Journal of Agricultural Socio-Economics (JASE)
eISSN 2745-6897 | pISSN 2745-6889
Volume 7 Issue 1 (2026) Page 61-76
DOI: http://dx.doi.org/10.33474/jase.v7i1.25132
Submit: 13-03-2026 | Accepted: 23-05-2026 | Publish: 30-06-2026

Spatial Heterogeneity and Determinants of Agricultural GRDP in East Java, Indonesia: A Geographically Weighted Regression Approach

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Abstract. Agriculture plays a strategic role in supporting regional economic growth, employment, and food security in East Java, Indonesia. However, its contribution to Agricultural Gross Regional Domestic Product (GRDP) differs markedly across districts and cities, indicating spatial and structural disparities. These variations suggest that agricultural performance is shaped by localized biophysical and socio-economic factors that global regression models often fail to capture. Previous studies have largely relied on single-commodity analyses or global approaches that assume spatial homogeneity, thereby overlooking spatial non-stationarity in the determinants of agribusiness. This study aims to analyze the spatial heterogeneity of agricultural GRDP determinants and evaluate how localized factors, including productivity, land conversion, labor, food prices, market access, agroindustry value added, and food diversification, differentially impact nine districts and cities in East Java. The novelty lies in integrating multidimensional upstream-to-downstream agribusiness variables within a Geographically Weighted Regression (GWR) framework, moving beyond traditional production-centric models to identify specific regional drivers. Using 2023 secondary data from nine districts/cities, the study employs Ordinary Least Squares (OLS) as a benchmark, followed by GWR with a Gaussian kernel and cross-validation bandwidth. The GWR model outperforms OLS, increasing R^2 from 0.75 to 0.89 and reducing AICc from 134.2 to 112.5, while residual Moran's I declines from 0.32 to –0.05. Agro-industry value added shows the strongest positive effect (0.38 in Banyuwangi), whereas land conversion negatively affects urban areas (–0.41 in Malang City). These findings confirm spatial non-stationarity and support place-based agricultural policy design.

Keywords: Agricultural GRDP; Spatial; Haterogeneity; GWR; Determinants

INTRODUCTION

Agriculture plays a strategic role in supporting regional economic growth, employment, and food security in East Java, Indonesia. However, its contribution to Agricultural Gross Regional Domestic Product (GRDP) differs markedly across districts and cities, indicating spatial and structural disparities (Shi et al., 2025). As one of Indonesia's principal agricultural regions, East Java relies heavily on the sector not only for primary production but also for sustaining rural livelihoods and strengthening regional economic resilience (Purwaningsih & Suseno, 2023; Sinha & Swain, 2022; Sobari & Jaya, 2023). From a socioeconomic perspective, these disparities are critical, as they directly reflect inequalities in farmer welfare and regional income, with lagging areas facing higher poverty risks due to uneven access to agribusiness infrastructure and markets (Sobari & Jaya, 2023). Therefore, understanding the spatial dynamics of agricultural GRDP is essential for designing effective and equitable development strategies at the sub-provincial level (Statistics Indonesia, 2023).

Despite its overall importance, agricultural performance is unevenly distributed across districts and municipalities, where some areas thrive on high productivity while others are constrained by land conversion and weak infrastructure (Pumhirunroj et al., 2026). These variations suggest that agricultural performance is shaped by localized biophysical and socio-economic factors that global regression models often fail to capture. Conventional approaches like Ordinary Least Squares (OLS) are insufficient because they assume spatial homogeneity, providing only a single average estimate that masks local realities (Zhao et al., 2024). By ignoring spatial non-stationarity, global models fail to recognize that a single factor, such as land conversion, can have a devastating impact in highly urbanized hubs while remaining neutral or even positive in more rural agricultural regions. This limitation necessitates a geographically adaptive framework to capture the localized, place-specific interactions among agribusiness determinants that are otherwise hidden within aggregate provincial statistics (Parlato et al., 2025).

