

Geo AI-Based Food Policy Navigation in South Sumatra

Dian Rizky¹, Badara Shofi Dana², Dani Shofi Nur Izza³

¹ Politeknik Negeri Jember, Jember, Indonesia

² UIN Sayyid Ali Rahmatullah Tulungagung, Tulungagung, Indonesia

³ UPN 'Veteran' East Java, Surabaya, Indonesia

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Abstract

Food price instability in South Sumatra is structural and recurring, exceeding the national inflation rate. This study develops a Geo AI-based food policy navigation system integrating satellite biophysical indicators, macroeconomic data, and machine learning to support the Regional Inflation Control Team (TPID). The data comprise a monthly panel from 11 of 17 districts (March 2021 to December 2025), selected based on available retail price data. Methods include GSTAR, SAR-X, SARIMAX, and XGBoost for forecasting; SHAP, Granger causality, and VAR decomposition for root cause diagnostics; PCA for the Composite Food Security Index (IKP Sumsel); Monte Carlo simulation for shock scenarios; and MCDA-SAW for policy prioritization. GSTAR achieves the highest accuracy (MAPE 2.56% for rice, 3.36% for eggs, 4.34% for chicken). Root causes vary across commodities, with 54.55% of districts under Alert status by December 2025 and karhutla as the most significant threat. The system integrates real-time satellite signals, including NDVI, rainfall, and forest fire hotspots, directly into TPID decision-making to enable anticipatory rather than reactive interventions. The study recommends differentiated 4K Strategy priorities for Musi Banyuasin, Ogan Komering Ilir, and Musi Rawas, and fire mitigation integrated into peatland food security policy.

Keywords

food price stability; food security; spatial spillover; remote sensing; Geo-AI

Corresponding Author:

Dian Rizky

Politeknik Negeri Jember, Jember, Indonesia; dian_rizky@polije.ac.id

1. INTRODUCTION

Food price stability is a fundamental pillar of food security because it determines households' ability to afford adequate food (Abdi et al., 2025; Guo, 2025). Price instability weakens household purchasing power, increases food inflation volatility, and constrains regional economic growth. South Sumatra recorded an inflation rate of 2.92% in the fourth quarter of 2025, which was slightly higher than the national inflation rate of 2.91%. Red chili, rice, and broiler chicken meat were the main contributors, accounting for 0.44%, 0.18%, and 0.09% of total inflation, respectively (Bank Indonesia, 2025). National Food Agency Price Panel data for 2021–2025 further reveal persistent structural pressures, as curly red chili prices increased cumulatively by 27.5%, medium-grade rice by 26.6%, and chicken eggs by 32.8%. These regional dynamics are also embedded within broader national inflation processes shaped by



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interactions between monetary and fiscal policies, particularly when inflation reaches specific thresholds (Dana & Musaiyaroh, 2024; Yuliati et al., 2025).

South Sumatra has substantial agricultural capacity, ranking fifth nationally in rice production, with 2.9 million tons produced from 521,092 hectares in 2024 (Bank Indonesia, 2025). Agriculture generated approximately IDR 90 trillion in Gross Regional Domestic Product and contributed 13.6% to the regional economy. A 19,340-km road network also supports the province, while previous studies demonstrate that transport connectivity is critical for maintaining food price stability during supply disruptions (Hossain & Kashem, 2025; Zhang et al., 2026). Nevertheless, production capacity and infrastructure have not eliminated food insecurity. Although the Bulog Food Supply and Price Stabilization Program distributed 36.4 million kg of rice in 2024, the prevalence of undernourishment increased from 6.53% in 2023 to 8.88% in 2024. This paradox suggests that production surpluses and policy interventions cannot ensure stable consumer prices when distribution systems remain insufficiently adaptive to local market conditions (Diawati & Rasyid, 2025).

The study therefore examines 11 of South Sumatra's 17 administrative units with complete and consistent monthly retail price data from the National Food Agency Price Panel and Statistics Indonesia. Six regencies were excluded because continuous observations were unavailable for at least one of four strategic commodities, which would compromise the balanced panel required for spatial-temporal modelling. This data-driven selection improves model reliability while minimizing potential selection bias.

