FORECASTING CONSUMER PRICE INDEX EXPENDITURE INFLATION FOR FOOD INGREDIENTS USING SINGULAR SPECTRUM ANALYSIS

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ABSTRACT

Inflation is an economic problem that significantly impacts the macro economy and people's real income if it occurs continuously. South Sulawesi Province often experienced significant inflation fluctuations during 2005-2019. In 2015, inflation in South Sulawesi reached 3.32%, ranking the highest in Eastern Indonesia. Ten food ingredients played an essential role in influencing inflation that year. However, until now, research on forecasting Consumer Price Index expenditure inflation for food ingredients in South Sulawesi using the Singular Spectrum Analysis method has never been carried out. The novelty in this research lies in using the Singular Spectrum Analysis method, which provides a new contribution to forecasting inflation trends in South Sulawesi and deepens understanding of regional inflation problems. This research aims to forecast consumer price index expenditure inflation for food ingredients in South Sulawesi using the Singular Spectrum Analysis method. This research used CPI expenditure inflation data for food ingredients from the official website of the Central Statistics Agency of South Sulawesi for the monthly period from January 2014 - June 2022. The forecasting results show that the lowest inflation rate is predicted to occur in December 2022 at -0,12%, while the highest level is expected to be reached in May 2023 at 0.43%. Furthermore, the mean absolute percentage error value of 3.54% indicates that the forecasting model has a very good level of accuracy. The results of this forecasting have the potential to be used by economic policymakers in South Sulawesi in designing more effective policies to overcome the problem of inflation, especially in the food ingredients and its impact on society. The practical implications of this research can help improve regional economic stability and community welfare.

Keywords: Inflation, singular spectrum analysis, south sulawesi, consumer price index.

INTRODUCTION

Time series analysis is data analysis related to time taken at fixed intervals. This analysis aims to find data patterns that can be extrapolated to predict the future (Guo et al., 2020; Robial, 2018; Turri et al., 2022). Time series data patterns can be horizontal, seasonal, trend, or cyclical.

One method for forecasting seasonal data is Singular Spectrum Analysis (SSA), a powerful part of time series analysis. According to Al'afi et al. (2020), seasonal time series data uses the spectral analysis method or spectrum analysis Schuster introduced in the 19th century. This method is implemented in several fields, such as meteorology, oceanography, and astronomy. According to Kalteh (2017) and Lubis et al. (2017), SSA is more flexible because it implements a nonparametric approach that does not require assumptions such as normally distributed or independent residuals. SSA has two forecasting methods: recurrent and vector (Sitohang & Darmawan, 2018). In addition, the SSA method can be used for stationary and non-stationary data. The best model is selected based on the smallest Mean Absolute Percentage Error (MAPE) value.

MAPE is used as a basis for model selection because it is expressed in easy-to-interpret percentage form. MAPE can help in comparing error rates relative to predicted values. In addition, MAPE is more robust to the influence of outliers than other absolute error measures such as Mean Absolute Error (MAE).Inflation is defined as price changes characterized by increased prices of several goods or services households use (Batley & Dekker, 2019; Khatimi & Alkaff, 2017). Inflation occurs when the prices of most goods or services increase and continue to grow. The calculation of price increases and developments is called the Consumer Price Index (CPI). The percentage increase in CPI is inflation (Endrayani & Dewi, 2016). Inflation still occurs frequently and is still the focus of current government problems in Indonesia. South Sulawesi Province is rich in food ingredients and is one of the primary sources of food ingredients in Indonesia. Rice is one of the contributors to inflation in South Sulawesi over an annual period.

Research related to CPI forecasting in South Sulawesi using SSA has been carried out. Satriani and Ibnas (2020) state that the CPI in South Sulawesi (January 2020 – December 2020) experiences an increase with a MAPE value of 1.32%. However, this research only focuses on the CPI in general. Research on forecasting CPI expenditure inflation on food ingredients in South Sulawesi using the SSA method has not been conducted. South Sulawesi is an economic pioneer with the largest and most important supplier of food ingredients in eastern Indonesia (Jam'an et al., 2018). However, the high demand from people inside and outside South Sulawesi and even abroad, the amount of money in circulation, rising production costs, and foreign factors can cause inflation. Therefore, time series analysis is suitable to see the pattern of development and increase in CPI expenditure inflation in the food ingredients in South Sulawesi. The results can be an initial reference in controlling inflation, especially through government policy and determining the inflation rate target desired by the government. This research aims to obtain forecasting results and accuracy values for forecasting CPI expenditure inflation in the food ingredients in South Sulawesi using the SSA method.

METHOD

This research used data on CPI expenditure inflation for food ingredients from the official website of the Central Statistics Agency of South Sulawesi (https://sulsel.bps.go.id/). The monthly data was taken from January 2014 to June 2022, so 102 time series observations were used. The variable used was the CPI expenditure inflation value of food ingredients in South Sulawesi. CPI is an index that calculates changes in the periodic average price of a set of foods consumed by residents or households during a specific period.

Research Procedure

The procedure in this research consisted of several stages. The first was to collect data sources and information for research, such as basic information related to data on CPI food ingredients and SSA methods. Data completeness was also checked at this stage, remembering that the time series had to be complete before being analyzed using the SSA forecasting technique. The available data was then analyzed descriptively through time series plots and descriptive statistics to obtain initial information regarding the CPI time series data pattern. This analysis was very useful for determining further analysis using the SSA method. Next, the CPI data was applied to the SSA forecasting technique using the R library (Rssa) program. The results of the previous steps were then interpreted especially the forecast values.

