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CROSS-VALIDATED SINGULAR SPECTRUM ANALYSIS FOR DECOMPOSING AND FORECASTING FARMERS' TERMS OF TRADE IN SOUTH SULAWESI

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Abstrak. Kebijakan seperti penentuan waktu pengadaan gabah di Sulawesi Selatan memerlukan ramalan Nilai Tukar Petani (NTP) yang memisahkan tren dari fluktuasi musiman panen. *Singular Spectrum Analysis* (SSA) mampu melakukan pemisahan ini tanpa asumsi model parametrik maupun stasioneritas, tetapi parameternya umumnya dipilih secara *trial and error* pada data yang juga dipakai untuk melaporkan akurasi. Penelitian ini menerapkan SSA rekuren berbasis tren pada NTP bulanan Sulawesi Selatan (2020–2025, 72 observasi BPS), memilih panjang jendela dan jumlah komponen melalui validasi silang *rolling-origin* pada data 2020–2024, dan mengujinya pada data 2025 terhadap metode naive, drift, *seasonal naive*, ETS, dan ARIMA. Model terpilih (panjang jendela 0,30 kali panjang deret, tiga komponen tren) memisahkan tren yang naik tajam pada 2023–2024 dan berbalik turun pada 2025 dari pola musiman kecil yang memuncak pada Februari dan terendah pada Juni, informasi yang tidak diberikan oleh metode naive, drift, dan ARIMA. MAPE SSA pada 2025 sebesar 2,71%, setara dengan metode pembanding (1,37–3,78%) meskipun tidak lebih baik daripada metode naive dan drift. Validasi silang juga menjaga akurasi yang dilaporkan tetap realistis: pemilihan parameter pada data 2025 akan melaporkan MAPE 1,16% untuk pengaturan yang MAPE validasi silangnya 33,44%. NTP diramalkan tetap di atas 100 pada 2026 (rata-rata tahunan 117,69). SSA dengan parameter hasil validasi silang menghasilkan dekomposisi yang dapat ditafsirkan dan ramalan yang kompetitif; parameternya perlu dipilih hanya pada data latih, dilaporkan bersama sensitivitasnya terhadap desain validasi, dan dibandingkan dengan metode sederhana.

Kata Kunci: **Nilai Tukar Petani, *Singular Spectrum Analysis*, Validasi Silang *Rolling-Origin*, Dekomposisi Deret Waktu, Sulawesi Selatan**

Abstract. Policies such as the timing of rice procurement in South Sulawesi need forecasts of the Farmers' Terms of Trade (NTP) that separate its trend from harvest-related seasonal swings. Singular Spectrum Analysis (SSA) makes this separation without assuming a parametric model or stationarity, but its parameters are usually tuned by trial and error on the data used to report accuracy. We applied trend-only recurrent SSA to the monthly NTP of South Sulawesi (2020–2025, 72 BPS observations), selected its window length and number of components by rolling-origin cross-validation within 2020–2024, and tested it on 2025 against naive, drift, seasonal naive, ETS, and ARIMA benchmarks. The selected model (window length 0.30 times the series length, three trend components) separated a trend that rose steeply in 2023–2024 and turned downward in 2025 from a small seasonal pattern that peaks in February and is lowest in June, information that the naive, drift, and ARIMA forecasts do not provide. Its 2025 MAPE of 2.71% was comparable to the benchmarks (1.37–3.78%), although the naive and drift forecasts were more accurate. Cross-validation also kept the reported accuracy realistic: choosing the parameters on the 2025 data would have reported a MAPE of 1.16% for a setting whose cross-validated MAPE was 33.44%. The NTP is projected to stay above 100 in 2026 (annual mean 117.69). SSA with cross-validated parameters thus offers an interpretable decomposition and competitive forecasts; its parameters should be chosen on training data only, reported with their sensitivity to the validation design, and compared with simple benchmarks.

