

Research Article

Determinant of Productivity in the Indonesian Agricultural Sector

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Abstract

In Indonesia, it has been detected that the share of Gross Value Added in the agricultural sector to the total Gross Domestic Product tends to decline. One of the causes of this decline is the decreasing number of farmers involved in the agricultural sector. This study aims to analyze the determinants of productivity in Indonesia's agricultural sector. This study uses secondary data sourced from the Central Bureau of Statistics and Bank Indonesia. The research reference used is 2023. The unit of analysis used for processing is 34 provinces in Indonesia. Data analysis using ridge regression. In modelling the variables that affect the productivity of the agricultural sector, there are three variables that have a significant association. These variables include the adoption of technology in agriculture, the categorization of the plantation sector, and the use of urban farming. The R square obtained was 0.8065, which means that 80.65% of the dependent variable can be explained jointly by the independent variables. In labor modelling, the variables that have significant associations are the number of farmers who own land and the Human Development Index. The R square obtained was 0.9451, which means that 94.51% of the dependent variable can be explained jointly by the independent variables. Complementing these findings, Cluster analysis revealed three distinct regional groups. Provinces such as Central Java and East Java fall into cluster with characterized by advanced agricultural performance, while several eastern and outer-island regions fall into clusters that indicating lower competitiveness and greater needs for technology and financial inclusion.

Keywords

Technology Adoption, Agricultural Labor, Productivity, Agricultural Sector

1. Introduction

Agriculture is a very important sector both in the world and in Indonesia. It not only contributes to the provision of food, but is also a source of livelihood for most of the population, especially in developing countries such as Indonesia. According to FAO (Food and Agriculture Organization), agriculture supplies more than 80% of the world's food needs and provides jobs for more than 1.3 billion people worldwide [1].

Existing conditions in Indonesia show that the share of

Gross Value Added in the Agricultural Sector to Total Gross Domestic Product (Figure 1) tends to decline [2]. One of the reasons for this decline is the decreasing number of farmers involved in the sector. Many farmers have switched professions because they feel less prosperous and do not get proper rewards from their agricultural products. According to the Central Bureau of Statistics, the number of farmers in Indonesia has decreased significantly in the last decade, which has

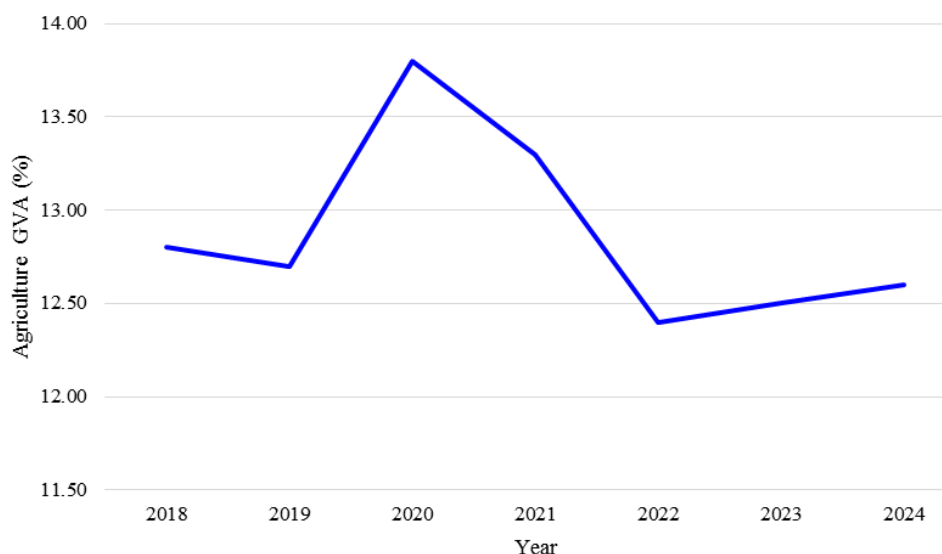
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an impact on food security and the sustainability of the agricultural sector [4].



Source: Central Bureau of Statistics, 2025 (processed)

Figure 1. Share of Gross Value Added in Agriculture Sector to Total Gross Domestic Product (Percent).

Amidst these challenges, the emergence of digitalization and agricultural technology is a new hope to increase productivity and efficiency in agricultural production. Technologies such as the use of drones, soil sensors, and smart farming apps can help farmers better manage their land, thereby increasing their yields and income. A study by Papadopoulos et al., shows that the application of digital technology in agriculture can increase productivity by 30% and reduce production costs by 20% [5].

Digitalization involves the incorporation of digital technologies into various aspects of agricultural practices, from precision farming to supply chain management. One notable example is the use of Internet of Things (IoT) devices and sensors to monitor soil conditions, crop health and climate patterns in *real-time*. Technologies enable farmers to make data-driven decisions, optimize resource use, and minimize environmental impacts [6].

Furthermore, the application of precision agriculture utilizes advanced technologies such as GPS-guided tractors and drones, resulting in the precise application of fertilizers and pesticides [7]. This not only increases productivity but also reduces input costs and minimizes the ecological footprint of agricultural practices.

On the other hand, human resource development in agriculture involves equipping farmers and agricultural workers with the necessary skills and knowledge to utilize digital technologies effectively. Training programs, workshops and educational initiatives are important components of this development. A study conducted by Khan, emphasized the importance of educating farmers on digital tools, ensuring they can harness the full potential of technological advancements [8].

Moreover, collaborative efforts between governments, educational institutions and the private sector are essential to build a skilled agricultural workforce capable of dealing with the complexities of modern agricultural practices. Investing in the education and training of agricultural professionals will drive innovation and adaptation to the evolving technological landscape.

With the potential of technology, there are also functions that can be empowered in improving the quality of human resources in the agricultural sector. One of them is the use of digital platforms that provide access to agricultural knowledge, market information, and financial services to empower farmers. This is in line with what was shown in the case of mobile-based agricultural extension services discussed by Zant, where the technology was able to improve farmers' capabilities, facilitate decision-making and market participation [9].

With the existing potential, the digitization process for the agricultural sector in Indonesia appears to be ongoing and will continue with various variations in each subsector, which includes the food crop agriculture, plantation, fisheries, livestock, and forestry subsectors. Digital technology innovation is alleged to have an impact on efficiency and productivity achievements. Likewise, the development of human resources in the agricultural sector through various counseling and training is considered capable of increasing productivity.