Data Analysis Technique

The data analysis technique consisted of several stages: (1) Input data into R software; (2) Carry out two stages of decomposition: Embedding and forming a Singular Value Decomposition

(SVD); (3) Carry out two stages of reconstruction: grouping and diagonal averaging; (4) Forecast using the SSA method; and (5) Conclude. The following is a detailed explanation of the data analysis stages.

Singular Spectrum Analysis (SSA)

According to Lubis et al. (2017), SSA is more flexible because it implements a nonparametric approach that does not require assumptions such as normally distributed or independent residuals. The SSA method can combine classical time series, multivariate statistics, multivariate geometry, dynamic systems, and signal processing (Sakinah, 2019). In addition, the SSA method can be used for stationary and non-stationary data. SSA uses trial and error, which means trying various values or sizes of Window Length (L) within a specified range of $2 < L < \frac{N}{2}$. The best model is selected based on the smallest MAPE value. Darmawan (2016) states that the SSA method decomposes the original time series data into several small parts grouped into trend, seasonal, and noise components. The following explains decomposition and reconstruction as stages of this method.

1. Decomposition

Decomposition has two stages: Embedding and SVD. Window Length (L) is an essential parameter in the decomposition stage (Darmawan, 2016).

a) Embedding

The first step in decomposition is embedding. Embedding is the stage where the initial time series data is converted into a trajectory matrix ($\mathbf{T}_x$). Yundari (2019) states that the results of the embedding that forms the trajectory matrix are in the form of a Hankel matrix. The Hankel matrix has the characteristic that the slope of the diagonal is constant from left to right. According to Asrof (2017), the Window Length (L) value is determined first before entering the SSA stage. The trajectory matrix has $L \times K$ dimension. The L value is determined by checking through trial and error with the specified range of $2 < L < \frac{N}{2}$. Meanwhile, according to Sumarjaya et al. (2020), the equation of K is $K = N - L + 1$. The trajectory matrix can be written in equation (1).

$$\mathbf{T}_x=(\mathbf{T}_{i,j})_{LxK} = \begin{bmatrix} x_1 & x_2 & \cdots & x_K \\ x_2 & x_3 & \cdots & x_{K+1} \\ \vdots & \vdots & \ddots & \vdots \\ x_L & x_{L+1} & \cdots & x_N \end{bmatrix} 5 \tag{1}$$

b) Singular Value Decomposition (SVD)

Darmawan (2016) suggests that SVD is the second step in decomposition. The SVD application is similar to the principal component analysis method by reducing data components and dimensions. The result of the SVD is a singular value in the form of an *eigenvalue*, *eigenvector*, and principal component or *eigentriple* of the path matrix. SVD begins with determining the *eigenvalue* ($\lambda_1,\lambda_2,\ldots,\lambda_L$) of matrix **S**, as in equation (2).

$$\mathbf{S} = \mathbf{T}_x \mathbf{T}_x^{\mathrm{T}} \tag{2}$$

The SVD of the trajectory matrix is written as $\mathbf{T}_{xp} = T_{x1} + T_{x2} + \ldots + T_{xd}$, which is given in equation (3).

$$\mathbf{T}_{xp} = T_{x1} + T_{x2} + \ldots + T_{xd} \tag{3}$$

$$\mathbf{T}_{xp} = U_1\sqrt{\lambda_1}V_1^T + U_2\sqrt{\lambda_2}V_2^T + \ldots + U_d\sqrt{\lambda_d}V_d^T$$
$$\mathbf{T}_{xp} = \sum_{i=1}^{d} U_i\sqrt{\lambda_i}V_i^T$$

where,

U_i = *Eigenvector*
$\sqrt{\lambda_1}$ = *Singular Value*
V_i^T = Principal Component

2. Reconstruction

The reconstruction stage has two steps: grouping and diagonal averaging. The grouping effect becomes a parameter at the reconstruction stage. The reconstruction results bring the forecasting results closer to the actual data. After using the L benchmark to decompose the SVD results, it will give a new initial series that has been carefully sorted (Ischak et al., 2018).

a) Grouping

According to Darmawan (2016), the eigenvector is the basis for grouping. The trajectory matrix with $L \times K$ size from decomposition results will be grouped into trend, seasonal, and noise. Trend grouping is based on all the varying components that form the trend on the graph. If there are two eigentriples (eigenvector, singular value, and principal component) that are similar on the graph and are next to each other, then the eigentriples are grouped in the seasonal data pattern. The rest, for eigenvectors with random graphs and no similarity to other graphs, are grouped into noise data patterns (Angelaus, 2017).

b) Diagonal Averaging

Transforming the grouping results into a new series form according to the amount of data (N) is a form of stage in diagonal averaging. Obtaining the singular value of the separated components is the goal at this stage, which can be used for forecasting. A matrix F is produced at this stage, as in equation (4).

$$\mathbf{F} = \begin{bmatrix} f_{11} & f_{21} & \cdots & f_K \\ f_{12} & f_{22} & \cdots & f_{K+1} \\ \vdots & \vdots & \vdots & \vdots \\ f_L & f_{L+1} & \cdots & f_N \end{bmatrix} \tag{4}$$

