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# A review of research on tourism demand forecasting: Launching the *Annals of Tourism Research* Curated Collection on tourism demand forecasting

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ABSTRACT

This study reviews 211 key papers published between 1968 and 2018, for a better understanding of how the methods of tourism demand forecasting have evolved over time. The key findings, drawn from comparisons of method-performance profiles over time, are that forecasting models have grown more diversified, that these models have been combined, and that the accuracy of forecasting has been improved. Given the complexity of determining tourism demand, there is no single method that performs well for all situations, and the evolution of forecasting methods is still ongoing.

This article also launches the *Annals of Tourism Research* Curated Collection on tourism demand forecasting, which contains past and hot off the press work on the topic and will continue to grow as new articles on the topic appear in *Annals*.

## Introduction

In general, tourism demand has shown sustained growth. This market, however, has undergone various fluctuations due to the volatility of determining factors and external interventions. Researchers, practitioners and policymakers have paid great attention to tourism growth cycles and demand undulation, as they seek to predict future flows of tourists. In most existing studies on tourism demand forecasting, the researchers' attention has been mainly concentrated on international tourist flows due to the fact that the international tourism is statistically better captured than domestic tourism, and only a handful of studies have focused on domestic travel (Athanasopoulos & Hyndman, 2008; Blunk, Clark, & McGibany, 2006), hotel room demand (Pan, Wu, & Song, 2012; Yang, Pan, & Song, 2014), or recreation site demand (Chen, Bloomfield, & Fu, 2003; Ellis & Doren, 1966). International tourism demand is measured in terms of tourist arrivals, tourism expenditure, or length of stay. These factors are generally analysed using aggregated rather than disaggregated data. These data are correlated with different types of volatility, such as the seasonality of both the origin and destination regions, the business cycles associated with exchange rates and income levels, or various externalities related to climate change or special events.

With the rapid expansion of international tourism due to social, economic, political and technological changes, tourism is spreading from developed countries to newly industrialised countries. This development may give rise to a mixture of costs and benefits, as more tourist destination countries/regions compete for the scarce resources (Lim, 2006). Therefore, accurate forecasts are critical for destinations where the decision-makers try to capitalise on developments in the tourism market and/or to balance their local ecological and social carrying capacities. In these contexts, forecasters of international tourism demand have tried to consider the overall conditions of origin markets, destinations, and even neighbouring or competing countries/regions that may affect their

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tourist flows (Fotheringham, 1983; Song, Li, & Cao, 2017). Given the importance of accurate forecasts for the dynamic and complex tourism market, over 600 studies on tourism demand modelling and forecasting have been published in the past several decades. These studies have mainly focused on model construction and performance evaluation. Some of them, however, have proposed novel hybrid models or used various combinations of methods.

Abundant empirical evidence and numerous meta-analyses and review articles have contributed to the theoretical and methodological development of tourism demand forecasting. However, a comprehensive review on the methodological development and evolution of forecasting methods has not yet been conducted. Previous reviews have captured certain periods of time, such as the 1960s to the 1990s (Crouch, 1994; Witt & Witt, 1995), 1995–2009 (Goh & Law, 2011), 2000–2007 (Song & Li, 2008) and 2007–2015 (Wu, Song & Shen, 2017). Some particular techniques such as Delphi (Lin & Song, 2015) or specific econometric models (Li, Song & Witt, 2005) have also been reviewed and assessed. Our extensive review covers a wide range of forecasting methods, from judgmental approaches to numerous kinds of quantitative methods, including time series, econometric and artificial intelligence (AI)-based models, which have been applied over the period from the 1960s to 2018.

The major goals of this study are to review the overall trends and evolution of tourism demand forecasting methods in a historical perspective, and to trace the development of four categories of forecasting methods (i.e., the time series, econometric, AI-based models, and judgmental methods) from their initial emergence in the tourism field to their current applications. To achieve the aims of this work, we propose to answer three research questions: How have tourism demand forecasting methods evolved over the past five decades (1968–2018)? What are the differences between the four categories of methodology for tourism demand forecasting, and what are the interdecadal trends of distinction or integration among those methods? Which methods have performed well, and what combinations of methods have improved forecast accuracy?

The remainder of this study is organised as follows. The second section presents the process of selecting the key studies. The third section explains the four categories of tourism demand forecasting methods, and describes the developments in each category. The fourth section traces the general trends in forecasting studies and in forecasting performance, with discussions of combination forecasts and hybrid models. The last section offers the study's conclusions, along with recommendations for future research and an assessment of the study's limitations.

## Key literature selection

To identify the overall trends and evolution of tourism demand forecasting methods, we conducted a broad-scale search of various databases including Google Scholar and Web of Science. We also searched for citations from published articles and academic books. We initially collected 679 relevant publications from 1958 to the first half of 2018, beginning with the earliest tourism demand studies by Menges (1958) in German and Guthrie (1961) in English. To deal with this large body of data in a non-cursory way, we undertook to identify a manageable pool of the most important studies. The method for selecting key studies involved three steps. First, all of the review articles, or non-tourism and non-forecasting studies, were excluded. Second, the articles were evaluated in terms of their comprehensiveness and impact. The mean and median values of annual citations for each paper were calculated. To highlight the most representative studies in each decade, we selected papers that received more citations than average for all studies published in the same decade. This selection process was done for each decade from the 1960s to the 2010s, except for the incomplete year of 2018. By this standard, we selected a pool of the 191 most influential studies. The means of total publications in each decade showed that publications in the 2000s (7.01) provided stronger support for the academic development of tourism forecasting studies than those in the 1990s (3.83). Next, 11 studies that were the first to adopt certain methods of tourism research were added to the pool of key papers, due to their pioneer status. Last but not least, we had all of the studies that had more than their decadal median number of citations, but below their decadal mean of citations (131 papers), along with all of the articles published in 2018, assessed by an expert panel comprising three academic and research staffs in the relevant fields. Nine more articles were selected to the list through this expert evaluation process, then a final pool of 211 key studies was finally determined.

The specific information on these 211 key studies is summarised in Table 1 and a full list of the initial dataset is available upon request. To obtain a more targeted focus, the remainder of this study concentrates on reviewing our selection of 211 key studies from the 1968–2018 period. However, we also informally considered the whole initial dataset of 679 publications, as we sought to gain broader insights, especially concerning judgmental methods.

Tourism demand forecasting articles are published in various discipline-focused journals, and several of these journals are primary forums for discussions in their particular fields. These journals include *Tourism Management* (66 key studies/116 in the initial dataset), *Tourism Economics* (10/87), the *Journal of Travel Research* (26/73), the *Annals of Tourism Research* (29/67) and the *International Journal of Tourism Research* (4/13). Some economics and business journals such as the *International Journal of Forecasting* (16/22) and *Applied Economics* (8/20), plus a few computer science journals such as *Expert Systems with Applications* (5/7) and *Mathematics and Computers in Simulation* (1/6) have also published relevant studies.

## Categorisation and findings

In the traditional typology of forecasting techniques, there are four main categories of methodology for tourism forecasting (Van Doorn, 1984). These categories include explorative methods (e.g., time series analysis, historical analogy, causal methods, projective scenarios and morphological analysis), speculative methods (e.g., Delphi, panel consensus, brainstorming or individual expert opinion), normative/explicative methods (e.g., subjective probabilistic forecasting, Bayesian statistics, pattern identification or prospective scenarios) and integrative methods (e.g., multimethod models, input-output analysis, dynamic systems models and cross-

**Table 1**
Summary of 211 Key Studies.

| Author (Year) | Forecasting methods | Sub-categories | Research context |
|---|---|---|---|
| *Period (211 key studies/679 initial dataset)* | | | |
| Before 1969 (2/11) | | | |
| Keintz (1968) | SR | SE | Demand modelling for international pleasure and business travel to/from the US<br>Significance of income, advertising and emigration |
| Laber (1969) | SR | SE | Finding key determinants of travel between Canada and the US |
| 1970–1979 (5/25) | | | |
| Artus (1972) | DL | DE | Determinants, price and exchange rate elasticities, and disturbance factors in foreign travel expenditure |
| Barry and O'Hagan (1972) | SR | SE | Determinants (i.e., price and income) of expenditure<br>British recreational tourist in Ireland |
| Geurts and Ibrahim (1975) | **SARIMA; A (Advanced)-ES** | BT | Compare model performance<br>Hawaii-bound tourists |
| Cesario and Knetsch (1976) | SR | SE | Recreation site demand (gravity model) and social benefit estimation model |
| English and Kernan (1976) | Delphi | J | Prediction of air travel and aircraft technology for the year 2000 |
| 1980–1989 (14/54) | | | |
| Fujii and Mak (1981) | ARX | XT | Methodological issues in time series forecasts<br>US travel demand for Hawaii |
| Fotheringham (1983) | SR | SE | Predicting spatial interaction (competing destination) from gravity model<br>US domestic airline travel |
| Fritz, Brandon, and Xander (1984) | Combined (SR, ARIMA) | CH | Compare and combine time series and econometric models<br>Forecast airline visitors to Florida |
| Kaynak and Macaulay (1984) | Delphi | J | Tourism planning for Nova Scotia<br>Future impacts of new technology on tourism and hospitality |
| O'Hagan and Harrison (1984) | AIDS | Sys | Market share of US tourist expenditure (incl. number of tourists, length of stay and daily expenditure) in 7 European countries |
| Uysal and Crompton (1984) | SR | SE | Effect of selected determinants on international tourist flows to Turkey |
| Van Doorn (1986) | Scenario | J | How to design scenario writing and what it predicts (e.g., tourism environment)<br>Define variables of tourism development (1929–2029) |
| Martin and Witt (1987) | SR | SE | Tourist price variable (living cost in destination)<br>Four origins and 8 destination (incl. the US, Canada and Europe) |
| Witt and Martin (1987) | ARX | XT | Seven explanatory variables<br>Germany and UK tourists to major destinations |
| Liu (1988) | Delphi | J | Forecast tourism to Hawaii by the year 2000 |
| Martin and Witt (1988) | SR | SE | Important role of substitute prices for both transport cost and living cost in destination<br>Market shares of major competing destinations (incl. the US and Europe) |
| Martin and Witt (1989a) | **Naïve 1**, 2; SR; A-ES; Trend; **AR** | BT, AT, SE | Compare forecasting accuracy of several quantitative techniques |
| Martin and Witt (1989b) | **Naïve 1**, 2; SR; A-ES; Trend; **AR** | BT, AT, SE | Compare forecasting accuracy of several quantitative techniques |
| Yong, Keng, and Leng (1989) | Delphi (scenario) | J | Develop future scenario and consensus for Singapore tourism industry |
| 1990–1999 (28/97) | | | |
| Clewer, Pack, and Sinclair (1990) | STSM | Sys | Forecasting model with intervention variables (sudden shocks to tourism demand)<br>International tourism demand for coastal and urban areas in Spain |
| Morley (1992) | SR | SE | Microeconomic theory for improving econometric specification<br>Effect of income and non-tourism goods' prices on tourism demand |

(*continued on next page*)

**Table 1** (*continued*)

| Author (Year) | Forecasting methods | Sub-categories | Research context |
|---|---|---|---|
| Smeral, Witt, and Witt (1992) | System of SR | Sys | Long-term forecasts of tourism import and exports under 3 differing scenarios |
| Witt, Newbould, and Watkins (1992) | Naïve 1, 2; **A-ES** | BT, AT | Accuracy of forecasting models differs in international vs. domestic tourism context demand<br>Domestic arrivals to Las Vegas |
| Chan (1993) | Naïve 1, 2; SR; ARIMA; **Trend (Sine)** | BT, AT, SE | Sine wave time series regression model<br>Forecast tourist arrivals in Singapore |
| Sheldon (1993) | **Naïve 1, 2**; **SR**; **A-ES**; Trend | BT, AT, SE | Expenditures vs. arrivals<br>Expenditure forecasts, in general, have higher errors |
| Syriopoulos and Sinclair (1993) | AIDS | Sys | Tourism expenditure by US and European tourists in Mediterranean countries<br>Different expenditure elasticities in traditional and new destinations |
| Kaynak, Bloom, and Leibold (1994) | Delphi | J | Predict future potential of tourism industry in South Africa |
| Witt, Witt, and Wilson (1994) | **Naïve 1**, 2; A-ES; Trend; AR; **ARIMA** | BT, AT | Using annual and seasonal data, compare differences in accuracy for international and domestic demand forecasting |
| Dharmaratne (1995) | **ARIMA**; SARIMA | AT | *Ex post* (accuracy of out-of-sample forecasts)<br>Long-stay visitors in Barbados |
| Gonzalez and Moral (1995) | **STSM**; ECM; **TFM**; ARIMA | AT, DE, Sys | Model for tourist expenditures vs. number of tourists<br>Two price indexes (substitute prices of origin and competitor countries)<br>Stochastic trend component |
| Syriopoulos (1995) | ECM | DE | Tourism consumption changes for Mediterranean destinations<br>Modelling short- and long-run effects<br>Different income elasticities between tourist origins |
| Gonzalez and Moral (1996) | **BSM**; Trend; ARIMA | AT | Evolution of international tourism demand in Spain<br>Stochastic trends (in periods of expansion or recession) and seasonalities |
| Kulendran (1996) | ECM | DE | Cointegration analysis<br>Australia inbound arrivals from 4 countries |
| Pattie and Snyder (1996) | **NN**; Trend; Naïve 1; A-ES; ARIMA | BT, AT, AI | Compare time series and neural network model<br>Demand for overnight stays in US national parks |
| Garcia-Ferrer and Queralt (1997) | **ARIMA**; **Trend (Dynamic Harmonic Regression)** | AT | Suggestions for improvement in forecasting tourist demand in Spain<br>Flaws in proxy input, specification, forecast horizon and error measurement |
| Kulendran and King (1997) | **ECM**; AR; **ARIMA**; **SR (ARMA error)**; BSM | BT, AT, DE | Australia inbound arrivals from 4 countries<br>Correct modelling of trends and seasonality of series |
| Qu and Lam (1997) | SR | SE | Two determinants (i.e., disposable income and visa) among 7 exogenous variables<br>Mainland Chinese tourism demand to Hong Kong |
| Akis (1998) | SR | SE | Income and relative prices<br>Demand for Turkey from 18 countries |
| Chu (1998a) | Naïve 1, 2; A-ES; Trend; Trend (Sine); **SARIMA** | BT, AT | Compare 6 forecasting models for 10 Asian Pacific destinations<br>Superior forecast accuracy of seasonal-nonseasonal ARIMA model |
| Chu (1998b) | Combined (SARIMA, Trend (Sine)) | CH | *Ex post* international tourism arrivals to Singapore<br>Combined vs. individual models |
| Kim and Song (1998) | **ECM**; VAR; Naïve 1; AR; MA; S (Simple)-ES; ARMA | BT, AT, DE, Sys | Cointegration analysis<br>Inbound tourism demand in South Korea<br>Significant effect of trade volume |
| Kim and Uysal (1998) | ARMAX | XT | Effect of price, events and trade volume on hotel demand in Seoul |
| Morley (1998) | ARX | XT | Diffusion model for tourism demand (effect of information flows)<br>Seven major sources of tourists to Australia |

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**Table 1** (*continued*)

| Author (Year) | Forecasting methods | Sub-categories | Research context |
|---|---|---|---|
| Kim (1999) | AR; A-ES; **SARIMA** | BT, AT | Trend and seasonality in time series<br>Disaggregated international tourist departures from Australia |
| Law and Au (1999) | **NN (Feedforward)**; Naïve 1; HA; S-ES; SR | BT, SE, AI | Japanese tourist arrivals in Hong Kong<br>Six nodes in input layer<br>Superiority of forecasting output from neural network |
| Papatheodorou (1999) | AIDS | Sys | Evolution of dependent variables over time (e.g., changing tastes)<br>Changes of market shares in Mediterranean region |
| Uysal and El Roubi (1999) | ARX; **NN** | XT, AI | Artificial neural networks outperform in terms of prediction bias and accuracy<br>Canadian tourism expenditures in US |
| 2000–2009(79/245) | | | |
| Garin-Munoz and Amaral (2000) | PDR | DE | Impact of economic determinants and event on tourism demand in Spain<br>Panel data set of 17 countries |
| Law (2000) | **NN (BP)**; Naïve 1; A-ES; HA; SR | BT, AT, SE, AI | Back-propagation learning process into nonlinear tourism demand data<br>Nonlinearly separable data (Taiwanese arrivals in Hong Kong since 1967) |
| Law and Au (2000) | Rough sets | AI | Tourism expenditure on shopping in Hong Kong |
| Lim and McAleer (2000) | SARIMA | AT | Deterministic and stochastic seasonality<br>Tourist arrivals from Hong Kong and Singapore to Australia |
| Song, Romilly, and Liu (2000) | **ECM**; Naïve 1; AR; ARMA; VAR | BT, AT, DE, Sys | General-to-specific methodology<br>Introducing destination preference index<br>*Ex post* from ECM<br>UK outbound tourism demand to 12 destinations |
| Vanegas and Croes (2000) | ARX | XT | Significant long-term effect of income on US demand to Aruba<br>*Ex post* and *ex ante* |
| Burger, Dohnal, Kathrada, and Law (2001) | **NN**; Naïve 1; S-ES; ARIMA; SR; HA | BT, AT, SE, AI | Compare forecasting accuracy of models<br>US demand for South Africa at metropolitan level |
| Cho (2001) | **ARIMAX**; **ARIMA**; S-ES | BT, AT, XT | Application of time series forecasting with economic indicators |
| Greenidge (2001) | STSM; BSM | AT, Sys | Time-varying components in regression<br>Tourist arrivals to Barbados |
| Kulendran and Witt (2001) | ECM; ARIMA; **SARIMA**; BSM; **Naïve 1** | BT, AT, DE | Cointegration/ECM methods |
| Lim and McAleer (2001a) | VEC | Sys | Cointegration analysis of seasonally unadjusted quarterly data<br>Hong Kong and Singapore tourists to Australia |
| Lim and McAleer (2001b) | S-ES; **A-ES** | BT, AT | Compare various exponential smoothing models<br>Asian tourist arrivals to Australia |
| Lim and McAleer (2001c) | HA; ARMA; **ARIMA** | BT, AT | Monthly seasonal variations<br>Asian tourist arrivals to Australia |
| Turner and Witt (2001) | **BSM**; STSM; Naïve 1 | BT, AT | Univariate vs. multivariate structural time series models<br>Disaggregated tourism demand to New Zealand |
| Weatherford, Kimes, and Scott (2001) | S-ES; MA; SR; SR (pickup); Naïve 1 | BT, DE | Predicting customer arrivals for hotel revenue management<br>Forecast aggregation and disaggregation |
| Webber (2001) | VEC | Sys | Effect of exchange rate volatility on long-run demand from<br>Australia to 9 destinations Cointegration analysis |
| De Mello, Pack, and Sinclair (2002) | AIDS | Sys | System of equations model<br>UK demand in neighboring destinations' changes (i.e., transition and integration) |
| Goh and Law (2002) | **SARIMA-In**; SARIMA; Naïve 1, 2; HA; S-ES; A-ES; ARIMA | BT, AT, XT | Multiplicative SARIMA with intervention (MARIMA)<br>Stochastic nonstationary seasonality |
| Huang and Min (2002) | SARIMA | AT | Impact of earthquake and recovery on tourism demand |
| Lim and McAleer (2002) | **ARIMA**; **SARIMA** | AT | Stationary and nonstationary time series data<br>Asian tourist arrivals to Australia |

