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Trade-Off Between Rice Cultivation Land and Forest Area in Indonesia: An Empirical Analysis

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ABSTRACT

This study aims to analyze the trade-off relationship between rice field area and forest area in Indonesia. The phenomenon of rice field expansion is often associated with reduced forest cover due to land conversion, so it is important to understand the extent of the relationship empirically. The data used is panel data from 34 provinces in Indonesia for the period 2018–2023 sourced from the Statistics Indonesia (BPS). The variables analyzed include rice field area as the independent variable, forest area as the dependent variable, and rice production and productivity as control variables. The analytical method used is Panel Least Squares (PLS). Furthermore, to test the robustness and consistency of the estimation results, this study applies Robust Least Squares (ROBUSTLS) as a robustness test method. The results of the Fixed Effects Model (FEM) indicate that increases in rice field area and improvements in rice productivity do not significantly affect forest area within provinces over time. However, the ROBUSTLS estimation demonstrates significant cross-sectional associations that reflect structural differences between provinces rather than short-term temporal dynamics. These findings imply that the trade-off between rice cultivation and forest conservation in Indonesia is driven more by long-term historical and institutional factors than by recent agricultural changes.

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1. INTRODUCTION

Agriculture has long been recognized as the cornerstone of human civilization and the foundation of economic development. Before the onset of industrialization, more than ninety percent of the world's labor force was engaged in agriculture, and the capacity of farmers to produce food surpluses was fundamental to the emergence of cities and the growth of nonfarm sectors (Huffman & Orazem, 2014). Improvements in agricultural productivity during the eighteenth and nineteenth centuries enabled societies to achieve higher labor productivity, improved nutrition, and declining mortality rates, thereby setting the stage for industrial revolutions and modern economic growth. In contemporary economies, agriculture continues to play a pivotal role in supporting human welfare, particularly in developing countries where a significant share of the population depends on farming for livelihood.

Agricultural development serves as the backbone of national economies by securing adequate food supplies for a growing population while providing employment and income. In many developing countries, agriculture remains a key driver of poverty reduction and rural welfare. The agricultural sector's efficiency and productivity determine a nation's capacity to meet domestic food demand without overexploiting natural resources. The close relationship between agricultural advancement and food production is evident in global trends over the past five decades. As a sample, China and India have demonstrated that reforms in land use, technology adoption, and rural market liberalization can significantly enhance food output and self-sufficiency. These improvements not only raise yields of staple crops such as rice and wheat but also optimize the use of limited arable land through intensified farming practices. Increased food production directly contributes to improved nutrition, labor productivity, and overall economic growth (Lazányi, 2009).

While agricultural growth remains essential for achieving food security and rural welfare, it is also one of the primary drivers of environmental degradation in tropical regions. According to

from agricultural expansion are consistent with the theoretical framework proposed by Angelsen (1999). Angelsen argues that deforestation in developing countries is largely driven by agricultural expansion, influenced by both population-based and market-based mechanisms. Illukpitiya & Yanagida (2010), the expansion of agricultural land, particularly at the forest margin has been a major contributor to global deforestation, with an estimated annual loss exceeding 17 million hectares of forest area. In many developing economies, including Indonesia, the conversion of forests into agricultural land represents an effort to meet the increasing demand for staple crops such as rice. However, this process often generates negative externalities in the form of biodiversity loss, reduced carbon sequestration, and disrupted ecological balance. Thus, the trade-off between agricultural intensification and forest conservation reflects a classic dilemma of development.

Based on Illukpitiya & Yanagida (2010), higher agricultural yields are frequently associated with increased deforestation, indicating a negative environmental feedback from food production expansion. As farming becomes more profitable, households at forest peripheries tend to intensify land use or expand cultivation into forested areas, especially when land-use regulations and conservation incentives are weak. This dynamic reflects the agriculture–forest trade-off, where the pursuit of short-term food security can erode the ecological assets vital for sustaining future agricultural capacity.

The deforestation

In the population approach, limited productivity and subsistence needs encourage farmers to clear more forest for cultivation, while in the market-based approach, higher crop prices, lower transport costs, and improved market access increase the profitability of frontier farming, thereby accelerating forest conversion. Angelsen's model further emphasizes that forest clearing is not merely a productive activity but also a form of investment and land-claim strategy. Where farmers convert forests to secure property rights. This framework underscores that even well-intentioned agricultural intensification or land titling programs can paradoxically increase deforestation when institutional controls and land governance are weak.

In the case of Indonesia, forest areascapes have long been intertwined with local livelihoods, where communities depend on both agricultural land and forest resources for survival. However, state-driven agricultural expansion and formalization policies often simplify traditional land-use systems, marginalizing local ecological practices and causing the loss of multifunctional landscapes that previously balanced production and conservation. The push to increase rice production has driven significant forest conversion, reflecting the agriculture–forest trade-off that prioritizes short-term food security over long-term ecological integrity. This tension underscores that success in agricultural development must be assessed not only by increased yields but also by how effectively land-use policies preserve ecosystem services and cultural sustainability within forest-dependent communities (Bong et al., 2019).

In parallel, Abduh (2023) illustrates that Indonesia's agricultural transformation over the past two decades has been marked by uneven regional development and declining agricultural contribution to GDP. Despite the decreasing share of agriculture in the national economy, rural dependency on this sector remains high, leading to persistent poverty and pressure on natural resources in less developed provinces. In Eastern Indonesia, where forest areas dominate the landscape, limited productivity and poor infrastructure have driven extensive land conversion as a coping mechanism for rural livelihoods. This process epitomizes the structural transformation trap described by Briones & Felipe (2013), where agricultural expansion becomes a short-term solution to economic stagnation but generates ecological degradation through deforestation. Therefore, the Indonesian case reflects a pressing need for sustainable agricultural transformation, a paradigm that balances rice production growth with forest conservation, leveraging agroforestry, land zoning, and community-based management to harmonize economic and environmental objectives.

