International Journal of Economics, Business and Innovation Research
https://e-journal.citakonsultindo.or.id/index.php/IJEBIR
E-ISSN : 2964-0865
IJEBIR

Analysis of the Influence of Human Capital, Harvested Land Area, and Informal Labor Characteristics on Rice Productivity in 38 Indonesian Provinces in 2020–2025

Jevon Thavea Anjaro[1], Deswara Arka Yakobus Assan[2], Jonathan Kevin Chandra[3], Yoel Satria Putra[4]

[1,2,3,4]Mathematics Study Program, Pelita Harapan University

Abstract

Amid Indonesia's growing population and declining agricultural land, this study investigated the effects of human capital (years of schooling), harvested area, and informal labor proportion on rice productivity across 38 provinces from 2020-2025. The research employed quantitative panel data analysis using fixed effects regression with robust standard errors on unbalanced panel data (N=212 observations) sourced from BPS and Ministry of Agriculture statistics. Diagnostic tests confirmed model suitability and addressed heteroscedasticity. Results revealed that human capital positively and significantly influenced rice productivity (+1.26 ton/ha per additional schooling year, p=0.003), while informal labor exerted a strong negative effect (-0.154 ton/ha per 1% increase, p=0.001); harvested area showed no significant impact (p=0.589). Simultaneously, all variables jointly affected productivity (F=6.62, p<0.001). The findings underscore the primacy of human capital development and labor formalization over land expansion for enhancing rice productivity, offering critical policy insights for achieving national food security targets.

Keywords: Fixed Effects Model, Human Capital, Informal Labor, Panel Data, Rice Productivity

INTRODUCTION

The agricultural sector plays a central role in supporting Indonesia's economy and food security, especially as the world's fourth most populous country. In the past two to three years, national rice production has fluctuated due to the COVID-19 pandemic and

Copyright at authors some right reserved this work is licensed under a Creative Commons Attribution-ShareAlike 4.0 International License.

climate change, with dependence on rice imports reaching 2.5 million tons in 2023 despite achieving self-sufficiency targets (Food and Agriculture Organization [FAO], 2021; Ministry of Agriculture of the Republic of Indonesia, 2022). Global trends indicate that agrarian countries like Indonesia must increase productivity per hectare to cope with projected population growth of up to 280 million by 2030, with rice contributing 52% of daily calorie consumption (Sukmana et al., 2023). The relevance of this topic is not only practical for national food policy but also scientific in testing production theories such as the Cobb-Douglas in the context of developing countries.

A closer look at the domestic context reveals structural challenges, with rice paddy land continuing to shrink by 1.2% annually due to conversion to non-agricultural uses, while the agricultural workforce is predominantly elderly, with an informal proportion reaching 70% (Sudarma et al., 2024; Susilowati, 2020). Statistics Indonesia (BPS) data from 2022–2024 shows that the national average rice productivity stagnated at 5.2 tons/ha, far below the potential of 8 tons/ha, particularly in food-granary provinces such as West Java and East Java (Sunardi, 2024). This phenomenon is exacerbated by low technology adoption among informal farmers, threatening long-term food security targets.

Previous research has explored rice production factors, consistently finding that harvested land area has a significant positive effect on output, while human capital through farmer education drives intensification (Rahman & Santoso, 2022). Panel studies in Southeast Asia also confirm that Mean Years of Schooling (MES) increases input efficiency by 15–20% through the adoption of superior varieties (Pratiwi et al., 2023). Similarly, spatial analysis in Indonesia found a strong correlation between land shrinkage and declining production in urban areas (Hidayat & Wijaya, 2024).

However, previous studies have shown inconsistencies regarding informal labor; some found a strong negative effect due to lack of training (ILO, 2018; Sari & Nugroho, 2021), while others found a neutral effect in rural areas due to the flexibility of farming families (Wulandari et al., 2023). Key limitations of these studies include the use of narrow cross-sectional data (only 10–20 provinces), the short pre-2020 period, and the absence of simultaneous variable integration in fixed-effects panel models, which reduces the robustness of cross-regional estimates (Susilowati, 2020; Sudarma et al., 2024).

*Research gap*What is clearly identified is the lack of a comprehensive analysis of the simultaneous influence of human capital (education), harvested land area, and the proportion of informal labor on rice productivity using panel data from 38 Indonesian provinces for the 2020–2025 period, including the recent expansion of Papua. This problem statement is crucial because demographic trends and post-pandemic land

Copyright at authors some right reserved this work is licensed under a Creative Commons Attribution-ShareAlike 4.0 International License.

conversion have not been fully mapped, hampering the evaluation of intensification policies.

