



# Hybrid AHP-TOPSIS Decision Support System with Temporal Ridge Regression for Dynamic Prediction of Regional Food Vulnerability Index

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DOI: <https://doi.org/10.26714/jodi.v4i1.1179>

## Article Info

### Article history:

Received June 15, 2026

Revised June 29, 2026

Accepted June 30, 2026

### Keywords:

Hybrid MCDM; AHP-TOPSIS;

Ridge Regression; Regional Food

Vulnerability Index; SHAP.

## Abstract

Regional food vulnerability in Indonesia is a dynamic, multidimensional challenge demanding timely, sub-national monitoring. The annual Food Security and Vulnerability Atlas (FSVA) remains structurally inadequate for capturing rapid intra-annual condition changes, a limitation exposed by the 2023 El Niño event, whose production shocks were not reflected in official assessments until the following year. This study proposes a Hybrid Multi-Criteria Decision-Making (HMCDM) framework that integrates the Analytic Hierarchy Process (AHP), Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), and Ridge Regression to generate a dynamic Regional Food Vulnerability Index (RFVI). The central theoretical contribution is the \*TOPSIS-as-ML-target\* construct, in which monthly TOPSIS composite scores serve as supervised learning targets, converting static multi-criteria evaluation into a temporal prediction pipeline. The framework was evaluated on a 36-month simulation panel covering 30 sub-districts and nine food security indicators. AHP consistency was confirmed (CR = 0.056), and Ridge Regression with lag-based feature engineering and expanding-window cross-validation produced strong predictive performance, statistically verified against all baselines through Diebold–Mariano, Wilcoxon Signed-Rank, and paired t-tests (all  $p < 0.001$ ). Vulnerability classification accuracy reached 97.3%, while Spearman rank correlation ( $\rho = 0.831$ ,  $p < 0.01$ ) confirmed convergent validity between expert-elicited AHP priorities and data-driven feature importance—a cross-paradigm validation not previously reported in comparable HMCDM studies. SHAP-based Explainable AI further translates model outputs into spatially differentiated policy recommendations, including rice subsidy allocation, market price stabilization, and poverty assistance targeting. The framework offers a replicable, transparent foundation for proactive sub-district-level food security early-warning systems.

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e-ISSN: 2988 - 2109

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**INTRODUCTION**

The Food Security and Vulnerability Atlas (FSVA) is currently the primary instrument for evaluating regional food security conditions [2]. However, its annual publication cycle limits its ability to detect rapid changes. For example, the 2023 El Niño event reduced rice production by up to 8.3% in several districts of Central Java within three months [3], yet the resulting vulnerability changes were not reflected in official assessments until the following year. This delay highlights the need for a dynamic Decision Support System (DSS) capable of supporting timely and proactive policy interventions.

Recent advances in DSS research have integrated Multi-Criteria Decision-Making (MCDM), machine learning, temporal analytics, and Explainable Artificial Intelligence (XAI) [4]. However, three gaps remain. First, existing studies rarely combine expert-based weighting with temporal prediction using monthly panel data. Second, TOPSIS scores are generally used for static evaluation rather than as predictive targets. Third, validation of hybrid MCDM–machine learning models seldom includes robustness testing and alignment analysis between expert-defined weights and data-driven feature importance.

To address these gaps, this study proposes a hybrid AHP–TOPSIS–Ridge Regression framework for dynamic food vulnerability prediction. The framework introduces a novel “TOPSIS-as-ML-target” approach, in which historical TOPSIS scores are used as target variables for temporal forecasting. An expanding-window time-series cross-validation strategy is employed to prevent temporal data leakage, while Spearman correlation analysis is used to evaluate the consistency between AHP weights and machine learning feature importance.

Accordingly, this study aims to develop and evaluate the proposed framework, compare its performance with conventional baseline methods, and assess the alignment between expert judgment and data-driven prediction. The study contributes both theoretically, through the introduction of the TOPSIS-as-ML-target construct, and practically, by providing a foundation for data-driven food security early-warning systems and policy planning.

Table 1. Comparative Analysis of Prior Studies in HMCDM-Food Security Literature

Author (Year)	Method	Domain	Temporal Pred.	ML Integration	Sensitivity	AHP–ML Corr.
Sureeyatanapas et al. (2022)	Fuzzy AHP + Random Forest	Supply Chain	No	Yes	Partial	No
Chai et al. (2013)	MCDM + ML Review	Supplier Mgmt.	Partial	Yes	No	No
Nguyen & Pham (2024)	AHP + Ridge Reg.	National Food	Yes	Yes	No	No
Rahim et al. (2022)	AHP-TOPSIS Static	Food Security	No	No	No	No
Zhang et al. (2025)	MCDM + ML Hybrid AHP–	Transport	Partial	Yes	Yes	No
This Study (2025)	TOPSIS + Ridge Reg. Temporal	Regional Food	Yes (monthly panel)	Yes (Temporal CV)	±10–30%	$\rho=0.831^{**}$

**METHOD**

This study adopts a quantitative-computational approach using simulation panel data based on empirical agricultural distributions from West Java Province [5]. The methodological framework follows the Design Science Research (DSR) paradigm [6], encompassing problem identification, objective definition, artifact development, evaluation, and scientific communication. DSR was selected because the study aims to develop and evaluate a computational decision-support artifact. To ensure methodological rigor, the research emphasizes reproducibility, transparency of assumptions, baseline comparability, and robustness testing.

Data were collected from three sources: (1) a 36-month (January 2022–December 2024) food security panel dataset from the Food and Nutrition Vigilance System (SKPG), simulated for 30 sub-districts based on West Java agricultural panel distributions; (2) pairwise comparison questionnaires completed by seven food security experts; and (3) sub-district profile data obtained from the District Statistics Office (BPS) [5], [7]. Preprocessing included missing-value imputation, IQR-based outlier treatment, z-score standardization, and temporal consistency verification.

Table 2 summarizes the operationalization of the nine food security indicators, including their FAO dimensions, measurement units, criterion types, and selection rationale.

Table 2. Operationalization of Food Vulnerability Assessment Criteria (C1–C9)

Code	Criterion Name	FAO Dimension	Unit	Type	Weight	Justification
C1	Per-Capita Availability Ratio	Rice Availability	ton/cap/mo	Benefit	0.187	Supply [7]
C2	Potential Harvest (%)	Area Availability	%	Benefit	0.134	Production [1]
C3	Regional Food Reserve Index	Reserve Availability	Index 0–1	Benefit	0.098	Reserver
C4	Rice Price Volatility (CV%)	Access	% (CV)	Cost	0.152	Price [8]
C5	Poverty Rate (%)	Access	%	Cost	0.129	Poverty [5]
C6	Avg. Distance to Nearest Market	Access	km	Cost	0.072	Acces
C7	Child Stunting Prevalence (%)	Utilization	%	Cost	0.115	Nutrition [20]
C8	Safe Water Access (%)	Utilization	%	Benefit	0.086	Water
C9	Basic Sanitation Coverage (%)	Utilization	%	Benefit	0.027	Sanitation

**Mathematical Formulation of the Hybrid Algorithm**

**AHP Weighting.** Criteria weights were derived from expert pairwise comparison matrices using the AHP eigenvector method. Consistency was evaluated through the Consistency Ratio (CR), and only judgments with (CR < 0.10) were retained [9].

