

## ECONOMIC PROJECTION OF BALIKPAPAN AS A BUFFERING CITY FOR INDONESIA'S NEW CAPITAL

Mega Silfiani<sup>1\*</sup>, Yustina Fitriani<sup>2</sup>

<sup>1</sup>Department of Science and Data Analytics, Institut Teknologi Kalimantan

<sup>2</sup>Department of Electrical Engineering, Informatics and Business, Institut Teknologi Kalimantan  
Jl. Soekarno-Hatta Km. 15, Karang Joang, Balikpapan, 76127, East Kalimantan, Indonesia

*Corresponding Author's Email: megasilfiani@lecturer.itk.ac.id*

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**Abstract:** As part of Indonesia's capital relocation plan to East Kalimantan, Balikpapan plays a critical role as a supporting city, facing opportunities and challenges in infrastructure, economic stability, and public services. This study forecasts two key economic indicators: monthly inflation and annual Gross Regional Domestic Product (GRDP), using Error, Trend, Seasonal (ETS) and Autoregressive Integrated Moving Average (ARIMA) methods. For monthly inflation, the SARIMA(0,1,1)(1,0,0)<sup>12</sup> model outperforms ETS(A,N,N) with a lower RMSE, providing higher accuracy in capturing inflation dynamics. For annual GRDP, both ETS(A,N,N) and ARIMA(0,0,0) yield similar accuracy, with ARIMA slightly better. These findings support data-driven planning to maintain price stability and foster economic growth. Accurate projections ensure Balikpapan's readiness as a sustainable, resilient city, aligning with SDG 8 (Economic Growth) and SDG 11 (Sustainable Cities and Communities).

**Keywords:** ARIMA, Economic Projection, ETS, GRDP, Inflation

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### 1. INTRODUCTION

As an integral part of the national development plan, Indonesia has decided to relocate its capital city to East Kalimantan Province. Strategically located as a logistics and transportation hub in the region, the city of Balikpapan will play a pivotal role as a supporting city for the new capital [1]. This role presents significant opportunities for economic growth, but it also demands preparedness in terms of infrastructure, economic stability, and public service quality. In this context, Balikpapan's ability to anticipate economic impacts and address its needs as a supporting city will be a key factor in the success of the capital relocation project [2].

As a supporting city, Balikpapan is projected to experience increased investment, population migration, and increasingly complex economic demands [1]. With growing pressures on infrastructure and public services, strategic data-driven planning is required to ensure sustainable development. One critical element of this planning is economic forecasting, which includes analysing inflation and Gross Regional Domestic Product (GRDP). Inflation projections help manage price stability for essential goods, ensuring affordability for the public. Meanwhile, GRDP projections provide a foundation for infrastructure and investment planning to support the development of strategic sectors in Balikpapan.

This study focuses on analyzing and forecasting two key economic indicators: monthly inflation and annual GRDP. Monthly inflation data reflects price dynamics that affect household purchasing power and economic stability [2], [3], [4] while annual GRDP captures aggregate economic capacity and serves as a primary indicator for long-term development policy design [5]. The integration of these two projection approaches is anticipated to yield a more holistic understanding of Balikpapan's economic preparedness to perform its function as a supporting city for the new capital.

To address these objectives, this study utilizes the Error, Trend, Seasonal (ETS) and Autoregressive Integrated Moving Average (ARIMA) models for forecasting. ETS was selected for its capability to capture complex seasonal and trend patterns, while ARIMA is recognized for its effectiveness in analyzing time series data with nonstationary properties [2], [3], [6]. By comparing the results of these two methods, the study aims to generate more accurate and relevant projections.

These projections provide not only practical implications for local governments and other stakeholders but also support the attainment of the Sustainable Development Goals (SDGs). In particular, this study aligns with SDG 8 (Decent Work and Economic Growth), which advocates inclusive and sustainable economic development, and SDG 11 (Sustainable Cities and Communities), which focuses on fostering cities that are inclusive, safe, and resilient. With targeted economic growth, Balikpapan is expected to create job opportunities for local communities, improve welfare, and enhance regional competitiveness.