This study aims to examine the partial and simultaneous effects of these three variables on rice productivity, with high urgency given the projected 2026 rice imports reaching 3 million tons if productivity does not increase by 10%. The novelty lies in the coverage of comprehensive panel data from 38 recent provinces and the integration of human capital theory with Cobb-Douglas in the context of informality, which goes beyond previous studies. The theoretical contribution enriches the regional agricultural economics literature, while the practical one provides policy recommendations for the Ministry of Agriculture to accelerate the transition to formal labor and education-based intensification.

Research Hypothesis

The hypotheses that will be tested empirically in this study are:

H_1: Human capital (education) has a positive and significant effect on rice productivity.

H_2: The area of harvested land has a positive and significant effect on rice productivity.

H_3: The proportion of informal workers in the agricultural sector has a negative and significant effect on rice productivity.

H_4: Human capital, harvested land area, and the proportion of informal labor together have a significant effect on rice productivity.

These hypotheses are formulated based on the Cobb-Douglas theoretical framework and Human Capital Theory.

RESEARCH METHODS

This study adopts a quantitative design with a panel data regression approach to test causal relationships between variables, in accordance with the positivist paradigm that emphasizes empirical hypothesis testing (Sugiyono, 2023; Sudaryono, 2022). As a spatial-temporal econometric study, this method is ideal for analyzing variations in rice productivity across provinces and time, based on a fixed-effects model that controls for fixed heterogeneity (Baltagi, 2021; Wooldridge, 2019). This approach also aligns with Emzir (2021) who recommends secondary panel data for agrarian policy research in Indonesia, as well as recent studies demonstrating its superiority in handling unbalanced regional data (Croissant & Millo, 2019).

The study population covers all 38 Indonesian provinces after the expansion of Papua, using a census sampling technique (total sampling) to ensure complete national

Copyright at authors some right reserved this work is licensed under a Creative Commons Attribution-ShareAlike 4.0 International License.

representation. The sample yields 212 observations from the 2020–2025 period in an unbalanced panel data structure, with new provinces such as Central Papua contributing only 2–3 years of data due to initial statistical limitations. This selection is justified to avoid exclusion bias from marginal regions, as recommended in regional panel analysis (Gujarati & Porter, 2022; Baltagi, 2021).

The main instrument is official secondary data operationalized as the dependent (rice productivity: tons/ha) and independent (RLS education: years; harvested land area: ha; proportion of informal labor: %) variables, with indicators directly from the Statistics Indonesia (BPS) and the Ministry of Agriculture to minimize measurement error. Instrument validity is guaranteed through standardized government primary sources, while reliability is verified through inter-annual consistency and descriptive tests (Sudarma et al., 2024; Sugiyono, 2023). This approach is consistent with secondary data protocols in agrarian research (Emzir, 2021; ILO, 2018).

The research procedure began with secondary data collection from BPS and the Ministry of Agriculture (2020–2025), followed by data cleaning to handle missing values in new provinces using the plm package in R. Next, descriptive exploration and diagnostic tests (Hausman, Breusch-Pagan) were conducted, followed by fixed effect model estimation with robust standard error HC1 to address heteroscedasticity (Wooldridge, 2019; Croissant & Millo, 2019). The final stage included coefficient interpretation and simultaneous F-tests, ensuring full replicability.

Data analysis techniques include fixed-effect panel regression models: , with the Hausman test for model selection, Breusch-Pagan for heteroscedasticity, and robust SE for valid inferences on unbalanced data. The analysis was run via R (plm package), supplemented by descriptive statistics and t/F tests for partial-simultaneous hypotheses (Baltagi, 2021; Sudaryono, 2022). This approach directly addresses the problem formulation in Chapter I empirically.$\text{Produktivitas}_{it} = \alpha_i + \beta_1(\text{Pendidikan}_{it}) + \beta_2(\text{Luas Lahan}_{it}) + \beta_3(\text{Tenaga Kerja Informal}_{it}) + \epsilon_{it}$

Ethical considerations focused on the use of anonymous, aggregated provincial public data, without involving individual subjects, thus adhering to the principles of confidentiality and non-maleficence. All data sources are appropriately credited per APA 7th, with replication of R code available for transparency, in line with ethical guidelines for secondary research in Indonesia (Sugiyono, 2023; Emzir, 2021).

Copyright at authors some right reserved this work is licensed under a Creative Commons Attribution-ShareAlike 4.0 International License.

