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Research Article

MODELING INDONESIA'S FOOD SECURITY INDEX USING SPATIAL ECONOMETRIC PANEL APPROACH

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Abstract
Food security is a pressing issue for economic stability and public well-being in Indonesia, where the 2020–2022 Food Security Index (FSI) remained at Priority 4 which indicate low provincial food security. This study examines the determinants of FSI across 34 provinces from 2020 to 2023 using a spatial panel approach to capture both temporal and spatial spillovers. Secondary data from the National Food Agency and the Central Statistics Agency (BPS) include poverty rate, electricity and clean water access, Desirable Dietary Pattern (DDP) score, per capita caloric intake, and mean years of schooling. Analysis employed panel regression and spatial-panel models particularly corporating the spatial fixed effects model. The SAR-FE model provided the best fit, with a significant positive spatiall ag coefficient. This study emphasizes that FSI in one province is influenced by neighboring provinces. These spillover effects highlight the interconnectedness of provincial food security and emphasizing that interventions in one region can affect adjacent areas. The combination of spatial and panel methodologies with individual fixed effects defines the novelty of this research. Such an approach, which is rarely utilized in the context of Indonesian food security, uncovers provincial-level spillover dynamics that previous studies relying solely on either spatial or panel frameworks tended to ignore. Findings provide actionable insights for coordinated regional policies and contribute to Sustainable Development Goal 2 (Zero Hunger) by promoting more equitable food availability and accessibility.

Keywords: Indonesia's Food Security Index, Spatial Panel Analysis, Spatial Spillover Effects

INTRODUCTION

Food is a fundamental human need, that must be adequately fulfilled to ensure people's well-being and overall prosperity (Mukhlis et al., 2021; Virtriana et al., 2022; Yusri et al., 2021). The availability and accessibility of sufficient, nutritious food play a crucial role in sustaining a nation's stability, as food security directly impacts public health, productivity, and economic growth (Manap & Ismail, 2019; Rusmawati et al., 2023). Ensuring food security aligns with the Sustainable Development

Goals (SDGs), particularly SDG 2 (Zero Hunger), which emphasize the importance of eradicating hunger, improving nutrition, and ensuring food access for all. Food security, as defined by the FAO and Indonesian Law No. 18 of 2012 on Food, is a condition in which all individuals, at all times, have physical, social, and economic access to sufficient, safe, nutritious, and affordable food that meets their dietary needs and cultural preferences, ensuring not only food availability at all levels, from the state to individuals, but also the ability to maintain a healthy, active, and productive life in a sustainable and equitable manner (Damayanti et al., 2022; FAO, 2014). Food security can be measured using the Food Security Index, which assesses factors such as food availability, affordability, quality, safety, and sustainability to determine a country's ability to provide sufficient and nutritious food for its population (Aryani et al., 2021; Virtriana et al., 2022).

Assessment through this index framework indicates that Indonesia's food security trajectory has been unstable, raising concerns about its resilience and sustainability. Data from the Global Food Security Index (GFSI) demonstrates that Indonesia's Food Security Index (FSI) has exhibited fluctuations in recent years, with a significant decline recorded in 2021. In 2020, Indonesia attained an FSI score of 61.4; however, this figure declined to 59.2 in 2021, resulting in a drop in the nation's food security ranking from 65th to 69th among 113 countries (Azhar et al., 2023). Nevertheless, by 2022, Indonesia's FSI showed signs of recovery, increasing to 60.2. Despite these variations, based on the established food security cut-off point, Indonesia's food security status in 2020, 2021, and 2022 remained classified under Priority 4, signifying that the country continues to be categorized as experiencing low food security. Despite temporal fluctuations, spatial disparities in the Food Security Index also exist across provinces. Data from Indonesia's National Food Agency indicates that in 2023, Papua and West Papua had the lowest scores, at 42.27 and 47.95, respectively, classifying them as having low food security (Indonesia's National Food Agency, 2023). In contrast, all provinces on the island of Java fell within the high food security category. This gap underscores regional disparities in food security, which may be influenced by factors such as infrastructure development, economic conditions, and nutritional adequacy.

Numerous studies have explored various factors that may influence food security, with agricultural production and socio-economic conditions being the most commonly analyzed. The National Food Agency of Indonesia has defined several key indicators for measuring the Food Security Index, including the ratio of normative per capita consumption, the percentage of the population living below the poverty line, the proportion of households with access to clean water and electricity, and life expectancy at birth (Aryani et al., 2021; Indonesia's National Food Agency, 2023). Meanwhile, several studies have examined the correlation between the Desirable Dietary Pattern (DDP) score and calorie intake in relation to food security at both the household and regional levels (Damayanti et al., 2022; Gantina et al., 2020). However, these variables are not commonly utilized in the modeling of the Food Security Index.

Research on food security modeling has been widely conducted using various methods, including logistic modeling, panel data analysis, and spatial-based modelling (Antara et al., 2023; Azhar et al., 2023; Kharisma & Abe, 2020; Prasada & Masyhuri, 2019; Sileshi et al., 2023; Valešová et al., 2017). However, given the complex and interdependent nature of food security across regions, employing spatial panel analysis is particularly crucial. By integrating both spatial dependences and temporal dynamics, this approach allows researcher to capture not only the direct effects of socioeconomic and infrastructural factors on food security, but also the spillover effects from neighboring provinces that traditional panel or spatial-only models failed to detect. Despite of this advantage, the application of spatial-panel framework particularly to Indonesian food security remains limited. Most prior studies either map spatial patterns without considering temporal trends (Fyndiani et al., 2025; Hastuti & Yulianto, 2024; Shohwah et al., 2025), or utilize panel analyses without accounting for spatial spillovers and leaving interconnected dynamics between provinces largerly unexplored (Durohman et al., 2025; Ningsih et al., 2025). This gap highlights the need for a spatial panel investigation to fully understand the determinants and propagation of food security across Indonesia.