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**Table 1** (*continued*)

| Author (Year) | Forecasting methods | Sub-categories | Research context |
|---|---|---|---|
| Cho (2003) | **NN (Elman)**; A-ES; ARIMA | AT, AI | Compare forecasting model accuracy<br>Neural networks for series without obvious pattern |
| Divisekera (2003) | AIDS | Sys | Consumer theory of choice<br>US, UK, New Zealand and Japan demands in Australia and alternative destinations |
| Du Preez and Witt (2003) | **SARIMA**; USS; MSS | AT, DE | Univariate vs. multivariate time series<br>Weak vs. rich cross-correlation structure<br>Demand of 4 European countries to Seychelles |
| Durbarry and Sinclair (2003) | ECM-AIDS | Sys | French tourism demand in neighboring countries<br>Changes in market shares |
| Goh and Law (2003) | Rough sets | AI | Improve accuracy by capturing useful information and discovering knowledge from data |
| Kulendran and Witt (2003a) | **ECM**; STSM; SARIMA; **ARIMA**; AR; **Naïve 1**; BSM | BT, AT, DE, Sys | International business travel forecasting<br>Trade openness and income<br>Model performance comparison |
| Kulendran and Witt (2003b) | TFM; **ECM**; **ARIMA**; SARIMA | AT, DE | Leading indicator transfer function model<br>UK demand to 6 destinations<br>Performance on short vs. long-term forecasts |
| Lanza, Temple, and Urga (2003) | AIDS | Sys | Impact of specialisation in tourism for 13 OECD economies |
| Song and Wong (2003) | SR-TVP | SE | Time-varying parameter approach<br>Demand for Hong Kong from 6 countries |
| Song, Wong, and Chon (2003) | ADLM | DE | General-to-specific approach (*ex ante*)<br>Travel cost, costs in competing destinations and word-of-mouth effect<br>Demand for Hong Kong from 16 origins |
| Song and Witt (2003) | **ADLM (GETS)**; ECM; ARX | XT, DE | General-to-specific approach<br>Demand for South Korea from 4 origins |
| Song, Witt, and Jensen (2003) | **SR**; ECM; Naïve 1; VAR; ARIMA; ADLM; **SR-TVP** | BT, AT, SE, DE, Sys | Forecasting competition of econometric models<br>International tourism demand to Denmark |
| Song, Witt, and Li (2003) | ADLM; ECM; ARX | XT, DE | General-to-specific approach<br>*Ex ante* forecasts future demand to 2010<br>Effect of habit persistence on Thai tourism demand |
| Weatherford and Kimes (2003) | **S-ES**; A-ES; HA; SR; **SR (pickup)** | BT, AT, SE | Arrival forecast for hotel revenue management<br>Compare forecasting methods |
| Akal (2004) | **ARMAX**; SR | XT, SE | Forecasting Turkey's tourism revenue (*ex ante*)<br>Effect of earlier (lagged) visit on current arrival |
| Chu (2004) | Naïve 1, 2; SR; **Trend** (Sine, **Cubic**) | BT, AT, SE | Cubic polynomial approach<br>Accuracy of forecasting model |
| Dritsakis (2004) | VECM | Sys | Cointegration analysis<br>German and British demand for Greece |
| Li, Song, and Witt (2004) | **ECM-AIDS**; AIDS | Sys | Static and dynamic unrestricted linear AIDS<br>Expenditure of UK tourists in 5 European countries and others |
| Lim (2004) | ARX | XT | Seasonal patterns and determinants of South Korean arrivals to Australia |
| Nadal, Font, and Rosselló (2004) | ECM | DE | Temporal variations in seasonality using Gini-coefficient<br>Balearic Islands tourism demand |
| Narayan (2004) | ADLM | DE | Cointegration/ECM within ADLM<br>Demand for Fiji from 3 origin countries |
| Wang (2004) | FTS; GM; **Markov-GM** | AI | Fuzzy time series and hybrid grey theory<br>Markov modification model<br>Tourist arrivals to Taiwan |
| Chan, Lim, and McAleer (2005) | ARMA-GARCH | AT | Static or constant conditional correlation volatility models<br>Arrivals in Australia from 4 countries |
| Croes and Vanegas (2005) | ARX | XT | Econometric estimations<br>Arrivals to Aruba from 'rich' and 'poor' countries |
| Hamilton, Maddison, and Tol (2005) | SR (with simulation) | SE | Climate change and international tourism demand |
| Kon and Turner (2005) | **NN**; **BSM**; Naïve 1; S-ES; A-ES; SR | BT, AT, SE, AI | Finding best structure for neural network models<br>Arrivals to Singapore from 6 major markets |

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**Table 1** (*continued*)

| Author (Year) | Forecasting methods | Sub-categories | Research context |
|---|---|---|---|
| Kulendran and Wong (2005) | ARIMA; SARIMA | AT | Deterministic vs. stochastic seasonality<br>*Ex post*, compare out-of-sample forecast accuracy and HEGY unit root test |
| Naudé and Saayman (2005) | PDR | SE, DE | Using cross-section and panel data<br>Tourism arrivals in 43 African countries<br>Key 'destination determinants' |
| Pai and Hong (2005) | **SVM-G**; ARIMA; SARIMA | AT, AI | SVM model with genetic algorithms<br>Improve neural network model in tourism arrival forecasting |
| Blake et al. (2006) | STSM | Sys | Integrate tourism indicators with structural time series forecasting and computable general equilibrium impact analysis |
| Blunk, Clark, and McGibany (2006) | ADLM; VAR | DE, Sys | Long-run impact of 9/11 attacks on US domestic airline travel |
| Bonham, Edmonds, and Mak (2006) | VEC | Sys | Impact of 9/11 and subsequent global events<br>Tourist arrivals in Hawaii |
| Garin-Munoz (2006) | PDR | SE, DE | Generalised method of moments estimation<br>Inbound demand to Canary Islands from 15 origin countries |
| Han, Durbarry, and Sinclair (2006) | AIDS | Sys | Sensitivity of tourism demand to changes in economic determinants<br>US demand in European destinations |
| Li, Wong, Song, and Witt (2006) | Naïve 1; ARIMA; SR; ADLM; VAR; ECM; **ECM-TVP**; **SR-TVP** | BT, AT, SE, DE, Sys | Econometric model with time-varying parameter<br>UK demand to 5 Western Europe destinations |
| Li, Song, and Witt (2006) | AIDS; **AIDS-TVP**; **Hybrid** (**AIDS-ECM**, AIDS-ECM-TVP) | Sys, CH | Time-varying parameter error correction AIDS model<br>Expenditure of UK tourists in 5 European countries and others |
| Palmer, Montano, and Sesé (2006) | NN | AI | Artificial neural network (multilayer perception)<br>Tourism expenditure in Balearic Islands |
| Song and Witt (2006) | VAR | Sys | Impulse response analysis using VAR<br>Tourist flows to Macau from 8 origins |
| Wong, Song, and Chon (2006) | **BVAR**; VAR; AR | BT, Sys | Bayesian VAR and unrestricted VAR models<br>International demand to Hong Kong |
| Aslanargun, Mammadov, Yazici, and Yolacan (2007) | ARIMA; NN; **Hybrid** (**various ARIMA-NN, NN-NN**) | AT, AI, CH | Compare time series and neural network models<br>Hybrid models in time series<br>Tourist arrivals to Turkey |
| Chen and Wang (2007) | **SVR-GA**; NN; ARIMA | AT, AI | Genetic algorithm support vector regression<br>Tourist arrivals to China |
| Garin-Munoz (2007) | PDR | DE | Dynamic model for short- and long-run elasticities<br>German demand to 17 Spanish destinations |
| Garin-Munoz and Montero-Martín (2007) | PDR | DE | Significant value of lagged dependent variable<br>Tourist arrivals from 14 countries to Balearic Islands |
| Koc and Altinay (2007) | ARIMA-DC | AT | Decomposition techniques Stochastic seasonality in expenditure |
| Wong, Song, Witt, and Wu (2007) | SARIMA; VAR; ECM; ADLM; **Combined** | AT, DE, Sys, CH | Combination vs. single model forecasts<br>*Ex post* forecasts<br>Tourist arrivals in Hong Kong from 10 origins |
| Zhang and Jensen (2007) | SR | DE | Supply-side factors associated with production in destinations<br>International tourism and trade flows |
| Athanasopoulos and Hyndman (2008) | USS; **Hybrid** (USS-ES, **USS-ES-X**) | AT, CH | Univariate state space (USS) models<br>Impact of global events on Australian domestic tourism demand |
| Chu (2008) | **ARIMA** (**ARFIMA**); SR; ARIMA; Naïve 1, 2; Trend (Cubic); Trend (Sine); SARIMA; Combined (SARIMA, Trend (Sine)) | BT, AT, SE, CH | Fractionally integrated ARIMA approach<br>*Ex post* forecasts for periods of economic and political shocks<br>Tourism demand for Singapore |
| Goh, Law, and Mok (2008) | Rough sets | AI | Rough sets of algorithms for tourism demand<br>Qualitative noneconomic factors (i.e., leisure time and climate index)<br>Long-haul travel demand to Hong Kong |

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**Table 1** (*continued*)

| Author (Year) | Forecasting methods | Sub-categories | Research context |
|---|---|---|---|
| Khadaroo and Seetanah (2008) | PDR | SE | Gravity framework<br>Transport infrastructure in determining destination attractiveness<br>Panel data set of bilateral flows among 28 countries |
| Lee, Song, & Mjelde (2008) | Hybrid (SARIMA, Trend, A-ES, Delphi) | CH | Forecasting demand for mega-event in South Korea<br>Combining quantitative and qualitative technique |
| Ouerfelli (2008) | **ECM**; BSM | AT, DE | Cointegration/ECM<br>Identifying demand and supply factors<br>Forecast European tourism demand in Tunisia |
| Wang and Hsu (2008) | FTS | AI | Constructing improved fuzzy time series<br>Taiwanese demand to the US |
| Athanasopoulos, Ahmed, and Hyndman (2009) | ES (Hierarchical) | AT | Hierarchical forecasting (*ex post*) to Australian domestic tourism market<br>Purpose of travel and geographical disaggregation |
| Bonham, Gangnes, and Zhou (2009) | **VEC**; VARX; ARIMA | AT, XT. Sys | System-based cointegration analysis<br>Demand (US and Japan) and supply (Hawaii) side influences |
| Chu (2009) | SARIMA; ARAR; **ARIMA** (**ARFIMA**) | AT | Three univariate ARMA-based models<br>Global tourist arrivals to 9 Asian-Pacific region |
| Coshall (2009) | Naïve 2; S-ES; ARIMA-GARCH; **Combined** (**ARIMA-GARCH, SES**) | BT, AT, CH | Combining volatility and smoothing forecasts<br>UK tourism demand to international destinations |
| Smeral (2009) | ECM | DE | Effect of financial and economic crisis on tourism demand<br>International travel (tourism imports) of EU-15 countries |
| Wang (2009) | ADLM | DE | Impact of crisis events and macroeconomic activity on changes in tourism demand<br>International inbound tourism to Taiwan |
| 2010–2018 (83/247) | | | |
| Díaz and Nadal (2010) | ARIMA, TFM, **AR-NN**, ANN | AT, DE, AI | Improving predictive ability of tourism demand model with meteorological explanatory variables |
| Guizzardi and Mazzocchi (2010) | STSM; **Naïve 1** | BT, Sys | Business cycle and tourism demand (i.e., lagged effects of business cycle on tourism cycles)<br>Cyclical element in structural time series model |
| Moore (2010) | **ECM**; Naïve 1 | BT, DE | Climate change effect on Caribbean tourism demand<br>Compare panel error correction model with Naïve model (*ex post*) |
| Smeral (2010) | ADLM; ECM | DE | Effect of world recession and economic crisis<br>Demand for outbound travels in Australia, Canada, the US, Japan, and EU-15 countries |
| Song, Li, Witt, and Fei (2010) | ADLM | DE | General-to-specific approach<br>Tourist arrivals (by income and word-of-mouth/habit persistence) vs. expenditure (by relative price) in Hong Kong |
| Song and Lin (2010) | ECM | DE | Inbound and outbound tourism to/from Asia<br>Interval demand elasticities and forecasts |
| Andrawis, Atiya, and El-Shishiny (2011) | Combined (Long-run ES, Short-run ES) | CH | Forecast combination Demand to Egypt from 33 countries |
| Assaf, Barros, and Gil-Alana (2011) | ARIMA; SARIMA; **Detrended-ARIMA**; Detrended-SARIMA | AT | Forecasts tourist arrivals to Australia (disaggregated monthly data) by using seasonal fractional integration |
| Athanasopoulos, Hyndman, Song, and Wu (2011) | **Naïve 1**; S-ES; **A-ES**; ARIMA; SR; ADLM; VAR; **SR-TVP** | BT, AT, SE, DE, Sys | Forecasting competition for tourism data (incl. monthly, quarterly and annual series) |
| Carson, Cenesizoglu, and Parker (2011) | ADLM | DE | Aggregating individual markets approach<br>*Ex post* forecasts for air travel demand |
| Chen (2011) | Naïve 1; S-ES; ARIMA; **Combined** (**Naïve 1, S-ES, ARIMA + NN, SVR**) | BT, AT, CH | Combining linear and nonlinear model<br>Taiwanese outbound tourism demand |
| Chu (2011) | AR; ARIMA (ARFIMA); **Trend (piece-wise)**; SARIMA | BT, AT | Forecasts of piecewise linear approach<br>Demand for Macau tourism |

