UNP JOURNAL OF STATISTICS AND DATA SCIENCE
Volume 4 Nomor 3 Tahun 2026 Halaman 406-416.

ISSN(*Print*) : 3025-5511
ISSN(*Online*): 2985-475X

Space-Time Modeling of Gold Prices with Missing Values Using Google Trends Data during the COVID-19 Pandemic

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Submitted : 18 Juni 2026
Revised : 16 Agustus 2026
Accepted : 31 Agustus 2026

ABSTRACT

Accurate gold price prediction is increasingly important during periods of economic uncertainty, such as the COVID-19 pandemic. However, daily gold price data may contain missing values, and conventional spatial weighting schemes may not adequately capture shifting inter-country relationships during extraordinary conditions. Therefore, an adaptive spatiotemporal modeling approach capable of integrating information from online search behavior is required. This study aims to predict gold prices in Austria, India, South Korea, and Turkiye during the COVID-19 pandemic using spatiotemporal autoregressive models, while addressing missing observations and integrating Google Trends data. The study compares the generalized space-time autoregressive with exogenous variables (GSTARX) model and the generalized space-time autoregressive integrated with exogenous variables (GSTARIX) model. Missing observations in the World Gold Council's gold price data were handled using the last observation carried forward (LOCF) imputation method. Google Trends data from the Google Shopping, Image Search, News Search, Web Search, and YouTube Search categories were utilized both to construct spatial weight matrices and as exogenous variables. Model performance was evaluated using the mean absolute percentage error (MAPE). The GSTARX model utilizing a spatial weight matrix based on Google Image Search yielded the best predictive performance, with a MAPE of 4.3%. Forecasting results indicate that gold prices in Austria remained relatively constant, whereas India showed a downward trend, South Korea experienced a significant decline, and Turkiye showed a significant increase. The findings demonstrate that Google Trends data can provide valuable information for establishing spatiotemporal relationships and enhancing gold price prediction capabilities during periods of extreme economic uncertainty. The proposed approach offers an alternative modeling framework for financial time-series data characterized by missing observations and dynamic inter-country dependencies.

Keywords: *forecasting, GSTARX, GSTARIX, imputation technique, spatial weighting matrix.*

I. INTRODUCTION

The generalized space-time autoregressive (GSTAR) model is a spatial time-series model that accounts for both temporal dependence and spatial interactions between regions. This model is widely used to describe and forecast phenomena characterized by inter-regional and temporal interdependencies. An extension of the GSTAR model is the GSTARX, which incorporates exogenous variables to provide additional information for explaining data dynamics and enhancing forecasting capabilities. Space-time models have been applied across various countries and research fields, including in Indonesia (Mubarak & Aslanargun, 2022; Munandar et al., 2025), Chile (Lagos-Álvarez et al., 2019), the United States (Lou et al., 2025), Turkiye (Güler & Erlat, 2025), the United Kingdom (Agarwal et al., 2025), and Africa (Coetzee & Kleynhans, 2025). These studies demonstrate the relevance of space-time modeling for phenomena influenced simultaneously by temporal dynamics and inter-regional relationships. However, the performance of GSTAR-based models relies heavily on the specification of the spatial weight matrix, as this matrix determines how inter-regional relationships are represented within the model.

In the application of time series models, stationarity is a crucial aspect because autoregressive models generally require the time series stochastic characteristics to remain relatively stable over time. Non-stationarity can manifest

DOI: https://doi.org/10.24036/ujsds/vol4-iss3/534

ISSN(*Print*) : 3025-5511
ISSN(*Online*): 2985-475X

in the mean or other characteristics of a time series and, if not properly addressed, can lead to inaccurate estimation and forecasting results. A commonly used approach to handle non-stationarity is differencing. First-order differencing is frequently employed when a series exhibits a stochastic trend in the mean. However, the required order of differencing must be determined empirically based on data characteristics rather than being arbitrarily assigned based solely on whether the non-stationarity occurs in the mean or the variance. When differencing is applied within the GSTAR framework, the model evolves into the generalized space-time autoregressive integrated (GSTARI) model. The integrated component enables the model to handle non-stationary spatial time series data following an appropriate differencing transformation. Autoregressive and integrated autoregressive models have been applied across various fields, including the environment (Liu et al., 2021; Zhu et al., 2021), health (Toğa et al., 2021; Yuan & Li, 2021), engineering (Yao et al., 2021), computing (Wang et al., 2020), energy (Kaytez, 2020), and agriculture (Mubarak et al., 2017). Furthermore, when exogenous variables are incorporated into the GSTARI model, it is referred to as the GSTARIX model.