Given the context above, this study addresses the identified gap by utilizing spatial-panel framework to examine the determinants of food security in Indonesia over the period 2020 – 2023, explicitly by integrating spatial spillover effects and temporal changes. The selected time horizon captures the most recent provincial conditions while reflecting the post-pandemic adjustment period, as the aftereffects of COVID-19 continued to influence economic stability, infrastructure access, and nutritional outcomes across regions. The analysis incorporates key socioeconomic factors, including poverty rate and life expectancy; infrastructural indicators, such as access to clean water and electricity; and nutritional dimensions, represented by the Desirable Dietary Pattern (DDP) score and per capita calorie intake.

By simultaneously accounting for those multidimensional determinants within a spatially interconnected framework, this study contributes methodologically through the application of spatial-panel to Indonesian food security and empirically ny identifying how provincial conditions interact and propagate across neighboring regions. The findings are expected to inform more coordinated and regionally responsive policy interventions on food security. Accordingly, this research goals are: (1) to examine the existence and magnitude of spatial spillover effects in provincial food security across Indonesia by capturing interregional dependence within a spatial-panel framework; (2) to evaluate the influence of key socioeconomic, infrastructural, and nutriotional determinants, including poverty rate, mean years of schooling, Desirable Dietary Pattern points, access to clean water and electricity, and per capita calorie intake on provincial food security when spatial and temporal dynamics explicitly considered. Furthermore, the policy implications of the identified spatial interactions and determinant effects will be elaborated to support the design of coordinated and regionally responsive food security strategies, thereby promoting sustainable and equitable food systems across provinces.

Food Security Index

The response variable in this study is the Food Security Index (FSI), which serves as a composite indicator capturing the multidimensional nature of food security across Indonesian provinces. Conceptually, food security encompasses availability, access, utilization, and stability dimensions, reflecting not only sufficient food supply but also economic accessibility, dietary adequacy, and resilience to shocks. To operationalize these dimensions, the FSI is constructed through a weighted aggregation of several standardized indicators representing structural and outcome-based aspects of food security. Methodologically, each indicator is first standardized using z-score transformation to ensure comparability across different measurement units and scales. The standardized values are subsequently rescaled to a 0–100 range using the distance-to-scale method, allowing for intuitive interpretation and consistent aggregation. This normalization process reduces dimensional bias and ensures that no single indicator dominates the index due to scale differences. The final FSI is computed as a linear combination of the normalized indicators using predetermined weights that reflect their relative importance within the food security framework (Indonesia's National Food Agency, 2023). As a composite measure, the FSI captures both structural determinants (such as poverty and infrastructure access) and outcome indicators (such as nutritional and health conditions), making it suitable for interprovincial comparison and longitudinal analysis. Its construction allows for consistent monitoring of spatial disparities and temporal dynamics, thereby providing a robust dependent variable for spatial panel econometric modeling. Higher FSI values indicate stronger food system performance and better overall food security conditions within a region.

Life Expectancy at Birth

Life expectancy is widely recognized as a structural indicator of population health and long-term human development, reflecting cumulative investments in nutrition, healthcare, sanitation, and socioeconomic conditions. In the context of food security, improved dietary adequacy and nutritional status reduce morbidity and mortality risks, thereby enhancing survival outcomes and overall human resilience (Ruel et al., 2013; Smith & Haddad, 2015). Empirical evidence indicates that better nutrition environments and stronger food systems are associated with improved health outcomes, particularly in developing countries where malnutrition remains a structural constraint (Headey et al., 2020). In Indonesia, life expectancy has been incorporated into multidimensional food and nutrition security assessments as an indicator reflecting sustained health and nutritional conditions (Aryani et al., 2021). These findings suggest that life expectancy captures structural health capacity that supports food system performance, and it is therefore theoretically expected to exert a positive influence on the Food Security Index.

Poverty Rate

The poverty rate is widely recognized as a structural determinant of economic vulnerability and food access, reflecting the proportion of the population unable to meet minimum basic consumption needs. From a theoretical perspective, food insecurity is strongly driven by income constraints and limited economic access rather than solely by food availability, as insufficient purchasing power restricts households' ability to obtain adequate and nutritious food (Headey & Ecker, 2013). Economic access therefore constitutes a central pillar of food security. Empirical evidence consistently demonstrates that higher poverty incidence is associated with greater undernourishment and food deprivation, particularly in low- and middle-income countries (FAO et al., 2022). Studies further show that poor households are disproportionately vulnerable to food price shocks and dietary inadequacy due to limited income buffers (Ivanic & Martin, 2008). In Indonesia, poverty disparities remain closely linked to unequal food consumption and nutritional outcomes, and poverty is incorporated as a key socioeconomic indicator in multidimensional food and nutrition security assessments (Aryani et al., 2021). These findings indicate that poverty captures structural constraints in economic access to food, and it is therefore theoretically expected to exert a negative influence on the Food Security Index.

Desirable Dietary Pattern

Desirable Dietary Pattern (DDP) reflects the quality and diversity of food consumption, measuring the extent to which dietary intake aligns with recommended nutritional composition across food groups. Within the food security framework, dietary diversity constitutes a central component of the utilization dimension, as food security requires not only sufficient caloric intake but also balanced nutrient consumption to support optimal health outcomes (FAO et al., 2022). From a theoretical perspective, diversified diets improve micronutrient adequacy, enhance immune function, and reduce vulnerability to nutrition-related diseases (Arimond & Ruel, 2004). Empirical studies consistently demonstrate that higher dietary diversity scores are strongly associated with improved nutritional status and lower levels of food insecurity at both household and regional levels (Headey et al., 2020; Jones, 2017). In the Indonesian context, the Desirable Dietary Pattern is incorporated into multidimensional food and nutrition security assessments as an indicator of dietary balance and food consumption structure (Aryani et al., 2021). These findings indicate that DDP captures qualitative aspects of food utilization and nutritional adequacy, and it is therefore theoretically expected to exert a positive influence on the Food Security Index.

