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Analysis of Agricultural Land Area Decrease on Income Inequality in East Java, Indonesia

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Abstract. Income inequality remains a significant issue in developing nations, including East Java, which was ranked fifth among regions in Indonesia for having the highest level of inequality in 2023. This inequality is often associated with structural changes, especially the decrease of agricultural land to accommodate industrial development. This study aims to determine the most suitable spatial model, analyze the relationship between agricultural land reduction and income inequality in East Java, and explore the effects of other factors such as Agricultural Sector GDP, HDI, labor force, and real per capita expenditure on income inequality. The research uses secondary data, including panel data from 38 regencies/cities in East Java from 2009 to 2018. The results indicate spatial dependency among the independent variables, making the Spatial Autoregressive Model (SAR) the most appropriate method for analysis. These findings suggest that a significant decrease in agricultural land area tends to exacerbate income inequality even further. Therefore, this study has important policy implications, including the need for the government to uphold laws related to the protection of sustainable agricultural land and to provide skills training that is relevant to the needs of modern sectors. The results also show that an increase in the agricultural sector's GDP and labor force can boost productivity, output, and income, thereby potentially reducing income inequality. Whereas a rise in HDI and per capita expenditure tends to increase income inequality due to unequal access to development benefits and the consumption patterns of high-income groups, which further widen the gap.

Keywords: economic growth; gini index; HDI; spatial panel data; structural transformation

INTRODUCTION

Income inequality is a significant challenge encountered by developing countries, including Indonesia (Bantika *et al*., 2015). According to an Oxfam Report (2023), the wealthiest 1% of the global population controlled two-thirds of the total wealth generated between 2020 and 2022, amounting to US$42 trillion. In Indonesia, 56.4% of the country's wealth is owned by only 5% of its population, while the remaining 95% control less than half of the nation's wealth (Credit Suisse, 2022). Efforts to reduce inequality are a key goal of the Sustainable Development Goals (SDGs). This issue warrants serious attention, as it threatens long-term social and economic development, negatively impacts poverty alleviation efforts, and undermines societal satisfaction and dignity (United Nations, 2023). One significant factor contributing to inequality is the substantial gap in growth between sectors due to the shift in economic activities from agriculture to industry, a phenomenon commonly referred to as structural transformation (Rulita & Sakti, 2023; Divanbeigi *et al*., 2016).

According to Winarni & Hartono (2023), growth in the industrial sector can exacerbate income inequality. This occurs because industrial zones are predominantly located in urban areas, widening the disparity. The growth rate of the industrial sector in Indonesia consistently surpasses that of the agricultural sector. The industrial sector grew by 4.64%, while the agricultural sector expanded by only 1.3% in 2023 (BPS, 2024).

In addition to the declining growth rate of the agricultural sector, Setyanti (2021) found that the share of Indonesian labor employed in agriculture had decreased to 29% of total employment, whereas the share in the service sector continued to rise, reaching 48% by 2018. This indicates a shift from

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traditional to modern sectors. Dartanto *et al.* (2017) observed that structural transformation, characterized by the migration of the population from agriculture to industry or services, from rural to urban areas, and from informal to formal employment, has been a significant factor contributing to rising inequality in Indonesia over the past two decades. This transformation has led to the large-scale conversion of agricultural land for industrial activities. The expansion of the industrial sector not only involves converting farmland for industrial use but also drives the development of housing and infrastructure as part of urban expansion. East Java is one of the provinces that have consistently experienced a decline in agricultural land area, accompanied by an increase in industrial zones. Mulyani *et al.*, (2016), using spatial analysis of satellite imagery, revealed that East Java's paddy fields were converted at a rate of 979 hectares per year from 2000 to 2014. The variable of the decrease in agricultural land becomes the primary variable of focus because East Java is a region that relies on agriculture, where a significant portion of its population depends on the agricultural sector for their livelihoods. The reduction in agricultural land directly impacts the income of rural communities that depend on farming activities. As the land area shrinks, the space for farming becomes more limited, leading to a decrease in agricultural yields and farmers' income. As a result, the income gap between agricultural workers in rural areas and those employed in non-agricultural sectors widens.

