to the rice plants themselves, which can reduce yield and disrupt the production process. Furthermore, reliance on chemical pesticides can disturb the ecological balance by killing beneficial insects and natural pest predators, potentially leading to secondary pest outbreaks.

These risks contribute to greater variability in yield outcomes, making production less predictable and increasing the overall risk faced by farmers. Environmental factors such as rainfall and wind can also affect pesticide effectiveness, adding another layer of uncertainty to their application. Therefore, while pesticides are essential in enhancing productivity, they must be used judiciously and with proper management practices to minimize their contribution to production risk.

Empirical studies have supported these findings. For example, Mumtahina et al. (2024) in Punjab, India, showed that proper pesticide application improved rice yields by controlling pests. Pathak et al. (2022) also demonstrated that pesticides effectively protected crops from pest attacks, contributing to yield increases. However, both studies emphasized the importance of correct application and monitoring to avoid long-term negative effects.

The use of pesticides in rice farming aligns with the theory of risk and uncertainty in agricultural production (Hardaker et al., 2015a; Hardaker et al., 2004a), which describes how unpredictable environmental and management factors influence outcomes. As explained by Hardaker et al., variability in inputs such as pesticide use—when mismanaged—can lead to inconsistent production results. Farmers who adopt responsible and targeted pesticide use can mitigate these risks, improve yield stability, and contribute to more sustainable rice farming (Damalas, 2021).

The Effect of the Planting Season on Production and Production Risks

The planting season was found to have no significant effect on rice production; however, it did have a significant negative effect on production risk. In this study, the planting season variable was categorized using a dummy: 0 for the dry season and 1 for the rainy season. The results indicated that planting during the rainy season significantly reduced the risks associated with rice production. This finding can be better understood in the context of climate change, which has introduced increasing variability in rainfall patterns, temperature extremes, and the frequency of extreme weather events. These changes have made traditional agricultural calendars less predictable, thereby influencing farmers' risk management decisions.

In many regions, climate change has caused irregular onset and duration of rainy and dry seasons, disrupting irrigation planning and crop growth cycles. However, in the study area, farmers have adapted by relying on deep wells during the dry season, which allow them to irrigate their rice fields independently of rainfall,

thereby stabilizing their production across different seasons. This access to alternative water sources reduces their vulnerability to seasonal changes, explaining why the planting season itself does not significantly impact production output.

On the other hand, the reduction in production risk during the rainy season can be attributed to the more reliable and widespread availability of water. In this region, rice fields located on mountain slopes benefit from effective irrigation canals that function optimally during the rainy season. These systems help prevent waterlogging and reduce the risk of floods or landslides, which are common concerns in areas where climate change has intensified rainfall. As a result, despite the general concerns associated with extreme weather in the rainy season, local infrastructure and geographical advantages mitigate those risks.

These findings contrast with the study by Johnson et al. (2023) in West Africa, where rice farmers in dry climate zones frequently experience severe water shortages during the dry season—particularly at critical growth stages like flowering and ripening—which significantly increases production risk. Meanwhile, Wang et al. (2024) emphasized that environmental and geographical factors heavily influence rice yields, and Liu et al. (2023) found that selecting optimal planting times within the season can reduce production risks and improve yields.

The Effect of the Agricultural Tools and Machinery on Production and Production Risk

The number of agricultural tools has a positive and significant effect on rice production. However, it does not affect the risk of rice production. The use of agricultural machinery can increase agricultural production capacity and efficiency. Agricultural machinery allows for more effective land preparation, planting, and crop management, thereby increasing rice yields. An empirical study by Peng et al., (2022) found that the efficiency of agricultural equipment allocation is higher in the central and eastern regions of China compared to the western regions. Yang & Zhang (2023) found that the socialization of the use of agricultural machinery helps reduce the financial, technical, and labour constraints faced by farmers, as well as facilitates the expansion of agricultural scale. The use of mechanization in rice production helps to improve crop yields and efficiency, but production risks caused by external factors such as climate change remain a major challenge. This study shows that while mechanization can support sustainable production, integration with broader agroecological practices is needed to reduce production risks significantly (Dorvlo et al., 2023). The study of Chandel et al., (2022) shows that technical efficiency in rice production can be improved through access to agricultural credit and information, not just with the use of agricultural machinery. Factors such as experience and land ownership status also affect technical efficiency, but not enough to reduce production risks caused by climate change and other environmental problems.