Diagonal averaging is formulated in equation (5).

$$g_k = \begin{cases} \dfrac{1}{k}\sum_{m=1}^{k} f^*_{m,k-m-1} \text{ untuk } 1 \le k < L^* \\ \dfrac{1}{L^*-1}\sum_{m=1}^{L^*-1} f^*_{m,k-m+1} \text{ untuk } L^* \le k < K^*+1 \\ \dfrac{1}{N-k+1}\sum_{m=k-K+1}^{N-K^*+1} f^*_{m,k-m+1} \text{ untuk } K^*+1 \le k \le N \end{cases} \tag{5}$$

With $L^* = min\ (L, K)$ and $K^* = max\ (L, K)$

Singular Spectrum Analysis (SSA) Forecasting

Some forecasting methods in SSA are recurrent and vector. A method that is relatively easy and often applied is the recurrent method by Golyandina and Korobeynikov (2014), which refers to the "Linear Recurrent Formula (LRF) in polynomial form" as in Equation 6.

$$x_{i+d}=\sum_{k=1}^{d} r_k x_{i+d-k} \text{ untuk, } 1\leq i\leq N\text{-}d \tag{6}$$

Meanwhile, the SSA model to obtain estimated values can be written as in Equation 7 (Yundari, 2019):

$$\hat{y}_i=\hat{y}_i^T+\hat{y}_i^S, \text{ for } 1=0, 1, 2, 3,\ldots,n \tag{7}$$

where,

$\hat{y}_i$= forecasting assumption

$\hat{y}_i^T$= Trend assumption

$\hat{y}_i^S$= Seasonal assumption

The recurrent forecasting method is used. At this stage, diagonal averaging is used to obtain reconstruction and continuation using the Linear Recurrence Formula (LRF).

Mean Absolute Percentage Error (MAPE)

The prediction model's accuracy level can be obtained by comparing the predicted value with the actual value (initial data). The level of forecast accuracy is based on (MAPE) values. The lower the MAPE value, the more accurate the model is in predictions. The MAPE formula is given in Equation 8.

$$\text{MAPE} = \frac{\sum_{i=1}^{N}\left|\left(\frac{X_i-F_i}{X_i}\right)\times 100\%\right|}{N} \tag{8}$$

where,

X_i = actual data value

F_i = forecasting data value

N = quantity of data

RESULT AND DISCUSSION

Descriptive Analysis

A time series plot of CPI expenditure inflation data for food ingredients in South Sulawesi is presented in Figure 1.

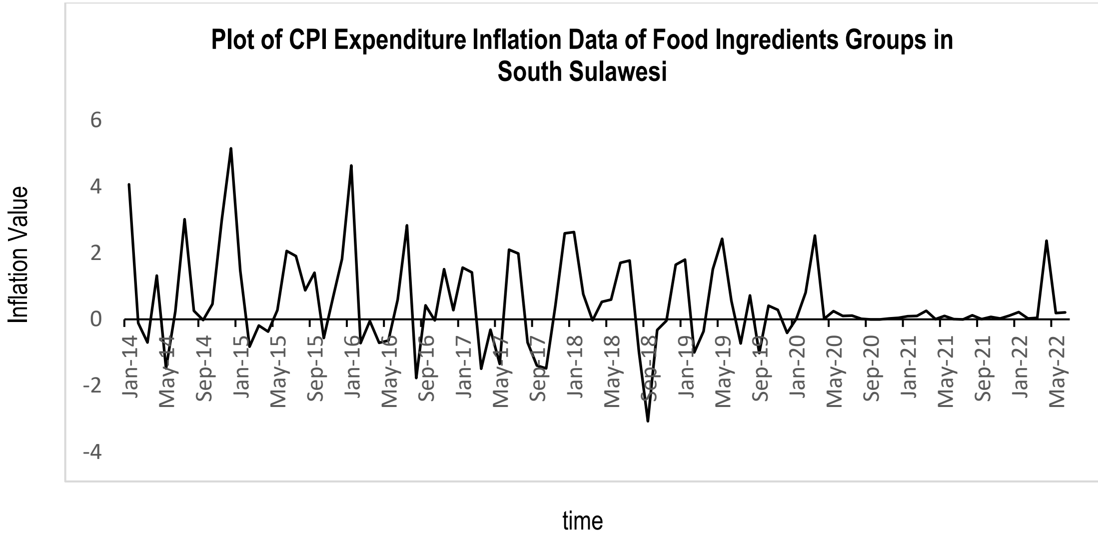


Figure 1. Plot of CPI Expenditure Inflation Data of Food Ingredients Groups in South Sulawesi in January 2014 – June 2022

From Figure 1, CPI expenditure inflation for food ingredients in South Sulawesi has fluctuated occasionally. There was an increase in inflation in December 2014, with a value of 5.15, and deflation in September 2018, with a value of -3.07. Analysis of the description of CPI expenditure inflation for food ingredients in South Sulawesi is presented in Table 1.

Table 1. Descriptive Analysis of CPI expenditure inflation for food ingredients in South Sulawesi

Variable	Min	Max	Mean	Standard Deviation
CPI expenditure inflation for food ingredients	-3,07	5,15	0,49	1,32

From January 2014 to June 2022, the average inflation value was 0.49, and the standard deviation was 1.32. The lowest inflation value or deflation was -3.07 in September 2018, and the highest in December 2014 was 5.15.

