Comparative Time Series Analysis and Forecasting Models for Monthly Tourist Arrivals in Maldives and Sri Lanka.

A report presented in partial fulfillment of the

requirements for the course module

STAT 42643 – Advanced Topics in Time Series Analysis

at Department of Statistics and Computer Science, Faculty of Science, University of Kelaniya

Sri Lanka.

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Abstract

This study examines monthly tourist arrivals in Sri Lanka and the Maldives over the past decade using univariate and multivariate time series models. The objective is to evaluate and compare forecasting models that best capture seasonal trends, pre- and post-COVID-19 variations, and overall tourism trends in both nations. The research employs Seasonal Autoregressive Integrated Moving Average (SARIMA) and Vector Autoregressive (VAR) models, analyzing their performance using key accuracy metrics such as RMSE and MAPE. The dataset, spanning from 2014 to 2024, is divided into pre-COVID (2014–2022 March) and post-COVID (2020 April – 2024) periods. Exploratory data analysis reveals strong seasonal patterns and a sharp decline in arrivals due to the pandemic, followed by a gradual recovery. SARIMA models effectively capture seasonality but struggle with pandemic-induced disruptions, while VAR models provide insights into interdependence between the two countries' tourism trends. Findings indicate that SARIMA models perform well for seasonal forecasting, whereas VAR models offer a broader understanding of cross-country influences. Future research should integrate external factors such as government policies and economic conditions to enhance forecast accuracy. This study contributes to improving tourism forecasting for policymakers and industry stakeholders.

Keywords: Time series forecasting, SARIMA, VAR model, tourism trends, COVID-19 impact.

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Chapter 01: Introduction

Tourism is one of the most significant contributors to the economies of Sri Lanka and the Maldives, providing employment, foreign exchange earnings, and economic development. The sector's performance is influenced by various factors, including global economic conditions, political stability, and unforeseen crises such as the COVID-19 pandemic. As tourism is inherently seasonal, understanding fluctuations in visitor arrivals and predicting future trends is essential for effective policymaking and business strategy. Forecasting models serve as valuable tools to aid decision-makers in allocating resources, improving infrastructure, and responding proactively to market changes. With increased unpredictability in international travel and the need for resilience in the tourism sector, it is crucial to adopt robust forecasting methodologies to enhance planning efforts and mitigate the risks associated with external shocks.

1.1 Background of study

The tourism industry in Sri Lanka and the Maldives has shown substantial growth over the years, driven by natural attractions, cultural heritage, and strategic marketing. However, tourism is highly sensitive to global economic fluctuations, political instability, and health crises such as the COVID-19 pandemic. The sharp decline in tourist arrivals during 2020 highlighted the vulnerability of the industry to external shocks. This study examines historical trends and evaluates forecasting models to enhance resilience in the tourism sector.

1.2 Research Problem

Accurate forecasting of tourist arrivals is vital for effective decision-making in the tourism industry. Traditional forecasting methods often fail to account for sudden disruptions and dynamic interdependencies between tourism markets. This study seeks to identify the most effective time series forecasting model by comparing univariate (SARIMA) and multivariate (VAR) approaches, ultimately improving the accuracy of tourism predictions for Sri Lanka and the Maldives.

1.3 Objectives

- To analyze historical trends in monthly tourist arrivals for Sri Lanka and the Maldives.
- To evaluate and compare the performance of SARIMA and VAR models in forecasting tourism trends.
- To assess the impact of external shocks, such as the COVID-19 pandemic, on forecasting accuracy.
- To provide recommendations for improving tourism forecasting and decision-making.

1.4 Significance of the study

Tourism is a key economic driver for Sri Lanka and the Maldives, making accurate forecasting crucial for strategic planning. This study will help policymakers, tourism authorities, and businesses understand patterns in tourist arrivals, optimize resource allocation, and develop data-driven strategies. By identifying robust forecasting models, this research aims to enhance the resilience of the tourism industry against future uncertainties.

Chapter 02: Literature Review

Study	Objectives/Summary	Methodology	Conclusions
Nagendrakumar et al. (2021) Modelling and Forecasting Tourist Arrivals in Sri Lanka	To estimate and forecast tourist arrivals for Sri Lanka from August 2021 to August 2025.	ARIMA model, time-series analysis, stationarity tests using monthly tourist arrival data (2000–2021).	The findings showed that events like the civil war and terrorism had a big effect on tourist arrivals, but the industry rebounded quickly.
Konarasinghe (2016) Patterns of Tourist Arrivals to Sri Lanka from Asian Countries	Analyzed trends and patterns of tourist arrivals from key Asian countries.	Descriptive statistics, ACF (Auto-Correlation Function), Time Series plots, ANOVA.	Tourist arrivals from India and Maldives were higher, with seasonal patterns and non-stationarity observed. .
Shareef & McAleer (2003) Modelling the Volatility in Monthly International Tourist Arrivals to the Maldives	Examined uncertainty and volatility of tourist arrivals from 8 major source countries.	Logarithmic transformations, volatility modeling, unit root tests, seasonal effects (using 1994–2003).	Monthly tourist arrivals to the Maldives showed fluctuations, with European countries as major sources.

Table 01: Literature review summary about the study

2.1 Research gap

- ❖ While there is extensive research on forecasting tourism demand, most studies focus on short term predictions or use a single forecasting model.
- ❖ Few studies Compare historical and future trends between two islands like Sri Lanka and the Maldives.
- ❖ Additionally, the impact of unique events like COVID-19 on forecasting accuracy remains underexplored.
- ❖ Addressing this gap is crucial for improving predictive models and informing better policymaking for tourism recovery and growth.

Chapter 03: Materials and Methods

3.1 Description of Data

The dataset consists of monthly tourist arrival records from 2014 to 2024 for Sri Lanka and the Maldives. The data was split into pre-COVID (2014–2020 March) and post-COVID (2020 April –2024) periods to account for disruptions caused by the pandemic.

3.2 Methodology

3.2.1 Data Pre-processing

The time series data for monthly tourist arrivals in Sri Lanka and the Maldives from 2014 to 2024 was first checked for consistency, ensuring no missing values or anomalies. The data was then transformed to achieve stationarity, which is a crucial requirement for time series modeling. Differencing was performed to eliminate trends in the data. To confirm stationarity, statistical tests such as the Augmented Dickey-Fuller (ADF) and KPSS tests were conducted. These preprocessing steps were essential to prepare the dataset for modeling, ensuring that the assumptions of stationarity were met and that the data was suitable for time series analysis.

3.2.2 Univariate Analysis: SARIMA Model

For the univariate analysis, the Seasonal Autoregressive Integrated Moving Average (SARIMA) model was utilized to forecast tourist arrivals. The Auto. ARIMA function was employed to automatically identify the optimal SARIMA model for both Sri Lanka and the Maldives. For Sri Lanka, the selected SARIMA model was ARIMA (0,1,0) (0,1,0) [12], which accounted for seasonality with a 12-month period. The Maldives model was ARIMA (1,1,1) (0,1,1) [12], also capturing seasonal effects. The models' performance was assessed using key accuracy metrics such as Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE), along with Autocorrelation Function (ACF) diagnostics to examine the residuals and model fit.

3.2.3 Multivariate Analysis: VAR Model

In the multivariate analysis, a Vector Autoregressive (VAR) model was employed to examine the interdependencies between the tourism trends in Sri Lanka and the Maldives. The lag length for the VAR model was selected using the Akaike Information Criterion (AIC), which suggested 10 lags for the model. The VAR model was trained in pre-COVID period data and used to forecast post-COVID tourism trends. This model allowed for a deeper understanding of how tourism arrivals in both countries influenced each other and provided forecasts that considered the dynamic relationship between the two nations' tourism markets, offering valuable insights for understanding cross-country influences on tourism.

Chapter 04: Results & Discussion

Variables:

Monthly Tourist arrivals in Sri Lanka
Monthly Tourist arrivals in Maldives

Original Dataset Descriptive Analysis
Sri Lanka Tourist arrivals

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
0	84858	132664	125157	178250	253169

Figure 01: Descriptive Sri Lanka Tourist arrivals

Interpretation:

Minimum=0
There was at least one month with no tourist arrivals, the reason for which is the COVID-19 pandemic.

1st Quantile= 84858
25% of the months had tourist arrivals below 84,858.

Median=132664
The median value for the dataset is 132,664, which indicates that half of the months had arrivals below 132664.

Mean=125157
The average number of monthly tourist arrivals is 125157. Mean is lower than the median.

3rd Quantile=178250
75% of the months had tourist arrivals below 178250.

Maximum=253169
The highest number of monthly tourist arrival is 253169.

Maldives Tourist arrivals

```
Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
   0  101992  119622  118444  144114  217392
```

Figure 02: Descriptive Maldives Tourist Arrivals

Interpretation:

Minimum=0
There was at least one month with no tourist arrivals, the reason for which is the COVID-19 pandemic.

1st Quantile= 101992
25% of the months had tourist arrivals below 101992.

Median=119622
The median value for the dataset is 119622, which indicates that half of the months had arrivals below 119622.

Mean=118444
The average number of monthly tourist arrivals is 118444. Mean is lower than the median.

3rd Quantile=144114
75% of the months had tourist arrivals below 144114.

Maximum=217392
The highest number of monthly tourist arrival is 217392.

Consider the Sri Lanka and Maldives tourist arrivals:

Tourist arrivals in the Maldives are more stable, whereas in Sri Lanka tourist arrivals are more varied.

