Modelling the Impact of Extreme Events in Forecasting Tourism Demand

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EXTENDED ABSTRACT

Since the turn of this century, the international tourism industry has been affected by numerous unanticipated political, economic and environmental events. Most notably, these include the attacks in New York City on September 11, 2001, Bali Bombings, the Second Gulf War, the 2004 Indian Ocean tsunami, shocks to oil price, among many others. Against this back drop, the worldwide tourism industry has been growing. This is a very promising forecast for the industry and should be taken seriously. This paper focuses on tourism destination countries, which give strong emphasis to the sustainability of their tourism industries, particularly the Maldives. Shareef (2004) classifies such countries as Small Island Tourism Economies (SITEs).

The main attributes of these economies are as follows. SITEs are sovereign island economies, surrounded by the tranquil ocean with white, unspoilt sandy beaches, where tourists travel by air and sea. These economies overwhelmingly depend on earnings from international tourism for foreign exchange to engage in international trade, expanding civilian infrastructure for sustainable development, improvement in healthcare and advancement of educational facilities and many others.

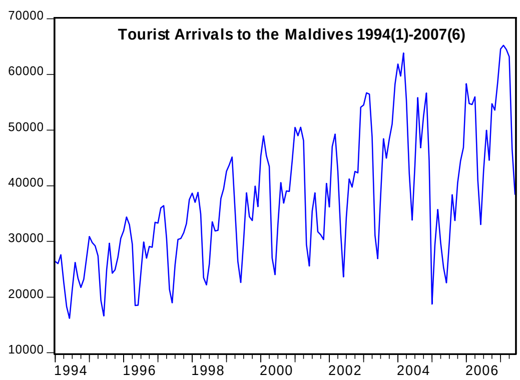

Figure 1: International Tourist Arrivals to the Maldives 1994(1) to 2007(6)

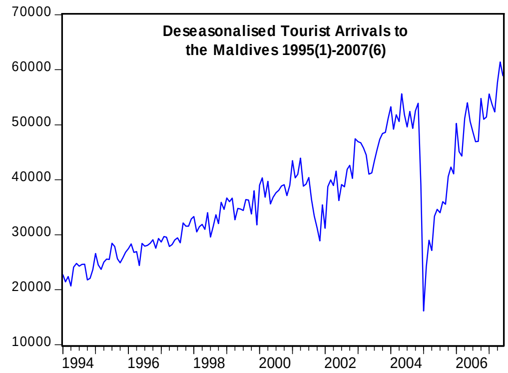

Figure 2: De-seasonalized International Tourist Arrivals to the Maldives 1994(1) to 2007(6)

As can be seen in Figure 1, since 1994 international tourist arrivals to the Maldives has been growing rapidly with a strong linear trend. Tourist arrivals are highly seasonal with the peak tourist season being the European winter months from December to March. Furthermore, the deseasonalized monthly tourist arrivals given in Figure 2 displays the adverse impact of the events on 11 September 2001 in New York City and the Indian Ocean Tsunami in 2004.

This paper addresses impact of the December 2004 Indian Ocean tsunami on international tourism demand and its macroeconomic policy implications for the Maldives. An assessment of the economic impact of the tsunami on inbound international tourism demand is particularly important to the Maldives due to 2 main reasons.

First, the large proportion of the Maldivian economy is dependent on international tourism and any adverse shock to the Maldivian tourism industry would affect the economy as a whole. Second, of all the countries in the Indian Ocean region that were affected by the by the tsunami, Maldives was the only country that was entirely hit by this devastating environmental calamity affecting the whole population and civilian infrastructure.

1. INTRODUCTION

Since the turn of this century, the international tourism industry has been affected by numerous unanticipated political, economic and environmental events. Most notably, these include the attacks in New York City on September 11, 2001, Bali Bombings, the Second Gulf War, the 2004 Indian Ocean tsunami, shocks to oil price, among many others. Against this back drop, the worldwide tourism industry has been growing. The latest figures released by the World Tourism Organisation estimates that the world tourism industry is to expand by around 5% per annum for the next 10 years. This is a very promising forecast for the industry and should be taken seriously.