Despite these advancements, empirical examinations of provincial agricultural productivity show uneven performance and region-specific constraints, indicating the need for localized policies tailored to provincial characteristics. [10] Existing literature acknowledges that technology adop-

tion, digitalization, and human capital development significantly influence agricultural performance and supply chain resilience [11]. However, most studies in Indonesia are micro-level or crop-specific (e.g., rice, tobacco) and do not simultaneously analyze these determinant factors at the provincial level. Moreover, while ridge regression and other regularization techniques have been applied in certain regional studies to address multicollinearity, their use in analyzing technology, urban farming, HDI, land ownership, and credit availability together remains limited. Additionally, although urban farming is increasingly recognized for its role in urban food security and value-added production, most Indonesian studies remain qualitative or city-level case studies, leaving its contribution to provincial agricultural productivity underexplored [12].

These gaps justify the need for a comprehensive, data-driven provincial analysis using robust econometric approaches, such as ridge regression, to evaluate multiple, potentially collinear determinants of agricultural productivity. It is within this framework that this study was conducted with the aim of analyzing (1) the determinants of productivity in

the Indonesian agricultural sector and (2) the determinants of labor absorption.

2. Materials and Methods

This study utilizes a comprehensive dataset encompassing key agricultural variables relevant to Indonesia's diverse farming systems, collected from official government sources such as the Indonesian Bureau of Statistics (BPS). The dataset includes variables capturing technology adoption rates, credit access, labor inputs, and socio-economic indicators such as the Human Development Index (HDI). These variables were selected based on their theoretical and empirical relevance to agricultural productivity and market dynamics, as established in prior literature and preliminary exploratory analyses (Table 1). The data underwent rigorous preprocessing steps, including normalization, outlier detection, and missing value imputation, to ensure robustness and comparability across regions and time periods [3].

Table 1. The variables used in this study.

Variables	Role and Definition	Source	Unit
Gross Value Added (GVA) of Agriculture Sector	GVA plays the role of variable dependent (Y). The value added by the agricultural sector in the process of producing goods and services. GVA is calculated by subtracting the value of outputs (production) from the value of inputs (intermediate costs).	BPS-Statistics	Million IDR
Agriculture Sector Labors	Labor plays the role of variable dependent (Y). All persons working in all businesses categorized under the Agricultural Sector.	BPS-Statistics	People
Technology Adoption by Farmers	The role of this variable is independent variable (X). Variable explain the use of digital technology by farmers includes the use of the internet/smartphones/information technology, the use of drones, and the use of artificial intelligence for agricultural activities.	Indonesian Agricultural Census 2023	Percentage
Plantation Dummy	The role of this variable is independent variable (X). Variable explain Grouping of regions with dominance in the plantation sub-sector.	Indonesian Agricultural Census 2023	0 = Plantation 1 = Other
Agriculture Sector Credit	Number of loans granted for business purposes in the agricultural sector. The role of this variable is independent variable (X)	Central Bank Indonesia	Million IDR
Utilization of Urban Farming	The number of agricultural business households in urban areas (urban village classification) that cultivate their farms on limited land, most of which do not utilize the land surface directly but use planting media such as pots and the like, as well as using technologies such as hydroponics, aquaponics, vertical culture, tarpaulin media and the like. The role of this variable is independent variable (X)	Indonesian Agricultural Census 2023	Percentage
Number of Farmers with Land	The number of households where a household member uses agricultural land (excluding land for aquaculture in the sea or public waters) and conducts agricultural activities but not as a farm laborer or family worker. The role of this variable is independent variable (X)	Indonesian Agricultural Census 2023	Percentage
HDI	Indicators to measure human development achievements are based on a number of basic components of quality of life through a three-dimensional approach that includes a long and healthy life; knowledge, and a decent life. The role of this variable is independent	BPS-Statistics	Point

Variables	Role and Definition	Source	Unit
	variable (X)		

Factors that are thought to affect the gross value added of the agricultural sector are (1) the level of technology adoption, (2) plantation dummy, (3) the amount of agricultural credit (4) urban farming, (5) the number of farmers with land, and (6) HDI. Data analysis using ridge regression.

Ridge regression is a linear regression technique that incorporates regularization to overcome some of the problems associated with ordinary least squares (OLS) regression, especially when dealing with multicollinearity (high correlation between predictor variables) and overfitting. Ridge regression adds a penalty term to the OLS objective function to prevent the model from becoming too complex and to regularize the estimated coefficients [13].

Predicted value formula:

$$(\hat{y}) = \beta_o + \sum_{i=1}^k \beta_i x_i$$

where:

- $\hat{y}$ is the predicted value of the dependent variable
 - β_o is the intercept
 - β_i is the regression coefficient for each variable x_i
 - Σ is the sum of k independent variables
- The objective function for ridge regression is:

$$J(\beta) = \sum_{i=1}^N (y_i - X_i^T \beta)^2 + \lambda \sum_{j=1}^p \beta_j^2$$

where:

$\sum_{i=1}^N (y_i - X_i^T \beta)^2$ is the first term (Measuring prediction errors)

$\lambda \sum_{j=1}^p \beta_j^2$ is the second term (Penalizes the magnitude of the coefficient)

N is the number of observations

p is the number of features (predictors)

y_i is the observed response for the i-th observation

X_i is the vector of predictor variables for the i-th observation

β is the vector of regression coefficients to be estimated

λ is the regularization parameter, which controls the strength of the *penalty term*

The above function describes the optimization method for objective function values in Ridge Regression. Its role is very important because it is this function that is minimized to obtain an estimate of β parameters that are "more stable" and not overfitting. The first term is the sum of the squared differences between the observed and predicted responses, and the second term is the regularization term that *penalizes* the magnitude of the coefficients. The regularization parameter λ is a hyperparameter that balances the trade-off between fitting the data well and keeping the coefficients small. Ridge regression is particularly useful when dealing with multicollinearity, where the predictor variables are highly correlated [14]. The regularization term helps shrink the coefficients, preventing them from becoming too large and unstable.

