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FORECASTING INFLATION IN NORTH SUMATRA PROVINCE USING ARIMA AND LINEAR REGRESSION MODELS

Gayus Simarmata[1], **Anil Hakim Syofra**[2], **Rajainal Saragih**[3]

[1]Department of Mathematics, University HKBP Nommensen Pematangsiantar, 21136, Indonesia
[2]Department of Mathematics Education, Universitas Asahan, 21216, Indonesia
[3]Department of Computer Engineering, Politeknik Bisnis Indonesia, 21151, Indonesia

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ABSTRACT

This study compares the forecasting performance of the ARIMA and multiple linear regression models in predicting monthly inflation in North Sumatra Province, Indonesia. The dataset consists of 132 monthly inflation observations from January 2015 to December 2025 obtained from the Consumer Price Index (CPI) published by the Central Statistics Agency (BPS). A quantitative comparative approach was applied using training and testing datasets, where forecasting evaluation was conducted during the out-of-sample period from January to December 2025. Forecasting performance was assessed using RMSE, MAE, N-BIC, and R^2. The results show that the ARIMA (1,0,1) model produced limited forecasting performance with an R^2 of 6,9%, RMSE of 0,600, and MAE of 0,456. The multiple linear regression model incorporating time trends and monthly dummy variables achieved a relatively higher R^2 of 16,3%, indicating better representation of seasonal inflation patterns. Overall, the findings provide exploratory empirical evidence for regional inflation forecasting.

Corresponding Author:
Gayus Simarmata,
Department Of Mathematics,
University HKBP Nommensen Pematangsiantar
Email: gayuspermata244@gmail.com

1. INTRODUCTION

Inflation is a key macroeconomic indicator that reflects price stability and overall economic conditions. Stable inflation is essential for maintaining purchasing power, supporting economic growth, and guiding monetary policy decisions [1]. Conversely, high and volatile inflation can create economic uncertainty and negatively affect economic performance and investment decisions [2]. Therefore, accurate inflation forecasting is crucial for effective economic planning and policy formulation.

At the regional level, inflation dynamics often differ from national trends due to local factors such as economic structure, distribution systems, geographical conditions, and consumption patterns [3]. In addition, regional inflation is frequently influenced by seasonal factors, including religious holidays and fluctuations in food commodity prices [4]. These characteristics highlight the importance of forecasting approaches capable of capturing both temporal dynamics and recurring seasonal patterns.

Various forecasting approaches have been applied in inflation analysis, particularly time-series and regression-based methods. Among these approaches, the Autoregressive Integrated Moving Average (ARIMA) model is widely used because it can capture autocorrelation structures and short-term temporal dynamics in time-series data [5], [6], [7]. However, standard ARIMA models do not explicitly accommodate seasonal effects unless seasonal extensions are incorporated. In contrast, multiple linear regression models with seasonal dummy variables provide a simpler framework for representing recurring seasonal fluctuations directly through explanatory variables. Consequently, both approaches offer different analytical perspectives for examining inflation behavior.

Previous studies on inflation forecasting have generally focused on national inflation trends or emphasized the application of a single forecasting method [8], [9], [10], [11], [12]. Comparative empirical studies examining autoregressive and regression-based approaches for regional inflation forecasting in Indonesia remain relatively limited [13], [14]. Consequently, empirical evidence regarding the comparative performance of baseline forecasting approaches in seasonally fluctuating regional inflation data is still limited.

More advanced forecasting approaches such as SARIMA, Holt-Winters exponential smoothing, and machine learning-based models were not included in this study. The primary objective of this research is to conduct a focused comparative evaluation between a standard autoregressive framework and a regression-based seasonal framework using relatively interpretable baseline models. Including more complex forecasting methods could broaden the modeling scope beyond the exploratory focus of this study.