## 2. METHODOLOGY

### 2.1. Inflation and GRDP (Gross Regional Domestic Product)

#### 1) Inflation

Inflation is an economic phenomenon characterized by a persistent increase in the general price level over a specific period [2], [3], [4]. Studies on inflation have become a central focus in economic literature due to its significant impact on economic growth, purchasing power, and overall welfare. Several theories explain the underlying causes of inflation, such as demand-pull inflation, which occurs when aggregate demand exceeds production capacity, and cost-push inflation, driven by rising production costs.

Moreover, inflation is influenced by monetary policies, such as excessive increases in the money supply, as outlined by the quantity theory of money. Empirical studies indicate that external factors, including fluctuations in global commodity prices and supply chain disruptions, contribute to inflation. In developing countries, structural factors such as inadequate infrastructure, market inefficiencies, and exchange rate volatility further exacerbate inflationary pressures.

#### 2) GRDP (Gross Regional Domestic Product)

Annual Gross Regional Domestic Product (GRDP) is an economic metric that quantifies the aggregate value of goods and services generated by all economic sectors within a region over the course of one year [5]. GRDP is utilized to reflect a region's economic capacity, monitor the development of key sectors, and evaluate the effectiveness of economic development policies. In the existing literature, GRDP is commonly employed as a reference indicator for evaluating economic growth, productivity levels, and regional welfare.

Various factors, including investment, labor force, infrastructure, government policies, and the dynamics of key sectors such as agriculture, industry, trade, and services, influence GRDP. Stable GRDP growth indicates increased production and economic activity, while a decline in GRDP may signal stagnation or an economic recession. Empirical studies highlight the significant role of increased investment and improved infrastructure quality in driving GRDP growth. Additionally, external factors such as global economic crises, pandemics, and fluctuations in commodity prices can affect GRDP performance.

### 2.2. Forecasting Methods

Time series models are analytical tools used to examine data generated by a process over time, where the observed values depend on their temporal context. The time series models employed in this study are the Autoregressive Integrated Moving Average (ARIMA) and Exponential Smoothing (ETS) models.

#### 1) Autoregressive Integrated Moving Average (ARIMA)

The Autoregressive Integrated Moving Average (ARIMA) is a time series analysis method designed to model data with a trend pattern [6]. The ARIMA model includes additional seasonal terms and is represented by  $(p, d, q)$ , where  $p$ ,  $d$ , and  $q$  denote the non-seasonal components. The notation for the ARIMA model is [7], [8], [9]:

$$Z_t = \frac{\theta_q(B)N_t}{\phi_p(B)(1-B)^d} \quad (1)$$

where  $\phi_p(B) = 1 - \phi_1 B - \phi_2 B^2 - \dots - \phi_p B^p$  is nonseasonal autoregressive,  $(1 - B)^d$  is nonseasonal differencing,  $\theta_q(B) = 1 - \theta_1 B - \theta_2 B^2 - \dots - \theta_q B^q$  is nonseasonal moving average,  $Z_t$  is actual data at period  $t$ . Meanwhile, an extension of ARIMA that accommodates seasonal components in time series

analysis is the Seasonal Autoregressive Integrated Moving Average (SARIMA). The mathematics notation of SARIMA (p,d,q) (P, D, Q)<sup>S</sup> is written as [7], [10]:

$$Z_t = \frac{\theta_q(B)\Theta_Q(B^S)}{\phi_p(B)\Phi_P(B^S)(1-B)^d(1-B^S)^D} N_t \quad (2)$$

where  $\phi_p(B) = 1 - \phi_1 B - \phi_2 B^2 - \dots - \phi_p B^p$  is nonseasonal autoregressive,  $\Phi_P(B^S) = 1 - \Phi_1 B^S - \Phi_2 B^{2S} - \dots - \Phi_P B^{PS}$  is seasonal autoregressive,  $(1-B)^d$  is nonseasonal differencing,  $(1-B^S)^D$  is seasonal differencing,  $\theta_q(B) = 1 - \theta_1 B - \theta_2 B^2 - \dots - \theta_q B^q$  is nonseasonal moving average,  $\Theta_Q(B^S) = 1 - \Theta_1 B^S - \Theta_2 B^{2S} - \dots - \Theta_Q B^{QS}$  is seasonal moving average,  $Z_t$  is actual data at period  $t$ .

