

Spatiotemporal Clustering of Key Food Commodity Prices Using Multivariate Time Series

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ABSTRACT

Food price stabilization remains a critical challenge in economic development planning and food security, particularly in developing countries like Indonesia, which exhibit high spatial and temporal diversity. To develop an efficient and adaptive predictive approach for understanding food commodity price dynamics, this study integrates multivariate time series clustering using a Dynamic Time Warping-based K-Means algorithm with a hybrid forecasting model that combines Vector Error Correction Model with Exogenous Variables and Long Short-Term Memory. The clustering evaluation results indicate reasonably cohesive group structures, with a silhouette score of 0.45 and a Davies-Bouldin Index of 0.67. Each cluster profile reveals significant differences in price trends, volatility, and anomaly patterns. Model validation using the Wilcoxon signed-rank test shows that the differences between cluster-level forecasts and individual-level actual values are generally statistically insignificant. These findings suggest that the proposed integrative approach can accurately capture regional price patterns and serve as a foundation for more data-driven and responsive policymaking in food price stabilization efforts. The 30-period forecasts for rice, eggs, and red onions reflected dynamic variations aligned with spatial characteristics: rice shows relatively stable behavior, eggs exhibit strong seasonal patterns, and red onions display the highest price volatility.

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1. INTRODUCTION

Fluctuations in food commodity prices present ongoing and complex challenges that impact economic stability, food security, and public welfare [1]. Price volatility undermines consumer purchasing power, disrupts producer income, and complicates policy planning. These challenges are intensified by Indonesia's socio-economic diversity, which creates region-specific temporal price behaviors requiring localized and context-aware policy responses [2]. To address these issues, data-driven frameworks that capture both spatial and temporal dynamics have become increasingly essential. Time series clustering has emerged as a powerful tool for analyzing regional price dynamics by grouping areas with similar temporal trends [3]. Clustering approaches are generally categorized into raw data-based, feature-based, and model-based methods [4]. Of these, raw data-based clustering is particularly suitable for regional economic analysis, as it preserves critical temporal attributes such as trend, seasonality, and volatility.

However, capturing complex dependencies and handling series of different lengths remains a challenge. Dynamic Time Warping (DTW) addresses these issues by aligning sequences temporally and improving pattern recognition across time series [5]. When integrated with K-

Means clustering, DTW enhances the identification of homogeneous regional groups, enabling more targeted and effective policy interventions.

In addition to clustering, accurate forecasting of food commodity prices is essential for proactive policy design. Traditional econometric models, such as Vector Autoregressive (VAR), Vector Error Correction Model with Exogenous Variables (VECMX), and VARIMAX have been widely used to capture relationships among economic indicators [6]. However, these models often fall short in handling the nonlinearities and high volatility typical of food price data. To address these limitations, hybrid approaches that combine classical econometrics with machine learning have gained traction. These models effectively capture both linear and nonlinear temporal dependencies, resulting in improved forecasting accuracy [7], [8].

A growing body of literature supports the use of such methods. Sumertajaya et al. [9], showed that DTW-based K-Means clustering yields more representative regional groupings than conventional techniques. Andayani et al. [10], reported that VECMX outperformed VARIMAX in forecasting rice prices on Java. Isnaini [11], linked food price volatility to income inequality, while Ghiffary et al. [12], highlighted varying forecasting performance between classical and deep learning models. Most recently, Tsabitah et al. [13], demonstrated the efficiency of time series clustering over individual city-level forecasting.

Despite these advances, many studies have yet to incorporate broader socio-economic variables into clustering and forecasting frameworks [14]. To bridge this gap, this study proposes a multivariate model that integrates exchange rates as exogenous variables within a hybrid VECMX–LSTM structure. It also applies DTW-based multivariate clustering to identify regionally coherent groups aligned with policy priorities [13].

A key innovation lies in the use of dynamic simulations to assess model robustness under various market scenarios [15]. Accordingly, the objectives of this study are twofold: (1) to classify regions based on multivariate food price dynamics using DTW-based K-Means, and (2) to develop a hybrid VECMX–LSTM model that enhances forecast accuracy and captures complex temporal structures. The findings aim to support regionally adaptive food price stabilization policies that are more responsive, inclusive, and data-driven.

2. RESEARCH METHOD

2.1 Data Sources

This study utilizes daily price data for staple food commodities obtained from Bank Indonesia through the *Pusat Informasi Harga Pangan Strategis Nasional* (PIHPS Nasional). Complementary macroeconomic data, in particular the daily Rupiah (IDR) exchange rate, are sourced from official publications of Bank Indonesia. The dataset spans from January 2018 to December 2024 and covers 34 provincial capital cities, allowing for a comprehensive and temporally rich analysis of regional food price dynamics under diverse economic conditions.

The food commodity dataset focuses on three strategic items: rice, eggs, and red onions, which serve as endogenous variables within the modeling framework. These commodities were selected due to their importance in household consumption and policy relevance [16]. Rice, as Indonesia's primary staple, is central to food security. Eggs represent an affordable and nutritionally essential protein source. Red onions are a fundamental component of traditional cooking and are strongly associated with price-sensitive household expenditures. These commodities allows for a multivariate analysis that captures interdependencies and cross-commodity effects in pricing behavior. In addition, the exchange rate is used as an exogenous variable to evaluate the macroeconomic influence of currency fluctuations on food price volatility. Incorporating exchange rate dynamics into the modeling framework provides a broader understanding of external economic factors and supports the development of regionally responsive policy strategies.

