Spatial Model for Food Security in Eastern Indonesia 2024

F N Shohwah, I F Arufi, M I Wicaksono, N L Meilawati, N C Meilani, and G P D Sohibien*

Politeknik Statistika STIS, Program Studi D-IV Statistika, West Jakarta, Indonesia

*Corresponding author's email: gamaputra@stis.ac.id

Abstract. Food security is the condition of meeting food needs for the country down to the individual level, as measured by the availability, affordability, utilization, and stability of food. Despite being a basic human need, food security in Indonesia is not evenly distributed, especially in Eastern Indonesia. Based on these findings, this study aims to provide a general picture of food security and the factors influencing it in districts/cities across Eastern Indonesia in 2024. The method used is the Spatial Durbin Model (SDM) with an inverse distance weighting matrix. The results show that the variables Distribution of GRDP of Sector Agriculture, Forestry and Fishing, Poverty Rate, Average Years of Schooling, Lag of Food Security Index, Lag of Open Unemployment Rate, and Lag of Poverty Rate have a significant influence on the Food Security Index variable in districts/cities in Eastern Indonesia in 2024.
Keywords: Eastern Indonesia, food security, spatial, spatial durbin model.

1. Introduction

Food is a basic human need. In Maslow's (1954) hierarchy of needs, food is part of psychological needs, namely the basic human needs for survival, including clothing and shelter [1]. The right to food is stated in the 1996 Rome Declaration. The declaration states that everyone has the right to access safe and nutritious food, underscoring the need for continuous efforts to overcome hunger and achieve food security. In Indonesia itself, the 1945 Constitution of the Republic of Indonesia also states that everyone has the right to a decent living. Therefore, it is the government's obligation to guarantee the fulfillment of the right to food for its citizens.

Act 18/2012 regulated food security in Indonesia, which is the condition of fulfilling food needs for the country, down to the individual level. The benchmark for fulfilling food needs includes four aspects, namely: (a) quantity, (b) quality (safe and nutritious), (c) spiritual food security (not contrary to religion, beliefs, and culture of the community), and (d) economic affordability. These aspects must be achieved so that people, down to individuals, can live healthy, active, and productive lives in a sustainable manner [2]. An indicator that can be used to measure the quality of fulfilling human food needs is food security. According to the FAO (Food and Agriculture Organization), food security is a condition in which all people, at all times, have physical, social, and economic access to sufficient, safe, and nutritious food that meets their nutritional needs and food preferences for an active and healthy life [3].

Food security consists of several key dimensions that have been globally agreed upon. According to the FAO, these dimensions are food availability, affordability, utilization, and stability. Food availability is a condition where food is available in terms of quantity and quality, both domestically and through imports. Food affordability is the ease of access for individuals to obtain adequate food resources that meet dietary needs. Food utilization is a condition where the food resources obtained can meet human physiological needs. Whereas food stability is a condition in which the previous indicators are met continuously so that individuals do not lose food security despite shocks (both economic and seasonal) [3].

Historically, food security policies have had varying approaches. During the Old Order era, food policy focused on ensuring adequate domestic rice production, namely rice self-sufficiency. During the New Order era, the government focused on empowering farmers and developing agricultural infrastructure. During the era of President Susilo Bambang Yudhoyono, the range of commodities expanded to include rice, corn, sugar, nuts, and meat. President Joko Widodo’s administration also focused on food self-sufficiency, followed by several programs such as rice development, farmer corporations, and community food barns [4].

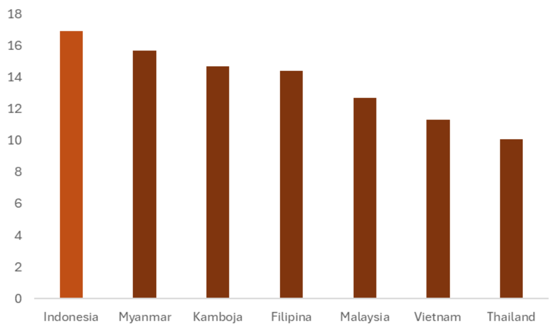


Figure 1. Global Hunger Index for Indonesia and 6 Southeast Asian countries in 2024.

