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Spatial impact on inflation of Java Island prediction using Autoregressive Integrated Moving Average (ARIMA) and Generalized Space-Time ARIMA (GSTARIMA)[☆,☆☆]

Anisya Safira, Riswanda Ayu Dhiya'ulhaq, Indah Fahmiyah, Mohammad Ghani[*]

Data Science Technology, Faculty of Advanced Technology and Multidiscipline, Universitas Airlangga, Surabaya, 60115, Indonesia

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ABSTRACT

Inflation is one of macroeconomic issues in Indonesia that needs to be controlled. Inflation could happen because of widespread increases in the cost of goods and services. Annual inflation rate in Indonesia on 2008 to 2023 are quite fluctuating and several periods are not achieved inflation target yet. One of the ways to control inflation is by making predictions for the upcoming period. Java Island is the biggest contributor on economy and Gross Domestic Product (GDP) in Indonesia so it can be considered as general indicator to measure overall inflation rate of Indonesia. Thus, data used in this study is monthly inflation at each province in Java Island from January 2008 to December 2023. This study using two methods, Autoregressive Integrated Moving Average (ARIMA) for univariate time series prediction and Generalized Space-Time ARIMA (GSTARIMA) for multivariate time series prediction with a spatial factor. The results of both models will be compared to determine which model has better accuracy. Based on RMSE value, GSTARIMA model has least average RMSE value, which is 0.113 compared with ARIMA model which has average RMSE value 0.319 thus it can conclude that spatial factors addition could increase accuracy on inflation prediction in Java Island.

- This paper purposes to get Java Island's inflation rate prediction to determine better policy on controlling cost of goods and services.
- Best model using GSTARIMA methods is GSTARMA(1,1) with distance invese matrix that indicate that coordinate point of each location increase performance of inflation rate prediction.
- The result indicate GSTARIMA has better accuracy than ARIMA for inflation prediction in Java Island based on RMSE value.

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* Corresponding author.
E-mail address: mohammad.ghani@ftmm.unair.ac.id (M. Ghani).

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Resource availability:	https://github.com/anisyasafiraa/ARIMA-GSTARIMA_Java-Island-Inflation

Background

Inflation is one of the most critical indicators in macroeconomics that needs to be controlled. In economic terms, inflation is a monetary phenomenon in a country, where its increase and decrease tend to cause economic turbulence thus efforts should be made to keep the inflation rate low to maintain economic stability [1]. According to the 2020 population census, Java Island is home to 56% of Indonesia's residents. The Central Bureau of Statistics (BPS) indicates that economic activity remains concentrated on Java, highlighting its crucial role in Indonesia's economic structure. In 2023, Java Island contributed 57.27% to the national economy and 5.18% to the Gross Domestic Product (GDP), making it a significant indicator for measuring Indonesia's overall inflation rate.

Inflation tends to increase rapidly if not addressed and will slow down economic growth [2]. Inflation adversely affects salaried workers, as a rapid increase in inflation compared to wage growth can lower the overall standard of living [3]. One approach to controlling inflation is by making predictions for future periods. Inflation is time series data and one of the most commonly used models for time series data is the Autoregressive Integrated Moving Average (ARIMA) model [4]. The ARIMA model developed before by Benvenuto et al. [5] to forecast spread of Covid-19, Poongodi et al. [6] to forecast bitcoin price, and by Shadab et al. [7] to forecast monthly solar radiation.

From several researches before, it is suspected that data may not only have a relationship with previous periods' data but also with data from surrounding locations. As ARIMA models focus only on time series forecasting without considering spatial effects, a model that extends the framework to incorporate spatial dependencies that making it more suitable for analyzing data with both temporal and spatial patterns is needed. Therefore, on this study, Space-Time Autoregressive (STAR) model will be used. However, STAR is only suitable for homogeneous locations thus Ruchjana [8] developed Generalized Space-Time ARIMA (GSTARIMA) model for heterogeneous locations. GSTARIMA developed before by Ajobo et al. [9] using Seemingly Unrelated Regression (SUR) estimation parameter method to forecast monthly rainfall and temperature in West African countries, Salsabila et al. [10] to forecast climate data and concluded that correct time order will produce a more accurate model, and by Mukhaiyar et al. [11] with an exogenous variable to forecast dengue fever cases in West Kalimantan Province.