2.2 Research Design

This study adopts a structured empirical approach that integrates forecasting and clustering techniques to analyze food commodity price dynamics across Indonesian regions. The overall research workflow consists of several stages as described below.

distance between two time series by finding an optimal warping path that aligns sequences, even when they differ in length or phase [19]. The algorithm generates a cost matrix representing the cumulative alignment distance along the path. Due to its robustness in handling temporal variations and misalignments, DTW is regarded as a superior metric for clustering time series data, particularly for irregular or asynchronous patterns [20].

2.4 Vector Error Correction Model with Exogenous Variable

The VECM is an extension of the VAR model designed to incorporate long-term equilibrium relationships among non-stationary variables. VECM is appropriate when all variables in the system are integrated of order one and exhibit cointegration [21]. The presence of cointegration, indicated by a cointegration rank $r > 0$, is a prerequisite for the implementation of VECM.

Unlike the standard VAR model, which captures only short-term dynamics, VECM integrates both short-term adjustments and long-term equilibrium by embedding error correction terms [22]. These terms act as mechanisms that guide the system back to its long-run equilibrium path when deviations occur, enabling the model to reflect real economic behavior more accurately. Formally, a VECM of order p with cointegration rank r is expressed as:

$$\Delta Y_t = \Phi_0 + \Phi_1 X_t + \Pi Y_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta Y_{t-i} + \varepsilon_t \quad (1)$$

with, Π is the cointegration coefficient matrix ($\Pi = \alpha\beta'$), of dimension $n \times k$, where α is the adjustment vector representing the speed of convergence to long-run equilibrium, and β is the cointegration vector (long-run parameters), Y_{t-i} is the lagged vector of endogenous variables at lag 1, with dimension $n \times 1$ and Γ_i is the coefficient matrix for the i -th differenced endogenous variables, with dimension $n \times n$ for each $i = 1, 2, \dots, p-1$.

VECM can incorporate multiple stationary exogenous variables, along with their respective lags, as independent variables in the model, known as the VECMX method. As an extension of the VECM, the VECMX allows for more flexible modeling by including exogenous variables that can influence the dynamics of the long-term relationships between endogenous variables. Thus, this model not only considers long-term equilibrium through the error correction term but also captures the effects of external exogenous variables on the system [23]. By including relevant exogenous variables, the VECMX improves estimation accuracy and reduces the potential for specification bias in modeling economic relationships. The VECMX model can be represented by the following equation, where X_i is the lagged vector of the i -th exogenous variable.

$$\Delta Y_t = \Pi Y_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta Y_{t-i} + \sum_{i=0}^s \Phi_1 X_{i,t-i} + \varepsilon_t \quad (2)$$

2.5 Long-Short Term Memory

LSTM network is an advanced architecture derived from the Recurrent Neural Network (RNN) framework, designed to overcome the limitations of traditional RNNs in capturing long-range dependencies. Specifically, LSTM addresses vanishing and exploding gradient problems, which often hinder effective training of RNNs on long sequential data [24]. At the core of LSTM lies the cell state (C_t), the main memory component that maintains and transfers information across extended sequences. This cell state functions like a conveyor belt, enabling data to flow with minimal modifications unless explicitly updated. Information flow is regulated by three specialized gates that control what is discarded, stored, or revealed at each time step.

LSTM architecture consists of three primary gates: the forget gate, input gate, and output gate [25]. The forget gate (f_t) determines which information from the previous cell state should be retained or discarded. The input gate (i_t) processes new information to be added to the cell state, using two activation functions: sigmoid (to determine which values to update) and tanh (to form the intermediate cell state ($\tilde{C}_t$)). The output gate (o_t) selects parts of the cell state to be emitted as the hidden state (h_t) output.

3. RESULTS AND DISCUSSION

3.1. Data Preprocessing and Exploration

The dataset, comprising daily prices of three staple food commodities and the Indonesian Rupiah–US Dollar exchange rate, underwent thorough preprocessing to improve data quality and analytical consistency. Key steps included standardizing the time series structure and addressing missing values through linear interpolation. This method was chosen due to the dataset's relatively stable short-term fluctuations and was applied independently by region and commodity to preserve intra-regional dynamics and avoid distortions from global imputation.

