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Article

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GENERAL & APPLIED ECONOMICS | RESEARCH ARTICLE

Forecasting international tourist arrivals in formulating tourism strategies and planning: The case of Sri Lanka

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Additional information is available at the end of the article

Abstract: In some developing countries, tourism-led growth strategy has been used to accelerate growth, generate employment opportunities and increase foreign exchange earnings. To maximise benefits from the tourism industry, appropriate policy decisions, infrastructure development and conducive business environments need to be developed. For that, accurate forecasting of international arrivals is vital. Tourism has been identified, as a driving force of post-war economic development in Sri Lanka. The main purpose of this study is to develop accurate forecasting models for total international arrivals in Sri Lanka and its top 10 source countries using SARIMA method. Monthly data from January 1984 to December 2016 were used as the training sample and data from January 2017 to December 2017 were used to evaluate the accuracy of the selected models. Results demonstrate that (a) achieving Sri Lankan Government's forecast of four million tourist arrivals by 2020 is highly unlikely, (b) accurate forecasting is necessary for tourism strategies and planning, and (c) the SARIMA method provides accurate forecasts in the presence of seasonality. Finally, the findings in this study will be useful for government agencies and private establishments in the industry in their policymaking, designing promotional campaigns, and planning infrastructure.

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PUBLIC INTEREST STATEMENT

Accurate forecasting of international tourist arrivals plays an important role in tourism planning and management as it provides the basis for appropriate policy decisions and infrastructure development. In this paper, we developed forecasting models for total international arrivals and international arrivals in Sri Lanka from 10 major source markets. Forecasts derived from the models suggest that arrivals by 2020 would be approximately 3 million, which is much lower than the government's forecast of 4 million tourists. This paper emphasises the need for a scientific approach to forecasting in order to obtain reasonably accurate predictions for future arrivals. The method suggested in this paper could also be used to forecast economic variables where seasonality is an issue.

Subjects: Tourism Management; The Business of Tourism; Tourism Planning and Policy; Economics of Tourism; The TourismIndustry

Keywords: forecasting; tourism demand; Sri Lanka; SARIMA; time series models

1. Introduction

Accurate forecasting in international tourist arrivals is essential for tourism planning and policymaking (Bangwayo-Skeete & Skeete, 2015; Chu, 2009; Hassani, Silva, Antonakakis, Filis, & Gupta, 2017; Silva, Hassani, Heravi, & Huang, 2019; Sun, Wei, Tsui, & Wang, 2019). Moreover, in particular, it is imperative for destination management (Liu, Tseng, & Tseng, 2018; Yang & Zhang, 2019), infrastructure development (Gunter & Önder, 2015; Yang & Zhang, 2019), and tourism investments. The development of policies and plans are particularly important in evaluating the scarcity of resources available to support development initiatives and the efficient allocation of these scarce resources (Jenkins, 2015). This is, in turn, of relevance when developing countries use tourism-led development strategies to facilitate inclusive economic growth, employment generation, an increase in foreign exchange earnings and poverty reduction. Some countries use tourism strategies and plans to stimulate the tourism sector by setting targets, particularly international tourist arrival targets, and developing policies to achieve those set targets. Very often the targets are set without accurate forecasting or without any forecasting of international tourist arrivals. This often leads to failure in achieving the targets because they are too ambitious (Fernando, 2016).

The main motivation of this paper is to demonstrate the role that accurate forecasting of international tourist arrivals can play in formulating tourism strategies and plans in developing countries, using Sri Lanka as a case study. We use Sri Lanka as a case study for the reason that its tourism sector suffered for close to three decades due to the ethnic conflicts and political violence which came about in the early 1980s and lasted until May 2009. Moreover, Sri Lanka currently lacks an accurate forecasting method which has resulted in a massive gap between forecasts and the actuals (Fernando, 2016). It is well documented that protracted civil wars and political violence have detrimental effects on economic growth, particularly within the tourism sector (Fernando, Bandara, Liyanaarachch, Jayathilaka, & Smith, 2013a). For this reason, developing countries emerging from protracted civil wars and conflicts very often experience post-conflict tourism booms as a result of strategies introduced to revive the long-suffered tourism sector during conflicts. Sri Lanka is no exception as tourism has become one of the fastest-growing sectors in the Sri Lankan economy. While Lonely Planet nominated Sri Lanka as the number one destination in the world to visit in 2013 and 2019, Forbes Magazine ranked Sri Lanka within "top ten coolest countries" to visit in 2015. Similarly, the New York Times nominated Sri Lanka as one of the top locations to visit (see Ministry of Tourism Development and Christian Religious Affairs [MTDCRA], 2016). Very recently GlobalData, a UK-headquartered digital media company, also listed Sri Lanka as the fourth fastest-growing tourism market in the world behind Iceland, Japan and Hungary for the period between 2017 and 2021 (The Island, 2018).

With the rising popularity of Sri Lanka as an international destination, the previous government launched the "Tourism Development Strategy 2011–2016" (TDS) by recognizing the key role that tourism could play in post-conflict development (Ministry of Economic Development, 2011). It has been followed up by the current government of Sri Lanka through the launch of the "Sri Lanka Tourism Strategic Plan 2017–2020" (TSP). This strategy seeks to position tourism as a central pillar of the economy and support the tourism vision 2025 which aims to achieve the UN's Sustainable Development Goals on tourism (MTDCRA, 2016). For these reasons, Sri Lanka provides an ideal case study to demonstrate the importance of accurate forecasting in international tourist arrivals in formulating tourism strategies and plans. The findings in this study will be useful to other countries for developing accurate forecasting models for tourism demand or any other economic variables where seasonality is an issue.

Against the above background, the main aim of this paper is to develop appropriate models to forecast both total international tourist arrivals and arrivals from the top 10 source countries to Sri Lanka. Arrivals from 10 major source markets contributed to 66.9% of the total international arrivals in 2016 (SLTDA, 2006–2017). We have three specific objectives. Firstly, we will demonstrate the importance of accurate forecasting of international tourist arrivals in countries like Sri Lanka which heavily depend on tourism to achieve their development goals. Secondly, given that Sri Lanka is constantly falling behind arrival targets, we discuss the possibility of achieving the set target of 4 million tourists by the end of 2020. Finally, strategies and policies required to minimise the gap between the targets and actual arrivals numbers are discussed.

This paper is structured into seven sections. The next section provides a brief overview of tourism in Sri Lanka by highlighting the contribution of tourism to the Sri Lankan economy. This demonstrates how Sri Lanka has formulated tourism strategies and plans without proper forecasting and emphasizes the need for accurate forecasting. Section 3 provides a brief literature review on forecasting international tourist arrivals to lay the foundation for the method and data used in this paper as described in Section 4. The results are presented in Section 5 and the detailed discussion on results and policy implications emanating from the results are presented in Section 6. The final section presents concluding remarks.

2. Nature of tourism industry and tourism planning in Sri Lanka

2.1. Overview of Sri Lankan tourism

Sri Lanka is an island in the Indian Ocean, southeast of the Indian subcontinent with a total area of 65,610 km^2 and a 1,340 km long coastline. Sri Lanka has more than 2,500 years' worth of written history, which has created many heritage sites for tourists to visit. In addition, tourists who visit Sri Lanka can enjoy a diverse range of tourism products, including pristine beaches, sports and adventure, mind and body wellness, scenic beauty of the country, wild life and nature, people and culture-related products, and many festivals throughout the year. These together offer visitors a very rich and enjoyable travel experience. Therefore, Sri Lanka has been blessed with an abundance of tourism assets ranging from "sun, sea and sand" to nature and historical heritage.

However, over several decades, since the early 1980s, tourism in Sri Lanka has suffered due to internal political conflicts and violence. Following the end of nearly three decades of brutal conflict in May 2009, Sri Lanka has witnessed an unprecedented rise in international tourist arrivals similar to the post-war tourism booms experienced by other countries in the region (e.g. Vietnam, Cambodia and Laos). International tourists are very sensitive to conflict and violence in destination countries. There is a large body of literature on recent trends in tourism (see Fernando, Bandara, & Smith, 2013b; IPS, 2017) and we do not intend to repeat the available literature. Rather, we present updated figures to highlight recent trends and patterns in relation to international tourist arrivals, the occupancy rate, employment in the tourism sector and foreign exchange earnings from tourism. As shown in Figure 1, the number of international tourist arrivals to Sri Lanka sharply increased after 2009 breaking all previous historical annual and monthly tourist arrivals records. The total number of arrivals nearly doubled within 2 years after the end of conflict and it has grown almost four times within 6 years (from 447,890 in 2009 to 855,975 in 2011 and 1,527,153 in 2014). The number of arrivals further increased in the following years, reaching 2,116,407 by the end of 2017. However, the year-on-year growth rate of arrivals is gradually declining indicating that the future arrival growth rate is likely to be lower unless the government launches an aggressive promotion campaign targeting both traditional and non-traditional markets and makes appropriate policy decisions to attract more tourists.

Until the beginning of this century, the Sri Lankan tourism sector depended primarily on traditional sources such as the UK and Germany. As can be seen from Figure 2, the UK and Germany dominated the Sri Lankan tourist market until about the year 2000 in terms of the number of arrivals. The proportion of arrivals from Western European countries was about two-thirds of the

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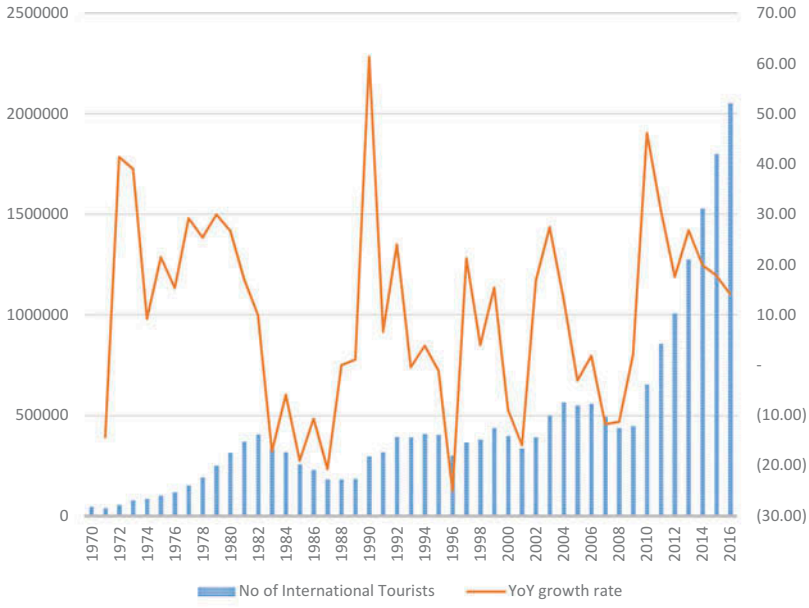

Figure 1. Annual tourist arrivals to Sri Lanka.

