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Abstract

Quantitative methods to forecasting tourist arrivals can be sub-divided into causal methods and non-causal methods. Non-causal time series methods remain popular tourism forecasting tools due to the accuracy of their forecasting ability and general ease of use. Since tourist arrivals exhibit seasonality, SARIMA models are often found to be the most accurate. However, these models assume that the time-series is linear. This paper compares the baseline seasonal Naïve and SARIMA forecasts of a seasonal tourist destination faced with a structural break in the data, with alternative non-linear methods, with the aim to determine the accuracy of the various methods. These methods include the unobserved components model, smooth transition autoregressive model (STAR) and singular spectrum analysis (SSA). The results show that the non-linear forecasts outperform the other methods. The linear methods show some superiority in short-term forecasts when there are no structural changes in the time series.

Key words: Forecasting, tourism demand, SARIMA, STAR, Spectrum analysis, basic structural model (BSM)

1 Introduction

In 2003, Song, Witt and Jensen indicated that there is an increasing interest in tourism demand forecasting from both a practitioner's and an academic per-

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spective. This was mainly driven by the increase in tourist arrivals worldwide and the subsequent growing importance of tourism for countries' economies in both the developed and developing world. The demand for accurate predictions of tourist arrivals and tourism revenue has led to an investigation and the application of a myriad of various modelling techniques. Three overviews of the various techniques used to model tourism demand can be found, with the latest overview given by Song and Li in 2008.

The review of Song and Li (2008) shows that there is a focus on quantitative techniques to model tourism demand when compared to qualitative techniques. These quantitative methods can be sub-divided into two main groups, namely econometric (or causal) methods and univariate time-series (or non-causal) methods. Econometric methods refer to the estimation of an econometric model that is the used to forecast tourism demand by estimating the relationship between tourism demand and the explanatory variables used (Chu 2009). Unlike causal econometric models that estimate the relationship between a dependent variable and explanatory variables, univariate time-series methods (non-causal or models) base forecasts on the history of the dependent variable. Univariate time-series methods remain popular tourism forecasting tools due to the accuracy of the forecasts they deliver and their general ease of use. In fact, the recent tourism forecasting competition by Athanasopoulos et al. (2011) confirmed the superiority of these time-series methods compared to econometric methods, although the time varying parameter (TVP) models did outperform other causal models such as autoregressive distributed lag (ADL) and vector autoregression (VAR).

Linear techniques remain the most prominent in tourism demand modelling, with only a handful of studies found to implement non-linear techniques. These include artificial neural networks, cubic polynomial models, fuzzy time series, GARCH models, switching and time-varying parameter regressions, learning curve models, structural time-series models and sine wave non-linear models (Song and Li 2008). In addition, one also finds that there are a number of papers that compare various linear techniques, although this is not the case when non-linear techniques are considered. This paper aims to contribute towards this area by modelling tourism demand (more specifically, tourist arrivals) using three non-linear univariate time-series methods, namely the unobserved components model (more specifically the basic structural model (BSM)), smooth transition autoregressive (STAR) and singular spectrum analysis (SSA), and compare it to the benchmark seasonal Naïve model as well as the popular seasonal ARIMA (linear) model.

Structural time series models identify the unobserved components of a time series (Cuaresma et al. 2004). The basic structural model (BSM) decomposes the time series into its various unobserved components, i.e. trend, seasonal, irregular and cyclical and has the advantage that it can treat these components as stochastic (Song et al. 2011). This model has been applied with success by a number of researchers in the tourism forecasting literature (see for example du Preez and Witt 2003; Greenidge 2001; Kulendran and Shan 2002; Kulendran and Witt 2003a; Turner and Witt 2001b; Kim and Moosa 2001, 2005; Vu and Turner

2005, 2006) and was also further expanded to include explanatory variables (structural time series model – STSM – see for example Blake et al. 2006; Eugenio-Martin, Sinclair and Yeoman 2005; Greenidge 2001; Witt and Turner 2002; Turner and Witt 2001b), although the BSM tend to outperform the STSM.

The STAR model allows for smooth transition of the autoregressive parameters, which allow them to change over time, and therefore it can capture the non-linear nature often found in tourism time series. There is, however, still a linear component in STAR models and it should still comply with second-order diagnostics. In terms of non-linear modelling, STAR is a parametric technique. Only one other paper could be found that used this time-series method in tourism forecasting to date. SSA, on the other hand, is a non-parametric technique without any assumptions about the distribution of the error term. While this method is widely applied in other time series forecasting, it has not gained popularity in tourism demand forecasting. Only one other paper could be found that applies SSA within a tourism demand context.

The remainder of this paper is structured as follows. Section 2 provides an overview of the recent developments in the tourism forecasting literature. In section 3, the data and methods to be used in the analysis are described together with the forecast evaluation metrics. The results are presented in section 4 and the paper concludes in section 5.

2 Literature review

Studies focusing on forecasting tourism demand between the 1960s and 1980s used traditional modelling techniques such as static regression methods and ARIMA time series models. Since the 1990s, more advanced econometric techniques have been used, including non-linear models such as artificial intelligence methods (Song and Hyndman 2011), although linear univariate time-series models remain the benchmark in tourism forecasting. The recent (post 1998) research in tourism forecasting can be grouped into three areas namely, (i) the combination and integration of forecasts, (ii) forecasting using non-linear methods and (iii) expansion of current methods to address the varying nature of tourism data, including seasonality.

In terms of combination and integration of tourism forecasts, Wong et al. (2007) showed that by combining various linear forecasts, the risk of forecasting failure is significantly reduced. Various other combinations followed, including volatility and smoothing forecast combination by Coshall (2009), a combination of long term and short term forecasts by Andrawis, Atiya and El-Shinshiny (2010), statistical (quantitative) and judgemental (qualitative) forecast combination by Song, Gao and Lin (2013) and a combination of linear and non-linear forecasts by Chen (2013). The non-linear methods employed by Chen (2013) include artificial neural networks (ANN) and support vector regression (SVR). In addition, how to combine the forecasts have also attracted attention (Chan et al. 2010).

Concerning non-linear forecasts, a number of papers have seen the light since the review by Song and Li in 2008. This area of tourism forecasting is drawing increasing attention and most of the contributions can be found in information technology journals (i.e. Knowledge-Based Systems and Expert Systems with Applications). Popular methods include artificial neural networks (see Chen, Lai and Yeh 2012; Claveria and Torra 2014; Shahrabi, Hadavandi and Asadi 2013) although the method is criticised for the large data sets required for the models to provide accurate results and the time-consuming training procedures that has to be followed (Shahrabi, Hadavandi and Asadi 2013). In 2014, Claveria and Torra evaluated the forecasting performance of ANN and STAR models for Catalonia with ARIMA models, and found that ARIMA outperforms the non-linear methods, especially in short-run forecasts. The second popular non-linear method is fuzzy rule-based systems (see Tsaur and Kuo 2011; Pai, Hung and Lin, 2014, Shahrabi, Hadavandi and Asadi 2013) and these are often used in combination with clustering and generic algorithms.

In terms of the third area of development, namely the expansion of models to address specific concerns in tourism time series, the focus has been on the treatment of seasonality and structural changes in the data. Earlier studies regarded seasonality in tourism demand as constant, but due to changes in climate and weather conditions, tourist activities and destinations, technology and politics, Song et al. (2011) claim that seasonality cannot be deemed as deterministic. To address this they propose the use of an unobserved components model (the BSM) and the expansion of the Structural Time-Series Model (STSM) to allow for time-varying parameters (TVP). A similar approach is followed by Zhou-Grundy and Turner (2014) for regional tourism demand forecasts in China. Shen, Li and Song (2009) investigated the effect of seasonality on forecasting performance, and found that the TVP model did not outperform the error-correction (ECM) model when tourism demand is quite seasonal. Brierley (2011) uses four seasonal time series methods, namely seasonal naïve, damped Holt-Winters, seasonal ARIMA and the enhanced transmission system (ETS) to eliminate the most unlikely forecast. He found no method to always be superior.

