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Strategic resilience: Integrating scheduling, supply chain management, and advanced operations techniques in production risk analysis and technical efficiency of rice farming in flood-prone areas

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A B S T R A C T

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Farmers face various risks such as production risks in the use of technology, pests, climate change and natural disasters. Farmers in disaster-prone areas have different responses depending on their behavior towards the risks posed. The main problem in this research is how farmers behave towards production risks due to flooding and the technical efficiency of rice farming in flood-prone areas. The aim of this research is to analyze farmers' behavior towards production risks due to flooding and the technical efficiency of rice farmers in flood-prone areas. The results of this research will provide important information for policy simulations that the government can implement towards farmers affected by natural disasters and for sustainable disaster mitigation strategies. The novelty of this research is that it combines two theories, namely risk behavior and agricultural technical efficiency in producing disaster mitigation strategies. The research location was determined purposefully in Pasuruan and Bojonegoro Regencies. The data in this research are primary and secondary data with the sample in this research being farmers. The sampling technique in this research is a multi-stage cluster sampling technique. The analysis method in this research uses Just Pope. and the Cobb-Douglas production function model with the Stochastic Production Frontier approach. The target of these research findings is a model of the types of behavior regarding the risks of farmers who are flood victims, as well as the level of technical efficiency of rice farming and the factors that influence it. The expected findings are policy recommendations regarding disaster mitigation from economic and agricultural risk aspects to create sustainable agriculture.

1. Introduction

The majority of Indonesians live from agriculture because Indonesia is an agricultural country (Iboko et al., 2023; Zabidi et al., 2022). The agricultural sector is very important to develop at every stage of development in Indonesia because it makes a significant contribution to Gross Domestic Income (GDP) (Islam et al., 2023; Mbah et al., 2023). The high demand for the food industry has encouraged efforts to increase rice production (Burggräf et al., 2023; Sanogo et al., 2023). This increase in production was caused by an increase in the use of superior varieties and planting area (Islam et al., 2023; Zabidi et al., 2022). Increasing the productivity of rice farming which results in increased production does not necessarily have a direct impact on increasing farmers' income (Ghimire et al., 2023; Hatta et al., 2023).

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If farmers do not use production factors effectively, there is unutilized potential to increase farming income and create a surplus (Ferrer et al., 2022; Gehring et al., 2022). Apart from that, low production and high costs will ultimately result in low farmer incomes (Nguyen-Thi-Lan et al., 2023; Talhelm et al., 2023). To achieve this, measuring the efficiency of use of production factors is necessary (Forgione & Migliardo, 2023; Sanogo et al., 2023). This is based on the idea that a high level of efficiency will be profitable because efficiency cannot be separated from an optimal combination of production factors (Burggräf et al., 2023; Mamgbi Zozimo et al., 2023). One way to find out how efficiently rice farming production factors are used is to calculate the technical efficiency value (Kanthilanka et al., 2023; Sanogo et al., 2023). Technical efficiency shows the relationship between input and output (Abualigah et al., 2023; Islam et al., 2023). Technical efficiency measures the extent to which a farmer converts input into output at the production level (Ghimire et al., 2023; Sanogo et al., 2023).

Agriculture is faced with conditions full of risk and uncertainty (Sanogo et al., 2023; Zabidi et al., 2022). Farmers as business actors face various sources of risk (Mbah et al., 2023; Motbaynor Workneh & Kumar, 2023). Farmers as business actors must determine their behavior towards risk because this is important in making decisions about farming management (Kanthilanka et al., 2023; Sanogo et al., 2023). Behavior towards risk is divided into risk seeking, neutral and risk averse (F. Wang et al., 2023; Xie et al., 2023). The dependence of agricultural activities on nature poses production risks (Khatri-Chhetri et al., 2023; MAO et al., 2023). Production risks result in a decrease in the quality and quantity of harvests, even though production is the main source of income for farmers (Islam et al., 2023; Nguyen-Thi-Lan et al., 2023). Indonesia has a diverse climate and topography that provides benefits and causes disasters. In the agricultural sector, disasters have a sustainable impact on farmers' lives (Zabidi et al., 2022; ZHAO et al., 2023). Farmers in disaster-prone areas have different responses to natural disasters that occur. This response depends on their behavior towards the risks posed (YUAN et al., 2022; Zabidi et al., 2022).

Rice is the main food crop commodity which is the heart of farmers in Indonesia, where rice is consumed by people every day (Hatta et al., 2023; Talhelm et al., 2023). However, rice farmers currently still face many problems, one of which is climate change which causes changes in the rainy and dry seasons, floods and landslides, pest attacks, and low prices for grain during the harvest season (Ferrer et al., 2022; van Aalst et al., 2023). This makes farmers have to face risks in rice farming, so farmers must have the ability to manage their farming with the changes that occur (Hatta et al., 2023; Zabidi et al., 2022).

Apart from facing production risks, farmers must also be able to manage their farming efficiently so that their farming goals are achieved, namely maximum production and profits (Begum et al., 2023; Mbah et al., 2023). Farming risk conditions influence farmers in allocating production inputs, where farmers are faced with several alternative choices of production factors which are expected to reduce production risks (Burggräf et al., 2023; Sanogo et al., 2023; Xie et al., 2023). Reducing production risks by using the right inputs automatically also increases the level of technical efficiency (Forgione & Migliardo, 2023; Sanogo et al., 2023). Therefore, farmers' decisions in using inputs for the ongoing production process are related to farmers' behavior in facing farming risks (Ghimire et al., 2023; Motbaynor Workneh & Kumar, 2023). Farming risk factors show changes or events in their farming business where farmers are faced with resource allocation choices that affect the production they produce (Nguyen-Thi-Lan et al., 2023; van Aalst et al., 2023).

2. Literature review

2.1 Strategic Resilience

Strategy is the art for individuals or groups to utilize their abilities and resources in order to achieve targets through procedures that are considered effective and efficient in achieving the expected goals. Meanwhile, resilience is the condition of a system and its parts that can anticipate, absorb, or recover from various unexpected events quickly and efficiently (Ghobakhloo et al., 2023; Kunisch et al., 2023). This includes protecting, enhancing, and repairing the underlying system structure and function, as well as an emphasis on learning aspects (Li et al., 2022; ZHAO et al., 2023). A resilience strategy consists of a number of interventions or actions that are expected to increase the resilience of a city, both at the system, agent and institutional levels (Smith & Shashkina, 2023; Varajão et al., 2023). With the existence of strategic resilience in the world of agriculture (Dowlati et al., 2023; Nelson & Ahmadpoor, 2023), it can provide an idea for rice farmers who want to plant rice to prepare all the needs for farming such as superior rice seeds that are resistant to pest and disease attacks, tolerant of environmental conditions, good fertilizer and adequate pesticides (Czakon et al., 2023; Kunisch et al., 2023). so that the harvest results obtained are as expected. Apart from that, the resilience strategy is also able to provide recovery in crop yield conditions from poor to better, so that crop yields are very satisfactory even in flood-prone areas (MAO et al., 2023; Oliveira et al., 2023).

2.2 Integrating Scheduling

Scheduling is an activity carried out to allocate facilities, equipment and labor, and determine the sequence of implementation for an operational activitym(Tantawy et al., 2022; Yeardley et al., 2022). Agriculture requires scheduling to allocate all activities to be carried out such as preparing labor, superior rice seeds, fertilizer, urea and pesticides to be used (Li et al., 2022; Martinazzo et al., 2023). Scheduling aims to minimize processing time, waiting time and harvest time so as to minimize losses (Fernandez-Viagas & Framinan, 2022; Zhang et al., 2022). Good scheduling also has several criteria such as; 1) overall completion time, namely by measuring the time required from the start of planting rice seeds to harvest (Gehring et al., 2022;

Zhang et al., 2022). 2) average, namely by calculating the average time required for planting rice to harvest (Fernandez-Viagas & Framinan, 2022; Tantawy et al., 2022). 3) average delay time, namely by calculating the average difference in harvest scheduling from the previous year to the current year (L. Chen & Zhou, 2023; Gehring et al., 2022). Apart from criteria, scheduling also has several objectives, namely increasing utility and reducing waiting time so that it can reduce and increase the productivity of rice farmers, minimize costs, and meet consumer needs in terms of rice quality and timeliness of rice delivery to consumers (Talhelm et al., 2023; van Aalst et al., 2023).

2.3 Supply Chain Management

Supply chain management is a series of actions that include planning, managing and activating products (Akkerman et al., 2023; Dzikriansyah et al., 2023). Every activity carried out requires good planning, and in the agricultural world the planning carried out includes everything related to planting rice seeds until harvest, processing resources regarding good labor, superior rice seeds, and processing the fertilizer that will be used (Abualigah et al., 2023; Taj et al., 2023). The function of supply chain management in the agricultural world is related to various physical costs which include material costs, storage costs, delivery transportation costs, and so on (Burgess et al., 2023; Z. Chen & Hammad, 2023). Apart from function, there is also a goal of supply chain management, namely being able to align demand with existing supply (Liu et al., 2023; Yontar, 2023). In addition, there are several problems or challenges that are often faced in supply chain operations, such as procurement management, supplier management, customer relationship management, risk management, and finding problems and dealing with them (Burgess et al., 2023; Z. Chen & Hammad, 2023). The supply chain must be able to provide products that are cheap, high quality, varied, and available on time to be a winner in the supply chain (Dzikriansyah et al., 2023; Liu et al., 2023).