North Sumatra Province represents a relevant case for inflation forecasting because its inflation movements are influenced not only by general macroeconomic conditions but also by recurring seasonal factors such as religious holidays, food commodity price fluctuations, and regional distribution patterns. These characteristics create an environment in which both temporal dependence and seasonal variation play important roles in inflation behavior.

The selection of ARIMA and multiple linear regression models in this study is motivated by their different analytical characteristics and their widespread application in empirical forecasting studies. ARIMA is employed to represent autocorrelation structures and temporal dependence within the inflation series, whereas the regression model is used to explicitly capture seasonal effects through monthly dummy variables and time trends. By comparing these two baseline approaches, the study seeks to examine how explicit seasonal representation may influence forecasting performance.

This study positions itself as a regional empirical case study focusing on monthly inflation forecasting in North Sumatra Province. Rather than proposing a new forecasting methodology, the study comparatively evaluates the performance of ARIMA and multiple linear regression models with seasonal dummy variables in representing inflation fluctuations. The findings are expected to provide exploratory empirical evidence regarding the comparative suitability of autoregressive and regression-based approaches for seasonally patterned inflation data.

2. RESEARCH METHOD

This study employs a quantitative comparative design to analyze and compare the forecasting performance of ARIMA and multiple linear regression models in predicting monthly inflation in North Sumatra Province using time-series data. The ARIMA model is selected due to its ability to capture temporal dependencies through autocorrelation structures, while the multiple linear regression model is used as a benchmark because of its simplicity and its capability to explicitly model seasonal patterns through monthly dummy variables and time trends. This study focuses on a comparison between a conventional univariate autoregressive model and a regression-based seasonal approach as baseline forecasting methods. More complex models such as SARIMA, Holt-Winters exponential smoothing, and machine learning approaches are excluded to maintain the exploratory focus on interpretable baseline models.

2.1 Research Data

The The data used in this study consists of monthly inflation data for North Sumatra Province obtained from the Consumer Price Index (CPI) published by the Central Bureau of Statistics (BPS) for the period January 2015 to December 2025, totaling 132 observations. The inflation variable analyzed in this study is month-to-month inflation, which refers to the monthly percentage change in the Consumer Price Index. Prior to analysis, the data underwent preprocessing stages including completeness checking, chronological ordering, and consistency verification. The results of the inspection show that the dataset contains no missing values or duplicate data, so no imputation process was required. The descriptive statistics of the inflation data are presented in Table 1.

Table 1: Results of Descriptive Statistics Calculation

Statistical Measure	Number of Observations	Mean	Median	Standard Deviation	Minimum	Maximum
Inflation Rate (%)	132	0.23%	0.19%	0.60%	-1.81%	1.66%

To evaluate forecasting performance, the dataset was split into a training set (January 2015–December 2024) and a testing set (January–December 2025). Model estimation was conducted using the training data, while out-of-sample forecasting performance was assessed using the testing data. As the study adopts a univariate framework based solely on historical inflation values, its explanatory power is limited due to the exclusion of macroeconomic variables such as exchange rates, fuel prices, interest rates, and distribution costs.

Prior to ARIMA estimation, stationarity was tested using the Augmented Dickey-Fuller (ADF) test at a 5% significance level. The results indicate that the inflation series is stationary at level form, requiring no differencing (d = 0). Model identification was performed using Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF), resulting in candidate models ARIMA (1,0,0), ARIMA (0,0,1), and ARIMA (1,0,1). Model selection was based on RMSE, MAE, Normalized Bayesian Information Criterion (N-BIC), R^2, and residual diagnostics. The comparison of candidate ARIMA models is presented in Table 2.