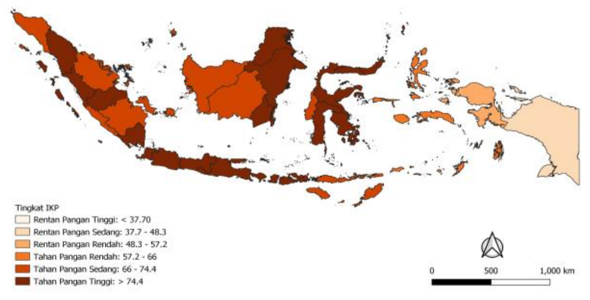


Figure 2. Distribution of the Food Security Index by province in Indonesia in 2024.

Despite government efforts and Indonesia’s reputation as an agricultural nation, Indonesia is still left behind its neighbors in Southeast Asia. Based on the 2024 Global Hunger Index, Indonesia had an index of 16.9, the highest among the seven countries compared. This lag can be further examined at the regional level within Indonesia [5]. Figure 2 shows that there is inequality in food security levels, especially in eastern Indonesia. The five provinces with the highest food security are Bali (88.23), Central Java (85.34), DKI Jakarta (85.13), West Sumatra (84.32), and DI Yogyakarta (84.15). Meanwhile, the five provinces with the lowest food security are Central Kalimantan (70.16), Riau Islands (66.29), Maluku (62.68), North Maluku (61.44), West Papua (51.36), and Papua (40.21) [6].

This gap in food security levels is an early indication of spatial dependence, in which areas with high levels of food security are also surrounded by areas with high levels of food security. Meanwhile, areas with food insecurity are concentrated in eastern Indonesia. This gap arises from unequal access to food, differences in geographic conditions, and educational levels within a region. This has been proven by previous research, which found that the open unemployment rate, poverty rate, and economic growth influenced the prevalence of food insufficiency in Indonesia in 2022 [7]. Food security in Papua Island in 2022 was also influenced by the poverty rate, the open unemployment rate, and the average length of schooling [8].

Eastern Indonesia, as the most vulnerable region, requires special attention. Therefore, spatial analysis is needed in Eastern Indonesia to develop more targeted policies tailored to the conditions of each region. However, previous studies still used a contiguity-based spatial weighting matrix, while Indonesia, especially Eastern Indonesia, is an archipelago, meaning many areas will have no neighbors. This study offers a novelty by using an inverse distance spatial weighting matrix, which assigns weights to the entire observation area, with the magnitude depending on the relative distance to other regions. This study was conducted at a single point in time (2024), so the food stability dimension (measured temporally) could not be assessed. However, the food stability dimension can be represented by the availability and affordability dimensions [4]. This study aims to provide a general overview of food security and the factors influencing it in districts/cities across Eastern Indonesia in 2024.

2. Research Method

2.1 Data Source

The data used in this study are secondary data from the Ministry of Agriculture and Forestry and Statistics Indonesia. The data used is the 2024 food security index in Eastern Indonesia. Computer programs used to support the research process include GeoDa, R, and QGIS.

2.2 Variables Used

The variables used in this study are divided into two categories: dependent and independent variables. The dependent variable of this study is the Food Security Index (FSI), with its predictor variables being Distribution of GRDP on Sector Agriculture, Forestry and Fishing (GRDP A), GRDP Per Capita (GRDP), Open Unemployment Rate (OUR), Poverty Rate (Poverty), and Average Years of Schooling (AYS).

2.3 Analysis Method

Descriptive analysis is the process of describing the state of data in simple terms. In this study, descriptive analysis was conducted using thematic maps to obtain a general overview of the distribution of food security in districts/cities in Eastern Indonesia in 2024.

Inferential analysis is conducted to meet the second research objective: to identify the variables influencing food security in districts/cities in Eastern Indonesia in 2024. The inferential analysis in this study used spatial regression analysis. The procedure for obtaining the spatial regression model used in the study is as follows:

1. Data processing with OLS regression
2. Testing classical assumptions in the OLS regression model
   Based on the formation of the model, regression analysis using the OLS method requires the fulfillment of classical assumptions, the testing of which is as follows:
   - Normality assumption test
     This study uses the Shapiro-Wilk test to test normality. This study refers to the Central Limit Theorem, which states that a large random sample will approach normal distribution.
   - Homoscedasticity assumption test
     This study uses the Breusch Pagan test to see whether there is heteroscedasticity or not. If the assumption is met, then area-based spatial modeling will be continued. If the assumption is violated, it is continued using point modeling.
   - Non-autocorrelation assumption test
     This study uses the Durbin-Watson test to see whether there is autocorrelation or not.
   - Multicollinearity check
     This study uses the VIF test; if the VIF value <10 then the multicollinearity assumption is met.