The GSTARX and GSTARIX models require an appropriate spatial weight matrix to represent inter-regional relationships. Conventionally, spatial weight matrices are constructed based on geographic proximity, physical distance, or other predetermined measures of spatial connection. While such approaches can be effective, relationships between regions cannot always be adequately represented solely by geographic distance particularly during extraordinary circumstances when public attention patterns and economic ties may shift rapidly. In this context, Google Trends serves as a valuable alternative data source, as it captures patterns of public search interest across time and geography. Various studies have demonstrated the utility of Google Trends for monitoring and forecasting diverse phenomena, including the incidence of pertussis (Nann et al., 2021), skin infestations and arthropod bites (Simonart et al., 2021), public attention regarding World Antimicrobial Awareness Week (Keitoku et al., 2021), unemployment insurance claims (Aaronson et al., 2022), and public interest in specific medical treatments (Cohen et al., 2021).

The potential of Google Trends as an information source for establishing spatial relationships has also been examined by Mubarak et al. (2021) through the development of a high-order spatial weighting matrix based on Google Trends. Their study employed a distance-based classification and compared various Google Trends keywords using six countries in a simulation. However, the Google Trends-based spatial weighting matrix was evaluated only within a simulation context and has not yet been directly applied to statistical models for empirical forecasting. This situation highlights a research gap regarding the utilization of Google Trends-derived spatial weighting matrices in spatiotemporal forecasting models. The present study aims to address this gap by integrating Google Trends information into GSTARX and GSTARIX models. In this study, Google Trends serves two functions: as an alternative source for constructing the spatial weighting matrix and as exogenous information within the forecasting models. The Google Trends categories utilized include Google Shopping, Image Search, News Search, Web Search, and YouTube Search.

Gold prices were selected as the subject of this study because gold is an investment asset that plays a crucial role during periods of economic and financial uncertainty. The COVID-19 pandemic generated significant uncertainty in global financial markets and influenced gold price dynamics through shifts in investor sentiment, monetary policy, and interlinkages with other financial markets. Various studies have examined gold price behavior during the COVID-19 pandemic from diverse perspectives, including the impact of COVID-19-related news and media coverage Atri et al. (2021), the influence of monetary policy in Turkiye Depren et al. (2021), spillover effects between gold and other financial markets (Elgammal et al., 2021; Mensi et al., 2021), and the relationship between exchange rates and gold prices Tanin et al. (2021). These studies highlight the importance of understanding gold price dynamics during extraordinary economic conditions. Beyond its economic value as an investment instrument, gold also holds social and cultural significance in several countries, including Indonesia and India (Irfani & Hamidah, 2020; Jain, 2025; Mahalakshmi & Selvan, 2025; Maysarah et al., 2025). However, research on gold prices during the COVID-19 pandemic has generally focused on country-specific dynamics, financial factors, or cross-market spillover effects, with few studies integrating cross-country public search behavior into a spatiotemporal forecasting framework.

In addition to the challenge of modeling spatial relationships, research on gold prices also faces the issue of missing observations. The gold price data from the World Gold Council used in this study contains systematically missing observations on Saturdays and Sundays. Although this situation stems from the reporting characteristics of financial market data rather than random data loss, the presence of missing observations must be addressed before applying a daily space-time forecasting model. Incomplete time series can disrupt the data's temporal structure, subsequently affecting both the estimation and forecasting processes. The issue of missing values has been

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ISSN(*Print*) : 3025-5511
ISSN(*Online*): 2985-475X

extensively studied across various fields, including biology, health, computing, and machine learning (Han & Kang, 2021; Khan et al., 2021; Levy-Loboda et al., 2021; Shahjaman et al., 2021). However, handling systematically missing observations in daily gold price data within a space-time modeling framework remains a practically relevant issue. In this study, the LOCF method is employed to complete the daily gold price series prior to modeling. This step enables the application of GSTARX and GSTARIX models to a consistent daily data structure.

Based on the foregoing, this study aims to forecast gold prices in Austria, India, South Korea, and Turkiye during the COVID-19 pandemic by comparing the GSTARX and GSTARIX models. The study's primary contribution lies in integrating Google Trends into the spatiotemporal forecasting framework through two approaches: as an alternative basis for constructing the spatial weight matrix and as an exogenous variable within the forecasting models. Furthermore, the study addresses systematic missing observations in daily gold price data using the LOCF method and evaluates model performance based on MAPE values. The findings are expected to provide empirical evidence regarding the ability of online search behavior to represent spatial relationships between countries and to offer an alternative approach for improving gold price forecasting during periods of extreme economic uncertainty, such as a pandemic.