Anggraeni et al. [4] developed ARIMA, GSTARIMA, and the ensemble model to forecast rainfall in Jember City. In this study, inflation predictions for each province on Java Island are conducted using the ARIMA and GSTARIMA methods. The model with better accuracy will be determined using the Root Mean Squared Error (RMSE) value as the evaluation metric. The forecasted inflation values are expected to inform policy-making by relevant stakeholders.

Method details

Time series data before further analysis need to be stationary [12]. The stationarity test is conducted to identify the presence of trends in terms of variance and mean. Variance stationarity test is performed by examining the Box-Cox plot where if a value of $\lambda \neq 1$ is obtained, data must be transformed based on λ value [13]. Subsequently, mean stationarity test is conducted using Augmented Dickey-Fuller (ADF) test. If p-values greater than significance level α is obtained, data must be differenced until p-values is less than significance level α [14].

Box and Jenkins [15] proposed ARIMA for forecasting univariate time series data. The ARIMA model performs short-term forecasting using an iterative approach to identify the most appropriate model based on past and present data of the dependent variable. In ARIMA modeling, three orders need to be determined, p which is Autoregressive order that identified based on Partial Autocorrelation Function (PACF) plot, q which is Moving Average order that identified based on Autocorrelation Function (ACF) plot, and d which is the number of data being differenced [16]. Subsequently, the significance of the parameters in each model is evaluated. If one or more parameters are found to be insignificant (p-values greater than α), that model is discarded, and another ARIMA model is identified. Parameter estimation method used in this study is Ordinary Least Squares (OLS). To determine the optimal time order (p and q) combination, the Root Mean Square Error (RMSE) will be used as the evaluation metric. The model with the lowest RMSE is assumed to provide the most accurate prediction results. ARIMA model for data that already stationary in mean with 0 (zero) differencing order is ARMA [7]. The ARMA model is expressed as follows:

$$Z_t = \sum_{k=1}^{p} \phi_k Z_{t-k} - \sum_{k=1}^{q} \theta_k a_{t-k} + a_t$$

where ϕ_k refers to Autoregressive (AR) estimator on lag k, θ_k refers to Moving Average (MA) estimator on lag k, and a_t refers to residual.

As ARIMA models primarily focus on time series forecasting without considering spatial effects, which are often play significant roles in regional economics, such as in the case of inflation, a GSTARIMA model is considered in this study to incorporate spatial dependencies. The GSTARIMA model is an extension of the STARIMA model designed to handle heterogeneous locations [4]. Hence, before proceeding to further analysis using the GSTARIMA model, a spatial autocorrelation test is needed. In this study, the Moran's I test will be conducted for this purpose. If the dataset demonstrates spatial autocorrelation, then the GSTARIMA model should be considered, allowing for an assessment of whether integrating spatial factors would enhance forecasting accuracy.

For GSTARIMA modeling, four orders need to be determined, p that identified based on Matrix Partial Autocorrelation Function (MPACF), q that identified based on Matrix Autocorrelation Function (MACF), d, and λ which is spatial order that generally limited to the first order due to proximity of locations and to simplify model interpretation [4,17]. The GSTARIMA model employs a spatial weight matrix, which, according to Wei [18], is a square matrix comprising weights corresponding to the locations as its elements. The GSTARMA model is expressed as follows:

$$\boldsymbol{Z}_t = \sum_{k=1}^{p} \left[\phi_{0k} + \phi_{1k}\boldsymbol{W}_{ij}\right]\boldsymbol{Z}_{t-k} - \sum_{k=1}^{q} \left[\theta_{0k} + \theta_{1k}\boldsymbol{W}_{ij}\right]\boldsymbol{a}_{t-k} + \boldsymbol{a}_t$$

where ϕ_k refers to diagonal matrix of AR order estimator, $\boldsymbol{\theta}_k$ refers to diagonal matrix of MA order estimator, $\boldsymbol{W}_{ij}$ refers to spatial weight matrix of size NxN (N refers to number of location used), and $\boldsymbol{a}_t$ refers to vector that consists of each location's residual.