Percentage of Households with Access to Clean Water

Access to clean water constitutes a fundamental component of food security because water availability directly influences food production, preparation, consumption, and nutritional absorption. Evidence from recent studies indicates that water security and food security share interconnected dimensions, including availability, access, utilization, and stability (Yudono et al., 2022). Adequate water supply supports agricultural productivity, ensures safe food preparation, and reduces the risk of waterborne diseases that impair nutrient absorption. Conversely, water insecurity constrains crop yields, limits household food preparation capacity, and increases exposure to health risks, which ultimately weakens nutritional outcomes and food security status. The literature further emphasizes that compromised water access at the household level often coincides with higher levels of food insecurity, demonstrating that water security functions as a structural determinant of food and nutrition well-being (Young et al., 2021). Collectively, these findings confirm that reliable access to safe water is essential for sustaining food availability, proper utilization, and overall food system stability.

Percentage of Households with Access to Electricity

Access to electricity is widely acknowledged as a key infrastructural determinant of food security as it influences agricultural production, income generation, and food utilization. Empirical studies show that improved electrification increases agricultural productivity through irrigation systems, reduces post-harvest losses through adequate storage facilities, and supports income diversification into non-farm sectors (Candelise et al., 2021). These mechanisms strengthen the availability and stability dimensions of food security and improve households' purchasing power. At the macro level, evidence also indicates that energy poverty is positively associated with undernourishment and higher starvation rates. Limited access to modern energy restricts food preparation, preservation, and economic activities, which increases the risk of food insecurity (Messie et al., 2023). Overall, electricity access functions as a structural foundation for food availability, economic access, and proper utilization rather than merely serving as a basic public utility.

Average Daily per Capita Calorie Consumption

Adequate caloric intake constitutes a fundamental dimension of food security, particularly within the availability and utilization pillars. From a theoretical perspective, food security requires not only physical access to food but also sufficient energy intake to meet minimum dietary requirements. Empirical studies provide clear support for this relationship. Evidence from Ethiopia shows a substantial gap in mean daily caloric intake between food-secure households (approximately 2654.6 kcal) and food-insecure households (approximately 1676.3 kcal), which indicates that energy adequacy plays a decisive role in determining household food security status (Jambo & Derso, 2025). Similarly, findings from the Democratic Republic of Congo reveal that households with calorie consumption far below recommended energy thresholds experience significantly higher levels of food insecurity (Stany et al., 2021). These results demonstrate that insufficient caloric intake reflects structural constraints in food access and consumption capacity, thereby reinforcing calorie intake as a robust and measurable indicator of food security.

RESEARCH METHOD

The study includes a panel dataset of 34 provinces over 4 years (2020 – 2023), resulting in a total of 136 observations. While formal statistical power calculation for panel data models is less straightforward than for simple cross-sectional designs, the combination of cross-sectional units and temporal observations provides sufficient variability to detect meaningful effects. The study utilizes secondary data sourced from publications by the National Food Agency and the official website of the Central Statistics Agency (BPS). The dataset is publicly available and compiled by the government through standardized administrative and survey procedures. No additional data collection was conducted by the authors. This study comprises one response variable and 6 predictor variables, each of which is described in the table below.

Table 1. Description of Variables

Category	Description	Type of Data
FoodSec (Y)	Food security index score	Ratio
LifeExp	Life expectancy at birth	Ratio
PovRate	Poverty rate	Ratio
DDP	Desirable Dietary Pattern score	Ratio
WaterAcc	Percentage of households with access to clean water	Ratio
ElecAcc	Percentage of households with access to electricity	Ratio
CalIntake	Average daily per capita calorie consumption	Ratio

The Figure 1 below presents the research procedure for modelling the association between the six predictors in Table 1 and the Food Security Index using a spatial panel approach. All data analyses in this study were conducted using R software, specifically employing the plm and splm packages for panel and spatial econometric modeling. The spatial panel framework integrate spatial dependence and temporal dynamics, which can capture spillover effects across neighboring provinces that standard cross-sectional or time-only models cannot address (Baltagi & Shu, 2025). This study specifically employs spatial individual fixed effects, which control for unobserved, time-invariant characteristics of each province thereby reducing bias and improving the validity of causal inferences in the presence of spatial autocorrelation (Guo & Qu, 2020).

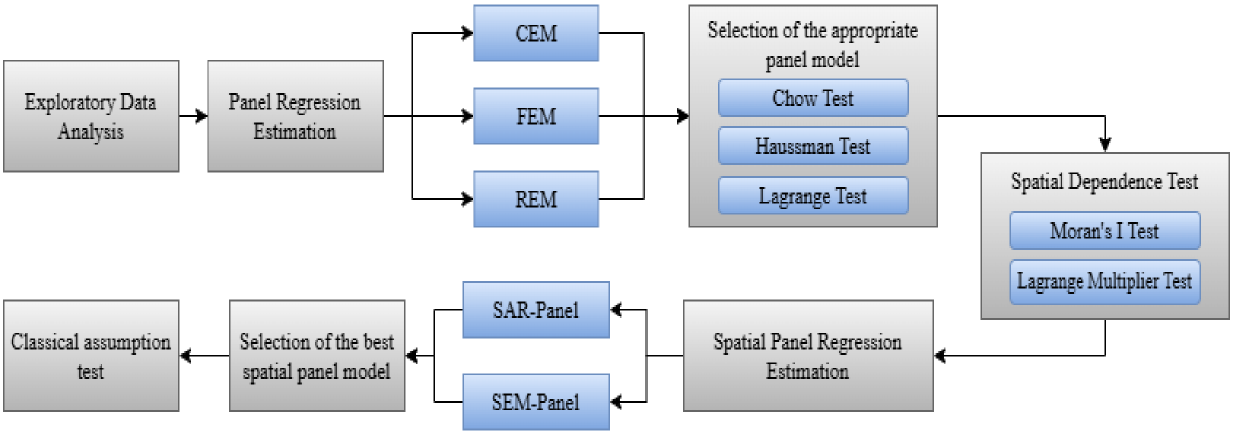


Figure 1. Research Methodology Flowchart

To provide a comprehensive theoretical foundation for the spatial panel approach employed in this study, the research procedure proceeded through the following steps:

