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Nonparametric Approach to Detecting Seasonality in Time Series: Application of the Kruskal-Wallis (KW) Test on Tourist Arrivals to Sri Lanka

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Abstract

This study applies the nonparametric Kruskal-Wallis (KW) test to determine the presence of seasonality in time series data of tourist arrivals in Sri Lanka. It illustrates the mechanism of the KW test for detecting seasonality in auto correlated data. The KW was originally developed for cross-sectional data with relevant assumptions to investigate the median differences between groups. Therefore, the KW test needs modifications and new assumptions to employ with time series data. Thus, the current research empirically evaluates the use of the test for detecting the seasonality of a time series using quarterly tourist arrivals to Sri Lanka from 1990 to 2019. As suggested in the study, formal unit root tests were conducted to trace stationarity and results of the ADF tests have shown that the original data are non-stationary while the first differences are stationary at the 5 per cent level of significance. The findings divulge that the Kruskal-Wallis test is versatile and can precisely detect the seasonality of a time series after making necessary treatments to the data to fulfil the assumptions. This study provides added graphical presentations of seasonal dynamics to strengthen the use of the test. In addition, the post hoc test provided more information on the statistical significance of the dynamics of seasonality. The Kruskal-Wallis test does not supply seasonal indices, which is a primary disadvantage of the test. Therefore, the current research proposed to use an amalgamation of other time series approaches with the Kruskal-Wallis test.

Keywords: Kruskal-Wallis test, seasonality, time series, tourist arrivals, unit roots.

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Introduction

A time series is a sequence of systematic observations continuously or discretely collected through equal time spaces for a well-defined variable in any field. According to Granger and Newbold (1986, p.1), a time series is ‘‘. . . a sequence of observations ordered by a time parameter’’. It assumes that any time series consists of patterns of data. These patterns generally include long-term movements termed trends, seasonal variations, cyclical variations, and irregularities. A single time series may not accommodate all these components in a single time series, and many time series involve one or two in particular, seasonality and long-term movements.

Seasonality is a frequent and common characteristic for many real-world time series where data have been collected in less than a year. Seasonality is the presence of fluctuations in a time series that recur at specific regular intervals less than a year. Commons and Page (2001) highlighted that seasonality is one of the inherited characteristics of tourism time series. Therefore, it is necessary to precisely define seasonality before conducting any study of tourism seasonality. Although tourism seasonality is a primary issue, it is a poorly understood concept in extant literature (Hinch & Jackson, 2000; Corluka, 2019). Therefore, it is difficult to find a unique and precise definition of seasonality in tourism (Corluka, 2019). Furthermore, it is necessary to investigate whether a time series is seasonal in forecasting activities, particularly in tourism forecasting. Therefore, the detection of seasonality is crucial in time series forecasting and decision-making.

The extant literature endeavored to develop diverse methods to detect, quantify, and compare seasonal patterns in the tourism industry. These techniques involve descriptive statistics, graphical methods, time series decomposition, dummy variable regression, Gini index, analysis of variance, and nonparametric approaches such as the Kruskal-Wallis (K-W) test. However, each method has its advantages as well as disadvantages, and thus, DeLurgio, (1988) and Koenig and Bischoff, (2003) suggested the use of different methods in a combination to detect tourism seasonality. Although the recent literature uses nonparametric methods such as the K-W and Freidman’s test in detecting tourism seasonality, it is hard to find studies that provide a comprehensive analysis considering the validity of these nonparametric techniques in detecting seasonality. Therefore, the subject matter of this study is the investigation of the aptness of the K-W test in detecting tourism seasonality with statistical significance. Therefore, the present study is significant to the literature because it contributes to the existing body of knowledge on tourism seasonality by providing validation for the use of the K-W test. The next section of this study reviews the extant literature on methods for detecting tourism seasonality. The third section illustrates the methodology, and empirical analysis is given in the fourth section. The conclusions are provided in the last section.

