Implementation of Time Series Clustering with DTW to Clustering and Forecasting Rice Prices Each Provinces in Indonesia

Dhiya Ulayya Tsabitah[1*], Yenni Angraini[2], and I Made Sumertajaya[3]
[1,2,3]Department Statistics FMIPA, IPB University, Bogor, Indonesia
*Corresponding author: dhiya.tsabitah@apps.ipb.ac.id

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ABSTRACT – **Indonesia faces a significant imbalance between domestic supply and demand, leading to escalating rice prices and pronounced regional disparities. To elucidate underlying price patterns and forecast future trends, this study employed Hierarchical Clustering Time-Series with DTW, which is effective for identifying correlations with time, and ARIMA modeling at both individual and cluster levels. Comprehensive analysis, incorporating visualization and threshold comparisons, identified Central Kalimantan as an outlier. Individual ARIMA models demonstrated exceptional performance, with MAPE <10%. The clustering time-series correlation using the Cophenetic coefficient, reached 0.68 forward linkages. Two clustering approaches were explored: (1) ignoring the outlier province, (2) excluding Central Kalimantan and incorporating it into a separate cluster. Optimal cluster measurement, the Elbow, Silhouette, Calinski-Harabasz, and Davies-Bouldin, yielded 6-7 clusters for the former approach and 3-5 clusters for the latter. Comparative analysis of individual and cluster forecasts, coupled with paired t-tests, revealed that Ward linkage in the second approach produced the most favorable results, with 27/34 provinces exhibiting cluster MAPE values ≤ their individual MAPE. This finding underscores the efficacy of cluster-based modeling in generating accurate and representative estimates for a substantial portion of provinces. A 12-period rice price forecast indicates a prevailing trend of rising prices in most regions of Indonesia.**

Keywords– **ARIMA, clustering time series, dynamic time warping, rice prices, ward linkage**

I. INTRODUCTION

Rapid population growth has led to increased demand for food, especially rice, as the staple food of Indonesian society [1]. Ironically, despite being the third-largest rice-producing country in the world, Indonesia continues to import a significant portion of its rice due to insufficient domestic production to meet its consumption needs [2]. The increase in rice consumption of 3.86% per capita in 2021 is not in alignment with national production, which averages only 34.5 million tons of milled rice [3]. The disparity between rising demand and limited production highlights the potential for greater reliance on imports to meet domestic consumption needs. However, relying of imports as a substitute strategy for national production has serious economic implications. The emergence of significant price disparities across regions threatens economic stability and exacerbates price inequality [4].

The dynamic nature of regional boundaries, with the continuous formation of new provinces, presents both opportunities and challenges for effective governance. These administrative changes enable governments to manage and exploit the diverse natural resources within each region more efficiently [5]. However, the heterogeneity of geographical and agricultural conditions across provinces necessitates a nuanced understanding of the production capabilities of key commodities. In the case of rice, a staple food for the Indonesian population, the limitations imposed by unfavorable geographical and environmental factors in certain provinces have contributed to supply shortages and price volatility [6].

Given the diverse geographical and agricultural conditions across provinces, it is crucial for the government to understand regional variations in rice prices, which can be substantial [6]. Central Kalimantan Province has uneven geographical conditions and agricultural environments, that often hinder its ability to meet local rice demand [7]. Hilly topography, inadequate agricultural infrastructure, and a varied tropical climate further impact agricultural productivity in this region. As a result, rice availability in Central Kalimantan is limited and leading to increased rice prices to meet local demand [8]. In this case, accurate rice price forecasting is crucial for strategic planning in the agricultural and economic sectors [9]. Accurate predictions can help policymakers and farmers prepare for market fluctuations and changes in environmental conditions that affect rice prices. Therefore, an analytical method is needed to provide insight into regional rice price patterns and forecast future trends.

Time series clustering, using a model-based approach to identify patterns, trends, and variability, is applied to each province based on rice prices [10]. The time variable of the data requires clustering methods that account for data similarity, correlation over time, temporal relationships, and time shifts. Dynamic Time Warping (DTW) addresses these requirements through its flexibility in analyzing time-based data. The strength of DTW lies in its robustness, enabling it to handle data fluctuations effectively. Time series clustering using DTW can identify groups of multivariate data with similar characteristics, providing valuable insights into complex patterns within the dynamics of commodity prices across spatial and temporal dimensions [11].

Several related studies include research by Munthe [12] on rice production modeling for 26 provinces in Indonesia and identified three optimal cluster with a silhouette coefficient value of 0.64. Wijaya and Ngatini [13] modeling rice prices in 18 provinces using the time-series clustering method, DTW distance between averages. With two optimum clusters consisting of 6 and 12 provinces, ARIMA modeling both have MAPE accuracy of 1.97% and 2.12%, better than the model without clusters of 3.12%. Then Ulinnuha et al. [14] in modeling rice prices for 32 provinces using time-series clustering with correlation distance, obtained an individual level MAPE of 1.24% and a cluster level of 1.16% from 3 replications and 4 optimal clusters. The research gap lies in the establishment of new provinces in 2014, which the total number of provinces in Indonesia to 34 and significantly impacting the dynamics of rice distribution and prices at the regional level. The administrative change has led to greater data dimensionality, necessitating an approach focused on minimizing total variance within clusters, such as Ward linkage [15]. The dimensionality reduction resulting from the clustering process aims to enhance the efficiency of modeling tasks. Therefore, the models produced, both individually and based on cluster results, must provide relevant, representative outcomes, and improve forecasting accuracy for each region represented by the respective clusters.