<u>Time series plot for monthly tourist arrivals in Sri Lanka</u>

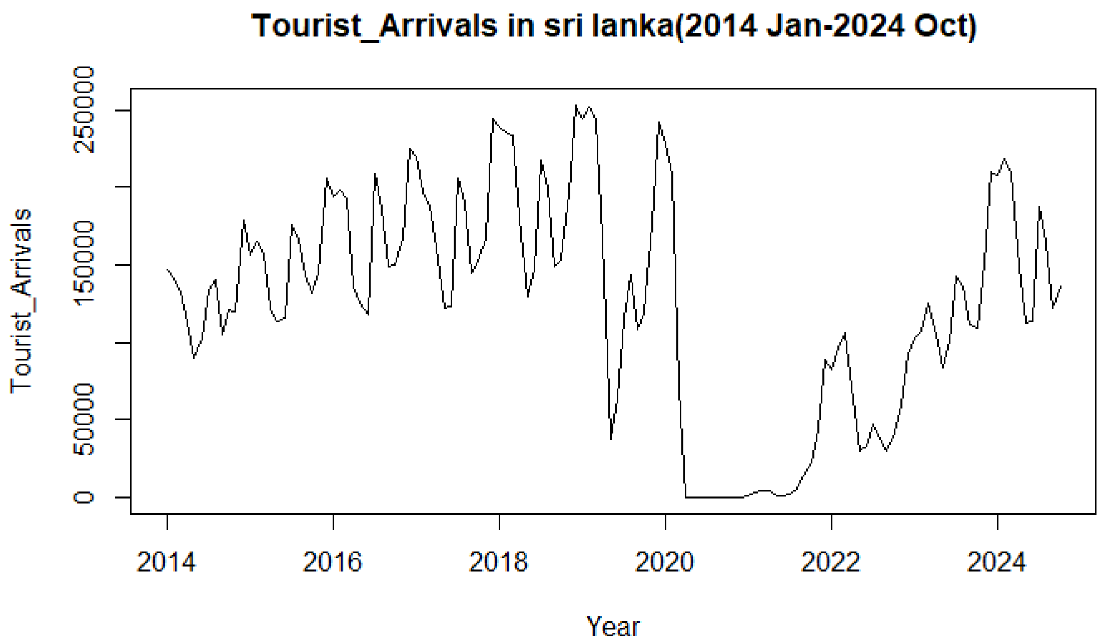

Figure 03: Time series plot for tourist arrivals in Sri Lanka

Interpretation:

This graph shows the trends in tourist arrivals to Sri Lanka between January 2014 and 2024 October. At the beginning, we see clear seasonal patterns, where tourist numbers go up and down regularly each year. However, in 2020, there is a sharp drop to almost zero arrivals, which happened due to the COVID-19 pandemic and global travel restrictions. After that, the recovery has been slow and uneven, with tourist numbers rising but not reaching the levels seen before 2020.

Time series plot for monthly tourist arrivals in Maldives.

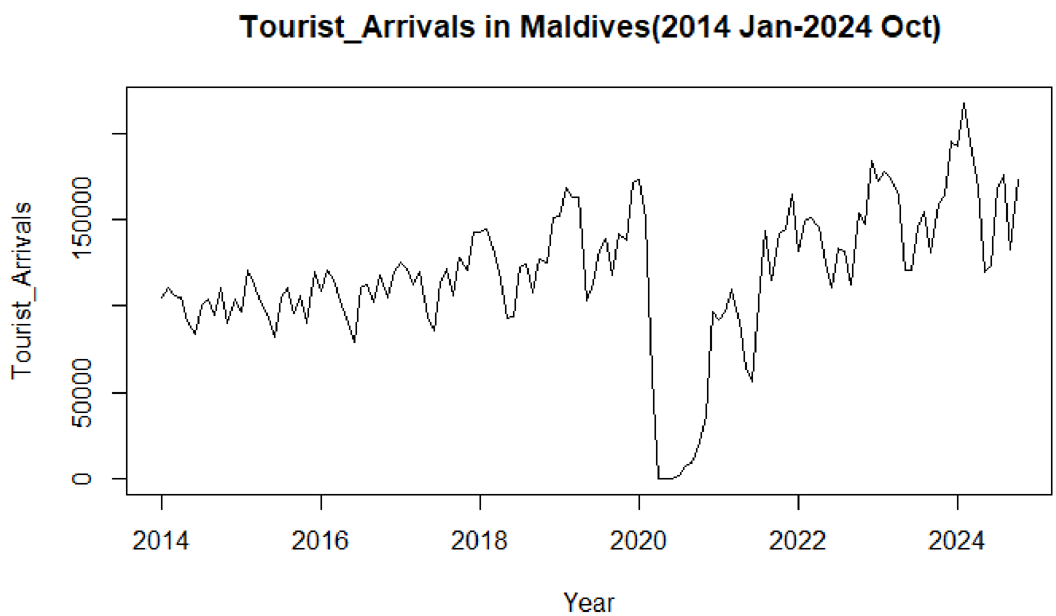

Figure 04: Time Series plot for tourist Arrivals in Maldives

Interpretation:

The time series plot shows the trends in tourist arrivals to the Maldives for the same period. Here, we see a strong seasonal pattern, with tourist numbers peaking regularly every year. Similar to Sri Lanka, there is a drop around 2020 due to the COVID-19 pandemic, when tourism almost stopped. However, the recovery in the Maldives happened much faster. By 2021, the tourist numbers began to rise again, and the peaks returned to stable levels.

<u>Compare time series plot for monthly tourist arrivals in Sri Lanka & Maldives.</u>

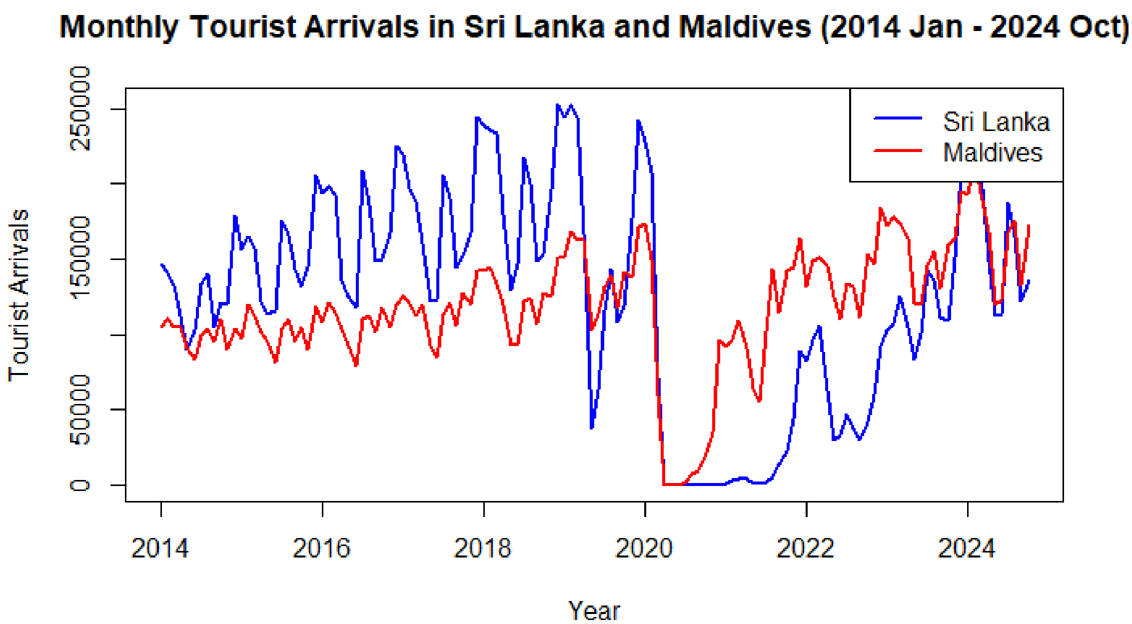

Figure 05: Time Series plot for Sri Lanka & Maldives together

Interpretation:

We can see the seasonal patterns and trend patterns. Similar to Sri Lanka and Maldives, there is a drop around 2020 due to the COVID-19 pandemic, when tourism almost stopped. However, the recovery in the Maldives happened much faster rather than Sri Lanka.

We can see that consider before COVID-19 Sri Lanka's tourist arrivals were greater than the Maldives tourist arrivals but after COVID-19 Maldives tourist arrivals were greater than Sri Lanka's tourist arrivals.

However, after COVID-19, the Maldives saw a faster recovery, with more tourists visiting compared to Sri Lanka. This suggests that Sri Lanka's tourism was more affected COVID-19 pandemic, while the Maldives managed it.

Check Stationarity.

ADF Test

```
[1] "ADF Test for Sri Lanka Arrivals:"

        Augmented Dickey-Fuller Test

data:  Original$SriLanka
Dickey-Fuller = -2.2668, Lag order = 5, p-value = 0.4656
alternative hypothesis: stationary

[1] "ADF Test for Maldives Arrivals"

        Augmented Dickey-Fuller Test

data:  Original$Maldives
Dickey-Fuller = -3.0134, Lag order = 5, p-value = 0.1552
alternative hypothesis: stationary
```

Figure 06: ADF test results for both time series

Null hypothesis: The series is not stationary.
Alternative hypothesis: The series is stationary.

Interpretation:
Since the p-value (0.4656) is greater than the common significance level of 0.05, we fail to reject the null hypothesis. This means there is not enough statistical evidence to conclude that the “Sri Lanka Arrivals” time series is stationary. It suggests that the series is not stationary.

Interpretation:
Since the p-value (0.1552) is greater than the common significance level of 0.05, we fail to reject the null hypothesis. This means there is not enough statistical evidence to conclude that the “Maldives Tourist Arrivals” time series is stationary. It suggests that the series is not stationary.

KPPS Test

```
[1] "KPSS Test for Sri Lanka Arrivals:"

        KPSS Test for Level Stationarity

data:  Original$SriLanka
KPSS Level = 0.68992, Truncation lag parameter = 4, p-value = 0.01446

[1] "KPSS Test for Maldives Arrivals:"

        KPSS Test for Level Stationarity

data:  Original$Maldives
KPSS Level = 0.5402, Truncation lag parameter = 4, p-value = 0.03261
```

Figure 07: KPPS Test Results for both Time Series

Null hypothesis: The series is stationary.
Alternative hypothesis: The series is not stationary.