International Journal of Economics, Business and Innovation Research
https://e-journal.citakonsultindo.or.id/index.php/IJEBIR
E-ISSN : 2964-0865
IJEBIR

RESULTS AND DISCUSSION

Model Selection Test: Hausman Test

The results of the Hausman test obtained are as follows:

Hausman Test

data: productivity ~ average_length_of_schooling + harvested_land_area + labor
chisq = 11.684, df = 3, p-value = 0.008549
alternative hypothesis: one model is inconsistent

The Chi-squared value obtained was 11.684 with a p-value of 0.0085. Since the p-value (0.0085) < α = 0.05, then H_0rejected. Decision: Fixed Effect Model (FEM) is the most appropriate and consistent model for this study. These results confirm that there are specific characteristics in each province (such as local agricultural policies, soil quality, topographic conditions, and irrigation infrastructure) that are correlated with the independent variables, so they must be controlled through FEM to avoid bias in the estimation of omitted variables.—in accordance with theoretical arguments.

Heteroscedasticity Test: Breusch-Pagan Test

After selecting the fixed effects model, a diagnostic test was performed to verify the homoscedasticity assumption. The results of the Breusch-Pagan test are:

Breusch-Pagan Test

data: productivity ~ education + land area + labor force + factor(province)
BP = 277.7, df = 40, p-value < 2.2e-16

The BP value is 277.7 with a p-value approaching zero (< $2.2e^{-16}$) shows that H_0Homoscedasticity is rejected, indicating that the model experiences heteroscedasticity. This is quite normal considering the contrasting structural differences between provinces on Java Island (with advanced irrigation infrastructure) and provinces outside Java, as well as the variation in observation time spans due to the unbalanced panel. Consequently, using ordinary standard errors will result in invalid significance values; correction using Robust Standard Error (HC1) is performed in the next estimation step.

Unbalanced Panel Descriptive Statistics

Before discussing the estimation results, it is important to note the characteristics of the data structure used. The output of the Fixed Effect model in R shows:

Unbalanced Panel: n = 38, T = 2-6, N = 212

Copyright at authors some right reserved this work is licensed under a Creative Commons Attribution-ShareAlike 4.0 International License.

International Journal of Economics, Business and Innovation Research
https://e-journal.citakonsultindo.or.id/index.php/IJEBIR
E-ISSN : 2964-0865
IJEBIR

This means that all 38 provinces were successfully included in the analysis (n = 38). The observation period ranged from 2 to 6 years (T = 2–6), reflecting the fact that the newly formed provinces in Papua—such as Central Papua, South Papua, Highland Papua, and Southwest Papua—have not had complete statistical data since 2020. The total number of valid observations after data cleaning (na.omit) was 212 rows (N = 212). This unbalanced panel approach actually strengthens regional representation in the analysis, as all provinces continue to contribute based on available data, without having to remove any province entirely (Croissant & Millo, 2019; Baltagi, 2021).

Fixed Effect Estimation Results with Robust Standard Error

Independent Variables	Coefficient (Estimate)	Standard Error (Robust)	t-Statistic	Prob (p-value)	Sig.
Education (X_1)	+1.2602	0.4234	2,9761	0.0033	**
Land Area (X_2)	$-1.26e^{-6}$	$2.34e^{-6}$	−0.5409	0.5893	ns
Informal Workforce (X_3)	−0.1540	0.0451	−3.4138	0.0007	***
R^2 (Within)	0.1040				
F-Statistic (Prob)	6.6178 (0.0002 ***)				
Number of Observations (N)	212 (Unbalanced Panel: n=38, T=2–6)				
Estimation Method	Fixed Effect + Robust SE (HC1)				

*Description: *** p < 0.001; ** p < 0.01; * p < 0.05; ns = not significant. Dependent variable: Rice Productivity (Ton/Ha).*

1. Education Variable (X_1 –Average Length of Schooling)

From the estimation results, a coefficient of +1.2602 was obtained with a p-value of 0.0033 which is below α = 0.01. Thus, H_1accepted: human capital (education) has a positive and significant effect on rice productivity.

Copyright at authors some right reserved this work is licensed under a Creative Commons Attribution-ShareAlike 4.0 International License.

Interpretation: For every one-year increase in the average length of schooling of a province's population, rice productivity in that province will increase by 1.26 tons/ha, all other things being equal. This represents a significant economic impact.

Justification: Higher education improves farmers' cognitive capacity to understand technical instructions for balanced fertilizer use, adopt new high-yielding seed varieties, and manage irrigation and post-harvest practices more efficiently. This finding is consistent with Human Capital Theory and supports the research findings of Taufik (2009).