3. Create a weighting matrix
   Spatial weight matrices, often called W matrices, can be formed with various weighting techniques. This study uses an inverse distance matrix. Weighting with inverse distance is done based on the actual distance between locations. Nearby locations get a larger weight value, while distant locations get a smaller weight [9]. The following is the inverse distance matrix formula:

$$W_{ij} = \frac{c(1+d_{ij})^{-a}}{\sum_{i \neq j} c(1+d_{ij})^{-a}} \tag{1}$$

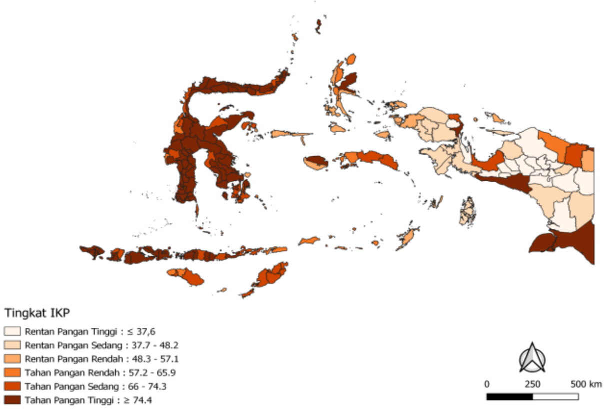
   where $i \neq j$ and satisfies $\sum_{i \neq j} W_{ij} = 1$
4. Testing spatial dependency with Moran's I, and continued with Lagrange Multiplier (LM) Test and Robust Test
5. Selecting the best model
   In this modeling, we use six spatial models, including SAR, SEM, SARMA, SDM, SDEM, and GNS as a comparison to determine the best model. The selection of the best model uses AIC based on the smallest AIC value. In this study, the model with the smallest AIC was obtained, namely the SDM model. The Spatial Durbin Model (SDM) is a spatial regression model that not only has spatial lag in the response variable but also in the predictor variable. The form of the SDM model has the following equation:

$$Y = \rho WY + a + X\beta + WX\theta + \varepsilon \tag{2}$$

   Description:
   Y : vector of response variables n *x 1*
   X : matrix of predictor variables n *x* k
   ρ : spatial lag coefficients of response variables
   α : vector of constant parameters n *x 1*
   W : spatial weighting matrix n *x* n
   β : vector of regression parameters k *x 1*
   θ : vector of spatial lag parameters of predictor variables k *x 1*
   ε : vector of errors n *x 1*
6. Test of parameter significance

3. Result and Discussion

3.1 Overview of the food security index in eastern Indonesia in 2024



.

Figure 3. Distribution of Food Security Index Variables.

Figure 3 shows the Food Security Index (FSI) levels of districts/cities in Indonesia, grouped into six categories. Most areas categorized as "High Level of Food Security" are spread across Sulawesi Island, Bali, and several districts in West Nusa Tenggara and southern Papua. Meanwhile, areas with low to very vulnerable food security are more common in northern and central Papua and North Maluku. The distribution of FSI values shows a clustered pattern, with areas of high food security tending to be concentrated in Sulawesi and parts of the southern region, while areas of low food security are more concentrated on the north and east sides of Eastern Indonesia.

3.2 Factors influencing food security in districts/cities in eastern Indonesia using the OLS regression model

Table 1. OLS regression parameter estimates.

Variable	*Estimate*	Std. *Error*	*p-value*
Intercept[a]	64.8389	7.2729	5.55e-16
GRDP A[a]	0.1696	0.0639	0.0088
GRDP	0.0047	0.0092	0.6071
OUR	-0.5834	0.5797	0.3156
Poverty[a]	-1.3471	0.1228	< 2e-16
AYS[a]	2.5085	0.7499	0.0010

[a] Significant at $\alpha = 5\%$

Furthermore, the parameter estimates obtained using the OLS method must satisfy the Best Linear Unbiased Estimator (BLUE) properties [10]. Therefore, it is crucial to test and examine the applicable classical assumptions.

