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Spatial Analysis of Agricultural Sector Labor Absorption Among Generation Z in Indonesia 2024

Amat Sugiyanto[1], Toto Gunarto[2], Arivina Ratih Yulihar Taher[3]
[1,2,3]Universitas Lampung

ABSTRACT: This study aims to analyze the factors that influence the absorption of agricultural labor from Generation Z in Indonesia with a spatial approach. The method used is spatial regression with the Spatial Error Model (SEM) model, using cross section data from 38 provinces in Indonesia in 2024. The data used is secondary data sourced from the official publication of the Ministry of Agriculture of the Republic of Indonesia. The dependent variable in this study is the employment of the agricultural sector in Generation Z, while the independent variables include production facilities assistance program, education level, income, harvest area, access to agricultural credit, agricultural micro assistance, and unemployment rate. The estimation results show that the SEM model is the best model in capturing the existence of spatial effects in the distribution of agricultural labor among regions. Four variables were found to have a significant effect on Generation Z employment, namely the production facility assistance program, education, income, and harvest size. Meanwhile, the variables of agricultural credit access, micro- assistance, and unemployment had no significant effect. These findings indicate that efforts to increase youth employment in the agricultural sector need to focus on providing production facilities, increasing land productivity, and improving the relevant agricultural vocational education system, taking into account the spatial context between regions.

KEYWORDS: Generation Z, Agricultural Sector, Labor Absorption, Spatial Regression, SEM, Indonesia

INTRODUCTION

As economies grow, developing countries such as Indonesia experience significant structural transformation with the industrial and service sectors expanding more rapidly than the agricultural sector. However, the agricultural sector continues to play an important role: in 2023, agriculture will still contribute around 12.53% to national GDP, making it one of the three main sectors in Indonesia's economic structure. The sector's contribution is also crucial for food security, rural employment, and economic stability-especially evident during the COVID-19 pandemic when agriculture was the main pillar. However, a major challenge arises from the resilience of labor regeneration: data shows an aging trend of farmers in Indonesia-the proportion of workers aged 60 and above increased from 7.6% in 1971 to 21.2% in 2020.

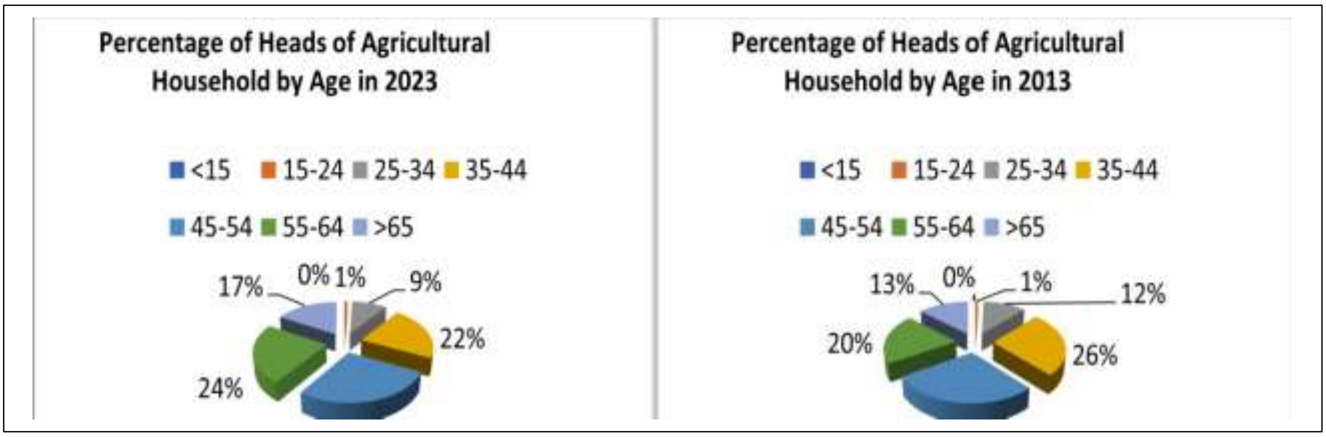
Demographic changes have a significant impact on the agricultural sector, both in positive and negative terms. On the positive side, an increase in the working-age population offers greater labor potential, which can support agricultural production if properly utilized. This demographic bonus opens up opportunities to strengthen the agricultural sector through increased adoption of agricultural technology, thereby improving production efficiency and productivity (Ji et al., 2017) . On the other hand, demographic changes also bring challenges, especially with urbanization and migration causing many young workers to shift to other sectors. As a result, the agricultural sector lacks a young workforce and relies more on older farmers. This phenomenon triggers a decline in efficiency and reliance on traditional farming practices, resulting in low productivity and food security in rural areas (Despotovic et al., 2015). In addition, other demographic factors, such as age, education and access to land, influence the propensity of younger generations to choose agricultural jobs, with many preferring service or industrial jobs. These factors exacerbate the risk of future farmer shortages and challenge the long-term sustainability of the agricultural sector (Haryati et al., 2024).