2. *Variable Area of Harvested Land (X_2)*

The coefficient obtained for the harvested land area variable is -1.2645×10^{-6}, with a p-value of 0.5893 which far exceeds $\alpha = 0.05$. Thus, H_2rejected: the area of harvested land does not have a significant effect on rice productivity.

Interpretation: Increasing the area of harvested land does not significantly impact productivity per hectare. This very small, near-zero coefficient indicates no systematic relationship between land scale and production efficiency per unit area in the 2020–2025 period. This finding is consistent across all observations, including in newly established provinces that only have 2–3 years of data.

Justification: Productivity is a ratio (yield/land). If a province expands its land without improving technology, seed quality, or irrigation systems, its productivity per hectare will remain unchanged. Provinces outside Java, which have vast tracts of land, often experience limited irrigation infrastructure, resulting in lagging productivity figures despite their vast harvested areas.

3. *Informal Labor Variable (X_3)*

This variable has a coefficient of −0.1540 with a p-value of 0.0007 which is highly significant (below $\alpha = 0.001$). Thus, H_3accepted: the proportion of informal labor has a negative and very significant effect on rice productivity.

Interpretation: For every 1 percentage point increase in the proportion of informal labor in a province's agricultural sector, rice productivity will decrease by 0.154 tons/ha, ceteris paribus.

Justification: The dominance of informal labor in agriculture has negative consequences for efficiency: (1) low specialization because informal workers generally do not have certification or technical training; (2) limited access to capital because the informal sector has difficulty obtaining bank credit for mechanization; (3) management

Copyright at authors some right reserved this work is licensed under a Creative Commons Attribution-ShareAlike 4.0 International License.

inefficiency due to unstructured work management (ILO, 2018). This finding provides an important policy message that formalization and professionalization of the agricultural workforce are key to increasing productivity, in line with the arguments developed.

4. Province-Specific Effect Analysis

Based on the results of the fixed effects model estimation, significant variations in intrinsic characteristics across regions in Indonesia were found regarding rice productivity. Object-specific intercept values reflect inherent factors or unobserved variables in the model, such as soil fertility, irrigation infrastructure quality, topographic conditions, and the effectiveness of local agricultural policies in each province. The processed data show that the provinces of Bali (62.54), East Java (62.01), Central Java (61.74), and West Java (61.55) have the highest specific effect values. This indicates that, without relying on additional land area or changes in labor structure, these provinces already have a very strong production base. The high values in Bali and Java are likely driven by highly integrated irrigation systems and the quality of volcanic soil, which is more fertile than in other regions. Furthermore, accessibility to agricultural technology and mechanization in these regions tends to be more advanced.

Regions such as West Nusa Tenggara (56.64) and Aceh (56.55) also demonstrated stable performance. Specifically, for West Nusa Tenggara, this success reflects the optimization of dryland areas and the massive dam infrastructure support in recent years. Meanwhile, the Papua Highlands region (53.04) performed quite competitively, indicating favorable local agro-climatic potential despite geographically challenging access. Conversely, provinces on the island of Kalimantan, such as West Kalimantan (32.63) and Central Kalimantan (31.33), as well as newly established regions like Southwest Papua (28.19), exhibited low fixed effect values. These values represent real structural challenges, including the quality of peatlands, which require higher land improvement costs, and limited access to agricultural production inputs in the newly established regions.

Overall, the difference in scores of more than 30 points between Bali and Southwest Papua indicates that rice productivity improvement policies in Indonesia cannot be generalized. Provinces with low fixed effect scores require specific interventions such as soil quality improvement and basic infrastructure development, while provinces in Java and Bali should focus on maintaining resource sustainability and the efficiency of existing technologies. All estimates in this model have also been

Copyright at authors some right reserved this work is licensed under a Creative Commons Attribution-ShareAlike 4.0 International License.

International Journal of Economics, Business and Innovation Research
https://e-journal.citakonsultindo.or.id/index.php/IJEBIR
E-ISSN : 2964-0865
IJEBIR

corrected using robust standard errors to ensure consistent and valid results despite the heterogeneity of data variance across regions due to the use of unbalanced panel data.

5. Model Robustness Analysis and Significance Comparison

To ensure the validity and reliability of the estimation model, this study compared the results of a standard fixed-effects model with a model corrected using robust standard errors. This step is crucial given the unbalanced nature of the panel data used, which often leads to heteroscedasticity or unequal variance. This correction results in more accurate statistical inferences and is free from bias that may arise from uneven data fluctuations across provinces.