- Normality Assumption
  In this study, the number of observations used is relatively large ($n > 30$), so based on the Central Limit Theorem (CLT), the residual distribution can be considered approximately normal even though the original distribution is not. Therefore, the residual normality assumption remains acceptable, and the regression model analysis remains valid for further analysis.
- Multicollinearity Check
  The VIF values obtained were lower than 10 for all independent variables, indicating no significant multicollinearity among the independent variables used.
- Homoscedasticity Assumption
  The test results indicate that the homoscedasticity assumption is met, as indicated by the Breusch-Pagan's p-value of 0.0726, which is greater than the 0.05 significance level. This suggests that the error variance is constant, indicating the absence of heteroscedasticity.
- Non-autocorrelation assumption
  The non-autocorrelation assumption was not met because the Durbin-Watson test produced a very small p-value of 3.81e-08, less than 0.05, indicating the presence of autocorrelation in the model residuals, making classical regression modeling less appropriate.

To determine whether there was a spatial pattern in the variables used in this study, a spatial autocorrelation test was conducted using the Moran's I index. This test aims to determine the extent to which the value of a variable in a region correlates with the value of the same variable in surrounding regions.

Table 2. Moran's I test.

Variable	Moran's I	*p-value*
Intercept[a]	0.4082	0.0000
GRDP A[a]	0.0837	0.0000
GRDP	0.0017	0.2448
OUR	0.1110	0.0975
Poverty[a]	0.3707	0.0000
AYS[a]	0.1668	0.0000
Residual OLS Model[a]	0.1541	< 2.2e-16

[a] Significant at $\alpha = 5\%$

Based on the results of the Moran's I test presented in Table 2, it can be concluded that the Food Security Index, Percentage of GRDP Sector A, Poverty Rate, and Average Years of Schooling show significant spatial relationships between regions. In contrast, GRDP Per Capita and the Open Unemployment Rate do not show significant spatial relationships. This spatial relationship indicates that regions with similar characteristics in food security, Percentage of GRDP Sector A, Poverty Rate, and Average Years of Schooling are often close to other regions with similar characteristics.

Table 3. Spatial dependency testing with LM test.

Spatial Dependency Testing	Statistics	*p-value*
Lagrange Multiplier *(lag)*	113.204	< 2.2e-16
Lagrange Multiplier *(error)*	108.723	< 2.2e-16
Robust Lagrange Multiplier *(lag)*	41.566	1.140e-10
Robust Lagrange Multiplier *(error)*	37.084	1.131e-09
Sarma	150.288	< 2.2e-16

Based on the results of the Lagrange Multiplier (LM) test in the table, it was found that both the LM lag and LM error were significant, with p-values of each less than 0.05. This indicates that there is spatial dependence in the data, both in the form of spatial lag and error. Furthermore, the Robust Lagrange Multiplier test also showed significant results for both types of models, namely Robust LM lag (p-value = 1.140e-10) and Robust LM error (p-value = 1.131e-09).

Table 4. Selection of the best model.

Spatial Model	AIC
SAR	1354.044
SEM	1366.162
SARMA	1347.576
SDM[a]	1339.219

SLX	1346.179
SDEM	1345.163
GNS	1341.007

[a] Model with the smallest AIC.

Based on the comparison of AIC values from various spatial models, the SDM model has the lowest AIC value of 1339.219, followed by the GNS and SDEM (Spatial Durbin Error Model) models. A lower AIC value indicates that the model explains data variation more effectively with minimal complexity penalties. Based on model efficiency and the smallest AIC value, the SDM was chosen as the best model in this study. In addition to having the most optimal performance statistically, the SDM model also matches the results of the Lagrange Multiplier test and the Moran's I index on the dependent variable.

Table 5. SDM model parameter estimation.