The objectives of this research are: (1) Exploration of rice selling price data from 2018 to 2023 in each province of Indonesia, (2) Identifying cluster-based patterns of increasing selling prices for rice based on groupings of similar price characteristics, (3) Comparing the performance of the ARIMA model with and without clusters to measure the accuracy of rice price predictions at the provincial level, and (4) Forecast the selling price of rice for the next 12 periods in each cluster.

II. LITERATURE REVIEW

Time series clustering is an approach for grouping time series data into similar clusters based on their growth patterns and temporal characteristics [14]. This analysis aims to identify groups or sets of time series that exhibit similar characteristics, enabling the discovery of underlying relationships and structures within the data. Common clustering methods include hierarchical and non-hierarchical methods. Hierarchical methods create a hierarchical structure of clusters without requiring a predetermined number of clusters, while non-hierarchical methods partition the data into a specified number of clusters [16]. Hierarchical clustering offers a significant advantage in terms of data visualization, making it particularly suitable for time series data. Aghabozorgi et al. [17] explained that hierarchical methods, with their ability to handle non-linear relationships and time-dependent patterns, are particulary well-suited for time series clustering.

Hierarchical clustering encompasses two fundamental methodologies for cluster construction: agglomerative and divisive. Agglomerative techniques commence with individual data points and sequentially merge them into increasingly larger clusters until a solitary, all-encompassing cluster is obtained. In contrast, divisive methods initiate with a single, all-inclusive cluster and recursively partition it into smaller, more homogeneous subclusters until each data point forms an individual cluster. Ward's linkage is a prevalent linkage criterion utilized in hierarchical clustering.

Ward's method aims to minimize the variance within each cluster [15]. The distance between two clusters in Ward's method is calculated as the sum of squared errors (SSE) between the two clusters. Importantly, SSE can only be calculated for clusters containing more than one data point, where x_{ij} represents the value of the i^{th} object in the j cluster, p denotes the number of variables, and n is the number of objects in the formed cluster [18].

$$SSE = \sum_{j=1}^{p}\left(\sum_{i=1}^{n} x_{ij}^{2} - \left(\frac{1}{n}\sum_{i=1}^{n} x_{ij}\right)^{2}\right) \tag{1}$$

Dissimilarity measurements are carried out using Dynamic Time Wrapping (DTW), an algorithm that calculates the minimum distance between two time series by mapping corresponding points, even when they have different lengths or time shifts [19]. Niennattrakul and Ratanamahatana [20] explain that given two time series $Q = q_1, q_2, \dots, q_i, \dots, q_n$ and $C = c_1, c_2, \dots, c_j, \dots, c_m$, the DTW distance calculation involves creating an $n \times m$ matrix, referred to as the local cost matrix. Each element (i,j) of this matrix represents the cumulative distance from the distance at (i,j) and the minimum of three adjacent elements to (i,j), where $0 \le i \le$ n and $0 \le j \le$ m. Element (i,j) is defined as:

$$e_{i,j} = d_{ij} + \min\{e_{(i-1)(j-1)}, e_{(i-1)(j)}, e_{(i)(j-1)}\} \tag{2}$$

where, $d(i,j)$ represents the actual distance between objects i and j. The calculation of $d(i,j)$ can be performed using various local distance measures, such as Euclidean distance, Manhattan distance, or other suitable measures. In this research, $e_{i,j}$ represents each element (i,j) of the global cost matrix, which is the sum of the squared distance between c_i and q_j, and the minimum cumulative distance of the three adjacent elements to (i,j). This matrix represents the alignment of the two time series Q and C.

The warping path (p) starts from the cell with the lowest cost function in the global cost matrix, which is typically (1,1). The cost function is associated with the warping path and is calculated using the global cost matrix, which encompasses all pairwise distances, as defined in Equation 3:

$$c_p(Q,C) = \sum_{k=1}^{K} c(q_{nk}, c_{mk}) \tag{3}$$

This equation calculates the total squared distance between corresponding points in the two time series, taking into account the optimal alignment determined by the warping path [21]. This makes DTW effective for handling variations and scales of dynamically moving time patterns, where P is the set of all possible wrapping paths, w_k is the k^{th} path (i, j) element on the wrapping path and K is the length of the wrapping path [13]. Equation 4 is the DTW distance equation:

$$D_{DTW}(R,S) = min_{\forall w \epsilon P}\left\{\sqrt{\sum_{k=1}^{K} d_{w_k}}\right\} \tag{4}$$

In this research, two forecasting analyses were carried out, at both individual and cluster levels. Forecasting is carried out using the Autoregressive Integrated Moving Average (ARIMA) method. ARIMA is a statistical method that leverages historical data patterns to generate forecasts [22]. ARIMA combines the Autoregressive (AR) model, which explains the relationship between current values and past values, Integrated (I) which involves differencing to achieve stationary, and the Moving Average (MA) model, which explains values current residual with past residual value. By utilizing autoregressive and moving average properties, ARIMA can capture patterns and trends at both individual and group entity levels [23]. Equation (2) is the general equation of ARIMA:

$$\Phi_p(B)(1-B)^d Y_t = \Theta_q(B) e_t \tag{5}$$

where $\Phi_p(B)$ is the p^{th} Autoregressive parameter coefficient, $\Theta_q(B)$ is the q^{th} Moving Average parameter coefficient, B is the backshift operator, $(1-B)^d$ is the d-differentiating process, and Y_t is the actual data at the t^{th} time t, e_t is the residual in the t^{th} period.

