DOI: https://doi.org/10.34123/jurnalasks.v17i2.817

POLITEKNIK STATISTIKA STIS

Jurnal Aplikasi Statistika & Komputasi Statistik
Vol. 17 No. 2, December 2025
e- ISSN: 2615-1367, p-ISSN:2086-4132

Available online at https://jurnal.stis.ac.id/

Spatial Heterogeneity of Food Security in Indonesia: Unpacking the Roles of Technology and Democracy Index

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ARTICLE INFO

Article history:
Received 11 June, 2025
Revised 10 December, 2025
Accepted 22 December, 2025
Published 31 December, 2025

Keywords:
Democracy; Food Security; ICT; Indonesia; Spatial Heterogeneity; Urbanization

Abstract

Introduction/Main Objectives: Food security is a key concern for all countries, especially Indonesia. Technological development and democratic quality are vital for sustainable food security. This study aims to determine the impact of technology and democracy on food security. **Background Problems:** The relationship between food security and these two factors remains uncertain. Moreover, the extant literature on the spatial impacts on food security yields results that are inconclusive. **Novelty:** This study offers a comprehensive depiction of the impact of spatial relationships between variables, with a particular focus on the quality of democracy and technology, on the multidimensionality of food security. **Research Methods:** A spatial lag model is applied to ascertain the impact of technological and democratic on multidimensional food security using data from 34 provinces in 2022. **Finding/Results:** The results reveal significant spatial dependence in Indonesia's food security. Technological development and democratic quality positively and significantly affect food security, while urbanization and food crop land expansion show negative and positive effects, respectively. Spatial spillover accounts for approximately 37%–38% of the total impact of each explanatory variable. These findings suggest that technology adoption, democratic strengthening, and interprovincial collaboration are crucial for improving food security.

1. Introduction

Food security represents a critical and multifaceted challenge with the potential to significantly hinder a nation's development and compromise its national security. At its core, food security is a region's ability to produce enough food to meet its own consumption needs [1] and to ensure that all people have consistent material and economic access to sufficient, nutritious, and safe food [2]. Alarmingly, a report from the Food and Agriculture Organization (FAO) indicates that approximately 783 million individuals globally faced hunger in 2022, with about one in ten experiencing severe food insecurity [3], [4]. The projected increase in the global population is expected to further amplify food demand and exacerbate existing food insecurity [5]. Consequently, food security is a crucial issue, explicitly recognized within the Sustainable Development Goals (SDGs), particularly for developing nations such as Indonesia [6].

Indonesia, as an emerging nation, confronts a persistent challenge in achieving comprehensive food security. Despite its classification as an upper middle-income country, Indonesia grapples with significant impediments to adequate food access, further compounded by the triple burden of malnutrition, encompassing the co-existence of undernutrition, overnutrition, and widespread micronutrient deficiencies. Statistical evidence from the *Badan Pusat Statistik* (BPS) reveals that approximately 4.85 percent of Indonesian households experienced moderate to severe food insecurity in 2022 [7]. This situation is underscored by a concurrent rise in undernourishment, escalating from 7.63 percent in 2019 to 10.21 percent in 2022, with a concerning prevalence across geographical regions, as 23 out of the nation's 34 provinces exhibited undernourishment rates exceeding the national average [8]. Furthermore, the most recent findings from the *Riset Kesehatan Dasar* (RISKESDAS) highlight the pervasive nature of micronutrient deficiencies, particularly affecting vulnerable demographic groups including children aged 0-59 months, adolescent girls, and pregnant and lactating women [9]. When viewed within a global context, Indonesia's 2022 rankings of 63rd in food security and 77th in hunger [10], [11]. Adding to the complexity of ensuring future food security for its populace, Indonesia faces formidable challenges posed by uncertain climate change patterns, ongoing environmental degradation, and the pressures associated with a large and rapidly growing population. Consequently, there is a compelling imperative for intensified and strategically focused interventions to effectively address the multifaceted and persistent challenges to food security across the Indonesian landscape.

A number of factors have been identified as potentially influential on food security, including technology and democracy. Technological development is a continuous and rapid process, with applications in all areas of life, including the food sector. [12] revealed that the application of technology (such as artificial intelligence (AI), blockchain technologies, mobile applications, Internet of Things (IoT), big data, and drones) in the food sector has been carried out in many ways, ranging from controlled environment agriculture, farming automation, and genetic editing. The utilization of such technologies has been demonstrated to enhance agricultural productivity [13], optimize supply chain efficiency [14], stabilize food prices [15], and improve the quality of food produced [16]. Hence, the advancement of technology is regarded as a pivotal solution for the establishment of sustainable food security [17], [18]. Furthermore, the capacity of technology to innovate, optimize, and revolutionize traditional practices offers a plethora of opportunities to mitigate the risks of food insecurity. However, in Indonesia, the rate of technology adoption in the agricultural sector remains low [19], [20]. This is further compounded by the disparate development of technology across different regions. Another pivotal factor that merits greater scrutiny in the pursuit of food security is the quality of democracy. Democracy is defined as institutional arrangements that enable individuals to engage in political processes freely [21]. In this sense, democracy is closely linked to governance and institutions. In the context of a flourishing democracy, the resultant governance and institutions are characterized by transparency and accountability, thereby fostering a foundation for political stability and policies that support food security [22], [23], [24]. Conversely, when democracy is poor, it engenders political tensions, government bureaucratic incompetence, and corruption, which hinder the achievement of food security [25]. As [26] have observed, a nation that respects democratic rules has never suffered from a famine. This perspective is predicated on the notion that the safeguarding of economic and social rights, including the right to food, is contingent on the promotion of political and civil liberties. While the academic literature acknowledges a correlation between the quality of democracy and the prevalence of food security, the precise nature and mechanisms underpinning this relationship remain to be systematically delineated. To address this gap in understanding, this study poses the following research questions: (1) Does technological development exert a significant influence on food security outcomes in Indonesia? (2) What specific role does democratic governance play in shaping food security within the Indonesian context?