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**Table 1** (*continued*)

| Author (Year) | Forecasting methods | Sub-categories | Research context |
|---|---|---|---|
| Coshall and Charlesworth (2011) | ARIMA-GARCH; S-ES; AR; Naïve 2; **Combined** (**ARIMA-GARCH, S-ES, AR, Naïve 2**) | BT, AT, CH | Goal programming approach to combination forecasting<br>UK outbound air travel to 18 European destinations |
| Fildes, Wei, and Ismail (2011) | **ADLM**; ADLM-TVP; VAR; Naïve 1, 2; AR; S-ES | BT, DE, Sys | General-to-specific approach<br>Air traffic flows and world trade growth |
| Hadavandi, Ghanbari, Shahanaghi, and Abbasian-Naghneh (2011) | Fuzzy System | AI | Fuzzy rule-based system for tourism forecasting<br>Tourist arrivals to Taiwan from 3 markets |
| Hong, Dong, Chen, and Wei (2011) | **SVR** (GA, **CGA**); ARIMA; SARIMA | AT, AI | SVR model with chaotic genetic algorithm<br>Tourist arrivals in Barbados |
| Shen, Li, and Song (2011) | ADLM; ECM; VAR; SR-TVP; Naïve 1; SARIMA; **Combined** | BT, AT, CH | Combination methods for international tourism demand forecasts<br>UK tourists to 7 destinations countries |
| Song, Li, Witt, and Athanasopoulos (2011) | Naïve 1, 2; BSM; STSM; ADLM; SARIMA; SR-TVP; **STSM-TVP** | BT, AT, DE, Sys | Structural time series and time-varying parameter regression approach<br>*Ex post* and *ex ante* forecasts<br>Tourist arrivals to Hong Kong from 4 key source markets |
| Song, Lin, Witt, and Zhang (2011) | ADLM-ECM | DE | Impact of financial and economic crisis<br>Demand elasticities for hotel rooms in Hong Kong |
| Tsaur and Kuo (2011) | FTS (Adaptive) | AI | Adaptive fuzzy time series model Taiwan's tourism demand |
| Chen, Lai, and Yeh (2012) | **NN** (BP, **EMD-BPNN**); ARIMA | AT, AI | Empirical mode decomposition (EMD) and neural network<br>International visitors to Taiwan |
| Choi and Varian (2012) | ARX | XT | Google Trends in predicting present (contemporaneous forecasting)<br>Travel demand to Hong Kong from 9 countries |
| Goh (2012) | ECM | DE | Impact of climate on tourism demand<br>Long- and short-haul travel to Hong Kong |
| Gounopoulos, Petmezas, and Santamaria (2012) | **ARIMA**; A-ES | AT | Impulse response analysis on impact of macroeconomic shocks<br>Tourist arrivals in Greece |
| Page, Song, and Wu (2012) | SR-TVP | DE | Impact of global events on inbound tourism demand in UK |
| Pan, Wu, and Song (2012) | Naïve 1; AR; ARMA; ARIMA; **ARX**; **ARMAX**; ARIMAX; ADL; SR-TVP; VAR | BT, AT, XT, DE, Sys | Forecasting performance of Google search data (*ex post*)<br>Hotel room demand |
| Smeral (2012) | ADLM | DE | Business cycle and tourism demand<br>Magnitudes of price and income effects |
| Teixeira and Fernandes (2012) | **NN (Feedforward, Cascade forward, Recurrent (Elman))** | AI | Compare artificial neural network and linear time series models<br>Hotel demand forecasting |
| Wu, Law, and Xu (2012) | **GP (Gaussian process regression model)**; ARMA; SVM (v-, g-) | AT, AI | Using Mercer kernels and Bayesian framework<br>Tourism demand in Hong Kong |
| Lin, Pai, Lu, and Chang (2013) | SARIMA; NN (Generalised Regression NN); **SVR** (**FLSSVRGA (fuzzy least square SVR GA)**, SVRGA; LSSVRGA) | AT, AI | Fuzzy least square SVR with genetic algorithms for seasonal revenue forecasting |
| Marrocu and Paci (2013) | SR (Spatial-AR) | SE | Spatial econometric interaction model for origin-destination dependence (vs. gravity model)<br>Demand and supply determinants of domestic tourism in 107 Italian provinces |
| Shahrabi, Hadavandi, and Asadi (2013) | **FS** (**MGFFS** (modular genetic-fuzzy forecasting system), GFS (genetic fuzzy system), ANFIS (adaptive neuro-fuzzy inference system)); SARIMA; NN | AT, AI | Hybrid intelligent system for tourism demand forecasting by combination of genetic fuzzy expert system and data pre-processing |
| Song, Gao, and Lin (2013) | ADLM; **Combined** (**ADLM, Delphi**) | DE | Web-based tourism demand forecasting system for Hong Kong (tourism arrivals, expenditure and demand for hotel rooms)<br>Combination of quantitative and judgmental forecasts |
| Cang (2014) | Naïve 1, 2; SARIMA; A-ES; SVR; **Combined** (linear, **nonlinear**) | BT, AT, AI, CH | Compare individual, linear combination and nonlinear combination models |
| Cang and Yu (2014) | Naïve 1, 2; SARIMA; A-ES; SVR; **Combined** (linear, **nonlinear**) | BT, AT, AI, CH | Optimal subset combination selection algorithm |
| Claveria and Torra (2014) | **ARIMA**; AR (SETAR); NN | BT, AT, AI | Neural networks vs. time series models<br>Inbound tourism demand to Catalonia |

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**Table 1** (*continued*)

| Author (Year) | Forecasting methods | Sub-categories | Research context |
|---|---|---|---|
| Morley, Rosselló, and Santana-Gallego (2014) | SR | SE | Gravity models for bilateral tourism flows |
| Pai, Hung, and Lin (2014) | **SVR** (**FCM-LLS-SVRGA** (fuzzy c-means logarithm least-square SVR-GA), FCM-LS-SVRGA, LLS-SVRGA, LS-SVRGA, SVRGA); NN (Genetic Regression NN); ARIMA | AI | Constructing amalgam of forecasting system (i.e., FCM with LLS-SVRGA)<br>Tourist arrivals to Taiwan and Hong Kong |
| Ridderstaat, Oduber, Croes, Nijkamp, and Martens (2014) | PDR | DE | Effect of seasonal patterns of pull and push climate elements<br>Recurrent fluctuations in tourism demand<br>US and Venezuela arrivals to Aruba |
| Saha and Yap (2014) | PDR | DE | Effect of political instability and terrorism on tourism industry<br>Panel data from 139 countries |
| Tsui, Balli, Gilbey, and Gow (2014) | **SARIMA**; **ARIMAX** | AT, XT | Forecasting air passenger throughput of Hong Kong<br>Future air passenger traffic under different scenarios |
| Yang, Pan, and Song (2014) | **ARMAX**; ARMA; AR (Threshold AR) | BT, AT, XT | Predictive power of Web traffic volume data of destination marketing organisation (DMO) in forecasting hotel demand |
| Akın (2015) | SARIMA; **SVM** (**v-SVM**); NN (MLP) | AT, AI | Model selection and comparison of forecasting accuracy<br>Monthly tourist arrival to Turkey from different countries |
| Bangwayo-Skeete and Skeete (2015) | **ADLM-MIDAS**; SARIMA; AR | BT, AT, Sys | Google Trends' search query time series data<br>Mixed-data frequency modelling |
| Chen, Liang, Hong, and Gu (2015) | **SVR** (**AGA-S** (Adaptive GA-Seasonal), AGA); NN (BP) | AI | Holiday daily tourist flow forecasting |
| Claveria, Monte, and Torra (2015a) | **Naïve 1**; NN (MLP, RBF, Elman) | BT, AI | Developing multivariate setting (multiple-input multiple-output)<br>Tourist arrivals to Catalonia |
| Claveria, Monte, and Torra (2015b) | **NN** (**MLP, RBF, Elman**) | AI | Performance evaluation of artificial neural network techniques |
| Guizzardi and Stacchini (2015) | Naïve 1; DL; BSM; **STSM** | BT, AT, DE, Sys | Hotel arrivals forecasting with supply-side soft information (i.e., business sentiment indicators) |
| Gunter and Önder (2015) | ADLM-ECM; VAR; **BVAR**; SR-TVP; ARMA; **S-ES**; Naïve 1 | BT, AT, DE, Sys | Univariate vs. multivariate models<br>International tourism demand for Paris |
| Hassani, Webster, Silva, and Heravi (2015) | **SSA**; ARIMA; A-ES; NN | AT, AI | Singular spectrum analysis (SSA) for forecasting tourism demand<br>In- and out-of-sample forecasts |
| Lin, Liu, and Song (2015) | ADLM | DE | General-to-specific approach<br>*Ex ante* forecasts Chinese outbound tourism to 11 destinations |
| Smeral and Song (2015) | **SR-VP** (**MGR, reference dependent**); SR-TVP | DE | Varying elasticities and time-varying parameter on forecasting performance |
| Yang, Pan, Evans, and Lv (2015) | ARMA; **ARMAX** | AT, XT | Compare predictive power of search data from Google and Baidu<br>Cointegration between online data and Chinese tourist volume to Hainan province |
| Balli, Balli, and Louis (2016) | PDR | DE | Impacts of immigrants and institutions on bilateral tourism flows<br>Flow from 34 OECD countries to 52 middle- and low-income countries<br>Gravity equation variables |
| Gunter and Önder (2016) | VAR; BVAR; **MA**; A-ES; Naïve 1; **Combined** | BT, AT, Sys, CH | Google Analytics website traffic indicators from DMO website to predict actual tourist arrivals to Vienna<br>Big data shrinkage methods |
| Önder and Gunter (2016) | **ADLM**; A-ES; Naïve 1 (Seasonal and classical) | BT, AT, DE | Forecasting with Google Trends Tourism demand to Vienna |
| Sun, Sun, Wang, Zhang, and Gao (2016) | **Grey Model** (CMCSGM (Cuckoo Markov Chain Segment Grey Model), MCSGM, SGM, MCGM, GM) | AI | Grey-Markov model optimised by Cuckoo search algorithm Foreign tourist arrivals to China |
| Xu, Law, Chen, and Tang (2016) | Naïve 1; HA; S-ES; A-ES; SR; ARIMA; NN; SVR (SVMRE (SVR with Fuzzy rule extraction)) | BT, AT, AI | Forecasting method by extracting fuzzy Takagi-Sugeno rules from trained support vector machines<br>Tourist arrivals to Hong Kong from 9 markets |

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**Table 1** (*continued*)

| Author (Year) | Forecasting methods | Sub-categories | Research context |
|---|---|---|---|
| Dogru, Sirakaya-Turk, and Crouch (2017) | PDR | DE | Alternative price and exchange rate<br>Fully modified ordinary least squares method<br>Inbound tourism demand for Turkey from 9 countries |
| Hassani, Silva, Antonakakis, Filis, and Gupta (2017) | ARIMA (ARIMA, ARFIMA); MA; A-ES; NN; Hybrid (TBATS: SS-ES-ARMA-Trend); **SSA** (**recurrent**, vector) | BT, AT, AI, CH | Forecasting accuracy evaluation<br>Best performance of recurrent SSA model vs. worst performance of neural networks and ARFIMA |
| Li, Pan, Law, and Huang (2017) | ARMA, **ARMAX** | AT, XT | Search engine query data for forecasting tourist volumes to Beijing<br>Composite search index adopted in a generalised dynamic factor model<br>*Ex post* forecasting evaluation |
| Pan and Yang (2017) | ARMAX; ARMAX-VP (State-varying parameter, MSDR) | XT, DE | Using big data (incl. search engine query, website traffic and weather information) to forecast weekly hotel occupancy |
| Park, Lee, and Song (2017) | SARIMA; **SARIMAX**; A-ES | AT, XT | Google-augmented models using Google Trends<br>Japanese tourist arrivals to South Korea<br>*Ex post* forecasts |
| Rodríguez (2017) | ARMA, **ARMAX** | AT, XT | Predictive power of Google Trends<br>Germany and UK tourist arrivals to Balearic Islands |
| Assaf, Li, Song, and Tsionas (2018) | VAR; BVAR; GVAR; **BGVAR**; ARMA | AT, Sys | Bayesian global vector autoregressive model<br>Global/regional integration and tourist flows |
| Athanasopoulos, Song, and Sun (2018) | ADLM; **Combined** (**ADLM, Bagging**) | DE, CH | Bootstrap aggregation (bagging) in forecasting tourism demand<br>General-to-specific approach<br>Tourism arrivals to Australia from 6 markets |
| Balli, Shahzad, and Uddin (2018) | **WC** (**MWC** (multivariate wavelet coherence), PWC (partial wavelet coherence)) | AT | Impact of economic policy uncertainties on tourism demand |
| Dergiades, Mavragani, and Pan (2018) | VAR | Sys | Google Trends in tourism arrival forecasting<br>Emerging biases (i.e., language and platform bias) and corrections |
| Hu, Jiang, and Lee (2018) | MCGM; MCSGM; CMCSGM; **Hybrid** (**NN-MCRGM** (Markov Chain-Rolling-GM); NN (Functional Link Net)-MCSSAIGM (Markov Chain-Segmented-Self Adaptive Intelligence-GM)) | AI, CH | Neural networks into Grey–Markov models<br>Number of foreign tourists using historical annual data from Taiwan and China |
| Lee (2018) | Trend (NHPP (nonhomogeneous Poisson process), negative binomial process); **Hybrid** (**Trend** (negative binomial process)**, AR**) | AT, CH | Forecasting hotel room demand<br>Booking arrivals (time-varying arrivals rates, high variability and strong inter-temporal correlations) |
| Li, Goh, Hung, and Chen (2018) | ARX | XT | Effect of relative climate variability on seasonal tourism demand<br>Quarterly panel data set of visitor arrivals from Hong Kong to 13 Chinese cities |
| Li, Chen, Wang, and Ming (2018) | ARIMA; VAR (VAR, PCA-VAR); **NN** (BPNN, PCA-BPNN, **PCA-ADE-BPNN**) | AT, Sys, AI | Baidu Index for tourist volume forecasting<br>Principal component analysis (PCA) and neural network model |
| Lin, Chen, and Liao (2018) | NN (EMD-BP) | AI | Improving accurate prediction of tourist capacity |
| Liu, Tseng, and Tseng (2018) | VAR | Sys | Big data (data of daily tickets, Web search queries, daily weather, calendar and public holidays) analysis for tourism arrival forecasting |
| Millán, Pablo-Romero, and Sánchez-Rivas (2018) | SARIMA | AT | Demand for rural tourism ("Oleotourism") in Andalusia |
| Nor, Nurul, and Rusiman (2018) | SARIMA; NN; **Combined** (**SARIMA, NN**) | AT, AI, CH | Combination forecasting model |
| Ognjanov, Tang, and Turner (2018) | Naïve 1; ARMA; A-ES; BSM; STSM; **SR-TVP**; VAR | BT, AT, DE, Sys | Forecasting tourist expenditure at regional level (31 provinces in mainland China) |
| Ongan and Gozgor (2018) | ADLM | DE | Effects of economic uncertainty on Japanese tourists to the US<br>Using the Economic Policy<br>Uncertainty index Unit root and cointegration tests |
| Rafiei Darani and Asghari (2018) | PDR | DE | Tourist arrivals in the Middle East region<br>Economic indexes (incl. trade freedom index, gross domestic product and purchasing power parity) |

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**Table 1** (*continued*)

| Author (Year) | Forecasting methods | Sub-categories | Research context |
|---|---|---|---|
| Wan and Song (2018) | HA; Naïve 1; DL; **ADLM**; Combined | BT, DE, CH | Forecasting turning points in growth cycles<br>Tourism demand for Hong Kong |
| Wang, Luo, Tang, and Ge (2018) | ARIMA; **NN** (NN, C (Clustering), E (EMD, empirical mode decomposition)) **C-C-NN** (Combination Clustering NN)) | AT, AI, CH | Combined foresting model by using artificial neural network and clustering algorithm |
| Wen, Liu, and Song (2018) | Naïve 1, 2; SR; **PDR** | BT, SE, **DE** | Forecast short-term domestic tourism demand<br>341 cities in China using panel data pooled models |
| Zhu, Lim, Xie, and Wu (2018) | **Copula-ECM** (**Frank**, Product) | DE | Tourist flow dependence in tourism demand modelling and forecasting<br>Demand for Singapore from 6 origins |

Note. BT: Basic time series models; AT: Advanced time series models; XT: Time series models with exogenous variables; SE: Static econometric models; DE: Dynamic econometric models; Sys: System of econometric models; J: Judgmental methods; AI: Artificial intelligence models; CH: Combination and hybrid models. A method in bold type refers to the best performance in forecasting competition.

impact analysis). Based on their review of empirical studies, Witt and Witt (1995) defined three categories of forecasting models, namely the causal models (econometric and spatial models), the time series models and the various qualitative methods. More recently, it has been universally acknowledged that the methodological approaches to forecasting tourism demand fall into four categories (Song & Li, 2008). The first three are the time series models, the econometric models and the AI-based models, which are the three types of quantitative approaches (Goh & Law, 2011; Peng, Song, & Crouch, 2014). The fourth category is judgmental methods, which can be used for both qualitative and quantitative forecasting (Lin & Song, 2015).

## *Time series and econometric models*

### *Time series models*

Time series models forecast tourism demand based on its historical patterns. These models attempt to identify the trends, slopes and cycles among time series data (i.e., using sequences of measurements made during successive periods). Unlike methods based on observing random samples, the time series forecasting models are based on successive values that represent consecutive measurements taken at regularly spaced intervals (such as monthly, quarterly or annual measurements). Once a pattern is established, the time series models generate predictions of future values for the time series to come. Time series models can be further divided into basic or advanced time series techniques (Peng et al., 2014).

The basic types of time series models include the Naïve, autoregressive (AR), single exponential smoothing (ES), moving average (MA) and historical average (HA) models. Due to their ease of implementation and their reasonable ability to capture historical patterns, time series models have been frequently used in tourism demand forecasting studies over the past five decades. In the pool of key studies analysed for this study, 55 of these papers used the basic time series models, for a total of 101 model/times. Among these models, the Naïve 1 and Naïve 2 are by far the most easily adopted and the most popular methods used in the tourism forecasting literature. Despite its simplicity, the Naïve 1 model is found to provide reasonably accurate predictions, especially for short forecasting horizons (Athanasopoulos, Hyndman, Song, & Wu, 2011; Claveria, Monte, & Torra, 2015a).

It is worth noting that due to the tremendous volume of output concerning the basic time series forecasting models, and their use in numerous cross-disciplinary studies over the past five decades, considerable ambiguity in terminology sometimes appears regarding these models. For example, although the calculation of HA follows the mathematical definition of a moving average, the term 'MA model' (or 'MA process') has a distinct definition in time series analysis. Even so, a mixed use of MA and HA is sometimes observed throughout the literature. Therefore, careful choices of terminology are recommended for future studies.