## 2) Error, Trend and Seasonal (ETS)

The foundational Error Trend Seasonal (ETS) model, consisting of two main equations—the forecast equation and the smoothing equation—was proposed in the late 1950s [11]. ETS models, incorporating several prominent exponential smoothing methods, were further developed by Hyndman et al. [12]. The ETS framework involves three unobservable components: level, trend, and seasonality [13], [14]. The ETS model is a state-space framework that combines a variety of conventional exponential smoothing methods with different state equations for different data components [14]. ETS provides a total of 30 possible ETS specifications [14], [15]. This flexibility allows the method to explore diverse types of time series data, even those that exhibit heterogeneity and nonlinearity [15]. Within the state-space framework, the following combinations of ETS (·, ·, ·) are possible, as expressed in Equation (3) [12], [13]:

$$E(\text{Error}) \in \{A, M\}, T(\text{Trend}) \in \{N, A, A_d, M, M_d\}, S \in \{N, A, M\}, \quad (3)$$

where  $A$  is notated as additive,  $M$  is notated as multiplicative,  $N$  is notated as none,  $A_d$  is notated as additive damped.

## 2.3. Research Procedures

Research procedures are explained as follows:

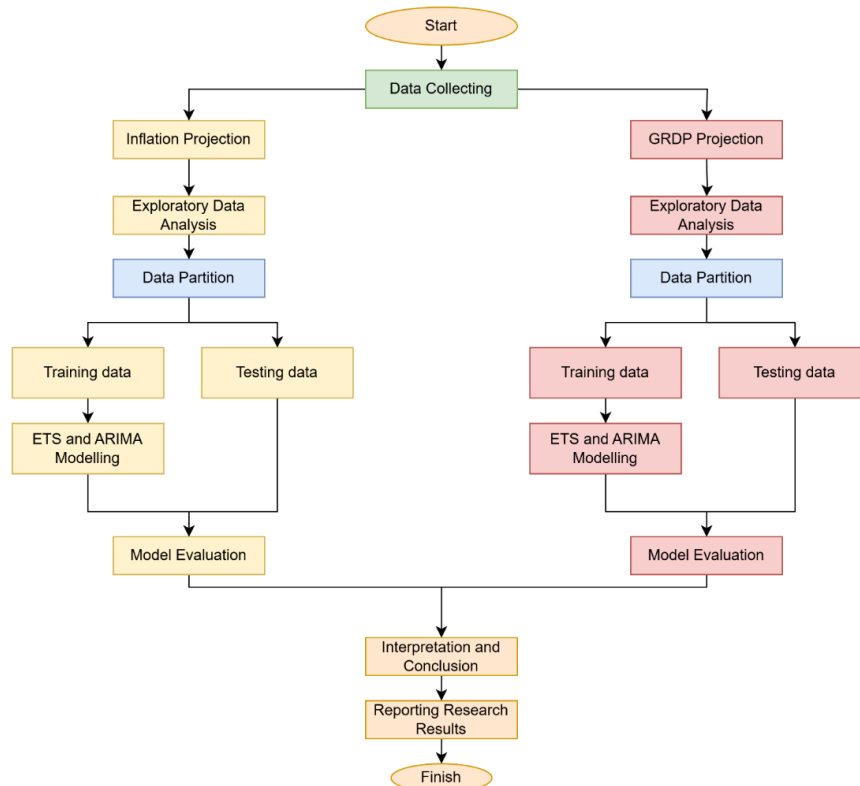


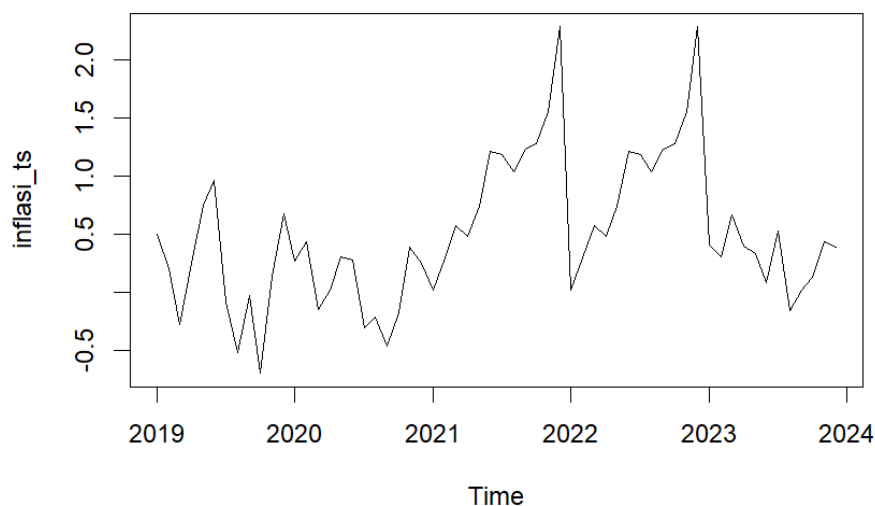
Figure 1. Research Flowchart

Figure 1 presents the overall research framework adopted in this study. The procedure begins with data collection, which provides the basis for two parallel lines of analysis: the projection of inflation and the projection of Gross Regional Domestic Product (GRDP). For each variable, an exploratory data analysis (EDA) is first conducted to examine the underlying patterns, trends, seasonality, and potential