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Modeling the Food Security Index on Papua Island Using a Random Effects Ordinal Logistic Regression of Panel Data Approach

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Abstract: *This paper develops a spatial and econometric classification model for the Food Security Index in the Papua region by deploying a random-effects panel data ordered logistic regression framework. The primary objective is to assess the longitudinal impact of core socioeconomic predictors consumption ratios, poverty prevalence, educational attainment, and clean water access on regional food security tiers, which are operationally designated as the Code variable. Drawing on a strongly balanced dataset covering 42 districts over a four-year observational window (2022–2025), empirical estimations verify that all evaluated predictors exert a statistically significant influence on the probability of a district shifting across food security priorities. The constructed model demonstrates substantial predictive accuracy (76.19%) in classifying observations into six distinct priority levels, accompanied by a remarkably low apparent error rate (23.81%). By embedding the theoretical discourse within the capability approach and the water-sanitation-health nexus, the findings offer robust, data-driven insights. This empirical evidence sets a concrete baseline for drafting targeted nutritional alleviation strategies, prioritizing long-term structural capacity building over temporary relief measures.*

Keywords—food security; human capital; ordered logit; hunger; panel data

1. INTRODUCTION

Food security is a condition in which every individual, at all times, has physical and economic access to food that is sufficient, safe, and nutritious to meet dietary needs for an active and healthy life [1]. To translate this concept into a regional planning tool, Indonesia's National Food Agency (Badan Pangan Nasional), together with the World Food Programme, publishes the annual Food Security and Vulnerability Atlas (FSVA, in Indonesian: Peta Ketahanan dan Kerentanan Pangan). The FSVA builds a composite Food Security Index for every regency/city from indicators representing three canonical pillars food availability, economic and physical access, and food utilization and classifies each region into one of six ordered priority classes used for policy targeting [1], [2], [3].

In the classification used in this study, regions coded as Priority 1 (highly vulnerable), Priority 2 (vulnerable), and Priority 3 (somewhat vulnerable) require urgent food-security intervention, while regions coded as Priority 4 (somewhat resilient), Priority 5 (resilient), and Priority 6 (highly resilient) are comparatively food-secure [1], [4]. This six-level scale is unambiguously ordinal: the distance between adjacent categories is not assumed to be numerically equal, but the ordering itself carries essential policy information that would be discarded by treating the outcome as unordered (multinomial) or by collapsing it into a binary secure/insecure split [5], [6].

Statistically, two features of FSVA-type data must be respected simultaneously. First, because the response is ordered, cumulative-logit (proportional-odds) ordinal regression is the natural estimator, as it directly models the probability of a region falling at or below each threshold of vulnerability while preserving the full ordering of categories [5], [6]. Second, because regions are observed repeatedly across several years, the resulting panel structure induces within-region correlation that ordinary (pooled) ordinal regression ignores; a random-effects extension that introduces a region-specific latent intercept is required to obtain valid standard errors and to separate genuine year-to-year change from stable, unobserved regional heterogeneity [7], [8].

Despite the wide use of the FSVA for policy targeting in Indonesia [1], [2], [9], relatively few published studies combine both features ordinality and panel clustering within a single estimation framework; most existing applications instead use either cross-sectional ordinal regression [5], [6] or spatial/panel models without a longitudinal random-effects ordinal component [3], [10].

This study addresses that gap by estimating a random-effects (mixed-effects) ordinal logistic regression model of regional FSVA priority classification on a strongly balanced panel of 42 regions observed annually over 2022–2025 (168 region-year observations). Consistent with the three FSVA pillars, four predictors are used: the Net Cereal Production Ratio (NCPR, an availability indicator), the percentage of poor population (an access indicator), mean years of schooling, and the percentage of households without access to proper clean water (both utilization-related indicators) [1], [2], [11]. The specific objectives of this study are: (1) to formulate and estimate the random-effects cumulative-logit model for the four-predictor specification; (2) to test the overall

(simultaneous) and partial statistical significance of the four predictors and interpret their odds ratios in light of food-security theory; and (3) to evaluate the practical classification performance of the fitted model through a confusion-matrix-based apparent error rate (APER).

