Spatial Spillover Effects in Food Security: A Spatial Lag Fixed Effects Model for Regencies and Cities in West Sumatra (2019–2023)

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Abstract. Food security is a key pillar of national development, reflecting a region's ability to sustain food availability, accessibility, utilization, and stability. The Food Security Index (FSI) serves as a crucial measure of this capability. Based on 2023 data, West Sumatra Province achieved the highest FSI score on the island of Sumatra. This study analyzes food security in 19 regencies and cities of West Sumatra from 2019 to 2023 using a Spatial Lag Fixed Effects Model. The research integrates spatial analysis and panel data approaches to identify determinants of the FSI and assess spatial spillover effects between regions. Secondary data were obtained from the Statistics Agency (BPS) and the National Food Agency. The results reveal significant spatial autocorrelation in most years, except 2023. The best-fitting model is the Spatial Lag Fixed Effects Model. Changes in land area, food expenditure, and rice productivity significantly improve FSI, while non-food expenditure and economic growth do not show a positive effect. The findings emphasize the importance of incorporating spatial dependencies in regional food security policies. Moreover, significant spillover effects indicate that improvements in one area can influence neighboring regions. Therefore, inter-regional cooperation and integrated food distribution policies are essential to achieving sustainable food security.
Keyword: Food Security, Food Security Index (FSI), Spatial Panel Analysis.

1. Introduction

Food security is an essential pillar of national development, playing a vital role in ensuring the well-being of the population and the stability of the economy. In a strategic move to enhance this critical sector, the government has earmarked a substantial budget of IDR 139.4 trillion for food security initiatives. This investment is primarily focused on elevating agricultural productivity, modernizing infrastructure, and empowering farmers with the necessary tools and knowledge to thrive.

The overarching policy envisions the creation of a robust and sustainable food system. Success in this endeavor will be gauged by a significant reduction in reliance on imported food products and a strong emphasis on promoting environmentally sustainable practices in agriculture. Furthermore, the initiative aims to foster a competitive agricultural landscape that not only meets the nutritional needs of the population but also supports local farmers and stimulates economic growth [1].

One of the indicators used to measure a region's ability to maintain food availability, accessibility, utilization, and stability is the Food Security Index (FSI) [2]. Based on 2023 data, West Sumatra

Province ranks as the fourth-best in score and has the highest index score on the island of Sumatra. Among regencies/cities, Tanah Datar Regency has the highest index score on Sumatra. Additionally, Solok City and Bukittinggi City are among the top five cities with the highest scores in Indonesia. On the other hand, some areas still have low index scores, such as the Mentawai Islands Regency with an index value of 53.86. This score places the area in priority level 3, or other words, in the vulnerable food insecurity category [3].

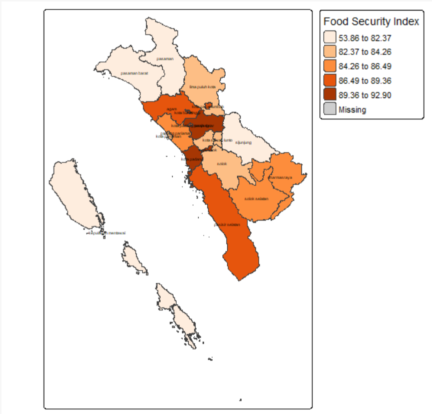

Figure 1. Map of Food Security Index for Regencies/Cities in West Sumatra in 2023.

Based on Figure 1, it is evident that regions tend to cluster together according to similar index values. This indicates a correlation between areas. If a region has a high FSI value, it will likely be surrounded by areas with similar FSI values. Conversely, areas with low food security will be surrounded by regions with similarly low food security. This relates to Tobler's Law, which states that "everything is related to everything else, but nearby things are more related than distant ones," highlighting the significance of spatial relationships in geographic phenomena [4].