The Effect of Education on Production and Production Risks

Farmer education does not affect production and production risks. This study found that elementary schools dominate the average farmer's education. In addition, farmers also do not have formal education in agriculture, which does not affect rice production and rice risks. Empirical studies in rural Vietnam using a non-linear regression model show that education has no significant effect on rice agricultural

productivity. The study found that other variables, such as land size, fertilizer use, and pesticides, had a greater influence on production yield than farmers' education levels (Ninh, 2021). Research by Chandel et al., (2022) using the stochastic frontier model found that farming experience and land ownership status have a greater impact on technical efficiency in rice production compared to the formal education of farmers. These results show that practical knowledge and field experience are more important in increasing productivity than formal education. Rice varieties are the agricultural input that has the most significant effect on rice production (Gava et al., 2024).

In addition, research examining the adoption of sustainable farming practices in Southeast Asia found that farmers' formal education did not significantly affect their decision to adopt these practices, aiming to reduce production risks. Factors such as access to technology, policy support, and environmental conditions are more decisive (Chang et al., 2024). An empirical study conducted in the arid climate zone of Burkina Faso revealed that farmers' formal education had no significant effect on their ability to manage water scarcity in irrigation-based agricultural systems. Factors such as farming experience and access to water resources are more critical in reducing rice production risks (Johnson et al., 2023). The study, which evaluated the impact of El Niño on rice production in Southeast Asia, found that climate variables such as high temperatures and drought had a much greater impact on rice production compared to formal farmer education. Adaptation through research and development of heat- and drought-resistant varieties is more effective in managing these risks (Ludher & Teng, 2023).

The Effect of Farming Experience on Production and Production Risks

Farming experience does not affect production. This is in line with the findings of Pickson et al., (2023), who found that the impact of climate change and political instability greatly affects rice production when compared to farming experience. This is because farming experience is not enough to overcome the challenges caused by climate variability and political instability. In addition, the findings of Solaymani (2023) analyzed the environmental impact on rice production in Malaysia and found that factors such as temperature and land area have a greater influence compared to farming experience. The findings of Solaymani (2023) emphasized that farming experience is not significant in increasing rice production when compared to other environmental and technical variables. A meta-analysis study revealed that farming experiences do not have a significant influence on farmers' adaptation to climate change in Southeast Asia. This study shows that variables such as access to technology and policy support are more important in determining rice productivity (Li et al 2024).

The Effect of Farmer Cards on Production and Production Risks

The Farmer Card (Kartu Tani) has a significant positive impact on rice production. This finding aligns with the research by Li et al., (2024), which highlights that integrating digital financial systems with the Farmer Card can address financial challenges in rural areas. Such integration increases farmer participation in insurance programs and enhances credit availability, both of which contribute significantly to improving rice production. Therefore, the use of the Farmer Card can effectively

boost overall rice production in the region. Additionally, Gurung et al., (2024) reported that membership in agricultural producer organizations – often associated with access to Farmer Cards for agricultural technology and inputs – has a significant positive impact on farmers' income and profit margins. Membership in these organizations helps smallholder farmers improve their access to production technologies, value-added services, and marketing opportunities, all of which contribute to increased rice production.

However, Nguyen et al., (2022) found that farmers' risk preferences and their adaptation strategies to climate change play a crucial role in rice production. While agricultural technologies, including the Farmer Card, can support production, they are insufficient to mitigate the significant risks posed by climate change and other environmental factors. Supporting this, a study in Nigeria using an instrumental variable probit model by Ambali et al., (2021) revealed that farmers' risk preferences and local environmental conditions have a more substantial influence on agricultural technology adoption decisions than the specific technology itself, such as the Farmer Card. This indicates that production risks are more strongly affected by external factors and risk preferences than by the use of tools like the Farmer Card.

The Farmer Card (Kartu Tani) had a significant positive effect on rice production. This finding aligns with research by Li et al. (2024), which highlights that integrating digital financial systems with the Farmer Card helps address financial challenges in rural areas. This integration facilitates farmers' access to credit and encourages participation in agricultural insurance programs, both of which support increased rice production. Moreover, Gurung et al. (2024) found that membership in agricultural producer organizations – frequently linked with access to the Farmer Card and modern agricultural inputs – has a significant positive impact on farmer income and profitability. These organizations improve smallholder farmers' access to production technologies, value-added services, and market opportunities, which ultimately contribute to enhanced productivity.

In relation to production risk, the Farmer Card plays a potentially important but indirect role. This can be seen through the results of regression analysis, which indicate that Farmer Cards doesn't have any significant effect towards Production Risks. By improving access to inputs and financial support mechanisms, it can reduce farmers' vulnerability to shocks such as crop failure due to pests, diseases, or unfavourable weather. However, the effectiveness of the Farmer Card in mitigating production risk is highly dependent on farmers' ability and willingness to adopt complementary risk management tools such as crop insurance, climate-resilient practices, and proper timing of input use.

