# Estimating the Potential Impact of Shocks to Tourism Demand in Recent History of Sri Lanka Using a Machine Learning Modeling Approach

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## *Abstract*

*This study investigates key factors influencing tourism demand in Sri Lanka over the past five decades, using a Machine Learning (ML) modeling approach. It also estimates potential losses in tourism earnings during periods of domestic and external shocks. The findings reveal that tourist arrivals were significantly affected by historical arrival patterns, macroeconomic variables such as domestic inflation and the exchange rate, and various shocks including periods of civil war, terrorist attacks, natural disasters, and financial crises. The COVID-19 pandemic was identified as the principal external shock. Among the ML models evaluated, Multiple Linear Regression (MLR) and Extreme Gradient Boosting Regression (XGBR) demonstrated the highest accuracy in predicting tourist arrivals across different historical episodes, outperforming models such as Support Vector Regression (SVR), K-Nearest Neighbor Regression (KNN), and Gradient Boosting Regression (GBR). The study successfully quantifies the loss in tourist arrivals and potential tourism earnings attributable to these shocks within a historical context.*

**Key words:** *domestic shocks, external shocks, machine learning, Sri Lanka, tourism demand forecasting*

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## 1. Introduction

Earnings from tourism is a key foreign exchange earner in Sri Lanka. For example, in 2023, earnings from tourism amounted to US dollars 2.1 billion, constituting the third largest source of foreign exchange after merchandise exports and workers' remittances (Central Bank of Sri Lanka, 2023). One of the main aspects that impact tourist arrival not only to Sri Lanka, but also to almost all other international destinations, is the conduciveness of the country to safely travel (Ma et al., 2020). In some unprecedented situations, such as during the COVID-19 pandemic, global safety became the key consideration.

In most other situations, the perceived safety in the domestic location remains important when traveling to a particular destination. The reduction in safety of traveling to Sri Lanka as a tourist has been witnessed in many occasions in the last five and half decades where official monthly tourist data is available. This study identified six distinct periods in Sri Lankan history, since 1970, where tourist arrivals were notably affected by distinct events that led to concerns on safety for tourist visitation as given in Table 1.

**Table 1: Periods in Sri Lanka's history where tourist arrivals were affected by shocks**

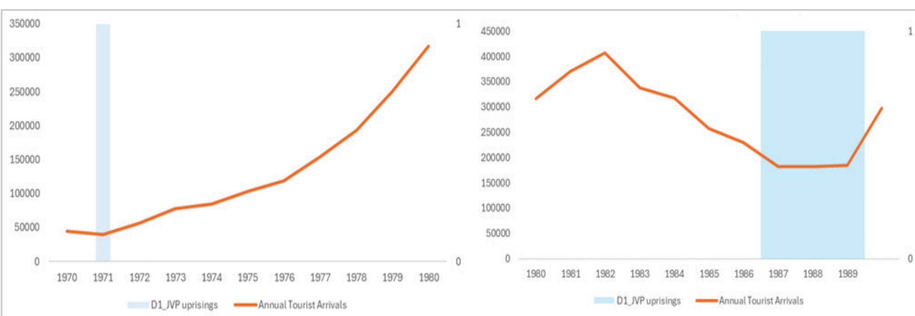
| Period | Event | Type of external / domestic shock |
|---|---|---|
| Apr 1971 – Oct 1971 and Jul 1987 – Jul 1989 | First JVP uprising and second JVP uprisings | Civil unrest |
| Jul 1983 – Jul 1987 | 1983 July Riots and First Eelam War | Civil conflict |
| May 1990 – Dec 1994 | Second Eelam War | Civil conflict |
| Apr 1995 – Feb 2002 | Third Eelam War | Civil conflict |
| Jul 2006 – May 2009 | Fourth Eelam War | Civil conflict |
| Apr 2019 – Dec 2022 | Easter Sunday attacks, COVID-19 pandemic and financial crisis | Terrorist attacks / global health pandemic / fuel crisis |

A brief description of these events in the historical context of tourist arrivals is detailed in sections below.

### 1.1. JVP uprisings

The JVP (Janatha Vimukthi Peramuna) uprisings in Sri Lanka refer to two significant insurrections led by the Marxist-Leninist political party JVP (Rich & Duyvesteyn, 2012). These uprisings had a profound impact on the political and social stability in Sri Lanka and the travel safety of tourists was a major concern. There was a state of emergency pronounced during most of the period, significantly deterring tourist arrivals to the country. The second JVP uprising was particularly brutal leading to a significant loss of lives. As a result, tourist arrivals came to a virtual standstill between 1987 to 1989 as illustrated in Figure 1.

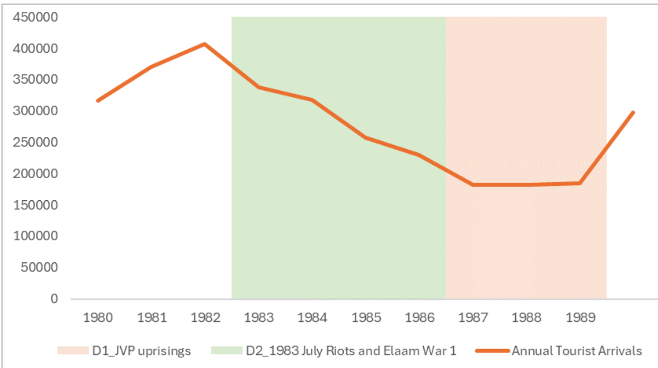
**Figure 1: First and second JVP uprisings in early 1970's and late 1980's**



### 1.2. 1983 Black July Riots and first Eelam War

1983 July riots were a series of violent attacks in Sri Lanka targeting the Tamil population sparked by the ambushing and killing of 13 Sri Lankan Army soldiers by the Liberation Tigers of Tamil Eelam (LTTE), a Tamil militant organisation, on July 23, 1983. The riots resulted in a significant loss of human lives resulting in the country becoming extremely unsafe for tourism, completely debilitating the tourism sector to decades of unreached potential (Ross & Samaranayake, 1986). The aftermath of the 1983 riots was the beginning of a full-blown civil conflict that led to the first Eelam War between the LTTE and the government of Sri Lanka. The Eelam War 1 lasted until 1987 until the Indo – Sri Lanka accord, but only a tense, temporary peace ensued for a limited time. The period also coincided with the 1987 JVP uprisings from 1987 that was widespread throughout the southern part of the country. The escalation of these twin conflicts had a profound impact on the tourism industry throughout the 1980s as illustrated in Figure 2.

