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Forecasting Foreign Tourists to West Sumatera Before and After COVID-19 Using ARIMA and Prophet and Its Impact on Foreign Exchange*

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Abstract

Foreign exchange earnings are very important for the improvement of the economy in Indonesia, where these foreign exchange earnings can be obtained through the tourism sector. One of the provinces in Indonesia that is a major tourist destination is West Sumatra. The number of foreign tourists coming to West Sumatra is influenced by various factors, one of which is the COVID-19 pandemic that resulted in a decrease in visitor numbers. The research was conducted to forecast the number of foreign tourists to West Sumatra using the ARIMA and Prophet methods, as well as to calculate the loss and foreign exchange earnings and the forecasting accuracy of both methods. The data for this study was taken from the BPS West Sumatra website regarding the number of foreign tourists to West Sumatra from 2015 to 2024. In this data, forecasting for the year 2020 will be done using the ARIMA method and forecasting for the year 2025 using the Prophet method. The data in this study tends to be stable before the pandemic, making the ARIMA method suitable. Meanwhile, after the pandemic, the data fluctuated, making the Prophet method suitable. From the results obtained, the best ARIMA model is ARIMA (1, 0, 1). The forecasting accuracy is 1.82% with an estimated foreign exchange loss of $52,095,688 for the year 2020. Meanwhile, using the Prophet method, the forecasting accuracy obtained is 12.13% with an estimated foreign exchange revenue of $208,546,812 for the year 2025.

Keywords: ARIMA, Foreign Exchange, Forecasting, Prophet, Foreign Tourists.

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1. Introduction

One of the sectors that plays an important role in economic, social, and cultural growth in Indonesia is the tourism sector. One of the regions with great tourism potential in Indonesia is West Sumatra, which is famous for its natural wealth and Minangkabau culture. Tourism is not without the presence of tourists, especially foreign tourists. These foreign tourist visits not only promote local culture but also have a significant economic impact through job creation and increased foreign exchange for the country. The number of visits from foreign tourists to West Sumatra can be seen in Figure 1.

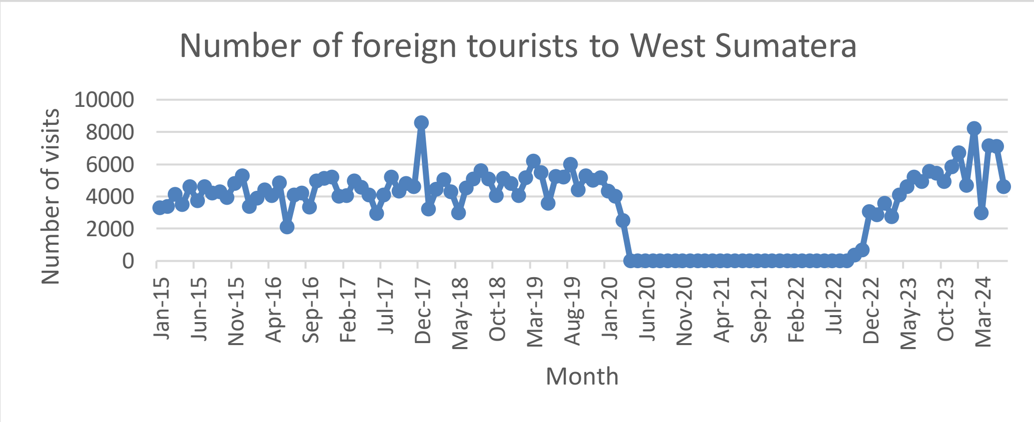

Figure 1: Number of foreign West Sumatera January 2015- June 2024

Figure 1 shows that there were fluctuations in tourist visits, which increased before the COVID-19 pandemic, and drastically decreased during the pandemic, with a significant recovery from late 2022 to early 2023. The existence of these fluctuations necessitates attention in the planning and management of tourist destinations. One of the strategies for better planning and management of tourist destinations is to forecast the number of foreign tourists to West Sumatra.

Forecasting is a process of estimating future events or outcomes based on existing data, trends, and historical information. The forecasting process involves analyzing past data to identify patterns or relationships that can be used to predict what might happen in the future. One requirement to achieve accurate forecasting results is to analyze past data to identify relevant patterns, trends, and relationships. Regression models, time series methods, or machine learning algorithms are applied to forecasting models to project future values. ARIMA and Prophet are among the forecasting methods that can be used for making predictions.