Mean Absolute Percentage Error (MAPE) is a metric used to assess model accuracy. By calculating the percentage difference between the actual value and the model-predicted value, MAPE provides an understanding of the model's ability to generate accurate forecasts [24]. The MAPE is formulated as follows, with Y_t representing the actual rice price in the t^{th} period, $\widehat{Y}_t$ representing the predicted rice price in the t^{th} period, and T representing the number of observations in the time series data:

$$MAPE = \frac{\sum_{t=1}^{T}\left|\frac{Y_t - \widehat{Y}_t}{Y_t}\right|}{T} \times 100\% \tag{6}$$

A model is considered accurate if it achieves a MAPE value below 10%. The performance of individual and cluster-level models was evaluated by comparing their MAPE values. The significant agreement between the two levels indicates the existence of an accurate predictive relationship at both individual and group entity levels [25].

III. METHODOLOGY

This research utilizes weekly secondary data sourced from Bank Indonesia's National Strategic Food Price Information Center (PIHIS). The dataset encompasses 34 Indonesian provinces from 2018 to 2023, comprising 53,210 observations with three variables: one response variable (rice price) and two predictor variables. Rice price, the response variable, is the average value of six rice qualities: lower quality rice I and II, medium quality rice I and II, and super quality rice I and II. Using the Clustering time series method, variations in rice prices are grouped based on time series into similar groups based on growth or temporal pattern characteristics [1]. The main analytical component of this method is identifying groups or collections of time series that have similar characteristics, so that time series in one group have higher similarity than time series in other groups.

This research employs a two-pronged approach, namely: individual-level ARIMA modeling and cluster-level ARIMA modeling. The following steps outline the clustering time series analysis procedure for rice price data:

1. **Data Preprocessing:** Data was preprocessed to optimize analysis, including imputation, exploration, and splitting.
2. **Individual-Level ARIMA Modeling:** ARIMA models were fitted to the rice price data of each province using the Box-Jenkins approach.
3. **Hierarchical Clustering:** Rice price data was clustered using a hierarchical clustering method with Dynamic Time Warping (DTW) as the dissimilarity measure.
4. **Prototype data:** The average values of all data points within the cluster were calculated as representative time series for subsequent cluster levels.
5. **Cluster-Level ARIMA Modeling:** ARIMA models were fitted to representative prototype data from each cluster.
6. **Model Evaluation:** Mean Absolute Percentage Error (MAPE) values were compared between cluster-level and individual-level models. If the cluster-level MAPE was less than or equal to the individual-level MAPE, the cluster-level model was considered more accurate.
7. **Significance Test:** Parametric testing to determine whether there is a difference in the average of two paired samples at the individual and cluster levels.
8. **Forecasting:** Rice prices were forecasted for the next 12 periods using the best-performing model.

IV. RESULTS AND DISCUSSIONS

Missing values can adversely affect the accuracy of analysis, necessitating an imputation process. Linear interpolation, which effectively handles linear data by drawing a straight line between adjacent data points, is employed for imputation. The choice of method is based on data characteristics, prioritizing data with minimal fluctuations in price changes over short periods. Imputation is performed on each provincial subset to preserve unique regional characteristics and minimize potential statistical distortions associated with global imputation methods. Figure 1, a graph of weekly rice price patterns, illustrates relatively stable price fluctuations from 2018 to 2022, providing a stark contrast to the price spike in the following year.

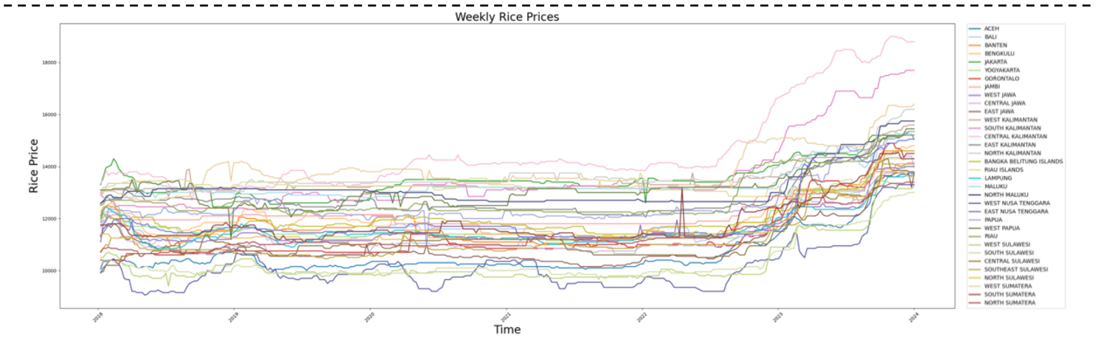

Figure 1 Weekly rice price plot

To analyze data movement patterns in each province, rice prices are aggregated into annual data. Based on Figure 2, the annual rice price graph reveals two provinces with a significant upward trend, while the other 32 provinces exhibit more uniform movements. This indicates an anomaly in the movement of rice prices in Central Kalimantan and South Kalimantan. An exploratory analysis of rice prices in Indonesia throughout 2022 reveals significant price variations between provinces. Figure 2 shows that, in the past year, Central Kalimantan had the highest rice price, reaching Rp 18,100 per kilogram, while West Nusa Tenggara recorded the lowest rice price, namely Rp 11,600 per kilogram. This highlights the significant price disparities between provinces, indicating the presence of regional price variations across Indonesia.