Table 2: Comparison of Candidate ARIMA Models

ARIMA Model	R-squared	RMSE	MAE	N-BIC	P Value	White Noise
(1,0,0)	4.9%	0.604	0.464	-0.896	0.583	White Noise
(0,0,1)	6.5%	0.600	0.458	-0.912	0.675	White Noise
(1,0,1)	6.9%	0.600	0.456	-0.872	0.600	White Noise

The results indicate that all candidate models satisfy the white-noise assumption based on the Ljung-Box test, as all p-values exceed 0.05. Among the models, ARIMA (1,0,1) achieves lower RMSE and MAE values and a higher R^2 compared to the others, and is therefore selected as the best-performing model for forecasting. ARIMA parameters were estimated using the training data, and their significance was evaluated using p-values at the 5% level. Residual diagnostics using the Ljung-Box test and autocorrelation analysis confirm that residuals do not exhibit significant autocorrelation, although minor fluctuations remain.

The multiple linear regression model was estimated using Ordinary Least Squares (OLS) with a time trend and monthly dummy variables to capture seasonality. Coefficient significance was assessed using t-tests and p-values at the 5% level. After confirming that the regression model is feasible through the F-test and that several independent variables significantly affect the dependent variable based on the t-test, the next step is to examine the extent to which the regression model explains the variation in the dependent variable. This can be identified from the coefficient of determination (R^2) presented in the Model Summary table 3 as follows.

Table 3: Model Summary Output Using SPSS 26

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	0.403^a	0.163	0.078	0.59056

Based on the regression results presented in the table, the R^2 value obtained is 0.163. This indicates that the independent variables are able to explain 16.3% of the variation in inflation changes, while the remaining variation is influenced by other factors outside the model. Meanwhile, the correlation coefficient (R) of 0.403 indicates a moderately strong relationship between the independent variables and the inflation rate.

Forecast performance for both models was evaluated using RMSE, MAE, N-BIC, and R^2, where lower error values indicate better performance and higher R^2 indicates stronger explanatory power. The study is limited by the absence of robustness checks such as rolling forecasting and cross-validation due to its exploratory scope and limited sample size

2.2 ARIMA Model

The ARIMA (p,d,q) model is used to capture time series patterns through a combination of autoregressive (AR), differencing (I), and moving average (MA) components. The differencing process of order dis applied to ensure that the data are stationary before parameter estimation is performed [15]. Mathematically, the ARIMA model for the inflation rate can be expressed as follows:

$$\pi_t = c + \phi_1\pi_{t-1} + \phi_2\pi_{t-2} + \cdots + \phi_p\pi_{t-p} + \theta_1\varepsilon_{t-1} + \theta_2\varepsilon_{t-2} + \cdots + \theta_q\varepsilon_{t-q} + \varepsilon_t \tag{1}$$

where π_t denotes the inflation rate at time t, c is a constant term, $\phi_1, \phi_2, \ldots, \phi_p$ are the autoregressive coefficients representing the influence of past values, $\theta_1, \theta_2, \ldots, \theta_q$ are the moving average coefficients capturing the effects of past errors, and ε_t is the error term.

The implementation of the ARIMA model in this study consisted of four main stages: (1) model identification using stationarity analysis, ACF, and PACF to determine the appropriate ARIMA order; (2) parameter estimation using training data and significance testing at the 5% level; (3) residual diagnostic testing through autocorrelation analysis and the Ljung-Box test to ensure that the residuals satisfy the white-noise assumption; and (4) forecasting and model evaluation using RMSE, MAE, N-BIC, and R^2.

2.3 Linear Regression Model

As a comparative method, this study also employs a multiple linear regression model by incorporating a time trend variable and monthly dummy variables to capture seasonal patterns in inflation data.

Linear regression is used to model the relationship between a dependent variable and one or more independent variables under the assumption of a linear relationship, where changes in the independent variables are proportionally followed by changes in the dependent variable [16]. The simple linear regression model can be expressed as follows:

$$\hat{Y} = a + bX \tag{2}$$

where Y is the dependent variable, X is the independent variable, a is the constant (intercept), and b is the regression coefficient (slope) that represents the magnitude of the effect of X on Y.