**Figure 2: Annual tourist arrivals during 1980's**

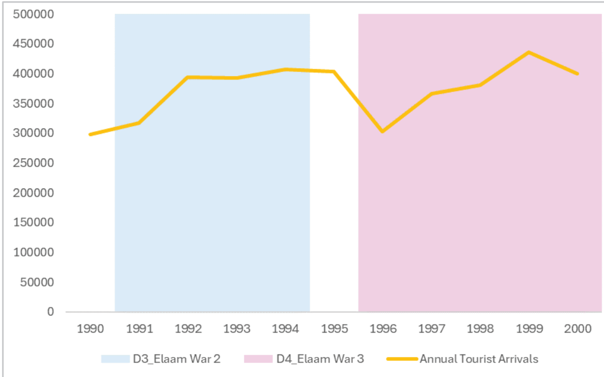



By the end of Eelam War 1 and JVP uprisings in the 1980s, Sri Lanka's promise as a major tourist attraction was permanently damaged (Bandara, 1997). These events were followed by Eelam War 2, with the withdrawal of Indian Peace Keeping Forces, and the continuation of the conflict between the LTTE and the Government. In addition to full blown military and guerilla conflicts in the North of the country, there were a number of major suicide attacks in the South that deterred most tourists. Eelam War 2 ended in 1995, with a notional peace accord for a brief period in 1995.

### 1.3. Third Eelam war

Eelam War 3 began in June 1995 and lasted until February 2002. In addition to the significant escalation of military conflicts, the LTTE continued its suicide bombings, targeting key political and military figures as well as civilians. Notable attacks include the bombing of the Central Bank in Colombo (1996), attack on the Temple of the Tooth (1998), attack on the Bandaranaike International Airport (July 2001), all epicenters of tourism. These, together with military offensives carried out by the Sri Lanka Army, created a significant deterrent to tourism, as illustrated in Figure 3.

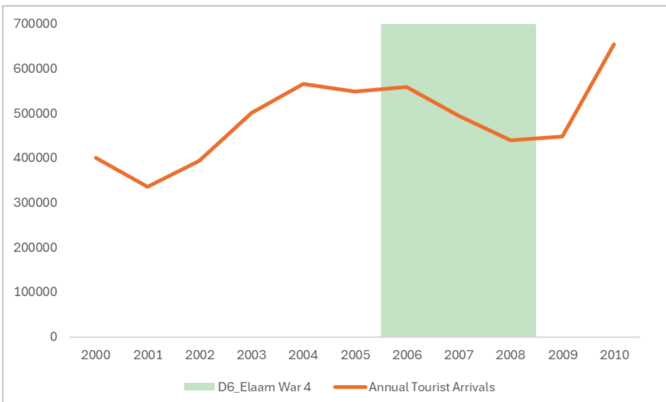
**Figure 3: Annual tourist arrivals during 1990's and early 2000's**




### 1.4. Fourth Eelam War

Eelam War IV began after a period of relative calm following a 2002 ceasefire agreement. The peace process eventually broke down, leading to the resumption of full-scale hostilities. The defeat of the LTTE in May 2009 marked the official end of the Civil War, which had lasted for over 25 years (Ashok Mehta, 2010). Tourist arrivals during this period remained stagnant, with concerns of safety as suicide bombings continued in the South with the North, East and Northeastern parts remaining inaccessible and unconducive to tourism.

**Figure 4: Annual tourist arrivals during late 2000's**



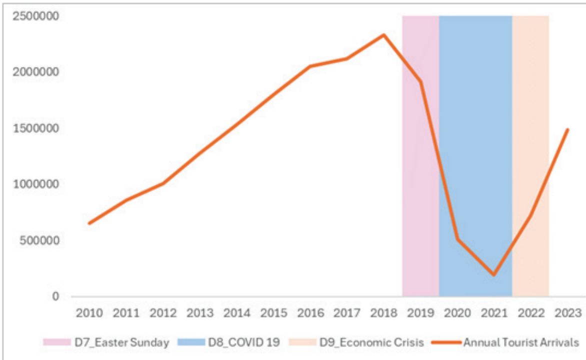

### 1.5. Easter Sunday Attacks, COVID-19 Pandemic, and 2022 Financial Crisis

**Easter Sunday attacks**. The Easter Sunday attacks in Sri Lanka were a series of coordinated terrorist bombings that took place on April 21, 2019. These attacks targeted churches and tourist hotels across the country, resulting in a significant loss of lives and raising safety concerns for tourism in the country. This event was the beginning of three consecutive disasters that devastated Sri Lanka's tourism sector from March 2019 to end 2022.

**COVID-19 pandemic.** The COVID-19 pandemic, caused by the novel coronavirus SARS-CoV-2, had a profound and unprecedented impact on global health and economies, and resulted in a complete standstill of global tourism. Many countries imposed strict lockdowns, travel bans, and quarantine measures to control the spread of the virus. This led to a sharp decline in both domestic and international travel, decimating the tourism industry in Sri Lanka as well.

**Financial crisis.** There was a significant financial crisis in Sri Lanka in the aftermath of the COVID-19 pandemic that was characterised by acute shortages of essential goods, including fuel, leading to widespread disruptions in daily life and economic activities. This situation also led to an unconducive environment for tourism. However, there was a year-on-year growth in tourist arrivals in most months during this period as the previous year had a significant low base due to the COVID-19 pandemic, as illustrated in Figure 5.

**Figure 5: Annual tourist arrivals (2010-2023)**




The objective of the study is to quantify the loss of tourism in the identified five distinct periods (with the second JVP uprising and First Eelam War in 1980's considered one event), in terms of the quantity of potential tourist arrivals if an event did not occur, and the potential loss in earnings from tourism during each period.