Labor trends in the agricultural sector point to the challenge of attracting young people, particularly Gen Z, to work in this field. Many members of Gen Z are more interested in sectors that offer a modern work environment and greater flexibility, such as technology or the service industry. The main reason is the perception that the agricultural sector is less promising in terms of career opportunities and competitive income than other sectors. In Bima District, for example, family economic, motivational and environmental factors play an important role in Gen Z's low interest in working in agriculture (Awaludin et al., 2024). In addition, it shows that the employment of this generation in the agricultural sector has decreased significantly, with many migrating to other sectors that are considered more “prestigious” or attractive (Bachtiar et al., 2023). Another factor that makes Gen Z tend to move away from the sector is the lack of commodity price stability and financial support, which is perceived to affect their profit prospects and career development in the agricultural sector (Ananda et al., 2024)

One of the consequences of this structural transformation at the global level is that the issue of aging farmers has received less attention than other issues, such as the issue of declining production due to climate change, even though the aging of farmers is a serious demographic challenge that needs attention because it concerns the sustainability of the agricultural sector. An increase in the number of farmers over 60 years old, and a decrease in the number of young farmers, is occurring in almost all parts of the world. Structural changes in the demographics of agricultural labor are also occurring in Asian countries, Europe, as well as the Americas, Canada, and countries in other parts of the continent. This shows that the declining interest in agricultural labor has become a common phenomenon that needs serious attention from policy makers in order to save the agricultural sector. The description of structural changes in the demographics of the workforce in the agricultural sector described below reinforces the general phenomenon that leads to the aging of farmers and the reduction of young workers in the agricultural sector. Based on academic studies and data from the Central Statistics Agency (BPS), Indonesia faces a serious threat to the sustainability of the farming profession. Predictions point to the possibility of no more farmers by 2063 if regeneration is not done immediately. This trend is reinforced by the decline in the proportion of youth working in the agricultural sector in the past decade, as well as the increasing urbanization that has led to the movement of young people from villages to cities in search of non-agricultural jobs. The issue of farmer aging and its manifestation in several countries needs to be studied in order to find alternative policies to encourage young workers to enter the agricultural sector, especially in the current era of free trade. The following is a review of the phenomenon of farmer aging in Indonesia and in several other countries (Susilowati, 2016). Labor mobility and the reluctance of young people to remain in the sector have led to an increase in the average age of farmers, and stagnant or lower yields and productivity. In many cases, regardless of the type of sector transition, unequal distribution of resources, especially capital, can result in less efficient outcomes and, sometimes, social tensions (Godoy et al., 2014).

Changes in the demographic structure of the agricultural sector in Indonesia are dominated by older farmers aged more than 55 years. This is happening at the same time as the number of young farmers is declining (Nisa Suriani et al., 2023). This condition will certainly have adverse implications for the future of agriculture in Indonesia. Agriculture is a relatively large sector that provides employment and food sources for the population. Several factors have contributed to the declining participation of the younger generation in agriculture, including a relatively higher income gap in the non-agricultural sector; a higher level of education; collaboration between older farmers and younger farmers that is not smooth (Susilowati, 2016).

Table 1. Percentage of Heads of Agricultural Household by Age in Indonesia



Source: Central Bureau of Statistics, 2024

The two diagrams above present data on the percentage distribution of Heads of Agricultural Business Households by age group in 2013 and 2023. It can be seen that the majority of heads of farming households in both years are in the productive age group of 35-64 years, but there is a shift in composition that is interesting to analyze. In 2013, the 35-44 years age group dominated with 28%, followed by 45-54 years (26%), and 55-64 years (20%). Whereas in 2023, the 35-44 group decreased slightly to 27%, but the proportion of 55-64 year olds increased to 24%, and the >65 year old group also increased from 13% to 17%. This indicates an aging trend in the age structure of household businesses, especially in the agricultural sector. The aging trend seen in the shift in the age composition of heads of households in agricultural businesses between 2013 and 2023 reflects the challenges of labor regeneration in the agricultural sector. The increase in the percentage of heads of households in the 55-64 and >65 age groups indicates that agriculture is increasingly dominated by the elderly, while the interest of the younger generation to enter the sector is still low. This risks reducing long-term productivity and slowing down the adoption of modern agricultural innovations. If not immediately intervened with policies that encourage young people's participation in agriculture such as farming incentives, access to capital, and agricultural technology training, national food security could be threatened due to the shrinking regeneration of productive farming actors.

Understanding the dynamics of Generation Z employment in the agricultural sector requires a thorough evaluation of the structural and policy factors that influence it. The literature suggests that access to agricultural credit and inputs assistance programs is an important foundation in creating an enabling agribusiness environment, providing capital and technological inputs that enable young farmers to operate productively (Odhiambo et al., 2023). In addition, education and applied training facilitate the ability of young people to utilize these technologies effectively and improve their financial and contractual literacy. The factor of adequate average income from agricultural businesses, supported by access to micro-assistance and microfinance services, is a real economic attraction for Generation Z to pursue a career in agriculture. In addition, the size of the harvest or landholding proves to be a determinant element-economies of scale allow for more intensive and profitable engagement for young farmers. Lastly, the high unemployment rate among Generation Z, if matched by appropriate credit and training policies, could divert young labor into agriculture as a productive employment alternative. Thus, interventions that combine financial, educational, structural, and agronomic aspects are needed to increase youth employment and realize a sustainable and highly competitive agricultural sector.

Access to agricultural credit and inputs assistance programs (such as training and farm inputs) have been shown to significantly increase the engagement of youth, especially Gen Z, in the agribusiness sector by increasing productivity and income, as evidenced by a number of studies in Africa and Asia that reported yield increases of 14-33% and household income increases of 40-59% after receiving credit and training (Boye et al., 2024). Applied education and training strengthens the ability of the younger generation to effectively utilize credit, technology and new inputs, and facilitates the adoption of modern agricultural practices. Adequate average income from farming activities, coupled with access to microfinance services, provide motivation for Gen Z to choose agribusiness as a viable career path. Crop size or land ownership also acts as an important factor
- youth with greater land access tend to engage in intensive farming and are actively involved in agribusiness value chains (Osabohien et al., 2021). On the other hand, the high unemployment rate among Gen Z encourages many to see agriculture as an employment alternative if supported by incentives such as access to credit, training and agribusiness opportunities (Boye et al., 2024).