Indonesia remains one of the world's largest rice-producing countries with an annual output of approximately 70.8 million tons in 2020 (Fathonah & Mashilal, 2021). Despite this achievement, the country continues to experience fluctuations in domestic rice availability and periodic dependence on imports, signaling structural challenges in maintaining consistent food self-sufficiency. The agricultural sector contributed significantly to national GDP, rising from 12.81% in 2018 to 13.17% in 2020 and demonstrated resilience during the COVID-19 pandemic. However, the available data also show that rice availability declined sharply from its peak in 2016 (47 million tons) to around 31 million tons in 2019, reflecting constraints in land availability, climate variability, and productivity stagnation.

In contrast to the vital role of agricultural land, Indonesia's forests represent one of the nation's most important ecological assets, covering approximately 120.4 million hectares, or 63% of the total land area (Ministry of Environment and Forestry Republic of Indonesia, 2024). These forests perform crucial ecological functions, including carbon sequestration, water regulation, biodiversity conservation, and climate stabilization. Yet, the State of Indonesia's Forests 2024 report highlights that deforestation and land-use change remain persistent challenges, largely driven by agricultural expansion and infrastructure development. Although recent years have seen notable progress in reducing deforestation rates through stricter regulations, community forestry programs, and satellite-based monitoring, the trade-off between maintaining forest ecosystems and expanding food production continues to shape Indonesia's environmental policy dilemma. The expansion of rice cultivation illustrates this conflict between national food security objectives and the country's commitment to forest sustainability under the FOLU Net Sink 2030 agenda.

Several recent studies in Indonesia have examined the spatial interactions between forest areas, rice fields, and settlements to understand land-use trade-offs. Sejati & Saputra (2021) conducted a spatial mapping study in South Konawe District using GIS and remote sensing to analyze the distribution and function of forest, settlement, and rice field areas. Their results showed that rice fields in the district occupied around 3.22% of total land, with a notable pattern of encroachment into limited production forest zones. This mismatch between designated land function and actual use caused ecological instability. Their findings emphasize that unplanned agricultural expansion often violates spatial allocation rules under Minister of Agriculture Decree No. 837/1980, indicating the lack of synchronization between local agricultural policy and environmental zoning. This study shows that when agricultural land expansion is not controlled by spatial planning regulations, it will endanger forest integrity and increase disaster risks. This aligns with the concept of land-use trade-offs that is at the heart of the current research.

Further supporting evidence comes from Arista et al. (2023). The study analyzed the availability and potential for expansion of agricultural land in Indonesia. It identifies that 50.19% of the potential agricultural expansion area lies within other use areas, limited production forests, and production forests. It is indicating a direct overlap between agricultural expansion targets and existing forest functions. Arista et al. (2023) argue that population growth and food security policies have accelerated the extensification of agriculture through forest clearing, particularly in Kalimantan, Sumatra, and Papua. Complementary findings from Sejati et al. (2025) highlight that in South Konawe, more than 92% of communities knowingly utilize forest areas for rice cultivation, driven by economic motives and food production goals.

Research by Dewi & Wulansari (2024) explains that national food security remains weak due to the mismatch between the LSD map and the RTRW, which causes overlapping land use even though Indonesia has a rice harvest area of more than 10 million hectares. The overlay results show that approximately 1.2 thousand hectares of food land in the RTRW do not match the LP2B or LSD zones, causing the conversion of rice fields to residential and industrial areas to continue. This research emphasizes that agricultural land protection in Indonesia is not yet effective spatially and institutionally because it has not been fully integrated between institutions (ATR/BPN, KLHK, Kementan, BIG, and PUPR). Weaknesses in geospatial data and the lack of synchronization between policies have resulted in the LSD policy being unable to significantly curb the rate of rice field conversion.

It is also known that of the total 120.5 million hectares of forest area, the majority of forest cover loss is due to community cultivation activities, agricultural expansion, and large-scale food estate projects. While land redistribution policies aim to improve community welfare and food productivity, their implementation often exacerbates deforestation and carbon emissions, particularly in Kalimantan and Papua (Gunawan et al., 2024).

This confirms that socio-economic pressures are major non-physical drivers of forest conversion. Collectively, these studies provide strong empirical support that Indonesia's agricultural expansion policies carry inherent environmental trade-offs, especially when extensification occurs through forest area reallocation. The synthesis of these findings justifies the need for empirical analysis at the national level to quantify the extent of the rice–forest trade-off in Indonesia, as proposed in this research.

This synthesis of studies highlights consistent patterns across Indonesia's agriculture and forestry sectors, including policies aimed at increasing food production, which often conflict with forest conservation objectives due to spatial and institutional overlaps in land-use governance. While previous research has provided valuable insights at the regional level and case studies such as in Demak (Dewi & Wulansari, 2024), South Konawe (Sejati et al., 2025), and broader national assessments (Arista et al., 2023; Gunawan et al., 2024), these studies still lack empirical and national quantitative analyses that capture the extent, direction, and magnitude of trade-offs between rice cultivation and land expansion or reduction. Most previous studies have focused on local mapping or policy evaluation but rarely integrate multi-year and multi-provincial datasets to statistically estimate the causal relationship between agricultural expansion and forest loss. Therefore, this study attempts to fill these empirical and methodological gaps by using panel data analysis in 34 provinces in Indonesia during 2018–2023, using forest area as the dependent variable, rice field area as the main explanatory variable, and rice production and productivity as control factors.

Building upon the theoretical frameworks of agricultural expansion and deforestation model (Angelsen, 1999), this research aims to provide robust empirical evidence of how agricultural development, particularly rice cultivation affects forest cover in Indonesia.

This research is crucial because provides a quantitative national perspective on a long-standing policy dilemma, hich has primarily been discussed qualitatively in prior studies. The findings offer policy-relevant insights for Indonesia's dual commitments, that is maintaining rice self-sufficiency under the National Food Security Strategy and achieving net zero emissions from the forestry and land use sector (FOLU Net Sink 2030). Then, this study identifying the strength and direction of the rice–forest trade-off, the study can guide policymakers in formulating integrated land-use and agricultural development strategies. This research also supports Indonesia's transition toward a more sustainable and resilient agro-ecological system that harmonizes food security with ecological integrity.