Concerning the treatment of irregular components in the data, the BSM allows for the inclusion of interventions in the model. Already in 2002, Goh and Law included interventions in the form of dummy variables in SARIMA models to account for structural changes and irregular components in tourism time-series. Chu (2011) shows that a piecewise linear regression model can be used with success if the structural changes in the data cause a change in the linear trend.

The current paper falls into the second and third areas identified above and aims to use non-linear methods to forecast tourist arrivals in a destination that shows clear seasonality and where a structural change in the data is evident.

3 Data and method

3.1 *Data*

The data used for the analysis is tourist arrivals in South Africa. South Africa is a growing destination in terms of tourism, with tourist numbers increasing from a low base of less than 1 million foreign tourists in 1990, to almost 10 million by 2007. It is therefore not surprising that the country is the second-most visited destination in Africa, after being surpassed by Morocco recently.

An analysis of arrival numbers indicates that the main source of tourists is other African countries, and most notably South Africa's neighbouring countries with Lesotho, Swaziland and Zimbabwe featuring strongly. This is followed by arrivals from Europe, with tourists from the United Kingdom taking the pole position, followed by tourists from Germany. The third most important intercontinental tourist market for the country is the US.

The data to be used in the analysis is therefore total arrivals, total European arrivals, total African arrivals and then arrivals from the following countries: Lesotho, Zimbabwe, the UK, Germany and the USA. Only tourists arriving for the purpose of 'holiday' are considered in the analysis, since it provides a consistent measure of tourist arrivals. The frequency is monthly and the data spans from January 2000 to December 2012. Figures 1 to 3 provide a graphical illustration of the various series.

It is evident from Figure 1 that tourists from Africa not only represent the largest portion of international tourists to South Africa, but, compared to European arrivals, it is also a growing market for South African tourism. A clear break in the African and total arrivals series is also visible, which is due to a change in the capturing of tourism statistics in South Africa. However, this only seems to affect the African markets, since it is not evident in the European arrivals series.

Futhermore, from Figure 1 it can be seen that seasonality is present in tourist arrivals to South Africa and that this is particularly true for arrivals from Europe. Figure 2 shows arrivals of the two African markets under investigation – Lesotho and Zimbabwe. It is evident that there is a strong growth in tourists from Zimbabwe for the period under investigation, while both series tend to show an increase in volatility over the last two years.

In Figure 3, the arrivals series for tourists from the UK, USA and Germany are shown. The only market that shows some increasing tendency is tourist arrivals from the USA, while arrivals from the UK and Germany are relatively stagnant and even have a slight declining trend. What is clear from the figure, though, is that seasonality is much more evident in intercontinental arrivals than in African arrivals.

3.2 *Methods and forecast evaluation*

The time series data used in this study are monthly data from 2000:01 to 2012:12. This study focuses on tourist arrivals in South Africa in total, arrivals from Africa, arrivals from Europe, and arrivals form Lesotho, Zimbabwe, Germany, the UK and the USA. The seasonal Naïve, SARIMA, BSM, STAR and SSA methods will be used to generate forecasts. Due to the seasonal nature of the data, ARIMA forecasts were not performed, but rather SARIMA. The Augmented Dickey-Fuller test is used to determine the integration order of the time series.

i) The seasonal naïve model

According to Goh and Law (2002:501), the Naïve approach assumes that tourism arrivals follow a random walk and trends and turning points can therefore not be predicted. For annual data, this implies that the previous year's observation is taken as the forecast, i.e.:

$$\hat{y}_{t+1} = y_t$$

Once more frequent data is observed, the seasonal naïve model postulates that the forecast is similar to the most recent observation of the corresponding quarter or month (Athanasopoulos et al. 2011).

ii) The SARIMA model:

The seasonal ARIMA model is an extension of Box and Jenkins' ARIMA model to allow for seasonality in the data (Chu 1998:602). The SARIMA accounts for seasonality that occurs in the AR and MA processes as well as when seasonal differencing is necessary. The SARIMA(p,d,q)(P,D,Q)$_m$ process is given by:

$$\Phi(B^m)\phi(B)(1-B^m)^D(1-B)^4 y_t = c + \Theta(B^m)\theta(B)\varepsilon_t$$

with $\Phi(z)$ and $\Theta(z)$ are polynomials of order P and Q (Athanasopoulos et al. 2011).

Finding the correct model specification is essential. In this paper, the Hannan-Rissanen model selection procedure was used to obtain the optimal lag structure for the SARIMA model. This procedure fit an AR(h) with a large order to obtain the residuals. The optimal lag (p and q) values are then determined by minimising the Akaike (AC), Hannan-Quinn (HQ) and Schwarz (SC) information criteria. Diagnostically, the final SARIMA models are scrutinised for autocorrelation, normality and ARCH effects.

iii) The Unobserved Components Model:

The basic structural model (BSM) decomposes the time series into three independent components, namely a trend (μ_t), seasonal (γ_t) and irregular (ε_t) component (Harvey and Peters 1990):

$$\gamma_t = \mu_t + \gamma_t + \varepsilon_t \qquad t = 1, ..., T$$

The trend is generated as an approximation to a linear trend:

$$\mu_t = \mu_{t-1} + \beta_{t-1} + \eta_t, \quad \text{and}$$

$$\beta_t = \beta_{t-1} + \zeta_t,$$

with η_t and ζ_t i.i.d. error terms.

While the irregular component (ε_t) is assumed to be a white noise stationary process, the seasonal component is generated by the following:

$$\gamma_t = \sum_{j=1}^{s-1} \gamma_{t-j} + \omega_t \qquad t = 1, ..., T,$$

with s the number of seasons and ω_t and i.i.d. error term (Harvey and Peters 1990). The model can be enhanced by including a cyclical component (Ψ_t) (Song et al. 2011):

$$y_t = \mu_t + \Psi_t + \gamma_t + \varepsilon_t \qquad t = 1, ..., T$$

The BSM is estimated using STAMP 8.0. Only models that exhibited strong to very strong convergence are considered.

iv) The Smooth Transition Autoregressive Model

The smooth transition autoregressive model (STAR) is a non-linear, non-causal model, where the parameter also changes over time. The STAR model is able to capture the movement of a time series that adjusts to the behaviour of economic agents (Shangodoyin, Adebile and Arnab 2009). The main advantage of the STAR models is that changes in a time series are influenced by changes of various agents and it is unlikely that these agents react simultaneously to economic signals.

This model allows a series to alternate between two distinct regimes, but transition between these regimes can be smooth, so that there can be a continuum of states between extreme regimes. Smooth transition autoregressive models allow the autoregressive parameters to change over time. Consider the non-linear autoregressive (NLAR) model (Botha and Marais 2006).

$$y_t = \alpha_0 + [\alpha_1 + \beta_1 f(y_{t-1})]y_{t-1} + \varepsilon_t$$

If f() is a smooth continuous function, the autoregressive coefficient $(\alpha_1 + \beta_1))$ will change smoothly along with the value of y_{t-1}.

There are two forms of the STAR models that allow for a varying degree of autoregressive decay. The logistic-STAR model generalises the standard autoregressive model such that the autoregressive coefficient is a logistic function.

$$y_t = \alpha_0 + \alpha_1 y_{t-1} + ...\alpha_p y_{t-p} + \theta[\beta_0 + \beta_1 y_{t-1} + ...\beta_p y_{t-p}] + \varepsilon_t$$

where

$$\theta = [1 + \exp\left(-\gamma\left(y_{t-d} - c\right)\right)]^{-1}$$

γ is the smoothness parameter, and c is the threshold. In the limit, as $\gamma \to 0$ or ∞ the LSTAR becomes an AR(p) model since the value of θ is constant. For intermediate values of γ the autoregressive decay depends on the value of y_{t-1}. The intercept and the autoregressive coefficients smoothly change between two extremes as the value of y_{t-1} changes.

