Pathways to secure food production: Structural inequalities at village levels in Yogyakarta

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Abstract

This study measures Food Production Security (FPS) at the village level in DI Yogyakarta across quantity, quality, structure, and ecology dimensions, and analyzes the role of resources, technology, and institutional capacity in supporting food production. Generally, FPS have positively correlated with the Food Security Index (FSI), yet misalignments signal dual aspects of food security. This study used an Entropy-Weighted TOPSIS approach, complemented by GeoAI modelling and Mixed Geographically Weighted Regression (MGWR) to assess spatial heterogeneity in Food Production Security (FPS). We found that higher FPS scores in urban areas reflect structural disparities in production inputs and infrastructure access. Spatial analysis highlights heterogeneous and dual-direction effects of capital, technology, climate, and environmental management factors, emphasizing the need for spatial-based policies. Collaborative strategies combining modern agricultural technologies, targeted extension services, and optimized use of organic fertilizers, and waste recycling demonstrate potential for sustainable improvement of FPS at village and sub-district levels.

Keywords: food security**;** agriculture; sustainable**;** spatial model
JEL Classification: Q18; C21; C55; R58

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1. Introduction

Ensuring adequate food availability across regions is a fundamental pillar of national food security. This security, however, cannot rely solely on the current supply of food, but also on the potential sustainable production capacity of food. To ensure food security, we must always base ourselves on agricultural production and address the uncertainty of the external environment with the certainty of domestic, stable production and supply.

In Indonesia, efforts of achieve sustainable food self-sufficiency continue to face significant challenges. This is evidenced by a 1.7 percent increase in the Global Food Security Index in 2022 and a positive trend in the reduction of food insecurity prevalence, which declined from 6.86 percent in 2018 to 4.5 percent in 2023 (BPS, 2024). However, these improvements contrast with the downward trend of staple food production.

According to BPS, in 2024, the harvested area for rice decreased by 1.64 percent (167.57 thousand hectares), while rice production fell by 1.54 percent, or around 480.04 tons, compared to 2023. This situation indicates a potential imbalance between the projected population growth, estimated to reach 309.63 million by 2025, and the capacity for food production, which may undermine the nation's ability to maintain self-reliance in staple food supply. This phenomenon echoes the concerns raised by Malthusian theory, which posits that population growth tends to outpace food supply unless countered by strategic technological and policy interventions.

At the regional scale, DI Yogyakarta offers an intriguing case. Although the province ranked sixth nationally in the 2023 Food Security Index (FSI), and has received several recognitions, including the AGFUND Prize in 2013 (BPN, 2013) and the SDGs Action Awards in 2023, structural issues persist. The 2024 Agricultural Economic Survey conducted by BPS reveals that over half of the region's farmland is classified as unsustainable, primarily due to inadequate input management, such as fertilizer use. This suggests that DI Yogyakarta's high FSI score may not fully reflect the province's resilience in terms of production security, which relies on the quality and sustainability of food production systems.

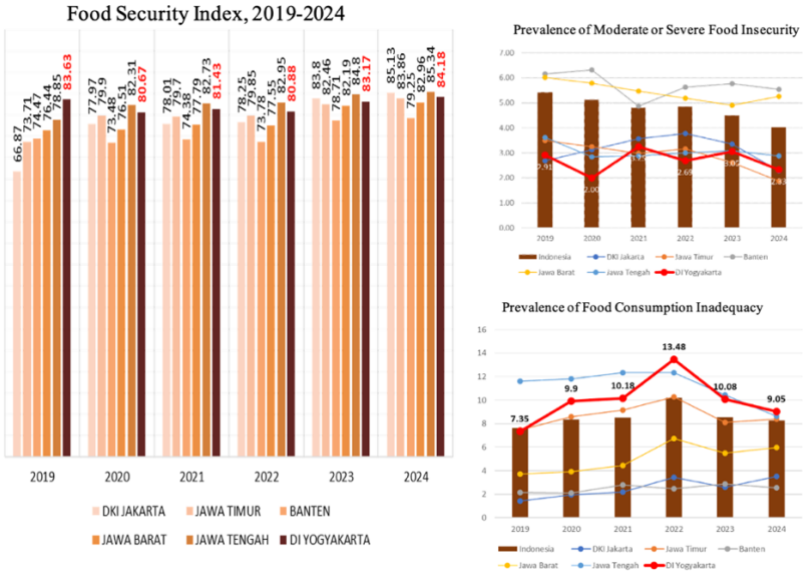
Figure 1 illustrates the dynamics of the Food Production Security Index (FSI) in DI Yogyakarta, which has experienced fluctuations and a slower growth rate than in other provinces in the Java Islands. Meanwhile, indicators of the prevalence of food consumption inadequacy and food insecurity have also shown instability; the prevalence of food consumption inadequacy increased in 2020 and decreased in 2023, whereas the prevalence of food insecurity moved in the opposite direction.

This discrepancy indicates a gap between public perception of food access and actual consumption realization, which is likely influenced by factors such as the post-COVID-19 pandemic effects that have driven price fluctuations, uneven food distribution, limited production inputs, and the purchasing power of the population.

In this context, food security has emerged as a strategic and multidimensional issue. This issue is particularly relevant in the context of the DI Yogyakarta, a province that is not a central food-producing region in Indonesia. The province faces district-level challenges, including limited agricultural land, pressure to convert land, and dependence on external food supplies. Therefore, assessing food production

security at the village level in DI Yogyakarta is a crucial case for examining how food production security manifests in regions with constrained production capacity and high development pressures, and for identifying localized vulnerabilities of food production that are masked at district or national levels.

Figure 1.
Growth of Food Security Index (2019-2024), Prevalence of Moderate-Severe Insecurity, and Prevalence of Food Consumption Inadequacy



Source: *Bapanas* (2025) and BPS (2025)

In this context, food security has emerged as a strategic and multidimensional issue. This issue is particularly relevant in the context of the DI Yogyakarta, a province that is not a central food-producing region in Indonesia. The province faces district-level challenges, including limited agricultural land, pressure to convert land, and dependence on external food supplies. Therefore, assessing food production security at the village level in DI Yogyakarta becomes a crucial case for examining how food production security manifests in regions with constrained production capacity and high development pressures, and how localized vulnerabilities of food production are masked at district or national levels.

However, studies on Food Production Security (FPS) at the village level remain highly limited in Indonesia. Most existing research continues to focus on aggregated regional scales such as districts, provinces, or the national level. For instance, Indri et al. (2022) analyzed the development rate of rice production and its determining factors in South Sumatra. Harini et al. (2021) examined food security at the district and municipal levels in DI Yogyakarta, while Widhiyastuti et al. (2023) investigated sustainable food agriculture in Sleman Regency.

Although these studies offer valuable insights, they have not yet developed a comprehensive index that captures food production security by incorporating both

production capacity and ecological dimensions. At the same time, existing national assessments, such as those conducted by the National Food Agency (Bapanas) through the three core dimensions of availability, accessibility, and utilization, also do not incorporate ecological conditions within their evaluation frameworks. Moreover, the measurement of food availability remains dependent mainly on harvested area, an indicator that inadequately reflects the quality or sustainability of local food production systems.

On the other hand, Hua et al. (2023) developed an FPS evaluation framework emphasizing production capacity, stability, and sustainability, showing that although FPS has improved in many regions, overall levels remain relatively low. Meng and Liu (2025) further expanded the concept by highlighting the importance of quantity, quality, structure, and ecological sustainability. This multidimensional perspective asserts that food production security depends not only on harvested output but also on the resilience, efficiency, and sustainability of underlying production systems.

This aligns with Ericksen's (2008) food system resilience framework, which emphasizes the adaptive capacity of food systems to socio-environmental pressures. In this regard, land resources and agricultural labor are not merely determinants of food availability, they must be accompanied by ecological protection to ensure long-term production viability. This issue becomes even more salient in regions experiencing rapid land conversion and agricultural intensification.

Spatial and social transformations influence production capacity (Peña-Rodríguez et al., 2023), while factors such as land conditions, agricultural labor participation, infrastructure, and access to markets play crucial roles in linking production to consumption (FAO, 2023; Barrett, 2008). Food availability is also shaped by labor availability, land quality, economic conditions, resource scarcity, and environmental degradation (Cui et al., 2021).