THEORITICAL FRAMEWORK

Labor Absorption

Within the framework of development economics theory, the dynamics of agricultural employment are often discussed through the dual-sector model, originally introduced by Lewis (1954) and expanded by Fei & Ranis (1961). The Lewis model explains that in developing countries there are two sectors-traditional agriculture with surplus low-wage labor, and modern sectors such as manufacturing-that gradually absorb surplus labor from elite agriculture for economic growth. Meanwhile, the Harris-Todaro model provides a perspective of inter-regional labor migration, where the decision to move is influenced more by urban income expectations than real job opportunities in rural areas (Todaro & Smith, 2012). The theory of structural change relates to the process of transforming the economy of a developing region or country, which initially had a subsistence nature and depended on the agricultural sector, into a more modern economic structure or centered on industrial activities (Todaro & Smith, 2012). Percentage of Agricultural Business Household Heads by Age in 2023.

RESEARCH METHOLOGY

This research uses two analysis approaches, namely descriptive and inferential analysis. Descriptive analysis was conducted through thematic map visualization to show the spatial pattern of employment in the agricultural sector at the provincial level in Indonesia in 2024. The data used in this research is secondary data. The data source of this research is the Ministry of Agriculture. Meanwhile, inferential analysis uses spatial regression method to evaluate the influence of independent variables, such as access to agricultural credit, inputs, education, income, micro-assistance, harvest area and unemployment, on the level of employment in the agricultural sector. By considering the existence of spatial effects between regions. All hypothesis testing was conducted with a significance level of 5%. The spatial regression analysis process was carried out using GeoDa software, which is designed to facilitate users in estimating spatial regression models, determining the appropriate model form, interpreting the estimation results, and conducting diagnostic tests to detect the presence of spatial correlation in the data (Anselin, 2005). The procedure for implementing spatial regression in this study follows several systematic stages.

Cross Section Spatial Regression Method

The cross section regression method is a statistical analysis approach used to study the relationship between one dependent variable (response) and one or more independent variables (predictors) based on data at one specific point in time, but covering various observation units. Spatial weighting is one of the important elements in spatial data analysis that serves to represent the spatial relationship between geographic locations or units of analysis. The spatial weighting matrix is used to determine the weights between observed locations based on the neighboring relationship between locations. The elements of the spatial weighting matrix are organized:

$$\begin{bmatrix} W_{11} & W_{12} & \cdots & W_{1N} \\ W_{21} & W_{i2} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ W_{N1} & W_{N2} & \cdots & W_{NN} \end{bmatrix}$$

The rows and columns of the weight matrix represent the regions that are the units of analysis. W_{ij} is the weight of the i-th and j-th region linkages, where $Wij \geq 0$, $Wij = Wji$ and $Wii = 0$ for i = 1,2,3, , N. Spatial regression is an econometric approach used when the data contains spatial elements, i.e. there is dependence or influence between geographic locations. This method is an extension of OLS (Ordinary Least Squares) regression, which assumptively requires no correlation between residuals (independence). However, in spatial data such as between administrative areas (villages, sub-districts, provinces), this assumption is often violated due to spatial autocorrelation which means that the value of an observation is influenced by the value of other geographically close observations. In general, there are two main models in spatial regression: Spatial Lag Model (SLM) and Spatial Error Model (SEM). The lag model is used when spatial effects occur in the dependent variable, while the error model is used when spatial effects occur in the residuals of the model.

Steps in Spatial Regression:

1. Creating a Spatial Weight Matrix

Determine the relationship between regions, for example: Contiguity (Queen/Rook) regions are direct neighbors. Distance-based regions within a certain radius are considered neighbors. This matrix will be used to calculate the spatial influence between observation units.

2. Spatial Autocorrelation Test (Moran's I)

Tests whether there is a spatial pattern in the dependent variable. If the Moran's I value is significant, then there is a spatial influence that needs to be modeled.

3. Local Spatial Autocorrelation Test - Local Moran's I (LISA)

Local Moran's I or LISA is a derivative of Global Moran's I that provides local information about the strength and pattern of spatial autocorrelation - not just an overview of the overall region. LISA helps identify “High-High” (high values surrounded by high values), “Low-Low”, and outliers such as “High-Low” or “Low-High” clusters.

4. Lagrange Multiplier Test (LM Test)

Determines the most appropriate spatial model:

LM-lag → if the effect is in the dependent variable (use SLM). LM-error → if the effect is in the error term (use SEM).

Robust LM is used if both are significant.

5. Spatial Regression Model Estimation

Running the SLM or SEM model using GeoDa software.

6. Diagnostic Test and Interpretation of Results

Check model validity and variable significance. Interpret the direct and indirect effects (spillover effects) between regions.

RESULTS AND DISCUSSION

Tabel 2. Thematic Map of Indonesia Depicting the Distribution of Values of The Generation Z Agricultural Labor Variable Across Provinces in Indonesia.

Source: data processed by Geoda

The figure shown is a thematic map of Indonesia depicting the distribution of values of the Generation Z agricultural labor variable across provinces in Indonesia. This variable appears to represent the amount of Generation Z labor in the agricultural sector, or at least some form of measure of Gen Z engagement in the agricultural sector. High Concentration (Dark Brown - YGENZ > 142,003): Seen in most parts of eastern and southern Indonesia, such as: South Sulawesi NTB and NTT Papua and West Papua East Java. These provinces have a high number of Gen Z workers in the agricultural sector. This may be related to the dominance of agriculture as the main livelihood and the high proportion of young people in the region. Low Value (White and Light Yellow - YGENZ < 15,766), Seen in provinces such as: DKI Jakarta Bali Riau Islands North Maluku South Papua. These regions have very low levels of Gen Z engagement in the agricultural sector. Most likely due to: High urbanization (such as Jakarta and Bali) Economy is not based on agriculture Younger generations are more involved in services or industry.