The following is a comparison table of significance values before and after using robust standard errors:

Independent Variables	Coefficient	P-Value (Regular)	P-Value (Robust)
Average Length of Schooling	1,260250	0.01208	0.00334
Harvested Land Area	-0.000001	0.82548	0.58929
Informal Workforce	-0.154042	0.00956	0.00080

Based on the comparison of significance levels in the table above, it was found that the use of robust standard errors actually strengthens the validity of the findings on the main variables. The variable average years of schooling shows a sharp increase in significance, where the probability value decreases from 0.012 in the standard model to 0.003 after correction. A similar trend occurs for the informal labor variable, whose significance value strengthens from 0.009 to 0.0008. This strengthening of significance values proves that despite the presence of heteroscedasticity in the initial data, the

Copyright at authors some right reserved this work is licensed under a Creative Commons Attribution-ShareAlike 4.0 International License.

influence of human capital and labor characteristics on rice productivity is significant and statistically consistent.

On the other hand, the harvested land area variable remained insignificant both before and after correction, with a probability value well above the 0.05 threshold. This confirms that in this research model, land area alone does not have a significant direct impact on productivity per unit area unless accompanied by human capital quality. Overall, the results of this robustness test indicate that the research model has a high level of precision, with estimates remaining unchanged and even tending to strengthen despite rigorous statistical correction procedures.

Simultaneous Test (F Test)

F test for joint significance

data: productivity ~ education + land area + labor force

F = 6.6178, df1 = 3, df2 = 171, p-value = 0.0002954

The F-test results show an F-statistic value of 6.6178 with a p-value of 0.0002954 which is much smaller than α = 0.05. Thus, H_4accepted: simultaneously (together), the variables of education, area of harvested land, and proportion of informal labor have a significant effect on rice productivity.

The model developed in this study was found to be statistically sound. Although the land area variable was partially insignificant, the combined strength of the education and informal labor variables was strong enough to make this model generally valid in explaining variations in rice productivity across 38 Indonesian provinces during 2020–2025, with a total of 212 valid observations. These results directly address the fourth research question formulated in Chapter I.

Copyright at authors some right reserved this work is licensed under a Creative Commons Attribution-ShareAlike 4.0 International License.

International Journal of Economics, Business and Innovation Research
https://e-journal.citakonsultindo.or.id/index.php/IJEBIR
E-ISSN : 2964-0865
IJEBIR

