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GSTARIMA Model with Missing Value for Forecasting Gold Price*

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Abstract

Gold is one of the investments that be a great demand. Selecting and applying the best GSTARIMA model for gold price forecasting was the aim of this study. However, the gold price data that has been obtained missing values. Missing value data has been imputed by the last data before the missing value and moving average techniques. The GSTAR (1) and GSTARI (1, 1) models have been combined with an imputation technique solved this problem. Based on the smallest RMSE value, the GSTARI (1, 1) model which has been combined with the imputation technique that used the last value was the best method because it produced the smallest RMSE when compared to other methods. Forecasting results shown that gold prices in the United States, United Kingdom, and Indonesia increased but gold prices in Turkey actually decreased. Forecasting gold prices in each of these countries become one of the references in investing in gold. Based on the results of gold price forecasting, gold prices changed but not significantly.

Keywords: GSTAR(1), GSTARI (1, 1), imputation technique, RMSE.

1. Introduction

Gold is one of the investments that be a great demand, especially for the long term. In addition, gold is still used for cultural activities in several countries such as Indonesia, Malaysia, Turkey, and Arab countries. So it takes a good model to be able to predict the price of gold in the future. Many statistical methods for forecasting included ARIMA (ArunKumar et al., 2021; Fan et al., 2021; M.-D. Liu et al., 2021; Selvaraj et al., 2020; Toğa et al., 2021; Yang et al., 2021), ARIMAX (Hossain et al., 2021; Li et al., 2020), multivariate time series (Koutlis et al., 2020; X. Liu & Lin, 2021; Quesada et al., 2021; Vanhoenshoven et al., 2020; R. Zhang & Jia, 2021), GARCH (Aras, 2021; Hung et al., 2020; Z. Liu & Huang, 2021; Marchese et al., 2020; Paul & Sharma, 2021; Salisu et al., 2020; Xing et al., 2021), vector autoregressive moving average (Dias & Kapetanios, 2018; Guefano et al., 2021; Jeong et al., 2021), etc.

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ARIMA and ARIMAX use univariate dependent variable (response). While the multivariate time series, GARCH, vector autoregressive moving average uses more than 2 responses (multivariate) to model or predict data for several periods in the future.

One of the new models used for the forecasting method was the generalized space time autoregressive moving integrated moving average (GSTARIMA). This model also used not only the effect of time but also the influence of location to be able to predict an object of research. Andayani et al. (2018) conducted a study related to the comparison of GSTARIMA and GSTARIMA with exogenous (GSTARIMAX). The research has been used the transfer function. In addition, there are already studies that have implemented the GSARIMAX model, namely Aulia and Saputro (2021). This study applied the GSTARIMA model to forecasting gold prices. However, the gold price data that has been obtained missing values. There have been related to missing values in time series cases included Zhang et al. (2021), Andiojaya & Demirhan (2019), Cinar et al. (2018), Fallah et al. (2020), etc. This research solved this problem by using imputation technique that uses last value and moving average so that the data has become complete. Furthermore, the combination of the GSTARIMA model and imputation techniques has been applied and forecasting has been carried out on the data. Finally, the best model that selected the smallest root mean square error (RMSE) has been used to forecast the data for the next several periods.

2. Methods

The gold price data from December 30, 2004 to August 13, 2021 used in this study comes from the World Gold Council for Indonesia, Turkey, United States, and United Kingdom. The data obtained missing values on weekend (Saturday and Sunday) so that the imputation technique has been used. Missing value data has been imputed by the last data before the missing value also known as last observation carried forward (LOCF) and moving average technique. The moving average in this research has been calculated by Equation 1. The illustration related to the imputation technique can be seen in Table 1.

$$MA_s = \frac{d_{n-s+1} + d_{n-s+2} + \cdots + d_n}{s} \tag{1}$$

where MA_s is the mean over the last s data-points, d_{n-s+1} is the initial data, d_n is final data, and s is the amount of data used for smoothing. Based on Table 1, gold price (1) used the latest data before missing value and gold price (2) used moving average with k=1. So the price of gold has been determined by MA_1=(1000+3000)/2 or 2000.