Singular Spectrum Analysis of CPI Expenditure Inflation for the Food Ingredient Group in South Sulawesi

1. Decomposition

Embedding and Singular Value Decomposition (SVD) are two stages in decomposition, which can be explained as follows:

a) Embedding

The results of the embedding that forms the trajectory matrix are in the form of a Hankel matrix. 102 time series observations were used, so the L value is within a specified range of $2 < L < 51$ (L value is in the range 3 – 50). Several L values were selected using trial and error with the following results: L=10 with MAPE 3.81; L=20 with MAPE 9.74; L=30 with MAPE 9.24; L=40 with MAPE 4.46; and L=50 with MAPE 4.78. Based on several L values tried, the value L=12 has the smallest MAPE value. For a value of L = 12, dimension K = (102 - L) +1 = 91 with a path matrix based on equation (1).

$$\mathbf{T}_x = \mathbf{T}_{i,j(12\text{x}91)} = \begin{bmatrix} 5{,}15 & 1{,}46 & \cdots & 0{,}21 \\ 2{,}98 & 5{,}15 & \cdots & 0{,}19 \\ \vdots & \vdots & \ddots & \vdots \\ 4{,}07 & -0{,}11 & \cdots & 0{,}01 \end{bmatrix}$$

b) Singular Value Decomposition (SVD)

The first step before getting the SVD value is to form a new matrix ($\mathbf{S}_{i,j}$) according to equation (2).

$$\mathbf{S}_{i,j(12\text{x}12)} = \begin{bmatrix} 165{,}21 & 57{,}66 & -7{,}64 & \cdots & 61{,}88 \\ 57{,}66 & 174{,}05 & 58{,}99 & \cdots & 27{,}90 \\ -7{,}64 & 58{,}99 & 174{,}23 & \cdots & -19{,}31 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ 61{,}88 & 27{,}90 & -19{,}31 & \cdots & 198{,}71 \end{bmatrix}$$

The next step is to create an SVD from the trajectory matrix. The SVD process will produce results in 12 eigentriples consisting of eigenvector, singular value, and principal component, respectively, in Table 2, 3, and 4.

Table 2. Eigenvector

	U_1	U_2	…	U_{12}
1	-0,45	0,11	…	-0,01
2	-0,14	0,40	…	-0,04
3	0,23	0,26	…	0,12
4	0,28	-0,16	…	-0,26
5	-0,02	-0,42	…	0,41
6	-0,39	-0,22	…	-0,44
7	-0,40	0,22	…	0,19
8	-0,24	0,41	…	0,11
9	0,29	0,15	…	-0,34
10	0,21	-0,26	…	0,43
11	-0,15	-0,40	…	-0,35
12	-0,39	-0,12	…	0,25

Table 3. Singular Value

i	λ_1	$\sqrt{\lambda_1}$
1	21,09	4,59
2	20,21	4,49
3	19,02	4,36
4	11,85	3,44
5	11,67	3,41
6	11,06	3,32
7	10,46	3,23
8	9,72	3,11
9	9,30	3,04
10	9,23	3,03
11	8,44	2,90
12	8,30	2,88

Table 4. Principal Component

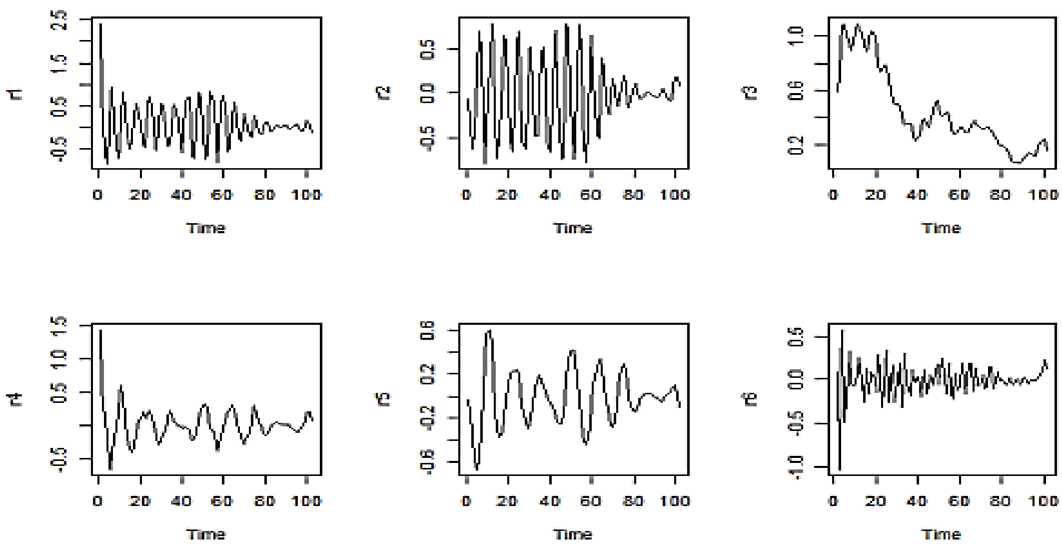
	V_1	V_2	…	V_{12}
1	-0,25	-0,02	…	-0,01
2	-0,08	-0,16	…	-0,11
3	0,08	-0,12	…	0,16
4	0,10	0,05	…	-0,13
5	0,01	0,19	…	0,04
6	-0,19	0,11	…	0,03
7	-0,23	-0,11	…	-0,08
8	-0,02	-0,21	…	0,07
9	0,11	-0,09	…	0,02
10	0,07	0,10	…	-0,01
11	-0,06	0,17	…	-0,05
⋮	⋮	⋮	⋮	⋮
91	0,01	-0,03	…	0,11