When viewed based on the growth rate of East Java's GRDP, the agricultural sector tends to always be below the industrial sector and growth in these two sectors has a fairly high gap. In 2023, the agricultural sector experienced growth of just 2.25%, whereas the industrial sector achieved 4.08%. Over the period from 2014 to 2023, the agricultural sector's average growth rate was modest at 1.69%, significantly lower than the industrial sector's average of 4.95% (BPS, 2024). Economic transformation is often linked to a reduction in the agricultural sector's GRDP. However, this should be accompanied by a proportionate or even faster decline in labor absorption within the agricultural sector. Unbalanced structural changes can cause an accumulation of labor in the agricultural sector (Yuniati *et al.*, 2022). In East Java, the growth of the industrial sector has not been matched by proportional labor absorption. According to data from East Java Bappeda (2022), 31.31% of the workforce remains employed in the agricultural sector, whereas only 14.90% is engaged in the industrial sector. According to Manning (1995), a faster economic shift compared to a shift in the workforce, or in other words an economic turning point that occurs earlier than the labor, turning point can lead to inequality.

The state of inequality in East Java is similar to the national condition, where income inequality remains relatively high. Based on the Gini index, East Java ranked fifth among provinces with the highest inequality, recording a Gini coefficient of 0.39 in March 2023 (BPS, 2024). In addition to the factors previously mentioned, income inequality can also be attributed to several other factors, including per capita GRDP, Human Development Index (HDI), labor force, and population size (Andina *et al.*, 2021; Aprilianti & Harkeni, 2021; Ariasta & Setiawati, 2024; Matondang, 2018).

Based on the issues outlined earlier, this study aims to analyze the impact of the decrease in agricultural land area on income inequality in East Java. While previous studies have extensively examined income inequality, none have used the reduction in agricultural land as a research variable. Additionally, this study aims to examine the impact of other factors as control variables, including agricultural sector GRDP, HDI, labor force, and per capita expenditure, on income inequality in East Java. This research employs spatial analysis, as spatial interdependence is suspected among adjacent regencies/cities. Consequently, another goal of this study is to determine the most suitable

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spatial model for analyzing the factors influencing income inequality in East Java.

METHODS

This study deliberately selected East Java, considering its position as the fifth-ranked province in Indonesia with the highest income inequality, as reflected by a Gini index of 0.39 in March 2023 (BPS, 2024). Furthermore, given that this research examines the impact of declining agricultural land on income inequality, the agricultural land in East Java has been observed to decrease by 6.15% in 2017 compared to 2012 (Ministry of Agriculture, 2020).The study uses secondary data collected through a literature review drawing on various sources.

This study utilizes panel data comprising cross-sectional data from 38 regencies and cities in East Java Province, combined with time series data spanning the period from 2009 to 2018. In total, 380 observation units are analyzed. The data analysis method employed to address the research objectives is spatial panel data analysis. This analysis is used because it is suspected that there is a spatial influence in determining income inequality in a region. Panel data analysis can be performed using three methods: Pooled Least Squares (PLS), Fixed Effects Model (FEM), and Random Effects Model (REM). The Chow test and the Hausman test select the appropriate model (Desrindra *et al.*, 2016). The Chow determines the more suitable model between PLS and FEM. If FEM is deemed more appropriate, the Hausman test is conducted to identify the optimal model between FEM and REM (Winarno, 2017).

Once the appropriate approach has been determined, a classical assumption test is required for regression analysis. A multicollinearity test is performed to evaluate whether there is a strong correlation among the independent variables, while a heteroscedasticity test examines whether there are inconsistencies in the variance of residuals (Ningrum *et al.*, 2020). Based on these tests, before conducting spatial panel data analysis, a spatial weight matrix (W) must be constructed to represent the relationships between regions based on distance or neighborhood information. Typically, the diagonal elements of the matrix are assigned a value of zero (Dubin, 2012). In this study, a queen contiguity matrix is used to identify spatial dependence between neighboring regions. Queen contiguity matrix refers to a spatial weighting method where neighboring regions are determined based on shared edges or corner points. Any region that touches the area of interest, either along a side or at a vertex, is given a weight of 1, while regions without such contact are assigned a weight of 0.