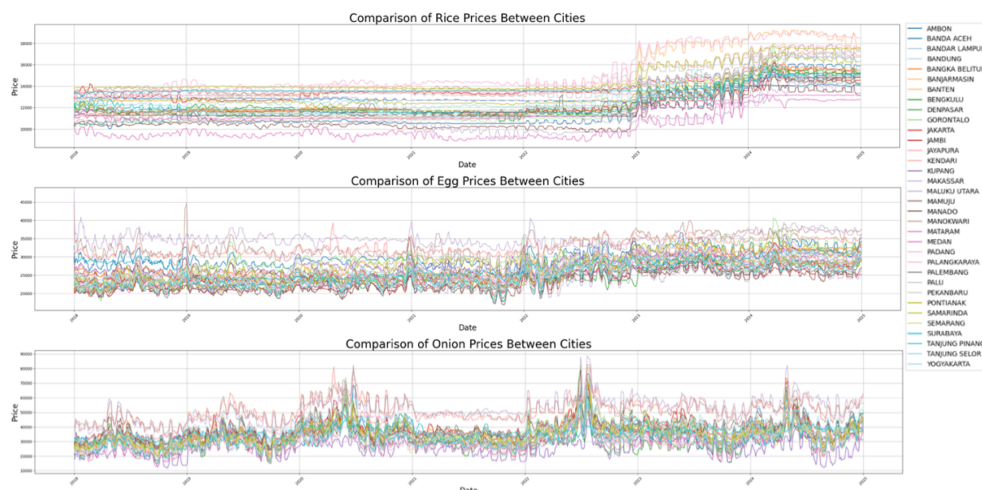


Figure 2. Line plot visualization of three food commodity prices

Visual analysis was conducted to understand temporal and spatial characteristics of the data, revealing trends, seasonality, and volatility that are not always apparent from numerical summaries. These insights guided the selection of appropriate modeling strategies. Figure 2 illustrates the price evolution of the three commodities over time. Rice prices showed relative stability during certain periods, likely reflecting government interventions such as subsidies and price stabilization aimed at maintaining affordability. However, spatial disparities existed, with cities like Jakarta and Surabaya exhibiting steadier trends than eastern regions, where higher volatility is linked to logistical and infrastructural challenges. Egg prices demonstrated more pronounced fluctuations with frequent sharp changes, indicating sensitivity to supply disruptions and demand shifts. Regional differences were notable, especially in remote areas where transport and storage costs add volatility. Red onion prices were the most volatile, marked by abrupt surges across regions due to perishability, localized production, and vulnerability to weather and supply chain issues. Persistent high prices in some urban areas suggest structural inefficiencies and supply constraints.

3.2. Individual-Level Modeling

3.2.1 Baseline Models: VECMX and LSTM

Time series data often exhibit non-stationary behavior, marked by changes in mean and variance over time. Such non-stationarity can lead to spurious regression, where apparent statistical relationships are misleading or non-causal. To address this, cointegration testing was performed using the Johansen Cointegration Test during the training phase. This method evaluates the joint behavior of all variables to assess the presence of long-run equilibrium relationships. As shown in Table 1, the trace statistics exceed the 5% critical values (29.79, 15.49, and 3.84), indicating that the null hypothesis of no cointegration (H_0) is rejected in most regions. These findings confirm that cointegration relationships exist among the variables. The VECMX model was then estimated separately for each region to reflect local heterogeneity in price behavior and structural conditions. Although initial lag selection varied by region based on the Akaike Information Criterion (AIC)

and Hannan–Quinn Information Criterion (HQIC), a uniform lag length of six was ultimately adopted. This decision was further supported by cross-correlation function (CCF) analysis, ensured consistent modeling of inter-commodity dynamics and enhanced comparability across regions.

Table 1. Cointegration test result and optimal lag for each region

Region	$H_0: \text{rank}(\Pi) \leq k$			Best Orde	Region	$H_0: \text{rank}(\Pi) \leq k$			Best Orde
	0	1	2			0	1	2	
Ambon	66.05*	18.98*	1.43	4	Banda Aceh	44.02*	14.11	0.34	6
Bandung	59.03*	18.11*	0.01	6	Bandar Lampung	71.70*	22.00*	0.28	4
Banten	79.49*	19.29*	0.13	6	Bangka Belitung	45.81*	18.22*	0.06	6
Bengkulu	51.95*	12.18	0.03	6	Banjarmasin	78.37*	30.46*	0.11	6
Denpasar	48.59*	17.04*	0.00	4	North Maluku	71.31*	19.61*	1.62	3
Jakarta	73.26*	18.21*	0.00	6	Manokwari	60.99*	16.93*	0.90	5
Jambi	46.82*	13.41	0.16	5	Palangkaraya	63.87*	28.87*	0.00	6
Jayapura	52.13*	18.06*	1.58	6	Palembang	57.48*	13.91	0.29	5
Kendari	34.96*	10.68	0.11	5	Pekanbaru	63.12*	16.64*	0.39	6
Kupang	51.75*	14.98	0.50	6	Pontianak	51.62*	19.44*	0.78	6
Makassar	55.12*	22.58*	0.12	6	Samarinda	38.92*	10.61	0.00	5
Mamuju	44.50*	17.00*	0.68	6	Semarang	65.84*	20.20*	0.02	4
Manado	61.12*	22.48*	0.39	6	Tanjung Pinang	23.49*	8.92	0.88	6
Mataram	46.67*	11.70	0.34	4	Tanjung Selor	61.35*	20.56*	0.36	6
Medan	45.71*	17.85*	1.04	4	Yogyakarta	68.77*	19.05*	0.04	6
Padang	43.62*	14.05	0.00	6	Gorontalo	46.70*	15.49*	1.24	6
Palu	52.28*	15.72*	0.03	6	Surabaya	66.08*	18.86*	0.22	6

* indicates the presence of a cointegration relationship in the data at a specific rank

Estimation results indicate that both endogenous and exogenous variables significantly influence food prices in the short and long run. A negative and statistically significant error correction term validates the presence of a long-run equilibrium and demonstrates the model's ability to correct deviations over time. Diagnostic tests revealed minor violations of classical assumptions, such as residual autocorrelation and non-normality but these were deemed acceptable given the forecasting context.

To compare classical and deep learning approaches, a standalone LSTM neural network was implemented as an alternative baseline model. Unlike VECMX, the LSTM model does not rely on econometric structure but instead learns nonlinear patterns and long-range dependencies directly from the original multivariate time series. The LSTM architecture consists of two stacked layers with 64 and 32 units, followed by dropout layers (rate = 0.2) and a fully connected dense output layer. The model was trained using the Adam optimizer with mean squared error (MSE) as the loss function. Hyperparameters including batch size, learning rate, and number of epochs were tuned using grid search, and early stopping based on validation loss was applied to prevent overfitting. This LSTM model serves as a nonlinear benchmark to evaluate forecasting performance against the VECMX model. Together, these two baseline models establish a reference point for assessing the benefits of the hybrid framework introduced in the next section.