2. Reconstruction

Grouping and diagonal averaging are two stages of reconstruction.

a) Grouping

Eigentriple grouping at the SVD stage is the initial stage of grouping. Eigentriples with similar characteristics will be grouped into the same group or component. Grouping is carried out through analysis of the graph formed, which gives rise to an eigenvector graph, as in Figure 2.



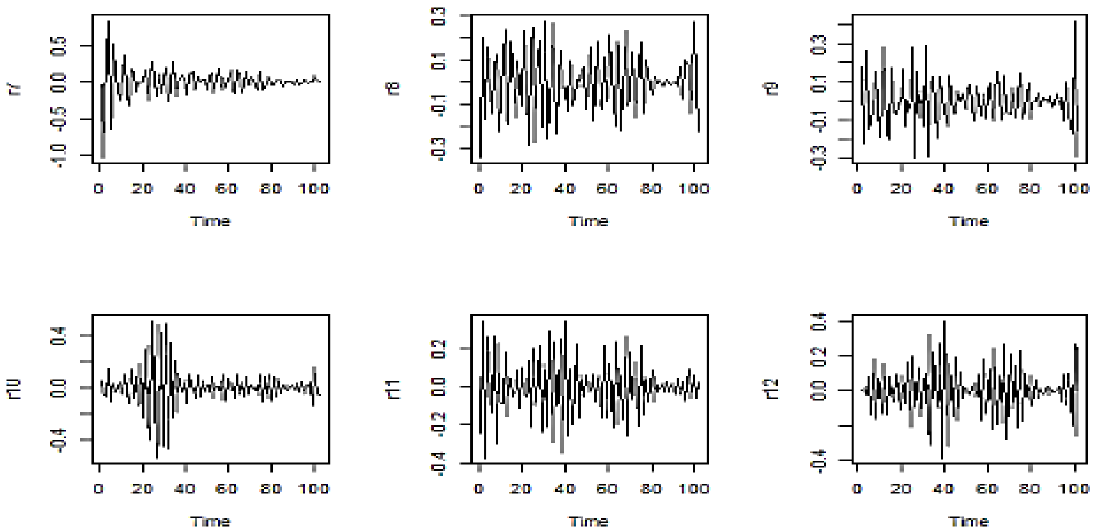


Figure 2. Eigenvector

The results are grouped into trend, seasonal, and noise. Based on Figure 2, eigenvector 3 forms a trend data pattern whose graph pattern continues to fall, as in Figure 3.

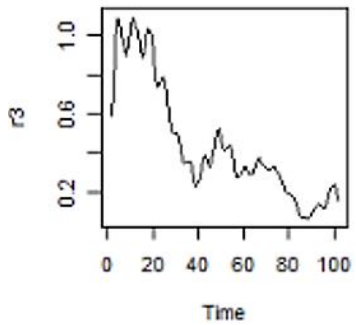


Figure 3. Trend

Eigenvectors 4, 5, 6, 7, 11, and 12 form graphic data patterns with similar graphs and are next to each other, so they are grouped into seasonal data patterns.