The spatial econometrics literature has increasingly emphasized the importance of accounting for spatial dependence and heterogeneity (Perdana et al., 2021). Geographically Weighted Regression (GWR) has been widely adopted to examine spatial variations in agricultural productivity and regional growth, as it is advantageous by allowing coefficients to vary across locations (Feng et al., 2020). However, existing studies often suffer from a narrow scope, predominantly focusing on single commodity analyses or a limited set of production side variables, which fail to reflect the complexity of the modern agribusiness ecosystem(Wicaksono, D., 2023). There is a significant research gap in integrating downstream dimensions, such as agroindustry value added and market access, within a unified spatial framework, especially at the granular district or city level (Abusiri et al., 2024). This study addresses these shortcomings by incorporating multidimensional agribusiness determinants into a GWR model to capture the diverse, place-specific drivers that global or commodity-specific models consistently overlook (Zhao et al., 2024).

Unlike earlier research, this study integrates multidimensional agribusiness variables, comprising upstream (productivity, land conversion, agricultural labor) and downstream (food prices, market access, agroindustry value added, and food diversification) within a Geographically Weighted Regression (GWR) framework (Hanin et al., 2024; Sobari & Jaya, 2023). The primary novelty lies in simultaneously modeling these diverse determinants to capture localized coefficient variations, thereby moving beyond conventional single-commodity or production-only analyses. By analyzing these interactions at the district/city levels, this research provides a deeper understanding of how structural drivers jointly influence agricultural GRDP across East Java's heterogeneous landscape (Hadianto et al., 2022). Accordingly, this study aims to identify the key determinants of agricultural GRDP, analyze the spatial variation of these determinants across districts and cities to reveal region-specific drivers, and formulate targeted place-based policy recommendations to mitigate structural disparities in East Java's agricultural sector.

METHODS

Study Area

This research focuses on nine strategically selected districts and municipalities in East Java Province, Indonesia, namely Malang City, Malang Regency, Batu City, Jember, Banyuwangi, Bojonegoro, Mojokerto, Sampang, and Nganjuk. The selection of these regions was based on a purposive sampling approach to represent a complete spectrum of East Java's agro-economic archetypes, ranging from primary production hubs such as Bojonegoro and Jember to urbanized agricultural centers such as Malang City and Batu City. By including these nine areas, the study captures high-performing districts with substantial GRDP, such as Banyuwangi, alongside regions facing systemic infrastructure and human capital constraints, like Sampang, thereby ensuring sufficient spatial variance to test the GWR model's sensitivity to localized structural disparities. The selection was guided by the region's heterogeneous agricultural characteristics, varying levels of urbanization, and their significant contributions to the province's agroeconomic dynamics (Carlucci et al., 2021; Hadianto et al., 2022).

Figure 1. Research Location

These areas span a spectrum of agroecological zones and socioeconomic contexts, enabling robust spatial analysis of determinants of agricultural Gross Regional Domestic Product (GRDP). By including urban and rural settings, the study captures a comprehensive view of spatial disparities and localized responses to structural changes in the agricultural sector, essential for designing effective, place-based policies (Allard, 2025; Mesang et al., 2025; Pumhirunroj et al., 2026).

Data Source

This study used secondary data from 2023, specifically cross-sectional data from nine districts and cities in East Java. The data on Agricultural GRDP (Y), land use (X_2), agricultural labor force (X_3), and productivity (X_1) were obtained from the East Java Central Statistics Agency (Statistics Indonesia, 2023), measured in billion IDR, percentage of total land, number of persons, and tons per hectare, respectively. Data regarding agro-industry value added (X6), measured in billion IDR, were sourced from the Ministry of Agriculture's 2023 annual reports, while the food price index (X_4) was derived from the 2023 Food Price Monitoring Center records (IDR/kg). Furthermore, the market access index (X_5) and food diversification index (X7) were developed as composite indices (scale 1–5) based on 2023 regional development planning reports and transportation agency datasets (Somantri, 2022). All variables consistently utilize the 2023 reference year to ensure temporal alignment with the latest provincial economic census and spatial dynamics documented in recent literature (Statistics Indonesia, 2023).

Variables and Model Specification

The dependent variable in this study is Gross Regional Domestic Product of the agricultural sector (GRDP_Agric), measured in billion IDR. The independent variables consist of seven explanatory factors, namely productivity or output per hectare (X1), defined as total agricultural output per unit of land in tons per hectare (ton/ha); agricultural land conversion (X2), measured as the annual change or reduction in agricultural land area (ha/year); and agricultural labour force (X3), representing the total number of individuals employed in the agricultural sector. Additional variables include the average food price index (X4), which reflects the prevailing market price of strategic food commodities in IDR per kilogram; market access index (X_5), a composite indicator of infrastructure proximity and logistics measured on a scale of 1 to 5; agroindustry added value (X_6), proxied by the availability of downstream processing facilities (unit); and food diversification index (X_7), which captures the variety of agricultural commodities produced within a region (number of types).