anomalies. Following EDA, the time series is partitioned into two subsets: training and testing. The training subset is then used to estimate the forecasting models, specifically the Error, Trend, Seasonal (ETS) and Autoregressive Integrated Moving Average (ARIMA) models, while the testing subset is reserved for out-of-sample evaluation. Model performance is assessed using appropriate accuracy measures, and the best-performing specifications for both inflation and GRDP are subsequently selected. The final stage of the framework involves synthesizing the empirical findings to derive interpretations and conclusions, which are then compiled and reported as the research output.

### 3. RESULT AND DISCUSSION

#### 3.1. Inflation Projection of Balikpapan City

Figure 1 presents the monthly inflation rate of Balikpapan City for the period January 2019 to December 2024. The figure shows notable variability in inflation, with marked movements around the onset of the COVID-19 pandemic in early 2020, followed by a steady upward trend that persisted until late 2021. This was then succeeded by a pronounced decline in early 2022, after which inflation fluctuated, rising and falling intermittently through the end of 2023.



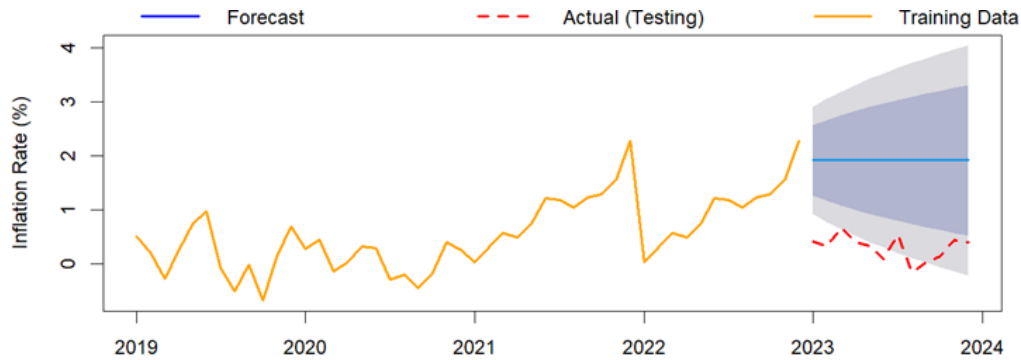
**Figure 1. Time Series Plot of Inflation in Balikpapan City**

After identifying Balikpapan's monthly inflation pattern, the data were split into two subsets: a training set and a test set. The training data were employed for model construction, whereas the testing data were used to assess model performance. Specifically, the ETS and ARIMA models were fitted using monthly inflation data for Balikpapan from January 2019 to December 2022, while the evaluation was conducted using data from January to December 2023.