Keywords: **Farmers' Terms of Trade, Singular Spectrum Analysis, Rolling-Origin Cross-Validation, Time Series Decomposition, South Sulawesi**

A. Introduction

Agriculture is a central sector of the economy of South Sulawesi Province, one of the main rice-producing regions of Indonesia. Statistics Indonesia (BPS) monitors the welfare of farm households through the Farmers' Terms of Trade (*Nilai Tukar Petani*, NTP), the ratio of

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the price index received by farmers to the price index paid by farmers, multiplied by 100. A value above 100 means that farm households have gained purchasing power relative to the base year, and studies of its determinants show that output prices drive most of its movements (Hamjaya et al., 2022; Widi, 2021). The NTP of South Sulawesi stayed slightly below 100 in 2020 and 2021, rose steeply in 2023 and 2024, peaked at 124.53 in February 2025, and fell back to about 119 by the end of 2025 (Badan Pusat Statistik Provinsi Sulawesi Selatan, 2026).

Forecasts of the NTP matter for policy in South Sulawesi. The government purchase price (HPP) for unhusked rice and its procurement act on farm-gate prices mainly during the harvest months (Badan Pangan Nasional, 2024), so policy makers need to know whether a fall in the NTP reflects the usual harvest season or a change in the trend. A series whose trend changed slope twice in six years also fits poorly into linear models that assume stationarity after differencing, such as the ARIMA-type models used in earlier NTP forecasts (Hasan & Djakaria, 2021). Singular Spectrum Analysis (SSA) can separate the trend from the seasonal pattern: this nonparametric technique splits a series into a slowly varying trend, oscillations, and noise without assuming a parametric model or stationarity, and it extends components that satisfy a linear recurrence relation into the future (Golyandina et al., 2001; Golyandina & Zhigljavsky, 2020). SSA has forecast European industrial production more accurately than ARIMA and Holt–Winters (Hassani et al., 2009), and in Indonesia it has been applied to rice production (Idrus et al., 2022), rice prices (Istiyanti et al., 2025), and the consumer price index of South Sulawesi (Satriani et al., 2020).

The window length L and the number of eigentriples r determine the result of SSA. Theoretical work recommends L close to half the series length for separability (Golyandina, 2010; Hassani et al., 2011) and relates the SSA forecast error to the window length and the signal dimension (Khan & Poskitt, 2017). Applied studies, however, usually fix L by a rule of thumb or by trial and error. The two SSA studies of the NTP illustrate this: Andhika et al. (2020) chose $L = 57$ by trial and error for the NTP of Bali, and Setyaningrum et al. (2023) set L to half the series length for the national NTP. When researchers compare the candidates on the hold-out period that later serves to report accuracy, the evaluation data take part in the choice and the reported accuracy becomes optimistic (Tashman, 2000). The research gap is that no SSA study of the NTP has yet selected its parameters without using the evaluation data, compared its forecasts with simple benchmarks, or measured how much test-set tuning inflates the reported accuracy.

The novelty of this study has two parts. Rolling-origin evaluation itself is a standard tool (Tashman, 2000; Hyndman & Athanasopoulos, 2021); what is new is its use to select the SSA parameters for the NTP and a measurement of how much tuning SSA on the test data overstates its accuracy. We also compare SSA with benchmark forecasts, examine how the selection depends on the validation design, describe the trend and seasonal components of the monthly NTP of South Sulawesi for 2020–2025, and forecast the index for 2026.

B. Research Methodology

1. Data

We used the monthly combined NTP of South Sulawesi Province from January 2020 to December 2025 ($N = 72$, base year 2018) published by BPS (Badan Pusat Statistik Provinsi Sulawesi Selatan, 2026). The series has no missing values, and the tsoutliers procedure of the *forecast* package, which flags unusually large residuals of a robust STL decomposition at its default threshold, found no outliers. The series covers the COVID-19 period of 2020–2021, which fell in the flat phase of the index; the noise component was not larger in 2020–2021 (standard deviation 0.29 points) than in 2022–2025 (0.51), so we kept these years. Observations from January 2020 to December 2024 (60 months) served to select the parameters, the 12

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observations of 2025 formed the test set, and all 72 observations served to estimate the final model for the 2026 forecast. Computations used R (R Core Team, 2024) with the *Rssa* (Golyandina & Korobeynikov, 2014) and *forecast* (Hyndman & Khandakar, 2008) packages.