The ARIMA model is one of the methods used to analyze and forecast time series data and is effective for short-term forecasting. This method combines three main components: Autoregressive (AR), Integration (I), and Moving Average (MA). With the Autoregressive (AR) and Moving Average (MA) aspects specifically aimed at analyzing stationary time series (Makridarkis et al., 1978). This means that the ARIMA method assumes that the data must be stationary, that is, stationary in mean and variance. ARIMA is also known as the Box-Jenkins time series method, which offers very good accuracy for short-term forecasting but tends to be less accurate for long-term forecasting. (Hablinawati & Nugraha, 2024). Whereas the Prophet method is a time series forecasting tool developed by a team at Facebook, designed to handle data that exhibits complex seasonal patterns and trends. Unlike some other forecasting methods, the Facebook Prophet Model is designed as one of the forecasting tools capable of handling various features in business time series, such as strong seasonality, trend changes, anomalies, and holiday effects. (S. J. Taylor & Letham, 2018). The main advantage of Prophet is its ability to deliver good results even with relatively small data and to handle challenges such as missing values and outliers.

One of the studies related to ARIMA was conducted by Soraya et al. (2024), who researched the forecasting of tourist visit numbers in the Province of West Nusa Tenggara (NTB) using the ARIMA Box-Jenkins method. The study produced the best ARIMA model. (1,2,1). Research using the Prophet method was conducted by Auliya et al. (2023), who carried out a study forecasting the number of visitors to the Gumul Paradise Island tourist attraction in Kediri Regency using the Prophet method. The study produced a Mean Absolute Percentage Error (MAPE) value of 9.758%, indicating that the Prophet method has a very good forecasting ability in predicting the number of visitors to the tourist attraction. Research related to foreign exchange was conducted by Bangun (2024), who studied the role of tourism in increasing the country's foreign exchange earnings. The results of the study showed that the tourism sector makes a significant positive contribution to the country's foreign exchange earnings. The main factors driving the increase in foreign exchange from this sector include the rise in the number of international tourist visits, the variety of tourism products, and the development of tourism-related infrastructure.

This research is a study to forecast the number of international tourist visits to West Sumatra before and after the COVID-19 pandemic using historical data from 2015 to 2024, as well as to calculate the losses and foreign exchange earnings. The results of this research are expected to assist the government, industry players, and local communities in planning policies that can maximize the benefits of the tourism sector and strengthen the regional economy.

2. Research Methods

The data used in this research is the number of foreign tourists visiting West Sumatra, which is secondary data published by the West Sumatra Provincial BPS through the official website of the West Sumatra Provincial BPS https://sumbar.bps.go.id/indicator/16/210/1/jumlah-wisatawan-mancanegara-wisman-yang-datang-ke-sumatera-barat-bulanan-.html. The data used is the number of foreign tourists to West Sumatra from January 2015 to June 2024.

2.1 Autoregressive Integrated Moving Average (ARIMA)

The ARIMA (Autoregressive Integrated Moving Average) method is a periodic time series analysis method known as Box-Jenkins. This method originates from the combination of two models, namely Autoregressive (AR) and Moving Average (MA), developed by George Box and Gwilym Jenkins. (Makridarkis et al., 1978). The Autoregressive Integrated Moving Average (ARIMA) model is a method that completely disregards independent variables in the forecasting process. ARIMA is very effective in providing accurate results for short-term forecasting, but less accurate when used for long-term forecasting (Tutupoho et al., 2024). The general form of the ARIMA model is ARIMA (p,d,q), where p indicates the order of the autoregressive (AR) component, d indicates the order of the integrated (I) component, and q indicates the order of the moving average (MA) component. If d = 0 and q = 0, the model is known as AR(p). Conversely, if d = 0 and p = 0, the model is called MA(q). When all three components are present, the model is referred to as autoregressive-integrated-moving average in the format ARIMA (p,d,q) (Fauzani & Rahmi, 2023).