Interpretation:
Since the p-value (0.0145) is less than the common significance level of 0.05, then reject the null hypothesis. This means there is enough statistical evidence to conclude that the "Sri Lanka Arrivals" time series is not stationary. It suggests that the series is not stationary.

Interpretation:
Since the p-value (0.0326) is less than the common significance level of 0.05, then reject the null hypothesis. This means there is enough statistical evidence to conclude that the "Maldives Tourist Arrivals" time series is not stationary. It suggests that the series is not stationary.

Consider the above test we can say that the two time series plots are not stationary.

Check Seasonality

```
        Kruskal-Wallis rank sum test

data:  Month by SriLanka
Kruskal-Wallis chi-squared = 128.97, df = 122, p-value = 0.3154

        Kruskal-Wallis rank sum test

data:  Month by Maldives
Kruskal-Wallis chi-squared = 129, df = 128, p-value = 0.4586
```

Figure 08: Kruskal-wallis test results

Null hypothesis: The series has not seasonal variation
Alternative hypothesis: The series has seasonal variation.

We can see that the p value is higher than the 0.05. We have not enough evidence to reject the null hypothesis. According to the test, we have not sufficient evidence that the series has seasonal variation.

ACF Plot for Tourist Arrivals in Sri Lanka

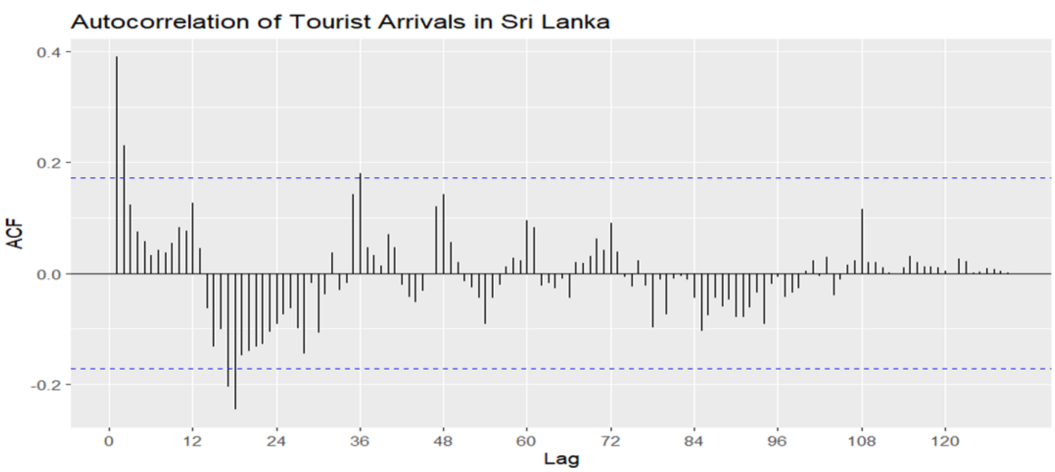

Figure 09: ACF plot for Tourist Arrivals in Sri Lanka

Interpretation:

The ACF plot for Sri Lanka shows strong short-term correlations, especially at lag 1, and a clear yearly seasonality at lag 12. This means tourist arrivals are influenced by both the previous month and annual patterns.

ACF Plot for Tourist Arrivals in Maldives

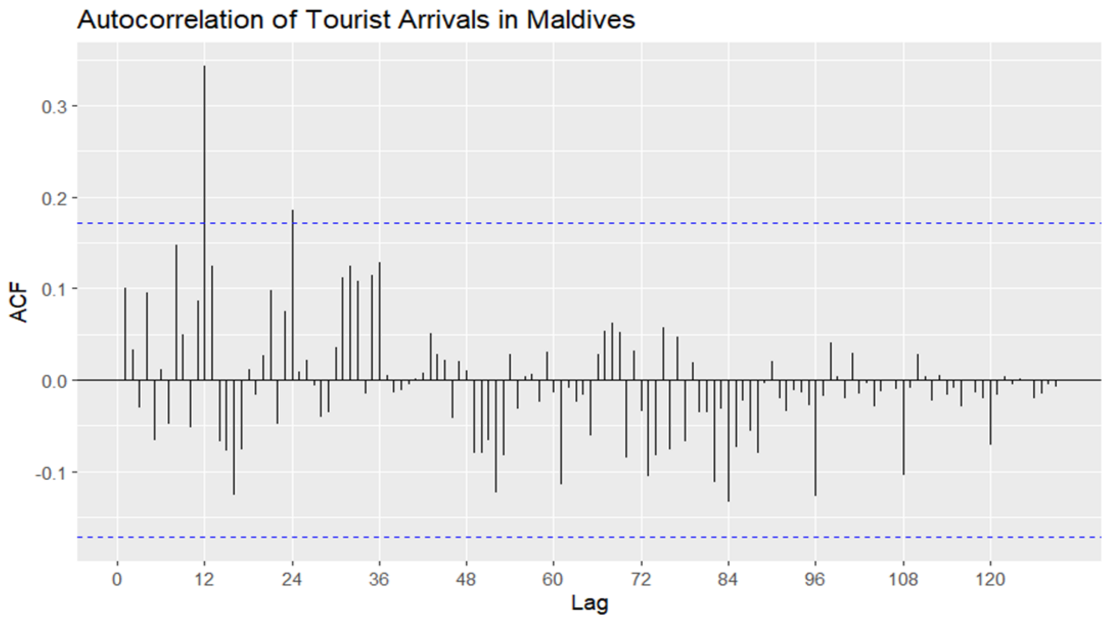

Figure 10: ACF plot for Tourist Arrivals in Maldives

Interpretation:

The ACF plot for Maldives highlights a strong yearly seasonality at lag 12 but weaker short-term correlations. However, the short-term correlations, such as with the previous month, are much weaker compared to Sri Lanka.

PACF Plot for Tourist Arrivals in Sri Lanka

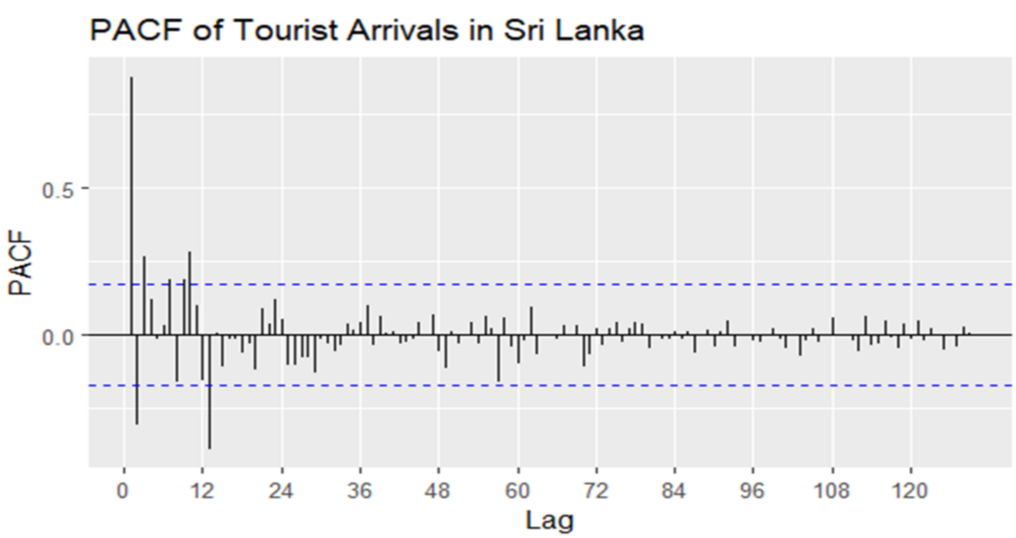

Figure 11: PACF plot for Tourist Arrivals in Sri Lanka

Interpretation:

This PACF plot shows significant spikes outside the significant lines at lags 1, 2, 9 and 12. This suggests that there is a correlation between the current month and previous month's arrivals. Overall, the PACF plot suggests that the monthly tourist arrivals in Sri Lanka exhibit a clear autoregressive pattern at lags 1, 2, 8 and 12.

PACF Plot for Tourist Arrivals in Maldives

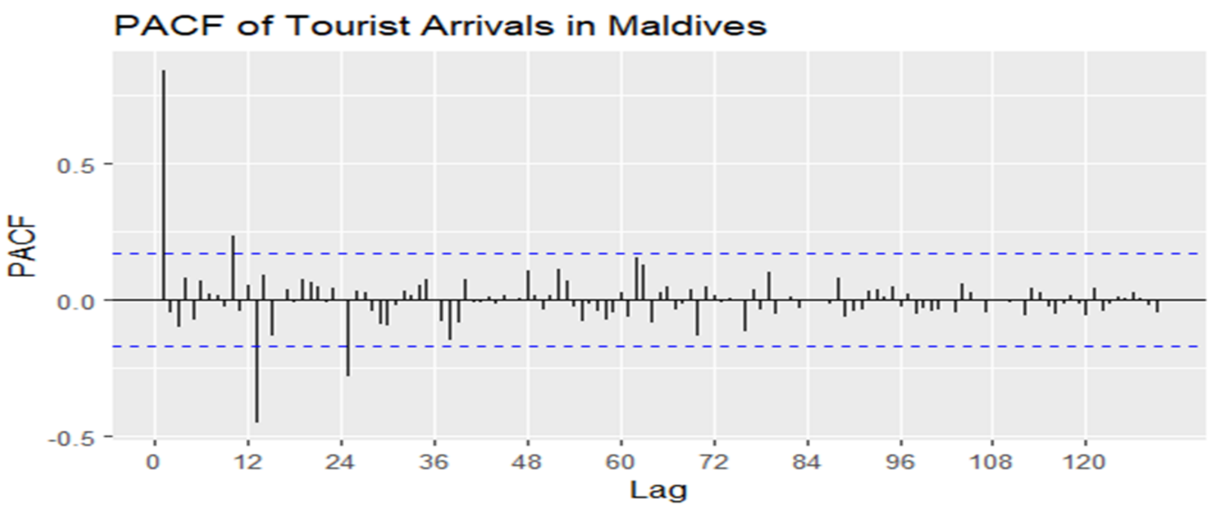

Figure 12: PACF plot for Tourist Arrivals in Maldives

Interpretation:

This PACF plot shows significant spikes outside the significant lines at lags 1, 10, 13 and 25. This suggests that there is a correlation between the current month and previous month's arrivals. Overall, the PACF plot suggests that the monthly tourist arrivals in Sri Lanka exhibit a clear autoregressive pattern at lags 1, 10, 13 and 25.