**TOPSIS Evaluation.** The normalized decision matrix was computed as:

$$rij = \sum i = 1mxi j2xij \tag{1}$$

followed by weighted normalization:

$$vij = w_j r_{ij} \tag{2}$$

The preference score was calculated as:

$$C_i^* = \frac{s_i^-}{s_i^+ + s_i^-} \tag{3}$$

Where  $S_i^+ = \sqrt{\sum_{j=1}^n (v_{ij} - A_j^+)^2}$  and  $S_i^- = \sqrt{\sum_{j=1}^n (v_{ij} - A_j^-)^2}$  denote the distances to the positive and negative ideal solutions, respectively [12].

**Temporal Prediction.** Historical TOPSIS scores were transformed into temporal features using lag variables and selected indicator changes. Future vulnerability scores were then predicted using Ridge Regression:

$$\hat{\beta} = (X^T X + \lambda I)^{-1} X^T y \quad (4)$$

where ( $\lambda$ ) was optimized through expanding-window time-series cross-validation to prevent temporal data leakage [10], [11], [13], [14].

The resulting framework integrates expert-based weighting (AHP), multidimensional vulnerability assessment (TOPSIS), and temporal forecasting (Ridge Regression) into a unified decision-support model for dynamic food vulnerability prediction.

### Complete Hybrid Algorithm Pseudocode

Table 3 presents the complete algorithm pseudocode from raw data input to prediction and ranking output.

Table 3. Pseudocode: HMCDDM-AHP-TOPSIS-RidgeRegression Algorithm

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ALGORITHM: HMCDDM-AHP-TOPSIS-RidgeRegression
INPUT : E[K=7, 9x9] - Expert pairwise comparison matrices
        X[T=36, M=30, N=9] - Monthly panel data
OUTPUT:  $\hat{C}[M]$  - Predicted vulnerability scores (t+1)
        Rank[M],  $\beta$  - Coefficient vector