In this study, three types of matrices will be utilized: the uniform matrix, which gives each location equal weight; the inverse distance matrix, which reflects the actual distance between each location; and the cross-correlation matrix, which uses normalized cross-correlation weights at specific lags and does not require spatial autocorrelation at each location. Parameters in GSTARIMA modeling will be estimated through the Ordinary Least Squares (OLS) method. Identifying parameter significance is unnecessary since both significant and insignificant estimators are incorporated, owing to the presence of a weighting matrix [19].

Diagnostic tests, including the white noise test and the residual normality test, are performed on the developed ARIMA and GSTARIMA models. The white noise test is conducted using the Q-Ljung Box test which is satisfied when p-value is greater than significance level α, while the normality test is performed using the Shapiro-Wilk test for the ARIMA model which is satisfied when p-values are greater than significance level α and the Mahalanobis d-squared test for the GSTARIMA model which is satisfied when 50% of d-squared values are less than $\chi^2_{\alpha,i}$ [10,13].

Given that the more complex approach, such as GSTARIMA, does not consistently give better accuracy compared to the simpler approach like ARIMA, this study aims to compare the prediction outcomes of both ARIMA and GSTARIMA models using outsample data. The goal is to determine whether integrating spatial relationships improves the accuracy of forecasting the actual monthly inflation rate over 12 periods in 2023. The best method will be identified based on the RMSE value.

Method validation

Exploratory data analysis

The dataset utilized in this study comprises the monthly inflation rates for all provinces on Java Island, including Banten, Special Region of Yogyakarta, DKI Jakarta, West Java, Central Java, and East Java, over 192 periods. Fig. 1 indicates that the inflation rates across these provinces are not significantly different from one another. The peak inflation rate was recorded in July 2013, attributed to a government-mandated increase in fuel oil prices, which subsequently led to an increase in the prices of other commodities such as transportation, information, communication, and financial services [20,21]. According to Fig. 1, Banten (in blue) has greater range of inflation rate than other provinces with highest rate 4.16% on July 2013 and lowest rate −0.77% on March 2011.

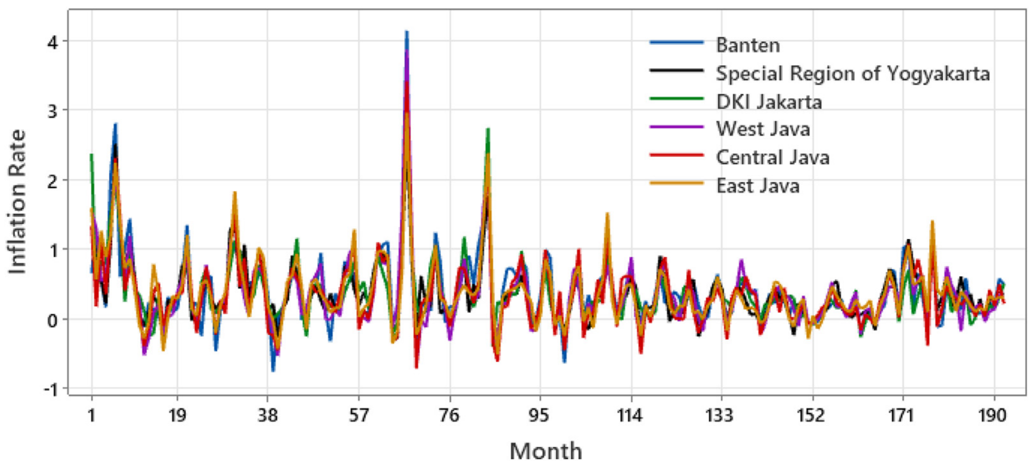

Fig. 1. Time series plot of monthly inflation rate from six provinces in Java Island (2008 – 2023).

Table 1
Result λ and Box-Cox transformation.