2. Singular Spectrum Analysis

Basic SSA embeds the series $X = (x_1, \ldots, x_N)$ into the $L \times K$ trajectory matrix, with $K = N - L + 1$,

$$\mathbf{X} = \begin{bmatrix} x_1 & x_2 & \cdots & x_K \\ x_2 & x_3 & \cdots & x_{K+1} \\ \vdots & \vdots & \ddots & \vdots \\ x_L & x_{L+1} & \cdots & x_N \end{bmatrix} \quad (1)$$

and decomposes it by singular value decomposition into elementary matrices $\mathbf{X} = \mathbf{X}_1 + \ldots + \mathbf{X}_d$. Each component is an eigentriple $(\sqrt{\lambda_i}, U_i, V_i)$, where λ_i and U_i are the eigenvalues and eigenvectors of $\mathbf{X}\mathbf{X}^T$. We grouped the eigentriples into trend, seasonal, and noise components and turned each group back into a time series by diagonal averaging (Golyandina et al., 2001). We based the grouping on the singular values, the dominant period of each component, paired eigenvector plots, and the weighted correlation (w-correlation)

$$\rho_{12}^{(w)} = \frac{\left(F^{(1)}, F^{(2)}\right)_w}{\|F^{(1)}\|_w \, \|F^{(2)}\|_w}, \qquad \left(F^{(1)}, F^{(2)}\right)_w = \sum_{i=1}^{N} w_i \, f_i^{(1)} f_i^{(2)} \quad (2)$$

where $w_i = \min(i, L, N - i + 1)$. Values near zero indicate well-separated components (Hassani, 2007). Forecasts followed the recurrent SSA algorithm, which extends the reconstructed signal of the first r eigentriples with a linear recurrence relation (Golyandina & Zhigljavsky, 2020),

$$\hat{y}_{N+h} = \sum_{j=1}^{L-1} a_j \, \hat{y}_{N+h-j}, \qquad h = 1, \ldots, 12 \quad (3)$$

where a_j are coefficients derived from the eigenvectors of the signal group. We computed vector SSA forecasts for comparison. Prediction intervals for 2026 came from the bootstrap of *Rssa* with 1,000 replications (Golyandina et al., 2018): it resamples the reconstruction residuals, which it assumes to be stationary and independent, adds them to the reconstructed signal, forecasts each simulated series, and takes quantiles of the simulated forecasts. We checked the empirical coverage of these intervals on the 2025 test data.

3. Parameter Selection and Evaluation

We expressed the window length as a proportion of the series length, $L = \text{round}(\rho N)$, with $\rho \in \{0.25, 0.30, \ldots, 0.50\}$ and $2 \le L \le \lfloor N/2 \rfloor$, since L and K yield the same decomposition (Golyandina et al., 2001); a proportion keeps the setting comparable across training series of different lengths (Golyandina, 2010). The number of leading eigentriples for forecasting was $r \in \{1, \ldots, 6\}$. Before seeing the test data, we fixed a rolling-origin design within 2020–2024 (Hyndman & Athanasopoulos, 2021; Tashman, 2000) with five origins, from December 2022 to December 2023 in steps of three months. At each origin we fitted the model to the data up to that month, compared a 12-month forecast with the observed values, and selected the combination with the lowest mean MAPE. The shortest training window has 36 months, which gives window lengths from 9 ($\rho = 0.25$) to 18 ($\rho = 0.50$) at the first origin.