2.4 Production Risk Analysis

Production risk is a risk that farming businesses always face (Begum et al., 2023; Burggräf et al., 2023). Production risk is a source of risk that originates from production activities, including crop failure, low productivity, damage to goods caused by pest and disease attacks, differences in climate and weather, human resource errors and much more (Mazzi, 2023; Mbah et al., 2023). Production risk usually describes the production received by farmers that does not match the farmers' expectations (Islam et al., 2023; F. Wang et al., 2023). Therefore, to find out how big the production risk is, we need to know how big the risk is to anticipate and overcome things that will happen (Begum et al., 2023; Mazzi, 2023).
Therefore, to reduce production risks, farming businesses must be able to use good strategies, tools and seeds so that all production activities run as expected (Nguyen-Thi-Lan et al., 2023; Xiong et al., 2023). Farming businesses must also have good farming skills and have knowledge about choosing superior seeds, choosing good fertilizer for plants, choosing pesticides to prevent pests and diseases in plants, understanding differences in climate and weather because this is very important to anticipate things that don't happen desired during the planting process until harvest (Hatta et al., 2023; Talhelm et al., 2023).

2.5 Technical Efficiency

Technical efficiency is the ability of a farm to use minimum inputs to produce maximum output at a certain technological level (Mamgbi Zozimo et al., 2023; Martinazzo et al., 2023). Technical efficiency is a necessity to measure allocative and economic efficiency (Martinazzo et al., 2023; Nguyen-Thi-Lan et al., 2023). Cultivation techniques and production components used in farming greatly influence farming efficiency (Can-ping et al., 2023; Cano-Leiva et al., 2023). Apart from that, farmers' socio-economic factors also influence efficiency, which is closely related to their ability to manage (Ghimire et al., 2023; Khatri-Chhetri et al., 2023). With technical efficiency, it can make it easier for farming businesses to minimize the costs incurred for rice cultivation, especially on land that is prone to flooding by using various methods that have been developed, apart from that, technology which is increasingly developing rapidly also greatly influences existing human resources to become more Good (Forgione & Migliardo, 2023; Nguyen-Thi-Lan et al., 2023). Not only that, good technical efficiency can also produce ideal production results so that it can increase farmers' income (Cano-Leiva et al., 2023; Islam et al., 2023).

3. Research Method

This research is survey research where the data used are primary data obtained through interviews and questionnaires. Supporting data in the form of data on the number of farmers, climate information, and seasonal data are taken from related agencies. This research is a quantitative study in which the data are analyzed quantitatively using risk function analysis and technical efficiency.

3.1 Data Collection Techniques

The data in this study are primary data and secondary data. Primary data was obtained through interviews and questionnaires from respondents. Secondary data were obtained from related agencies, including the Department of Agriculture, BNPB, and local government. The samples in this study were farmers in the research locations, namely in Bojonegoro and Pasuruan

Regencies.sampling technique in this study was a multi-stage cluster sampling technique, namely the sampling process was carried out through two or more stages. The multi-stage cluster sampling technique in this study used four stages, namely: 1) Determining the research location District, 2) Determining the sub-district in district, 3) Determining the village to be the research location, 4) Determining the sample according to the profile of the research objectives in the selected village.

3.2 Research Locations and Sampling Techniques

The research locations were determined purposely according to the research objectives. The research location was conducted in Bojonegoro Regency and Pasuruan Regency. This location was chosen because it is a rice center in East Java and is a flood-prone area every year.

3. Data Analysis

3.1 Data Analysis Method of Input Effects on Production and Production Risk

Production risk faced by farmers is analyzed using the Just and Pope (1979) model which explains that the resulting production is not only influenced by production factors, but also influenced by risk factors. The assumptions used are input and output in competitive markets so that prices are known with certainty or there is no price risk. The Just and Pope (1979) model is:

$$y = f(x, z) + u = f(x, z) + g(x, z)\varepsilon \quad (1)$$

where:

y = production achieved f(x,z) = function average production
g(x,z) = risk function or variance function
x = inputs / production factors used (x1, …, xj)
z = quasi-fixed number of inputs (z1, …, zk)
ε = error term with $E(\varepsilon)=0$ and var $(\varepsilon) = \sigma 2$

The Just and Pope function model requires that no restrictions are placed on the risk effect using the condition that $\partial[var(y)/\partial Xj]$ has a possible value of ≤ 0 or ≥ 0 which indicates that the input is risk increasing or risk decreasing to the production risk faced by farmers. The production function used in this study is the Cobb-Douglas production function in the form of natural logarithms. The model used to estimate the parameter estimation of the Cobb-Douglas function is the Stochastic Frontier Production Function approach. Factors that are thought to directly affect production are input factors used by farmers, namely land, seeds, chemical fertilizers, pesticides, labor (Basrowi & Maunnah, 2019; Basrowi & Utami, 2023; Marwanto et al., 2020; Suseno & Basrowi, 2023; Suwarno et al., 2020). The model is composed based on the specifications of the Cobb-Douglas production function in the form of natural logarithms.

Production and Risk Function is assumed to be in the form of COBB-Douglas production function using natural logarithm, as follows:

$$f(x): lnProdi = \beta_0 + \beta_1 lnLusi + \beta_2 lnBnhi + \beta_3 lnU + \beta_4 lnZA + 5lnNPK + \beta_6 lnPesi + \beta_7 lnTKi + \beta_8 lnPOi + \varepsilon \quad (2)$$

where:

$$f(x): lnProdi = \beta_0 + \beta_1 lnLusi + \beta_2 lnBnhi + \beta_3 lnU + \beta_4 lnZA + 5lnNPK + \beta_6 lnPesi + \beta_7 lnTKi + \beta_8 lnPOi + \varepsilon$$
$$g(x): ln\ \sigma 2Prodi = \alpha_0 + \alpha_1 lnLusi + \alpha_2 lnBnhi + \alpha li4\ l4ii + \alpha 5lnNPKi + \alpha_6 lnPesi + \alpha_7 lnPesi + \alpha_8 lnPOi + \varepsilon$$

expected parameter value is $\beta_0, \beta_1, \beta_2, \beta_3, \beta_4, \beta_5, \beta_7, \beta_8, \alpha_0 > 1$ The $\alpha_2, \alpha_3, \alpha_4, \alpha_5, \alpha_6, \alpha_7, \alpha_8 <0$ or > 0

If α <0 input is reduced risk, α> 0 input is increasing the risk where:

$\sigma 2Prodi$	=	$(Y - Yi)2$
$\sigma 2Prodi$	=	Rice production variant
lnProd	=	Total production/output (kg)
lnLus	=	Land area (ha)
lnBnh	=	Seed amount (kg)
lnU	=	Total Urea fertilizer (kg)
lnZA	=	Total ZA fertilizer (kg)
lnNPK	=	Total fertilizer NPK (kg)
lnPes	=	Amount of pesticides (kg)
lnTK	=	Amount of labor used (HOK)
lnPO	=	Amount of organic fertilizer (kg)

i	=	Number of respondent farmers
$\beta 0$	=	Int ersep
$\beta 1 - \beta 8$	=	parameter coefficient in the estimated production function
$\alpha 1 - \alpha 8$	=	parameter coefficient in the estimated risk function
ε	=	error term with E(ε)=0 and var (ε) = $\sigma 2$

3.2 Behavioral Analysis Method Farmers Against Production Risk and Its Impact on Input Allocation

The analytical method used is the risk model developed by Just and Pope. In this model, farming risk is assumed to be input and output in a competitive market so that the price is known with certainty or there is no price risk (Hatta et al., 2023; Promkhambut et al., 2023). Another assumption is that farmers in conducting their farming try to maximize utility where maximizing this utility uses an income maximization approach in farming, and farmers get production y at the price level p. Maximization of utility (expected utility) which is a normalized function of expected profit (Burggräf et al., 2023; van Aalst et al., 2023). The utility function can be written as $E = \left[U\left(\frac{\pi^e}{p}\right)\right]$. Expected profit (π^e) formulated as follows:

$$\pi^e = py - w'x = pf(x,z) - w'x + pg(x,z)\varepsilon \tag{3}$$

where:

π^e = Exoected profit
p = output price (Rp)
y = production/output
w = variable input prices vector ($w_1, \ldots, w_j$)
x = number of input used

The normalized expected profit is formulated as follows:

$$\frac{\pi^e}{p} = y - \frac{w'}{p} = f(x,z) - \frac{w'x}{p} + g(x,z)\varepsilon = f(x,z) - \widetilde{w'}x + g(x,z)\varepsilon \tag{4}$$

$\widetilde{w}$: the vector of normalized input price $\widetilde{w_j} = \frac{w_j'}{p}\ \forall j = 1, \ldots \ldots j$