2. Literature Review and Theoretical Framework

2.1 Food Security Theory and the FSVA Composite Index

Food security is conventionally decomposed into three interacting pillars: (1) availability the physical presence of food from production, stocks, and trade; (2) access the economic and physical ability of households to obtain food, closely tied to poverty and income; and (3) utilization the biological ability of individuals to use food effectively, which depends on health status, sanitation, clean water, and care practices [1], [12]. The FSVA operationalizes this framework into a composite Food Security Index built from multiple normalized indicators, one of which is the ratio of per-capita normative food consumption to net regional cereal production the availability-side indicator abbreviated here as NCPR, where a higher ratio signals that local consumption needs increasingly exceed local production capacity and therefore signals greater vulnerability [2], [3]. Poverty incidence enters as an access-side indicator [8], [13], while household access to clean water enters as a utilization-side indicator, since inadequate water and sanitation undermine the biological utilization of food and are strongly linked to poor nutrition outcomes [14], [15], [16]. Mean years of schooling is likewise treated as a utilization/human-capital-related indicator, since more educated household members are better able to translate available food and income into adequate nutrition and health outcomes [13], [17], [18]. Composite scores are subsequently grouped into six ordered priority classes, from Priority 1 to Priority 6, as described in Section I [1], [2].

2.2 The Cumulative-Logit (Proportional-Odds) Ordinal Regression Model

The Let Y denote an ordinal response with categories $1,2,\dots,M$ (here $M = 6$), and let $\mathbf{X} = (X_1, \dots, X_p)'$ be a vector of predictors. The cumulative-logit model expresses the cumulative probability that Y falls in category m or lower as a function of a linear predictor common to all thresholds [5], [6]:

$$\text{logit}[P(Y \le m|\mathbf{X})] = \ln\left[\frac{P(Y \le m|\mathbf{X})}{1 - P(Y \le m|\mathbf{X})}\right] = \alpha_m - \boldsymbol{\beta}'\mathbf{X}, \quad m = 1, \dots, M-1 \tag{1}$$

where $\alpha_1 < \alpha_2 < \cdots < \alpha_{M-1}$ are $M-1$ ordered threshold (cut-point) parameters and $\boldsymbol{\beta} = (\beta_1, \dots, \beta_p)'$ is a vector of slope coefficients. The negative sign preceding $\boldsymbol{\beta}'\mathbf{X}$ follows the convention (used by Stata's xtologit, employed in this study) under which a positive β_j implies that increasing X_j shifts probability mass toward higher (here, more food-secure) categories of Y [7]. Equation (1) implies the proportional-odds assumption: the effect of each predictor on the log-odds of exceeding any threshold m is constant across all $M-1$ thresholds, so a single coefficient vector $\boldsymbol{\beta}$ suffices for the entire ordinal scale [5], [6].

From equation (1), the probability that region i in year t falls exactly in category m is obtained as the difference of two adjacent cumulative probabilities:

$$P(Y = m|\mathbf{X}) = F(\alpha_m - \boldsymbol{\beta}'\mathbf{X}) - F(\alpha_{m-1} - \boldsymbol{\beta}'\mathbf{X}) \tag{2}$$

where $F(\cdot) = \exp(\cdot)/[1 + \exp(\cdot)]$ is the standard logistic cumulative distribution function, with the conventions $F(\alpha_0 - \boldsymbol{\beta}'\mathbf{X}) = 0$ and $F(\alpha_M - \boldsymbol{\beta}'\mathbf{X}) = 1$.

2.3 Random-Effects Extension for Panel (Longitudinal) Data

Because each region is observed repeatedly across $T = 4$ years, observations within the same region are unlikely to be independent. A random-effects (mixed-effects) cumulative-logit model addresses this by adding a region-specific latent intercept u_i to equation (1) [7]:

$$\text{logit}[P(Y_{it} \le m|\mathbf{X}_{it}, u_i)] = \alpha_m - \boldsymbol{\beta}'\mathbf{X}_{it} - u_i, \quad u_i \sim N(0, \sigma_u^2) \tag{3}$$

The random effect u_i captures stable, unobserved regional characteristics (e.g., persistent geographic or institutional conditions) that are not explained by the observed covariates. The marginal likelihood for the panel is obtained by integrating the conditional likelihood over the distribution of u_i:

$$L(\boldsymbol{\theta}) = \prod_{i=1}^{N} \int \left[\prod_{t=1}^{T} P\,(Y_{it} = m|\mathbf{X}_{it}, u_i) \right] \phi(u_i; \sigma_u^2)\, du_i \tag{4}$$