Bouxine (2024) identifies six interrelated aspects affecting food production, agricultural practices, technological progress, resource management, food processing, economic factors, and climate impacts, which reinforce Debertin's (2012) neoclassical production function framework (Cobb–Douglas), where multiple inputs interact to shape agricultural outcomes.

This study adopts and modifies the FPS framework introduced by Meng and Liu (2025), which evaluates four core dimensions: quantity, quality, structure, and ecology. Following their recommendation, this study applies the entropy-weighted TOPSIS method and uses a specific region to account for spatial heterogeneity. However, limited longitudinal data on land, production, cropping structure, and food production quality at the village level pose substantive analytical challenges.

To address these constraints, machine learning techniques are used to identify the most influential drivers of FPS and reduce overfitting. At the same time, Multiscale Geographically Weighted Regression (MGWR) captures local variations and spatial heterogeneity (Ramdan et al., 2025). Furthermore, this study incorporates Geospatial Artificial Intelligence (GeoAI), specifically Graph Convolutional Networks (GCNs), to model spatial interconnections between villages more adaptively and generate predictive insights that compensate for missing data in subsequent years.

Based on this background, this study has three objectives. First, it aims to measure and map the level of Food Production Security (FPS) across urban and rural areas in DI Yogyakarta using four dimensions: quantity, quality, structural integrity, and ecological sustainability. Second, it seeks to identify how resource constraints affect FPS across regions, capturing spatial disparities in food production potential.

Third, it evaluates the role of resources and technology in strengthening resilient, sustainable food availability, providing a stronger foundation for designing targeted intervention strategies at both the village and municipal levels in DI Yogyakarta.

2. Methodology

This study utilizes secondary data sourced from the 2023 Agricultural Census (ST2023) and the 2024 Village Development and Potential Survey (PODES). The survey collected comprehensive information on the conditions, facilities, and development potential of 438 villages and urban-rural areas in the DI Yogyakarta, covering aspects such as demographics, employment, housing, environmental conditions, natural disasters and mitigation efforts, education, health, socio-cultural dynamics, transportation, communication and information, financial and economic activities, and village assets.

Additionally, the data sources for this study also include websites or publications released by *Bapanas* and the Ministry of Villages, as well as satellite-based rainfall data obtained from the Climate Hazards Center InfraRed Precipitation with Station data (CHIRPS). The unit of analysis in this study is the urban-rural level. To construct the Food Production Security (FPS) Score, this study has led to the adoption of the Food Production Security concept introduced by Meng & Liu (2025) around four key dimensions: quantity, quality, structure, and ecological safety of food production.

Specifically, quantity security is the most basic connotation and fundamental guarantee of FPS (Cui et al., 2021), as reflected in the sustained food supply capacity of main producing areas, including food crop output, production stability, and transferability. Quality security is a higher requirement for central food-producing regions, which implies not only ensuring food quality but also capturing both socioeconomic vulnerability and nutritional resilience. Complementing these, the food quality subdimension incorporates measures of the proportion of poor households in decile 1, undernourished population (Bapanas, 2024; FAO et al., 2022), farmer support programs, including access to subsidized inputs, seed assistance, and fertilizers, which contribute to productivity and resilience (Meng & Liu, 2025).

Structure security extends quantity and quality consideration by evaluating the configuration and scale of agricultural production. The average cultivated area per agricultural holding (Gollin, 2021; Meng & Liu, 2025) reflects the structural capacity of farms to achieve economies of scale, while the prevalence of small-scale farming (Gollin, 2021) highlights structural constraints that may impede modernization and productivity improvement.

Ecological security is a prerequisite for achieving quantity, quality, and structural security, as environmental pressures fundamentally shape long-term agricultural sustainability (FAO, 2023). Indicators such as crop failures due to ecological hazards (BPS, 2023; FAO, 2023), river pollution (FAO, 2020; Satterthwaite et al., 2010), and intensity of pesticide use (Meng & Liu, 2025) represent key ecological risks. These threats often stem from excessive use of agricultural inputs or environmental degradation processes that directly reduce agricultural productivity.

In addition to the core FPS variables, this study also includes a set of predictor variables representing financial, social, economic, technological, climatic, and cultural factors that shape local agricultural performance (Bouxine, 2024).

These indicators include access to agricultural credit, extension services, cooperative activity, availability of agricultural inputs, digital infrastructure, rainfall

variability, disaster exposure, waste management practices, and community participation. Together, these predictors allow for a deeper understanding of the enabling conditions and constraints influencing food production security at the regional level.

A detailed operational definition of each indicator, along with its data source and reference, is provided in Appendix 1, where the complete variable set used of construct the FPS Score is documented. The entropy-weighted TOPSIS method is employed in this study to objectively construct the Food Production Security (FPS) score based on multi-indicator data. This approach integrates two core techniques: Entropy Weighting, which determines the weight of each indicator based on its intrinsic informational value, and Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), which evaluates the relative proximity of each village to an optimal solution (Meng & Liu, 2025; Liu et al., 2022).

The initial stage involves constructing a decision matrix of $X = [x_{ij}]$, where i is urban-rural and j is an indicator. The matrix is normalized using the $maximum$ approach (Meng & Liu, 2025) to standardize the scale across indicators. The entropy measures the level of uncertainty or information dispersion within each indicator, the greater the data variation, the greater its contribution to decision-making. Subsequently, the entropy value is used to calculate the objective weight of each indicator through the following formula:

$$e_j = -k \sum_{i=1}^{m} r_{ij} \, ln \, r_{ij}, \;\; w_{ij} = \frac{1 - e_j}{\sum_{j=1}^{n} (1 - e_j)} \tag{1}$$

where r_{ij} represents the normalized value of the regions i on the indicator j and k Is the scale constant? An indicator with greater variability or more diverse, the higher r_{ij} or the lower its entropy values e_j, is considered more informative and thus given greater weight w_{ij}. After obtaining the indicator weights, the TOPSIS method is applied to determine the distance of each alternative to the positive and negative optimal solutions. The optimal solution is positive if the maximum value of each indicator is achieved, and vice versa. The relative closeness distance is calculated using the formula:

$$C_i = \frac{D^-}{D_i^+ + D_i^-} \tag{2}$$

with C_i is the preference score of regions i, D_i^+ and D_i^- represent the distance to the positive and negative optimal solutions, respectively. The C_i value approaching 1 indicates that a region is closer to the optimal condition in terms of food production security.

The application of the Entropy-weighted TOPSIS method is effective in minimizing subjectivity in determining indicator weights, enhancing the stability of evaluation results, and avoiding the inclusion of weakly contributing indicators or models that may reduce decision-making accuracy (Zhou et al., 2024).

In addition, this method is straightforward, with no statistical test, in the field of decision-making, especially in multi-criteria decision analysis (MCDA) (Zhao et al,

2022). The Mixed Geographically Weighted Regression (MGWR) model is a combination of the global regression model and the GWR model.

According to Fotheringham et al. (2002) and Mei et al. (2006), in the MGWR model, some predictor variables are modelled using the global regression model because they have the same influence on the response variable at every observation point. Meanwhile, other predictor variables are modelled using GWR because they exert different influences on the response variable at each observation point due to spatial heterogeneity. The general equation of the MGWR model is as follows:

$$Y_i = \beta_0(u_i, v_i) + \sum_{k=1}^{q} \beta_k(u_i, v_i) x_{ik} + \sum_{k=q+1}^{p} \beta_k x_{ik} + \varepsilon_i \quad (3)$$

where i urban-rural Y_i is the observed value of the predictor variable at region i; x_{ik} denotes the value of the predictor variable k at the observation point i; $\beta_0(u_i, v_i)$ is the local intercept coefficient; $\beta_k(u_i, v_i)$ represents the local regression coefficient of the predictor k at location i, β_k is the global regression coefficient of predictor k that remains constant across all locations, and ε_i is the random error term at location i. This model is employed to identify the influence of resource constraints, including capital, technology, and environmental factors, on food production security across regions in the DI Yogyakarta.