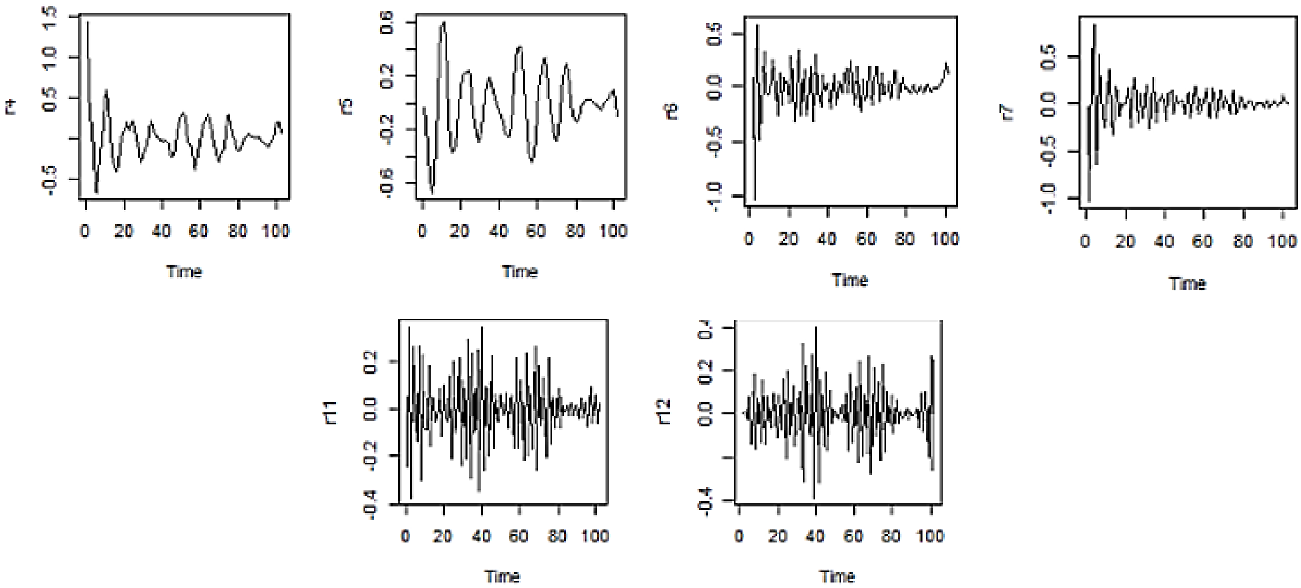


Figure 4. Seasonal

The rest, for eigenvectors with random graphs and no similarities with other graphs, are grouped into noise data patterns, as in Figure 5.

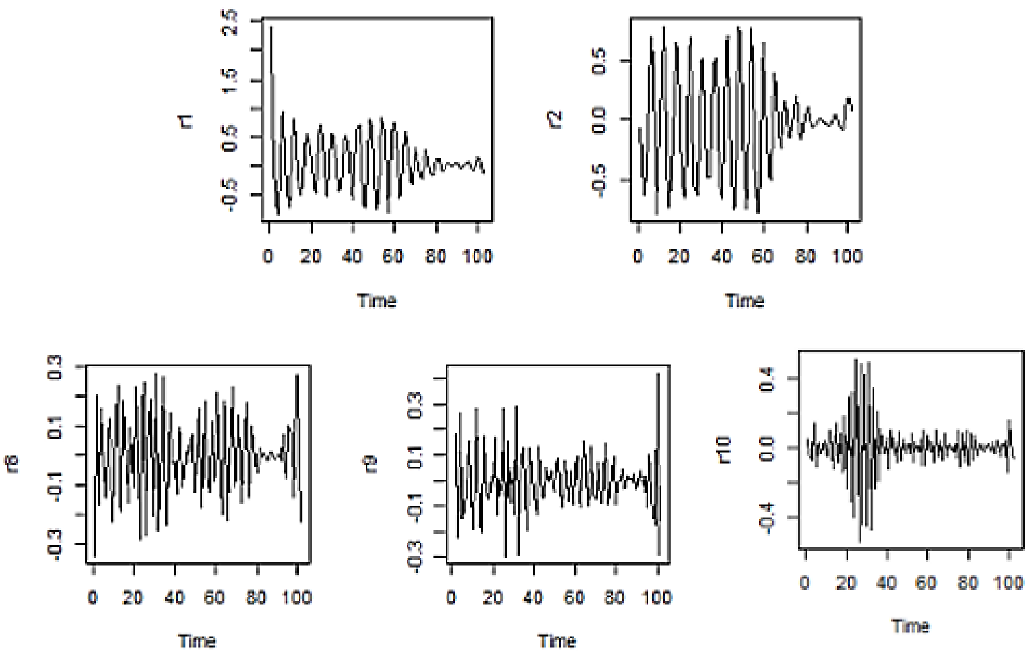


Figure 5. Noise

b) Diagonal Averaging

This stage produces a grouping that will be transformed into a new form. This stage produces components from the data. At this stage, obtaining singular values from the separated components and using them in forecasting is the goal. Diagonal averaging is obtained by calculation using equation (5), and the results are shown in Table 3.

Table 3. Diagonal Averaging Results

Nth Time	Reconstruction		Diagonal Averaging
	Trend	Seasonal	
1	0,59	1,22	1,81
2	0,71	-1,27	-0,56
3	0,92	-0,15	0,77
4	1,08	0,92	2,00
5	1,08	-2,37	-1,29
⋮	⋮	⋮	⋮
102	0,16	0,38	0,54

The next step is to forecast from a series of models formed by solving the time series data above using the recurrent forecasting method in SSA.

Singular Spectrum Analysis (SSA) Forecasting

In the final stage, SSA forecasting uses the recurrent method (R-forecasting). Forecasting is carried out for the subsequent 12 periods using equation (6).

Table 6. Results of Inflation Forecasting for Food Ingredients in South Sulawesi

Month	Forecast		Inflation Forecasting for Food Ingredients in South Sulawesi
	Trend Component	Seasonal Component	
July 22	0,23	0,00	0,23
Aug 22	0,22	-0,08	0,14
Sep 22	0,22	-0,13	0,09
Oct 22	0,21	-0,37	-0,16
Nov 22	0,20	-0,11	0,09
Dec 22	0,19	-0,31	-0,12
Jan 23	0,18	-0,12	0,06
Feb 23	0,18	0,09	0,27
Mar 23	0,18	-0,04	0,14
Apr 23	0,17	0,24	0,41
May 23	0,16	0,27	0,43
Jun 23	0,16	0,15	0,31