Variable	*Estimate*	Std. *Error*	*p-value*
Intercept[a]	78.687	35.900	0.028
GRDP A[a]	0.128	0.055	0.020
GRDP	0.009	0.007	0.191
OUR[a]	1.517	0.517	0.003
Poverty[a]	-0.473	0.148	0.001
AYS[a]	2.238	0.629	3.77e-3
lag.GDRPA	0.248	0.228	0.277
lag.GDRP	-0.032	-0.032	0.715
lag.OUR[a]	-5.397	2.144	0.011
lag.Poverty[a]	-1.281	0.608	0.035
lag.AYS	-6.291	4.057	0.121
Rho[a]	0.770	0.138	0.002

[a] Significant at $\alpha = 5\%$

The results of parameter estimation with the SDM model can be seen in the following equation:

$$\widehat{FSI}_I = 0.7707^* \sum_{j=1,i\neq j}^{185} w_{ij}FSI_j + 78.6876^* + 0.1286^* GRDPA_i + 1.5170^* OUR_i - 0.4737^* Poverty_i + 2.2388^* AYS_i + 0.0091\, GRDP_i + 0.2483 \sum_{j=1,i\neq j}^{185} w_{ij}GRDPA_j - 1.2815^* \sum_{j=1,i\neq j}^{185} w_{ij}Poverty_j - 6.2915 \sum_{j=1,i\neq j}^{185} w_{ij}AYS_j - 0.0321 \sum_{j=1,i\neq j}^{185} w_{ij}GRDP_j \quad (3)$$

Based on the estimation results of the SDM model, it was found that most of the main variables and their spatial lags (variable values in neighboring areas) have a significant influence on the dependent variable. It was found that the variables Percentage of GRDP Sector A, Poverty Rate, Average Years of Schooling (AYS), Lag of Food Security Index, Lag of Open Unemployment Rate, and Lag of Poverty Rate have a significant influence on the dependent variable. The coefficients for the six variables are statistically significant with a very small p-value, which is less than 0.05, indicating that these factors have a strong influence on the variables analyzed.

Based on the spatial model above, the spatial influence between regions on the IFS ($w_{ij}IFS_j$) shows a significant influence. The Open Unemployment Rate (OUR) and the Poverty Rate have a significant influence, both directly and indirectly, on the FSI. Meanwhile, the Average Years of Schooling (AYS) and the Percentage of GRDP Sector A (GRDP A) only have a significant direct influence on the FSI.

This indicates that local factors, such as OUR and poverty, both directly and indirectly through spatial influences from surrounding areas, significantly affect a region's FSI. Meanwhile, factors such as AYS and GRDP A play a more direct role in influencing food security without significant spatial influences.

The percentage of GRDP Sector A ($GDPBA_i$) locally has a positive but small and insignificant impact on food security. This may be due to a lack of support for the agricultural sector, including insufficient infrastructure and market access. However, the spatial lag of GDPBA indicates a larger and more significant positive impact. Spillover effects from the agricultural sector in neighboring areas contribute to improving food security in the region. This finding aligns with the research of Safitri et al., who concluded that the agricultural sector has a significant impact on supporting regional food security [11]. This sector's contribution not only increases GRDP but also strengthens the community's socio-economic resilience to food fluctuations (availability, access, and sustainability of production).

GRDP per capita shows a very small, insignificant positive effect on food security. This is supported by previous research by Widada et al., which showed that GRDP had no significant effect on the FSI [12]. The insignificant influence of GRDP per capita as a measure of economic growth indicates the existence of social inequality, resulting in unequal access to food for the community.

The Open Unemployment Rate (OUR) shows a positive, significant coefficient locally, contradicting the theory that high unemployment rates can reduce purchasing power and food security. This may be due to the OUR's limitations in representing food vulnerability comprehensively. The decline in the OUR may occur not due to increased formal employment opportunities, but rather due to a shift in the workforce from unemployed to informal workers. In 2024, approximately 47.42% of workers in Eastern Indonesia were informal workers [13]. At the same time, informal workers in Eastern Indonesia still have an average net income below the minimum wage due to low productivity and the lack of legal protection [14,15]. Therefore, in the context of Eastern Indonesia, a low OUR does not necessarily indicate strong food security, considering that the majority of the population still has low incomes and limited access to food [16].