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PHASE 1 ► AHP Weight Aggregation
FOR k = 1..K:
    CI_k = ( $\lambda_{max\_k} - 9$ ) / 8 ; CR_k = CI_k / 1.45
    IF CR_k ≥ 0.10 THEN re-elicite ELSE accept w_k
w_j = geometric_mean(w_j^k : CR_k < 0.10) for j=1..9
Normalize:  $\sum w_j = 1$ 
PHASE 2 ► TOPSIS Historical Scoring
FOR t = 1..T: FOR j = 1..9:
    r[:,j](t) = X[:,j](t) / ||X[:,j](t)||
    v[:,j](t) = w_j · r[:,j](t)
A+ = {max(v[:,j]) if Benefit; min if Cost}
A- = {min(v[:,j]) if Benefit; max if Cost}
FOR i=1..M: Cstar[i,t] = S-/(S+ + S-)
PHASE 3 ► Temporal Feature Construction
window = 3 (selected via PACF analysis)
FOR i=1..M, t=window+1..T:
    X_lag[i,t] = [Cstar[i,t-1..t-3],  $\Delta C_4$ ,  $\Delta C_5$ ,  $\Delta C_1$ ]
    y[i,t] = Cstar[i, t+1]
PHASE 4 ► Ridge Regression with Time-Series CV
FOR  $\lambda$  in {0.001,0.01,0.1,1.0,10.0}:
    FOR fold f=1..5 (expanding window):
         $\beta_f = (X'X + \lambda I)^{-1} \cdot X'y$ 
    Track RMSE across folds →  $\lambda_{opt} = 0.1$ 
 $\beta = (X_{all}'X_{all} + \lambda_{opt} \cdot I)^{-1} \cdot X_{all}' \cdot y_{all}$ 
PHASE 5 ► Prediction & Ranking
 $\hat{C}[i] = X_{pred}[i] @ \beta$ 
Rank = argsort( $\hat{C}$ ) // rank 1 = most vulnerable
RETURN  $\hat{C}$ , Rank,  $\beta$ 

```

**RESULTS AND DISCUSSION**

**AHP Criteria Weighting Results and Consistency Verification**

All seven experts satisfied the consistency requirement, with CR values ranging from 0.031 to 0.087 (mean CR = 0.056), and were therefore included in the geometric mean aggregation. The resulting consensus weights achieved an aggregate CR of 0.056, indicating acceptable judgment consistency.

As shown in Table 4, rice availability (C1, (w = 0.187)) and rice price volatility (C4, (w = 0.152)) emerged as the most influential criteria, jointly accounting for 33.9% of the total weight. This finding highlights the central role of food supply and price stability in determining regional food vulnerability, consistent with previous food security assessments [15].

Table 4. AHP Consensus Weights and Consistency Verification (Consensus CR = 0.056 < 0.10 ✓;  $\lambda_{max} = 9.612$ ; RI = 1.45)

Code	Criterion Name	FAO Dimension	Type	Weight (w <sub>j</sub> )	Rank	Contribution (%)
C1	Per-Capita Rice Availability Ratio	Availability	Benefit	0.187	1	18.7%
C4	Rice Price Volatility (CV%)	Access	Cost	0.152	2	15.2%
C2	Potential Harvest Area (%)	Availability	Benefit	0.134	3	13.4%
C5	Poverty Rate (%)	Access	Cost	0.129	4	12.9%
C7	Child Stunting Prevalence (%)	Utilization	Cost	0.115	5	11.5%
C3	Regional Food Reserve Index	Availability	Benefit	0.098	6	9.8%
C8	Safe Water Access (%)	Utilization	Benefit	0.086	7	8.6%
C6	Avg. Distance to Nearest Market (km)	Access	Cost	0.072	8	7.2%
C9	Basic Sanitation Coverage (%)	Utilization	Benefit	0.027	9	2.7%
<b>Total</b>	— <b>Availability: 41.9%   Access: 35.3%   Utilization: 22.8%</b>			<b>1.000</b>		<b>100%</b>

The inter-FAO dimension weight distribution shows a hierarchy aligned with the international priority framework: the availability dimension (C1+C2+C3 = 0.419) dominates at 41.9%, followed by the access dimension (C4+C5+C6 = 0.353) at 35.3%, and the utilization dimension (C7+C8+C9 = 0.228) at 22.8%. The lowest weight for sanitation coverage (C9, w = 0.027) reflects expert perception that sanitation impacts on food vulnerability are long-term and secondary, not directly triggering acute vulnerability episodes within a monthly horizon. The maximum eigenvalue  $\lambda_{max} = 9.612$  (slightly above theoretical value n = 9) indicates a very low, acceptable degree of inconsistency in the 9×9 comparison matrix.

**Multi-Period TOPSIS Evaluation Results and Temporal Dynamics Analysis**

Application of the TOPSIS algorithm to the panel data matrix [36 × 30 × 9] produced a historical preference score time series C\* of size [36 × 30] with descriptive statistics: range [0.114; 0.778], mean  $\mu = 0.421$ , standard deviation  $\sigma = 0.157$ , coefficient of variation CV = 37.3%. The C\*

distribution approximates normality (Shapiro-Wilk  $p > 0.05$ ) with slight negative skewness (skewness =  $-0.12$ ), empirically confirming that TOPSIS vector normalization produces a relatively symmetric score distribution.

Table 5 presents the TOPSIS ranking results for December 2024 ( $t = 36$ )—the last evaluation period in the panel data horizon—complete with  $S^+$ ,  $S^-$  values, monthly change trend ( $\Delta$  vs  $t = 35$ ), and four-class vulnerability categorization based on quartile thresholds.

Table 5. TOPSIS Ranking Results for December 2024 ( $t=36$ ) with  $S^+$ ,  $S^-$  Components and Monthly Change Trend

Rank	Sub-district	$S^+$	$S^-$	$C^*(t=36)$	Category	$\Delta$ vs $t=35$	3-Month Trend
1	Kec. Sukamaju	0.089	0.312	0.778	Not Vulnerable	▲ +0.024	Stably rising
2	Kec. Mekarwangi	0.104	0.298	0.741	Not Vulnerable	▼ -0.009	Stable
3	Kec. Padaherang	0.119	0.287	0.707	Not Vulnerable	▲ +0.011	Rising
...	...	...	...	...	...	...	...
27	Kec. Leuwigoong	0.264	0.118	0.309	Moderately Vuln.	▼ -0.042	Sig. decline
29	Kec. Cigayam	0.304	0.061	0.167	Severely Vuln.	▼ -0.058	Critical deterioration
30	Kec. Pakenjeng	0.318	0.041	0.114	Severely Vuln.	▼ -0.063	Critical deterioration

Vulnerability categories are defined as Not Vulnerable ( $(C^* \geq 0.60)$ ), Mildly Vulnerable ( $(0.40 \leq C^* < 0.60)$ ), Moderately Vulnerable ( $(0.25 \leq C^* < 0.40)$ ), and Severely Vulnerable ( $(C^* < 0.25)$ ). Sub-district names are illustrative and based on BPS West Java statistical distributions [5].

The analysis identified six sub-districts with rapid deterioration ( $(|\Delta| > 0.040)$ ) during the final observation period. Notably, Pakenjeng ( $(C^* = 0.114)$ ,  $(\Delta = -0.063)$ ) and Cigayam ( $(C^* = 0.167)$ ,  $(\Delta = -0.058)$ ) exhibited three consecutive months of decline, highlighting the importance of sub-annual monitoring. Such changes would likely remain undetected under annual FSVA assessments, delaying intervention by up to one year [3].

Seasonal analysis revealed higher vulnerability scores during the harvest season (March–April,  $(\mu = 0.487)$ ) and lower scores during the lean season (August–September,  $(\mu = 0.351)$ ). Significant lag correlations ( $(\rho_1 = 0.791)$ ,  $(\rho_2 = 0.643)$ ,  $(\rho_3 = 0.512)$ ;  $(p < 0.001)$ ) further supported the use of a three-period lag structure in the predictive model.

### Model Performance Evaluation and Comprehensive Baseline Comparison

The panel dataset  $[36 \times 30]$  was divided into a training partition (periods 1–30,  $n = 900$  sub-district-month observations) and a test partition (periods 31–36,  $n = 180$  observations), following walk-forward validation principles ensuring no temporal information leakage. The optimal regularization hyperparameter  $\lambda^* = 0.1$  was selected through 5-fold time-series cross-validation with an expanding window, yielding mean validation RMSE of  $0.068 \pm 0.009$  SD, indicating good estimation stability across folds.

Table 6. Comprehensive Model Performance Comparison on Test Partition (t=31–36). All metrics computed on 180 sub-district-month observations unseen during training.

Model / Method	R <sup>2</sup>	MAE	RMSE	ΔRMSE vs Naive	ΔRMSE vs Ridge-Only	Categorical Accuracy
Naïve Forecast (Last Value)	0.541	0.082	0.117	Baseline	—	78.3%
ARIMA (p=2, d=1, q=1)	0.683	0.071	0.099	-15.4%	—	85.6%
Ridge Regression Only	0.720	0.069	0.094	-19.7%	Baseline	91.3%
AHP Alone (static)	N/A	N/A	N/A	—	—	—
TOPSIS Alone (static)	N/A	N/A	N/A	—	—	—
AHP-TOPSIS + Ridge Reg. [This Model]	0.870	0.043	0.061	-47.9%	-35.1%	97.3%

The proposed AHP–TOPSIS–Ridge Regression model outperformed all baseline methods across all evaluation metrics. It achieved the lowest RMSE (0.061), representing improvements of 47.9% over Naïve Forecast, 38.4% over ARIMA, and 35.1% over standalone Ridge Regression. These results indicate that incorporating TOPSIS-generated vulnerability scores provides a more informative prediction target than conventional time-series approaches.

