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Forecasting International Tourist Arrivals in West Sumatra with SARIMA and Triple Exponential Smoothing for Post-Pandemic Tourism Recovery

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Abstract

The Covid-19 pandemic has significantly impacted the tourism sector, leading to a drastic decline in regional revenue derived from this industry. To accelerate the recovery of the tourism sector, reliable forecasting methods are required to estimate tourist arrivals. This paper presents the use of time series SARIMA and Triple Exponential Smoothing (Holt-Winters) methods to predict the number of international tourist arrivals in the post-pandemic period. The analysis reveals that the SARIMA method with ARIMA (2,0,1)(1,0,1)$_5$ parameters, which accounts for seasonal trends over a five-month period. The SARIMA method achieved a MAPE of 21.90%, indicating better predictive performance.The predictions generated by these methods are expected to assist governments and tourism-related industries in developing promotion strategies, infrastructure planning, and optimal resource allocation.

Keywords— *Holt-Winters, International Tourist, Post-Pandemic, SARIMA.*

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1. INTRODUCTION

The Covid-19 pandemic has significantly impacted the global tourism sector, including Indonesia. Quarantine measures and travel restrictions were enforced to curb the virus's spread, resulting in a 74 percent decline in international tourist arrivals in 2020 compared to the previous year [1]. The financial losses amounted to approximately 1.1 trillion USD. Although the tourism sector began recovering in 2021, the growth remained sluggish, with international arrivals increasing by only 4 percent, still far below pre-pandemic levels. Recovery was more pronounced in Europe and North America, while Asia and the Pacific experienced slower progress due to prolonged restrictions and varying policy responses across different nations.

In Indonesia, the number of international tourist arrivals declined by 75 percent in 2020 [2]. Despite hopes for recovery in the following years, the figures remained below target. As restrictions eased and borders reopened, the recovery process varied across regions. In West Sumatra, for instance, international tourist arrivals at Minangkabau International Airport (BIM) saw a drastic decline, and the occupancy rate of star-rated hotels fluctuated, reaching only 53.44 percent in December 2020 [3]. Additionally, variations in travel regulations and the slow resumption of international flights further hampered recovery. Government and industry collaboration is crucial for revitalizing the tourism sector. According to the Central Statistics Agency (BPS), a positive trend was observed in December 2023, with international arrivals at BIM reaching 6,710 visits, signaling a gradual revival. However, challenges persist, including shifts in tourist preferences, increased competition among travel destinations, and economic uncertainties that continue to affect recovery.

For West Sumatra, the tourism sector is a vital contributor to Regional Original Income (PAD). Accurate forecasting of international tourist arrivals is essential for informed decision-making in budget allocation, policy formulation, and marketing strategies. Reliable predictions allow governments and businesses to anticipate demand fluctuations, allocate resources efficiently, and develop promotional campaigns that align with market trends. Modern predictive techniques, such as big data analytics and machine learning, have been widely adopted to enhance forecasting accuracy [4]. However, statistical approaches like Seasonal

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Autoregressive Integrated Moving Average (SARIMA) and Triple Exponential Smoothing (Holt-Winters) remain highly relevant for time series analysis, especially in identifying seasonal trends and fluctuations.

SARIMA is an extension of ARIMA designed to model seasonal variations by incorporating relationships between past values and periodic influences [5] [6]. This model has demonstrated superior accuracy in forecasting non-stationary data, such as international tourist arrivals in Hong Kong [7]. Meanwhile, Triple Exponential Smoothing, particularly the Holt-Winters method, is effective in capturing dynamic trends, making it suitable for forecasting during recovery phases [8]. Studies have shown that Holt-Winters performs well in predicting seasonal data, ensuring reliable trend estimations[7][9].The comparative effectiveness of these models in different contexts highlights the necessity of selecting appropriate forecasting methods based on data characteristics and recovery trends.