The other form of the STAR model is the exponential form (ESTAR), where

$$\theta = \left[1 - \exp\left(-\gamma\left(y_{t-d} - c\right)^2\right)\right]$$

For the ESTAR model, as γ approached zero or infinity, the model becomes an AR(p) model since θ is constant. Otherwise, the model displays non-linear behaviour. The ESTAR model has proven to be useful for periods surrounding the turning points of a series in that such periods have different degrees of autoregressive decay than others. For a full discussion, see Lutkepohl and Kratzig (2004) or Enders (2009).

For the purposes of this paper, the process set out in Lutkepohl and Kratzig (2004) was followed. The initial testing for linearity is based on three stages. Firstly, a linear AR model is specified so that the lag length p is determined. The selection of p is based on the Schwarz Information Criteria. Secondly, the residuals from the AR model are tested for non-linearity. Thirdly, the appropriate smooth transition (LSTAR or ESTAR) model is selected according to the most significant transition variable. The STAR model with seasonal dummies will also be fitted to the data and the process is similar to the normal STAR modelling process.

v) Singular spectrum analysis

Singular spectrum analysis (SSA) is a non-parametric method where the time series is decomposed and reconstructed. It is therefore able to not only address seasonality, but also irregular components in the data, such as structural breaks caused by either data collection or disasters (either natural or man-made). It can be applied to both stationary and non-stationary data, which implies that any complex time series can be modelled using SSA, as long as it displays some noteworthy structure (Hassani 2011).

The SSA consists of two stages, namely decomposition and reconstruction. In the first stage, the time series is decomposed into a varying trend, fluctuating components (i.e. season, cyclical) and a random component (Hassani 2007). In the second stage, the series is reconstructed by eliminating the noise (or random) component, which renders a smoothed time series that can be forecasted more accurately (Hassani 2011).

Both these stages consist of two steps each, which are explained in Hassani (2007 and 2011) as follows: Consider a time series of length T, i.e. $Y_T = (y_1, ..., y_T)$. The decomposition stage's first step is embedding that transfers the one-dimensional time series into a multidimensional series $X_1, X_2, ..., X_K$, with vectors $X_i = (y_i, y_{i+1}, ..., y_{i+L-1})'$; for $i = 1, 2, ..., K$ and $K = N - L + 1$, with L indicating the window length and lies between 2 and T. The result of the process is a trajectory matrix $\mathbf{X}$, which is a Hankel matrix (i.e. the elements along the diagonal $i + j = cons$ are equal).

Step 2 of stage one makes a singular value decomposition (SVD) of the trajectory matrix. The SVD can be written as $\mathbf{X} = \mathbf{X}_1 + ... + \mathbf{X}_d$, where $X_i = \sqrt{\lambda_i} U_i V_i$, with λ_i indicating d singular values of matrix $\mathbf{X}$ such that the set $\{\sqrt{\lambda_i}\}$ is the spectrum of matrix $\mathbf{X}$, U_i indicating d factor orthogonal functions and V_i are d eigenvectors of the trajectory matrix (referred to as principal components). Since the matrices have a rank of one, they are elementary matrices and the collection $(\sqrt{\lambda_i} U_i V_i)$ is called the ith eigentriple of the matrix.

The two steps in the reconstruction stage (stage 2) are firstly, grouping and secondly, diagonal averaging. In the grouping step, the elementary matrices are split into groups and the matrices in each group are summed. The grouping is based on the eigentriples and aims to identify several groups, $I_1, ..., I_m$, that correspond to the representation $X = X_{I_1} + ... + X_{I_m}$. Step 2 entails diagonal averaging that transforms each matrix into a time series through a process of Hankelisation. The diagonals in the Hankel matrix relate to the values in the series and therefore define the time series. According to Hassani (2007: 243), it "is equivalent to the decomposition of the initial time series $Y_T = (y_1, ..., y_T)$ into a sum of m series: $y_t = \sum_{k=1}^{m} \tilde{y}_t^{(k)}$, where $\tilde{Y}_T^{(k)} = \left(\tilde{y}_1^{(k)}, ..., \tilde{y}_T^{(k)}\right)$ corresponds to the matrix $\mathbf{X}_{I_k}$.

For SSA, only one parameter has to be decided on, namely the window length (L). While guidelines are given ($2 \leq L \leq \frac{T}{2}$), the choice of L is still arbitrary. According to Beneki, Eeckels and Leon (2009), the window length should be equal to any known periodic component in the data, and if there is more than one periodic component, it should be large enough to cover all the components. They propose that an L equal to 0.20-0.25 of T should be sufficient to capture all the dynamics of the time series.

vi) Forecasting evaluation

The forecast horizons to assess the forecast accuracy of the three non-linear models (BSM, STAR and SSA) in comparison with the Naïve 1 and SARIMA models are h=24, since we use monthly data (Athanasopoulos et al. 2011). The one month, two months, 12 and 24 months ahead forecast horizons will be considered. The models are estimated over the period 2000:01 to 2010:12 and *ex post* forecasts will be generated for the hold-out period 2011:01 to 2012: 12. The estimated models are used to forecast the South African tourist arrivals from each of the regions (Total, African and International) and five countries. Point forecasts rather than prediction intervals will be used (Kim et al. 2011), since the SARIMA intervals have too narrow intervals and underestimate uncertainty. The same applies to the AR model that underlies the STAR model.

The forecast accuracy is evaluated based on the non-statistical measures, the mean absolute percentage error (MAPE) and the root mean square percentage error (RMSPE). These are most commonly used in forecast evaluation in tourism forecasting (Song and Li 2008; Chu 2009). These measures are defined by taking the observation y_t and the forecast value $\hat{y}_t$ at a point in time, t and n, the number of forecasts.

$$\begin{aligned}
MSE &= \frac{1}{T}\sum\nolimits_{t=1}^{T}(y_t - \hat{y}_t)^2 \text{ or } RMSE = \sqrt{MSE} \text{ or} \\
RMSPE &= \sqrt{\frac{1}{T}\sum\nolimits_{t=1}^{T}(y_t - \hat{y}_t)^2}(100\%) \\
MAPE &= \frac{1}{T}\sum\nolimits_{t=1}^{T}\frac{|y_t - \hat{y}_t|}{|y_t|}(100\%)
\end{aligned}$$

The MSE (RMSE) is an absolute performance measure and the MAPE is a relative performance measure. The most commonly use measure is the MSE (Aslanargun et al. 2007).

4 Results and discussion

4.1 *Estimated models*

Some of the models adopted in this paper require stationary data. The ADF test results are presented in Table 1, although the ADF, PP and KPSS test were all used and compared with different deterministic assumptions. These comparative results are summarised in Appendix A. The ADF and PP results with no deterministic assumption are similar. The PP and KPSS yielded similar results when including a trend, with a few exceptions. The KPSS without a trend also confirmed some of the results from the ADF and PP. The eight series were tested for unit roots in their logarithmic forms with the ADF (different significant deterministic assumption for each series). All are I(1), except the Europe and UK arrivals, which are I(0) as tabulated below. The models which require stationary data (i.e. seasonal ARIMA, the linear part of the STAR and DSTAR models) were therefore estimated using the differenced time-series data, while the BSM and the SSA were estimated using level data.

i) SARIMA model

The Hannan-Rissanen model selection criteria were used to choose the optimal p and q terms for the SARIMA specification. The optimal lag (p and q) values are then determined according to minimising the Akaike (AC), Hannan-Quinn (HQ) and Schwarz (SC) information criteria. The latter was used. These are tabulated in Table 2 together with the diagnostic test results.

Diagnostically, all the models showed no autocorrelation in the residuals (except for Total, Africa and UK), and this was confirmed with the ACF results showing that all the autocorrelations were within the 95% confidence interval. All the models showed that the residuals were non-normal and in most models there was some volatility left in the residuals – this is possibly an indication of non-linear behaviour. However, the ACF showed that the autocorrelations accounted for the seasonality in the SARIMA models, since no seasonality is left in the residuals. To summarise, there seem to be different specifications for each country, with some models following an AR-specification and others rather an MA-specification.

ii) BSM model

A general to specific approach was followed with the BSM models. All the models were initially estimated with a trend, seasonal, cyclical and irregular component, and based on the results, components were removed in order to improve the estimation. All the final models contain a trend, seasonal and irregular component, although only two series (UK and Africa) also contains cyclical components. The final models were chosen based on the AIC and SC criterion and are displayed in Table 3 together with the diagnostic tests.