The drivers of food price instability in South Sumatra are multidimensional and persistent. Climate anomalies and peatland forest fires simultaneously disrupt agricultural production by reducing vegetation health and burning cropland, while thick haze constrains transport visibility and delays interregional food distribution. Seasonal demand surges during Ramadan and major religious holidays further intensify these dual production and distribution shocks (Bank Indonesia, 2026). This pattern aligns with evidence showing that food price volatility in developing countries stems from the combined effects of production shocks, fragmented distribution systems, and seasonal demand fluctuations that public policy does not adequately anticipate (Maruejols et al., 2026; Wiggins et al., 2026). Existing early warning systems remain largely reactive because they rely on historical prices and rarely incorporate satellite-derived biophysical indicators that can detect production disturbances before they reach markets.

Previous studies have developed food price models using spatial information and remote sensing data. However, these efforts remain fragmented in their analytical scope (Xing & Sieber, 2023). Some focus exclusively on price forecasting without identifying the underlying determinants of price fluctuations (Shafi et al., 2023). Others construct food security indices without examining the

mechanisms of price formation (Ratnasari & Kusumawardani, 2015). Meanwhile, the growing application of machine learning to inflation forecasting shows that hybrid approaches, which combine econometric and learning-based models, consistently outperform single models across forecast horizons (Slimani & Chourabi, 2026). Despite this progress, research simulating the impacts of shock scenarios on district-level food prices remains limited in the Indonesian context, particularly in South Sumatra. This gap highlights the need for an integrated analytical framework that combines price prediction, root-cause diagnosis, food security assessment, shock-scenario simulation, and policy recommendations within a unified analytical process.

This study develops a GeoAI-based early warning system integrating satellite-derived biophysical indicators, including NDVI, EVI, rainfall, soil moisture, and forest fire hotspots, with distribution indicators based on Nighttime Lights (NTL), validated as reliable proxies for subnational economic activity (Levin & Zhang, 2017; Li et al., 2026; Mellander et al., 2015). Socioeconomic variables include retail and producer prices, agricultural GRDP, food social assistance, and regional fiscal capacity. These integrated data support food price forecasting, root cause diagnosis, and spatially prioritized policy recommendations for the South Sumatra Regional Inflation Control Team. This approach aligns with growing applications of machine learning for inflation forecasting in Indonesia, where exogenous macroeconomic variables demonstrate predictive power (Ikrom et al., 2026). The research follows a cascading structure in which each stage informs the next: forecasting spatial and temporal food prices, diagnosing drivers of price instability, constructing a monthly Composite Food Security Index, simulating alternative shocks, and developing a spatial policy mix to prioritize interventions.

The study contributes empirically by quantifying interdistrict price spillovers and examining the relationship between forest fires and food prices. Methodologically, it develops proxy indicators for farm-retail price spreads, NTL-based distribution conditions, and fuel price–transport distance interactions, improving applicability where administrative data are unavailable. Practically, it produces operational food price forecasts and spatially prioritized policy recommendations to support evidence-based interventions by the Regional Inflation Control Team, Bank Indonesia, and the National Food Agency.

2. METHODS

2.1. Data Type and Sources

This study employed a quantitative approach using monthly secondary panel data from 11 regencies and municipalities in South Sumatra Province: Banyuasin, Empat Lawang, Lahat, Muara Enim, Musi Banyuasin, Musi Rawas, Ogan Ilir, Ogan Komering Ilir, Ogan Komering Ulu Selatan, Ogan Komering Ulu Timur, and Palembang City. The dataset covered March 2021–December 2025 and

examined four strategic commodities: medium-grade rice, curly red chili, broiler chicken meat, and chicken eggs.

We compiled data from official databases and satellite observations and grouped them into three categories. Biophysical indicators included NDVI and EVI (MODIS and Sentinel-2), rainfall (CHIRPS and BMKG), land surface temperature (MODIS LST), soil moisture (NASA SMAP), forest-fire hotspots and burned areas (NASA FIRMS and KLHK SiPongi), PM2.5 concentrations, harvested rice area (BPS KSA), and Night-Time Lights intensity (VIIRS). Price and macroeconomic indicators comprised retail and producer prices, retail fuel prices, agricultural GRDP, and district minimum wages. Socioeconomic and institutional indicators included per capita consumption, food social assistance realization, religious holiday calendars, disaster records, and regional fiscal capacity. Integrating these multidimensional indicators enabled the analysis to capture environmental, market, macroeconomic, and socioeconomic determinants of spatial-temporal food price dynamics in South Sumatra.