1. Conduct data exploration.
2. Estimate the parameters of the Common Effect Model (CEM), Fixed Effect Model (FEM), and Random Effect Model (REM).
   These are the three main approaches in panel data regression.
   a. CEM assumes that both intercept and slope are constant across entities and over time.
   b. FEM allows each entity to have its own intercept, controlling for time-invariant characteristics.
   c. REM treats individual-specific effects as random variables uncorrelated with the regressors.
3. Select the appropriate model based on the Chow test and the Hausman test.
   a. The Chow test is used to decide between the CEM and FEM by testing whether intercepts are equal across entities. The hypotheses used are as follows:
      $H_0 : \alpha_1 = \alpha_2 = \cdots = \alpha_N$ (CEM)
      H_1 : at least one $\alpha_i \neq 0$ where $i = 1, 2, \ldots, n$ (FEM)
      The F-statistic is used to test the hypotheses and is defined as follows (Baltagi, 2005)
      $$F = \frac{(SSE_{CEM} - SSE_{FEM})/(N-1)}{SSE_{FEM}/(NT-N-p)} \sim F_{(N-1,\ NT-N-p)}$$
   b. The Hausman test is applied to compare FEM and REM, testing for correlation between individual effects and regressors. The hypotheses used are as follows:
      $H_0 : E(X_{it}, w_{it}) = 0$ (REM)
      $H_1 : E(X_{it}, w_{it}) \neq 0$ (FEM)
      The F-statistic is used to test the hypotheses and is defined as follows (Greene, 2002).
      $$W = [\boldsymbol{b} - \widehat{\boldsymbol{\beta}}]'[Var(\widehat{\boldsymbol{\beta}})]^{-1}[\boldsymbol{b} - \widehat{\boldsymbol{\beta}}] \sim \chi^2_{(p-1)}$$
      Where $\boldsymbol{b}$ and $\widehat{\boldsymbol{\beta}}$ represent the estimated parameter vectors for REM and FEM, respectively, excluding the intercept.
4. Generate an inverse distance matrix using latitude and longitude data of each province.
   A spatial weights matrix is constructed based on geographical distance between provinces. The inverse distance matrix assumes that closer regions exert stronger spatial influence on each other (Chen & Liu, 2012).
5. Conduct spatial dependency tests using Moran's I and the Lagrange Multiplier test for both lag and error terms.
   a. The Moran's I test is used to examine whether there is spatial autocorrelation between locations in the data (Bian-Ling, n.d.).
   b. LM tests is used to examine whether there is spatial dependence in a model (Anselin *et al.*, 2008)
6. Estimate the parameters of the SAR and SEM panel models.

These models integrate both spatial and temporal dimensions for more robust estimation when both spatial interaction and panel structure are present. The spatial autoregressive-fixed effect (SAR-FE) model is a type of spatial model in which the observed variable depends on the response variable observed in neighbouring individuals, as well as on factors observed in the panel data (Elhorst, 2010). The general equation for the SAR-FE model is as follows:

$$y_{it} = \lambda \sum_{j=1}^{N} w_{ij} y_{ij} + \boldsymbol{X}_{it}\boldsymbol{\beta} + \mu_i + \varepsilon_{it}$$

Meanwhile, the spatial error model-fixed effect (SEM-FE) assumes that the response variable depends on spatially correlated errors and factors observed in individual i at time t, along with local characteristics observed in panel data (Nabila & Yotenka, 2021). The general equation for the equation for the SEM-FE model is as follows:

$$y_{it} = \boldsymbol{X_{it}\beta} + \mu_i + \phi_{it}$$
$$\phi_{it} = \rho \sum_{j=1}^{N} w_{ij} \phi_{jt} + \varepsilon_{it}$$

where:
y_{it} is the response variable of individual i at time t.
λ is the spatial lag coefficient.
ρ is the spatial error coefficient.
ϕ_{jt} represents the spatial error autocorrelation of individual i at time t.
μ_i is the spatial-specific effect of individual i.
w_{ij} represents the spatial weight matrix W for individual i and individual j.
$\boldsymbol{X_{it}}$ is a row vector of dimension $1 \times p$ containing predictor variables.
$\boldsymbol{\beta}$ is a row vector of dimension $p \times 1$ representing slope variables.
ε_{it} is the error term for individual i at time t, where $\varepsilon_{it} \sim N(0, \sigma^2)$

7. Compare panel, spatial, and spatial-panel models based on R² and AIC values.
   a. R-squared (R²) assesses the explanatory power of the model. The R-squared value range between 0 and 1, with a higher R-squared value generally indicating a better fitting model. It is calculated as follows (Gujarati, 2004).

   $$R_k^2 = 1 - \frac{\sum_{i=1}^{N} \sum_{t=1}^{T} (y_{it} - \hat{y}_{it})}{\sum_{i=1}^{N} \sum_{t=1}^{T} (y_{it} - \bar{y}_{it})}$$

   b. AIC is a widely used statistical metric for model selection, by balancing goodness of fit and complexity and penalizing models with excessive parameters to prevent overfitting. A lower AIC value indicated a better-fitting model, althought it has tendenciy to select models with large number of parameters (Agiakloglou & Tsimpanos, 2023).

   $$AIC = -2Log(L) + 2p$$

   Where $Log(L)$ is the maximum value of log-likelihood, and p is the number of parameters estimated from the econometric model.
8. Choose the best spatial panel model based on the Likelihood Ratio Test.
   The Likelihood Ratio Test is a statistical method used to compare the fit of two models: a restricted model and an unrestricted model. The test evaluates whether the additional parameters in the unrestricted model significantly improve model fit (Elhorst, 2014).

   $$LR = -2s \sim \chi^2_{(N-1)}$$

Where s represents the difference between log-likelihood of the restricted model and the unrestricted model.