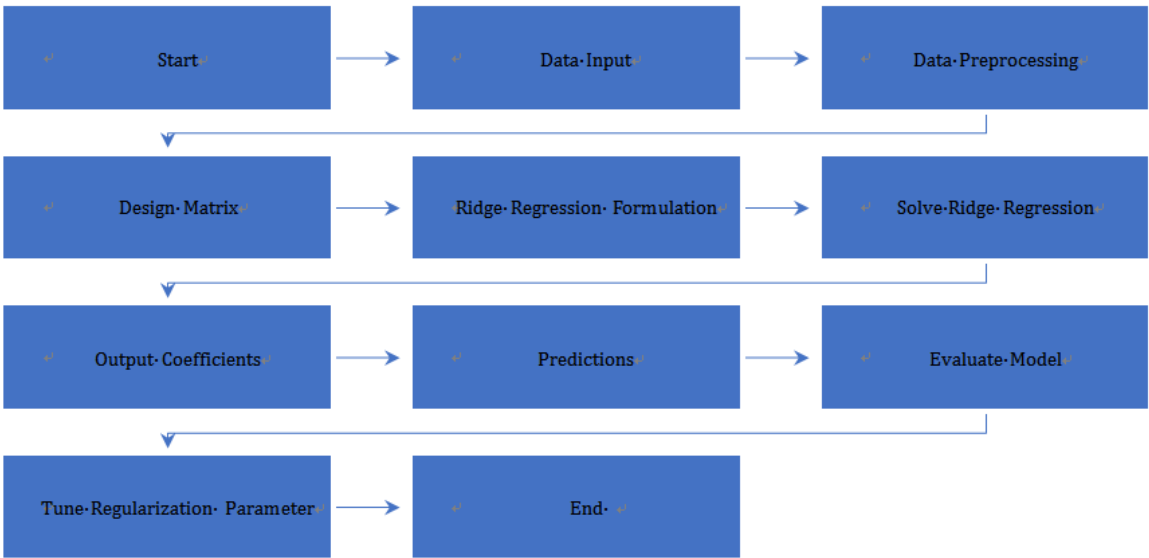


Figure 2. Ridge Regression Stages.

This study also employs a spatial clustering approach to group Indonesian provinces based on the multidimensional indicators presented in Table 1. The purpose of forming these clusters is to generate a clearer understanding of regional patterns and to support more targeted and context-specific policy recommendations. Spatial clustering enables the identification of provinces with similar characteristics, reducing analytical complexity and improving the precision of proposed interventions.

All variables used in the clustering process are directly derived from Table 1, which contains standardized provincial-level indicators relevant to the research objectives. Prior to analysis, the dataset was cleaned, normalized, and examined for missing values to ensure consistency across regions. Normalization was applied to avoid scale bias between variables with different measurement units.

The study applies a hierarchical agglomerative clustering technique, selected for its ability to reveal natural groupings without requiring prior assumptions about the number of clusters. The Euclidean distance metric was used to measure similarity between provinces, while Ward's linkage method was employed to minimize within-cluster variance during the merging process. This combination ensures the formation of compact and distinct spatial clusters.

To quantify similarity between provinces, the study employs the Euclidean distance, the most widely used metric in quantitative clustering. For two provinces A and B, the distance is calculated as:

$$d(A, B) = \sqrt{\sum_{k=1}^n (A_k - B_k)^2}$$

This metric effectively captures multidimensional differences based on the indicators in Table 1 and is suitable for continuous, standardized data.

To determine the most meaningful number of clusters, the study combines:

Dendrogram inspection.

Identifying large vertical jumps indicates meaningful split points.

Statistical validity indices, including:

Calinski–Harabasz Index.

Silhouette Coefficient.

The optimal solution is selected based on the highest average silhouette score and the clearest separation on the dendrogram. This ensures both statistical validity and interpretability for policy making.

Research Conceptual Framework

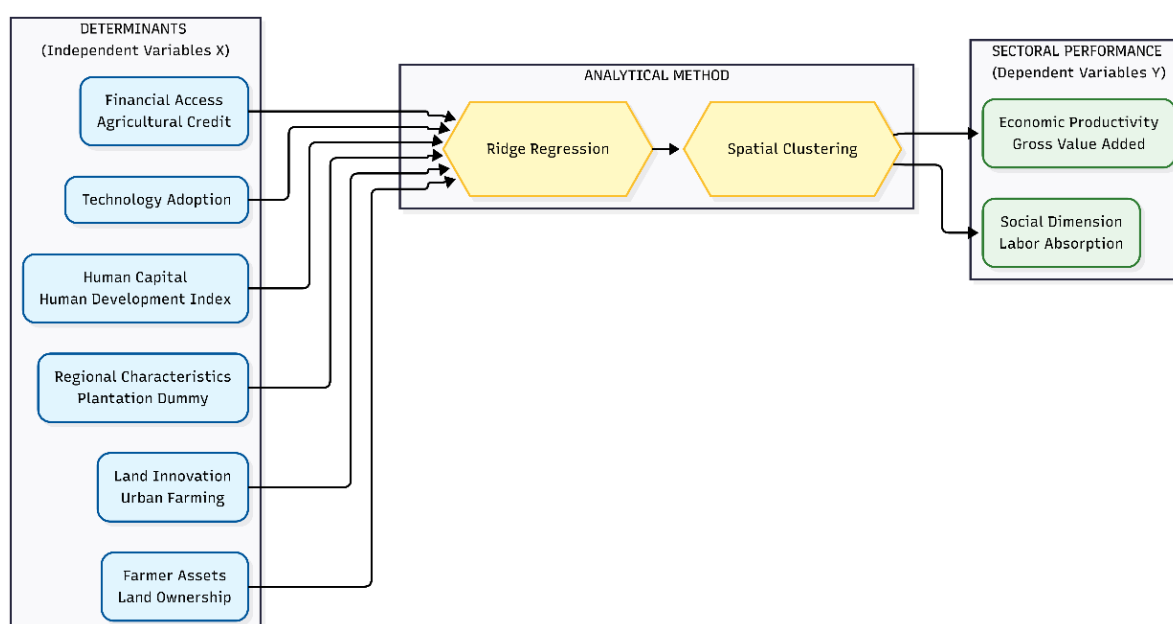


Figure 3. Diagram of Conceptual Framework.

