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APPLICATION OF THE GENERALIZED SPACE TIME AUTOREGRESSIVE (GSTAR) METHOD IN FORECASTING THE CONSUMER PRICE INDEX IN FIVE CITIES OF SOUTH SULAWESI PROVINCE

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ABSTRACT

Changes in the Consumer Price Index (CPI) over time reflect the rate of increase (inflation) or decrease (deflation) of goods and services for daily household needs. The CPI and inflation serve as barometers for economic growth stability, as controlled inflation can increase people's purchasing power over time. According to the Central Statistics Agency (2023), in December, the year-on-year (y-o-y) inflation for five cities in South Sulawesi (Bulukumba, Watampone, Makassar, Parepare, and Palopo) was 2.81 percent, with a CPI of 117.35. Of the five cities, the highest y-o-y inflation occurred in Makassar at 2.89 percent, with a CPI of 117.49, while the lowest y-o-y inflation occurred in Palopo at 2.21 percent, with a CPI of 115.60. CPI forecasting is one way to predict future inflation values. This study aims to develop the best GSTAR model for forecasting CPI data for five cities in South Sulawesi, a topic that has not been extensively covered in previous research. The goal is to provide valuable information for maintaining CPI stability in South Sulawesi and to support the formulation of better economic policies. The study focuses on five cities within South Sulawesi, where direct relationships between cities are possible, allowing the spatial model to be limited to the first-order. The data used in this study consists of monthly CPI data from January 2014 to March 2023. The location weights used in the model include uniform weights, inverse distances, and normalized cross-correlations. The model development steps include testing for data stationarity, determining the space-time sequence, calculating location weights, estimating parameters, testing model adequacy, comparing Root Mean Square Error (RMSE), and selecting the best model for forecasting. The best GSTAR model found is GSTAR (1;1)-I(2) with inverse distance weighting, which yielded the smallest RMSE value. The results show that the forecasted values closely match the actual values for each city from March to September 2023.

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1. INTRODUCTION

Forecasting is a technique for estimating a value in the future by taking into account the past and current [1]. Forecasting predicts the future quantitatively and qualitatively based on relevant data from the past [2]. One of the most developed forecasting methods currently is the time series. A time series is a sequence of observations made sequentially in time [3].

Time Series model can not only be used for data with one variable (univariate), but also be used for data with many variables (multivariate) [4]. Unlike the univariate time series, which only discusses time, the multivariate time series also discusses space, a concept known as the space time model [5][6]. Pfeifer and Deutsch first introduced the space time model, also known as the Space Time Autoregressive (STAR) model.

STAR is a multivariate Time series method that involves time and location elements with uniform location characteristics [7]. The STAR model produces constant parameter values for all locations, making it more applicable to homogeneous locations and less suitable for heterogeneous locations [8] [9]. Therefore, this model was then refined through a model that tends to be more flexible in determining its parameters, known as Generalized Space time Autoregressive (GSTAR). In the GSTAR model, Autoregressive parameter values vary between locations with the assumption that location characteristics are heterogeneous [10].

Previous researchers, such as [11], used the GSTAR model to predict inflation on the island of Java using a uniform location weighting matrix, resulting in the best GSTAR model (1:1). Researchers [12] used normalized cross-correlation and inverse distance location weights to forecast farmer exchange rates in three provinces on the island of Sumatra. This research yielded the best model, the GSTAR (1;1)-I(1) model with normalized cross- correlation weights. Another study was conducted by [13], which involved modeling the inflation value on Sulawesi Island using an inverse distance weighting matrix, resulting in the creation of the GSTAR (1;1)-I(1) model.

Inflation, an economic problem and a phenomenon of monetary policy, is a persistent concern for countries such as Indonesia [14]. Inflation is a persistent tendency to increase the prices of goods and services in general [15]. Spatial aspects influence the rise and fall of inflation between regions, making regional influence study material for predicting inflation values. In addition to spatial influences, past inflation tends to shape inflation values. From these two perspectives, we can assert that the information about inflation is a product of space and time [16]. If domestic prices of goods and services increase, then inflation will increase.