2. METHOD, DATA, AND ANALYSIS

2.1. Research Framework

The theoretical and empirical evidence reviewed above illustrates that the interaction between agricultural development and forest sustainability is characterized by a fundamental trade-off driven by both economic and demographic forces. In developing countries such as Indonesia, the expansion of rice farming areas often competes with the preservation of forest ecosystems that provide essential environmental services. This study adopts the conceptual foundation of Trade-Off Theory of Land Allocation (Barbier & Burgess, 1997; Angelsen, 1999) to construct a comprehensive analytical framework linking agricultural expansion, food production, and forest conservation. Within this framework, land conversion decisions are viewed as economic responses to changes in agricultural profitability, technological progress, and policy incentives.

The research framework posits that increases in rice farming land area, while contributing to higher food production and economic welfare, may exert downward pressure on forest area due to competing land demands. Meanwhile, improvements in rice productivity are expected to mitigate the need for further land expansion, thereby potentially reducing deforestation pressure. Building upon these theoretical premises, this study develops an empirical model that captures the quantitative trade-off relationship between rice field area and forest area across Indonesia's provinces over the 2018–2023 period. The conceptual structure guides the formulation of the following research hypotheses that empirically test the nature, direction, and magnitude of the rice–forest trade-off in the Indonesian context.

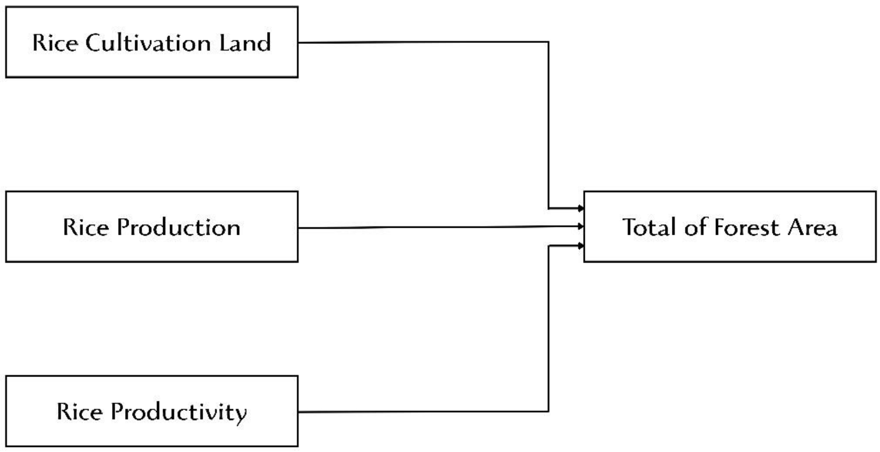

Figure 1. Research Framework

Figure 1 illustrates the conceptual framework that underpins this study. The model depicts the hypothesized relationship between rice cultivation land, rice production, rice productivity, and the total forest area in Indonesia. In this framework, the expansion of rice cultivation land is expected to have a negative relationship with the total forest area. This assumption is based on the premise that an increase in land allocated for rice farming often occurs through the conversion of forested areas, particularly in provinces where agricultural expansion is the primary strategy to meet food security targets. Such conversion represents a classical land-use trade-off, where gains in agricultural area are achieved at the expense of forest cover and its associated ecosystem services.

Meanwhile, rice production and rice productivity are included as control variables to capture the efficiency and output effects of agricultural intensification. On one hand, higher rice production may correlate with reduced forest area if it results primarily from extensive land expansion. On the other hand, higher rice productivity is expected to reduce the pressure on forest conversion by enabling increased food output without requiring additional land. Thus, productivity improvement serves as a potential mitigating factor within the trade-off relationship. Overall, the framework suggests that the balance between Indonesia's goals of rice self-sufficiency and forest conservation depends largely on how agricultural growth is achieved.

2.2. Research Hypothesis

The expansion of rice farming contributes to national food security and rural livelihoods. However, its growth often comes at the expense of forest ecosystems. Rice expansion, particularly in provinces with limited agricultural land, often involves the conversion of forest land to agricultural land. This results in reduced forest cover and ecological imbalance. Angelsen (1999) explains that agricultural expansion is a major driver of deforestation in developing countries.

Empirical evidence in Indonesia also supports this trade-off dynamic. For example, a study by Indra et al. (2024) showed that in areas like North Penajam Paser, rice paddy areas initially expanded due to accessibility and flat terrain, but then declined as forest and mixed plantation areas were converted to agricultural zones. Similarly, Hasanah et al. (2023) found that land conversion from forest to agricultural land and plantations has been a dominant contributor to forest loss in several provinces. This reflects unsustainable land-use change patterns driven by food and economic pressures. Similar findings were observed by Delang (2002) in Northern Thailand, where rice paddy expansion and rural colonization led to long-term forest cover decline, illustrating that agricultural growth results in deforestation when pursued through extensive practices.

In the Indonesian context, these findings underscore that efforts to achieve rice self-sufficiency have historically relied on an extensification strategy, clearing new land rather than optimizing existing land. While this strategy temporarily increases production, it undermines forest sustainability by reducing biodiversity, disrupting the carbon cycle, and increasing vulnerability to natural disasters. Based on this empirical and theoretical background, it can be assumed that the greater the expansion of rice paddy fields, the smaller the forest area. Therefore, the first hypothesis (H1) proposed is there is a negative and significant relationship between the expansion of rice farming land and forest area in Indonesia.

In addition to looking at the trade-off between rice farming land and forests, this study also uses production and productivity as control variables. The inclusion of these variables aims to capture the broader effects of agricultural performance on forest dynamics. Rice production reflects the total output resulting from the combined effects of land area, technology, and input use, while rice productivity indicates the efficiency of land utilization in generating output per hectare. These two variables help distinguish whether increases in rice output are achieved through extensive growth (land expansion) or intensive growth (technological improvement and better input management).