## 2. Literature Review

The impact of the civil conflict on Sri Lanka tourism has been studied to a certain extent in the past literature available to the author. A study by Fernando et al. (Fernando et al., 2013) examines the volatility in international tourist arrivals to Sri Lanka, particularly during the civil war from 1983 to 2009, highlighting the impact of political violence and financial shocks on tourism. The paper employs a GARCH econometric models to analyse tourism demand and volatility in tourist arrivals. The study assesses the impact of variables like war and exchange rates on tourist arrivals, revealing significant relationships. Another study by Gamage et al. (1997) studied the impact of political upheavals from 1983 to 1989 on Sri Lanka's international tourism, earnings from tourism, household income, gross tourism expenditure and on tourism related employment. The results indicate that the loss of tourist arrivals is about ten per cent on average annual basis between 1983 and 1989, resulting in a loss of around US dollars one billion during the period. However, the study does not use a solid econometric model to arrive at these conclusions. In much more recent study by Dunusinghe and Beligahawaththa (2021), it was found that tourist arrivals and tourism receipt were lower by around 20 per cent in a year which witnessed terrorist attacks compared to a normal year using an autoregressive model. Further, in the short run, employment in the industry declined by around 11 per cent following a major terrorist attack on civilian targets. Above studies were the only published studies the author could find in available literature on the impact of shocks to Sri Lanka's tourism industry in relation to its recent political history. There are no recent studies of quantification of the impact of the triple effect of the Easter Sunday attacks, COVID-19 pandemic and the subsequent financial crisis.

Although there is limited literature on the quantification of impact of shocks on tourist arrivals in the Sri Lankan context, many such studies in international contexts are available. As per such literature, external and domestic shocks have led to many negative shocks. Such negative shocks include global, regional or country specific health risks, terrorist attacks, civil wars, natural disasters such as earthquakes, tsunamis as well as political instability. However, there could be positive shocks to tourism as well, such as the hosting of a major sporting event in the country that will positively drive tourism demand. For example, out of many literatures on quantifying the impact of COVID-19 pandemic on tourist arrivals, one study by Arbulu et al. (2021) have concluded that the COVID-19 pandemic resulted in a potential 89% drop in tourist arrivals in Balearic Islands, using Monte Carlo simulations.

In a study by Beautels et al. (2009) on the macroeconomic impact of the SARS outbreak in Beijing in the early 2000's, the authors estimate that the irrecoverable losses amounted to about USD 1.4 billion, roughly 300 times the cost of treating SARS related patients. In a study that looks at the impact of terrorism and related fatalities in potential loss of tourism to Kenya from 2010 to 2013 using a dynamic panel model, it was found that a 1% increase in fatalities due to terrorism leads to a 0.13% decrease in tourist arrivals, equating to about 2,507 visitors (Buigut & Amendah, 2016).

Natural disasters such as earthquakes and typhoons are also a significant deterrent to future tourist arrivals. For example, in Taiwan, a study by Liu (Liu, 2014) suggest that the tourism industry in the Taiwan Maolin National Scenic Area suffered significant losses due to Typhoon Morakot in 2009. The author estimates the loss in tourist visitors in 2009 due to the typhoon to be approximately 700,000, with a loss in earnings from tourism that is estimated to be over three times the loss of tourism infrastructure. In a similar study, it was found that a severe earthquake in the Marmara region in Turkey in 1999 resulted in a loss of around 20% potential tourist arrivals during the year (ÇïFtcï & Bayram, 2021).

## 3. Methodology

The methodology of the study is structured as follows: Firstly, the historical time periods where the potential loss in tourism to be calculated is defined. Then, a feature selection process is done to determine which independent variables to be considered for each period based on statistically significant independent variables. Thereafter, the types of machine learning models considered are defined and the criteria used to determine the performance of the ML models are discussed.

### 3.1. Historical Time Periods Considered for Separate Modeling

As detailed in section 1, five time periods in history of Sri Lanka that were affected by adverse domestic and external shocks were considered in this study. These models, termed model 1 to model 5, are detailed in Table 2 below.

**Table 2: Models considered based on time period**

| Model | Event | Period |
|---|---|---|
| Model 1 | 1983 July Riots, first Eelam War and second JVP uprising | Jul 1983 – Jul 1989 |
| Model 2 | Second Eelam War period | May 1990 – Dec 1994 |
| Model 3 | Third Eelam War | Apr 1995 – Feb 2002 |
| Model 4 | Fourth Eelam War | |
| Model 5 | Easter Sunday attacks, COVID-19 pandemic and financial crisis | Apr 2019 – Dec 2022 |

### 3.2. Feature Selection Process

The primary aim of the feature selection process is to identify the appropriate dependent variables for each model considered in section 3.1 above.

**Dependent Variable:** Monthly tourist arrivals data since 1970 was considered as the dependent variable in the study.

**Independent variables considered in initiation of each model:** The features among the different options available as independent variables considered is one of the key aspects of the feature selection process. This was done in two steps. Firstly, all possible options for a particular model were considered in the initiation of each model. The types of independent variables considered involved time dependent variables, econometric variables, web data and dummy variables to represent each historical episode when there was a shock to tourist arrivals. The list of independent variables considered is given below in Table 3.

**Table 3: Independent variables considered for the modeling process**

| Variable type | Description | Abbreviation |
|---|---|---|
| Time dependent variables | Monthly tourist arrivals with a 12-month lag | TA_12M_lag |
| Econometric variables | Colombo Consumer Price Index | CCPI |
| | USD_LKR exchange rate | USD_LKR |
| Web based data | Google Search Index | GSI |
| | TripAdvisor website reviews | TAWR |

| | | |
|---|---|---|
| Dummy variables | JVP uprisings | D1 |
| | 1983 July riots and first Eelam War | D2 |
| | Second Eelam War | D3 |
| | Third Eelam War | D4 |
| | Fourth Eelam War | D5 |
| | Easter Sunday attacks, COVID-19 pandemic and financial crisis | D6 |

It must be noted that for each specific model (as defined in Table 2) considered, the independent variables considered at the initiation of the feature selection varied. For example, Google Search Index data and TripAdvisor review data was available only from 2004 and 2007 respectively and hence considered for some of the models only. Similarly, all dummy variables were not applicable all models considered, as can be seen in Table 4 below.