In addition, this study also employs several machine learning (ML) models to predict Food Production Security (FPS) indicators at urban-rural areas level in DIY, namely Random Forest (RF) (Breiman, 2001), eXtreme Gradient Boosting (XGBoost) (Chen & He, 2023), and Graph Convolutional Network (GCN) (Ma et al., 2024). Unlike the first two ML methods, GCN is a deep learning method capable of processing graph-structured data, where spatial units are represented as nodes and their adjacency relationships as edges. This property allows GCN to effectively utilize spatial interdependencies among neighboring villages, thereby improving the accuracy of FPS predictions at the micro-regional level.

3. Results and Discussion

The construction of Food Production Security (FPS) indicators began with the determination of entropy-based weights for 17 variables representing the dimensions of quantity, quality, structure, and ecology. These variables were classified under a modified urban-rural framework and processed using the Entropy-Weighted TOPSIS method.

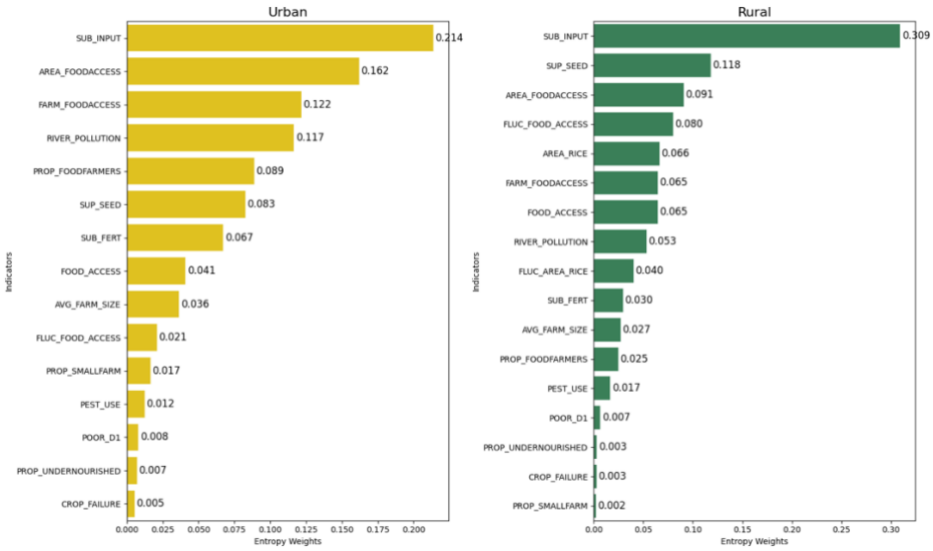
The resulting weights reflect both regional conditions and disparities, highlighting variations in food production capacity and sustainability. Moreover, the entropy weights indicate the extent to which each indicator contributes informational value to the FPS score calculation. A higher weight signifies a greater role of the indicator in differentiating conditions between regions, thereby emphasizing its strategic relevance in assessing localized food production security.

Based on Figure 2**,** the proportion of farmers receiving subsidized production inputs and infrastructure assistance holds the highest entropy weight across both rural and urban areas in the DI Yogyakarta. In urban areas, the second- and third-most influential indicators are the proportion of access to food supply infrastructure

adjusted by agricultural land area and the proportion of access adjusted by the number of food crop farmers, respectively.

Conversely, in rural areas, these positions are held by the proportion of farmers receiving seed assistance, followed by the proportion of access to food supply infrastructure adjusted by the proportion of agricultural land. This indicates that, in both rural and urban areas, the quantity and quality of production inputs, including access to equipment, seeds, and the alignment of potential with technical support, remain the most decisive factors differentiating the level of food production security across regions in DI Yogyakarta.

Figure 2.
Distribution of Entropy Weights by Urban-Rural in DI Yogyakarta



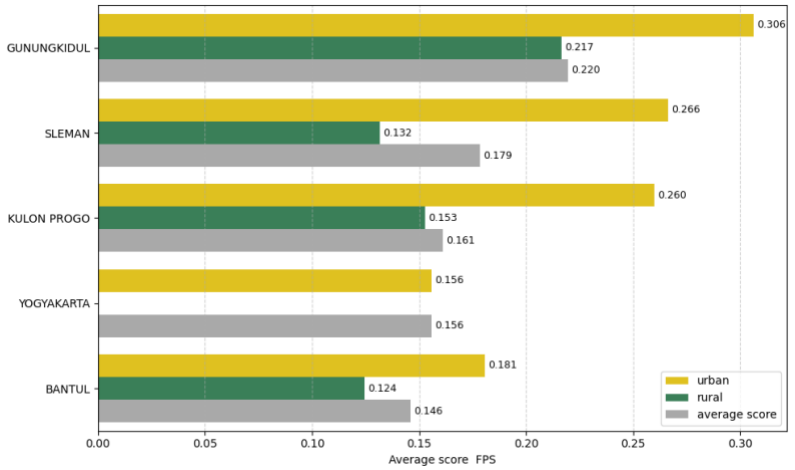
Source: Bapanas (2025) and BPS (2025)

On the other hand, urban areas highlight the growing significance of ecological indicators, notably river pollution, which ranks among the top five in terms of entropy weight. This underscores the rising importance of environmental factors, especially water quality, in evaluating food production security within urban contexts.

Deterioration of water quality due to river contamination can directly impact land productivity, the sustainability of irrigation systems, and the safety of agricultural products (Satterthwaite et al., 2010; Cui et al., 2021). These observations are consistent with the FAO Report (2023), which emphasizes that environmental degradation constitutes a significant threat to food security in densely populated urban regions, where domestic and industrial activities increasingly compromise the availability of fertile land. Meanwhile, rural areas continue to exhibit greater dependence on other input interventions, such as increased access to food supply infrastructure and the proportion of agricultural land. This pattern aligns with the FAO Report (2023), which notes that rural regions are more vulnerable to input price fluctuations and rely heavily on subsidy-based policy support.

Overall, these indicators were used to construct the FPS scores for each regency/city in the DI Yogyakarta based on area type. The ranking of regencies/cities from the highest to lowest average FPS (Figure 3.) is as follows: Gunung Kidul Regency (0.220), Sleman Regency (0.179), Kulon Progo Regency (0.161), Yogyakarta City (0.156), and Bantul Regency (0.146). Furthermore, the results indicate that urban areas have higher average FPS scores compared to rural areas. This pattern is notable given that domestic production capacity in urban areas is relatively limited (Appendix 2). However, as indicated by the dominant indicator weights (Figure 2), urban areas exhibit an advantage in access to food production infrastructure.

Figure 3.
Average FPS Scores by Regency/City Based on Urban-Rural Classification



Source: Bapanas (2025) and BPS (2025)

Conversely, the lower FPS scores in rural areas suggest the presence of structural gaps in terms of inputs, information, and access to production facilities. These findings signal the need for targeted evaluation and policy interventions to strengthen production capacity and improve access, particularly in rural regions. Note that Yogyakarta City has no FPS score for rural areas since all the villages in this region are categorized as urban areas.

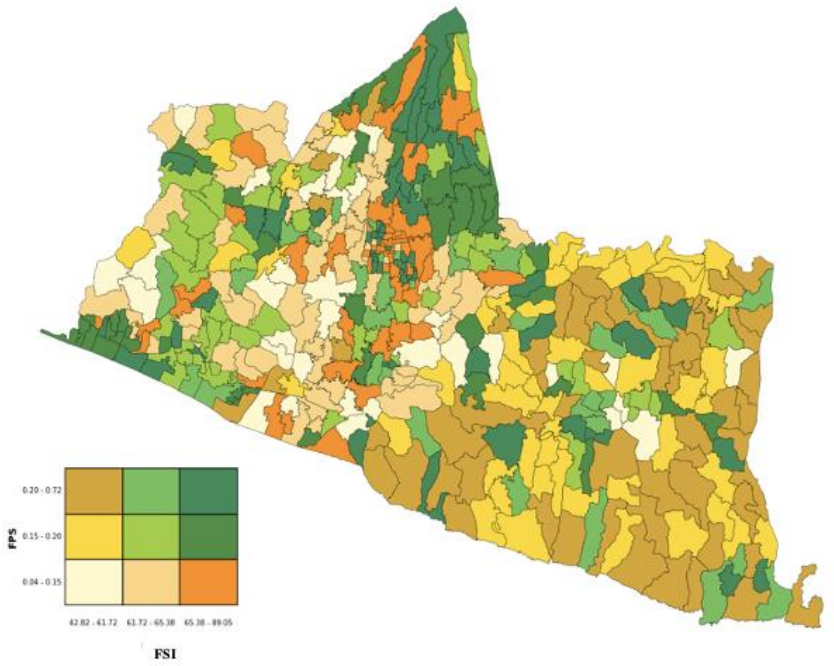
To examine the relationship between production security and food security, Figure 4 presents an interaction map of the Food Security Index (FSI) and the Food Production Security (FPS) for each village/city in DI Yogyakarta. In general, villages/cities with high FSI values also tend to exhibit relatively high FPS scores, as indicated by the green shading in several areas, particularly in Sleman Regency, Kulon Progo Regency, and Yogyakarta City. This pattern suggests that good food availability, access, and utilization (components of FSI) in most of these areas align with adequate local food production security (FPS).