Spatial Approach to Generation Z Agriculture Sector Labor Absorption in Indonesia in 2024

Before conducting spatial regression analysis, the initial stage is to form an Ordinary Least Squares (OLS) model as a basic model to see the relationship between the dependent variable and the independent variable. This OLS model is also known as a multiple linear regression model, which serves to estimate the effect of each independent variable on the dependent variable without considering spatial elements. This model is used as an initial reference to identify the potential presence of spatial autocorrelation that can affect the validity of the estimation. The following shows the parameter estimation results of the multiple linear regression model used in this study.

Tabel 3. Ordinary Least Squares (OLS) Model

Variabel	Koefisien	Std. Error	t-Statistik	Probabilitas
CONSTANT	18.18460	5.13309	3.54263	0.00132
X1_AC	-0.00236	0.00877	-0.26907	0.78972
X2_PBSP	-0.27482	0.09892	-2.77818	0.00934
X3_PDDK	-0.27539	0.07210	-3.81977	0.00063
X4_LO_RRPB	-1.90804	0.79117	-2.41166	0.02221
X5_BM	0.28290	0.23778	1.18976	0.24347
X6_LOG_LP	0.27446	0.06535	4.19973	0.00022
X7_PNG	0.04284	0.06624	0.64676	0.52271
R-squared: 0.764934 Adjusted R-squared: 0.710085n				
F-statistic: 13.9463				

Source: data processed by Geoda

The Jarque-Bera test with JB value = 1.2098 and p-value = 0.5461 (df = 2) shows that you fail to reject the null hypothesis, so the residuals are normally distributed. This is because JB calculates the deviation from normal skewness and kurtosis, and a p-value > 0.05 indicates that the residual distribution is close enough to normal. The Breusch-Pagan test with a statistical value = 4.1832 and p-value = 0.7585 (df = 7) also shows that it fails to reject the hypothesis of homoscedasticity, which means that the residual variance is constant and there is no significant heteroscedasticity. The commonly considered safe centered VIF value is < 3 (some sources set a threshold of < 5 or < 10 for higher tolerance). Your table shows the centered VIF values for variables X1 to X7 are in the range of 1.57-2.90, which means there is no serious multicollinearity. Next, spatial autocorrelation was checked through Moran's I test. The spatial weighting matrix used is the KNN neighborliness criterion. The K-Nearest Neighbors (KNN) method in the context of spatial analysis is a technique for constructing a spatial weight matrix that ensures each location has the same number of neighbors (i.e. k nearest), independent of absolute distance. The results of the Moran's I test are presented in the following table.

Tabel. 4 Moran's I

Jenis Uji	MI / DF	Nilai (Value)	Probabilitas (Prob)
Moran's I (error)	0.1066	1.8687	0.06166

Source: data processed by Geoda

The results of Moran's I (error) with a value of MI/DF = 0.1066, statistic ≈ 1.8687, and p ≈ 0.0617 indicate the presence of weak positive spatial autocorrelation in the residuals of the OLS model-since the value is slightly above the 5% significance threshold, but can still be considered significant at the 10% level. At the province level, the Global Moran's I (error) results with a value of I = 0.1066 and p = 0.0617 indicate a weak positive spatial autocorrelation pattern but close to significant in the OLS model residuals. A value of I > 0 indicates that provinces with high residuals tend to be clustered together, and vice versa for low residuals. Although the p-value of 0.0617 is slightly above the conventional significant threshold (0.05), a significance level of 10% can still be considered to indicate the presence of a marginal spatial pattern, which implies clustering and potentially missed spatial variables in the model. This means that the OLS model may not fully explain variations between provincial locations that are influenced by spatial factors such as geographic distribution, infrastructure, and regional characteristics. Therefore, although the OLS assumptions are generally still valid, it is necessary to conduct further analysis in the form of residual visualization (e.g. through Moran scatterplot or hotspot mapping) and testing alternative spatial models (such as Spatial Lag or Spatial Error) to capture spatial effects that may not be captured by conventional models.

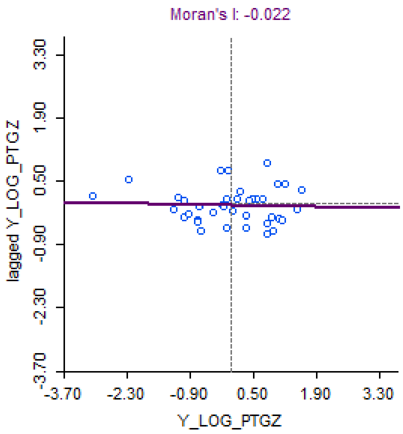


Figure 1. Moran Scatterplot

Source: data processed by Geoda

Moran's I = −0.022 indicates a slight negative spatial autocorrelation or tendency towards dispersion meaning that provinces with high values tend to be located near provinces with low values, and vice versa. However, because the value is so close to zero, the majority of province pairs do not show any particular spatial pattern. In the scatterplot, the distribution of points is almost randomly distributed around the zero line with no clear diagonal clustering pattern such as high–high (upper right quadrant) or low–low (lower left). This reinforces the interpretation of the very small Moran's I value, which implies no or very small spatial effects in the distribution of the data. In summary: There is no significant spatial clustering pattern among provinces the marginal negative value only indicates a slight tendency towards dispersion. This means that your model does not need to be modified to a spatial model based solely on these data, especially if the p-value significance test does not show significant autocorrelation. If you want to be more certain, you can perform a local analysis such as Local Moran's I.