Source: Sri Lanka Tourism Development Authority (SLTDA) annual reports

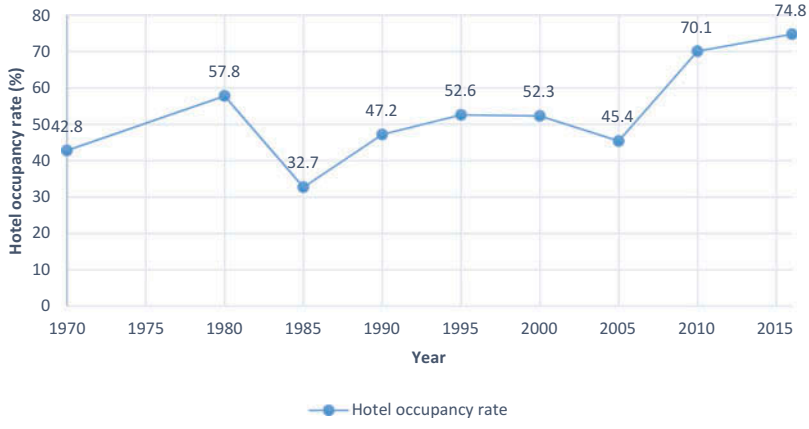

Figure 2. Hotel occupancy rate of 1970–2016.

Source: Sri Lanka Tourism Development Authority (SLTDA) annual reports

total arrivals while Asia, particularly India and China, contributed around 20 to 30% (IPS, 2017, p. 130). This trend has changed over the last 15 years and India has become the main source of tourist arrivals with arrivals from China also increasing sharply. The top 10 source countries are presented in Table 1. Rapid economic growth in both India and China, the proximity of India and its close economic relationship with Sri Lanka, and Chinese involvement in the Sri Lankan economy through its infrastructure and other development projects have been the main reasons for these changes in trends and patterns in tourist arrivals to Sri Lanka.

Although the arrival numbers from Europe, particularly from the UK and Germany, have not increased at a similar rate to that of India and China, these two traditional markets are still important in terms of guest nights. This demonstrates that traditional tourism sources are still important. Tourists from these countries tend to spend more time in Sri Lanka than tourists from India and China. The average duration of a tourist's stay in the country has been around 10 nights and this has not changed much over the last two decades or so according to data published by SLTDA.

Table 1. Top 10 source markets from 2000 to 2016

2000		2005		2010		2016	
Country	**Market Share (%)**	**Country**	**Market Share (%)**	**Country**	**Market Share (%)**	**Country**	**Market Share (%)**
UK	21.2	India	20.6	India	19.4	India	17.4
Germany	17.6	UK	16.9	UK	16.1	China	13.2
India	8.0	Germany	8.4	Maldives	7.0	UK	9.2
France	6.5	France	4.9	Germany	5.4	Germany	6.5
Netherlands	6.7	Australia	4.7	Australia	5.1	France	4.7
Italy	4.2	USA	4.6	France	4.8	Maldives	4.6
Australia	4.1	Maldives	4.5	Canada	3.2	Australia	3.6
Japan	2.6	Canada	3.9	USA	2.9	Russia	2.8
Belgium	2.6	Japan	3.1	Netherlands	2.7	USA	2.6
Pakistan	2.5	Netherlands	2.8	Japan	2.2	Japan	2.1
Total Top 10	74.8	Total Top 10	74.3	Total Top 10	68.9	Total Top 10	66.9

Source: Ceylon Tourist Board (2000–2005) and SLTDA annual reports (2006–2016)

With the post-conflict tourist boom after 2010, the hotel occupancy rate has increased sharply as shown in Figure 2. During the period of conflict, the hotel occupancy rate was low and fluctuated between 30% and 60% depending on several episodes of peace talks and breakouts of violence during the conflict period. It was below 50% during the last stage of conflict. With the rapid increase in tourist arrivals after the end of conflict, the hotel occupancy rate has increased sharply to over 70% and reached a peak level of nearly 75% in 2016 (SLTDA, 2017).

Figure 3 illustrates that the number of total employees in the tourism sector, including direct and indirect employment, has increased sharply after 2009 demonstrating the new employment activities that the tourism boom has created both directly and indirectly in tourism-related activities. Foreign exchange earnings from tourism have also increased significantly after the end of conflict which is consistent with the sharp increase in arrival numbers (see Figure 4). Tourism has become the third biggest foreign exchange earner in the country after migrant remittances and ready-made garment exports.

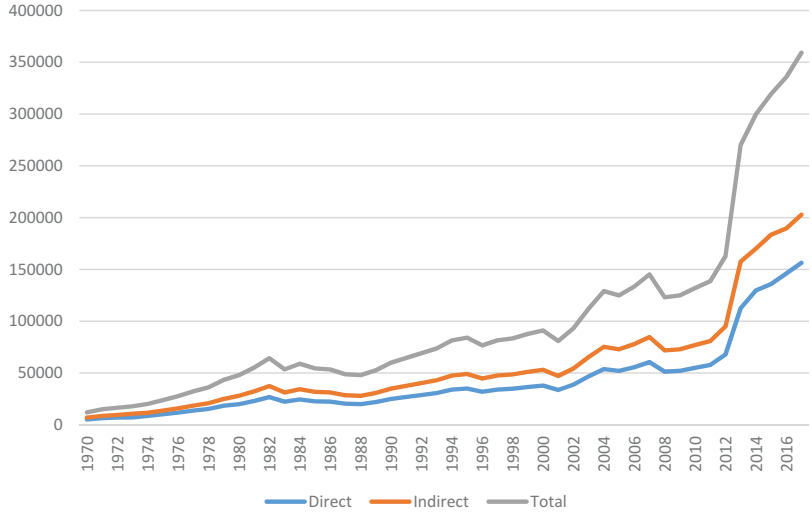

Figure 3. Tourism boom and employment generation.

Source: Sri Lanka Tourism Development Authority (SLTDA) annual reports

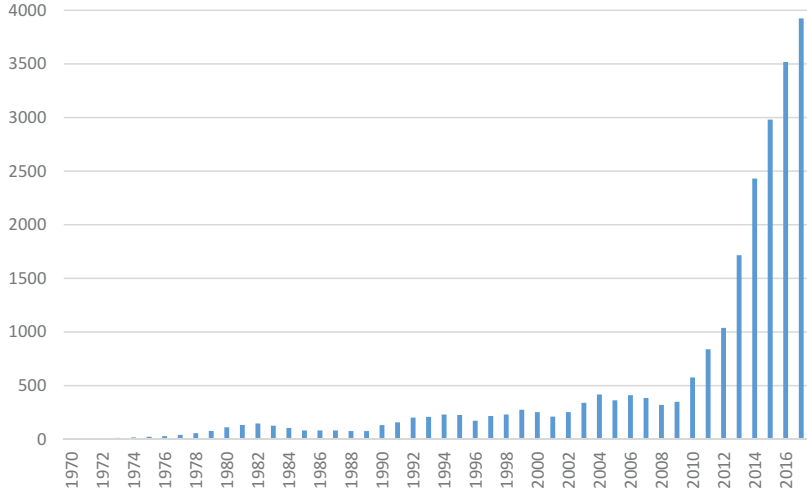

Figure 4. Foreign exchange earnings from international tourism (in USD millions).

Source: Sri Lanka Tourism Development Authority (SLTDA) annual reports

All the above facts demonstrate that the Sri Lankan economy is currently experiencing a tourism boom. This is evidenced by a record-breaking number of international tourist arrivals, foreign exchange earnings, employment generation and investment in the tourism sector. However, as the present government has correctly identified in its Tourism Strategic Plan 2017–2020 (hereafter TSP), growth in the sector "has taken place predominantly organically, without a definite vision and without coordinated planning" (MTDCRA, 2016, p. 3). The TSP further states that Sri Lanka's current tourism sector "lies along the continuum from exploration to development, depending on the destination" by using Butler's (1980) concept of tourism life-cycle. The government has identified that the tourism sector "has not fully captured its true potential and thus has not reaped the expected benefits" (MTDCRA, 2016, p. 4). That is why the current government is labelling tourism in Sri Lanka as "A Story of Untapped Potential" in its TSP (See MTDCRA, 2016 for details).

In order to estimate direct and indirect contribution of tourism in the Sri Lankan economy, the World Travel & Tourism Council (WTTC) has used an economy-wide approach to calculate the total contribution of tourism to GDP, foreign exchange earnings and total employment in an economy (both directly and indirectly). It has made a comprehensive estimation on tourism contribution to GDP and employment in its recent publications by capturing the above-mentioned direct, indirect, and induced effects by identifying relevant sectors (WTTC, 2017). While the direct contribution of the tourism and travel sector was about 5.3% of GDP in 2017 with this predicted to increase up to 5.7 by 2028, the total contribution (both direct and indirect) to GDP was about 11.6% of GDP in 2017. This is predicted to increase up to 12.3 by 2028. Similarly, in 2017, the total direct employment in the sector was around 404,000 (5.1% of total employment) and the total employment (direct and indirect) was around 875,000 (11.0% of total employment). The total employment of the economy due to an expansion in tourism is predicted to increase up to 898,000 and 1,037,000 (12.8% of total employment) by 2028. The total foreign exchange earnings from tourism, which was around US$ 4.7 billion (25.3% of total export earnings), are predicted to increase up to US$ 9.4 billion (30.2% of total export earnings) by 2028.

2.2. Recent developments in tourism strategies and planning in Sri Lanka

World Tourism Organization predicted that global international tourist arrivals will reach the 1.8 billion mark by 2030 with a 43 million increase each year until 2030. The Asia Pacific region is expected to get the most of share (UNWTO, 2011). Consequently, the prevailing peaceful environment in Sri Lanka and UNWTO forecasts on the phenomenal growth in the industry offer a great opportunity for Sri Lanka. However, there are some challenges that Sri Lanka is currently facing. First, the room occupancy rate is increasing rapidly; in 2017 it stood at 73.27% (SLTDA, 2017). This signifies the importance of improving infrastructure and capacity in the hotel and leisure sector to accommodate and facilitate the growing numbers of tourists. Second, the Sri Lankan Government expected to achieve 2.5 million international tourists by 2016 but the actual number was just over 2 million. As a result, the Sri Lankan Governments target of achieving 4.5 million tourists by 2020 was revised to 4 million. In contrast, Pacific Asia Travel Association (PATA) predicts 3.7 million tourists by 2020 with an annual growth rate of 10.4%. However, from a realistic perspective, it seems that these numbers are very ambitious given the fact none of the previous targets were achieved, and the arrivals growth rate is declining.

To make use of new opportunities created by the post-conflict tourism boom and manage the Sri Lankan tourism sector, tourism authorities need to use proper planning and analytical tools in terms of forecasting and analysing the impacts of tourism on the Sri Lankan economy. In many countries, econometrics and input-output modelling or computable general equilibrium (CGE) modelling techniques have been used for this purpose. Unfortunately, it appears that Sri Lankan tourism planners have not used such techniques in setting targets for the tourism sector or measuring the contribution of the sector to the economy in the past. This practice has given rise to some misleading projections as noted above. For example, targets for tourist arrivals in the Tourism Development Strategy (TDS) implemented during the period between 2011 and 2016 were not based on proper forecasting techniques.