In contrast, Gunung Kidul Regency is predominantly characterized by medium to high FPS scores but low FSI values (depicted in yellow–brown shades). Areas with both high FSI and FPS are only observed in limited parts of the regency.

This indicates that relatively moderate-to-high production security in most areas of Gunung Kidul has not yet been accompanied by strengthened access to and

utilization of food, highlighting a gap in the translation of production capacity into comprehensive food security.

Figure 4.
Map of the Food Security Index (FSI) and Food Production Security (FPS) Scores in DI Yogyakarta



Source: Bapanas (2025) and BPS (2025)

To deepen the understanding of the interaction between these two indicators, Figure 5 presents a quadrant plot categorizing FPS and FSI scores into four groups based on their respective mean values. Overall, urban areas (yellow) in the DI Yogyakarta predominantly exhibit above-average food security conditions (FSI). In contrast, villages with below-average FSI scores are concentrated mainly in rural areas (green). However, when viewed from the perspective of local food production security (FPS), the distribution of rural and urban areas above and below the average FPS score appears more balanced.

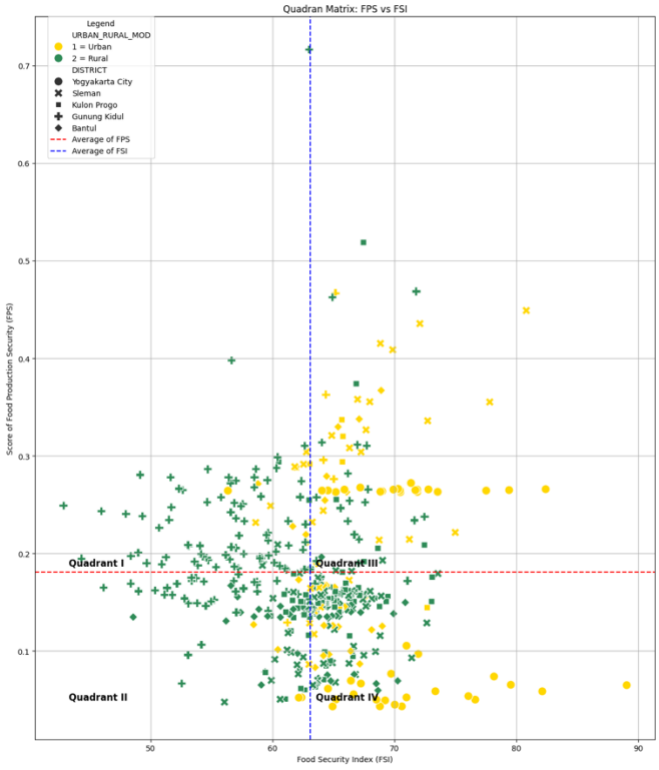
Quadrant III comprises villages and municipalities with both FSI and FPS scores above the regional average. This quadrant is primarily populated by urban areas (yellow) in Yogyakarta City (depicted as diamond symbols) and Sleman District (square symbols), along with several rural villages (green) in Gunung Kidul District (triangle-up symbols).

These findings suggest that while urban areas tend to perform better in terms of overall food security, certain rural regions also demonstrate strong production capacity, highlighting the potential for integrated food system resilience across diverse territorial contexts.

Quadrant IV comprises villages with above-average FSI but below-average FPS, indicating areas that exhibit relatively strong food security yet weak local production

security. Many villages in Bantul, Kulon Progo, and parts of Yogyakarta City and Sleman fall into this category.

Figure 5.
FPS–FSI Quadrant Matrix in DI Yogyakarta



Source: Bapanas (2025) and BPS (2025)

On the other hand, Quadrants I and II are predominantly occupied by rural areas, mainly from Gunung Kidul, Kulon Progo, and Bantul. These areas highlight the need to improve food access, distribution, and utilization to ensure that food security (FSI) aligns with local production potential.

Overall, this descriptive analysis provides a foundational understanding of the duality between food security and production security in DI Yogyakarta. Some areas manage to maintain a balance between access and production, while others remain dependent on external factors to sustain production security. The integration of spatial maps with the quadrant matrix emphasizes the urgency of differentiated interventions, such as strengthening production in areas with high FSI but low FPS (Quadrant IV) and implementing comprehensive measures in vulnerable areas (Quadrants I & II).

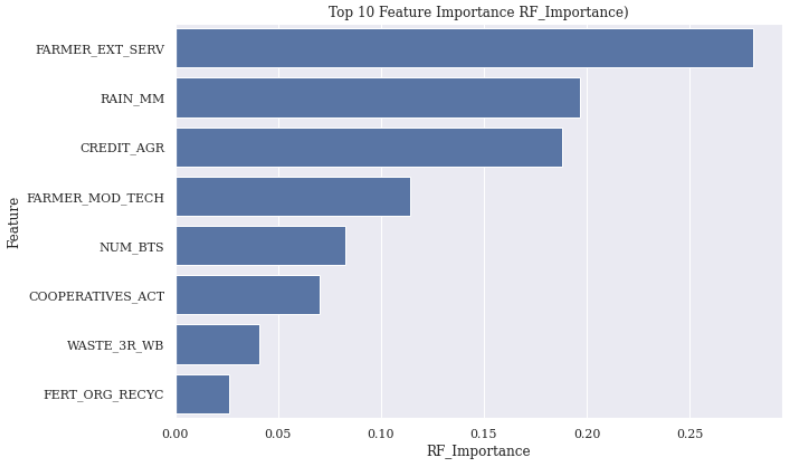
These findings reinforce the importance of a place-based policy approach in formulating regional food security strategies, given the spatial dynamics shaped by geographic, ecological, and socio-economic factors. Consequently, to support more

precise policymaking, further spatial analysis is conducted to identify the significant variables influencing food production security in each area.

Before conducting spatial modelling, a variable selection approach was applied using the feature importance method from the Random Forest algorithm (Appendix 5.) to identify the factors that contribute most significantly to food production security (FPS). This approach was implemented to enhance the efficiency of spatial modelling, prevent overfitting, and improve the interpretability of results. As noted by Rodriguez-Licea et al. (2023), machine learning-based spatial modelling should be preceded by a feature selection stage that considers the importance of local contributors.

Figure 6 shows that 8 out of the 14 most dominant variables influencing FPS and representing various dimensions (capital, technology, and environment) in the DI Yogyakarta consist of a combination of capital, technological, and environmental factors. These include the proportion of farmers receiving extension services, average annual rainfall, proportion of farmers with access to credit, proportion of farmers utilizing modern technology, the number of BTS towers, the number of cooperatives and village-owned enterprises in the agricultural sector, the presence of temporary waste disposal sites, and initiatives promoting the use of organic fertilizers and recycling practices.

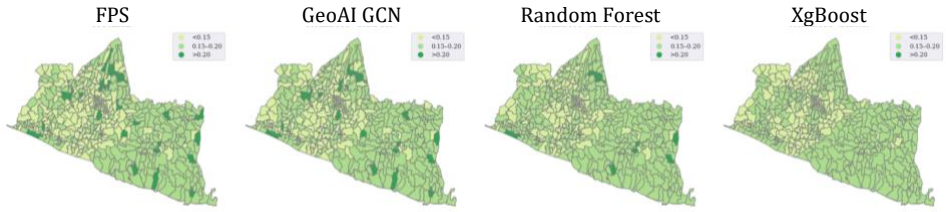
Figure 6.
Top 8 Important Variables by Random Forest Method



Source: Bapanas (2025) and BPS (2025)

After identifying the key variables, FPS prediction models were developed using XGBoost, Random Forest, and a Graph Convolutional Network (GCN) for GeoAI. The prediction results are presented in Figure 6, and the performance of each model was quantitatively evaluated (Appendix 5). The results indicate that the GCN model outperformed the other two models. This finding is consistent with Ma et al. (2024), who reported that Graph Neural Network-based models are more adaptive to heterogeneous patterns and spatial topologies that conventional tabular models cannot capture.