Several countries have adopted data-driven approaches to post-pandemic tourism recovery, leveraging predictive analytics to develop targeted policies and marketing strategies [6][10]. This research seeks to apply such methods in West Sumatra, where seasonal variations significantly influence tourist arrivals. Unlike traditional forecasting approaches that rely on simple historical trends, this study integrates advanced statistical modeling to provide more accurate predictions, helping policymakers and industry stakeholders to formulate more responsive and adaptive strategies [11].

Despite the growing application of predictive models in tourism forecasting, studies specifically focusing on Indonesia’s post-pandemic international tourist arrivals remain limited. Most existing research has either concentrated on global or national trends without addressing regional disparities, such as those observed in West Sumatra. Additionally, while big data and machine learning methods have gained traction, statistical models like SARIMA and Holt-Winters remain underutilized in forecasting regional tourism trends in Indonesia. The lack of region-specific studies limits policymakers' ability to develop targeted recovery strategies that account for local dynamics and seasonality.

Furthermore, previous studies on tourism forecasting in Indonesia have predominantly focused on short-term fluctuations without adequately analyzing long-term recovery patterns. Given the unique economic and policy challenges faced by different provinces, understanding how international tourist arrivals behave over time is crucial. This study bridges these gaps by providing a region-specific analysis, applying robust statistical methodologies to predict international tourist arrivals and assess their implications for tourism recovery strategies. By doing so, it contributes both to the empirical body of knowledge in tourism forecasting and to practical policymaking efforts in regional tourism management.

The study contributes to the tourism sector by providing an empirical analysis of predictive modeling using SARIMA and Holt-Winters, offering insights into optimizing promotional strategies, resource allocation, and policy-making. Additionally, this research highlights the feasibility of employing these statistical models to support regional tourism development in Indonesia. The findings will also serve as a foundation for future research in tourism forecasting, offering methodological insights that can be applied to other regions facing similar post-pandemic recovery challenges.

This study utilizes data on international tourist arrivals to West Sumatra from the BPS website, covering a 24-month period from October 2022 to September 2024. By implementing SARIMA and Holt-Winters, this research aims to generate accurate forecasts that aid stakeholders in designing effective recovery strategies. The findings are expected to enhance decision-making processes within the tourism industry, improve resilience in the face of economic uncertainties, and provide a methodological framework for future forecasting studies in Indonesia's post-pandemic tourism sector.

2. METHODS

This research uses data on international tourist visits to West Sumatra following the COVID-19 pandemic, sourced from the website of the Central Statistics Agency (BPS) of West Sumatra. The dataset includes monthly international tourist arrivals from October 2022 to September 2024, covering a 24-month period.

The data is applied using two effective analytical methods for forecasting time series data: SARIMA and Holt-Winters. The SARIMA (Seasonal Autoregressive Integrated Moving

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Average) method is known for its effectiveness in capturing seasonal patterns, while Holt-Winters (Triple Exponential Smoothing) excels in identifying trends and reducing data fluctuations.

2.1. Seasonal Autoregressive Integrated Moving Average (SARIMA)

SARIMA represents an advanced extension of the ARIMA (Autoregressive Integrated Moving Average) methodology. ARIMA is a widely utilized technique in time series analysis for forecasting future values. SARIMA extends ARIMA by accommodating data characterized by both seasonal and non-stationary patterns. This model was introduced by Box and Jenkins and further elaborated by KM Krishna et al. [12] is structured as follows:

$$\Phi(B^S)\Phi(B)(1-B^S)^D(1-B)^d Z_t = \mu + \theta_Q(B^S)\theta\varepsilon_t \quad (1)$$

The SARIMA model is expressed as SARIMA $(p,d,q)(P,D,Q)_S$. The autoregressive term is represented by $\Phi(B)$ with an order of p, while the moving average term is indicated by $\theta(B)$ with order q. Seasonal autoregressive and moving average components are denoted as $\Phi_P(B^S)$ and $\theta_Q(B^S)$ with respective orders P and Q. Regular differencing is written as $(1-B)^d$ with order d, and seasonal differencing is expressed as $(1-B^S)^D$ with order D. The parameter S represents the seasonal cycle length in the dataset.