Literature Review

Seasonality is one of the most discussed areas in tourism literature. Therefore, there are diverse definitions of tourism seasonality. Bar-On (1975, as cited in Bar-On, 1999), Manning and Powers (1984), Hylleberg (1986), Butler (1998), Swarbrooke and Horner (2007), and Lim and McAleer (2008) are some of the most cited definitions of tourism seasonality. Seasonality is the systematic, intra-year movements in economic time series that are often caused by non-economic phenomena, such as climatic changes and the regular timing of religious festivals

(Thomas & Wallis, 1971). As Koenig and Bischoff (2003) highlighted, definitions vary according to the purpose or objectives of the researchers. Therefore, there are difficulties in precisely detecting and evaluating tourism seasonality (Lundtorp, 2001). Scholars and practitioners use different methods to detect tourism seasonality. These techniques vary from simple graphs to more advanced statistical models including four main approaches: (i) descriptive statistics, (ii) graphical methods, (iii) regression methods, and (iv) time series methods. These approaches generally include the coefficient of seasonal variation (Yacoumis, 1980; Bigović, 2011; De Cantis, Ferrante, & Vaccina, 2011), seasonality ratio (Yacoumis, 1980; Bender, Schumacher, & Stein, 2005; Bigovic, 2012; Corluka, Mikinac, & Milenkovska, 2016), seasonal indicator (Jeffrey & Bardon, 1999; Ćorluka, Vukušić, & Kelić, 2018; Alzboun, 2018), seasonality share (Ćorluka et al., 2018), seasonal index (Falkner, 1924; Shiskin, Young, & Musgrave, 1967; Granger, 1978; Cleveland, Cleveland, Mcrae, & Terpenning, 1990; Lind, Marchal, & Wathen, 2018), Lorenz curve (Lim & McAleer, 2008; Karamustafa & Ulama, 2010; De Cantis et al., 2011; Halpern, 2012; Petrevska, 2013; Ćorluka et al., 2018), Gini coefficient (Lundtorp, 2001; Koenig & Bischoff, 2003; Bender et al., 2005; Lim & McAleer, 2008; Karamustafa & Ulama, 2010; Bigovic, 2012; Ćorluka et al. 2018), amplitute ratio (Kuznets, 1933; Koenig & Bischoff, 2003), seasonality range (Koenig & Bischoff, 2005), and dummy variable regressions (Crum, 1925; Suits, 1957; Hylleberg, 1986; DeLurgio, 1988; Miron, 1990; Miron, 1994; Franses, 2008; Lim & McAleer, 2008; Kurukulasooriya & Lelwala, 2014).

There is a new trend of using nonparametric methods such as the K-W test for detecting seasonality in time series. The K-W test is a nonparametric alternative to one-way ANOVA when assumptions of parametric tests are violated (Kruskal & Wallis, 1952). The K-W approach is the most commonly used nonparametric procedure in time series analyses (Theobald & Price, 1984; Kurukulasooriya & Lelwala, 2011, 2014; Gnanapragasam, Cooray, & Dissanayake, 2016; Marcos, Viegas, De Costa, Freitas, & Russo, 2016; Hopken, Eberle, Fuchs, & Lexhagen, 2020; Ollech & Webel, 2020; Molinaro & DeFalco, 2022). However, scholars and researchers use the K-W test without examining the applicability of the test. Researchers have also neglected the assessment of the validity of the assumption of the K-W test to auto-correlated data. At the very inception, the K-W test was introduced to the cross-sectional data to investigate the statistical significance of the median differences among different groups or populations. Therefore, it is questionable to use the K-W test for time series data in its original form. Thus, the objective of the current study is to fill this knowledge gap by providing a comprehensive analysis for detecting seasonality in a time series with special reference to the tourist arrivals time series in Sri Lanka using the K-W test. Accordingly, the current study assesses the usual assumptions and their validity of the K-W approach for detecting tourism seasonality in a time series context.

Materials and Methods

It is important to understand the concept of seasonality before the discussion of the proposed methodology. As mentioned in the introductory section, seasonality divulges recurring patterns in a time series that are generally repeated for less than a year. These repetitive patterns are caused by many factors, including natural causes such as weather fluctuations, business, and administrative procedures such as school holidays, and social and cultural events such as Christmas, the trading day effect, and moving holidays. Seasonality is crucial for data analysts in making informed decisions and in forecasting activities. Visual inspection of the data, autocorrelation analysis, and decomposition techniques such as seasonal decomposition of time series are some of the common methods used to confirm the existence of seasonality in a time series. Although they are effective in detecting seasonality, their robustness is questionable due to the inherited personal bias. Therefore, the K-W test presents a robust statistical approach to confirm the existence of seasonality in a time series.