Rice production is expected to have a negative relationship with forest area when production increases are achieved primarily through land expansion rather than intensification. According to Hasanah (2023), in developing countries, agricultural production growth that relies heavily on land clearing often leads to deforestation as forests are converted to meet rising food demand. This pattern has been observed in Indonesia, where food security policies emphasizing rice self-sufficiency have encouraged the conversion of forest land into cultivation areas, particularly in Kalimantan and Sumatra (Arista et al., 2023; Gunawan et al., 2024). Moreover, Indra et al. (2024) highlight that regional agricultural productivity constraints have prompted farmers to expand their production base through extensification rather than technological adaptation. Therefore, as rice production grows in a land-extensive manner, it tends to reduce forest cover. Based on this rationale, the second hypothesis (H2) is rice production has a negative and significant effect on forest area in Indonesia.

In contrast, rice productivity is hypothesized to have a positive and significant effect on forest area, as productivity gains reduce the need for new agricultural land by increasing yield efficiency on existing farmland. Studies by Illukpitiya & Yanagida (2010) and Abduh (2023) show that productivity growth through technological innovation, improved irrigation, and efficient resource management can mitigate deforestation pressures by decoupling production increases from land expansion. Likewise, Fathonah & Mashilal (2021) found that provinces with higher rice productivity in Indonesia tend to experience more stable forest areas due to reduced reliance on extensification strategies. Hence, improvements in rice productivity are expected to safeguard forest resources by enhancing food production efficiency. Therefore, the third hypothesis (H3) proposed is rice productivity has a positive and significant effect on forest area in Indonesia.

2.3. Model Specification

To empirically analyze the trade-off between rice farming land and forest area in Indonesia. These frameworks suggest that agricultural expansion often leads to a reduction in forest area when production growth relies primarily on land conversion rather than productivity improvement. Accordingly, the econometric specification used in this study is formulated as follows:

$$Forest_{it} = \alpha + \beta_1 RiceArea_{it} + \beta_2 Production_{it} + \beta_3 Productivity_{it} + \mu_i + \lambda_i + \varepsilon_{it} \ldots (1)$$

Where:

$Forest_{it}$: total forest area in province (i) and year (t)
$RiceArea_{it}$: total area of rice farming land
$Production_{it}$: total rice production
$Productivity_{it}$: rice productivity
μ_i : unobserved province-specific effect
λ_i : year-specific effect
ε_{it} : stochastic error term

To capture proportional relationships and reduce heteroskedasticity, the model is also estimated in logarithmic form as:

$$\ln(Forest_{it}) = \alpha + \beta_1 \ln(RiceArea_{it}) + \beta_2 \ln(Production_{it}) + \beta_3 \ln(Productivity_{it}) + \mu_i + \lambda_i + \varepsilon_{it} \ldots (2)$$

This functional form allows the coefficients $(\beta_1, \beta_2, \beta_3)$ to be interpreted as elasticities, representing the percentage change in forest area associated with a one-percent change in each explanatory variable. Then, the expected signs of the coefficients are as follows:

Table 1. Expected Signs and Interpretation

No	Variable	Description	Expected Sign
1	RiceArea	Rice farming land area	Negative (-)
2	Production	Rice production (output)	Negative (-)
3	Productivity	Rice yield (tons/ha)	Positive (+)

Hence, it is expected that $\beta_1 < 0$, $\beta_2 < 0$, and $\beta_3 > 0$.

2.4. Estimation Technique

To empirically estimate the relationship between rice farming land expansion and forest area in Indonesia, this study employs the Panel Least Squares (PLS) method, which integrates both cross-sectional and time-series dimensions of data. The use of panel data enables the researcher to account for variations across provinces (spatial dimension) and over time (temporal dimension), providing more informative, less collinear, and more efficient estimates than purely cross-sectional or time-series approaches (Ferdiansyah et al., 2025).

Following Moussa & Ceesay. (2021), this study applies three panel data estimation approaches under the Panel Least Squares framework:

- Pooled Ordinary Least Squares (Pooled OLS) model assumes homogeneity across provinces and time, estimating a single common intercept and slope for all observations.
- Fixed Effects Model (FEM) assumes that differences across provinces are captured by individual intercepts (μ_i), allowing for correlation between province-specific effects and explanatory variables.
- Then, Random Effects Model (REM) which is contrast with the other, the random effects model assumes that provincial-specific effects are random and uncorrelated with explanatory variables. The random effects approach is estimated using the Generalized Least Squares (GLS) technique to ensure efficient estimation under the assumption of no correlation between μ_i and the regressors.

To determine the most appropriate estimation technique, the following model comparison tests are conducted sequentially (Ferdiansyah et al., 2025).

- Chow Test, to compares the Pooled OLS and Fixed Effects models. If the test statistic is significant ($p < 0.05$), the Fixed Effects Model is preferred, indicating heterogeneity across provinces.
- Breusch–Pagan Lagrange Multiplier (LM) Test, to compares Pooled OLS and Random Effects models. A significant result supports the use of the Random Effects Model.
- Hausman Test, to compares the Fixed and Random Effects models. If the test is significant, the null hypothesis of no correlation between individual effects and regressors is rejected, favoring the Fixed Effects Model.

In this study, the final selection of the model depends on the Hausman test outcome. If unobserved provincial effects correlate with the independent variables, the Fixed Effects Model is chosen as the best estimator.

2.5. Robustness Test

To ensure the reliability and consistency of the estimated coefficients, this study performs a robustness test using the Robust Least Squares (ROBUSTLS) estimation method. The Robust Least Squares approach is applied as a complement to the Panel Least Squares (PLS) estimation to evaluate whether the observed relationships between variables remain stable when the data contain outliers, heteroskedasticity, or non-normal residual distributions.