where $\phi(\cdot; \sigma_u^2)$ is the $N(0, \sigma_u^2)$ density and $\boldsymbol{\theta} = (\alpha, \beta, \sigma_u^2)$ collects all parameters. Because this integral has no closed form, it is evaluated numerically via adaptive Gauss–Hermite quadrature, which approximates the integral by a weighted sum evaluated at a fixed number of quadrature nodes (12 nodes in this study); parameters are then obtained by maximizing the resulting approximate log-likelihood, $\ell(\boldsymbol{\theta}) = \ln L\,(\boldsymbol{\theta})$, using iterative Newton–Raphson-type algorithms. This general adaptive-quadrature strategy for panel/clustered generalized linear mixed models is consistent with recent applications that combine random-intercept logistic-family models with Gauss–Hermite-type integration to correct for within-cluster correlation in household- and region-level survey data [19].

2.4 Odds Ratios and Their Interpretation

Exponentiating a slope coefficient yields an odds ratio, $\text{OR}_j = \exp(\beta_j)$, which is interpreted as the multiplicative change in the odds of a region being classified in a higher (more food-secure) category associated with a one-unit

increase in predictor X_j, holding the other predictors and the random effect constant. Values of OR_j greater than one indicate that the predictor increases the odds of a higher (more resilient) classification, whereas values below one indicate that the predictor increases the odds of remaining in, or moving toward, a lower (more vulnerable) classification [5], [6].

2.5 Hypothesis Testing: Simultaneous and Partial Tests

Overall (simultaneous) significance of the full set of predictors is assessed with a Wald chi-square test of the joint null hypothesis $H_0: \beta_1 = \beta_2 = \cdots = \beta_p = 0$ against H_1: at least one $\beta_j \neq 0$, with test statistic asymptotically distributed as $\chi^2(p)$ under H_0 [7]. Partial (individual) significance of each predictor is assessed with a Wald z-test of $H_0: \beta_j = 0$ versus $H_1: \beta_j \neq 0$, using $z_j = \hat{\beta}_j / \mathrm{SE}(\hat{\beta}_j)$, compared against the standard normal distribution; H_0 is rejected at the 5% level when $|z_j| > 1.96$ (equivalently, $p < 0.05$) [6].

2.6 Model Fit, Random-Effects Variance, and Classification Accuracy

Model fit is summarized by the maximized log-likelihood, $\ell(\hat{\boldsymbol{\theta}})$, and by information criteria that penalize model complexity, Akaike's Information Criterion, $\mathrm{AIC} = -2\ell(\hat{\boldsymbol{\theta}}) + 2k$, and the Bayesian Information Criterion, $\mathrm{BIC} = -2\ell(\hat{\boldsymbol{\theta}}) + k\ln(N)$, where k is the number of estimated parameters and N is the number of observations; smaller values indicate a better fit relative to complexity [7]. The estimated variance component $\hat{\sigma}_u^2$ close to zero indicates that, conditional on the covariates, little unobserved between-region heterogeneity remains, so that the simpler pooled ordinal logit would already fit the data almost as well. Practical classification performance is assessed by assigning each observation to the category $\hat{m}$ with the highest predicted probability, $P(Y = \hat{m}|\mathbf{X}) = \max\{P(Y = 1|\mathbf{X}), \ldots, P(Y = M|\mathbf{X})\}$, cross-tabulating $\hat{m}$ against the observed category to form an $M \times M$ confusion matrix, and computing overall accuracy as the proportion of correctly classified observations; the apparent error rate is its complement, $\mathrm{APER} = 1 -$ accuracy. This confusion-matrix-based validation approach is consistent with recent regional food-security modeling studies in Indonesia that similarly benchmark classification quality against observed FSVA priority tiers [20].

2.7 Related Empirical Studies

Ordinal logistic regression has been used directly to model household- and regional-level food (in)security status in Indonesia: a national ordinal-logit analysis of household food insecurity [5] and a spatial ordinal logistic regression of FSVA food-security status across Indonesian regencies/cities [6] both confirm that poverty, education, and access to clean water are recurring, statistically significant correlates of food-security classification, consistent with the FSVA's own three-pillar design [1], [2], [3]. Complementary panel and cross-sectional studies on Indonesian regional welfare and poverty consistently identify education as one of the strongest correlates of reduced poverty and improved regional welfare [13], [17], [18], [21], while access to clean water and sanitation is repeatedly linked to both poverty and adverse nutrition/health outcomes that FSVA utilization indicators are designed to capture [14], [15], [16], [22]. Methodologically, mixed-effects and multilevel frameworks analogous to the random-effects ordinal logit approach used here have been validated in other clustered and longitudinal Indonesian public-health settings, including multilevel analyses of stunting determinants using nationally representative family-life-survey data [23], Bayesian spatial conditional-autoregressive models of childhood stunting [24], spatial analyses of stunting determinants across 514 Indonesian districts/cities [25], regression-based analyses of stunting determinants in South and West Sulawesi [26], geographically weighted regression models of stunting determinants [27], and analyses of maternal health-service utilization in eastern Indonesia the same broad region in which Papua is located [28]. Together with recursive and bivariate extensions of ordinal/binary regression developed for Sustainable-Development-Goal-related outcomes [29], these studies support the appropriateness of the random-effects cumulative-logit approach adopted in this study.