9. Perform classical assumption tests such as residual normality and homoscedasticity on the final model.
   a. Normality test (e.g., Kolmogorov-Smirnov test) ensures residuals follow a normal distribution.
   b. Homoscedasticity test (e.g., Park test) checks for constant variance in residuals across observations.
10. Interpret the final model.

The final model's coefficients are interpreted to understand the direction and magnitude of the effect of each predictor on food security, considering both spatial and temporal dynamics.

RESULTS AND DISCUSSION

Data Exploration

The purpose of the exploratory analysis of the Food Security Index (FSI) from 2020 to 2023 is to identify patterns of change, annual variations, and overall trends throughout the period. Figure 2 below illustrates the trend of the average FSI from 2020 to 2023. The index shows a marginal increase from 72.11 in 2020 to 74.02 in 2023. While the trend indicates an upward movement, the increase is relatively modest and not significant.

The scatterplot and correlation matrix given in Figure 3 (a) highlights a strong correlation between Food Security Index and various factors. FSI exhibits a positive correlation with life expectancy at birth (LifeExp), desirable dietary score (DDP), daily calorie intake per capita (CalIntake), and percentage household with access to clean water and electricity (WaterAcc, ElecAcc). In contrast, it shows a negative correlation with poverty rate (PovRate). Furthermore, the correlation matrix also confirms that the selected predictor variables have a statistically significant relationship with response variable, reinforcing their relevance in explaining variations in food security index.

The scatterplot matrix in Figure 3 (b) also illustrates the strong temporal correlation between food security index scores from 2020 to 2023. It is indicating that observations within each province are highly dependent over time. The correlation coefficients which range from 0.95 to 0.99 indicate a strong positive relationship. The consistently high correlations accross years are likely due to the relatively insignificant annual increases in food security scores which leading to minimal year-to-year variations.

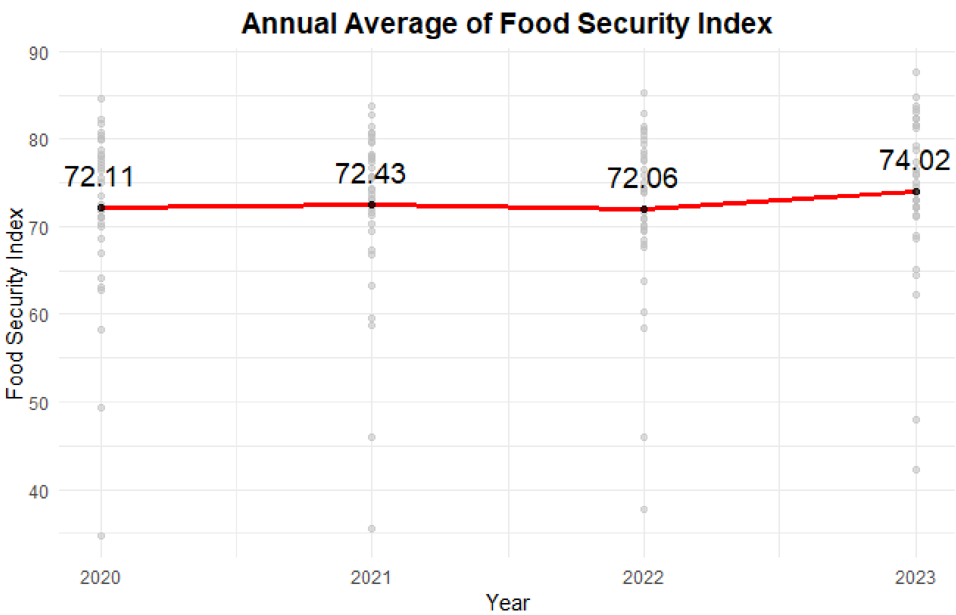
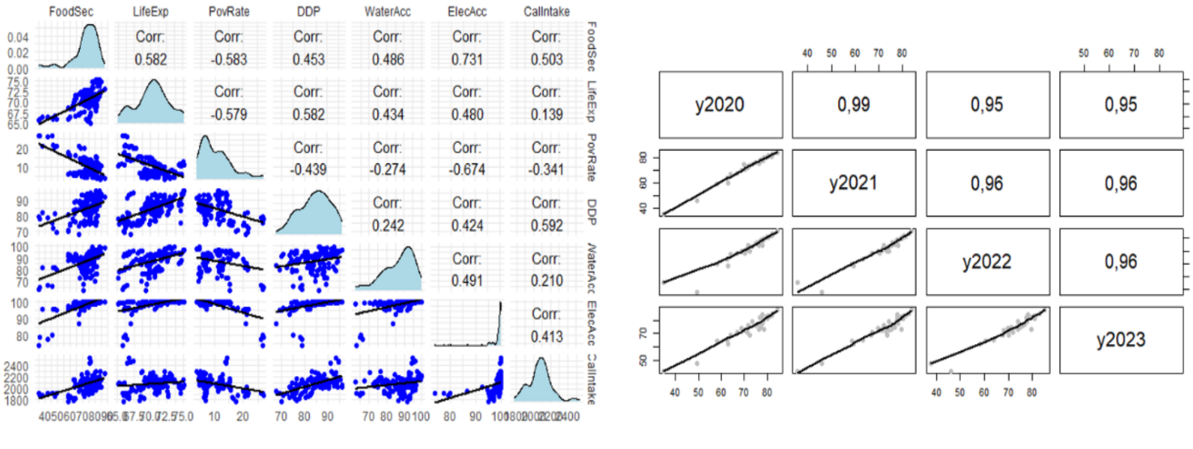


Figure 2. Trend of Food Security Index



(a) (b)

Figure 3. (a) Correlation Matrix of Variables and (b) Year-to-Year Correlation of FSI

Figure 4 provides a visualization of the Food Security Index in Indonesia for the year 2023 and highlighting variations across different provinces. Java Island, as the most densely populated region and the center of urbanization has the highest scores of food security as represented by the lightest color. Moving eastward, the index scores gradually decline with Papua Island displaying the darkest shades which is indicating the lowest levels of food security. Additionally, changes in the Food Security Index between 2020 and 2023 are illustrated in Figure 5. Although the majority of provinces have seen an improvement in their scores, certain provinces have shown a decline. These provinces include West Sumatra, Bangka Belitung Islands, Central Borneo, West Sulawesi, Southeast Sulawesi, North Sulawesi, North Maluku, and West Papua.