One indicator for determining inflation is the Consumer Price Index (CPI). The Consumer Price Index (CPI) is an index that determines the average price change over a specific period, based on a collection of goods and services that residents or households have consumed. The public generally consumes a group of goods or services, and the CPI calculation aims to determine changes in their prices [17]. The CPI and inflation serve as a barometer for the stability of economic growth, as controlled inflation ensures an increase in people's purchasing power over time. According to the Central Statistics Agency (2023), in December there was a combined year-on-year (y-on-y) inflation for five cities in South Sulawesi (Bulukumba, Watampone, Makassar, Parepare, and Palopo) of 2.81 percent with the Consumer Price Index amounting to 117.35. Of the five CPI cities in South Sulawesi, the highest (y-on-y) inflation occurred in Makassar at 2.89 percent, with a CPI of 117.49. Meanwhile, the lowest inflation (y-on-y) occurred in Palopo at 2.21 percent, with a CPI of 115.60 [18].

An increase in the CPI can lead to a rise in the inflation rate. Therefore, we need information that accurately describes the state of inflation based on the CPI. Estimating the CPI figures for several future periods or forecasts is one possible solution. We expect CPI forecasting to provide relevant information to predict future inflation, thereby aiding in the formulation of more effective policies [19]. Based on this, the author forecasted CPI data in five cities in South Sulawesi Province: Bulukumba, Makassar, Palopo, Watampone, and Parepare. This was done because no previous research had previously applied the GSTAR model to forecast CPI data in these cities in South Sulawesi Province. This is important for formulating more appropriate and effective economic policies for regions with different characteristics in South Sulawesi.

2. RESEARCH METHODS

2.1 Generalized Space Time Autoregressive Model

The Generalized Space Time Autoregressive (GSTAR) model is an extension or development of the Space Time Autoregressive (STAR) model. The STAR model has constant parameter values everywhere, but the GSTAR model has variable autoregressive (AR) parameter values between locations in the form of a weighting matrix, which makes it easier to use in a wider range of places [10]. Equation (1) illustrates how to write the GSTAR model using $(\rho; \lambda_1, \lambda_2, \lambda_3, \dots, \lambda_k)$.

$$z_i(t) = \sum_{k=1}^{p} \sum_{i=1} \left| \phi_{k0}^{(i)} Z_i(t-k) + \sum_{i=1}^{\lambda k} \phi_{kl}^{(i)} W^{(l)} Z_i(t-k) \right| + e(t) \tag{1}$$

where $\phi_{k0}^{(i)}$ is a diagonal matrix autoregressive parameter $\phi_{k0}^{(1)}, \dots, \phi_{k0}^{(N)}$ and same goes to $\phi_{kl}^{(i)}$, $W^{(l)}$ is a weight matrix, $e(t)$ is the matrix residuals in GSTAR model. From Equation (1), if we make it in matrix notation, we get Equation (2).

$$\begin{bmatrix} Z_{1(t)} \\ Z_{2(t)} \\ \vdots \\ Z_{N(t)} \end{bmatrix} = \begin{bmatrix} \phi_{k0}^{(1)} & 0 & \cdots & 0 \\ 0 & \phi_{k0}^{(2)} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \phi_{k0}^{(N)} \end{bmatrix} \begin{bmatrix} Z_{1(t-k)} \\ Z_{2(t-k)} \\ \vdots \\ Z_{N(t-k)} \end{bmatrix} +$$

$$\begin{bmatrix} \phi_{kl}^{(1)} & 0 & \cdots & 0 \\ 0 & \phi_{kl}^{(2)} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \phi_{kl}^{(N)} \end{bmatrix} \begin{bmatrix} 0 & W_{12} & \cdots & W_{1N} \\ W_{21} & 0 & \cdots & W_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ W_{N1} & W_{N2} & \cdots & 0 \end{bmatrix} \begin{bmatrix} Z_{1(t-k)} \\ Z_{2(t-k)} \\ \vdots \\ Z_{N(t-k)} \end{bmatrix} + \begin{bmatrix} e_{1(t)} \\ e_{2(t)} \\ \vdots \\ e_{N(t)} \end{bmatrix} \tag{2}$$