Assuming the producer maximizes the expected utility of the profit that expected normalized $E = \left[U\left(\frac{\pi^e}{p}\right)\right]$, then the first-order condition (FOC) :

$$E\left[U'\left(\frac{\pi^e}{p}\right)\ (f_j(x,z) - \ \widetilde{w_j} + g_j(x,z)\varepsilon\right] = 0 \quad \forall j = 1, \ldots \ldots j \tag{5}$$

where:

$U'\left(\frac{\pi^e}{p}\right)$ = normalized marginal utility of the expected profit
f_j = first derivative of the production function with respect to the j-th variable input
g_j = first derivative of the production function with respect to the j-th variable input

To obtain function of risk behavior, equation (5) can be rewritten as follows:

$$f_j(x,z) = \ \widetilde{w_j} - g_j(x,z)\ \frac{E\left[U'\left(\frac{\pi^e}{p}\right)\varepsilon\right]}{E\left[U'\left(\frac{\pi^e}{p}\right)\right]} = \widetilde{w_j} - g_j(x,z)\theta_1 \ \ \forall j = 1, \ldots \ldots j \tag{6}$$

where:

$$\frac{E\left[U'\left(\frac{\pi^e}{p}\right)\varepsilon\right]}{E\left[U'\left(\frac{\pi^e}{p}\right)\right]} = \theta_1$$

and the value of θ_1 is the value of behavior towards risk. So the risk behavior function is:

$$f_j = \widetilde{w_j} - g_j\theta_1$$

If, $g_j > 0$ and $\theta_1 < 0 \Rightarrow f_j < \widetilde{w_j} - g_j\theta_1 \Rightarrow f_j$ must increase so that $f_j = \widetilde{w_j} - g_j\theta_1$, or input x1 must go down.

then :
$g_j > 0$ and $\theta_1 < 0$ then producers behave risk averse
$g_j > 0$ and $\theta_1 > 0$ then producers behave risk seeking or risk taker

If, $g_j < 0$ and $\theta_1 > 0 \Rightarrow f_j < \widetilde{w_j} - g_j\theta_1 \Rightarrow f_j$ must increase so that $f_j = \widetilde{w_j} - g_j\theta_1$, or the input x1 must increase.
then :
$g_j < 0$ and $\theta_1 > 0$ then producers behave risk averse
$g_j < 0$ and $\theta_1 < 0$ then producers behave risk seeking or risk taker

3.3 Method of Analysis of Factors Affecting Farmer Behavior on Production Risk

The analysis method used is probit regression model. The probit regression model is a qualitative response model based on the normal distribution probability function. Observations with certain characteristics will be one of the categories as the main objective of probability estimation. The probit regression model is a model that analyzes the dependent variable with only two values. The probit regression model is a non-linear model so the method used to estimate the probit model is the *Maximum Likelihood* (ML) method, to interpret the coefficient values of the probit regression model. The value of the probit model estimator cannot be interpreted directly because the probability value is based on the normal Z distribution, so it can only interpret the sign of the coefficient directly (Basrowi & Utami, 2020, 2023; Mustofa et al., 2023; Soenyono & Basrowi, 2020). The probit model equation is:

$$Yij = X'\beta + \varepsilon \tag{2}$$

where, *Y* is the dependent variable and *X* is the independent variable that explains *Y*. β is the estimated parameter coefficient and εi is the error term. The dependent variable in binary form is shown by Y_{ij}, Y is worth 1 and 0. In this study *Y* shows the behavior of farmers towards production risk, worth 1 if farmers are risk seekers and 0 if they are risk averse. Further explanation of the variables used in the probit regression model is as follows:

Y (farmer's behavior towards risk)	= Farmer's risk taker is worth 2, risk averse is worth 1 and is 0 for risk neutral
X1 Age	= Farmer's age, the variable unit is year.
X2 Education	= The length of time a farmer has been studying is measured by years
X3 Farming experience years	= The length of time a farmer has been doing farming is measured by
X4 Number of family dependents	= Number of family dependents, measured by people
X5 Frequency of counseling and training	= Frequency of farmers attending counseling and training in one season growing frequency is measured
X6 Off farm income measured in rupiah (Rp)	= Total income from outside the farm is
D1 growing season	= Rainy planting season 1, worth 0 if the growing season is dry
D2 Use of cultivation technology	= Farmers use technology equal to 1.0 otherwise method

3.4 Method of Analysis of Factors Affecting Farmer Behavior on Production Risk

The production function model used in measuring technical efficiency is the Cobb Dauglas production function with the Stochastic Production Frontier approach (Alexandro & Basrowi, 2024b, 2024a; Kittie & Basrowi, 2024; Purwaningsih et al., 2024). The production function model can be written as follows:

$$lnProdi = \beta_0 + \beta_1 lnLusi + \beta_2 lnBnhi + \beta_3 lnU + \beta_4 lnZA + \beta_5 lnNPK + \beta_6 lnPesi + \beta_7 lnTKi + \beta_8 li + \varepsilon \tag{2}$$

where:

lnProd	=	Total production/output (kg)
lnLus	=	Land area (ha)
lnBnh	=	Total Seeds (kg)
lnU	=	Total Urea fertilizer (kg)
lnZA	=	Total ZA fertilizer (kg)
lnNPK	=	Total NPK fertilizer (kg)

lnPes	=	Amount of pesticides (kg)
lnTK	=	amount of labor used (HOK)
lnPO	=	amount of organic fertilizer (kg)
i	=	Number of respondent farmers
β_0	=	Intercept
$\beta_1 - \beta_8$	=	coefficient of estimated parameter variable/factor of production
$(\beta_1 - \beta_8 > 0)$	=	Error (inefficiency effect in the model)
V_i - U_i		
V_i	=	Random variable, where the variable is an external factor (climate, pest attack or error in modeling) the distribution is symmetrical and the distribution is normal (V_{ij}~ N (0, σv^2)
U_i	=	Positive random variable (the variable is assumed to have an influence on technical inefficiency and a relationship with internal factors. This variable also has a half-normal distribution (V_{ij}~ |N(0, σv^2|).

Measurement of efficiency technical quality of potato production is measured using the following formula (Coelli, *et al* 2005):

$$lnProdi = \beta_0 + \beta_1 lnLusi + \beta_2 lnBnhi + \beta_3 lnU + \beta_4 lnZA + \beta_5 lnNPK + \beta_6 lnPesi + \beta_7 lnTKi + \beta_8 li + \varepsilon \quad (2)$$

where y_i is the actual production of the observations, y^* is the potential production conjecture of the stochastic frontier function. Technical efficiency for a farmer range from 0 to 1. This technical efficiency has a value opposite to the effect of technical inefficiency (Hamdan & Basrowi, 2024; Junaidi, Masdar, et al., 2024; Miar et al., 2024; Nuryanto et al., 2019).

3.4 Methods of Analysis of the Influence of Production Risk Behavior and Other Factors on the Level of Technical Efficiency

In estimating the factors that affect the level of technical efficiency, a tobit regression model is used. This study uses tobit regression because the value of the dependent variable, namely the technical efficiency index, is constrained between 0 – 1. The model for calculating TE *(Technical Efficiency)* is analyzed separately. In estimating the tobit regression parameters, MLE *(Maximum Likelihood Estimator)* (Hadi et al., 2019; Hamdan & Basrowi, 2024; Junaidi, Basrowi, et al., 2024; Purwaningsih et al., 2024). The estimation model for factors that affect the level of efficiency using the Tobit regression model is:

$$TE = \delta_0+\delta_1 Z_1 +\delta_2 Z_2+\delta_3 Z_3+\delta_4 Z_4+\delta_5 Z_5+\delta_6 Z_6+\delta_7 D_1+\delta_8 D_2+\delta_9 D_3+\delta_{10} D_4+\varepsilon \quad (2)$$

where:

TE	=	value of technical efficiency
Z_1 Age	=	age/age of farmer (years)
Z_2 PDK	=	length of education (years)
Z_3 LU	=	farming experience (years)
Z_4 AK	=	number of family dependents (people)
Z_5 FPL	=	frequency of counseling and training attended by farmers during the planting season (number 1.2)
Z6Off	=	total income from outside agriculture is measured by rupiah (rp)
D_1 M	=	dummy planting season, 1 if applying planting season 1 and 0 others.
D_2 T	=	dummy technology, 1 if using technology, and 0 if not
D_2 Risk behavior	=	worth 2 risk seekers, risk averse worth 1 and risk neutral 0
δ_n	=	coefficient of variable parameter estimated
ε	=	random error term assumed to be free and is freely distributed and the distribution is normally truncated with n (0, δ)

4. Result and Discussion

4.1 Result

The effect of inputs on the risk of rice production in flood-prone areas

Bojonegoro Regency

Several studies on production risk using the Just and Pope (1979) model show that only a few variables have a significant effect because the model emphasizes more on seeing signs from the parameter coefficients so that it can be seen whether these inputs increase or decrease production risk (Ferrer et al., 2022; Hatta et al., 2023). The results of the data analysis show that the inputs that reduce production risk during the rainy season are land area, urea and labor, while those that increase production risk are seeds, NPK and pesticides (L. Chen & Zhou, 2023; Forgione & Migliardo, 2023). Seeds have a significant effect on increasing production risk (Kanthilanka et al., 2023; J. Wang et al., 2023). Farmers in Bojonegoro Regency use various seed varieties, namely ciherang, inpari 32, sitbagendit (Hatta et al., 2023; Sanogo et al., 2023). Seeds used during the rainy season should be resistant to waterlogging so that production risks can be reduced (Zabidi et al., 2022; ZHAO et al., 2023). In the dry season, the inputs that reduce production risk are land area, seeds, urea and pesticides, while the inputs that increase production risk are NPK and labor (Kanthilanka et al., 2023; Mbah et al., 2023).