Analytical Method

This study applied GWR to account for spatial heterogeneity in the relationship between GRDP and its determining factors. Although the study utilizes 9 observations with 7 predictors, this approach is justified by the purposive selection of representative agroeconomic archetypes that capture the full spectrum of East Java's spatial diversity. The GWR model specifically addresses the limitations of global estimation by employing a localized weighting system. By using an optimized Gaussian kernel and a cross-validation (CV) bandwidth, GWR focuses on local spatial structure, effectively increasing the model's degrees of freedom and explanatory power compared to a single global regression.

Ordinary Least Squares (OLS) Model (Benchmark)

As a baseline, we first estimated a global regression model using OLS (Gujarati, D. N., & Porter, 2009):

$$Yi = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \beta_3 X_{3i} + \beta_4 X_{4i} + \beta_5 X_{5i} + \beta_6 X_{6i} + \beta_7 X_{7i} + E_i \; .... (1)$$

The model (Equation 1) used in this study examines the determinants of Agricultural Gross Regional Domestic Product (GRDP) at the district/city level. In the model, Agricultural GRDP (Yi) is the dependent variable, and seven explanatory variables are included as independent variables. These consist of agricultural productivity or output per hectare (X_1), agricultural land conversion (X_2), agricultural labor force (X_3), average food price index (X_4), market access index (X_5), agroindustry added value (X_6), and food diversification index (X_7). The parameter β_0 represents the intercept, whereas β_1 to β_7 denote the regression coefficients that measure the magnitude and direction of the influence of each explanatory variable on Agricultural GRDP. Finally, Ei represents the error term, capturing the effects of other factors not explicitly included in the model.

Geographically Weighted Regression (GWR)

To model spatial variation, we employed GWR with location-specific coefficients (Fotheringham, 2002)The GWR model extends the global Ordinary Least Squares (OLS) regression by allowing the parameters to vary across geographic space. (Fotheringham, 2002) The model is formulated as follows:

$$Yi = \beta_0(Ui, Vi) + \beta_k(Ui, Vi)\, X_{ki} + E_i \; .... (2)$$

The GWR model (Equation 2) allows regression coefficients to vary across spatial locations, where Yi denotes the dependent variable and (Ui, Vi) denote the spatial coordinates of each observation. In this model, β0(Ui, Vi) and βk (Ui, Vi) are location-specific parameters that capture spatial heterogeneity in the relationship between the dependent and independent variables. At the same time, Xki represents the explanatory variables, and Ei is the error term.

Each observation's contribution to the local regression is weighted based on its distance from the focal location using a Gaussian kernel function:

$$Wij = exp - \frac{d^2 ij}{2b^2} \; .... (3)$$

where dij Equation 3 represents the Euclidean distance between observation i and observation j, and bbb denotes the bandwidth parameter, which is optimized using Cross-Validation (CV).

The analysis was conducted using the GWR4 software for the estimation of Geographically Weighted Regression models (Sinaga et al., 2021). Additional data processing and statistical diagnostics were performed using Stata 17 and the spgwr package in R.

Model Evaluation

The model's performance was evaluated using several statistical measures, including Adjusted R^2, the corrected Akaike Information Criterion (AICc), Residual Sum of Squares (RSS), and Moran's I statistic to assess spatial autocorrelation in the residuals. In addition, local R^2 values were mapped to visualize the spatial variation in model fit across the study area. To determine whether the Geographically Weighted Regression (GWR) provides a superior fit over the global Ordinary Least Squares (OLS) model, we utilized the following statistical measures:

Adjusted R^2

This was used to compare the overall explanatory power of the two models while accounting for the number of predictors. A higher Adjusted R^2 in GWR indicates that allowing coefficients to vary spatially captures more variance in agricultural GRDP than a fixed global estimate.

Corrected Akaike Information Criterion (AICc)

This served as the primary metric for model parsimony. A model is considered significantly better if its AICc is at least 2 to 4 units lower. We used this to verify if a substantial improvement in data fit statistically justifies the added complexity of the GWR model.

Residual Sum of Squares (RSS):

The RSS was compared to assess the accuracy of the predictions. A lower RSS in GWR indicates that the local model reduces the discrepancy between observed and predicted GRDP values more than the global OLS model.