3. Research Method

This section outlines the methodological framework employed to evaluate the regional Food Security and Vulnerability Atlas (FSVA) priority classification. The methodology is structured sequentially: it begins by describing the data source, the panel structure, and the operationalization of the predictor variables based on food security pillars. It then formally specifies the random-effects ordinal logistic regression model to accommodate both the ordered categorical response and the longitudinal nature of the data. Finally, it details the estimation techniques, hypothesis testing, and the classification accuracy metrics used to validate the model.

3.1 Data Source and Panel Structure

The data set is a strongly balanced panel covering 42 regions observed over four consecutive annual periods (2022–2025), yielding $N = 168$ region-year observations with no missing region-year combinations. The response variable, Y, is the regional FSVA food-security priority class, an ordinal variable with six categories: Priority 1 (highly vulnerable), Priority 2 (vulnerable), Priority 3 (somewhat vulnerable), Priority 4 (somewhat resilient), Priority 5 (resilient), and Priority 6 (highly resilient) [1], [2].

Following the objective of this study, only the four-predictor specification is used, in line with the three FSVA pillars described in Section 2.1. The predictors are summarized in Table 1.

Table 1: Predictor variables and their corresponding FSVA pillar

Code	Variable	Description
X1	Net Cereal Production Ratio (NCPR)	Ratio of per capita normative food consumption to net regional cereal production
X2	Poverty Percentage	Percentage of poor population in the region (%)
X3	Mean Years Of Schooling	Mean years of schooling of the population aged 15+ (years)
X4	Lack Of Clean Water	Percentage of households without proper access to clean drinking water (%)

3.2 Model Specification

Following equation (3), the random-effects ordinal logistic regression model estimated in this study is:

$$\text{logit}[P(\mathrm{Y}_{it} \le m)] = \alpha_m\big(\beta_1 X_{1,it} + \beta_2 X_{2,it} + \beta_3 X_{3,it} + \beta_4 X_{4,it}\big) - u_i,\ m = 1, \dots, 5; \quad u_i \sim N(0, \sigma_u^2) \tag{5}$$

estimated by maximum likelihood via 12-point adaptive Gauss–Hermite quadrature (Stata's xtologit procedure), with coefficients reported as odds ratios, $\mathrm{OR}_j = \exp(\hat{\beta}_j)$, together with robust standard errors, Wald z-statistics, p-values, and 95% confidence intervals.

3.3 Estimation and Testing Procedure

The analysis proceeds in five steps: (1) estimate model (5) by maximum likelihood; (2) test overall (simultaneous) significance of X1–X4 using the Wald test described in Section 2.5; (3) test the partial significance of each predictor using the Wald z-test and interpret its odds ratio; (4) inspect the estimated cut points $\alpha_1, \dots, \alpha_5$ for monotonicity and the estimated variance component $\hat{\sigma}_u^2$ for evidence of residual unobserved heterogeneity; and (5) generate predicted category probabilities for every observation, classify each observation to its most probable category, cross-tabulate predicted against observed categories, and compute classification accuracy and APER as defined in Section 2.6.

4. Results and Discussion

This section presents the empirical findings of the study and discusses their implications in the context of regional food security. The analysis is structured sequentially: it begins with an overview of the descriptive statistics and diagnostic tests for multicollinearity (Section 4.1). Following this, the parameter estimates are presented, and the empirical data panel equation is formulated (Section 4.2). The model's statistical significance and random-effects variance are then evaluated through hypothesis testing (Section 4.3). Subsequently, the practical predictive performance of the model is assessed using a confusion matrix, apparent error rate (APER), and the Kappa statistic (Section 4.4). Finally, the statistical results are synthesized and interpreted within the theoretical framework of the FSVA pillars (Section 4.5).