Research related to food security by Putri and Suripto [5] and Nisa and Lubis [6] employed panel data analysis, using per capita expenditure as a measure of consumer purchasing power. Based on the analysis results, it was concluded that an increase in expenditure will improve the Food Security Index (FSI). In other words, easier access to food, whether economically or physically, will enhance food security. Furthermore, the study by AW et al. [7] shows that increased rice productivity will align with higher food security levels through the FSI. Similarly, Prabayanti [8] indicates that an increase in harvested area and rice production has a positive and significant effect on the FSI. Additionally, Yahya et al. [9] demonstrate that economic growth has a positive and significant influence on food security in Indonesia.

Research related to food security analysis in West Sumatra Province was conducted by Evalia et al. [10], who used OLS regression, and Refnaldo et al. [11], who employed panel data regression. However, these studies have not yet emphasized the importance of spatial analysis in identifying factors that influence food vulnerability for more comprehensive results. A study by Mardison [12] employed spatial analysis using the Spatial Error Model (SEM) approach to identify factors influencing the prevalence of inadequate food consumption (PoU), a measure of food security, in regencies/cities in West Sumatra. This research shows a significant spatial correlation between regions, but has not yet conducted panel data analysis. These findings highlight the importance of integrating spatial analysis into food security research in West Sumatra. Therefore, this study aims to identify the spatial dynamics and spillover effects of food security in regencies/cities across West Sumatra Province, examining regional and temporal variations.

Next, the methods section will explain the scope of the research, analysis methods, and the stages of analysis in the study. Based on the background, it is also necessary to provide information about the patterns and characteristics of the Food Security Index of West Sumatra Province, which will be explained in the results and discussion section. Therefore, this study will be conducted to obtain a more comprehensive picture of the conditions of the Food Security Index in West Sumatra Province. Subsequently, spatial panel data analysis will be performed using the Food Security Index (FSI) as the dependent variable and the suspected influencing factors as independent variables. Finally, the conclusion section presents a summary of the research and offers recommendations.

However, previous studies on food security in West Sumatra have primarily employed cross-sectional or non-spatial panel approaches, which overlook spatial dependencies between neighboring regions. This gap limits the understanding of how regional interconnections shape food security outcomes. Therefore, this study contributes by integrating spatial econometrics with panel data analysis to capture both temporal and spatial dimensions of food security. This approach allows for identifying not only local determinants but also inter-regional spillover effects, extending the work of Elhorst [19] and Kopczewska [26], who emphasize the importance of spatial linkages in socio-economic analysis.

2. Research Method

2.1. Research Scope

This research uses descriptive and inferential analysis methods. Descriptive analysis employs thematic maps to illustrate the food security patterns of regencies/cities in West Sumatra Province. Inferential analysis uses the Spatial Data Panel method to examine the characteristics of food security. Microsoft Excel 2021 and R Studio software are used to analyze the data. The units of analysis are 19 regencies/cities in West Sumatra Province.

Data collection methods include secondary data from publications by the Statistics Agency (BPS) and the National Food Agency. The Food Security Index (FSI) serves as the dependent variable. The independent variables include changes in harvest area, food expenditure, non-food expenditure, rice productivity, and economic growth. These variables are consistent with the indicators employed by Nisa & Lubis [6] and Prabayanti [8] in assessing regional food security using economic and agricultural determinants.

Table 1. Research Variables.

No	Variable	Unit
1	Food Security Index (FSI) (Y)	Index (0-100)
2	Changes in harvest area (PLP / X_1)	Percent(%)
3	Food Expenditure per Capita (Peng_Makanan / X_2)	Million Rupiahs / Person / Month
4	Non-Food Expenditure per Capita (Peng_NonMakanan / X_3)	Million Rupiahs / Person / Month
5	Rice Productivity (PV / X_4)	Quintal per Hectare
6	Economic Growth (PE / X_5)	Percent (%)

2.2. Spatial Weight Matrix

The spatial weight matrix is constructed to represent the spatial correlation between regions. A well-designed spatial weight matrix plays an essential role in producing accurate and consistent estimates in spatial econometric models [13]. The matrix is created using a combination of geographic distance and non-geographic distance, making it a customized spatial weighting matrix. Tanjung and Pasaribu [14] employed a customized spatial weighting matrix, based on migration data between regencies/cities, to represent economic distance between regions. This study uses the difference in per capita GRDP (Gross Regional Domestic Product) to indicate economic spatial correlation. The smaller the difference between regencies/cities, the larger the value, or in other words, the stronger the relationship between those regions. .