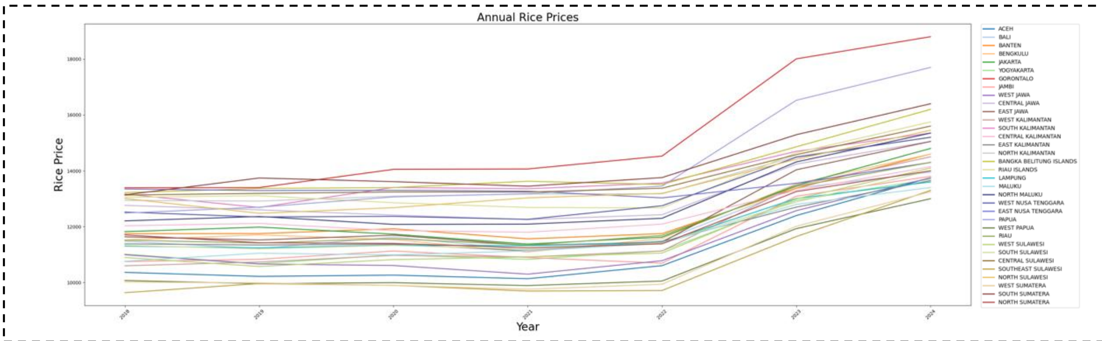

Figure 2 Annual rice price plot

Information on provincial rice price disparities is crucial for effective clustering. By analyzing these differences, we can identify patterns or groups of regions with similar price characteristics. Based on the data pattern and range, 259 of the 313 data points from 2018 to 2022 were used as training data to optimize the balance between model generalization and overfitting.

ARIMA modeling was applied to training data for each province. Stationarity checks were conducted using ACF and PACF plots and the formal ADF test. The ACF and PACF plots exhibited a tail-off pattern, suggesting that the data was not stationary. Additionally, the ADF test yielded p-values greater than 0.05, confirming the non-stationarity of the data. Therefore, differencing was necessary to achieve stationarity.

The best ARIMA model for each province was selected based on the lowest AIC value among candidate models. Diagnostic tests, including the Ljung-Box and Jarque-Bera tests, were performed to assess the independence and normality of the residuals. While the Jarque-Bera test indicated non-normality, the distribution of residuals was approximated as normal due to its symmetrical shape and similarity to the normal distribution. ARIMA models were used to forecast rice prices for the next 12 periods for each province. Model performance was evaluated using the Mean Absolute Percentage Error (MAPE). Table 1 shows that all models achieved a MAPE of less than 10%, indicating their ability to accurately represent actual data.

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Table 1 Individual-level ARIMA modelling and forecasting

Province	Model	AIC	P-value		MAPE Testing (%)
			L-jung Box	Jarque Bera	
Aceh	ARIMA(4,1,3)	2791.09	0.91	0.00	0.63
North Sumatera	ARIMA(1,1,2)	2635.67	0.87	0.00	0.43
West Sumatera	ARIMA(2,1,2)	3142.33	0.96	0.00	0.33
Riau	ARIMA(2,1,2)	2774.14	0.84	0.00	0.24
Jambi	ARIMA(3,1,4)	2638.79	0.89	0.00	0.25
...	...	...	...	...	...
West Sulawesi	ARIMA(2,1,2)	3010.87	0.85	0.00	0.62
Maluku	ARIMA(2,1,0)	2665.74	0.89	0.00	0.75
North Maluku	ARIMA(2,1,2)	2597.92	0.69	0.00	0.46
West Papua	ARIMA(2,1,3)	3276.37	0.96	0.00	0.57
Papua	ARIMA(0,1,1)	3280.47	0.86	0.00	0.86

Hierarchical clustering with Ward linkage methods was employed to group provinces. Dissimilarities between provinces were calculated using the Dynamic Time Warping (DTW) distance metric, which compares two time series and finds the optimal alignment based on time movement patterns. Table 2 presents the DTW distances between provinces in terms of rice prices.

Each row and column in Table 2 represents a different province. A value of 0 indicates a comparison within the same province. For instance, Banten and South Sumatra exhibit a low DTW distance of 41750, suggesting a high level of similarity in their rice price patterns. In contrast, Aceh and West Sumatra have a greater DTW distance, indicating lower similarity in their rice price patterns.

Table 2 Dynamic Time Warping (DTW) distance matrix

Province	Aceh	North Sumatera	West Sumatera	...	North Maluku	West Papua	Papua
Aceh	0	117700	899950		744850	602500	490200
North Sumatera	117700	0	715350		542500	365400	319600
West Sumatera	899950	715350	0		173250	100250	189550
....	...	...	...	0	...	...	...
North Maluku	744850	542500	173250		0	55150	172300
West Papua	602500	365400	100250		55150	0	92700
Papua	490200	319600	189550		172300	92700	0

Evaluation of the time series clustering was conducted using cophenetic coefficients. A correlation value close to 1 indicates that the dendrogram accurately represents the original distances in the dataset. Based on the evaluation results, a value of 0.68 was obtained, suggesting a good quality clustering.

Next, optimal cluster numbers were determined based on four accuracy parameters: the Elbow Method, Silhouette Score, Davies-Bouldin Index, and Calinski-Harabasz Index. The elbow point on the elbow plot, where the curve transitions from steep to gradual, indicates the optimal number of clusters. Higher Silhouette and Calinski-Harabasz Index values, and lower Davies-Bouldin Index values, suggest better cluster quality.