Province	λ	First Transformation		Second Transformation	
		Transformation	λ	Transformation	λ
Banten (Z_1)	0.50	$\sqrt{Z_t}$	0.50	$\sqrt{Z_t}$	1
Yogyakarta (Z_2)	0.00	$ln(Z_t)$	1	–	–
Jakarta (Z_3)	−0.50	$1/\sqrt{Z_t}$	1	–	–
West Java (Z_4)	0.50	$\sqrt{Z_t}$	0.50	$\sqrt{Z_t}$	1
Central Java (Z_5)	0.50	$\sqrt{Z_t}$	0.50	$\sqrt{Z_t}$	1
East Java (Z_6)	0.00	$ln(Z_t)$	1	–	–

Table 2
Augmented Dickey-Fuller test.

Province	Banten	Yogyakarta	Jakarta	West Java	Central Java	East Java
τ	−5.34	−4.62	−4.98	−5.52	−5.72	−4.76
P. Value	0.01	0.01	0.01	0.01	0.01	0.01

Stationary test

Before further analysis, it is essential to conduct a stationarity test on insample data (monthly inflation rate on 2008—2022). The stationarity test is performed to identify the presence of trends in the data concerning variance and mean. Table 1 shows that each province has varying values of λ, necessitating different transformations to achieve stationarity in variance, as presented in the "Transformation" column. After ensuring stationarity in variance, a stationarity test in mean is required using the Augmented Dickey-Fuller (ADF) test. As indicated in Table 2, it can be concluded that all data are stationary in mean, with p-values less than the significance level α (0.05). Consequently, the order of differencing, denoted as d, is determined to be 0 (zero), indicating that the model to be formed here is ARMA(p, q), suitable for time series data that are already stationary in mean [22].

ARIMA

Stationary data obtained before will be used for ARIMA modeling. Based on the ACF and PACF plots in Fig. 2, there are cut-offs after certain time lags that can be considered as candidates for time order. The appropriate order is crucial for producing a good and accurate model for forecasting or modeling time series [10]. Each dataset has different time order candidates, resulting in different models formed for each province. ARMA models will be formed using several combinations of these time order candidates for each province, and the parameter estimation values will be determined using the Ordinary Least Squares (OLS) method. After that, a parameter significance test will be conducted. To achieve the main purpose of this paper, which is to compare the ARIMA and GSTARIMA methods for inflation rate prediction, it is necessary to determine the best-performing model for each method.

Table 3 shows the best-performing ARMA models based on RMSE values for each province along with their parameter estimates. These models has passed significant parameters test with p-values less than α(0.05). Additionally, all model passed the white noise using Q-Ljung Box statistic test and residual normality test using Shapiro-Wilk statistic test, which are fulfilled when p-values are greater than α(0.05). However, model for Banten's inflation rate prediciton did not pass residual normality test. This occured due to the presence of an outlier in the insample data which can cause the residual normality test to be unfulfilled.

GSTARIMA

From a statistical perspective, to determine the effect or spatial autocorrelation of spatial data, Moran's I test can be utilized using inverse distance matrix as spatial weight matrix. The hypothesis of spatial autocorrelation test is as follows:

$H_0 : I = 0$ (there is no spatial autocorrelation)

$H_1 : I \neq 0$ (there is spatial autocorrelation)

Table 4 presents the result of Moran's I test which indicate the presence of spatial autocorrelation as evidenced by $Z(I) > Z\alpha_{/2}$ thus inflation rate of each province in Java Island influence each other.

The GSTARIMA model consists of two types of order, spatial order that generally limited to the first order and time order that identified based on MACF and MPACF plots. Both plots presents three symbols, (+) indicated the correlation of each location is two times greater than the standard error, (-) indicated correlation of each location is two times less than the standard error, and (.) indicated no correlation. Time lags that frequently show (+) and (-) rather than (.) suggest significant MACF or MPACF, and conversely. Thus, according to Fig. 3, MACF is significant at lag 1, 5, and 6 while MPACF is significant on lag 1. Lag 5 and 6 on MACF will not be used as greater lags are assumed to be less significant. Although higher-order model might capture intricate patterns in time series data, estimating and interpreting them can lead to greater challenges [10]. With d order set to 0 (zero), the model formed later here is GSTARMA(p, q), GSTARIMA models for space-time series data that are already stationary in mean.