Despite its advantages, some studies suggest that the Farmer Card alone is not sufficient to reduce production risks significantly. Nguyen et al. (2022) emphasized that farmers' risk preferences and their adaptation strategies in response to climate change have a more pronounced impact on production stability. Supporting this, Ambali et al. (2021), using an instrumental variable probit model in Nigeria, demonstrated that environmental conditions and farmers' attitudes toward risk were stronger determinants of agricultural technology adoption than access to tools like the Farmer Card. This indicates that while the Farmer Card can support increased production, its role in directly mitigating production risk remains limited unless

combined with broader adaptation strategies and supportive environmental conditions.

The Effect of Extension Intensity on Production and Production Risks

The results of the risk function analysis in this study showed that the intensity of agricultural extension had a significantly negative effect on rice production risk. This indicates that the more frequently farmers in the study area participated in extension activities, the lower the variability or uncertainty in their rice production outcomes. Agricultural extension in this region played a crucial role in disseminating knowledge about appropriate input use, improved cultivation techniques, pest and disease control, and climate-adaptive strategies. Farmers who received more frequent guidance were better equipped to respond to unpredictable environmental factors—such as erratic rainfall or pest outbreaks—which are key contributors to production risk in rice farming. Moreover, consistent extension support helped ensure that farmers could make timely and informed decisions throughout the production cycle, thus reducing the likelihood of severe yield fluctuations.

These findings are consistent with those of Danso-Abbeam et al. (2018), who conducted research in northern Ghana and found that participation in agricultural extension programs significantly increased productivity and farm income. Extension services provided farmers with access to new technologies and improved management practices, which in turn reduced the likelihood of crop failure. Similarly, Raj and Garlapati (2020), along with Aremu and Reynolds (2024), emphasized the importance of climate-smart extension services in helping farmers adapt to risks posed by climate change, including drought and flooding. These services equipped farmers with techniques for better soil and water management, contributing to more resilient and sustainable agricultural systems.

The importance of extension services is also supported by the theory of risk and uncertainty in agricultural production proposed by Hardaker et al. (2015a, 2004b), which explains that production variability is primarily driven by unpredictable factors such as climate conditions, pest and disease pressures, and fluctuating input availability. Government-supported extension programs act as a buffer against these uncertainties by equipping farmers with timely information and effective strategies to cope with risks. Furthermore, Yan et al. (2023) found that personalized extension services can significantly improve farmers' adoption of safer and more sustainable practices, such as the use of biological pesticides, thereby reducing risks associated with poor chemical usage and its impact on soil and plant health.

CONCLUSION

The purpose of this study was to examine the variables influencing rice production in Purbalingga Regency, Central Java, as well as the related production hazards. The results showed that rice production and/or production risk are highly influenced by land area, urea fertilizer, pesticide use, agricultural implements, farmer cards, planting season, and extension intensity. Significantly, it was demonstrated that factors including land area, extension intensity, and appropriate use of fertilizer and pesticides decreased production risk, highlighting the significance of these factors in risk mitigation plans.

Overall, the findings show that governmental interventions and agricultural inputs, like the issuance of farmer cards and agricultural extension services, are essential for increasing rice output while lowering related risks. These results emphasize that in order to ensure resilient and sustainable rice farming systems, it is imperative to include climate-adaptive agricultural techniques, provide access to high-quality inputs, and fortify institutional support.

AUTHOR CONTRIBUTION STATEMENT

[Author 1]: conceptualization, methodology, data collection, writing – original draft preparation. [Author 2]: supervision, validation, writing – review & editing. [Author 3]: data analysis, visualization. [Author 4]: literature review, statistical analysis. [Author 5]: interpretation of results, writing – review & editing. [Author 6]: data curation, field coordination. [Author 7]: critical review, refinement of manuscript. All authors have read and approved the final manuscript

DECLARATION OF COMPETING INTEREST

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

ACKNOWLEDGMENT

The authors would like to thank the farmers in Toyareka Village, Purbalingga Regency, who participated in this study and shared their valuable time and insights. Appreciation is also extended to the Faculty of Economics and Business, University of Wijayakusuma Purwokerto, for academic support. Special thanks to the National Yunlin University of Science and Technology, Taiwan, for providing academic collaboration and guidance.

ETHIC STATEMENT

Ethical review and approval were waived for this study as it did not involve medical, psychological, or vulnerable populations and posed minimal risk to participants. Informed consent was obtained from all respondents prior to participation. All data collected was anonymized and kept strictly confidential.

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