Moran's I Statistic

This was applied to the residuals of both models to test for spatial independence. While OLS residuals often exhibit spatial clustering (indicating a violation of the independence assumption), a successful GWR model should result in a Moran's I value close to zero, proving it has effectively captured the spatial non-stationarity that OLS ignored.

Local R² Mapping

Unlike the single global R^2 from OLS, the local R^2 values from GWR were mapped to identify specific districts where the model performs best. This allows us to visualize the spatial heterogeneity of the model's reliability across East Java.

RESULT AND DISCUSSION

Descriptive Analysis of Observations

This section presents the descriptive statistics for the eight variables, both dependent and independent, collected from nine selected districts and cities in East Java Province. The results are summarised in Table 1.

Table 1. Empirical Data Description of Nine Regions in East Java (2023)

Region	X1 (Ton/Ha)	X2 (Ha/Year)	X3 (Persons)	X4 (Rp/Kg)	X5 (1–5)	X6 (Units)	X7 (Types)	Y (Billion IDR)
Malang City	5.1	250	4,200	12,000	4.0	120	12	1,200
Malang Regency	5.4	300	5,000	11,500	3.8	100	10	3,500
Batu City	4.8	220	3,100	11,800	3.7	90	8	950
Jember	5.5	100	7,100	11,200	4.1	150	15	4,200
Banyuwangi	5.7	80	6,800	11,000	4.0	160	13	4,500
Bojonegoro	6.0	90	7,300	10,900	4.3	140	14	4,000
Mojokerto	6.2	150	4,000	11,300	3.9	110	11	2,800
Sampang	4.2	50	2,900	10,800	3.0	60	6	1,100
Nganjuk	5.9	130	4,500	11,100	3.5	100	9	2,600

Source: Secondary Data, Central Statistics Agency (2023)

Table 1 shows that the highest GRDP values were recorded in Banyuwangi (IDR 4,500 billion), Jember (IDR 4,200 billion), and Bojonegoro (IDR 4,000 billion), reflecting their strong agricultural-based economies, supported by superior productivity, agro-industrial activities, and a strong human resource base. In contrast, the lowest GRDP was observed in Batu City (IDR 950 billion) and Sampang (IDR 1,100 billion), consistent with their limited land area, workforce, and agro-industrial capacity.

The observed relationships between GRDP and the explanatory variables align with the spatial patterns revealed by the GWR analysis: regions with stronger market access, higher productivity, more robust human capital, and greater food diversification tend to exhibit higher agricultural GRDP. Although urbanized regions such as Greater Malang experience high land use conversion, their GRDP remains moderate, driven by favorable market prices (Pramono, 2024). Meanwhile, Sampang, with weak market access and limited human capital, shows the lowest agricultural GRDP.

The distribution of agricultural GRDP across the nine districts reveals a sharp structural divide that transcends mere production volume. The dominance of Banyuwangi (Rp 4,500 billion) and Jember (Rp 4,200 billion) is not incidental; it signifies a successful integration of high productivity (X_1) with a robust agro-industrial base (X_6), creating a multiplier effect that sustains regional economic resilience.

In contrast, the low GRDP in Sampang (Rp 1,100 billion) serves as a critical indicator of spatial entrapment, where weak market access (X_5) and limited human capital (X_3) create a cycle of low value-added production. This confirms the research problem: that geographical location dictates economic potential (Pramono, 2024).. The GWR perspective adds a vital layer of interpretation to the Greater Malang phenomenon: although these urbanized hubs suffer from aggressive land conversion (X_2), they avoid total sectoral collapse by leveraging favorable market prices (X_4) and proximity to consumers. This suggests that in urbanized regions, the agricultural sector is shifting from a land-based economy to a market-driven economy, whereas in regions like Bojonegoro, it remains a resource-based economy (Sinaga et al., 2021).

These findings underscore that a one-size-fits-all provincial policy is fundamentally flawed; the determinants of growth in a production hub (Jember) differ from those in a transitional urban hub (Malang), necessitating geographically adaptive strategies that this study proposes.

