Determining Food Price Stabilization Priorities Across Indonesian Provinces Using K-Means Based on Strategic Food Price Disparity and Volatility

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Abstract

For the Indonesian government, food security is one of its priorities, and price stability across provinces serves as one measure of progress. To help identify where stabilization efforts are most needed, we used K-Means clustering to group 37 provinces based on the National Food Agency's publicly available monthly consumer prices for 17 strategic food items from October 2024 to January 2026. Seven features described each province, namely price level relative to the national median and coefficient of variation for three food groups, and the share of months above reference prices. A stability rule (at least two provinces and a mean bootstrap Jaccard of at least 0.75 in every cluster) selected four clusters, which a consumer price pressure index then ordered into tiers P1 (highest) to P4. P1 (Central and South Papua, provisional) and P2 (five other Maluku–Papua provinces) had prices 13–50% above the median and exceeded reference prices in 87% of months. P4 (12 provinces, including Java except Jakarta) had the lowest mean prices, the most volatile chili prices, and about 80% of national paddy output. In the agency's distribution program, 94% of inter-provincial volume came from P4, but the shipments did not favor higher-priority tiers, and P1 received only one shipment in 2024–2026. Because the data are open, the segments can be updated with each release and used to match stabilization instruments to each province.

Keywords: *food price stabilization, K-Means, regional price disparity, price volatility, reference price*

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Introduction

From data on 1.27 million preschool children in 44 developing countries, Headey and Ruel [1] linked a 5% rise in real food prices to a 9% higher risk of wasting. A 10% rise in food prices goes with a 3.5% rise in moderate or severe food insecurity [2]. Indonesian food prices also vary widely across regions. Retail rice costs less in surplus provinces than in deficit provinces that depend on inflows [3], and food prices appear to be the main channel through which inflation spills over between neighboring provinces [4]. Rice prices hit a record in early 2024, and the government relied on large imports to lower them before year-end [5].

Under Indonesia's 2025–2029 government policy, the target for price stability is for the coefficient of variation of staple food prices across time and regions to fall from 20–25% in 2025 to 10–15% in 2029 [6]. The National Food Agency (Badan Pangan Nasional, NFA) coordinates to achieve this target [6]. Its tools include supply and price stabilization operations (SPHP), subsidized food markets (Gerakan Pangan Murah, GPM), and food distribution facilitation (Fasilitasi Distribusi Pangan, FDP) from surplus to deficit regions [7]. When consumer prices exceed the consumer reference price (harga acuan penjualan, HAP), the agency may assign state food enterprises to sell at that price [8].

The target is one national figure, while the NFA allocates its instruments province by province. A planner choosing where the next FDP shipment or GPM event should go needs to see, for each province, how high and how unstable its prices are and how often they break the legal reference price. Indonesian K-Means studies of food prices group commodities, districts and cities, or province-commodity-month records. They seldom test whether their clusters survive resampling, and, to our knowledge, none of them uses reference prices or compares its clusters with program records [9]–[12].

We group provinces with a single algorithm, K-Means, and spend our effort on choosing and testing the number of clusters. We ask three questions. RQ1: how many stable segments do the 37 provinces with adequate data form between October 2024 and January 2026? RQ2: how do the segments rank in consumer price pressure, and how stable is that ranking? RQ3: do the segments agree with data the model never saw (production, the Food Security Index, and the reach of the GPM and FDP programs)? Because the data are open, the NFA or a provincial office can repeat the analysis with each new release.

Literature Review

Studies of Indonesian food prices agree that location shapes them. Theresia et al. [13] found that Java transmits producer price volatility to the other islands and that chili and shallot prices show strong volatility clustering. Wilujeng et al. [14] linked more resilient provincial food systems, led by Java, with less volatile food prices. Persada et al. [3] distinguished rice-surplus provinces with low prices from rice-deficit provinces with high prices, finding that BULOG, the state food logistics company, tended to adjust distribution after prices had changed. In North Maluku, port tariffs and sea freight costs reduced GRDP per capita in small-island districts [15]. Together, these studies describe two problems: high price levels in eastern deficit provinces and sharp swings in perishable food prices. None of them sort all provinces into groups that map onto the NFA's instruments.