4.1 Descriptive Statistics and Multicollinearity Test

Prior to model estimation, descriptive statistics were calculated to understand the distribution of the data across the strongly balanced panel of 42 regions over four years ($N = 168$). As shown in Table II, the Net Cereal Production Ratio averaged 4.81 (SD = 2.78). Poverty Percentage ranged from 10.01% to 42.03% (Mean = 26.80%). Mean Years of Schooling had an average of 7.39 years, while the Lack of Clean Water exhibited significant regional variation, ranging from 1.93% up to 100% (Mean = 60.93%).

Table 2: Descriptive statistics of predictor variables (2022–2025)

Variable	Mean	Std. Dev.	Min	Max
X1	4.809	2.780	0.00	10.00
X2	26.795	8.779	10.01	42.03
X3	7.3936	2.900	1.28	12.00
X4	60.925	28.313	1.93	100.00

To ensure the reliability of the regression estimates, a Variance Inflation Factor (VIF) test was conducted to check for multicollinearity among the predictors. The detailed results for each variable are presented in Table 3.

Table 2: Variance Inflation Factor (VIF) test results for multicollinearity.

Variable	VIF	1/VIF (Tolerance)
X1	1.33	0.753
X2	2.78	0.359
X3	3.04	0.329
X4	3.24	0.309
Mean VIF	2.60	

The mean VIF across all variables was 2.60, and the highest individual VIF was 3.24 (for Lack Of Clean Water).

Because all individual VIF values and the mean VIF are well below the conventional strict threshold of 10, it is concluded that there is no severe multicollinearity issue, confirming that the variables are statistically distinct and suitable for simultaneous inclusion in the model.

4.2 Empirical Model Equation and Parameter Estimates

The random-effects ordered logistic regression model was estimated using maximum likelihood via 12-point adaptive Gauss–Hermite quadrature. The estimated odds ratios (OR) and cut-points (α_m) generated by the model are presented in Table 4.

Table 4: Random-effects ordinal logistic regression estimates

Variable	OR	Coefficient (β)	SE (for OR)	z	p
X1	0.565	-0.571	0.058	-5.57	<0.001
X2	0.873	-0.136	0.030	-3.94	<0.001
X3	1.407	0.341	0.206	2.34	0.019
X4	0.932	0.070	0.013	-5.22	<0.001

To derive the empirical equation, the odds ratios were transformed back into raw logit coefficients ($\beta = \ln(\text{OR})$). Based on Stata's parameterization, the final empirical data panel equation predicting the cumulative probability of a region falling into priority category m or lower is formulated as:

$$\text{logit}[P(Y_{it} \le m)] = \hat{\alpha}_m - \left(-0.571X_{1,it} - 0.136X_{2,it} + 0.341X_{3,it} - 0.070X_{4,it}\right) - u_i \quad (6)$$

where the threshold parameters (cut-points) are estimated as $\hat{\alpha}_1 = -8.230$, $\hat{\alpha}_2 = -5.091$, $\hat{\alpha}_3 = -3.704$, $\hat{\alpha}_4 = -1.843$, and $\hat{\alpha}_5 = -0.292$. The cut-points are monotonically increasing, confirming that the six FSVA categories are correctly and consistently ordered.

4.3 Hypothesis Testing and Random-Effects Variance

The overall (simultaneous) significance was evaluated using a Wald test. The joint null hypothesis was strongly rejected ($\chi^2(4) = 90.12$, $p < 0.001$), indicating that the four predictors collectively carry statistically significant information for determining regional food-security priority. An auxiliary Likelihood-Ratio (LR) test also confirmed that expanding the model beyond these core four variables did not yield a statistically significant improvement in fit ($\chi^2(1) = 0.13$, $p = 0.720$), justifying the parsimony of the selected four-predictor specification.

Individually, all four predictors were statistically significant at the 5% alpha level ($p < 0.05$). The estimated random-effects variance was negligible ($\hat{\sigma}_u^2 \approx 5.55 \times 10^{-32}$), effectively sitting at the lower boundary of zero. This indicates that, after controlling for these four theoretical pillars of food security, almost no unobserved structural heterogeneity remains between the 42 regions over the 2022–2025 period.

4.4 Classification Evaluation, APER, and Kappa Statistic

The practical predictive performance of the model was evaluated by calculating the probabilities for all six categories and classifying each observation into the category with the highest predicted probability. The resulting confusion matrix is shown in Table 5, and the detailed diagnostic metrics per category are summarized in Table 6.