2.2. Triple Exponential Smoothing (Holt-Winters)

This method is used when the data exhibits both trends and seasonal behavior. To address seasonal behavior, a third equation parameter has been developed, known as the Triple Exponential Smoothing method, or commonly referred to as the Holt-Winters method, named after its creators. There are two models within the Holt-Winters method, depending on the type of seasonality: the Multiplicative Seasonal Model and the Additive Seasonal Model. In general, this method can directly handle seasonal factors [13]. The steps involved in the Holt-Winters method are as follows:

a. Smoothed value is performed using the following equation:

$$F_t = \alpha\left(\frac{Y_t}{I_{t-S}}\right) + (1-\alpha)(F_{t-1} + b_{t-1}) \quad (2)$$

b. Trend estimate is done using the following equation:

$$b_t = \gamma(F_t - F_{t-1}) + (1-\gamma)b_{t-1} \quad (3)$$

c. Seasonal Smoothing is performed using the following equation:

$$I_t = \beta\left(\frac{Y_t}{F_t}\right) + (1-\beta)I_{t-S} \quad (4)$$

d. Forecast Calculation is as follows:

$$\hat{Y}_t = (F_t + mb_t)I_{t-S+m} \quad (5)$$

where:
S is the length of the seasonality
b is trend component is the smoothed trend value
I is seasonal adjustment factor is the seasonal smoothing component
$\hat{Y}_t$ is forecast for period t
B_t is trend for period t
F_t is Smoothed observation for period t

2.3 Forecasting accuracy measurement

The forecasting process inherently involves a degree of uncertainty caused by errors and the limitations of the forecasting model in capturing other elements within the data series. Therefore, it can be concluded that the magnitude of deviation in the forecast results may be due to unexpected factors (outliers). In such cases, no forecasting method can provide highly accurate results, or it can be said that the method used is unable to precisely predict the trend, seasonal, or cyclical components that may exist in the data series. This indicates that the applied method is not appropriate [14]. If Y_t represents the actual data for period t and $\hat{Y}_t$ represents the forecasted (fitted) value for the same period, the error can be defined as:

$$e_t = Y_t - \hat{Y}_t \quad (6)$$

The accuracy measures that can be used to assess the performance of a forecasting method in modeling time series data include Mean Absolute Percentage Error (MAPE), Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE). The best model is determined by the smallest values of MAPE, MAE, and RMSE [15]. The mathematical formulations for MAPE, MAE, and RMSE are as follows [16]:

a. Mean Absolute Percentage Error (MAPE) measures the average absolute difference between actual values (Y_t) and predicted values $(\hat{Y}_t)$. MAPE reflects the model's percentage error which can be written in the equation form as,

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{Y_t - \hat{Y}_t}{Y_t}\right| \times 100\% \quad (7)$$

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b. Mean Absolute Error (MAE) represents the average of the absolute differences between observed values and predicted values. The mathematical expression for MAE is as follows:

$$MAE = \frac{1}{n}\sum_{t=1}^{n}\left|Y_t - \hat{Y}_t\right| \quad (8)$$

c. Root Mean Squared Error (RMSE) is derived by taking the square root of the Mean Squared Error (MSE), ensuring its value is expressed in the same unit as the original data, which enhances its interpretability. The formula of RMSE is:

$$RMSE = \sum_{t=1}^{n}\left(Y_t - \hat{Y}_t\right) \quad (9)$$

2.4 Analysis Steps

The analysis steps using the SARIMA and Holt-Winters methods are as follows:

a. Conducting data exploration of international tourist arrivals to West Sumatra from October 2022 to September 2024 on a monthly basis.
b. Identifying seasonal patterns in the data based on the data plot.
c. Performing predictions using the SARIMA and Holt-Winters methods.
d. Evaluating the prediction results using Mean Absolute Percentage Error (MAPE), Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE).
e. Concluding and analyzing the most optimal prediction model based on the methods used.