Visualizing Training & Testing Time Series plots

Training Test: Precovid-19

Testing Test: Postcovid-19

Training set

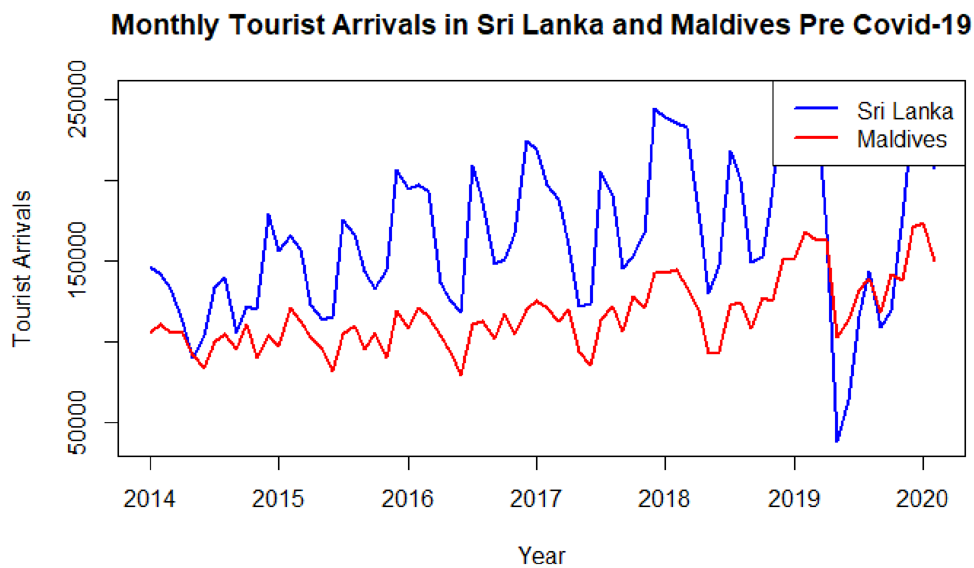

Figure 13: Pre-Covid Period Time Series Plot

Testing set

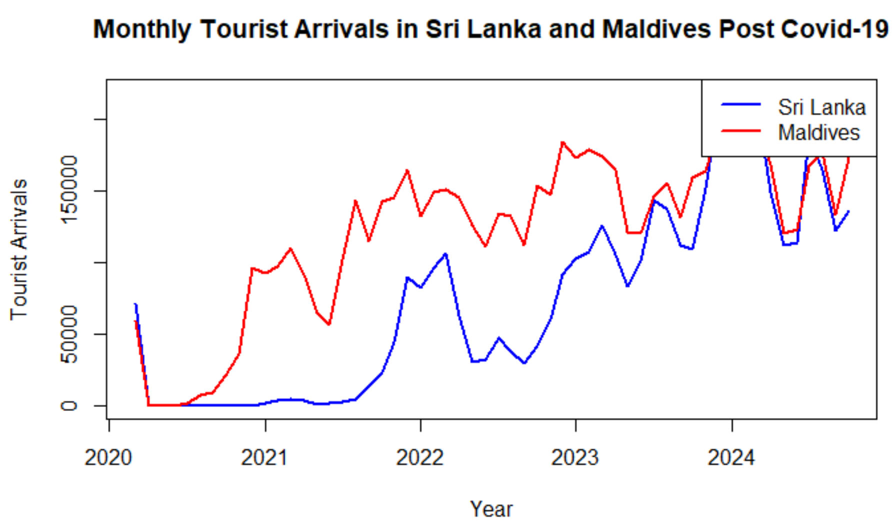

Figure 14: Post-Covid Period Time Series Plot

Nonstationary series convert to stationary series

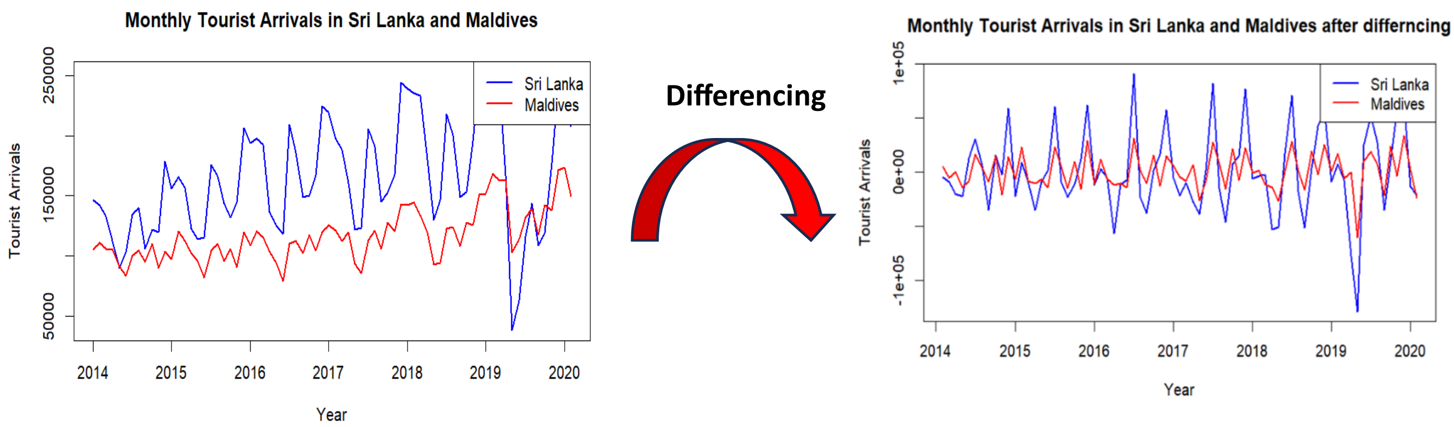

Figure 15: Pre-Differencing & After-Differencing

Interpretation:

These graphs show the time series for monthly tourist arrivals in Sri Lanka and Maldives before and after differencing. The original series is not stationary but after differencing series is stationary, its mean that after differencing removing trend and seasonality patterns.

Check Stationarity after differencing.

ADF Test

After Differencing -Sri Lanka

```
        Augmented Dickey-Fuller Test

data:  Diff_SL
Dickey-Fuller = -6.7781, Lag order = 5, p-value = 0.01
alternative hypothesis: stationary
```

After Differencing -Maldives

```
        Augmented Dickey-Fuller Test

data:  Diff_MAL
Dickey-Fuller = -5.9255, Lag order = 5, p-value = 0.01
alternative hypothesis: stationary
```

Null hypothesis: The series is not stationary.
Alternative hypothesis: The series is stationary.

Interpretation:
Since the p-value (0.01) is less than the common significance level of 0.05, we can reject the null hypothesis. This means there is enough statistical evidence to conclude that the "Sri Lanka Arrivals" time series is stationary. It suggests that the series is stationary.

Interpretation:
Since the p-value (0.01) is less than the common significance level of 0.05, we can reject the null hypothesis. This means there is enough statistical evidence to conclude that the "Maldives Tourist Arrivals" time series is stationary. It suggests that the series is stationary.

KPPS Test

After Differencing -Sri Lanka

```
        KPSS Test for Level Stationarity

data:  Diff_SL
KPSS Level = 0.042378, Truncation lag parameter = 4, p-value = 0.1
```

After Differencing -Maldives

```
        KPSS Test for Level Stationarity

data:  Diff_MAL
KPSS Level = 0.034112, Truncation lag parameter = 4, p-value = 0.1
```

Null hypothesis: The series is stationary.

Alternative hypothesis: The series is not stationary.

Interpretation:
Since the p-value (0.1) is greater than the common significance level of 0.05, then do not reject the null hypothesis. This means there is not enough statistical evidence to conclude that the "Sri Lanka Arrivals" time series is not stationary. It suggests that the series is stationary.

Interpretation:
Since the p-value (0.1) is greater than the common significance level of 0.05, then do not reject the null hypothesis. This means there is not enough statistical evidence to conclude that the "Maldives Tourist Arrivals" time series is not stationary. It suggests that the series is stationary.

Consider the above test we can say that the two time series plots are stationary.