Table 2. Comparison evaluation of forecasting performance VECMX and LSTM model

Region	VECMX		LSTM		Region	VECMX		LSTM	
	RMSE	MAPE	RMSE	MAPE		RMSE	MAPE	RMSE	MAPE
Ambon	6770	12.12	2753	3.28	Banda Aceh	8082	14.89	1600	2.24
Bandung	7009	14.52	1450	2.32	Bandar Lampung	8848	20.87	2163	3.21
Banten	8446	7.25	1327	1.98	Bangka Belitung	7355	9.45	1820	2.07
Bengkulu	9563	12.33	1502	2.87	Banjarmasin	6204	13.20	1564	2.55
Denpasar	12787	29.26	2988	6.46	Manokwari	10403	16.01	2828	4.43
Gorontalo	7107	13.48	1995	2.24	North Maluku	13787	15.84	1957	1.77
Jakarta	7965	12.20	1634	2.21	Padang	5321	10.10	955	1.89
Jambi	11022	28.59	2404	4.67	Palangkaraya	5568	12.81	1099	1.98
Jayapura	13194	20.14	2136	7.00	Palembang	7444	15.01	1813	2.91
Kendari	5065	9.41	1378	3.39	Pekanbaru	5003	9.04	1170	2.29
Kupang	8982	16.26	1103	2.59	Pontianak	6140	13.43	1182	3.16
Makassar	5775	14.40	1914	4.97	Samarinda	5640	8.02	1922	3.54
Mamuju	5971	14.98	1760	3.81	Semarang	11531	27.26	1788	4.59
Manado	8375	11.39	2138	3.15	Surabaya	9841	25.05	1912	4.24
Mataram	8158	17.51	1529	3.21	Tanjung Pinang	3788	7.49	811	1.49
Medan	6154	13.05	1397	2.11	Tanjung Selor	4824	8.99	1861	4.05
Palu	4884	9.76	1247	2.13	Yogyakarta	9470	23.40	2856	5.83

Table 2 presents the forecasting performance of the VECMX and standalone LSTM models across all regions, evaluated using two standard metrics: Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE). RMSE quantifies the average magnitude of prediction errors in absolute terms, while MAPE offers a scale-independent measure by expressing the error as a percentage of actual values.

The results demonstrate substantial variation in model performance across regions. While the VECMX model successfully captures long-term equilibrium relationships, its predictive accuracy tends to deteriorate in the presence of nonlinear fluctuations and abrupt short-term shocks. In contrast, the LSTM model generally yields lower RMSE and MAPE values in several regions, indicating its superior ability to model nonlinear temporal patterns. However, the performance of LSTM is not uniformly dominant, as its effectiveness varies depending on the region and the nature of local price dynamics. This comparative evaluation underscores the complementary strengths and limitations of each baseline model, motivating the development of a hybrid approach that seeks to integrate the economic interpretability of VECMX with the nonlinear learning capacity of LSTM, as elaborated in the next section.

3.2.1 Hybrid Model Architecture and Tuning

The hybrid VECMX–LSTM framework was developed to address the limitations of both baseline models. VECMX provides interpretability and a solid theoretical foundation through its ability to model long-run equilibrium relationships. However, its linear structure limits responsiveness to short-term nonlinear shocks. Conversely, the LSTM model captures nonlinear temporal dynamics effectively but lacks economic structure and is prone to overfitting without proper regularization. The hybrid approach leverages the strengths of both models by using VECMX to model the linear components and LSTM to learn the nonlinear residuals.

Residuals from the VECMX model were extracted for each region, representing deviations between the predicted and actual values. These residuals were standardized to ensure training stability and consistency across regions. A fixed-length sliding window technique was applied to convert the residual time series into a supervised format suitable for LSTM-based sequence modeling. The LSTM architecture used in the hybrid model mirrors that of the baseline LSTM, including the number of units, dropout rates, activation functions, and hyperparameter tuning strategies. The key difference lies in the input: instead of raw multivariate price series, the hybrid model processes standardized VECMX residuals formatted as supervised sequences. This enables the LSTM to capture nonlinear dynamics not explained by the linear component. All procedures were conducted separately for each region to reflect spatial heterogeneity in price behavior. By integrating linear and nonlinear modeling components, the hybrid framework offers a more accurate and adaptable forecasting approach, especially in contexts structural economic relationships coexist with irregular local shocks.

Table 3. Comparison evaluation of forecasting performance VECMX and hybrid model

Region	VECMX		Hybrid		Region	VECMX		Hybrid	
	RMSE	MAPE	RMSE	MAPE		RMSE	MAPE	RMSE	MAPE
Ambon	6770	12.12	1497	1.36	Banda Aceh	8082	14.89	1377	1.71
Bandung	7009	14.52	1197	1.63	Bandar Lampung	8848	20.87	1478	1.98
Banten	8446	7.25	1149	1.63	Bangka Belitung	7355	9.45	1306	1.31
Bengkulu	9563	12.33	897	1.29	Banjarmasin	6204	13.20	942	1.56
Denpasar	12787	29.26	868	1.23	Manokwari	10403	16.01	1365	1.46
Gorontalo	7107	13.48	1602	1.63	North Maluku	13787	15.84	1339	1.15
Jakarta	7965	12.20	1324	1.30	Padang	5321	10.10	1084	1.61
Jambi	11022	28.59	856	1.38	Palangkaraya	5568	12.81	894	1.30
Jayapura	13194	20.14	1939	2.06	Palembang	7444	15.01	1754	2.46
Kendari	5065	9.41	1745	0.85	Pekanbaru	5003	9.04	1112	1.47
Kupang	8982	16.26	1342	2.05	Pontianak	6140	13.43	854	1.25
Makassar	5775	14.40	969	1.67	Samarinda	5640	8.02	938	1.41
Mamuju	5971	14.98	1096	1.63	Semarang	11531	27.26	1600	2.27
Manado	8375	11.39	2054	1.99	Surabaya	9841	25.05	1438	2.02
Mataram	8158	17.51	743	1.22	Tanjung Pinang	3788	7.49	1609	1.68