Figure 7.
Predicted Maps from XGBoost, Random Forest, GCN, and FPS



Source: Bapanas (2025) and BPS (2025)

Although the GeoAI model exhibited superior predictive performance, it does not provide explicit insights into the localized spatial relationships between predictor variables and Food Production Security (FPS). Consequently, a follow-up spatial analysis was conducted to capture spatial variation in the influence of predictors across villages and municipalities in DI Yogyakarta.

The inferential analysis began with the construction of an Ordinary Least Squares (OLS) model, serving as a baseline that does not incorporate geographic factors in its parameter estimation. Based on classical assumption tests (Appendix 6), the OLS residuals exhibited significant spatial autocorrelation (Moran's I p-value = 0.0010) and non-normal distribution (Jarque–Bera p-value = 7.14e–114).

Despite the non-normality, the Central Limit Theorem (CLT) suggests that coefficient estimates may still approximate a normal distribution given the large sample size (n = 438). Additionally, no heteroskedasticity was detected (Breusch–Pagan p-value = 0.9163), and all predictor variables had VIF values below 10, indicating no multicollinearity.

On the other hand, comparative evaluation of spatial models (Appendix 7.) revealed that the Geographically Weighted Regression (GWR) model performed better empirically, as indicated by lower AIC and BIC values and higher pseudo-R^2.

Although the Multi-scale Geographically Weighted Regression (MGWR) model yielded slightly lower performance metrics than GWR, it refines the GWR approach by applying variable-specific bandwidths, allowing for the detection of multi-scale spatial influence structures (Fotheringham et al., 2017).

Based on both theoretical considerations and empirical evidence, this study adopts MGWR as the primary model, as it better captures multi-scale spatial dependencies and heterogeneous spatial variation across the study area. Based on Table 2, farmers receiving extension services, annual rainfall, presence of waste banks or recycling facilities, and promotion of organic fertilizer and recycling exhibit significant global effects at the 5% significance level. The varying bandwidths indicate that each variable exerts different influences across locations.

For instance, the presence of waste banks or recycling facilities and the promotion of organic fertilizer and recycling have small bandwidths, suggesting intense and localised effects in specific areas, whereas farmers receiving extension services and annual rainfall have larger bandwidths, indicating relatively uniform impacts across regions.

Table 1.
Result of the MGWR Model

Variable	Est.	p-value	Bandwidths	p-value
Intercept	0.286	0.000	437.000	0.049*
Farmer_ext_serv	0.001	0.000*	398.000	0.045*
Credit_agr	0.000	0.936	136.000	0.025*
Farmer_mod_tech	0.002	0.280	435.000	0.050*
Cooperative_act	-0.000	0,642	437.000	0.047*
Rain_mm	-0.000	0.005*	437.000	0.049*
Num_bts	-0.002	0.114	421.000	0.049*
Waste_3r_wb	-0.032	0.000*	43.000	0.010*
Fert_org_recyc	0.027	0.004*	43.000	0.010*
Log-Likelihood			501.119	
AIC			-963.756	
AICc			-961.892	
BIC			-885.211	
(Pseudo) R^2			0.116	
Adj. R^2			0.090	

*) Significance 5%

Source: Bapanas (2025) and BPS (2025)

Furthermore, the summary of parameters in Table 2 shows that the presence of waste banks/recycling facilities has the highest negative coefficient distribution (Min = -0.078; Max = -0.031; Mean = -0.057), indicating a consistent adverse effect on production security in most areas. This likely reflects suboptimal management or the limited capacity of temporary waste-disposal sites to support agricultural production. In contrast, promotion of organic fertilizer and recycling exhibits a dual directional effect, with a positive mean (Mean = 0.026; Max = 0.045) and a slight negative minimum (Min = -0.011), highlighting the importance of promoting organic fertilizer use to enhance production sustainability consistent with FAO (2023) and Gautama et al. (2020) while also acknowledging potential negative impacts due to land type, crop selection, or improper application rates (Thomas et al., 2019).

Specifically, the positive and significant coefficient for farmers receiving extension services ($\beta = 0.001$; $p < 0.01$) indicates that intensified farmer extension and mentoring programs significantly increase local food production capacity (Shibli et al., 2021; Zhang et al., 2023). This aligns with Debertin (2012), who emphasized that enhancing human capital through agricultural education and extension can reduce knowledge gaps and promote technology adoption across regions.

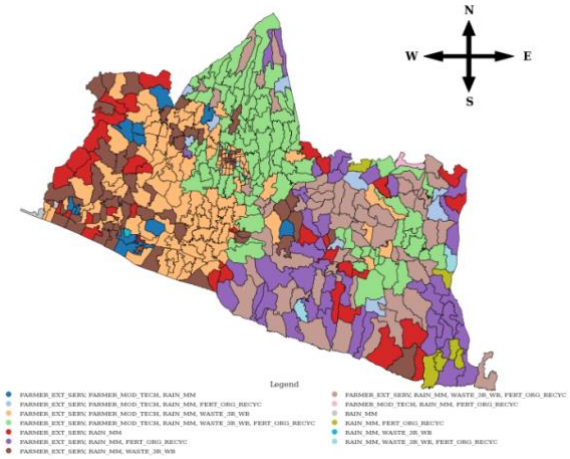
Table 2.
Summary of MGWR Model Testing Results

Variable	Min	Mean	Median	Max
Intercept	0,232	0,232	0,232	0,233
Farmer_ext_serv	0.001	0.001	0.001	0.001
Credit_agr	-0.000	-0.000	-0.000	0.000
Farmer_mod_tech	0.004	0.004	0.004	0.004
Cooperative_act	-0.000	-0.000	-0.000	-0.000
Rain_mm	-0.000	-0.000	-0.000	-0.000
Num_bts	-0.001	-0.001	-0.001	-0.001
Waste_3r_wb	-0.078	-0.057	-0.054	-0.031
Fert_org_recyc	-0.011	0.026	0.030	0.045

Source: Bapanas (2025) and BPS (2025)

Conversely, Rain_mm (β = -0.000; p < 0.01) and Waste_3r_wb (β = -0.032; p < 0.01) show significant negative impacts on production security. These results corroborate findings by Bouxine (2024) and Ericksen (2008), which assert that extreme rainfall and inadequate waste management can disrupt food production stability, particularly in flood-prone areas such as parts of Sleman and Kulon Progo.

Figure 8.
Spatial Visualization of Different Sets of Significant Variables on FPS at the Village Level



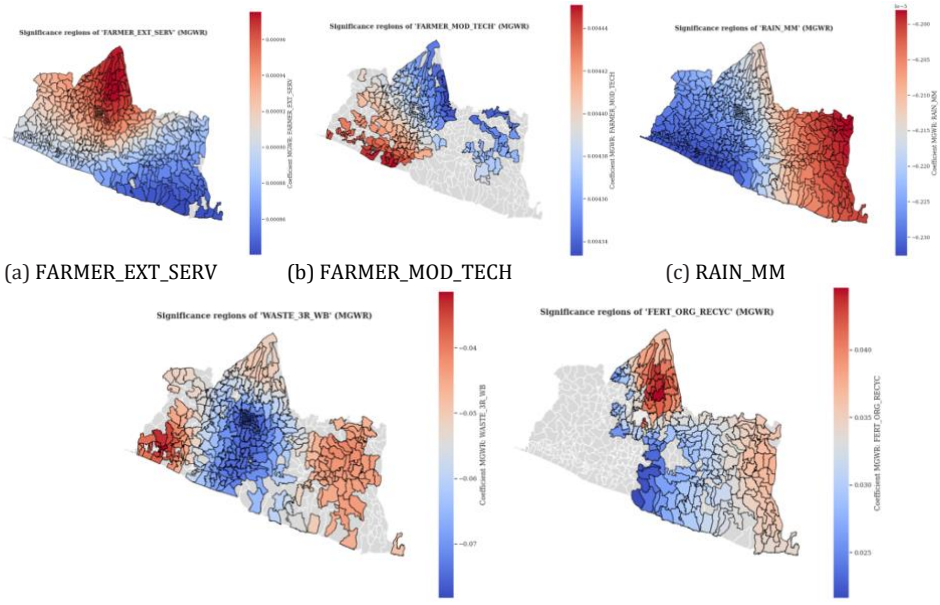
Source: Processed by Author

Additionally, recycling or waste bank initiatives primarily focus on household waste management, with limited application in agriculture (e.g., compost production), often constrained by technical and economic challenges, thereby limiting sustainability (Asteria & Heruman, 2016). Poorly managed facilities may also create potential land-use conflicts and local environmental pollution (Arifa et al., 2019; Makmur et al., 2013).