Table 1: Simulation of imputation technique

Date	Gold price	Gold price (1)	Gold price (2)
January 1, 2021	1000	1000	1000
January 2, 2021	NA	1000	2000
January 3, 2021	3000	3000	3000

Furthermore, the complete data has been divided into 2 parts, namely training data (December 30, 2004 – December 31, 2019) and testing data (January 1, 2020 - August 13, 2021). The generalized space time autoregressive integrated moving average (GSTARIMA) model that has been used in this study can be seen in equation 2. This research has been limited to the GSTAR (1) and GSTARI (1,1) models.

$$\nabla \boldsymbol{Y}_i(t) = \sum_{k=1}^{p} \sum_{l=0}^{\lambda_k} \boldsymbol{\phi}_{kl}^{(i)} \boldsymbol{W}^{(l)} \nabla \boldsymbol{Y}_i(t-k) + \boldsymbol{\varepsilon}_i(t) - \sum_{k=1}^{q} \sum_{l=0}^{m_k} \boldsymbol{\theta}_{kl}^{(i)} \boldsymbol{W}^{(l)} \boldsymbol{\varepsilon}_i(t-k) \tag{2}$$

where $\nabla \boldsymbol{Y}_i(t) = (1-B)^d Y_t$ is N-dimensional vector, p is autoregressive order, q is moving average order, d is differencing order, λ_k is spatial order of the k-autoregressive condition, m_k is spatial order of k-th moving average condition, $\boldsymbol{\phi}_{kl}^{(i)}$ is parameter for autoregressive, $\boldsymbol{W}^{(l)}$ is spatial weighting matrix, $\boldsymbol{\theta}_{kl}^{(i)}$ is parameter for moving average, and $\boldsymbol{\varepsilon} it$ is error. This research has been assumed all neighboring areas. The minimum root mean square error (RMSE) value has been used in this study to select the best model as in equation 3.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{i=n}\left(Y_i - \hat{Y}_i\right)^2}{n}} \tag{3}$$

where Y_i is the actual value of the gold price for each country, $\hat{Y}_i$is the predict value of the gold price for each country, and n is the number of testing data.

3. Results

The graph of gold prices in the United States (USD), United Kingdom (GBP), Turkey (TRY), and Indonesia (IDR) can be seen in Figure 1. Gold prices in each country measured in troy ounces. In the picture the number in the index represented the date. The number 1 as the smallest number represented December 30, 2004, while the number 6071 as the largest number represented August 13, 2021. Based on Figure 1, it can be seen that the line broken every Saturday and Sunday. This indicated missing values in the data and the problem has been handled. Gold prices increased for all these countries, relatively. Based on Figure 1 also, it has been seen that the relative gold price pattern for the United States and the United Kingdom is the same. In the same figure, the pattern of gold prices in Turkey has shown a relatively exponential increase which was quite different from the gold price in Indonesia which increased linearly. In the 2800-5000th data, gold prices decreased in the United States and the United Kingdom, but the gold price increased what happened in Turkey and Indonesia.

Based on Figure 2, it has been seen that the imputation technique used the latest data and moving averages. In the picture, the black line represented gold price data which still has a missing value. Still in the same picture, the red line represents the imputation technique used the last value, while the green line represented the imputation technique of moving average with k=1. Relatively, the last value and moving average imputation techniques that have been used are quite close to the original value of gold prices in the United States, United Kingdom, Turkey, and Indonesia.