II. METHOD

The gold price data used in this study comes from the World Gold Council. The gold price was the price in each country for troy ounces. Also, the data has a missing value every Saturday and Sunday. So, in this research, the LOCF imputation technique has been carried out solved this problem. Simulations with LOCF for gold price data are shown in **Table 1**. Based on this table, the missing value data on Saturday and Sunday have been imputed by the original data on Friday.

Table 1. Simulation of missing value imputation

Day	Date	Original	Imputation	Combined
Monday	January 1, 2021	100,010	-	100,010
Tuesday	January 2, 2021	100,200	-	100,200
Wednesday	January 3, 2021	100,100	-	100,100
Thursday	January 4, 2021	100,001	-	100,001
Friday	January 5, 2021	100,010	-	100,010
Saturday	January 6, 2021	-	100,010	100,010
Sunday	January 7, 2021	-	100,010	100,010
Monday	January 8, 2021	100,015	-	100,015
Tuesday	January 9, 2021	100,200	-	100,200
Wednesday	January 10, 2021	100,150	-	100,150

In addition, this study has been limited to a few countries such as Austria, India, Korea, and Turkiye. So that the keyword "gold price" in the Google Trends data has been translated through each of the main languages in each country. The summary of keywords in Google Trends data and currency can be seen in **Table 2**. In addition, data on gold prices for the four countries from the World Gold Council has been started at the start of COVID-19. The time was between January 1, 2020 to December 17, 2021. And also, data from Google Trends data and the World Gold Council in the form of daily data.

Table 2. Keywords and currencies for each country

No	Country	Language	Keyword	Currency
1	Austria	German	Goldpreis	Euro (EUR)
2	India	English	Gold price	Rupee India (INR)
3	Korea	Korean	황금 가격	South Korean Won (KRW)
4	Turkiye	Turkish	Altın fiyat	Turkish Lira (TL)

After LOCF technique solved the missing values, the data has been divided into training and testing data. Training data from January 1, 2020 to July 31, 2021. Meanwhile, testing data from August 1, 2021 to December 17, 2021. Furthermore, the data has been modeling GSTARX and GSTARIX as in Equation (1) and Equation (2). The autoregressive order has been limited to order 1. In this model the exogenous variables that have been used are

DOI: https://doi.org/10.24036/ujsds/vol4-iss3/534

ISSN(*Print*) : 3025-5511
ISSN(*Online*): 2985-475X

Google Shopping, Image Search, News Search, Web Search, and Youtube Search which has been converted into a dummy variable.

$$G^{(i)}(t) = \sum_{a=1}^{a=p} \sum_{b=0}^{b=\lambda_a} \delta_{ab}^{(i)} M^b G^{(i)}(t-a) + \sum_{c=1}^{c=q} \gamma_c^{(i)} Q_c^{(i)} + \varepsilon^{(i)}(t) \tag{1}$$

$$\nabla G^{(i)}(t) = \sum_{a=1}^{a=p} \sum_{b=0}^{b=\lambda_a} \delta_{ab}^{(i)} M^b \nabla G^{(i)}(t-a) + \sum_{c=1}^{c=q} \gamma_c^{(i)} Q_c^{(i)} + \varepsilon^{(i)}(t) \tag{2}$$

where $\nabla G^{(i)}(t)$ is the differencing for the i-th region, $\delta_{ab}^{(i)}$ is the order of generalized space time autoregressive for the i-th region, M^b is the spatial weighting matrix, $\nabla G^{(i)}(t-a)$ is the a-th lag of differencing for the i-th region, $\gamma_c^{(i)}$ is the parameter of the exogenous variable for the i-th region, $Q_c^{(i)}$ is the exogenous variable for the i-th region, and $\varepsilon^{(i)}(t)$ is for the i-th region. Also, the spatial weighting matrix has adopted the inverse distance that are shown in equation (3).

$$M_{(i)(j)} = \begin{pmatrix} 0 & \frac{1}{m_{(1)(2)}} & \cdots & \frac{1}{m_{(1)(j)}} \\ \frac{1}{m_{(2)(1)}} & 0 & \cdots & \frac{1}{m_{(2)(j)}} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{1}{m_{(i)(1)}} & \frac{1}{m_{(i)(2)}} & \cdots & 0 \end{pmatrix} \tag{3}$$

where $m_{(i)(j)} = m_{(j)(i)}$, i is the i-th location, j is the j-th location.