This study constructs a comprehensive conceptual framework to analyze the dynamics of the agricultural sector in Indonesia, focusing on two primary performance dimensions: economic productivity and labour absorption. Conceptually, the study posits Gross Value Added (GVA) as the primary proxy for productivity, while the total workforce serves as the indicator for human capital participation. These dependent

variables are hypothesized to be influenced by a constellation of external and internal sectoral factors.

Within this framework, productivity drivers are examined through the lenses of modernization and regional characteristics. The study postulates that technology adoption (encompassing the utilization of the internet, smartphones, and smart agricultural tools) plays a pivotal role in enhancing efficiency

and yield. Furthermore, the framework integrates sub-sectoral characteristics via a plantation dummy variable to discern performance disparities between plantation-dominated regions and general agriculture, while also accounting for urban farming utilization to capture the phenomenon of modern agriculture within constrained land areas.

Conversely, financial and human resource dimensions are integrated to explain labour dynamics. Agricultural credit is analyzed as a potential financial catalyst for farming enterprises. Meanwhile, the Human Development Index (HDI) and the number of land-owning farmers are utilized to elucidate workforce trends. Specifically, the study conjectures a complex relationship wherein improved human capital (HDI) may correlate negatively with agricultural labour quantity due to aspirational shifts toward non-agricultural sectors, whereas substantial land ownership is posited to drive labour absorption.

To rigorously test these hypothesized relationships, the analytical framework employs a Ridge Regression approach. This method is specifically selected for its robustness in mitigating multicollinearity and for applying statistical penalties to yield more stable and unbiased estimation models, com-

plemented by Spatial Clustering to map regional characteristics.

3. Results

3.1. Descriptive Statistics of Research Variables

Based on the descriptive analysis of the data, technology adoption among farmers across provinces in Indonesia showed considerable variation with a minimum of 4,536 farmers and a maximum of 2,690,604 farmers. The average adoption of technology was 400,014.24 farmers with a high standard deviation of 625,191.13, reflecting significant disparities between provincial regions in Indonesia. Agricultural credit also shows large variations, with an average of IDR 14,375.65 billion, a minimum of IDR 1,154.40 billion, and a maximum of IDR 151,108.41 billion, and a standard deviation of IDR 28,015.52 billion. This shows the disparity in access to credit between regions (Table 2).

Table 2. Descriptive Statistics of Research Variables.

Variables	Unit	Minimum	Average	Maximum	Standard Deviation
Technology adoption	People (farmers)	4,536.00	400,014.24	2,690,604.00	625,191.13
Plantation dummy	Dummy				
Agriculture sector credit	Billion Rupiah	1,154.40	14,375.65	151,108.41	28,015.52
Utilization of <i>urban farming</i>	People (farmers)	20.00	385.45	3,213.00	720.33
Number of farmers with land	People (farmers)	43,819.00	842,212.82	5,427,568.00	1,186,474.04
Human Development Index	Points	63.01	73.47	81.09	3.39
Gross Value Added in agriculture	Billion Rupiah	4,010.99	33,498.02	140,063.63	36,569.63
Agriculture sector labor	People	46,961.00	899,869.70	4,884,642.00	1,029,612.86

The utilization of urban farming has a minimum of 20 farmers and a maximum of 3,213 farmers, with an average of 385.45 farmers and a standard deviation of 720.33, indicating that the practice of *urban farming* is still uneven. Meanwhile, the number of farmers with land ranges from 43,819 to 5,427,568 farmers, with an average of 842,212.82 farmers and a standard deviation of 1,186,474.04, which also reflects significant differences between regions. The Human Development Index (HDI) has an average of 73.47 points, a minimum of 63.01 points, and a maximum of 81.09 points, and a standard deviation of 3.39. Gross value added in agriculture has an average of 33,498.02 billion rupiah with significant variation, where the minimum value is 4,010.99 billion rupiah and the maximum is 140,063.63 billion rupiah, and the

standard deviation is 36,569.63 billion rupiah. Finally, labor in the agricultural sector has a minimum of 46,961 people, a maximum of 4,884,642 people, with an average of 899,869.70 people and a standard deviation of 1,029,612.86, indicating an uneven distribution of labor. Overall, this data illustrates the large disparities in various aspects of agriculture, including technology adoption, access to credit, utilization of urban farming, and the size of the agricultural workforce.

3.2. Distribution of Gross Value Added in the Agricultural Sector in Indonesia

Analysis of the value-added of the agricultural sector in Indonesia shows significant disparities between provinces,

which are reflected in the 2023 agricultural value-added distribution map (Figure 4). Overall, this map suggests that achieving more equitable growth in the agricultural sector requires integrated policies that focus on the development of

less developed regions. Thus, appropriate interventions can help increase the value-added of the agricultural sector and reduce disparities between provinces in Indonesia.



Figure 4. Distribution of Gross Value Added (GVA) in the Agricultural Sector in Indonesia by Province, 2023.

3.3. Determinants of Productivity in Agricultural Sector and Agricultural Labor Absorption Using Ridge Regression

In modeling the variables affecting gross value added in the agricultural sector, there are three variables that have significant associations. These variables include the adoption of technology in agriculture, the categorization of the plantation sector, and the utilization of urban farming. Technology

adoption as well as urban farming utilization have positive associations, while the plantation sector dummy has a negative association. HDI has an association with agriculture gross value added at the 7% real level. Credit to the agricultural sector and farmers with land are not associated with gross value added in the agricultural sector. The R square obtained was 0.8065, which means that 80.65% of the dependent variable can be explained jointly by the independent variables (Table 3).

Table 3. Estimation of Ridge Regression Model.

Independent Variable	Dependent Variable			
	ln(Gross Value Added in Agriculture Sector)		ln(Agricultural Labor)	
	Coefficient	P-Value	Coefficient	P-Value
(Intercept)	28.33123	0.045*	29.732878	0.001*
ln(Technology Adoption)	0.45372	0.009*	0.053259	0.581
Dummy Agriculture	-0.50261	0.007*	-0.122832	0.236

Independent Variable	Dependent Variable			
	ln(Gross Value Added in Agriculture Sector)		ln(Agricultural Labor)	
	Coefficient	P-Value	Coefficient	P-Value
0 = Plantation 1 = Other				
ln(Agriculture Sector Credit)	0.01234	0.890	-0.001121	0.983
ln(Urban Farming Utilization)	0.36658	0.014*	0.058415	0.485
ln(Number of Farmers with Land)	-0.07686	0.770	0.810181	0.000*
ln(HDI)	-5.72163	0.061	-6.506684	0.001*
R-Squared	0.8065		0.9451	
F-stat	23.23	0.000*	92.77	0.000*

*) significant at the 5 percent level.