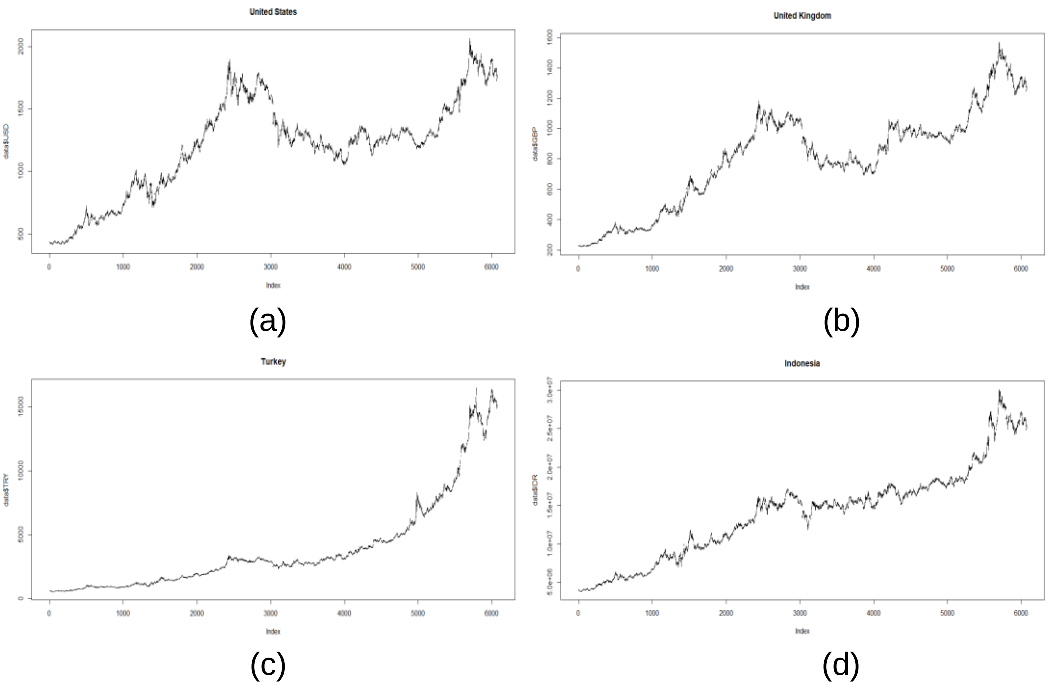


Figure 1: Gold price graphs in each country (a) United States, (b) United Kingdom, (c) Turkey, and (d) Indonesia

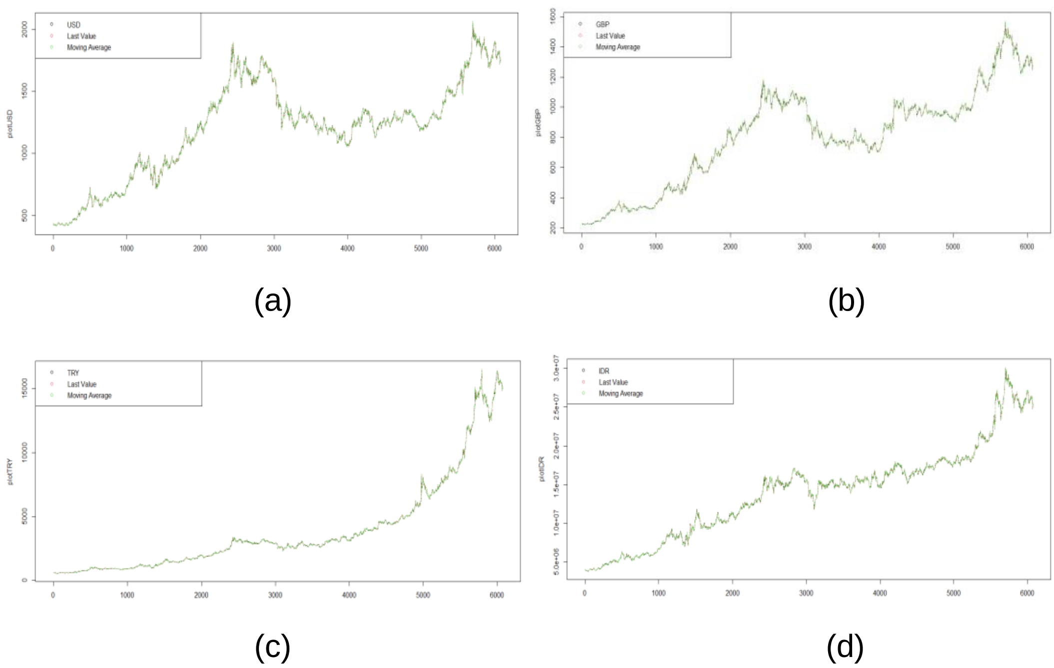


Figure 2: Graphs with missing values and the imputation results in each country (a) United States, (b) United Kingdom, (c) Turkey, and (d) Indonesia

Based on Figure 2 also, it has been seen that the data had non-stationary indications. So the data already need used differencing process. So in this study the models that have been used GSTAR (1) and GSTARI (1, 1). The model has been combined with the missing value imputation method which used the last value and moving average. Based on Table 2, model 1 was the GSTAR (1) model which has been combined with the last value imputation technique. Still in the table, model 2 was the GSTARI (1, 1) model which has been combined with the last value imputation technique. Model 3 in Table 2 was the GSTAR model (1) which has been combined with the moving average imputation technique. While model 4 was the GSTARI (1, 1) model which has been combined with the moving average imputation technique.