According to Makridarkis et al. (1978), the ARIMA method is often written using the backshift operator B. The notation B means the operator with a power of one, but the power B can be more than one. In general, this operator is defined as follows:

$$B\,X_t = X_{t-1}$$

The backshift operator B can be extended to be differentiated by (1 - B) (Hartati, 2017). When X_t is multiplied by 1 - B, the following equation will result:

$$(1-B)X_t = X_t - BX_t = X_t - X_{t-1}$$

The general form of the ARIMA (p, d, q) model can be written as follows:

$$\begin{gathered}(1\text{-}B)\,(1-\phi_1 B)X_t = \mu + (1-\theta_1 B)\,e_t \\ \phi_p(B)(1-B)^d X_t = \mu + \theta_q(B)e_t\end{gathered} \qquad (1)$$

According to Makridarkis et al. (1978), in forecasting using the ARIMA method, there are 5 steps that must be taken, namely:

2.1.1. Identification

Where at this stage the data must be stationary in mean and variance. If the data is not stationary in variance, a Box-Cox transformation is used by estimating the parameter λ. The Box-Cox test is used to assess variance stationarity, while differencing and the Augmented Dickey-Fuller (ADF) test are performed for data that is not stationary in mean. After the data is stationary, the initial ARIMA model can be determined based on how many times differencing is needed for the model. (p, d, q).

2.1.2. Parameter Estimation

This stage is conducted after the data is stationary, by determining the model values (p, d, q) through patterns in the Autocorrelation Function (ACF) and Partial Autocorrelation Function. (PACF).

2.1.3. Diagnostic Check

This is a stage to ensure the model's feasibility. This includes parameter significance tests with the t-test, as well as residual assumption tests such as white noise and normality. The white noise test is conducted using the Ljung-Box test, while the normality test uses the Kolmogorov-Smirnov test.

2.1.4. Conducting Forecasting

This stage requires an evaluation of the model's accuracy. The best model is selected based on prediction error rates such as Mean Percentage Error (MPE), Mean Square

Error (MSE), Mean Absolute Error (MAE), or Mean Absolute Percentage Error (MAPE). Once the best model is determined, forecasting for the upcoming period can be conducted.

2.1.5. Conclusion

Where this process emphasizes the importance of each stage to ensure the accuracy and validity of the forecasting results using the ARIMA method.

2.2 Prophet

Prophet is a forecasting method originally developed by Facebook to address issues on their platform. This method combines linear and non-linear models in the forecasting process, by identifying trends, seasonal patterns, and holiday effects. (Tarigan, 2024). Prophet is a time series forecasting model designed to handle common patterns that frequently appear in business data. This model has intuitive and easily adjustable parameters without the need to understand the technical details of the model itself, making it easier for analysts to effectively tune the model. Prophet is also available as open-source software that can be used in Python and R. (Taylor & Letham, 2018).

Here are some advantages of the Prophet model (Taylor & Letham, 2018):

a. Flexibility, where this model easily adjusts seasonal patterns with different periods and allows for changes in trend assumptions as needed for analysis.
b. Unlike ARIMA, this model does not require regular time intervals and does not need interpolation of missing values, such as from outlier removal.
c. The fitting process is quick, allowing for the interactive exploration of different model specifications.
d. The parameters of this model are easy to understand and modify by analysts, who can add new assumptions or components as needed for the analysis.

Prophet uses a time series model that can be decomposed into three main components: trend, seasonality, and holidays, which are combined in the following equation (Taylor & Letham, 2017):

$$y(t) = g(t) + s(t) + h(t) + \epsilon_t \tag{2}$$

Where:

$g(t)$: trend function that models non-periodic changes in time series data.

$s(t)$: represents periodic changes (such as weekly and annual seasonality).

$h(t)$: represents the effect of holidays that may occur on an irregular schedule for one or more days.

ϵ_t : error values that reflect changes that cannot be explained by the model.

The forecasting process using the Prophet method is carried out in three main steps: data collection, data processing, and result evaluation. The data processing stage includes data filling, data processing, transformation, and the application of the Prophet algorithm. (Auliya dkk, 2023).

Here is a summary of the revised and explained steps for the article:

2.2.1 Data Collection

Data collection is an important initial process in research. The first step is to determine the type and source of relevant data. Data can be obtained through methods such as surveys, interviews, observations, or secondary sources like reports and databases. After collection, the data needs to be verified for accuracy and consistency, then organized and stored properly. This process not only involves the collection of raw data but also initial processing to ensure the data provides useful insights. (Auliya et al., 2023).