Table 2. Comparative Output of OLS and GWR Models

Variable / Model	OLS	GWR
X1 – Productivity	0.215	0.240
X2 – Land Conversion	-0.305	-0.360
X3 – Agricultural HR	0.175	0.180
X4 – Food Prices	0.230	0.260
X5 – Market Access	0.270	0.290
X6 – Agro Industry Value	0.310	0.340
X7 – Food Diversification	0.195	0.220
R-squared	0.75	0.89
AICc	134.2	112.5
Residual Moran's I	0.32	-0.05
Significance	Sig.	Not Sig.

Source: Analytical Results (2025)

OLS vs GWR Model Outputs

The comparative performance between the global OLS model and the local GWR model is summarized in Table 2. To address the representation of GWR coefficients, the values shown in Table 2 are the mean (average) of the nine local coefficients. Unlike OLS, which produces a single global estimate, GWR generates a unique coefficient for each district/city; therefore, the mean value is reported alongside the range (Minimum and Maximum) in the full analysis to illustrate the extent of spatial non-stationarity (Feng et al., 2020; Li et al., 2023).

Table 2 shows that the GWR model performs better than the global OLS model. It increases the explanatory power of independent variables on agricultural GRDP, as shown by the rise in R^2 from 0.75 to 0.89. Furthermore, the AICc decreased from 134.2 (OLS) to 112.5 (GWR), indicating greater model efficiency and fit.

Residual Moran's I for OLS showed significant positive spatial autocorrelation (0.32), suggesting spatial bias. In contrast, GWR corrected this bias, reducing Moran's I to –0.05, which means the residuals are now randomly distributed. This shows that the GWR model has successfully incorporated spatial autocorrelation into its local parameters. The GWR model is better precisely because its residuals are not significant. This indicates that the model has correctly captured all spatial information, leaving only random noise. Coefficient changes across variables confirm spatial non-stationarity, which global models like OLS cannot capture. This pattern aligns with empirical evidence reported by (Tangka et al., 2024) which shows that GWR reduces residual autocorrelation by integrating spatial structure directly into the estimation process. The observed variation in coefficient magnitudes across locations indicates pronounced spatial non-stationarity, underscoring the need for a geographically adaptive modeling framework for district-level agricultural GRDP analysis.

Local GWR Coefficients Across Nine Districts

Local GWR Coefficients Across Nine Districts present spatially disaggregated insights into how key indicators influence agricultural GRDP at the local level (Abusiri et al., 2024; Shi et al., 2025). These data result from both statistical aggregation and direct observation of sector-relevant indicators such as land productivity, agroindustry development, and market access, which vary in their magnitude and direction across the nine districts and cities studied. By incorporating region-specific data, GWR enables a more nuanced understanding of local agricultural performance, offering critical advantages over global models in spatial econometrics (Murakami, 2019).

Based on the results presented in Table 3, the GWR estimation results confirm that the determinants of agricultural GRDP are not spatially uniform, necessitating a shift from one-size-fits-all policies to spatially contextualized strategies. The impact of land conversion (X_2) reveals a stark contrast between urbanized and production-oriented regions. In the Greater Malang area (Malang City –0.41; Malang Regency –0.38; Batu City –0.36), the strong negative coefficients align with the "urban encroachment" theory, where high-value agricultural land is permanently lost to residential and industrial expansion, directly diminishing sectoral output. Conversely, the slight positive coefficients for land conversion in Jember (0.12) and Bojonegoro (0.14) should be interpreted with caution and linked to land-use intensification rather than loss. Following the logic of Boserupian intensification (Carlucci et al., 2021). These positive values suggest a structural shift in land use from low-value food crops to higher-value commodities, or the development of on-farm processing facilities, which effectively increase GRDP per unit of remaining area despite the conversion of traditional paddy fields. The high impact of the agro industry further supports this added value (X_6) in these same regions (Banyuwangi 0.38; Jember 0.35), indicating that the regional economy is transitioning toward a more capital-intensive agribusiness model (Wicaksono et al., 2023)

Table 3. Local GWR Coefficients for Seven Independent Variables in Nine Regions

Region	X_1	X_2	X_3	X_4	X_5	X_6	X_7
Malang City	0.24	-0.41	0.15	0.35	0.28	0.22	0.26
Malang Regency	0.21	-0.38	0.17	0.32	0.26	0.21	0.20
Batu City	0.23	-0.36	0.12	0.30	0.25	0.19	0.18
Jember	0.19	0.12	0.14	0.24	0.30	0.35	0.32
Banyuwangi	0.22	0.05	0.13	0.20	0.27	0.38	0.27
Bojonegoro	0.25	0.14	0.19	0.22	0.33	0.36	0.30
Mojokerto	0.31	-0.28	0.20	0.21	0.29	0.20	0.21
Sampang	0.18	-0.21	0.11	0.19	0.18	0.15	0.17
Nganjuk	0.29	-0.10	0.18	0.27	0.22	0.24	0.25