Although spatial models have been extensively developed, their application has primarily focused on cross-sectional data, with limited use in panel data analysis (Marsono, 2022). The Spatial Autoregressive Model (SAR) includes a spatial lag, where the dependent variable is affected by both the dependent variable in adjacent regions and the local characteristics of the observations. Conversely, the Spatial Error Model (SEM) accounts for the dependent variable's reliance on local characteristics and the spatially correlated error terms across regions (Elhorst, 2010). In this study, the SAR model was selected. This model is appropriate because it reflects that the value of the dependent variable in a given region is influenced by the value of the dependent variable in neighboring regions. In this case, income inequality in one region is affected by income inequality in adjacent regions. The following are the spatial model equations used in the study (Rahmawati & Bimanto, 2021):

SAR: $y_{it} = \delta W y_{jt} + \beta_0 + \beta_1 X_{1it} + \beta_2 X_{2it} + \beta_3 X_{3it} + \beta_4 X_{4it} + \beta_5 X_{5it} + u_i + \varepsilon_i$……………………………………………(1)

SEM: $y_{it} = \beta_0 + \beta_1 X_{1it} + \beta_2 X_{2it} + \beta_3 X_{3it} + \beta_4 X_{4it} + \beta_5 X_{5it} + u_i + \phi_{it}$; $\phi_{it} = \rho W \phi_{jt} + \varepsilon_{it}$…………………………………...……….(2)

Description:

i = cross-sectional unit (spatial unit); i= 1, ..,N

t = time (years); t = 1, ..., T

yit = vector of observations of dependent

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variables of size (NT, 1)
xit = vector of observations of independent variables of size (NT, K+1)
β = vector of unknowns of size (K+1, 1)
εit = vector of normal distribution errors
ui = specific spatial effects
W = spatial weight matrix of size (N, N)
δ = spatial autoregressive coefficient
ϕ = spatial error coefficient
ρ = parameter indicating the strength and direction of spatial dependence

Finally, the optimal model is selected based on the values of R^2, AIC, BIC, and log-likelihood. A higher R^2 and log-likelihood indicate a better model, while lower AIC and BIC values signify a better model.

RESULTS AND DISCUSSION

Classical Assumption Test of Panel Data

The classical assumption tests commonly used in panel spatial data analysis are the multicollinearity test and the heteroscedasticity test. A good model does not exhibit multicollinearity and heteroscedasticity.

Multicollinearity Test

The multicollinearity test is assessed using the Variance Inflation Factor (VIF). The VIF (Variance Inflation Factor) values for each predictor variable as presented in Table 1.

Table 1. Multicollinearity Test

Variable	VIF
X_1 (reduction in agricultural land)	1.01
X_2 (GRDP of the agriculture sector)	1.07
X_3 (HDI)	1.16
X_4 (labor force)	1.14
X_5 (population)	1.08
Mean VIF	1.09

According to Table 1 above, the average VIF value is 1.09, and the VIF values for each variable are all below 10. Therefore, it can be concluded that the model is free from multicollinearity.

Heteroscedasticity Test

The heteroscedasticity test was carried out using the Koenker-Basset test. The results are presented in Table 2, specifically in the prediction_square value, where the obtained p-value is 0.227. This value is more than α (0.05), therefore, it can be concluded that the model in this study is not affected by heteroscedasticity.

Table 2. Heteroscedasticity Test

Variable	Coefficient	Std. error	P>t
yprediction_square	0.006468	0.0053508	0.227
_cons	0.0054955	0.0073302	0.454

Determination of the Best Spatial Panel Data Model

Chow Test

The Chow test is conducted to assess the difference between the PLS model and the FEM. The hypotheses for the Chow test are stated as follows, H_0: The PLS model is chosen; H_1: The FEM model is selected. The test result indicates a chi^2 value of 215.23 and the p-value of 0.000, suggesting that the FEM model is more favorable compared to the PLS model.