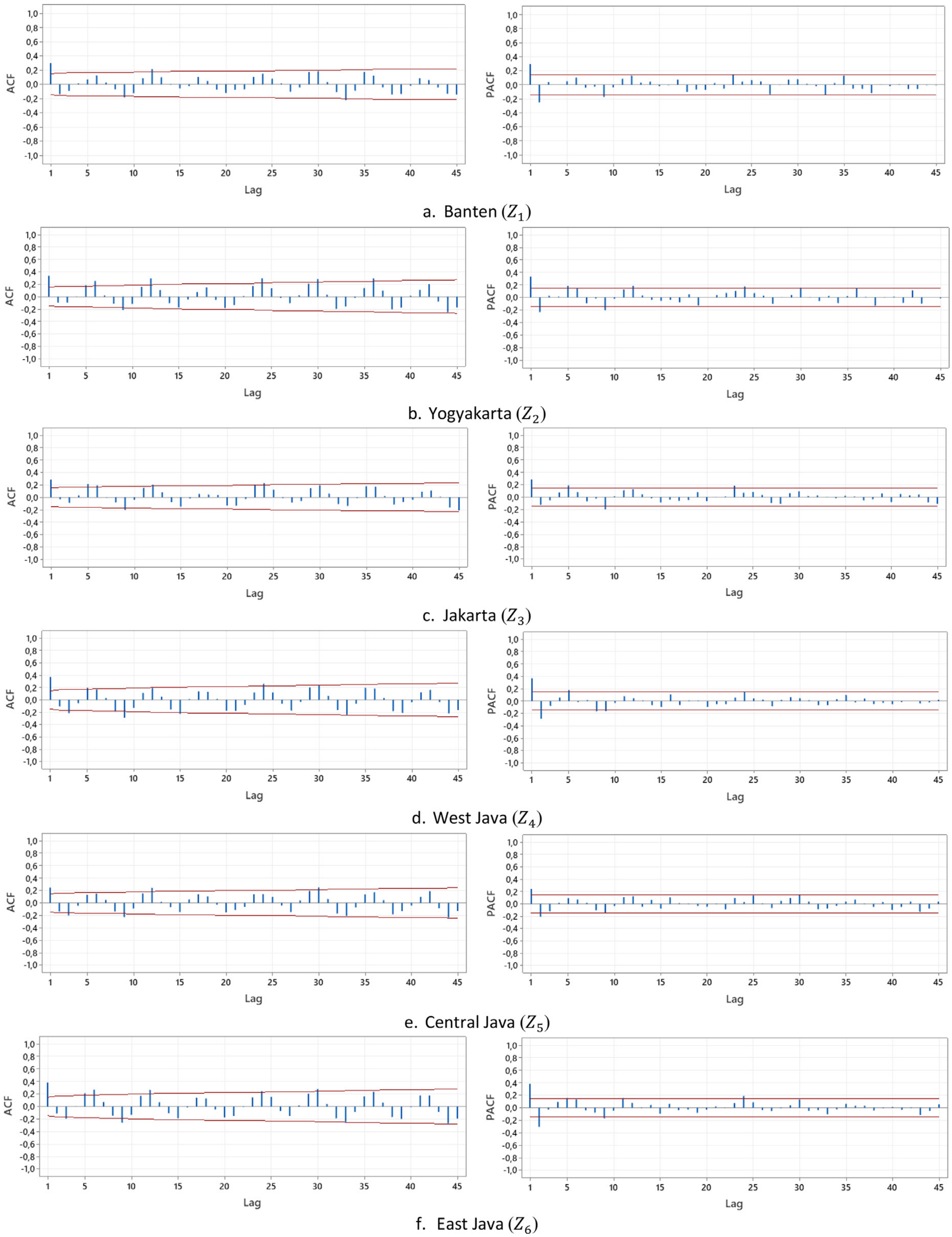

Fig. 2. ACF (left) and PACF (right) plot of inflation rate.

Table 3
ARIMA Model, RMSE values on insample data, and P.values of residual assumption test.