The ETS modeling in this study was conducted using the R software, with the results as follows:

<b>Table 1. Summary of ETS Modelling Results on Monthly Inflation in Balikpapan City at R</b>				
<b>Model</b>	<b><math>\alpha</math></b>	<b>AIC</b>	<b>AICc</b>	<b>BIC</b>
ETS(A,N,N)	0.575	124.3551	124.9006	129.9687

Table 1 indicates that the appropriate model for Balikpapan's monthly inflation is ETS(A,N,N). This model suggests an additive error structure with no discernible trend or seasonal patterns. The projection of Balikpapan's monthly inflation is illustrated in Figure 2.



**Figure 2. Actual Data VS ETS Projections**

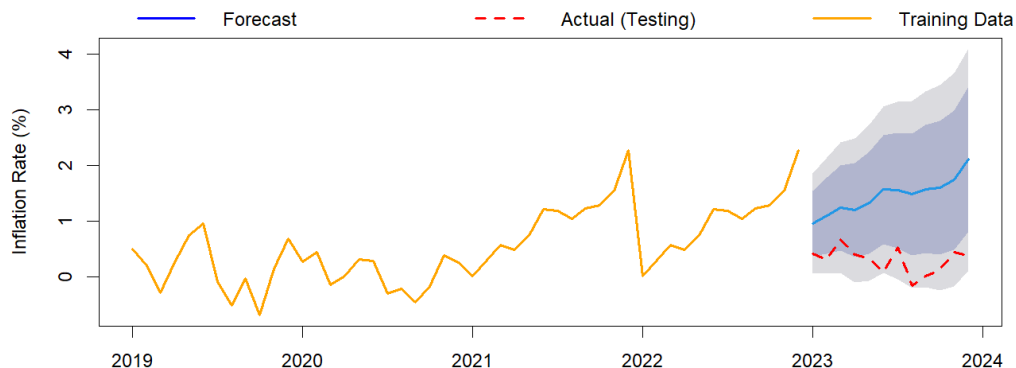
The projection of Balikpapan's monthly inflation generated by the ETS(A,N,N) model shows constant values for the next year. This is due to the simplicity of the ETS(A,N,N) model, which only incorporates an additive error structure without trend or seasonal components.

Following the ETS modelling, the ARIMA model was subsequently developed. In this study, the ARIMA modelling was performed using the R software. Table 2 summarises parameter estimates and diagnostic checks for the ARIMA model applied to Balikpapan's monthly inflation data.

**Table 2. Summary of ARIMA Modelling Results on Monthly Inflation in Balikpapan City in R**

Model	Parameter Estimation			Ljung-Box		Normality Test
	Parameter	Estimate	P-value	Lag	P-value	P-value
ARIMA(0,1,1)(1,0,0) <sup>12</sup>	$\theta_1$	-0.4003	0.0136	12	0.9227	0.5178
	$\Phi_1$	0.5097	0.0016	24	0.9659	
				36	0.7051	

Table 2 reveals that the selected model is SARIMA(0,1,1)(1,0,0)<sup>12</sup>. During the parameter estimation phase, all parameters were found to be statistically significant. The diagnostic checks confirmed that the model satisfies the assumptions of white noise and normal distribution. Subsequently, the projection of Balikpapan's monthly inflation using this model is presented in Figure 3.



**Figure 3. Actual Data VS ARIMA Projections**

Figure 3 shows that the projections generated by the ARIMA model exhibit an upward trend, whereas the test data show fluctuations. Nevertheless, the testing data values remain within the lower and upper bounds of the 95% confidence interval of the projections. Following the development of the ETS and ARIMA models, a comparison of the two models is presented in Table 3..

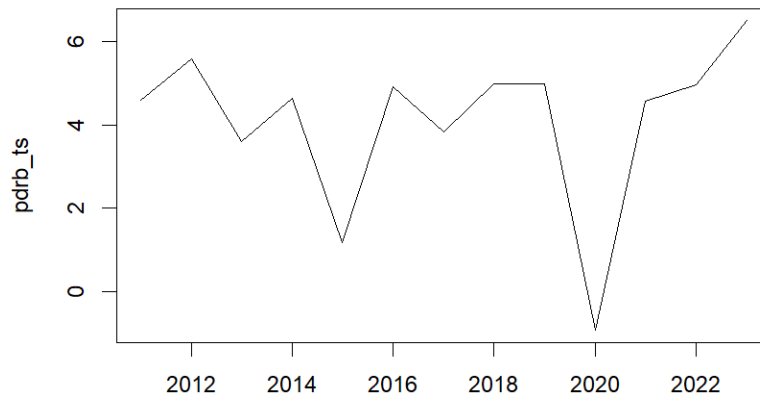
**Table 3. Summary of Balikpapan Inflation Modelling Evaluation**