Researchers have used clustering to turn such evidence into policy tiers. Oyebamiji and Türkekul [16] ran K-Means on a food security index for 122 countries and attached distinct priorities to four ordered tiers. Liu et al. [17] clustered Chinese provinces by egg price dynamics to make price policy more precise, and their data showed that producing clusters had the most volatile prices. In Indonesia, Novelan and Aryza [18] used K-Means in food distribution planning, combining it with capacitated vehicle routing so that high-priority delivery areas are not neglected. Sumertajaya et al. [19] grouped 103 districts by daily price movements and found that Papua spanned all four types. Tsabitah et al. [11] placed Jayapura, Manokwari, and North

Maluku in their own cluster. Qomari et al. [9] clustered 44 commodities and chose five clusters by the elbow method. Denny [10] clustered province-commodity-month rows into ten clusters, a number none of the study's three indices suggested, and Valentika et al. [12] turned clusters of 70 regencies into indicative monitoring priorities. Qomari et al., Denny, and Valentika et al. did not test cluster stability by resampling, and none of these studies used the reference prices that trigger government action.

K-Means is fast and straightforward, but it requires the number of clusters, k, to be chosen beforehand. Its results also depend on the initial cluster centers, and it tends to favor compact, roughly spherical groups [20]. Choosing k from an elbow plot can be misleading: Schubert [21] shows that these plots can look similar even when the data have no underlying clusters. Schubert therefore recommends criteria that allow $k = 1$, such as the gap statistic.

Stability checks offer another way to assess the results by testing whether clusters hold up when the data are perturbed. In the clusterwise approach, each original cluster is matched to its most similar counterpart in each bootstrap sample using the Jaccard coefficient [22]. Whether stability should determine k remains debated [22], so we use it as a minimum requirement. Even without clear gaps in the data, dividing observations into homogeneous groups can still be useful for a practical purpose such as targeting [23].

Research Methodology

3.1 Data and features

We used the NFA's open release of monthly provincial consumer prices, January 2021 to January 2026. Each provincial value is the simple mean of retail prices in the province's regencies and cities [24]. We analyzed October 2024 to January 2026 (16 months), the first full months under the consumer reference prices of NFA Regulation 12/2024 [8]. We kept 17 foods with at least 96% coverage and grouped them as staples (medium and premium rice, sugar, packaged cooking oil, packaged wheat flour, soybean, salt), horticulture (shallot, garlic, curly red chili, bird's eye chili), and animal products (beef, broiler meat, eggs, Indian mackerel, tuna, milkfish). A province entered the model if it had at least 12 observed months and no more than 25% of its commodity-month prices missing. Highland Papua failed this rule (10 months, 45% missing), leaving 37 provinces.

For province p, commodity $c \in C_g$ of group g and month t, the level of price P_{pct} relative to the national median $\tilde{P}_{ct}$ and the volatility are

$$L_{pg} = 100\left[\exp\left(\frac{1}{|C_g|}\sum_{c\in C_g}\frac{1}{T_{pc}}\sum_t \ln\frac{P_{pct}}{\tilde{P}_{ct}}\right)-1\right], V_{pg} = \frac{100}{|C_g|}\sum_{c\in C_g}\frac{s_{pc}}{\overline{P}_{pc}}$$

where T_{pc} is the number of observed months and $s_{pc}/\overline{P}_{pc}$ the coefficient of variation (CV) of the monthly prices. Reference-price exceedance is the share of months above the upper bound of the reference price H_{pc}, averaged over the ten commodities that have one:

$$E_p = \frac{100}{|R|}\sum_{c\in R}\frac{1}{T_{pc}}\sum_t \mathbf{1}\left[P_{pct} > H_{pc}\right]$$

We used the consumer HAP as the reference price for soybean, shallot, garlic, chili, sugar, and beef [8], and for eggs and broiler meat [25]. For premium rice, we used the regional maximum retail price (harga eceran tertinggi, HET) [26]. For garlic, sugar, and premium rice, we applied the higher ceilings that the regulations set for Maluku and Papua. Medium rice is excluded from E_p since its HET was changed in August 2025 [27], but it is included in a robustness check using the ceiling in effect in each month. All seven features were standardized as z-scores.

3.2 K-Means, choice of k and priority tiers

We ran K-Means with k-means++ seeding and 100 restarts for $k = 2, \ldots, 8$ and recorded the silhouette, Calinski–Harabasz, and Davies–Bouldin indices and the gap statistic with uniform and principal-component references ($k = 1, \ldots, 8$) [21]. Cluster stability is the mean clusterwise Jaccard coefficient over 2,000 bootstrap samples of provinces [22]. A sample that contains no member of a cluster scores 0 for that cluster. We fixed the decision rule after an exploratory run and before the final run: the largest k at which every cluster has at least two provinces and a mean Jaccard of at least 0.75, the level the documentation of the R package fpc treats as stable [28].