2.2. Data Collection

We compiled data from official secondary databases and satellite imagery. We obtained price and macroeconomic data from the National Food Agency Price Panel and the South Sumatra Food Information System, and aggregated daily observations into monthly averages. We extracted satellite-derived biophysical indicators using Google Earth Engine, including NDVI and EVI, CHIRPS rainfall, MODIS land surface temperature, NASA SMAP soil moisture, and NASA FIRMS hotspots. Vegetation indices and land surface temperature were aggregated as monthly averages, whereas rainfall and hotspot occurrences were aggregated as monthly totals.

Socioeconomic and fiscal variables, including agricultural Gross Regional Domestic Product, district minimum wages, per capita consumption, food social assistance, and regional fiscal capacity, were available annually and converted into monthly observations using a twelve-month forward-fill procedure. We disaggregated annual harvested rice area into monthly estimates using NDVI- and crop-phenology-based weights following the Chow–Lin approach with an auxiliary indicator.

We harmonized all variables into a district-month panel using geographic identifiers and time periods. To address unavailable administrative data, we developed engineered features, including farm–retail price spreads as proxies for supply pressure, Night-Time Lights around ports and major transport corridors as proxies for logistics activity, fuel price–distribution distance interactions, moving-standard-deviation price volatility, NDVI anomalies, and spatial price lags based on Moran spatial autocorrelation.

2.3. Data Analysis

The data were analyzed using a five-stage cascading framework. Each stage output served as input for the next. This approach ensured a systematic transition from price prediction to policy formulation. The first stage addressed hypotheses H1, H2, and H3 through spatiotemporal food price prediction. We used the Generalized Space-Time Autoregressive (GSTAR) model as the primary model because it captures both temporal dependence and spatial interaction. We constructed the spatial weight matrix W using inverse Euclidean distance between district capitals and row-standardized it so each row sums to one. We extracted district capital coordinates from the Indonesian Geospatial Information Portal as a shapefile (Badan Informasi Geospasial, n.d.). This specification captures the principle that spatial price transmission intensity diminishes with geographic distance (Anselin, 1988). We compared its performance with SAR X, SARIMAX, and Extreme Gradient Boosting (XGBoost). We evaluated model accuracy using Mean Absolute Percentage Error (MAPE) under walk-forward validation. We examined spatial price spillovers using Moran's I statistic.

$$Y_{it} = \phi_0 Y_{i,t-1} + \phi_1 \sum_j w_{ij} Y_{j,t-1} + \beta X_{it} + \epsilon_{it} \quad (1)$$

where Y_{it} is the commodity price in district i during month t , ϕ_0 is the temporal autoregressive coefficient, ϕ_1 is the spatial autoregressive coefficient, w_{ij} is the spatial weight between districts i and j , X_{it} is the vector of explanatory variables, and ϵ_{it} is the random error.

$$MAPE = \frac{1}{n} \sum_t \left| \frac{Y_t - \hat{Y}_t}{Y_t} \right| \times 100\% \quad (2)$$

where n is the number of observations, Y_t is the observed price, and $\hat{Y}_t$ is the predicted price.

$$I = \frac{n}{S_0} \frac{\sum_i \sum_j w_{ij} (Y_i - \bar{Y})(Y_j - \bar{Y})}{\sum_i (Y_i - \bar{Y})^2} \quad (3)$$

where S_0 is the sum of all spatial i and j are commodity prices in districts i and y prices in districts i and j , and $\bar{Y}$ is the average commodity price.

The second stage addressed hypotheses H1 and H2 through root cause diagnostics. SHAP values quantified each predictor's contribution to food price forecasts. Granger causality identified causal relationships among variables. Variance decomposition quantified each shock's contribution within the VAR framework. Isolation Forest detected anomalous price periods. The identified drivers were grouped into Production, Distribution, Demand, Policy and Inertia.

$$\phi_i = \sum_S \frac{|S|!(|F|-|S|-1)!}{|F|!} [f(S \cup \{i\}) - f(S)] \quad (4)$$

where ϕ_i is the SHAP value of indicator i , F is the complete set of predictors, S is a subset of predictors, and $f(\cdot)$ is the prediction function.

$$Y_t = a + \sum_{k=1}^p b_k Y_{t-k} + \sum_{k=1}^p g_k X_{t-k} + e_t \quad (5)$$

where Y_t is the commodity price, X_{t-k} is the explanatory variable at lag k , p is the lag order, and e_t is the random error.