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As shown in Figure 4, predictions for tourist arrivals in the TDS were based on an assumption that consolidates the preliminary and then final target exponential growth without using a proper forecasting method. According to these predictions, a 12.9% to 28.6% growth in tourist arrivals was expected in the first 4 years (2011–2014). Following this, the growth rate of tourist arrivals was expected to accelerate up to 48.1% in 2015 before stabilising at around 25% growth in 2016. As shown in Figure 5 however, although actual tourist arrivals were more than expected for the first 4 years of the strategy (from 2011 to 2014), Sri Lanka failed to achieve the target set by the TDS by the end of 2015 and 2016 (that is 2.5 million). In part, this is likely due to the fact these targets were set purely based on the assumption that the capacity of hotel accommodation would increase in 2015 and 2016. There was no consideration of the demand side of tourist arrivals and no proper forecasting techniques were used by planners in setting targets (Fernando et al., 2013b).

As mentioned above, it is clear that the government has not used forecasting techniques for setting targets in the TDS and instead relied on assumptions. However, over the last few years, there have been some attempts to use simple modelling techniques to forecast tourist arrivals and employment generation in Sri Lanka. For Embuldeniya (2016, 2017) carried out two modelling exercises to forecast tourist arrivals and employment generation for the period 2016 to 2020. In these studies, simple regression techniques were used for forecasting. In the 2016 study, it was predicted that the number of arrivals to Sri Lanka would be four million by the year 2020. However, it is unlikely this will be achieved by that time considering the actual number of arrivals in 2017 was only 2.116 million, which is considerably less than the predicted figure of 2.77 million. Embuldeniya (2017) later revised forecasting numbers in the previous study by using actual arrival figures between 2008 and 2016. According to this revised forecasting, based on the best-fit trend analysis, it is predicted that the number of arrivals will be 3.94 million by 2020. Again it is highly unlikely this will be achieved. It is clear that the simple forecasting techniques used in the above two studies need to be improved with training provided for planners in the SLTDA rather than depending on hired local and international consultants.

3. Literature review

While there is no uniformly accepted way to measure tourism demand, the four most commonly used variables are the number of tourist arrivals/departures, tourist expenditure/tourist receipts in the destination country, the number of tourist nights spent at tourist accommodation in the destination country, and the length of stay (Divisekera, 2003; Durbarry & Sinclair, 2003; Lim,

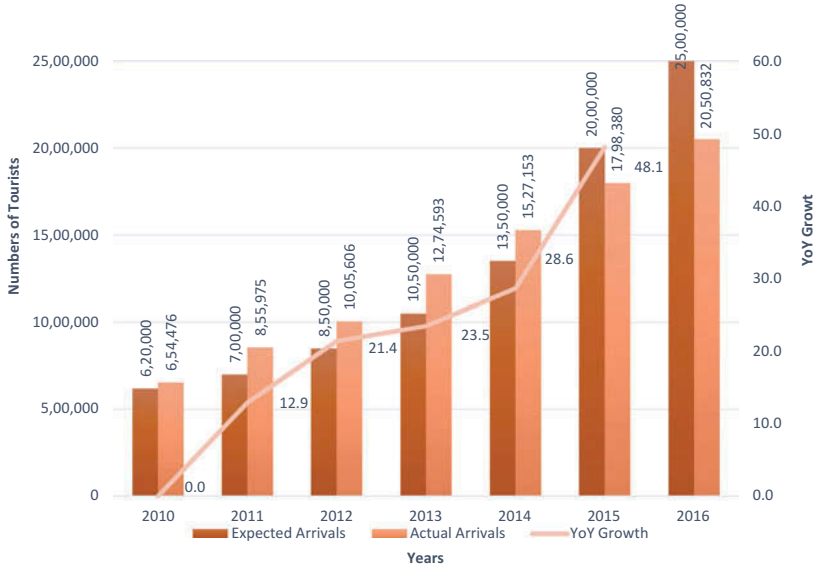

Figure 5. TDS's targets and achievements in tourist arrivals
Source: Fernando (2016).

1997; Peng, Song, Crouch, & Witt, 2015; Song & Li, 2008). The number of tourist arrivals, in particular, is a commonly used approach to measuring tourism demand as the absolute number of tourist arrivals are taken into account (Garín-Muñoz, 2007). That is, arrival data is usually available in the destination country while departure data is available in the origin country. The main advantage of tourist arrival data is that it is independent of the vacation length compared to overnight stays (Broekel & Alfken, 2015). Further, Neumayer (2004) found that the bivariate correlation between arrivals and the receipt is 0.91 indicating a very high correlation between the two. As such, forecasting international tourist arrivals to a destination country is particularly useful in tourism planning and making policy decisions.

Forecasting tourism demand has been a popular topic among tourism researchers given the constant growth of world tourism, availability of more advanced techniques, and the need for more accurate forecasts of tourism demand at the destination countries (Claveria & Torra, 2014). Moreover, the method used to forecast tourism demand can be categorised into three themes, namely, causal econometric models, time series models (Coshall & Charlesworth, 2010) and artificial intelligence-based methods (Yao et al., 2018). Error correction models (ECM), time-varying parameter (TVP) models, vector autoregressive (VAR) models, and linear almost ideal system (LAIDS) models are the most popular causal econometric methods used in modelling tourism demand (Claveria & Torra, 2014; Han, Durbarry, & Sinclair, 2006) while autoregressive moving average (ARIMA) models (Claveria & Torra, 2014; Gounopoulos, Petmezas, & Santamaria, 2012), and exponential smoothing (ES) models have gained popularity over other methods such as self-exciting threshold autoregressions (SETAR) and Markov-switching regime models (Claveria & Torra, 2014). In addition to these time series techniques, special temporal forecasting (Yang & Zhang, 2019), autoregressive mixed-data sampling (Bangwayo-Skeete & Skeete, 2015), structural time series modelling (Greenidge, 2001), and seasonal ARIMA models (Baldigara & Mamula, 2015; Ma, Liu, Li, & Chen, 2016) and ARAR (Chu, 2008) algorithm have also been used in developing forecasting models for tourism demand. Artificial intelligence-based models are also becoming popular among tourism researchers and various expressions of these methods have been tested and utilised for forecasting tourism demand including the automated neural network autoregressive algorithm (NNAR) (Silva et al., 2019), artificial neural network (Claveria & Torra, 2014; Yao et al., 2018) and evolutionary fuzzy system (Hadavandi, Ghanbari, Shahanaghi, & Abbasian-Naghneh, 2011). Moreover, NNAR method is not suitable for highly seasonal data (Silva et al., 2019) which is one of the critical factors in tourism demand for many countries (Greenidge, 2001; Pham, Driml, & Walters, 2018; Song & Li, 2008; Yao et al., 2018).

In addition to the above methods, machine learning techniques are also gaining popularity in the recent literature (Sun et al., 2019). In light of this however, previous studies suggest that seasonal ARIMA models, which are an extension to traditional ARIMA methods, perform relatively well in forecasting international tourism demand (Baldigara & Mamula, 2015). Moreover, SARIMA models outperform ARIMA models (Yao et al., 2018), SETAR and Artificial neural network models (Claveria & Torra, 2014), and multivariate methods (Greenidge, 2001). Seasonal ARIMA models take seasonality, which is a very common feature in the tourism data, into account. Therefore, such models fit tourism data well and are proven reliable in tourism forecasting contexts (Chu, 2008). However, there is no single method identified in the literature which constantly outperforms all other methods (Hassani et al., 2017). Therefore, it is imperative to identify the most suitable method for tourism demand forecasting given the nature of data at hand.

As mentioned in the previous section there are no serious attempts in forecasting tourist arrivals in Sri Lanka with the exception of Embuldeniya (2016, 2017) and Kodippili and Senaratne (2017). Embuldeniya (2016) forecasts total tourist arrivals from 2016 to 2020 using the "polynomial trend with best fit" method and forecasted 4 million tourists by 2020. However, later this was revised to 3.94 million (Embuldeniya, 2016). Further based on these predictions, the expected arrival of tourists by 2017 was 2.77 million but the actual number was just over 2.1 million. This indicates a substantial gap between the forecast and actual figures. Kodippili and Senaratne (2017), in

comparison, provided monthly forecasts from April 2017 to March 2018. However, as the accuracy of their SARIMA model has not been evaluated, it is hard to ascertain whether the model is appropriate. Moreover, none of these studies attempted to forecast arrivals at the disaggregate level. Therefore, in the next section, we use a larger sample and a better approach in an attempt to develop a more accurate tourism forecasting model for Sri Lanka at the disaggregate level. This is an uncommon strategy, but it is important for policy purposes (Chu, 2008; Hadavandi et al., 2011).

4. Data and methods

4.1. Descriptive statistics

In this study, data from January 1984 to December 2016 are used as the model estimation sample and the most recent data from January 2017 to December 2017 are kept aside for evaluation and validation of the forecasting model. Tables 2–5 provide the descriptive statistics for monthly tourist arrivals in levels, logarithms, the log-difference (or the growth rates), and log-12 month-seasonal difference, for total international arrivals and inbound tourist numbers from the top 10 source markets. The following section describes the nature of data in all four cases with respect to total international arrivals and arrivals from top 10 source markets.

Standard deviation of the monthly international tourist arrivals, in levels, show a higher value than the other transformation of arrivals. Logarithms of data for all the series also look better than their counterparts in levels but standard deviation is lower compared to that of levels. When the series are transformed into log-difference or the growth rates and log 12-month seasonal difference, standard deviation is lower for the series compared to their counterparts in levels and logs. For data series to be normally distributed, the kurtosis needs to be close to three. In levels, the data series exhibits a higher kurtosis. In addition, considerable positive skewness is evident in all series. Jarque-Berra (JB) test statistics reveal that the null hypothesis (i.e. the series is normally distributed) is rejected for all series at the 5% significance level at levels. Logarithm series of India, France, Russia, Japan, the log-difference series of total arrivals in Australia, USA, Japan, and the 12-monthly seasonally differenced logarithm series of USA all seem to be normally distributed at 5% level. Moreover, Figures 6–9 show the arrival data at level, logarithm, log-difference and 12-month seasonal difference over the time and visually show which transformation of data looks better. The above descriptive statistics and Figures 6–9 suggest that log-differenced series and the 12-month seasonally differenced series look better than their counterparts in levels and logarithm as those two transformations of data reduce the standard deviation substantially and visually show that these two transformations of data look stationary. However, we need to further examine the unit roots of these before making the final decision about data transformation for the forecasting model.