To check the robustness of this choice, we repeated the selection with 13 monthly origins (December 2022 to December 2023), compared the two best candidates with the Diebold–Mariano test (Diebold & Mariano, 1995), and evaluated candidate sets that keep harmonic pairs together, {1–3}, {1–5}, and {1–7}, because the first four eigentriples split the 12-month pair. To measure what cross-validation contributes, we also evaluated the 36 combinations on the 2025 test data, as a trial-and-error search would. We compared SSA with five benchmarks under the same schemes: the naive (random walk) forecast, the random walk with drift, the seasonal

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naive forecast, ETS, and automatic ARIMA (Hyndman & Khandakar, 2008). We measured accuracy with the MAE, the RMSE, the mean absolute scaled error (MASE), which scales the MAE by the in-sample MAE of the naive forecast (Hyndman & Koehler, 2006), and

$$\text{MAPE} = \frac{100\%}{n}\sum_{t=1}^{n}\left|\frac{y_t-\hat{y}_t}{y_t}\right| \quad (4)$$

where y_t is the observed value, $\hat{y}_t$ the forecast, and $n = 12$.

C. Results and Discussion

1. Characteristics of the NTP and Parameter Selection

The NTP had a mean of 107.23 and a standard deviation of 9.84 over 2020–2025. The annual mean rose from 96.97 in 2020 to 117.87 in 2024 and 121.67 in 2025, with the fastest growth in 2023 (7.49%) and 2024 (9.23%). The augmented Dickey–Fuller test did not reject a unit root ($p = 0.677$) and the KPSS test rejected trend stationarity ($p < 0.01$). Because SSA does not require stationarity, we decomposed the series without differencing.

Table 1 lists the five combinations with the lowest mean cross-validated MAPE in the pre-specified design. The best, $\rho = 0.30$ and $r = 3$, had a mean MAPE of 5.01%, and the runner-up, $\rho = 0.25$ and $r = 5$, had 5.05% with a smaller standard deviation. The two did not differ significantly (Diebold–Mariano test over 13 monthly origins, $p = 0.13$). The selection was also sensitive to the validation design. With 13 monthly origins, $\rho = 0.25$ and $r = 5$ ranked first (5.71%) and the five-origin choice ranked 11th (7.82%), and with pair-respecting sets the lowest mean MAPE came from $\rho = 0.25$ and eigentriples 1–7 (4.76%). We kept the pre-specified choice, because changing the design after seeing these results would itself be a form of tuning, and we report the alternatives. Every combination with $r = 4$ had a mean MAPE above 15%; this reflects the split of the 12-month pair rather than a property of the series. Candidates that include the seasonal pair were competitive in cross-validation but gave larger errors on the 2025 test data (7.04% for $\rho = 0.25$, $r = 5$, and 8.09% for eigentriples 1–7), so the evidence that the seasonal component improves the forecasts is weak, and we forecast with the trend only. With $\rho = 0.30$, $L = 18$ for the 60-month training series and $L = 22$ for the full series.

Table 1 Five best combinations in rolling-origin cross-validation (five origins)

Rank	ρ	*r*	*L* (*N* = 60)	Mean MAPE (%)	SD (%)
1	**0.30**	**3**	**18**	**5.01**	**3.05**
2	0.25	5	15	5.05	1.59
3	0.25	3	15	6.04	3.18
4	0.25	2	15	6.11	4.87
5	0.25	6	15	6.13	2.94

Note: Mean and standard deviation (SD) of the MAPE over five forecast origins, 12-month horizon.