Visualization and Interpretation

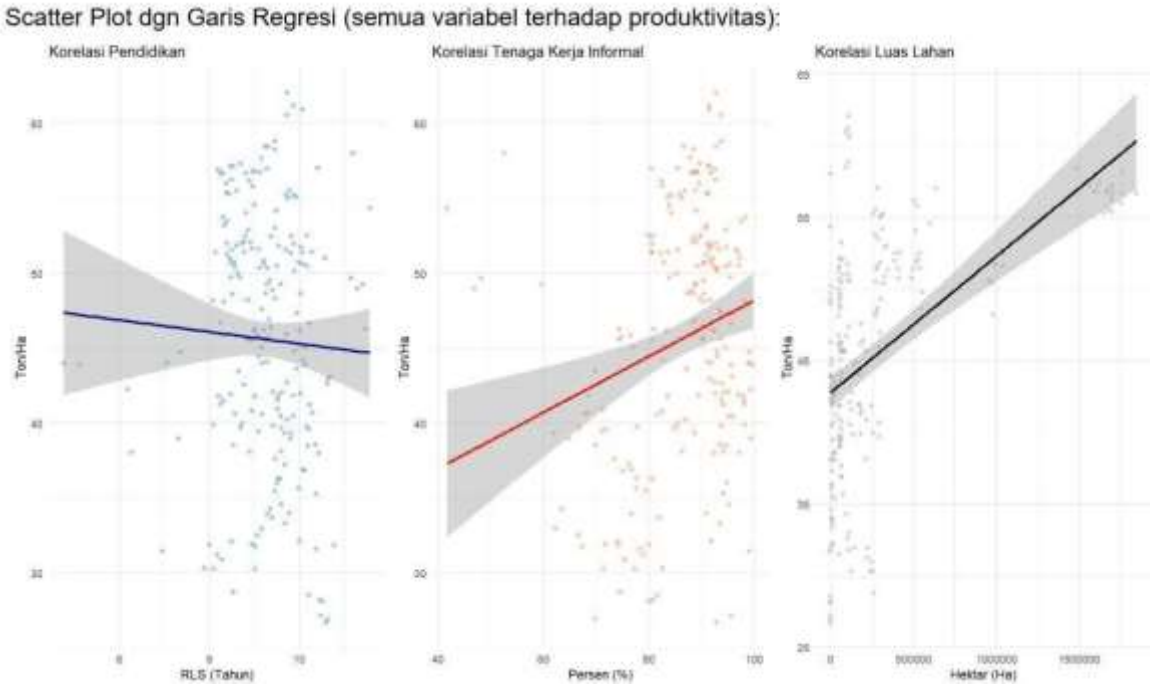


Figure 1. Scatter Plot of the Relationship between Independent Variables and Rice Productivity

1. Scatter Plot with Regression Line

Figure 1 displays a scatter plot of the relationship between each independent variable and rice productivity bivariately. The visualized data are 212 valid observations from the unbalanced panel.

Interpretation of the Education Correlation Plot (X_1) vs. Productivity (Y): The regression line in the left panel (blue) shows a relatively flat slope with a wide confidence interval, but is generally positive. The data are quite widely distributed, indicating that productivity variation is not solely determined by RLS. However, after controlling for provincial fixed effects in the Fixed Effects model, the positive effect of education becomes statistically significant (p = 0.0033). This is consistent with the argument that the effect of education only becomes apparent after inter-provincial heterogeneity is controlled (Munte, 2025).

Interpretation of the Correlation Plot of Informal Labor (X_3) vs Productivity (Y): The middle panel (red) shows a visible upward trend from the bottom left to the top right in the

Copyright at authors some right reserved this work is licensed under a Creative Commons Attribution-ShareAlike 4.0 International License.

International Journal of Economics, Business and Innovation Research
https://e-journal.citakonsultindo.or.id/index.php/IJEBIR
E-ISSN : 2964-0865
IJEBIR

raw bivariate data. However, it is important to understand that this is a bivariate plot that has not controlled for other variables. After being controlled for through the Fixed Effect Model, the coefficient of informal labor is actually negative and significant (-0.154; p = 0.0007). This is a classic example of omitted variable bias in bivariate analysis: provinces with a high proportion of informal workers also tend to have large areas of land (which is positively correlated bivariately with productivity). Once controlled, the negative effect of informality is clearly revealed.

Interpretation of Land Area Correlation Plot (X_2) vs. Productivity (Y): The right panel (black) shows a positive trend in the bivariate data, but after being controlled in the Fixed Effects model, this effect is no longer significant (p = 0.589). This strengthens the argument that productivity per hectare is not determined by the area of land harvested, but rather by the quality of its management.

Time Series Analysis

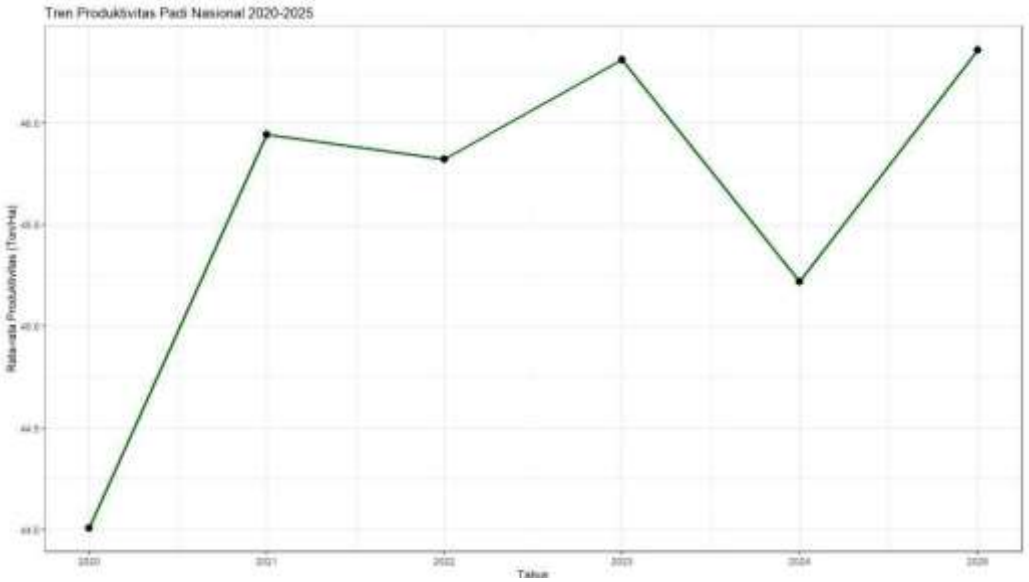


Figure 2. Average National Rice Productivity Trends 2020-2025

1. Temporal Dynamics (Trends 2020–2025)

The time series graph (Figure 2) shows that the average national rice productivity experienced fluctuating dynamics during the 2020–2025 period. In 2020, productivity was at its lowest point of around 44.0 tons/ha, then jumped sharply to 45.9 tons/ha in 2021. In 2022, it experienced a slight decline to 45.8 tons/ha before increasing again to a peak of