It is evident that for a number of models, a deterministic seasonal effect is present and provides the optimal specification. For most of the remaining models, a deterministic seasonal component also leads to strong evidence of convergence, although it is not necessarily the optimal specification. In almost all cases, the models are well behaved with normally distributed random errors.

iii) STAR model

For the STAR specification, the procedure posited by Lutkepohl and Kratzig (2004) was followed. The lag structure was determined within the VAR framework and the SC was used for all the models except for Germany where the HQ specification was used since it yielded better results (see Table 4). For Zimbabwe, the HQ and SC showed an optimal lag of 9, although with this lag structure some of the diagnostic tests showed matrix problems and therefore 8 lags were used.

After the lag structure was determined, the linearity testing showed that the LSTAR model was the most appropriate model and that the time series did indeed show some non-linearity. The appropriate transition variables for each model are tabulated in the table below and were determined through the Jmulti software developed by Lutkepohl and Kratzig (2004).

Total arrivals, Africa, Zimbabwe and UK showed some volatility that was unaccounted for by the STAR specification and the parameters for the Total, Lesotho, Germany and the US arrivals were not constant, confirming a smooth continuous change in the parameters. All the models showed no error correlations except for African arrivals.

iv) STAR with seasonal dummies model

For the STAR specification with seasonal dummies, the process is similar to the standard STAR process. At first the specification is done with dummies according to the lag structure identified with the standard STAR model. Linearity testing showed that different forms of STAR are appropriate for different destinations. The significant transition variables for the different forms of STAR are tabulated below. There are dummy variables for the linear as well as non-linear part of the specification.

Table 5 indicates which seasonal dummy variables are significant. The identified model for UK was linear when dummies were added; this means that the dummies accounted for the non-linearity identified in the standard STAR model and therefore the specification was a simple AR model. The diagnostic results from the ARCH-LM test showed that all non-linearity was accounted for with the STAR with seasonal dummies.

Comparing the two STAR specifications, without and with dummies in Tables 4 and 5 respectively, it is evident that the unaccounted volatility in the residuals for the STAR without dummies (Table 4), have been accounted for by incorporating dummies with the STAR model (Table 5).

v) SSA model

As indicated earlier, for the SSA the window length has to be chosen. Based on the suggestions of Beneki, Eeckels and Leon (2009) and Hassani (2007), the window length (L) for all the series is chosen on 24. Since the data is monthly, the chosen length should be multiples of 12 and using the criterion of 0.2-0.25 of T, L=24 was chosen. This resulted in 24 eigentriples that had to be inspected for grouping. The results of the SVD step for the 'Europe's series are presented below as an example, which assists in identifying the groups that should be extracted for the next stage of the analysis. Figure 4 illustrates the first 12 principal components extracted for the series.

To distinguish the harmonic components from the noise components, pairwise scatter plots of the eigenvectors can also be assessed. According to Hassani (2007), the harmonic components follow a sine/cosine sequence and Figure 5 illustrates some of these paired eigenvectors for the Europe series. The pairs correspond to harmonic components with periods 12, 4, 6, 2.5 and 3, respectively, and are ordered according to their contribution to in the SVD step.

The periodograms of the paired eigentriples show the periodic harmonics and tell us which eigentriples must be regarded in the grouping stage. A sharp spike in more than one period indicates a noise component, while the spike at one period only identifies the signal components.

The second stage of SSA entails the grouping of the trend and harmonic components, and separating the noise. The trend components are normally the ones with the lowest variance (e.g. component 1 in Figure 4), while the paired eigentriples in Figures 5 and 6 assist in identifying the seasonality or harmonic components. The eigentriples not chosen form the residual (or noise) components. Table 6 summarises the extracted trend and harmonic eigentriples for each series under investigation.

The eigentriples extracted above are used to reconstruct the series. Figure 7 below illustrates the reconstructed series for European arrivals in South Africa, which form the basis for forecasting. We use vector forecasting as our forecasting method, although the results are quite similar if we use the recurrent method. Figure 7 also illustrates the forecast generated for the European arrivals series.

4.2 *Forecasting accuracy*

The forecasts from these models were evaluated by calculating the MAPE and RMSPE for each forecast horizon. The seasonal Naïve forecast evaluation is presented in Table 7.

The seasonal Naïve forecast was overall accurate one and two periods ahead, except for arrivals from Lesotho. Over a longer forecast horizon, the forecasts weakened considerably, with only total arrivals and African arrivals showing errors less than 15% over the 24 month horizon. The inaccuracy especially over a longer forecast horizon may be attributed to the inability of the Naïve model to take an increasing or decreasing trend into consideration. Table 8 presents the SARIMA models' forecast evaluation.

The SARIMA models were accurate on the short forecast horizon for arrivals from Europe, the UK and the US - below 10%. Over a longer forecast horizon, total arrivals improved as well as arrivals from Africa and Germany. The forecasts for arrivals from Europe, Germany, the UK and the US showed fairly accurate results over the total forecast horizon. This may be attributed to the clear seasonal components that these series exhibit from the figures presented earlier. Overall, the SARIMA models produced more accurate forecasts than the Naïve models. The Naïve models for arrivals from Lesotho were marginally better for the different forecast horizons and this may be due to these series' non-seasonal behaviour.

The BSM forecasts (Table 9) are very accurate over the 1-year forecasting horizon, with almost all forecasting errors less than 10%. In general, the forecasts are very accurate, although the best performing models are those for Europe and the UK. It is evident that the BSM also forecasts very well for Zimbabwe and Lesotho – the two time series that exhibit large structural breaks. The BSM overall outperformed the SARIMA model with the exception of the US and Germany.

In Table 10 it is evident that over the short-term forecasting horizon, the STAR forecast performed well for total arrivals, Europe, Zimbabwe and Germany. Overall, over the longer forecast horizon, forecasts improved for all except arrivals from Europe and Germany. Since STAR is a non-linear model that learns over time, it is not surprising that the forecasts improve over time.

The STAR model showed better forecasts for total arrivals and arrivals from Africa, Lesotho and Zimbabwe than the SARIMA model. This is due to non-linear rather than non-seasonal behaviour in these series. The STAR did not capture the seasonal components in the seasonal series such as arrivals from Europe, Germany, the UK and the US as accurately as the SARIMA model. The BSM also accounted for seasonality and therefore outperformed the STAR across almost all the forecast horizons. The STAR performed better than the Naïve model showing it capture the non-linearity underlying the seasonal series.

The STAR with dummies was fitted to account for both seasonality and non-linearity. The results, overall, improved from the standard STAR where almost all forecast errors, over all forecast horizons are below 10% (Table 11). The STAR model did not account for the seasonality in Europe, Germany and the UK, however, these forecast improved noticeably over the entire forecast horizon when the seasonal dummies were added. The STAR, however, did outperform in the case of Germany over the shorter forecast horizon. The STAR with seasonal dummies also outperformed the BSM except for Lesotho, Zimbabwe and the UK in the short-term.

The SSA forecasts (Table 12) seem to be very effective in the short term, with all the 1-month forecasting errors below 10% (except for Lesotho). Even the 2-month forecasts are quite accurate with forecasting errors mainly less than 15%, while the 1-year forecasts are also good with all forecasting errors below 20% (except for Zimbabwe). The STAR and BSM, however do outperform the SSA overall.