Conversely, the spatial lag of the OUR shows a significant negative effect on food security. This indicates that unemployment rates in surrounding areas impact food security in a region. This effect may reflect interregional economic dependencies, such as labor mobility, limited cross-regional food distribution, and widespread socioeconomic pressures resulting from high regional unemployment.

Poverty Rate shows a significant negative impact on food security directly. Furthermore, the spatial lag of poverty shows a larger and more significant negative impact, which strengthens the indication that poverty in surrounding areas worsens food security conditions in an area. This finding is consistent with the results of research by Wardhana et al. in West Java, which showed that poverty in neighboring areas exacerbates poverty in the local area through a spatial spillover mechanism [17].

Average Years of Schooling (AYS) directly has a positive and significant impact on food security, indicating that higher education can improve accessibility and community capacity in managing food security. Higher educational attainment is associated with decent employment opportunities, increased income, and ultimately increased access to food [18]. Furthermore, higher education also encourages better food utilization through more hygienic, efficient, effective, and nutritious food management. However, the spatial lag of AYS shows a negative and insignificant coefficient. This means that education levels in neighboring areas have no impact on food security in a given region. This indicates that the influence of education occurs only locally.

4. Conclusion and Suggestions

Based on the results of the analysis of the Food Security Index in Eastern Indonesia, it was found that there was spatial dependency between districts/cities that influenced food security, which was reflected through the Moran's I test. Modeling using the Spatial Durbin Model (SDM) method provided the best results with the smallest AIC, indicating that this model is most suitable for describing spatial relationships between regions.

The modeling results show that the variables Distribution of GRDP Sector A, Poverty Rate, AYS, Lag of FSI, Lag of OUR, and Lag of Poverty Rate have a significant influence on food security. Meanwhile, the variables GRDP Per Capita and its lag, lag of GRDP Sector A, and lag of AYS do not show a significant influence on FSI.

Variables that have a positive influence, such as AYS and the Percentage of GRDP Sector A, need to be improved to strengthen food security in a region. The government needs to reaffirm related policies to strengthen food security, such as the 12-year compulsory education policy and increased productivity in agriculture, forestry and fishing sector to improve affordability, availability, and optimal utilization of food by the community, thus enhancing food security.

Although there are areas where the OUR has demonstrated a positive impact, it does not necessarily reflect an improvement in the labor market, as BPS considers informal workers to be part of the working population. An increase in informal workers could contribute to a decline in the OUR without improving the welfare of the informal workforce [15]. Therefore, it is necessary to improve the welfare of informal sector workers. This begins by increasing the productivity of informal sector workers to secure decent wages and ensure their rights, given their low incomes in Eastern Indonesia. Meanwhile, ensuring food affordability for all is crucial to achieving food security. This can be achieved through the establishment of strategic policies such as stabilizing staple food prices, increasing staple food subsidies, optimizing social assistance, and optimizing free lunches to strengthen Indonesia's food security, particularly in the eastern region. Furthermore, the government needs to address poverty to reduce it and improve community welfare and food security. This must be done not only in one region, but across all regions, as poverty has spatial impacts on surrounding areas.

References

[1] A. H. Maslow, Motivation and Personality. New York: Harper & Row, 1970.

[2] Indonesian Government, "Undang-undang (UU) Nomor 18 Tahun 2012 tentang Pangan", 18/2012. [Online]. Available: [BPK Website]. Accessed: July 2, 2025.

[3] FAO, "An Introduction to the Basic Concepts of Food Security", 2008, EC - FAO Food Security Programme. [Online]. Available: https://www.fao.org/4/al936e/al936e00.pdf.

[4] Z. Rozaki, "Food security challenges and opportunities in indonesia post COVID-19," Advances in Food Security and Sustainability, vol. 6, no. 6, pp. 119–168, 2021, doi: https://doi.org/10.1016/bs.af2s.2021.07.002.

[5] Welthungerhilfe (WHH), Concern Worldwide, and Institute for International Law of Peace and Armed Conflict (IFHV), "2024 Global Hunger Index: How Gender Justice Can Advance Climate Resilience and Zero Hunger," WHH, Berlin, 2024.

[6] Badan Pangan Nasional, 2024, "Indeks Ketahanan Pangan (IKP) Provinsi Update Tahun 2024", Badan Pangan Nasional. [Online]. Available: https://satudata.badanpangan.go.id/datasetpublications/2dd/ikp-prov-2024.