**Table 4: Independent variables considered for each model**

| Model | Event | Independent variables considered |
|---|---|---|
| Period 1 | 1983 July Riots, first Eelam War and second JVP uprising | TA_12M_lag, CCPI, USD_LKR |
| Model 2 | Second Eelam War period | TA_12M_lag, CCPI, USD_LKR, D1 |
| Model 3 | Third Eelam War | TA_12M_lag, CCPI, USD_LKR, D1, D2 |
| Model 4 | Fourth Eelam War | TA_12M_lag, CCPI, USD_LKR, GSI, TAWR, D1, D2, D3 |
| Model 5 | Easter Sunday attacks, COVID-19 pandemic and financial crisis | TA_12M_lag, CCPI, USD_LKR, GSI, TAWR, D1, D2, D3, D4 |

### 3.3. Selection of Statistically Important Independent Variables for Each Model

To identify which of the independent variables are statistically significant, a simple MLR model was used for each of the five models to obtain the p-statistics as given in Table 5.

**Table 5: Statistical significance of independent variables for each model**

| Independent variable | p-statistic | | | | |
|---|---|---|---|---|---|
| | Model 1 | Model 2 | Model 3 | Model 4 | Model5 |
| TA_12M_lag | 9.40E-41** | 1.77E-30** | 4.75E-76** | 6.21E-34** | 9.1E-131** |
| CCPI | 0.305916 | 0.086845 | 0.846129 | 0.0586558 | 1.85E-07** |
| USD_LKR | | 0.030512** | 0.945837 | 0.5666581 | 0.19895 |
| GSI | | | | 0.3561392 | 0.155412 |
| TAWR | | | | 0.3345097 | 0.06789 |
| D1 | | 0.001286** | 4.45E-09** | 5.388E-07** | 2.31E-08** |
| D2 | | | 0.997591 | 0.4658497 | 0.781641 |
| D3 | | | | 0.0001267** | 0.000194** |
| D4 | | | | | 0.00519 |
| D5 | | | | | 4.32E-18** |
| D6 | | | | | |

### 3.4. Forecasting Timeline of Each Model and Selected Independent Variables

Based on the results in Section 3.3, the time period to use actual data, the projected period and the independent variables considered for the five models were identified as given in Table 6.

**Table 6: Statistical significance of independent variables for each model**

| Period Classification | Event | Time period of actual data used (prior to event) | Projected period | Independent variables considered |
|---|---|---|---|---|
| Period 1 | 1983 July Riots, first Eelam War and second JVP uprising | Jan 1970 -Jun 1983 | Jul 1980 – Dec 1989 | TA_12M_lag |
| Period 2 | Second Eelam War | Jan 1970 -Apr 1990 | May 1990 – Dec 1994 | TA_12M_lag<br>USD_LKR, D1 |
| Period 3 | Third Eelam War | Jan 1970 -Dec 1994 | Jan 1995 – Dec 1999 | TA_12M_lag, D1 |
| Period 4 | Fourth Eelam War | Jan 1970 -June 2006 | July 2006 – May 2009 | TA_12M_lag<br>D1, D3 |
| Period 5 | Easter Sunday attacks, COVID-19 and financial crisis | Jan 1970 –Mar 2019 | Apr 2019-Sep 2022 | TA_12M_lag<br>CCPI<br>D1, D3, D5 |

### 3.5. Machine Learning Models Considered in the Study

Four different ML models were considered for the evaluation of each model. All these machine learning models are widely used in machine learning based tourism demand forecasting both in the Sri Lankan context and globally. A brief description of each ML model based on literature *(James et al., 2013)* is given below.

**Multiple Linear Regression (MLR):** In machine learning, MLR is a supervised learning technique that models the relationship between two or more independent variables (features) and a continuous dependent variable (target). This is done by fitting a linear equation to observed data. MLR can be useful for predicting outcomes based on several predictors, such as using past data.

**Support Vector Regression (SVR):** SVR is a supervised machine learning algorithm derived from Support Vector Machines, designed for predicting continuous values. For non-linear data, SVR can be extended using kernels, such as the polynomial or radial basis function (RBF) kernel, enabling the model to fit complex, non-linear relationships.

**k-Nearest Neighbour Regression (KNN):** KNN is a non-parametric, instance-based machine learning algorithm used for predicting continuous target variables. Unlike typical regression techniques that assume a specific functional form, KNN regression relies on the idea that similar instances in feature space produce similar outcomes.

**Gradient Boosting (GBR) and Extreme Gradient Boosting Regression (XGBR): G**BR and XGBR are high performance supervised ML algorithm based on boosting, an ensemble learning technique. It builds a series of weak prediction models, typically decision trees, in a sequential manner, where each model focuses on correcting the errors of the previous one. XGBR is particularly known for its speed and efficiency, achieved by advanced optimisation techniques like tree pruning, parallelisation, and regularisation. One of the advantages of XGBR is its flexibility, as it can handle missing values, perform well with high dimensional data, and adapt to different types of distributions. It is widely used for its strong predictive performance in various applications, such as time series forecasting.

### 3.6. Evaluation of Performance of Machine Learning Models

The evaluation of the performance of the ML models was based on general statistical modelling performance criteria such as Root Mean Square Error (RMSE), mean absolute percentage error (MAPE) and the r-square value. Brief definitions of these performance evaluating statistical indicators are given below.

**RMSE:** RMSE is a common metric used to measure the accuracy of a predictive model, especially in regression tasks. It quantifies the average magnitude of errors between the predicted values and the actual values.

**MAPE:** MAPE is a metric used to evaluate the accuracy of a regression model by measuring the average absolute percentage difference between predicted and actual values. MAPE is particularly useful because it expresses errors as a percentage, making it easy to interpret and compare across different datasets or models.

**r-square:** $r^2$ is a statistical metric that measures the proportion of variance in the dependent variable that is predictable from the independent variables in a regression model. It gives insight into how well the independent variables explain the variation in the target variable.