A considerable number of studies have already been conducted on the subject of food security. However, the majority of these have adopted an approach that has been critiqued as one-sided [27] or have focused exclusively on agricultural performance [28], [29], which limits their ability to accurately depict food security conditions in their totality. Achieving sustainable food security necessitates consideration of all pertinent factors. The Food and Agriculture Organization (FAO) has identified four interrelated elements of food security: availability, affordability, utilization, and stability. Despite the existence of numerous studies that employ indicators encompassing these four dimensions, these studies have not incorporated spatial effects in their modelling [30], [31], [32]. Indeed, it is imperative to incorporate spatial effects into the modelling of the relationship between explanatory variables and response variables when location is designated as the unit of analysis [33]. This necessity arises from the recognition that distinct regions possess unique food security characteristics, which can exert influence on one another. Moreover, with the advent of rapid developments in the social economy, logistics and transportation, information dissemination, and modernization of agricultural equipment, there has been a significant increase in the flow of food production, distribution, and consumption between regions [34]. As a result, spatial dependence on food security in various regions has become increasingly prominent. Consequently, the achievement of food security is inextricably linked to spatial considerations. However, despite the crucial concern of food security in Indonesia, scholarly attention to its nuanced dimensions, particularly spatial heterogeneity, remains limited. Moreover, the determinants of food security, such as the roles of technology and governance, are also underexplored within the Indonesian context.

In light of the aforementioned observations, the research objective of this study is to empirically estimate the relationships among food security, technology, and democratic governance, while also examining the spatial effects inherent within these relationships across the diverse landscape of Indonesia. This study contributes to the existing body of knowledge by employing food security indicators that comprehensively encompass all relevant dimensions, thereby providing a more nuanced understanding of the condition. To achieve these objectives, a spatial model that accounts for area-specific effects is applied. This methodological choice enables the determination of both direct and indirect relationships between the variables under investigation, thereby promising to yield more insightful research findings. Additionally, the significance of this study lies in its potential to offer crucial perspectives and evidence-based insights for planners and policymakers, facilitating the formulation of effective strategies aimed at achieving sustainable food security throughout Indonesia.

The remainder of the article is divided into three sections. Section 2 provides a detailed discussion of the research method, including the data that was employed and the analytical tools that were applied. Section 3 contains the results and further discussion. Finally, Section 4 offers a conclusion in the form of a synopsis of the article's findings and a set of policy recommendations.

2. Material and Methods

2.1. Data

This study was constructed using secondary data encompassing 34 Indonesian provinces in 2022. That year was chosen because Indonesia's food security situation is poor globally. Furthermore, the year 2022 provides a clearer picture of post-pandemic recovery and the challenges that remain. The dependent variable applied is a food security index created from three dimensions: availability, affordability, and utilization [35]. The employment of these three dimensions is predicated on their consideration of the availability of data at the smallest geographical level. The study incorporates the Information and Communication Technology Development Index and the Indonesian Democracy Index as the primary variables to represent technological development and the quality of democracy, respectively. Concomitantly, the study includes urbanization and agricultural land utilization as additional explanatory variables. These two variables were selected on the grounds that they are capable of describing the conditions from upstream to downstream with regard to food security, particularly in light of the challenges currently faced by Indonesia. The rapid process of urbanization, particularly in developing countries such as Indonesia, exerts a significant influence on the demand for food, consequently affecting food consumption and distribution patterns. Conversely, the density of food crop land emerges as a pivotal factor in determining agricultural productivity. Moreover, in Indonesia, with its substantial population and rapid growth, pressure on agricultural land is increasing. A comprehensive description and the data sources utilized are presented in Table 1.

Table 1. Detail of research variables

Variable	Definition	Unit	Source
Food Security Index (FSI)	An index that measures the achievement of food security development in a region on a scale of 0 to 100	Point	Ministry of Agriculture
Information, technology and communication development index (ICT)	An index that measures the standardised level of ICT development in a region on a scale of 0 to 10	Point	BPS-Statistics of Indonesia
Indonesia democracy index (IDI)	A composite indicator that shows the level of democratic development in Indonesia on a scale of 0 to 100	Point	BPS-Statistics of Indonesia
Urbanization (URB)	Ratio of urban population to total population	Percent	BPS-Statistics of Indonesia
Food crop land density (FCLD)	Ratio of harvested area of food crops (rice, corn, soybean, sweet potato, and cassava) to the total area of the province	Percent	Ministry of Agriculture and BPS-Statistics of Indonesia

2.2. Spatial Autocorrelation Presence Test

The analytical apparatus employed in this study is spatial area modelling, a methodology that utilizes the unit of analysis as a location, thereby enabling the consideration of spatial effects within the model. The initial step involves ascertaining the existence of spatial correlation. Spatial autocorrelation emerges when there is a correlation among the values of a single variable that is exclusively attributable to its relatively proximate location. The Global Moran's I and Geary's C indices are generally applied to this assessment, with the calculation formula presented below [36], [37].

$$\text{Moran's I} = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}(y_i - \bar{y})\left(y_j - \bar{y}\right)}{\sum_{i}^{n}(y_i - \bar{y})^2 \sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}} \tag{1}$$

$$C^* = \frac{(n-1)\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}\left(y_i - y_j\right)^2}{2\sum_{i}^{n}(y_i - \bar{y})^2 \sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}} \tag{2}$$

where n represents total regions, w_{ij} is the spatial weight matrix between the i^{th} and j^{th} location, y and dan $\bar{y}$ are the dependent variable and the average value of the dependent variable, respectively. After the Moran's I index is normalised by variance, the value will be between -1 and 1. $I > 0$ indicates positive spatial correlation, the larger the value, the more obvious the spatial correlation; $I < 0$ indicates negative spatial correlation, the smaller the value, the greater the spatial difference; $I = 0$, spatial randomness. The value of Geary's C index is generally between 0 and 2. When $C > 1$, it means negative correlation, and when $C < 1$, it means positive correlation.

The significance of Moran's I and Geary's C is determined by computing a p-value and a z-score based on the null hypothesis of no spatial dependence (i.e., complete spatial randomness). If the p-value is greater than 0.05, we fail to reject the null hypothesis, thereby suggesting that the spatial distribution of the values could be attributable to random chance. Conversely, if the p-value is less than 0.05, the null hypothesis is rejected, indicating the presence of spatial dependence.

2.3. Spatial Area Modelling

The spatial economics literature provides two main approaches to modelling spatial correlation [37]. Spatial dependence is theorized as a long-run equilibrium of underlying spatial-temporal processes. Spatial dependence based on time-lag relationships has been demonstrated to describe diffusion processes in space. Consequently, spatial autoregressive (SAR) models encompass spatial lags of the dependent. Conversely, when spatial dependence emanates from omitted variables that demonstrate spatial dependence, the resultant model incorporates the spatial lags of the explanatory variables and the dependent variable, hereby establishing the corresponding model as a spatial error model (SEM). Meanwhile, the integration of models with spatially autoregressive models (Spatial lag) and a spatial error model, designated as the "general spatial autocorrelation model"[38]. The incorporation of a weight matrix is pivotal in introducing spatial dependence into the analysis, thereby defining the spatial component structure. Specifically, the spatial matrix W in the horizontal model assumes the form n x n, where the elements are non-negative and sparsity is observed. The elements of this matrix are defined as $w_{ij} = 1$ for neighborhoods and $w_{ij} = 0$ to avoid observations being identified as neighbors. The spatial weighting matrix applied in this research is the k-Nearest Neighbor (KNN) distance weighting. The KNN was selected due to its accessibility and its capacity to establish connections between disconnected neighbors, a functionality that is particularly advantageous in sparsely populated regions, such as islands [39].