As highlighted by Ismail & Rasheed (2021), the Ordinary Least Squares (OLS) estimator is highly sensitive to deviations from its classical assumptions which may bias coefficient estimates and inflate standard errors. Robust regression techniques such as M-estimation and Total Least Squares (TLS) were developed to overcome this limitation by reducing the influence of outlying observations. The principle of robustness, as first introduced by Huber (1964) and formalized by Rousseeuw & Leroy (2003), emphasizes resistance of parameter estimates to small departures from model assumptions, ensuring that results remain stable under imperfect data conditions.

The Robust Least Squares (RLS) approach modifies the traditional OLS objective function by introducing a weighted residual minimization scheme. While OLS minimizes the sum of squared residuals $min_\beta \sum_{i-1}^{n} e_i^2$. RLS minimizes a bounded influence function that downweights the effect of large residuals $min_\beta \sum_{i-1}^{n} p(e_i)$. Where $p(.)$ is a robust loss function that grows slower than the quadratic function for large errors. This ensures that extreme observations (outliers) exert limited influence on the fitted model.

This research applying robust estimation because the provincial-level agricultural and forest data in Indonesia may contain measurement errors, policy-induced shocks, or unobserved spatial effects that cause deviations from the ideal OLS assumptions. Following Shi et al. (2023), who proposed the Robust Total Least Squares (RTLS) method for uncertain data, robust regression offers more stable and accurate parameter estimates by simultaneously accounting for errors in both dependent and independent variables and by eliminating gross errors or outliers in the data. In this research, robust estimation is applied to the following model (2). The Robust Least Squares method serves to verify whether the main coefficients remain statistically significant and directionally consistent when controlling for outlier effects in the data.

3. RESULT AND DISCUSSION

3.1. Descriptive Statistics

This subsection presents the descriptive statistics of the variables used in this study, namely forest area, rice cultivation land area, rice productivity, and rice production across 34 provinces in Indonesia over the 2018–2023 period. Descriptive analysis is essential to provide an initial overview of data distribution, regional heterogeneity, and structural disparities that underpin the panel regression analysis. The data reveal substantial variation in forest area across provinces, reflecting Indonesia's diverse ecological and geographical conditions.

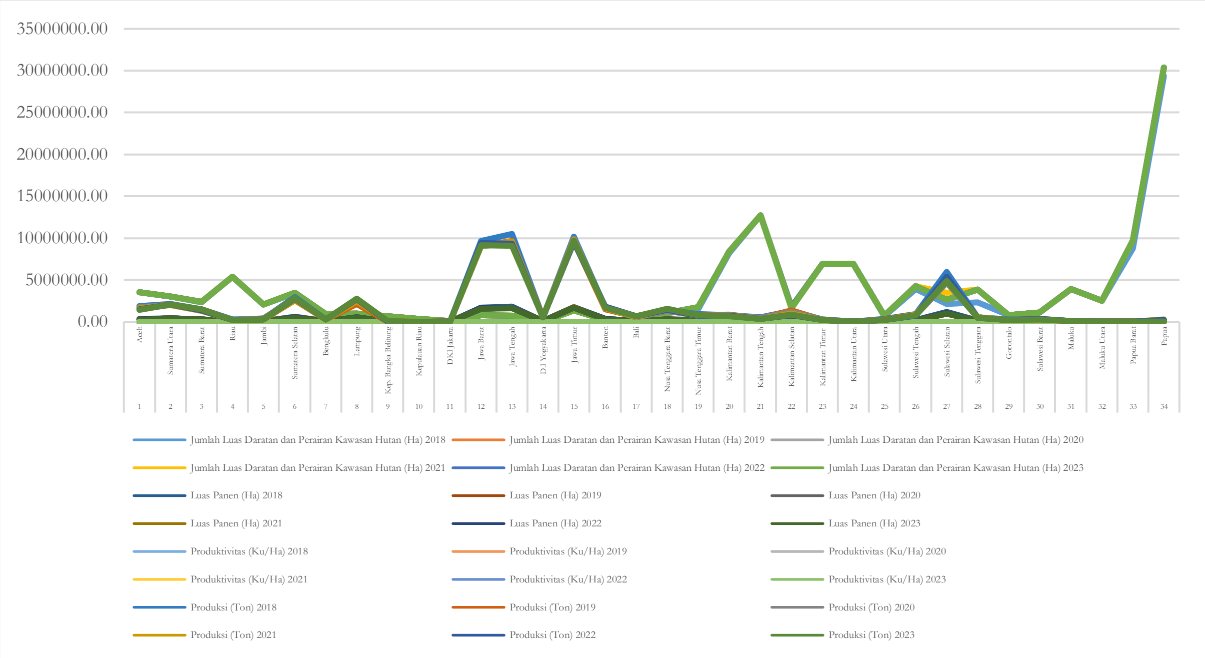

Figure 1. Data of Forest and Rice in Indonesia Per Province

Source: (BPS, 2025b, 2025a)

Provinces in eastern Indonesia, particularly Papua, West Papua, and Central Kalimantan, possess exceptionally large forest areas, exceeding 30 million hectares in Papua and 12 million hectares in Central Kalimantan. In contrast, provinces on Java Island, such as the Special Region of Yogyakarta and the Jakarta Capital Special Region, exhibit very limited forest coverage, with forest areas of approximately 16 thousand hectares and 108 thousand hectares, respectively. This pronounced contrast reflects strong structural heterogeneity across provinces, justifying the application of a fixed effects panel approach to control for unobserved province-specific characteristics.

Rice cultivation land also demonstrates substantial inter-provincial disparity. Major rice-producing provinces on Java Island record the largest rice farming areas, exceeding 1.6–1.8 million hectares, and function as Indonesia's primary rice production centers. Conversely, forest-dominated and island-based provinces such as the Riau Islands, West Papua, and Papua exhibit extremely small rice cultivation areas, in some cases below 1,000 hectares, indicating the marginal role of rice farming within their overall land-use structures. Rice productivity further varies considerably across regions, ranging from below 30 quintals per hectare in provinces such as the Bangka Belitung Islands and West Kalimantan to above 60 quintals per hectare in Bali, East Java, and the Jakarta Capital Special Region, reflecting unequal levels of agricultural efficiency and technological adoption.