2.2.2 Data Processing

Data processing is the stage that prepares data for further analysis and includes several steps:

a) Data Filling (Dat Filling)
   Data imputation handles missing or incomplete values in the dataset. The methods used include imputation (mean, median, mode), interpolation, or statistical models. The main goal is to maintain the integrity and accuracy of the dataset.
b) Data Processing (Data Processing)
   Data processing includes data cleaning by correcting errors, removing duplicates, and handling inconsistent values. In the Prophet algorithm, the dataframe format must conform to the 'ds' (date) and 'y' (predicted value) columns. (Oktavia & Wanti, 2024).
c) Data Transformation (Data Transformation)
   Data transformation separates the dataset into training data (to train the model) and test data (to test the model). This ensures that the model is not only good at predicting the training data but also effective at predicting new data.
d) Implementation of the Prophet Algorithm
   The application of the Prophet algorithm involves two stages: fitting and forecasting. In fitting, the model is adjusted to historical data to determine the optimal parameters. After fitting, the model is used to forecast future data. Test data is then used to evaluate the accuracy of the model's predictions.

2.2.3 Evaluation of Results

The evaluation of results aims to measure the model's accuracy by comparing predictions with actual values. One of the methods used is the mean absolute percentage error (MAPE), which calculates the average percentage error between predicted values and actual values. A lower MAPE indicates a more accurate model. This evaluation ensures that the model is not only effective in theory but also in practice.

2.3 Mean Absolute Percentage Error (MAPE)

Mean Absolute Percentage Error (MAPE) is one of the accuracy indicators used to assess the accuracy of forecasting (Agustina, 2023). The Mean Absolute Percentage Error (MAPE) value is a measure used to assess the accuracy of a forecasting model by comparing the prediction error to the actual value. MAPE calculates the average of the absolute percentage error between the predicted value and the actual value. Lower MAPE values indicate a higher level of accuracy of the forecasting model, while higher MAPE values indicate that the model is less accurate. MAPE is often used because it gives a clear picture of how good the forecasting model is in terms of percentage error relative to the true value.

MAPE values are categorized into 4 categories which are presented in Table 1 below from (Chang, 2007):

Table 1: Description of MAPE value

MAPE	Description
<10%	Very Good
10% - 20%	Good
20% - 50%	Reasonable
>50%	Innaccurate

2.4 Foreign Exchange

Foreign exchange reserves, often referred to as international reserves and foreign currency liquidity (IRFCL) or official reserve assets, are defined as all foreign assets held by the monetary authority and can be used at any time. The functions of foreign exchange reserves include financing balance of payments imbalances, maintaining monetary stability through intervention in the foreign exchange market, and for other purposes (Palembangan et al., 2020). Foreign exchange reserves are assets in the form of deposits in the form of foreign currency used to meet foreign financing needs (Rahmawati et al., 2020). Foreign exchange reserves refer to the total amount of foreign currency held by both the government and the private sector (Ulfa, 2022). So that foreign exchange reserves are a collection of foreign assets owned by a country's monetary authority, such as the central bank and are an important indicator of a country's economic health and financial stability. Where these assets can be in the form of foreign currency, gold, and international securities.

To calculate the value of foreign exchange from the tourism sector can be written as follows:

$$DSP = DKW$$

Description:
DSP : Foreign exchange from the tourism sector
DKW: Foreign exchange from foreign tourist visits
To calculate the prediction of foreign exchange earnings, it can be written as follows:

$$P = RPW \times JKP \quad (3)$$

Description:
P : Foreign exchange prediction
RPW: Average foreign tourist expenditure
JKP : Number of forecasted visits
To calculate the potential loss of foreign exchange can be written as follows:

$$K_{devisa} = (JKP - JKA) \times RPW \quad (4)$$

Description:
Kdevisa : Potential foreign exchange loss
RPW : Average foreign tourist expenditure
JKP : Number of Forecasting visits
JKA : Actual number of visits

3. Results and Discussion
3.1 ARIMA
In conducting ARIMA forecasting analysis of the number of foreign tourist visits to West Sumatra, assisted by R Studio software. The following are the stages of forecasting analysis using the ARIMA method and assisted by R Studio software.