When the four methods are compared over the different forecast horizons, the results are in favour of the non-linear methods. A summary of the results is provided in Table 13. In general, the SSA, STAR with dummies and the BSM are more accurate than any of the other methods in the short term. The SARIMA forecasts are only superior for arrivals from the USA, and only in the very short term. Similarly, seasonal Naïve forecasts only perform well in the short run and only for a limited number of series. Table 13 also clearly shows that the STAR with seasonal dummies, followed by the BSM, dominates when longer-term forecasts (1-2 years) are considered. Interesting though is that the series with the clear structural breaks, i.e. Lesotho and Zimbabwe, are more accurately forecasted using non-linear methods (i.e. STAR) in the short run as well. These findings are in contrast to the findings of Claveria and Torra (2014) who indicated that the ARIMA models outperform the non-linear methods, especially in the short term. The findings in this paper shows that the non-linear models such as the STAR and BSM outperform the forecast accuracy of linear models for tourist arrivals in South Africa – a tourist destination characterised by seasonality and a clear structural break in some of the data series.

5 Conclusions

The aim of the paper was to investigate the applicability of non-linear forecasting methods for tourism demand series. Tourism demand is characterised by strong seasonal patterns and the modelling and forecasting thereof are complicated by adverse events that cause structural breaks in the data. The demand for South Africa as a destination exhibits all these characteristics – i.e. strong seasonality as well as a structural break due to different capturing methodology of the data. Therefore, it is ideal to test the success that non-linear methods have in forecasting tourism demand.

The linear model included in the analysis is the seasonal ARIMA, while the seasonal Naïve model served as the basis for comparison. The three non-linear methods used were the BSM, STAR and SSA, with SSA having the additional benefit that it is not limited by the normality assumption of the error term. In addition, the STAR model is augmented by including seasonal dummies since the BSM identified deterministic seasonal dummies as a valid model assumption.

The results of the analysis showed that the non-linear methods perform much better than the linear SARIMA model and the baseline seasonal Naïve model. In fact, the STAR model with seasonal dummies is the best choice for longer-term forecasts (i.e. 12 months and more) for all the tourism time series. Clear trends that can be identified and that could assist in choosing the more accurate forecasting methodology to implement in various circumstances include: firstly, the forecasting accuracy of non-linear models increase as the forecasting horizon increases; secondly, non-linear models (especially STAR, BSM and SSA) perform well in the very short-term when structural breaks occur; thirdly, it is not evident that the SARIMA model is much more superior than the seasonal naïve model in the very short-term; fourthly, forecasts of time series that have strong seasonality as well as structural breaks benefit from using the BSM or STAR with seasonal dummies in both the short- and long term. An interesting observation is evident in the forecasts of UK arrivals, where the BSM outperform all other methods in both the long- and the short-term. In this instance, the STAR models indicated that the series follows an AR-process once seasonality is accounted for, which might indicate that BSM generates more accurate forecasts for series where non-linearity is only caused by seasonality.

Since no explanatory variables are included, the research does not lend itself to any policy application. This could be addressed and future research might evolve by expanding the non-linear methods used in this paper to a multivariate framework.

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Table 1: ADF Unit root test results

	Trend or intercept	Level	First difference
Total	None	1.32	-3.74***
Africa	None	0.86	-2.09**
Europe	Intercept	-3.05**	
Lesotho	None	-0.01	-13.97***
Zimbabwe	Intercept and trend	-13.2	-2.96***
Germany	None	-0.28	-12.57***
UK	Intercept	-3.04**	
US	None	2.21	-4.99***

Source: Estimation output
***99%; ** 95% and * 99% rejection of the null hypothesis (showing the test t-statistics)

Table 2: Optimal lag and diagnostic tests for the SARIMA specification

	SC-p	SC-q	BG Test* Ho: No autocorrelation	JB Test** Ho: Normal distribution	ARCH LM Ho: No ARCH effects	ACF
Total	1	0	Reject (0.05)	Reject(0.0)	Accept (0.1)	Within
Africa	1	0	Reject (0.03)	Reject (0.0)	Reject (0.02)	Within
Europe	2	0	Accept(0.73)	Reject(0.0)	Reject (0.02)	Within
Lesotho	0	1	Accept(0.84)	Reject(0.0)	Reject (0.05)	Within
Zimbabwe	2	0	Accept(0.61)	Reject(0.0)	Reject (0.02)	Within
Germany	2	0	Accept(0.24)	Reject(0.0)	Reject (0.0)	Within
UK	0	2	Reject (0.0)	Reject(0.0)	Accept (0.06)	Within
US	0	2	Accept(0.99)	Reject(0.0)	Reject (0.0)	Within

Source: Estimation results
*Breuch Godfrey and *Jarque-Bera (p-values in ())

Table 3: Components and diagnostic tests for the BSM specification

	Trend*	Seasonal*	Bowman-Shenton Ho: Normal distribution	Durbin Watson Ho: No auto-correlation	Hetero-skedasticity Ho: Homoske-dasticity	Ljung-Box Statistic Ho: randomness
Total	S	S	Accept	Accept	Accept	Accept
Africa	S	S	Accept	Accept	Accept	Reject
Europe	S	S	Accept	Accept	Accept	Accept
Lesotho	S	D	Accept	Accept	Accept	Accept
Zimbabwe	D	D	Accept	Accept	Accept	Reject
Germany	S	D	Reject	Accept	Reject	Accept
UK	D	D	Reject	Accept	Accept	Accept
US	S	S	Accept	Accept	Accept	Accept

* S = stochastic, D= deterministic
Source: Estimation results

Table 4: Optimal lag and diagnostic tests for the STAR specification

	HQ	SC	Linear	Trans-ition	JB test * Ho: Normal distribution	ARCH-LM Ho: No ARCH effects	Parameter constancy Ho: parameters constant	BG test* Ho: no error correlation
Total	8	8	LSTAR	1	Accept(0.62)	Reject (0.0)	Reject (0.0)	Accept(0.4)
Africa	10	4	LSTAR	4	Reject (0.0)	Reject (0.0)	Accept(0.64)	Reject (0.02)
Europe	10	10	LSTAR	5	Reject (0.0)	Accept(0.66)	Accept (0.1)	Accept(0.35)
Lesotho	3	3	LSTAR	1	Reject (0.0)	Accept(0.5)	Reject (0.0)	Accept(0.41)
Zimbabwe	9	9	LSTAR	6	Reject (0.0)	Reject (0.0)	Reject (0.0)	Accept(0.5)
Germany	5	1	LSTAR	4	Reject (0.0)	Accept(0.99)	Accept(0.78)	Accept(0.96)
UK	10	10	LSTAR	1	Accept (0.44)	Reject (0.0)	Accept(0.5)	Accept(0.48)
US	1	1	LSTAR	1	Reject (0.0)	Accept(0.9)	Reject (0.0)	Accept(0.19)

Source: Estimation results
*Jarque-Bera and Breuch Godfrey (p-values in ())

Table 5: Optimal lag and diagnostic tests for the DSTAR specification

	HQ	SC	Linear	Tran-sition	Jarque–Bera Ho: Normal distribution	ARCH-LM Ho: No ARCH effects	Significant dummies Linear part	Significant dummies Non-linear part
Total	8	8	LSTAR	1	Reject (0.0)	Accept(0.055)	All (S1,-S11)	S2, S10
Africa	10	4	ESTAR	1	Reject (0.0)	Accept(0.96)	All (except S2, S5)	All (except S1)
Europe	10	10	LSTAR	2	Reject (0.0)	Accept(0.97)	All(except S1)	None
Lesotho	3	3	ESTAR	2	Reject (0.0)	Accept(0.76)	None	None
Zimbabwe	9	9	LSTAR	8	Reject (0.0)	Reject(0.02)	All (except S4, S7, S8, S10, S11)	S2, S11
Germany	5	1	ESTAR	2	Reject (0.0)	Accept(0.47)	All (except S2, S3, S8, S9)	All (except S1)
UK	10	10	Linear	1	Reject (0.0)	Accept(0.93)	All	None
US	1	1	LSTAR	1	Reject (0.0)	Accept(0.99)	All (except S3, S6)	None

Source: Estimation results

Table 6: Selected eigentriples for the various series

Series	Eigentriples
Total	1-3, 5-6
Africa	1, 3-6, 11-12, 14-15
Europe	1-7, 10-11, 14
Lesotho	1, 4-8
Zimbabwe	1, 4-9, 11-12
Germany	1-5, 8-11
UK	1-13
US	1-7, 15-16