Rice production patterns are consistent with variations in both land availability and productivity. Provinces on Java Island dominate national rice output, with Central Java and East Java producing more than 9–10 million tons annually, while forest-rich provinces such as West Papua, North Kalimantan, and Maluku contribute relatively small shares, often below 100 thousand tons per year. Overall, these descriptive statistics confirm strong spatial heterogeneity in forest endowment, agricultural land allocation, and rice production performance across Indonesian provinces, providing an essential empirical foundation for examining the trade-off between rice cultivation expansion and forest conservation in the subsequent econometric analysis.

3.2. Result of Classical Assumption Test

Prior to estimating the panel regression model, a series of classical assumption tests were conducted to ensure the reliability and validity of the empirical results. In panel data analysis, these tests are essential to detect potential econometric problems that may bias coefficient estimates or weaken statistical inference. This study focuses on three key classical assumption tests, namely multicollinearity, heteroskedasticity, and autocorrelation. The multicollinearity test is conducted first, as it directly affects model specification and the stability of coefficient estimates.

The multicollinearity test was initially performed by examining the correlation matrix among all explanatory variables included in the preliminary model, namely lnRiceArea, lnProduction, and lnProductivity. The results of this test are presented in Table 2.

Table 2. Correlation Matrix of Explanatory Variables (Initial Specification)

Variable	LNPRODUCTION	LNPRODUCTIVITY	LNRICEAREA
LNPRODUCTION	1.000	0.540	0.996
LNPRODUCTIVITY	0.540	1.000	0.467
LNRICEAREA	0.996	0.467	1.000

Source: Processed By Eviews

The results indicate an extremely high correlation coefficient (0.996) between lnProduction and lnRiceArea, which clearly signals the presence of severe multicollinearity. This outcome is theoretically expected, as rice production is mathematically derived from cultivated land area and productivity. In logarithmic form, rice production can be expressed as the sum of rice area and productivity, resulting in a near-perfect linear relationship between these variables.

The presence of severe multicollinearity implies that retaining lnProduction together with lnRiceArea and lnProductivity in the same regression model would lead to unstable coefficient estimates, inflated standard errors, and unreliable statistical inference. Therefore, the initial model specification (2) in model specification is not econometrically appropriate due to the violation of the no-multicollinearity assumption.

To address this issue and ensure the robustness of the estimation results, the model specification was revised by excluding lnProduction from the main regression model. This adjustment allows the analysis to focus more clearly on the core trade-off mechanism between land extensification (represented by rice cultivation area) and agricultural intensification (represented by rice productivity), without violating econometric assumptions. Following this revision, the multicollinearity test was re-estimated using the final set of explanatory variables, namely lnRiceArea and lnProductivity. The results are reported in Table 3.

Table 3. Correlation Matrix of Explanatory Variables (Final Specification).

Variable	LNRICEAREA	LNPRODUCTIVITY
LNRICEAREA	1.000	0.467
LNPRODUCTIVITY	0.467	1.000

Source: Processed By Eviews

The correlation coefficient between lnRiceArea and lnProductivity is well below the commonly accepted threshold, indicating that no serious multicollinearity problem exists in the final model. Accordingly, the revised and econometrically sound specification used in this study is expressed as follows:

$$\ln(Forest_{it)} = \alpha + \beta_1 \ln(RiceArea_{it}) + \beta_2 \ln(Productivity_{it}) + \mu_i + \lambda_i + \varepsilon_{it} \text{ ... (3)}$$

This final specification provides a stable and theoretically consistent foundation for subsequent autocorrelation analysis, heteroskedasticity testing, and panel regression estimation.

Following the multicollinearity test and the revision of the model specification, a heteroskedasticity test was conducted to examine whether the variance of the error term is constant across cross-sectional units. Given the heterogeneous nature of Indonesian provinces in terms of land endowment, economic structure, and agricultural practices, the presence of heteroskedasticity is a common concern in regional panel data. The heteroskedasticity test was performed using the Panel Cross-section Heteroskedasticity Likelihood Ratio (LR) Test. The results of the test are reported in Table 4.

Table 4. Panel Cross-section Heteroskedasticity Test

Test Statistic	Value	df	Probability
Likelihood Ratio (LR)	287.0719	34	0.0000

Source: Processed By Eviews

The null hypothesis of homoskedastic residuals is strongly rejected at the 1% significance level. This result indicates the presence of cross-section heteroskedasticity, meaning that the variance of the residuals differs across provinces. Such a condition is expected in panel data involving regions with diverse ecological characteristics and land-use structures.

To address this issue and ensure efficient estimation, the model was re-estimated using Panel EGLS with cross-section weights, which corrects for heteroskedasticity by allowing error variances to differ across cross-sections. The estimation results of the heteroskedasticity-corrected model are presented in Table 5.

Table 5. Panel EGLS Estimation with Cross-section Weights

Variable	Coefficient	Std. Error	t-Statistic
C	29.7645	0.5534	53.7836
LNRICEAREA	0.1710	0.0187	9.1587
LNPRODUCTIVITY	-4.4818	0.1902	-23.5634

Source: Processed By Eviews

The weighted estimation results indicate that both explanatory variables are statistically significant at the 1% level. The high adjusted R-squared value (0.829) suggests that, after correcting for heteroskedasticity, the model explains a substantial proportion of the variation in forest area across provinces and over time.

To examine the presence of serial correlation in the residuals, the Durbin–Watson (DW) statistic was used as an indicator of autocorrelation in the panel regression model. The DW statistic obtained from the unweighted estimation is 0.093, while the weighted estimation yields a DW value of 0.412, as summarized in Table 6.