For example, in general the GSTAR model in Equation (2) with time order 1 and spatial order 1 at different locations or GSTAR (1;1) can be expressed in Equation (3).

$$Z_i(t) = \phi_{10} Z_i(t-1) + \phi_{11} w Z_i(t-1) + e(t) \tag{3}$$

For example, there are five locations. then we get Equation (4).

$$\begin{bmatrix} Z_1(t) \\ Z_2(t) \\ Z_3(t) \\ Z_4(t) \\ Z_5(t) \end{bmatrix} = \begin{bmatrix} \phi_{10}^1 & 0 & 0 & 0 & 0 \\ 0 & \phi_{10}^2 & 0 & 0 & 0 \\ 0 & 0 & \phi_{10}^3 & 0 & 0 \\ 0 & 0 & 0 & \phi_{10}^4 & 0 \\ 0 & 0 & 0 & 0 & \phi_{10}^5 \end{bmatrix} \begin{bmatrix} Z_1(t-1) \\ Z_2(t-1) \\ Z_3(t-1) \\ Z_4(t-1) \\ Z_5(t-1) \end{bmatrix} +$$

$$\begin{bmatrix} \phi_{11}^1 & 0 & 0 & 0 & 0 \\ 0 & \phi_{11}^2 & 0 & 0 & 0 \\ 0 & 0 & \phi_{11}^3 & 0 & 0 \\ 0 & 0 & 0 & \phi_{11}^4 & 0 \\ 0 & 0 & 0 & 0 & \phi_{11}^5 \end{bmatrix} \begin{bmatrix} 0 & w_{12} & w_{13} & w_{14} & w_{15} \\ w_{21} & 0 & w_{23} & w_{24} & w_{25} \\ w_{31} & w_{32} & 0 & w_{34} & w_{35} \\ w_{41} & w_{42} & w_{43} & 0 & w_{45} \\ w_{51} & w_{52} & w_{53} & w_{54} & 0 \end{bmatrix} \begin{bmatrix} Z_1(t-1) \\ Z_2(t-1) \\ Z_3(t-1) \\ Z_4(t-1) \\ Z_5(t-1) \end{bmatrix} + \begin{bmatrix} e_1(t) \\ e_2(t) \\ e_3(t) \\ e_4(t) \\ e_5(t) \end{bmatrix} \tag{4}$$

2.2 Location Weighting

The GSTAR model frequently uses uniform weights, distance inverse, binary, and cross correlation as location weights [20]. This research uses uniform location weights, inverse distances, and normalized cross-correlation. Data where the locations are homogeneous or have the same distance between them often use uniform location weighting, which provides the same weight value for each location. The uniform weighting equation is formulated in Equation (5) [21].

$$W_{ij} = \frac{1}{n_i} \tag{5}$$

where W_{ij} is the weight between location i and j, n_i is number of locatoins adjacent to the i location. Meanwhile, the weight of the distance between i-th location and the j-th location is expressed by **Equation (6) [20]**.

$$W_{ij} = \frac{\frac{1}{d_{ij}}}{\sum_{j=1}^{N} \frac{1}{d_{ij}}} \tag{6}$$

The weighting matrix is formulated in **Equation (7) [21]**.

$$W_{ij} = \frac{r_{ij}(1)}{\sum_{j \neq i} |r_{\ ij}(1)|} \tag{7}$$

2.3 Research Data

This case study in GSTAR modeling was applied to forecast the CPI for five cities in South Sulawesi Province, namely Bulukumba, Makassar, Palopo, Watampone and Parepare. The data is divided into training data and testing data, where the percentage composition used is 90% and 10%. CPI data January 2014-March 2022 is used as training data, which will be used for GSTAR modeling. Meanwhile, CPI data for April 2022-March 2023 will be used as testing data to compare the forecasting performance of the GSTAR model.