Table 7: Forecast evaluation of the seasonal Naïve model

	Forecast horizon	1	2	12	24
Total	MAPE	**7.44**	**6.43**	**6.9**	**8.83**
	RMSPE	**7.44**	**6.78**	**7.91**	**10.08**
Africa	MAPE	**8.15**	**7.03**	**7.98**	11.21
	RMSPE	**8.15**	**7.57**	**9.15**	12.74
Europe	MAPE	**0.25**	**0.16**	17.97	17.87
	RMSPE	**0.25**	**0.18**	22.4	22.02
Lesotho	MAPE	20.19	22.29	19.21	21.48
	RMSPE	20.19	22.02	21.97	24.45
Zimbabwe	MAPE	**7.91**	**5.24**	**7.47**	12.08
	RMSPE	**7.91**	**6.73**	**13.77**	17.75
Germany	MAPE	**9.99**	**7.77**	19.66	19.77
	RMSPE	**9.99**	**7.88**	18.56	18.03
UK	MAPE	**9.69**	**6.14**	21.71	26.88
	RMSPE	**9.69**	**6.58**	23.96	25.96
US	MAPE	**9.98**	14.39	14.16	14.85
	RMSPE	**9.98**	15.38	25.25	25.53

Source: Estimation results

Table 8: Forecast evaluation of the SARIMA models

	Forecast horizon	1	2	12	24
Total	MAPE	18.68	12.11	**6.08**	**6.95**
	RMSPE	18.68	15.14	**8.24**	**9.38**
Africa	MAPE	22.69	15.57	**7.9**	**9.63**
	RMSPE	22.69	19.36	**10.44**	**12.54**
Europe	MAPE	**4.42**	**2.72**	**7**	**6.26**
	RMSPE	**4.42**	**3.07**	**7.83**	**6.99**
Lesotho	MAPE	26.62	18.34	16.19	18.82
	RMSPE	26.62	23.75	18.02	21.28
Zimbabwe	MAPE	14.86	14.41	12.15	12.51
	RMSPE	14.86	14.78	13.24	15.74
Germany	MAPE	16.84	**8.63**	**8.14**	**8.92**
	RMSPE	16.84	**11.31**	**9.42**	**11.64**
UK	MAPE	**5.66**	**6.41**	**10.2**	16.87
	RMSPE	**5.66**	**6.6**	**11.98**	16.02
US	MAPE	**0.2**	**2.38**	**5.74**	**6.05**
	RMSPE	**0.2**	**3.35**	**9.98**	**10.43**

Source: Estimation results

Table 9: Forecast evaluation of the BSM models

	Forecast horizon	1	2	12	24
Total	MAPE	11.73	**8.78**	**6.81**	**9.24**
	RMSPE	11.73	**9.94**	**7.51**	**10.54**
Africa	MAPE	18.41	11.34	**7.00**	11.01
	RMSPE	18.41	15.38	**9.05**	13.76
Europe	MAPE	**8.38**	**6.81**	**5.06**	**5.24**
	RMSPE	**8.38**	**6.85**	**5.77**	**5.53**
Lesotho	MAPE	16.28	**9.44**	**6.64**	**6.19**
	RMSPE	16.28	**14.2**	**9.24**	**8.7**
Zimbabwe	MAPE	**4.06**	**2.28**	**7.46**	10.07
	RMSPE	**4.06**	**3.38**	**10.86**	15.64
Germany	MAPE	17.15	14.4	12.41	13.52
	RMSPE	17.15	14.4	15.29	18.05
UK	MAPE	**0.8**	**0.48**	**5.46**	**8.35**
	RMSPE	**0.8**	**0.53**	**8.57**	**10.16**
US	MAPE	**8.82**	11.14	**6.59**	**7.07**
	RMSPE	**8.82**	11.56	**7.53**	**7.88**

Source: Estimation results

Table 10: Forecast evaluation of the STAR models

	Forecast horizon	1	2	12	24
Total	MAPE	**8.25**	**14.81**	**7.41**	**6.99**
	RMSPE	**8.25**	**14.87**	**8.87**	**8.15**
Africa	MAPE	17.89	18.35	**8.27**	**7.88**
	RMSPE	17.89	18.46	**10.29**	**10.35**
Europe	MAPE	**4.13**	**10.12**	15.09	13.79
	RMSPE	**4.13**	**12.25**	14.45	12.93
Lesotho	MAPE	28.26	25.37	**10.41**	**9.64**
	RMSPE	28.26	27.43	**13.86**	**12.83**
Zimbabwe	MAPE	**8.27**	**5.72**	**8.13**	**8.44**
	RMSPE	**8.27**	**7.1**	**10.2**	**10.53**
Germany	MAPE	**10.94**	13.24	19.43	20.67
	RMSPE	**10.94**	13.68	16.84	18.08
UK	MAPE	21.87	14.35	15.37	17.43
	RMSPE	21.87	15.08	15.09	15.71
US	MAPE	28.08	15.32	**11.68**	**13.27**
	RMSPE	28.08	19.19	**13.42**	**16.03**

Source: Estimation results

Table 11: Forecast evaluation of the STAR with seasonal dummies models

	Forecast horizon	1	2	12	24
Total	MAPE	10.22	**7.82**	**3.83**	**3.74**
	RMSPE	10.22	**8.74**	**4.72**	**4.43**
Africa	MAPE	15.94	**9.93**	**3.88**	**3.9**
	RMSPE	15.94	13.34	**6.19**	**6.82**
Europe	MAPE	**3.28**	**3.18**	**5.42**	**4.73**
	RMSPE	**3.28**	**3.17**	**7.86**	**6.42**
Lesotho	MAPE	14.4	11.64	**4.74**	**5.29**
	RMSPE	14.4	13.4	**7.05**	**7.34**
Zimbabwe	MAPE	**3.4**	**7.51**	**5.71**	**4.36**
	RMSPE	**3.4**	**7.36**	**7.42**	**5.42**
Germany	MAPE	20.57	12.3	**7.9**	**8.61**
	RMSPE	20.57	14.13	**9.98**	**10.46**
UK	MAPE	**3.02**	**4.75**	**8.31**	**10.83**
	RMSPE	**3.02**	**5.34**	**9.64**	**11.31**
US	MAPE	**5.36**	**4.59**	**5.69**	**5.62**
	RMSPE	**5.36**	**4.6**	**7.11**	**7.95**

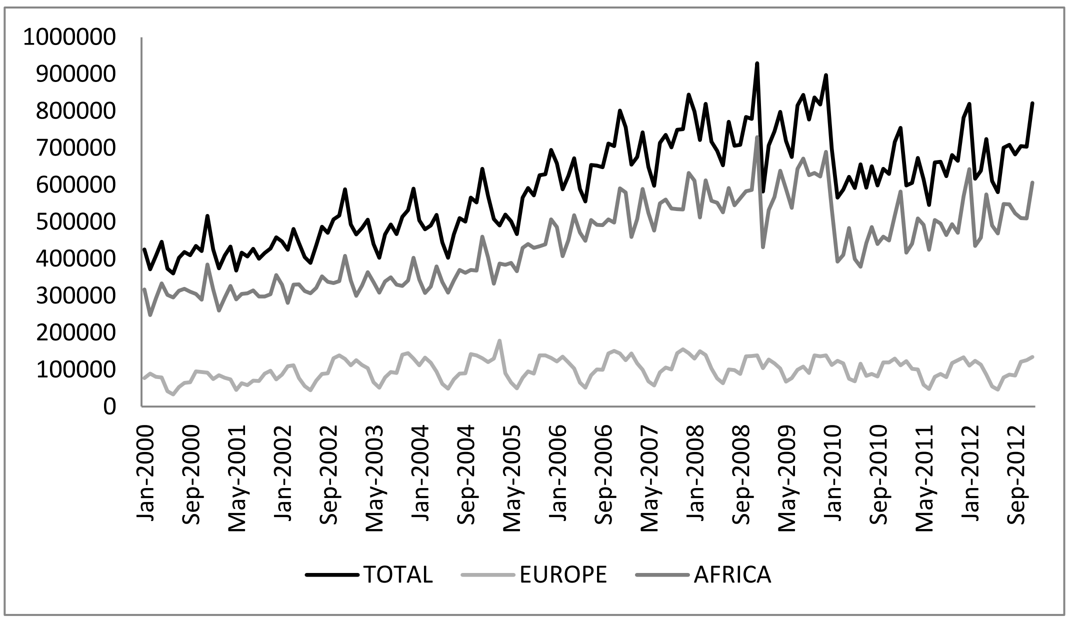
Table 12: Forecast evaluation of the SSA models