Method	RMSE
ETS	1.631453
SARIMA	1.227051

Table 3 demonstrates that the most suitable model for Balikpapan's monthly inflation is SARIMA. This conclusion is because the RMSE of the SARIMA model is lower than that of the ETS model.

### 3.2 GRDP (Gross Regional Domestic Product) Projection of Balikpapan City

Gross Regional Domestic Product (GRDP) is an economic metric that reflects the aggregate value of goods and services generated by all economic sectors within a particular region over a specified period. As an indicator of a city's economic performance, GRDP offers insights into its economic growth rate and overall productivity. It is widely used to evaluate a city's economic condition, track the development of strategic sectors, and assess the effectiveness of implemented economic policies. Furthermore, GRDP projections support governments and other stakeholders in designing budgets, investment strategies, and infrastructure development plans that are consistent with the city's anticipated growth trajectory.



**Figure 4. Time Series Plot of Balikpapan's GRDP**

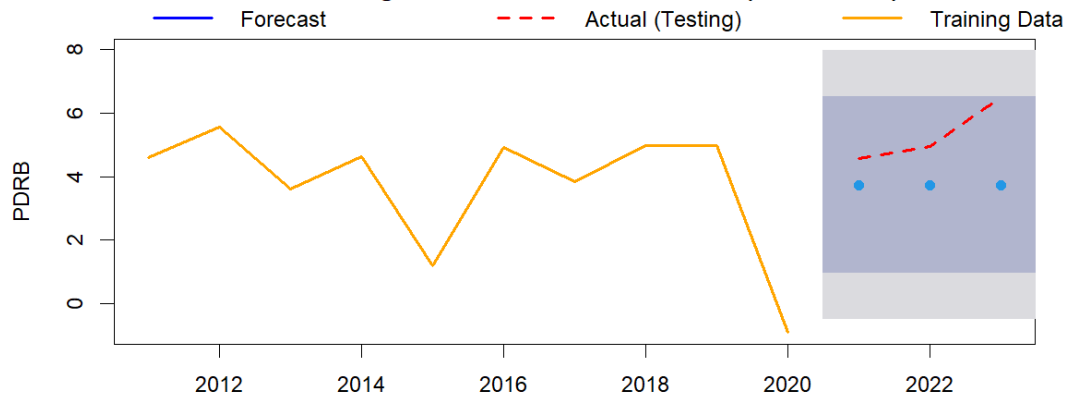
The annual GRDP chart of Balikpapan City from 2011 to 2023 (Figure 4) illustrates significant economic fluctuations. Initially, there was a steady increase, peaking around 2012, followed by a notable decline starting in 2013, reaching its lowest point in 2016. Subsequently, GRDP showed a gradual recovery and remained relatively stable up to 2019. In 2020, it experienced a sharp downturn, most likely attributable to the effects of the COVID-19 pandemic. Between 2021 and 2023, GRDP exhibited a robust rebound, with substantial growth toward the end of the period, indicating notable economic improvement in Balikpapan following the crisis.

After identifying the GRDP pattern of Balikpapan City, the data were divided into two subsets: a training and a testing dataset. The training data was used for modelling, while the test data was used for model evaluation. The training dataset used for the ETS and ARIMA models consists of Balikpapan's annual GRDP data from 2011 to 2020, while the testing dataset covers 2021 to 2023. The ETS modelling in this study was performed using the R software, with the results as follows:

**Table 4. Summary of ETS Modeling Results on Balikpapan City's Annual GRDP in R**

Model	$\alpha$	AIC	AICc	BIC
ETS(A, N, N)	0.1e-04	42.24998	46.24998	43.15773

The ETS model used to model Balikpapan City's GRDP is configured as ETS(A,N,N), indicating an additive component for the level (A) and no components for trend or seasonality (N). From the modelling results, the smoothing parameter for the level ( $\alpha$ ) is minimal, at 0.0001, suggesting minimal adjustment to new data changes. The initial level state is estimated at 3.741, with a residual standard deviation ( $\sigma$ ) of 2.1658, reflecting variability in the data that remains unexplained by the model. The GRDP projections for Balikpapan City using the ETS model are illustrated in Figure 5.