Table 2: Parameter estimates form all models.

Parameter	Model 1	Model 2	Model 3	Model 4
$\boldsymbol{\phi}_{10}^{(1)}$	1.000e+00***	-5.892e-03	1.000e+00***	-5.838e-02.
$\boldsymbol{\phi}_{11}^{(1)}$	-1.400e-08	-6.813e-07	-1.657e-08	-1.902e-05*
$\boldsymbol{\phi}_{10}^{(2)}$	9.997e-01***	-3.890e-02.	9.997e-01***	-1.538e-01***
$\boldsymbol{\phi}_{11}^{(2)}$	7.586e-08	3.119e-06	6.970e-08	2.656e-06
$\boldsymbol{\phi}_{10}^{(3)}$	1.001e+00***	7.930e-02***	1.001e+00***	-4.712e-03***
$\boldsymbol{\phi}_{11}^{(3)}$	-1.260e-07	-5.361e-05***	-1.352e-07	-7.748e-05
$\boldsymbol{\phi}_{10}^{(4)}$	0.9998069***	-0.02521	0.9998275***	-0.15870***
$\boldsymbol{\phi}_{11}^{(4)}$	2.8297528	85.68698	2.6882170	96.84617

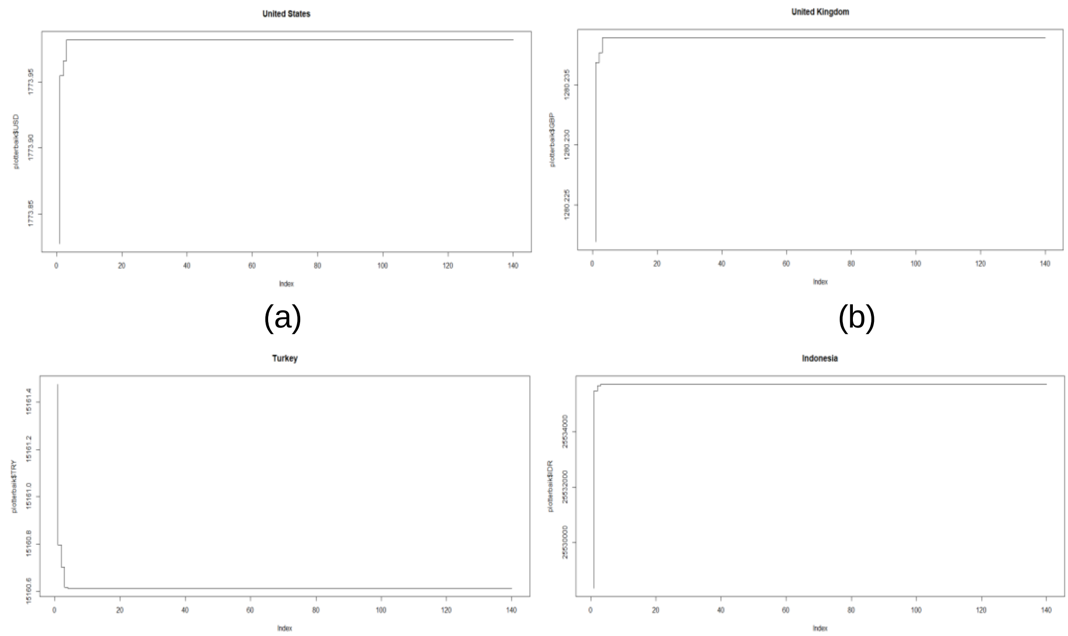
Parameter estimation for all models, both GSTAR(1) and GSTARI (1, 1) can be seen in **Table 2**. Based on the table, $\boldsymbol{\phi}_{10}^{(1)}$ is the lag parameter of the gold price in the United States, $\boldsymbol{\phi}_{11}^{(1)}$ is the parameter of the influence of neighbors on the price of gold in the United States, $\boldsymbol{\phi}_{10}^{(2)}$ is the lag parameter of the gold price in the United Kingdom, $\boldsymbol{\phi}_{11}^{(2)}$ is the parameter of the influence of neighbors on the price of gold in the United Kingdom, $\boldsymbol{\phi}_{10}^{(3)}$ is the lag parameter of the gold price in the Turkey, $\boldsymbol{\phi}_{11}^{(3)}$ is the parameter of the influence of neighbors on the price of gold in the Turkey, $\boldsymbol{\phi}_{10}^{(4)}$ is the lag parameter of the gold price in the Indonesia, and $\boldsymbol{\phi}_{11}^{(4)}$ is the parameter of the influence of neighbors on the price of gold in the Indonesia. Based on the table, there are several parameters that have a significant effect on gold prices in each country. In model 1 and model 3, there are 4 significant parameters at p-value 0% included $\boldsymbol{\phi}_{10}^{(1)}$, $\boldsymbol{\phi}_{10}^{(2)}$, $\boldsymbol{\phi}_{10}^{(3)}$, dan $\boldsymbol{\phi}_{10}^{(4)}$. It can also be seen that the parameters $\boldsymbol{\phi}_{10}^{(3)}$ and $\boldsymbol{\phi}_{11}^{(3)}$ are significant parameters at p-value 0% in model 2. The model also had a parameter $\boldsymbol{\phi}_{10}^{(2)}$ which was significant at a p-value 10%. In the parameter model 4, $\boldsymbol{\phi}_{10}^{(1)}$ was significant at 10% p-value and parameter $\boldsymbol{\phi}_{11}^{(1)}$ was significant at p-value 5%. Finally, the parameters $\boldsymbol{\phi}_{10}^{(3)}$ and $\boldsymbol{\phi}_{10}^{(4)}$ have been significant at p-value 0%.