The smallest mean absolute percentage error (MAPE) selected the best model from all model simulations. The MAPE value for each simulation has been using equation (4). Finally, based on the best model, gold prices have also been forecast in Austria, India, Korea, and Turkiye from December 18, 2021 to March 31, 2022. For the record, the price of gold in testing and the previous forecasting in the form of differencing values has been changed to its original form by re-transformation.

$$\forall_i \in MAPE = \frac{100\%}{T} \sum_{t=1}^{t=T} \left| \frac{G^{(i)}(t) - G'^{(i)}(t)}{G^{(i)}(t)} \right| \tag{4}$$

where $G^{(i)}(t)$ is actual value dan $G'^{(i)}(t)$ is predicted value.

III. RESULT AND DISCUSSION

Based on gold price data obtained from the World Gold Council during the COVID-19 pandemic, Figure 1 presents a comparison between actual gold price data and imputed data for Austria, India, South Korea, and Turkiye. The figure illustrates missing observations in the daily gold price series particularly on weekends which were subsequently filled using the LOCF method. The horizontal axis represents the sequence of daily observations, with 0 corresponding to January 1, 2020, and 717 corresponding to December 17, 2021. The black line represents the actual gold price data, while the red line represents the data following LOCF imputation. The two lines largely overlap where data exists, indicating that the imputation process did not alter the values of actual observations. Divergence between the two series occurs primarily at points where data was originally missing, as the LOCF method utilizes the value from the most recent available observation.

Descriptive statistics further indicate that the imputation process resulted in only minor changes to the distributional characteristics of gold prices. For Austria, the actual data showed a mean of 1,533.90 EUR and following imputation, these values became 1,533.85 EUR. For India, the mean of the actual data was 132,041.43 INR, whereas the post-imputation values were 132,010.19 EUR. For South Korea, the actual data yielded a mean of 2,070,817.49 KRW and following imputation, these values became 2,070,829.59 KRW. Meanwhile, Turkiye's actual data showed a mean of 14,096.88 TRY, whereas post-imputation values were 14,072.65 TRY. Furthermore, the minimum and maximum values for all four countries remained unchanged after the imputation process, indicating that the method did not generate new values outside the observed gold price range.

DOI: https://doi.org/10.24036/ujsds/vol4-iss3/534

ISSN(*Print*) : 3025-5511
ISSN(*Online*): 2985-475X

Overall, the differences in descriptive statistics between the actual and imputed data were relatively minor. Changes in the mean, median, and standard deviation resulted from filling in missing weekend observations using the last available value, rather than from alterations to the actual data itself. These findings demonstrate that the LOCF method effectively completes the daily time-series data structure while preserving the key characteristics of the gold price distribution. Consequently, the imputation process can be viewed as a preprocessing step to maintain temporal data continuity, rather than a process that substantially alters the underlying gold price patterns. This is crucial for subsequent GSTARX and GSTARIX analyses, which require a complete and temporally consistent observation structure for estimation and forecasting.

Gold price movement patterns also revealed differing dynamics across countries during the COVID-19 period. Price patterns in Austria, India, and South Korea showed relatively similar movements, whereas Turkiye exhibited a significantly different pattern. This difference indicates that gold price dynamics in Turkiye are likely influenced by country-specific economic and financial conditions that differ from those of the other three countries. The existence of these differing dynamics across countries further supports the use of a spatio-temporal modeling framework, as this approach allows for the simultaneous analysis of temporal relationships within each country and spatial relationships between countries.

During the COVID-19 period, the center of the country that was formed based on Google Trend data has been shown in Table 3. For South Korea, no search for the keyword "gold price" was found which has been translated into Korean in the Google Shopping and News Search categories. However, for the Image Search and Web Search categories, Gyeonggi has represented the center of South Korea. Carinthia has appeared in the Image Search and Youtube Search categories for Austria. In the Google Shopping and Image Search categories, Dadra and Nagar Haveli have appeared as the center of the Indian state. In addition, only Turkiye which displayed a different location for each category of Google Shopping, Image Search, News Search, Web Search and Youtube Search.