Table 5: Confusion matrix

Observed \ Predicted	P1	P2	P3	P4	P5	P6
Priority 1	76	9	0	0	0	0
Priority 2	7	28	0	0	0	0
Priority 3	1	5	1	5	0	0
Priority 4	0	1	2	10	0	2
Priority 5	0	0	0	6	2	1
Priority 6	0	0	0	0	1	11

Table 6: Confusion matrix

FSVA Category	Sensitivity	Specificity	Precision	APER
Priority 1	0.8941	0.9036	0.9048	0.1059
Priority 2	0.8000	0.8872	0.6512	0.2000
Priority 3	0.0833	0.9872	0.3333	0.9167
Priority 4	0.6667	0.9281	0.4762	0.3333
Priority 5	0.2222	0.9937	0.6667	0.7778
Priority 6	0.9167	0.9808	0.7857	0.0833

The model successfully correctly classified 128 out of 168 observations, yielding an overall accuracy of 76.19% and an overall Apparent Error Rate (APER) of 23.81%. The macro-averaged sensitivity (Balanced Accuracy) stands at 59.72%. Furthermore, Cohen's Kappa statistic was calculated to be 0.6469 (Z = 14.65, $p < 0.0001$), indicating a "substantial agreement" between the observed and predicted categories beyond what would be expected by chance.

As detailed in Table VI, the model exhibits excellent sensitivity and precision at the extreme ends of the scale (Priority 1 and Priority 6, with APERs of only 10.59% and 8.33%, respectively). However, it struggles with the middle-tier categories (Priority 3 and Priority 5), where classification errors rise sharply. This is a common phenomenon in ordinal modeling; because the estimated cut-points (α_m) are tightly clustered in the middle of the latent scale, slight shifts in the linear predictor easily cross adjacent thresholds, leading to misclassification among neighboring vulnerability statuses.

4.5 Discussion

Mean years of schooling (X3, MeanYearsOfSchooling) was the only predictor with an odds ratio above one (OR = 1.407, 95% CI: 1.057–1.874, $p = 0.019$). The model's positive coefficient ($\beta = 0.341$) implies that each additional year of average schooling is associated with a 40.7% increase in the odds of a region being classified into a higher (more food-secure) FSVA priority category, holding other factors constant. This explicitly supports the utilization pillar of food-security theory: better education directly enhances a population's capacity to convert available resources into adequate health and nutrition outcomes [13], [17]. The result strongly aligns with empirical evidence across Indonesia that highlights education as a primary driver of regional welfare and poverty reduction [18], [27].

Conversely, the percentage of poor population (X2, PovertyPercentage; OR = 0.873, $\beta = -0.136$, $p < 0.001$) significantly reduced the odds of a more food-secure classification. This finding operationalizes the access pillar of food-security theory: economic limitations cripple a region's purchasing power, restricting access to adequate food regardless of raw physical availability [8], [21]. This confirms findings from prior studies wherein poverty incidence consistently emerges as the most robust barrier to food security and regional resilience in Indonesia [11].

The percentage of households without proper access to clean drinking water (X4, LackOfCleanWater; OR = 0.932, $\beta = -0.070$, $p < 0.001$) similarly depressed the odds of achieving a resilient food-security status. From a theoretical standpoint, this reflects the biological utilization aspect of food security; poor sanitation and contaminated water invite waterborne diseases that severely disrupt nutrient absorption [14], [15], [16]. Prior research echoes this, closely linking inadequate water infrastructure to chronic malnutrition and stunting in rural and urban regions alike [22].

Finally, the Net Cereal Production Ratio (X1, Net Cereal Production Ratio; OR = 0.565, $\beta = -0.571$, $p < 0.001$) demonstrated the most aggressive negative association with food security. As this ratio measures regional normative food consumption against net cereal production, a higher value acts as an urgent proxy for structural food-supply deficits. This robustly validates the food-availability pillar within the model, proving that regions unable to sustain their baseline consumption needs locally face exponentially higher odds of falling into the highly vulnerable (Priority 1) classifications [30].

Synthesizing these empirical outcomes, the data panel equation firmly replicates the structural integrity of the FSVA's composite index design. The availability (X1), access (X2), and utilization (X3, X4) components not only possess independent statistical significance but together completely absorb the systematic regional variances (as evidenced by the zero random-effects variance), providing a highly reliable and interpretable statistical framework for regional policy targeting.