The proposed methodology of this study was first presented by Kruskal & Wallis (1952) for rank data or continuous data that can be converted into ranks. It is an alternative to the one-criterion analysis of variance and thus is known as the one-criterion analysis of variance for rank data. When several independent samples are coming from the same population, they are invariably random samples. Then, the question arises whether sample differences are statistically robust or/and significant. Kruskal and Wallis (1952) suggested the following test statistic for the investigation of significant differences among samples based on their means.

$$H = \frac{12}{N(N+1)} \sum_{i=1}^{c} \frac{R_i^2}{n_i} - 3(N+1) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (1)$$

Where C denotes the number of samples, n_i is for the number of observations in the ith sample, $N = \sum n_i$ which is the number of observations in all samples combined, and R_i is the sum of the ranks in the ith sample.

Larger values of H tend to reject the null hypothesis that there are no significant differences between the groups. Kruskal and Wallis, 1952 have shown that H is distributed in a chi-square distribution with (c-1) degrees of freedom when large samples come from identical continuous populations. The accepted minimum sample size is 5 to satisfy the chi-square distribution for H (see more details in Kruskal & Wallis, 1952). The H test is based on a few assumptions, as given below, and the validity of these assumptions should be assessed for the time series data.

i). The dependent variable must be an ordinal or continuous level (i.e., interval or ratio). The current study uses quarterly tourist arrivals as the dependent variable and thus, the variable here is a continuous which is an interval or ratio scale of the measurement. Therefore, this assumption is satisfied by the data. The validity of the usage of ranks is comprehensively provided by Kruskal and Wallis (1952). The rankings are possible for continuous data.

ii). The independent variable should consist of two or more categories, i.e., independent groups. Typically, the K-W H test is used when there are three or more categorical independent groups. The present study uses quarterly tourist arrivals, and each quarter with many observations is considered an independent group. The quarters of the years are independent and thus, the assumption is satisfied. Further autocorrelation coefficients will help in detecting independence between quarters.

iii). The K-W test expects independent observations within and between groups. This means that there is no relationship between the observations in each group (within each quarter) or between the groups themselves (Between quarters). This assumption is violated with time series data because they are autocorrelated. Furthermore, time series may be stationary or nonstationary in its original form. When time series is stationary there is no issue. Nonstationary series exhibit deterministic or stochastic trends showing the relationship between data points in different time points. Detrending the data before the analysis resolves the problem when the time series is nonstationary. Detrended data generate a random series that retains only the seasonal component when the original series has the seasonal component (DeLurgio, 1988). An autocorrelation analysis can be conducted to prove this assumption.

iv). Normality is a rigorous assumption in ANOVA and is usually violated in practice. However, it is not required by the K-W test which is less sensitive to outliers. However, the K-W test comes with an additional data consideration leading to the fourth assumption, i.e., it requires the determination of whether the distributions in each group (i.e., the distribution for each group of the independent variable) have the same shape (which also means the same location and variability). Time series also assumes a constant variance; therefore, this assumption can be justified with the time series property of constant variance. If this assumption is violated, natural logarithmic values or a suitable transformation is suggested. Location parameters such as mean, and median can be estimated to observe the validity of the assumption with usual t test or with an alternative nonparametric test like Mann Whiteney U test.

If there are ties, each observation is given as the mean ranks for which it is tied. Then, the H statistic is computed from equation (1) and is divided by the factor, $\left[1-\frac{\sum T}{N^3-N}\right]$ which is generally known as adjustment factor for H test. Therefore, when tied observations are available, equation (2) is more appropriate.

$$H=\frac{\frac{12}{N(N+1)}\sum_{i=1}^{c}\frac{R_i^2}{n_i}-3(N+1)}{1-\frac{\sum T}{N^3-N}} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (2)$$

The discussion hitherto reveals that H test is possible to apply with some modifications or transformations for the data in a time series. The following major steps are suggested to perform the K-W test for detecting tourism seasonality.

i). Determining the stationarity of data: Observe time series plot and determine the type of trend, i.e., whether the trend is deterministic or stochastic. Test the time series for stationarity to confirm that the time series is free from unit-root problems. Any of the unit root test (ADF, ADF-GLS, Philips Perron etc.) is proposed in this step.