## 4. Results

For each period considered, the performance of different ML model is considered first under each section. Thereafter, based on the results, the most appropriate ML model is selected and used to predict tourist arrivals under modelling condition of no domestic or external shocks during the period. Thereafter, the potential annual loss in tourist arrivals and earnings from tourism considered under Section 4.1 to 4.5. Section 4.6 summarises the results obtained from each period modelled.

### 4.1. Period 1 - Evaluation of the Impact of the 1983 Black July riots subsequent Eelam War 1 and 2nd JVP uprising in the 1980s on Tourist Arrivals

We estimate the start of the 1983 Black July riots as the beginning of the period of shock ending with the end of the second JVP resurrection in December 1989. The actual monthly tourist arrivals in the period from 1970 to July 1983 was used for the modelling process with 70 percent of observations used to train the model and 30 per cent of observations used to test the model. The results of the performance of each model are given in Table 7.

**Table 7: Performance of each ML model for actual data in 'Period 1'**

| Model | R-Square | MAE | RMSE |
|---|---|---|---|
| MLR | 0.948 | 1793.7 | 2516.0 |
| SVR | 0.935 | 1826.9 | 2572.1 |
| KNN | 0.970 | 1557.8 | 1901.7 |
| GBR | 0.942 | 2043.5 | 2645.9 |
| XGBR | 0.926 | 2270.4 | 2989.4 |

As the KNN model indicated better model performance, it was used to predict tourist arrivals with as given in Table 8.

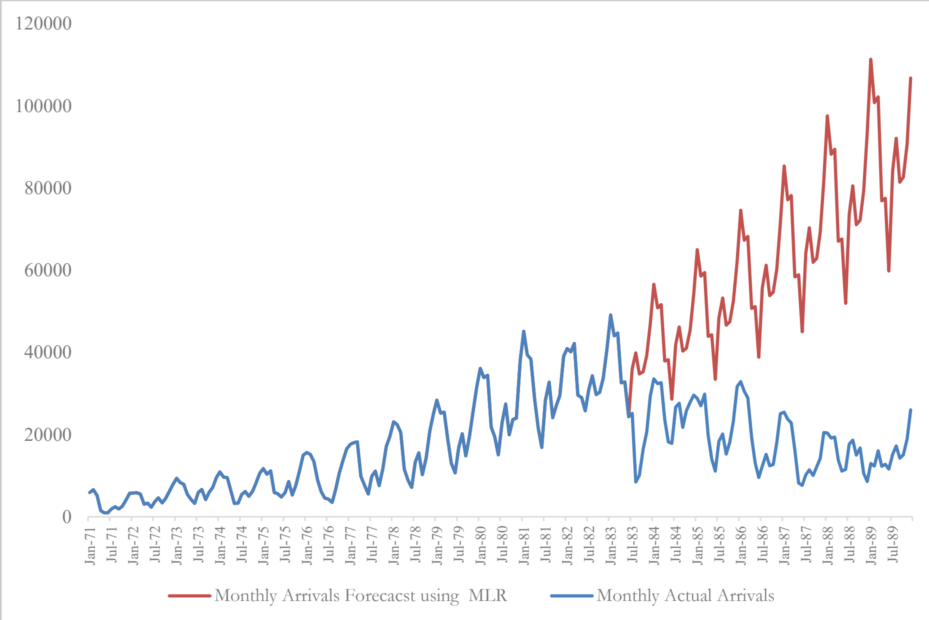
**Table 8: Forecast of monthly tourist arrivals based on KNN model for 'Period 1'***

| Month | 1982 | 1983 | 1984 | 1985 |
|---|---|---|---|---|
| Jan | 40,932 | 49,104 | 41,554 | 42,189 |
| Feb | 40,148 | 44,038 | 41554 | 42,189 |
| Mar | 42178 | 44,710 | 41,554 | 42,189 |
| Apr | 29,606 | 32,556 | 36,975 | 40,278 |
| May | 28,972 | 32,850 | 36,975 | 40,278 |
| Jun | 25,772 | 24,350 | 28,764 | 32,921 |
| Jul | 30,942 | 35,942 | 37,758 | 41,038 |
| Aug | 34,332 | 39,983 | 41,554 | 42,189 |
| Sep | 29,754 | 34,592 | 36,243 | 39,689 |
| Oct | 30,296 | 36,790 | 36,243 | 39,689 |
| Nov | 33,748 | 39,983 | 40,824 | 42,189 |
| Dec | 40,550 | 39,983 | 41,554 | 42,189 |
| **Annual tourist arrivals** | **407,230** | **454,881** | **461,552** | **487,027** |

*Highlighted months indicates projections. Unhighlighted months are actual tourist arrivals prior to the event.

Despite the KNN model having the best r-square value and the least errors, it can be seen from the above forecasted results the model produces inconsistent results for a regression problem. The same number is forecasted to two or three consecutive months in some instances, which is inconsistent with the seasonal pattern that is expected from monthly tourist arrivals forecast. Considering this, and the fact that the Multiple Linear Regression (MLR) models are extensively used in literature to carry out similar studies, the same forecasting was carried out using a MLR model and results in more optimal results with a clear seasonal pattern as given in Figure 6.

**Figure 6: Monthly tourist arrivals forecast using a MLR model (Jul 1983-Dec 1989)**




Based on the predicted monthly tourist arrivals with an absence of a shock from July 1983 to December 1989, the potential loss in annual tourist arrivals and annual earnings were calculated, as given in Table 9.