4.2. Unit root tests

As the presence of unit root can lead to adverse consequences in both estimation and inference, it is imperative to incorporate stationary variables into the forecasting model. Stationarity of the variables at levels, logarithms, log-difference and log 12-month seasonal difference is tested using the Augmented Dickey Fuller (ADF) (Fuller, 1996) test which is used to test the null hypothesis of a unit root against the alternative hypothesis of no unit root or stationarity. The ADF test equation is as follows.

$$\Delta y_t = \propto \ + \beta t + (\rho - 1) y_{t-1} + \delta_1 \Delta y_{t-1} + \ \ldots \ + \delta_{p-1} \Delta y_{t-p-1} + \varepsilon_t \tag{1}$$

Where; $\propto$ —a constant term

βt—the coefficient of a simple time trend

ρ—parameter of interest

Δ—the first difference operator

Table 2. Descriptive statistics (Level from January 1984 to December 2016)

	TA	India	China	UK	Germany	Maldives	France	Australia	Russia	USA	Japan
Mean	47,752.2	7420.5	2108.9	6143.8	5334.3	1948.5	2804.3	1773.3	1065.3	1334.6	1579.2
Median	34,432.5	4005.5	228.0	5622.0	4859.5	736.5	2286.0	1084.5	348.0	894.0	1350.0
Maximum	224,791.0	37,945.0	32,186.0	23,948.0	16,264.0	16,275.0	14,602.0	14,023.0	10,700.0	8220.0	5233.0
Minimum	7650.0	352.0	12.0	740.0	966.0	124.0	216.0	162.0	8.0	186.0	342.0
Std. Dev.	39,432.8	7394.7	5265.5	4136.0	2787.0	2472.7	2126.7	1880.7	1855.5	1131.7	879.0
Skewness	2.1	1.7	3.5	1.1	0.9	2.5	2.1	2.7	2.9	2.3	1.5
Kurtosis	7.4	5.7	15.1	4.7	3.6	10.6	8.7	12.8	11.8	9.8	5.7
Jarque-Bera	616.1	312.1	3199.5	130.1	55.6	1359.1	818.4	2055.1	1837.8	1109.6	271.2
Probability	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Observations	396	396	396	396	396	396	396	396	396	396	396

Table 3. Descriptive statistics (Logarithm from January 1984 to December 2016)

	TA	India	China	UK	Germany	Maldives	France	Australia	Russia	USA	Japan
Mean	10.5	8.5	6.0	8.5	8.4	7.0	7.7	7.1	6.0	6.9	7.2
Median	10.4	8.3	5.4	8.6	8.5	6.6	7.7	7.0	5.9	6.8	7.2
Maximum	12.3	10.5	10.4	10.1	9.7	9.7	9.6	9.5	9.3	9.0	8.6
Minimum	8.9	5.9	2.5	6.6	6.9	4.8	5.4	5.1	2.1	5.2	5.8
Std. Dev.	0.7	1.0	1.6	0.8	0.6	1.1	0.7	0.9	1.3	0.7	0.5
Skewness	0.5	0.0	0.9	−0.4	−0.4	0.5	−0.2	0.2	0.3	0.5	0.1
Kurtosis	3.2	2.4	3.2	2.4	2.7	2.3	3.1	2.5	3.0	2.7	2.8
Jarque-Bera	17.6	5.4	54.1	19.1	10.7	26.9	2.0	7.3	5.7	15.0	1.3
Probability	0.0	0.1	0.0	0.0	0.0	0.0	0.4	0.0	0.1	0.0	0.5
Observations	396	396	396	396	396	396	396	396	396	396	396

Table 4. Descriptive statistics (Log-difference from January 1984 to December 2016)

	TA	India	China	UK	Germany	Maldives	France	Australia	Russia	USA	Japan
Mean	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Median	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Maximum	0.6	1.0	2.9	1.1	0.8	1.1	1.8	1.2	2.4	0.8	0.9
Minimum	−0.7	−1.0	−1.5	−0.9	−1.5	−1.6	−1.3	−1.4	−3.4	−0.9	−0.8
Std. Dev.	0.2	0.2	0.5	0.3	0.3	0.4	0.5	0.4	0.6	0.3	0.3
Skewness	0.1	−0.5	0.9	0.2	−0.5	−0.2	0.4	0.1	−0.3	0.2	0.1
Kurtosis	3.2	6.2	7.9	3.7	4.8	4.0	3.3	3.3	6.0	2.9	2.8
Jarque-Bera	2.1	184.4	445.1	10.6	71.7	18.4	11.9	3.2	152.4	3.0	0.8
Probability	0.3	0.0	0.0	0.0	0.0	0.0	0.0	0.2	0.0	0.2	0.7
Observations	395	395	395	395	395	395	395	395	395	395	395

Table 5. Descriptive statistics (12-month seasonal difference from January 1984 to December 2016)

	TA	India	China	UK	Germany	Maldives	France	Australia	Russia	USA	Japan
Mean	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Median	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Maximum	0.7	1.3	2.6	0.9	1.4	1.6	1.7	1.1	2.5	0.8	1.0
Minimum	−0.6	−1.0	−2.9	−1.1	−1.3	−1.7	−1.5	−1.5	−3.0	−0.8	−0.7
Std. Dev.	0.2	0.3	0.6	0.2	0.3	0.3	0.3	0.3	0.6	0.3	0.3
Skewness	0.1	0.2	−0.4	0.0	0.2	−0.2	0.3	−0.3	−0.1	−0.1	0.2
Kurtosis	6.2	5.3	6.3	6.0	7.9	5.7	7.0	5.9	6.2	3.4	3.8
Jarque-Bera	161.9	82.9	183.0	147.6	382.4	117.9	265.3	135.3	167.8	2.7	11.2
Probability	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.3	0.0
Observations	383	383	383	383	383	383	383	383	383	383	383

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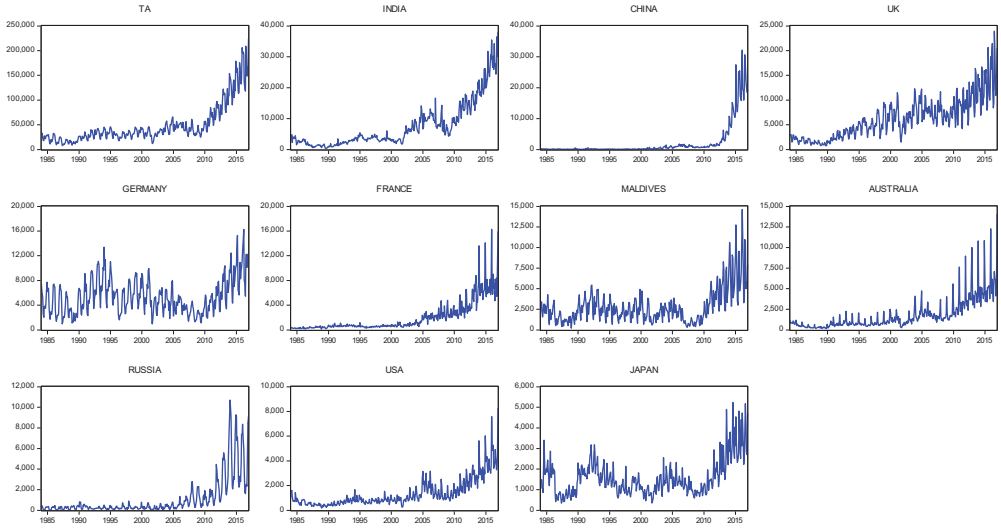

Figure 6. International tourist arrivals to Sri Lanka at level from January 1984 to December 2016.

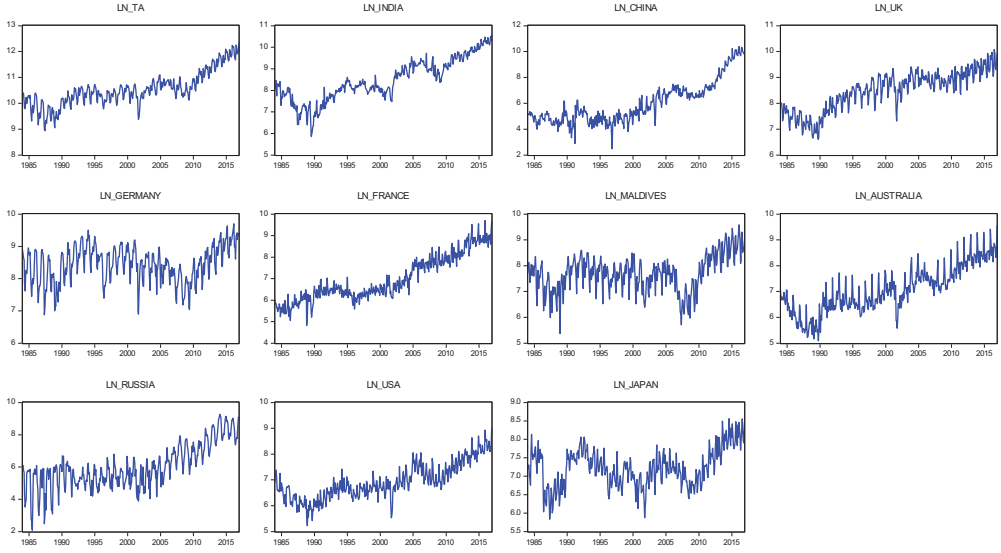

Figure 7. International tourist arrivals to Sri Lanka at logarithm from January 1984 to December 2016.

δ_i- parameters

p—the lag order of the autoregressive process

When performing these tests, a constant term and a trend were included in the test equation at level and logarithm whereas only a constant term was included in the log-differenced series and the log 12-month seasonal differenced series. Moreover, in all cases, appropriate number lag length was selected based on Schwarz Information Criterion (SIC) (Schwarz, 1978) subject to maximum of 16 lags. Unit root test results are presented in Table 6.

The null hypothesis of ADF tests is that the series is non-stationary or has a unit. Logarithm series of Australia do not have a unit root at 1%. All data series are stationary at 1% at log-difference and 12-month seasonal difference. Therefore, given the descriptive statistics and unit

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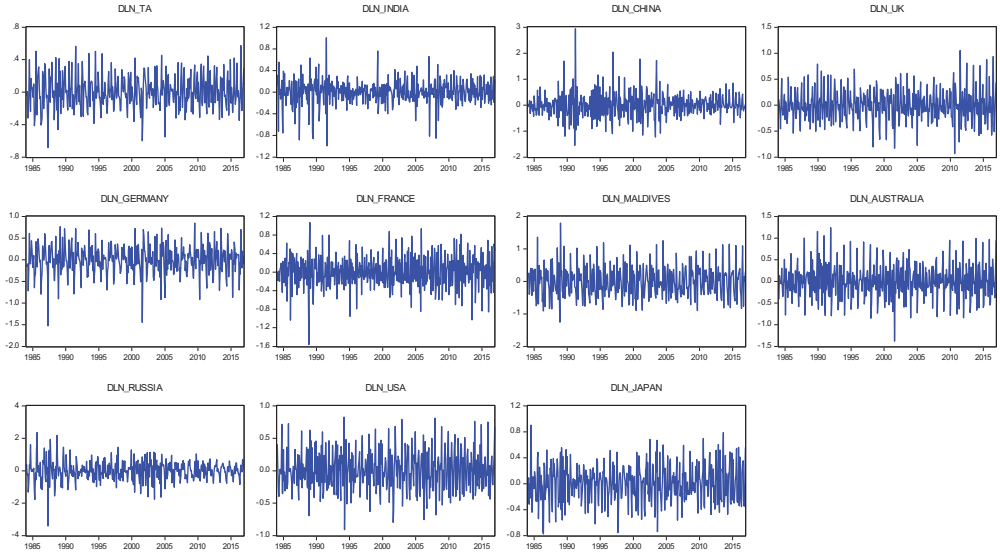

Figure 8. International tourist arrivals to Sri Lanka at log-difference from January 1984 to December 2016 December 2016.