ii). Detrending data: If the time series is nonstationary, the data should be detrended using an appropriate detrending method. It is assumed that the cyclical component is not prevailing in the data (since many of the practical time series are free from cyclical components) and irregularity is negligible. If there are significant irregularities, a suitable data imputation is proposed.

iii). Preparing data: Forming time series data into groups (into months or quarters) corresponding to the time intervals for comparison is requested. For example, if we assume monthly seasonality, the time series must be divided into 12 groups, one for each month and data needs to be arranged accordingly.

iv). Ranking of data: Ranking of the data within each month/quarter is required. Assign a rank of one to the smallest value, 2 to the second smallest, and so on. Ties are handled by assigning the average rank to the tied observations.

v). Calculating the Test Statistic: Calculate the K-W test statistic, H, which measures the variability between the groups. This statistic follows a chi-squared distribution. Software applications will do the job accurately.

vi). Determining Significance: Assess the statistical significance of H using a chi-squared distribution table or statistical software. If H is statistically significant, it suggests that there are median/mean rank differences between the groups, indicating the presence of seasonality.

vii). Conducting multiple comparisons (post hoc tests): As in the case of the usual ANOVA, once it rejects the null hypothesis of no mean or median difference between months or quarters, it is important to investigate where the differences are. That is, which populations are different from which? Therefore, post hoc analysis will be useful in determining the significance of seasonal dynamics between different seasons, i.e., months or quarters. Any of the post hoc test can be used in this step.

When the K-W test rejects the null hypothesis, it is vital to conduct multiple comparisons to investigate the significantly different seasons as mentioned in previous section. Equation (3) gives the test statistic for post hoc tests. Post hoc analysis is similar to the Turkey method of further analysis of the ANOVA model.

$$D = \left| \bar{T}_i - \bar{T}_j \right| \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots (3)$$

Where $\bar{T}_i$ and $\bar{T}_j$ are the mean ranks of samples i and j, respectively. The test is carried out by comparing the test statistic D with a quantity that we compute from the critical point of the chi–square distribution at the same level of significance as the original K-W test was conducted. The critical point for the pared comparisons is given in equation (4).

$$C_{kw} = \sqrt{\chi^2_{\alpha,k-1} \frac{N(N+1)}{12} \left(\frac{1}{n_i} + \frac{1}{n_j} \right)} \dots\dots\dots\dots\dots\dots\dots.\dots\dots (4)$$

Where $\chi^2_{\alpha,k-1}$ is the critical point of the chi – square distribution used in the original test. By comparing the value of statistic D with C_{kw} for every pair of populations, it can perform all pairwise comparisons jointly at the level of significance at which the K-W H test was performed. We reject the null hypothesis if and only if $D > C_{kw}$.

As mentioned earlier in this section, unit root tests help figure out the stationarity of a time series. Although there are various kinds of unit root tests presented in the literature, this paper employs the Dickey-Fuller unit root test (Dickey & Fuller, 1979). Three different null hypotheses are tested using the equations (5) to (7). Equation (5) is useful to test whether the time series follows a random walk process (no drift and no trend).

$$\Delta Y_t = \delta Y_{t-1} + \sum_{i=1}^{m} \alpha_i \Delta Y_{t-i} + \varepsilon_t \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots (5)$$

Equation (6) is useful to test whether the random walk process has a drift component.

$$\Delta Y_t = \beta_1 + \delta Y_{t-1} + \sum_{i=1}^{m} \alpha_i \Delta Y_{t-i} + \varepsilon_t \dots\dots\dots\dots\dots\dots\dots\dots\dots (6)$$

Equation (7) is useful for testing whether the random walk process follows a drift around a deterministic trend.

$$\Delta Y_t = \beta_1 + \beta_1 t + \delta Y_{t-1} + \sum_{i=1}^{m} \alpha_i \Delta Y_{t-i} + \varepsilon_t \dots\dots\dots\dots\dots\dots (7)$$

Traditionally, three different null hypotheses are tested using the equations (5) to (7). Each null hypothesis involves the testing of whether $\delta = 0$ against the alternative hypothesis $\delta < 0$. A more negative test statistic leads to the rejection of the null hypothesis. MacKinnon's (1996) critical values or p-values helpful in rejecting or accepting the null hypothesis. Acceptance of the null hypothesis leads to the acceptance of the unit roots of the time series, which illustrates the nonstationarity. When the original time series is nonstationary, similar unit root tests must be conducted for the first differenced time series too.