Figure 2. Local Moran's I

Source: data processed by Geoda

There is one province in red (High–High), which indicates that the province has a high Y_LOG_PTGZ value (absorption of Generation Z in the agricultural sector) and is surrounded by neighboring provinces with similar values. This means that there is a local positive cluster, where spatially it is an attractive center or 'hotspot' in terms of absorbing young generation labor perhaps in agricultural centers such as Central Java or East Java. Three provinces in blue show the Low–Low cluster, which has a low value and is surrounded by provinces with similar values. This indicates an area that is less than optimal in absorbing Generation Z labor in the agricultural sector. Most provinces are gray ("Not Significant"), indicating that there is no clear spatial pattern, either positive or negative clustering. The data shows variations that tend to be random without prominent local patterns in the spatial context.

Tabel 5. Spatial Diagnostics

TEST	MI/DF	VALUE	PROB
Moran's I (error)	0.1066	1.8687	0.06166
Lagrange Multiplier (lag)	1	0.0619	0.80344
Robust LM (lag)	1	2.1332	0.14414
Lagrange Multiplier (error)	1	1.0531	0.30478
Robust LM (error)	1	3.1244	0.07713
Lagrange Multiplier (SARMA)	2	3.1864	0.20328

Source: data processed by Geoda

Moran's I (error) shows a value of MI/DF = 0.1066, statistic ≈ 1.8687, and p = 0.0617. This indicates a weak positive spatial autocorrelation a tendency for residual clustering, although not significantly strong at the 5% level, it can be considered marginal at the 10% level. Lagrange Multiplier (LM lag) test: statistic = 0.0619 (df = 1), p = 0.80344 very insignificant, indicating no spatial lag effect (spillover on the dependent variable). Robust LM (lag): statistic = 2.1332, p = 0.14414 also not significant, reinforcing that the spatial lag model is not needed. LM error: statistic = 1.0531, p = 0.30478 and Robust LM error: statistic = 3.1244, p = 0.07713 both values indicate that there is an indication of spatial error (spatial in the residual), but not strong enough at the 5% level, although Robust LM error approaches significance at the 10% level. This suggests the possibility of hidden spatial effects. The SARMA test (combined lag + error) is not significant (statistic = 3.1864, p = 0.20328), so a comp lex spatial model (lag + error) is not needed. Overall, the spatial test shows that labor absorption in the agricultural sector between provinces has little spatial autocorrelation in the residuals, but it is not statistically strong. The LM test confirms that the spatial lag model is not necessary, and the spatial error model is only marginal, with no strong indication for the complex SARMA model. Thus, OLS is still suitable for use, even though there is a slight indication of spatial heterogeneity in the error.

Determining Factors for Absorption of Generation Z Workforce in the Agricultural Sector in Indonesia in 2024

The OLS model is still viable, but indications of spatial error encourage consideration of using the Spatial Error Model (SEM), especially if one wants to improve estimation efficiency and account for variables that may be spatially hidden. In other words, even though the basic OLS assumptions are still met, the presence of spatial error indications provides a strong reason to proceed to the SEM model to strengthen the validity of the analysis results and policy inferences.

6. Spatial Error Model (SEM)

Variable	Coefficient	Std. Error	z-value	Probability
CONSTANT	18.883	4.68113	4.03385	0.00005
X1_AC	-0.00144023	0.00751014	-0.191771	0.84792
X2_PBSP	-0.285261	0.0904199	-3.15485	0.00161
X3_PDDK	-0.28297	0.0616932	-4.58673	0.00000
X4_LO_RRPB	-2.01555	0.725812	-2.77696	0.00549
X5_BM	0.307332	0.212769	1.44444	0.14862
X6-LOG_LP	0.272319	0.057131	4.76657	0.00000
X7_PNG	0.0554359	0.0570041	0.972489	0.33081
LAMBDA	0.231159	0.219007	1.05549	0.29120

R-squared : 0.773575

Source: data processed by Geoda

Based on the results of the Spatial Error Model (SEM) analysis for provincial data, several important findings were obtained in a summary: The model shows an R-squared value of 0.7736, slightly higher than OLS, indicating an increase in variance explanation when the spatial effect on the residuals is included. The Lambda coefficient = 0.231 (p = 0.291) indicates the presence of positive spatial autocorrelation, although not significant (p > 0.05), which means there is still an indication of spatial influence in the error component. Most variables still show similar relationships: X2_PBSP (-0.285, p = 0.0016), X3_PDDK (-0.283, p < 0.001), X4_LO_RRPB (-2.016, p = 0.0055) are significantly negative, while X6-LOG_LP (0.272, p < 0.001) is significantly positive; other variables are not significant.

The SEM model shows that the significant variables influencing the absorption of Generation Z labor in the agricultural sector (Y) are the production facility assistance program (X2), education (X3), income (X4), and harvest area (X6), while credit access (X1), micro assistance (X5), and unemployment (X7) are not significant. The coefficient of the production assistance program (X2) is negative and significant, reinforcing the findings of the ENABLE-TAAT research in Africa, which states that training and agribusiness inputs increase the income of young farmers by 30–50% (Kosec et al., 2018). Empirical studies show that higher education can reduce the interest of the younger generation in entering the agricultural sector. For example, the study by (Girdziute et al., 2019) in Uganda found that educated young people are more likely to choose "white-collar" or non-agricultural jobs because agriculture is considered less prestigious, carries high risks, and offers relatively low income. With higher education, Gen Z becomes more critical of agricultural working conditions, which are often labor-intensive and less modern, leading them to shift to the service, technology, or industrial sectors. The income variable (X4) shows that the higher the average per capita income in a province, the lower the absorption rate of Generation Z in the agricultural sector. This phenomenon can be explained through the "relative income dilemma": because the non-agricultural sector, such as industry and services, offers higher income and long-term career prospects, the younger generation migrates to these sectors, resulting in a decrease in participation in the agricultural field. Research by (Rashidin et al., 2020) in Pakistan noted that the increase in non-agricultural income significantly reduced income and involvement in farming, as the younger workforce preferred sectors that offered better compensation. Additionally, (Ridha et al., 2017) found that agribusiness is often viewed as a low-income job and dependent on external factors such as weather, causing a s hift in interest among Generation Z.