K-Means gives the clusters no order. We ranked them with a consumer price pressure index (CPPI), $\mathrm{CPPI}_p = \frac{1}{2}[z(E_p) + z(\overline{L}_p)]$, where z standardizes across provinces and $\overline{L}_p$ is the mean of the three price levels. We chose these two components because exceedance triggers market interventions [8] and price level guides surplus-to-deficit distribution [7]. Ordered by mean CPPI, the clusters become tiers P1 (highest) to P4. Because the CPPI reuses model features, the ordering describes the clusters and does not test them. We checked it with 1,000 bootstrap samples and with weights on E_p from 0 to 1.

3.3 External checks and robustness

We compared the tiers with data outside the model, namely 2024 production shares from the Ministry of Agriculture [29], the 2025 Food Security Index (IKP), the share of regencies and cities holding a GPM in 2025, and the 2024–2026 FDP shipment records [24]. For inter-provincial FDP shipments we tested whether their volume came from P4 more than under random tier labels (20,000 permutations) and, with origins fixed, whether it went to higher-priority tiers more than under random labels. We also re-ran K-Means with $k = 4$ under 19 alternative settings (another seed, winsorized features, a 25-month window, alternative exceedance definitions and reference prices, medium rice added, South Papua's soybean series removed, detrended volatility, merged price levels, and each feature dropped in turn) and compared each partition with the main one by the adjusted Rand index (ARI) [30]. We used Python with scikit-learn.

Results

4.1 Number of clusters

The validity indices point to different values of k (Table 1). Silhouette and Calinski–Harabasz favor $k = 2$, which separates the seven Maluku–Papua provinces from the rest. Davies–Bouldin favors $k = 7$, and the gap statistic selects $k = 5$ with a uniform reference and $k = 1$ with a principal-component reference. Principal component analysis shows that one dimension, mainly price level and reference-price exceedance, accounts for 67% of the differences among provinces, which form a continuous gradient from the low-price provinces centered on Java to Maluku–Papua. The stability rule selects $k = 4$ (minimum Jaccard 0.78, for P1). At $k = 5$ and $k = 6$ the least stable cluster falls below 0.75, and $k = 7$ and $k = 8$ contain single-province clusters. However, this choice is close to the threshold. The minimum Jaccard for $k = 3$ is only 0.01 below it, and a threshold of 0.70 would select $k = 5$. We therefore treat the four clusters as a practical segmentation for targeting.

Table 1. Cluster validity and stability (37 provinces)

k	Cluster sizes	Silhouette	Calinski–Harabasz	Davies–Bouldin	Minimum bootstrap Jaccard
2	30, 7	0.511	32.6	0.873	0.87
3	18, 12, 7	0.306	27.0	1.066	0.74
4	**18, 12, 5, 2**	**0.328**	**28.0**	**0.970**	**0.78**
5	12, 12, 6, 5, 2	0.336	28.9	0.950	0.72
6	12, 12, 6, 3, 2, 2	0.347	27.6	0.863	0.64

k	Cluster sizes	Silhouette	Calinski–Harabasz	Davies–Bouldin	Minimum bootstrap Jaccard
7	12, 12, 6, 3, 2, 1, 1	0.340	28.3	0.688	0.63
8	12, 7, 6, 5, 3, 2, 1, 1	0.307	28.7	0.763	0.63

4.2 Four segments and their priority order

Table 2. Profiles of the four segments (means over member provinces)

Tier	Provinces	Price vs. median (staples / horticulture / animal)	CV (staples / horticulture / animal)	Months above reference	CPPI	Jaccard
P1	Central Papua, South Papua	+19% / +50% / +33%	8.2 / 20.0 / 6.2%	87%	1.96	0.78
P2	Maluku, North Maluku, Papua, West Papua, Southwest Papua	+13% / +30% / +17%	3.4 / 9.7 / 6.3%	87%	1.42	0.85
P3	18 provinces in Sumatra, Kalimantan, Sulawesi, East Nusa Tenggara, Riau Islands, Bangka Belitung, and Jakarta	+1% / +2% / +2%	2.5 / 17.2 / 4.6%	54%	0.01	0.82
P4	Jambi, South Sumatra, Lampung, Banten, West Java, Central Java, Yogyakarta, East Java, Bali, West Nusa Tenggara, South Kalimantan, South Sulawesi	−5% / −12% / −5%	2.0 / 21.8 / 3.2%	26%	−0.93	0.94