For numerous reasons, international tourism is of interest to all of us. Whether travelling is for leisure, social, or commercial reasons, worldwide travellers are increasing at a rapid rate. International tourism as a leisure activity has become widespread and it is classed into many different categories such as sun, sea, and sand tourism, diving, desert and wildlife safaris, Robinson Crusoe hideaways, and so forth. Prominent international airlines are investing unparalleled amounts of capital in sophisticated aircrafts to serve the ever growing international tourism industry.

This paper focuses on tourism destination countries, which give strong emphasis to the sustainability of their tourism industries, particularly the Maldives. Shareef (2004) classifies such countries as Small Island Tourism Economies (SITEs). The main attributes of these economies are as follows. SITEs are sovereign island economies, surrounded by the tranquil ocean with white, unspoilt sandy beaches, where tourists travel by air and sea. These economies overwhelmingly depend on earnings from international tourism for foreign exchange to engage in international trade, expanding civilian infrastructure for sustainable development, improvement in healthcare and advancement of educational facilities and many others. SITEs in general have a large pool of unskilled or semi-skilled labour and tourism development in such economies is ideal for creating employment.

This paper addresses impact of the December 2004 Indian Ocean tsunami on international tourism demand and its macroeconomic policy implications for the Maldives. An assessment of the economic impact of the tsunami on inbound international tourism demand is particularly important to the Maldives due to 2 main reasons. First, the large proportion of the Maldivian economy is dependent on international tourism and any adverse shock to the Maldivian tourism industry would affect the economy as a whole. Second, of all the countries in the Indian Ocean region that were affected by the by the tsunami, Maldives was the only country that was entirely hit by this devastating environmental calamity affecting the whole population and civilian infrastructure.

The empirical analysis in this paper is based on the Box and Jenkins (1976) ARIMA framework. In the remainder of the paper, in Section 2 a brief overview of tourism and SITEs are given followed by the impact of the 2004 tsunami in the Maldives in Section 3. Seasonality of tourist arrivals is discussed in Section 4. In Section 5 time series properties of the data used are analysed and a detailed exposition of the methodology used is examined in Section 6. The empirical results and forecasting evaluations of the estimated models are assessed in Sections 7 and some concluding remarks are given in Section 8.

2. TOURISM ANALYSIS AND SITEs

The focus of the tourism economics literature is on microeconomics of the international tourism industry. Some of these issues are in relation to aspects of efficient hotel management, contingent valuation of parks and heritage sites, forecasting tourist numbers for marketing and promotional purposes, among others. The emergence of the assessment of SITEs is mainly because by-and-large SITEs depend on international tourism for macroeconomic reasons. There are national-level agencies set up in most SITEs to oversee the day-to-day running of their respective tourism industries, planning and implementing tourism master plans, marketing and promoting their tourism industries at international tourism fairs.

In general tourism in SITEs is of national importance, because it affects the entire economy. There are significant linkages from other sectors of their economies to the tourism industries in SITEs. Due to this important linkage other sectors have grown along with tourism expansion. The most growth was witnessed in the transport and telecommunications sector, which has incorporated state-of-art technology in their services. Furthermore, primary sectors such as fisheries and agriculture have made significant contributions through providing the exotic culinary flavours to the guests.

Tourism provides employment for a substantial part of the population in SITEs, because the large proportion of the population constitutes semi or unskilled labour. The expansion of tourism industries in SITEs has given positive impetus to the active labour force in SITEs. Consequently, the World Development Indicators of World Bank shows favourable trends in socio-economic indicators for Maldives. The structures of the economies of SITEs are such that there are very few economic activities, with one dominant activity such as fisheries, agriculture or tourism. When one dominant activity loses its prominence, another dominant activity replaces it. Until 1988, the dominant economic activity in Maldives used to be fisheries.