Research by Bachtiar et al., (2023), by analyzing Sakernas 2020 data from 34 provinces, shows that income in the agricultural sector significantly affects the absorption of Generation Z labor. When income increases but the exchange rate does not compensate, the number of workers actually decreases. This is closely related to Generation Z's perception of agricultural work, which is considered less financially promising and unstable in terms of income, leading to a drastic decline in their interest. the higher the income received by workers in the agricultural sector, the greater their tendency to move to the service sector, which in turn reduces the absorption capacity of the agricultural sector for young labor. This is explained by the logistic regression model which shows that income not only contributes to the decision to leave agriculture but also becomes one of the main driving factors for migration to sectors considered more stable and economically secure. In other words, increased income, if not supported by factors such as land ownership, access to capital, technical training, and long-term career guarantees, will prompt Gen Z to shift to the service sector, which offers more attractive non-monetary incentives, including flexibility, social status, and career prospects. Therefore, even though income in the agricultural sector has increased nominally, without structural improvements and enhanced non-financial incentives, this sector will actually experience a reduction in the absorption of young labor, particularly Generation Z, because they tend to choose other sectors that offer relatively more competitive compensation in terms of welfare and life assurance (Yusvianto, 2018).

A larger harvest area in the agricultural sector is an important indicator related to the increased absorption of labor, including from the Gen Z demographic. Research conducted by Andriyani & Aznuriliana, (2022) found that a larger land area increases job opportunities in this sector because the scale of farming becomes broader and more complex, requiring more labor, from land preparation to harvesting. This is reinforced by agricultural economic theory, which states that large-scale land production drives the need for a greater workforce, including daily laborers and youth as part of the absorption strategy. Research by Maswadi, (2017) in the city of Pontianak shows that the area harvested particularly for vegetable and horticultural commodities correlates positively with the number of workers employed. Generation Z, who often take advantage of part-time work opportunities during the harvest season, will be attracted to large-scale farming because it offers practical opportunities to gain experience and income even without owning land. Therefore, the increase in harvest area essentially expands the capacity to absorb labor, including from the youth, by increasing the demand for field operators, harvesters, and logistics throughout the production cycle.

Although access to agricultural credit is believed to facilitate capital and increase productivity, various empirical studies have found that this variable does not have a significant impact on the absorption of Generation Z labor, and in some contexts, it is negative. According to Rozci et al., (2023) in their study, the limitations of Information and Communication Technology (ICT) among farmers result in very low access to information about government credit programs. The lack of procedural understanding and fear of formal schemes cause farmers to prefer informal access—which is often non-transparent and does not support business expansion resulting in no absorption of new labor, including from the younger generation. Although it is expected to increase business capital and productivity, access to agricultural credit does not always contribute positively to the absorption of Generation Z's workforce, and under certain conditions, it even has a negative effect. This is explained by a case study on coffee farmer credit conducted by Sartika & Karyani, (2018) in West Java, which found that although 92% of coffee farmers needed additional capital, only 41.9% accessed bank credit, the rest opted for non-formal credit, and nearly 3.2% did not access credit at all. These findings indicate that formal access to credit often does not reach young farmers, either due to strict collateral requirements, high interest rates, or lack of information, causing Gen Z to fail to utilize credit for agricultural expansion. Furthermore, the study shows that the selective attitude towards credit approaches where young farmers prefer using their own or non-formal capital results in small-scale businesses that do not require additional labor. On the other hand, an article from Republika (2023) presents evidence that although KUR (Kredit Usaha Rakyat) can increase the average income of farmers, it does not significantly affect profits or the ability of agricultural businesses to absorb more labor, because the increase in capital is more directed towards improving production facilities, not increasing the volume of labor. Thus, limited access to credit, which tends to be consumptive or aimed at increasing capital efficiency without expanding production scale does not support job creation, and in many cases, triggers micro-scale agricultural practices that are unattractive to Generation Z. Therefore, the variable of credit access shows an insignificant, even negative, relationship with the absorption of young labor in the agricultural sector if it is not accompanied by guarantees of productive capital and incentive support for business expansion that absorbs labor.

Although agricultural microfinance is often seen as a solution to increase the working capital of small-scale farmers, several empirical studies actually show that this variable does not have a significant impact, and in some cases, it has a negative effect on the absorption of Generation Z's labor. A study by Makabori & Tapi, (2019) on students at Polbangtan Manokwari shows that the perception and motivation of young people towards the agricultural sector are not sufficiently driven by financial assistance alone internal factors (motivation, knowledge, personality) and external factors (socio-economic status, family support) remain inadequate even with the opportunity to obtain microfinance. indicating that the younger generation perceives the agricultural sector as having a "non-prestigious" social image and uncertain income. In such conditions, micro-capital assistance is often channeled for short-term needs (such as the purchase of inputs or simple tools), rather than for expansion or scales that require additional labor, making its role insignificant in creating new jobs. Furthermore, micro capital variables tend not to influence Gen Z's decision to be active in the field, because what is needed is not just access to capital, but also structural support such as land ownership, social security, technical training, and the improvement of professional image. Thus, micro assistance that is only partially financial does not encourage the absorption of young labor and can even reinforce micro-scale practices that are unattractive to Gen Z, if not accompanied by a comprehensive policy approach that adjusts their perceptions, social networks, and professional needs.