Table 1

Results of the analysis of the risk function of Bojonegoro Regency

Variable	Rainy Season			Drought Season		
	Coefficient	Standard Error	T - calculate	Coefficient	Standard Error	T - calculate
Konstanta	* 1.032067	0.418805	2.464315	* 0.517324	0.278529	1.857346
Luas Lahan	-0.075485	0.062853	-1.200977	-0.000251	0.049046	-0.005126
Benih	* 0.078518	0.055519	1.414251	-0.004359	0.024690	-0.176552
Urea	-0.066131	0.058937	-1.122067	* -0.094511	0.057472	-1.644475
NPK	0.058660	0.053307	1.100414	0.034218	0.046904	0.729527
Pesticides	0.032735	0.031208	1.048940	-0.007987	0.027937	-0.285900
HR	-0.049694	0.072808	-0.682533	0.051939	0.074836	0.694040
R-square	0.046			0.065		
F-count	0.751			0.809		

Note: *significant at α = 0.1;
** significant at α = 0.05
*** significant at α = 0.01

Pasuruan Regency

Table 2

Results of the analysis of the risk function of Pasuruan Regency

Variable	Rainy Season			Drought Season		
	Coefficient	Standard Error	T - calculate	Coefficient	Standard Error	T - calculate
Konstanta	0.039678	0.274456	0.144570	0.030065	0.271285	0.144963
Luas Lahan	0.016493	0.041351	0.398846	0.016503	0.041351	0.407632
Benih	-0.005437	0.046744	-0.116313	- 0.004421	0.033001	-0.116313
Urea	0.090860	0.059926	1.516202	0.091060	0.061119	1.801462
NPK	-0.028715	0.033927	-0.846375	-0.024057	0.033398	-1.649021
Pesticide	-0.066656	0.031992	-2.083492	-0.066656	0.031992	-2.083492
Human Resources	-0.010362	0.060917	-0.170102	-0.010362	0.060917	-0.170102
R-square	0,131			0,185		
F-count	3.183			2.348		

Note: *significant at α = 0.1;
** significant at α = 0.05
*** significant at α = 0.01

The results of the data analysis show that the inputs that reduce production risk during the rainy and dry seasons are the same, namely seeds, NPK, pesticides and labor, while those that Raising the risk of production is land, and urea (Kanthilanka et al., 2023; Martinazzo et al., 2023; Promkhambut et al., 2023).

Farmer behavior towards production risk in flood-prone areas

Bojonegoro Regency

Table 3

Respondent Farmer's Behavior towards Production Risk

Farmer's Behavior towards	Rainy		Season	
	Farmer's Risk (Person)	Percentage (%)	Farmer (Person)	Percentage (%)
Risk seeker	14	14	36	36
Risk Averse	87	87	64	64
Risk Neutral	0	0	0	0
Total	100	100	100	100

Source: Primary data analysis 2022

Based on the results of the analysis it is known that when planting in the rainy season the respondent farmers tend to be risk averse or do not dare to accept the risk, which is equal to 87%, while when planting in the dry season it is 64%.

Pasuruan Regency

Table 4
Respondent Farmer's Behavior towards Production Risk

Farmer's Behavior towards	Rainy		Season	
	Farmer's Risk (Person)	Percentage (%)	Farmer (Person)	Percentage (%)
Risk seeker	93	93	74	74
Risk Averse	7	7	26	26
Risk Neutral	0	0	0	0
Total	100	100	100	100

Source: Primary data analysis 2022

Based on the results of the analysis above, in Pasuran district, farmers' behavior during the rainy season tends to be risk seeker by 93%. Meanwhile, in the dry season it is 74%.

The effect of farmer risk behavior on the allocation of production inputs in Bojonegoro Regency

Farmers' Production Risk Preferences for Each Production Input

The behavioral analysis model used is the model developed by Just and Pope (1979) based on the derivative of the utility function, yielding the value of θ and the first derivative of the risk function or g_j (Liu et al., 2023; Talhelm et al., 2023). These two values can be used to determine a farmer's risk preference for input allocation (Ferrer et al., 2022; Mbah et al., 2023). This means that farmers who are risk seekers of inputs are more willing to allocate inputs in larger quantities than farmers who are risk averse (Nguyen-Thi-Lan et al., 2023; Promkhambut et al., 2023).

Table 5
Production Risk Preference for each Production Input (Rainy Season)

Variable	Average Value θ	Average Value g_j	Risk Preference
Seed	-452.7663966	0.476208	Risk averse
Urea	-124484.2022	-0.000223	Risk seeker
NPK	-162096.2001	0.000314	Risk averse
Pesticide	-2.140555767	107.14904	Risk averse
Labor	-160626.506	-0.001012	Risk seeker

Source: Primary data analysis 2022

Based on the results of the analysis above, it can be concluded that the production risk for each production input during the rainy season in Bojonegoro Regency is found in the input allocation made by farmers who tend to be risk seekers for urea and labor (Mbah et al., 2023; YUAN et al., 2022).

Table 6
Production risk preference for each input Production (Dry)

Variable	Average Value θ	Average Value g_j	Risk Preference
Seed	-2.7435	-5.5937	Risk
Urea	-13811.1537	-0.000298	Risk Seeker
NPK	-11716.8438	0.004276	Risk averse
Pesticides	-3.7921	-22.14292	Risk seeker
Labor	-18687.289	0.022428	Risk averse

Source: Primary data analysis 2022

Based on the results of the analysis above, it can be seen that the production risk of production inputs during the dry season in Bojonegoro Regency is that the input allocation is in seeds, urea and pesticides (Khatri-Chhetri et al., 2023; van Aalst et al., 2023).

Pasuruan Regency

Farmers' Production Risk Preferences for Each Production Input

Table 7
Results of Analysis of Factors Influencing Farmer Behavior on Production Risk

Variable	Average Value θ	Average Value g_j	Preference Risk
Seed	11.9674	-10.6909	Risk averse
Urea	-52207.1077	0.006023	Risk averse
NPK	90533.1823	-0.000028	Risk averse
Pesticide	-0.0541	-85.9242	Risk seeker
Labor	1612437.51	-0, 000275	Risk averse

Source: Primary data analysis 2022

Based on the results of the analysis above, it is known that farmers' risk for each production input in Pasuruan Regency, during the rainy season, farmers' input allocation is more likely to be pesticide risk seekers.

Table 8

Production Risk Preference for each Production Input (Dry)

Variable	Average Value θ	Average Value g_j	Risk Preference
Seed	-77201.193	0.00002	Risk averse
Urea	476824 .321	-0.000011	Risk averse
NPK	3738.931	-0.000001	Risk averse
Pesticides	7795.795	0.000074	Risk seekers
Labor	725215.177	-0.001489	Risk averse

Source: Primary data analysis 2022

Based on the research results above, it can be seen that during the dry season farmers in Pasuruan district are more likely to be risk-seeking pesticides, the same as in the rainy season.

Factors influencing behavior Farmer production risks in flood-prone areas

Bojonegoro Regency

Table 9

Results of Analysis of Factors Influencing Farmer Behavior on Production Risk

Variable	Coefficient	Standard Error	z - Statistical
Constant	*-0.433639	0.218991	-1.980172
Age	**0.014788	0.004230	3.496316
Education	0.005205	0.008975	0.57953
Farming duration	*-0.0051 77	0.003192	-1.622028
Dependents of Family Members	0.005814	0.019079	0.304756
Frequency of Counseling and Training	0.029078	0.031387	0.926439
Offarm Revenue	***5.27E-08	1.19E-08	4.447640
DUMMY Offarm	***-0.239574	0.056736	-4.222580

Note: significant at α = 0,1;
** significant at α = 0.05
*** significant at α = 0.01

Factors that have a significant effect on farmer production risk behavior are age, length of farming/farming experience, off-farm income and planting season. From this it can be seen that the growing season determines the behavior of farmers towards risk, the results of the analysis show that in the rainy season farmers are more likely to be risk averse (Mbah et al., 2023; F. Wang et al., 2023).