Medan	6154	13.05	1255	1.22	Tanjung Selor	4824	8.99	1160	1.44
Palu	4884	9.76	1029	1.43	Yogyakarta	9470	23.40	1168	1.67

Table 3 presents the forecasting performance of VECMX and the hybrid VECMX–LSTM approach using RMSE and MAPE. Overall, the hybrid model consistently outperforms both baseline models across regions. In several cases, the reduction in RMSE is substantial, indicating that the sequential integration of linear and nonlinear components enhances predictive accuracy.

The hybrid model's superior performance stems from its capacity to capture nonlinear patterns that are not sufficiently modeled by VECMX or standalone LSTM. Importantly, this accuracy is achieved through rigorous training procedures that ensure generalizability. Key regularization strategies include dropout layers in each hidden layer, early stopping based on validation loss, and systematic hyperparameter tuning via grid search. The input to the hybrid LSTM component, standardized residuals from VECMX, was structured using a sliding window technique. This process preserves distributional stability, prevents data leakage, and enables the LSTM to learn short-term nonlinear patterns excluded from the linear model. In summary, the hybrid model not only delivers substantial improvements in forecasting performance but also adheres to essential methodological standards, ensuring robustness, generalizability, and reproducibility.

3.3. Clustering Model

The clustering approach in this study adopts a predictive framework, using forecasted values of key food commodity prices across regions over a 30-period horizon as input. The main objective is to identify homogeneous regional groups based on multivariate temporal patterns in food price dynamics. To address potential temporal misalignments across regional series, the K-Means algorithm was implemented with DTW as the distance metric. As shown in Figure 3, the DTW distance matrix quantifies pairwise dissimilarities among cities based on aggregated distances across three price variables: rice, chicken eggs, and red onions. DTW accounts for temporal shifts and misalignments, making it more suitable for capturing dynamic patterns in economic time series. The resulting DTW matrix provides the foundation for clustering, ensuring that regions are grouped according to the similarity of their temporal evolution rather than pointwise proximity.

$$\begin{bmatrix} 0 & 177114 & 229758 & 127962 & \dots & 217080 & 129922 & 101856 & 200725 \\ 177114 & 0 & 122906 & 83472 & \dots & 133081 & 137480 & 140100 & 118524 \\ \vdots & \vdots & \vdots & \vdots & \dots & \vdots & \vdots & \vdots & \vdots \\ 101856 & 140100 & 170698 & 99977 & \dots & 169996 & 95483 & 0 & 153361 \\ 200725 & 118524 & 610066 & 98457 & \dots & 76856 & 157063 & 153361 & 0 \end{bmatrix}$$

Figure 3 Dynamic Time Warping distance matrix

Due to the high dimensionality of the DTW distance matrix, Multidimensional Scaling (MDS) was employed to project the pairwise distances into a two-dimensional coordinate system, while preserving relative dissimilarities among regions. The resulting low-dimensional representation was then used as input for the K-Means clustering algorithm. To determine the optimal number of clusters, two commonly used methods were applied: the Elbow Method and the Silhouette Score.

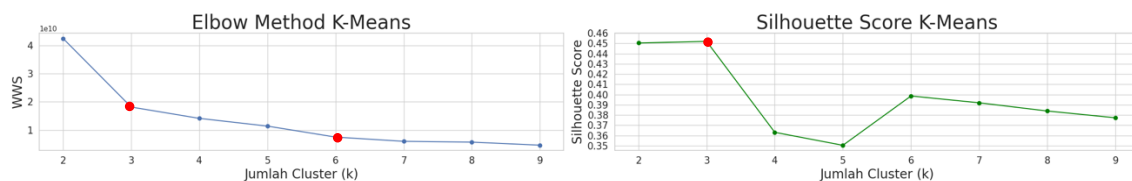


Figure 4. Optimal K-value determination for clustering

As shown in Figure 4, the Elbow curve indicates an inflection point at three clusters, suggesting that additional clusters offer limited improvements in reducing within-cluster variance.

In contrast, the Silhouette Score reaches its maximum at six clusters, implying stronger internal cohesion and clearer separation between clusters with a finer granularity.

Cluster interpretation was performed by analyzing the prototype series (centroids) for each group, which serve as representative patterns summarizing the typical temporal trajectories of grouped cities. The final clustering structure, determined based on the results of both the Elbow and Silhouette analyses, is summarized in Table 3. Each cluster reflects a common temporal pattern among its member cities, offering insights into regional food price dynamics and underlying socioeconomic structures. These formations also provide a foundation for developing cluster-level forecasting models, which are later benchmarked against city-level hybrid models to evaluate performance and generalizability. The final clustering configuration yielded a Silhouette Score (SS) of 0.45 and a Davies-Bouldin Index (DBI) of 0.67, indicating adequate internal cohesion and separation among clusters. These metrics reinforce the validity of the clustering structure in identifying temporally consistent patterns across cities.