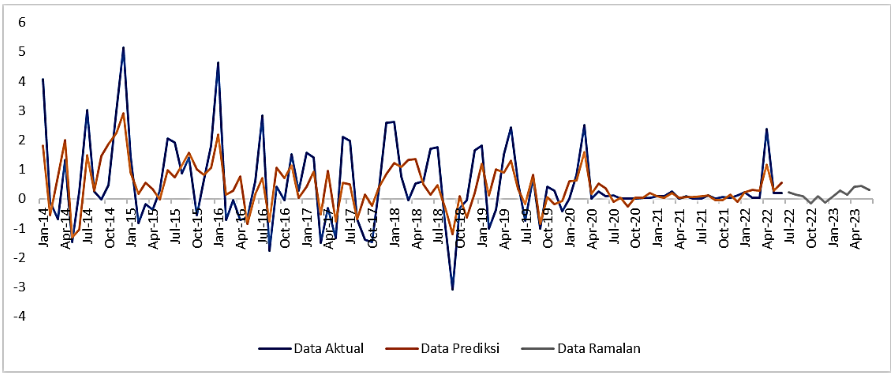


Figure 6. Comparison of Forecast and Actual Data

Figure 6 shows a forecast results graph, almost the same as the actual data graph. So, the magnitude of the error in forecasting is 3.54%, calculated using MAPE.

SSA is applied in various fields, such as medical engineering, hydrology, and economics (Wan et al., 2022). Forecasting consumer price index expenditure inflation in the food ingredients in South Sulawesi Province has been carried out using the SSA method. SSA has two forecasting methods: recurrent (R-forecasting) and vector (V-forecasting). The recurrent method is the basic method that is often used because it is relatively easier (Sitohang & Darmawan, 2018). The vector method is a modification of the recurrent method. The difference between R-forecasting and V-forecasting is that R-forecasting carries out direct continuation with the help of the Linear Recurrent Formula (LRF), while V-forecasting is related to L-continuation. This usually causes the approximate continuation to give different results (Jatmiko et al., 2017). This research uses a recurrent method (R-forecasting). The research results show that the forecasting model produced using the SSA method has a very good level of accuracy, as seen from the mean absolute percentage error value of 3.54%.

Some advantages of the Consumer Price Index expenditure inflation forecasting technique using the SSA method are that the SSA method is a robust time series analysis and forecasting tool (Golyandina & Korobeynikov, 2014). SSA allows the separation of inflation data into major components, such as trend, seasonal, and cyclical components. This helps to understand underlying inflation patterns and behaviour, which can help make more accurate forecasts. Inflation often has a seasonal component related to price changes at certain times of the year. The SSA method can help identify and model these seasonal components effectively (Wan et al., 2022).

The weakness of this research is that it only applies the recurrent method (R-forecasting) of the two forecasting methods in SSA, which can influence the forecasting results. Therefore, it is hoped that future research can use both forecasting methods in SSA and compare them.

CONCLUSION

From the results of forecasting using the SSA method on CPI expenditure inflation data for the food ingredients in South Sulawesi, the lowest inflation rate is predicted to occur in December 2022 at -0,12%, while the highest level is expected to be reached in May 2023 at 0.43%. The criteria for the model's goodness are based on the MAPE value. The MAPE value obtained is 3.54%, so the forecasting using the SSA method on CPI expenditure inflation for food ingredients in South Sulawesi has very good model accuracy. The results of this forecasting have the potential to be used by economic policymakers in South Sulawesi in designing more effective policies to overcome the problem of inflation, especially in the food ingredients, and its impact on society. The practical implications of this research can help improve regional economic stability and community welfare.

REFERENCES

Al'afi, A. M., Widiart, W., Kurniasari, D., & Usman, M. (2020). Peramalan Data Time Series Seasonal Menggunakan Metode Analisis Spektral. *Jurnal Siger Matematika*, *1*(1), 10–15. https://doi.org/10.23960/jsm.v1i1.2484

Angelaus, A. (2017). Forecasting the Amount of Foreign Tourist Travelers to Indonesia by Entrance Guide Using Singular Spectrum Analysis and Arima Forecasting the Amount of Foreign Tourist Travelers to Indonesia by Entrance Guide Using Singular Spectrum. Institut Teknologi Sepuluh November.

Asrof, A. (2017). Peramalan Produksi Cabai Merah di Jawa Barat Menggunakan Metode Singular Spectrum Analysis (SSA). *STATISTIKA: Journal of Theoretical Statistics and Its Applications*, *17*(2), 77–87. https://doi.org/10.29313/jstat.v17i2.2839

Batley, R., & Dekker, T. (2019). The Intuition Behind Income Effects of Price Changes in Discrete Choice Models, and a Simple Method for Measuring the Compensating Variation. *Environmental and Resource Economics*, *74*(1), 337–366. https://doi.org/10.1007/s10640-019-00321-2

Darmawan, G. (2016). Identifikasi Pola Data Curah Hujan pada Proses Grouping dalam Metode Singular Spectrum Analysis. *Seminar Nasional Pendidikan Matematika*, 1–7.

Endrayani, N. K. E., & Dewi, M. H. U. (2016). Analisis Faktor-Faktor yang Mempengaruhi Tingkat Kemiskinan Kabupaten/Kota di Provinsi Bali. *E-Jurnal Ekonomi dan Bisnis Universitas Undayana*, *5*(1), 63–88. https://ojs.unud.ac.id/index.php/EEB/article/download/17369/12362

Golyandina, N., & Korobeynikov, A. (2014). Basic Singular Spectrum Analysis and Forecasting with R. *Computational Statistics and Data Analysis*, *71*, 934–954. https://doi.org/10.1016/j.csda.2013.04.009

Guo, Y., Hu, S., Wu, W., Wang, Y., & Senthilnath, J. (2020). Multitemporal time series analysis using machine learning models for ground deformation in the Erhai region, China. *Environmental Monitoring and Assessment*, *192*(7). https://doi.org/10.1007/s10661-020-08426-8

Ischak, R., Asrof, A., & Darmawan, G. (2018). Peramalan Rata-Rata Harga Beras di Tingkat Penggilingan Menggunakan Model Singular Spectrum Analysis (SSA). *Seminar Nasional Matematika dan Pendidikan Matematika*, 57–64.