Residual plots after differencing

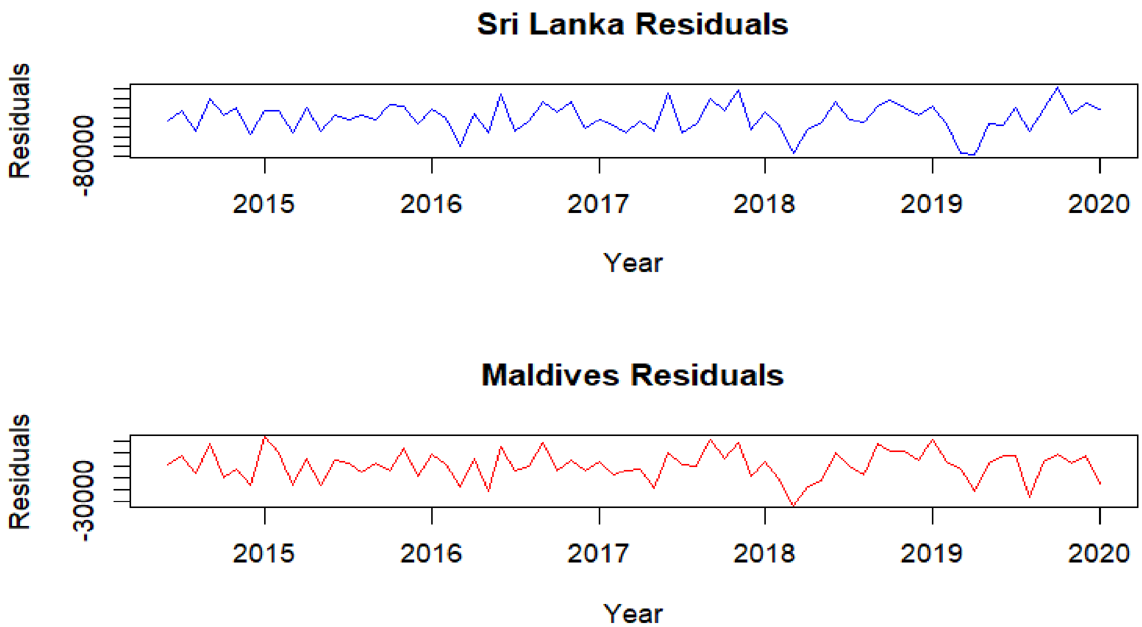

Figure 16: Residual plots for Sri Lanka & Maldives

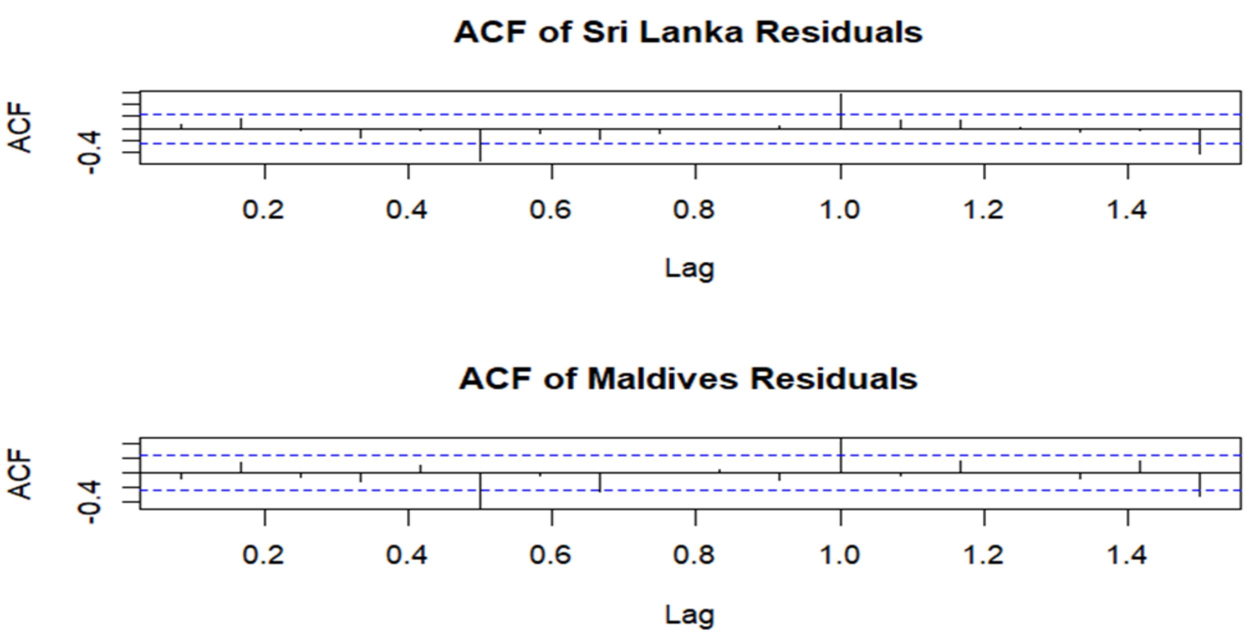

Figure 17: ACF plots for Residuals in Sri Lanka & Maldives

Test for residuals are white noise or not using Ljung-box Test

```
        Box-Ljung test

data:  sri_residuals
X-squared = 30.507, df = 10, p-value = 0.0007074
```

we can conclude that the Sri Lanka tourist arrival residuals are distinguishable from a white noise series. P-Value is less than 0.05.

```
        Box-Ljung test

data:  mal_residuals
X-squared = 26.143, df = 10, p-value = 0.003553
```

we can conclude that the Maldives tourist arrival residuals are distinguishable from a white noise series. P-Value is less than 0.05

Fit Univariate SARIMA Models for Original Data

SARIMA model for Sri Lanka

```
Series: SL_train
ARIMA(0,1,0)(0,1,0)[12]

sigma^2 = 355170872:  log likelihood = -687.04
AIC=1376.08   AICc=1376.15   BIC=1378.2
```

Figure 18: SARIMA Model for Sri Lanka

Consider trend component:

No autoregressive (AR) terms, no moving average (MA) terms. It's like a white noise.

Contains a differencing term (d=1) to make the series stationary.

Consider Seasonal component:

No seasonal AR or MA terms. Seasonal differencing (d=1) is applied for the yearly pattern (12 months).

SARIMA model for Maldives

```
Series: MAL_train
ARIMA(1,1,1)(0,1,1)[12]

Coefficients:
         ar1      ma1     sma1
      0.3915  -0.9112  -0.3249
s.e.  0.1557   0.0676   0.1464

sigma^2 = 84019142:  log likelihood = -642.85
AIC=1293.69   AICc=1294.41   BIC=1302.14
```

Figure 20: SARIMA Model for Maldives

Consider trend component:

One autoregressive (AR) term (ar1 = 0.3915).

One moving average (MA) term (ma1 = -0.9112).

Differencing (d=1) to make the series stationary.

Consider Seasonal component:

One seasonal MA term (sma1 = -0.3249).

Seasonal differencing (D=1) for yearly seasonality (12 months).

Forecasting

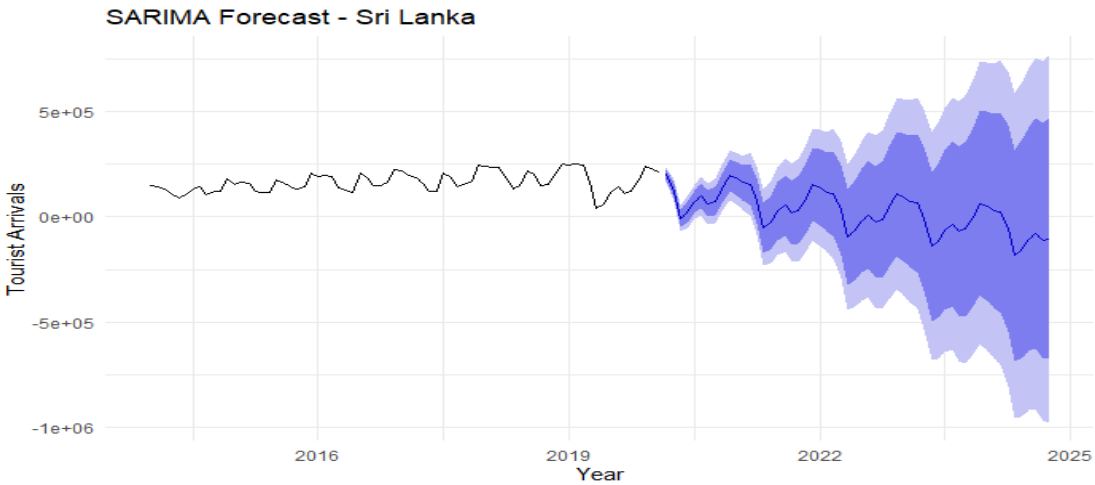

Figure 21: SARIMA Forecasting for Sri Lanka

The forecast captures the seasonal patterns (peaks and troughs) well.
The trend shows stability with some variability.

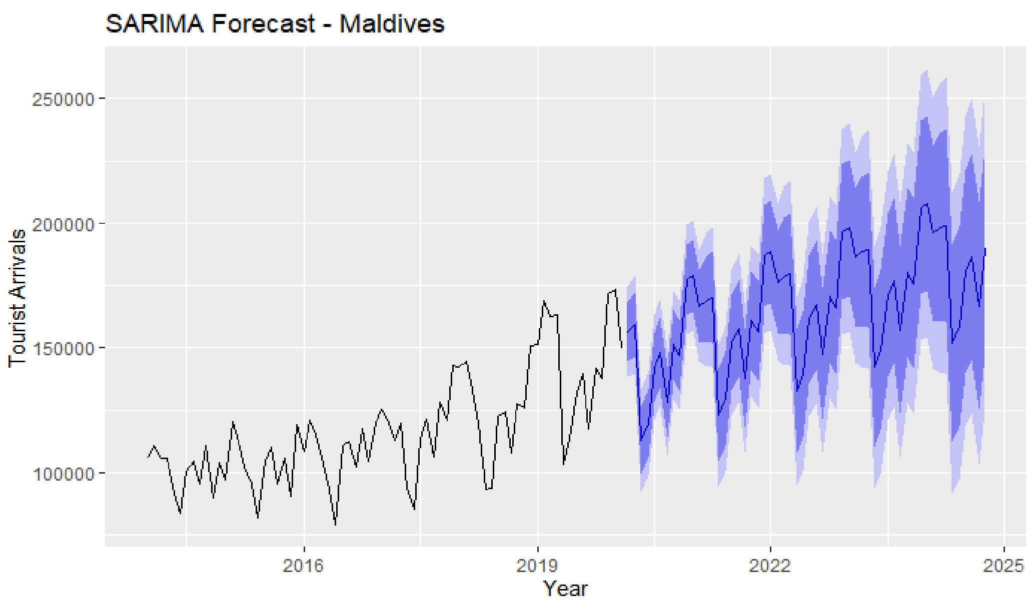

Figure22: SARIMA forecasting for Maldives

This forecast for tourist arrivals in the Maldives shows the seasonal patterns (peaks and troughs) are well.
The trend indicates a steady increase over time.