Figure 8 further illustrates that farmers receiving extension services exert a significantly positive influence in northern areas, particularly in Sleman Regency and parts of the northwest. This underscores the critical role of field extension and mentoring in enhancing farmers' capacity to adopt technological innovations and sustainable cultivation practices (Debertin, 2012; Shibli et al., 2021).

Conversely, southern and southeastern areas (southern Bantul and Gunungkidul) exhibit lower influence, indicating the need to strengthen extension capacity in these regions. Intensive institutional support through programs already implemented in Yogyakarta, such as Farmer Field Schools, Lumbung Mataraman, and Technical Guidance by DI Yogyakarta Agriculture Office, should be expanded and prioritized in areas with high agricultural potential but low local food production security scores.

Figure 9.
Spatial Distribution of Parameter Estimates



(a) FARMER_EXT_SERV (b) FARMER_MOD_TECH (c) RAIN_MM

(d) WASTE_3R_WB (e) FERT_ORG_RECYC

Source: Processed by Author

Regarding the variable annual rainfall, it shows a significant negative effect, concentrated in the eastern and southeastern areas, including the northern and central Gunung Kidul Regency. These regions are vulnerable to rainfall fluctuations, which can disrupt production stability, particularly on dry, sloping lands with limited irrigation infrastructure (Ericksen, 2008; Bouxine, 2024).

Therefore, optimizing the presence of water reservoirs and integrating irrigation systems suited to the topography of drylands, along with enhancing farmers' adaptive capacity to technological solutions, is necessary to mitigate climate risks.

Meanwhile, the variable adoption of modern agricultural technology shows a significant positive effect in the northwest (parts of Sleman and Kulon Progo) and in the southern and eastern areas (southern Bantul and southwestern Gunung Kidul).

This suggests that the implementation of modern agricultural technologies such as hydroponics, aquaponics, and other innovations can help maintain food production security, particularly in densely populated or land-constrained regions. These findings are consistent with De Sousa et al. (2023), who highlighted that home-based hydroponic systems can bring food production closer to consumers and reduce dependence on vulnerable supply chains.

From an environmental management perspective, WASTE_3R_Wpresence of waste management facilities, recycling centres, or waste banks) is dominated by negative coefficients across most western areas (Kulon Progo and Bantul), central areas (Yogyakarta City and Gunung Kidul), and northern areas (Sleman). This indicates that the integration of waste management facilities with agricultural production systems remains suboptimal.

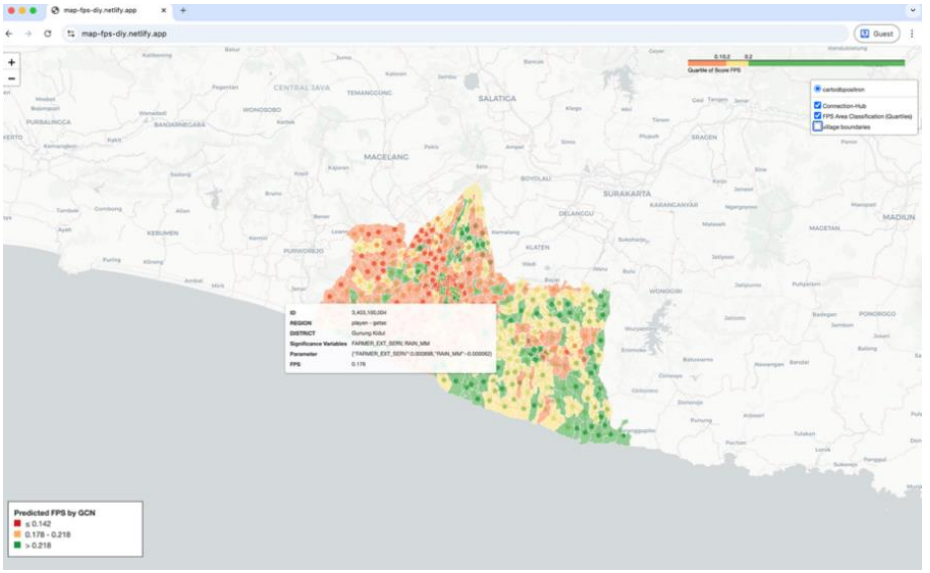
Consequently, it may lead to land-use conflicts, local pollution, and limited utilization for agriculture, thereby reducing the contribution of temporary waste disposal sites to FPS (Asteria & Heruman, 2016; Arifa, Cita, & Ilman, 2019; Makmur et al., 2013). Therefore, evaluating usage, optimizing spatial planning, and integrating temporary waste-disposal sites with agricultural programs, such as utilising organic waste for farming, are essential.

Additionally, promotion of organic fertilizer and recycling shows a significant positive effect in northern Sleman and parts of eastern Gunung Kidul, indicating that agricultural practices emphasizing organic fertilizer use and waste recycling can enhance food production security (Gautama et al., 2020; FAO, 2023). This aligns with ongoing organic agriculture initiatives in Sleman (Antaranews, 2023). Conversely, parts of Bantul show negative coefficients, suggesting the need for context-specific strategies. This highlights the importance of evaluating organic fertilizer and recycling practices considering topography, crop type, and application rates (Thomas et al., 2019), particularly given that the average FPS in Bantul is below the regional mean for DI Yogyakarta.

Overall, these maps confirm that no single factor dominates across the entire region. Instead, food production security in each village is influenced by a unique combination of climate factors (rainfall), capital (extension services), production infrastructure (modern technology use, organic fertilizer), and environmental management (temporary waste disposal sites), consistent with findings by Meng & Liu (2025).

Finally, to facilitate interpretation and support the formulation of place-based policies, this study provides a web-based dashboard (currently in prototype development) that offers open access to maps of significant variable coefficients for each area (Figure 10). This tool is designed to directly support more targeted and adaptive food and agricultural policy planning, in alignment with the diverse characteristics of villages and cities across DI Yogyakarta.

Figure 10.
Dashboard for Food Production Security in DI Yogyakarta, 2023



Source: Processed by Author

4. Conclusion

Ensuring food production security is a crucial priority in areas with limited resources and ecological pressures. The findings of this study, which measures food production security (FPS) at the village level in DI Yogyakarta, offer additional insights into a more precise evaluation approach for ensuring sustainable food production, as well as a method for diagnosing inequalities in production access between rural and urban areas. The conclusions of this study are as follows:

First, the quantity and quality of production inputs such as support for production equipment, access to food supply facilities, seed availability, alignment with local potential, and technical assistance remain the most decisive factors in determining interregional production security. Food Production Security index in urban areas is consistently higher than in rural areas, primarily due to differences in access to production inputs and supporting facilities.

Factors such as agricultural extension services, adoption of modern technology, and fertilizers and recycling programs contribute positively to the FPS index. At the same time, high rainfall and the presence of waste management facilities exhibit adverse effects in several locations. Moreover, the influence of these factors varies locally, particularly in Sleman, Kulon Progo, Bantul, and Gunung Kidul, highlighting the need for context-specific approaches to strengthening FPS. These findings reinforce that variations in input capacity, infrastructure quality, and ecological conditions across regions strongly shape food production security at the village level. Accordingly, this study provides a strong empirical foundation for the design of more adaptive food production policies. It can serve as a reference for other regions facing similar challenges in enhancing their production capacity.