Table 6. Durbin–Watson Statistics

Model Specification	Durbin–Watson Statistic
Unweighted Panel Model	0.093
Weighted Panel EGLS Model	0.412

Source: Processed By Eviews

Both values are substantially below the benchmark value of 2, indicating the presence of positive serial correlation in the residuals. This result suggests that shocks affecting forest area in a given year tend to persist into subsequent periods, which is plausible in the context of land-use change and forest dynamics. The classical assumption tests reveal that while the final model specification is free from multicollinearity, cross-section heteroskedasticity and serial correlation are present in the panel data. These conditions are typical in regional land-use studies and justify the use of heteroskedasticity-consistent and robust estimation methods. Consequently, the empirical results reported in the next section are based on estimation techniques that account for these issues, ensuring the robustness and credibility of the findings.

3.3. Result of Panel Least Square Analysis

The analysis follows a systematic panel data procedure, beginning with the pooled least squares estimator, followed by fixed and random effects models, and concluding with formal model selection tests. The pooled least squares (PLS) model is first estimated as a baseline specification that assumes homogeneous intercepts across provinces and time periods.

Table 7. Pooled Least Squares (PLS) Estimation Results

Variable	Coefficient	Std. Error	t-Statistic	Probability
C	28.2807	1.6753	16.8808	0.0000
LNRICEAREA	0.2788	0.0497	5.6108	0.0000
LNPRODUCTIVITY	-4.5229	0.4904	-9.2222	0.0000
Model Statistics		**Value**		
R-squared				0.3026
Adjusted R-squared				0.2957
F-statistic (Prob.)				43.6153 (0.0000)
Durbin–Watson				0.0931
Observations				204

Source: Processed By Eviews

While the PLS results indicate statistically significant coefficients, the specification ignores unobserved provincial heterogeneity and exhibits severe serial correlation, as reflected by the very low Durbin–Watson statistic. These limitations motivate the use of more appropriate panel estimators.

To control for time-invariant provincial characteristics, the model is re-estimated using the Fixed Effects Model (FEM). The results are reported in Table 8.

Table 8. Fixed Effects Model (FEM) Estimation Results

Variable	Coefficient	Std. Error	t-Statistic	Probability
C	14.2723	0.2811	50.7698	0.0000
LNRICEAREA	-0.0091	0.0123	-0.7392	0.4608
LNPRODUCTIVITY	0.0377	0.0587	0.6417	0.5219
Model Statistics		**Value**		
R-squared				0.9990
Adjusted R-squared				0.9988
F-statistic (Prob.)				4834.91 (0.0000)
Durbin–Watson				1.5739
Effects				Cross-section fixed

Source: Processed By Eviews

After accounting for province-specific effects, both rice cultivation area and rice productivity become statistically insignificant, indicating that forest area dynamics are largely driven by structural provincial characteristics rather than short-run within-province changes.

Formal model selection tests support the adoption of the Fixed Effects Model. The Chow test strongly rejects the pooled specification (p =

0.0000), confirming the presence of significant cross-sectional heterogeneity. Although the Hausman test is statistically undefined due to negligible differences between fixed and random effects estimators, the random effects model exhibits extremely low explanatory power and fails to capture provincial heterogeneity.

Table 9. Model Selection Tests Summary

Test	Decision	Evidence
Chow Test (PLS vs FEM)	Reject PLS	p = 0.0000
Random Effects Performance	Rejected	$R^2 \approx 0$
Hausman Test	Undefined	Variance matrix not positive definite
Final Model	Fixed Effects Model (FEM)	Strong heterogeneity & institutional relevance

Source: Processed By Eviews

The empirical evidence consistently indicates that forest area dynamics in Indonesia are dominated by province-specific structural factors. Therefore, the Fixed Effects Model (FEM) is accepted as the final and most appropriate specification for subsequent analysis and discussion.

3.4. Result of Robustness Test

This study conducts a robustness test to assess whether the main findings of the panel least squares analysis are sensitive to potential outliers and distributional irregularities in the data. Given the substantial disparity in forest area, rice cultivation scale, and productivity across Indonesian provinces, the presence of extreme observations is likely. To address this concern, the model is re-estimated using Robust Least Squares (ROBUSTLS) with M-estimation, which down-weights the influence of outliers and provides more reliable parameter estimates under non-normal error distributions.

The robustness test focuses on verifying whether the direction and interpretation of the relationship between rice-related variables and forest area remain consistent when alternative estimation techniques are applied. The ROBUSTLS estimation results are presented in Table 10.

Table 10. Robust Least Squares (ROBUSTLS) Estimation Results

Variable	Coefficient	Std. Error	z-Statistic	Probability
C	27.9568	1.3475	20.7466	0.0000
LNRICEAREA	0.3117	0.0400	7.7977	0.0000
LNPRODUCTIVITY	-4.5166	0.3945	-11.4495	0.0000

Robust Statistics	Value
Rw-squared	0.4715
Deviance	207.6241

Scale (MAD)	0.9766
Observations	204
Robust Statistics	Value

Source: Processed By Eviews

The robust estimation indicates that rice cultivation area is positively associated with forest area, while rice productivity exhibits a negative and statistically significant relationship. These results are consistent in sign with the pooled estimates, suggesting that provinces with larger rice cultivation areas and higher productivity levels tend to display distinct forest area patterns relative to other provinces. The robustness test confirms that the main conclusions of this study are not driven by extreme observations or outliers. Instead, the contrast between the robust cross-sectional estimates and the fixed effects results suggests that the observed rice–forest relationship is structural in nature and largely shaped by long-standing regional characteristics, such as ecological endowment, land-use history, and institutional arrangements.

3.5. Discussion

This study sets out to examine whether expansion of rice cultivation and improvements in rice productivity are associated with changes in forest areas across Indonesian provinces, and to assess the trade-off between food production and forest conservation. The empirical analysis shows that cross-regional (between-province) associations between rice variables and forest area are present, but within-province temporal dynamics (the core focus of the policy question: does rice expansion cause deforestation over time within provinces?) are not statistically supported by preferred estimator.

The original specification is model (2) includes rice cultivation area, rice production, and rice productivity simultaneously as explanatory variables. However, the multicollinearity test indicates that lnProduction is almost perfectly correlated with lnRiceArea (correlation coefficient = 0.996). This outcome is not surprising, as rice production is mechanically defined by the identity lnProduction = lnRiceArea + lnProductivity. Including these variables simultaneously therefore leads to severe multicollinearity, resulting in unstable coefficient estimates and unreliable statistical inference.