	Forecast horizon	1	2	12	24
Total	MAPE	**4.12**	**12.44**	17.55	16.53
	RMSPE	**4.12**	13.38	18.41	17.37
Africa	MAPE	**9.9**	**11.12**	17.56	18.39
	RMSPE	**9.9**	**10.93**	21.68	22.25
Europe	MAPE	**5.56**	**6.66**	**12.96**	**13.34**
	RMSPE	**5.56**	**6.86**	**14.97**	**14.51**
Lesotho	MAPE	22.62	18.03	**8.55**	**8.55**
	RMSPE	22.62	20.96	**11.66**	**11.98**
Zimbabwe	MAPE	**4.39**	19.07	20.39	20.99
	RMSPE	**4.39**	20.09	21.3	21.87
Germany	MAPE	**2.49**	**8.2**	14.09	15.29
	RMSPE	**2.49**	**10.46**	15.01	18.14
UK	MAPE	**0.81**	**1.81**	15.51	21.95
	RMSPE	**0.81**	**2.22**	17.1	20.68
US	MAPE	**9.56**	**9.58**	**12.68**	**13.47**
	RMSPE	**9.56**	**9.59**	**15.28**	**15.53**

Table 13: Forecast comparison

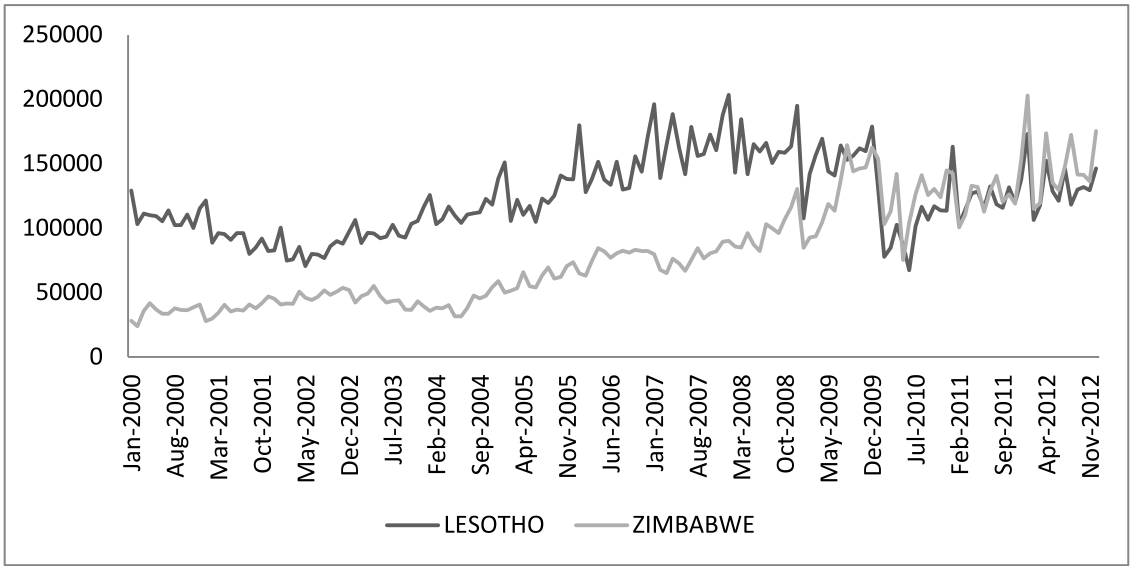
	Forecast horizon			
	1	**2**	**12**	**24**
Total	SSA	NAIVE	DSTAR	DSTAR
Africa	NAIVE	NAIVE	DSTAR	DSTAR
Europe	NAIVE	NAIVE	BSM	BSM/DSTAR
Lesotho	DSTAR	BSM	DSTAR	DSTAR
Zimbabwe	DSTAR	BSM	DSTAR	DSTAR
Germany	SSA	NAIVE	DSTAR/SARIMA	DSTAR
UK	BSM	BSM	BSM	BSM
US	SARIMA	SARIMA	DSTAR	DSTAR/BSM