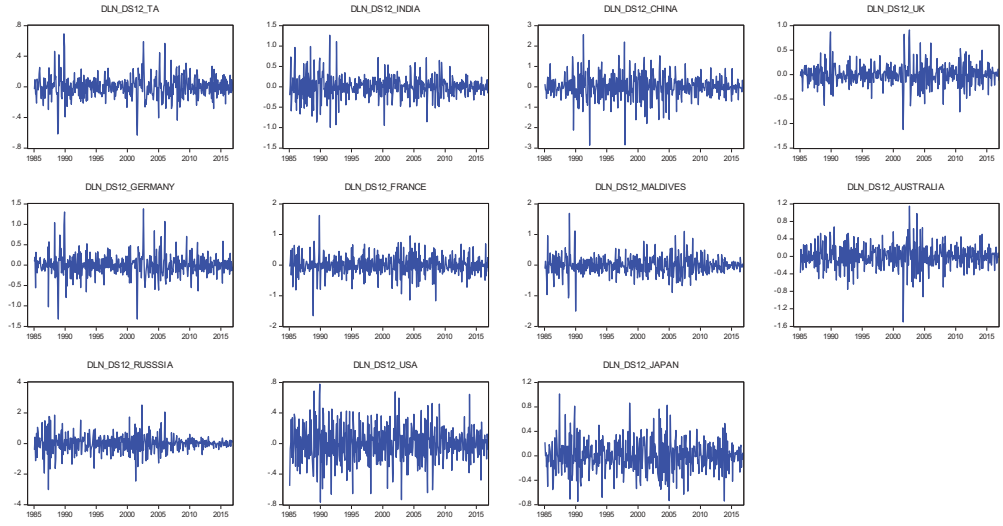

Figure 9. International tourist arrivals to Sri Lanka at 12-month seasonal difference from January 1984 to December 2016.

root test results, the most appropriate transformation methods for the series are either log-difference or 12-month seasonal difference.

4.3. Methods

In this study, we used the Box-Jenkin's seasonal autoregressive integrated moving average (SARIMA) approach to identify the best model to forecast total international tourist arrivals and inbound tourists from top 10 source markets to Sri Lanka. The Box-Jenkin's approach to SARIMA modelling involves a three-step process, namely, model identification, parameter estimation, and diagnostic checking to ensure that the selected model is adequate to forecast the selected series (Box & Jenkins, 1970). The selected model then can be used to forecast future arrivals. Previous research suggests that international tourist arrivals to a destination country exhibit seasonal patterns (Baldigara & Mamula, 2015; Chang & Liao, 2010). For this reason, when modelling international tourist arrivals, the SARIMA model has been used by many researchers as the method yields appropriate model to forecast tourist arrivals. SARIMA method can effectively

Table 6. ADF unit root test results

	Level	Logarithm	Log-diffrence	12-month seasonal difference of logarithm
Total Arrivals	1.68	−2.27	−6.14***	−8.96***
India	3.86	0.82	−15.18***	−7.47***
China	−2.12	−2.18	−13.75***	−7.41***
UK	−1.26	−2.54	−7.51***	−8.29***
Germany	−1.21	−1.88	−7.55***	−8.88***
Maldives	0.38	−1.72	−6.79***	−8.49***
France	−0.05	−2.04	−5.80***	−7.56***
Australia	−0.26	−4.13***	−5.16***	−8.64***
Russia	0.68	0.37	−8.45***	−9.32***
USA	0.13	−3.08	−7.26***	−8.44***
Japan	−1.44	−2.74	−5.17***	−8.14***

Note: ***, **, and * indicate the significance at 1%, 5% and 10%, respectively.

capture complex relationships in data series as it takes both seasonal and non-seasonal error terms and observations of lagged variables into account when training the model. Therefore, the model can produce reasonable forecasts which are in line with recent changes in the data series. The SARIMA model can be specified as follows.

$$\varphi_p(B)\phi_p(B^S)\nabla^d\,\nabla_S^D y_t = \theta_p(\mathrm{B})\Theta_Q(B^S)\tau_t \tag{2}$$

where

p and q—the non-seasonal autoregressive and moving average order, respectively,

d—the number of non-seasonal differences,

D—the number of seasonal differences,

$\varphi_p(B) = 1 - \varphi_1 B - \varphi_2 B^2 - \ldots . \varphi_p B^p$- the AR operator,

$\theta_q(B) = 1 - \theta_1 B - \theta_2 B^2 - \ldots\ldots - \theta_q B^q$—the moving average operator,

B is the backshift operator defined in a way that $B^s y_t = y_{t-s}$.

$\phi_p(B^s) = 1 - \phi_S B^S - \phi_{2S} B^{2S} - \ldots . \phi_{pS} B^{pS}$—the seasonal autoregressive operator, $\Theta_p(B^s) = 1 - \Theta_S B^S - \Theta_{2S} B^{2S} - .. \Theta_{QS} B^{QS}$—the seasonal moving average operator,

y_t has both seasonal and non-seasonal components, and is differenced d times (length one) and D times (length s),

∇^d—the non-seasonal differencing operator,

∇_s^D—the seasonal differencing operator.

The SARIMA process is described as

$$\mathrm{ARIMA}\ (\mathrm{p},\ \mathrm{d},\ \mathrm{q})\ (\mathrm{P},\ \mathrm{D},\ \mathrm{Q}) \tag{3}$$

where p, d, q is non-seasonal AR, differencing and MA order, and P,D,Q denotes the seasonal AR, differencing and MA order, respectively. In this study, we identified the preferred model specification and then parameters of the same models were estimated and diagnosed for the suitability of the models. Moreover, three competing models were identified for each case. Those three competing models were compared for adequacy using in-sample model fit and the out-of-sample forecast errors/accuracy. Based on the in-sample model fitness and the other diagnostic tests, the preferred model was selected for each data series. The forecast accuracy of the models was then evaluated to ascertain how well the selected models perform. Although there are several methods to evaluate forecast accuracy, in this study we use mean absolute error (MAE), root mean squared error (RMSE) and mean absolute percentage error (MAPE).

Assume that the forecast sample is j = T + 1, T + 2, ..., T + h and actual value and forecasted values in time t is y_t and $\hat{y}_t$ respectively. Under these conditions, the above-mentioned forecast error statistics can be calculated as follows:

$$MAE = \frac{1}{h}\sum_{t=T+1}^{T+h} |\hat{y}_t - y_t| \tag{4}$$

$$RMSE = \frac{1}{h}\sum_{t=T+1}^{T+h} (\hat{y}_t - y_t)^2 \tag{5}$$

$$MAPE = \frac{100}{h}\sum_{t-T+1}^{T+h} \left|\frac{\hat{y}_t - y_t}{y_t}\right| \tag{6}$$

5. Results

Before we estimate the parameters, it is necessary to select the appropriate orders for p, d, q, P, D, and Q in the SARIMA model. First, stationary series of the international tourist arrival is necessary to proceed. The first difference of the logarithm of arrivals and the 12-month seasonal difference of arrivals is stationary based on the Augmented Dickey Fuller test. Therefore, both these stationary series seem appropriate in the model building and the most suitable transformation was selected using the Automatic ARIMA forecasting feature of Eviews software. In order to choose the non-seasonal and seasonal autoregressive terms and moving average terms, the Autocorrelation function (ACF) and the Partial Autocorrelation Function (PACF) were used as both of these are considered useful in identifying the SARIMA model (Wei, 2006). ACF and PACF were used to select the appropriate orders for seasonal and non-seasonal AR and MA terms. The ACF and PACF for data series are not given here due to space limitation. It was evident that the seasonal lags (12, 24, and 36) are significant in both ACF and PACF leading to the conclusion that seasonal terms are required in the models. Based on these, we estimated several models subject to a number of conditions such as maximum non-seasonal differencing 2, maximum non-seasonal AR and MA terms 4, and maximum seasonal AR and MA terms 2. In order to identify the best three models for each case, we used Automatic ARIMA forecasting feature available in Eviews 10. The well-known Airline model, ARIMA(0,1,1)$(0,1,1)_{12}$ introduced by Box, Jenkins, and Reinsel (2008) was also tested but was not suitable in any of the cases to model international tourist arrivals to Sri Lanka. This led to the conclusion that a more complex model than the airline model is required. Eviews 10 software was used to aid the analysis.

5.1. Parameter estimation

The parameters of the competing models were estimated using Eviews 10 software. The maximum likelihood estimation method was used in the estimation process. Table 7 presents the parameters of the estimated models. Estimated results suggest that the coefficients of all the models are highly significant except for some. Therefore, these models are further investigated in the next stage to identify the best model for each case.

Table 7. Parameter estimates for the competing models

	Non Seasonal Terms								Seasonal Terms				
Models	**AR(1)**	**AR(2)**	**AR(3)**	**AR(4)**	**MA(1)**	**MA(2)**	**MA(3)**	**MA(4)**	**SAR(12)**	**SAR(24)**	**SMA(12)**	**SMA(24)**	**sigmasq**
Total arrivals													
ARIMA(3,1,3)(2,0,1)12	0.5567**	0.8083***	−0.632***		−0.5844**	−0.9298***	0.6359***		1.2054***	−0.2073***	−0.9276***		0.0145***
ARIMA (2,1,2)(1,0,2)12	1.4723***	−0.6193***			−1.5147***	0.5796**			0.9974***		−0.7016***	−0.2088	0.0146***
ARIMA (3,1,3)(2,1,2)12	0.8501***	0.9015***	−0.8360***		−0.9150	−0.9752	0.9398		0.6522***	−0.2951***	−1.3400***	0.4569**	0.0142
India													
ARIMA (3,1,3) (1,0,2)12	−0.6441***	−0.3488***	0.4742***		0.3406***	0.0734	−0.7682***		0.9682***		−0.7893***	0.1029**	0.0436***
ARIMA(1,1,1)(1,0,1)12	0.4632***				−0.7651***				0.9649***		−0.8805***		0.0450***
ARIMA(3,1,3) (1,1,1)12	−0.6467***	−0.3545***	0.4771***		0.3495***	0.0781	−0.7660***		0.0979*		−0.9111***		0.0445***
China													
ARIMA (3,1,4) (2,0,1)12	−0.7427***	0.2935	0.6199***		0.3094*	−0.7877***	−0.6391***	0.3422***	1.1690***	−0.1690***	−0.9994***		0.1656***
ARIMA (2,1,3) (2,0,1)12	−1.4512***	−0.7908***			0.9937***	−0.0294	−0.5566***		1.1540***	−0.1540***	−0.9993***		0.1684***
ARIMA (1,1,1) (1,0,0)12	0.3289***				−0.7831***				0.4435*		−0.2904		0.1780***
UK													
ARIMA (3,1,3) (2,0,1)12	−0.1129**	−0.4572***	0.6264***		−0.0888	0.2446	−0.9146		1.2897***	−0.2906***	−0.9574***		0.0291
ARIMA (1,1,1) (2,0,2)12	0.6729***				−0.9150***				1.6992***	−0.6999***	−1.4579***	0.4586***	0.0295***
ARIMA (3,1,3) (1,1,2)12	−0.1141**	−0.4571***	0.6365***		−0.0833	0.2534	−0.9067		0.6902***		−1.4221	0.4222	0.0282
Germany													
ARIMA (1,1,1) (1,0,2)12	0.7076***				−0.9162***				0.9963***		−0.7825***	−0.1203***	0.0469***
ARIMA (1,1,1) (1,0,1)12	0.6923***				−0.9023***				0.9940***		−0.8718***		0.0476***
ARIMA (1,1,1) (2,0,1)12	0.7067***				−0.9162***				1.1273***	−0.1302***	−0.9184***		0.0469***
France													
ARIMA (1,1,1) (1,0,2)12	0.5702***				−0.8307***				0.9973***		−0.6927***	−0.1981***	0.0591***
ARIMA (1,1,1) (1,0,1)12	0.5782***				−0.8176***				0.9957***		−0.8589***		0.0611***
ARIMA (1,1,1) (2,0,2)12	0.5781***				−0.8256***				0.5527*	−0.2634***	−1.2597***	0.3829	0.0581***