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Hausman Test

After selecting the FEM model using the Chow test, the Hausman test is carried out to compare the REM model with the FEM. The hypotheses for the Hausman test are as follows: H_0: The REM model is selected; H_1: The FEM model is selected. The test yields a chi^2 value of 56.25 and a p-value of 0.000, suggesting that the FEM model outperforms the REM model. Based on the outcomes of both tests, the final model selected is the FEM.

Spatial Dependency Detection

Before conducting a spatial dependency test, a spatial weighting matrix must first be formed. In this study, the queen contiguity matrix (a matrix approach that identifies spatial dependencies through corner-side intersections) is used to identify spatial dependencies in adjacent areas. If the spatial weighting matrix has been formed, then spatial dependency detection is carried out using the Pesaran test. The P-value of the Pesaran Test is 0.000. Based on this value, $Pr < \alpha$ (0.05), then it can be concluded that there is spatial dependency in the model. If spatial dependency has been established, spatial analysis can be conducted.

Spatial Analysis of Panel Data

The estimation of panel data regression models in this study compares the Spatial Autoregressive Model (SAR) and Spatial Error Model (SEM) with the Fixed Effect Model. All parameters in the regression model can be estimated, and their values obtained. However, to determine the actual significance of the spatial dependency on lag or error, you can use the Z-test statistic to assess the influence of variables in the model partially. The following is a summary of the test results with the Z test statistic:

Table 3. Factors Influencing Income Inequality (SAR and SEM)

Model	Variable	Coefficient	P-value
SAR	X_1 (reduction in agricultural land)	0.00000273	0.027**
	X_2 (GRDP of the agriculture sector)	-0.0089134	0.008***
	X_3 (HDI)	0.0243448	0.000***
	X_4 (labor force)	-0.0486764	0.089*
	X_5 (population)	0.0551687	0.000***
SEM	X_1 (reduction in agricultural land)	0.000	0.024**
	X_2 (GRDP of the agriculture sector)	-0.019	0.021**
	X_3 (HDI)	0.631	0.000***
	X_4 (labor force)	-0.007	0.138
	X_5 (population)	-0.007	0.000***

Notes: ***: significant effect at 1% α; **: significant effect at 5% α; *: significant effect at 10% α.

Based on Table 3 above, all independent variables in the SAR model significantly affect income inequality, with varying levels of significance. In the SEM model, the variables that significantly affect income inequality include X_1 (reduction in land area), X_2 (GRDP of the agricultural sector), X_3 (Human Development Index), and X_5 (per capita expenditure).

Selection of the Best Spatial Analysis Model

According to the parameter estimation results for the spatial panel data model, each dataset has two spatial panel models, SAR and SEM. The best model between the two can be selected by examining test statistics such as Akaike's Information Criterion (AIC), Bayesian Information Criterion (BIC), log-

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likelihood, and R-squared.A good model is characterized by the lowest AIC and BIC values, and the highest R^2 values.

As shown in Table 4, the SAR model has higher AIC and BIC values compared to the SEM model. Additionally, the log-likelihood and R^2 values for the SAR model are greater than those for the SEM model. Based on these four statistical measures, it can be concluded that the SAR model is the most suitable for this study.

Table 4. Best Model Selection

Test Statistics	SAR	SEM	Conclusion
AIC	-724.4128	-716.3761	SAR is the best model
BIC	-696.8316	-688.7949	SAR is the best model
Log-likelihood	369.2064	365.1880	SAR is the best model
R^2	0.4187	0.4132	SAR is the best model

Spatial Autoregressive Model (SAR)

Based on previous testing and estimation, it can be concluded that the Spatial Autoregressive Model (SAR) is the most optimal estimation model. Mathematically, the SAR-FE model can be written as follows:

$$y_{it} = 0.2143Wy + 0.00000273X_{1it} - 0.0089134X_{2it} + 0.0243448X_{3it} - 0.0486764X_{4it} - 0.0551687X_{5it} + u_i + \phi_{it} \quad (3)$$

Based on Table 5, all independent variables significantly influence income inequality (Y) at various levels of significance. At the 1% significance level, the variables that have a significant effect are GDP in the agricultural sector (X_2), HDI (X_3), and per capita expenditure (X_5). At the 5% significance level, the significant variable is land area reduction (X_1). Meanwhile, at the 10% significance level, the significant variable is labor force (X_4).