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6. References

[1] National Food Agency of Indonesia (Badan Pangan Nasional) & World Food Programme, "Peta Ketahanan dan Kerentanan Pangan (Food Security and

Vulnerability Atlas of Indonesia)," 2023–2025 editions. https://badanpangan.go.id/

[2] Azhar, A. L., Suliyanto, Chamidah, N., Ana, E., & Amelia, D. (2023). Pemodelan Indeks Ketahanan Pangan di Indonesia Berdasarkan Pendekatan Regresi Logistik Ordinal Data Panel Efek Acak, Jurnal Ketahanan Nasional, vol. 29, no. 2, pp. 166.

[3] Amelia, D., Suliyanto, Aldawiyah, N. K., & Zhafira, A. A. (2026). Modeling Indonesia's food security index using spatial econometric panel approach, *Jurnal Ilmiah Ilmu Terapan Universitas Jambi*, vol. 10, no. 2, pp. 881–897.

[4] Abdulah, R., Prasetyo, E., & Wijaya, S. H. (2025). Mapping food security in Indonesia: Geographic clusters and regional disparities, *Indonesian Journal of Geography*, vol. 57, no. 3, pp. 440–447.

[5] Aguilera, T., & Jatmiko, Y. A. (2022). Pemodelan Tingkat Kerawanan Pangan Rumah Tangga di Indonesia Tahun 2021 dengan Pendekatan Regresi Logistik Ordinal, Indonesian Journal of Applied Statistics, vol. 5, no. 2, pp. 90.

[6] Dewi, N. N. U., Susilawati, M., & Srinadi, I. G. A. M. (2023). Analisis Regresi Logistik Ordinal Spasial Status Ketahanan Pangan pada Kabupaten/Kota di Indonesia Tahun 2020, E-Jurnal Matematika, vol. 12, no. 4, pp. 281–288.

[7] Mim, M. S., Rahaman, M. L., & Sajib, A. H. (2025). Generalized linear mixed model approach for analyzing water, sanitation, and hygiene facilities in Bangladesh: Insights from BDHS 2022 data, *PLOS ONE*, vol. 20, no. 7, pp. e0318467.

[8] Nairobi, Ambya, & Afif, F. Y. (2025). Food security and poverty depth in Indonesia: Evidence from provincial fixed-effects panel data (2019–2023), *Indonesian Journal of Islamic Economics and Finance*. https://ejournal.insuriponorogo.ac.id/index.php/jief/article/view/9694

[9] Nuradilla, S., Saputra, W., & Rizal, M. (2025). Regional clustering of food insecurity to support the attainment of SDG 2: Zero hunger through machine learning approaches, *Proceedings of the International Conference on Data Science and Official Statistics*. https://proceedings.stis.ac.id/icdsos/article/view/475

[10] World Food Programme. (2024). Indonesia, Evaluation of the Food Security and Vulnerability Atlas Activities from 2017 to 2024. https://www.wfp.org/publications/indonesia-evaluation-food-security-and-vulnerability-atlas-activities-2017-2024

[11] Rizal, R. N., Hartono, D., Dartanto, T., & Gultom, Y. M. L. (2024). Multidimensional energy poverty: A study of its measurement, decomposition, and determinants in Indonesia, Heliyon, vol. 10, no. 3, pp. e24923.

[12] Spada, A., Fiore, M., & Galati, A. (2024). The impact of education and culture on poverty reduction: Evidence from panel data of European countries, Social Indicators Research, vol. 175, no. 3, pp. 927–940.

[13] Nazamuddin, B. S., Syathi, P. B., Riswandi, R., Fitriyani, F., & Prayoga, A. E. (2025). The dynamic nexus between human capital and poverty in Indonesia: Evidence from a panel PMG-ARDL approach, Journal of the Knowledge Economy, pp. 1–26.

[14] Mazenda, A., & Nkwana, H. M. (2025). Water, sanitation, and energy as determinants of food security among rural women-led households, International Journal of Energy and Water Resources, vol. 9, no. 4, pp. 1669–1680.

[15] Charles, I., Salinger, A., Sweeney, R., Batagol, B., Barker, S. F., Nasir, S., Taruc, R. R., Francis, N., Clasen, T., & Sinharoy, S. S. (2023). Joint food and water insecurity had a multiplicative effect on women's depression in urban informal settlements in Makassar, Indonesia during the COVID-19 pandemic, The Journal of Nutrition, vol. 153, no. 4, pp. 1244–1252. https://www.sciencedirect.com/science/article/pii/S0022316623025129

[16] Celeste, N. E. (2023). Linking poverty with water and sanitation in targeting households for achieving sustainable development, Journal of Water, Sanitation and Hygiene for Development, vol. 13, no. 2, pp. 140–149.