The advanced time series models differ from the basic models in that they integrate additional time series features, such as trends and seasonality. Among the various types of advanced exponential smoothing models, several kinds of trend analyses and Box-Jenkins type methods (Box & Jenkins, 1976), such as autoregressive integrated moving average (ARIMA) methods, are regularly used, and such methods are attracting increasing attention (Gounopoulos, Petmezas, & Santamaria, 2012; Lim & McAleer, 2002). Advanced ES methods remedy the flaws of simple ES by integrating both trend and seasonal terms into the model. Some other methods, in addition to performing decompositions of trends, are sometimes used to fit tourism demand data with trend curves for further analysis. In particular, the sinewave and cubic form methods are found to provide effective predictions for diverse scenarios (Chan, 1993; Chu, 2004). A variety of ARIMA models are widely used in time series analyses of tourism demand. Their considerations of both current and lagged observations (AR components), of both current and lagged random shocks (MA components), of the degrees of integration (I components) and sometimes of seasonality adjustments (S components), make these ARIMA models very flexible in modelling tourism demand. Within our pool of key studies, the ARIMA-type models are adopted 103 times, in 74 out of the 211 key studies. Among the papers that use time series techniques (118 papers), those that use of ARIMA-type models account for more than 60%. Among the 74 studies that use ARIMA-type models, 56 find that these models outperform other techniques in assessing at least one destination and forecast horizon (Du Preez & Witt, 2003; Kulendran & Witt, 2001).

The seasonal ARIMA (SARIMA) model has attracted a tremendous amount of attention (33 papers) and is shown to provide outstanding forecasts (12 papers). Several recent developments in time series techniques are based on ARIMA-type models, including the ARFIMA (autoregressive fractional integrated moving average) model (Chu, 2009), the ARIMA-GARCH (generalised autoregressive conditional heteroskedastic) model (Chan, Lim, & McAleer, 2005) and the SARIMA-In model, which integrates interventions from special events (Goh & Law, 2002). In the past five decades, due to increasing cross-disciplinary collaboration, some methods that were previously used in other disciplines (such as spectrum analysis or wavelet analysis) have also appeared in the tourism demand literature (Balli, Shahzad, & Uddin, 2018; Hassani, Webster, Silva, & Heravi, 2015).

Due to the nature of tourism activity, seasonality has long been acknowledged as a key feature in tourism demand forecasting (Song & Li, 2008). Indeed, seasonality is accounted for in many of the models mentioned above. Based on the concept of the Naïve 1 model, a seasonal-Naïve model is adopted in many tourism demand studies (Jackman & Greenidge, 2010; Önder & Gunter, 2016). The Holt-Winters type of ES, which includes a seasonal component, is found to outperform other types of ES in the forecasting of tourism demand by Asian tourists in Australia (Lim & McAleer, 2001b). Various types of trend analyses and versions of the basic structural model (BSM) are also applied to decompose and analyse the seasonal patterns of tourism demand (Turner & Witt, 2001). The previously mentioned SARIMA model has performed well since its introduction in tourism studies, and has attracted steadily increasing attention over time. The number of our key studies that use SARIMA rose from 3, to 13, to 18 over the last three decades. In addition to these frequently adopted methods, some seasonality-sensitive versions of classical time series models can be found throughout the tourism demand literature. These models include the seasonal-AR, used in an analysis of international arrivals in the Canary Islands (Gil-Alana, 2010), the ARIMA-seasonal decomposition model, used to investigate Turkish inbound tourism (Koc & Altinay, 2007), and the seasonal fractional-ARIMA, used to estimate Spanish tourism demand (Gil-Alana, De Gracia, & Cuñado, 2004).

*Econometric models*

During the past five decades, the continuous interest in econometric forecasting models has contributed to the search for cause and effect relationships between economic factors and tourism demand under differing empirical settings. Although the time series models indicate which trends in a historical data series will most shape the future, the econometric models focus instead on establishing the structure of causality, or determining how significantly the various explanatory variables affect future demand. The econometric forecasting models start from ‘specifying potential causality’ (as supported by demand theory), and they proceed to ‘sorting out’ the defective from the effective variables. In performing this function, econometric forecasting models have played a distinctive role in tourism demand forecasting research and practice over the past five decades.

The most basic econometric forecasting model involves a single static regression (SR). The main use of such simple models is to determine the influence of various factors in causing the current values. To avoid the spurious regression problem, the variables included in these regressions are usually required to be stationary. Many of the early studies in analysing tourism demand fall into this category (Laber, 1969; Martin & Witt, 1987). In more recent years, SR has been sometimes adopted as a benchmark for evaluations of tourism demand forecasting (Athanasopoulos et al., 2011). To account for the intertemporal relationships among tourism demands and their various influencing factors, modern econometric methods such as the distributed lag (DL) model, the autoregressive distributed lag model (ADLM) and the error correction model (ECM) have been introduced into this field. In particular, the DL models consider not just the current values, but also the previous values of the influencing factors that determine current tourism demand. However, the application of DL models in tourism demand forecasting is limited due to competition from their more general and advanced counterpart, the ADLMs. The DL models are usually used as one of the benchmarks in forecasting evaluations and comparisons (Guizzardi & Stacchini, 2015; Wan & Song, 2018). In addition to assessing the influence of lagged influencing factors, the ADLMs also integrate the influence of lagged demand variables.

Building on the foundation of the ADLM, the ECM further considers both the long-run relationship between tourism demand and its influencing factors, and the short-run error correction mechanism in determining tourism demand. The ADLM and the ECM both play very significant roles in the analysis of tourism demand. Within our pool of key studies, 111 papers apply an econometric approach. Among these papers, 26 use the ADLM and 24 use the ECM, so that these models are used in half of the selected econometric approach studies (Kulendran & King, 1997; Smeral, 2010; Song & Witt, 2003). Overall, the performances of the ADLM and the ECM in modelling or forecasting tourism demand are found to be extraordinary. Among the 26 papers that test the ADLM, 16 find it to be the ‘best performing’ model. Among the 24 papers that test the ECM, 17 find it to be the ‘best performing’ among the various alternative models included in those studies. Due to its flexible form, the ADLM can be used with other features that represent parameter assumptions or data utilisation. For instance, the time-varying parameter (TVP) is found to work well with both the ADLM and the ECM for capturing gradual structural changes (Li, Wong, Song, & Witt, 2006; Song, Witt & Jensen, 2003). Mixed-data sampling (MIDAS) is integrated with a reduced form of ADLM for using mixed-frequency data to estimate tourist arrivals in the Caribbean (Bangwayo-Skeete & Skeete, 2015). The authors of that study use the term ‘AR-MIDAS’, indicating that the functional form of the model used is a partial adjustment model, or a reduced ADLM.

Whereas the ADLM and the ECM extend the static single equation model by introducing time dynamics, the already dynamic time series models discussed in the previous subsection can be given similar extensions by including exogenous variables. One of these models is usually known as the ARIMAX model, where X represents the exogenous variables. Both the ADLM and the ECM emphasise measurement of the cause and effect relationships between influencing factors and tourism demand. On the other hand, the ARIMAX models focus heavily on discerning the dynamics of tourism demand.

Li, Goh, Hung, and Chen (2018) adopt an ARX model for investigating the influence of relative climate variability on tourism demand. It is worth noting that the ARX model has the same functional form as a reduced ADLM, and it is sometimes referred to as a partial adjustment model (Hendry, 1995, p. 232). The ARMAX model outperforms the ARMA model in forecasting hotel occupancies (Pan & Yang, 2017). In forecasting the numbers of airport passengers in Hong Kong, Tsui, Balli, Gilbey, and Gow (2014) find that the ARIMAX model generates better long-run forecasts than the SARIMA model. The SARIMAX model also generates better forecasts of the demand for Korean destinations by Japanese tourists than the standard time series models, such as the SARIMA or the Holt-Winters ES (Park, Lee, & Song, 2017). Like the ADLM and the ECM, the ARIMAX-type models also work well when combined with static varying parameters (VP) and MIDAS features for modelling and forecasting tourism demand (Bangwayo-Skeete & Skeete, 2015; Pan & Yang, 2017).

Another extension of the time series models with exogenous variables is found in the use of the BSM. By including explanatory variables in the BSM, the structural time series model (STSM) can investigate the influence of exogenous variables, with an emphasis on trends and on seasonal and cycle components. Some applications of the STSM in tourism demand modelling and forecasting can be found in the papers by Greenidge (2001), Guizzardi and Stacchini (2015) and Ognjanov, Tang, and Turner (2018).

Another stream of studies extends the static single equation model by capturing the interdependency of multiple demand equations or time series. Instead of modelling the demand using a single equation, this stream of studies estimates and forecasts tourism demand using multiple equations. The almost ideal demand system (AIDS) is one such extension. Since its establishment in the 1980s (Deaton & Muellbauer, 1980), AIDS has received a strong underpinning of economic theory. This system has proved capable of capturing the demand for certain products and services, as measured in market share within an economic system. In terms of tourism demand modelling and forecasting, various versions of AIDS are used to estimate the market shares of US outbound tourists travelling to Europe (O'Hagan & Harrison, 1984). Other similar studies estimate Australian inbound demand by a number of international markets (Divisekera, 2003). One such study estimates consumer expenditures on various tourism-related goods and services within 13 European countries (Lanza, Temple, & Urga, 2003). Although the classical AIDS models are estimated within a static system, the AIDS model can be easily extended into a dynamical system. For example, Li, Song, and Witt (2004, 2006) integrate the ECM features into AIDS, and they find that the dynamic AIDS models perform very well in forecasting UK tourist demand for various European destinations. Furthermore, TVP techniques can be combined with the AIDS and ECM-AIDS models to improve their forecast accuracies on tourism demand and expenditure (Li, Song, et al., 2006).

The vector autoregressive (VAR) model and the vector error correction model (VECM) represent another type of extension of the single static equation model. These extension models can capture the interdependency of multiple time series. Within a VAR framework, all of the explanatory variables are treated as endogenous, with an assumption that all of the variables affect each other intertemporally. The use of the VAR model in tourism demand forecasting can be traced back to the late 1990s (Kim & Song, 1998), with a total count of 27 uses documented in our key pool of studies. These studies include those by Assaf, Li, Song and Tsionas (2018), Blunk et al. (2006), Song and Witt (2006), and Wong, Song, Witt, and Wu (2007). However, only Blunk et al. (2006) and Song and Witt (2006) find that the classical VAR model is promising in terms of predictive performance. In many cases, the classical VAR is outperformed by other modern econometric techniques (Song & Li, 2008).

In an attempt to improve the performance of the classical VAR model, Wong, Song, and Chon (2006) develop the Bayesian VAR (BVAR) model by imposing informative restrictions (Bayesian priors) into the model estimation. They find that the BVAR shows significantly better forecasting performance than its non-Bayesian counterpart. Furthermore, Pesaran, Schuermann, and Weiner (2004) expand the classical VAR model into a global VAR (GVAR) framework. This framework is further developed by Assaf et al. (2018), who introduce Bayesian estimation techniques (BGVAR) for modelling and forecasting the demand for international travel within Southeast Asia.

The panel data regression (PDR) is another type of analysis that is often used in tourism demand studies. Unlike the other models discussed above that emphasise functional form and parameterisation, the PDR highlights those features of the data used to estimate the demand models. This regression incorporates information regarding both the intertemporal movements and the cross-sectional heterogeneity of the tourism demand data. Indeed, the panel data analysis can be used in many of the aforementioned models, with the features of PDR being integrated (see for example, Naudé & Saayman, 2005, Saha & Yap, 2014, and Dogru, Sirakaya-Turk, & Crouch, 2017). To date, the use of the PDR in tourism demand forecasting has been relatively rare, with Wen, Liu, and Song (2018) being the only exception.

Regarding the selection of influencing factors in the econometric models, the most important determinants of tourism demand have been found to be tourists' income levels, exchange rates, the prices of tourism products in the destinations relative to those in the origins (i.e., relative price) and the prices of tourism products in competing destinations (i.e., substitute price) (Li et al., 2005; Song & Li, 2008). Other factors, such as climate change (Moore, 2010), political stability (Saha & Yap, 2014), one-off events (Page, Song, & Wu, 2012), terrorist attacks (Bonham, Edmonds, & Mak, 2006) and financial crises (Song, Lin, Witt, & Zhang, 2011) are also found to have important effects on tourism demand. The search engine data from sources such as the Google and Baidu indices have proved to be good indicators of tourism demand fluctuations, although these data have no direct causal relationships with the demand variables (Dergiades, Mavragani, & Pan, 2018; Yang, Pan, Evans, & Lv, 2015).

Most of the models discussed in this section include various explanatory variables with multiple lags for each variable. Therefore, a variable selection algorithm is needed to avoid over-fitting. The traditional approach in econometric forecasting of tourism demand is based on the specific-to-general modelling approach, which starts by constructing a relatively simple model with ordinary least squares (OLS) estimation. This approach has been tested and re-specified by introducing additional explanatory variables into the initial model (Gray, 1966; Loeb, 1982).

The specific-to-general approach is often criticised for its excessive data mining. The general-to-specific (GETS) approach, however, starts with a general model that contains as many variables as possible, including their lags, as suggested by economic theory. The general model is then reduced to a specific form by eliminating the insignificant or wrongly signed variables through repeated estimations. The GETS approach in tourism demand studies is a relatively new practice. The use of the ADLM is usually combined with the GETS approach (Önder & Gunter, 2016; Song & Witt, 2000; Song, Witt & Li, 2003). The specification starts with a general ADLM to remove unnecessary variables sequentially. Then the GETS approach overcomes both the data mining and the

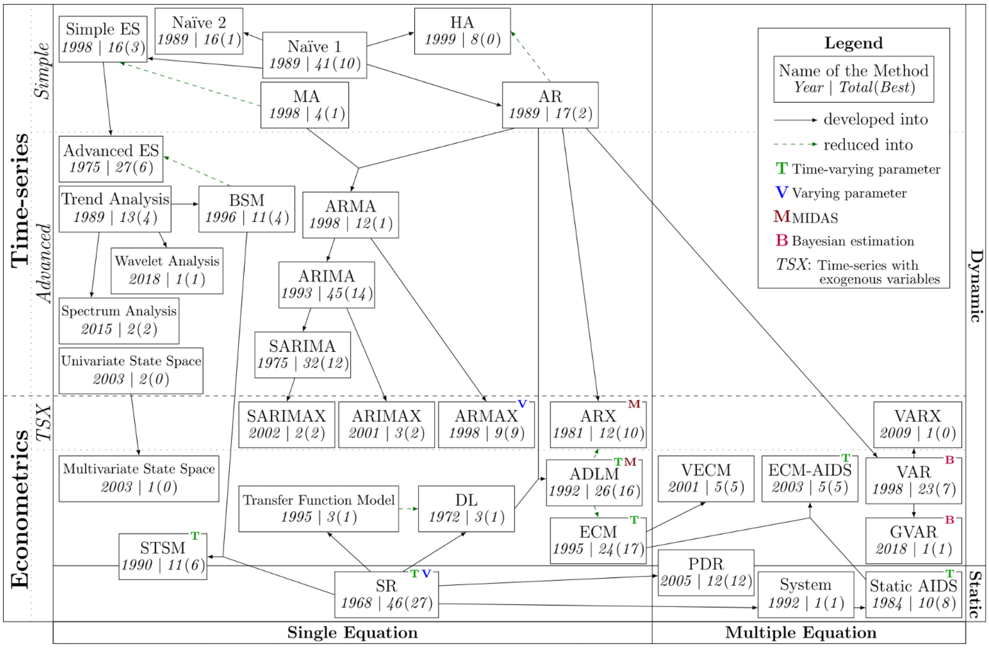


**Fig. 1.** Time series and econometric methods of tourism demand forecasting.

spurious regression problems (Song & Witt, 2003). One of the problems in using the GETS approach is that the unstable decision rule used in eliminating the insignificant variables for model reduction may not be 'optimal' in terms of model estimation and forecasting. To solve this potential problem, Athanasopoulos, Song, and Sun (2018) demonstrate that the bootstrap aggregation GETS models can provide optimal model reduction and generate more reliable forecasts than the simple GETS models.

The time series and econometric models are the major tools used in social sciences, including the modelling of tourism demand and forecasting research. The methodological developments and models discussed above are in fact closely related, with the later models resolving certain problems caused by the earlier models. For example, the ARX model is introduced so that the effects of exogenous variables can be considered in the AR process. Fig. 1 summarises all of the models discussed in this section, and shows the links among them. These models are classified according to two dimensions, with single versus multiple equations on the horizontal axis, and static versus dynamic models on the vertical axis. In addition, the year of each model's first appearance in the pool of key studies, its total number of applications, and the number of 'best performing cases' are listed under the name of each model. Additional model features, such as the time-varying parameter (T), the state-varying parameter (V), mixed-data sampling (M), or Bayesian estimation (B) are denoted on the top right of each model.

*AI-based models*

The data-driven and model-free approaches used in AI-based models are capable of explaining non-linear data without a priori knowledge about the relationships between input and output variables. As the most frequently used AI-based technique, the artificial neural network (ANN) model has been demonstrated to have strong viability and flexibility for processing imperfect data, or for handling almost any kind of nonlinearity. These capabilities explain why ANNs have become important tools in forecasting studies. Although neural network models have been shown to have superior forecasting performance compared to traditional linear and nonlinear methods (Law & Au, 1999; Pai & Hong, 2005; Uysal & El Roubi, 1999), their explanatory value is often questioned by researchers. Zhang, Patuwo, and Hu (1998) indicate that researchers often criticise ANNs for lacking a theoretical background, and for containing a 'black box' of hidden layers between the input and output variables. The input variables in predicting the outputs are difficult to disentangle within the network, and the transparency of the optimisation process (for adjusting weights) is often overlooked. The fundamental issue with the 'black box' nature of AI-based models is that 'a small amount of liquid' can be mathematically described, but it would be impossible to represent 'an ocean' (Robbins, 2016).