Due to the narrow productive bases in SITEs, the emphasis of economic policy focus tends to be on tourism as a reliable source of foreign exchange to stimulate international trade. Expansion of tourism enhances international trade by broadening the choice of goods and services available through increasing imports. Sustainability of international tourism in SITEs is vital to maintain a steady flow of foreign exchange and therefore to gradually accumulate foreign exchange reserves. This would enable a consistent and healthy inflow of imports. However, SITEs heavily on imports induces foreign exchange velocity. Hence, foreign exchange received tends to leave the economy sooner than desirable in order to pay for imports. In that regard, management of foreign exchange reserves and tourism management have to be carefully executed in order to maintain a stable exchange rate.

In SITEs there are various levies in the form of taxes or service charges attached to provision of services in the tourism sectors and the proceeds of such levies go directly as government revenue. Therefore, tourism revenues play an important role in determining development expenditure.

3. THE IMPACT OF THE 2004 TSUNAMI TO THE MALDIVES

As the biggest ever national disaster in the history of Maldives, the 2004 Boxing Day Tsunami caused widespread damage to the infrastructure on almost all the islands. The World Bank, jointly with the Asian Development Bank (World Bank (2005)), declared that the total damage of the Tsunami disaster was USD 420 million, which is 62% of the annual GDP. In the short run, the Maldives will need approximately USD 304 million to recover fully from the disaster to the pre-tsunami state.

A major part of the damage was to housing and tourism infrastructure, with the education and fisheries sectors also severely affected. Moreover, the World Bank damage assessment highlighted that significant losses were sustained in water supply and sanitation, power, transportation and communications. Apart from tourism, the largest damage was sustained by the housing sector, with losses close to USD 65 million. Approximately, 1,700 houses were destroyed, another 3,000 were partially damaged, 15,000 inhabitants were fully displaced, and 19 of the 200 inhabited islands were declared uninhabitable.

The World Bank also stated that the tourism industry would remain a major engine of the economy, and that the recovery of this sector would be vital for Maldives to return to higher rates of economic growth, full employment and stable government revenue. In the Asian Development Bank report, similar reactions were highlighted by stating that it would be vitally important to bring tourists back in full force, as tourism is the most significant contributor to GDP. In fact, tourism is of vital importance to the Maldivian economy.

In the initial macroeconomic impact assessment undertaken by the World Bank, the focus was only on 2005. The real GDP growth rate was revised downward from 7% to 1%, consumer prices were expected to rise by 7%, the current account balance was to double to 25% of GDP, and the fiscal deficit was to increase to 11% of GDP, which is unsustainable, unless the government were to implement prudent fiscal measures.

A significant proportion of research in the literature on empirical tourism demand has been based on annual data (see Shareef (2005)), but such analyses are useful only for long-term development planning. An early attempt to improve the short-term analysis of tourism was undertaken by Shareef and McAleer (2005), who modelled the volatility (or predictable uncertainty) in monthly international tourist arrivals to the Maldives.

This paper provides an econometric analysis of the impact of the 2004 Indian Ocean Tsunami. Such an assessment is vital to for macroeconomic planning and policy in the Maldives, because forty per cent of government revenue and seventy per cent of foreign exchange comes from tourism. Furthermore, more than seventeen per cent of the total labour force is employed by the tourism industry. Moreover, tourism has other important linkages with the transport and telecommunications industries of Maldives.

4. SEASONALITY

Monthly international tourist arrivals to the Maldives show very strong seasonal patterns monthly seasonal indices are calculated using

EViews 5.1, are given in Table 1 below and the seasonal concentrations can be readily identified.