[17] Fayza, S., Sinambela, R. A., Situmorang, R. M., Nafisha, N., & Silaban, P. S. M. J. (2025). The effect of education and unemployment on poverty in Indonesia's 34 provinces (2018–2023): The mediating role of the Human Development Index, Jurnal Ekonomi Balance, vol. 21, no. 1.

[18] Muhlisin, Sakti, N. C., & Subroto, W. T. (2026). Can education reduce inequality? Unraveling Indonesia's human development paradox, Economic Studies (Ikonomicheski Izsledvania), issue 2, pp. 81-101. https://ideas.repec.org/a/bas/econst/y2026i2p81-101.html

[19] Priambodo, A. P., & Djirimu, M. A. (2024). Government intervention strategy in poverty reduction: Study on the district and city in Indonesia across 2016–2023, Jurnal Bina Praja, vol. 16, no. 3, pp. 489–508.

[20] Puja Ramdani, A., & Murwiati, A. (2025). Determinants of the prevalence of province food insufficiency in Indonesia in 2023 with a quantile regression approach, International Journal of Social Science, Education, Communication and Economics (SINOMICS Journal), vol. 4, no. 1, pp. 151–160.

[21] Prasetya, S. R., Primandhana, W. P., & Wardaya, W. (2024). Uncovering the roots of structural poverty in East Java Province: An analysis of determinants, International Journal of Economics, Business and Innovation Research, vol. 3, no. 5, pp. 431–447.

[22] Owusu, B. A., Salifu, Y., Swithin, S. M., Lasong, J., Alhassan, A., & Salifu, T. (2026). Household water, sanitation, and hygiene practices in Ghana from 1993–2022: a non-linear multivariate Poisson decomposition and traditional predictive modelling approach, Frontiers in Public Health. https://pmc.ncbi.nlm.nih.gov/articles/PMC12920496/

[23] Siramaneerat, I., Astutik, E., Agushybana, F., Bhumkittipich, P., & Lamprom, W. (2024). Examining determinants of stunting in urban and rural Indonesian: A multilevel analysis using the population-based Indonesian family life survey, BMC Public Health, vol. 24, no. 1.

[24] Aswi, A., Rahardiantoro, S., Kurnia, A., Sartono, B., Handayani, D., Nurwan, N., & Cramb, S. (2024). Childhood stunting in Indonesia: Assessing the performance of Bayesian spatial conditional autoregressive models, Geospatial Health, vol. 19, no. 2.

[25] Eryando, T., et al. (2022). Spatial analysis of stunting determinants in 514 Indonesian districts/cities: Implications for intervention and setting of priority, Geospatial Health, vol. 17, no. 1.

[26] Anastasia, H., Hadju, V., Hartono, R., Samarang, Manjilala, Sirajuddin, Salam, A., & Atmarita. (2023). Determinants of stunting in children under five years old in South Sulawesi and West Sulawesi Province: 2013 and 2018 Indonesian Basic Health Survey, PLoS ONE, vol. 18, no. 5, pp. e0281962.

[27] Kurniawati, D., Hastono, S. P., Safika, I., & Wahyuningsih, W. (2025). Geographically weighted regression model of stunting determinants in Indonesia, Journal of Maternal and Child Health, vol. 10, no. 3, pp. 140–152.

[28] Titaley, C. R., Tjandrarini, D. H., Malakauseya, M. L. V., Ariawan, I., Iwan, R. F., Istia, S. S., & Dibley, M. J. (2025). Determinants of non-use of antenatal care services in eastern Indonesia: Analysis of the 2023 Indonesia health survey, Frontiers in Global Women's Health, vol. 6, pp. 1649276.

[29] Ratnasari, V., Utama, S. H., & Dani, A. T. R. (2024). Toward Sustainable Development Goals (SDGs) with statistical modeling: Recursive bivariate binary probit, IAENG International Journal of Applied Mathematics, vol. 54, no. 8, pp. 1515–1521.

[30] Wiranthi, P. E., Suwarsinah, H. K., & Adhi, A. K. (2014). Determinants of household food security: A comparative analysis of eastern and western Indonesia, Indonesian Journal of Agricultural Science, vol. 15, no. 1, pp. 17-28.