2. Decomposition into Trend, Seasonal, and Noise Components

Because SSA was applied to the uncentred series, the first eigentriple represents the mean level and carries 99.95% of the squared norm; Table 2 therefore reports the shares of the remaining eigentriples. Around the mean, the reconstructed trend accounts for 99.51% of the variance of the series, the seasonal component for 0.58%, and the noise for 0.21%. Eigentriples 2 and 3 have periods of 36 and 18 months, longer than the window length ($L = 22$) and comparable to the series length. They vary slowly and do not complete a cycle within the window, so we treat them, following the usual SSA convention for slowly varying components (Golyandina & Zhigljavsky, 2020), as part of the trend that describes its acceleration in 2023–2024 and its reversal in 2025. Eigentriples 4–5 (about 12 months) and 6–7 (about six months) appear as pairs in the singular values and as dark blocks in the w-correlation matrix (Figure 1). The pair 6–7 is clean (singular value ratio 1.04, w-correlation 0.93), whereas the pair 4–5 is

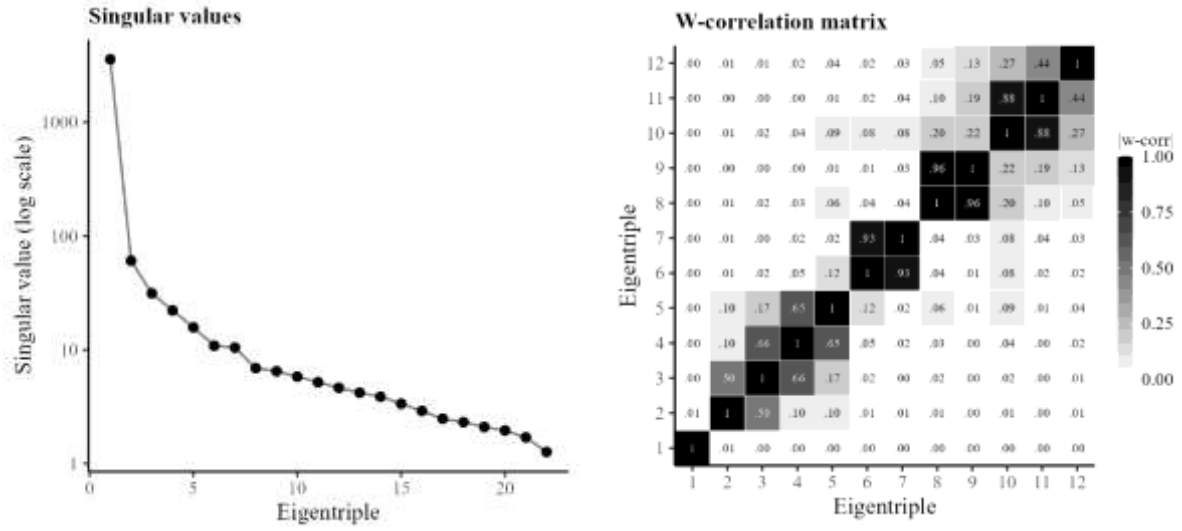
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imperfect (ratio 1.41) because the series contains only six annual cycles and the seasonal amplitude changed over time. Eigentriples 8 and 9 form a pair with a period of 3.8 months that was unstable across window lengths, so we assigned them to noise together with the remaining eigentriples. The w-correlation was 0.004 between the trend and the seasonal group and 0.061 between the seasonal group and noise, and the same grouping held with $L = 20$ and $L = 24$.

Table 2 Leading eigentriples of the SSA decomposition ($N = 72, L = 22$)

Eigentriple	Singular value	Share excl. ET1 (%)	Period (months)	Group
1	3578.925	–	72.0	Trend (level)
2	60.747	62.70	36.0	Trend
3	31.338	16.69	18.0	Trend
4	22.151	8.34	14.4	Seasonal
5	15.717	4.20	12.0	Seasonal
6	10.853	2.00	5.5	Seasonal
7	10.462	1.86	5.5	Seasonal
8	6.902	0.81	3.8	Noise

Note: Shares are $\lambda_i/\Sigma_{j\geq 2}\lambda_j$. Eigentriples 9–22 were assigned to noise.