The general form of the spatial area model that includes all types of interaction effects can be written as [38]:

$$\mathbf{y} = \lambda\mathbf{W}\mathbf{y} + \delta\mathbf{1_n} + \mathbf{X}\boldsymbol{\beta} + \mathbf{W}\mathbf{X}\boldsymbol{\theta} + \mathbf{u} \quad (3)$$

$$\mathbf{u} = \gamma\mathbf{W}\mathbf{u} + \boldsymbol{\varepsilon} \quad (4)$$

where $\mathbf{y}$ represents a vector of the dependent variable for each unit in the sample with the size of n×1, $\mathbf{X}$ is a matrix of independent variables with the size of n×k, $\boldsymbol{\beta}$ and $\boldsymbol{\theta}$ are a vector of parameter estimation coefficients with the dimension of k×1, and $\mathbf{1_n}$ is a vector of ones corresponding to the constant term, with parameter δ to be estimated. γ denotes the intensity of interdependence among regression residuals, while λ is the spatial dependence coefficient that captures the spatially lagged dependent variable and describes the intensity of spatial interaction. In addition, $\mathbf{Wy}$ represents the interaction effects on the dependent variable, $\mathbf{WX}$ reflects the interaction effects between the independent variables, and $\mathbf{Wu}$ denotes the interaction effects between the error terms of the different units. Both $\mathbf{u}$ and $\boldsymbol{\varepsilon}$ represent the total error and the error term, respectively.

The SAR model is predicated on the principle that the spatial matrix, otherwise known as spatial dependence, manifests exclusively in relation to the endogenous variable. This enables the examination of whether the formation of a distinct middle or class influences the formation of a different class in neighboring areas. The model is obtained by restricting the coefficients to the spatial autocorrelation coefficients of the residuals, designated as ε (γ = 0), and the absence of interaction between the independent variables (θ = 0). Consequently, the SAR model equation is as follows:

$$\mathbf{y} = \lambda\mathbf{W}\mathbf{y} + \delta\mathbf{1_n} + \mathbf{X}\boldsymbol{\beta} + \mathbf{u} \quad (5)$$

Meanwhile, when spatial autocorrelation is observed in the disturbances ($\lambda = 0$ and θ = 0), the SEM model becomes an appropriate approach. In such instances, the formulation of the modeling equation is as follows:

$$\mathbf{y} = \delta\mathbf{1_n} + \mathbf{X}\boldsymbol{\beta} + \mathbf{u} \quad (6)$$

The selection of an appropriate spatial dependency model is a critical initial step. The diagnostic tool used is called the Lagrange Multiplier (LM) test. Two types of Lagrange multiplier (LM) tests were conducted: the classical LM test proposed by [40] and the robust LM test proposed by [41]. Each of these tests consists of LM Error and LM Lag tests. In instances where the outcomes of the classical LM test demonstrate significant LM error and LM lag, the implementation of robust LM testing is imperative. In the event that either the LM error or the LM lag is found to be significant, the model will be selected. Conversely, if both are found to be significant, the spatial model is selected based on the largest test statistic. The description of the LM test is listed in Table 2. In the event that the LM error or robust LM error test results are found to be significant, this serves as an indication that the SEM model is a more appropriate one to utilize. Conversely, when the LM Lag or robust LM Lag test results are significant, it indicates that the SAR model is more representative.

Table 2. Lagrange Multiplier (LM) test

LM Test	Detects	Hypothesis
LM Error	The effect of spatial dependency in errors	$H_0: \gamma = 0$ $H_1: \gamma \neq 0$
LM Lag	The effect of spatial dependency in lag	$H_0: \lambda = 0$ $H_1: \lambda \neq 0$
Robust LM Error	The effect of spatial dependency in errors	$H_0: \gamma = 0$ $H_1: \gamma \neq 0$
Robust LM Lag	The effect of spatial dependency in lag	$H_0: \lambda = 0$ $H_1: \lambda \neq 0$

Subsequent to the acquisition of the requisite specifications, a meticulous interpretation of the results is imperative. In this context, [38] propose a methodology that facilitates the calculation of direct and indirect effects. The direct effect is defined as the result of the impact of a change in the explanatory variable a. Meanwhile, the indirect effect is defined as the interaction where a change in the condition of the independent variable of region j has an effect on the social class of region i. Furthermore, the summation of these two effects is denoted as the total effect. Meanwhile, the modeling in this study uses R as its statistical software.

2.4. Model Evaluation

Classical assumptions

The validity and reliability of the statistical model are contingent upon the fulfillment of certain classical assumptions, as posited by [42]. There are several assumptions that must be met for this method to be employed. These include the assumptions of normality, homoscedasticity, and non-multicollinearity. In order to ascertain the fulfillment of the aforementioned assumptions, classical assumption testing is conducted. The results of this testing are documented in Table 3.

Table 3. Classical assumptions test

Classical Assumptions Test	Detects	Hypothesis/Value
Jarque-Berra Test	Non-Normality	H_0: the errors are normally distributed H_1: the errors are not normally distributed
Breusch-Pagan Test	Heteroscedasticity	H_0: constant variance of errors H_1: non-constant variance of errors
Variance Inflation Factor (VIF)	Multicollinearity	$VIF < 5$ (No evidence of collinearity) $5 \leq VIF < 10$ (Weak collinearity) $VIF > 10$ (Strong collinearity)

Goodness of fit

The goodness of fit of the model is determined using two measures, the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC), to determine the most appropriate model, whether it is an non-spatial model or a spatial regression model. The calculation of AIC and BIC is outlined as follows [43], [44].

$$AIC = -2 \ln L + 2k \tag{7}$$

$$BIC = -2 \ln L + 2k \ln N \tag{8}$$

In the above equation, L denotes the value of the likelihood, N signifies the number of recorded measurements, and k represents the number of estimated parameters. The superiority of a model is regarded when its AIC and BIC are lower.