Table 1. Research Variables

No	Variable	Information
1	Z_1	Bulukumba City Monthly CPI
2	Z_2	Makassar City Monthly CPI
3	Z_3	Palopo City Monthly CPI
4	Z_4	Watampone City Monthly CPI
5	Z_5	Parepare City Monthly CPI

3. RESULTS AND DISCUSSION

3.1 Descriptive Analysis

Descriptive analysis was used to find out the general picture of CPI data in five cities of South Sulawesi Province, namely the cities of Bulukumba, Makassar, Palopo, Watampone and Parepare. **Table 2** presents the descriptive statistics of CPI data in five cities in South Sulawesi Province.

Table 2. Data Descriptive Statistics CPI in South Sulawesi

Location	N	Mean	Standard Deviation	Minimum	Maximum
Bulukumba	99	125.2	13.33	104.5	144.8
Makassar	99	120.9	12.26	104	140
Palopo	99	119.2	11.20	103.3	136.6
Watampone	99	118.1	10.58	102.8	135.1
Parepare	99	117.6	9.39	103.6	132.6

The CPI data pattern can be seen through the Time Series plot of CPI data in five cities in **Figure 1**.

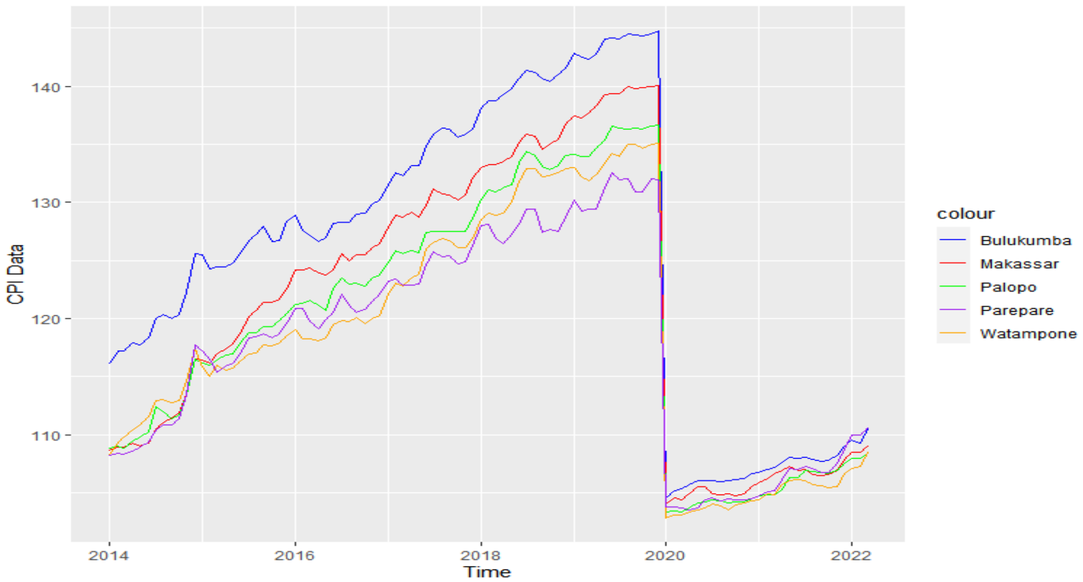


Figure 1. Plot of CPI Data for Five Cities in South Sulawesi

Figure 1 shows that the movement of CPI data for five cities increased from 2014 to 2019 and decreased in 2020. The CPI in 2020 reached its lowest point since 2014, namely 2.04%. One of the reasons for this could be the Covid-19 pandemic, which has caused demand for goods and services to decrease significantly.