[7] M. G. Yahya, I. P. Utami, and S. Ariansyah, "Pemodelan Spasial Prevalensi Ketidakcukupan Konsumsi Pangan Menggunakan Pendekatan Ketahanan Pangan di Indonesia Tahun 2022," Seminar Nasional Official Statistics, vol. 2023, no. 1, pp. 869–878, Oct. 2023, doi: https://doi.org/10.34123/semnasoffstat.v2023i1.1910.

[8] None Dewi Sri Hastuti and None Safa'at Yulianto, "Factors Affecting the Resilience Index Food in Papua Province and West Papua Province Using a Spatial Model Approach," J Statistika Jurnal Ilmiah Teori dan Aplikasi Statistika, vol. 17, no. 1, pp. 635–644, Jul. 2024, doi: https://doi.org/10.36456/jstat.vol17.no1.a9087.

[9] I. R. Ramadani, R. Rahmawati, and A. Hoyyi, "ANALISIS FAKTOR-FAKTOR YANG MEMPENGARUHI GIZI BURUK BALITA DI JAWA TENGAH DENGAN METODE SPATIAL DURBIN MODEL," Jurnal Gaussian, vol. 2, no. 4, pp. 333 - 342, Oct. 2013. Doi: https://doi.org/10.14710/j.gauss.2.4.333 - 342.

[10] M. Marizal and H. Atiqah, "Pemodelan Indeks Pembangunan Manusia di Indonesia dengan Geographically Weighted Regression (GWR)," *Jurnal Sains Matematika dan Statistika*, vol. 8, no. 2, pp. 133–145, Sep. 2022, doi: http://dx.doi.org/10.24014/jsms.v8i2.17886.

[11] M. G. Safitri, M. Agustin, I. Syahroni, and E. Kurniati, "Peran Sektor Pertanian dalam Mewujudkan Ketahanan Pangan untuk Pemberdayaan Ekonomi di Pulau Sumatera," *Jurnal Ekonomi dan Pembangunan Indonesia*, vol. 3, no. 1, pp. 195–204, 2024. doi: https://doi.org/10.61132/jepi.v3i1.1158.

[12] Widada, A. W., Masyhuri, M., and Mulyo, J. H. "Determinant factors of food security in Indonesia," *Agro Ekonomi*, vol. 28, no. 2, pp. 205-219, 2017, doi: https://doi.org/10.22146/jae.26245.

[13] Statistics Indonesia, 2024, "Labour Force Situation in Indonesia, August 2024", Statistics Indonesia. [Online]. Available: https://www.bps.go.id/id/publication/2024/12/09/6f1fd1036968c8a28e4cfe26/keadaan-angkatan-kerja-di-indonesia-agustus-2024.html.

[14] Statistics Indonesia, 2025, "Statistical Yearbook of Indonesia", Statistics Indonesia. [Online]. Available: https://www.bps.go.id/id/publication/2025/02/28/8cfe1a589ad3693396d3db9f/statistik-indonesia-2025.html.

[15] Statistics Indonesia, 2025, "Indikator Pekerjaan Layak di Indonesia 2024", Statistics Indonesia. [Online]. Available: https://www.bps.go.id/id/publication/2025/04/28/1ecc9dec1ef7a591babf5962/indikator-pekerjaan-layak-di-indonesia-2024.html.

[16] OECD, "Breaking the Vicious Circles of Informal Employment and Low-Paying Work", OECD Publishing, Paris, 2024. doi: https://doi.org/10.1787/f95c5a74-en.

[17] D. Wardhana, R. Ihle, and W. Heijman, "Agro-clusters and Rural Poverty: A Spatial Perspective for West Java," *Bulletin of Indonesian Economic Studies*, vol. 53, no. 2, pp. 161–186, Nov. 2017, DOI: https://doi.org/10.1080/00074918.2017.1298722.

[18] M. Mutisya, M. W. Ngware, C. W. Kabiru, and N. Kandala, "The effect of education on household food security in two informal urban settlements in Kenya: a longitudinal analysis," Food Security, vol. 8, no. 4, pp. 743–756, Jul. 2016, doi: https://doi.org/10.1007/s12571-016-0589-3.