Copyright at authors some right reserved this work is licensed under a Creative Commons Attribution-ShareAlike 4.0 International License.

47.3 tons/ha in 2023. Productivity fell again to around 45.2 tons/ha in 2024—possibly due to the impact of El Niño—before rising again to 47.4 tons/ha in 2025. This national average is calculated based on available observations per year in the unbalanced panel.

2. The "Within" Effect in the Time Dimension

Because the study uses a fixed effect (within-province) model, the relevant temporal interpretation is the changes that occur within the same unit (within-province) over time. The education variable (RLS) consistently increases annually in almost all provinces, gradually pushing the productivity frontier upward. On the other hand, changes in the proportion of informal workers between years—for example, when there is an increase in layoffs in the formal sector that encourages migration back to the informal agricultural sector—are detected to have a negative effect on rice productivity in the respective year.

3. The Phenomenon of Stagnation in Harvested Land Area

Over time, increases or decreases in harvested land area at the provincial level have not consistently been accompanied by comparable changes in productivity. This trend reinforces the regression findings that the government's strategy of solely focusing on expanding planted areas without any accompanying quality intensification has not resulted in significant efficiency gains over the past six years.

4. Handling Autocorrelation and Unbalanced Panel

In panel data with a temporal dimension, there is the potential for autocorrelation—where one year's productivity is influenced by the previous year's productivity due to the continuous cropping cycle. The application of Robust Standard Error (HC1) in model estimation automatically accommodates the interference from this intertemporal correlation. The unbalanced panel structure—where the newly created provinces only have 2–3 years of data—is handled automatically by the plm package in R, which only calculates within-variation based on available observations without introducing bias in other provinces (Croissant & Millo, 2019). Thus, the statistical inference results obtained remain valid and reliable as a basis for drawing conclusions (Baltagi, 2021).

CONCLUSION

This study concludes that human capital through average years of schooling has a positive and significant effect on rice productivity in 38 Indonesian provinces for the

Copyright at authors some right reserved this work is licensed under a Creative Commons Attribution-ShareAlike 4.0 International License.

period 2020–2025, with each additional year of education increasing productivity by 1.26 tons per hectare. The proportion of informal labor has a negative and highly significant impact, where a 1 percentage point increase reduces productivity by 0.154 tons per hectare due to minimal training and access to technology. Simultaneously, these three variables have a significant effect on productivity with an F-statistic of 6.6178 and a p-value of 0.0003, although the area of harvested land has no partial effect. This finding emphasizes the urgency of human resource-based intensification rather than land extensification.

The main limitations of this study are the use of aggregate provincial secondary data that does not capture sub-provincial variations, and the 2020–2025 period, which does not fully capture the impact of Papua's post-2022 expansion. Future research suggests including moderating variables such as irrigation investment or fertilizer subsidies, and expanding the analysis to the district level with balanced panel data. Practically, these results recommend that the Ministry of Agriculture prioritize farmer vocational training programs and formal certification to reduce informality, in order to achieve the productivity target of 8 tons per hectare and reduce rice imports by 2026.

BIBLIOGRAPHY

Central Statistics Agency. (2020–2025a). Harvested area, productivity, and rice production by province. BPS RI.https://www.bps.go.id/id/statisticsTable/3/WmpaNk1YbGFjR0pOUjBKYWFIQlBSU3MwVHpOVWR6MDkjMw==/panen-area--productivity--and-rice-production-according-to-province--2024.html

Central Statistics Agency. (2020–2025b). Average length of schooling of the population aged 15 years and over by province. BPS RI. https://www.bps.go.id/id/statistics-table/2/MTQyOSMy/rata-rata-lama-sekolah-penduduk-umur-15-tahun-ke-atas-menurut-provinsi.html

Central Statistics Agency. (2020–2025c). Harvested area, production, and productivity of rice by province. BPS RI. https://www.bps.go.id/id/statistics-table/2/MTQ5OCMy/luas-panen--produksi--dan-produktivitas-padi-menurut-provinsi.html

Central Statistics Agency. (2020–2025d). Percentage of informal agricultural workforce. BPS RI. https://www.bps.go.id/id/statistics-table/2/MTE3MSMy/persentase-tenaga-kerja-informal-sektor-pertanian--persen-.html

Copyright at authors some right reserved this work is licensed under a Creative Commons Attribution-ShareAlike 4.0 International License.