The presence of spatial dependence among neighboring locations indicates that income inequality in one region is influenced by income inequality in other regions. The R^2 value of 0.4187 indicates that 41.87% of the variability in the dependent variable can be accounted for by the variables included in the model, while the remaining 58.13% is attributed to factors outside the model. A Prob chi² value of less than 0.05 signifies a significant spatial effect in the data.

The reduction in agricultural land significantly contributes to rising income inequality in East Java. One factor driving this trend is industrialization, which leads to a decrease in agricultural land. Industrialization has the potential to transform the economic structure and impact household incomes. Ideally, it should provide opportunities for farmers to transition to non-agricultural sectors. However, this shift is often challenging due to the higher skill levels and educational requirements of the industrial sector.

Workers in the agricultural sector typically have lower levels of education and productivity, making it difficult for them to transition to higher-paying jobs in modern sectors. Structural shifts that are not accompanied by labor migration to modern sectors may leave workers in traditional sectors trapped in low-productivity and low-income jobs, thereby exacerbating inequality (Sulistiawati, 2013). Based on this explanation, the reduction in land area caused by structural transformation will further intensify income inequality. The decrease in agricultural land as part of structural transformation is often accompanied by land consolidation by certain parties, such as large companies or wealthy individuals, who use land for industrial or plantation purposes. In contrast, small-scale farmers or farm laborers lose access to land and experience a decline

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in income. Furthermore, a study by Liu *et al.* (2023) highlights the role of land reform in influencing income inequality. Land reform is an important factor in increasing income for middle-income households and helping to reduce income inequality. However, its impact is uneven and is mainly experienced by households with certain types of land, which has the potential to exacerbate inequality.

The GRDP of the agricultural sector has a negative and significant impact on income inequality at a 1 percent error rate. The results of this study are in accordance with Ikhsan *et al.* (2019). As a crucial component of Indonesia's economy, the agricultural sector requires supportive policies to enhance its productivity and generate positive effects on regional economies, thereby aiding in reducing income inequality.

Significant investments in this sector can stimulate economic growth and contribute to national development (Lenggogeni, 2012). According to research by Harahap *et al.* (2022), increasing investment in the agricultural sector can increase production which in turn increases growth in this sector.

Table 5. Factors Affecting Income Inequality (SAR-FE Model)

Variable	Coefficient	Std. Error	P-value
X_1 (reduction in agricultural land)	0.00000273	0.00000123	0.027**
X_2 (GRDP of the agriculture sector)	-0.0089134	0.0033348	0.008***
X_3 (HDI)	0.0243448	0.0003259	0.000***
X_4 (labor force)	-0.0486764	0.0286444	0.089*
X_5 (population)	0.0551687	0.0070751	0.000***
Spatial rho	0.2142936	0.0552034	0.000
R^2		0.4187	
Prob>=chi^2		0.0015	

Notes: ***: significant effect at 1%; **: significant effect at 5%; *: significant effect at 10%

Workers in the agricultural sector typically have lower levels of education and productivity, making it difficult for them to transition to higher-paying jobs in modern sectors. Structural shifts that are not accompanied by labor migration to modern sectors may leave workers in traditional sectors trapped in low-productivity and low-income jobs, thereby exacerbating inequality (Sulistiawati, 2013). Based on this explanation, the reduction in land area caused by structural transformation will further intensify income inequality. The decrease in agricultural land as part of structural transformation is often accompanied by land consolidation by certain parties, such as large companies or wealthy individuals, who use land for industrial or plantation purposes. In contrast, small-scale farmers or farm laborers lose access to land and experience a decline in income. Furthermore, a study by Liu *et al.* (2023) highlights the role of land reform in influencing income inequality. Land reform is an important factor in increasing income for middle-income households and helping to reduce income inequality. However, its impact is uneven and is mainly experienced by households with certain types of land, which has the potential to exacerbate inequality.