This empirical study uses quarterly tourist arrivals from all countries to Sri Lanka from 2009 to 2019. The secondary data were obtained from the annual reports of Sri Lanka Tourism Development Authority (SLTDA). The sample period was selected assuming less irregularities and no cyclical patterns. However, there are no issues of degrees of freedom and sample size because there 120 observations for the sample period.

Empirical Analysis and Discussion

The primary step in any time series analysis is to construct a time series graph of the variable of interest. The visual impression of the time series graph helps to identify the global trend of the variable, the nature of seasonal patterns, shifts and abrupt changes in the series, cyclical fluctuations, variability, and outliers. Figure 1 illustrates quarterly total tourist arrivals (TTA) to Sri Lanka for the years from1990 to 2019.
The visual impression of Figure 1 depicts a cubic form of global trends in quarterly TTA. Furthermore, the figure presents a significant seasonal behaviour of TTA during the period of interest. There are no pronounced shifts or drifts in the tourism time series for the sample period considered, except for an outlier due to the Easter Sunday Attack. It is in the last observations in the series and thus can be removed from the analysis without violating the aim of the research. The seasonal component is proportional to the global trend; thus, the

logarithmic values of the original variable must be taken and used in the analysis. The logarithmic values of the TTA are also depicted in the same diagram, Figure 1, and it is obvious that the effect of the outlier is drastically reduced because of the stabilization of variability by taking logarithmic values.

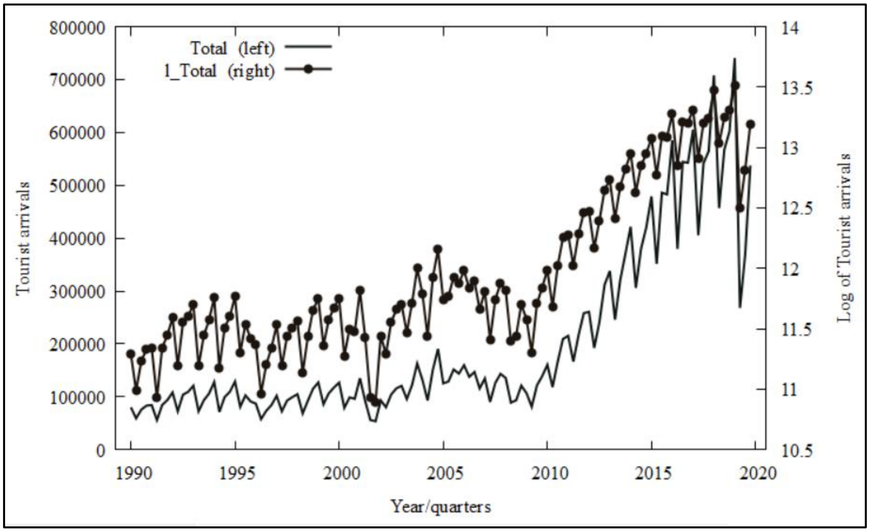

Figure 1: Time series graph of the TTA and log TTA 1990-2019

The TTA also exhibits a trend and thus seems nonstationary. Next the descriptive statistics are examined to understand the nature of the data and Table 1 presents these statistics. Mean, median and mode are significantly different between quarters stating that the data distribution is deviating from symmetry. The Shapiro-Wilk test rejects the null hypothesis of normality ($p<0.001$) of the sample data for four quarters. The Shapiro-Wilk test is more appropriate for this analysis since the sample size is less than 50 observations per season. Further, the vertical and horizontal symmetry of the sample data evaluate the normality.

Table 1: Descriptive statistics for quarterly total tourist arrivals

	Quarter			
	Quartr1	Quater2	Quarter3	Quarter4
Valid	30	30	30	30
Mode	120053.24	82458.00	106026.70	116045.68
Median	130302.00	91154.50	121660.50	129838.50
Mean	228367.40	151729.033	197501.87	219584.40
Std. Error of Mean	36126.64	21455.31	28838.03	31278.45
Std. Deviation	197873.75	117515.59	157952.41	171319.11
Coefficient of variation%	86.6	77.5	80.0	78.0