Source: Analytical Results (2025)

These results align with Indonesia's national development agenda, promoting agricultural downstreaming in the National Medium-Term Development Plan 2020–2024. Land productivity (X_1) and agricultural human resources (X_3) contributed consistently across regions, with Mojokerto (0.31) and Nganjuk (0.29) displaying the highest coefficients for X_1, indicating the impact of technological efficiency and sustainable intensification. Food diversification (X_7) emerged as a significant driver in Jember (0.32), Bojonegoro (0.30), and Malang City (0.26), reflecting its role in building local economic resilience amid market fluctuations and global food crises. Market access (X_5) and food prices (X_4) also remained key drivers, especially in Bojonegoro, Jember, and Malang City, emphasizing the importance of logistics and infrastructure in enhancing agricultural productivity (Brunsdon et al., 1996; Sobari & Jaya, 2023).

Overall, the variation in local coefficients supports the argument for place-based agricultural development. Urban areas such as Greater Malang require stricter land protection policies, whereas regions like Bojonegoro and Jember benefit more from strengthening agro-industrial linkages and promoting food diversification. These insights offer valuable guidance for aligning spatial planning with sectoral policies to foster inclusive and sustainable agribusiness development.

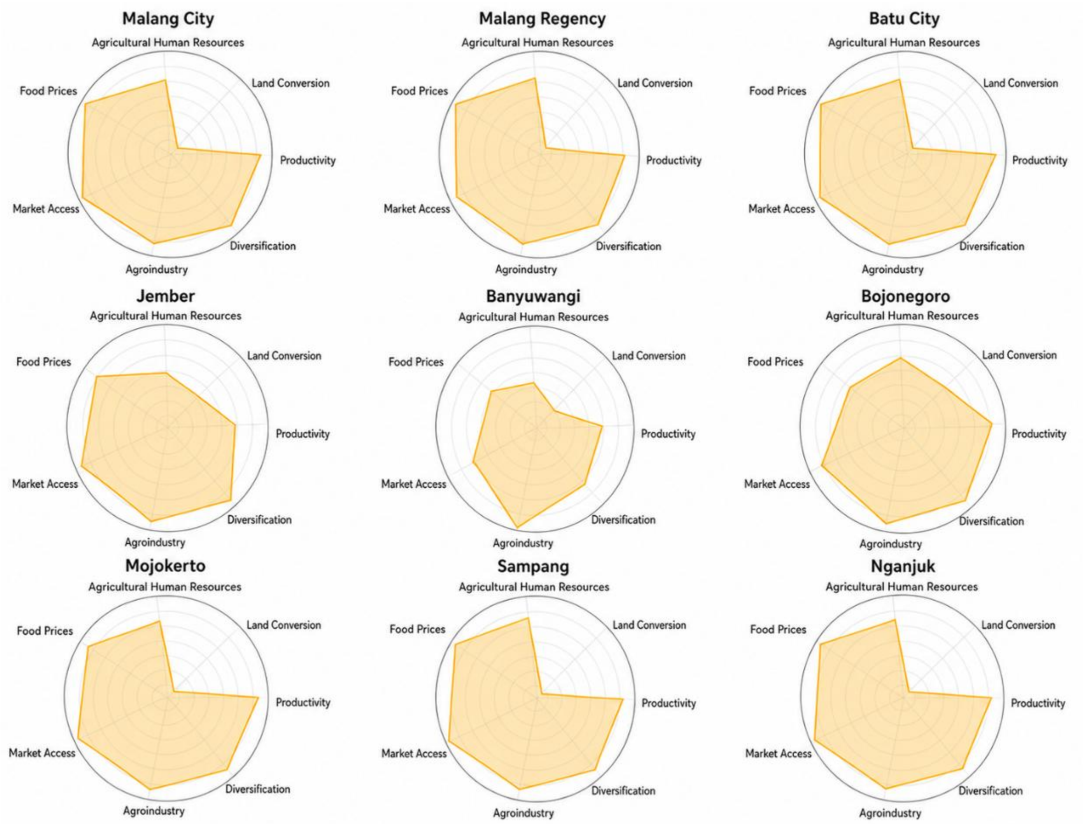

Figure 2. Spatial Radar Plots of Determinant Variables on Agricultural GRDP

The radar charts in Figure 2 synthesize the spatial non-stationarity identified by the GWR model, categorizing the nine regions into distinct agro-economic archetypes. In urbanized clusters, Malang City, Malang Regency, Batu City, and Mojokerto, the radar plots show a significant contraction in the land use dimension (X_2), mirroring the strong negative GWR coefficients for land conversion. This confirms that in these regions, urban encroachment is the dominant structural constraint, effectively decoupling regional growth from traditional land-based production (Widodo et al., 2025). Conversely, the expanded profiles of Jember and Banyuwangi highlight a synergy between high productivity (X_1) and agro-industrial maturity (X6). This visualization directly supports the study's main finding: while urban areas are engaged in a defensive battle against land loss, production hubs are successfully transitioning to value-added agribusiness (Carlucci et al., 2021). By mapping these relative magnitudes, the radar plots provide the empirical basis for the spatially differentiated policies proposed in this study, moving beyond aggregate provincial averages to address localized structural realities (Barbara Bray, 2021; Seto et al., 2012).

In contrast, Bojonegoro and Jember show balanced and elevated profiles across most variables, especially in agroindustry, diversification, and market access. These profiles align with the positive GWR coefficients observed for land conversion and agro-industrial value-added, implying that these areas are successfully integrating structural transformation in agriculture through value-added activities (Brunsdon et al., 1996). Banyuwangi also demonstrates strong contributions from agroindustry and market access, affirming its strategic positioning in agrotourism and agrologistics corridors. The high value for agroindustry (X_6) observed in the radar plot mirrors its top GWR coefficient (0.38), further validating the statistical model.