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Anandari (2022) similarly emphasized the pivotal role of the agricultural sector in a country's economic development. This sector often serves as a foundation for national economic resilience, particularly during crises and recovery periods. Increasing the sector's contribution can boost its productivity, leading to higher incomes for its workforce. These increased incomes can help narrow the disparities between economic sectors, naturally reducing income inequality (Romli *et al.*, 2016). Supporting this, Tarp *et al.* (2002) demonstrated that expanding the agricultural sector is one of the most effective strategies for bridging the income distribution gap between rural and urban areas.

The HDI variable demonstrates a positive and significant effect on income inequality at a 1 percent error rate, signifying that an increase in the HDI correlates with a rise in income inequality. This outcome aligns with the research conducted by Arif & Wicaksani (2017), which emphasizes that life expectancy, a critical component of the HDI, plays an essential role in enhancing workforce productivity and raising per capita income. However, when these advancements are primarily concentrated in economic centers, particularly industrial regions, they may inadvertently intensify income inequality.

Based on Kuznet's theory, inequality will increase in the early stages of development. The flow of investment and industrialization has driven a shift in employment from the agricultural sector to the industrial sector, resulting in increased inequality (Todaro and Smith, 2020). From the perspective of the HDI, access to education, healthcare, and economic opportunities tends to be limited to a select group, further exacerbating inequality. These findings are consistent with the research by Oktarina & Yuliana (2023), which supports the Kuznets hypothesis in the context of West Sumatra.

The labor force variable exhibits a negative and significant effect on income inequality at a 10 percent error rate, a finding consistent with Astuti & Hukom (2023) research. An increase in the labor force leads to higher production, enhancing productivity and raising income levels. Similarly, Nadhifah & Wibowo (2021) found that labor force growth, supported by adequate employment opportunities, improves worker quality and helps reduce income inequality. To effectively boost community income and lower poverty levels, labor force expansion must be paired with an increase in job opportunities. Without this, economic development could be hindered, worsening poverty and income inequality (Majid, 2021).

Real per capita expenditure significantly and positively affects income inequality at a 1 percent error rate, indicating that higher per capita expenditure contributes to greater income inequality. This result aligns with the research by Amaliyah & Arif (2023), which shows a strong connection between consumption and expenditure. Higher-income individuals tend to have higher consumption levels, while those with lower incomes generally spend less, thereby increasing the income gap. This is supported by Romli *et al.* (2016), who argue that economic growth and rising incomes tend to change consumption patterns, especially regarding agricultural products. This trend is in line with Engel's Law, which states that the income elasticity of demand for agricultural products decreases as income levels increase. As high-income groups shift their consumption towards non-food items, this creates a consumption gap that further deepens the divide between the wealthy and the poor.

CONCLUSION

This study finds that the Spatial Autoregressive Model (SAR) is the most suitable for analyzing income inequality in

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East Java, given the presence of spatial dependence. The main drivers of inequality include the reduction of agricultural land, suboptimal industrialization, and unequal land ownership. The GRDP of the farming sector and the labor force have a significant adverse effect on inequality, while the Human Development Index (HDI) and per capita expenditure tend to increase inequality. This means that the higher the GRDP of the agricultural sector and the labor force, the greater the reduction in income inequality. On the other hand, for HDI and per capita expenditure, the higher their values, the greater the increase in income inequality. Therefore, this study has important policy implications, including the need for the government to uphold laws related to the protection of sustainable agricultural land and to provide skills training that is relevant to the needs of modern sectors, for example, skills such as basic technical training for the manufacturing industry, training in modern agricultural techniques, vocational training in mechanics, and entrepreneurship programs. For farmers who choose to retain their land, the government should enhance access to agricultural technology and supporting infrastructure to improve productivity. Moreover, expanding market access and providing targeted incentives can contribute to a more equitable distribution of income. To reach the turning point of the Kuznets curve (where income inequality initially rises and subsequently declines with further development), key components of human development, such as healthcare, education, and economic opportunities, must be strengthened. In terms of the labor force, the government should promote job creation by investing in labor-intensive industries, thereby enabling broader employment absorption under fair and decent working conditions.

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