Although theoretically, unemployment in the agricultural sector namely the availability of unemployed labor that could be absorbed should encourage the entry of Generation Z into this sector, empirical research actually shows that this variable does not have a significant impact, and in some cases, it has the potential to create negative effects on the absorption of young labor. According to Hardai Hasibuan et al., (2019), who studied the North Sumatra region, the variable of agricultural unemployment does not have a significant effect on the absorption of labor in this sector. The OLS results show that although there is unemployed labor, this does not automatically mean there is a reabsorption by agricultural activities. The statistical model shows that the variable of agricultural unemployment is not included as a key determinant for regeneration in the agricultural sector. This may be due to the local workforce especially the youth avoiding the agricultural sector not because there are no jobs, but because of structural factors such as lack of access to capital, unavailability of owned land, low wages, and the social perception that agricultural work is less prestigious. Additionally, unemployment in the agricultural sector is often seasonal, while Generation Z seeks stability in full-time jobs with consistent income. Therefore, even though the unemployment rate in the agricultural sector is high, Generation Z chooses to seek opportunities in the service and industrial sectors. Thus, the statistically available agricultural unemployment variable does not significantly impact their absorption, and under certain conditions, it can show a negative trend because if high unemployment indicators are accompanied by low wages and job quality, this will further strengthen the negative perception that hinders Gen Z's involvement.

The coefficient of determination (R-squared) value of 0.773575 indicates that approximately 77.36% of the variation or change in labor absorption in the agricultural sector among Generation Z in Indonesia can be explained by the seven independent variables used in the model, namely: production facility assistance programs, education level, income, harvest area, agricultural credit access, micro assistance, and unemployment rate. Thus, this regression model can be categorized as having strong explanatory power, as more than three-quarters of the variation in the dependent variable can be explained by the observed variables. This indicates that these variables collectively play an important role in influencing the extent to which Generation Z is absorbed into the agricultural sector. For example, an increase in harvested area and the availability of agricultural production facilities tends to increase the demand for labor, thereby positively impacting absorption. On the other hand, factors such as education and income can have a negative influence because highly educated or income-stable Gen Z individuals tend to avoid the agricultural sector, which is considered less prospective. Nevertheless, there is still about 22.64% of variation that cannot be explained by this model, likely stemming from other factors outside the model such as social perceptions of agriculture, cultural values, access to digital technology, family experience in agriculture, and the dynamics of the non-agricultural sector that compete with the agricultural sector. Therefore, although this high R-squared value indicates that the model is quite strong, further research is still needed to capture other factors that are more qualitative or contextual that may influence Generation Z's work decisions in the agricultural field.

CONCLUSION

The Spatial Error Model (SEM) explains that approximately 77% of the variation in Generation Z's absorption in the agricultural sector can be understood through a combination of variables such as production aid programs, education, income, and harvest area. The results show that production aid programs, education, and income have significant and negative impacts meaning that, despite being intended to support agriculture, these factors actually shift Gen Z's interest to other sectors. Conversely, the harvest area has a significant positive effect, indicating that larger agricultural enterprises are more capable of absorbing more young labor. The positive but insignificant spatial residual autocorrelation indicates the presence of other unmeasured local variables. These findings emphasize that to increase Gen Z's interest in agriculture, policies must focus on enhancing economic incentives and real opportunities such as adequate land access, income guarantees, and agricultural vocational programs that can attract and retain young people in this sector.

REFERENCES

1) Ananda, H., Subhilhar, Harahap, R. H., & Kusmanto, H. (2024). The effect of grain price stability and capital availability on gen-z’s interest in farmer entrepreneurship in Serdang Bedagai Regency. *IOP Conference Series: Earth and Environmental Science*, *1302*(1). https://doi.org/10.1088/1755-1315/1302/1/012139
2) Andriyani, D., & Aznuriliana, A. (2022). Pengaruh Ump Dan Luas Lahan Terhadap Penyerapan Tenaga Kerja Sektor Pertanian Di Provinsi Indonesia. *Jurnal Ekonomi Pertanian Unimal*, *5*(2), 53. https://doi.org/10.29103/jepu.v5i2.8824
3) Anselin, L. (2005). Spatial regression analysis in R: a workbook. *Urbana*, *51*, 61801.
4) Awaludin, M., Maryam, S., & Fadliyanti, L. (2024). Analysis of the Determining Factors of Generation Z’s Interest in Working in the Agricultural Sector In Bima Regency. *Journal of Economics, Finance And Management Studies*, *07*(06), 3043–3054. https://doi.org/10.47191/jefms/v7-i6-01
5) Bachtiar, B. A., Haq, F. S., Janah, M., Amalia, N. R., Novaldi, J., & Budiasih, B. (2023). Penyerapan Tenaga Kerja Sektor

Pertanian Tanaman Pangan pada Generasi Z. *Seminar Nasional Official Statistics*, *2023*(1), 491–502. https://doi.org/10.34123/semnasoffstat.v2023i1.1706