2.3. Moran's I test

Global spatial autocorrelation is used to see whether there is a general correlation between regions. Global Moran's I statistic is used to measure spatial autocorrelation. This statistic can be formulated as follows:

$$I = \frac{\sum_i \quad \sum_j \quad w_{ij}(x_i-\mu)(x_j-\mu)}{(x_i-\mu)^2} \tag{1}$$

Whereas μ is the average of the variables tested; x_i is the i-th tested variable; w_{ij} spatial weighting matrix with dimensions. According to Anselin [15], the decision regarding this test is to reject H_0 if the p-value < α. The Global Moran's I value ranges from -1 to 1, or if the value is positive, then there is positive spatial autocorrelation and clustering occurs, where areas with high characteristics tend to be surrounded by areas with high characteristics as well. If the z-value is negative, then there is negative spatial autocorrelation, and neighboring areas have different characteristics. Meanwhile, if the value $I \cong E(I)$then there is no spatial pattern, or the characteristic values are randomly dispersed.

2.4. Panel Data Model

Panel data regression models are regression models based on data that consider spatial and temporal dimensions. Panel data consists of individual units collected over a certain period [16]. In panel data regression, there are three types of models as follows:

Pooled Model

$$y_{it} = \alpha + \beta x'_{it} + u_{it} \tag{2}$$

Fixed Effect Model

$$y_{it} = \alpha_i + \beta x'_{it} + u_{it} \tag{3}$$

Error Effect Model

$$y_{it} = \alpha_0 + \beta x'_{it} + w_{it} \tag{4}$$

$$w_{it} = \varepsilon_i + u_{it} \tag{5}$$

Whereas *i* is the *cross-section* for the cities and regencies $(i = 1,2, \dots, 19)$, *t* states the period of time $(t = 2019,2020, \dots, 2023)$, y_{it} the dependent variable of region i in year t; x_{kit} is the k-th independent variable in region *i* for year *t*. The Parameter α represents the intercept, while α_i is the intercept of the regression model for *i*. The coefficient β is the coefficient of the independent variable. The error coefficient u_{it} is the residual from the equation and is normally distributed. The coefficient e_i is the error from the unit effect.

Chow test

The Chow test is used to determine whether a panel model with fixed effects (Fixed Effect Model/FEM) is more appropriate than a pooled OLS model. This test examines the null hypothesis that all cross-sectional unit intercepts are the same (no fixed effects). To test this hypothesis, the following test statistic is used:

$$F = \frac{(RSS_P - RSS_{FE})/(N-1)}{RSS_{FE}/(N(T-k)} \tag{6}$$

Whereas, RSS_P the residual sum of squares from the pooled OLS model; RSS_{FE} is the residual sum of squares from the fixed effect model. N is the number of cross−sectional units, T is the time period, and k is the number of estimated parameters. The decision for this test is to reject H_0 if the value F_{hitung} greater than the critical value $F_{\alpha;N-1,N(T-k)}$ or p-value<α [17]. Next, the model that will be chosen is the fixed effect model.

Hausman test

The Hausman test is used to determine whether the Fixed Effect (FE) or Random Effect (RE) model is more appropriate for panel data analysis. If individual effects are correlated with the independent variables, then the Fixed Effect model is more suitable; conversely, if there is no correlation, the Random Effect model can be used because it is more efficient [17]. The Hausman test statistic is as follows:

$$H = \left(\hat{\beta}_{RE} - \hat{\beta}_{FE}\right)'\left[Var\left(\hat{\beta}_{RE}\right) - Var\left(\hat{\beta}_{FE}\right)\right]^{-1}\left(\hat{\beta}_{RE} - \hat{\beta}_{FE}\right) \quad (7)$$

Whereas, $\hat{\beta}_{RE}$ *and* $\hat{\beta}_{FE}$ Vector of parameter estimates from the Random Effect and Fixed Effect models. $Var\left(\hat{\beta}_{RE}\right)$ *and* $Var\left(\hat{\beta}_{FE}\right)$ the variance-covariance matrix of each model's estimates. The decision for this test is to reject H_0 if the value H_{hitung} greater than the critical value $\chi^2_{\alpha,1}$ or p-value $< \alpha$ [16]. Next, the model that will be chosen is the fixed effect model.