Province	Model	Parameter			RMSE	White Noise (P. Value)	Normality Test (P. Value)
		Estimator	Approx. Estimate	P. Value			
Banten (Z_1)	ARMA([1,9,12])	ϕ_1	0.652	0.000	0.094	0.199	0.000
		ϕ_9	0.346	0.000			
		θ_1	−0.320	0.000			
		θ_9	−0.489	0.000			
		θ_{12}	0.227	0.000			
Yogyakarta (Z_2)	ARMA([1,2,6,9,12])	ϕ_1	0.794	0.000	0.257	0.267	0.122
		ϕ_2	−0.292	0.000			
		ϕ_9	0.045	0.000			
		θ_1	−0.644	0.000			
		θ_6	0.463	0.000			
		θ_{12}	0.514	0.000			
Jakarta (Z_3)	ARMA([1,5,9,12])	ϕ_5	0.689	0.000	0.132	0.635	0.054
		ϕ_9	0.304	0.000			
		θ_1	0.223	0.002			
		θ_{12}	0.189	0.018			
West Java (Z_4)	ARMA([1,3,5,9])	ϕ_9	0.981	0.000	0.118	0.542	0.056
		θ_1	0.513	0.000			
		θ_3	−0.467	0.000			
		θ_5	0.497	0.000			
Central Java (Z_5)	ARMA([1,9,12],)	ϕ_9	0.974	0.000	0.133	0.950	0.079
		θ_1	0.331	0.000			
		θ_{12}	0.271	0.001			
East Java (Z_6)	ARMA([1–3,5])	ϕ_2	0.195	0.006	0.290	0.195	0.067
		ϕ_5	0.538	0.000			
		θ_1	0.585	0.000			
		θ_3	−0.163	0.026			
		θ_5	−0.302	0.001			

Table 4
Moran's I test result.

I	E(I)	Var(I)	Z(I)	Critical Point	Conclusion
0.198	−0.200	0.039	2.013	1.96	Significant

Schematic Representation of Cross Correlations

Variable/Lag	0	1	2	3	4	5	6
Banten	++++++	++++++	......	......	......	......	..+..+
Yogyakarta	++++++	++++++	......	......	......	++++++	++++++
Jakarta	++++++	++++++	......	......	......	++++++	++++++
West_Java	++++++	++++++	......	...---	......	++++++	++++++
Central_Java	++++++	++++++	......	...-..	......	++++++	++++++
East_Java	++++++	++++++	......	......	......	++++++	++++++

+ is > 2*std error, - is < -2*std error, . is between

Schematic Representation of Partial Cross Correlations

Variable/Lag	1	2	3	4	5	6
Banten	....++	-.....	+.....	......	......	......
Yogyakarta	.....+	......	+.....	......	......	...-..
Jakarta	++....	...--.	.....+	......	+.....	.....-
West_Java	+.++..	....-.	......	.+....	......	......
Central_Java	...+..	......	......	......	......	.....+
East_Java	.+...+	.....-	......	......	......	.+....

+ is > 2*std error, - is < -2*std error, . is between

Fig. 3. MACF (left) and MPACF (right) plots.

Based on Fig. 3, the subsequent models are GSTARMA(1,0), GSTARMA(1,1), and GSTARMA(0,1). Three spatial weight matrices used in this study, uniform matrix, inverse distance matrix, and cross correlation matrix. All model formed will be compared using these weight matrices. Since identifying parameter significance is unnecessary, we proceed to residual assumption test. Table 5 presents the results of the white noise test, indicating that not all models met the criteria. In the GSTARMA(1,1) model, only model with the uniform matrix failed the white noise test in Central Java Province. Moreover, the GSTARMA(0,1) model with all three weight matrices failed the white noise test in more than three provinces. Table 5 also presents the percentage of d-squared values less than $\chi^2_{\alpha,i}(12.59)$, indicating that the residuals of all models are normally distributed.

Salsabila et al. [10] stated that choosing the correct order will produce a more accurate model. To determine which model has better performance, we will used RMSE values as the performance metrics, the effectiveness of GSTARIMA models employing different weight matrices—uniform, inverse distance, and cross-correlation. The findings on Table 6 indicate that the GSTARMA(1,1) model utilizing the inverse distance weight matrix provided better forecast accuracy than those using the uniform or cross-correlation matrices. This suggests that incorporating spatial dependencies through the inverse distance weight matrix enhances the model's predictive accuracy. Moreover, the coordinate points utilized to construct the inverse distance matrix significantly impact inflation

Table 5
Result of residual assumption test.