The third stage constructs the South Sumatra Composite Food Security Index using min-max normalization and Principal Component Analysis. The index is based on the four Food and Agriculture Organization pillars: availability, access, utilization, and stability.

$$Z_{kit} = \frac{X_{kit} - X_{k,min}}{X_{k,max} - X_{k,min}} \quad (6)$$

where X_{kit} is the value of the indicator k for district i during month t , while $X_{k,min}$ and $X_{k,max}$ represent the minimum and maximum values of the indicator k .

$$IKP_{it} = \sum_k w_k Z_{kit} \times 100 \quad (7)$$

where IKP_{it} is the Composite Food Security Index, w_k is the weight derived from Principal Component Analysis, and Z_{kit} is the normalized indicator value.

The fourth stage evaluated hypothesis H4 through shock scenario simulation. A reduced-form regression estimated price elasticity, while the SAR coefficient represented spatial propagation. Monte Carlo simulation with 1,000 iterations generated projected price changes under four scenarios.

$$\Delta P_i(s) = e_i M_s + \phi_1 \sum_j w_{ij} \Delta P_j(s) + \mu_i \quad (8)$$

where $\Delta P_i(s)$ is the projected price change in district i under scenario s , e_i is the price elasticity, M_s is the shock magnitude, w_{ij} is the spatial weight, and $\mu_i(s)$ is the random error.

The fifth stage formulated spatial food policy recommendations. Rule-based mapping linked the dominant causes of price instability with the Four K Strategy. District priorities were determined using Multi-Criteria Decision Analysis with the Simple Additive Weighting method. Sensitivity analysis evaluated the robustness of the prioritization.

$$S_i = \sum_{k=1}^4 w_k r_{ik} \quad (9)$$

where S_i is the priority score for district i , r_{ik} is the normalized score of criterion k , and w_k is the weight assigned to criterion k , with $\sum w_k = 1$.

2.4. Variables and Measurements

Table 1 presents the operational definitions of the variables used in each research objective.

Table 1. Variable Definitions and Measurements

A. Spatial-Temporal Food Price Prediction			
Variable	Operational Definition	Indicator/Proxy	Scale and Source
Food price (Y)	Monthly average retail price of strategic food commodities	Medium rice, curly red chili, broiler chicken meat, chicken eggs	Ratio; National Food Agency Price Panel
Biophysical predictors	Land and weather conditions affecting agricultural production	NDVI, EVI, rainfall, land surface temperature, disaggregated harvested area	Ratio; MODIS, Sentinel 2, CHIRPS

Price and macroeconomic predictors	Cost and purchasing power factors along the food supply chain	Producer price, farm retail spread, fuel price × distribution distance, agricultural GRDP, district minimum wage	Ratio; National Food Agency, SiPangan South Sumatra, Ministry of Energy and Mineral Resources
Socioeconomic predictors	Household demand and purchasing power	Per capita consumption, food assistance, religious holidays, disasters, Night Time Lights	Ratio or Dummy; SUSENAS, Ministry of Social Affairs
Spatial predictor	Spatial dependence of food prices among neighboring districts	Spatial price lag using inverse Euclidean distance weight matrix W (row-standardized)	Ratio; Processed data; District capital coordinates from BIG
B. Root Cause Diagnostics			
Category	Operational Definition	Trigger Indicators	Scale and Source
Production	Supply disruption caused by environmental conditions	NDVI, EVI, harvested area, rainfall, forest fire hotspots	Ratio; Satellite data
Distribution	Constraints in regional logistics	Fuel price × distance, corridor Night Time Lights, disaster events	Ratio; Ministry of Energy and Mineral Resources, VIIRS, National Disaster Agency
Demand	Seasonal and structural consumption pressure	Religious holidays, food assistance, Night Time Lights, per capita consumption	Dummy or Ratio; National holiday calendar, Ministry of Social Affairs
Policy and inertia	Effects of policy intervention and historical price persistence	Lagged prices, Food Supply and Price Stabilization Program realization	Ratio; National Food Agency, Bulog
C. Composite Food Security Index			
FAO Pillar	Operational Definition	Indicators	Scale and Source
Availability	Adequacy of physical food supply	NDVI, NDVI anomaly, harvested area, farm retail spread	Ratio; Satellite data, National Food Agency
Access	Household economic access to food	Retail price, district minimum wage, food assistance	Ratio; National Food Agency, Regional Manpower Office, Ministry of Social Affairs
Utilization	Household food consumption and purchasing power	Per capita consumption, Night Time Lights	Ratio; Susenas, VIIRS
Stability	Resilience to food price	Price volatility,	Ratio; Processed data,