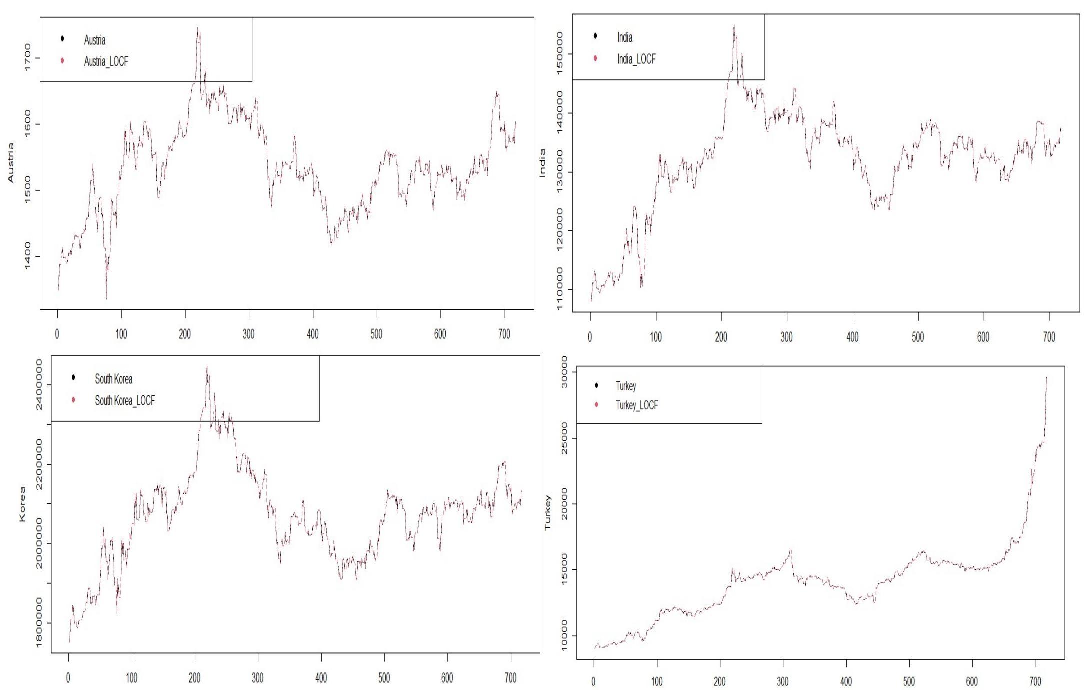

Figure 1. The price of gold and its imputation

DOI: https://doi.org/10.24036/ujsds/vol4-iss3/534

UNP JOURNAL OF STATISTICS AND DATA SCIENCE
Volume 4 Nomor 3 Tahun 2026 Halaman 406-416.
ISSN(*Print*) : 3025-5511
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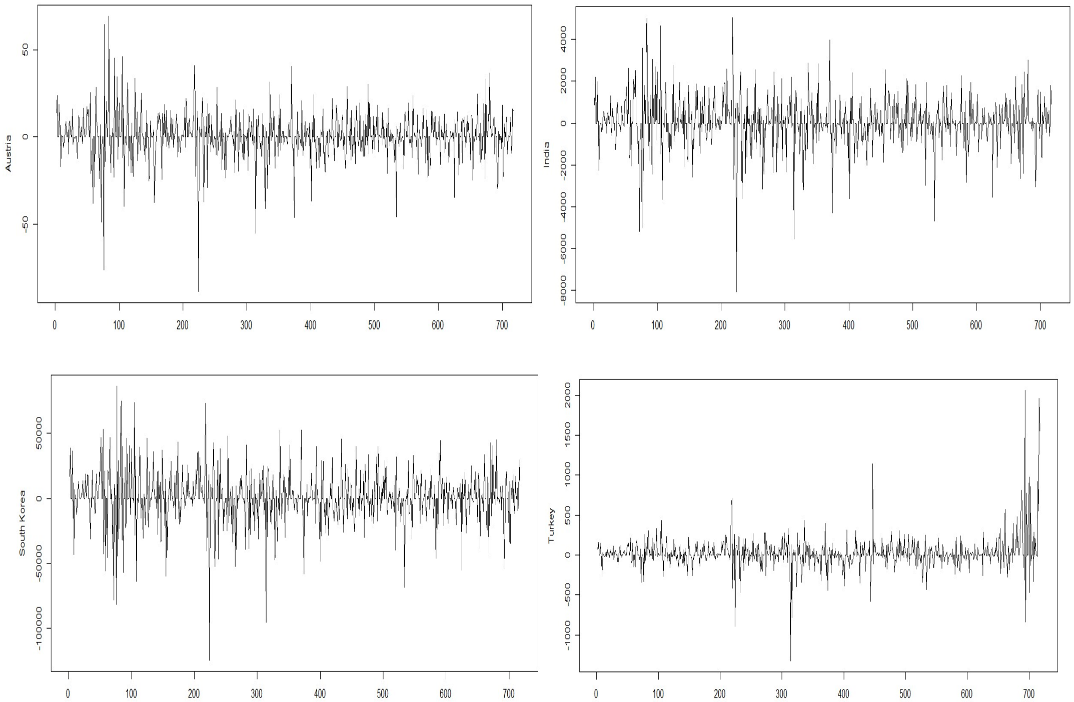