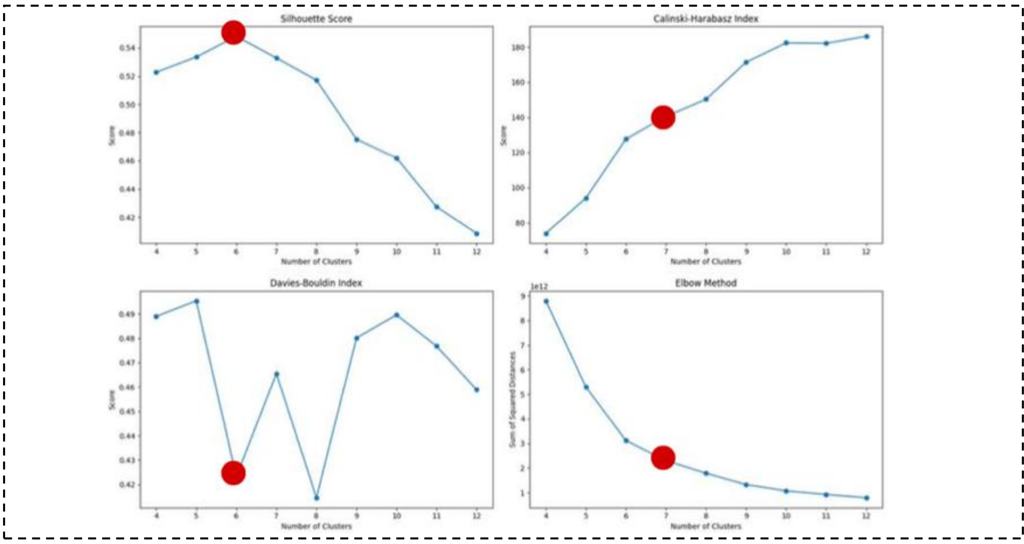


Figure 3 Weekly rice price plot

The test results in Figure 3 indicate that the optimal number of clusters is seven. However, the clustering results isolated Central Kalimantan as a single cluster. Therefore, using DTW distances, the average distance of each province was compared to an outlier threshold based on the standard deviation of the average distances. Provinces with a distance greater than the threshold were considered outliers. The results show that out of the 34 provinces, only Central Kalimantan was identified as an outlier.

To optimize the clustering process, two approaches were considered: (1) **Ignoring Outliers:** Modeling was conducted for all 34 provinces without considering outliers and (2) **Mapping Outlier Province:** Central Kalimantan, identified as an outlier, was grouped into a separate cluster, and modeling was performed on the remaining 33 provinces. In Approach 1, cluster cutting was determined by analyzing the dendrogram to ensure all provinces were included in a cluster. For Approach 2, the optimal number of clusters was determined based on the results shown in Figure 4. Both approaches resulted in optimal cluster numbers of 5 and 7, respectively.

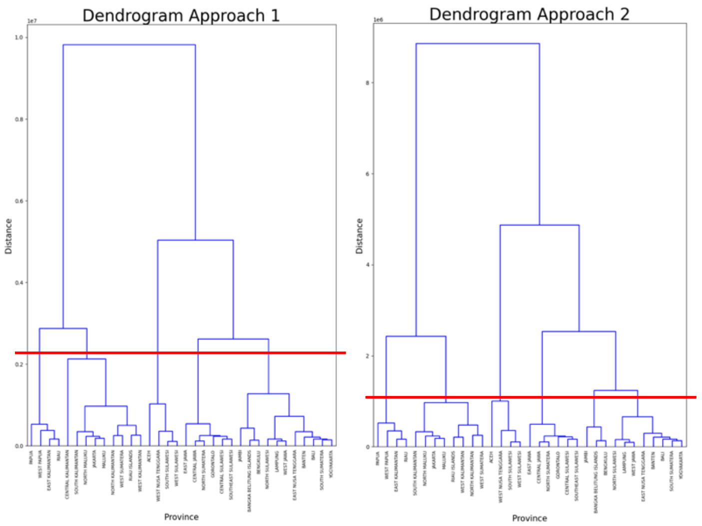


Figure 4 Dendogram result from grouping 34 provinces

Figure 3 illustrates the clustering results for 34 provinces, grouping provinces with similar rice price patterns. For each cluster in Approaches 1 and 2, a prototype was calculated by averaging the values of cluster members. These prototype data were then subjected to ARIMA modeling, with the results presented in Table 3.

Table 3 Cluster-level ARIMA modelling and forecasting

Approach 1				Approach 2			
Cluster	Model	AIC	MAPE Testing (%)	Cluster	Model	AIC	MAPE Testing (%)
1	ARIMA(1,1,2)	2762.36	0.30	1	ARIMA(1,1,2)	2762.36	0.33
2	ARIMA(1,1,2)	2499.82	0.24	3	ARIMA(2,1,1)	2487.69	0.32
3	ARIMA(1,1,1)	2687.35	0.48	4	ARIMA(1,1,1)	2687.35	0.48
4	ARIMA(1,1,1)	2479.04	0.49	5	ARIMA(1,1,1)	2479.04	0.49
5	ARIMA(0,1,1)	2539.46	0.33	6	ARIMA(1,1,0)	2589.56	0.31
				7	ARIMA(0,1,1)	2635.97	0.31

Comparative analysis of forecasting using individual ARIMA models and cluster-based forecasting is used to measure the effectiveness between the two approaches. The model accuracy metric used to compare modeling results is the Mean Absolute Percentage Error (MAPE). MAPE is flexible in the context of performance comparisons, so in this research, where there are performance comparisons both between clusters and provinces, it can be approached well.