(*Continued*)

Table 7. (*Continued*)

	Non Seasonal Terms								Seasonal Terms				
Models	**AR(1)**	**AR(2)**	**AR(3)**	**AR(4)**	**MA(1)**	**MA(2)**	**MA(3)**	**MA(4)**	**SAR(12)**	**SAR(24)**	**SMA(12)**	**SMA(24)**	**sigmasq**
Total arrivals													
Maldives													
ARIMA (4,1,3) (1,0,1)12	−1.6591***	−0.2889**	0.4482***	0.0683	1.0700***	−0.7768***	−0.8557***		0.8438***		−0.4649***		0.0596***
ARIMA (2,1,2) (2,0,1)12	0.0009	0.1875			−0.6238	−0.2354			1.0761***	−0.1578	−0.6859***		0.0618***
ARIMA (1,1,1) (1,0,2)12	0.2427***				−0.8503***				1.0953***	−0.1690*	−0.7268***		0.0625***
Australia													
ARIMA (1,1,2) (2,0,2)12	0.9376***				−1.3266***	0.3307***			1.7175***	−0.7175***	−1.4633***	0.4642***	0.0409***
ARIMA (3,1,1) (2,0,1)12	0.5785***	0.2280***	0.0932*		−0.9928***				1.1612**	−0.1658***	−0.8591***		0.0425***
ARIMA (2,1,3) (2,1,2)12	1.1396***	−0.2249			−1.5587***	0.7665	−0.1954		−0.1652	0.2006***	−0.5408	−0.3343	0.0418***
Russia													
ARIMA (3,1,2) (1,0,1)12	−0.5643***	0.5760***	0.1924***		0.0367	−0.9633			0.9464***		−0.5620***		0.1801
ARIMA (2,1,1) (1,0,1)12	0.4156***	0.1628***			−0.9557***				0.9464***		−0.5827***		0.1841***
ARIMA (4,1,4) (0,1,1)12	0.1497	0.1566*	0.7990***	−0.2425***	−0.7161***	−0.1488*	−0.8469***	0.7189***			−0.5982***		0.1816***
USA													
ARIMA (4,1,3) (2,0,1)12	−0.00068	−0.6519***	0.5228***	0.1220*	−0.3914	0.5687	−0.8809		1.1752***	−0.1931***	−0.8069***		0.0356
ARIMA (2,1,1) (2,0,1)12	0.4663***	0.0915			−0.8689***				1.1541***	−0.1721***	−0.8073***		0.0367***
ARIMA (1,1,1) (2,0,1)12	0.4552***				−0.8273***				1.1597***	−0.1764***	−0.8213***		0.0369***
Japan													
ARIMA (3,1,4) (1,0,2)12	−0.4204***	0.2965***	0.9398***		0.0910	−0.4500***	−0.9038	0.2664	0.9969***		−0.7521***	−0.1566***	0.0386
ARIMA (2,1,1) (2,0,1)12	0.5093***	0.1427**			−0.8489***				1.1423***	−0.1441**	−0.9401***		0.0398***
ARIMA (1,1,1) (2,0,1)12	0.3777***				−0.6855***				1.1322***	−0.1348**	−0.9345***		0.0405***

Note: ***, **, and * indicate the significance at 1%, 5% and 10%, respectively.

5.2. Diagnostic checking

Once the models are estimated, we need to check the adequacy of the models. For this purpose, ACF and PACF were examined to see if there is any remaining autocorrelation in the models. White noise tests were also performed. Both ACF and PACF reveal that the estimated models have captured most of the autocorrelation in the series and hence the estimated models seem to be appropriate in terms of ACF and PACF. Figure 4 represents the ACF and PACF of the residuals for the competing models of total arrivals. Error terms of the estimated models were then tested for white noise using the Ljung-Box Q test. Prior to calculating the test statistics for this, the residuals ($\widehat{\varepsilon_t}$) needed to be extracted for the estimated models. Then, the following equation was used to calculate the sample autocorrelations of the residuals of the fitted models ($\hat{r}_k$) using the T residuals.

$$\hat{r}_k = \frac{\sum_{t=k+1}^{T} \hat{\varepsilon}_t \hat{\varepsilon}_{t-k}}{\sum_{t=1}^{T} \hat{\varepsilon}_t^2} \qquad ,K = 1, 2 \cdots \tag{7}$$

Using the above equation, a set of autocorrelations$\hat{r}_1$, $\hat{r}_2$, ...$\hat{r}_m$ are obtained. These were then used to test the null hypothesis of serially independent residuals against the alternative hypothesis of they are not serially independent. The test statistics were calculated using the following equation (Ljung & Box, 1978, p. 298).

$$\hat{Q}(r) = T(T+2) \sum_{k=1}^{m} (T-k)^{-1} r_k^2 \tag{8}$$

The results in Table 8 indicate that error terms of all the chosen models pass the white noise test except that of Australia and Maldives. However, selected models of both Australia and Maldives have a good in-sample model fitness and the magnitude of the q stat is small. Consequently, all of the chosen models are adequate.

5.3. Model selection

When selecting the models, Box et al. (2008) recommend starting with a multiplicative seasonal ARIMA model in modelling series with seasonal patterns. However, they further suggest exploring non-multiplicative SARIMA models in case the multiplicative SARIMA models do not fit the data well. In this study, we experimented with several multiplicative SARIMA models and the best three models, based on AIC, BIC and the significance of the parameters, were selected for further investigation. As described in the previous section, all the selected models have white noise error terms except for Australia and Maldives. The next step was to select the most appropriate forecasting model for predicting international tourist arrivals to Sri Lanka. The preferred model for each series was the first model while the second model was preferred for Germany and France. The preferred models have lowest AIC, BIC and they fit the data well based on MAE, RMSE and MAPE (Table 8). The best model is selected based on AIC and BIC but in cases where AIC and BIC suggest two different models, the simpler model is chosen. If the MAPE is less than or equal to 10%, the forecasting based on such models is highly accurate (Lewis, 1982). Moreover, if the same is between 10% and 20%, the model is accurate. Therefore, the selected SARIMA models were used to generate accurate forecasts for international tourist arrivals to Sri Lanka and results indicate that the aggregate model outperforms in all cases in terms of forecast accuracy. Of interest, the Chinese models have the lowest forecast accuracy but still provide reasonable forecasts.

5.4. Validation and forecast

In this research, we estimated univariate forecasting models using the SARIMA approach to forecast total international tourist arrivals and the arrivals from top 10 source markets in Sri Lanka. As seasonality is common in tourism data, the SARIMA approach was appropriate as it accounts for seasonality in data. Using the out-of-sample data from January 2017 to December 2017, we compared the forecasts of the models and the results in Table 9 indicate that all the models perform well except a few. The selected model to forecast total arrivals is

Table 8. Diagnostic test results for competing models

Model	Ljung and Box Test		Model Fit Comparison				
	Q-stat	p-value	AIC	SIC	MAE	RMSE	MAPE
Total Arrivals							
ARIMA(3,1,3)(2,0,1)12	39.12	0.06	−1.28	−1.18	4,154.25	6,654.09	9.02
ARIMA (2,1,2)(1,0,2)12	37.37	0.14	−1.28	−1.20	4,068.61	6,477.00	9.15
ARIMA (3,1,3)(2,1,2)12*	31.03	0.23	−1.31	−1.20	4,296.48	6,685.58	9.17
India							
ARIMA (3,1,3) (1,0,2)12	37.93	0.08	−0.23	−0.13	888.45	1,427.87	15.08
ARIMA(1,1,1)(1,0,1)12*	42.28	0.11	−0.23	−0.18	907.99	1,484.03	14.96
ARIMA(3,1,3) (1,1,1)12	40.88	0.06	−0.17	−0.08	888.66	1,380.65	15.33
China							
ARIMA (3,1,4) (2,0,1)12*	34.88	0.11	1.13	1.24	511.13	1,551.50	40.30
ARIMA (2,1,3) (2,0,1)12	46.12	0.02	1.13	1.22	349.71	1,077.02	34.25
ARIMA (1,1,1) (1,0,0)12	50.47	0.02	1.14	1.19	437.19	1,477.18	31.72
UK							
ARIMA (3,1,3) (2,0,1)12	22.49	0.71	−0.57	−0.47	792.90	1,202.22	13.09
ARIMA (1,1,1) (2,0,2)12*	26.13	0.67	−0.56	−0.49	793.56	1,209.82	13.24
ARIMA (3,1,3) (1,1,2)12	23.25	0.67	−0.59	−0.48	781.47	1,178.05	12.99
Germany							
ARIMA (1,1,1) (1,0,2)12	31.41	0.45	−0.13	−0.07	739.45	1,019.46	16.45
ARIMA (1,1,1) (1,0,1)12	37.80	0.22	−0.12	−0.07	750.81	1,030.74	16.73
ARIMA (1,1,1) (2,0,1)12*	31.64	0.44	−0.13	−0.07	739.09	1,019.25	16.43
France							
ARIMA (1,1,1) (1,0,2)12	40.73	0.11	0.11	0.17	420.33	583.79	19.07
ARIMA (1,1,1) (1,0,1)12	63.98	0.00	0.14	0.19	437.12	608.87	19.74
ARIMA (1,1,1) (2,0,2)12*	40.75	0.09	0.07	0.14	421.05	594.91	18.10
Maldives							
ARIMA (4,1,3) (1,0,1)12	54.71	0.00	0.09	0.19	347.79	710.07	19.11
ARIMA (2,1,2) (2,0,1)12	63.29	0.00	0.11	0.19	368.21	727.06	19.24
ARIMA (1,1,1) (1,0,2)12*	71.43	0.00	0.11	0.17	374.25	736.95	19.47
Australia							
ARIMA (1,1,2) (2,0,2)12	53.49	0.00	−0.22	−0.14	255.45	422.98	16.17
ARIMA (3,1,1) (2,0,1)12	51.58	0.01	−0.22	−0.14	260.92	443.24	16.17
ARIMA (2,1,3) (2,1,2)12*	50.92	0.00	−0.24	−0.14	264.01	430.66	16.12
Russia							
ARIMA (3,1,2) (1,0,1)12	38.65	0.11	1.20	1.28	211.04	434.83	33.86
ARIMA (2,1,1) (1,0,1)12*	40.66	0.12	1.21	1.27	213.19	437.11	34.66
ARIMA (4,1,4) (0,1,1)12	33.48	0.18	1.21	1.31	214.02	427.67	33.16
USA							
ARIMA (4,1,3) (2,0,1)12	33.24	0.16	−0.40	−0.28	180.51	275.11	14.69
ARIMA (2,1,1) (2,0,1)12	36.66	0.19	−0.39	−0.32	181.33	280.31	14.80
ARIMA (1,1,1) (2,0,1)12*	39.27	0.15	−0.39	−0.33	183.01	282.29	14.94
Japan							