In labor modeling, the R square obtained was 0.9451, which means that 94.51% of the dependent variable can be explained by the independent variable. The variables that have significant associations are the number of farmers who own land and the Human Development Index. Both variables have different directions of association with the amount of labor absorption in the agricultural sector. The Human Development Index has a negative association with a relatively large coefficient, while land ownership by farmers has a positive association. Technology adoption, plantation dummy, urban farming, and agricultural credit are not associated with agricultural employment.

4. Discussion

4.1. Determinants of Productivity in Agricultural Sector

Research by Sharmiladevi revealed that the agricultural sector in Indonesia has varying contributions to Gross Regional Domestic Product in each province, with some regions showing low value-added due to limited access to resources and adequate infrastructure [15]. This is in line with findings from Central Bureau Statistics Indonesia which noted that provinces with high agricultural potential are often unable to maximize their productivity due to factors such as low education and lack of investment in agricultural technology [4].

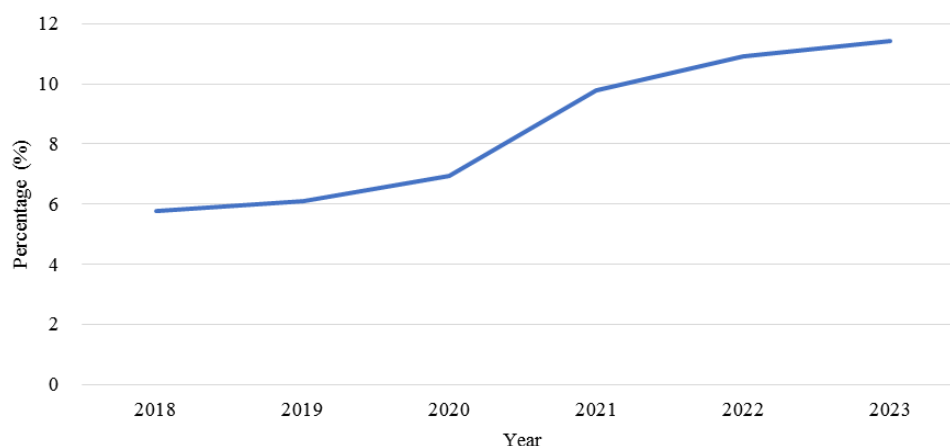
Furthermore, research by Xu et al., emphasizes the importance of leading sector development to reduce regional inequality [16]. The research recommended improving accessibility and infrastructure as strategic measures to increase agricultural productivity in underdeveloped areas. This research shows that by improving the quality of educa-

tion and labor skills, as well as improving facilities and infrastructure, provinces that are currently lagging behind can potentially increase their contribution to the national economy.

4.1.1. Technology Adoption

Looking at the association of technology and gross value added in the agriculture sector, it is currently undergoing a digital revolution, with the integration of technology delivering significant value added across its spectrum. From precision farming to automated systems and data-driven decision-making, technology is transforming the way food is grown, managed and marketed, resulting in increased efficiency, productivity and sustainability. One of the key contributions of technology is precision agriculture, which leverages sensors, drones and AI to collect and analyze data on soil conditions, crop health and weather patterns. This allows farmers to tailor their inputs, such as water, fertilizer, and pesticides, to the specific needs of each crop, optimizing resource utilization and minimizing waste [17]. Precision agriculture results in higher yields, improved crop quality, and reduced environmental impact.

The Central Bureau of Statistics as represent in Figure 5 revealed an increase in the percentage of the population aged 10 years and above in the agricultural sector accessing the internet annually from 2018 to 2023, indicating great potential for technology utilization in agriculture. This trend reflects the wider adoption of digital technology by farmers to access market information, weather forecasts, modern cultivation techniques, and agricultural e-commerce platforms. With adequate infrastructure and increased digital literacy, the agricultural sector can be increasingly integrated with technology, opening up new opportunities for farmers to improve their welfare and competitiveness in the digital economy era [18].



Source: Central Bureau Statistics 2024 (processed).

Figure 5. Percentage of Population 10 Years and Over in the Agricultural Sector Accessing the Internet in the Last 3 Month.

Automation is another important aspect of technological influence. Automated farming systems handle tasks such as planting, harvesting and irrigation, reducing labor costs and improving operational efficiency [19]. This frees up time for farmers to undertake other activities, such as market research and product development, adding further value to their business [20].

In addition, technology empowers data-driven decision-making. *Platforms* that collect and analyze agricultural data from various sources, including weather forecasts, market trends, and crop performance, provide farmers with valuable insights to optimize their operations. This data-driven approach enables informed decision-making regarding planting strategies, resource allocation, and risk management, ultimately leading to increased profitability and resilience [11].

4.1.2. Plantation Sector

While often overshadowed by more flashy agricultural subsectors, the plantation sector also adds significant value to the broader agricultural landscape. One of the hallmarks of the plantation sector is its focus on high-value, export-oriented crops. Coffee, tea, cocoa, rubber and palm oil are some examples of commodities produced by plantations, which often command premium prices on the international market [21]. This export orientation generates substantial foreign exchange earnings for producing countries, strengthens national economies and contributes to development efforts [22].

In addition, the plantation sector is characterized by an integrated value chain, encompassing not only cultivation but also processing, marketing, and distribution. This vertical integration allows for greater control over quality, price, and market access, maximizing profits and obtaining a greater share of value added [23]. In addition, investment in processing infrastructure in plantations creates local jobs and

stimulates the development of downstream industries [24].

Compared to other agricultural subsectors, such as subsistence farming or cereal production, the plantation sector often shows higher labor productivity and capital intensity. This can be attributed to economies of scale achieved through large-scale landholdings, the application of advanced technologies, and investments in human resource development for skilled workers [25]. As a result, the plantation sector can generate significant surplus value and contribute to rural development through improved infrastructure and social services. However, it is important to recognize the potential environmental and social challenges associated with the plantation sector. Concerns regarding deforestation, land degradation, and labor exploitation have plagued the industry in certain regions. Sustainable practices and responsible management are essential to ensure the long-term viability and positive impact of the plantation sector [26].