Figure 2. Differencing results

The results of first-order differencing applied to gold prices in Austria, India, South Korea, and Turkiye are presented in Figure 2. First-order differencing was performed by calculating the change in gold prices between two consecutive observation periods; thus, the resulting values represent the magnitude of the price increase or decrease from one day to the next. Positive values indicate an increase in gold prices, while negative values indicate a decrease. Conversely, values close to zero suggest that the price change between periods was relatively small. In general, the differencing results reveal that most gold price changes cluster around zero, interspersed with some relatively large positive and negative fluctuations. This indicates that, following first-order differencing, the trend patterns present in the raw (level) gold price data are reduced, and the series focuses more on price changes over time. This is evidenced by a median value of zero across all four countries, indicating that at least half of the daily changes reflect either no price change or values very close to it. Consequently, differencing shifts the analytical focus from the absolute level of gold prices to the dynamics of daily price changes.

Based on Table 3, the distance between countries has been shown in Table 4. The keyword "gold price" had no search in the Google Shopping and News Search categories in South Korea during COVID-19. The alternative distance between different countries was very dependent on the trend center based on keywords. For example, the distance between Austria and Turkiye, in the Image Search category, the distance was 2,194.37 km. While in the web search category, the distance between the two was 2,292.23 km. Even the distance got closer when the youtube search category was 1,410.47 km. The matrix has been applied to the GSTARX and GSTARIX models. So, the total model simulations that have been used were 6. All of model simulations have been applied to gold price data during COVID-19 which has been imputed by LOCF.

Table 3. Country centers based on the keyword “gold price”

Category	**Austria**	**India**	**South Korea**	**Turkiye**
Google Shooping	Lower Austria	Dadra and Nagar Haveli	*	Bitlis
Image Search	Carinthia	Dadra and Nagar Haveli	Gyeonggi	Gümüşhane
News Search	Tyrol	Arunachal Pradesh	*	Van
Web Search	Upper Austria	Punjab	Gyeonggi	Adıyaman
Youtube Search	Carinthia	Andaman and Nicobar Islands	Seoul	Balıkesir

DOI: https://doi.org/10.24036/ujsds/vol4-iss3/534

ISSN(*Print*) : 3025-5511
ISSN(*Online*): 2985-475X

Table 4. Distance between countries by category (km)

Image Search				
	Austria	India	South Korea	Turkiye
Austria	*	6,081.95	8,531.35	2,194.37
India	6,081.95	*	5,514.37	3,888.97
South Korea	8,531.35	5,514.37	*	7,233.31
Turkiye	2,194.37	3,888.97	7,233.31	*
Web Search				
	Austria	India	South Korea	Turkiye
Austria	*	5,432.47	8,383.41	2,292.23
India	5,432.47	*	4,733.32	3,463.75
South Korea	8,383.41	4,733.32	*	7,473.25
Turkiye	2,292.23	3,463.75	7,473.25	*
Youtube Search				
	Austria	India	South Korea	Turkiye
Austria	*	8,316.39	8,531.35	1,410.47
India	8,316.39	*	4,539.10	7,181.92
South Korea	8,531.35	4,539.10	*	8,117.40
Turkiye	1,410.47	7,181.92	8,117.40	*

Table 5. MAPE for each model (%)

GTSARX for Image Search				**GTSARX for Web Search**			
Austria	India	South Korea	Turkiye	Austria	India	South Korea	Turkiye
2.109	3.277	2.359	9.559	1.928	2.160	9.768	9.390
4.326				5.811			
GTSARX for Youtube Search				**GTSARIX for Image Search**			
Austria	India	South Korea	Turkiye	Austria	India	South Korea	Turkiye
2.250	1.953	12.253	9.222	1.981	7.347	1.440	9.638
6.419				5.102			
GTSARIX for Web Search				**GTSARIX for Youtube Search**			
Austria	India	South Korea	Turkiye	Austria	India	South Korea	Turkiye
1.979	7.398	1.419	9.637	1.978	7.392	1.415	9.639
5.108				5.106			