(*Continued*)

Model	Ljung and Box Test		Model Fit Comparison				
	Q-stat	p-value	AIC	SIC	MAE	RMSE	MAPE
ARIMA (3,1,4) (1,0,2)12	20.75	0.76	−0.29	−0.18	232.26	329.53	15.82
ARIMA (2,1,1) (2,0,1)12	20.21	0.91	−0.29	−0.22	230.56	327.41	16.01
ARIMA (1,1,1) (2,0,1)12*	26.02	0.72	−0.28	−0.22	234.24	333.02	16.19

Note: * indicates the selected model.

ARIMA $(3,1,3)(2,1,2)_{12}$ which is based on both non-seasonally and seasonally differenced data. This model could be regarded as a high accuracy model as the out-of-sample MAPE is less than 10%. When it comes to disaggregate models for the top 10 source countries, selected models for India, Australia, USA and Japan are highly accurate, while other models, with the exception of Russia, are good forecasting models. Although the accuracy of the selected model of Russia is lower in comparison to the other models, it still provides reasonable forecasts. Therefore, all the selected models are appropriate in generating forecasts. Interestingly, in all cases, out-of-sample model accuracy is greater than that of the in-sample model which is a rare case in the forecasting literature. Monthly and annual forecasts generated from the selected models are shown in Table 10 and Table 11 respectively.

6. Discussion and policy implications

6.1. Findings

Our results suggest that the SARIMA model has a good fit with international arrival data. Furthermore, seasonality is evident in arrivals in all cases, as the seasonal moving average terms and seasonal autoregressive terms are significant in all the models including aggregate model and disaggregate models. Forecasting based on the aggregate model suggests that total international arrivals by 2020 will be approximately 3 million (Appendix 1) which is far less than the Sri Lankan Government's target of 4 million. Therefore, there is a gap between the forecast generated by the model and the target proposed by the policymakers. Disaggregated forecasts for the major source markets provide valuable inputs for devising tourism promotion strategies and activities in line with the government targets for the future. India and China have become the top two source markets and given our forecasts it is likely that Sri Lanka is on track to achieve the government's target of 450,000 tourists from India by 2018 (Hindustan Times, 2018). Moreover, our forecasts reveal that by 2020, tourists from India will exceed 500,000. On the other hand, China was not an important source market until the end of political violence in 2009. However, Chinese tourist arrivals have been growing since then, and by 2015, it became number two in terms of arrivals surpassing that of the UK. This is not a surprise given that China is the world's biggest source market (UNWTO, & GTERC, 2017). Our forecasts suggest that Chinese arrivals may exceed the one million mark by 2020 based on the forecasts generated by our model. Chinese arrivals to Sri Lanka are fuelled by many factors including the peaceful environment, increased economic relationship between the two nations and the aggressive promotional campaigns carried out in China by the Sri Lankan Government (Deyshappriya, 2018).

The UK has long been an important market for Sri Lanka. Although the UK was the top source market until 2008, it is now the third in terms of arrivals. Based on our forecast, arrivals from the UK may grow at a moderate rate until 2020 and will exceed the 200,000 mark by 2018 and 230,000 by 2020. Given these forecasts, it is unlikely that the government will reach their target of 500,000 arrivals from the UK by the end of 2020 (French, 2017). Like many other countries, arrivals from Germany have also been growing steadily since the end of war in 2009. We estimate that arrivals from Germany will be closer to 150,000 by the end of 2018 and 175,000 by 2020. Although

Table 9. Forecast error comparison of the competing models

Model	MAE	RMSE	MAPE	Models	MAE	RMSE	MAPE
Total Arrivals				**Maldives**			
ARIMA(3,1,3)(2,0,1)12	12090.00	15495.53	6.82	ARIMA (4,1,3) (1,0,1)12	347.79	710.07	19.11
ARIMA (2,1,2)(1,0,2)12	12246.69	15233.59	6.87	ARIMA (2,1,2) (2,0,1)12	1081.99	1306.53	17.97
ARIMA (3,1,3)(2,1,2)12*	14256.01	16865.43	8.29	ARIMA (1,1,1) (1,0,2)12*	1051.90	1302.33	17.24
India				Australia			
ARIMA (3,1,3) (1,0,2)12	2806.82	4013.05	8.05	ARIMA (1,1,2) (2,0,2)12	590.92	455.07	7.78
ARIMA(1,1,1)(1,0,1)12*	2846.33	4019.55	8.20	ARIMA (3,1,1) (2,0,1)12	449.66	583.83	7.37
ARIMA(3,1,3) (1,1,1)12	2555.77	3336.84	7.32	ARIMA (2,1,3) (2,1,2)12*	466.84	602.72	7.77
China				Russia			
ARIMA (3,1,4) (2,0,1)12*	3474.45	4061.45	15.42	ARIMA (3,1,2) (1,0,1)12	903.0248	1030.246	32.8023
ARIMA (2,1,3) (2,0,1)12	2681.93	3149.33	11.75	ARIMA (2,1,1) (1,0,1)12*	920.2785	1048.013	33.19
ARIMA (1,1,1) (1,0,0)12	3448.46	4365.86	14.74	ARIMA (4,1,4) (0,1,1)12	860.7982	949.1644	30.5114
UK				USA			
ARIMA (3,1,3) (2,0,1)12	1992.60	2345.46	13.18	ARIMA (4,1,3) (2,0,1)12	422.4013	516.2058	8.9459
ARIMA (1,1,1) (2,0,2)12*	1643.37	2033.28	10.99	ARIMA (2,1,1) (2,0,1)12	367.7331	485.5174	7.5632
ARIMA (3,1,3) (1,1,2)12	1808.02	2133.18	12.14	ARIMA (1,1,1) (2,0,1)12*	366.1226	488.5725	7.5629
Germany				Japan			
ARIMA (1,1,1) (1,0,2)12	1188.17	1399.69	12.58	ARIMA (3,1,4) (1,0,2)12	264.8818	374.1892	7.7615
ARIMA (1,1,1) (1,0,1)12	1162.47	1381.44	12.28	ARIMA (2,1,1) (2,0,1)12	210.6379	413.5766	6.7036
ARIMA (1,1,1) (2,0,1)12*	1188.78	1404.79	12.59	ARIMA (1,1,1) (2,0,1)12*	231.1057	421.004	7.1765
France							
ARIMA (1,1,1) (1,0,2)12	875.01	1124.56	11.82				
ARIMA (1,1,1) (1,0,1)12	923.60	1144.54	12.59				
ARIMA (1,1,1) (2,0,2)12*	881.79	1049.79	12.53				

Note: *Indicates the selected model.

Table 10. Monthly international tourist arrival forecasts from Jan 2018 to Dec 2020

Month	Total arrivals	India	China	UK	Germany	France	Maldives	Australia	Russia	USA	Japan
2018											
Jan	148,732	36,411	62,317	18,010	14,230	12,053	8,825	7,984	10,788	6,542	4,361
Feb	251,638	32,490	58,242	20,269	15,070	14,445	7,833	5,296	9,185	5,519	4,810
Mar	145,163	35,273	43,385	20,203	15,791	13,567	10,004	6,279	8,606	6,124	4,534
Apr	195,658	34,224	41,469	15,017	9,831	9,169	8,601	6,121	6,417	4,593	3,529
May	101,285	39,577	33,330	10,544	7,255	5,658	8,938	4,485	3,404	4,532	3,043
Jun	188,720	35,622	46,802	11,692	6,243	5,098	8,617	6,608	3,003	5,691	3,198
Jul	156,924	34,654	63,226	21,840	10,590	13,346	8,620	7,684	3,736	6,439	4,160
Aug	240,987	34,312	61,330	20,934	11,046	12,374	8,399	6,735	4,414	5,377	6,038
Sep	125,880	36,573	46,361	15,143	9,694	6,593	9,210	6,850	4,257	4,303	4,633
Oct	217,128	40,775	44,741	14,474	11,892	8,529	8,139	5,465	6,991	4,862	3,520
Nov	163,241	38,853	42,740	16,072	14,003	10,326	10,998	7,450	10,462	5,535	3,847
Dec	307,993	42,377	42,188	22,312	14,621	11,479	14,431	16,374	11,031	9,350	4,774
2019											
Jan	183,045	39,726	91,048	19,072	15,165	14,528	9,521	8,703	11,863	7,279	4,624
Feb	265,739	35,590	83,557	21,406	16,009	17,901	8,580	5,800	10,188	6,158	5,086
Mar	177,625	38,528	65,664	21,175	16,730	16,349	10,686	6,739	9,579	6,831	4,808
Apr	204,427	37,422	58,865	16,043	10,458	10,917	9,343	6,831	7,256	5,175	3,746
May	123,198	43,054	49,911	11,310	7,692	6,493	9,662	5,029	3,981	5,102	3,242
Jun	197,271	38,896	68,267	12,538	6,637	5,902	9,446	7,253	3,536	6,401	3,400
Jul	191,570	37,875	91,761	22,609	11,206	15,933	9,314	8,284	4,349	7,205	4,416
Aug	259,636	37,515	91,592	21,944	11,672	15,040	9,136	7,327	5,092	6,039	6,405
Sep	154,570	39,897	66,523	16,259	10,256	7,826	9,907	7,526	4,920	4,852	4,918
Oct	232,626	44,312	66,562	15,596	12,573	9,898	8,921	6,119	7,869	5,482	3,743

(*Continued*)

Table 10. (*Continued*)