3. Results and Discussion

3.1. Characteristics of food security in Indonesia

The characteristics of Indonesia's food security for 2022 are obtainable in Table 4, which provides a summary of the statistical data for each variable included in this study. The mean value of the food security index is 71.971, with a high range and standard deviation. This suggests that discrepancies exist with respect to the levels of food security observed among Indonesian provinces. A further examination of the remaining four variables revealed that the ICT variable exhibited the lowest standard deviation, followed by the quality of democracy. In contrast, the variable with the greatest standard deviation is the density of harvested land area for food crops. This indicates that there is a relatively consistent level of technological advancement and quality of democracy across different locations in Indonesia, whereas the harvested land area of each individual province varies considerably.

Table 4. Summary of statistics on research variables

Variable	Obs	Min	Max	Mean	Med	Std
FSI	34	37.800	85.190	71.971	73.910	9.916
ICT	34	3.220	7.640	5.881	5.825	0.698
IDI	34	62.930	85.620	77.949	78.780	5.433
URB	34	21.393	100	48.850	44.052	18.459
FCLD	34	0.076	67.634	13.745	4.780	19.587

Figure 1 illustrates the spatial distribution of the food security index across Indonesia's provinces. Overall, the index values exhibit notable variation nationwide, with the western and central regions generally displaying higher levels of food security compared to the eastern regions. However, an exception within the western region is the Riau Islands province, which demonstrates low food security levels. An examination of the distribution pattern reveals a tendency for areas with high food security to cluster geographically. For instance, the provinces of Java and Bali exemplify this, exhibiting high food security indices. This situation is likely reinforced by factors such as ease of access, the presence of robust infrastructure, a high quality of human capital, and the advancement of the regional economy. This observed clustering pattern suggests a spatial dependency on the surrounding areas.

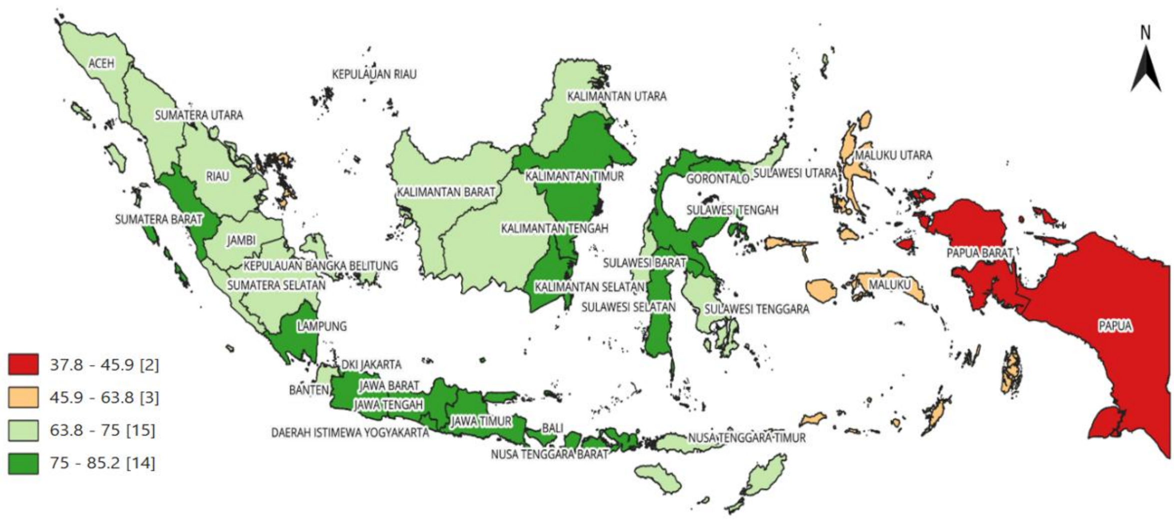

Figure 1. Food security index distribution by provinces, 2022

3.2. Spatial dependence of Indonesia's Food Security

Table 5 presents the results of spatial correlation testing conducted using Moran's I and Geary's C tests. The Moran's I index value for provincial food security is significantly greater than zero, while the Geary's C index is significantly less than one across all significance levels. These findings provide robust statistical evidence confirming the presence of spatial autocorrelation in provincial food security across Indonesia during the 2022 period. In other words, the geographical distribution of provincial food security is not random but exhibits clear spatial dependencies. Regions with similar food security profiles tend to be located in close proximity, forming spatial clusters or agglomerations. This spatial dependence can be attributed to the spillover effects of shared needs, such as resource flows, between neighboring regions. Furthermore, it suggests an indirect association with factors like economic interdependencies and the diffusion of policies aimed at achieving food security at the regional level.

Table 5. Global spatial correlation test

Variable	Morans'I	Geary's C
FSI	0.621^{***} (0.000)	0.265^{***} (0.000)