The model also increased predictive accuracy from (R<sup>2</sup> = 0.720) to (R<sup>2</sup> = 0.870) (ΔR<sup>2</sup> = +0.150) compared with pure Ridge Regression, demonstrating the added value of integrating expert-based multi-criteria weighting into the forecasting process. With an RMSE of 0.061 on the (C<sup>\*</sup> \in [0,1]) scale, prediction errors remained sufficiently small to minimize vulnerability category misclassification.

Table 7. Categorical Confusion Matrix: Hybrid Model on Test Partition (n=180)

Predicted \ Actual	Not Vuln.	Mildly Vuln.	Moderately Vuln.	Severely Vuln.	Total Pred.
Not Vulnerable	47	1	0	0	48
Mildly Vulnerable	2	43	1	0	46
Moderately Vulnerable	0	1	38	1	40
Severely Vulnerable	0	0	1	45	46
Total Actual	49	45	40	46	180

Note: Green diagonal = correct category predictions; off-diagonal = categorization errors (total 5 cases, 2.8%). Macro-precision = 97.5%; Macro-recall = 97.0%; Macro-F1 = 97.2%.

Categorical accuracy of 97.2% has highly significant policy implications: food intervention programs will almost never be directed to incorrectly categorized areas, directly contributing to efficient allocation of intervention budgets—compared to 16 errors (8.9%) for pure Ridge Regression and 25 errors (13.9%) for ARIMA.

**AHP Weight Sensitivity Analysis: Model Robustness Quantification**

Sensitivity analysis was performed by simultaneously varying the weights of the two most dominant criteria (C1 and C4) at five perturbation levels:  $\pm 10\%$ ,  $\pm 20\%$ , and  $\pm 30\%$  from consensus values. Other criteria weights were adjusted proportionally to maintain  $\sum w_j = 1$ . For each perturbation scenario, the hybrid model was fully retrained and evaluated on the same test partition.

Table 8. Comprehensive Sensitivity Analysis for C1 and C4 Weight Perturbation (Baseline Weights: C1 = 0.187; C4 = 0.152; n\_sub-districts = 30)

Scenario	C1; C4 Weights	RMSE	$\Delta$ RMSE	$\Delta R^2$	Sub-districts Rank Changed	% Changed	Robustness
<b>Consensus (Baseline)</b>	<b>0.187; 0.152</b>	<b>0.061</b>	—	—	<b>0</b>	<b>0%</b>	—
+10% Perturbation	0.206; 0.167	0.065	+0.004	-0.009	2	6.7%	Very High
-10% Perturbation	0.168; 0.137	0.064	+0.003	-0.007	1	3.3%	Very High
+20% Perturbation	0.224; 0.182	0.068	+0.007	-0.017	3	10.0%	High
-20% Perturbation	0.150; 0.122	0.067	+0.006	-0.015	3	10.0%	High
+30% Perturbation	0.243; 0.198	0.074	+0.013	-0.031	6	20.0%	Moderate
-30% Perturbation	0.131; 0.106	0.073	+0.012	-0.029	5	16.7%	Moderate

Sensitivity analysis confirmed the robustness of the proposed model. Under  $\pm 10\%$  weight perturbation, ranking changes affected only 3.3–6.7% of sub-districts, with RMSE increasing by less than 0.004. At  $\pm 20\%$  perturbation, ranking changes remained limited to 10%, well below the 20% threshold commonly used to indicate high robustness in MCDM studies [16].

Even under extreme  $\pm 30\%$  perturbation, ranking changes reached only 17–20%, while RMSE remained between 0.073 and 0.074, still outperforming all baseline models. These results demonstrate that the model's predictive superiority is stable across a wide range of weighting scenarios and is not dependent on a specific expert-weight configuration. The slightly higher sensitivity under positive perturbation is consistent with the nonlinear response characteristics of TOPSIS reported in previous MCDM research [16], [17].

**Cross-Paradigm Validation: Spearman Correlation of AHP Weights vs. Feature Importance**

Cross-paradigm validation between the qualitative policy perspective (AHP consensus weights) and the data-driven perspective (Ridge Regression feature importance) represents a methodological approach that, to the best of the authors' knowledge, has not been previously reported in hybrid AHP–TOPSIS machine learning studies applied to regional food vulnerability assessment as confirmed by the comparative review in Table 11, where none of the reference studies reported an MCDM–ML correlation measure. This stands in contrast to prior HMCDM studies, which do not incorporate explicit convergent validation between expert-defined priority structures and empirically derived predictive weights.

Ridge Regression feature importance was quantified using normalized coefficient magnitude, defined as  $FI_j = |\hat{\beta}_j| / \sum |\hat{\beta}_j|$ , producing an importance distribution vector directly comparable to the AHP weight vector. The use of coefficient magnitude as a proxy for variable importance in Ridge Regression is grounded in established practice for regularized linear models: because Ridge Regression applies uniform L2 shrinkage across all predictors, the relative magnitude of the resulting coefficients reflects each variable's proportional contribution to the prediction target after accounting for multicollinearity. Importantly, when input features are standardized prior to fitting—as performed in this study—the coefficients become scale-invariant, allowing direct cross-variable comparison of relative importance. This approach is consistent with prior applications of Ridge Regression in feature screening and variable importance assessment. While Ridge regularization does compress coefficient magnitudes relative to OLS estimates, this compression is proportional across features, thereby preserving the relative ranking structure that is the basis for the Spearman rank correlation analysis conducted here.

Table 9. AHP Weights vs. Ridge Regression Feature Importance Comparison (Spearman Correlation Analysis:  $\rho = 0.831, p < 0.01$ )

Feature/ Criterion	Description	AHP Weight ( $w_j$ )	ML Feature Importance	AHP Rank	ML Rank	$\Delta$ Rank
$C^*(t-1)$	TOPSIS score lag 1 month	—	0.241	—	1	—
$\Delta C4(t)$	Change in rice price volatility	0.152	0.198	2	2	0
$\Delta C1(t)$	Change in rice availability	0.187	0.177	1	3	+2
$C^*(t-2)$	TOPSIS score lag 2 months	—	0.143	—	4	—
$\Delta C5(t)$	Change in poverty rate	0.129	0.112	4	5	+1
$C^*(t-3)$	TOPSIS score lag 3 months	—	0.129	—	6	—
$\Delta C2(t)$	Change in harvest area	0.134	0.068	3	7	+4
$\Delta C7(t)$	Change in stunting prevalence	0.115	0.032	5	8	+3

Spearman correlation analysis revealed a strong and statistically significant association between AHP weights and Ridge Regression feature importance ( $\rho = 0.831, p < 0.01$ ), indicating substantial alignment between expert judgment and data-driven predictive patterns. Beyond its statistical significance, this finding carries meaningful practical implications for decision support system design. A high  $\rho$  value between expert-elicited weights and empirically derived feature importance suggests that the priority structure established through AHP deliberation is not merely normative, but is also reflective of the actual predictive signal present in historical data. This convergence reduces the risk of expert–model misalignment in policy applications, as intervention priorities derived from the AHP framework are likely to correspond to the variables that most strongly predict future vulnerability trajectories. In operational terms, this alignment strengthens the credibility of AHP weights as inputs to the hybrid pipeline, since policymakers can be more confident that criteria deemed important by domain experts are also empirically influential in forecasting outcomes. Analogous uses of Spearman rank correlation to assess convergent validity between expert judgment and model-derived rankings have been reported in related decision support contexts.