Month	Index	Month	Index
Jan.	1.16	Jul.	0.88
Feb.	1.21	Aug.	1.06
Mar.	1.23	Sep.	0.95
Apr.	1.09	Oct.	1.00
May	0.76	Nov.	1.05
Jun.	0.65	Dec.	1.14

Table 1: Seasonal Indexes

Regardless of whether the monthly seasonal indices are calculated based on levels or on a transformed series such as logarithms, they are qualitatively similar. Seasons in tourism are determined in months and the allocated index for a given month is always 1. If the calculated index exceeds 1, then the monthly tourist arrivals exceed the trend and cyclical components due to underlying seasonal factors. During 1994-2007, the peak month for international tourist arrivals has been March, whereas the lowest month in is June. Given that nearly 80 per cent of tourists to the Maldives are from Western Europe the above indexes are perfectly plausible.

5. TESTING FOR UNIT ROOTS

Figure 1 illustrates monthly international tourist arrivals to the Maldives from January 1994 to June 2007 and its deseasonalised counterpart in Figure 2. The graphical displays of these two series suggest that they are non-stationary.

Prior to estimating the mean of the univariate time series, it is sensible to test for unit roots in the series as there are adverse consequences for estimation and inference in the presence of unit roots. In the classical regression model, it is assumed that the variables are stationary and that the errors of the regression model are stationary, with zero mean and finite variance. In the case where the series are non-stationary, the judgment would be otherwise and leads to a spurious regression (see Granger and Newbold (1974)).

In this section, we model univariate time series data where lagged dependent variables are included to capture dynamics. If the series are non-stationary, then the variance of the data generating process will become infinitely large, so that statistical inference will be affected. In this context, we conduct the Phillips-Perron (1990) (PP) test for stationarity, with truncated lags of order 5 for series in levels, deseasonalised-levels, deseasonalised-logarithms, and log-differences.

The Phllips-Perron test involves estimating the following auxiliary regression equation.

$$\Delta y_t = \alpha y_{t-1} + x_t^{'}\delta + \varepsilon_t \qquad (1)$$

where $\alpha = \rho - 1$, in order to test the hull hypothesis $H_o : \alpha = 0$ against the alternative hypothesis, namely $H_1 : \alpha < 0$. The test is evaluated using a modified t-ratio of the form:

$$\hat{t}_\alpha = t_\alpha \left(\frac{\gamma_o}{f_o} \right)^{1/2} - \frac{T(f_o - \gamma_o)(se(\hat{\alpha}))}{2 f_o^{1/2} s} \qquad (2)$$

where $\hat{\alpha}$ is the estimate, t_α is the *t*-ratio of $\hat{\alpha}$, $se(\hat{\alpha})$ is the standard error of $\hat{\alpha}$, and s is the standard error of the regression. In addition, γ_o is a consistent estimate of the error variance in the above regression. The remaining f_o is an estimator of the residual spectrum at frequency zero. The above equation is also known as the non-augmented Dickey-Fuller test equation.

These tests have been conducted using several different lags, but the results were robust to such changes. The choice over implementing the PP test over the widely used augmented Dickey-Fuller (ADF) test is due mainly to the presence of GARCH errors. ADF tests incorporate techniques explicitly accommodating a serial correlation structure in the errors, but not heteroscedasticity. However, the PP test takes into account both serial correlation and heteroscedasticity using non-parametric techniques. As mentioned in Phillips and Perron (1990), the PP test has exhibited higher power compared with the ADF test on numerous occasions.

Unit Root Test	Tourist Arrivals		SA-Tourist Arrivals	
	Levels	1st-Diff.	Levels	1st-Diff.
ADF	-1.37	-4.23	-2.07	-14.31
PP	-3.71	-	-1.74	-15.41
Unit Root Test	**Log Tourist Arrivals**		**SA-Log Tourist Arrivals**	
	Levels	**1st-Diff.**	**Levels**	**1st-Diff.**
ADF	-1.63	-4.67	-2.55	-11.68
PP	-4.03	-	-2.15	-18.67

Notes: The CV for ADF and PP at 5% is 2.88.
H_o: tourist arrivals have a unit root.