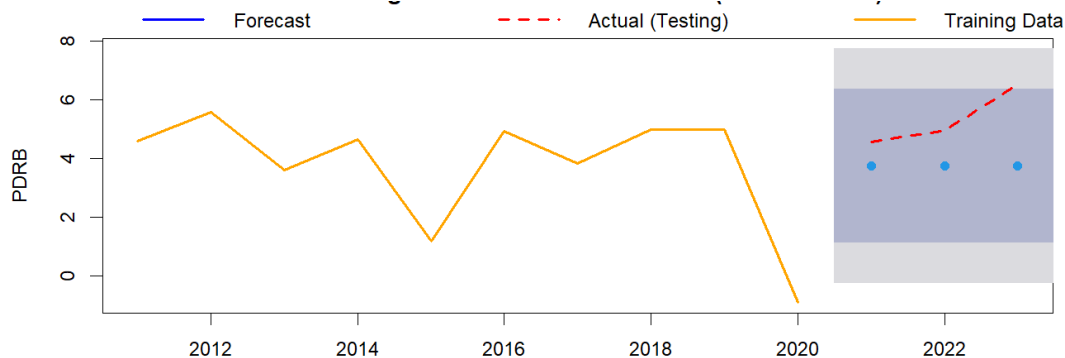
**Figure 5. Actual Data VS ETS Projections in Balikpapan's GRDP**

Figure 5 compares the actual annual GRDP data for Balikpapan City (test data) with projections generated by the ETS model for the 2021–2023 period. The projections indicate a gradual increase in GRDP from 2021 to 2023, with the grey area representing the forecast's confidence interval. However, comparing the model's predictions with the observed data indicates that the model slightly underestimates GRDP during the testing period, as the actual values generally lie just above the model's forecasts.

**Table 5. Summary of ARIMA Modeling Results on Balikpapan City's Annual GRDP in R**

Model	Parameter Estimation			Ljung-Box		Normality Test
	Parameter	Estimate	P-value	Lag	P-value	P-value
ARIMA(0,0,0)	$\mu$	3.7410	0.0136	3	0.7762	0.3782
				6	0.4986	
				9	0.3899	

The ARIMA(0,0,0) model has residuals that are not significantly correlated and follow a normal distribution, indicating that this constant-mean model is statistically suitable for Balikpapan City's GRDP data. However, the simplicity of this model may limit its ability to capture more complex patterns in the data. The GRDP projections for Balikpapan City using the ARIMA model are shown in Figure 6.



**Figure 6. Actual Data VS ARIMA Projections in Balikpapan's GRDP**

Figure 6 illustrates a comparison between the actual annual GRDP data of Balikpapan City for the testing period (2021–2023) and the projections generated by the ARIMA model. The orange line represents the training data from 2011 to 2020, while the solid blue line shows the predictions for 2021–2023. The ARIMA model projections demonstrate a stable trend at the average GRDP value, with minimal significant fluctuations in the predicted values. However, the actual data for the testing period is slightly above the model's projections, particularly in 2022 and 2023. This suggests that the ARIMA model tends to underestimate the increase in GRDP during these years.



Overall, the ARIMA model provides reasonably accurate projections but does not fully capture the upward trend in GRDP observed in recent years. This model is more suited to stable data patterns and may be less responsive to changes or emerging trends in Balikpapan City's annual GRDP.

A comparison of forecasting accuracy for Balikpapan City's annual GRDP using two different methods—ETS and ARIMA—is provided below. Both models were evaluated based on their RMSE (Root Mean Squared Error) values for the testing period from 2021 to 2023. RMSE is a metric that measures how far the model's predictions deviate from actual values, with lower RMSE values indicating better accuracy. Table 6 presents the RMSE comparison between the ETS and ARIMA models, helping determine which method is more suitable for projecting Balikpapan City's annual GRDP.