2.5. Assumptions test

Testing assumptions is crucial to verify that the panel regression model accurately reflects the data. Gujarati [18] highlights two key assumptions for panel data: residual normality and multicollinearity. Furthermore, autocorrelation tests are necessary to examine the relationship between residuals over different locations. Conversely, tests for residual variance homogeneity are typically not performed, as error variances often differ across locations and are challenging to equalize.

2.6. Spatial Dependency tests

Spatial dependence tests are used to determine whether there is any dependence between neighboring regions. One of the tests for dependence/spatial dependence effects is the Lagrange Multiplier, which is used to identify spatial dependence among regions. This test is used to select the best model, either the spatial lag model or the spatial error model, developed by Anselin et al. in Elhorst [19].

2.7. *Spatial Data Panel Model*

$$y_{it} = \delta \sum_{j=1}^{n} w_{ij} y_{jt} + \sum_{k=1}^{K} \beta_k x_{kit} + u_i + e_{it} \quad (8)$$

$$e_{it} = \rho \sum_{j=1}^{N} w_{ij} e_{jt} + \varepsilon_{it} \quad (9)$$

Based on the above equation, the possible model formed in this research is

$$IKP_{it} = \delta \sum_{j=1}^{19} w_{ij} IKP_{jt} + \beta_1 PLP_{it} + \beta_2 Peng\_Makanan_{it} + \beta_3 Peng\_Nonmakanan_{it} + \beta_4 PV_{it} - \beta_5 PE_{it} \quad (10)$$

$$e_{it} = \rho \sum_{j=1}^{19} w_{ij} e_{jt} + \varepsilon_{it} \quad (11)$$

Whereas IKP_{it} is food security index for *i* th regencies or cities and for *t* th time; PLP_{it} is changes in harvest area for *i* th regencies or cities and for *t* th time;$Peng\_Makanan_{it}$ is food expenditure per capita ;$Peng\_NonMakanan_{it}$ is non food expenditure per capita for *i* th regencies or cities and for *t* th time;PE_{it} is economic growth for *i* th regencies or cities and for *t* th time. The w_{ij}spatial weighting matrix with 19 x 19 dimension. The parameter δ is the spatial autoregressive coefficient, while β is a vector of independent variable coefficients. The coefficient ρ is the spatial autocorrelation coefficient. The error coefficient is for region i. The coefficient is the error from the model equation for region j and year t. Additionally, the error is the spatial error for region i in year t. For this study, all hypothesis tests in this study were conducted at a 10% significance level (α = 0.10). This threshold aligns with exploratory regional studies where the number of spatial units is limited, following the recommendations of Anselin Anselin [15], Elhorst [19].

The research stages adapted from Pasaribu et al. [20] regarding the steps for forming a spatial panel regression model are as follows: 1.

1. Conduct a descriptive analysis of the Food Security Index in West Sumatra
2. Form the Spatial Weighting Matrix
3. Perform Moran's I test on the formed spatial weighting matrix
4. Determine the panel regression model using the Hausman test and the Chow test
5. Conduct Classical Assumption Tests
6. Perform hypothesis testing for spatial correlation using the Lagrange Multiplier (LM-lag and LM-error) tests, and conduct further spatial correlation hypothesis testing with the Robust LM test if both LM-lag and LM-error are significant