Despite their theoretical and methodological limitations, AI-based techniques have been applied widely to predict diverse phenomena in various scientific disciplines (Díaz & Sbert, 2011). The success of these techniques has encouraged tourism researchers to use them in forecasting tourism demand. Therefore, AI techniques have been widely used for tourism forecasting over the past 20 years. The applications of AI methods in forecasting tourism demand include the support vector regression (SVR) (Chen, Liang, Hong & Gu, 2015; Hong, Dong, Chen, & Wei, 2011), the fuzzy time series (Tsaur & Kuo, 2011; Wang, 2004), the rough sets approach (Goh, Law, & Mok, 2008) and grey theory (Sun, Sun, Wang, Zhang, & Gao, 2016). However, ANNs have been the most frequently used AI-based models (Chen, Lai, & Yeh, 2012; Claveria et al., 2015a; Claveria, Monte, & Torra, 2015b; Law, 2000; Pattie & Snyder, 1996; Teixeira & Fernandes, 2012).

Various ANN models, such as the multilayer perceptron (MLP), the radial basis function (RBF) and the Elman network, have been used in various empirical studies on tourism demand forecasting. The empirical results indicate that the ANN models tend to perform well when the quality of the time series data is questionable. Pattie and Snyder (1996) apply the neural network method to forecast the demand for tourism with reasonable success. After their study, other studies that compared the forecasting performance of neural networks and classical forecasting techniques began to appear in the late 1990s. These studies have compared the performance of ANNs versus that of the multivariate regression and time series models (Law & Au, 1999; Uysal & El Roubi, 1999). Kon and Turner (2005) confirm that the neural network methods can perform well for short-term forecasting, and this finding provides practical implications for emerging destinations with relatively shorter records of tourism demand under unstable tourism conditions.

More recent studies have found that traditional time series models may outperform ANNs in dealing with pre-processed data (in which the outliers are eliminated and the original series is smoothed) (Claveria & Torra, 2014). Experiments combining ANN models with traditional time series approaches have emerged as an important focus of tourism demand forecasting studies. For instance, Nor, Nurul, and Rusiman (2018) propose to combine the Box-Jenkins and ANN models, and Chen (2011) combines linear models (such as the Naïve, ES or ARIMA models) with nonlinear AI models (such as back-propagation neural networks or SVRs) to evaluate the models' turning points in forecasting performance.

SVRs have also frequently appeared in tourism demand forecasting studies. SVR approaches are proposed for use with genetic algorithms (GA) for the selection of the parameters in SVMs (support vector machines), thereby creating a hybrid approach known as the GA-SVR. This method was first proposed for tourism demand modelling and forecasting by Pai, Hong, Chang and Chen (2006) and by Chen and Wang (2007). Then, Hadavandi, Ghanbari, Shahanaghi, and Abbasian-Naghneh (2011) proposed a hybrid AI model of fuzzy rule-based systems, the genetic fuzzy system (GFS), which used GAs for the learning rule base and the tuning database of a fuzzy system. The GFS extracts useful patterns of tourist arrivals information with a descriptive rule induction approach. This proposed GFS model has been successfully used to forecast tourist arrivals to Taiwan from a number of source markets, including Hong Kong, the US and Germany.

In the broadest terms, Goh and Law (2011) divide AI-based tourism demand forecasting models into two categories: AI-based time series methods and AI-based casual methods. Examples of using the first type of these methods include the studies of grey theory-based fuzzy time series forecasting that are conducted by Wang (2004) and by Yu and Schwartz (2006). Parallel to those studies, Uysal and EI Roubi (1999) compare the forecasting performance of an ANN model to that of a multiple regression model with partial adjustment (e.g., with inclusion of a lagged dependent variable). These models are both applied to depict the relationships between Canadian tourist expenditure in the US and various influencing factors, such as the per capita income of Canadian tourists, the relative consumer price index between the US and Canada, the relative exchange rates between US and Canadian dollars and the seasonable dummies. The results show that the ANN model outperforms the partial adjustment regression model. Based on the determinants of tourism demand, Law (2000) presents a neural network model that incorporates the back-propagation learning process to forecast the nonlinearly separable tourist arrivals. The results show that the ANN outperforms the multiple regression models. Goh et al. (2008) apply the rough sets approach by incorporating two noneconomic variables, a leisure time index and a climate index into the traditional regression framework. Their results demonstrate that the rough sets method with non-economic variables outperforms the regression models with the same datasets in forecasting tourist arrivals from the UK and the US to Hong Kong. However, one observation from these studies is that the specific multiple regression models used do not apply the latest econometric advances (such as error correction and cointegration analysis) into their model specifications.

In an era of big data, changes in the knowledge system commonly emerge due to changes in the objects of knowledge. Big data (or Web data) has therefore become an important driving force in the development of AI-based forecasting models. The data used in traditional forecasting methods were often aggregated in nature, with time lags. The search engine data from sources such as Google Trends, Google Analytics and the Baidu Index have become new data sources for tourism demand forecasting (Li, Chen, Wang, & Ming, 2018). However, questions remain about the contributions and interpretations of the analytical results when such data-driven techniques are applied in our knowledge domain (Song & Liu, 2017). Many technical challenges remain, which need to be addressed in exploring better methodologies for data shrinkage. These methodologies need to be considered with a view to improving the forecasting performance of tourism demand models (Park et al., 2017) and to preventing the over-parameterisation of models using big data (Gunter & Önder, 2016).

*Judgmental methods*

Judgmental techniques are designed to provide a complete and definitive description of future developments by using the accumulated experience and insight of individual experts or groups of people. Lin and Song (2015) define judgmental forecasting as involving the techniques of 'asking' the experts, stakeholders and the public, plus using judgment-aided methods for developing scenarios. The use of Delphi techniques and scenario-building are the two most popular techniques used in tourism studies (Uysal & Crompton, 1985).

The Delphi model is a well-established judgmental method for long-term demand forecasting (Vanhove, 1980). The aim of this method is to generate debate and build consensus regarding the uncertainty in tourism demand, especially for cases in which our knowledge regarding the demand variables and their determinants is imperfect (Kaynak & Macaulay, 1984). As a unique method of eliciting and refining group judgment, the Delphi technique allows candid responses and indirect interactions between anonymous experts, while simultaneously exposing agreements and disagreements (Briedenhann & Butts, 2006). However, this collective judgment of experts involves subjective individual opinions, which are often biased. Therefore, this approach has been criticised for its difficulty in accuracy evaluation. As indicated by an early Delphi study by English and Kernan (1976), the dispersions used in estimating the values/occurrences of certain future events can be too high for delivering a reliable consensus.

During the 1970 s to 1990 s, the applications of speculative techniques using developments in computers or other technologies were regarded as critical changes of direction for research (Kaynak & Macaulay, 1984). The year 2000 is commonly seen as a psychologically important turning point in the use of expert panels (English & Kernan, 1976; Kaynak & Macaulay, 1984; Liu, 1988). Kaynak and Macaulay (1984) use the Delphi technique to gather data on tourism research, to assess the future impacts of tourism and to strengthen regional databases. The combination of all these functions is intended to provide an effective policy-making tool for solving management or planning problems in the tourism and hospitality fields. More recently, the Delphi technique has been applied to new research issues such as rural tourism planning, (Briedenhann & Butts, 2006), determining the indicators for sustainable tourism (Miller, 2001) and measuring the impacts of economic crises on the tourism and hospitality industry in China (Jones, Lee & Chon, 2011).

Moutinho and Witt (1995) propose a non-Delphi consensus forecasting approach for analysing selected scenarios through applying scientific and technological developments. This non-Delphi consensus method encourages the panel of experts to exchange and discuss their views as they seek to forecast the tourism environment. The methodological limitations of Delphi might be ameliorated through this group discussion approach, as it supports the clarification of reasoning regarding the futures envisioned by experts. This approach to scenario construction has been used in policy formulation and societal studies, and climate change has been one of the important factors embedded in the scenario studies. Yeoman et al. (2007) conceive two scenarios to better understand the impact of energy usage and climate change on the future of Scottish tourism. Peeters and Dubois (2010) show 70 scenarios that envisage improvements in energy efficiency through combining all possible technologies and strategies and four automated backcasting scenarios. Unlike the study of Peeters and Dubois (2010), the research by Yeoman et al. (2007) uses economic assumptions concerning the scenarios for both energy consumption and environmental pollution, especially with regard to the airline sector.

The study by Tideswell, Mules, and Faulkner (2001) applies the Delphi method along with several quantitative forecasting models. Since that study, a number of other studies involving judgmental forecasting have reflected the complementarity of an integrative approach. As tourism demand forecasting through the qualitative approach has been generally criticised for involving human bias, Frechtling (2001) suggests that the integration of the Delphi technique and quantitative methods could be very useful for achieving convergent validity. This suggestion is confirmed in recent research by Lin and Song (2015).

The judgmental approach helps to overcome the limitations of time series forecasts (Kaynak, Bloom & Leibold, 1994). Empirical studies are being conducted to revise the quantitative forecasts with Delphi adjustments for tourist arrivals forecasting (Edgell, Seely, & Iglarsh, 1980). Such studies also combine time series forecasts with Delphi surveys for more accurate results (Tideswell et al., 2001). Song, Gao, and Lin (2013) propose a tourism demand forecasting system with both quantitative and judgmental forecasting modules. In their study, scenario analysis and dynamic Delphi surveys by users and experts are applied to adjust the forecasts of the ADLM models.

## Rise and fade: competition, evolution and forecast accuracy

### *General trends in the tourism demand forecasting literature*

Fig. 2 summarises the applications of various models in the pool of key studies (left panel), and it counts the numbers of 'best performances' for each model (right panel). In our review, we consider that if a study uses more than one model without performing an accuracy comparison, then all of the utilised models are considered as the 'best performing' models in that study.

Our observations on the methodological developments over the past five decades indicate two general trends in tourism demand forecasting studies. First, the various forecasting methods can be divided into two broad categories, namely qualitative or quantitative approaches. Although the Delphi technique has made contributions in this area, the primary methodological developments in tourism demand forecasting have been in quantitative methods. The currently available quantitative approaches can be divided into three categories: non-causal time series models, causal econometric models and AI-based models. More recently, combined and hybrid models have emerged, and an increasing number of studies on such models have been published since 2010. In our review, the combined forecasting method is defined as an approach that generates a set of forecasts for the same demand variable by using different methods, and then combines these forecasts into one final, summarised forecast. A hybrid forecasting model involves a single model that integrates the features of two or more models.

The second general trend we observe concerns the chronological development of forecasting methods. During the 1960s and 1970s, the SR approach was dominant in tourism demand studies, which were mainly concerned with investigating the determinants of tourism demand. More forecasting models were applied in the tourism and hospitality field in the 1980s, as researchers sought to consider the time series structure of tourism demand data. In that decade, some scholars were still using SR models in their studies, and they paid considerable attention to the improvement of time series models (e.g., Naïve, AR, ES and trend analysis). In the 1990s, the applications of time series models continued to rise, but also models based on dynamic regressions grew more popular (e.g., the Box-Jenkins method with exogenous variables and the ADLM). New systems-based econometric models (e.g., STSM, VAR and AIDS) or AI-based models also emerged. In the 2000s this trend continued, with a flourishing of development for econometric models, AI-based models and combined or hybrid methods.

The two decades between 1990 and 2009 were a time when researchers proposed diverse methods of tourism demand forecasting. They discovered numerous 'shining' features of various methods, which they sought to combine for improved results. Since 2010, the advanced time series and econometric models have been dominant in the tourism demand forecasting literature. However, the combined models and AI-based models have been making great strides in terms of methodological development. AI-based methods

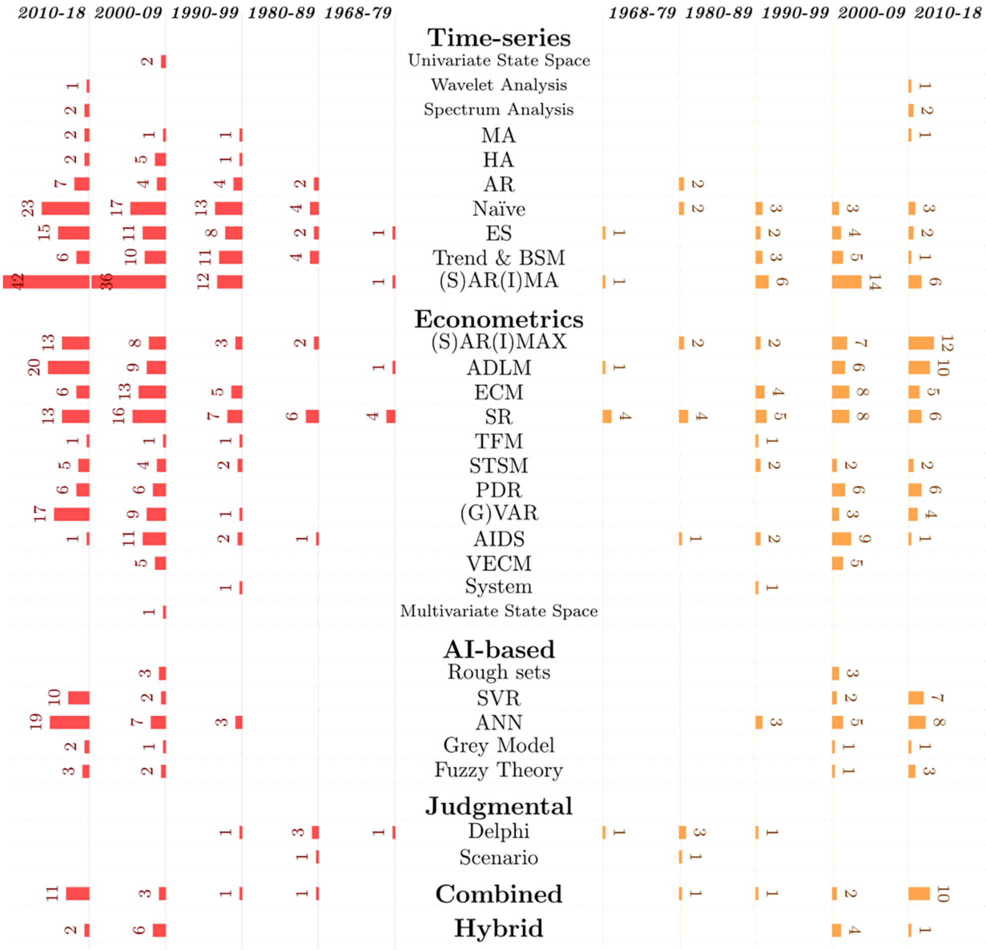


**Fig. 2.** Method-performance profile (1968–2018).

have been widely applied, and subsequently the combined or hybrid approaches of mixing AI with other quantitative models have improved the accuracy of forecasts. Recently developed approaches in econometrics (such as the MIDAS method) are also being introduced in tourism demand analysis and forecasting.

Currently, the use of Internet data in tourism forecasting is another driving factor in the development of forecasting methods. The Internet provides an enormous amount of information for tourism demand analysis, and this inspires researchers to explore new data sources such as Google Trends or Baidu Index for tourism demand modelling and forecasting. Data selection and shrinkage methods are also being developed. One of the best examples of such improvement in tourism demand forecasting is the least absolute shrinkage and selection operator (LASSO) and factor model (Song & Liu, 2017). Various time series models, augmented by Google data or other Internet data as exogenous variables, have appeared in the published studies of tourism forecasting. Various optimisation algorithms for using multidimensional tourism information data have been proposed and combined with neural network models (Li, Chen et al., 2018).

Song and Li (2008) indicated in their review that no model can universally outperform all others in terms of forecasting accuracy. This inconclusive result is also reflected in Athanasopoulos et al., (2011) and Gunter and Önder (2015). As a result, efforts have been made to include more models in tourism demand forecasting comparison overtime. The review of the tourism forecasting studies suggests that on average, 2.5 models were considered in each study since 1990, whereas those numbers were just 1.9 before the 1990s and 1.1 before the 1980s. Nonetheless, it should be noted that the comparisons of forecasting methods usually involve only a few subjectively selected models. Therefore, the conclusions drawn from such comparisons, as noted by Song and Li (2008, p. 213), 'are subject to very specific conditions'.

*Combination and hybrid models*

The ambiguity of performance in previous models has called forth an emerging trend of using combined and hybrid models for tourism demand forecasting. In their pioneering study of forecast combination in the tourism field, Fritz, Brandon, and Xander (1984, p. 221) emphasise that 'the combination of several competing forecasts can reduce the errors and achieve improvement in overall accuracy'. In our pool of key studies, 24 of them fall into this category. Of these, 17 investigate forecast combination models and 7 involve the use of hybrid models. Although the first combined forecast was performed quite early (Fritz et al., 1984), the majority of combined and hybrid forecast studies have been conducted since the late 2000s. Out of the 24 selected studies performed to date, 21 of them found that the combined or hybrid forecast models outperformed other forecasting techniques. In the future, we expect that the combined and hybrid forecasting models will further develop and play an increasingly significant role in the forecasting of tourism demand.