Figure 1. Provincial food price segments (K-Means, $k = 4$), October 2024–January 2026

P4 has the lowest mean prices and the most stable staple and animal prices (Table 2, Figure 1), yet its chili prices are the most volatile of all segments (CV 36% for bird's eye chili and 28% for curly red chili). P3 sits near the national median, but sugar, premium rice, and garlic were above their reference prices in 94%, 86%, and 81% of months. In P2, prices of eggs, broiler meat, shallot, and bird's eye chili exceeded the single national HAP in 97–100% of months, while horticultural prices moved less than elsewhere. P1 has the highest prices, with bird's eye chili 67% and eggs 56% above the median, and the most volatile staples. In South

Papua, that staple volatility comes from soybean and salt. Sugar exceeded its HAP in at least 71% of months in every segment. Medium rice, which the main exceedance feature leaves out, was above the HET in force in 77% of months on average and in 63% in P4.

Mean CPPI values are 1.96 for P1, 1.42 for P2, 0.01 for P3 and −0.93 for P4. The order holds for every weight on exceedance up to 0.95; at full weight P2 edges ahead of P1. In the bootstrap, P1 and P4 provinces kept their tier in 98% and 100% of samples, P3 provinces in 81%, and P2 provinces in 77% (97% when both P1 provinces were drawn). In 17 of the 436 pairs of provinces from different tiers, the province in the lower-priority tier has the higher CPPI. Papua and Southwest Papua, for example, score above South Papua, and North Kalimantan (P3) scores above Maluku (P2). We place the 17 provinces in these pairs on a watch list.

4.3 Comparison with data outside the model

Table 3. Segments compared with production, food security, and program reach

Tier	Share of national output 2024 (paddy / maize / shallot)	IKP 2025	Regencies/cities with GPM 2025	FDP inter-provincial volume received, 2024–2026
P1	0.42% / 0.05% / 0.01%	47.8	38%	12 t (1 shipment, March 2024)
P2	0.28% / 0.14% / 0.08%	57.7	69%	290 t (10 shipments, all to Tual)
P3	18.9% / 22.3% / 15.3%	71.4	85%	227 t (41 shipments)
P4	80.4% / 77.5% / 84.6%	76.3	88%	382 t (39 shipments)

P4 produced about 80% of national paddy, maize, and shallot in 2024 (Table 3). The Food Security Index falls from P4 to P1 (Kruskal–Wallis $p < 0.001$). One of the IKP's 12 indicators measures price variation, so this check shares some information with the price data. GPM coverage also falls from P4 to P1. Across the four tiers the difference is not significant ($p = 0.064$), but P1–P2 had lower coverage than the other provinces (Mann–Whitney $p = 0.026$). Of the inter-provincial FDP volume (91 shipments, 911 t), 94% came from P4 provinces against 32% under random labels ($p = 0.007$). With the origins fixed, the share of volume going to higher-priority tiers was close to chance (55% vs. 53%, $p = 0.59$). However, this test relies on only a few destinations, because three provinces received 74% of the volume. Since October 2024, no shipment has reached P1, and Papua, West Papua, Southwest Papua, and North Maluku did not receive any shipment during the whole period.

4.4 Robustness

Ten of the 19 alternative runs reproduce the main partition (ARI 1.00), among them the run without the exceedance feature and the run with medium rice added. Two runs move only the line between P1 and P2. South Papua's soybean price jumped from about Rp8,500 to Rp14,400 in May 2025. When this series is removed, or when a 25-month window is used, South Papua joins P2, and the stability rule then selects $k = 3$ in the first case and $k = 2$ in the second. When staple volatility is dropped, P1 and P2 merge and P3 splits (ARI 0.71). In the other runs only border provinces move: North Kalimantan joins P2 in five runs (ARI 0.83–0.93), and West Nusa Tenggara, South Kalimantan, and West Sulawesi change tier when we drop a volatility feature (ARI 0.80–0.83). Overall, the high-price block (P1–P2), P3, and P4 remain stable across settings. P1 is a provisional sub-group of this block, and planners should recheck the watch-list provinces before allocating instruments. Removing the exceedance feature does not change the partition or the tier order. However, we keep it because it shows which commodities exceed their reference prices in each segment.