Table 3: RMSE for all models

	United Stated	United Kingdom	Turkey	Indonesia	Average
Model 1	256.000	162.807	2792.226	3059265.534	1529633.412
Model 2	17.089	12.743	155.594	262309.406	131154.726
Model 3	256.297	163.154	2765.776	3087194.257	1543597.755
Model 4	256.403	163.331	2771.700	3093345.071	1546673.164

Root mean square error (RMSE) has been used in this study to determine the best model. Based on Table 3, the RMSE values was vary widely. The highest RMSE value for gold prices in the United States has been owned by model 4, which was 256.403 while the lowest value has been owned by model 2. This indicated that model 2 was the best model for determining gold price predictions in the United States. This model had also relatively become the best model determined gold prices in the United Kingdom, Turkey, and Indonesia. Based on Table 3 also, relatively the worst model that has been used to model the gold price was model 4. However, there have been interested things in estimated gold prices in Turkey. Model 1 was the model that was relatively the worst for determining the price of gold there.

Furthermore, the GSTARI (1, 1) model which has been combined with the last value imputation technique (model 2) has been used to forecast gold prices for the United States, United Kingdom, Turkey, and Indonesia from August 14, 2021 to December 31, 2021. Based on Table 4, the forecasting results that have been obtained from the model can be seen in Figure 3. Based on Figure 3, in the index, 1 represented August 14, 2021 and 140 represented December 31, 2021. The estimated parameters of the model can be seen in Table 4. The parameter $\boldsymbol{\phi}_{11}^{(3)}$ that has been obtained with an estimated value of 3.520e-05 was significant at a p-value of 10%. The most significant parameter was $\boldsymbol{\phi}_{11}^{(4)}$ with an estimated value of -2.261e+02. The parameters that have been obtained significant at a p-value of 5%.



(a) (b) (c) (d)

Figure 3: Gold price forecast graphs in each country (a) United States, (b) United Kingdom, (c) Turkey, and (d) Indonesia

Table 4: Best model parameter estimation

Parameter	Estimate	Parameter	Estimate
$\boldsymbol{\phi}_{10}^{(1)}$	-3.932e-02	$\boldsymbol{\phi}_{10}^{(3)}$	1.583e-02
$\boldsymbol{\phi}_{11}^{(1)}$	6.963e-06	$\boldsymbol{\phi}_{11}^{(3)}$	-3.520e-05.
$\boldsymbol{\phi}_{10}^{(2)}$	-3.098e-02	$\boldsymbol{\phi}_{10}^{(4)}$	-2.834e-04
$\boldsymbol{\phi}_{11}^{(2)}$	5.370e-07	$\boldsymbol{\phi}_{11}^{(4)}$	-2.261e+02*