(a) (b)

Figure 1 Singular values (a) and w-correlation matrix of eigentriples 1–12 (b)

Figure 2 shows the reconstructed components. The trend rises from 96.51 in early 2020 to 122.60 in the second quarter of 2025 and then turns downward. The seasonal component is small: its range is about 15% of the range of the trend, and its mean effect peaks in February (+0.93) and March (+0.78) and is lowest in June (−0.72) and July (−0.61). This timing is consistent with the rice calendar of South Sulawesi, in which farm-gate prices of unhusked rice tend to be high in the lean months before the main harvest and fall when the harvest raises local supply. Because the combined NTP also includes horticulture, plantations, livestock, and fisheries, this link remains a hypothesis that the food-crop subsector index could test. The seasonal amplitude grew from 0.84 points in 2020–2022 to 2.69 points in 2023–2025, but its timing stayed the same. The noise is consistent with normality (Shapiro–Wilk, $p = 0.459$) but retains autocorrelation (Ljung–Box, $p < 0.001$).

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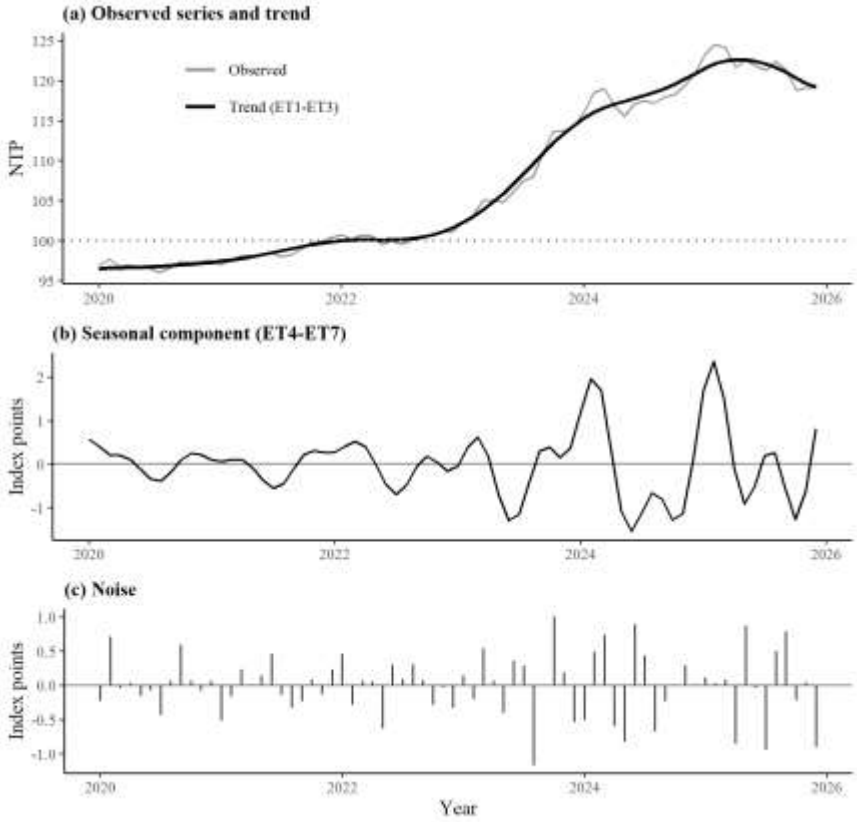


Figure 2 SSA reconstruction: observed series and trend (a), seasonal component (b), and noise (c)

3. Comparison with Benchmarks and with Trial-and-Error Selection

Estimated on 2020–2024 with $L = 18$ and three eigentriples, recurrent SSA forecast 2025 with a MAPE of 2.71% (MAE 3.30, RMSE 3.77), and vector SSA with 2.73%. Table 3 compares SSA with the benchmarks. SSA was more accurate than the seasonal naive, ETS, and ARIMA forecasts on the 2025 test data, but less accurate than the naive (1.37%) and drift (2.55%) forecasts; in cross-validation, the drift forecast had the lowest error under both designs. The NTP moves slowly, and its level in December 2024 (121.01) was close to most values of 2025, which favours the naive forecast. The recurrent SSA forecast was 5.3–6.3 points too low in January–March and 3.3–4.4 points too high in October–December (Figure 3a), because the model could not anticipate the peak of February 2025 and the decline that followed. Its bootstrap intervals were too narrow: only 3 of the 12 observed values fell inside the 80% and the 95% intervals, because the bootstrap treats the autocorrelated residuals as independent and the forecast omits the seasonal component.