3.1.1 Identification
Identification of constancy in variance is done using the Box-Cox test, where data constancy in variance is obtained if the lambda (λ) value or rounded value is close to 1 (Wei, 2006). Data stationarity test can be seen in table 2.

Table 2: Data Stationarity Test

Data	Stability in Variance	Stability in Mean		Description
	Box-Cox Test (Rounded Value)	ADF Test	p-value	
Original Data	0,3039327	-3,9107	0,0196	Not stationary in variance but already stationary in mean
Data Transformation	1	-3,9107	0,0196	Stationary in variance and mean

Table 2 shows that the results of the Box-Cox test on the initial data obtained rounded value results that were not close to 1, so the transformation was carried out with Log and the results were tested again and the rounded value was 1, so the data was stationary in variance. Furthermore, the identification of stability in the average is done by conducting the Augmented Dickey-Fuller test (ADF Test), and the initial data shows that the data is stationary in the average due to the p-value <α.

3.1.2 Parameter Estimation
This stage is done by determining the value of the model (p, d, q) through the pattern on the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF). Autoregressive (p) and Moving Avarage (q) order can be done by looking at the Autocorrelation Function (ACF) plot and Partial Autocorrelation Function (PACF) plot using stationary time series data. Plot ACF and PACF can be seen in Figure 2.

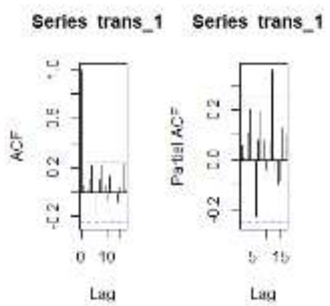

Figure 2: Plot ACF and PACF

In Figure 2, it can be seen that the white noise line that passes through the ACF plot is 2 lags, and in the PACF there is 1 lag. So it is concluded that the maximum p value obtained is 1 and the maximum q value obtained is 2 with a d value of 0 due to the absence of differncing. So it is concluded that the maximum ARIMA model that can be formed is (1, 0, 2), with the description being the model (0, 0, 1), (0, 0, 2), (1, 0, 0), (1, 0, 1), (1, 0, 2).

3.1.3 Diagnostic Check

The estimation of the 5 temporary models described is then tested for model significance and diagnostic testing of the selected model that the model is indeed effective enough to be used. Diagnostic checking process can be seen in Table 3.

Table 3: Model Testing and Model Diagnostics

ARIMA Model	P-value	White Noise	Normality	Description
ARIMA (0, 0, 1)	0.673	0.9973	0.3733	Not significant, white noise diagnostics and normality are met
ARIMA (0, 0, 2)	0.9656	0.9968	0.3891	Not significant, white noise diagnostics and normality are met
ARIMA (1, 0, 0)	0.6698	0.9898	0.3785	Not significant, white noise diagnostics and normality are met
ARIMA (1, 0, 1)	2.2e-16	0.5987	0.3863	Significant, white noise diagnostics and normality are met
ARIMA (1, 0, 2)	2.2e-16 dan 0.6097	0.947	0.298	Not significant, white noise diagnostics and normality are met

It can be seen in Table 3 that only one model is significant, namely the ARIMA (1, 0, 1) model, for other models there is no significant, so it is concluded that the best model is the ARIMA (1, 0, 1) model.

3.1.4 Forecasting

Furthermore, the best model that has been selected is carried out in the forecasting process, where the forecasting process carried out is to determine the number of foreign tourist visits to West Sumatra for the next 12 month period. The forecasting results and MAPE values are shown in Table 4 below.

Table 4: Results of Forecasting the Number of Foreign Tourist Visits to West Sumatra

Tahun	Jan	Feb	Mar	Apr	May	Jun	Jul	Agt	Sep	Oct	Nov	Dec	MAPE
2020	4754	4742	4730	4719	4709	4698	4689	4679	4670	4661	4653	4644	1.82%

Table 4 shows that the number of monthly visitors from January to December 2020. There is a decrease in the number of visitors from month to month, starting from 4,754 visitors in January to reach 4,644 visitors in December. The average percentage error (MAPE) of this forecast data is 1.82%, which indicates that the model used to forecast the number of visitors has very good accuracy, with relatively small variations from the actual values. This decline in visitor numbers may reflect a downward trend that may be caused by various factors, including the economic situation or the pandemic.