2.4 Forecast Accuracy Indicators

Model performance is evaluated using three indicators, namely Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and the Normalized Bayesian Information Criterion (N-BIC). RMSE measures the variation of the dependent series relative to the model's predicted values and is expressed in the same unit as the dependent variable [17, 18, 19]. RMSE is defined as follows:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - \hat{x}_i)^2} \tag{3}$$

MAE measures the average absolute difference between the actual and predicted values and is expressed in the original unit of the data. MAE is used to assess forecasting accuracy, indicating how far the predictions deviate from the actual values. MAE is defined as follows:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|x_i - \hat{x}_i| \tag{4}$$

N-BIC is a model fit measure that also accounts for model complexity. This indicator is based on the Mean Square Error (MSE) with a penalty for the number of parameters and the length of the data.

$$BIC = -2\ln(L) + k\ln(n), \qquad N\text{-}BIC = \frac{BIC}{2} \tag{5}$$

where x_i represents the actual value, $\hat{x}_i$ denotes the forecasted value, n is the number of observations, L is the likelihood value of the model, and k is the number of parameters. Models with lower RMSE, MAE, and N-BIC values indicate better forecasting performance.

All data analysis procedures were conducted using SPSS version 26, which was utilized for model estimation, diagnostic testing, and the calculation of forecasting accuracy.

3. RESULT AND ANALYSIS

The data used in this study consist of the monthly inflation rate of North Sumatra Province from January 2015 to December 2025, with a total of 132 observations. The descriptive analysis results indicate that the average inflation rate is 0.23% with a standard deviation of 0.60%, a minimum value of -1.81%, and a maximum value of 1.66%. These findings suggest that inflation remains relatively low but exhibits considerable short-term fluctuations, thus requiring a modeling approach capable of capturing such dynamics. To better observe the pattern of inflation movements, the data are visualized in graphical form in Figure 1.

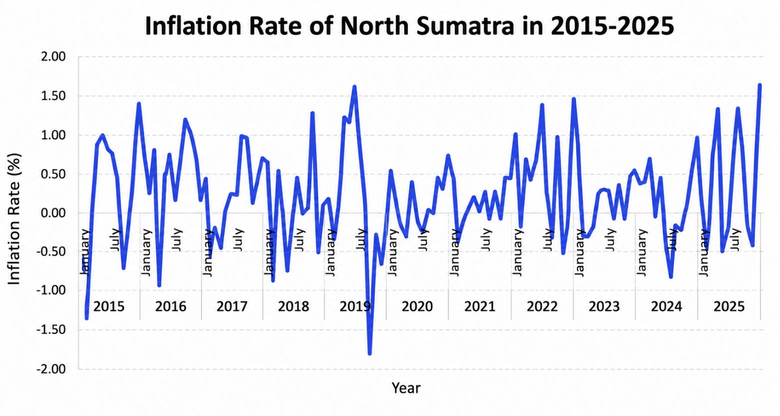

Figure 1. Monthly Inflation Trend of North Sumatra Province, 2015-2025

Based on Figure 1, inflation exhibits a fluctuating pattern around zero up to nearly 2%, with several occurrences of deflation. In addition, a recurring pattern can be observed in certain months, indicating the presence of a seasonal component. Economically, this phenomenon can be explained by consumption patterns, such as increased demand during religious holidays and fluctuations in food commodity prices. These findings are consistent with previous studies indicating that regional inflation is strongly influenced by seasonal patterns and consumption cycles [20].

Furthermore, to identify the appropriate model, ACF and PACF analyses are conducted as presented in Figure 2.