Pasuruan Regency

Table 10

Results of Analysis of Factors Influencing Farmer Behavior on Production Risk

Variable	Coefficient	Standard Error	z - Statistical
Constant	* -1.862052	0.932304	-1.997257
Age	** 0.041990	0.014095	2.979064
Education	-0.044131	0.046240	-0.954385
Farming duration	*0.018920	0.011106	1.703483
Dependents of Family Members	0.079008	0.107213	0.736923
Frequency of Counseling and Training	0.122838	0.249691	0.491960
Of farm Revenue	3.09E-08	7.68E-08	0.402047
DUMMY Of farm	*** 0.971137	0.272936	3.558113

Note: significant at α = 0,1;
** significant at α = 0.05
*** significant at α = 0.01

Factors that have a significant effect on farmer production risk behavior are age, length of farming/farming experience, and planting season. From this it can be seen that the growing season determines the behavior of farmers towards risk, the results of the analysis show that during the rainy season farmers are more likely to be risk seekers (Nguyen-Thi-Lan et al., 2023; Zachmann et al., 2022).

The level of technical efficiency of rice farming in flood-prone areas

Bojonegoro Regency

The distribution of technical efficiency of rice farmers in Bojonegoro Regency can be seen in Tables 11 and 12, while the value of the technical efficiency of each farmer can be seen in Figures 1 and 2.

Table 11
The distribution of technical efficiency levels in rainy season

Technical efficiency level of	farmers (person)	Percentage (%)
0 - 0.25	30	30
0.26 - 0.5	43	43
0.51 - 0.7	21	21
0.71 – 0.85	5	5
0.86 - 1	1	1
TOTAL	**100**	**100**
Min	0.107	
Max	0.999	
Average	0.394	

Source: Primary data analysis 2022

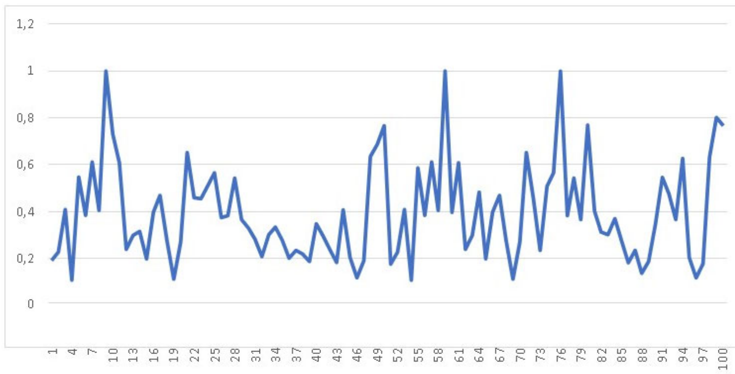

Fig. 1. Technical efficiency level of rice farmers in Bojonegoro Regency during the rainy season

Based on the results of the analysis above, the level of technical efficiency in the rainy season has a minimum value of 0.107, a maximum value of 0.999 and an average value of 394.

Table 12
Distribution of Technical Efficiency Levels in the dry season

Efficiency Levels of	Farmers (people)	Percentage (%)
0 - 0.25	3	3
0.26 - 0.5	14	14
0.51 - 0.7	31	31
0.71 – 0.85	47	47
0.86 – 1	5	5
TOTAL	**100**	**100**
Min	0.897	
Max	0.231	
Average	0.671	

Source: Primary data analysis 2022

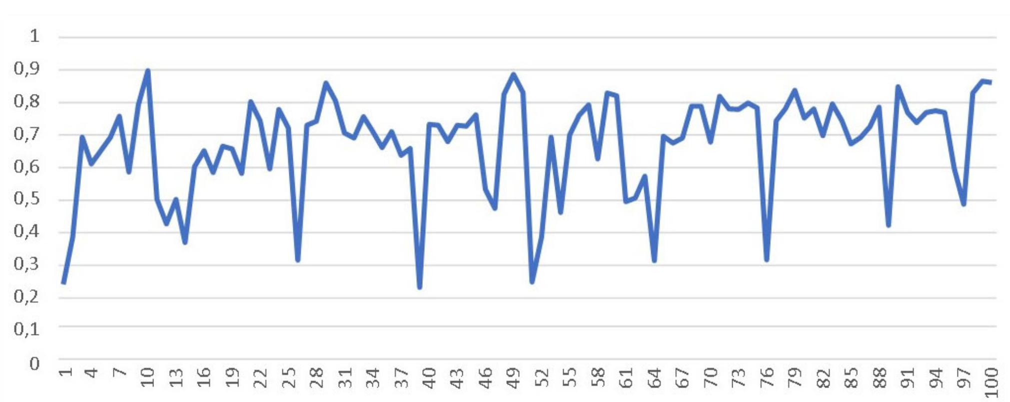

Fig. 2. The level of technical efficiency of rice farmers in Bojonegoro Regency during the dry season Rainfall

Based on the results of the analysis above, the level of technical efficiency in the dry season has a minimum value of 0.897, a maximum value of 0.231, and an average value of 0.671.

Pasuruan Regency

The distribution of technical efficiency of rice farmers in Pasuruan Regency can be seen in Table 13 and Table 14, while the value of the technical efficiency of each farmer can be seen in Fig. 3 and Fig. 4.

Table 13
The distribution of technical efficiency levels in rainy season

levels	N	Percentage (%)
0 - 0.25	2	2
0.26 - 0.5	4	4
0.51 - 0.7	20	20
0.71 – 0.85	49	49
0.86 – 1	15	15
TOTAL	**100**	**100**
Min	0.103	
Max	0.899	
Average	0.735	

Source: Primary data analysis 2022

Fig. 3. The level of technical efficiency of rice farmers in Pasuruan Regency during the rainy season

Based on the results of the analysis above, the level of technical efficiency in the dry season has a minimum value of 0.103, a maximum value of 0.899, and an average value of 0.735.

Table 14
The distribution of technical efficiency levels in rainy season

levels	Table (people)	Percentage (%)
0 - 0.25	0	0
0.26 - 0.5	7	7
0.51 - 0.7	26	26
0.71 – 0.85	44	44
0.86 – 1	23	23
TOTAL	100	100
Min	0.364	
Max	0.906	
Average	0.755	

Source: Primary data analysis 2022

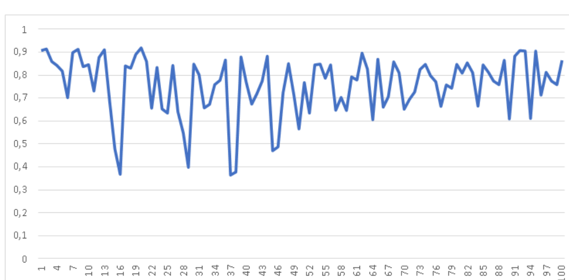

Fig. 4. The level of technical efficiency of rice farmers in Pasuruan Regency during the dry season

Based on the results of the data analysis above, the level of technical efficiency in the dry season has a minimum value of 0.364, a maximum value of 0.906 and an average value of 0.755.

The factors that affect the level of technical efficiency in the two regions show different results. In Bojonegoro Regency, the risk behavior of farmers affects the level of technical efficiency, where farmers who are risk seekers are more accepting of risks. Farmers are bolder in determining inputs, so they are more efficient.

5. Discussion

Based on the results of the research above, the influence of input on the risk of rice production in flood-prone areas in Bojonegoro Regency is that the input that increases the risk of production in the rainy season is seeds, NPK fertilizer and pesticides, while the input that reduces the risk of production in the rainy season is the rainy season. are land, urea, and labor (Begum et al., 2023; Islam et al., 2023). In the dry season, inputs that increase risk are NPK fertilizer and labor, while those that reduce risk are land, seeds, urea and pesticides (Martinazzo et al., 2023; Tohidimoghadam et al., 2023; ZHAO et al., 2023). Pasuruan Regency, the inputs that increase production risk in the rainy and dry seasons are the same, namely land and urea, while the inputs that reduce risk are seed production, NPK, pesticides and labor (Hatta et al., 2023; Mbah et al., 2023). Urea, pesticides and labor have a significant influence on risk. Urea poses a production risk in both the rainy and dry seasons, this happens because most farmers do not know the fertilizer doses in these two seasons, another thing is because the rainy season is unpredictable so fertilizer is not done on time and in the dosage (Johnson et al., 2023; Promkhambut et al., 2023). In the rainy and dry seasons, farmers are more likely to behave as risk seekers or dare to take risks, even though in the rainy season the number of risk seekers is greater than in the dry season (Johnson et al., 2023; Promkhambut et al., 2023).

Farmers' behavior towards production risks in flood-prone areas in Bojonegoro district (Martinazzo et al., 2023; Zabidi et al., 2022). In the rainy season, most farmers behave in a risk averse manner, while in the dry season the number of risk averse is less than in the rainy season (Abualigah et al., 2023; Begum et al., 2023). Farmers in Bojonegoro Regency, which are in flood-prone areas, mostly behave in a risk-averse manner, this is of course influenced by seasonal conditions where floods occur in the rainy season, and in the dry season they take precautions by irrigating with pumps (Mbah et al., 2023; ZHAO et al., 2023). Meanwhile, in Pasuruan Regency, during the rainy and dry seasons, farmers are more likely to behave as risk seekers or dare to take risks, even though in the rainy season the number of risk seekers is greater than in the dry season (Khatri-Chhetri et al., 2023; Xiong et al., 2023).