3.2 GSTAR Model Identification

The GSTAR model has two orders, namely time order and spatial order. Generally, one can limit the spatial order to the first order, and determine the time order by looking at the optimal lag length in the VAR model. The Schwarz Information Criterion (SIC) selects the optimal lag length in the VAR model based on its smallest value. Table 3 presents the SIC value of CPI data for five cities in South Sulawesi.

Table 3. SIC Value of CPI Data

Lag	SIC
1	-3 .3 514
2	- 2.3276
3	-1.3820
4	-0.5685
5	0.0458
6	1.0945
7	2.1130
8	2.9606
9	3.9383
10	4.2443

Table 3 shows that the SIC value, which is -3.0870 at lag 1, has the smallest value, leading to the formation of the VAR model with order p = 1. We used data that underwent differentiation. So the model formed is VARIMA (1, 2.0).

3.3 Location Weight

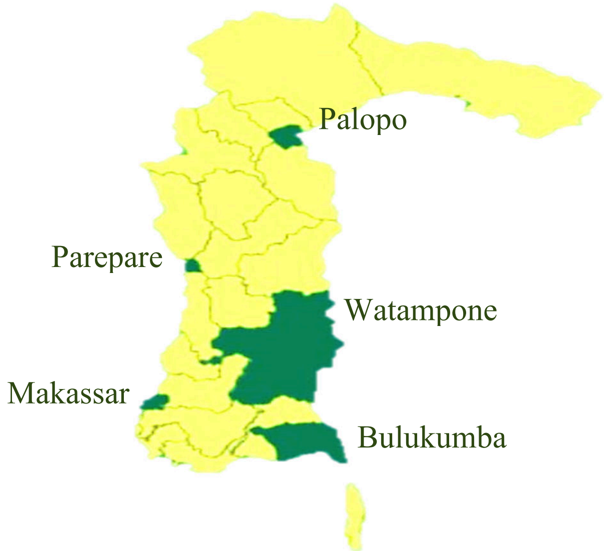


Figure 2. Map of Cities in South Sulawesi

This research uses uniform location weights, inverse distances, and normalized cross-correlation. The following formula forms the uniform weight matrix:

$$W = \begin{bmatrix} 0 & 0{,}25 & 0{,}25 & 0{,}25 & 0{,}25 \\ 0{,}25 & 0 & 0{,}25 & 0{,}25 & 0{,}25 \\ 0{,}25 & 0{,}25 & 0 & 0{,}25 & 0{,}25 \\ 0{,}25 & 0{,}25 & 0{,}25 & 0 & 0{,}25 \\ 0{,}25 & 0{,}25 & 0{,}25 & 0{,}25 & 0 \end{bmatrix}$$

Meanwhile, the inverse distance matrix obtained is:

$$W = \begin{bmatrix} 0 & 0{,}2516 & 0{,}2224 & 0{,}4137 & 0{,}1122 \\ 0{,}2973 & 0 & 0{,}2851 & 0{,}2018 & 0{,}2158 \\ 0{,}2586 & 0{,}2805 & 0 & 0{,}2620 & 0{,}1990 \\ 0{,}7953 & 0{,}3283 & 0{,}4331 & 0 & 0{,}1935 \\ 0{,}1981 & 0{,}3223 & 0{,}3020 & 0{,}1776 & 0 \end{bmatrix}$$

And the cross-correlation matrix formed is:

$$W = \begin{bmatrix} 0 & 0{,}2505 & 0{,}2500 & 0{,}2472 & 0{,}2524 \\ 0{,}2516 & 0 & 0{,}2492 & 0{,}2478 & 0{,}2514 \\ 0{,}2505 & 0{,}2489 & 0 & 0{,}2491 & 0{,}2515 \\ 0{,}2495 & 0{,}2492 & 0{,}2507 & 0 & 0{,}2507 \\ 0{,}2518 & 0{,}2499 & 0{,}2504 & 0{,}2479 & 0 \end{bmatrix}$$

3.4 White Noise Residual Test

We conduct the model suitability test to verify the fulfillment of the model's assumptions. Table 4 presents the results of the residual white noise assumption test for each local weight in the GSTAR (1;1)-I(2) model.