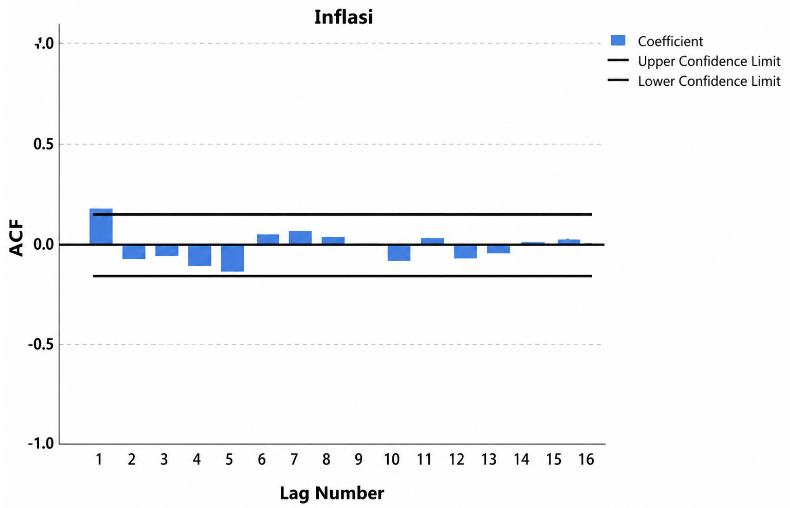

Figure 2. Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) Plots of Monthly Inflation Data in North Sumatra Province.

Based on Figure 2, significant autocorrelation appears only at the first lag, while subsequent lags fall within the confidence bounds. This indicates that the data are stationary at the level, and no differencing process is required. The ARIMA (1,0,1) model produced an RMSE value of 0.600 and an MAE value of 0.456, with a coefficient of determination (R^2) of 6.9%. In this study, the coefficient of determination (R^2) represents the proportion of inflation variability that can be explained by the forecasting model. The relatively low (R^2) value indicates that the ARIMA model has limited capability in explaining monthly inflation fluctuations in North Sumatra Province.

This condition may occur because the standard ARIMA model primarily relies on internal autocorrelation structures and does not explicitly accommodate seasonal effects. Although the ARIMA model is effective in capturing general time-series dynamics, it tends to produce relatively stable and flat forecasts when applied to regional inflation data characterized by recurring seasonal patterns. The forecasting plot also shows relatively wide prediction intervals, indicating a considerable degree of forecasting uncertainty. This is consistent with recent studies stating that ARIMA models have limitations in explaining complex economic phenomena when external variables or seasonal components are not explicitly incorporated [21]. The forecasting results using the ARIMA model are presented in Figure 3.

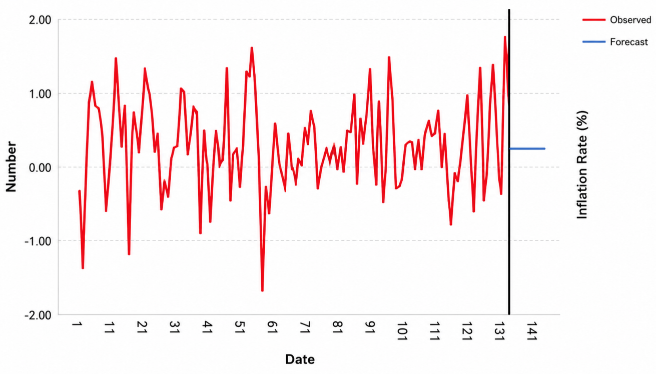

Figure 3. Comparison of Actual and Forecasted Monthly Inflation Values Using the ARIMA (1,0,1)

Based on Figure 3, the ARIMA model is able to follow historical patterns; however, it produces forecasts that tend to be relatively flat in future periods. In addition, the relatively wide prediction intervals indicate a high level of uncertainty. This suggests that the ARIMA model is less optimal in capturing seasonal patterns, as it relies solely on internal data relationships. The axis labels have been clarified and the figure resolution has been improved to enhance readability.

As a comparison, a linear regression model incorporating a time trend and monthly dummy variables is employed. The forecasting results of the linear regression model are presented in Table 4.