The influence of farmers' risk behavior on the allocation of production inputs in Bojonegoro Regency in the rainy season, the input allocation made by farmers tends to be risk seeking for urea and labor, while in the dry season the input allocation is seeds, urea and pesticides (Martinazzo et al., 2023; Zabidi et al., 2022). In The Pasuruan Regency, in the rainy season, input allocation by farmers is more likely to be pesticide risk seekers, as is the case in the dry season (Kanthilanka et al., 2023; Mbah et al., 2023). The influence of socio-economic factors, technology, and planting season on the production risk behavior of farmers in flood-prone areas in Bojonegoro district, factors that have a significant influence on production risk behavior are age, length of farming, farming income, and planting season (Promkhambut et al., 2023; Sanogo et al., 2023). Pasuruan Regency factors that have a real influence on production risk behavior are age, length of farming and planting season.

The level of technical efficiency of rice farming in flood-prone areas in Bojonegoro Regency regarding the level of technical efficiency in the rainy season is 0.394, while in the dry season it is 0.671. The level of technical efficiency in Bojonegoro Regency is relatively low because it is below 0.7. In the Pasuruan Regency the level of technical efficiency in the rainy season is 0.735, while in the dry season it is 0.755. The level of technical efficiency of farmers in Pasuruan Regency is not much different because the input locations in both seasons are almost the same (Islam et al., 2023; Martinazzo et al., 2023). The influence of production risk behavior and other factors on the technical efficiency of rice farming in flood-prone areas (MAO et al., 2023; Zabidi et al., 2022). Bojonegoro Regency, the factors that influence the technical efficiency of rice farming in flood-prone areas are age, number of dependents in the family, outside income, and risky production behavior, while in Pasuruan Regency, the factors that influence the technical efficiency of rice farming in flood-prone areas namely age, education, and number of dependents in the family (Begum et al., 2023; Martinazzo et al., 2023).

6. Conclusion

The influence of inputs on the risk of rice production in flood-prone areas in Bojonegoro Regency is that inputs that increase production risk in the rainy season are seeds, NPK fertilizer and pesticides and in the dry season, inputs that increase risk are NPK fertilizer and labor. Meanwhile, in Pasuruan district, the inputs that increase production risk in the rainy and dry seasons are the same, namely land and urea. Farmers' behavior towards production risks in flood-prone areas in Bojonegoro district. In the rainy season, most farmers behave in a risk averse manner, while in the dry season the number of risk averse is less than in the rainy season. Meanwhile, in the Pasuruan Regency, during the rainy and dry seasons, farmers are more likely to behave as risk seekers or dare to take risks. The influence of farmers' risk behavior on the allocation of production inputs in Bojonegoro Regency in the rainy season, the input allocation made by farmers tends to be risk seeking for urea and labor, while in the dry season the input allocation is seeds, urea and pesticides. In The Pasuruan Regency, in the rainy season, input allocation by farmers is more likely to be pesticide risk seekers, as is the case in the dry season. The level of technical efficiency of farmers in Pasuruan Regency is not much different because the input locations in both seasons are almost the same. The influence of production risk behavior and other factors on the technical efficiency of rice farming in flood-prone areas. Bojonegoro Regency, the factors that influence the technical efficiency of rice farming in flood-prone areas are age, number of dependents in the family, outside income, and risky production behavior, while in Pasuruan Regency, the factors that influence the technical efficiency of rice farming in flood-prone areas namely age, education, and number of dependents in the family.

References

Abualigah, L., Hanandeh, E. S., Zitar, R. A., Thanh, C. Le, Khatir, S., & Gandomi, A. H. (2023). Revolutionizing sustainable supply chain management: A review of metaheuristics. *Engineering Applications of Artificial Intelligence*, *126*(PA), 106839. https://doi.org/10.1016/j.engappai.2023.106839

Akkerman, R., Buisman, M., Cruijssen, F., de Leeuw, S., & Haijema, R. (2023). Dealing with donations: Supply chain management challenges for food banks. *International Journal of Production Economics*, *262*(May), 108926. https://doi.org/10.1016/j.ijpe.2023.108926

Alexandro, R., & Basrowi, B. (2024a). Measuring the effectiveness of smart digital organizations on digital technology adoption : An em- pirical study of educational organizations in Indonesia. *International Journal of Data and Network Science*, *8*(1), 139–150. https://doi.org/10.5267/j.ijdns.2023.10.009

Alexandro, R., & Basrowi, B. (2024b). The influence of macroeconomic infrastructure on supply chain smoothness and national competitiveness and its implications on a country ' s economic growth : evidence from BRICS. *Uncertain Supply Chain Management*, *12*(1), 167–180. https://doi.org/10.5267/j.uscm.2023.10.007

Basrowi, B., & Maunnah, B. (2019). The Challenge of Indonesian Post Migrant Worker's Welfare. *Journal of Advanced Research in Law and Economics; Vol 10 No 4 (2019): JARLE Vol X Issue 4(42) Summer 2019DO - 10.14505//jarle.v10.4(42).07*. https://journals.aserspublishing.eu/jarle/article/view/4716

Basrowi, B., & Utami, P. (2020). Building Strategic Planning Models Based on Digital Technology in the Sharia Capital Market. *Journal of Advanced Research in Law and Economics; Vol 11 No 3 (2020): JARLE Volume XI Issue 3(49) Summer 2020DO - 10.14505/jarle.v11.3(49).06*. https://journals.aserspublishing.eu/jarle/article/view/5154

Basrowi, B., & Utami, P. (2023). Development of Market Distribution through Digital Marketing Transformation Trends to Maximize Sales Turnover for Traditional Beverage Products. *Journal of Distribution Science*, *21*(8), 57–68. https://doi.org/10.15722/jds.21.08.202308.57

Begum, R., Sharmin, S., Mitra, S., Akhi, K., Deb, L., Kamruzzaman, M., & Khan, M. A. (2023). Production risk and technical inefficiency of bean (Phaseolus vulgaris) cultivation in Bangladesh: Do socio-economic factors matter? *Social Sciences and Humanities Open*, *7*(1), 100417. https://doi.org/10.1016/j.ssaho.2023.100417

Burgess, P. R., Sunmola, F. T., & Wertheim-Heck, S. (2023). A review of supply chain quality management practices in sustainable food networks. *Heliyon*, *9*(11), e21179. https://doi.org/10.1016/j.heliyon.2023.e21179

Burggräf, P., Adlon, T., Minderjahn, R., Schäfer, N., & Fassmer, T. (2023). Application of stochastic risk simulation to increase depth of production planning. *International Journal of Naval Architecture and Ocean Engineering*, *15*, 100545. https://doi.org/10.1016/j.ijnaoe.2023.100545

Can-ping, D. U. N., Rui, W., Kai-liang, M. I., Yu-ting, Z., Hai-peng, Z., Pei-yuan, C. U. I., Yan-le, G. U. O., Hao, L. U., & Hong-cheng, Z. (2023). One-time application of controlled-release bulk blending fertilizer enhanced yield, quality and photosynthetic efficiency of late japonica rice. *Journal of Integrative Agriculture*. https://doi.org/10.1016/j.jia.2023.10.007

Cano-Leiva, J., Cantos-Sanchez, P., & Sempere-Monerris, J. J. (2023). The effect of privately managed terminals on the technical efficiency of the Spanish port system. *Case Studies on Transport Policy*, *13*(May), 101026. https://doi.org/10.1016/j.cstp.2023.101026

Chen, L., & Zhou, Y. (2023). Low carbon economic scheduling of residential distribution network based on multi-dimensional network integration. *Energy Reports*, *9*, 438–448. https://doi.org/10.1016/j.egyr.2023.04.192

Chen, Z., & Hammad, A. W. A. (2023). Mathematical modelling and simulation in construction supply chain management. *Automation in Construction*, *156*(October), 105147. https://doi.org/10.1016/j.autcon.2023.105147

Czakon, W., Klimas, P., & Kawa, A. (2023). Re-thinking strategic myopia: A necessary condition analysis of heuristic and firm's performance. *Industrial Marketing Management*, *115*(December 2022), 99–109. https://doi.org/10.1016/j.indmarman.2023.09.015

Dowlati, M., Seyedin, H., Behnami, A., Marzban, A., & Gholami, M. (2023). Water resources resilience model in climate changes with community health approach: Qualitative study. *Case Studies in Chemical and Environmental Engineering*, *8*(August), 100521. https://doi.org/10.1016/j.cscee.2023.100521

Dzikriansyah, M. A., Masudin, I., Zulfikarijah, F., Jihadi, M., & Jatmiko, R. D. (2023). The role of green supply chain management practices on environmental performance: A case of Indonesian small and medium enterprises. *Cleaner Logistics and Supply Chain*, *6*(March 2022), 100100. https://doi.org/10.1016/j.clscn.2023.100100

Fernandez-Viagas, V., & Framinan, J. M. (2022). Exploring the benefits of scheduling with advanced and real-time information integration in Industry 4.0: A computational study. *Journal of Industrial Information Integration*, *27*(July 2020), 100281. https://doi.org/10.1016/j.jii.2021.100281