Table 4. Test of White Noise Residual Assumptions of the GSTAR Model (1;1)-I(2)

Location Weight	Statistics	Df	p-value	Decision
Uniform Weight	35.14293	25	0.0856	White Noise
Distance Inverse Weights	32.93248	25	0.1328	White Noise
Cross Correlation Normalized Weights	33.41513	25	0.1210	White Noise

The white noise residual test results in Table 4 demonstrate that the GSTAR model residuals (1;1)-I(2) from each location weight have met the residual assumptions, as evidenced by the resulting p-value is more than 0.05.

3.5 Selection of the Best Model

We determine the best location weight by comparing the accuracy of the forecast with the actual value of each GSTAR (1;1)-I(2) model and looking at the smallest RMSE value for each location weight that meets the white noise assumption. Table 5 presents a comparison of the RMSE of each location weight in the GSTAR(1;1)-I(2) model.

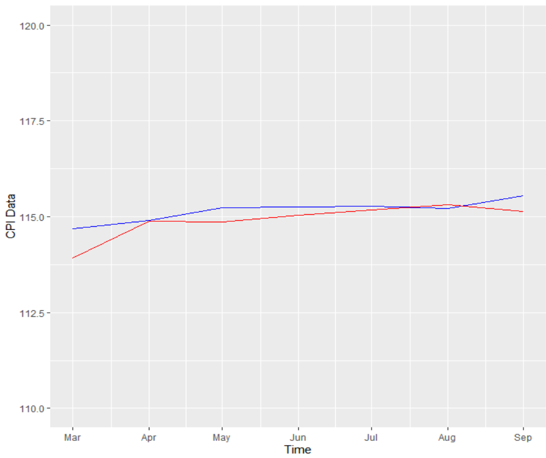
Table 5. Comparison of RMSE for Each Location Weight in the GSTAR(1;1)-I(2)

Location	RMSE		
	Uniform Weight	Distance Inverse Weights	Cross Correlation Normalized Weights
Bulukumba	1.2972	0.8303	0.8196
Makassar	1.3762	1.3781	1.3769
Palopo	1.3837	1.3872	1.3839
Watampone	2.0327	1.2894	1.3832
Parepare	1.5020	1.4989	1.5004
Average	1.5184	1.2768	1.2928

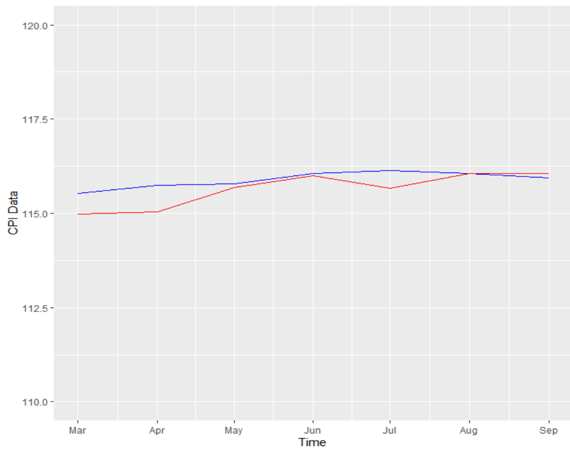
The RMSE comparison of each location weight of the GSTAR (1;1)-I(2) model, based on Table 4, yields the smallest average RMSE value using the inverse distance weight, which is 1.2768.