	Quarter			
	Quartr1	Quater2	Quarter3	Quarter4
Skewness	1.607	1.425	1.411	1.210
Std. Error of Skewness	0.427	0.427	0.427	0.427
Z of Skewness	3.760	3.340	3.300	2.830
Kurtosis	1.289	0.785	0.637	-0.033
Std. Error of Kurtosis	0.833	0.833	0.833	0.833
Z of Kurtosis	1.55	0.94	0.77	-0.04
Shapiro-Wilk	0.698	0.752	0.745	0.769
P-value of Shapiro-Wilk	< .001	< .001	< .001	< .001

Source: Author's computations from sample data

Though the sample data have achieved vertical symmetry under 5 percent level of significance (all Z values of Kurtosis are in between -1.96 and +1.96), it does not pass the horizontal symmetry since all z values of skewness lie outside of the range of -1.96 and +1.96. The data represent a positively skewed distribution for four quarters. Further, the difference between mean and the median is also considerably high. The coefficient variation for each quarter is not same and thus higher variation within a quarter is profound. This concludes that the sample data violates the assumptions of ANOVA. Therefore, it is not possible use the sample data as its original form to detect seasonality of total inbound tourist arrivals. One of the major reasons for the violation of the assumptions of ANOVA is due to the autocorrelated nature and the existence of trend of the data. Therefore, it is necessary to find out if there is a trend in the data.

According to the proposed methodology following the step 1 for detecting seasonality, data should be stationary. Therefore, the Augmented Dickey Fuller (ADF) was conducted to confirm the stationarity of the variable. Table 2 summarizes the results of different ADF tests for log TTA (LTTA) and logged first differences in TTA (DLTTA). The ADF test was conducted under three different specifications, as given in equations (5) to (7) and results are presented in columns 2 to 4 in Table 2 respectively. The results of the ADF tests suggest that the original data (the level form data) are nonstationary, and the first differences are stationary under any of the conventional significant levels.

Table 2: Results of the Augmented Dickey-Fuller test for quarterly total tourist arrivals (TTA)

Variable	Without constant	With constant	With constant and trend	Conclusion
	Tau Statistic	Tau Statistic	Tau Statistic	
LTTA	1.11887 (0.9323)*	-0.903019 (0.788)	-2.4837 (0.3363)	I (1)
DLTTA	-16.3578 (0.0000)	-16.9204 (0.0000)	-16.9322 (0000)	I (0)

* P values are given in parentheses.

Therefore, the detrended tourist arrivals are useful as given in step 2 in methodology for the KW test for detecting tourism seasonality. There are numerous methods to remove the trend from a time series. Since the global trend is quadratic type and thus, most appropriate trend type was detected and predicted trend values from the quadratic trend model was employed in detrending data. As Figure 2 illustrates the logged detrended data of TTA. There are no cyclical components in the series and one significant outlier was detected at the end of the series. This study removes the outlier since removing the outlier at the end of the series has no impact on the process of detecting seasonality. Therefore, the first differences in logged data are appropriate to detect seasonality.

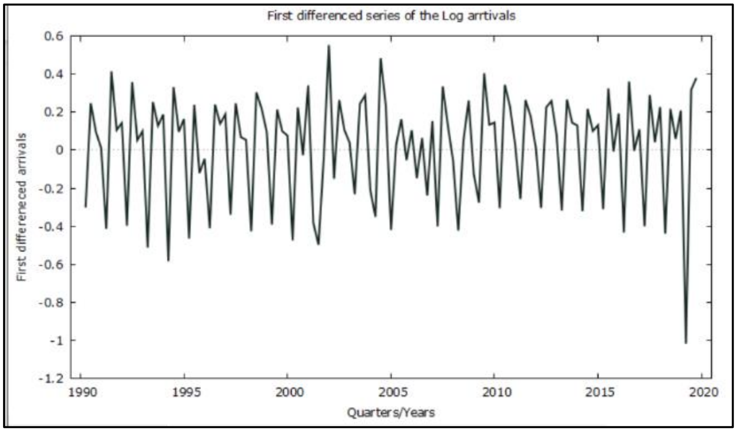

Figure 2: Time series graph of first differences in the logged total arrivals

The graphical illustrations will provide evidence for the confirmation of the results of the study. Accordingly, Figure 3 illustrates the boxplots for each quarter of the detrended data.