4.1.3. Urban Farming

Another adaptive form of agricultural technology development is the development of *urban* farming. Urban farming is the practice of growing food in urban environments that is rapidly changing the agricultural landscape. Its impact goes beyond food production and adds significant value to the agricultural sector through various socio-economic and environmental benefits. Urban agriculture promotes food security, particularly in densely populated areas, by shortening supply chains and diversifying food sources. This mitigates the risks associated with long-distance transportation and volatile food prices [27]. This local production empowers people, especially those facing food insecurity, to access fresh and nutritious food [28]. In addition, urban agriculture contributes to economic diversification and job creation, with the establishment of local food systems that generate new employment opportunities in areas such as agriculture, food processing and distribution [29]. These economic activities

stimulate the local economy and foster entrepreneurship, especially among marginalized communities [30]. In this study, the utilization of *urban farming* by 1 percent has the potential to increase the added value of the agricultural sector by 0.36 percent. However, *urban farming* is still only massive around Java, suggesting that there is great potential for further development in other regions. In addition to economic benefits, urban farming also offers environmental benefits by reducing the impact of urban surface heat and increasing biodiversity. Green spaces in cities improve air quality and mitigate the impacts of climate change [31]. In addition, urban agriculture can contribute to waste reduction through composting and rainwater collection, thus creating a more sustainable urban environment [32]. The social impact of urban agriculture is also noteworthy, as by creating shared spaces for cultivation and education, urban agriculture encourages community engagement and social cohesion [33]. These green spaces provide opportunities for recreation, physical activity, and mental well-being, thus contributing to improved quality of life for urban residents [34].

4.2. Determinants of Agricultural Labor Absorption Sector

4.2.1. Human Development Index (HDI)

For decades, the agricultural sector has served as the lifeblood of human civilization, nourishing society and driving economic growth. However, in the new era, progress as measured by the Human Development Index (HDI), which includes advances in education, health and technology, appears to be driving a decline in agricultural employment. At the heart of this trend lies the transformative power of mechanization and technological innovation. As economies progress, investments in automated machinery, precision farming techniques, and advanced crop management systems dramatically increase labor productivity [35]. A modern harvester can now do the work of dozens of manual laborers, making their traditional roles obsolete. As a result, there is less need for human labor in the fields, so the size of the agricultural workforce is shrinking relative to the economy as a whole.

Beyond technology, urbanization and economic diversification play an important role in this dynamic. Rising HDI often coincides with rapid urbanization, driven by increased educational opportunities and the attraction of higher-paying jobs in the service and manufacturing sectors [36]. As individuals migrate to urban centers in search of better livelihoods and modern lifestyles, the amount of labor in the agricultural sector in rural areas naturally declines. Moreover, as economies diversify, their reliance on agriculture as the main engine of growth decreases. The emergence of new industries and sectors that offer alternative sources of income and employment has further reduced the share of agricultural labor in the total labor force.

Adding to the complexity is the role of education and changing aspirations. Increased access to education, which is a hallmark of rising HDI, equips young people with new skills and opens the door to diverse career paths. They may be less attracted to the rigors of traditional agricultural work, and instead seek *prestige* and higher incomes when compared to professions in other sectors. This shift in aspirations contributes to a shrinking labor pool in the agricultural sector, potentially exacerbating existing trends.

However, it is important to realize that this relationship is not a universally predictable and observable outcome. There are a number of factors that cause the younger generation to be uninterested in working in the agricultural sector, namely (1) greater off-farm income, (2) image of agriculture, (3) increased education, (4) narrow farmland ownership, and (5) ease of rural accessibility [37, 38] also revealed a number of factors that cause youth disinterest in the agricultural sector, namely (1) the existence of a social stigma against the agricultural sector, and (2) the majority of parents are reluctant to have their children work as farmers.

Hence, despite the negative correlation between HDI and labor force in the agricultural sector, the underlying dynamics are far from deterministic. A deep understanding of these context-specific factors is critical for policymakers and development practitioners seeking to navigate this complex transition. Ensuring inclusive and sustainable growth in developing countries requires recognizing the challenges posed by a shrinking agricultural workforce, while capitalizing on the opportunities posed by technological progress and economic diversification. Only in this way can the paradox of progress be transformed into a catalyst for equitable development and shared prosperity.

4.2.2. Farmers with Land

On the other hand, land, the very foundation of agriculture, has a unique power to shape the lives of those who work it. In addition to production, land ownership can also significantly influence the size and composition of the agricultural labor force, fostering an often-overlooked positive relationship between the two factors. This study investigates the intricacies of land tenure and its impact on the number of agricultural workers, and explores the economic, social and psychological mechanisms underlying this relationship.

One of the most direct implications of land tenure lies in its ability to incentivize agricultural sector investment and engagement. When farmers own the land they cultivate, they have a vested interest in long-term productivity and profits. This translates into increased investment in labor, technology, and infrastructure, all of which contribute to the expansion of the labor force in the agricultural sector [39]. Landowners are more likely to hire additional workers to manage larger farms, adopt labor-intensive farming practices, or invest in processing and value-added activities, all of which create new employment opportunities in the agricultural sector.

In addition, land tenure fosters entrepreneurial spirit and

risk-taking, encouraging innovation and diversification in agriculture. With secure tenure, farmers are more likely to experiment with new crops, technologies and marketing strategies, potentially creating niche markets and specialized production systems that require additional skilled labor [40]. This diversification not only expands the scope of agricultural labor but also increases resilience to external shocks and commodity price fluctuations.

Beyond the economic sphere, land ownership also strengthens the social fabric and cultural identity of farming communities. Owning farmland can provide a sense of belonging, stability and pride, and foster a stronger connection to the land and the agricultural way of life. This, in turn, can attract younger generations to a career in agriculture, augmenting the labor force and ensuring the survival of traditional knowledge and practices [41]. In addition, strong landowning communities often exhibit greater social cohesion and collaboration, leading to collective investments in infrastructure, education and skills development, thus further increasing the attractiveness and viability of the agricultural sector as a career path.