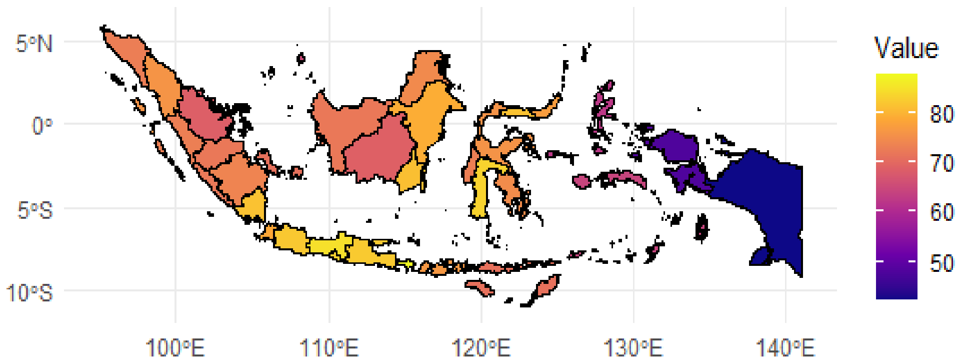


Figure 4. Thematic Map of Indonesia's Food Security Index in 2023

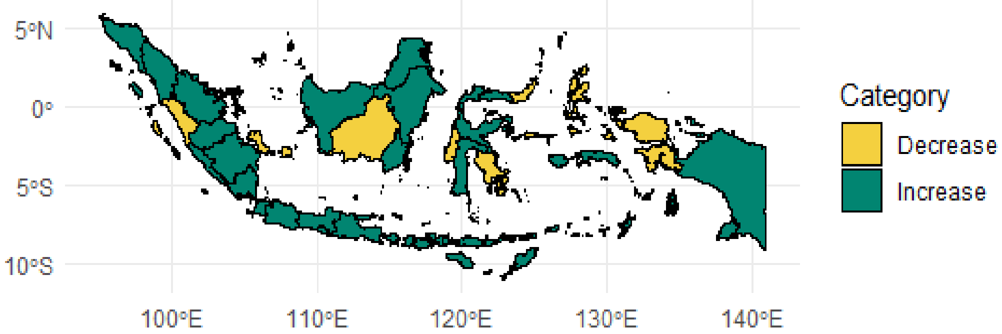


Figure 5. Thematic Map of Changes in Food Security Index 2020-2023

Panel Regression Analysis

Table 2 below presents the panel regression estimation results for three models: Common Effect, Fixed Effect, and Random Effect.

Table 2. Regression Results for Different Panel Data Models

	Common Effect		Fixed Effect		Random Effect	
	Coeff	**P-value**	**Coeff**	**P-value**	**Coeff**	**P-value**
LifeExp	1.6857	0.0000	4.2085	0.0000	1.6941	0.0008
PovRate	0.0161	0.9090	-1.6023	0.0065	-0.3959	0.0909
DDP	-0.3206	0.0081	-0.2543	0.0031	-0.0764	0.2662
WaterAcc	0.0726	0.3090	-0.3037	0.0204	-0.0031	0.9745
ElecAcc	1.0676	0.0000	0.3713	0.1142	0.6445	0.0024
CalIntake	0.0280	0.0000	0.0065	0.1900	0.0084	0.0499
F Statistics	46.8295		5.88016		72.117	
F sig.	0.0000		0.0000		0.0000	
R^2	0.685		0.268 (within)		0.358	
SSE	4099.8		338.08		533.99	

Based on Table 2, all three models are statistically significant when evaluated using the F-statistic. This shows that at least one predictor variable plays a role in explaining the response variable and confirms that the models can explain variance in the response variable. Among these regression models, the best panel model is selected using the Chow test and the Hausman test.

Table 3. Test Results for Panel Model Selection

Chow Test Alternate Hypothesis: FEM better than CEM		Haussman Test Alternate Hypothesis: FEM better than REM	
Statistic	P-Value	Statistic	P-Value
32.368	0.0000	27.247	0.0001

Based on Table 3 the Chow test results indicate that the Common Effect Model (CEM) is rejected, as the p-value is less than 0.05. Similarly, the Hausman test, with a p-value of 0.0001, confirms the rejection of the Random Effect Model (REM). Therefore, FEM is the preferred model for this analysis.

Spatial-Panel Regression Analysis

Before proceeding with spatial modeling, certain assumption must be met, including the spatial autocorrelation which can be evaluated using Moran's I test and the spatial dependency which can be assessed through the LM test. The results of Moran's I test for each year of observation on the Food Security Index as a response variable are presented in the Table 4 below.

Table 4. Moran's I Test Result

Year	I	I_0	P-Value
2020	0.0993	-0.0303	0.0000
2021	0.1059	-0.0303	0.0000
2022	0.1099	-0.0303	0.0000
2023	0.0998	-0.0303	0.0000

Based on Moran's I test on Table 4, it can be concluded that there is spatial autocorrelation among locations in the food security index within the study area during the 2020–2023 period. This is indicated by the positive and statistically significant Moran's I values (p-value < 0.05) for each year of observation.

In the previous section, the Fixed Effect Model (FEM) was identified as the best panel model. Before performing spatial-panel modeling, it is necessary to conduct the LM lag and LM error tests for the FEM using an inverse distance weight matrix. The test results are presented in Table 6 below. Since both the LM lag and LM error tests are significant, we proceed with estimating the parameters for both models, as shown in Table 7 below.