	shocks	disaster events, forest fire hotspots	National Disaster Agency
D. Shock Scenario Simulation			
Variable	Operational Definition	Indicator or Parameter	Scale and Source
Shock scenario	Type of simulated disruption	Large-scale forest fires, crop failure in Ogan Komering Ilir, Eid demand surge, interregional flooding	Categorical; Scenario design
Price elasticity	Sensitivity of food prices to shock magnitude	Coefficient estimated from the GSTAR model	Ratio; Processed data
Spatial propagation	Spatial transmission of food price shocks	SAR spatial coefficient using weight matrix W	Ratio; Processed data
Impact projection	Estimated price increase under each scenario	Mean percentage and 95% confidence interval	Ratio; Monte Carlo simulation with 1,000 iterations
E. Food Policy Navigation (MCDA-SAW)			
Criterion	Operational Definition	Input Source	Weight
Price magnitude	Projected food price increase	Stage 1 forecast	30%
Food security status	Composite Food Security Index score	Stage 3 index	30%
Shock impact	Estimated impact under alternative scenarios	Stage 4 simulation	25%
Fiscal capacity	Regional fiscal capability to support interventions	Regional government budget	15%

Source: Authors (2026) Edited

3. FINDINGS AND DISCUSSION

Food prices in South Sumatra showed substantial spatial and temporal variation from 2021 to 2025. Medium rice showed a steady upward trend, while curly red chili showed the highest price volatility due to supply disruptions and seasonal harvest cycles. Broiler chicken meat and chicken eggs displayed recurring seasonal fluctuations, particularly during Ramadan and Eid al Fitr. Spatial analysis revealed greater price dispersion in several inland districts than in Palembang City. In contrast, correlation analysis confirmed a strong association between retail and producer prices and identified a negative relationship between rainfall and vegetation conditions in major rice-producing areas. These findings indicate that production conditions, market integration, and seasonal demand jointly shape food price dynamics.

Table 6. Comparison of Medium Grade Rice Price Prediction Model MAPE per District/City (%)

District/City	GSTAR	SAR-X	SARIMAX	XGBoost
Banyuasin	3.26	97.87	16.16	4.29
Empat Lawang	2.13	110.35	236,172.34*	7.93
Lahat	2.45	87.33	9.93	8.14
Muara Enim	1.74	43.11	11.96	7.01
Musi Banyuasin	3.01	72.73	14.51	3.67
Musi Rawas	2.52	107.93	10.60	7.13
Ogan Ilir	2.53	73.20	8.54	4.85
Ogan Komering Ilir	2.69	47.67	9.42	6.76
OKU Selatan	2.71	167.99	14.32	8.30
OKU Timur	2.91	39.43	12.82	7.54
Kota Palembang	2.19	138.39	8.21	4.57
Average	2.56	89.84	29.32	6.57

*The exploded error value for SARIMAX in Empat Lawang District indicates model convergence failure —source: processed data, 2026.

Table 6 compares the forecasting performance of four models for medium-grade rice prices across 11 districts and municipalities in South Sumatra. GSTAR consistently achieved the highest accuracy, producing the lowest prediction errors in all regions, with MAPE values ranging from 1.74% in Muara Enim to 3.26% in Banyuasin and an overall average of 2.56%. XGBoost ranked second, with an average MAPE of 6.57%, although its performance varied across districts. By contrast, SAR-X generated substantially higher errors, averaging 89.84%. In comparison, SARIMAX recorded an average MAPE of 29.32% and produced an extreme error in Empat Lawang due to convergence failure under highly volatile conditions. Overall, GSTAR clearly outperformed the competing models, demonstrating its ability to capture both temporal persistence and spatial dependence in regional food price dynamics.

Table 7. Comparison of Price Prediction Model MAPE for Red Chili, Broiler Chicken, and Eggs (Average, %)

Commodity	GSTAR	SAR-X	SARIMAX	XGBoost
Red Chili	17.90	-	67.71	29.93
Broiler Chicken	4.34	-	n/a (exploded)	6.17
Eggs	3.36	110.37	n/a (exploded)	6.71

Source: processed data, 2026.

Table 7 compares the average forecasting accuracy of four models for red chili, broiler chicken, and chicken egg prices. GSTAR consistently delivered the best predictive performance, with MAPE values of 17.90%, 4.34%, and 3.36%, respectively. XGBoost ranked second for broiler chicken and chicken eggs but remained less accurate than GSTAR. SARIMAX performed poorly for red chili and failed to converge for broiler chicken and chicken eggs, producing exploded errors. SAR-X likewise failed to

generate reliable estimates for several commodities. Overall, GSTAR demonstrated the most robust forecasting performance across strategic food commodities, particularly under varying degrees of price volatility, by effectively capturing both temporal persistence and spatial interactions.