Ferrer, A. J. G., Thanh, L. H., Kiet, N. T., Chuong, P. H., Trang, V. T., Hopanda, J. C., Carmelita, B. M., Gummadi, S., & Bernardo, E. B. (2022). The impact of an adjusted cropping calendar on the welfare of rice farming households in the Mekong River Delta, Vietnam. *Economic Analysis and Policy*, *73*, 639–652. https://doi.org/10.1016/j.eap.2021.12.018

Forgione, A. F., & Migliardo, C. (2023). Mafia risk perception: Evaluating the effect of organized crime on firm technical efficiency and investment proclivity. *Socio-Economic Planning Sciences*, *88*(December 2022), 101619. https://doi.org/10.1016/j.seps.2023.101619

Gehring, M., Volk, R., & Schultmann, F. (2022). On the integration of diverging material flows into resource-constrained project scheduling. *European Journal of Operational Research*, *303*(3), 1071–1087. https://doi.org/10.1016/j.ejor.2022.03.047

Ghimire, B., Dhakal, S. C., Marahatta, S., & Bastakoti, R. C. (2023). Technical efficiency and its determinants on lentil (Lens culunaris) production in Nepal. *Farming System*, *1*(3), 100045. https://doi.org/10.1016/j.farsys.2023.100045

Ghobakhloo, M., Iranmanesh, M., Foroughi, B., Babaee Tirkolaee, E., Asadi, S., & Amran, A. (2023). Industry 5.0 implications for inclusive sustainable manufacturing: An evidence-knowledge-based strategic roadmap. *Journal of Cleaner Production*, *417*(April), 138023. https://doi.org/10.1016/j.jclepro.2023.138023

Hadi, R., Shafrani, Y. S., Hilyatin, D. L., Riyadi, S., & Basrowi, B. (2019). Digital zakat management, transparency in zakat reporting, and the zakat payroll system toward zakat management accountability and its implications on zakat growth acceleration. *International Journal of Data and Network Science*, *8*(1), 103–108. https://doi.org/10.5267/j.ijdns.2018.12.005

Hamdan, H., & Basrowi, B. (2024). Do community entrepreneurial development shape the sustainability of tourist villages? Hamdana*. *Uncertain Supply Chain Management*, *12*(1), 407–422. https://doi.org/10.5267/j.uscm.2023.9.014

Hatta, M., Sulakhudin, Burhansyah, R., Kifli, G. C., Dewi, D. O., Kilmanun, J. C., Permana, D., Supriadi, K., Warman, R., Azis, H., Santari, P. T., & Widiastuti, D. P. (2023). Food self-sufficiency: Managing the newly-opened tidal paddy fields for rice farming in Indonesia (A case study in West Kalimantan, Indonesia). *Heliyon*, *9*(3), e13839. https://doi.org/10.1016/j.heliyon.2023.e13839

Iboko, M. P., Dossou-yovo, E. R., Obalum, S. E., & Oraegbunam, C. J. (2023). *Paddy rice yield and greenhouse gas emissions : Any trade-off due to co-application of biochar and nitrogen fertilizer ? A systematic review*. *9*(April). https://doi.org/10.1016/j.heliyon.2023.e22132

Islam, S., Mitra, S., & Khan, M. A. (2023). Technical and cost efficiency of pond fish farms: Do young educated farmers bring changes? *Journal of Agriculture and Food Research*, *12*(March), 100581. https://doi.org/10.1016/j.jafr.2023.100581

Johnson, J. M., Ibrahim, A., Dossou-Yovo, E. R., Senthilkumar, K., Tsujimoto, Y., Asai, H., & Saito, K. (2023). Inorganic fertilizer use and its association with rice yield gaps in sub-Saharan Africa. *Global Food Security*, *38*(March), 100708. https://doi.org/10.1016/j.gfs.2023.100708

Junaidi, A., Basrowi, B., Sabtohadi, J., Wibowo, A. M., Wiboho, S. S., Asgar, A., Pramono, E. P., & Yenti, E. (2024). The role of public administration and social media educational socialization in influencing public satisfaction on population services : The mediating role of population literacy awareness. *International Journal of Data and Network Science*, *8*(1), 345–356. https://doi.org/10.5267/j.ijdns.2023.9.019

Junaidi, A., Masdar, A. Zum, Basrowi, B., Robiatun, D., Situmorang, J. W., Lukas, A., Asgar, A., Herlina, L., Manulu, L. P., & Payung, L. (2024). Uncertain Supply Chain Management Enhancing sustainable soybean production in Indonesia : evaluating the environmental and economic benefits of MIGO technology for integrated supply chain sustainability. *Uncertain Supply Chain Managemen*, *12*(1), 221–234. https://doi.org/10.5267/j.uscm.2023.10.003

Kanthilanka, H., Ramilan, T., Farquharson, R. J., & Weerahewa, J. (2023). Optimal nitrogen fertilizer decisions for rice farming in a cascaded tank system in Sri Lanka: An analysis using an integrated crop, hydro-nutrient and economic model. *Agricultural Systems*, *207*(March), 103628. https://doi.org/10.1016/j.agsy.2023.103628

Khatri-Chhetri, A., Sapkota, T. B., Maharjan, S., Cheerakkollil Konath, N., & Shirsath, P. (2023). Agricultural emissions reduction potential by improving technical efficiency in crop production. *Agricultural Systems*, *207*(March), 103620. https://doi.org/10.1016/j.agsy.2023.103620

Kittie, S., & Basrowi, B. (2024). Environmental education using SARITHA-Apps to enhance environmentally friendly supply chain efficiency and foster environmental knowledge towards sustainability. *Uncertain Supply Chain Management*, *12*(1), 359–372. https://doi.org/10.5267/j.uscm.2023.9.015

Kunisch, S., Birkinshaw, J., Boppel, M., & Choi, K. (2023). Why do firms launch corporate change programs? A contingency perspective on strategic change. *Scandinavian Journal of Management*, *39*(4), 101297. https://doi.org/10.1016/j.scaman.2023.101297

Li, J., Ai, Q., Chen, M., & Huang, K. (2022). Aggregator's scheduling and offering strategy for renewable integration based on information gap decision theory. *Energy Reports*, *8*, 163–171. https://doi.org/10.1016/j.egyr.2022.05.131

Liu, J., Wu, J., & Gong, Y. (2023). Maritime supply chain resilience: From concept to practice. *Computers and Industrial Engineering*, *182*(June), 109366. https://doi.org/10.1016/j.cie.2023.109366

Mamgbi Zozimo, T., Kawube, G., & W. Kalule, S. (2023). The role of development interventions in enhancing technical efficiency of sunflower producers. *Journal of Agriculture and Food Research*, *14*(November 2022), 100707. https://doi.org/10.1016/j.jafr.2023.100707

MAO, H., QUAN, Y. rong, & FU, Y. (2023). Risk preferences and the low-carbon agricultural technology adoption: Evidence from rice production in China. *Journal of Integrative Agriculture*, *22*(8), 2577–2590. https://doi.org/10.1016/j.jia.2023.07.002

Martinazzo, R., Muller, C. A., Teixeira, L. C., Stumpf, L., Antunes, W. R., Metz, L. E. G., Valgas, R. A., Bamberg, A. L., & Silveira, C. A. P. (2023). Leather-based fertilizers from Personal Protective Equipment (PPE) reverse logistics: Technical efficiency and environmental safety. *Resources, Conservation and Recycling Advances*, *18*(April), 200153. https://doi.org/10.1016/j.rcradv.2023.200153

Marwanto, I. G. G. H., Basrowi, B., & Suwarno, S. (2020). The Influence of Culture and Social Structure on Political Behavior in the Election of Mayor of Kediri Indonesia. *International Journal of Advanced Science and Technology*, *29*(05 SE-Articles), 1035–1047. http://sersc.org/journals/index.php/IJAST/article/view/9759

Mazzi, A. (2023). Environmental and safety risk assessment for sustainable circular production: Case study in plastic processing for fashion products. *Heliyon*, *9*(11), e21352. https://doi.org/10.1016/j.heliyon.2023.e21352

Mbah, L. T., Molua, E. L., Bomdzele, E., & Egwu, B. M. J. (2023). Farmers' response to maize production risks in Cameroon: An application of the criticality risk matrix model. *Heliyon*, *9*(4), e15124. https://doi.org/10.1016/j.heliyon.2023.e15124

Miar, M., Rizani, A., Pardede, R. L., & Basrowi, B. (2024). Analysis of the effects of capital expenditure and supply chain on economic growth and their implications on the community welfare of districts and cities in central Kalimantan province. *Uncertain Supply Chain Management*, *12*(1), 489–504. https://doi.org/10.5267/j.uscm.2023.9.003

Motbaynor Workneh, W., & Kumar, R. (2023). The technical efficiency of large-scale agricultural investment in Northwest Ethiopia: A stochastic frontier approach. *Heliyon*, *9*(9), e19572. https://doi.org/10.1016/j.heliyon.2023.e19572