7. Model estimation and goodness of fit.

3. Result and Discussion

3.1. Food Security Index in Sumatera Barat

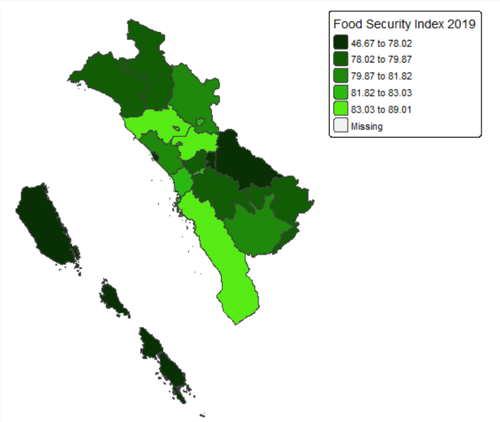

Figure 2. Food Security Index Map of Regencies/Cities in West Sumatra Province in 2019.

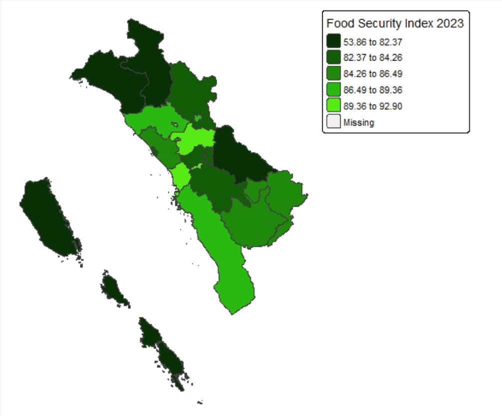

Figure 3. Food Security Index Map of Regencies/Cities in West Sumatra Province in 2023.

The comparison between Figure 1 and Figure 2 shows the dynamics of food security in West Sumatra Province from 2019 to 2023. Overall, there has been a positive shift in the food security categories of several regencies/cities, marked by a decrease in the number of areas classified as 'Very Vulnerable' and 'Vulnerable,' and an increase in areas categorized as 'Resilient' and 'Very Resilient.' This improvement indicates enhancements in the aspects of food availability, access, and utilization in those regions. However, there are still some areas, particularly in the Mentawai Islands regency, that have not shown significant improvement and remain in the vulnerable category. This highlights the need for more targeted, region-based policy interventions to address disparities in food security across different areas.

By 2023, a clear shift in the spatial pattern of food security is visible, with more regions moving into higher FSI categories. This improvement indicates an overall enhancement in food security, likely driven by increased government investment, infrastructure development, and policy actions during the study period. However, the continued presence of some low-performing regions suggests spatial spillover effects, where a region's food security is influenced not only by its conditions but also by those of neighboring areas. These spatial dynamics highlight the importance of regionally integrated strategies that consider both local and surrounding area circumstances.

3.2. Formation of the Spatial Weighting Matrix

The formation of a customized spatial weighting matrix is based on combining a geographic distance matrix with a non-geographic distance matrix. The geographic distance spatial weighting matrix is created using the k-nearest neighbors method with a k = 3. The choice of k = 3 for the k-nearest neighbors matrix follows prior empirical evidence that smaller k values (between 3 and 5) effectively capture regional dependence without excessive smoothing [29]. In this study, k = 3 provided the most stable Moran's I values across years, ensuring each region retained meaningful spatial connections while avoiding overconnectivity. Then, the non-geographic matrix is organized based on economic distances between regencies or cities, which are calculated by taking the absolute difference in per capita GRDP values between two regions. The formula for the economic distance between regions i and j is given as follows:

$$d_{ij}^{e} = |PDRBpc_i - PDRBpc_j| \quad (12)$$

Whereas d_{ij}^{e} the economic distance between region i and region j. $PDRBpc_i$ is the Gross Regional Domestic Product per capita of region i and $PDRBpj$ is the Gross Regional Domestic Product per capita of region j.

To form the spatial weight matrix from the economic distance, the distance values are then transformed into similarity values through weighting, for example, by using the inverse of the distance:

$$w_{ij}^{e} = \frac{1}{d_{ij}^{e} + \epsilon} \quad (13)$$

Whereas w_{ij}^{e} economic weight element between region i and region j. $PDRBpc_i$is a small constant to avoid division by zero. The combined spatial weight matrix is formed by merging the geographic and non-geographic spatial weight matrices using an averaging method, then row standardization is performed so that each row of the weighting matrix sums to one.