6) Boye, M., Ghafoor, A., Wudil, A. H., Usman, M., Prus, P., Fehér, A., & Sass, R. (2024). Youth Engagement in Agribusiness: Perception, Constraints, and Skill Training Interventions in Africa: A Systematic Review. *Sustainability (Switzerland)*,*16*(3). https://doi.org/10.3390/su16031096
7) Despotovic, A., Joksimovic, M., & Jovanovic, M. (2015). Impact of demographic changes on agricultural development in Montenegro. *Ekonomika Poljoprivrede*, *62*(3), 613–625. https://doi.org/10.5937/ekopolj1503613
8) Girdziute, L., Besuspariene, E., Nausediene, A., Novikova, A., Leppala, J., & Jakob, M. (2019). *Youth ' s (Un) willingness to work in agriculture sector*. *1*.
9) Godoy, D., Dewbre, J., PIN, Amegnaglo, C. J., Soglo, Y. Y., Akpa, A. F., Bickel, M., Sanyang, S., Ly, S., Kuiseu, J., Ama, S., Gautier, B. P., Officer, E. S., Officer, E. S., Eberlin, R., Officer, P., Branch, P. A., Oduro-ofori, E., Aboagye Anokye, P., … Swanson, B. E. (2014). The future of food and agriculture: trends and challenges. In *The future of food and agriculture: trends and challenges* (Vol. 4, Issue 4). www.fao.org/publications%0Ahttp://www.fao.org/3/a-i6583e.pdf%0Ahttp://siteresources.worldbank.org/INTARD/825826-1111044795683/20424536/Ag_ed_Africa.pdf%0Awww.fao.org/cfs%0Ahttp://www.jstor.org/stable/4356839%0Ahttps://ediss.uni-goettingen.de/bitstream/han
10) Hardai Hasibuan, A. P., Ginting, R., & Effendi, I. (2019). Faktor-Faktor yang Mempengaruhi Penyerapan Tenaga Kerja Pada Sektor Pertanian di Sumatera Utara. *AGRISAINS: Jurnal Ilmiah Magister Agribisnis*, *1*(1), 10–17. https://doi.org/10.31289/agrisains.v1i1.212
11) Haryati, N., Lasitya, D. S., Nurirrozak, M. Z., Herdianti, D. F., Fibrianingtyas, A., & Hidayat, A. R. T. (2024). Demographics and course choices: impact on youth farming intention in Indonesia. *International Journal of Adolescence and Youth*,*29*(1). https://doi.org/10.1080/02673843.2024.2358088
12) Ji, Y., Hu, X., Zhu, J., & Zhong, F. (2017). Demographic change and its impact on farmers' field production decisions.*China Economic Review*, *43*, 64–71. https://doi.org/10.1016/j.chieco.2017.01.006
13) Makabori, Y. Y., & Tapi, T. (2019). Generasi Muda dan Pekerjaan di Sektor Pertanian: Faktor Persepsi dan Minat (Studi Kasus Mahasiswa Politeknik Pembangunan Pertanian Manokwari). *Jurnal Triton*, *10*(2), 1–20.
14) Maswadi. (2017). Analisis Hubungan Antara Luas Panen Produksi Tenaga Kerja Pertanian Terhadap PDRB di Kota Pontianak. *Jurnal Social Economic of Agriculture*, *6*(2), 9–15. https://jurnal.untan.ac.id
15) Nisa Suriani, Yoanna Pusvita Sari, Fitri Handayani, & Helmi Noviar. (2023). The Younger Generation and the Future of Agriculture. *Jurnal Triton*, *14*(2), 384–392. https://doi.org/10.47687/jt.v14i2.468
16) Odhiambo, B. O., Gathungu, E., & Opondo, F. (2023). Determinants of Credit Access and Amount of Credit by Youth in Rachuonyo North Sub-County. *OALib*, *10*(07), 1–15. https://doi.org/10.4236/oalib.1110323
17) Osabohien, R., Wiredu, A. N., Nguezet, P. M. D., Mignouna, D. B., Abdoulaye, T., Manyong, V., Bamba, Z., & Awotide, B.(2021). Youth participation in agriculture and poverty reduction in Nigeria. *Sustainability (Switzerland)*, *13*(14), 1–19. https://doi.org/10.3390/su13147795
18) Rashidin, S., Javed, S., & Liu, B. (2020). Ramifications of households non-farm income on agricultural productivity: Evidence from rural area of Pakistan. *Journal of Tekirdag Agricultural Faculty*, *17*(2), 108–123. https://doi.org/10.33462/jotaf.518975
19) Ridha, R. N., Burhanuddin, B., & Wahyu, B. P. (2017). Entrepreneurship intention in agricultural sector of young generation in Indonesia. *Asia Pacific Journal of Innovation and Entrepreneurship*, *11*(1), 76–89. https://doi.org/10.1108/apjie-04-2017-022
20) Rozci, F., Dona Wahyuning Laily, dan, Studi Agribisnis, P., Pertanian, F., Pembangunan Nasional, U., & Timur, J. (2023). Pengaruh Kredit Pertanian Terhadap Kesejahteraan Petani di Indonesia The Effect of Agricultural Credit on Farmers Welfare in Indonesia. *Jurnal Ilmiah Manajemen Agribisnis*, *11*(2), 92–102.
21) Sartika, S. R., & Karyani, T. (2018). Studi Kasus: Aksesbilitas Petani Kopi terhadap Kredit dari Lembaga Keuangan Bank.*Jurnal Agro Industri Perkebunan*, *6*(2), 87. https://doi.org/10.25181/jaip.v6i2.954
22) Susilowati, S. H. (2016). Fenomena Penuaan Petani dan Berkurangnya Tenaga Kerja Muda serta Implikasinya bagi Kebijakan Pembangunan Pertanian. *Forum Penelitian Agro Ekonomi*, *34*(1), 35. https://doi.org/10.21082/fae.v34n1.2016.35-55
23) Todaro, M. P., & Smith, S. C. (2012). *Economic Development Twelfth Edition (12th ed.) Pearson*.
24) Yusvianto, A. Y. (2018). *PERPINDAHAN TENAGA KERJA DARI SEKTOR PERTANIAN (SEKTOR PRIMER) KE SEKTOR JASA (SEKTOR TERSIER) (Studi Kasus di Kota Batu) Disusun oleh :*