Table 8. Moran's I Value and Spatial Coefficient per Commodity

Commodity	ϕ_0 (Temporal)	ϕ_1 (Spatial)	MAPE (%)	Moran's I	p-value	Significance
Medium Rice	0.9286	0.760	2.56	0.3504	0.019	Significant
Red Chili	0.7745	0.2051	17.90	-0.2805	0.200	Not significant
Broiler Chicken	0.7071	0.2948	4.34	-0.3142	0.134	Not significant
Eggs	0.8272	0.1771	3.36	-0.2213	0.279	Not significant

Source: processed data, 2026.

Medium grade rice exhibited positive and significant spatial autocorrelation (Moran's I = 0.3504; $p = 0.019$), indicating that price increases in one district are associated with increases in neighbouring districts and therefore require interdistrict coordination (Chen & Zhao, 2023). Conversely, red chili, broiler chicken, and eggs showed negative and insignificant Moran's I values ($p > 0.05$), indicating localized price dynamics that allow targeted district interventions. These findings support H1, H2, and H3 and provide evidence for spatial price transmission theory (Waiswa & Yavuz, 2023).

GSTAR outperformed SAR X, SARIMAX, and XGBoost, confirming that food prices reflect both temporal persistence and spatial market linkages. SARIMAX instability and convergence failures under volatile conditions highlight the limitations of conventional statistical models for nonlinear food price dynamics (Diawati & Rasyid, 2025). Unlike previous studies that apply remote sensing primarily to yield prediction (Shafi et al., 2023) or food vulnerability mapping (Ratnasari & Kusumawardani, 2015), this study integrates satellite-derived biophysical indicators, spatial price transmission, and walk-forward validation into a unified forecasting framework. This transforms forecasting into an operational early warning system, consistent with hybrid econometric and machine learning approaches to inflation forecasting (Krukovets, 2024).

SHAP analysis identifies lagged price as the dominant predictor in Palembang City, confirming strong temporal persistence (Maimunif & Madyatmadja, 2026). High rainfall is the second most influential factor, increasing prices through crop damage and distribution disruption, while forest fire hotspots exert extreme effects during major fires. Rice harvest area counterbalances prices through greater supply. Granger causality at lag 2 identifies per capita consumption ($p = 0.0090$) and forest fire hotspots ($p = 0.0341$) as significant, while rainfall, NDVI, and natural disasters are insignificant. These heterogeneous mechanisms reinforce commodity-specific policy intervention

Table 9. Granger Causality Test Results for Food Prices in Palembang City

Independent Variable	p-value Lag 1	Note Lag 1	p-value Lag 2	Note Lag 2
Rainfall	0.5941	Not significant	0.4950	Not significant
Holiday Index	0.4842	Not significant	0.4546	Not significant
Rice Center NDVI	0.9924	Not significant	0.7718	Not significant
Per Capita Consumption	0.6550	Not significant	0.0090	Significant
Forest Fire Hotspot	0.3713	Not significant	0.0341	Significant
Soil Moisture	0.0655	Not significant	0.1926	Not significant

Source: processed data, 2026. Variables with insignificant *p*-values at both lag 1 and lag 2, including natural disasters, agricultural GRDP, social assistance realization, EVI, burned area, PM2.5, surface temperature, and rice harvest area, are not shown in this summary table.

Variance decomposition shows strong structural rigidity in Palembang rice prices, with over 95% of forecast error variance through period 8 explained by price innovations, while exogenous shocks remain marginal. Isolation Forest detects two consecutive anomalies in late 2023, coinciding with the rise toward Rp13,000/kg, and another latent anomaly in early 2025. Root cause decomposition reveals heterogeneous mechanisms: medium rice is dominated by price inertia and policy intervention (53–85%), with Bulog's SPHP under KPSH buffering consumers; red chili reached a 72.0% surge in September 2025, with 61% attributed to inertia; broiler chicken is demand driven (33–36%), while eggs are production driven (29–37%). These findings support commodity-specific stabilization policies.

Commodity-specific root cause heterogeneity supports H1 and H2, confirming that food inflation is difficult to control because its drivers vary across commodities (Algieri et al., 2025; Nuño-Ledesma & von Massow, 2023). While Dorosh et al. (2025) identify production, distribution, and demand as core sources, this study adds policy intervention and price inertia as a fourth dimension, particularly for regulated commodities such as rice. Its dynamic monthly framework enables TPID to identify when and why price pressures emerge and adjust interventions accordingly. IKP classified Muara Enim as Safe (83.30), three regions as Watch (70–77), Ogan Ilir as Caution (42.56), and six as Alert, representing 54.55% in December 2025. Validation against FSVA yielded a mean correlation of 0.8682 and 100% success, confirming strong alignment.