It can be concluded in this ARIMA process that the best model obtained is the ARIMA (1, 0, 1) model with the number of forecasts for the number of foreign tourists visiting West Sumatra in 2020 or 12 periods ahead is 56348 people, with the MAPE value obtained is 1.82%.

3.2 Prophet

3.2.1 Data Collection

Data collection can be seen in figure 1. The data on the number of tourists from January 2022 to June 2024 shows significant fluctuations. After nine months without tourists, the number began to increase in October 2022 and peaked in December 2022 with 3062 tourists. During 2023, the number of tourists fluctuated and reached 6710 in December. In 2024, the highest peak occurred in February with 8228 travelers, then decreased to 4631 in June 2024.

3.2.2 Data Processing

a) Data Filling
Data filling handles missing or incomplete values in the dataset. There were no missing values in the data, so we proceeded to the next step.

b) Data Processing
Data processing already has a dataframe format that matches the 'ds' (date) and 'y' (forecasted value) columns.

c) Data Transformation
Training data is used from January 2022 to December 2023. While the test data is taken from January 2024 to June 2024.

d) Implementasion of the Prophet Algorithm
Forecasting results can be seen in Table 5.

Table 5: Forecasting Results of the Number of Foreign Tourist Visits to West Sumatra in July 2024 - December 2025

	Jan	Feb	Mar	Apr	Mei	Jun	Jul	Agt	Sep	Oct	Nov	Dec	MAPE
2024	4689	8228	2976	7166	7107	4631	12743	9213	7394	7765	5941	11304	12,13%
2025	13459	11966	8858	11497	11546	10231	14768	12738	11630	11830	11007	14893	

Table 5 shows that the data on the number of tourists from June 2024 to December 2025 shows significant fluctuations. With the total number of visitors in 2025 is 144423 people.

3.2.3 Result Evaluation

The data on the number of tourists from June 2024 to December 2025 shows significant fluctuations. In mid-2024, the number of tourists ranged from 4631 to 12743, with a peak in July. In 2025, the number of tourists continued to fluctuate, with the highest peak recorded in December 2025 at 14893. In general, there was an increase in the number of tourists in 2025 compared to the previous year. The prediction error rate, measured using MAPE, is 12.13%, indicating that the model has a fairly good level of accuracy in predicting the number of tourists.

3.3 Foreign Exchange

To calculate the value of foreign exchange earnings for 2025 and the potential loss of foreign exchange during COVID-19, formulas (3) and (4) were used. The results obtained are shown in Table 6 below.

Table 6: Foreign Exchange Value

Estimate	Value
Potential Loss of Foreign Exchange during Covid-19 (2020)	USD 52,095,688
Foreign Exchange Earnings in 2025	USD 208,546,812

Table 6 shows the value of tourism-related foreign exchange. The potential foreign exchange loss due to the Covid-19 pandemic in 2020 is estimated at USD 52,095,688. Meanwhile, the expected foreign exchange earnings in 2025 are projected to increase significantly to USD 208,546,812.

3.2.4 Conclusions

The forecasting analysis of foreign tourist visits to West Sumatra using the ARIMA and Prophet models provides valuable insights into tourism trends and their broader implications. The ARIMA model effectively identifies stable patterns, making it useful for short-term predictions, while the Prophet model captures more pronounced seasonal fluctuations, offering a broader perspective on long-term trends. These differences highlight the importance of selecting forecasting methods that align with the specific characteristics of the data and the intended purpose of the analysis. The results indicate a significant drop in tourist visits throughout 2020, which aligns with the economic challenges and travel restrictions during the Covid-19 pandemic. This decline underscores the vulnerability of the tourism sector to global disruptions. However, projections for the coming years suggest a strong recovery, reflecting the sector’s resilience and potential for future growth. This resurgence emphasizes the need for adaptive policies and strategic planning to support sustainable tourism development. Based on these insights, several recommendations can be made to enhance forecasting accuracy and policy effectiveness. Increasing the amount of data used in the analysis can improve the reliability of predictions, while a direct comparison between ARIMA and Prophet using the same dataset can provide a clearer understanding of their respective strengths. Additionally, evaluating the economic impact of tourism should go beyond visitor numbers, incorporating factors such as the length of stay and spending patterns to provide a more comprehensive assessment of the sector’s contribution to economic growth.

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