Table 3 Forecast accuracy of SSA and benchmark methods

Method	CV MAPE, 5 origins (%)	CV MAPE, 13 origins (%)	Test MAPE 2025 (%)	Test MAE 2025	Test MASE 2025
SSA ($\rho = 0.30$, $r = 3$)	5.01	7.82	2.71	3.30	4.56
Naive	5.27	5.51	1.37	1.67	2.30
Random walk with drift	3.89	4.15	2.55	3.08	4.25
Seasonal naive	8.98	9.24	3.40	4.17	5.75
ETS	4.99	5.29	3.78	4.55	6.28
ARIMA	4.53	4.73	3.68	4.44	6.12

Note: CV = rolling-origin cross-validation within 2020–2024, 12-month horizon. MASE scales the MAE by the in-sample MAE of the one-step naive forecast.

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Table 4 compares the cross-validated choice with trial-and-error selection on the test data. On the 2025 data, the 36 SSA combinations had MAPE values from 1.16% to 25.19%, with a median of 5.36% and an interquartile range of 2.74–8.12%; a configuration chosen at random would give 7.25% on average. The lowest test MAPE, 1.16%, came from ρ = 0.40 (L = 24) with six eigentriples, less than half the error of the cross-validated model. The same configuration had a mean cross-validated MAPE of 33.44% over 2020–2024, the third-worst of all candidates, whereas the cross-validated choice ranked ninth on the test data. A study that tuned SSA in this way would report the minimum of 36 test errors, which lies far below the error a forecaster can expect for a year not yet observed.

Table 4 Cross-validated versus trial-and-error selection of the SSA parameters

Selection procedure	ρ	*r*	*L*	MAPE test 2025 (%)	Mean MAPE CV (%)	Rank (CV)
Rolling-origin CV	0.30	3	18	2.71	5.01	1
Trial and error on test data	0.40	6	24	1.16	33.44	34

Note: Rank (CV) is the position among the 36 candidates by mean cross-validated MAPE over 2020–2024 (five origins).

4. Forecast of the NTP for 2026

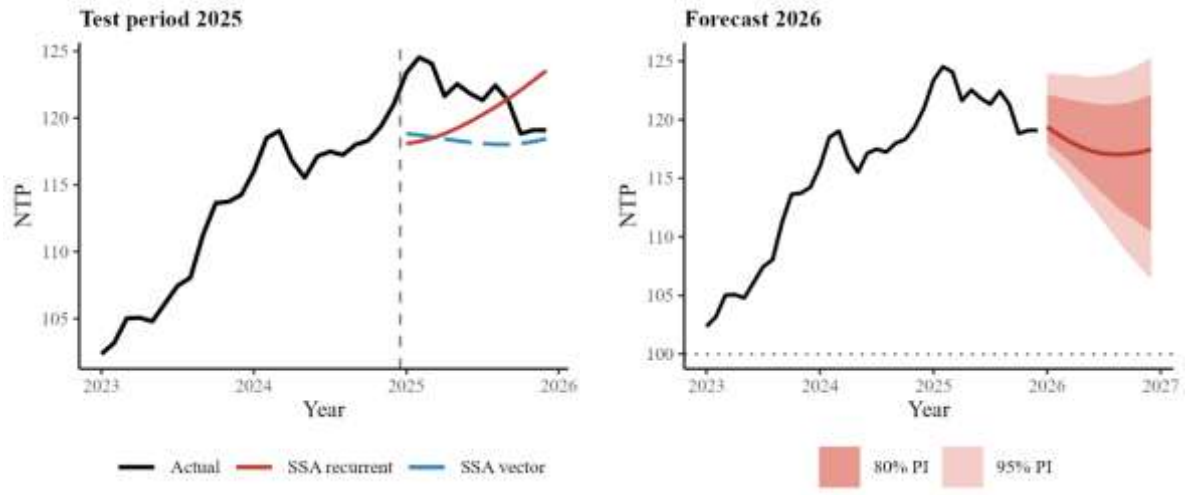
The final model, estimated from all data for 2020–2025 with L = 22 and eigentriples 1–3, projects the NTP to decline from 119.38 in January to 117.03 in August 2026 and to rise slightly to 117.47 in December, with an annual mean of 117.69, about 3.3% below 2025 (Table 5, Figure 3b). Once the reversal entered the data, the model followed it. All point forecasts and the lower 95% limits stay above 100, which suggests that the terms of trade of farmers in South Sulawesi will remain favourable in 2026, although the coverage check on 2025 shows that these intervals understate the true uncertainty. The forecast contains only the trend; the mean seasonal effect, between −0.72 and +0.93 points, is small next to the 26-point rise of the trend over 2020–2025. If the seasonal pattern persists, the observed NTP should lie slightly above the trend forecast in February–March and slightly below it in June–July, the months of the main rice harvest, when the procurement of unhusked rice at the HPP would matter most for farm-gate prices. We present this as a hypothesis consistent with the seasonal pattern rather than as a result of the forecasting model.