3.3. Moran's I test

Table 2. Moran's I tests result

Year	*p-values*	Decision
2019	0.05915	Reject H0
2020	0.05824	Reject H0
2021	0.01696	Reject H0
2022	0.06721	Reject H0
2023	0.1518	Accept H0

Spatial autocorrelation measured through the global Moran's I is presented in Table 2. By using the significance level of 10% (α = 0.10), positive spatial dependence on the Food Security Index (FSI) is indicated by a positive and significant global Moran's I value for each year except 2023, based on the results of the spatial autocorrelation test. This suggests that regencies/cities with high FSI tend to cluster together, and those with low FSI also tend to group. For panel datasets it is not strictly necessary to compute Global Moran's I separately for every year as a precondition for spatial modelling. In practice Moran's I can still be used as an exploratory diagnostic for each year, but formal model selection and inference for panel models should rely primarily on panel-specific LM or Robust LM test. Therefore, in this study we report year-wise Moran's I for descriptive purposes and base model selection and spatial dependence inference on LM and Robust LM panel tests as recommended in the spatial panel literature [28].

3.4. Data Panel Model Identification

Table 3. Chow test and Hausman test result

Test	Calculated Statistics	Critical Values	*p-values*	Decision
Chow test	26.838	1.8442	0.0000*	Reject H_0
Hausman test	31.728	11.0705	0.0000*	Reject H_0

The first step in choosing a panel model is to determine whether to use the Common Effect Model (CEM) or the Fixed Effect Model (FEM) using the Chow test. Table 3 shows that the calculated F-statistic is greater than the critical value, and the p-value is less than 0.1. This leads to the rejection of the null hypothesis (H_0), indicating that at a 10% significance level, the FEM is more appropriate than the CEM. After the Chow test, the Hausman test is conducted to decide between the FEM and the Random Effect Model (REM). The results in Table 2 indicate that the test statistic exceeds the critical value, and the p-value is less than 0.1. Therefore, the null hypothesis (H_0) is rejected. Therefore, at a 10% significance level, the FEM is chosen over the REM.

3.5. Assumption tests

Table 4. VIF values

Variable	VIF
PLL	1,0503
Peng_Makanan	3,2127
Peng_NonMakanan	3,1561
PV	1,5644
PE	1,0587

Before performing the spatial panel data regression model, several tests were conducted on the independent and dependent variables. The initial test used was multicollinearity testing by calculating the VIF value. As shown in Table 4, the model variables used did not have VIF values exceeding 10, indicating that multicollinearity is not present. Next, a normality test was conducted using the Jarque-Bera test, with a test statistic value of 1.6801 and a p-value of 0.4317. The test decision was to accept H0. Thus, it can be concluded that the residuals of the selected fixed effect model are normally distributed.

3.6. Spatial Dependency tests

Table 5. Spatial Dependency tests result

Test	Calculated Statistics	Critical Point	*p-values*	Decision
LM-lag	18.235	3,84	0.0000*	Reject H0
LM-error	16.708	3,84	0.0000*	Reject H0
RLM-lag	2.8041	3,84	0.09402**	Reject H0
RLM-error	1.2773	3,84	0.2584	Accept H_0

Based on the results in Table 5, it is found that there is a spatial effect from the lag of the FSI variable as the dependent variable, indicated by the LM-Lag test and the RLM-Lag test, which have p-value values less than 10 percent (significant at $\alpha = 10\%$). Meanwhile, the results of the LM-Error test and the RLM-Error test show different conclusions. The LM-Error test results indicate that there is a spatial effect on the error of the model, whereas the RLM-Error test results show that there is no spatial effect on the error of the model because the p-value is less than 10 percent (significant at $\alpha = 10\%$). Therefore, the model option that can be selected is the Spatial Lag model (which only includes the spatial component on the lag of the dependent variable).