2.5 *Flowchart Analysis*

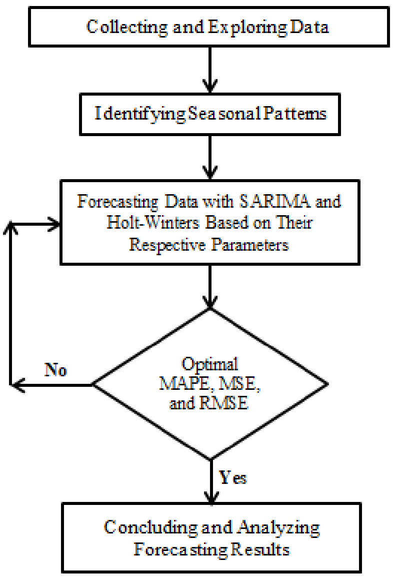

Figure 1. Flowchart Comparison of SARIMA and Holt-Winters

3. RESULTS

3.1 Seasonal Autoregressive Integrated Moving Average (SARIMA)

The exploration of international tourist arrival data to West Sumatra was conducted through a time series plot based on the monthly data of international tourist numbers following the COVID-19 pandemic, as shown in Figure 1.

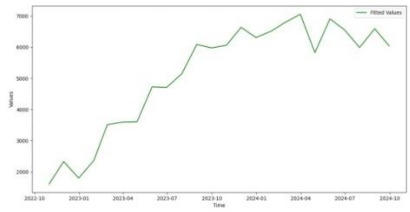

Figure 2. Plot of International Tourist Arrivals to West Sumatra

For approximately two years, from April 2020 to September 2022, the number of international tourist arrivals to West Sumatra was recorded as zero, reflecting the impact of the COVID-19 pandemic. Based on Figure 1, it can be observed that international tourist arrivals to West Sumatra were first recorded again on the BPS website in October 2023, with 373 tourists. This number continued to increase, reaching 8,232 tourists as of the most recent data in September 2024.

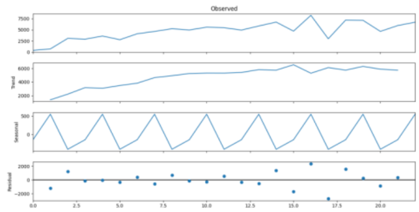

Figure 3. Components of International Tourist Arrival Data

Furthermore, to explore the data in more detail, the components contained in the international tourist arrival data can be observed in Figure 2. Based on Figure 2, it is evident that the data exhibits an upward trend and seasonal patterns. Since the data contains trend, seasonal, and random components, it is suitable to be modeled using the SARIMA method.

The initial step before making predictions using SARIMA is to test the stationarity of the data. Non-stationary data can lead to misleading or inaccurate estimates from

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the model. Therefore, it is necessary to conduct a stationarity test on the time series data. The Augmented Dickey-Fuller (ADF) test is used for this purpose. The results of the ADF test show a p-value of 0,0662, which is greater than the significance level ($\alpha = 0{,}05$), indicating that the data is non-stationary. Subsequently, differencing is performed to address the non-stationarity of the data. The results of the ADF test after differencing are shown in Table 1.

Table 1. ADF Test Results After Differencing

	Augmented Dickey Fuller test
t-statistic	-8,1660
p-value	0,0000

Based on Table 1, the p-value is less than the significance level ($\alpha = 0.05$), indicating that the data is stationary after the first differencing.

The determination of the best model is based on several possible models, and the model with the minimum values of MAPE, MAE, and RMSE is selected. Due to the limited data available, which is 24 months, model selection is carried out through trial and error, starting by determining the optimal seasonal trend value. The candidate models tested in the initial stage are shown in Table 2.