Month	Total arrivals	India	China	UK	Germany	France	Maldives	Australia	Russia	USA	Japan
2018											
Nov	195,794	42,294	62,352	17,234	14,852	11,767	11,655	8,341	11,524	6,212	4,099
Dec	338,577	45,990	61,595	23,556	15,498	13,446	14,867	18,023	12,116	10,348	5,056
2020											
Jan	225,700	43,211	134,614	20,149	16,064	17,196	10,226	9,673	12,980	8,110	4,906
Feb	300,426	38,862	120,819	22,572	16,948	21,715	9,311	6,454	11,238	6,883	5,393
Mar	221,807	41,953	97,311	22,210	17,704	19,369	11,361	7,475	10,602	7,622	5,100
Apr	229,869	40,791	85,661	17,053	11,088	12,895	10,061	7,574	8,150	5,811	3,977
May	153,433	46,699	73,155	12,055	8,159	7,384	10,370	5,558	4,619	5,730	3,444
Jun	220,235	42,340	100,502	13,361	7,045	6,849	10,179	8,032	4,128	7,160	3,611
Jul	240,583	41,267	133,405	23,507	11,870	18,834	10,023	9,239	5,021	8,036	4,687
Aug	297,794	40,888	135,168	23,017	12,360	17,946	9,857	8,118	5,830	6,761	6,790
Sep	191,440	43,391	96,980	17,342	10,866	9,178	10,605	8,335	5,643	5,456	5,217
Oct	261,966	48,014	97,611	16,677	13,312	11,448	9,654	6,802	8,801	6,151	3,975
Nov	235,760	45,903	91,576	18,365	15,724	13,334	12,296	9,295	12,629	6,950	4,353
Dec	383,395	49,768	89,841	24,831	16,404	15,586	15,332	19,997	13,242	11,450	5,362

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Table 11. Annual forecasts 2018–2020

Country	2018	%	2019	%	2020	%
Total arrivals	2,243,349	100	2,524,077	100	2,962,408	100
India	441,139	20	481,099	19	523,087	18
China	586,133	26	857,697	34	1,256,641	42
UK	206,511	9	218,743	9	231,139	8
Germany	140,266	6	148,747	6	157,544	5
France	122,636	5	146,000	6	171,733	6
Maldives	112,614	5	121,037	5	129,275	4
Australia	87,332	4	95,973	4	106,551	4
Russia	82,292	4	92,274	4	102,883	3
USA	68,866	3	77,083	3	86,120	3
Japan	50,447	2	53,544	2	56,815	2

Sri Lanka does not carry out aggressive promotional campaigns in Germany, it is still an important market given the average duration of stay and their spending. On the other hand, French tourist arrivals are expected to surpass 120,000 in 2018 and 170,000 by 2020. Even though France records a lower average length of stay (9.9 days) compared to the UK and Germany, it is still greater than that of India and China.

Our forecasts also reveal that arrivals from Maldives may record a moderate growth reaching around 130,000 arrivals by 2020. Although Maldives is not a market that the Sri Lankan Government looks at aggressively (Rifau, 2013), these numbers suggest still it is an important market which is among the top 10. Maldivian arrivals are mainly driven by the increased connectivity between the two countries (Rifau, 2013).

Despite the fact that Sri Lanka is a long-haul destination for Australians, Australia has long been in the top 10 source markets. Australian arrivals are predicted to be around 82,000 in 2018 and 96,000 in 2020, recording a moderate growth. Starting in October 2018, Sri Lankan airlines, the national carrier of Sri Lanka, commenced daily direct flights to Melbourne. This could result in lower airfares to Sri Lanka and increased connectivity between the two nations which is likely to further boost Australian arrivals. Moreover, tour operators are offering joint Sri Lanka-Maldives tour packages leading to further increases in Australian arrivals (Samath, 2018).

Russia is a good market for Sri Lankan tourism given its large population, severe climate, and the preference of Russians towards the Asian destinations (Ceylon Digest, 2017). However, Sri Lanka is yet to capitalise on these opportunities. Based on our forecasts, Russian arrivals are likely to exceed 82,000 in 2018 and 102,000 in 2020.

Although arrivals from USA are in the top 10 list, Sri Lanka is yet to be realised as a preferable destination by Americans. Arrivals from USA are forecast to exceed 68,000 by 2018 and 86,000 by 2020. It is also important to note that the relative importance of Japan is declining over the years, although we expect a slight growth in Japanese arrivals in the future. Given historical trends, arrivals will be about 57,000 by 2020.

6.2. Policy implications

Given that the gap between the forecast and government target is nearly 1 million, there is much to do in order to achieve the target. Firstly, there should be sufficient number of flights to bring tourists into the country as majority of tourists come by air transport—in 2016 it was 98.7% (SLTDA, 2006–2017). Therefore, improving the connectivity, especially between Asia and the

Western Europe, is crucial as the majority of tourist flow is from those two regions. Secondly, carrying out targeted promotional campaigns in the major source countries, in particular, India, China, the UK, USA, Russia and Japan, could further boost arrivals. For instance, as most of India's tourists to Sri Lanka come from Delhi, Mumbai, Bengaluru and Chennai (Hindustan Times, 2018), promotional campaigns in other cities could further increase numbers as Sri Lanka is both a short-distance and affordable market for Indians. In 2017, outbound Chinese tourists were more than 145 million and so while arrivals to Sri Lanka are currently negligible, there is a huge opportunity for Sri Lanka to further increase the number of Chinese visitors. However, as Sri Lanka needs to compete with closer and cheaper markets like Thailand and Vietnam (Hindale, 2018), research-led strategies to attract more Chinese arrivals are of great importance. On the other hand, compared to the other countries in the top 10 list, the UK records the longest average duration of stay which is 14.3 days in 2016 (SLTDA, 2006–2017). When tourists stay longer, they are more likely to travel around the country. This could benefit the communities in rural areas who are dependent on tourism so for this reason effective strategies are needed to attract more British tourists. Given that Sri Lanka is offering tourism products such as diving, surfing, bird-watching, trekking, hot air ballooning, white water rafting, and eco-tourism, which appeal to American high-end travellers (Sunday Times, 2018), it is worth promoting these products in the USA to further attract more American travellers to Sri Lanka. Thirdly, it is worth investigating the slower growth in arrivals from Japan, given the higher level of purchasing power of the Japanese and the historical relationship between the two nations. This insight can then be used to inform appropriate strategies to make Sri Lanka a preferable destination for the Japanese. Finally, Sri Lanka can also look into other ways of attracting tourists such as making it easy to obtain visa and allowing visa-free entry for selected countries. This could help both in attracting more tourists and managing seasonality.

As Sri Lanka expects a huge influx of tourists in the future, there is much to do to facilitate those tourists. Firstly, there is a critical need to increase the accommodation capacity. In 2016, the occupancy rate was 74.76% (SLTDA, 2006–2017) and the total arrivals for the same year was just over 2 million. As the government seeks to more than double this number, it is clear that the existing room capacity is not sufficient to accommodate the expected number of tourists. Encouraging domestic investors and foreign investors in this regard seems as a viable solution. Secondly, attracting trained human resources employees into the industry is important as it has an impact on the service quality and ability to meet the expectation of incoming tourists. Failure to do this can have an adverse impact on the future arrivals which can then affect the competitive environment that attracts tourists. Finally, infrastructure such as airport, road system, and local flights needs to be improved to cater the increased number of tourists in the future. Sri Lanka, as a tourism country, has a huge potential as it provides a diverse range of tourism products which appeal to tourists from various source markets. However, managing this industry requires appropriate policies to ensure a sustainable tourism industry in Sri Lanka. Although improving connectivity between major source markets and Sri Lanka, and targeted promotional campaign is important to attract more tourists to Sri Lanka, changes in the attractiveness of the other destinations which are substitute and/or complementary destinations for Sri Lanka such as the Maldives and India, political stability in Sri Lanka and maintaining a peaceful environment could affect the future arrivals. Moreover, the government should take appropriate steps to identify sustainable number of tourists, as over-tourism can lead to many issues such as negatively affecting world heritage sites at risk, locals, and environmental sustainability of the destination (Seraphin, Sheeran, & Pilato, 2018).

7. Conclusions

The tourism industry has become an important contributor to the Sri Lankan economy. The Sri Lankan Government is planning to position tourism as a central pillar in the economy in its TSP as they recognise it has missed opportunities and that "tourism has been a story of untapped potential". As of current, it is planning to achieve some ambitious tasks without accurate forecasting for arrivals at the destination level and as we have demonstrated, the exponential growth of international tourist arrivals to Sri Lanka after the end of more than three-decade-old war in 2009, is rapidly increasing.

Due to this fact, the contribution of the tourism industry towards the Sri Lankan economy is continuously increasing in terms of foreign exchange earnings, employment and GDP. Moreover, the Sri Lankan Government has identified the role of the tourism industry in the post-war development strategy and indicated higher priority for the industry. As it is expected that this growth is likely to continue in the future, there is a critical need to improve infrastructure facilities, room capacity, and accommodation to facilitate the growing numbers of international visitors to Sri Lanka. Therefore, accurate forecasts are of paramount importance in this regard. Consequently, this study focused on developing an accurate forecasting model for international tourist arrivals to Sri Lanka.

The selected forecast models generally satisfied the necessary conditions and had a high accuracy in forecasting international tourist arrivals to Sri Lanka as the MAPE is lower. However, the model developed for Chinese arrivals and the forecasts generated from that model should be causally used as the accuracy is lower compared to other models. Moreover, forecasts generated from the models indicate that the government's forecast of 4 million tourist arrivals by 2020 is highly unlikely. There are several implications of this study. Firstly, the government needs to seriously think about generating accurate forecasts of arrivals using a scientific methodology when setting future targets rather than being too ambitious about the future. As discussed, Sri Lanka has constantly failed to achieve all previous targets indicating an issue in setting future targets. Secondly, in order to further boost arrivals, promotional campaigns in major source countries, and increasing connectivity, in particular, between Sri Lanka and Asia and Western Europe are recommended given the importance of those two regions. An integrated, holistic and combined effort of government institutions such as Ministry of Tourism, Sri Lanka Tourism Development Authority, Airlines, Sri Lankan diplomatic missions in source countries, and private organizations in the tourism and hospitality industry is required in this venture. Thirdly, Sri Lanka should also pay attention to developing more hotel rooms and other physical infrastructure as well as attracting trained labour into tourism sector to provide a better service for the incoming tourists. This will ensure a sustainable tourism industry given that tourist arrivals in Sri Lanka are growing at an above-average rate and the current occupancy rate is around 70%. Failing to meet service quality standards could adversely affect future arrivals.

All in all, this research contributes to the tourism demand forecasting literature by showcasing the importance of forecasting for a country which depends on tourism and provides valuable inputs for better planning and devising policies for the tourism industry. Moreover, the SARIMA method, which performs well in forecasting time series with seasonality, could be used in forecasting other economic variables where seasonality is an issue. In the future, it is worth investigating whether the accuracy of these forecasting models could be further improved with other emerging methods such as machine learning, artificial intelligence-based methods and the incorporation of big data into time series models. As tourists are heterogenous in terms of their motivation to visit a destination (Ercolano, Gaeta, & Parenti, 2018), future research may also focus on investigating the motivation of tourists as this provides valuable input for developing effective tourism policies and promotional campaigns when using findings of these studies in conjunction with forecasts.

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