3.6 CPI Data Forecasting

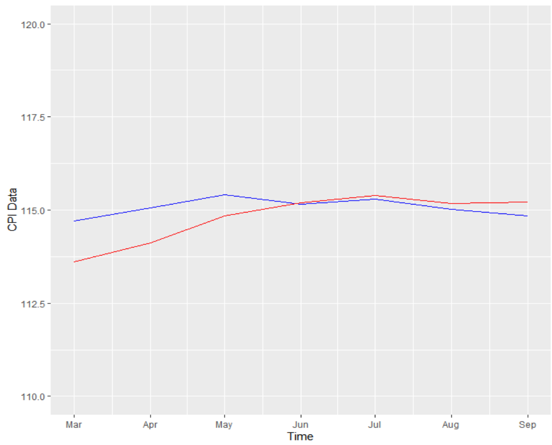
We forecast CPI data for five cities using the best model for the next 8 months, from April 2023 to September 2023. We use Model GSTAR (1;1)-I(2) with inverse distance weighting to forecast CPI data for five cities. Figure 2 presents the forecast results with inverse distance weights where the blue line is the actual data and the red line is the forecast data.



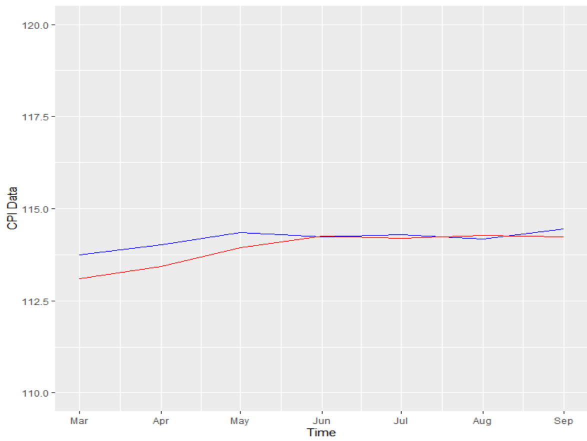
(a)



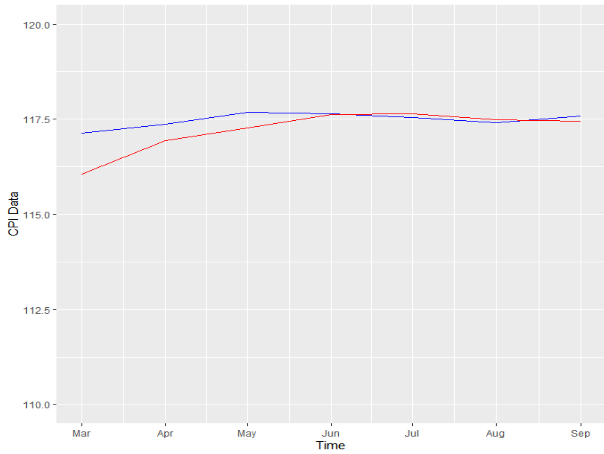
(b)



(c)



(d)



(e)

Figure 2. The Plot of Actual and Forecast Data of the CPI in Five Cities of South Sulawesi, (a) Bulukumba, (b) Makassar, (c) Palopo, (d) Watampone, (e) Parepare

The forecast results of the GSTAR (1;1)- I(2) model with inverse distance location weights closely match the actual values in each city from March to September 2023, with Bulukumba in April 2023 and Makassar in August 2023 showing the closest match to the actual data. This indicates that the CPI forecast results for five cities can be accurately predicted.

4. CONCLUSIONS

The model obtained from the GSTAR model is the GSTAR (1;1)-I(2) model. The time order used is the order p = 1, which is obtained through Vector Autoregressive (VAR) identification by looking at the optimal lag length using the Schwarz Information Criterion (SIC) criterion, which is selected based on the smallest value. We utilized data that underwent two differentiations. The GSTAR (1;1)-I(2) model, which uses inverse distance weights, yields the best GSTAR model, meeting white noise assumptions and producing model residuals with the smallest average RMSE value, 1.2768.

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