The forecasts from individual models can also be combined in various ways, including the use of average-based methods, forecast error-based weightings and regression-based integrations. The average-based methods use Pythagorean (arithmetic, geometric or harmonic) means to combine individual forecasts. This type of combination method is easy to apply, and the weights attached to individual forecasts are irrelevant to the forecasting models (Coshall & Charlesworth, 2011; Wong et al., 2007). Forecasting error-based methods follow the suggestions made by Bates and Granger (1969), and they give more weight to the better-performing forecasting models, which have fewer out-of-sample errors than the worse-performing models (Coshall, 2009; Fritz et al., 1984). Regression-based methods consider individual forecasts as input variables, and they perform linear or non-linear regressions to fit the actual values (Cang, 2014; Shen, Li, & Song, 2011). Forecast combinations can also be conducted hierarchically, by performing adjustments after an initial forecast (Chen, 2011; Song et al., 2013). The individual forecasts being combined are usually generated by different methods. However, it has been confirmed that combining forecasts from the same model family can also increase the stability of the variable and lag selection process. In an investigation of international tourism demand for Australia, Athanasopoulos et al. (2018) show that the bootstrap aggregating of ADLM forecasts can significantly improve forecasting accuracy. In addition to the studies on various approaches in combining the individual models, some researchers also examined which set of individual models should be included in the forecasts combination (Chen, 2011; Coshall & Charlesworth, 2011).

*The rise and fade of forecasting techniques*

Throughout the 50 years of development in tourism demand forecasting, some methods have faded from use gradually, and others have been used increasingly often. Among the 21 tourism demand studies from before 1990 that are included in our pool of key studies, 5 adopted a judgmental forecast method. As stated in the previous sections, expert opinion can be a good basis for forecasting when historical demand data are unavailable. However, due to the improvements in data quality and computational power, statistical techniques have become predominant in tourism demand forecasting research nowadays. Indeed, it is much easier for the experts to predict the occurrence of a particular event or the direction of change than to predict the specific volume of tourism demand and expenditure. Therefore, instead of adopting judgmental forecast methods alone, recent studies have found that the integration of experts' opinions with statistical techniques can provide outstanding forecast accuracy (Lee, Song & Mjelde, 2008; Song et al., 2013).

In contrast with the decline of judgmental forecasting, AI-based models have gained increasing popularity. This approach has shown extraordinary capability for handling big data, and AI-based models are proven to have superior accuracy in predicting tourism demand volumes. However, due to the lack of a theoretical foundation in economic and human behaviour, it is easier for AI-based models to answer the question 'What has happened?' than to answer the question 'Why has it happened?'. To answer the second question, researchers are still primarily reliant on econometric-based techniques. The integration of econometric models and AI-based techniques is potentially beneficial for the field of tourism demand modelling and forecasting.

Another interesting trend can be observed in the comparative studies to identify 'best performing' models. These studies, over time, show a rise and fade of system forecasts. In particular, 11 studies in our sample adopted AIDS between 2000 and 2009, whereas only 1 such paper appeared since then. Two practical reasons are postulated in regard to this phenomenon. First, as the literature on demand systems is well developed, and as such systems involve multiple parts working simultaneously, it is difficult to improve the forecasting models methodologically. Therefore, the main research interest is attracted towards other 'promising' directions. Second, as system forecasts consist of multiple demand equations with multiple variables and potentially multiple lags, a fully specified system of equations usually involves a large number of parameters to be estimated. The requirements for data quality and quantity are therefore high, and the forecasting accuracy can be jeopardised as a result. Nonetheless, with the recent development in computational science and big data, the use of system forecasting models may experience another rising tide, possibly in combination with other data driven methods such as AI-based techniques.

Until the present, the main focus of the tourism demand literature has remained on time series and econometric models. The models showing the best performances have shifted through the decades with new developments. In the 1980s, most researchers concentrated their attention on either univariate dynamic (time series) methods (4 papers) or multivariate static (static regression) models (4 papers). No clear concentration can be observed for the studies done in the 1990s, as the tourism demand field came into an era of contending models. Between 2000 and 2009, multiple equation forecasts received increasing attention, and this approach commonly outperformed older methods. Approaches involving AIDS, PDR, VECM, VAR and STSM were each found to outperform other studied models (in 9, 6, 5, 3 and 2 papers, respectively). The AI-based technique also emerged as a new approach to tourism demand forecasting (12 studies), and advanced time series methods dominated the field (with 27 studies proposing the Box-Jenkins method and its variates as the best performing). After 2010, univariate time series methods faded from use. Among the 83 papers selected from this period, only 11 found that univariate time series methods outperformed other forecasting techniques. Instead, multivariate dynamic models emerged as the most favoured, with a growing emphasis on either the 'dynamic' models (i.e., the Box-Jenkins methods with exogenous variables) or the 'multivariate' approach, as in the ADLM.

*Data, parameter and estimation*

Although the earlier trends primarily related to changes in the functional forms of tourism demand modelling, some of the more recent advances have mainly concerned data utilisation, parameterisation and estimation. MIDAS enables forecasting based on mixed-frequency data, and this approach is confirmed to provide improvements in forecasting accuracy (Bangwayo-Skeete & Skeete, 2015). TVPs can capture the structural changes in time dimensions, and such parameters are proven to work well with the AIDS (Li, Song, et al., 2006), STSM (Song, Li, Witt & Athanasopoulos, 2011) and SR models (Song, Witt & Jensen, 2003). Similarly, other types of varying parameters, such as the sign-dependent varying parameter (Smeral & Song, 2015) or the state-varying parameter (Pan & Yang, 2017) are helpful in modelling regime shifts. Bayesian estimations are also found to show promise for improving forecasting accuracy, as these estimations incorporate informative precedents into the tourism demand forecasting models (Assaf et al., 2018; Wong et al., 2006).

## Conclusions

Tourism demand forecasting methods have been evolving over the past five decades. In the drive to achieve superior forecasting accuracy, researchers have carried out forecasting competitions, tested combined forecasts that were generated by various models and developed new forecasting/estimation methods. In reviewing 211 key studies on tourism demand modelling and forecasting, this study summarises the general trends of development among four categories of forecasting methods. The interconnections between the two most frequently used model classes – the non-causal time series models and the causal econometric models – are the focus of this review. Due to the inconsistency in forecasting performance and the limited explanatory power of the non-causal time series models, researchers in tourism forecasting have increasingly turned to using extensions of the time series models that incorporated exogenous variables and multivariate dimensions. Advanced time-varying parameter techniques have gained popularity, as these methods reflect the possibility of structural changes through time. The increasingly superior performances of combination and hybrid models prove that these combined forecasts cannot be less accurate than either of their constituent forecasts (Calantone, Di Benedetto & Bojanic, 1988). Moreover, judgmental methods are increasingly used to enhance the accuracy of the quantitative forecasting models.

In response to the growing importance of combination and hybrid models, more developments and scientific applications of these models are expected. The development of AI-based models is notable in the most recent tourism demand forecasting studies, despite the theoretical and technological limitations of these methods. Several empirical studies show that AI-based methods outperform their time series and econometric counterparts that are based on big data analytics. The combinations of neural network and counterpart models have also demonstrated superior performance. The combination techniques, especially those that involve the selection of forecasting combination weighting schemes, need to be thoroughly explored and evaluated in future studies.

Considerable efforts have been made by tourism forecasting researchers to generalise their econometric models, with a view to fostering better understanding about the determinants of current and future demands for tourism through using aggregate data (at the destination and source market levels). However, empirical evidence has suggested that forecasting accuracies vary across destination and source market pairs. International flows of people, cross-border employment, cultural difference, globalisation or disglobalisation movements and shifts in environmental sustainability have all made tourism decision-making a more complex process, especially in terms of international travel. The use of aggregated data may cause model mis-specifications in depicting the tourism decision-making process (Masiero, 2016). For this reason, the methods of forecasting international tourism demand require more meticulous attention to discerning the indicators of tourism demand through applications of disaggregated or micro-data, and to comprehensive analyses of many geographical, social, political and environmental factors.

Although the utilisation of big data in tourism forecasting is still in its infancy stage, the potential of big data for forecasting accuracy improvement is huge. However, the challenges faced by tourism forecasters include: firstly, developing new modelling and forecasting techniques and estimation methods in handling the traditional time series and high frequency big data simultaneously; secondly, framing the forecasting research questions with the existing and new consumer behavior theories with a view to better capitalising the tourism big data instead of just focusing mainly on data mining; and lastly, drawing researchers from different fields, such as computing and engineering, who may provide better solutions to computation cost reduction and forecasting efficiency in tourism.

This overall review of the developments in forecasting methods over the past five decades serves the important purpose of suggesting beneficial directions for future research. However, the subjectivity involved in selecting our pool of 211 key studies may be seen as a limitation of this study. This review primarily focuses on tracing the development of forecasting methods. The tasks of identifying the determinants of tourism demand, isolating the factors affecting demand elasticity, and estimating the effects of intervening events on different scenarios have been largely ignored, due to the constraints of space.

## Statement of Contribution

The main contribution of this study is a comprehensive review of method development and evolution in tourism demand forecasting studies during the past five decades (1960s–2018). This extensive review covers a wide range of methods from judgmental approach to different quantitative methods, such as time series, econometric, and artificial intelligence based models.

This review article adopts a social science perspective in terms of data collection and analysis. In addition, tourism demand modeling and forecasting is an important topic of tourism economics, which is widely recognized as a social science discipline.

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## References

Akal, M. (2004). Forecasting Turkey's tourism revenues by ARMAX model. *Tourism Management, 25*(5), 565–580.
Akın, M. (2015). A novel approach to model selection in tourism demand modeling. *Tourism Management, 48*, 64–72.
Akis, S. (1998). A compact econometric model of tourism demand for Turkey. *Tourism Management, 19*(1), 99–102.
Andrawis, R. R., Atiya, A. F., & El-Shishiny, H. (2011). Combination of long term and short term forecasts, with application to tourism demand forecasting. *International Journal of Forecasting, 27*(3), 870–886.
Artus, J. R. (1972). An econometric analysis of international travel. *IMF Staff Papers, 19*(3), 579–614.
Aslanargun, A., Mammadov, M., Yazici, B., & Yolacan, S. (2007). Comparison of ARIMA, neural networks and hybrid models in time series: Tourist arrival forecasting. *Journal of Statistical Computation and Simulation, 77*(1), 29–53.
Assaf, A. G., Barros, C. P., & Gil-Alana, L. A. (2011). Persistence in the short-and long-term tourist arrivals to Australia. *Journal of Travel Research, 50*(2), 213–229.
Assaf, A. G., Li, G., Song, H., & Tsionas, M. G. (2018). Modeling and forecasting regional tourism demand using the Bayesian global vector autoregressive (BGVAR) model. *Journal of Travel Research*. https://doi.org/10.1177/0047287518759226.
Athanasopoulos, G., Ahmed, R. A., & Hyndman, R. J. (2009). Hierarchical forecasts for Australian domestic tourism. *International Journal of Forecasting, 25*(1), 146–166.
Athanasopoulos, G., & Hyndman, R. J. (2008). Modelling and forecasting Australian domestic tourism. *Tourism Management, 29*(1), 19–31.
Athanasopoulos, G., Hyndman, R. J., Song, H., & Wu, D. C. (2011). The tourism forecasting competition. *International Journal of Forecasting, 27*(3), 822–844.
Athanasopoulos, G., Song, H., & Sun, J. A. (2018). Bagging in tourism demand modeling and forecasting. *Journal of Travel Research, 57*(1), 52–68.
Balli, F., Balli, H. O., & Louis, R. J. (2016). The impacts of immigrants and institutions on bilateral tourism flows. *Tourism Management, 52*, 221–229.
Balli, F., Shahzad, S. J. H., & Uddin, G. S. (2018). A tale of two shocks: What do we learn from the impacts of economic policy uncertainties on tourism? *Tourism Management, 68*, 470–475.
Bangwayo-Skeete, P. F., & Skeete, R. W. (2015). Can Google data improve the forecasting performance of tourist arrivals? Mixed-data sampling approach. *Tourism Management, 46*, 454–464.
Barry, K., & O'Hagan, J. (1972). An econometric study of British tourist expenditure in Ireland. *Economic and Social Review, 3*(2), 143.
Bates, J. M., & Granger, C. W. (1969). The combination of forecasts. *Journal of the Operational Research Society, 20*(4), 451–468.
Blake, A., Durbarry, R., Eugenio-Martin, J. L., Gooroochurn, N., Hay, B., Lennon, J., ... Yeoman, I. (2006). Integrating forecasting and CGE models: The case of tourism in Scotland. *Tourism Management, 27*(2), 292–305.
Blunk, S. S., Clark, D. E., & McGibany, J. M. (2006). Evaluating the long-run impacts of the 9/11 terrorist attacks on US domestic airline travel. *Applied Economics, 38*(4), 363–370.
Bonham, C., Edmonds, C., & Mak, J. (2006). The impact of 9/11 and other terrible global events on tourism in the United States and Hawaii. *Journal of Travel Research, 45*(1), 99–110.
Bonham, C., Gangnes, B., & Zhou, T. (2009). Modeling tourism: A fully identified VECM approach. *International Journal of Forecasting, 25*(3), 531–549.
Box, G. E. P., & Jenkins, G. M. (1976). *Time series analysis: Forecasting and control.* San Francisco: Holden-Day.
Briedenhann, J., & Butts, S. (2006). Application of the Delphi technique to rural tourism project evaluation. *Current Issues in Tourism, 9*(2), 171–190.
Burger, C., Dohnal, M., Kathrada, M., & Law, R. (2001). A practitioners guide to time-series methods for tourism demand forecasting—A case study of Durban, South Africa. *Tourism Management, 22*(4), 403–409.
Calantone, R. J., Di Benedetto, A., & Bojanic, D. C. (1988). Multimethod forecasts for tourism analysis. *Annals of Tourism Research, 15*(3), 387–406.
Cang, S. (2014). A comparative analysis of three types of tourism demand forecasting models: Individual, linear combination and non-linear combination. *International Journal of Tourism Research, 16*(6), 596–607.
Cang, S., & Yu, H. (2014). A combination selection algorithm on forecasting. *European Journal of Operational Research, 234*(1), 127–139.
Carson, R. T., Cenesizoglu, T., & Parker, R. (2011). Forecasting (aggregate) demand for US commercial air travel. *International Journal of Forecasting, 27*(3), 923–941.
Cesario, F. J., & Knetsch, J. L. (1976). A recreation site demand and benefit estimation model. *Regional Studies, 10*(1), 97–104.
Chan, F., Lim, C., & McAleer, M. (2005). Modelling multivariate international tourism demand and volatility. *Tourism Management, 26*(3), 459–471.
Chan, Y. M. (1993). Forecasting tourism: A sine wave time series regression approach. *Journal of Travel Research, 32*(2), 58–60.
Chen, C. F., Lai, M. C., & Yeh, C. C. (2012). Forecasting tourism demand based on empirical mode decomposition and neural network. *Knowledge-Based Systems, 26*, 281–287.
Chen, K. Y. (2011). Combining linear and nonlinear model in forecasting tourism demand. *Expert Systems with Applications, 38*(8), 10368–10376.
Chen, K. Y., & Wang, C. H. (2007). Support vector regression with genetic algorithms in forecasting tourism demand. *Tourism Management, 28*(1), 215–226.
Chen, R., Liang, C. Y., Hong, W. C., & Gu, D. X. (2015). Forecasting holiday daily tourist flow based on seasonal support vector regression with adaptive genetic algorithm. *Applied Soft Computing, 26*, 435–443.
Chen, R. J., Bloomfield, P., & Fu, J. S. (2003). An evaluation of alternative forecasting methods to recreation visitation. *Journal of Leisure Research, 35*(4), 441–454.
Cho, V. (2001). Tourism forecasting and its relationship with leading economic indicators. *Journal of Hospitality & Tourism Research, 25*(4), 399–420.
Cho, V. (2003). A comparison of three different approaches to tourist arrival forecasting. *Tourism Management, 24*(3), 323–330.
Choi, H., & Varian, H. (2012). Predicting the present with Google Trends. *Economic Record, 88*, 2–9.
Chu, F. L. (1998a). Forecasting tourism demand in Asian-Pacific countries. *Annals of Tourism Research, 25*(3), 597–615.
Chu, F. L. (1998b). Forecasting tourism: A combined approach. *Tourism Management, 19*(6), 515–520.
Chu, F. L. (2004). Forecasting tourism demand: A cubic polynomial approach. *Tourism Management, 25*(2), 209–218.
Chu, F. L. (2008). A fractionally integrated autoregressive moving average approach to forecasting tourism demand. *Tourism Management, 29*(1), 79–88.
Chu, F. L. (2009). Forecasting tourism demand with ARMA-based methods. *Tourism Management, 30*(5), 740–751.
Chu, F. L. (2011). A piecewise linear approach to modeling and forecasting demand for Macau tourism. *Tourism Management, 32*(6), 1414–1420.
Claveria, O., Monte, E., & Torra, S. (2015a). A new forecasting approach for the hospitality industry. *International Journal of Contemporary Hospitality Management, 27*(7), 1520–1538.
Claveria, O., Monte, E., & Torra, S. (2015b). Tourism demand forecasting with neural network models: Different ways of treating information. *International Journal of Tourism Research, 17*(5), 492–500.
Claveria, O., & Torra, S. (2014). Forecasting tourism demand to Catalonia: Neural networks vs. time series models. *Economic Modelling, 36*, 220–228.
Clewer, A., Pack, A., & Sinclair, M. T. (1990). Forecasting models for tourism demand in city dominated and coastal areas. *Papers in Regional Science, 69*(1), 31–42.
Coshall, J. T. (2009). Combining volatility and smoothing forecasts of UK demand for international tourism. *Tourism Management, 30*(4), 495–511.
Coshall, J. T., & Charlesworth, R. (2011). A management orientated approach to combination forecasting of tourism demand. *Tourism Management, 32*(4), 759–769.
Croes, R. R., & Vanegas, M., Sr (2005). An econometric study of tourist arrivals in Aruba and its implications. *Tourism Management, 26*(6), 879–890.
Crouch, G. I. (1994). The study of international tourism demand: A survey of practice. *Journal of Travel Research, 32*(4), 41–55.
De Mello, M., Pack, A., & Sinclair, M. T. (2002). A system of equations model of UK tourism demand in neighbouring countries. *Applied Economics, 34*(4), 509–521.
Deaton, A., & Muellbauer, J. (1980). An almost ideal demand system. *The American Economic Review, 70*(3), 312–326.
Dergiades, T., Mavragani, E., & Pan, B. (2018). Google Trends and tourists' arrivals: Emerging biases and proposed corrections. *Tourism Management, 66*, 108–120.