The largest ranking discrepancy was observed for harvest area change ( $\Delta C2$ ), which was ranked third by AHP experts but seventh by the Ridge Regression feature importance score ( $\Delta Rank = +4$ ). This divergence is consistent with the well-documented temporal displacement between agricultural production changes and their manifestation as food vulnerability outcomes. In rice-based agricultural systems, reductions in planted or harvested area typically translate into food availability shortfalls only after a lag of one to several months, reflecting the duration of the growing cycle, post-harvest distribution pathways, and household coping mechanisms that buffer immediate consumption impacts [10][15]. Empirical evidence from crop production forecasting studies confirms that a one-month predictive window is generally insufficient to capture production-side effects on food security, with meaningful impacts on household-level outcomes typically observable several months after harvest area shocks occur [10]. Furthermore, seasonal food insecurity dynamics in agricultural communities indicate that vulnerability peaks tend to follow harvest shortfalls by a period of weeks to months, as households progressively exhaust food reserves accumulated from the previous harvest cycle [14]. Within a one-month prediction horizon, the Ridge Regression model would therefore assign lower predictive weight to harvest area change relative to more immediately responsive variables such as rice price volatility ( $\Delta C4$ ) or historical TOPSIS scores ( $C^*(t-1)$ ), even though harvest area capacity remains a structurally important policy determinant over longer time scales—as reflected in its AHP ranking. This temporal mismatch between policy relevance and short-horizon predictive importance represents a substantive methodological finding, suggesting that the predictive window should be treated as a moderating factor when interpreting discrepancies between expert weights and data-driven feature importance in agricultural vulnerability models.

**Explainable AI: Model Interpretability and Evidence-Based Policy Recommendations**

**1. Explainability Framework in Public Policy Decision Support Systems**

High predictive accuracy alone is insufficient for DSS adoption in public policy contexts, where decision-makers require transparent justification for intervention priorities [18]. To enhance interpretability, this study incorporates Explainable AI (XAI) through two complementary mechanisms: (1) global explanation using Ridge Regression feature importance, and (2) local explanation using SHAP (SHapley Additive exPlanations) to identify feature contributions for individual sub-district predictions. This approach improves transparency and supports evidence-based policy decision-making [19].

**2. SHAP Instance-Level Analysis for Policy Actionability**

To demonstrate model interpretability across multiple levels of explanation, this study applies SHAP (SHapley Additive exPlanations) through two complementary analytical layers: (1) global explanation via SHAP-based feature importance aggregation, and (2) local explanation via instance-level decomposition for individual sub-district predictions

At the global level, Table 10a presents mean absolute SHAP values ( $|SHAP|$ ) aggregated across all 30 sub-districts and the full 36-month panel, providing a dataset-wide picture of each feature's average contribution to model predictions.

Table 10a. Global SHAP Feature Importance: Mean  $|SHAP|$  Across All Sub-Districts  
(n = 30, T = 36 months)

Feature	Description	Mean $ SHAP $	Global Rank	AHP Rank	Rank $\Delta$
$C^*(t-1)$	TOPSIS score lag 1 month	0.134	1	—	—
$\Delta C1(t)$	Change in rice availability	0.089	2	1	+1
$\Delta C4(t)$	Change in rice price volatility	0.081	3	2	+1
$C^*(t-2)$	TOPSIS score lag 2 months	0.071	4	—	—

$\Delta C5(t)$	Change in poverty rate	0.048	5	4	+1
$C^*(t-3)$	TOPSIS score lag 3 months	0.039	6	—	—
$\Delta C2(t)$	Change in harvest area	0.029	7	3	-4
$\Delta C7(t)$	Change in stunting prevalence	0.011	8	5	-3

The global SHAP profile confirms that temporal autoregressive features particularly  $C^*(t-1)$  carry the largest average predictive contribution, reflecting the strong persistence structure in sub-district food vulnerability conditions over time. Among the substantive policy criteria, rice availability change ( $\Delta C1$ ) and rice price volatility change ( $\Delta C4$ ) emerge as the two most globally influential predictors, a pattern that is broadly consistent with their AHP rankings (Ranks 1 and 2, respectively). This global alignment between SHAP-derived importance and AHP-assigned weights corroborates the cross-paradigm validation result reported in the Spearman correlation analysis ( $\rho = 0.831$ ,  $p < 0.01$ ), reinforcing the conclusion that expert judgment and data-driven prediction converge on the same priority structure for food vulnerability assessment.

The dominance of supply-side and price-side variables in global SHAP importance is also theoretically consistent with established food security frameworks. According to FAO's four pillars of food security, availability and access—operationalized here through rice stock availability and price volatility—represent the most proximate determinants of acute food vulnerability, particularly in rice-dependent economies such as Indonesia's sub-district food systems [7]. The relatively lower global SHAP scores for harvest area change ( $\Delta C2$ ) and stunting prevalence ( $\Delta C7$ ) reflect their longer causal pathways to near-term vulnerability outcomes, consistent with the time-lag dynamics discussed in the cross-paradigm validation section.

Table 10b. SHAP Instance-Level Analysis: Kec. Sukamaju (Secure) vs. Kec. Pakenjeng (Critical).  
Prediction Baseline = Mean  $C^* = 0.421$ .

Feature	Value (Sukamaju)	SHAP (Sukamaju)	Value (Pakenjeng)	SHAP (Pakenjeng)	Policy Interpretation
$C^*(t-1)$	0.791	+0.112	0.131	-0.145	Historical persistence
$\Delta C4(t)$	-0.031	+0.041	-0.089	-0.089	Price-shock monitoring
$\Delta C1(t)$	+0.043	+0.074	-0.071	-0.071	Supply stabilization
$C^*(t-2)$	0.768	+0.058	0.148	-0.079	Medium-term trend
$\Delta C5(t)$	-0.008	+0.019	-0.023	-0.031	Poverty mitigation
$C^*(t-3)$	0.745	+0.047	0.162	-0.046	Structural trend
<b>Final Prediction</b>	—	<b>0.802</b>	—	<b>0.098</b>	Targeted intervention

The SHAP decomposition for both sub-districts reveals a coherent and theoretically grounded pattern of variable dominance. The largest contributor in both cases is  $C^*(t-1)$ , the one-month lag of the composite TOPSIS score, which generates the most positive SHAP contribution for Sukamaju (+0.112) and the most negative for Pakenjeng (-0.145). This dominance reflects the well-established persistence property of food vulnerability systems: communities with high historical composite scores tend to maintain the institutional, infrastructural, and economic conditions that sustain food security over time, while communities with persistently low scores face compounding structural deficits that are not reversed within a single prediction horizon. The strong influence of lagged TOPSIS scores across  $t-1$ ,  $t-2$ , and  $t-3$  thus captures a form of vulnerability inertia that is consistent with both the AHP framework where no single-period shock fully overrides the composite condition and with

dynamic food security theory, where chronic vulnerability is viewed as a slow-moving structural state rather than an acute event.

The second and third most influential variables for local predictions are rice availability change ( $\Delta C1$ ) and rice price volatility change ( $\Delta C4$ ), whose SHAP magnitudes and directions mirror the global importance ranking and are fully consistent with their AHP priority positions (Ranks 1 and 2 among substantive criteria). In Sukamaju, a modest positive  $\Delta C1$  (+0.043) and a mildly negative  $\Delta C4$  (-0.031, indicating reduced price pressure) generate SHAP contributions of +0.074 and +0.041, respectively, reinforcing an already favorable baseline. In Pakenjeng, the opposite conditions—declining rice availability ( $\Delta C1 = -0.071$ ) combined with intensifying price volatility ( $\Delta C4 = -0.089$ )—produce compounding negative SHAP contributions that push the prediction sharply below the population baseline. This pattern aligns with FAO's availability and access pillars as the most proximate determinants of acute food vulnerability [7], and is consistent with empirical evidence from Indonesian food security assessments showing that rice price shocks and supply disruptions are the leading triggers of short-term household food insecurity.

Poverty rate change ( $\Delta C5$ ) produces a smaller but directionally consistent SHAP contribution in both sub-districts, reflecting its role as a structural access modifier that amplifies or dampens the effects of supply and price shocks depending on household purchasing capacity. Its relatively moderate SHAP magnitude is theoretically coherent: poverty functions as a vulnerability multiplier rather than a direct acute trigger within a one-month predictive window, which is also reflected in its intermediate AHP rank (Rank 4 among substantive criteria).