Evaluate the Accuracy

Sri Lanka

```
                    ME     RMSE       MAE       MPE     MAPE      MASE
Training set -736.4108  17110.7  11678.33 -2.672742 9.443338 0.5234654
Test set     50109.7679 140608.7 113186.66       NaN      Inf 5.0734407
```

Maldives

```
                    ME      RMSE       MAE       MPE     MAPE     MASE
Training set   1249.549  8114.976  5655.801 0.6869745 4.617036 0.593120
Test set     -44899.218 60916.631 45673.527      -Inf      Inf 4.789752
```

Fit Univariate SARIMA Models for Differencing dataset

SARIMA model for Sri Lanka after differencing

```
Series: Diff_SL
ARIMA(2,0,1) with zero mean

Coefficients:
         ar1      ar2      ma1
      0.8951  -0.4372  -0.7147
s.e.  0.1220   0.0800   0.1229

sigma^2 = 1.023e+09:  log likelihood = -1519.92
AIC=3047.84   AICc=3048.16   BIC=3059.27
```

Figure 23: SARIMA Model for Differencing dataset Sri Lanka

Two autoregressive (AR) term (ar1 = 0.3915,ar2= -0.4372).

One moving average (MA) term (ma1 = -0.7147).

SARIMA model for Maldives after differencing

```
Series: Diff_MAL
ARIMA(0,0,0) with zero mean

sigma^2 = 497858727:  log likelihood = -1474.71
AIC=2951.42   AICc=2951.45   BIC=2954.28
```

Figure 24: SARIMA Model for Differencing dataset Maldives

No Autoregressive term and no moving average term. It's like a white noise.

Forecasting

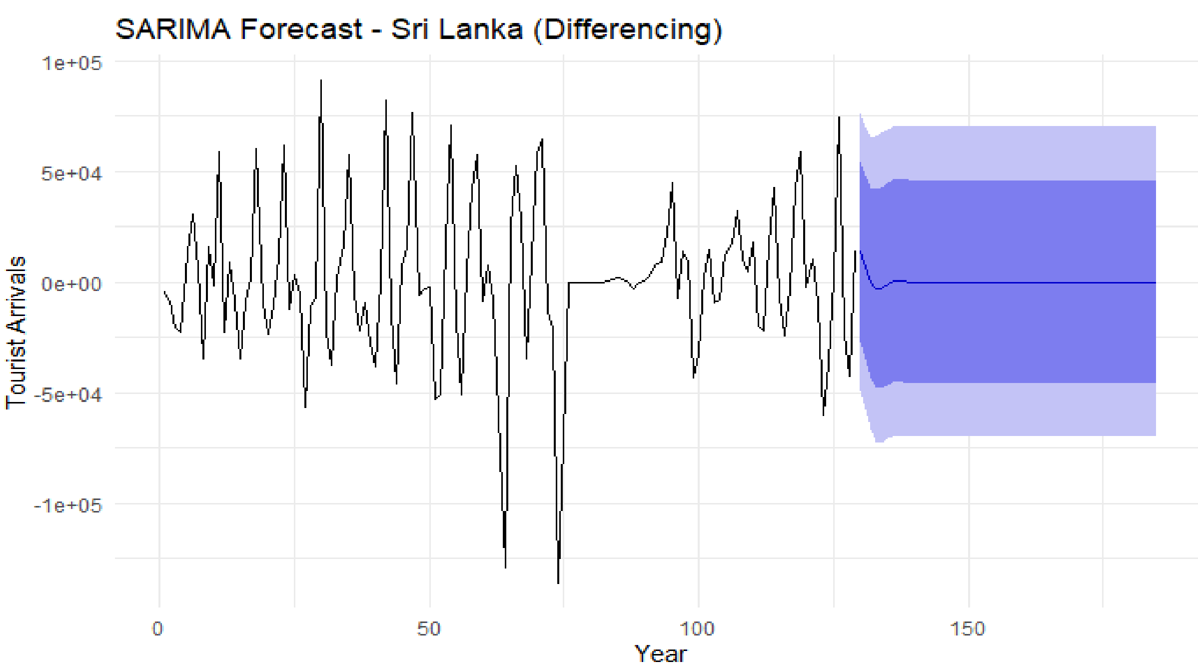

Figure 25: SARIMA Forecast for Differencing dataset Sri Lanka

The forecast captures the no trend and seasonality for differencing series.

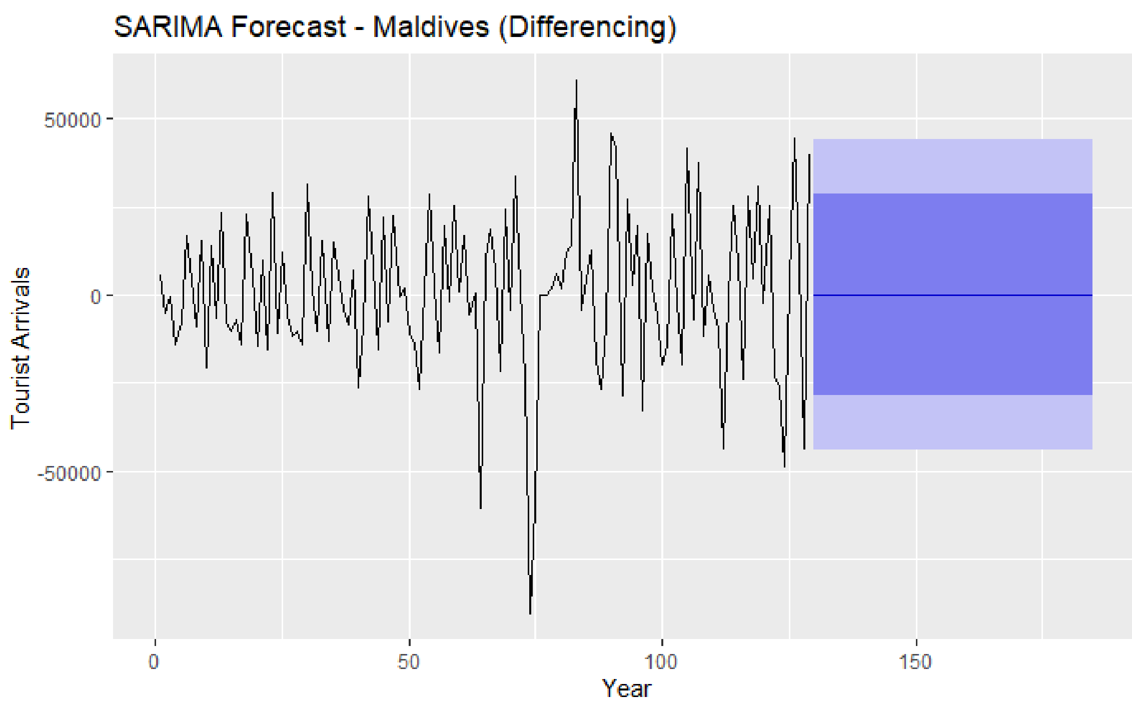

Figure 26: SARIMA Forecast for Differencing dataset Maldives

The forecast captures the no trend and seasonality for differencing series.

Evaluate the accuracy.

Sri Lanka after differencing

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	-736.4108	17110.7	11678.33	-2.672742	9.443338	0.5234654
Test set	50109.7679	140608.7	113186.66	NaN	Inf	5.0734407

Maldives after differencing

	ME	RMSE	MAE	MPE	MAPE	MASE
Training set	1249.549	8114.976	5655.801	0.6869745	4.617036	0.593120
Test set	-44899.218	60916.631	45673.527	-Inf	Inf	4.789752

Multivariate (Bivariate) Time series with VAR Model

lag selection results

```
$selection
AIC(n)  HQ(n)  SC(n) FPE(n)
    10     10     10     10
```

```
$criteria
                  1            2            3            4            5            6            7            8            9           10
AIC(n) 3.952845e+01 3.944650e+01 3.947338e+01 3.954724e+01 3.933611e+01 3.873765e+01 3.864528e+01 3.860333e+01 3.822330e+01 3.787267e+01
HQ(n)  3.963548e+01 3.960705e+01 3.968745e+01 3.981483e+01 3.965721e+01 3.911227e+01 3.907342e+01 3.908499e+01 3.875848e+01 3.846137e+01
SC(n)  3.980059e+01 3.985472e+01 4.001767e+01 4.022760e+01 4.015254e+01 3.969015e+01 3.973385e+01 3.982798e+01 3.958402e+01 3.936947e+01
FPE(n) 1.469380e+17 1.354877e+17 1.394019e+17 1.504877e+17 1.223335e+17 6.762346e+16 6.213004e+16 6.017584e+16 4.167749e+16 2.982150e+16
```

Var Forecast in Sri Lanka

```
$SriLanka
             fcst       lower      upper       CI
 [1,]   55204.370   22015.975  88392.765 33188.40
 [2,]  -85532.957 -129047.636 -42018.279 43514.68
 [3,] -115763.150 -162090.947 -69435.352 46327.80
 [4,]  -17897.437  -67068.913  31274.039 49171.48
 [5,]   36663.804  -12592.260  85919.869 49256.06
 [6,]   24587.816  -25533.152  74708.784 50120.97
 [7,]  -27846.896  -80963.812  25270.020 53116.92
 [8,]   13894.488  -39380.314  67169.289 53274.80
 [9,]   69718.838   16434.417 123003.260 53284.42
[10,]   53497.056    -480.409 107474.521 53977.46
[11,]  -40227.957  -94892.380  14436.467 54664.42
[12,]    2725.636  -53465.445  58916.718 56191.08
```