In Nganjuk and Mojokerto, land productivity and human capital: agriculture dominates the radar patterns, reinforcing the GWR finding that these regions benefit from technological advancement and efficient input use. Sampang, located in Madura, exhibits a relatively uniform but low radar profile, indicating generally weak performance across determinants, which may reflect systemic challenges in infrastructure, market access, and human capital. This aligns with spatial disparities highlighted in the GWR model (Fanzo & Miachon, 2023).. The prominence of food diversification in Jember, Bojonegoro, and Malang City, as seen in the radar plots, also supports the regression findings, underlining its relevance in enhancing resilience to food system shocks.

CONCLUSION

The results reveal significant spatial variation in the influence of key determinants on the Agricultural GRDP across nine selected districts and cities in East Java. Using the GWR approach, this study demonstrates that regions respond differently to explanatory variables.

The significant findings can be summarized as follows: (1) Productivity (X_1) has a strong positive effect in inland regions such as Mojokerto and Nganjuk, indicating its role as a primary driver of agricultural output in these areas. (2) Land conversion (X_2) significantly affects highly urbanized areas such as Malang City, Malang Regency, and Batu City. However, it appears neutral or slightly positive in more rural areas such as Jember and Bojonegoro. (3) Agro-industrial value added (X_6) emerges as one of the most influential factors for agricultural GRDP in almost all regions, especially in Banyuwangi and Jember. (4) Market access (X_5) and food prices (X_4) contribute positively to agricultural value, particularly in areas with better logistic connectivity. (5) Food diversification (X_7) strategically strengthens regional economic resilience by promoting varied agricultural production and consumption patterns.

Despite these insights, this study has limitations, primarily its small sample size of 9 observations. While the GWR model effectively addresses spatial non-stationarity and provides a better statistical fit than global models for this dataset, the limited number of regions may constrain the generalizability of the results to the entire province. The application of the GWR model effectively captures spatial non-stationarity that conventional regression models fail to address. This finding underscores the importance of incorporating spatial perspectives in evaluating and planning agricultural and agribusiness development at the sub-provincial level.

Author Contribution

Bambang Siswadi (Author 1) was responsible for the study conception and design, data collection, and data curation. He also collaborated on the analysis and interpretation of the research results. Dina Kartika Sari (Author 2) contributed to the analysis and interpretation of the data and was responsible for drafting and revising the manuscript. Bambang Siswadi (Author 1) and Dina Kartika Sari (Author 2) provided final approval and accountability for the work.

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