Table 5: 10 initial data of gold price forecasting results

No	Date	USD	GBP	TRY	IDR
1	14-Aug-21	1773.827	1280.222	15161.47	25528362
2	15-Aug-21	1773.955	1280.237	15160.80	25535469
3	16-Aug-21	1773.966	1280.238	15160.70	25535654
4	17-Aug-21	1773.982	1280.239	15160.62	25535694
5	18-Aug-21	1773.982	1280.239	15160.61	25535700
6	19-Aug-21	1773.982	1280.239	15160.61	25535706
7	20-Aug-21	1773.982	1280.239	15160.61	25535706
8	21-Aug-21	1773.982	1280.239	15160.61	25535706
9	22-Aug-21	1773.982	1280.239	15160.61	25535706
10	23-Aug-21	1773.982	1280.239	15160.61	25535706

The explanation regarded Figure 3 was easier to understand if looked at Table 5. In Table 5 there were 10 preliminary forecasting results from August 14, 2021 to August 23, 2021. Forecasting results for gold prices in the United States increased until August 17, 2021 and started constant in the value of 1773.982 USD from August 18, 2021 to December 31, 2021. For forecasting the price of gold in the United Kingdom that has been obtained, the relative increased from August 14, 2021 to August 17, 2021 at 1280.239 GBP then constant from 18 August 2021 to 31 December 2021, the same as the gold price in United States. An increase in gold price forecasting results has also occurred in Indonesia. The price of gold has increased from August 14, 2021 to August 19, 2021, then constant at 25535706 IDR until December 31, 2021. If the previous three countries forecast gold prices increased but Turkey was different. The price of gold in Turkey decreased which on August 14, 2021 had a price of 15161.47 TRY but on August 18, 2021 it fallen to 15160.61 TRY. The value remained constant until December 31, 2021.

4. Conclusion and Discussion

In this study, gold price modeling for the United States, United Kingdom, Turkey, and Indonesia used 2 models, namely generalized space time autoregressive with first order autoregressive as GSTAR (1) and generalized space time autoregressive with integrated autoregressive with first order autoregressive and first order differencing as GSTARI(1, 1). Prior to modeling the gold price data, an imputation technique has been applied which used the last value and moving average to solve the missing value problem. Based on the smallest RMSE value, the GSTARI (1, 1) model which has been combined with the imputation technique used the last value was the best method because it produces the smallest RMSE when compared to other methods.

Forecasting results shown that gold prices in the United States, United Kingdom, and Indonesia increased but gold prices in Turkey actually decreased. Based on the forecast that has been obtained, the United States gold price for August 14, 2021 was in the position of 1773,827 USD/troy ounce. The relative price of gold increased until August 17, 2021 at the position of 1773,982 USD/troy ounce. Furthermore, the gold price moved constant at the same price until December 31, 2021. The same pattern occurred in the United Kingdom. The result of forecasting gold prices in the United Kingdom on August 14, 2021 was in the position of 1280,222 GBP/troy ounce. The gold price relatively risen until August 17, 2021 at the position of 1280,239 USD/troy ounce and finally moved constant until December 31, 2021. Unlike the case with gold price forecasting in the United States and United Kingdom, gold price forecasting in Turkey decreased relatively. Based on the forecast that has been obtained, Turkey's gold price for August 14, 2021 was in the position of 15161.47 TRY/troy ounce. The gold price relatively decreased until August 18, 2021 at the position of 15160.61 TRY/troy ounce. Furthermore, the gold price forecast has been moved constant at the same price until December 31, 2021. Forecasting gold prices in Indonesia relatively increased longer than the United States and United Kingdom. On August 14, 2021, the price of gold in Indonesia was at the position of 25528362 IDR/troy ounce and increased until August 19, 2021 at the position of 25535706 IDR/troy ounce. Finally, the forecasting of gold prices in Indonesia moved steadily at the same price until December 31, 2021.

Forecasting gold prices in each of these countries become one of the references in investing in gold. Based on the results of gold price forecasting, gold prices changed but not significantly. For forecasting gold prices in the United States, United Kingdom, and Turkey, only changed a few decimal digits. This was different from the results of forecasting gold prices in Indonesia, which had undergone a significant change of several tens of thousands of IDR. This has been influenced by the currency value of the IDR itself.

The research that has been done still had potential to be developed. Other countries also need to be added for further research. In addition, it was also necessary to use other spatial matrix weighting so that the influence of neighbors can have a significant influence on gold prices in each country. Simulation of all possible autoregressive orders and moving averages is also an interesting thing to develop such as orders 2, 3, and so on. The limit of k=1 for the moving average technique also needs to be increased so that the optimal k value can be seen for the existing missing value imputation.

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