Var Forecast in Maldives

```
$Maldives
             fcst        lower     upper       CI
 [1,]  18135.1953   -1302.4422  37572.83 19437.64
 [2,]  -3259.0505  -28148.5207  21630.42 24889.47
 [3,] -48713.3279  -74388.4958 -23038.16 25675.17
 [4,]   9563.6866  -16763.5981  35890.97 26327.28
 [5,]   8621.1666  -17795.7145  35038.05 26416.88
 [6,]    736.6513  -25805.7262  27279.03 26542.38
 [7,]  -3229.5503  -30700.0904  24240.99 27470.54
 [8,]  30967.2392    2202.6037  59731.87 28764.64
 [9,]   4881.8032  -24001.0747  33764.68 28882.88
[10,]  29569.4242     348.8152  58790.03 29220.61
[11,] -14675.1297  -43903.6031  14553.34 29228.47
[12,] -14291.2962  -43713.6781  15131.09 29422.38
```

Var Forecast – Sri Lanka

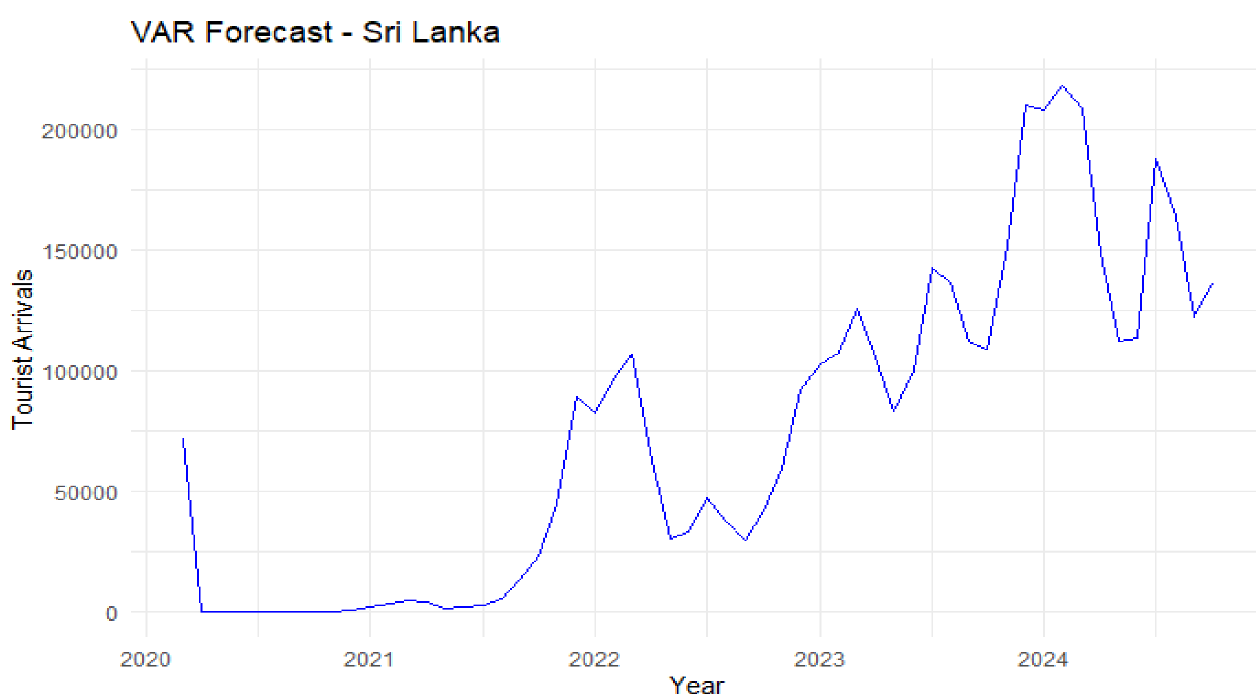

Figure 27: VAR Forecast for Sri Lanka

Var Forecast – Maldives

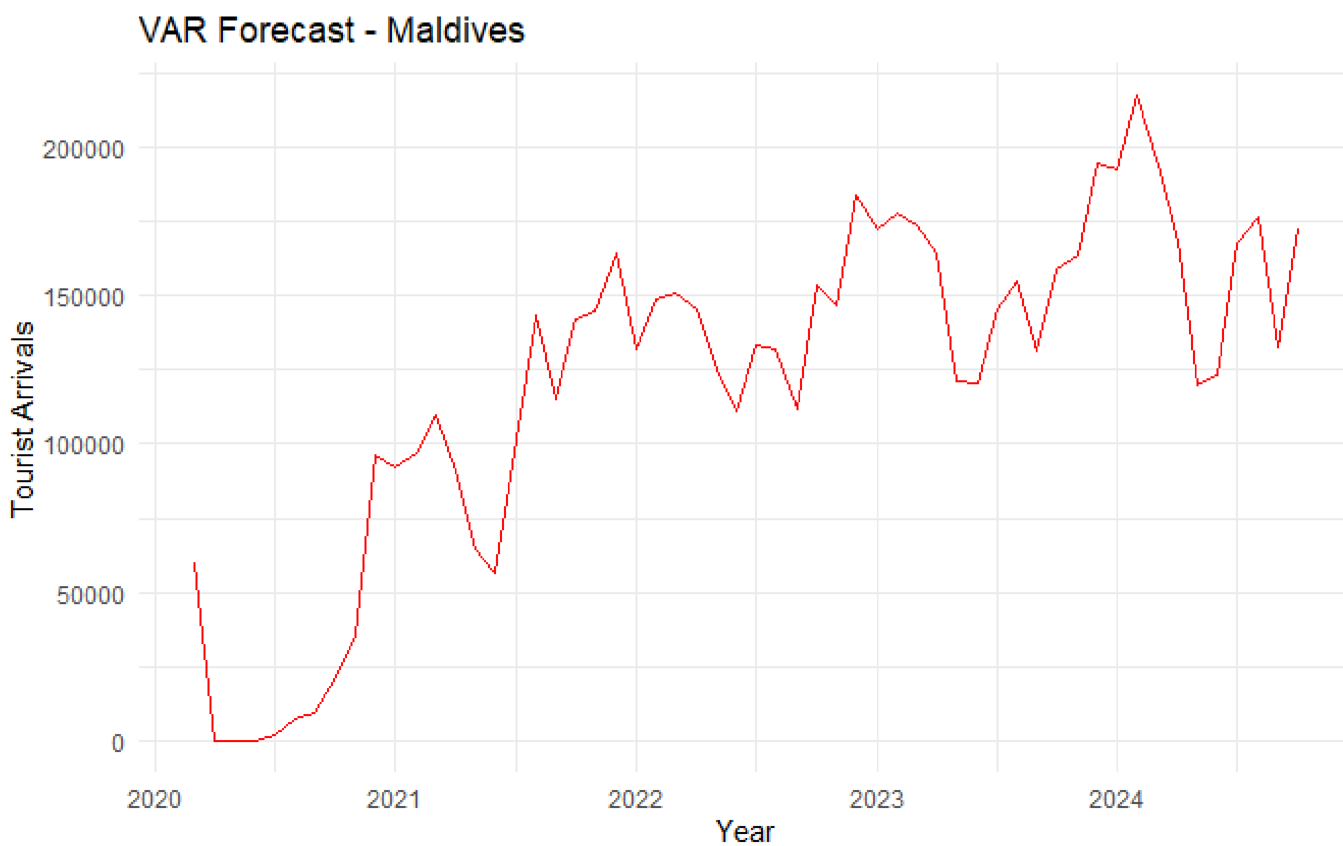

Figure 28: VAR Forecast for Maldives

Comparison of Actual and Forecast Tourist arrivals- Sri Lanka

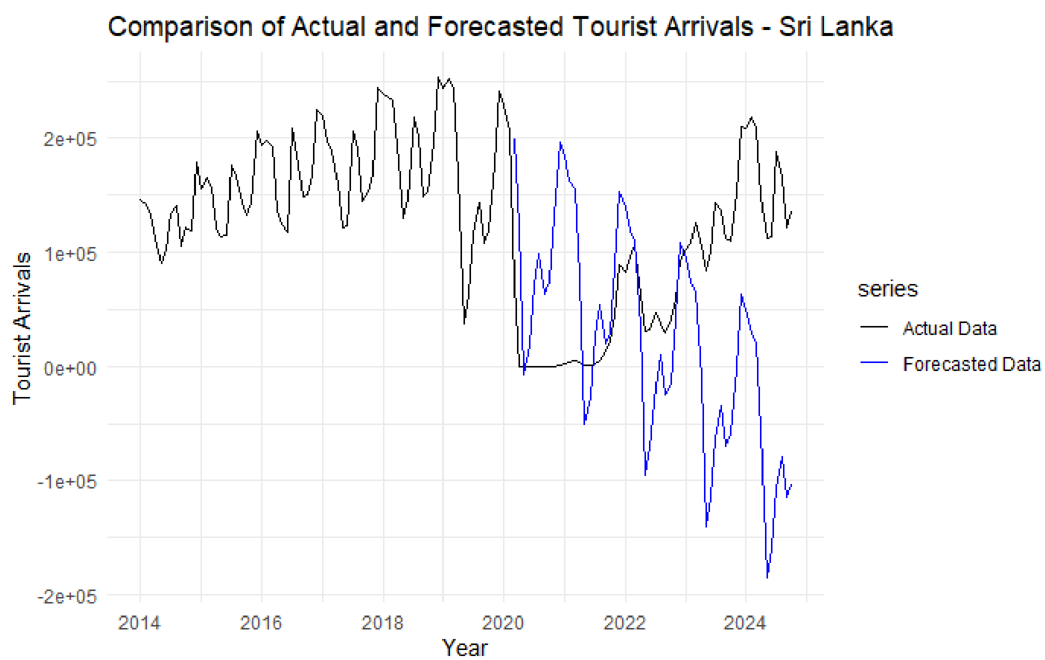

Figure 29: Forecast vs Actual Data plots for Sri Lanka

The forecasted data does not match the actual values well after COVID-19, showing that the model had trouble predicting sudden changes and the uneven recovery.