Table 2. First Stage Candidate Models

Model	MAPE	MAE	RMSE
ARIMA(1,0,1)(1,1,1)2	41,88%	1976,995	2493,104
ARIMA(1,0,1)(1,1,1)3	30,96%	1440,723	1858,577
ARIMA(1,0,1)(1,0,1)3	25,87%	1250,732	1592,542
ARIMA(1,0,1)(1,0,1)5	25,58%	1233,522	1518,879

Based on Table 2, the best model identified is ARIMA(1,0,1)(1,0,1)$_5$, which has the smallest values for MAPE, MAE, and RMSE, with a seasonal component observed in a 5-month period. This indicates that international tourist arrivals exhibit a seasonal pattern with a 5-month cycle. Following this, a trial and error approach was used to determine the best model for the 5-month seasonal pattern. The candidate models tested in the second stage are shown in Table 3.

In the second stage, the best model identified is ARIMA(2,0,1)(1,0,1)$_5$, which has the smallest values for MAPE, MAE, and RMSE. Based on the MAPE value, the model error rate is 21.90%. The optimum MAE and RMSE values are 1,051.8031 and 1,357.1169, respectively. The prediction results for international tourist arrivals to West Sumatra using the SARIMA method can be displayed in Figure 3.

Table 3. Second Stage Candidate Models

Model	MAPE	MAE	RMSE
ARIMA(1,0,1)(1,0,2)5	27,40%	1327,2461	1708,8211
ARIMA(1,0,1)(2,0,1)5	25,35%	1220,1135	1508,2690
ARIMA(1,0,1)(2,0,2)5	30,15%	1474,8489	1832,4481
ARIMA(2,0,2)(2,0,2)5	29,79%	1580,1219	1853,2508
ARIMA(2,0,1)(1,0,1)5	21,90%	1051,8031	1357,1169
ARIMA(2,0,1)(2,0,1)5	24,73%	1216,8621	1549,3770
ARIMA(2,0,1)(1,0,2)5	23,89%	1168,4723	1458,3717
ARIMA(2,0,1)(2,0,2)5	23,28%	1160,9489	1416,9807

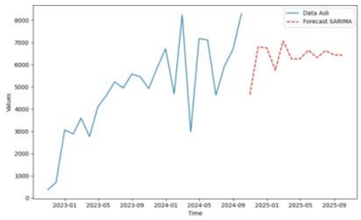

Figure 4. Forecasting International Tourist Arrivals Using SARIMA

3.2 Triple Exponential Smoothing (Holt-Winters)

In Figure 1, it can be observed that the international tourist arrival data forms a seasonal plot and shows an upward trend. Next, a prediction was made using the Holt-Winters method. After determining the optimal parameters through data processing in Python, the parameters along with the MAPE, MSE, and RMSE values are shown in Table 4.

Table 4. Model Parameters and Evaluation

Periode	Parameter			MAPE	MAE	RMSE
	α	β	γ			
3	0,2471	0,2376	0,0289	42.81%	975,69	1331,08
4	0,2303	0,1924	0,0749	39,82%	926,65	1250,42
5	0,2279	0,2107	0,0486	39,48%	903,61	1191,59
6	0,1460	0,1063	0,0001	62,81%	1104,79	1370,34

Based on Table 4, it can be seen that the best model for the Holt-Winters method is the model with a 5-period seasonality, with the parameters $\alpha = 0{,}2279, \beta = 0{,}2107$ and $\gamma = 0{,}046$ The model error rate is reflected in the MAPE value of 39,48%, and the corresponding MAE and RMSE values are 903,61 and 1.191,59, respectively.

The prediction results for international tourist arrivals to West Sumatra using the Holt-Winters method can be displayed in Figure 4.

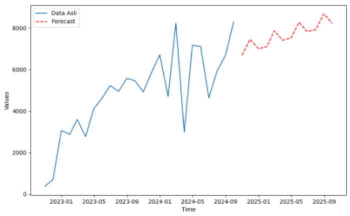

Figure 5. Forecasting International Tourist Arrivals Using Holt-Winters

4. DISCUSSIONS

Based on the forecasting results using the Seasonal Autoregressive Integrated Moving Average (SARIMA) and Triple Exponential Smoothing (Holt-Winters), the optimal prediction was achieved at a 5-month period. The predicted international tourist arrivals to West Sumatra for the next seven months can be seen in Table 5 and Table 6.