**Table 9: Forecast of monthly tourist arrivals based on KNN model for 'Period 1'**

| Year | Tourist average stay period | Spending per day (USD) | Realised Tourist Arrivals | Realised Tourist Earnings (USD mn) | Potential Tourist Arrivals | Potential Tourist Earnings Estimate (USD mn) | Estimated Loss in Potential Tourist Earnings (USD mn) |
|---|---|---|---|---|---|---|---|
| 1983 | 9.6 | 38.8 | 337,550 | 125.8 | 459,743 | 171.3 | 45.5 |
| 1984 | 8.9 | 37.1 | 317,734 | 104.9 | 532,634 | 175.8 | 70.9 |
| 1985 | 9.2 | 34.7 | 257,466 | 82.2 | 615,003 | 196.3 | 114.1 |
| 1986 | 10.9 | 32.7 | 230,106 | 82.1 | 708,061 | 252.6 | 170.5 |
| 1987 | 13.2 | 34.0 | 182,620 | 82.0 | 813,237 | 365.2 | 283.2 |
| 1988 | 12.6 | 33.3 | 182,662 | 76.6 | 932,091 | 390.9 | 314.3 |
| 1989 | 10.7 | 38.4 | 184,732 | 76.0 | 1,066,396 | 438.7 | 362.7 |
| **Total** | | | **1,692,870** | **629.6** | **5,127,165** | **1,990.8** | **1,361** |

The realised tourist arrivals during the period of 1983 to 1989 was around 1.692 million. However, the model estimate that there was the potential of over 5.127 million tourist arrivals during this period. In essence, the potential loss of tourist arrivals is around 67.0% based on the estimated potential. Further, the loss in nominal value term could be around USD 1.36 billion, which is significant loss considering the time period.

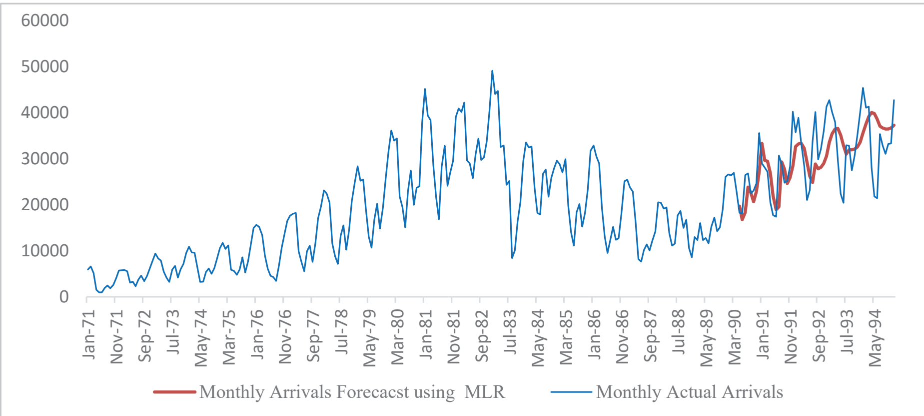
### 4.2. Period 2 – Evaluation of the Impact of first Eelam War on Tourist Arrivals

Although the KNN regression model performs slightly better than the MLR model, previous experience in model 2 showed that given similar model performance, the MLR model is better at predicting seasonal distributed time series such as monthly tourist arrivals in the context of Sri Lanka. Hence, the MLR model is used to evaluate the performance of the model.

**Table 10: Performance of each ML model for actual data in 'Period 2'**

| Model | R-Square | MAE | RMSE |
|---|---|---|---|
| MLR | 0.900 | 2,646.4 | 3,582.5 |
| SVR | 0.843 | 2,726.4 | 3,453.0 |
| KNN | 0.911 | 2,645.2 | 3,477.3 |
| GBR | 0.790 | 4,109.4 | 5,176.5 |
| XGBR | 0.899 | 2,809.1 | 3,586.9 |

**Figure 7: Monthly tourist arrivals forecast using a MLR model (May 1990 – Dec 1994)**




After almost a decade of suppressed tourism, the early 1990's witnessed a gradual revival in tourist arrivals in the first half of 1990's, although it did not see a same growth as was observed prior to the 1983 July riots and subsequent events thereafter. Based on the forecast, the forecasted arrivals are more or less similar to the actual tourist arrivals in the first half of the 1990s. Hence, it can be deduced that Eelam War 2, which was mainly confronted to the Northern part of the country except for occasional terrorist attacks on the southern part of the country may not have contributed significantly to reduce the already suppressed tourist arrivals prior to the beginning of Eelam War 2.

### 4.3. Period 3 – Evaluation of the Impact of second Eelam War on Tourist Arrivals

The performance of ML models for period 3 is given in Table 11. Although the XGBR regression model performs slightly better than the MLR model, previous experience in model 2 showed that given similar model performance, MLR model is better at predicting seasonal distributed time series compared to a purely machine learning model. Hence, the MLR model was used to evaluate the performance of the model (Figure 8).

**Table 11: Performance of each ML model for actual data in 'Period 3'**

| Model | R-Square | MAE | RMSE |
|---|---|---|---|
| MLR | 0.841 | 3194.6 | 4378.2 |
| SVR | 0.161 | 4850.2 | 5102.2 |
| KNN | 0.804 | 3848.1 | 4958.2 |
| GBR | 0.767 | 3871.0 | 5300.7 |
| XGBR | 0.842 | 3075.2 | 4367.3 |