Note: ( ) represents the *p-value*

$^{*},^{**},^{***}$ denote 10%, 5%, and 1% significance respectively

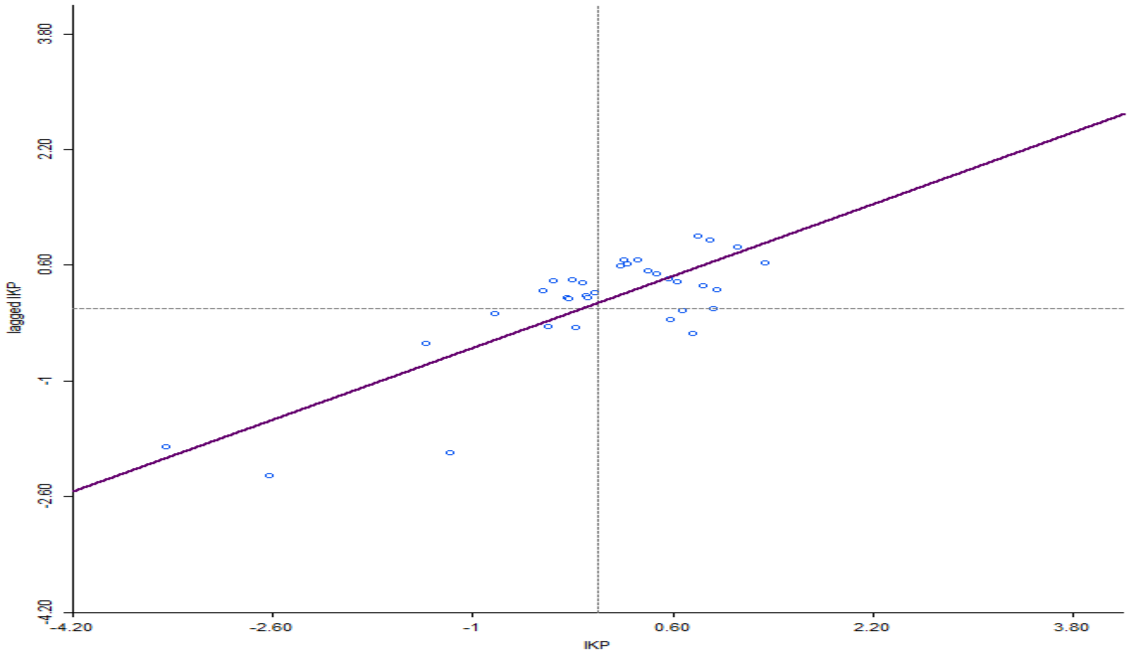

Figure 2. Moran scatter plot for Indonesia provincial food security index

The occurrence of local spatial correlation can be identified through the use of the Moran scatter plot presented in Figure 2. The figure illustrates the phenomenon of spatial clustering through four quadrants with most provinces located in regions showing positive correlation in the first and third quadrants. These results provide evidence that food security has significant positive spatial spillover effects.

3.3. Spatial econometric modelling of Indonesia's food security

As outlined by [42], the process of spatial model construction commences with the estimation of a non-spatial model (see Table 6). This is followed by the utilization of the LM test, which serves to ascertain the most appropriate spatial area model. The outcomes of LM tests are presented in Table 8. The classical LM test yielded significant results for both the LM for the spatial error model and the LM for the spatial lag model. Therefore, the model selection is determined by examining the outcomes of the robust LM test, wherein the LM results for the spatial lag model are found to be statistically significant.

Table 6. Regression estimates

Variable	OLS	Spatial Area Model	
		SEM	SAR
Intercept	-38.549**	-10.081	-39.857***
	(16.542)	(14.143)	(12.956)
ICT	7.896***	6.269***	6.449***
	(2.362)	(1.743)	(1.860)
IDI	0.936***	0.625***	0.631***
	(0.247)	(0.186)	(0.202)
URB	-0.217**	-0.129*	-0.166**
	(0.083)	(0.076)	(0.065)
FCLD	0.124**	0.187***	0.087*
	(0.059)	(0.060)	(0.051)
W X FSI ($\boldsymbol{\lambda}$)	-	-	0.421***
			(0.115)
W X $\boldsymbol{\varepsilon}$ ($\boldsymbol{\gamma}$)	-	0.517**	-
		(0.125)	
Indicators of model goodness			
R^2	0.715	0.794	0.799
AIC	220.784	216.292	213.446
BIC	229.942	226.976	224.131
Log-Likelihood	-104.392	-101.1459	-99.72315
Diagnostic Test			
Jarque-Berra test	0.227	0.347	2.404
Breusch-Pagan Test	5.994	7.736	2.096

Note: ( ) represents the standard error

*,**,*** denote 10%, 5%, and 1% significance respectively

Moreover, an examination of the model goodness indicators (see Table 6) reveals that the spatial lag model exhibits the lowest AIC, BIC, and Log-Likelihood values and the highest R^2 among the alternative models [37]. Thus, the spatial lag model is selected as the model to be utilized for subsequent analysis.

Table 7. Variance Inflation Factor

Independent Variable	Value
ICT	2.818
IDI	1.866
URB	2.424
FCLD	1.361

Prior to any interpretation of the selected model, it is first necessary to ascertain whether the model assumptions have been met (see Table 6 and Table 7). As can be seen from the table, all of the assumptions have been validated. This is attributable to the fact that the test results indicate insignificant values and a VIF value that is less than 5. It can thus be concluded that the estimation results of the selected model are accurate and reliable.

Table 8. Testing spatial effects

Spatial Dependece Test	Statistics	Prob
LM_ρ for spatial lag model	7.462	0.006^{***}
LM_λ for spatial error model	3.182	0.074^{*}
Robust LM_ρ for spatial lag model	4.534	0.033^{**}
Robust LM_λ for spatial error model	0.253	0.615

Note: *,**,*** denote 10%, 5%, and 1% significance respectively

Table 6 displays the parameter estimates for each variable within the spatial lag model. In general, the explanatory variables are found to be significant in relation to provincial food security in Indonesia. The ICT variable, which is the primary focus of this study, has been demonstrated to exert a positive influence on provincial food security. This suggests that the progression of ICT can assist in attaining food security within each province. This outcome aligns with research conducted by [13] and [43]. The quality of democracy, an important variable in this study, has also been found to encourage the realization of food security in Indonesia. This finding is consistent with the studies of [28] and [44].

The following variables that were found to have a significant effect on provincial food security were urbanization and food crop land density. Urbanization has been shown to exert a negative influence on food security, indicating that an increase in urbanization will result in a decline in food security. This relationship is further validated by empirical evidence derived from studies [48] and [49]. In contrast, the density of agricultural land exhibits a positive correlation. Consequently, increasing the area dedicated to food crop agriculture is expected to enhance regional food security in Indonesia. This direction of relationship is also found in studies [50] and [51].

The modeling results also demonstrate that there are interrelated food security conditions between provinces, as indicated by the direction of the estimates and the significance of the parameter λ. This indicates that food security in Indonesia has a positive externality. In other words, the food security conditions in neighboring provinces exert a beneficial effect on food security in the focal province. Such a phenomenon may result from the implementation of policies or efforts to strengthen food security that are aligned with the needs of geographically proximate regions. The aforementioned favorable impact may also be attributed to the stimulation of a desire to enhance food security in the region, prompted by the observation of more robust food security in neighboring regions.

3.4. Average marginal effect of independent variables on food security

Subsequent analyses were conducted to determine how much influence the changes in each explicatory variable had on the food security index. Since the estimated SAR coefficients are biased and cannot be interpreted as marginal effects [38], the regression results provide only a preliminary assessment of the direction of action of each factor. Consequently, a more detailed decomposition of the overall effect (as illustrated in Table 6) is necessary. The decomposition of the effect is divided into three effects, namely direct, indirect, and total, which are presented in Table 9. Approximately 37%–38% of the effect of each independent variable on food security is attributed to spatial spillover effects.