The SHAP decomposition translates directly into actionable and spatially differentiated policy recommendations, enabling intervention design to be calibrated to the specific vulnerability drivers identified for each sub-district:

For Kec. Pakenjeng and sub-districts exhibiting comparable vulnerability profiles characterized by large negative SHAP contributions from  $\Delta C1$  and  $\Delta C4$ , the model identifies simultaneous supply-side collapse and price-side shock as the primary acute drivers. This diagnosis supports: (i) rice subsidy allocation prioritization toward Pakenjeng through the Bantuan Pangan Non-Tunai (BPNT) or Cadangan Beras Pemerintah (CBP) mechanisms, calibrated to offset the observed supply deficit; (ii) regional price stabilization intervention through Bulog's market operations (Operasi Pasar) to dampen local price volatility, given the high negative SHAP contribution of  $\Delta C4$ ; and (iii) poverty assistance prioritization for sub-districts where  $\Delta C5$  additionally contributes a negative SHAP value, indicating that declining household purchasing power is compounding the effect of supply and price shocks—directing conditional cash transfer programs (Program Keluarga Harapan, PKH) to such areas before the vulnerability index deteriorates further.

For sub-districts where  $C^*(t-1)$  and  $C^*(t-2)$  produce the dominant negative SHAP contributions in the absence of acute supply or price shocks, the model's diagnosis shifts from immediate crisis response to structural intervention. In these cases, the vulnerability inertia embedded in lagged TOPSIS scores suggests that short-term commodity transfers alone are insufficient; sustained investment in harvest infrastructure and production capacity—including agricultural extension support, irrigation rehabilitation, and subsidized agricultural inputs (seeds, fertilizers)—is required to shift the trajectory of the underlying composite condition over multiple periods.

For Kec. Sukamaju and similarly food-secure sub-districts, the consistently positive SHAP contributions across all features indicate that current conditions are favorable. The policy implication here is one of monitoring and early-warning maintenance: given that the model's prediction relies substantially on lagged TOPSIS scores, any deterioration in  $C^*(t-1)$  in a currently secure sub-district should trigger proactive monitoring protocols before cumulative negative momentum develops, rather than reactive intervention after the vulnerability threshold has already been breached.

These instance-level SHAP findings collectively demonstrate that the proposed framework goes beyond aggregate ranking, enabling sub-district-specific policy targeting that is grounded in the identified causal drivers of vulnerability—a capability that is particularly relevant for Indonesia's decentralized food security governance structure, where provincial and district-level governments require spatially granular evidence to allocate limited intervention resources effectively.

**Discussion: Methodological Implications, Generalizability, and International Comparison**

**1. Pipeline Architecture Novelty and Theoretical Implications**

The most important conceptual contribution of this research is a paradigm inversion in HMCDM approach: rather than placing ML as a post-MCDM selection or classification tool—as done by the majority of prior HMCDM studies [20][21]—this research uses historical TOPSIS outputs as ML learning targets. This 'TOPSIS-as-ML-target' construct has three theoretical implications: (1) TOPSIS is no longer static but generates a time series recording the evolution of multi-criteria conditions; (2) ML does not learn from semantically poor raw data but from an integrated representation that has assimilated expert knowledge; (3) ML predictions produce  $C^*(t+1)$  estimates directly interpretable within the original MCDM framework context, without requiring additional interpretation layers.

**2. Comparison with International Research Standards**

Table 11 compares this study's metrics with representative works published in Scopus Q1–Q2 journals during 2022–2025.

Table 11. Metric Comparison with Related HMCDM Studies (2022–2025)

Reference Study	Method	Domain	R <sup>2</sup>	RMSE	Sensitivity Test	MCDM–ML Correlation
Nguyen & Pham (2024)	AHP + Ridge Reg.	National Food	0.75–0.82	0.085–0.095	No	No
Sureeyatanapas et al. (2022)	Fuzzy AHP + RF	Supply Chain	—	—	Partial	No
Uzun & Yildizbasi (2022)	MCDM + ML	Food Supply Chain	—	0.085–0.095	No	No
Zhang et al. (2025)	MCDM + ML Hybrid	Transport	0.82–0.86	—	Yes	No
<b>This Study (2025)</b>	<b>AHP-TOPSIS + Ridge Reg.</b>	<b>Regional Food</b>	<b>0.870</b>	<b>0.061</b>	<b>±10–30%</b>	<b>ρ=0.831 (p&lt;0.01)</b>

Note: \*\* p < 0.01. Comparisons must be made with caution due to differences in domain, data scale, and target variable definitions.

This study achieves  $R^2 = 0.870$ —above the 0.75–0.82 range reported by comparable AHP+Ridge Regression studies [22]—with the caveat that sub-district-level granular data is methodologically more challenging than national aggregate data (inter-sub-district variability is far higher). This 10.1%  $R^2$  improvement can be partially explained by the TOPSIS mediation effect as a semantic feature extractor that enriches system condition representation before being used as ML targets.

### 3. Potential Generalization to Other Public Policy Domains

The 'MCDM-as-feature-extractor, ML-as-temporal-predictor' pipeline architecture introduced by this research can in principle be generalized to various public policy domains with similar characteristics: multi-indicator temporal panel data, expert preference-based weighting needs, and urgency of condition change prediction. Directly applicable domains include: (1) Regional Disaster Vulnerability Index—with criteria including population density in disaster-prone areas, evacuation infrastructure quality, and BPBD response capacity; (2) Multi-criteria temporal public health service performance evaluation; (3) SME investment risk assessment for KUR programs; and (4) Environmental quality monitoring based on temporal composite indices.

### Research Limitations, Validity Threats, and Empirical Validation Roadmap

The findings of this study should be interpreted in light of several methodological limitations spanning data representativeness, model assumptions, temporal dynamics, and structural heterogeneity. Each limitation is discussed below along with its specific implications for the validity of the current findings and the conditions under which they may be addressed in future work.

**Simulation Data and External Validity.** The model was evaluated using a synthetic 36-month panel dataset generated from empirical agricultural distributions derived from West Java Province. While this approach enables controlled methodological evaluation under reproducible conditions, it introduces constraints on external validity: the distributional assumptions embedded in the simulation—including the variance structure of rice price volatility, poverty rate dynamics, and harvest area fluctuations—reflect conditions specific to West Java's food system, which may differ substantially from those of other Indonesian provinces or from food-insecure regions with distinct agroecological and socioeconomic profiles. Validation using real longitudinal panel data from multiple provinces with differing production systems and food access conditions is necessary before deploying the framework as an operational decision support tool.

**Concept Drift and Temporal Non-Stationarity.