**Figure 8: Monthly tourist arrivals forecast using a MLR model (May 1990 – Dec 1994)**

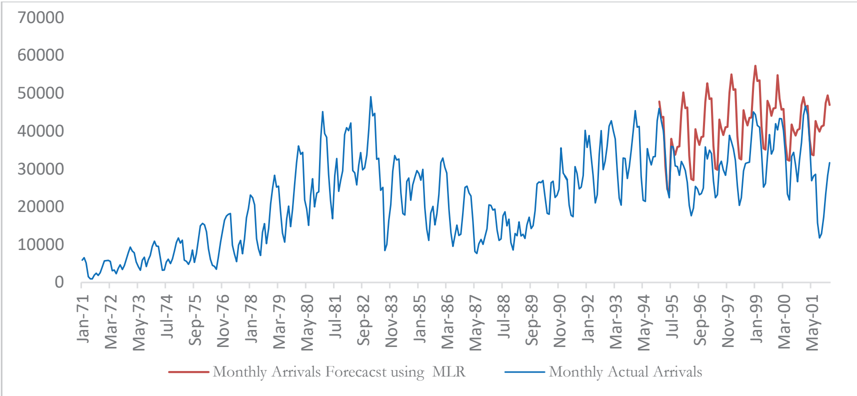



**Table 12: Estimation of potential loss in earnings from tourism in 'Period 3'**

| Year | Realised Tourist Arrivals | Potential Tourist Arrivals | Tourist average stay period | Spending per day (USD) | Realised Tourist Earnings (USD mn) | Potential Tourist Earnings (USD mn) | Estimated Loss in Potential Tourist Earnings (USD mn) |
|---|---|---|---|---|---|---|---|
| 1995 | 407,511 | 439,087 | 10.0 | 36.9 | 148.6 | 156.1 | 7.5 |
| 1996 | 403,101 | 470,172 | 9.8 | 40.2 | 119.1 | 172.8 | 53.7 |
| 1997 | 302,265 | 500,769 | 10.1 | 43.4 | 160.4 | 198.2 | 37.8 |
| 1998 | 381,063 | 530,929 | 10.4 | 42.9 | 169.9 | 207.9 | 38.0 |
| 1999 | 396,115 | 561,576 | 10.3 | 49.3 | 201.0 | 220.5 | 19.5 |
| 2000 | 400,414 | 490,048 | 10.1 | 47.4 | 191.9 | 234.9 | 43.0 |
| 2001 | 336,594 | 501,291 | 10.4 | 47.3 | 165.7 | 246.8 | 81.1 |
| **Total** | **2,626,043** | **3,250,747** | | | **1,157** | **1,437** | **280.5** |

The realised tourist arrivals during the period of 1995 to 1999 was around 1.889 million. However, the model estimates that there was the potential of over 2.3 million tourist arrivals during this period. Hence, it can be estimated that the potential loss of tourist arrivals is around 16% based on the estimated potential. Further, the loss in nominal value terms was estimated to be around USD 289.3 million.

### 4.4. Period 4 – Evaluation of the Impact of the third Eelam War on Tourist Arrivals

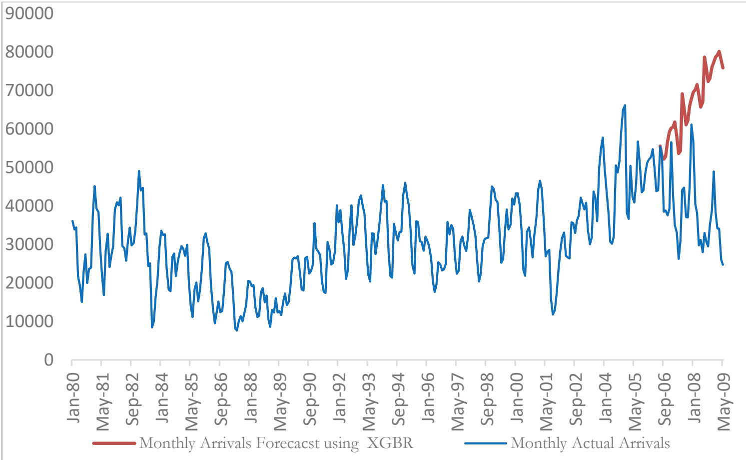
The performance of selected ML models for 'Period 4' is given in Table 13. The XGBR model performance was far higher when comparing the performance of each modelling approach in the above case. Hence, the XGBR model was used to evaluate the performance of the model.

**Table 13: Performance of each ML model for actual data in 'Period 4'**

| Model | R-Square | MAE | RMSE |
|---|---|---|---|
| MLR | 0.821 | 4496.4 | 5896.7 |
| SVR | 0.511 | 4961.1 | 6969.8 |
| KNN | 0.782 | 5142.0 | 6908.2 |
| GBR | 0.813 | 4611.4 | 6022.0 |
| XGBR | 0.914 | 2880.4 | 4081.5 |

It was observed that the XGBR model in this case gave much more better results in terms of forecasting, despite the model not showing significant prominence to seasonal fluctuations. It can be also observed visually that the seasonal. Based on the results in Section 3.3, fluctuations predicted by the model is less prominent in the XGBR model but shows a clear increasing trendline.

**Figure 9: Monthly tourist arrivals forecast using a MLR model (May 1990 – Dec 1994)**




Estimated potential loss in tourism during 'Period 4' is given in Table 14.

**Table 14: Estimation of potential loss in earnings from tourism in 'Period 4'**

| Year | Tourist average stay period | Spending per day (USD) | Realised Tourist Arrivals | Realised Tourist Earnings (USD mn) | Potential Tourist Arrivals | Potential Tourist Earnings (USD mn) | Estimated Loss in Potential Tourist Earnings (USD mn) |
|---|---|---|---|---|---|---|---|
| 2006 | 10.4 | 70.5 | 559,603 | 410.3 | 638,647 | 468.3 | 58.0 |
| 2007 | 10 | 77.8 | 494,008 | 384.4 | 739,970 | 575.8 | 191.4 |
| 2008 | 9.5 | 76.7 | 438,475 | 319.5 | 865,961 | 631.0 | 311.5 |
| 2009 | 9.1 | 85.7 | 447,890 | 349.3 | 972,728 | 758.6 | 409.3 |
| **Total** | | | **1,939,976** | **1,463.5** | **3,217,306** | **2,433.6** | **970.1** |

The realised tourist arrivals during the period of 2006 to 2009 was around 1.463 million. However, the model estimates that there was the potential of over 3.2 million tourist arrivals during this period. Consequently, the potential loss of tourist arrivals is around 40% compared to the estimated potential. The loss in nominal value term was estimated to be around USD 970 million during 'Period 4'.

### 4.5. Period 5 – Evaluation of the Impact of Easter Sunday Attacks, COVID-19 Pandemic and Financial Crisis on Tourist Arrivals

Performance of the ML models during 'Period 5' is given in Table 15. It can be observed that both the MLR model and the XGBR model performance are much better than the other models considered.

**Table 15: Performance of each ML model for actual data in 'Period 5'**

| Model | R-Square | MAE | RMSE |
|---|---|---|---|
| MLR | 0.821 | 4496.4 | 5896.7 |
| SVR | 0.511 | 4961.1 | 6969.8 |
| KNN | 0.782 | 5142.0 | 6908.2 |
| GBR | 0.813 | 4611.4 | 6022.0 |
| XGBR | 0.914 | 2880.4 | 4081.5 |

Hence, given the experience that the MLR models seem to give more rational forecasts, particularly in forecasting the seasonal patterns in tourist arrivals, the MLR model was used to forecast the performance for 'Period 5', based on average tourist stay period of 10 days, not considering the increase in tourist stay period due to quarantine requirements in 2020.