Table 10. Summary of Root Cause Contribution per Commodity, Average 2025 (%)

Commodity	Production (%)	Distribution (%)	Demand (%)	Policy & Inertia (%)
Medium Rice	~8	~5	~4	53-85
Red Chili	~19	~16	~16	37-61
Broiler Chicken	~14	~6	33-36	43-48
Eggs	29-37	~11	~11	34-48

Source: processed data, 2026.

The wide gap in IKP scores among districts, ranging from 0.00 for Musi Banyuasin to 83.30 for Muara Enim, where the extremely low value results from the min-max normalisation placing Musi Banyuasin at the relative vulnerability floor, provides empirical evidence that reinforces the argument by Pakravan-Charvadeh et al. (2020) and Poudel and Gopinath (2023). Food insecurity is not evenly distributed within a single administrative region, so a uniform provincial food security policy risks missing its target. Paradoxically, South Sumatra, a national rice granary, has more than half its regions under Alert status. This reaffirms Diawati and Rasyid's (2025) argument that a production surplus does not automatically guarantee price stability and consumer-level food security unless the distribution system and policy response are anticipatory. The added value of IKP Sumsel compared to the Bapanas FSVA lies in its monthly temporal resolution and its forward-looking nature, achieved by integrating price volatility from the T1 model. It can therefore capture changes in food security status more responsively than the annually updated and retrospective FSVA. This represents a relevant methodological contribution to TPID's operational early warning system.

Table 11. Food Security Status per District/City, December 2025

District/City	IKP	Status
Muara Enim District	83.30	Safe
OKU Selatan District	77.26	Watch
Empat Lawang District	73.34	Watch
Banyuasin District	70.76	Watch
Ogan Ilir District	42.56	Caution
Palembang City	35.08	Alert
Ogan Komering Ilir District	28.95	Alert
OKU Timur District	11.00	Alert
Lahat District	10.84	Alert

Musi Rawas District	2.28	Alert
Musi Banyuasin District	0.00	Alert*

Source: processed data, 2026.

The forest fire scenario (S1) generates the largest impact, with Ogan Komering Ilir (OKI) most vulnerable at 35.75% (95% CI: 17.1 to 53.3%), followed by Ogan Ilir (27.45%), Musi Banyuasin (25.91%), and Banyuasin (22.73%). This reflects eastern South Sumatra's forest fire exposure, disrupting production and distribution. The local harvest failure in OKI (S2) produces a more localized impact, peaking at 8.88% in OKI. The Lebaran demand surge (S3) affects districts relatively evenly at 8 to 12%, with Palembang highest at 11.95% as the province's major consumption center. Cross-regional flooding (S4) has the smallest impact. Overall, OKI is the most vulnerable region in three scenarios, confirming its critical role in South Sumatra's food system.

Table 12. Projected Food Price Increases under Various Shock Scenarios (% , Mean)

District/City	S1 Forest Fire	S2 OKI Harvest Failure	S3 Lebaran Demand	S4 Cross-Regional Flood
Banyuasin	22.73	1.24	8.96	0.51
Musi Banyuasin	25.91	0.44	8.65	0.18
Ogan Ilir	27.45	1.22	8.95	2.78
Ogan Komering Ilir	35.75	8.88	8.88	3.39
Kota Palembang	10.05	1.33	11.95	0.78

Source: processed data, 2026. This summary table omits districts with minimal impact across all scenarios, including Empat Lawang, Lahat, Musi Rawas, Muara Enim, OKU Selatan, and OKU Timur.

These findings support H4, showing that simulated forest-fire shocks exerted the strongest downward pressure on food prices among the tested scenarios. They reinforce the stability pillar of food security (FAO, 2006), demonstrating that resilience to sudden shocks is essential for sustaining food availability, access, and utilization. The magnitude of forest-fire effects also provides quantitative evidence of their dual impact on food systems, linking environmental and food-energy dimensions rarely quantified in Indonesian regional studies. Local production shocks (S2) produced more contained effects than systemic spatial shocks (S1), consistent with the stronger interregional linkages observed for rice. The study contributes district-level estimates with confidence intervals, offering actionable evidence for TPID beyond qualitative and national risk assessments.