Dharmaratne, G. S. (1995). Forecasting tourist arrivals in Barbados. *Annals of Tourism Research, 22*(4), 804–818.
Díaz, M.Á., & Nadal, J. R. (2010). Forecasting British tourist arrivals in the Balearic Islands using meteorological variables. *Tourism Economics, 16*(1), 153–168.
Díaz, M.Á., & Sbert, J. M. (2011). Forecasting daily air arrivals in Mallorca Island using nearest neighbour methods. *Tourism Economics, 17*(1), 191–208.
Divisekera, S. (2003). A model of demand for international tourism. *Annals of Tourism Research, 30*(1), 31–49.
Dogru, T., Sirakaya-Turk, E., & Crouch, G. I. (2017). Remodeling international tourism demand: Old theory and new evidence. *Tourism Management, 60*, 47–55.
Dritsakis, N. (2004). Cointegration analysis of German and British tourism demand for Greece. *Tourism Management, 25*(1), 111–119.
Du Preez, J., & Witt, S. F. (2003). Univariate versus multivariate time series forecasting: An application to international tourism demand. *International Journal of Forecasting, 19*(3), 435–451.
Durbarry, R., & Sinclair, M. T. (2003). Market shares analysis: The case of French tourism demand. *Annals of Tourism Research, 30*(4), 927–941.
Edgell, D. L., Seely, R. L., & Iglarsh, H. J. (1980). Forecasts of international tourism to the USA. *International Journal of Tourism Management, 1*(2), 109–113.
Ellis, J. B., & Doren, C. S. (1966). A comparative evaluation of gravity and system theory models for statewide recreational traffic flows. *Journal of Regional Science, 6*(2), 57–70.
English, J. M., & Kernan, G. L. (1976). The prediction of air travel and aircraft technology to the year 2000 using the Delphi method. *Transportation Research, 10*(1), 1–8.
Fildes, R., Wei, Y., & Ismail, S. (2011). Evaluating the forecasting performance of econometric models of air passenger traffic flows using multiple error measures. *International Journal of Forecasting, 27*(3), 902–922.
Fotheringham, A. S. (1983). A new set of spatial-interaction models: The theory of competing destinations. *Environment and Planning A: Economy and Space, 15*(1), 15–36.
Frechtling, D. C. (2001). *Forecasting tourism demand: Methods and strategies.* Oxford: Butterworth-Heinemann.
Fritz, R. G., Brandon, C., & Xander, J. (1984). Combining time-series and econometric forecast of tourism activity. *Annals of Tourism Research, 11*(2), 219–229.
Fujii, E. T., & Mak, J. (1981). Forecasting tourism demand: Some methodological issues. *The Annals of Regional Science, 15*(2), 72–82.
Garcia-Ferrer, A., & Queralt, R. A. (1997). A note on forecasting international tourism demand in Spain. *International Journal of Forecasting, 13*(4), 539–549.
Garin-Munoz, T. (2006). Inbound international tourism to Canary Islands: A dynamic panel data model. *Tourism Management, 27*(2), 281–291.
Garin-Munoz, T. (2007). German demand for tourism in Spain. *Tourism Management, 28*(1), 12–22.
Garin-Munoz, T., & Amaral, T. P. (2000). An econometric model for international tourism flows to Spain. *Applied Economics Letters, 7*(8), 525–529.
Garin-Munoz, T., & Montero-Martín, L. F. (2007). Tourism in the Balearic Islands: A dynamic model for international demand using panel data. *Tourism Management, 28*(5), 1224–1235.
Geurts, M. D., & Ibrahim, I. (1975). Comparing the Box-Jenkins approach with the exponentially smoothed forecasting model application to Hawaii tourists. *Journal of Marketing Research, 12*(2), 182–188.
Gil-Alana, L. A. (2010). International arrivals in the Canary Islands: Persistence, long memory, seasonality and other implicit dynamics. *Tourism Economics, 16*(2), 287–302.
Gil-Alana, L. A., De Gracia, F. P., & Cuñado, J. (2004). Seasonal fractional integration in the Spanish tourism quarterly time series. *Journal of Travel Research, 42*(4), 408–414.
Goh, C. (2012). Exploring impact of climate on tourism demand. *Annals of Tourism Research, 39*(4), 1859–1883.
Goh, C., & Law, R. (2002). Modeling and forecasting tourism demand for arrivals with stochastic nonstationary seasonality and intervention. *Tourism Management, 23*(5), 499–510.
Goh, C., & Law, R. (2003). Incorporating the rough sets theory into travel demand analysis. *Tourism Management, 24*(5), 511–517.
Goh, C., & Law, R. (2011). The methodological progress of tourism demand forecasting: A review of related literature. *Journal of Travel & Tourism Marketing, 28*(3), 296–317.
Goh, C., Law, R., & Mok, H. M. (2008). Analyzing and forecasting tourism demand: A rough sets approach. *Journal of Travel Research, 46*(3), 327–338.
Gonzalez, P., & Moral, P. (1995). An analysis of the international tourism demand in Spain. *International Journal of Forecasting, 11*(2), 233–251.
Gonzalez, P., & Moral, P. (1996). Analysis of tourism trends in Spain. *Annals of Tourism Research, 23*(4), 739–754.
Gounopoulos, D., Petmezas, D., & Santamaria, D. (2012). Forecasting tourist arrivals in Greece and the impact of macroeconomic shocks from the countries of tourists' origin. *Annals of Tourism Research, 39*(2), 641–666.
Gray, H. P. (1966). The demand for international travel by the United States and Canada. *International Economic Review, 7*(1), 83–92.
Greenidge, K. (2001). Forecasting tourism demand: An STM approach. *Annals of Tourism Research, 28*(1), 98–112.
Guizzardi, A., & Mazzocchi, M. (2010). Tourism demand for Italy and the business cycle. *Tourism Management, 31*(3), 367–377.
Guizzardi, A., & Stacchini, A. (2015). Real-time forecasting regional tourism with business sentiment surveys. *Tourism Management, 47*, 213–223.
Gunter, U., & Önder, I. (2015). Forecasting international city tourism demand for Paris: Accuracy of uni- and multivariate models employing monthly data. *Tourism Management, 46*, 123–135.
Gunter, U., & Önder, I. (2016). Forecasting city arrivals with Google Analytics. *Annals of Tourism Research, 61*, 199–212.
Guthrie, H. W. (1961). Demand for tourists' goods and services in a world market. *Papers in Regional Science, 7*(1), 159–175.
Hadavandi, E., Ghanbari, A., Shahanaghi, K., & Abbasian-Naghneh, S. (2011). Tourist arrival forecasting by evolutionary fuzzy systems. *Tourism Management, 32*(5), 1196–1203.
Hamilton, J. M., Maddison, D. J., & Tol, R. S. (2005). Climate change and international tourism: A simulation study. *Global Environmental Change, 15*(3), 253–266.
Han, Z., Durbarry, R., & Sinclair, M. T. (2006). Modelling US tourism demand for European Destinations. *Tourism Management, 27*(1), 1–10.
Hassani, H., Silva, E. S., Antonakakis, N., Filis, G., & Gupta, R. (2017). Forecasting accuracy evaluation of tourist arrivals. *Annals of Tourism Research, 63*, 112–127.
Hassani, H., Webster, A., Silva, E. S., & Heravi, S. (2015). Forecasting US tourist arrivals using optimal singular spectrum analysis. *Tourism Management, 46*, 322–335.
Hendry, D. F. (1995). *Dynamic econometrics.* New York: Oxford University Press.
Hong, W. C., Dong, Y., Chen, L. Y., & Wei, S. Y. (2011). SVR with hybrid chaotic genetic algorithms for tourism demand forecasting. *Applied Soft Computing, 11*(2), 1881–1890.
Hu, Y. C., Jiang, P., & Lee, P. C. (2018). Forecasting tourism demand by incorporating neural networks into Grey–Markov models. *Journal of the Operational Research Society*. https://doi.org/10.1080/01605682.2017.1418150.
Huang, J. H., & Min, J. C. (2002). Earthquake devastation and recovery in tourism: The Taiwan case. *Tourism Management, 23*(2), 145–154.
Jackman, M., & Greenidge, K. (2010). Modelling and forecasting tourist flows to Barbados using structural time series models. *Tourism and Hospitality Research, 10*(1), 1–13.
Jones, D. L., Lee, A., & Chon, K. (2011). Future issues in sales, marketing, and revenue management in Greater China: What keeps you up at night? *Journal of Travel & Tourism Marketing, 28*(6), 598–614.
Kaynak, E., Bloom, J., & Leibold, M. (1994). Using the Delphi technique to predict future tourism potential. *Marketing Intelligence & Planning, 12*(7), 18–29.
Kaynak, E., & Macaulay, J. A. (1984). The Delphi technique in the measurement of tourism market potential: The case of Nova Scotia. *Tourism Management, 5*(2), 87–101.
Keintz, R. M. (1968). A study of the demand for international travel to and from the United States. *Travel Research Bulletin, 7*(1), 6–10.
Khadaroo, J., & Seetanah, B. (2008). The role of transport infrastructure in international tourism development: A gravity model approach. *Tourism Management, 29*(5), 831–840.
Kim, J. H. (1999). Forecasting monthly tourist departures from Australia. *Tourism Economics, 5*(3), 277–291.
Kim, S., & Song, H. (1998). Analysis of inbound tourism demand in South Korea: A cointegration and error correction approach. *Tourism Analysis, 3*(1), 25–41.
Kim, Y., & Uysal, M. (1998). Time-dependent analysis for international hotel demand in Seoul. *Tourism Economics, 4*(3), 253–263.
Koc, E., & Altinay, G. (2007). An analysis of seasonality in monthly per person tourist spending in Turkish inbound tourism from a market segmentation perspective. *Tourism Management, 28*(1), 227–237.

Kon, S. C., & Turner, L. W. (2005). Neural network forecasting of tourism demand. *Tourism Economics, 11*(3), 301–328.
Kulendran, N. (1996). Modelling quarterly tourist flows to Australia using cointegration analysis. *Tourism Economics, 2*(3), 203–222.
Kulendran, N., & King, M. L. (1997). Forecasting international quarterly tourist flows using error-correction and time-series models. *International Journal of Forecasting, 13*(3), 319–327.
Kulendran, N., & Witt, S. F. (2001). Cointegration versus least squares regression. *Annals of Tourism Research, 28*(2), 291–311.
Kulendran, N., & Witt, S. F. (2003a). Forecasting the demand for international business tourism. *Journal of Travel Research, 41*(3), 265–271.
Kulendran, N., & Witt, S. F. (2003b). Leading indicator tourism forecasts. *Tourism Management, 24*(5), 503–510.
Kulendran, N., & Wong, K. K. (2005). Modeling seasonality in tourism forecasting. *Journal of Travel Research, 44*(2), 163–170.
Laber, G. (1969). Determinants of international travel between Canada and the United States. *Geographical Analysis, 1*(4), 329–336.
Lanza, A., Temple, P., & Urga, G. (2003). The implications of tourism specialisation in the long run: An econometric analysis for 13 OECD economies. *Tourism Management, 24*(3), 315–321.
Law, R. (2000). Back-propagation learning in improving the accuracy of neural network-based tourism demand forecasting. *Tourism Management, 21*(4), 331–340.
Law, R., & Au, N. (1999). A neural network model to forecast Japanese demand for travel to Hong Kong. *Tourism Management, 20*(1), 89–97.
Law, R., & Au, N. (2000). Relationship modeling in tourism shopping: A decision rules induction approach. *Tourism Management, 21*(3), 241–249.
Lee, C. K., Song, H. J., & Mjelde, J. W. (2008). The forecasting of International Expo tourism using quantitative and qualitative techniques. *Tourism Management, 29*(6), 1084–1098.
Lee, M. (2018). Modeling and forecasting hotel room demand based on advance booking information. *Tourism Management, 66*, 62–71.
Li, G., Song, H., & Witt, S. F. (2004). Modeling tourism demand: A dynamic linear AIDS approach. *Journal of Travel Research, 43*(2), 141–150.
Li, G., Song, H., & Witt, S. F. (2005). Recent developments in econometric modeling and forecasting. *Journal of Travel Research, 44*(1), 82–99.
Li, G., Song, H., & Witt, S. F. (2006). Time varying parameter and fixed parameter linear AIDS: An application to tourism demand forecasting. *International Journal of Forecasting, 22*(1), 57–71.
Li, G., Wong, K. K., Song, H., & Witt, S. F. (2006). Tourism demand forecasting: A time varying parameter error correction model. *Journal of Travel Research, 45*(2), 175–185.
Li, H., Goh, C., Hung, K., & Chen, J. L. (2018). Relative climate index and its effect on seasonal tourism demand. *Journal of Travel Research, 57*(2), 178–192.
Li, S., Chen, T., Wang, L., & Ming, C. (2018). Effective tourist volume forecasting supported by PCA and improved BPNN using Baidu index. *Tourism Management, 68*, 116–126.
Li, X., Pan, B., Law, R., & Huang, X. (2017). Forecasting tourism demand with composite search index. *Tourism Management, 59*, 57–66.
Lim, C. (2004). The major determinants of Korean outbound travel to Australia. *Mathematics and Computers in Simulation, 64*(3–4), 477–485.
Lim, C. (2006). A survey of tourism demand modelling practice: Issues and implications. In L. Dwyer, & P. Forsyth (Eds.). *International handbook on the economics of tourism* (pp. 45–72). Cheltenham: Edward Elgar Publishing.
Lim, C., & McAleer, M. (2000). A seasonal analysis of Asian tourist arrivals to Australia. *Applied Economics, 32*(4), 499–509.
Lim, C., & McAleer, M. (2001a). Cointegration analysis of quarterly tourism demand by Hong Kong and Singapore for Australia. *Applied Economics, 33*(12), 1599–1619.
Lim, C., & McAleer, M. (2001b). Forecasting tourist arrivals. *Annals of Tourism Research, 28*(4), 965–977.
Lim, C., & McAleer, M. (2001c). Monthly seasonal variations: Asian tourism to Australia. *Annals of Tourism Research, 28*(1), 68–82.
Lim, C., & McAleer, M. (2002). Time series forecasts of international travel demand for Australia. *Tourism Management, 23*(4), 389–396.
Lin, K. P., Pai, P. F., Lu, Y. M., & Chang, P. T. (2013). Revenue forecasting using a least-squares support vector regression model in a fuzzy environment. *Information Sciences, 220*, 196–209.
Lin, S. J., Chen, J. Y., & Liao, Z. X. (2018). A EMD-BP integrated model to forecast tourist number and applied to Jiuzhaigou. *Journal of Intelligent & Fuzzy Systems, 34*(2), 1045–1052.
Lin, V. S., Liu, A., & Song, H. (2015). Modeling and forecasting Chinese outbound tourism: An econometric approach. *Journal of Travel & Tourism Marketing, 32*(1–2), 34–49.
Lin, V. S., & Song, H. (2015). A review of Delphi forecasting research in tourism. *Current Issues in Tourism, 18*(12), 1099–1131.
Liu, J. C. (1988). Hawaii tourism to the year 2000: A Delphi forecast. *Tourism Management, 9*(4), 279–290.
Liu, Y. Y., Tseng, F. M., & Tseng, Y. H. (2018). Big data analytics for forecasting tourism destination arrivals with the applied vector autoregression model. *Technological Forecasting and Social Change, 130*, 123–134.
Loeb, P. D. (1982). International travel to the United States: An econometric evaluation. *Annals of Tourism Research, 9*(1), 7–20.
Marrocu, E., & Paci, R. (2013). Different tourists to different destinations: Evidence from spatial interaction models. *Tourism Management, 39*, 71–83.
Martin, C. A., & Witt, S. F. (1987). Tourism demand forecasting models: Choice of appropriate variable to represent tourists' cost of living. *Tourism Management, 8*(3), 233–246.
Martin, C. A., & Witt, S. F. (1988). Substitute prices in models of tourism demand. *Annals of Tourism Research, 15*(2), 255–268.
Martin, C. A., & Witt, S. F. (1989a). Accuracy of econometric forecasts of tourism. *Annals of Tourism Research, 16*(3), 407–428.
Martin, C. A., & Witt, S. F. (1989b). Forecasting tourism demand: A comparison of the accuracy of several quantitative methods. *International Journal of Forecasting, 5*(1), 7–19.
Masiero, L. (2016). *International tourism statistics – UNWTO benchmark and cross-country comparison of definitions and sampling issues. UNWTO Statistics and TSA Issue Paper Series*. Madrid, Spain: World Tourism Organization.
Menges, G. (1958). Die touristische konsumfunktion der Schweiz 1929–1956. *SWISS Journal of Economics and Statistics, 94*(3), 328–334.
Millán, M. G., Pablo-Romero, M. P., & Sánchez-Rivas, J. (2018). Oleotourism as a sustainable product: An analysis of its demand in the south of Spain (Andalusia). *Sustainability, 10*(1), 101–120.
Miller, G. (2001). The development of indicators for sustainable tourism: Results of a Delphi survey of tourism researchers. *Tourism Management, 22*(4), 351–362.
Moore, W. R. (2010). The impact of climate change on Caribbean tourism demand. *Current Issues in Tourism, 13*(5), 495–505.
Morley, C. L., Rosselló, J., & Santana-Gallego, M. (2014). Gravity models for tourism demand: Theory and use. *Annals of Tourism Research, 48*, 1–10.
Morley, C. L. (1992). A microeconomic theory of international tourism demand. *Annals of Tourism Research, 19*(2), 250–267.
Morley, C. L. (1998). A dynamic international demand model. *Annals of Tourism Research, 25*(1), 70–84.
Moutinho, L., & Witt, S. F. (1995). Forecasting the tourism environment using a consensus approach. *Journal of Travel Research, 33*(4), 46–50.
Nadal, J. R., Font, A. R., & Rosselló, A. S. (2004). The economic determinants of seasonal patterns. *Annals of Tourism Research, 31*(3), 697–711.
Narayan, P. K. (2004). Fiji's tourism demand: The ARDL approach to cointegration. *Tourism Economics, 10*(2), 193–206.
Naudé, W. A., & Saayman, A. (2005). Determinants of tourist arrivals in Africa: A panel data regression analysis. *Tourism Economics, 11*(3), 365–391.
Nor, M. E., Nurul, A. I., & Rusiman, M. S. (2018). A hybrid approach on tourism demand forecasting. *Journal of Physics: Conference Series, 995*(1), 1–11.
O'Hagan, J. W., & Harrison, M. (1984). Market shares of US tourist expenditure in Europe: An econometric analysis. *Applied Economics, 16*(6), 919–931.
Ognjanov, B., Tang, Y., & Turner, L. (2018). Forecasting international tourism regional expenditure. *Chinese Business Review, 17*(1), 38–52.
Önder, I., & Gunter, U. (2016). Forecasting tourism demand with Google Trends for a major European city destination. *Tourism Analysis, 21*(2–3), 203–220.
Ongan, S., & Gozgor, G. (2018). Tourism demand analysis: The impact of the economic policy uncertainty on the arrival of Japanese tourists to the USA. *International Journal of Tourism Research, 20*(3), 308–316.
Ouerfelli, C. (2008). Co-integration analysis of quarterly European tourism demand in Tunisia. *Tourism Management, 29*(1), 127–137.
Page, S., Song, H., & Wu, D. C. (2012). Assessing the impacts of the global economic crisis and swine flu on inbound tourism demand in the United Kingdom. *Journal of Travel Research, 51*(2), 142–153.
Pai, P. F., & Hong, W. C. (2005). An improved neural network model in forecasting arrivals. *Annals of Tourism Research, 32*(4), 1138–1141.
Pai, P. F., Hong, W. C., Chang, P. T., & Chen, C. T. (2006). The application of support vector machines to forecast tourist arrivals in Barbados: An empirical study. *International Journal of Management, 23*(2), 375–385.