Table 6. LM Test for Panel Model

LM Test	Statistics	P-Value	Conclusion
LM Lag	6.5086	0.0107	Spatial lag dependence
LM error	9.0371	0.0026	Spatial error dependence

Table 7. Comparison of SAR-FE and SEM-FE Model Estimates

	SAR-FE		SEM-FE	
	Coeff	P-value	Coeff	P-value
Lambda (λ)	0.4149	0.0105	-	-
Rho (ρ)	-	-	0.5602	0.0000
LifeExp	3.3093	0.0002	4.2085	0.0002
PovRate	-1.5611	0.0011	-1.6023	0.0003
DDP	-0.2578	0.0001	-0.2543	0.0000
WaterAcc	-0.3130	0.0031	-0.3037	0.0014
ElecAcc	0.4553	0.0175	0.5115	0.0071
CalIntake	0.0048	0.2399	0.0065	0.6438
Log-Likelihood	-252.5258		-392.195	
R^2	0.975		0.973	
AIC	521.05		800.39	

Model Evaluation and Interpretation

The AIC and R^2values for three types of models—the Fixed Effects Model (FEM), the Spatial Error Model (SEM), and the spatial-panel models (SAR-FE and SAM-FE)—are compared to determine the best-fitting model. Based on Table 8 below, the SAR-FE model is identified as the best model, as it has the highest R^2 value of 0.975, although its AIC value is not the lowest. Furthermore, the selection of the SAR-FE specification is supported by the Likelihood Ratio (LR) test, which compares the restricted model (SAR with common effects) against the unrestricted model (SAR with individual fixed effects). The LR statistic of 177.338 with a p-value of 0.000 rejects the null hypothesis that the common-effect specification is adequate and confirming that the inclusion of individual fixed effects significantly improves model fit. This result indicates that food security dynamics in Indonesia are shaped by persistent provincial heterogeneity that cannot be captured by a pooled cross-sectional approach. Therefore, the spatial panel model with fixed effects is more appropriate, as it accounts for both spatial dependence and unobserved time-invariant provincial characteristics which leading to more reliable estimation of the Food Security Index.

Table 8. Models Comparison

Model	AIC	R^2
FEM	-	0.268
SAR-FE	521.05	0.975
SEM-FE	800.39	0.973

Several classical assumption tests are conducted on the selected SAR-FE model. The results of the partial t-test on Table 7 indicate that the variables LifeExp, PovRate, DDP, WaterAcc, and ElecAcc, as well as the lag parameter Lambda, are statistically significant with a p-value < 0.05, whereas the variable CalIntake is not significant. Additionally, the SAR-FE model satisfies the normality assumption of residuals, as presented in Figure 6 and meets the homoscedasticity assumption based on the Park Test results shown in Table 9.

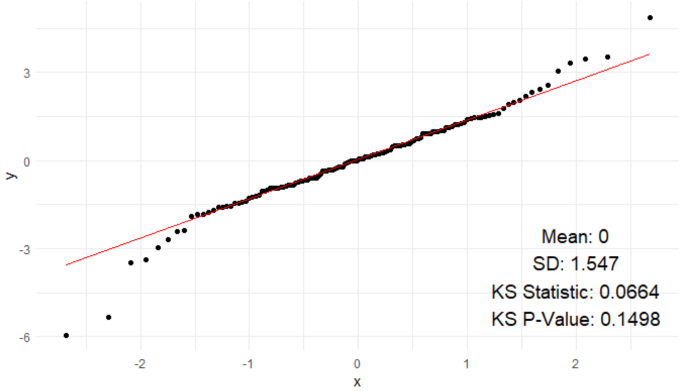


Figure 6. Normality Test on SAR-FE Residuals Model

Table 9. Result of Park Test for Homoscedasticity

Variable	t-Statistics	P-Value
Log(LifeExp)	-1.148	0.139
Log(PovRate)	-0.373	0.710
Log(DDP)	0.184	0.854
Log(WaterAcc)	0.095	0.924
Log(ElecAcc)	-0.261	0.794
Log(CalIntake)	0.153	0.879

The final model can be expressed as shown in equation as below:

$$\hat{Y}_{it} = 4.2085LifeExp_{it} - 1.6023PovRate_{it} - 0.2543DDP_{it} - 0.3037WaterAcc_{it}$$
$$+0.5115ElecAcc_{it} + 0.0065CalIntake_{it} + 0.4149\sum_{j=1}^{N} w_{ij}Y_{jt} + \hat{\mu}_i$$

Based on the estimation results of the Spatial Autoregressive Fixed Effects (SAR-FE) model, several key insights can be drawn regarding the determinants of the food security index across provinces in Indonesia. The positive spatial coefficient empirically indicates that food security in one province is influenced by the food security conditions of neighboring provinces, confirming the presence of spillover effects. Therefore, an increase in the Food Security Index in neighboring provinces is associated with a proportional increase in the index of a given province, holding other determinants constant. Empirical evidence from Indonesia supports this interpretation. Spatial analyses have documented significant clustering patterns, where provinces with low food security tend to concentrate in eastern regions, while higher-performing provinces cluster in western Indonesia, reflecting structural and market linkages across contiguous areas (Abdullah, 2025). However, the significant spatial lag coefficient reflects more than simple geographic clustering. It indicates that changes in food security in one province systematically influence neighboring provinces over time, thereby confirming the presence of dynamic spillover effects. In the context of Indonesia, empirical spatial analyses have documented regional interdependence in food security patterns, suggesting that improvements in infrastructure, distribution systems, or policy interventions in one province may generate measurable externalities across provincial borders (Tanjung & Tanur, 2025). Thus, the SAR-FE specification provides stronger evidence of structural interprovincial linkage than ordinary spatial regression.

Regarding structural determinants, life expectancy at birth demonstrates a positive and statistically significant effect on food security. This finding aligns with the theoretical perspective that life expectancy captures cumulative investments in nutrition, healthcare, sanitation, and socioeconomic development (Headey et al., 2020). The estimation results indicate that an increase in life expectancy at birth contributes to an improvement in food security. This finding suggests that provinces with higher life expectancy at birth tend to have better food security conditions, possibly due to better overall health and living standards. By incorporating life expectancy as an explanatory variable within a spatial-panel setting, this study advances prior literature that typically treats health outcomes as consequences rather than structural determinants of food security.