3.7. Estimation results and Goodness of fit

Table 6. Spatial Panel Model Result

Variabel	Coefficient	Standard Error	*p-values*
Main Model			
PLP	0,0498	0,0099	0.0000*
Peng_Makanan	4,3451	1,3786	0.0016*
Peng_NonMakanan	3,979	0,0037	0.2891
PV	0,2431	0,0657	0.0002*
PE	-0,1844	0,0861	0,9769
Spatial			
lambda	0,3322	0,0836	0.0000*
Goodness of fit Model			
AIC	384.5973		

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R^2	0,9605

*significant at 10%

Based on Table 6, the obtained model equation is as follows:

$$\widehat{IKP_{it}} = -7{,}7933 + 0{,}0498PLP_{it} + 4{,}4351Peng\_Makanan_{it} + 3{,}979Peng\_Nonmakanan_{it} + 0{,}2431PV_{it} - 0{,}18444PE_{it} + 0{,}3322wIKP_{it}$$

To answer the research question, it is very important to analyze the influence of spatial variables on the Food Security Index (FSI). The estimated lambda value of 0.3322 and its significance indicate the presence of dependence among regencies/cities in the model. This means that the FSI in one area affects nearby areas, and the spatial lag in neighboring regions has similar characteristics. The R^2 value in the model is 0.9605. This means that changes in harvest area, food expenditure, non-food expenditure, rice productivity, and economic growth as independent variables in the model can explain 96 percent of the variation in food security variables. The coefficient of determination, R^2, is commonly used to measure the goodness of fit of a model. Additionally, all independent variables significantly influence the dependent variable, the Food Security Index (FSI), except for the non-food expenditure variable.

The interpretation of the Harvest Area Change Coefficient (PLP) is that a one percent increase in rice field area will result in an increase of the FSI index by a certain point (assuming other variables remain constant). This is consistent with research findings indicating that expanding agricultural land and increasing food production are key factors in addressing food insecurity in Indonesia, especially in regions that are agricultural centers [21]. An increase in harvest area is a primary factor in boosting food production and supporting food security [22]. The rice harvest area is considered an input, the rice production volume is the output, and the food security index is the outcome [6]. According to Cobb-Douglas modeling, an increase in rice harvest area will lead to higher rice production, which in turn impacts the improvement of the food security index.

Furthermore, an increase in per capita expenditure of one million rupiahs per person in an area will raise the FSI index value by 4.4351 points. This result aligns with research by Solana [23], where a significant increase in food expenditure supports the improvement of FSI because it indicates better access and food consumption in terms of both quantity and quality. More stable and affordable food prices are expected to increase community consumption, which will ultimately improve the socio-economic conditions of the community.

An increase in non-food expenditure by one million rupiahs per person in a regency/city will raise the food security index value in that regency/city by 3.979. However, this study has not yet proven that an increase in non-food expenditure will improve the level of food security. Areas with high levels of prosperity indicate that their communities will be able to meet their needs not only for food but also for non-food items. This is similar to what is observed in Engel's law, which states that the proportion of total expenditure allocated to food decreases as income increases [24]. The comparison between food and non-food expenditures in this study reveals that only food expenditures are significant. This suggests that the consumption pattern of people in West Sumatra tends to favor food expenditure in terms of food security levels.

An increase in productivity of one quintal per hectare in a regency/city will raise the food security index value in that regency/city by 0.2431 points. This research aligns with the findings of AW et al. [6], which states that as an area increasingly improves its productivity to obtain food (mainly rice), the Food Security Level in that area will also improve. Food security measurement is not only influenced by quantity, which is measured through the amount of production, but also by the quality aspect. Higher rice productivity in a region indicates that the quality of the harvest results is better. The quality of rice produced can be improved through the use of irrigation, pesticides, and certified seeds as important input factors in rice farming [25].

An increase of one percent in economic growth in a regency/city will decrease the FSI value in that regency/city by an average of 0.1844. However, this study has not yet proven that an increase in economic growth will improve food security levels. Ideally, economic growth would stimulate the purchasing power of the community so that food consumption can be maximized [12]. The negative effect of economic growth on food security indicates a structural transformation bias where growth is concentrated in non-agricultural sectors such as mining, trade, and services, which do not directly contribute to food availability or affordability. This pattern is consistent with the findings of Suryani and Nugroho [30] has found that economic expansion dominated by non-agricultural output can worsen food security in peripheral regions. Consequently, growth that is not inclusive of agricultural productivity may lead to higher inequality in food access.