Mustofa, M. A., Suseno, B. D., & Basrowi. (2023). *Uncertain Supply Chain Management Technological innovation and the environmentally friendly building material supply chain : Implications for sustainable environment*. *11*, 1405–1416. https://doi.org/10.5267/j.uscm.2023.8.006

Nelson, L., & Ahmadpoor, N. (2023). An examination of flood resilience in London Borough of Southwark. *Urban Climate*, *52*, 101692. https://doi.org/10.1016/j.uclim.2023.101692

Nguyen-Thi-Lan, H., Fahad, S., Ho-Ngoc, N., Nguyen-Anh, T., Pham-Van, D., Nguyen-Thi-Viet, H., Do-Hoang, P., Do-Kim, C., & To-The, N. (2023). Crop farming and technical efficiency of tea production nexus: An analysis of environmental impacts. *Journal of the Saudi Society of Agricultural Sciences*, *22*(3), 158–164. https://doi.org/10.1016/j.jssas.2022.09.001

Nuryanto, U. W., Basrowi, B., & Quraysin, I. (2019). Big data and IoT adoption in shaping organizational citizenship behavior: The role of innovation organiza- tional predictor in the chemical manufacturing industry. *International Journal of Data and Network Science*, *8*(1), 103–108. https://doi.org/10.5267/j.ijdns.2018.12.005

Oliveira, N., Lumineau, F., & Ariño, A. (2023). Time in international strategic alliances: Progress and prospect. *Journal of World Business*, *58*(4). https://doi.org/10.1016/j.jwb.2023.101456

Promkhambut, A., Yokying, P., Woods, K., Fisher, M., Li Yong, M., Manorom, K., Baird, I. G., & Fox, J. (2023). Rethinking agrarian transition in Southeast Asia through rice farming in Thailand. *World Development*, *169*, 106309. https://doi.org/10.1016/j.worlddev.2023.106309

Purwaningsih, E., Muslikh, M., Suhaeri, S., & Basrowi, B. (2024). Utilizing blockchain technology in enhancing supply chain efficiency and export performance , and its implications on the financial performance of SMEs. *Uncertain Supply Chain Management*, *12*(1), 449–460. https://doi.org/10.5267/j.uscm.2023.9.007

Sanogo, K., Touré, I., Arinloye, D. D. A. A., Dossou-Yovo, E. R., & Bayala, J. (2023). Factors affecting the adoption of climate-smart agriculture technologies in rice farming systems in Mali, West Africa. *Smart Agricultural Technology*, *5*(March). https://doi.org/10.1016/j.atech.2023.100283

Smith, R. L. Q., & Shashkina, O. (2023). A way forward to integrating cascading risk into local resilience strategies in Central Asia. *Progress in Disaster Science*, *17*(December 2022), 100273. https://doi.org/10.1016/j.pdisas.2022.100273

Soenyono, S., & Basrowi, B. (2020). Form and Trend of Violence against Women and the Legal Protection Strategy. *International Journal of Advanced Science and Technology*, *29*(05 SE-Articles), 3165–3174. http://sersc.org/journals/index.php/IJAST/article/view/11636

Suseno, B. D., & Basrowi, B. (2023). HighTech and Innovation Role of the Magnitude of Digital Adaptability in Sustainability of Food and Beverage Small Enterprises Competitiveness. *HighTech and Innovation Jo*, *4*(2), 270–282.

Suwarno, S., Basrowi, B., & Marwanto, I. G. G. H. (2020). Technology of Qualitative Analysis to Understand Community Political Behaviors in Regional Head Election in Wates District, Kediri, Indonesia. *International Journal of Advanced Science and Technology*, *29*(05 SE-Articles), 2624–2635. http://sersc.org/journals/index.php/IJAST/article/view/11159

Taj, S., Imran, A. S., Kastrati, Z., Daudpota, S. M., Memon, R. A., & Ahmed, J. (2023). IoT-based supply chain management: A systematic literature review. *Internet of Things (Netherlands)*, *24*(October), 100982. https://doi.org/10.1016/j.iot.2023.100982

Talhelm, T., Wu, S. J., Lyu, C., Zhou, H., & Zhang, X. (2023). People in rice-farming cultures perceive emotions more accurately. *Current Research in Ecological and Social Psychology*, *4*(May), 100122. https://doi.org/10.1016/j.cresp.2023.100122

Tantawy, E. S. F., Amer, G. M., & M.Fayez, H. (2022). Scheduling Home Appliances with Integration of Hybrid Energy Sources using Intelligent Algorithms. *Ain Shams Engineering Journal*, *13*(4), 101676. https://doi.org/10.1016/j.asej.2021.101676

Tohidimoghadam, A., PourSaeed, A., Bijani, M., & Samani, R. E. (2023). Rural sustainable livelihood resilience to climate change: A strategic analysis. *Environmental and Sustainability Indicators*, *20*(August), 100292. https://doi.org/10.1016/j.indic.2023.100292

van Aalst, M. A., Koomen, E., Tran, D. D., Hoang, H. M., Nguyen, H. Q., & de Groot, H. L. F. (2023). The economic sustainability of rice farming and its influence on farmer decision-making in the upper Mekong delta, Vietnam. *Agricultural Water Management*, *276*(December 2022), 108018. https://doi.org/10.1016/j.agwat.2022.108018

Varajão, J., Fernandes, G., & Amaral, A. (2023). Linking information systems team resilience to project management success. *Project Leadership and Society*, *4*(August). https://doi.org/10.1016/j.plas.2023.100094

Wang, F., Wang, X., Liu, D., & Liu, H. (2023). Comprehensive safety risk evaluation of fireworks production enterprises using the frequency-based ANP and BPNN. *Heliyon*, *9*(11), e21724. https://doi.org/10.1016/j.heliyon.2023.e21724

Wang, J., Vaddu, S., Bhumanapalli, S., Mishra, A., Applegate, T., Singh, M., & Thippareddi, H. (2023). A systematic review and meta-analysis of the sources of Campylobacter in poultry production (preharvest) and their relative contributions to the microbial risk of poultry meat. *Poultry Science*, *102*(10), 102905. https://doi.org/10.1016/j.psj.2023.102905

Xie, Y., Hu, C., Qin, Z., Chen, J., Huo, X., & Tao, Y. (2023). Ecological-health risks assessment and characteristic pollutants identification of heavy metals in the soils of a coking plant in production in Guangxi, China. *Ecological Indicators*, *154*(August), 110830. https://doi.org/10.1016/j.ecolind.2023.110830

Xiong, X. Bin, Zhao, Z. Y., Wang, P. Y., Mo, F., Zhou, R., Cao, J., Liu, S. T., Zhang, F., Wesly, K., Wang, Y. B., Fang, X. W., Tao, H. Y., & Xiong, Y. C. (2023). Aging rate, environmental risk and production efficiency of the low-density polyethylene (LDPE) films with contrasting thickness in irrigated region. *Ecotoxicology and Environmental Safety*, *264*(August), 115399. https://doi.org/10.1016/j.ecoenv.2023.115399

Yeardley, A. S., Ejeh, J. O., Allen, L., Brown, S. F., & Cordiner, J. (2022). Integrating machine learning techniques into optimal maintenance scheduling. *Computers and Chemical Engineering*, *166*(June), 107958. https://doi.org/10.1016/j.compchemeng.2022.107958

Yontar, E. (2023). The role of blockchain technology in the sustainability of supply chain management: Grey based dematel implementation. *Cleaner Logistics and Supply Chain*, *8*(November 2022), 100113. https://doi.org/10.1016/j.clscn.2023.100113

YUAN, P. li, WANG, J. ping, GUO, C., GUO, Z. yuan, GUO, Y., & CAO, C. gui. (2022). Sustainability of the rice–crayfish farming model in waterlogged land: A case study in Qianjiang County, Hubei Province, China. *Journal of Integrative Agriculture*, *21*(4), 1203–1214. https://doi.org/10.1016/S2095-3119(21)63787-5

Zabidi, N. A., Nazri, F., Syafinaz, I., Amin, M., Salahuddin, M., Basri, M., Basha, R. K., & Othman, S. H. (2022). Smart Farming for Sustainable Rice Production: An Insight into Applications, Challenges and Future Prospects. *International Journal of Biological Macromolecules*, *2*(2), 33–47. https://doi.org/10.1016/j.rsci.2023.08.004

Zachmann, L., McCallum, C., & Finger, R. (2022). Data on Swiss grapevine growers' production, pest management and risk management decisions. *Data in Brief*, *51*, 109652. https://doi.org/10.1016/j.dib.2023.109652

Zhang, Q., Lusby, R. M., Shang, P., & Zhu, X. (2022). A heuristic approach to integrate train timetabling, platforming, and railway network maintenance scheduling decisions. *Transportation Research Part B: Methodological*, *158*(February), 210–238. https://doi.org/10.1016/j.trb.2022.02.002

ZHAO, T., HE, A., Khan, M. N., YIN, Q., SONG, S., & NIE, L. (2023). Coupling of reduced inorganic fertilizer with plant-based organic fertilizer as a promising fertilizer management for colored rice in tropical regions. *Journal of Integrative Agriculture*, 1–21. https://doi.org/10.1016/j.jia.2023.04.035