Table 4: Forecasting Results of the Linear Regression Model

No	Year	Month	Forecast	No	Year	Month	Forecast
121	2025	January	0.47	133	2026	January	0.759
122	2025	February	-0.36	134	2026	February	0.759
123	2025	March	0.27	135	2026	March	0.759
124	2025	April	0.17	136	2026	April	0.759
125	2025	May	0.32	137	2026	May	0.759
126	2025	June	0.42	138	2026	June	0.759
127	2025	July	0.28	139	2026	July	0.759
128	2025	August	0.28	140	2026	August	0.759
129	2025	September	0.16	141	2026	September	0.759
130	2025	October	0.15	142	2026	October	0.759
131	2025	November	0.15	143	2026	November	0.759
132	2025	December	0.74	144	2026	December	0.759

Based on Table 1, the regression model produces a more varied forecasting pattern and is able to follow inflation fluctuations across months. This indicates that the use of monthly dummy variables is effective in capturing seasonal patterns. The R^2 value of 16.3% shows that the regression model has better explanatory power compared to the ARIMA model, although it is still relatively low.

To further compare the performance of the two models, the evaluation results are presented in Table 5.

Table 5: Comparison of Forecasting Results between ARIMA and Linear Regression Models

Model	R Squared	RMSE	MAE	N-BIC	Description
ARIMA (1,0,1)	6.9%	0.600	0.456	-0.872	Lower Accuracy
Linear Regression	16.3%	0.049	0.444	-361.534	Higher Accuracy

The comparison results indicate that the multiple linear regression model achieved better forecasting performance than the ARIMA framework based on lower RMSE and MAE values, a lower N-BIC value, and a higher R^2. Specifically, the regression model produced an R^2 value of 16.3%, compared to 6.9% for ARIMA (1,0,1), indicating that the regression approach explained a relatively larger proportion of the variation in monthly inflation data. In addition, the regression model generated substantially lower RMSE (0.049) and MAE (0.444) values than the ARIMA model (RMSE = 0.600; MAE = 0.456), suggesting improved short-term forecasting accuracy. The lower N-BIC value obtained by the regression model also indicates a comparatively better balance between model fit and model complexity.

Nevertheless, these findings should be interpreted cautiously. Although the regression model outperformed ARIMA statistically, the explanatory power of both models remains relatively weak, as reflected by the low R^2 values. An R^2 value of 6.9% for ARIMA and 16.3% for the regression model implies that most of the variation in month to month inflation remains unexplained by the included variables and model structures. Therefore, the forecasting capability of both models should be regarded as exploratory rather than definitive.

In the context of regional macroeconomics, low explanatory power is not unexpected because month-to-month inflation is highly volatile and sensitive to temporary shocks, administrative price adjustments, and short-term supply disruptions. Unlike year-on-year inflation, monthly inflation tends to fluctuate irregularly due to unstable food prices, transportation costs, and seasonal consumption behavior. Consequently, relying solely on historical autoregressive patterns or deterministic monthly dummy variables is insufficient to fully capture the complexity of regional inflation dynamics in North Sumatra.

The weak model fit also indicates the presence of omitted variable bias. Provincial inflation is influenced by multiple structural and non-stationary macroeconomic factors that were not incorporated into the present models. Variables such as food supply shocks caused by climate anomalies (e.g., El Niño), regional distribution inefficiencies, fuel price adjustments, exchange rate fluctuations, and monetary policy indicators such as the BI-Rate may substantially affect inflation movements. The exclusion of these variables limits the ability of both models to capture abrupt price changes and dynamic structural shifts, resulting in relatively large unexplained residual variance.

These findings are consistent with previous empirical studies in emerging economies. Prior studies [22], [6] reported that regional inflation is strongly affected by supply-chain frictions, spatial dynamics, and structural macroeconomic changes, thereby reducing the effectiveness of standard univariate autoregressive models. At the same time, the relatively better performance of the regression model supports findings from [10], which suggest that incorporating seasonal components can improve short-term inflation forecasting by accounting for cyclical consumption and recurring demand fluctuations.