Based on **Table 5**, model performance was evaluated using the MAPE, where lower values indicate better forecasting accuracy. The results show that performance varied depending on the specific model and the Google Trends category used to construct the spatial weight matrix. The Image Search-based GSTARX model yielded the lowest average MAPE (4.326%) compared to the other GSTARX and GSTARIX models. This model produced MAPE values of 2.109% for Austria, 3.277% for India, 2.359% for South Korea, and 9.559% for Turkiye. Although the MAPE value for Turkiye was relatively higher than that of the other three countries, the model's overall performance remained the best based on the average MAPE. Conversely, the YouTube Search-based GSTARX model produced the highest average MAPE (6.419%). These results demonstrate that the Google Trends category used to construct the spatial weight matrix influences the model's forecasting capability. Based on the lowest MAPE value, the GSTARX model utilizing a Google Image Search-based spatial weight matrix was selected as the best model and subsequently used to forecast gold prices for the period from December 18, 2021, to March 31, 2022.

Based on **Figure 3,** Gold price forecasting results for Austria indicate a relatively stable pattern throughout the forecast period. At the start of the period, the gold price was projected at 1,603.35 EUR, gradually declining to 1,586.79 EUR by March 31, 2022. This represents a decrease of approximately 16.56 units, or 1.03%, over the forecast period. The pattern suggests that the model anticipates Austrian gold prices remaining relatively constant, with a slight downward tendency. These relatively minor changes indicate that, based on the historical dynamics utilized in the model, no significant price fluctuations are projected for Austria during this period.

For India, the forecast results reveal a more pronounced downward trend. The gold price was projected at 137,536.59 INR at the beginning of the period, gradually falling to 130,856.22 INR by March 31, 2022 a decline of approximately 6,680.37 units, or 4.86%. This pattern indicates that the GSTARX model predicts a gradual downward trend in gold prices in India throughout the forecast period. Although the percentage decline is greater

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than that of Austria, the change remains relatively moderate compared to the patterns projected for South Korea and Turkiye.

In contrast to Austria and India, South Korea exhibits a much sharper decline. The gold price at the start of the forecast period was projected at 2,134,803.26 KRW, steadily falling to 1,667,359.08 KRW by the end of the period. Consequently, the gold price is estimated to have dropped by approximately 467,444.18 units, or 21.90%. These results indicate that the model projects a significant downward trend in South Korean gold prices. This substantial decline also demonstrates that the dynamics of gold prices in South Korea during the forecast period differ significantly from those in Austria and India.

Meanwhile, Turkiye displays a pattern that differs markedly from the other three countries. The price of gold is projected to start at 29,642.66 TRY and rise consistently, reaching 123,894.08 TRY by March 31, 2022. Overall, this represents an increase of approximately 94,251.42 units, or 317.96%. Thus, the model projects a very sharp rise in gold prices in Turkiye over the forecast period. This pattern stands out as the most prominent feature of the forecast results, indicating that the dynamics of gold prices in Turkiye follow a different pattern compared to those in Austria, India, and South Korea.