The poverty rate shows a robust negative and significant effect, confirming that income deprivation constrains economic access to food. Unlike cross-country studies that primarily capture macroeconomic vulnerability, this provincial analysis reveals how intranational poverty disparities contribute to spatial clustering of food insecurity. When spatial dependence is explicitly modeled, the negative effect of poverty reflects not only local income constraints but also regional inequality transmission mechanisms. This reinforces the argument that poverty reduction policies can generate spatial multiplier effects beyond administrative boundaries.

Interestingly, the Desirable Dietary Pattern (DDP) score demonstrates a negative relationship with FSI. This finding aligns with critiques suggesting that dietary diversity indicators may not fully capture caloric sufficiency or affordability constraints (Manikas *et al*., 2023; Wijaya *et al*., 2020). Within a spatial framework, the negative coefficient may reflect structural imbalances in food distribution systems or measurement discrepancies between compositional diet quality and aggregate food security indices. This nuance highlights the importance of interpreting nutritional indicators within broader multidimensional and spatial contexts.

Clean water access is also negatively associated with food security, a result that appears counterintuitive but is theoretically plausible when considering infrastructure–cost trade-offs. While clean water is essential for public health and food preparation, the economic burden associated with improved water access may offset its benefits. High costs and infrastructure disparities might reduce food affordability, contributing to an unexpected negative relationship between clean water access and food security (Kayser *et al*., 2013; Li *et al*., 2024). Evidence from Linderhof et al. (2021) suggests that improvements in water infrastructure may involve transitional fiscal burdens, uneven service provision, or institutional inefficiencies that offset short-term welfare gains. In a fixed-effects spatial model, such dynamics may manifest as negative partial effects after controlling for time-invariant provincial characteristics. This indicates that infrastructure expansion alone is insufficient without complementary income and affordability mechanisms.

In contrast, electricity access exerts a positive and significant influence on food security. Electrification enhances agricultural productivity, cold storage systems, processing efficiency, and market connectivity, thereby strengthening availability and stability dimensions. Within the SAR framework, this effect likely generates both direct impacts and indirect spillovers across neighboring provinces through integrated supply chains and regional economic networks. The presence of such spillover channels underscores the importance of estimating spatial multipliers rather than relying solely on local marginal effects.

This study also found that there is no significant association between calorie intake and food security in Indonesia, suggesting that energy consumption alone does not adequately reflect provincial food security conditions. Although caloric intake is often used as a proxy for food security, we also found out that recent studies emphasize that energy adequacy alone does not capture the multidimensional nature of food security (Novotny et al., 2023). Reliance on calorie-based indicators may underestimate food insecurity because households can meet minimum energy requirements while still lacking dietary diversity and micronutrient adequacy. Similarly, empirical findings reported that food security outcomes are shaped by broader socioeconomic and access-related factors beyond caloric sufficiency (Mahbub, 2020). These findings reinforce the argument that calorie intake represents only the quantitative dimension of food consumption and cannot fully explain variations in food security across regions. Therefore, comprehensive assessment requires multidimensional indicators that incorporate dietary quality, access conditions, and structural socioeconomic factors to more accurately capture the complexity of food security dynamics in Indonesia.

Overall, this study achieves its two primary objectives. First, it empirically confirms the existence and magnitude of spatial spillover effects in provincial food security across Indonesia, validating the application of a spatial-panel econometric framework. Second, it demonstrates that key socioeconomic, infrastructural, and nutritional determinants significantly influence food security when spatial and temporal dynamics are explicitly incorporated. Compared with previous spatial analyses conducted at the cross-country level, the novelty of this research lies in its subnational focus, multidimensional determinant structure, and integration of human development, infrastructure, and dietary indicators within a unified spatial autoregressive fixed-effects model.

From a policy perspective, the presence of significant spatial spillovers implies that food security strategies should be regionally coordinated rather than administratively isolated. Provincial interventions in poverty alleviation, electrification, and human capital development may generate cross-border multiplier effects, thereby enhancing aggregate national food system resilience. However, the unexpected negative coefficients on DDP and clean water suggest that infrastructure and nutritional policies must be accompanied by affordability, equity, and distributional reforms to ensure inclusive food security improvements. Despite these contributions, limitations remain. The static SAR-FE specification does not capture dynamic adjustment processes, and potential endogeneity between socioeconomic variables and food security outcomes may persist. Future research could extend the analysis using dynamic spatial panel models or spatial Durbin specifications to decompose direct and indirect effects more explicitly.

CONCLUSION

This study shows that provincial food security in Indonesia cannot be fully understood using a conventional Fixed Effects Model (FEM), as it ignores interprovincial interactions. The Spatial Autoregressive Fixed Effects (SAR-FE) model better captures both spatial dependence and temporal heterogeneity, revealing significant spatial spillover effects where improvements in one province's food security positively influence neighboring provinces. Key determinants include life expectancy, poverty rate, and electricity access, which respectively promote or constrain food security, while factors such as dietary diversity and clean water access highlight the need to consider affordability and structural distribution. These findings suggest that effective food security policies should be coordinated regionally rather than implemented in isolation, integrating human development, infrastructure, and socioeconomic interventions to generate cross-provincial benefits. From a research perspective, the study underscores the importance of spatial-panel approaches in capturing multidimensional and interconnected dynamics of food security at the subnational level.

AUTHOR CONTRIBUTIONS

Dita Amelia: Funding Acquisition, Supervision, Conceptualization, Methodology, Software, Validation, Writing – Review Editing, Project Admin. Suliyanto: Funding Acquisition, Supervision, Methodology, Software, Validation, Writing – Review Editing, Project Admin. Najwa Khoir: Software, Formal Analysis, Investigation, Data Curation, Writing – Original Draft Preparation. Azizah Atsariyyah: Software, Formal Analysis, Investigation, Data Curation, Writing – Original Draft Preparation.

CONFLICTS OF INTEREST

The author declares no conflict of interests

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