However, it is important to realize that the positive relationship between land ownership and labor force in the agricultural sector is not always direct. Unequal land distribution, where a small number of individuals own large tracts of land, can lead to landlessness and underemployment among rural communities. This concentration of ownership can hinder agricultural development and limit opportunities for new entrants to the sector, thereby reducing the overall economic and social benefits of land ownership.

Therefore, ensuring equitable access to land and promoting secure land tenure arrangements are critical to maximizing the positive impact of land ownership on agricultural labor. Policies such as land redistribution programs, lease agreements, and investments in rural infrastructure can play an important role in creating an environment where land ownership means increased employment opportunities and improved livelihoods for rural communities.

4.3. Policy Recommendations and Implementation Strategies

Building on the comprehensive quantitative analysis and discussion of market mechanisms, this section outlines detailed policy recommendations aimed at fostering sustainable agricultural development in Indonesia. The evidence underscores the critical importance of promoting technology adoption, ensuring equitable land access, and revitalizing youth participation in agriculture. These priorities are essential to enhance productivity, employment, and market efficiency, while addressing structural challenges revealed through advanced data segmentation and econometric modeling.

First, accelerating technology adoption emerges as a cornerstone policy. The positive and significant impact of digital and precision agricultural technologies on gross value-added

highlights the need for expanded investments in digital infrastructure, extension services, and farmer training programs. Policies should prioritize affordable access to modern inputs such as GPS-guided equipment, drones, and data analytics platforms, coupled with capacity-building initiatives that empower farmers to effectively utilize these tools. Implementation frameworks must incorporate multi-stakeholder collaboration involving government agencies, private sector innovators, and local cooperatives to ensure technology dissemination is contextually appropriate and inclusive. Monitoring mechanisms should track adoption rates, productivity gains, and barriers encountered, enabling adaptive management and continuous improvement. Potential obstacles include limited rural connectivity, financial constraints, and resistance to change, which can be mitigated through targeted subsidies, microcredit schemes, and participatory extension approaches that build trust and demonstrate tangible benefits [5].

Second, equitable land access is vital for sustaining agricultural employment and productivity. The strong positive association between land ownership and labor absorption underscores the urgency of land tenure reforms and policies that facilitate secure, transparent, and fair land distribution. Strategies should focus on simplifying land registration processes, protecting smallholder rights, and promoting land consolidation where appropriate to enhance economies of scale. Implementation requires coordinated efforts across legal, administrative, and community levels, with stakeholder engagement to address conflicts and ensure social acceptability. Policy evaluation frameworks such as cost-benefit analysis and multi-criteria decision analysis can guide prioritization and resource allocation, balancing economic efficiency with social equity. Barriers such as bureaucratic inertia, vested interests, and land disputes necessitate robust governance structures and conflict resolution mechanisms to ensure policy effectiveness and sustainability.

Third, revitalizing youth participation in agriculture is essential to counteract demographic challenges and ensure sectoral sustainability. Policies should integrate education, vocational training, and entrepreneurship support tailored to young people's aspirations and constraints. Digital literacy and agri-tech innovation hubs can attract youth by linking agriculture with modern technology and business opportunities. Implementation strategies must involve collaboration between educational institutions, government programs, and private sector partners to create enabling environments. Monitoring and evaluation should assess youth engagement levels, skill acquisition, and employment outcomes to refine interventions. Addressing social stigma and parental reluctance, as identified in recent studies, requires community outreach and awareness campaigns to reshape perceptions of agriculture as a viable and rewarding career [7].

Across these policy domains, the integration of advanced policy evaluation methodologies enhances implementation feasibility. Employing frameworks such as implementation

science facilitates understanding of contextual factors, stakeholder dynamics, and adaptive pathways, ensuring policies are responsive and resilient. Market simulation models, informed by econometric estimates and segmentation results,

provide scenario analyses that help anticipate outcomes, optimize resource allocation, and identify potential unintended consequences. These tools support evidence-based decision-making and foster iterative learning.

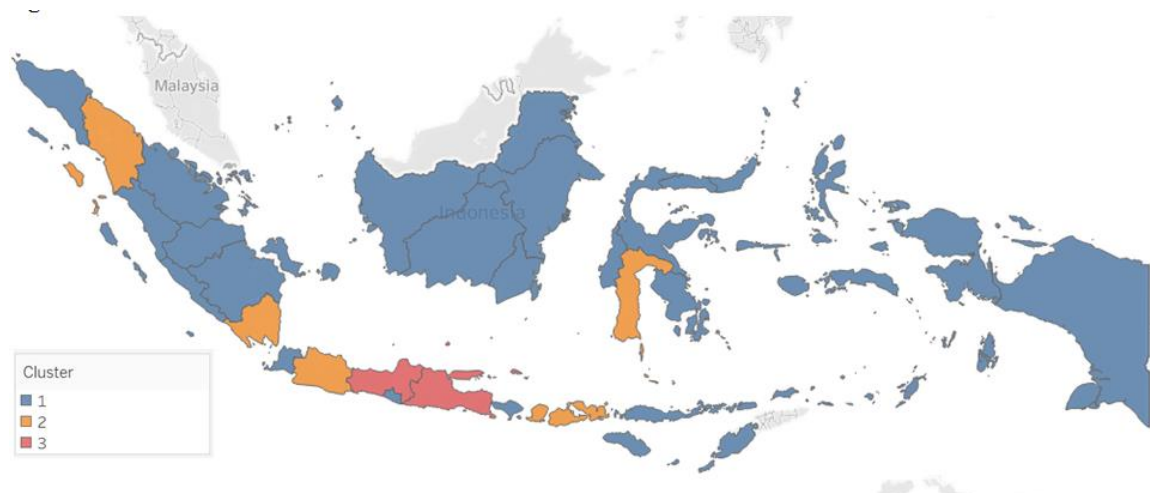


Figure 6. Cluster Analytics to Determined Undeveloped Area.

This comprehensive policy framework is also designed to address the observed disparities in agricultural development across Indonesia, as delineated by the three distinct regional clusters. The goal is to foster equitable growth and bolster national agricultural productivity through targeted interventions tailored to each cluster's unique characteristics.