To address this issue and ensure econometric validity, the original specification is revised by excluding ln(Production). The revised model referred to as model (3), retains lnRiceArea and lnProductivity to separately capture the effects of land extensification and agricultural intensification. Model (3) is both theoretically meaningful and econometrically defensible, as it explicitly distinguishes between expansion of cultivated land and improvements in productivity while avoiding redundancy in variable construction. Formal model selection tests (Chow and Hausman diagnostics), together with the pronounced time-invariant heterogeneity across provinces, support the use of the Fixed Effects Model (FEM) as the primary estimator for analyzing within-province dynamics. To further validate the robustness of the findings, additional estimations using Robust Least Squares

(ROBUSTLS) and EGLS-based approaches are employed to account for cross-sectional heterogeneity and potential outlier influence.

This study investigates the relationship between rice cultivation and forest area across Indonesian provinces by explicitly separating land extensification and agricultural intensification effects. By employing a fixed effects panel framework, the analysis focuses on within-province temporal dynamics, while robustness estimations capture cross-provincial structural patterns. H1 posits that expansion of rice cultivation area reduces forest area. The Fixed Effects Model (FEM) shows that the coefficient of rice area is negative but statistically insignificant, indicating that short-term changes in rice cultivation within provinces do not significantly affect forest area. This result suggests that rice extensification, at least over the observed period, is not a primary driver of deforestation within provinces.

This finding is consistent with panel-based studies that control for location-specific fixed effects and report weak or insignificant within-unit effects of agricultural expansion on forest loss (Angelsen & Kaimowitz, 2001; Ferretti-gallon & Busch, 2014). In contrast, the ROBUSTLS estimation produces a positive and statistically significant coefficient, reflecting cross-sectional differences across provinces. Similar patterns have been documented in cross-sectional analyses, where agricultural land use correlates with forest outcomes due to historical land allocation rather than recent expansion ((Barbier & Burgess, 2001; Rudel et al., 2009)). Overall, the evidence does not support H1 at the within-province level.

For the H2 which concerns the effect of rice production on forest area. This hypothesis is not examined in the final empirical specification due to severe multicollinearity between rice production and rice cultivation area. Accordingly, H2 is excluded from the main analysis and remains unanswered. Moreover, H3 hypothesizes that higher rice productivity preserves forest area by reducing incentives for land expansion. Under the FEM, rice productivity exhibits a positive but statistically insignificant effect, implying that year-to-year productivity improvements within provinces do not translate into measurable forest conservation outcomes. This result aligns with studies arguing that intensification does not automatically reduce land pressure when market access and commercialization effects dominate (Angelsen, 2010; Byerlee et al., 2010).

The ROBUSTLS results, however, reveal a negative and statistically significant relationship between productivity and forest area, indicating that provinces with higher rice productivity tend to have smaller forest areas. This finding mirrors cross-country and cross-regional studies showing that highly productive agricultural regions often coincide with historically deforested landscapes (Lambin & Meyfroidt, 2011; Pendrill et al., 2019). Thus, while intensification appears negatively associated with forest area in cross-sectional comparisons, this relationship reflects long-term structural and historical processes rather than short-term productivity gains. Consequently, H3 is not supported in the within-province dimension.

Taken together, the results indicate that the rice–forest relationship in Indonesia is primarily shaped by structural, cross-provincial differences rather than short-term agricultural dynamics within provinces. This conclusion is consistent with the broader land-use literature emphasizing the dominant role of historical land-use trajectories, ecological endowments, and institutional factors in determining forest outcomes (Geist & Lambin, 2002; Lambin et al., 2003). From a policy standpoint, these findings imply that forest conservation strategies should prioritize structural and institutional interventions, such as land-use zoning, tenure reform, and region-specific development planning, rather than relying solely on short-term changes in rice cultivation or productivity. Provinces with long-established agricultural systems require policies addressing legacy land conversion, while forest-rich regions benefit more from preventive measures that limit new deforestation. The empirical evidence suggests that deforestation dynamics in Indonesia are driven more by long-standing regional characteristics than by short-term rice sector developments.

4. CONCLUSION AND SUGGESTION

This study examines the relationship between rice cultivation and forest area across 34 Indonesian provinces during 2018–2023 by distinguishing agricultural extensification (rice area) from intensification (productivity). The main empirical result shows that neither short-term changes in rice cultivation area nor productivity within provinces significantly affect forest area. Meanwhile, robust cross-sectional estimates reveal significant associations that reflect long-term structural, historical, and ecological differences across regions rather than policy-relevant year-to-year adjustments. This suggests that the rice–forest relationship in Indonesia is driven primarily by long-term development trajectories rather than short-term agricultural dynamics.

Theoretically, the study contributes to land-use scholarship by showing the importance of separating within-province temporal effects from between-province structural patterns when analyzing agricultural drivers of deforestation. Empirically, the findings reinforce panel-based evidence that cross-sectional correlations may overstate agricultural impacts on forest outcomes, whereas fixed-effects estimation attenuates these impacts once unobserved heterogeneity is controlled. A methodological contribution arises from the exclusion of rice production due to multicollinearity, underscoring the need for conceptual clarity when agricultural output aggregates extensification and intensification mechanisms.

Despite these contributions, the analysis is limited by provincial-level aggregation, a relatively short observation window, and the inability to estimate production effects due to identification constraints. Future research may extend the temporal scope, employ finer spatial data, integrate remote-sensing approaches, or apply causal identification techniques such as instrumental variables. From a policy perspective, the results imply that forest conservation in Indonesia depends more on structural land governance than on short-term agricultural interventions. Strengthening land-use zoning, tenure systems, and permanent forest estate enforcement, while shifting agricultural policy from land expansion toward productivity enhancement, would better align food security objectives with forest protection and Indonesia's FOLU Net Sink 2030 goals.

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