**Table 6. Summary of Forecasting Model on Balikpapan City's Annual GRDP in R**

Method	RMSE
ETS	1.801
ARIMA	1.8009

Table 6 presents a comparison of forecasting accuracy for Balikpapan City's annual GRDP between the ETS and ARIMA methods, based on RMSE (Root Mean Squared Error) values. The results indicate that both methods exhibit very similar RMSE values: 1.801 for ETS and 1.8009 for ARIMA, with a negligible difference. This suggests that both ETS and ARIMA models can predict annual GRDP with nearly identical levels of accuracy. Although the difference is not statistically significant, ARIMA shows a slight advantage in predictive accuracy, as indicated by its marginally lower RMSE.

The analysis of inflation and GRDP projections conducted in this study has several limitations. First, the models used, namely ETS and ARIMA, are relatively simple and may not capture complex patterns in the data, such as interactions between economic variables or the direct impact of external factors. Additionally, ARIMA assumes data stationarity, which may not be fully satisfied, particularly in inflation data influenced by global economic dynamics or government policies. Another limitation is the relatively short data range—2019–2023 for inflation and 2011–2023 for GRDP—which may restrict the models' ability to identify long-term patterns or structural economic trends. The irregularities caused by the COVID-19 pandemic also present challenges, as the models may not fully capture them. Furthermore, this analysis relies solely on inflation and GRDP as single variables without considering other influencing factors, such as interest rates, money supply, or global commodity prices, which could improve the accuracy of the projections.

Future research could address these limitations through several avenues. First, incorporating external variables, such as interest rates, global commodity prices, unemployment rates, and foreign investment, could enhance the accuracy and relevance of the models for predicting inflation and GRDP. Employing more advanced modelling techniques, such as SARIMA with seasonal components, multivariate time-series regression models (e.g., VAR or VECM), or machine learning approaches, could capture more complex patterns in the data. Extending the data range and conducting long-term projections would also allow for the identification of structural changes and broader economic trends. Additionally, future research could integrate scenario-based analyses to evaluate the impacts of changes in global commodity prices, exchange rate fluctuations, or monetary policies on inflation and GRDP.

For GRDP analysis, sectoral decomposition could be employed to understand the contributions of individual economic sectors to growth. Meanwhile, for inflation, seasonal analysis could be included to evaluate its effects on price patterns, particularly in vulnerable sectors such as food or energy. Validating the models using alternative error metrics, such as Mean Absolute Percentage Error (MAPE) or Mean Bias Error (MBE), is crucial to ensure the consistency and robustness of the projections. Moreover, the models' results could be used to simulate the impacts of specific economic policies, such as changes in tax rates, government spending, or subsidy policies, on inflation and GRDP. Finally, further studies could focus on the long-term effects of the COVID-19 pandemic, including the post-pandemic economic recovery, and provide more accurate and relevant projections aligned with current economic dynamics. These steps would provide more profound, more valuable insights to policymakers and stakeholders.



#### 4. CONCLUSION

Based on the findings, the projections of Balikpapan City's monthly inflation and annual GRDP highlight the importance of selecting accurate forecasting models to support sustainable development planning as a supporting city for Indonesia's new capital (IKN). For monthly inflation, the SARIMA(0,1,1)(1,0,0)<sup>12</sup> model proved more accurate than the ETS(A,N,N) model, as evidenced by its lower RMSE value, making it better suited to capturing price fluctuations. Meanwhile, for annual GRDP projections, both the ETS(A,N,N) and ARIMA(0,0,0) models provided nearly identical predictive accuracy, with ARIMA showing a slight advantage. These results offer a comprehensive understanding of Balikpapan's economic dynamics and serve as a crucial foundation for data-driven strategic planning. Stable inflation projections and realistic GRDP growth planning will bolster Balikpapan's preparedness to address increased investment, population migration, and infrastructure demands as a supporting city for the IKN. With proper planning, Balikpapan has the potential to become an inclusive, resilient, and sustainable city, aligning with national development goals and the achievement of the Sustainable Development Goals (SDGs).

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