For Cluster 3 as represent in [Figure 6](#), representing advanced agricultural regions (Central Java and East Java), the primary policy thrust should focus on identifying and replicating their success models. This involves in-depth studies to pinpoint the crucial factors underpinning their achievements, such as modern farming practices, robust irrigation infrastructure, effective market access, strong farmer institutions, and supportive local government policies. The insights gained should be meticulously documented and disseminated through comprehensive guides, training modules, and pilot programs, enabling wider adoption in other clusters. Furthermore, these regions should be strategically developed as agricultural innovation hubs, fostering research and development in areas like superior seed varieties, precision agriculture technologies, and sustainable farming methods. Facilitating robust partnerships among universities, research institutions, private entities, and local farmers will be crucial for accelerating innovation adoption. While already advanced, Cluster 3 must also be encouraged to continuously enhance the value-added of its agricultural products through post-harvest processing, standardization, and certification. Promoting commodity diversification is essential to mitigate risks and enhance food security, alongside active promotion and branding of their premium agricultural products in both domestic and international markets.

Conversely, Cluster 2 comprises regions with significant

agricultural potential requiring optimized financial inclusion, technology adoption, and urban farming initiatives. Policy interventions for this cluster must prioritize expanding farmers' access to crucial financial resources, including agricultural credit, insurance, and sharia-compliant financing. These programs should be easily accessible and tailored to farmers' needs, potentially through collateral-free loans or collective guarantee schemes. Financial literacy education is paramount to empower farmers in managing their finances, making sound investments, and understanding the importance of savings. Facilitating partnerships between financial institutions and farmer groups will streamline collective financing disbursements. Concurrently, increasing the adoption of agricultural technology necessitates intensive socialization and training on relevant modern techniques, such as drip irrigation, simplified farming tools, balanced fertilization, and market price information systems. Providing subsidies or incentives for appropriate farming tools and technologies, alongside the development of demonstration plots, will be instrumental in showcasing direct benefits. Furthermore, forging partnerships with agritech providers and startups should be actively encouraged. The strategic development of urban farming is another key area, involving the identification of suitable vacant or underutilized land in urban and peri-urban areas. Technical assistance and training should be provided to urban communities interested in methods like hydroponics, vertical farming, and aquaponics. Promoting urban farming as a source of local food, an environmental enhancer, and a community economic empowerment tool is vital, as is establishing local markets for urban farming produce to ensure sustainability. Despite possessing better land ownership, policies should protect farmers from land frag-

mentation and facilitate land consolidation for more efficient agricultural practices, encouraging optimal land utilization through intercropping or suitable crop diversification.

Finally, Cluster 1 encompasses regions where agricultural potential remains largely uncompetitive due to the dominance of other sectors. For these areas, a thorough assessment is needed to identify specific local agricultural commodities with a comparative advantage, focusing on their comprehensive development from upstream to downstream. Critical investments in foundational agricultural infrastructure, including farm roads, post-harvest facilities, and access to clean water, are essential. Improving inter-regional connectivity will further facilitate the distribution of agricultural products. Strengthening farmer institutions through the formation and empowerment of farmer groups and agricultural cooperatives will enhance farmers' bargaining power, accompanied by technical and managerial assistance. While other sectors may be dominant, policies must actively support agriculture as a strategic complementary sector for local food security. Encouraging partnerships between agriculture and these dominant sectors (e.g., tourism, mining) can create mutually beneficial value chains. Providing alternative skills training for communities not fully engaged in agriculture is also crucial. Lastly, enhancing farmers' access to vital information on market prices, weather patterns, and agricultural technologies is paramount, as is assisting them in building market networks and forging partnerships with buyers.

Across all clusters, several overarching recommendations apply. Establishing a robust and integrated agricultural data system is crucial for informed policy-making. Local governments must be encouraged to develop specific agricultural action plans tailored to their respective clusters. Multi-stakeholder collaboration among central and local governments, the private sector, academia, research institutions, and civil society is indispensable for holistic agricultural development. Finally, all policy recommendations must integrate sustainable environmental practices and climate change mitigation strategies to ensure long-term resilience. Through the systematic implementation of these targeted and synergistic policies, Indonesia's agricultural sector can achieve widespread development, elevate farmer welfare, and significantly strengthen national food security.

In summary, these policy recommendations highlight a holistic, multi-dimensional strategy that integrates technological innovation, land reform, and human capital development within a framework of rigorous evaluation and participatory governance:

- 1) Expand digital infrastructure and farmer connectivity.
- 2) Strengthen the adoption of modern agricultural technologies.
- 3) Promote the expansion of urban farming beyond Java.
- 4) Reform agricultural credit schemes to improve access.
- 5) Enhance land tenure security and support land consolidation.
- 6) Develop region-specific agricultural policies based on

cluster analysis.

- 7) Improve farmer training and digital literacy pro-grams.
- 8) Strengthen governance in plantation subsectors.
- 9) Encourage youth participation through agri-tech entrepreneurship.
- 10) Integrate agricultural policy with broader human development strategies.

Overcoming existing barriers requires coordinated action, adequate funding, and sustained commitment from all stakeholders. Embedding these strategies within robust implementation frameworks will strengthen agricultural market mechanisms, promote inclusive growth, and build long-term resilience in the face of evolving economic and environmental challenges.

5. Conclusions

The conclusion of this study shows that agricultural productivity in Indonesia varies widely between provinces due to differences in technological readiness, land structure, and socio-economic conditions. Technology adoption, plantation characteristics, and urban farming significantly increase agricultural value added, while labor absorption is shaped mainly by land ownership and HDI. Higher HDI often corresponds to lower agricultural labor due to migration and shifting career aspirations. To improve national productivity and sectoral resilience, Indonesia must prioritize technology expansion, equitable land access, youth involvement, and region-specific development strategies.

Abbreviations

BPS	Badan Pusat Statistik (Indonesian Bureau of Statistics)
DEA	Data Envelopment Analysis
FAO	Food and Agriculture Organization
GPS	Global Positioning System
GVA	Gross Value Added
HDI	Human Development Index
IDR	Indonesian Rupiah
IoT	Internet of Things
OLS	Ordinary Least squares
PAM	Policy Analysis Matrix

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Author Contributions

I Made Tamba is the sole author. The author read and approved the final manuscript.

Conflicts of Interest

The author declares no conflicts of interest.

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