Table 2: Unit Root Tests

For the tourist arrivals in levels and in natural logarithms the ADF test suggests that there is a unit root and the series are I(1). However, the PP Test does not reject the null hypothesis indicating the monthly tourist arrivals and their natural logarithms are already stationary, does not require differencing and are I(0). With respect to the seasonally-adjusted monthly tourist arrivals both ADF and PP tests reveal that there is a unit root and requires differencing to achieve stationarity.

6. METHODOLOGY

The following time series models were considered for estimation for the empirical assessment of the impact of the 2004 tsunami on monthly international tourist arrivals in the Maldives.

a) Linear Trend

$$\hat{y}_t = \alpha + \beta t + \varepsilon_t \qquad (2)$$

where $\hat{y}_t$ is the forecast deseasonalised monthly tourist arrivals and t is a linear time index. The parameters α and β are the intercept and the slope of the trend line, respectively. The model is generally estimated through simple regression in which y_t is the dependent variable and t as the independent variable.

b) Random Walk (RW) with drift

$$\hat{y}_t = \alpha + y_{t-1} + \varepsilon_t \qquad (3)$$

where $\hat{y}_t$ is the forecast deseasonalised monthly tourist arrivals and α is the mean first difference of the first difference which is the average change from one period to the next. Therefore, the current period's value will equal to the last period's value plus a constant. This is called the 'random walk' model because the model assumes that the from one period to the next the original time series merely takes a random "step" away from its last recorded position. The term α is called drift and when $\alpha = 0$ it is just RW.

c) Geometric Random Walk

The RW model above with the constant term was capable of describing the series with irregular linear growth, but it is quite evident from Figure 2 that the monthly deseasonalised tourist arrivals series displays irregular exponential growth. Taking the first difference of the series there is evidence that the variance increase as the level of the original series increases over time confirming the existence of heteroscedasticty. Transforming the series to natural logarithms shows that there is a more linear trend as well as stabilization of the variance. The forecasting model known as the geometric random walk model is as follows:

$$\log y_t = \alpha + \log y_{t-1} + \varepsilon_t \qquad (4)$$

d) Simple Moving Average (SMA)

$$\hat{y}_t = \alpha + \frac{y_{t-k}}{k} + \varepsilon_t \qquad (5)$$

where $\hat{y}_t$ is the one-period-ahead forecast of monthly international tourist arrivals made at time $t-1$ and equals to the simple average of the last k terms. This average is "centred" at period $t-(k+1)/2$, which implies that the estimate of the local mean will tend to lag behind the true value of the of the local mean by about $(k+1)/2$ periods. Hence, we say that the average of the date in the SMA is $(k+1)/2$ relative to the period for which the forecast is computed. This is the amount of time by which forecasts will tend to lag behind turning points in the data.

e) Simple Exponential Smoothing (SES)

The SMA described above has the undesirable property that it treats the last k observations equally and completely ignores all the preceding observations. Intuitively, historical data should be discounted in a more gradual fashion and the SES model accomplishes this through a smoothing constant α and let S_t denotes the smoothed series at t and is estimated as follows:

$$S_t = \alpha y_t + (1-\alpha)S_{t-1} + \varepsilon_t \qquad (6)$$

Therefore, the current smoothed value is an interpolation between the previous smoothed value and the current observation, where α controls the closeness of the interpolated value to the most recent observations. The forecast for the next period is simply the current smoothed value:

$$\hat{y}_{t+1} = S_t \qquad (7)$$

f) Linear Exponential Smoothing (LES)

If the trend as well as the mean is varying over time, a higher order smoothing model is needed to track the varying trend. The simplest time varying trend model is the LES model which uses two different smoothed series that are centred at different points in time. The forecasting formula is based on an extrapolation of a line through the two centres. The SES model in (6) is smoothed to obtain the LES series using the same α to the S_t series and is as follows.