Model – Weight Matrix	P. Values of White Noise Test						Percentage of Dsquared $< \chi^2_{\alpha,i}(12.59)$
	Banten	Yogyakarta	Jakarta	West Java	Central Java	East Java	
$GSTARMA(1,0)_1$							
- Uniform	0,139	0,242	0,366	0,452	0,011	0,114	100
- Inverse Distance	0,726	0,256	0,796	0,620	0,081	0,116	100
- Cross Correlation	0,127	0,256	0,796	0,620	0,081	0,116	100
$GSTARMA(1,1)_1$							
- Uniform	0,389	0,731	0,103	0,587	0,897	0,892	100
- Inverse Distance	0,541	0,931	0,771	0,974	0,685	0,792	100
- Cross Correlation	0,252	0,890	0,650	0,618	0,626	0,961	100
$GSTARMA(0,1)_1$							
- Uniform	0,000	0,494	0,000	0,000	0,111	0,770	99.34
- Inverse Distance	0,000	0,483	0,000	0,000	0,000	0,950	100
- Cross Correlation	0,000	0,662	0,000	0,000	0,138	0,973	100

Table 6
Comparison of RMSE values.

Model - Weight matrix	Province						Average
	Banten	Yogyakarta	Jakarta	West Java	Central Java	East Java	
$GSTARMA(1,0)_1$							
- Uniform	0.143	0.289	0.131	0.136	0.146	0.305	0.192
- Inverse Distance	0.134	0.289	0.128	0.138	0.142	0.305	0.189
- Cross Correlation	0.143	0.289	0.128	0.138	0.142	0.305	0.191
$GSTARMA(1,1)_1$							
- Uniform	0.140	0.280	0.129	0.136	0.141	0.296	0.187
- Inverse Distance	0.130	0.282	0.128	0.130	0.138	0.296	0.184
- Cross Correlation	0.141	0.281	0.127	0.132	0.135	0.296	0.185
$GSTARMA(0,1)_1$							
- Uniform	0.596	0.309	0.469	0.589	0.349	0.331	0.440
- Inverse Distance	0.299	0.298	0.557	0.301	0.588	0.318	0.394
- Cross Correlation	0.598	0.307	0.461	0.590	0.336	0.322	0.436

Table 7
Comparison of RMSE value on outsample data.

Province	ARIMA	GSTARIMA
Banten (Z_1)	0.212	0.080
Yogyakarta (Z_2)	0.244	0.155
Jakarta (Z_3)	0.256	0.078
West Java (Z_4)	0.672	0.173
Central Java (Z_5)	0.516	0.062
East Java (Z_6)	0.146	0.130

rate prediction compared to the uniform matrix, which assumes equal weighting for all locations, and the cross-correlation matrix, which does not consider the correlation between the distances of each location but only focuses on the inflation rate.

The best performance of forecasting models

The objective of this study is to ascertain which model exhibits superior performance in forecasting. In this section, we will evaluate the forecasting performance of each model for predicting monthly inflation rates across different provinces in 2023. The effectiveness of these models was evaluated using outsample data and the RMSE value as the performance metric to determine whether incorporating spatial relationships improves forecast accuracy. The graph in Fig. 4 visually illustrates the comparison of forecast results between ARIMA (in red), GSTARIMA (in green), and the actual values (in blue). It is evident that both models closely approximate the actual values; hence, we will employ RMSE as the evaluation metric. The model with the smaller RMSE value will be considered superior.

Table 7 reveals that the model with the smallest RMSE in each area is the GSTARIMA model rather than ARIMA. The results demonstrate that the GSTARIMA model, particularly when utilizing an inverse distance weight matrix, outperformed the ARIMA model in terms of forecast accuracy. This suggests that accounting for spatial dependencies between provinces enhances the model's predictive capability, leading to more accurate inflation forecasts. It can be concluded that for datasets with significant spatial re-