Policy navigation demonstrates that the 4K strategy can operate without spatial coordination as the primary mechanism. Medium rice, with significant spatial spillovers (Moran's $I = 0.3504$), requires KAD to stabilize interconnected markets, whereas red chili, broiler chicken, and eggs require localized

instruments because spatial autocorrelation is insignificant. Production-driven districts such as Ogan Komering Ilir require fertilizer subsidies, seed assistance, irrigation optimization, and KPSH. Distribution-driven districts such as Banyuasin and Musi Banyuasin need stronger local logistics and market connectivity, while districts affected by price inertia require KPSH and market operations (Bank Indonesia, 2026; Bapanas, 2024). MCDA SAW ranks Musi Banyuasin, Ogan Komering Ilir, and Musi Rawas as top priorities, with implementation potentially reducing price pressure by 0.9 to 1.3% monthly.

Table 13. Priority and Intervention Recommendations for Food Prices per District/City

District/City	IKP	Status	Dominant Root Cause	Policy Recommendation
Banyuasin	71	Watch	Distribution (34%)	KAD, strengthening food logistics and distribution
Musi Banyuasin	0	Alert	Distribution (28%)	KAD, strengthening food logistics and distribution
Ogan Komering Ilir	29	Alert	Production (27%)	Fertilizer, seed, and irrigation subsidies, KPSH and CPP
Kota Palembang	35	Alert	Policy & Inertia (34%)	Fertilizer, seed, and irrigation subsidies, KPSH and CPP
Musi Rawas	2	Alert	Policy & Inertia (36%)	KPSH, market operations, CPP optimization
Lahat, OKU Timur, Empat Lawang, Muara Enim, Ogan Ilir, OKU Selatan	2-83	Varied	Policy & Inertia (30-36%)	KPSH, market operations, CPP optimization

Source: processed data, 2026.

This root cause-based policy navigation directly addresses Diawati and Rasyid (2025), who criticized conventional food price interventions as generic and non-anticipatory. By linking policy instruments to dominant district-level causes, including production, distribution, and price inertia, the framework enables spatially precise interventions rather than uniform regional policies. Consistent priority rankings across the MCDA SAW sensitivity test demonstrate robustness to alternative criteria weights, supporting its use for TPID decision-making despite uncertainty in weighting. Overall, integrating five connected stages, from price prediction and root cause diagnosis to food security assessment, shock simulation, and policy navigation, represents the study's primary novelty compared with previous research addressing these components separately.

4. CONCLUSION

This study demonstrates that a GeoAI-based early warning system addresses all four hypotheses. Biophysical and distribution indicators significantly influence food price volatility, supporting H1 and

H2; spatial spillovers are significant for commodities with strong policy intervention, particularly rice, supporting H3; and forest fire shocks generate the largest price impacts, confirming H4. By integrating forecasting, root cause diagnostics, food security assessment, shock simulation, and policy mix navigation, the framework provides an actionable system that addresses dimensions previously examined separately.

Practical Policy Recommendations for TPID and Bapanas. Four practical policy actions are proposed. First, the GeoAI system should operate as a monthly early warning instrument, with forecasts and recommended interventions updated continuously. Second, the 4K Strategy should be differentiated by commodity: KAD should prioritize spatially interconnected commodities such as medium rice (Moran's $I = 0.3504$), whereas KPSH should target market-driven commodities such as red chili, broiler chicken, and eggs. Third, alert-status districts should receive priority intervention according to their exposure to price shocks. Fourth, food price stabilization should incorporate forest fire mitigation, particularly in eastern South Sumatra, where the simulated fire scenario generated a 35.75% price impact in Ogan Komering Ilir.

Expansion Roadmap to the Six Uncovered Districts and Municipalities. Expansion to Prabumulih, Pagar Alam, Lubuklinggau, Ogan Komering Ulu, Musi Rawas Utara, and Penukal Abab Lematang Ilir should combine subdistrict SiPangan price records, Chow Lin disaggregation of incomplete annual series, and validated satellite proxies such as Nighttime Lights and NDVI anomalies. This approach would extend the balanced panel from 11 to all 17 administrative units while maintaining methodological consistency.

Key limitations include the five-year observation period, inverse Euclidean spatial weights that may not reflect actual transport networks, and Monte Carlo simulations that depend on assumed shock magnitudes and price elasticities. Future research should extend the time series, incorporate network-based spatial weights, and conduct broader sensitivity analyses.

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