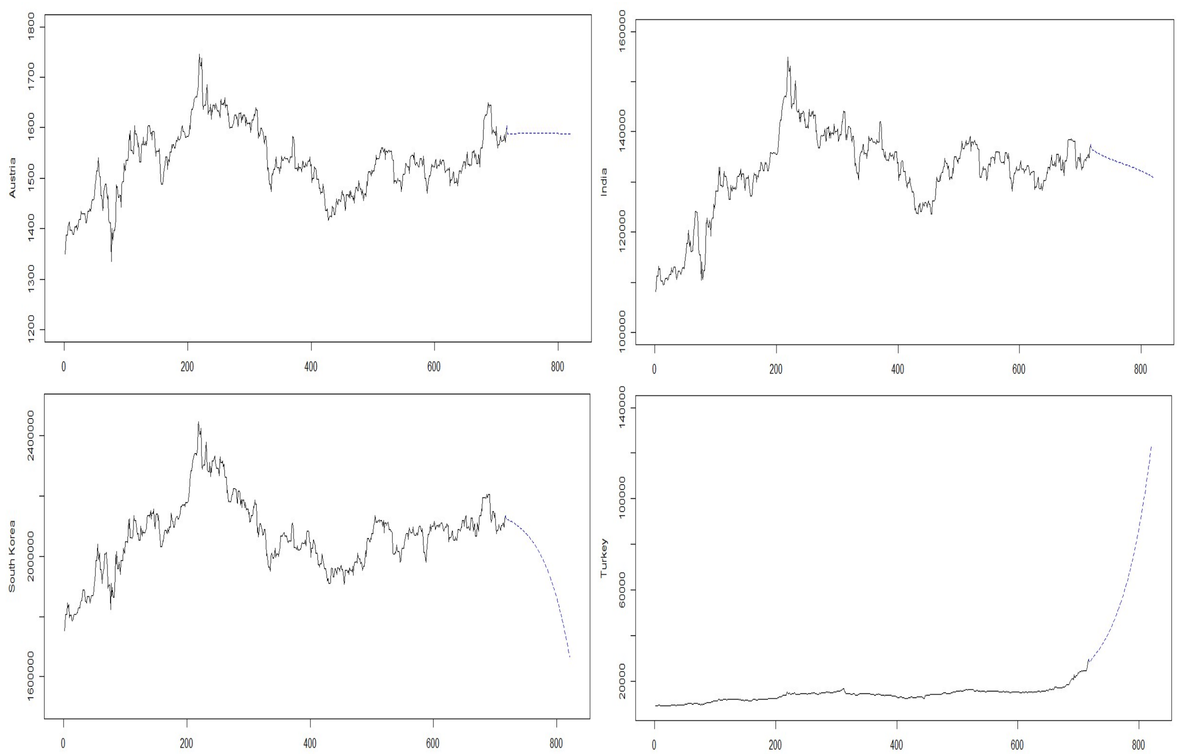

Figure 3. Forecasting graph of the gold price in each country

IV. CONCLUSION

In certain cases, the data has missing values. So, it is necessary to solve this problem because it can reduce the accuracy of the model. Especially in the time series field, of course missing values violates the assumption of sequential data. Gold price data from the World Gold Council is one of the data that has missing values every Saturday and Sunday. This research solved the problem by LOCF technique. Of course, the gold price data for Saturday and Sunday was the same as Friday.

This research provided an alternative center of the country other than capital. This determination based on Google Trend data by object of the research. In this study, the keyword was “gold price”. These keywords have been translated into each language. For Austria was “goldpreis”, India was “gold price”, South Korea was “황금 가격”, and Turkiye was “altın fiyat”. Based on these keywords, each country center has been raised according to the

DOI: https://doi.org/10.24036/ujsds/vol4-iss3/534

ISSN(*Print*) : 3025-5511
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categories in the Google Trends data. In South Korea there had no gold price search in the Google Shopping and News Search categories during COVID-19. So, in total there are 3 categories such as Image Search, Web Search, and Youtube Search.

Furthermore, the GSTARX and GSTARX models used all categories from Google Trends data for exogenous variables. However, for the spatial weighting matrix simulation, only Image Search, Web Search and Youtube Search categories have been used. Based on MAPE, the best model was GSTARX where the spatial weighting matrix by Image Search category. Logically, the graph of changes in the price of gold is preferable to look at when compared to numbers. In general, in this model the influential parameters were lag 1 of the gold prices in each country itself. Based on these parameters, the gold price has been forecasted from December 18, 2021 to March 31, 2021. Relatively speaking, the gold price forecast in Austria is constant, India is decreasing, South Korea is decreasing significantly, and Turkiye increasing significantly. Also, gold prices in Turkiye had different from Austria, India, or South Korea.

This research has the potential to be developed from imputation techniques, Google Trends data categories, spatial weighting, models, number of series and number of countries. Imputation techniques related to parametric such as regression or nonparametric statistics such as moving average smoothing are also recommended. Regarding Google Trend data, this research used 1 keyword. Keywords that are more than 1 provide more alternatives and simulations that can be compared. In addition, the spatial weighting that has been used in the study is limited to order 1 so that further research can use a higher order of spatial order. The spatial order can then be applied to the GSTARX, GSTARIX, and generalized space time autoregressive integrated with exogenous variable moving average (GSTARIMAX) models, other space time models to get better forecasting accuracy than the model in this study. The addition of series and number of countries for more research is recommended to see the pattern of gold prices and the effect of gold prices between countries. Even if possibles the models and techniques that have been used in this research can be applied to big data.

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