$$S_t^* = S_t + (1-\alpha)S_{t-1}^* + \varepsilon_t \qquad (8)$$

where S_t^* is the LES series and the forecast series is given by

$$\hat{y}_{t+1} = a_t + b_t \qquad (9)$$

where $a_t = 2S_t - S_t^*$ which is the estimated series in levels at time t and $b_t = (\alpha/(1-\alpha))(S_t - S_t^*)$ which is the estimated trend at time t.

g) ARIMA

In theory, the Autoregressive Integrated Moving Average (ARIMA) models developed by Box and Jenkins (1976) are the most general class of models in forecasting time series where stationarity can be achieved through differencing or transforming the series into logarithms. ARIMA models are fine-tuned versions of the above mentioned models from (a) to (f) and fine-tuning involves adding lags of the differenced series or lags of the forecast errors to the forecasting equations. This is done in order to eliminate any traces of autocorrelation from forecast errors. The models described above are special cases of ARIMA models. A non-seasonal ARIMA model is classified as an ARIMA (p,d,q) model where p is the number of AR terms, d is the number of non-seasonal differences, and q is the lagged forecast errors of in the prediction equation.

The ARIMA (0,1,0) is the random walk model, ARIMA (1,1,0) is the differenced first order AR model. The ARIMA (0,1,1) without the constant is the SES and ARIMA (0,1,1) with constant is SES with growth. Furthermore, ARIMA (0,2,1) or (0,2,2) without the constant is the LES. In this paper, mixed ARIMA models such as ARIMA (1,1,1) are estimated in the general-to-specific modelling approach to achieve the most parsimonious model.

$$\hat{tr} = \underset{(16.68)}{23,363} + \underset{(15.70)}{0.6\hat{tr}_{t-1}} - \underset{(-10.11)}{0.37\hat{tr}_{t-2}} - \underset{(-14.11)}{19,323D_{ts}} - \underset{(-3.74)}{2,345D_{9/11}} + \underset{(15.19)}{1.4t^2} + \underset{(9.93)}{0.71\varepsilon_{t-2}} + \underset{(7.47)}{0.51\varepsilon_{t-3}} \tag{10}$$

$$R^2 = 0.93 \qquad DW = 1.949 \qquad BG-SC-LM-Test: p-value = 0.729$$

$$\log\hat{tr} = \underset{(8.61)}{6.70} + \underset{(3.63)}{0.02}\log\hat{tr}_{t-1} + \underset{(5.13)}{0.33\log\hat{tr}_{t-2}} - \underset{(-8.56)}{0.47D_{ts}} - \underset{(-2.61)}{0.16D_{9/11}} + \underset{(8.86)}{3.29e^5t^2} + \underset{(12.5)}{0.74\varepsilon_{t-1}} \tag{11}$$

$$R^2 = 0.92 \qquad DW = 2.00 \qquad BG-SC-LM-Test: p-value = 0.073$$

$$\Delta_1 SA\_\hat{tr} = \underset{(0.242)}{129.97} - \underset{(-11.43)}{0.9\Delta_1 SA\_\hat{tr}_{t-1}} - \underset{(-3.00)}{0.23\Delta_1 SA\_\hat{tr}_{t-2}} - \underset{(-2.80)}{4,059D_{ts}} - \underset{(-16.10)}{0.79\varepsilon_{t-1}} \tag{12}$$

$$R^2 = 0.10 \qquad DW = 1.99 \qquad BG-SC-LM-Test: p-value = 0.978$$

$$\Delta_1 SA\_\log\hat{tr} = \underset{(3.27)}{8.12e^5} + \underset{(2.11)}{0.86}\Delta_1 SA\_\log\hat{tr}_{t-1} - \underset{(-2.42)}{0.000454D_{ts}} - \underset{(-2.08)}{1.18\varepsilon_{t-1}} + \underset{(-3.67)}{0.19\varepsilon_{t-3}} \tag{13}$$