Jam'an, J., Mardiyati, S., & Ruliaty, R. (2018). Analisis Trend Produksi, Konsumsi, dan Harga Komoditas Pangan Strategis di Sulawesi Selatan. *Agrokompleks, 19*(1), 1-8. https://doi.org/10.51978/japp.v19i1.123

Jatmiko, Y. A., Rahayu, R. L., & Darmawan, G. (2017). Perbandingan Keakuratan Hasil Peramalan Produksi Bawang Merah Metode Holt-Winters dengan Singular Spectrum Analysis (Ssa). *Jurnal Matematika "MANTIK," 3*(1), 13. https://doi.org/10.15642/mantik.2017.3.1.13-24

Kalteh, A. M. (2017). Enhanced Monthly Precipitation Forecasting Using Artificial Neural Network and Singular Spectrum Analysis Conjunction Models. *INAE Letters*, *2*(3), 73–81. https://doi.org/10.1007/s41403-017-0025-9

Khatimi, H., & Alkaff, M. (2017). Penerapan Support Vector Regression (SVR) untuk Peramalan Inflasi Bulanan Nasional. *Jurnal Teknologi Informasi Universitas Lambung Mangkurat (JTIULM), 2*(2), 29–34. https://doi.org/10.20527/jtiulm.v2i2.21

Lubis, D. A., Johra, M. B., & Darmawan, G. (2017). Peramalan Indeks Harga Konsumen dengan

Metode Singular Spectral Analysis (SSA) dan Seasonal Autoregressive Integrated Moving Average (SARIMA). *Jurnal Matematika "MANTIK,"* *3*(2), 74–82. https://doi.org/10.15642/mantik.2017.3.2.74-82
Robial, S. M. (2018). Perbandingan Model Statistik pada Analisis Metode Peramalan Time Series (Studi Kasus: PT. Telekomunikasi Indonesia, Tbk Kandatel Sukabumi). *Jurnal Ilmiah SANTIKA*, *8*(2), 1–17. https://doi.org/10.37150/jsa.v8i2.400
Sakinah, A. M. (2019). Akurasi Peramalan Long Horizon dengan Singular Spectrum Analysis. *Kubik: Jurnal Publikasi Ilmiah Matematika*, *3*(2), 93–99. https://doi.org/10.15575/kubik.v3i2.4111
Satriani, S., & Ibnas, R. (2020). Peramalan Indeks Harga Konsumen (IHK) di Sulawesi Selatan dengan Menggunakan Metode Singular Spektrum Analysis (SSA). *Jurnal MSA (Matematika dan Statistika Serta Aplikasinya)*, *8*(1), 82-89. https://doi.org/10.24252/msa.v8i1.17441
Sitohang, Y. O., & Darmawan, G. (2018). Perbandingan Akurasi Recurrent Forecasting dan Vector Forecasting pada Metode Singular Spectrum Analysis dalam Peramalan Jumlah Wisatawan Mancanegara yang Masuk Melalui Bandara Ngurah Rai Bali Tahun 2017. *Euclid*, *5*(1), 125-135. https://doi.org/10.33603/e.v5i1.382
Sumarjaya, I. W., Ayu, I. G., & Srinadi, M. (2020). Peramalan Nilai Tukar Petani Menggunakan Metode Singular Spectrum Analysis. *E-Jurnal Matematika, 9*(3), 171–176. https://doi.org/10.24843/MTK.2020.v09.i03.p295
Turri, J. A. O., Anokye, N. K., dos Santos, L. L., Júnior, J. M. S., Baracat, E. C., Santo, M. A., & Sarti, F. M. (2022). Correction to: Impacts of Bariatric Surgery in Health Outcomes and Health Care Costs in Brazil: Interrupted Time Series Analysis of Multi-Panel Data. *BMC Health Services Research*, *22*(83). https://doi.org/10.1186/s12913-022-07486-5
Wan, L., Gao, Q., Deng, Y., Ke, Y., Ma, E., Yang, H., Lin, H., Li, H., Yang, Y., Gong, J., Li, J., Xu, Y., Liu, J., Li, J., Liu, J., Zhang, X., Huang, L., Feng, J., Zhang, Y., … Zhong, H. (2022). GP73 is a Glucogenic Hormone Contributing to SARS-CoV-2-induced Hyperglycemia. *Nature Metabolism, 4*(1), 29-43. https://doi.org/10.1038/s42255-021-00508-2
Yundari, A. W. H. (2019). Prediksi Outflow Uang Kartal di Kalimantan Barat dengan Metode Singular Spectrum Analysis (SSA). *Bimaster : Buletin Ilmiah Matematika, Statistika Dan Terapannya*, *8*(3), 545–554. https://doi.org/10.26418/bbimst.v8i3.33903