Therefore, the superior statistical performance of the regression model should not be interpreted as evidence of definitive forecasting superiority. Instead, the results suggest that models incorporating seasonal and structural components may provide a more appropriate framework for analyzing regional inflation characterized by recurring seasonal fluctuations and complex macroeconomic disturbances.

4. CONCLUSION

Based on the analysis results, the multiple linear regression model demonstrated comparatively better performance than the ARIMA (1,0,1) model in forecasting monthly inflation in North Sumatra Province, particularly in representing recurring seasonal fluctuations. The inclusion of monthly dummy variables enabled the regression model to capture seasonal inflation patterns more explicitly than the standard ARIMA approach, which primarily relies on temporal autocorrelation structures. Nevertheless, the forecasting performance of both models remained relatively limited, as indicated by the low coefficient of determination values obtained in this study.

The findings suggest that regional inflation dynamics are influenced not only by historical inflation patterns and seasonal effects but also by broader macroeconomic factors that were not incorporated into the forecasting framework. Consequently, the explanatory capability of both models should be interpreted cautiously, especially for broader forecasting applications.

This study contributes as a regional empirical case study by providing a comparative evaluation of autoregressive and regression-based forecasting approaches for seasonally fluctuating inflation data. However, the study remains limited by its univariate framework, the exclusion of additional macroeconomic variables, and the absence of broader robustness validation procedures. Future research is therefore recommended to incorporate multivariate forecasting models, additional macroeconomic indicators, and alternative forecasting validation techniques to improve forecasting reliability and explanatory performance.

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REFERENCES

[1] D. Effrosynidis, E. Spiliotis, G. Sylaios, and A. Arampatzis, "Time series and regression methods for univariate environmental forecasting: An empirical evaluation," *Science of the Total Environment*, vol. 875, p. 162580, 2023. [Online]. Available: https://doi.org/10.1016/j.scitotenv.2023.162580

[2] J. Sharmin, M. Safoan, S. M. R. Karim, M. Sanour, and T. Alom, "Inflation and macroeconomic stability in bangladesh: Effects on growth, investment, remittances and finance," *South Asian Journal of Social Studies and Economics*, vol. 22, no. 9, pp. 388–399, 2025. [Online]. Available: https://doi.org/10.9734/sajsse/2025/v22i91165

[3] G. W. Beck and M. M., "Regional inflation dynamics within and across euro area countries and a comparison with the united states," *Economic Policy*, vol. 24, no. 57, pp. 142–184, 2009. [Online]. Available: https://doi.org/10.1111/j.1468-0327.2009.00214.x

[4] H. Aginta, "Spatiotemporal analysis of regional inflation in an emerging country: The case of indonesia," *Regional Science Policy and Practice*, vol. 14, no. 3, pp. 667–689, 2022. [Online]. Available: https://doi.org/10.1111/rsp3.12539

[5] G. Alomani, M. Kayid, and M. F. A. El-aal, "Global inflation forecasting and uncertainty assessment: Comparing arima with advanced machine learning," *Journal of Radiation Research and Applied Sciences*, vol. 18, no. 2, p. 101402, 2025. [Online]. Available: https://doi.org/10.1016/j.jrras.2025.101402

[6] Y. M. Maiga, "Empirical approach to modelling and forecasting inflation using arima model: Evidence from tanzania," *Journal of Agricultural Studies*, vol. 12, no. 2, pp. 58–76, 2024. [Online]. Available: https://doi.org/10.5296/jas.v12i2.21695

[7] L. Putri, "Forecasting inflation rate in indonesia using autoregressive integrated moving average method," *UNP Journal of Statistics and Data Science*, vol. 3, pp. 288–295, 2025. [Online]. Available: https://doi.org/10.24036/ujsds/vol3-iss3/377