$$R^2 = 0.15 \qquad DW = 1.98 \qquad BG-SC-LM-Test: p-value = 0.768$$

7. EMPIRICAL RESULTS AND FORECASTING PERFORMANCE

Using the econometric software EViews 5.1, single equation models (10) to (13) for monthly tourist arrivals—ARIMA (2,0,3), log-tourist arrivals—ARIMA (2,0,1), first difference of tourist arrivals—ARIMA (2,1,1) and first difference of log-tourist arrivals—ARIMA (1,1,3), respectively are estimated in Ordinary Least Squares (OLS). The figures given in parenthesis are the asymptotic t-ratios. For the models (10) and (11), 12 seasonal dummies were included and the insignificant ones were eliminated to achieve the most parsimonious model.

Furthermore, these models are estimated for the sample period 1 January 1994 to 30 June 2006 and validated over 1 July 2006 to 30 June 2007. The data is provided by the Ministry of Tourism of the Republic of Maldives.

Generally, as a guide to model selection, Akaike Information Criterion (AIC) and Schwarz Criterion (SC) are used and the models with the lowest AIC and SC are chosen for evaluation.

The coefficient estimates for all of the estimated models vary in sign but at conventional significance levels of 5% all of the estimated coefficients except one are significantly different from zero. The Breusch-Godfrey Serial Correlation LM Test showed that the null hypothesis of no serial correlation is upheld in the case of all the estimated models. Hence, the autoregressive and moving average processes included in the evaluation have removed any traces of serial correlation of the errors.

To identify the impact of the 11 September 2001 and the 2004 tsunami two qualitative dummy variables are introduces. They take the values 0 until the event happened and 1 after the event. These two variables are denoted by $D_{9/11}$ and D_{ts}, respectively and they are all negative indicating a temporary decline in the number of monthly tourist arrivals. There is some evidence suggesting the after effect in tourist arrivals in the month following the two events under analysis. With respect to the estimated equation in levels, there was a decline of 2,345 in October 2001 and 19,232 in January 2005. Furthermore, it took just one month for tourist arrivals to revert back to the mean trend after 11 September 2001. However, in the case of the 2004 tsunami it took almost twelve months and the current trends in 2007 are even better. This is because there has been a capacity constraint due to destruction of 21 resorts which had to be completely shut down.

The impact of 11 September 2001 is statistically significant on in 2 cases out of the 4 models estimated showing that that the impact was negligible. However, the impact of the 2004 tsunami was significant in all the 4 cases but qualitatively the most one can conclude is that the data suggests a short lived decline in tourist arrivals. Once the tourism infrastructure was restored to the pre-tsunami levels with full bed capacity Maldives' tourism has come back to its mean trend and growth levels.

Model	**Forecasting Accuracy Measure**		
	RMSE	**MAE**	**MAPE**
tr	4390.2	3162.3	8.568
log*tr*	0.1059	0.0774	0.737
Δ_1SA-*tr*	4295.7	2559.3	367.5
Δ_1SA-log*tr*	0.0152	0.0100	306.0

Table 3: Forecasting Evaluation

The models' performance in the validation period is theoretically the best indicator of their forecasting accuracy. Therefore, the estimated models are assessed against standard forecasting evaluation criteria namely, the Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE) for their forecasting performances. The forecasting evaluations of the estimated models are given in Table 3 above. Overall the log-model (11) gives the best forecasting performance across all the three criteria.

8. CONCLUSION

This paper examined the impact of extreme events such as the events of 11 September 2001 and the 2004 tsunami on monthly international tourist arrivals to the Maldives. Several time series models based on the Box-Jenkins (1976) framework were modelled and tested and the ARIMA (2,0,3) model produced the best forecasting accuracy.

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