Based on these findings, several policy recommendations can be proposed. First, improving access to production inputs and basic infrastructure should be prioritized, especially in lagging rural areas. Second, the expansion of agricultural extension programs and the adoption of modern technologies should target villages with low FPS but high production potential. Third, the optimization of supporting infrastructure, such as irrigation systems, reservoirs, and waste management facilities, must be strengthened so that ecological risks do not diminish local production capacity. Lastly, strategies to enhance FPS should account for spatial variation, allowing interventions to be tailored to the socio-economic and ecological characteristics of each area within DI Yogyakarta.

Possible limitations of this study include, first, the limited availability of village-level data that constrained both the temporal scope and the number of variables that could be analyzed. Future research could benefit from datasets with more extended time spans to enhance the validity and generalizability of the findings. Second, household-level analysis is needed to deepen understanding of actual food production security practices and to enable a more comprehensive exploration of FPS dynamics across the entire study area.

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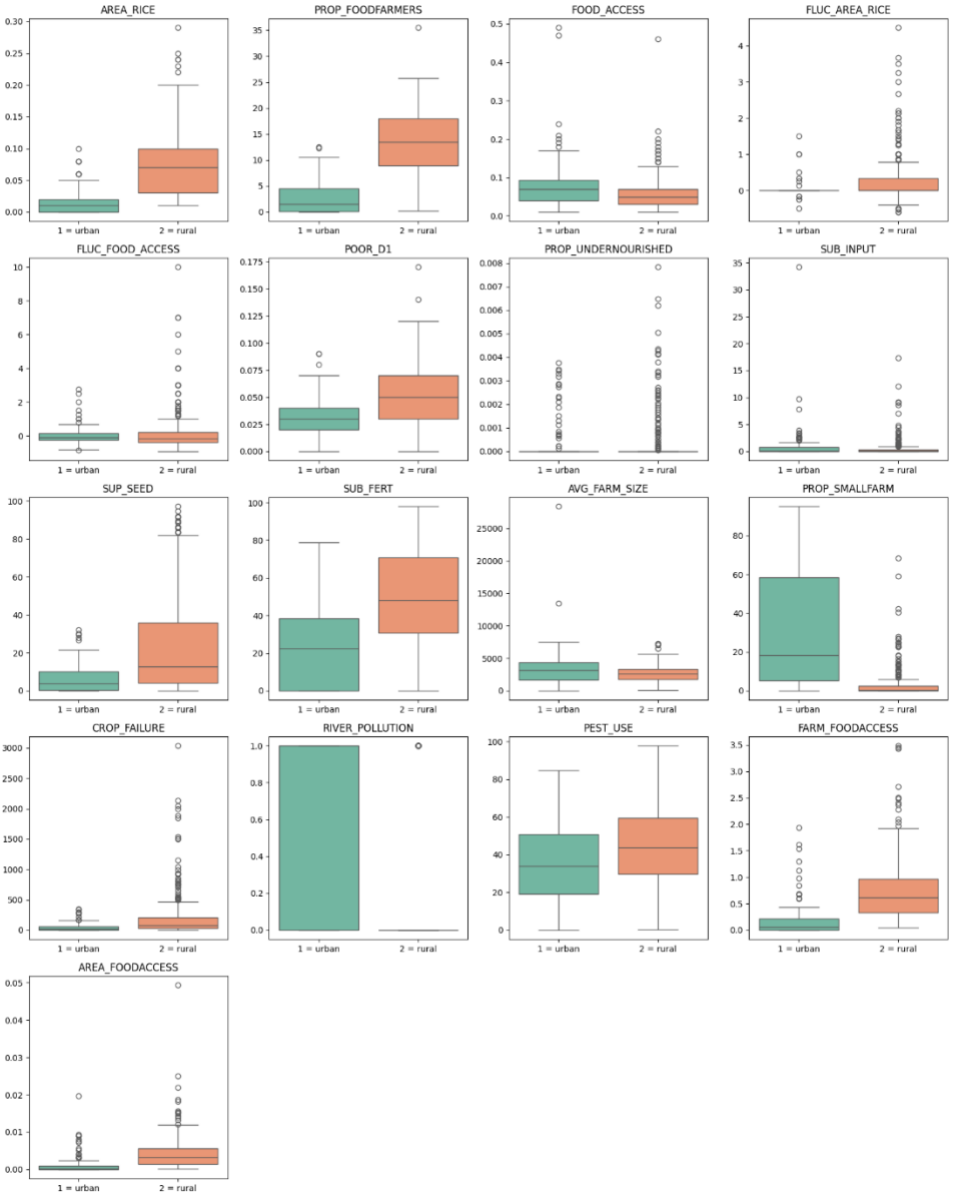
Appendix 1. Definition, Data Sources, and References of Research Variables

Dimension	Indicators	Data Sources	Reference
Core Variables for Food Production Security (FPS) Score			
Quantity	Output		
	(+) Staple food availability (AREA_RICE) ✓ Ratio of rice field area to land area	Bapanas (FSVA 2024)	Bapanas (2022), FAO (2021)
	(+) Farmers (PROP_FOODFARMERS) ✓ Proportion of food crop farmers to total population	BPS (ST2023)	Sajidin et al (2023), Peña-Rodríguez et al. (2023)
	Transferability		
	(+) Food distribution access(FOOD_ACCESS) ✓ Number of food outlets /total household	Bapanas (FSVA 2024)	Bapanas (2022)
	(+) Distribution access and farmers interaction (FARM_FOODACCESS) ✓ Farmer proportion x food distribution access	BPS (ST2023), Bapanas (FSVA 2024)	FAO (2023), Barrett (2008)
	(+) Land availability and distribution access interaction (AREA_FOODACCESS) ✓ Staple food availability x food distribution access		FAO (2020), Gollin (2021)
	Stability		
	(+) Dynamics of agriculture land capacity (FLUC_AREA_RICE) ✓ Change in staple food availability (2024 - 2021)/2021	Bapanas (FSVA 2021, 2024)	Peña-Rodríguez et al. (2023)
	(+) Dynamics of distribution access (FLUC_FOOD_ACCESS ✓ Change in food distribution access (2024-2021)/2021		Peña-Rodríguez et al. (2023)
Quality	Demand		
	(-) Vulnerability of Socioeconomic (POOR_D1) ✓ Ratio of poor people in decil 1 / total population	Bapanas (FSVA 2024)	Bapanas (2022), FAO et al. (2022)
	(-) Vulnerability of Food Consumption (PROP_UNDERNOURISHED) ✓ Proportion of undernourished and food-insecure population / total population	BPS (PODES 2024)	FAO et al. (2022)
	Food Quality		
	(+) Strengthening farmers' capacity (SUB_INPUT)	BPS (ST2023)`	OECD/FAO (2022)