Discussion

Our results are consistent with earlier studies that used different data. As in Sumertajaya et al. [19], where Papua's districts spread over several price types, Papua's provinces in our results fall into two tiers. The cities in the separate Jayapura–Manokwari–North Maluku cluster

of Tsabitah et al. [11] belong to provinces that are grouped together in our P2. The stable staple and animal prices in P4 support the finding that food prices in Java are less volatile [14]. However, chili prices in P4 are volatile, which is in line with the strong volatility clustering in chili [13] and with the volatile producing clusters in China [17]. In our data, chili price swings are concentrated in the producing provinces, while the highest price levels are in Maluku–Papua. Our order therefore differs from that of Valentika et al. [12], who gave the highest monitoring priority to the cluster with the most volatile chili, while our CPPI measures consumer price pressure. Denny [10] kept ten clusters even though the study's own indices did not support that number. We chose k with a stability rule instead, although the result still depends on the threshold and on one soybean series. Table 4 lists the instruments we suggest for each tier.

Table 4. Stabilization instruments matched to the tiers

Tier	Main price problem	Instruments to prioritize
P1 (provisional)	Highest price level, unstable staples, and one FDP shipment	FDP destination priority with P4 origins, wider GPM coverage, and better price recording
P2	Persistent high level, with the single national HAP exceeded in 97–100% of months	FDP routes beyond Tual, sea logistics [15], and a zoned HAP for eggs, broiler meat, shallot, and bird's eye chili, as already set for garlic and sugar [8]
P3	Near-median level, with frequent exceedance for premium rice and garlic	Sales at the HAP by state food enterprises when garlic prices exceed it [8], SPHP operations [7], and monitoring of North Kalimantan
P4	Low level, volatile chili, and a production base	FDP origin role and upstream measures for chili and shallot in Java [13]

The FDP records bear most directly on policy. The program moves food out of the production base, as designed. Its shipments did not favor the provinces under the highest price pressure, even though the NFA describes FDP as a surplus-to-deficit transfer [7] and P1–P2 produce the least food. Novelan and Aryza [18] designed their routing model for a similar purpose, so that high-priority delivery areas are not passed over. The records do not say why shipments went where they did. They may follow requests from regional governments or existing transport links. Sugar and medium rice exceeded their reference prices in most months in every tier, which points to causes at the national level. Eggs, broiler meat, shallot, and bird's eye chili exceeded their single national HAP in 85–100% of months in P1–P2 against 8–56% elsewhere. The HAP takes distribution cost into account [8], and the NFA can review the egg and broiler HAP at any time [25]. With zoned values, exceedance in P2 could signal local stress.

The study period covers only 16 months. Provincial prices are simple means of district prices and hide differences inside large provinces. The reference-price mapping also rests on some assumptions. For example, soybean uses the HAP for imported soybean at tofu and tempe makers. We could not rank Highland Papua, and P1 depends on South Papua's incomplete series. With a mean silhouette of 0.33 at $k = 4$, the segments cut a continuous gradient and serve as a working partition. The external checks show associations and cannot establish causal effects.

Conclusion

We grouped 37 Indonesian provinces into four food price segments for October 2024–January 2026, using K-Means and a stability rule fixed before the final run (RQ1). Ranked by consumer price pressure, the segments run from the Maluku–Papua block (P1–P2), where prices sat 13–50% above the median and above reference prices in 87% of months, to twelve producing provinces centered on Java (P4). The order holds for exceedance weights up to 0.95. P1 and P4 provinces kept their tier in 98–100% of bootstrap samples and P2 and P3 provinces in 77–81%, and the line between P1 and P2 rests on South Papua (RQ2). The segments line up

with production and food security, P1–P2 had lower GPM coverage, and most inter-provincial FDP volume left P4 without favoring higher-priority destinations (RQ3).

For the NFA and regional governments, the results suggest three steps. FDP should give explicit destination priority to P1 and P2, whose seven provinces received FDP food in only two cities, Merauke and Tual, in 2024–2026. The single national HAP for eggs, broiler meat, shallot, and bird's eye chili could follow the zoning already used for garlic and sugar. For P4, which had the most volatile chili prices, we suggest supply-side instruments. Sugar and medium rice exceeded their references in most months in every tier, a pattern that regional targeting alone is unlikely to fix. These steps are in line with the government's 2029 target for price variation across regions, although we did not measure their effect. Future work can take the analysis down to regencies and cities and test the segments against household food insecurity.

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