Table 5. Predicted International Tourist Arrivals to West Sumatra Using SARIMA

Actual		Prediction		
Nov-23	5840	Nov-24	6260	7,19
Des-23	6710	Des-24	6260	-6,71
Jan-24	4689	Jan-25	6647	41,77
Feb-24	8228	Feb-25	6310	-23,31
Mar-24	2976	Mar-25	6622	122,53
Apr-24	7166	Apr-25	6436	-10,19
Mei-24	7107	Mei-25	6422	-9,63

Table 6. Predicted International Tourist Arrivals to West Sumatra Using Holt-Winters

Actual		Prediction		
Nov-23	5840	Nov-24	8.098,7386	38,68
Des-23	6710	Des-24	6.836,9160	1,89
Jan-24	4689	Jan-25	8.072,4283	72,16
Feb-24	8228	Feb-25	7.389,5488	-10,19
Mar-24	2976	Mar-25	8.650,5357	190,68
Apr-24	7166	Apr-25	8.706,9328	21,50
Mei-24	7107	Mei-25	7.445,1101	4,76

In Table 5 and Table 6, it can be observed that the highest predicted number of international tourist arrivals to West Sumatra in the next seven months is expected in March 2025. Based on the Holt-Winters prediction, a 190% increase in international tourist arrivals is forecasted. The SARIMA method also shows similar results, with the maximum predicted arrivals occurring in March 2025, indicating an increase of 122%.

In this case, the forecasting results from the SARIMA and Holt-Winters models demonstrate fairly good performance [17]. However, based on the obtained MAPE value of 21.90%, the SARIMA model exhibits better forecasting results compared to the Holt-Winters model [18]. A MAPE value of 21.90% indicates that the SARIMA model has a reasonably good level of accuracy, although there is still an error margin that should be considered. If possible, further optimization, such as selecting more optimal parameters or combining models, could be implemented to improve accuracy [19] [20]. Aligned with predictions indicating that international tourist arrivals in West Sumatra will peak in March 2025, with significant increases according to the Holt-Winters and SARIMA methods, this presents an opportunity for policymakers to formulate strategies for post-COVID-19 tourism recovery. In this context, policymakers can integrate information and communication technology into marketing strategies and tourism product development initiatives [21]. This can be achieved by utilizing mobile applications that provide comprehensive information about tourist destinations, as well as implementing web-based information systems to support local SMEs in enhancing the visibility and sales of their products [22] [23]. Furthermore, it is crucial to conduct regular data analysis using statistical methods to understand trends in tourist visits, ensuring that policies are more responsive to changing market demands. Thus, collaboration between the government, tourism industry stakeholders, and local communities will enhance the appeal of destinations and support sustainable regional economic growth.

5. CONCLUSION

The prediction of international tourist arrivals post-COVID-19 is based on a limited dataset spanning 24 months, which resulted in the best estimates using both the SARIMA and Triple Exponential Smoothing methods, with the same seasonal pattern over a five-month period. The SARIMA method demonstrated a better model with a prediction error rate measured using MAPE of 21.90%, indicating that the predictions are fairly accurate. These prediction results indicate that the highest number of international tourist arrivals is expected in March 2025. This has significant strategic implications for the government and stakeholders in the tourism sector in West Sumatra. By understanding the projected international tourist arrivals, relevant parties can formulate more effective promotional strategies and optimize human resources and facilities at tourist

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destinations. Additionally, these predictions allow for more thorough planning regarding infrastructure, including transportation and accommodation, which are crucial factors in enhancing the comfort of tourists.

6. IMPLICATIONS AND RECOMMENDATIONS

Based on the findings of this study, it is recommended that future research expand the scope of the data used to enhance the accuracy of predictions regarding international tourist arrivals post-COVID-19. Additionally, the consideration of supplementary analytical methods and more complex modeling is highly advised to obtain more comprehensive results. Future studies should also explore other factors influencing tourist behavior, in order to provide deeper insights into the dynamics of the tourism sector in the future.

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