Table 5 SSA forecast of the NTP of South Sulawesi, January–December 2026

Month	Fcst	Lo 80	Hi 80	Lo 95	Hi 95	Month	Fcst	Lo 80	Hi 80	Lo 95	Hi 95
Jan	119.38	118.07	122.17	117.04	123.99	Jul	117.11	113.58	121.28	111.21	123.80
Feb	118.83	117.41	121.99	116.20	123.88	Aug	117.03	112.85	121.30	110.18	123.86
Mar	118.33	116.69	121.81	115.30	123.86	Sep	117.04	112.13	121.39	109.11	124.13
Apr	117.88	115.90	121.63	114.33	123.86	Oct	117.11	111.63	121.54	108.16	124.44
May	117.53	115.13	121.49	113.25	123.68	Nov	117.25	110.98	121.83	107.26	124.84
Jun	117.27	114.34	121.38	112.26	123.68	Dec	117.47	110.44	122.18	106.38	125.33

Note: Fcst = point forecast; Lo/Hi = limits of the 80% and 95% bootstrap prediction intervals (1,000 replications). On the 2025 test data these intervals covered 3 of 12 observed values.

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(a) (b)

Figure 3 Actual values and SSA forecasts for the 2025 test period (a), and SSA forecast for 2026 with 80% and 95% prediction intervals (b)

D. Conclusion

SSA separated the monthly NTP of South Sulawesi into a trend that rose steeply in 2023–2024 and turned downward in 2025 and a small seasonal component, with mean monthly effects between −0.72 and +0.93 points, that peaks in February–March and is lowest in June–July. Rolling-origin cross-validation over five origins selected a window length of 0.30 times the series length and three trend eigentriples, which forecast 2025 with a MAPE of 2.71%. This accuracy was comparable to that of standard benchmarks but not better than the naive and drift forecasts, and the selection among close candidates changed when we used monthly origins. Tuning on the test data would have reported a MAPE of 1.16% for a configuration with a cross-validated MAPE of 33.44%, against a median test MAPE of 5.36% for the 36 candidates. Researchers who forecast the NTP or similar BPS indices with SSA should therefore select the parameters on training data only, report the sensitivity of the choice to the validation design, and compare the forecasts with simple benchmarks. The NTP is forecast to remain above 100 in 2026, with an annual mean of 117.69. This study used only the combined index; future research could apply the procedure to the subsector indices, use block bootstrap intervals that respect the autocorrelation of the residuals, and test whether multivariate SSA with commodity prices helps to anticipate turning points such as the one in 2025.

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