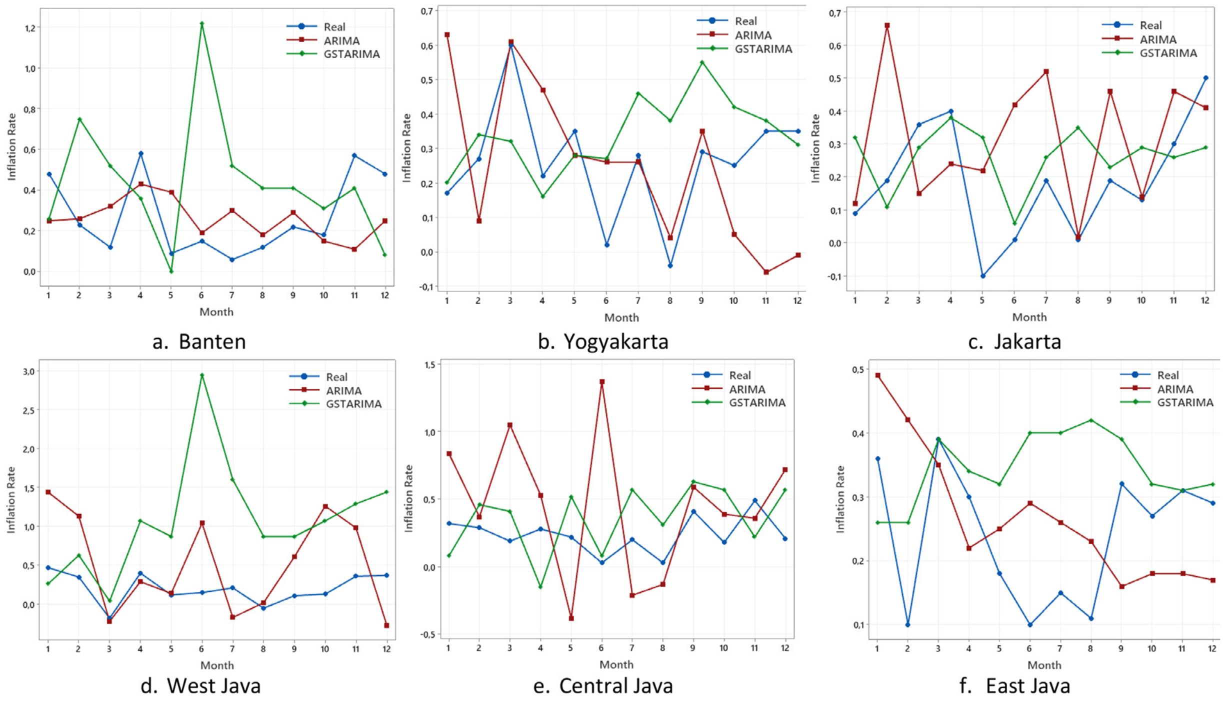

Fig. 4. Comparison of prediction result of monthly inflation rate on 2023.

lationships, the GSTARIMA model proves to be a more effective forecasting tool compared to the traditional ARIMA model. This highlights the importance of considering spatial elements into time series forecasting to achieve better accuracy and more reliable predictions on inflation.

Limitations

This study encountered challenges arising from the presence of outlier data, which resulted in the failure to meet the normality residual assumption test for Banten province on ARIMA model. To address this issue in future research, alternative methods capable of handling outlier data should be explored. Moreover, to enhance the accuracy of inflation rate predictions, additional economic indicators could be incorporated as predictor variables. These may include indicators such as economic growth, per capita income, unemployment rate, among others.

Ethics statements

As an expert scientist and along with co-authors of the concerned field, the paper has been submitted with full responsibility, following due ethical procedure, and there is no duplicate publication, fraud, plagiarism, or concerns about animal or human experimentation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

CRediT authorship contribution statement

Anisya Safira: Conceptualization, Formal analysis, Investigation, Writing – original draft, Writing – review & editing, Software. **Riswanda Ayu Dhiya'ulhaq:** Conceptualization, Formal analysis, Investigation, Writing – original draft, Writing – review & editing, Software. **Indah Fahmiyah:** Supervision, Conceptualization, Methodology, Writing – original draft, Writing – review & editing, Validation. **Mohammad Ghani:** Supervision, Conceptualization, Methodology, Writing – original draft, Writing – review & editing, Validation.

Data availability

Data will be made available on request.

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The data used obtained from Central Bureau of Statistics (BPS) of each province in Java Island.

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