Table 7. Direct and Indirect Effects for Independent Variable

Variable	Direct	Indirect	Total
PLP	0,0514	0,0232	0,0745
Peng_Makanan	4,4821	2,0250	6,5071
Peng_NonMakanan	4,2054	1,8548	5,960
PV	0,2508	0,1133	0,3641
PE	-0,1903	-0,0859	-0,2762

In spatial regression models, there is an issue related to simultaneity that limits the direct interpretation of the coefficients of independent variables due to the spatial component in the dependent variable [25]. Therefore, to interpret the magnitude of each independent variable's effect, the values of the direct effect and the indirect effect or spillover are used. The significant spillover effects highlight that improvements in agricultural and expenditure factors in one regency can enhance food security in neighboring regions through shared markets, trade routes, and information networks. Zhang et al. [31] has emphasized that interregional agricultural collaboration and technology diffusion are key drivers of spatial spillovers in food security.

Table 6 shows that a one percent increase in land area change in a regency/city will raise the average percentage of the food security index in that regency/city by 0.05. Meanwhile, in terms of indirect effects, it is known that a one percent increase in land area change in a regency/city will raise the average percentage of the food security index in other regencies/cities by 0.02.

Additionally, a one million rupiahs increase in per capita expenditure per person in a regency/city will increase the food security index value in that regency/city by an average of 4.48. In terms of indirect effects, a one million rupiahs per person increase in per capita expenditure in a regency/city will increase the food security index value in other regencies/cities by an average of 2.02.

An increase in non-food expenditure of one million rupiahs per person in a regency/city will raise the food security index value in that regency/city by an average of 4.20. Meanwhile, from the indirect effect side, non-food expenditure of one million rupiahs per person in a regency/city will increase the food security index value in other regencies/cities by an average of 1.85 percent.

An increase in productivity of one quintal per hectare in a regency/city will raise the food security index value in that regency/city by an average of 0.25. From the indirect effect side, the productivity of one quintal per hectare in a regency/city will increase the food security index value in other regencies/cities by an average of 1.85. These results also indicate that increased rice production to meet food needs can have a positive impact on communities in other areas.

A one percent increase in economic growth in a regency/city will decrease the food security index value in that regency/city by an average of 0.1902. From the indirect effect side, a one percent increase in economic growth per person in a regency/city will decrease the food security index value in other regencies/cities by an average of 0.08.

4. Conclusion

Based on the research results, it can be concluded that there is a significant spatial dependence in the Food Security Index (FSI) among regencies and cities in West Sumatra, especially from 2019 to 2023. The best model, as determined by the Chow and Hausman tests, is the Fixed Effects model. According to the Lagrange Multiplier test, the most suitable spatial model is the Spatial Lag Model. Factors such

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as changes in land area (PLP), food expenditure, and rice productivity have a positive and significant influence on FSI. Conversely, non-food expenditure and economic growth have not yet been shown to have a positive relationship with FSI. Therefore, regional food security policies should focus on improving food distribution connectivity, ensuring affordable prices, promoting nutrition education, and enhancing supporting infrastructure for optimal food utilization. Additionally, there is an indirect (spillover) effect from these variables on surrounding areas, highlighting the importance of inter-regional cooperation in improving food security. Recognizing the indirect effects of food security variables on surrounding areas underscores the importance of regional cooperation. This can foster collaboration between neighboring regions, enhancing food security on a broader scale. Furthermore, future research should conduct a more detailed analysis of the influence of independent variables on food security using appropriate spatial analysis methods. Future research also could expand this study by incorporating additional spatial determinants such as climate variability, transportation accessibility, and agricultural diversification [27]. Strengthening data granularity at the sub-district level would enhance the precision of spatial food policy interventions.

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