Table 3. Evaluation of clustering result and regional mapping

K	Region	SS	DBI
14	Ambon, Banda Aceh, Bandung, Bangka Belitung, Banten, Kendari, Jakarta, Gorontalo, Palembang, Pontianak, Palangkaraya, Tanjung Pinang, Manado, Tanjung Selor	0.45	0.67
3	17 Bandar Lampung, Bengkulu, Pekanbaru, Makassar, Kupang, Jambi, Denpasar, Medan, Mataram, Mamuju, Semarang, Samarinda, Padang, Palu, Surabaya, Banjarmasin, Yogyakarta		
3	Jayapura, Manokwari, Maluku Utara		
6	Banjarmasin, Kupang, Pontianak, Padang, Palu, Pekanbaru	0.40	0.69
8	Banten, Banda Aceh, Samarinda, Tanjung Pinang, Palangkaraya, Palembang, Kendari, Bandung		
3	Jayapura, Manokwari, Maluku Utara		
6	6 Bangka Belitung, Manado, Jakarta, Gorontalo, Ambon, Tanjung Selor		
8	Bandar Lampung, Semarang, Medan, Makassar, Mamuju, Surabaya, Bengkulu, Yogyakarta		
3	Jambi, Mataram, Denpasar		

To assess the statistical consistency of cities within the same cluster, the Wilcoxon signed-rank test was applied to forecasted time series. This non-parametric test evaluated pairwise similarity for both $K = 3$ and $K = 6$ cluster configurations. The goal was to determine whether cities grouped together at $K = 3$ remained statistically similar when separated into smaller clusters. A random sample of within-cluster city pairs was tested to ensure generalizability without excessive computation. As shown in Table 4, several city pairs split at $K = 6$ still exhibited high p-values ($p > 0.05$), indicating no significant differences in their forecast distributions. These results support the internal validity of the clustering structure and emphasize the value of post-hoc statistical testing to reinforce unsupervised classification outcomes.

Table 4 Wilcoxon test and cluster comparison across city pairs

Pair of Cities		Wilcoxon test			Cluster Relationship		
		Rice	Egg	Onion	Significant	K=3	K=6
Banjarmasin	Kupang	0.80	0.55	0.54	Aligned	Cluster 2	Cluster 1
Semarang	Jambi	0.76	0.80	0.67	Aligned	Cluster 2	Cluster 5, 6
Banten	Manado	0.07	0.53	0.14	Aligned	Cluster 1	Cluster 2, 4
Jambi	Kupang	0.08	0.31	0.82	Aligned	Cluster 2	Cluster 1, 6
Semarang	Samarinda	0.15	0.68	0.21	Aligned	Cluster 2	Cluster 2, 5
Bandung	Kendari	0.31	0.79	0.71	Aligned	Cluster 1	Cluster 2
Manado	Palangkaraya	0.56	0.46	0.07	Aligned	Cluster 1	Cluster 2, 4

Figure 5 provides visual confirmation of the clustering validity by illustrating temporal fluctuations in shallot prices for each identified cluster. Although absolute price levels differ across cities, cities grouped into the same cluster tend to exhibit similar temporal behaviors in terms of trend direction, volatility, and timing of price surges or declines. These patterns imply that cities within a cluster are subject to similar market conditions, possibly arising from comparable production structures, logistics infrastructure, or shared exposure to macroeconomic shocks. The strong alignment in temporal behavior further affirms the effectiveness of the DTW-based clustering approach in capturing dynamic similarity across spatial units.

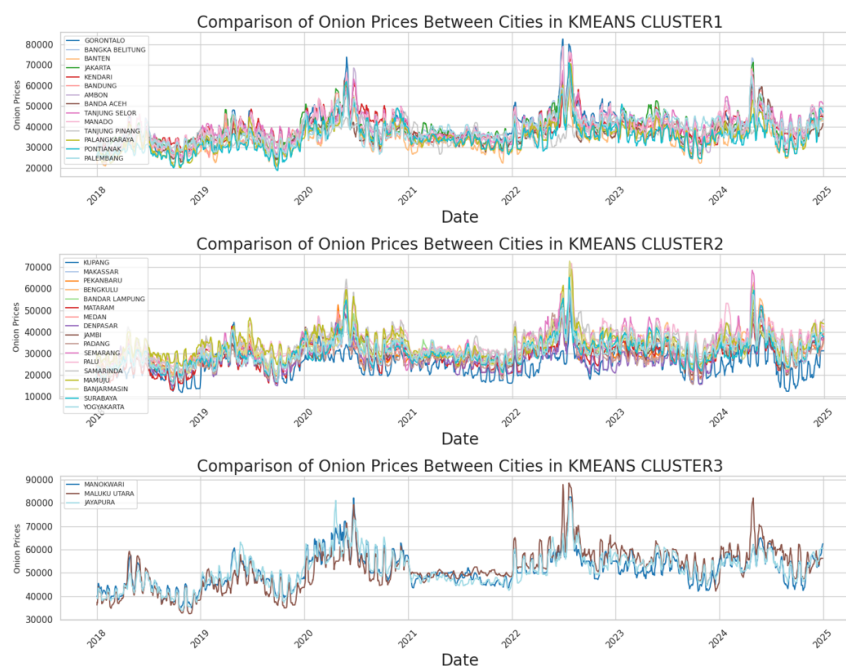


Figure 5. Visualization of red onion prices trends

Beyond statistical grouping, the resulting clusters reveal meaningful structural, geographic, and socio-economic patterns that deepen our understanding of regional disparities in Indonesia's food markets. These insights not only validate the clustering outcomes but also enhance their relevance for policy design particularly in food security, supply chain management, and regional development planning.