Figure 1: Total arrivals broken down into European and African arrivals



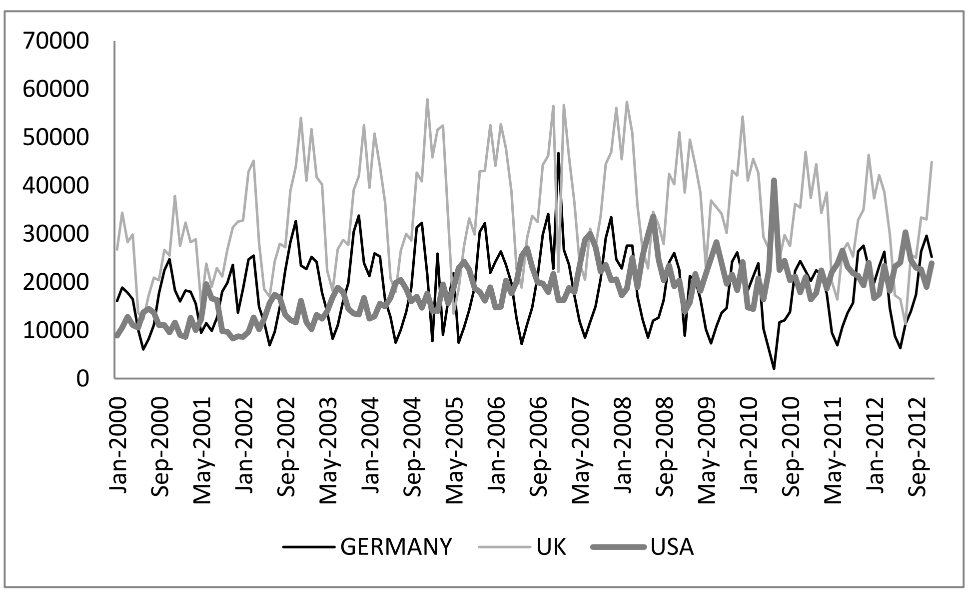
Source of data: Statistics South Africa

Figure 2: Arrivals from Lesotho and Zimbabwe



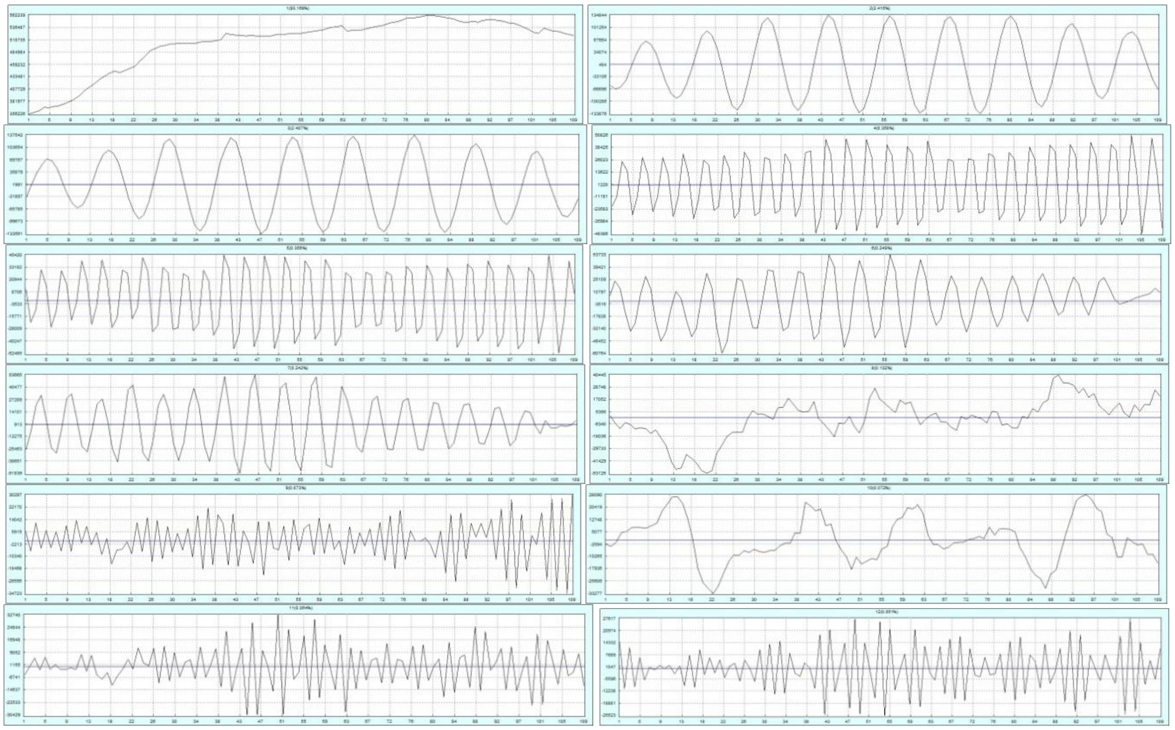
Source of data: Statistics South Africa

Figure 3: Arrivals from Germany, UK and USA



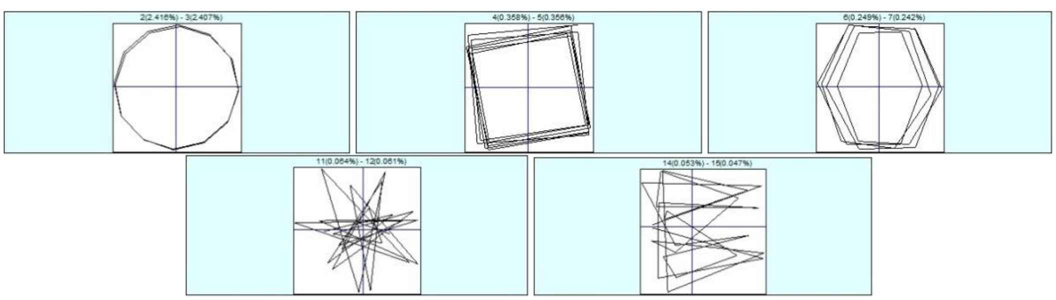
Source of data: Statistics South Africa

Figure 4: Principal Components of first 12 eigentriples of the Europe series



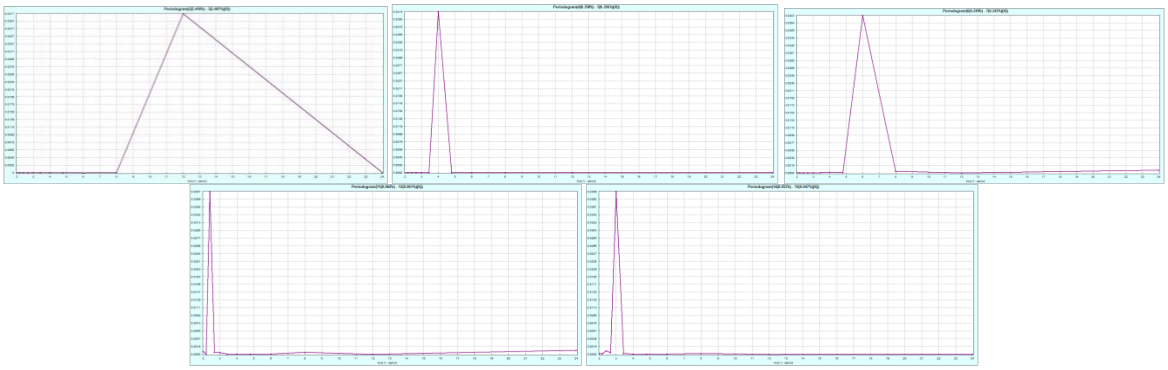
Source: Estimation output

Figure 5: Selected eigenvector pairs for the Europe series (2-3, 4-5, 6-7, 11-12, 14-15)



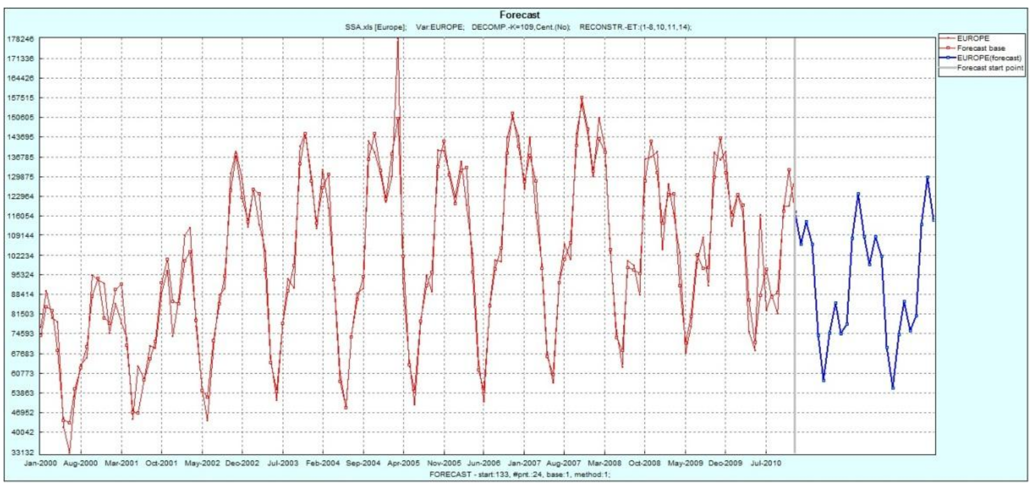
Source: Estimation output

Figure 6: Periodograms of the paired eigentriples for the Europe series



Source: Estimation output

Figure 7: Reconstructed series and forecasts for European arrivals



Source: Estimation output

APPENDIX A

	ADF (no trend)		ADF (trend)		PP (no trend)		PP (trend)	KPSS (intercept)		KPSS (trend)	
	Level	**1st dif**	**Level**	**1st diff**	**Level**	**1st diff**	**Level**	**Level**	**1st diff**	**Level**	**1st diff**
TOTAL	0.93	0.00	0.88	0.02	0.76	0.00	0.00	1.29	0.03	0.18	0.03
EUROPE	0.91	0.00	0.93	0.00	0.21	0.00	0.00	0.83	0.03	0.15	0.05
GERMANY	0.77	0.00	0.72	0.00	0.25	0.00	0.00	0.09		0.13	
UK	0.80	0.00	0.97	0.00	0.18	0.00	0.00	0.75	0.01	0.18	0.07
USA	1.00	0.00	0.98	0.00	0.57	0.00	0.00	1.40	0.17	0.13	
AFRICA	0.88	0.00	0.71	0.07	0.81	0.00	0.00	1.23	0.05	0.09	
LESOTHO	0.62	0.00	0.45	0.00	0.53	0.00	0.00	0.76	0.07	0.10	
ZIMBABWE	0.99	0.00	0.48	0.02	0.94	0.00	0.00	1.34	0.03	0.19	0.09

*ADF & PP = p-values and KPSS= LM-statistic (5% critical value for intercept=0.463 & trend=0.146)

The null hypothesis for the ADF and PP tests are that the variable contains a unit root. The null hypothesis for the KPSS test is that the variable is trend stationary. The ADF and PP tests without time trends give similar results. The KPSS and PP when accounting for a trend give similar results, with a few exceptions.