Comparative analysis in Table 4 shows that Approach 1 yields favorable results for 24 out of 34 provinces. In particular, clusters that exhibit lower or equivalent average percentage error (MAPE) values compared to their member provinces demonstrate superior forecasting performance. These findings, obtained from a cluster analysis covering multiple regions, underscore the efficacy of the proposed approach in producing accurate and representative estimates at the provincial level.

Careful comparative analysis of cluster and individual province forecasts shows a positive correlation in 24 of the 34 provinces studied. In particular, clusters that demonstrate lower or equivalent mean absolute percentage error (MAPE) values compared to their constituent provinces showcase superior forecast accuracy. The identified clusters not only improve understanding of regional forecasting dynamics but also provide a basis for policymakers and decision-makers to optimize resource allocation and planning.

Table 4 Comparison of MAPE from the evaluation of the ward linkage in approach 1

Cluster	MAPE	Comparison of MAPE in Ward Linkage (%)					
				ARIMA(1,1,2)			
1		**Papua***	**West Papua***	East Kalimantan	Riau		
	Individu	0,86	0,57	0,46	0,24		
	Cluster	0,63	0,45	0,48	0,40		
				ARIMA(2,1,1)			
		Riau Island	North Maluku	South Kalimantan	**Jakarta***	**Maluku***	**West Kalimantan***
	Individu	0,41	0,46	0,47	0,27	0,75	0,51
2	Cluster	0,48	0,53	0,53	0,27	0,70	0,35
		North Kalimantan*	West Sumatera	Central Kalimantan			
	Individu	0,48	0,33	0,45			
	Cluster	0,35	0,81	0,86			
				ARIMA(1,1,1)			
3		**Aceh***	**West Nusa Tenggara***	**West Sulawesi***	**South Sulawesi***		
	Individu	0,63	0,89	0,62	0,42		
	Cluster	0,55	0,80	0,55	0,41		
				ARIMA(1,1,1)			
4		**East Java***	**Central Java***	**North Sumatera***	Gorontalo	**Southeast Sulawesi***	**Central Sulawesi***
	Individu	0,65	0,50	0,43	0,66	0,53	0,94
	Cluster	0,64	0,50	0,41	0,73	0,50	0,89
				ARIMA(0,1,1)			
		Yogyakarta*	**South Sumatera***	**East Nusa Tenggara***	**Lampung***	**West Java***	**North Sulawesi***
	Individu	0,41	0,70	0,78	0,38	0,59	0,63
5	Cluster	0,32	0,48	0,72	0,29	0,43	0,53
		Banten*	**Bali***	**Jambi***	**Bengkulu***	**Bangka Belitung***	
	Individu	0,39	0,91	0,25	0,39	0,39	
	Cluster	0,37	0,74	0,30	0,42	0,38	

*provinces in bold indicate that the cluster MAPE is smaller, the same as the individual MAPE

Table 5 indicates that Approach 2, using Ward linkage, yields superior clustering results. Of the 34 provinces compared, 27 provinces had cluster MAPE values smaller than individual ones. Lower cluster MAPE values indicate that the cluster-based modeling approach can produce estimates that are close to individual estimates for several member provinces. This suggests that homogeneous characteristics within clusters lead to increased precision in future predictions.

Next, a comparison of the average modeling evaluation based on individual and cluster MAPE was carried out to compare the modeling results with and without clustering. In cluster 3, the individual MAPE value is slightly greater than the cluster MAPE. This suggests that all clusters resulting from modeling can capture and represent patterns in the data to produce accurate predictions.

Table 5 Comparison of MAPE from the evaluation of the ward linkage in approach 2

Cluster	MAPE	Comparison of MAPE in Ward Linkage (%)					
				ARIMA(1,1,2)			
1		**Papua***	**West Papua***	East Kalimantan	Riau		
	Individu	0,86	0,57	0,46	0,24		
	Cluster	0,63	0,45	0,48	0,40		
				ARIMA(2,1,2)			
2		**Central Kalimantan***					
	Individu	0,45					
	Cluster	0,45					
				ARIMA(2,1,1)			
3		Riau Island	North Maluku	South Kalimantan	**Jakarta***	**Maluku***	**West Kalimantan***
	Individu	0,41	0,46	0,47	0,27	0,75	0,51
	Cluster	0,48	0,53	0,53	0,27	0,70	0,35