As the primary variable, ICT exerts a direct influence on food security, with a coefficient of 6.966. Thus, a one-unit increase in the technology development index will result in a 6.966-point increase in the food security index. Concurrently, the spillover effect from the ICT variable is 4.170, whereby an increase in the technology development index in neighboring provinces will have an impact on food security in the main province to the extent of 4.170 points. Therefore, the overall effect of ICT is 11.136. All three effect magnitudes are statistically significant. The relationship between ICTs and food security can be examined through a number of channels [52]. Firstly, ICT can function as a potential medium for disseminating information to farmers regarding novel technologies, superior input management techniques, and refined farming methodologies, capable of engendering an escalation in productivity levels. Secondly, farmers can be made aware of superior sales opportunities for their produce. Finally, ICTs have the capacity to optimize the efficiency of agricultural markets, reduce price volatility, and increase food availability. Furthermore, ICT has the potential to enhance the flow of information between farmers, food producers, traders, and consumers, thereby reducing food wastage and augmenting food reliability in the supply chain [5].

Table 9. Direct, indirect, and total effects of each independent variable

Variable	Direct	Indirect	Total
ICT	6.966***	4.170*	11.136***
	(1.989)	(2.355)	(3.861)
IDI	0.682***	0.408*	1.090***
	(0.213)	(0.220)	(0.379)
URB	-0.180**	-0.107*	-0.287**
	(0.070)	(0.068)	(0.126)
FCLD	0.094*	0.056	0.150*
	(0.055)	(0.037)	(0.086)

Note: *,**,*** denote 10%, 5%, and 1% significance respectively

Democratic development, which represents the core variable, has a discernible impact on the three types of effects. The total effect is 1.090, which is the sum of the direct and indirect effects. The direct effect of the variable is 0.682, indicating that a one-point increase in the democracy index is associated with a 0.682-point increase in the food security index. The spillover effect of the democratic development variable is 0.408, suggesting that a one-point rise in the democracy index is linked to a 0.408-point rise in the food security index. As articulated by [44], a democratic system empowers the public to engage in the decision-making processes pertaining to food policy, thereby ensuring that the policies implemented are more attuned to the interests of the people and more responsive to the food needs of the community. Furthermore, the enhancement of democratic quality will precipitate the formation of institutions and governance that prioritize food security. The strengthening of institutions and the refinement of governance can serve to mitigate the factors that impede food security, including corruption and political instability. In this context, the promotion of better democracy engenders the formation of policies that are more pro-community, more transparent, and more responsive to food security issues. Consequently, this contributes to sustainable food security and addresses the challenges that Indonesia has been facing, such as climate change, natural disasters, and food distribution inequality. On the other hand, the promotion of mature democracy is conducive to the development of improved infrastructure, greater access to information, and more equitable social and economic policies, which contribute to augmented food security. As a nation that endorses democratic principles, the evolution of this system fosters the development of enhanced infrastructure, improved access to information, and more equitable social and economic policies, which contribute to food security.

Temporarily, the overall impact of urbanization is -0.287, with direct impacts contributing -0.180 and indirect impacts contributing -0.107. This magnitude signifies that an incremental one percentage point increase in the urban population results in a decrement of 0.180 points in the food security index. A similar phenomenon is observed when considering the spillover effect of an incremental one percentage point increase in the urban population of a neighboring province, which exerts a negative influence on the food security index of the focal province, reducing it by 0.107 points. The urbanization effect channel has been statistically substantiated. [53] explained that urbanization has a negative effect on food security from two perspectives, namely food production and consumption. The relocation of workers from rural to urban areas will reduce the amount of labor dedicated to food production. Concurrently, the expanding urban population necessitates the acquisition of additional land for urban expansion, resulting in encroachment on adjacent agricultural land and the limitation of agricultural investment. This phenomenon is further compounded by the fact that while food production is set to decline, demand is set to rise, resulting in a state of food instability and food accessibility. Another channel through which urbanization exerts its influence is through extreme weather events. This is because urbanization encourages extreme weather events, such as rising temperatures, rainfall, and flooding, which will affect production yields, distort food supply, and disrupt the distribution of agricultural logistics [50].

The direct, indirect, and total effects of changes in harvested land density have been calculated to be 0.094, 0.056, and 0.150, respectively. Although the effects are positive, the spillover effects of this variable are found to be insignificant. This is due to the fact that land density does not invariably translate into sufficient food diversity to ensure robust food security. In the context of agricultural production, a region's exclusive focus on a singular crop, such as rice or corn, may not yield the optimal spillover effect for neighboring areas. Consequently, the sole effect can be attributed to the direct effect, whereby a one-percent point increase in food crop harvesting density is associated with a 0.094-point increase in the food security index. [4] explained that land utilization for agriculture has an impact on increasing food availability, and with the fulfilment of the amount of food production, the demand for food can also be met, thus realizing stability.

4. Conclusion

The degree of food security within Indonesian provinces in 2022 demonstrates variability and agglomeration patterns, with the eastern region of the nation exhibiting consistently suboptimal food security levels. The observed phenomenon is further substantiated by the presence of a spatial correlation in the food security capabilities of provinces within Indonesia. In other words, provinces with similar food security characteristics are proximate to each other or can exert influence on each other. Consequently, spatial modelling emerges as a suitable approach to analyze the interplay between technological advancement and the quality of democracy on food security. The efficacy of both variables in supporting Indonesia's regional food security has been substantiated through empirical evidence. The impact of technological development and democratic quality as core variables is not only direct, but also indirect. These findings elucidate the relationship between the two variables and food security, which has been ambiguous until now. Moreover, evidence has been demonstrated that urbanization and agricultural land have a role in ensuring food security, albeit in contradictory ways. The expansion of land for food production is identified as a key factor in improving food security. However, urbanization is hypothesized to hinder the realization of this expansion in Indonesia. Furthermore, approximately 37%–38% of the impact of each variable on food security is attributable to spatial spillover effects. This figure underscores the necessity of incorporating considerations of interregional interactions and cross-provincial influences in the pursuit of food security.

The results of this study suggest several policy recommendations for policymakers and government authorities in achieving sustainable food security at both the national and regional levels. Firstly, the development and implementation of sophisticated technological frameworks is imperative within all domains pertinent to the production, distribution, and consumption of foodstuffs. Secondly, the quality of democracy must be strengthened to create policies and institutions that support food security by involving public participation and decentralizing food decision-making. Thirdly, it is imperative to leverage the full potential of resources present in both rural and urban regions to ensure food security in all provinces. Finally, the enhancement of collaboration and mutual learning is imperative to cultivate coherent and sustainable interregional food policies.

This study may serve to address the gaps in previous research, yet there is still room for improvement in similar studies in the future. The use of regional data necessitates the consideration of omitted variable bias (OVB) at the provincial level, a component that has not been addressed in this study. The incorporation of robust and sensitivity analyses could offer a solution to bolster the rigor of similar studies in the future.

Ethics approval

Approval for ethics was not required for this study.