The first cluster comprises major metropolitan centers such as Jakarta, Bandung, and Surabaya. These cities show synchronized price movements with relatively moderate volatility, reflecting their deep integration into national and interregional supply chains. Functioning primarily as consumption hubs, they rely heavily on inflows from production zones, making them highly responsive to central policy instruments like price ceilings, subsidies, and emergency market operations. At the same time, their dependence on complex logistics networks makes them susceptible to systemic shocks, including fuel price fluctuations and regulatory changes. These characteristics underscore the need for robust contingency frameworks and integrated national coordination.

In contrast, the second cluster includes mid-sized cities across Sumatra and Sulawesi—such as Makassar, Medan, Palembang, and Bandar Lampung—that exhibit more erratic price behavior. Pronounced seasonality and frequent volatility spikes point to localized production challenges, fluctuating yields, and infrastructure bottlenecks such as limited port access or inadequate road networks. Moreover, inconsistent local policy implementation and fragmented market structures contribute to instability. These regions appear to be in a transitional state: partially self-sufficient, yet still vulnerable to both supply chain disruptions and distribution inefficiencies.

The third cluster consists of peripheral and remote regions including Jayapura, Manokwari, Ternate, and North Maluku. Interestingly, these areas display a surprising degree of price stability, especially for staple items like rice and eggs. This pattern may stem from localized production systems, relatively low per capita demand, and ongoing government intervention in the form of price controls or subsidized distribution. Despite their logistical isolation, these regions may have evolved adaptive and resilient food systems tailored to local ecological and cultural conditions.

Taken together, these clusters reflect more than just statistical similarity—they represent distinct regional food system archetypes shaped by economic function, infrastructure capacity, and policy exposure. Understanding these underlying dynamics allows for more nuanced policy

formulation. Rather than a one-size-fits-all approach, interventions can be stratified by cluster type—targeting shared constraints and opportunities among regions that face similar structural realities. Such a differentiated strategy is essential to ensuring both equity and effectiveness in the design of Indonesia’s food resilience programs.

3.4. Cluster-Level Modeling

Cluster-level modeling was conducted by first constructing representative prototypes for each group. These prototypes were created by averaging the multivariate time series of all cities within the same cluster, effectively capturing the general temporal behavior of each region while smoothing local fluctuations. This aggregated approach enables a consistent and interpretable basis for evaluating forecasting performance across regions.

Using these prototype series, the same modeling framework applied at the individual level was implemented at the cluster level. Johansen cointegration tests confirmed the presence of long-run equilibrium relationships among the variables in each prototype. Trace statistics for the null hypothesis $H_0: rank(\Pi) \leq k$ consistently exceeded the 5% critical values, denoted by asterisks, indicating statistically significant cointegration. Despite the existence of cointegration, the linear VECMX model demonstrated limited forecasting capability, as reflected in relatively high RMSE and MAPE values across clusters. These findings suggest that VECMX alone is inadequate for capturing the nonlinear characteristics embedded in the prototype series. In response, a hybrid VECMX–LSTM model was employed. As presented in Table 5, this model significantly improved prediction accuracy across all clusters. The results highlight the hybrid framework’s effectiveness in modeling both linear and nonlinear dynamics in multivariate time series at the regional level.

Table 5. Evaluation result of VECMX and hybrid for each cluster

Cluster	$H_0: rank(\Pi) \leq k$			Orde	VECMX Model		Hybrid Model	
	0	1	2		RMSE	MAPE	RMSE	MAPE
1	44.430*	14.383	0.934	7	5048	10.17	2159	2.80
2	42.611*	12.929	0.618	7	6577	10.75	2484	3.94
3	59.069*	13.064	2.738	7	6047	10.68	2269	3.67

3.5. Model Performance Evaluation

Generalizability and robustness of the cluster-based modeling approach were evaluated through an additional validation step, which involved comparing the predicted values generated by the cluster-level models with the predicted at the individual level for each region within the corresponding clusters. This comparative assessment aimed to examine how the cluster-level forecasts could reflect the temporal dynamics and variability of individual regions.

Table 6. Comparison cluster and individual forecast

Region	Rice		Egg		Onion		Wilcoxon Test			
	RMSE	MAPE	RMSE	MAPE	RMSE	MAPE	Rice	Egg	Onion	
1	Banda Aceh	521	3.72	961	2.84	1140	2.35	1.01	0.58	0.50
	Jakarta	155	0.82	766	2.11	2184	4.01	0.95	0.70	0.60
										
	Manado	421	2.93	918	2.24	1868	2.76	0.33	0.75	0.66
	Tanjung Selor	321	1.92	971	2.73	1802	3.14	0.19	0.29	0.43
2	Bandar Lampung	225	1.36	532	1.64	2103	4.60	0.09	1.08	0.06
	Bengkulu	134	0.76	817	2.49	2590	5.73	0.76	0.67	0.05
										
	Denpasar	180	0.95	730	1.81	1658	4.12	0.23	1.04	0.45
	Surabaya	132	0.75	1202	3.59	1202	3.59	0.12	0.35	0.55
3	Jayapura	224	1.16	1314	3.47	2116	3.27	0.59	1.02	0.07
	Manokwari	290	1.55	785	1.94	2128	2.70	0.47	0.12	0.28
	North Maluku	313	1.73	418	0.81	2168	4.46	0.60	1.05	0.05

Table 6 presents a comparative evaluation of forecasting performance between individual-level and cluster-based models for three key commodities: rice, chicken eggs, and red onions.

Performance was assessed using RMSE and MAPE, which reflect the magnitude of absolute and relative forecasting errors, respectively. Across most regions, both error metrics fall within acceptable ranges, indicating that the cluster-based models effectively captured dominant price movement patterns. Forecasts from cluster-level models generally align closely with those from individual models.