Cluster	MAPE	Comparison of MAPE in Ward Linkage (%)					
				ARIMA(2,1,1)			
3		**North Kalimantan***	West Sumatera				
	Individu	0,48	0,33				
	Cluster	0,35	0,81				
				ARIMA(1,1,1)			
4		**Aceh***	**West Nusa Tenggara***	**West Sulawesi***	**South Sulawesi***		
	Individu	0,63	0,89	0,62	0,42		
	Cluster	0,55	0,80	0,55	0,41		
				ARIMA(1,1,1)			
5		**East Java***	**Central Java***	**North Sumatera***	Gorontalo	**Southeast Sulawesi***	**Central Sulawesi***
	Individu	0,65	0,50	0,43	0,66	0,53	0,94
	Cluster	0,64	0,50	0,41	0,73	0,50	0,89
				ARIMA(1,1,0)			
6		**Jambi***	**Bengkulu***	**Bangka Belitung***			
	Individu	0,65	0,39	0,39			
	Cluster	0,64	0,42	0,38			
				ARIMA(0,1,1)			
7		**Yogyakarta***	**South Sumatera***	**East Nusa Tenggara***	**Lampung***	**West Java***	**North Sulawesi***
	Individu	0,41	0,70	0,78	0,38	0,59	0,63
	Cluster	0,32	0,48	0,72	0,29	0,43	0,53
		Banten*	**Bali***				
	Individu	0,39	0,91				
	Cluster	0,37	0,74				

*provinces in bold indicate that the cluster MAPE is smaller, the same as the individual MAPE

Both Approach 1 (5 clusters, 23 provinces) and Approach 2 (7 clusters, 27 provinces) yielded optimal clustering results using Ward linkage, as indicated by MAPE evaluations. These results suggest that cluster-based modeling can effectively represent over 75% of Indonesian provinces, achieving excellent MAPE values below 10%.

A comparative analysis of individual and cluster-based model performance was conducted using Mean Absolute Percentage Error (MAPE). Table 6 presents the MAPE values for both approaches. Notably, all clusters exhibited MAPE values below 10%, indicating strong model performance. However, minor discrepancies were observed in specific clusters, where individual MAPE values slightly exceeded cluster-level MAPE values. Nevertheless, these differences were minimal, suggesting that cluster-based modeling effectively captures underlying data patterns, leading to improved prediction accuracy.

Table 6 Comparison of MAPE between individual and cluster model

Approach	MAPE	*Cluster* (%)						
		1	2	3	4	5	6	7
1	Individual	0,53	0,46	0,64	0,62	0,53		
	Cluster	0,49	**0,55***	0,37	0,61	0,47		
2	Individual	0,53	0,45	0,46	0,64	0,62	0,34	0,60
	Cluster	0,49	0,45	**0,50***	0,37	0,61	0,33	0,49

* The bold font indicates that the cluster MAPE is larger than the individual MAPE.

Due to the varying number of clusters in each approach, a direct comparison is challenging. Therefore, alternative methods, such as statistical hypothesis testing, could be explored to conduct a more comprehensive evaluation of the two approaches. A paired sample t-test was employed to determine if significant differences exist between individual and cluster MAPE values in both approaches. The null hypothesis (H_0) states that there is no difference between the two, while the alternative hypothesis (H_1) suggests a difference. The t-test was conducted with a significance level of 5%. If the p-value exceeds 0.05, H_0 is accepted, indicating no significant difference.

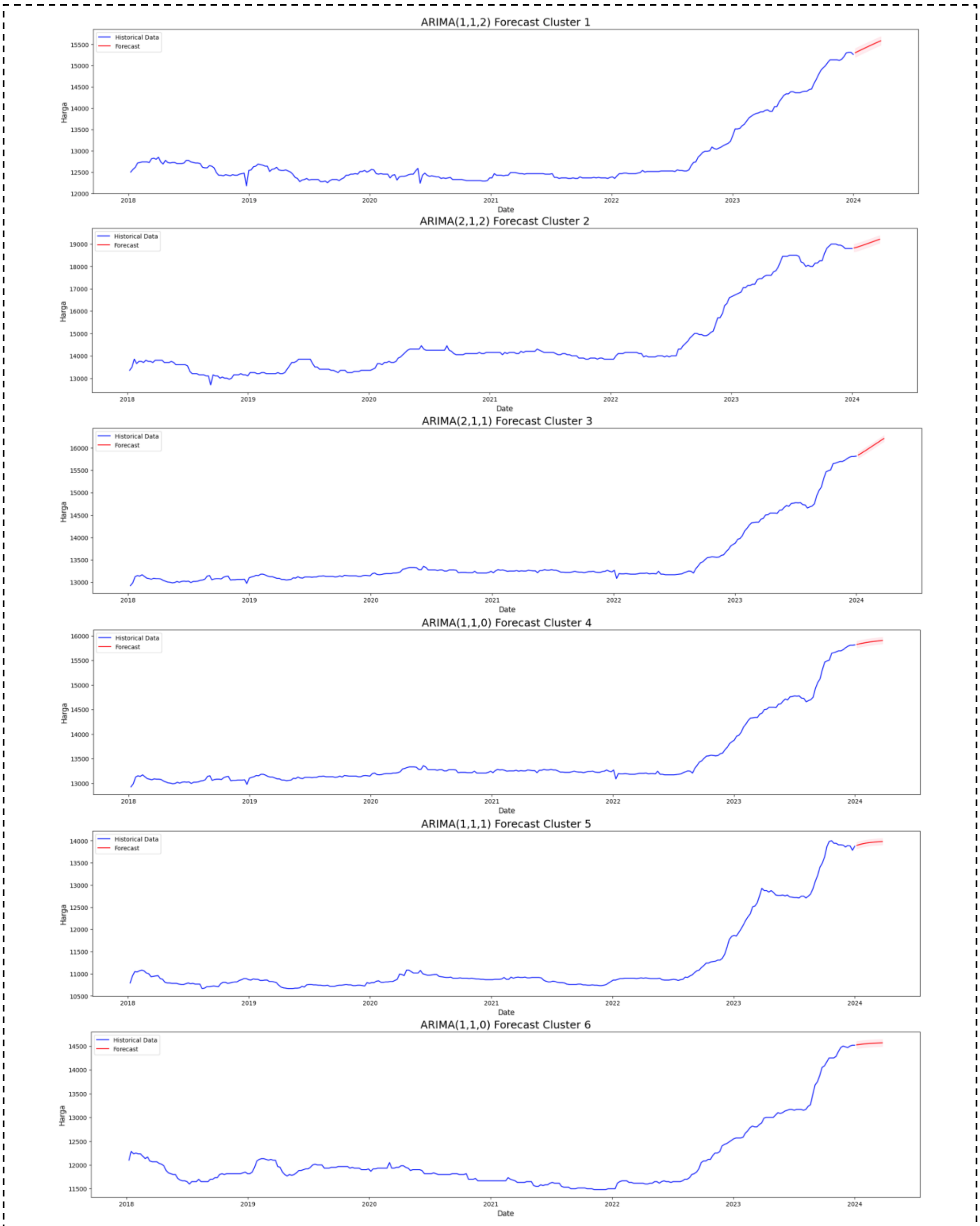
Table 7 Comparison of MAPE from the evaluation of the ward linkage in approach 2