Acknowledgments

We would like to express our gratitude to Politeknik Statistika STIS, who provided the necessary resources and facilities to conduct this research.

Competing interests

All the authors declare that there are no conflicts of interest.

Funding

This study received no external funding.

Underlying data

Derived data supporting the findings of this study are available from the corresponding author on request.

Credit Authorship

Ditto Satrio Wicaksono: Conceptualization, Methodology, Formal Analysis, Writing—Original Draft, **Novi Hidayat Pusponegoro:** Conceptualization, Supervision, Resources, Final Draft. **Arbi Setiyawan:** Supervision, Final Draft.

References

[1] Z. Zhang, K. Shi, L. Tang, K. Su, Z. Zhu, and Q. Yang, "Exploring the spatiotemporal evolution and coordination of agricultural green efficiency and food security in China using ESTDA and CCD models," *J Clean Prod*, vol. 374, Nov. 2022, doi: 10.1016/j.jclepro.2022.133967.
[2] FAO, "Rome Declaration on World Food Security," Rome, 1996.
[3] FAO, IFAD, UNICEF, WFP, and WHO, *The state of food security and nutrition in the world 2023*. Rome: FAO, 2023. doi: 10.4060/cc3017en.
[4] C. M. Viana, D. Freire, P. Abrantes, J. Rocha, and P. Pereira, "Agricultural land systems importance for supporting food security and sustainable development goals: a systematic review," Feb. 01, 2022, *Elsevier B.V.* doi: 10.1016/j.scitotenv.2021.150718.
[5] M. K. Anser *et al.*, "Impact of ict adoption and governance interaction on food security in West Africa," *Sustainability*, vol. 13, no. 10, May 2021, doi: 10.3390/su13105570.
[6] United Nations, "Work of the statistical commission pertaining to the 2030 agenda for sustainable development," 2017.
[7] BPS-Statistics Indonesia, "Prevalence of moderate or severe food insecurity in the population, based on the food insecurity experience scale (FIES." Accessed: Dec. 13, 2024. [Online]. Available: https://www.bps.go.id/en/statistics-table/2/MTQ3NCMy/prevalence-of-moderate-or-severe-food-insecurity-in-the-population--based-on-the-food-insecurity-experience-scale--fies---percent-.html
[8] BPS-Statistics Indonesia, "Prevalence of undernourishment," Accessed: Dec. 13, 2024. [Online]. Available: https://www.bps.go.id/en/statistics-table/2/MTQ3MyMy/prevalence-of-undernourishment.html
[9] World Food Programme, "Indonesia annual country report 2022," 2022.
[10] Economist Impact, "Global food security index 2022," 2022. [Online]. Available: http://economistimpact.
[11] K. Von Grebmer *et al.*, "Global hunger index food systems transformation and local governance," 2022.
[12] A. Schnack, F. Bartsch, V. S. Osburg, and A. Errmann, "Sustainable agricultural technologies of the future: determination of adoption readiness for different consumer groups," *Technol Forecast Soc Change*, vol. 208, Nov. 2024, doi: 10.1016/j.techfore.2024.123697.
[13] R. Gouvea, D. Kapelianis, S. Li, and B. Terra, "Innovation, ICT & food security," *Glob Food Sec*, vol. 35, Dec. 2022, doi: 10.1016/j.gfs.2022.100653.

[14] I. H. Su, L. Wu, and K. H. Tan, "The future of the food supply chain: a systematic literature review and research directions towards sustainability, resilience, and technology adoption," *Journal of Digital Economy*, vol. 2, pp. 303–316, Dec. 2023, doi: 10.1016/j.jdec.2024.03.001.

[15] A. M. Heshmati, "Impacts of improved agricultural technologies on food security and child nutrition in rural Ethiopia," *Cogent Food Agric*, vol. 9, no. 2, 2023, doi: 10.1080/23311932.2023.2276565.

[16] G. Muha-Ud-Din *et al.*, "CRISPR/Cas9-based genome editing: A revolutionary approach for crop improvement and global food security," Jan. 01, 2024, *Academic Press*. doi: 10.1016/j.pmpp.2023.102191.

[17] B. T. W. Hertel, U. L. C. Baldos, and K. O. Fuglie, "Trade in technology: a potential solution to the food security challenges of the 21st century," *Eur Econ Rev*, vol. 127, Aug. 2020, doi: 10.1016/j.euroecorev.2020.103479.

[18] M. B. Zegeye, A. H. Fikire, and A. B. Assefa, "Impact of agricultural technology adoption on food consumption expenditure: evidence from Rural Amhara Region, Ethiopia," *Cogent Economics and Finance*, vol. 10, no. 1, 2022, doi: 10.1080/23322039.2021.2012988.

[19] S.- Suprehatin, "Determinants of agricultural technology adoption by smallholder farmers in developing countries: perspective and prospect for Indonesia," *Jurnal Penelitian dan Pengembangan Pertanian*, vol. 40, no. 1, p. 21, May 2021, doi: 10.21082/jp3.v40n1.2021.p21-30.

[20] B. Hidayati, Ermitayusida, V. A. Qurrata, Nasikh, and W. Huang, "The digital agriculture model for sustainable food system: an analysis of agricultural technology adoption in East Java, Indonesia," *J Sustain Sci Manag*, vol. 18, no. 4, pp. 173–191, Apr. 2023, doi: 10.46754/jssm.2023.04.013.

[21] Md. A. Rahaman, "Governance and democracy," in *Global Encyclopedia of Public Administration, Public Policy, and Governance*, Springer International Publishing, 2017, pp. 1–6. doi: 10.1007/978-3-319-31816-5_1819-1.

[22] D. Cassimon, O. Fadare, and G. Mavrotas, "The combined effect of institutional quality and capital flows on food and nutrition security and undernourishment in Sub-Saharan Africa," *PLoS One*, vol. 17, no. 10 October, Oct. 2022, doi: 10.1371/journal.pone.0275345.

[23] N. N. Soko, S. Kaitibie, and N. N. Ratna, "Does institutional quality affect the impact of public agricultural spending on food security in Sub-Saharan Africa and Asia?," *Glob Food Sec*, vol. 36, Mar. 2023, doi: 10.1016/j.gfs.2022.100668.

[24] Y. Khan, Š. Bojnec, U. Daraz, and F. Zulpiqar, "Exploring the nexus between poor governance and household food security," *Economic Change and Restructuring*, vol. 57, no. 2, Apr. 2024, doi: 10.1007/s10644-024-09679-w.