Some discrepancies are observed, particularly for red onion prices where regions such as Bengkulu and Denpasar exhibit relatively higher RMSE and MAPE values compared to others. However, these values remain within acceptable bounds and do not indicate model failure. Instead, they may reflect localized anomalies or structural dynamics not fully captured by the cluster centroid. Importantly, despite the relatively higher errors, Wilcoxon signed-rank test results for these regions still yield p-values above the 0.05 significance threshold. This suggests no statistically significant difference between the forecasts generated by individual and cluster-based models, even in areas with higher observed errors. These findings reinforce the robustness of the cluster-based modeling approach, which remains statistically valid and practically reliable, even in cases with localized variation. The ability of the model to maintain comparable forecasting performance across diverse regions supports its application in scalable and regionally adaptive forecasting systems.

3.6. Forecasting 30-Period

Forecasting results depicted in Figure 6 reveal distinct price trajectories across the three identified clusters, highlighting regional disparities in agricultural capacity, logistics infrastructure, and consumption behavior. Among the three commodities, rice shows the most stable price trend, characterized by low volatility and a mild upward movement, particularly evident in Cluster 2. This stability may reflect the influence of government interventions such as subsidies, price ceilings, or distribution regulations.

In contrast, egg prices display pronounced seasonal fluctuations, especially in Clusters 1 and 2. These patterns likely stem from cyclical demand surges during national holidays, religious observances, or school terms. The volatility in these clusters may also suggest limited local production and a reliance on interregional supply. Red onion exhibits the highest price instability across clusters. Cluster 1 shows sharp price increases, possibly due to supply disruptions or distribution inefficiencies. Cluster 3 records the most stable and lowest price levels, indicating potential local surpluses or more efficient logistics. These differentiated patterns across commodities and clusters underscore the need for region and commodity-specific policy interventions that account for temporal variability and structural supply-demand factors. Such a targeted approach is essential for promoting price stability, equitable access, and improved food security at the regional level.

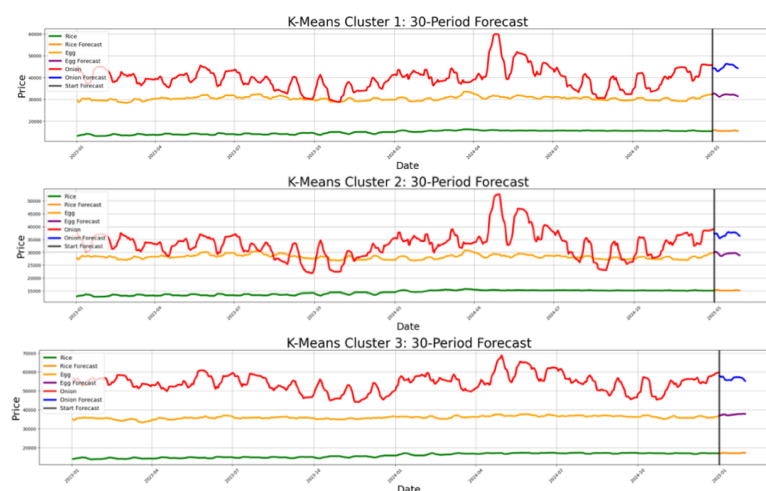


Figure 6. Predicted values for the next 30 periods

For the purpose of analytical labeling, interpretive labels were assigned to each cluster based on the temporal dynamics and structural features of the grouped regions. Cluster 1, which includes major urban centers such as Jakarta, Bandung, Ambon, and Manado, is characterized by high volatility and synchronized price movements. These patterns suggest strong reliance on inter-regional supply chains and sensitivity to national policy interventions. Cluster 2, composed of regional trade hubs such as Medan, Makassar, Denpasar, and Semarang, displays relatively moderate price stability, though subject to seasonal fluctuations. This suggests the presence of functional logistics infrastructure and partial local production capacity. Cluster 3, encompassing remote eastern regions like Jayapura, Manokwari, and North Maluku, exhibits the most stable price dynamics, particularly for rice and eggs. This stability likely arises from localized, self-sufficient production systems and minimal exposure to national market volatility. These qualitative labels enhance the interpretive value of the clustering results by going beyond statistical similarity, offering practical insights into the structural heterogeneity across Indonesia's regional food and providing a basis for targeted policy design.

4. CONCLUSION

Integrating predictive-based time series clustering with a hybrid VECMX–LSTM forecasting framework provides a robust strategy for modeling multivariate price dynamics of key food commodities across Indonesia's provincial capitals. The clustering approach utilizes 30-step-ahead forecasts, generated individually for each region as inputs for the K-Means algorithm, with (DTW). The resulting cluster structure demonstrates strong statistical validity, supported by a Silhouette Score of 0.45 and a Davies-Bouldin Index of 0.67, and is further reinforced through post-hoc validation using the Wilcoxon signed-rank test. Forecasting accuracy improves substantially through the hybrid VECMX–LSTM model, which effectively captures both long-run equilibrium relationships and nonlinear short-term fluctuations that are often missed by conventional models. Comparisons between cluster-based forecasts and actual individual-level observations reveal high levels of alignment, with most deviations remaining statistically insignificant and within acceptable margins. Moreover, the 30-period forecasts reveal distinct temporal behaviors across clusters—ranging from the relative stability of rice prices, to the seasonal fluctuations of eggs, and the high volatility of red onions—reflecting underlying structural disparities in production, logistics, and consumption. These findings underscore the value of combining predictive clustering with hybrid modeling to support regionally adaptive, data-driven food policy design, capable of responding to both structural heterogeneity and temporal complexity within Indonesia's food system.

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