<u>Comparison of Actual and Forecast Tourist arrivals- Maldives</u>

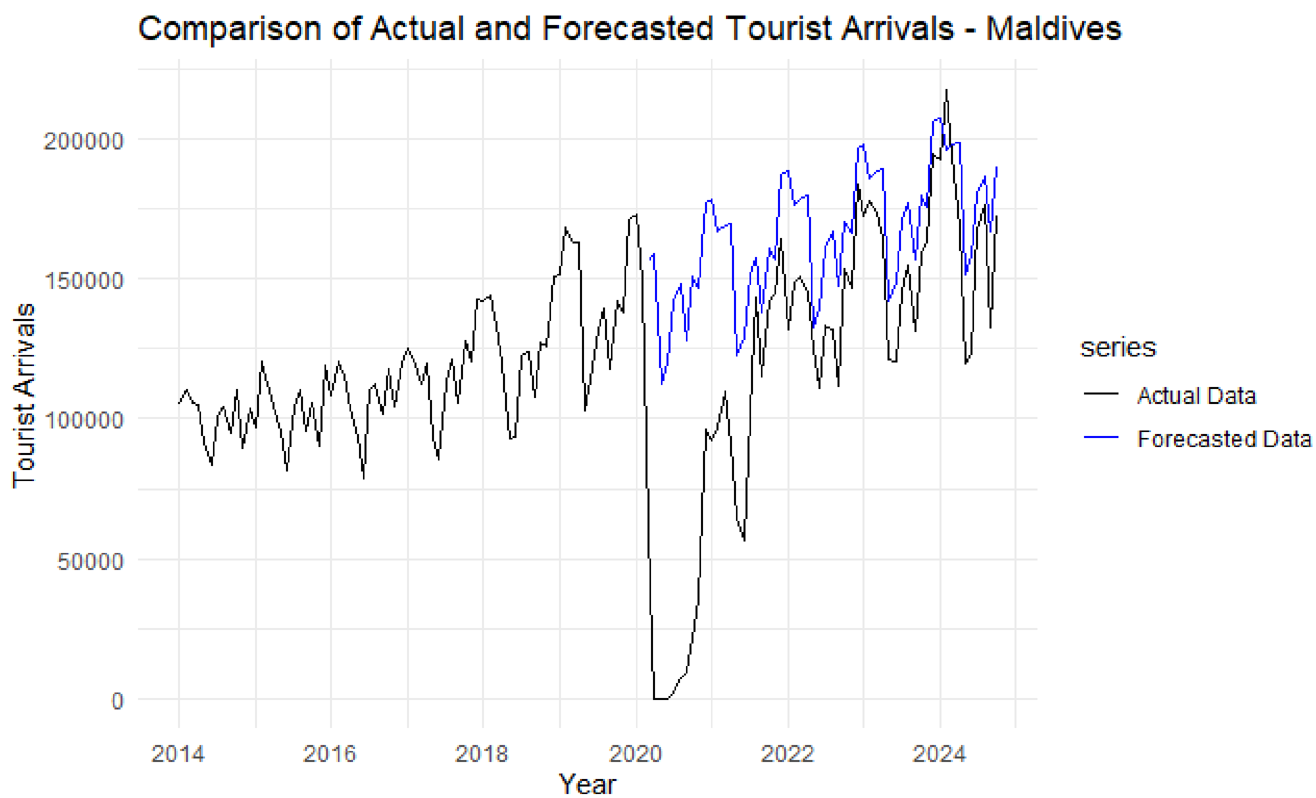

Figure 30: Forecast vs Actual Data plots for Sri Lanka

The forecasted data closely follows the actual tourist arrivals for the Maldives after COVID-19, showing that the model captured the recovery trend well.

Chapter 05: Conclusions & Recommendations

5.1 Conclusions

This study examined the trends in monthly tourist arrivals for Sri Lanka and the Maldives from 2014 to 2024, focusing on forecasting models to capture seasonal variations and external disruptions such as the COVID-19 pandemic. By employing both univariate and multivariate time series models—SARIMA and VAR—the research compared their effectiveness in predicting tourism trends. The findings highlight that SARIMA models effectively capture seasonality but struggle with significant external shocks, whereas VAR models provide insights into cross-country influences on tourism. The COVID-19 pandemic caused a sharp decline in tourist arrivals in 2020, followed by a gradual recovery, demonstrating the vulnerability of the tourism sector to global disruptions.

The research confirms that accurate forecasting models are essential for strategic decision-making in the tourism industry, helping policymakers and stakeholders allocate resources efficiently. While SARIMA models perform well for short-term seasonal forecasting, VAR models offer a broader understanding of how tourism patterns in Sri Lanka and the Maldives are interrelated. The study also underscores the importance of incorporating external economic, political, and policy-related factors into forecasting models to enhance accuracy. Overall, the results contribute to improving tourism planning and resilience, supporting the sustainable development of the sector.

5.2 Recommendations

- **Improving Forecasting Methods**
  Future studies should include important economic factors like exchange rates, inflation, and travel restrictions when predicting tourist arrivals. Using a mix of SARIMA, VAR, and machine learning models can make forecasts more accurate.

- **Handling Unexpected Events**
  Since COVID-19 had a big impact on tourism, it is important to create models that can adjust to sudden changes. Methods like detecting sudden shifts in data and analyzing unexpected events should be included in forecasting models.

- **Using Data for Better Decisions**
  Governments and tourism authorities should rely on data to make better plans for the tourism industry. Accurate forecasts can help them manage resources wisely, improve infrastructure, and attract tourists during low seasons.

- **Working Together as a Region**

  Since Sri Lanka and the Maldives have connected tourism patterns, they should work together on tourism policies, promotional campaigns, and travel agreements. This collaboration can help both countries recover faster from global crises.

- **Focusing on Sustainable Tourism**

  Forecasting models should also consider environmental factors and the number of tourists a place can handle. This will help ensure that tourism grows in a way that benefits both the economy and the environment in the long run.

By following these recommendations, tourism officials and businesses can improve prediction accuracy, prepare better for unexpected events, and ensure that the tourism industry in Sri Lanka and the Maldives remains strong and sustainable.

Chapter 06: References

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Chapter 07: Appendix

We get Month, Sri Lanka Arrivals & Maldives Arrivals as the variables

Month	Sri Lanka	Maldives
2014-01	146575	105296
2014-02	141878	110705
2014-03	133048	105560
2014-04	112631	105309
2014-05	90046	91296
2014-06	103175	83347
2014-07	133971	100191
2014-08	140319	104186
2014-09	105535	95114
2014-10	121576	110331
2014-11	119727	89778
2014-12	178672	103744
2015-01	156246	97073
2015-02	165541	120468
2015-03	157051	112427
2015-04	122217	102242
2015-05	113529	95389
2015-06	115467	81506
2015-07	175804	104517
2015-08	166610	110144
2015-09	143374	95511
2015-10	132280	105498
2015-11	144147	90218
2015-12	206114	119255
2016-01	194280	108396
2016-02	197697	120639
2016-03	192841	115131
2016-04	136367	103493
2016-05	125044	93228
2016-06	118038	79034
2016-07	209351	110432
2016-08	186288	112282
2016-09	148499	101909
2016-10	150419	117489
2016-11	167217	104572
2016-12	224791	119530
2017-01	219360	125336
2017-02	197517	121052
2017-03	188076	112665
2017-04	160249	119774
2017-05	121891	93491
2017-06	123351	85222
2017-07	205482	113175
2017-08	190928	121310
2017-09	145077	105984
2017-10	152429	127986
2017-11	167511	120506
2017-12	244536	143041
2018-01	238924	142351
2018-02	235618	144286
2018-03	233282	133466
2018-04	180429	119713
2018-05	129466	92913
2018-06	146828	93786
2018-07	217829	122332
2018-08	200359	123992
2018-09	149087	107620
2018-10	153123	127393
2018-11	195582	125604
2018-12	253169	150818
2019-01	244239	151552
2019-02	252033	168583
2019-03	244328	162843
2019-04	166975	163114
2019-05	37802	103022
2019-06	63072	113475
2019-07	115701	132144
2019-08	143587	139338
2019-09	108575	117619
2019-10	118743	141928
2019-11	176984	137921
2019-12	241663	171348
2020-01	228434	173347
2020-02	207507	149786
2020-03	71370	59627
2020-04	0	0
2020-05	0	36
2020-06	0	0
2020-07	0	1752
2020-08	0	7628
2020-09	0	9538
2020-10	0	21515
2020-11	0	35759
2020-12	393	96412

2021-01	1682	92021
2021-02	3366	96882
2021-03	4581	109585
2021-04	4168	91200
2021-05	1497	64613
2021-06	1614	56166
2021-07	2429	101818
2021-08	5040	143599
2021-09	13547	114896
2021-10	22771	142066
2021-11	44294	144725
2021-12	89506	164284
2022-01	82327	131764
2022-02	96507	149008
2022-03	106500	150748
2022-04	62980	145280
2022-05	30207	125522
2022-06	32856	110889
2022-07	47293	133561
2022-08	37760	131862
2022-09	29802	111986
2022-10	42026	153737
2022-11	59759	146886
2022-12	91961	184051
2023-01	102545	172499
2023-02	107639	177913
2023-03	125495	173514
2023-04	105498	164357
2023-05	83309	120959
2023-06	100388	120363
2023-07	143039	145620
2023-08	136405	154854
2023-09	111938	130967
2023-10	109199	159141
2023-11	151496	163658
2023-12	210352	194696
2024-01	208253	192385
2024-02	218350	217392
2024-03	209181	194227
2024-04	148867	168366
2024-05	112128	119875
2024-06	113470	123284
2024-07	187810	167529
2024-08	164609	176175
2024-09	122140	132795
2024-10	135907	172621

Table 0 : Raw Data Tourist Arrivals