Pai, P. F., Hung, K. C., & Lin, K. P. (2014). Tourism demand forecasting using novel hybrid system. *Expert Systems with Applications, 41*(8), 3691–3702.
Palmer, A., Montano, J. J., & Sesé, A. (2006). Designing an artificial neural network for forecasting tourism time series. *Tourism Management, 27*(5), 781–790.
Pan, B., Wu, D. C., & Song, H. (2012). Forecasting hotel room demand using search engine data. *Journal of Hospitality and Tourism Technology, 3*(3), 196–210.
Pan, B., & Yang, Y. (2017). Forecasting destination weekly hotel occupancy with big data. *Journal of Travel Research, 56*(7), 957–970.
Papatheodorou, A. (1999). The demand for international tourism in the Mediterranean region. *Applied Economics, 31*(5), 619–630.
Park, S., Lee, J., & Song, W. (2017). Short-term forecasting of Japanese tourist inflow to South Korea using Google trends data. *Journal of Travel & Tourism Marketing, 34*(3), 357–368.
Pattie, D. C., & Snyder, J. (1996). Using a neural network to forecast visitor behavior. *Annals of Tourism Research, 23*(1), 151–164.
Peeters, P., & Dubois, G. (2010). Tourism travel under climate change mitigation constraints. *Journal of Transport Geography, 18*(3), 447–457.
Peng, B., Song, H., & Crouch, G. I. (2014). A meta-analysis of international tourism demand forecasting and implications for practice. *Tourism Management, 45*, 181–193.
Pesaran, M. H., Schuermann, T., & Weiner, S. M. (2004). Modeling regional interdependencies using a global error-correcting macroeconometric model. *Journal of Business and Economic Statistics, 22*(2), 129–162.
Qu, H., & Lam, S. (1997). A travel demand model for Mainland Chinese tourists to Hong Kong. *Tourism Management, 18*(8), 593–597.
Rafiei Darani, H., & Asghari, H. (2018). Study of international tourism demand in Middle East by panel data model. *International Journal of Culture, Tourism and Hospitality Research, 12*(1), 80–88.
Ridderstaat, J., Oduber, M., Croes, R., Nijkamp, P., & Martens, P. (2014). Impacts of seasonal patterns of climate on recurrent fluctuations in tourism demand: Evidence from Aruba. *Tourism Management, 41*, 245–256.
Robbins, B. (2016). Machine learning: How black is this beautiful black box. Retrieved from https://towardsdatascience.com/machine-learning-how-black-is-this-black-box-f11e4031fdf, (Accessed on May 26, 2018).
Rodríguez, Ó. G. (2017). Forecasting tourism arrivals with an online search engine data: A study of the Balearic Islands. *Pasos, 15*(4), 943–958.
Saha, S., & Yap, G. (2014). The moderation effects of political instability and terrorism on tourism development: A cross-country panel analysis. *Journal of Travel Research, 53*(4), 509–521.
Shahrabi, J., Hadavandi, E., & Asadi, S. (2013). Developing a hybrid intelligent model for forecasting problems: Case study of tourism demand time series. *Knowledge-Based Systems, 43*, 112–122.
Sheldon, P. J. (1993). Forecasting tourism: Expenditures versus arrivals. *Journal of Travel Research, 32*(1), 13–20.
Shen, S., Li, G., & Song, H. (2011). Combination forecasts of international tourism demand. *Annals of Tourism Research, 38*(1), 72–89.
Smeral, E. (2009). The impact of the financial and economic crisis on European tourism. *Journal of Travel Research, 48*(1), 3–13.
Smeral, E. (2010). Impacts of the world recession and economic crisis on tourism: Forecasts and potential risks. *Journal of Travel Research, 49*(1), 31–38.
Smeral, E. (2012). International tourism demand and the business cycle. *Annals of Tourism Research, 39*(1), 379–400.
Smeral, E., & Song, H. (2015). Varying elasticities and forecasting performance. *International Journal of Tourism Research, 17*(2), 140–150.
Smeral, E., Witt, S. F., & Witt, C. A. (1992). Econometric forecasts: Tourism trends to 2000. *Annals of Tourism Research, 19*(3), 450–466.
Song, H., Gao, B. Z., & Lin, V. S. (2013). Combining statistical and judgmental forecasts via a web-based tourism demand forecasting system. *International Journal of Forecasting, 29*(2), 295–310.
Song, H., & Li, G. (2008). Tourism demand modelling and forecasting—A review of recent research. *Tourism Management, 29*(2), 203–220.
Song, H., Li, G., & Cao, Z. (2017). Tourism and economic globalization: An emerging research agenda. *Journal of Travel Research*. https://doi.org/10.1177/0047287517734943.
Song, H., Li, G., Witt, S. F., & Athanasopoulos, G. (2011). Forecasting tourist arrivals using time-varying parameter structural time series models. *International Journal of Forecasting, 27*(3), 855–869.
Song, H., Li, G., Witt, S. F., & Fei, B. (2010). Tourism demand modelling and forecasting: How should demand be measured? *Tourism Economics, 16*(1), 63–81.
Song, H., & Lin, S. (2010). Impacts of the financial and economic crisis on tourism in Asia. *Journal of Travel Research, 49*(1), 16–30.
Song, H., Lin, S., Witt, S. F., & Zhang, X. (2011). Impact of financial/economic crisis on demand for hotel rooms in Hong Kong. *Tourism Management, 32*(1), 172–186.
Song, H., & Liu, H. (2017). Predicting tourist demand using big data. In Z. Xiang & D. R. Fesenmaier (Eds.), Analytics in smart tourism design: Concepts and methods (pp. 13-29). Retrieved from https://link.springer.com/content/pdf/10.1007/978-3-319-44263-1.pdf, (Accessed on June 29, 2018).
Song, H., Romilly, P., & Liu, X. (2000). An empirical study of outbound tourism demand in the UK. *Applied Economics, 32*(5), 611–624.
Song, H., & Witt, S. F. (2000). *Tourism demand modelling and forecasting: Modern econometric approaches.* Oxford: Pergamon.
Song, H., & Witt, S. F. (2003). Tourism forecasting: The general-to-specific approach. *Journal of Travel Research, 42*(1), 65–74.
Song, H., & Witt, S. F. (2006). Forecasting international tourist flows to Macau. *Tourism Management, 27*(2), 214–224.
Song, H., Witt, S. F., & Jensen, T. C. (2003). Tourism forecasting: Accuracy of alternative econometric models. *International Journal of Forecasting, 19*(1), 123–141.
Song, H., Witt, S. F., & Li, G. (2003). Modelling and forecasting the demand for Thai tourism. *Tourism Economics, 9*(4), 363–387.
Song, H., & Wong, K. K. (2003). Tourism demand modeling: A time-varying parameter approach. *Journal of Travel Research, 42*(1), 57–64.
Song, H., Wong, K. K., & Chon, K. K. (2003). Modelling and forecasting the demand for Hong Kong tourism. *International Journal of Hospitality Management, 22*(4), 435–451.
Sun, X., Sun, W., Wang, J., Zhang, Y., & Gao, Y. (2016). Using a Grey–Markov model optimized by Cuckoo search algorithm to forecast the annual foreign tourist arrivals to China. *Tourism Management, 52*, 369–379.
Syriopoulos, T. C. (1995). A dynamic model of demand for Mediterranean tourism. *International Review of Applied Economics, 9*(3), 318–336.
Syriopoulos, T. C., & Sinclair, M. T. (1993). An econometric study of tourism demand: The AIDS model of US and European tourism in Mediterranean countries. *Applied Economics, 25*(12), 1541–1552.
Teixeira, J. P., & Fernandes, P. O. (2012). Tourism time series forecast – Different ANN architectures with time index input. *Procedia Technology, 5*, 445–454.
Tideswell, C., Mules, T., & Faulkner, B. (2001). An integrative approach to tourism forecasting: A glance in the rearview mirror. *Journal of Travel Research, 40*(2), 162–171.
Tsaur, R. C., & Kuo, T. C. (2011). The adaptive fuzzy time series model with an application to Taiwan's tourism demand. *Expert Systems with Applications, 38*(8), 9164–9171.
Tsui, W. H. K., Balli, H. O., Gilbey, A., & Gow, H. (2014). Forecasting of Hong Kong airport's passenger throughput. *Tourism Management, 42*, 62–76.
Turner, L. W., & Witt, S. F. (2001). Forecasting tourism using univariate and multivariate structural time series models. *Tourism Economics, 7*(2), 135–147.
Uysal, M., & Crompton, J. L. (1984). Determinants of demand for international tourist flows to Turkey. *Tourism Management, 5*(4), 288–297.
Uysal, M., & Crompton, J. L. (1985). An overview of approaches used to forecast tourism demand. *Journal of Travel Research, 23*(4), 7–15.
Uysal, M., & El Roubi, M. S. (1999). Artificial neural networks versus multiple regression in tourism demand analysis. *Journal of Travel Research, 38*(2), 111–118.
Van Doorn, J. W. (1984). Tourism forecasting and the policymaker: Criteria of usefulness. *Tourism Management, 5*(1), 24–39.
Van Doorn, J. W. (1986). Scenario writing: A method for long-term tourism forecasting? *Tourism Management, 7*(1), 33–49.
Vanegas, M., Sr, & Croes, R. R. (2000). Evaluation of demand: US tourists to Aruba. *Annals of Tourism Research, 27*(4), 946–963.
Vanhove, N. (1980). Forecasting in tourism. *The Tourist Review, 35*(3), 2–7.
Wan, S., & Song, H. (2018). Forecasting turning points in tourism growth. *Annals of Tourism Research, 72*, 156–167.
Wang, C. H. (2004). Predicting tourism demand using fuzzy time series and hybrid grey theory. *Tourism Management, 25*(3), 367–374.
Wang, C. H., & Hsu, L. C. (2008). Constructing and applying an improved fuzzy time series model: Taking the tourism industry for example. *Expert Systems with Applications, 34*(4), 2732–2738.
Wang, J., Luo, Y. Y., Tang, L. Y., & Ge, P. (2018). Modeling a combined forecast algorithm based on sequence patterns and near characteristics: An application for tourism demand forecasting. *Chaos Solitons & Fractals, 108*, 136–147.
Wang, Y. S. (2009). The impact of crisis events and macroeconomic activity on Taiwan's international inbound tourism demand. *Tourism Management, 30*(1), 75–82.

Weatherford, L. R., & Kimes, S. E. (2003). A comparison of forecasting methods for hotel revenue management. *International Journal of Forecasting, 19*(3), 401–415.
Weatherford, L. R., Kimes, S. E., & Scott, D. A. (2001). Forecasting for hotel revenue management: Testing aggregation against disaggregation. *Cornell Hotel and Restaurant Administration Quarterly, 42*(4), 53–64.
Webber, A. G. (2001). Exchange rate volatility and cointegration in tourism demand. *Journal of Travel Research, 39*(4), 398–405.
Wen, L., Liu, C., & Song, H. (2018). Pooling in tourism demand forecasting. *Journal of Travel Research*. https://doi.org/10.1177/0047287518800390.
Witt, C. A., Witt, S. F., & Wilson, N. (1994). Forecasting international tourist flows. *Annals of Tourism Research, 21*(3), 612–628.
Witt, S. F., & Martin, C. A. (1987). Econometric models for forecasting international tourism demand. *Journal of Travel Research, 25*(3), 23–30.
Witt, S. F., Newbould, G. D., & Watkins, A. J. (1992). Forecastin domestic tourism demand: Application to Las Vegas arrivals data. *Journal of Travel Research, 31*(1), 36–41.
Witt, S. F., & Witt, C. A. (1995). Forecasting tourism demand: A review of empirical research. *International Journal of Forecasting, 11*(3), 447–475.
Wong, K. K., Song, H., & Chon, K. S. (2006). Bayesian models for tourism demand forecasting. *Tourism Management, 27*(5), 773–780.
Wong, K. K., Song, H., Witt, S. F., & Wu, D. C. (2007). Tourism forecasting: To combine or not to combine? *Tourism Management, 28*(4), 1068–1078.
Wu, D. C., Song, H., & Shen, S. (2017). New developments in tourism and hotel demand modeling and forecasting. *International Journal of Contemporary Hospitality Management, 29*(1), 507–529.
Wu, Q., Law, R., & Xu, X. (2012). A sparse Gaussian process regression model for tourism demand forecasting in Hong Kong. *Expert Systems with Applications, 39*(5), 4769–4774.
Xu, X., Law, R., Chen, W., & Tang, L. (2016). Forecasting tourism demand by extracting fuzzy Takagi-Sugeno rules from trained SVMs. *CAAI Transactions on Intelligence Technology, 1*(1), 30–42.
Yang, X., Pan, B., Evans, J. A., & Lv, B. (2015). Forecasting Chinese tourist volume with search engine data. *Tourism Management, 46*, 386–397.
Yang, Y., Pan, B., & Song, H. (2014). Predicting hotel demand using destination marketing organization's web traffic data. *Journal of Travel Research, 53*(4), 433–447.
Yeoman, I., Lennon, J. J., Blake, A., Galt, M., Greenwood, C., & McMahon-Beattie, U. (2007). Oil depletion: What does this mean for Scottish tourism? *Tourism Management, 28*(5), 1354–1365.
Yong, Y. W., Keng, K. A., & Leng, T. L. (1989). A Delphi forecast for the Singapore tourism industry: Future scenario and marketing implications. *International Marketing Review, 6*(3), 35–46.
Yu, G., & Schwartz, Z. (2006). Forecasting short time-series tourism demand with artificial intelligence models. *Journal of Travel Research, 45*(2), 194–203.
Zhang, G., Patuwo, B. E., & Hu, M. Y. (1998). Forecasting with artificial neural networks: The state of the art. *International Journal of Forecasting, 14*(1), 35–62.
Zhang, J., & Jensen, C. (2007). Comparative advantage: Explaining tourism flows. *Annals of Tourism Research, 34*(1), 223–243.
Zhu, L., Lim, C., Xie, W., & Wu, Y. (2018). Modelling tourist flow association for tourism demand forecasting. *Current Issues in Tourism, 21*(8), 902–916.

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