[25] Abdullah, W. Qingshi, M. A. Awan, and J. Ashraf, "The impact of political risk and institutions on food security," *Current Research in Nutrition and Food Science*, vol. 8, no. 3, pp. 924–941, Dec. 2020, doi: 10.12944/CRNFSJ.8.3.21.

[26] A. Sen, *Development as freedom*. New York: Oxford University Press, 1999.

[27] A. Awad, "The determinants of food insecurity among developing countries: are there any differences?," *Sci Afr*, vol. 19, Mar. 2023, doi: 10.1016/j.sciaf.2022.e01512.

[28] G. Mohamed, F. Chiad, M. Abdesslam, B. Omar, and M. S. M. AL-Absy, "Identifying determinants of food security using panel data analysis: evidence from maghreb countries," *Economies*, vol. 12, no. 4, Apr. 2024, doi: 10.3390/economies12040091.

[29] A. I. Ogunniyi, G. Mavrotas, K. O. Olagunju, O. Fadare, and R. Adedoyin, "Governance quality, remittances and their implications for food and nutrition security in Sub-Saharan Africa," *World Dev*, vol. 127, Mar. 2020, doi: 10.1016/j.worlddev.2019.104752.

[30] S. Kaur and H. Kaur, "Determinants of food security in Sub-Saharan Africa, South Asia and Latin America," in *Global Economic Cooperation*, New Delhi: Springer, 2016. doi: https://doi.org/10.1007/978-81-322-2698-7_6.

[31] M. K. Anser *et al.*, "Social inclusion, innovation and food security in West Africa," *Sustainability (Switzerland)*, vol. 13, no. 5, pp. 1–12, Mar. 2021, doi: 10.3390/su13052619.

[32] E. B. Yiadom, R. K. Dziwornu, J. K. M. Mawutor, and R. F. Amankwah, "Exploring the relationship between extreme weather events, urbanization, and food insecurity: Institutional quality perspective," *Environmental Challenges*, vol. 13, Dec. 2023, doi: 10.1016/j.envc.2023.100775.

[33] D. S. Wicaksono *et al.*, "Modeling factors affecting educated unemployment on java island using geographically weighted poisson regression model," *Barekeng: Jurnal Ilmu Matematika dan Terapan*, vol. 18, no. 1, pp. 0615–0626, Mar. 2024, doi: 10.30598/barekengvol18iss1pp0615-0626.

[34] C. Zhao, C. Li, J. Liu, H. Lian, and W. Yamaka, “Analysis of factors affecting the spatial association network of food security level in China,” *Agriculture (Switzerland)*, vol. 14, no. 11, Nov. 2024, doi: 10.3390/agriculture14111898.

[35] National Food Agency, “Food security index 2022,” Jakarta, 2022.

[36] R. C. Geary, “The contiguity ratio and statistical mapping,” 1954.

[37] L. Anselin, *Spatial Econometrics: Methods and models*. Kluwer Academic, 1988.

[38] J. LeSage and R. K. Pace, *Introduction to spatial econometrics*. Taylor & Francis Group, LLC, 2009. [Online]. Available: https://www.researchgate.net/publication/339938974

[39] M. Mawarni and I. Machdi, “Dynamic nearest neighbours for generating spatial weight matrix,” in *2016 International Conference on Advanced Computer Science and Information Systems (ICACSIS)*, Malang: IEEE, 2016, pp. 257–262. doi: 10.1109/ICACSIS.2016.7872771.

[40] L. Anselin, A. K. Bera B’, R. Florax, and M. J. Yoon, “Simple diagnostic tests for spatial dependence,” *Reg Sci Urban Econ*, vol. 26, pp. 77–104, 1996.

[41] J. Elhorst, “Spatial panel data analysis,” in *Handbook of Applied Spatial Analysis*, Springer Berlin Heidelberg, 2010. doi: 10.1007/978-3-642-03647-7.

[42] D. N. Gujarati and D. C. Porter, *Basic econometrics*, 5th ed. McGraw-Hill, 2009.

[43] H. Akaike, “A new look at the statistical model identification,” *IEEE*, vol. 19, no. 6, 1974.

[44] M. Stone, “Comments on model selection criteria of akaike and,” *Journal of the Royal Statistical Society. Series B (Methodological)*, vol. 41, no. 2, pp. 276–278, 1979.

[45] J. P. Elhorst, *Spatial econometrics from cross-sectional data to spatial panels*. New York, 2014. [Online]. Available: http://www.springer.com/series/10096

[46] M. Masha, E. Bojago, Y. Abrham, D. Leja, and M. W. Delango, “Determinants of food insecurity and coping mechanisms in Offa District, Southern Ethiopia,” *J Agric Food Res*, vol. 14, Dec. 2023, doi: 10.1016/j.jafr.2023.100782.

[47] D. Rossignoli and S. Balestri, “Food security and democracy: do inclusive institutions matter?,” *Canadian Journal of Development Studies*, vol. 39, no. 2, pp. 215–233, Apr. 2018, doi: 10.1080/02255189.2017.1382335.

[48] S. Szabo, “Urbanisation and food insecurity risks: assessing the role of human development,” *Oxford Development Studies*, vol. 44, no. 1, pp. 28–48, Jan. 2016, doi: 10.1080/13600818.2015.1067292.

[49] M. U. Farrukh, M. K. Bashir, M. F. Rola-Rubzen, and A. Ahmad, “Dynamic effects of urbanization, governance, and worker’s remittance on multidimensional food security: an application of a broad-spectrum approach,” *Socioecon Plann Sci*, vol. 84, Dec. 2022, doi: 10.1016/j.seps.2022.101400.

[50] E. B. Yiadom, R. K. Dziwornu, J. K. M. Mawutor, and R. F. Amankwah, “Exploring the relationship between extreme weather events, urbanization, and food insecurity: institutional quality perspective,” *Environmental Challenges*, vol. 13, Dec. 2023, doi: 10.1016/j.envc.2023.100775.

[51] X. Cao, J. Han, and X. Li, “Analysis of the impact of land use change on grain production in Jiangsu Province, China,” *Land (Basel)*, vol. 13, no. 1, Jan. 2024, doi: 10.3390/land13010020.

[52] E. Nakasone and M. Torero, “A text message away: ICTs as a tool to improve food security,” *Agricultural Economics (United Kingdom)*, vol. 47, pp. 49–59, Nov. 2016, doi: 10.1111/agec.12314.

[53] C. C. Lee, M. Zeng, and K. Luo, “The impact of urbanization on food security in China,” *International Review of Economics and Finance*, vol. 93, pp. 1159–1175, Jun. 2024, doi: 10.1016/j.iref.2024.05.037.