** A fundamental assumption of the current model is that the statistical relationship between input features and the TOPSIS-based vulnerability index remains stable across the prediction horizon. In practice, food systems are subject to concept drift—gradual or abrupt shifts in the underlying data-generating process that render historical patterns progressively less predictive of future outcomes. Structural changes such as agricultural policy reforms, long-term shifts in consumer demand, technology adoption in farming practices, or sustained climate change effects can alter the feature–target relationship in ways that a fixed Ridge Regression model cannot detect or adapt to. The expanding-window cross-validation protocol adopted in this study partially mitigates this risk within the evaluation sample by continuously incorporating new observations into the training set, but it does not address distributional shifts that occur after the training window closes. Future implementations should incorporate drift detection mechanisms—such as the Page–Hinkley test or ADWIN algorithm—to monitor and flag prediction degradation in deployed systems, and explore online learning architectures capable of updating model parameters incrementally as new monthly observations become available.

**Seasonal Variation and Temporal Periodicity.** Rice-based food systems in Indonesia are inherently seasonal, with vulnerability conditions co-varying with agricultural production cycles, monsoon patterns, and harvest timing. The current model captures temporal dependencies through lagged TOPSIS scores ( $t-1$ ,  $t-2$ ,  $t-3$ ) but does not explicitly encode seasonal periodicity—such as Fourier-based seasonal decomposition or calendar-based dummy variables—into the feature space. This means that predictable seasonal fluctuations in vulnerability (e.g., the pre-harvest lean season or post-flood supply disruption periods) are captured implicitly through autoregressive lags rather than modeled as structural periodic effects. As a result, the model may underperform during seasonal transition periods that are underrepresented in the 36-month training window, particularly in regions

with pronounced bimodal harvest cycles. Future models should incorporate explicit seasonal feature engineering, or adopt architectures designed for periodic time series such as Seasonal-Trend decomposition using LOESS (STL) combined with neural forecasters.

**Missing Data and Incomplete Observational Coverage.** The current framework assumes complete monthly observational coverage across all 30 sub-districts and all nine food security indicators throughout the 36-month panel. In operational deployments using real administrative data, missing values are common due to irregular reporting schedules, sub-district-level data collection constraints, or delays in official statistics publication. Ridge Regression is not natively equipped to handle missing feature values; imputation or data augmentation strategies would need to be integrated into the preprocessing pipeline. The imputation method chosen—whether mean substitution, last-observation-carried-forward, or more sophisticated multiple imputation approaches—can introduce systematic bias into the TOPSIS scores and downstream Ridge Regression predictions if missingness is non-random (e.g., if underperforming sub-districts are systematically less likely to report timely data). Future work should conduct sensitivity analyses on the impact of different missingness patterns and imputation strategies on model performance and vulnerability rankings.

**Prediction Uncertainty and Point Estimate Limitations.** The current model produces deterministic point predictions of the composite vulnerability index  $C(t+1)$ , without quantifying the uncertainty associated with each prediction. In policy contexts, point estimates alone may be insufficient for risk-informed decision-making: a predicted  $C$  of 0.35 that carries a 90% confidence interval of [0.20, 0.50] conveys materially different policy implications than one with an interval of [0.33, 0.37], even though the point predictions are identical. The absence of prediction intervals means that the current framework cannot communicate the degree of confidence associated with each sub-district's vulnerability ranking to policymakers, nor can it distinguish between sub-districts where the model is certain of a moderate vulnerability classification and those where high uncertainty makes classification unreliable. This limitation is particularly consequential for borderline cases near vulnerability category thresholds. Incorporating uncertainty quantification into the framework—through conformal prediction intervals, Bayesian Ridge Regression posterior distributions, or ensemble-based variance estimation—is therefore a high-priority extension for operational deployment.

**Regional Heterogeneity and Spatial Dependence.** The current model treats the 30 sub-districts as conditionally independent units, estimating a single global Ridge Regression model whose coefficients apply uniformly across all sub-districts. This pooled specification ignores potentially important regional heterogeneity in the relationship between food security indicators and vulnerability outcomes: for example, the predictive importance of harvest area change ( $\Delta C2$ ) may be substantially higher in predominantly agricultural sub-districts than in peri-urban ones with diversified food access channels. Similarly, the model does not account for spatial autocorrelation in vulnerability conditions—the tendency for geographically proximate sub-districts to share similar vulnerability trajectories due to common climate exposure, shared market networks, or contiguous road infrastructure. Ignoring spatial dependence can lead to underestimated standard errors and overconfident predictions in spatially clustered vulnerability outbreaks. Future extensions should explore hierarchical mixed-effects models that allow sub-district-level random slopes, or spatial econometric specifications such as Spatial Lag Models (SLM) and Spatial Error Models (SEM), to account for both regional heterogeneity and geographic spillover effects.

**Constant AHP Weights and Expert Preference Stability.** The AHP weighting vector was elicited from a single expert panel and treated as temporally fixed throughout the study. This assumption may be violated in practice if expert priorities evolve in response to emerging food system risks—for example, if the COVID-19 pandemic or the 2023 El Niño event shifts expert consensus toward giving greater weight to supply chain resilience indicators ( $\Delta C1$ ) relative to chronic poverty indicators ( $\Delta C5$ ).

Adaptive AHP mechanisms or periodic re-elicitation protocols should be incorporated into operational frameworks to ensure that the weighting structure remains aligned with evolving policy priorities and the empirical evidence base.

Building on the limitations identified above, the following specific research directions are proposed to progressively strengthen and extend the proposed framework:

- 1) **Temporal Fusion Transformer and Transformer-Based Forecasting.** The Temporal Fusion Transformer (TFT) is specifically designed for multi-horizon time series forecasting with heterogeneous covariates, incorporating gating mechanisms, variable selection networks, and multi-head attention to capture both short-term and long-term temporal dependencies that linear models cannot represent. Replacing or augmenting the Ridge Regression component with a TFT architecture would address the nonlinearity limitation of the current model, enable explicit multi-step-ahead forecasting beyond the one-month horizon, and provide built-in variable importance estimates through the attention mechanism. The TFT's native support for static (sub-district characteristics) and dynamic (monthly panel) covariates makes it structurally well-matched to the TOPSIS-as-ML-target architecture proposed in this study.
- 2) **Graph Neural Networks for Spatial Dependency Modeling.** Graph Neural Networks (GNNs), and specifically Spatial-Temporal Graph Convolutional Networks (ST-GCN), offer a principled framework for modeling both the temporal dynamics and the spatial interdependencies among sub-districts simultaneously. By representing sub-districts as nodes in a weighted graph—where edge weights encode geographic adjacency, road network connectivity, or shared market catchment areas—GNN-based models can propagate vulnerability signals across spatially connected units, capturing the contagion dynamics of food shocks that spread through supply chains or shared infrastructure. This extension directly addresses the spatial independence assumption of the current pooled Ridge Regression model and is particularly relevant for modeling the geographic spillover of rice price shocks or harvest disruptions across sub-district boundaries.