[8] S. Sofiana, "Comparative study of traditional and modern models in time series forecasting for inflation prediction," *International Journal of Applied Information Management*, vol. 5, no. 3, pp. 155–167, 2025. [Online]. Available: https://doi.org/10.47738/ijaim.v5i3.108

[9] M. Iqbal and A. Naveed, "Forecasting inflation: Autoregressive integrated moving average model," *European Scientific Journal*, vol. 12, no. 1, pp. 83–92, 2016. [Online]. Available: https://doi.org/10.19044/esj.2016.v12n1p83

[10] M. Coker, "Short-term inflation forecasting in sierra leone: A comparison of vector autoregressive var(p), arimax, and arima models," *International Journal of Scientific Research and Management*, vol. 13, no. 05, pp. 9090–9111, 2025. [Online]. Available: https://doi.org/10.18535/ijsrm/v13i05.em16

[11] Safwandi, "Time series model using autoregressive integrated moving average (arima) method for inflation in indonesia," *Jurnal Investasi Islam*, vol. 8, no. 1, pp. 13–25, 2023. [Online]. Available: https://doi.org/10.32505/jii.v8i1.5891

[12] M. Rizwana, A. Muhammad, and N. Jumanic, "Forecasting inflation in pakistan using arima model," *Journal of Financial Economics Research*, vol. 10, no. 2, pp. 1–23, 2025. [Online]. Available: https://doi.org/10.20547/jfer2510203

[13] V. Sheremirov and H. Stein, "Global inflation, regional factors," *Federal Reserve Bank of Boston Working Paper*, no. 25, 2025. [Online]. Available: https://doi.org/10.29412/res.wp.2025.06

[14] J. Nagayasu, "Heterogeneity and convergence of regional inflation (prices)," *Journal of Macroeconomics*, vol. 33, no. 4, pp. 711–723, 2011. [Online]. Available: https://doi.org/10.1016/j.jmacro.2011.07.002

[15] N. K. Kwak and M. J. Schniederjans, "An alternative solution method for goal programming problems: The lexicographic goal programming case," *Socio-Economic Planning Sciences*, vol. 19, no. 2, pp. 101–107, 1985.

[16] Ajiono and T. Hariguna, "Comparison of three time series forecasting methods on linear regression, exponential smoothing and weighted moving average," *IJIIS International Journal of Informatics and Information Systems*, vol. 6, no. 2, pp. 89–102, 2023. [Online]. Available: https://doi.org/10.47738/ijiis.v6i2.165

[17] G. E. P. Box, G. M. Jenkins, G. C. Reinsel, and G. M. Ljung, *Time Series Analysis: Forecasting and Control*, 5th ed. Canada: John Wiley & Sons, 2016.

[18] K. Singh and P. Rashmi, "Water quality management using statistical analysis and time-series prediction model," *Applied Water Science*, vol. 4, no. 4, pp. 425–434, 2014. [Online]. Available: https://doi.org/10.1007/s13201-014-0159-9

[19] Y. Shin, *Time Series Analysis in the Social Sciences: The Fundamentals*. University of California Press, 2017. [Online]. Available: https://doi.org/10.1525/california/9780520293168.001.0001

[20] G. Bontempi, S. B. Taieb, and L. Borgne, "Machine learning strategies for time series forecasting," in *Business Intelligence: eBISS 2012*. Berlin, Heidelberg: Springer, 2013, pp. 62–63. [Online]. Available: https://doi.org/10.1007/978-3-642-36318-4_3

[21] R. J. Hyndman and G. Athanasopoulos, *Forecasting: Principles and Practice*, 2014.

[22] I. Khandelwal, R. Adhikari, and G. Verma, "Time series forecasting using hybrid arima and ann models based on dwt decomposition," *Procedia Computer Science*, vol. 48, pp. 173–179, 2015. [Online]. Available: https://doi.org/10.1016/j.procs.2015.04.167