Baltagi, B. H. (2021). Econometric analysis of panel data (6th ed.). Springer. https://doi.org/10.1007/978-3-030-53953-5

Croissant, Y., & Millo, G. (2019). Panel data econometrics with R. John Wiley & Sons. https://doi.org/10.1002/9781119504641

Emzir. (2021). Qualitative research methodology: Qualitative data analysis techniques from theoretical, empirical, and applied sources to content, communication, organization, and disciplines. Student Library.

Food and Agriculture Organization. (2021). The state of food and agriculture 2021: Making agrifood systems more resilient to shocks and stresses. F.A.O. https://doi.org/10.4060/cb4476en

Gujarati, D. N., & Porter, D. C. (2022). Basic econometrics (6th ed.). McGraw-Hill Education.

Hidayat, A., & Wijaya, A. (2024). Spatial analysis of rice field conversion and its implications for rice production in Indonesia. Journal of Geography, 16(2), 45-58.

International Labor Organization. (2018). Women and men in the informal economy: A statistical picture (3rd ed.). ILO.

Ministry of Agriculture of the Republic of Indonesia. (2020–2025). National rice harvest area and production data. Ministry of Agriculture of the Republic of Indonesia.

Ministry of Agriculture of the Republic of Indonesia. (2022). Strategic Plan of the Ministry of Agriculture 2020–2024 (revised). Ministry of Agriculture of the Republic of Indonesia.

Munte, ST (2025). The influence of farmer education level on the adoption of agricultural technology. Circle-Archive, 1(7), 123-135.

Pratiwi, I., Santoso, A., & Rahman, F. (2023). Human capital and rice productivity: Panel evidence from Southeast Asia. Journal of Agricultural Economics, 74(1), 89-104. https://doi.org/10.1111/1477-9552.12512

Rahman, F., & Santoso, A. (2022). Factors of rice production in Indonesia: A Cobb-Douglas approach. Journal of Agricultural Economics, 10(2), 78-92.

Sari, DP, & Nugroho, AD (2021). The impact of labor informality on agricultural productivity in Central Java. Indonesian Agribusiness Journal, 9(1), 34-47.

Sudarma, IM, Dj., WS, & Setiawan, IGBD (2024). Agricultural land conversion and its impact on farmer welfare and food security in Bali Province. Journal of Agricultural Economics and Agribusiness (JEPA), 8(1), 113–124. https://doi.org/10.21776/ub.jepa.2024.008.01.9

Sugiyono. (2023). Quantitative, qualitative, and R&D research methods. Alfabeta.

Copyright at authors some right reserved this work is licensed under a Creative Commons Attribution-ShareAlike 4.0 International License.

Sukmana, A., et al. (2023). Global rice production trends and food security challenges in developing countries. Food Policy, 115, 102-115. https://doi.org/10.1016/j.foodpol.2023.102115

Sunardi. (2024). The influence of education and training on farmer performance in the agribusiness sector. Faculty of Agriculture Student Assignment, 1(2). https://coursework.uma.ac.id/index.php/pertanian/article/view/1268

Susilowati, SH (2020). The phenomenon of aging farmers and the reduction of the young workforce and its implications for agricultural development policy. Agro-Economic Research Forum, 34(1), 35–55. https://media.neliti.com/media/publications/135268-ID-fenomena-penuaan-petani-dan-berkurangkan.pdf

Sudaryono. (2022). Industrial economic research methods. Student Library.

Taufik. (2009). Human capital and its effect on economic growth: A case study of selected countries in East and Southeast Asia [Master's Thesis, Gadjah Mada University]. ETD Repository, Gadjah Mada University. https://etd.repository.ugm.ac.id/penelitian/detail/44589

Wulandari, P., et al. (2023). Informal labor flexibility and rice productivity in rural Indonesia. Agricultural Economics Review, 24(3), 56-70.

Wooldridge, J. M. (2019). Introductory econometrics: A modern approach (7th ed.). Cengage Learning.

Copyright at authors some right reserved this work is licensed under a Creative Commons Attribution-ShareAlike 4.0 International License.