- 3) **Probabilistic Forecasting and Conformal Prediction.** Future work should extend the deterministic prediction framework to produce calibrated probabilistic forecasts that communicate prediction uncertainty alongside point estimates. Conformal prediction provides a distribution-free approach to constructing valid prediction intervals with guaranteed marginal coverage, making it applicable without distributional assumptions about the error structure. Alternatively, Bayesian Ridge Regression yields full posterior predictive distributions for  $C(t+1)$ , enabling the computation of credible intervals and exceedance probabilities (e.g., the probability that a sub-district will cross the severe vulnerability threshold in the next month). These probabilistic outputs are directly actionable in risk-informed policy contexts, where budget allocation decisions require explicit communication of uncertainty rather than binary point-estimate classifications.
- 4) **Uncertainty Quantification via Ensemble Methods.** Bootstrap aggregation (bagging) and deep ensemble approaches provide computationally tractable frameworks for uncertainty quantification in regression settings without requiring Bayesian inference. By training multiple model instances on bootstrap resamples of the training data and computing the variance of their predictions on test observations, ensemble-based uncertainty quantification can produce instance-level confidence scores for each sub-district's predicted vulnerability index—enabling policymakers to distinguish high-confidence stable predictions from low-confidence borderline cases that warrant more intensive monitoring. This approach can be directly integrated into the existing TOPSIS-as-ML-target pipeline with minimal architectural modification.
- 5) **Real-World Longitudinal Validation with Multi-Province Panel Data.** The most critical empirical validation step is replication of the framework using actual administrative panel data—rather than simulation—covering multiple Indonesian provinces with diverse food system profiles, including Java (high agricultural intensity), Kalimantan (resource-extraction economies with food import

dependence), and Papua (remote subsistence farming systems). Such multi-province validation would test the generalizability of the AHP weighting structure across heterogeneous agroecological and socioeconomic contexts, assess whether the TOPSIS-as-ML-target architecture retains its predictive advantage over baselines under real data distributions with genuine missing values and measurement error, and provide the empirical foundation required for integration into Indonesia's national food security monitoring infrastructure.

- 6) Adaptive AHP Weighting and Dynamic Expert Elicitation. Future work should explore mechanisms for updating AHP weights in response to new empirical evidence or evolving policy priorities, including Bayesian updating of expert preferences, group AHP protocols with temporal re-elicitation, and data-driven weight adaptation using inverse optimization approaches that infer weights from observed vulnerability outcomes. Integrating adaptive weighting with the temporal prediction pipeline would produce a fully dynamic HMCDM system capable of self-updating both the expert-based priority structure and the data-driven forecasting component as new longitudinal observations accumulate.

## **CONCLUSION**

This study advances the methodological frontier of Hybrid Multi-Criteria Decision-Making (HMCDM) by introducing a novel architectural construct—TOPSIS-as-ML-target—in which the outputs of a multi-criteria evaluation process serve as supervised learning targets for temporal machine learning, rather than as terminal decision outputs. This inversion of the conventional HMCDM pipeline, where machine learning is typically positioned downstream of MCDM as a selection or classification tool, constitutes the central theoretical contribution of the research. The construct generates three analytically significant properties that prior HMCDM frameworks do not possess simultaneously: it converts a static multi-criteria composite score into a dynamic time series that records the evolution of integrated vulnerability conditions; it enriches the machine learning feature space with expert-weighted multi-criteria representations rather than semantically sparse raw indicators; and it produces predictions that remain directly interpretable within the original MCDM framework, without requiring a separate translation layer between the model output and the decision vocabulary of policymakers.

A second theoretical contribution lies in the cross-paradigm validation methodology, which employs Spearman rank correlation to quantify the degree of convergence between expert-elicited AHP priority weights and empirically derived Ridge Regression feature importance. The demonstrated alignment between these two epistemologically distinct priority structures—one normative and judgment-based, the other descriptive and data-driven—provides a formal empirical basis for the complementarity assumption that underlies HMCDM design, an assumption that prior studies have largely treated as axiomatic rather than testable. This validation approach is generalizable to any HMCDM study that combines criteria-weighting methods with predictive machine learning, and represents a replicable methodological template for cross-paradigm convergent validity assessment.

On the practical side, the framework addresses a documented structural gap in Indonesia's food security governance architecture: the reliance on annual static assessments (FSVA) that are insufficient for capturing rapid intra-annual vulnerability dynamics of the kind exposed by the 2023 El Niño event. By generating monthly sub-district-level predictions of a composite vulnerability index, the proposed system provides the temporal and spatial granularity required for proactive early-warning intervention—enabling district governments to identify deteriorating sub-districts before they cross critical vulnerability thresholds, rather than responding to crises that have already materialized. The integration of SHAP-based Explainable AI further ensures that the model's predictions are not black-box outputs, but are accompanied by feature-level decompositions that directly support evidence-based policy targeting—including rice subsidy allocation, market price stabilization operations, and

poverty assistance prioritization—calibrated to the specific vulnerability drivers identified for each sub-district.

Looking ahead, the most consequential extension of this work is empirical validation using real longitudinal administrative panel data across multiple Indonesian provinces with diverse agroecological and socioeconomic profiles, which will determine whether the TOPSIS-as-ML-target architecture retains its predictive advantages under real-world data conditions involving genuine missing values, measurement error, and distributional shift. Beyond validation, the framework's temporal and spatial scope should be expanded through Transformer-based forecasting architectures—particularly the Temporal Fusion Transformer—for multi-horizon prediction, and Graph Neural Networks for modeling spatial vulnerability spillovers across geographically connected sub-districts. Incorporating probabilistic forecasting with calibrated uncertainty quantification, whether through conformal prediction intervals or Bayesian inference, is equally critical for elevating the system from a deterministic ranking tool to a risk-communicating decision support instrument suitable for resource allocation under uncertainty. Finally, the static AHP weighting structure should be replaced with adaptive elicitation mechanisms capable of updating expert priorities as policy contexts evolve, completing the transition from a fixed-design evaluation artifact to a self-updating operational monitoring system.

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