**Figure 10: Monthly tourist arrivals forecast using a MLR model (Apr 2019 – Dec 2022)**

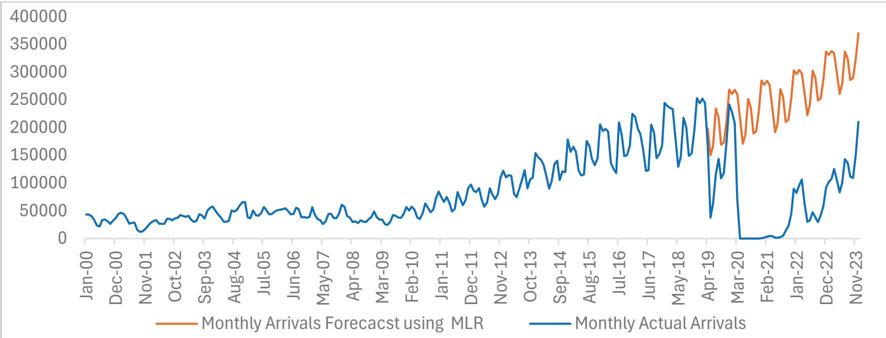



**Table 16: Estimation of potential loss in earnings from tourism in 'Period 5'**

| Year | Realised Tourist Arrivals | Potential Tourist Arrivals | Tourist average stay period | Spending per day (USD) | Realised Tourist Earnings (USD mn) | Potential Tourist Earnings (USD mn) | Estimated Loss in Potential Tourist Earnings (USD mn) |
|---|---|---|---|---|---|---|---|
| 2019 | 1,913,702 | 2,533,892 | 10.4 | 181.2 | 3607 | 4,776 | 1169 |
| 2020 | 507,704 | 2,752,077 | 8.5 | 158.1 | 682 | 3,699 | 3,017 |
| 2021 | 194,495 | 2,977,950 | 15.1 | 172.6 | 507 | 4,369* | 3,862 |
| 2022 | 719,978 | 3,342,980 | 9.3 | 169.0 | 1136 | 5,276 | 4,140 |
| 2023 | 1,487,303 | 3,773,360 | 8.4 | 164.7 | 2068 | 5,247 | 3,179 |
| **Total** | **4,823,182** | **15,380,259** | | | **8,001** | **23,366** | **15,366** |

While it was obvious that the three catastrophic events had a detrimental effect on country's tourist arrivals, this is the first study known to the other to quantify the potential loss in nominal terms due to these episodes. Accordingly, it is estimated that there is a potential loss of over 10 million tourist arrivals due to Easter Sunday attacks, the COVID-19 pandemic and the financial crisis from 2019 to 2023. The potential loss in nominal earnings from tourism are estimated to be over USD 15 bn. This is a staggering loss that was one of the key reasons to, among others, to the Balance of Payments crisis that occurred starting from early 2022. The potential loss in earnings from tourism is around 68% of the estimated potential tourist earnings if there was no shock to the tourism industry during the period.

### 4.6. Summary of the Impact of Domestic and External Shocks on Tourist Arrivals in Sri Lanka in the Past Five Decades

The summary of the loss potential to Sri Lanka's tourism due to domestic and external shocks studied is given in Table 17.

**Table 17: Summary of potential loss of earnings from tourism due to domestic and external shocks in Sri Lanka (1970 -2024)**

| Episode | Period | Realised Tourist Arrivals | Realised Tourist Earnings (USD mn) | Potential Tourist Arrivals (in millions) | Potential Tourist Earnings Estimate (USD mn) | Estimated Loss in Potential Tourist Earnings (USD mn) | Estimated loss as % of Potential Tourist Earnings |
|---|---|---|---|---|---|---|---|
| 1983 July riots, JVP uprising and Eelam War1 | 1983-1989 | 1,692,870 | 630 | 5,127,165 | 1,991 | 1,361 | 68.4% |
| Easter Sunday, COVID -19 and Financial Crisis | 2019-2023 | 4,823,182 | 8,001 | 15,380,259 | 23,366 | 15,366 | 65.8% |
| Eelam War 4 | 2006-2009 | 1,939,976 | 1,464 | 3,217,306 | 2,434 | 970 | 39.9% |
| Eelam War 3 | 1995-1999 | 1,189,035 | 799 | 2,259,408 | 1,088 | 289 | 26.6% |

As summarised above, in four of the five periods considered in the study, earnings from tourism were significantly affected by external and domestic shocks. Based on the above analysis, the Easter Sunday attacks, COVID-19 and the subsequent financial crisis resulted in the highest estimated potential loss in earnings from tourism of around USD 15 billion from 2019 to 2023. This loss was a major blow to the country's Balance of Payments (BOP) and alongside a significant loss in Workers' Remittances during the same period contributed to a severe BOP crisis, partially contributing to the country's external debt default.

Furthermore, considering the estimated loss as a percentage of total potential, it can be observed that the 1980s episodes and the latest episode beginning from 2019, had the most profound impact that was above 65% loss to the country.

## 5. Contributions and Policy Implications

This study quantitatively establishes the detrimental impact that adverse safety conditions have on Sri Lanka's tourism industry. It offers several unique contributions to the existing literature on tourism demand in the country. To the author's knowledge, this is the first comprehensive study to quantify the loss in tourism earnings in Sri Lanka due to various episodes of external and domestic shocks. It is also among the few tourism demand studies that incorporate macroeconomic variables, such as the exchange rate and inflation, into predictive forecasting models for tourist arrivals. Furthermore, it is one of the first studies to examine tourism demand forecasting in Sri Lanka following the three consecutive shocks of the Easter Sunday attacks, the COVID-19 pandemic, and the financial crisis. The findings provide valuable insights for policymakers, emphasizing the critical importance of mitigating shocks—where possible—given their significant potential to disrupt the broader economy, which remains heavily reliant on tourism.

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