		Paired Differences					
			Confidence Interval				
		Mean	Lower	Upper	t	df	p-value
Approach 1	MAPE 1	0,057	-0,089	0,203	1,45	6	0,198
Approach 2	MAPE 2	0,058	-0,213	0,329	0,98	4	0,381

A paired t-test was conducted to assess the significance of the difference between individual and cluster-based MAPE values. The results indicate that Approach 1 exhibits a higher t-value (1.98) compared to Approach 2 (0.38), suggesting a larger difference between individual and cluster-level modeling in Approach 1. Additionally, the p-value for Approach 1 (0.198) is closer to the 5% significance level than that of Approach 2 (0.38). This implies that Approach 1 has a higher probability of detecting a significant difference between individual and cluster-level MAPE values.

Overall, while both approaches demonstrate a significant relationship between individual and cluster-level modeling, Approach 1 exhibits a stronger tendency toward significant differences. Based on these findings, Approach 2, which successfully clusters 27 out of 34 provinces into a smaller number of clusters, is deemed more effective in modeling and forecasting rice prices. This approach offers a more efficient and accurate representation of price dynamics across different provinces, reducing the number of models required while maintaining predictive accuracy.

The 12-period forecasts generated using Approach 2 indicate a general upward trend in rice prices across most provinces in Indonesia. This suggests that policymakers and stakeholders should closely monitor price fluctuations and implement appropriate measures to mitigate potential impacts on food securi



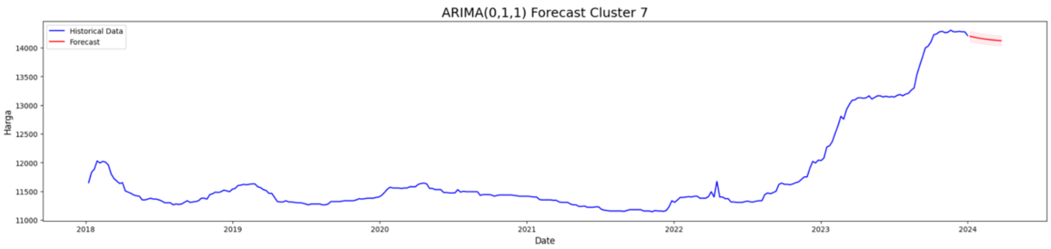


Figure 5 Forecasting rice prices for the nex 12 periods for each cluster

Based on the results of the rice price analysis, the cluster grouping reveals heterogeneous dynamics. Clusters 1, 2, and 3 experienced a significant price spike, characterized by a sharp upward trend. In contrast, Cluster 2 is projected to reach a price of Rp 19,000/kg, which is notably higher than the predicted price of Rp 16,000/kg for provinces in Clusters 1 and 3. Clusters 4, 5, and 6 exhibited an initial price increase followed by stabilization, potentially due to market adjustment mechanisms responding to temporary factors. Conversely, Cluster 7 displayed a downward price trend that stabilized at the beginning of the third week of the forecast period.

V. CONCLUSIONS AND SUGGESTIONS

In this section, the authors state their conclusion, and suggestion for the future research. The research employed hierarchical clustering with Ward linkage and DTW distance to group provinces based on similar rice price patterns. The optimal number of clusters was determined using various validity indices, including the elbow method, silhouette score, Calinski-Harabasz index, and Davies-Bouldin index. Central Kalimantan was identified as an outlier and was excluded from the primary clustering analysis.Two clustering approaches were considered: (1) clustering all 34 provinces and (2) clustering 33 provinces excluding Central Kalimantan. The second approach, with 7 clusters, demonstrated superior performance, as indicated by lower MAPE values compared to individual ARIMA models for 27 out of 34 provinces. This suggests that clustering can improve the accuracy of rice price forecasts, particularly for provinces with similar price patterns.The 12-period forecasts generated using the cluster-based approach revealed a general upward trend in rice prices across most provinces. However, specific clusters exhibited distinct price patterns, highlighting the importance of considering regional variations. These findings provide valuable insights for policymakers and stakeholders to make informed decisions regarding resource allocation and planning. Future research could explore alternative clustering techniques or incorporate additional factors like socioeconomic indicators and climatic conditions to further refine the clustering and forecasting models.

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