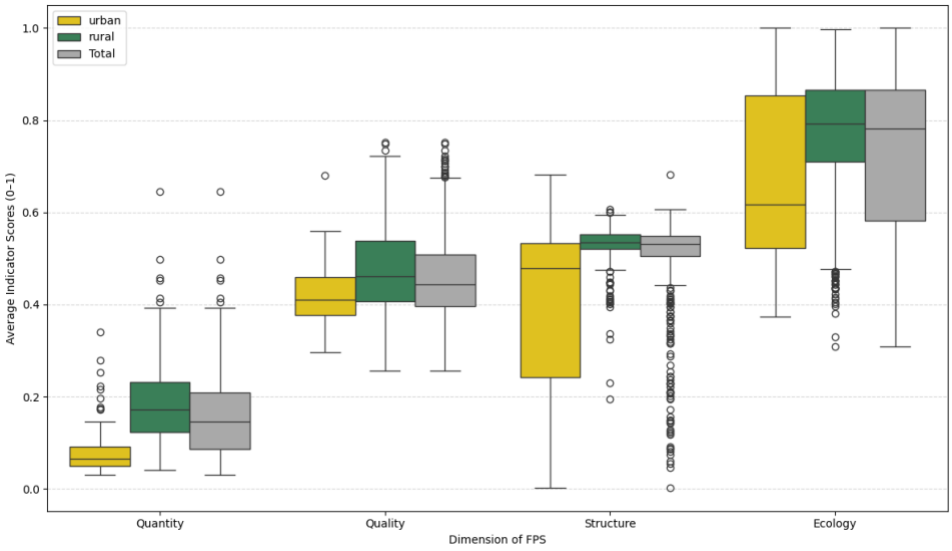
Dimension	Indicators	Data Sources	Reference
	✓ Proportion of farmers receiving subsidized agricultural inputs and infrastructure support to total farmers		
	(+) Resilience of crop varieties and yields (SUP_SEED) ✓ Proportion of farmers receiving seed assistance to total farmers	BPS (ST2023)	OECD/FAO (2022)
	(+) Agricultural productivity (SUB_FERT) ✓ Proportion of farmers receiving subsidized fertilizers to total farmers	BPS (ST2023)	OECD/FAO (2022), Meng & Liu (2025)
Structure	Planting Structure		
	(+) Farm size (AVG_FARM_SIZE) ✓ Average food crop cultivated area per agricultural holding	BPS (ST2023)	Gollin (2021), Meng & Liu (2025)
	(-) Small-Scale Production (PROP_SMALLFARM) ✓ Proportion of farmers with land < <0,2 ha	BPS (ST2023)	Gollin (2021)
Ecological	Pollutan Intensity		
	(-) Crop failure (CROP_FAILURE) ✓ Proportion of farmers affected by ecological disasters such as crop failure, insect, and pest infestation	BPS (ST2023)	FAO (2023)
	(-) (RIVER_POLLUTION) ✓ River pollution status (1: yes ; 0:no)	BPS (PODES 2024)	FAO (2020), FAO (2023), Satterthwaite et al (2010)
	(-) Environmental degradation risk (PEST_USE) ✓ Proportion of farmers using pesticides to total farmers	BPS (ST2023)	Meng & Liu (2025)
	Predictor Variables		
Financial Modal	CREDIT_AGR ✓ Percentage of farmers with access to agricultural credit	BPS (ST2023)	Haryanto et al., 2023
Social Modal	FARMER_EXT_SERV ✓ Percentage of farmers receiving agricultural extension services	BPS (ST2023)	Zhang et al. (2023), Shibli et al. (2023)
Economic Modal	COOPERATIVES_ACT ✓ Number of active agricultural cooperatives and village-owned enterprises in the agricultural sector	BPS (PODES 2024), Kemendesa (SIDesa 2024)	Haryanto et al., 2023
	INPUT_AGR_STORE ✓ Availability of agricultural input and equipment shops/stores (1: yes, 0: no)	BPS (PODES 2024)	Zhang et al. (2023), Shibli et al. (2023)

Dimension	Indicators	Data Sources	Reference
	CREDIT_FOOD_ENERGY ✓ Availability of credit facilities for food and energy security (1: yes, 0: no)	BPS (PODES 2024)	Haryanto et al., 2023
Teknologi – Skill & Infrastructure	NUM_BTS ✓ Number of Base Transceiver Station	BPS (PODES 2024)	Purwanto et al. (2022); Zhang et al. (2023)
	FARMER_MOD_TECH ✓ Percentage of agricultural holdings using modern technologies (hydroponics, aquaponics, etc.)"	BPS (ST2023)	Shibli et al. (2023); Nugraha et al. (2022)
Climate	RAIN_MM ✓ Average annual rainfall (mm/year)	CHIRPS	Bouxine (2024) dan Ericksen (2008)
	NUM_DISAST ✓ Number of ecological disaster events (landslides to droughts)	BPS (PODES 2024)	Meng & Liu (2025)
Culture and Management Waste	FERT_ORG_RECYC ✓ Existence of programs promoting organic fertilizer use and waste recycling (1: yes, 0: no)	BPS (PODES 2024)	FAO (2023), Gautama et al (2020), Thomas et al (2019)
	WASTE_3R_WB ✓ Existence of temporary waste disposal sites tps3r facilities, or waste banks (1=yes, 0=no)"	BPS (PODES 2024)	Bouxine (2024) dan Ericksen (2008)
	HOUSEHOLD_WASTE ✓ Main household waste disposal method (1 = river/drainage/pit/burning/irrigation/other, 0 = collected/transported)	BPS (PODES 2024)	Shibli et al. (2023); Nugraha et al. (2022)
	COMM_PARTICIPATE ✓ Community participation in collective work ((1 = yes, 0 = no)	BPS (PODES 2024)	Zhang et al. (2023), Shibli et al. (2023)

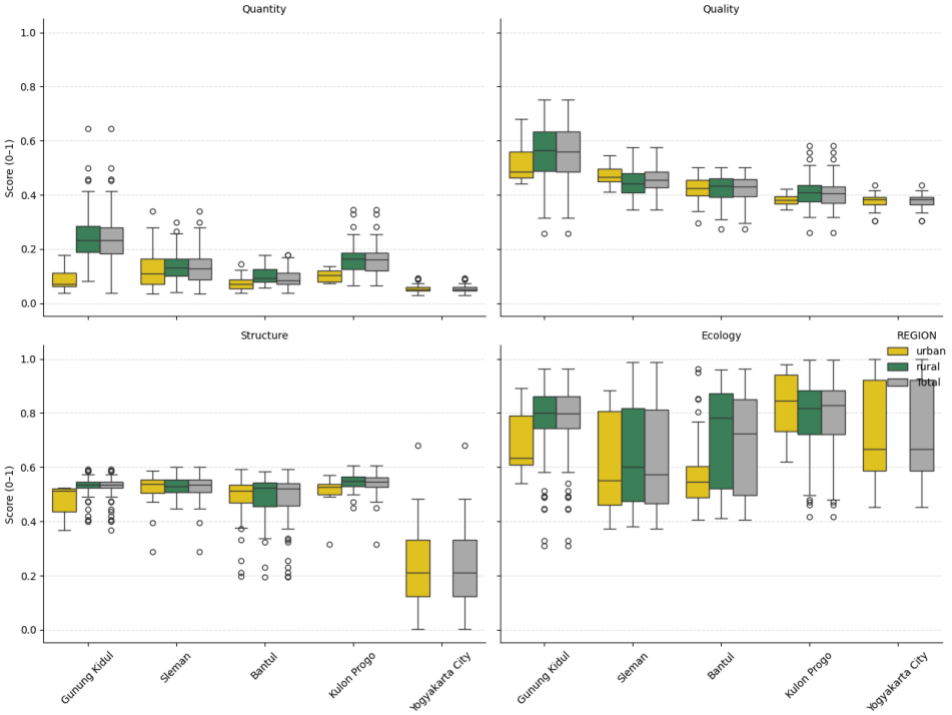
Appendix 2. Distribution of FPS Indicators by Area Type



Appendix 3. Distribution of Dimension Scores by Area Type



Appendix 4. Distribution of FPS Dimension Scores per Regency/City by Area Type



Appendix 5. Model Evaluation Results for Random Forest, XGBoost, and GCN

Model GeoAI	RMSE	MAE
Random Forest	0.07994	0.05915
XGBoost	0.08224	0.06138
GCN	0.06821	0.04905

Appendix 6. Classical Assumption Test Results for the OLS Model

Assumptions	Test	P-value	Conclusion
Autocorrelation	Moran's I Test	0.001	Autocorrelation of Residuals
Normality	Jarque-Bera Test	< 0.001	Non-Normality of Residuals
Heteroskedasticity	Breusch Pagan Test	0.916	Homoscedasticity of Residuals

Multicollinearity		
Variable	VIF	Conclusion
FARMER_EXT_SERV	1.025	VIF<10, Non- Multicollinearity
CREDIT_AGR	1.056	
FARMER_MOD_TECH	1.137	
COOPERATIVES_ACT	1.127	
RAIN_MM	1.049	
NUM_BTS	1.142	
WASTE_3R_WB	1.083	
FERT_ORG_RECYC	1.116	

Appendix 7. Comparison of Spatial Model Evaluation Results

Model	OLS	SAR	SEM	GWR	MGWR
Log-Likelihood	484.984	491.294	490.457	503.861	501.119
AIC	-951.968	-962.588	-962.915	-966.079	-963.756
AICc	-949.453	–	–	-963.896	-961.892
BIC	-2.606.471	-921.766	-926.175	-881.081	-885.211
(Pseudo) R^2	0,072	0,0972	0,071	0,12361111	0,116
Adj. R^2	0.087	–	–	0,096	0,090
Notes	–	Significant Rho	Significant Lambda	Single Bandwidth,	Variable-Specific Bandwidth, Capturing Heterogeneity per Predictor