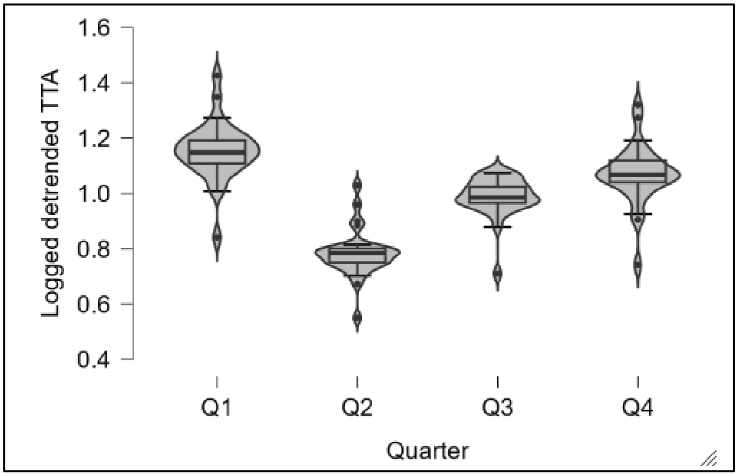

Figure 3: Boxplots for detrended quarterly TTA

According to Figure 3, quarterly distributions of tourist arrivals do not follow a similar pattern in terms of location and spread/shape. Therefore, ANOVA will not be the best approach for detecting seasonality. Further, seasonal dynamics are prominent between quarters. The visual impression of the confirms the existing similar seasonal variations. Figure 4 illustrates the seasonal sub series plot for the detrended TTA. Seasonal sub series plot reveals that seasonal dynamics exist between and within quarters. According to the objectives of the current study, within quarter seasonal dynamics are not discussed and it is beyond the scope of this research. Graphical illustrations provide clear evidence for the existence of quarterly seasonal variations of total inbound tourist arrivals. The next step is to utilize the prepared data (quarter wise detrended tourist arrivals) to investigate the seasonal variation using the KW test.

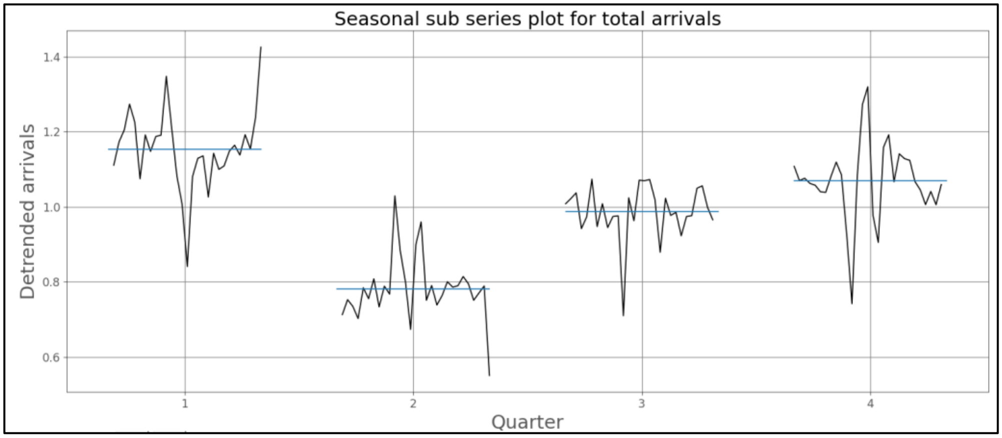

Figure 4: Seasonal sub series plot for the detrended tourist arrivals

The results of the KW test are presented in Table 3. The K-W test is performed for both level and detrended tourist arrivals. The K-W H test reveals statistically significant difference between quarters of logged detrended total tourist arrivals (LDTTA) with $\chi2(3) = 80.689$ (P <0.001). Therefore, it can conclude that there is statistical evidence at 5% level of significance to accept the research hypothesis that significant seasonal differences exist among quarters of the year. Therefore, the K-W tests proves that what the graphical illustrations given earlier. Accordingly, it can be concluded that with necessary adjustment to the auto correlated data, The K-W test provides reliable information to confirm the existence of seasonal component of a time series and further provides statistical significance for the evidence. It is a positive side of the K-W test compared to the trend-Seasonal decomposition. It provides information to confirm the existence of seasonal components and seasonal indices as well. However, the trend-seasonal decomposition never provides the statistical inference to confirm the prevailed seasonality.

When the null hypothesis of the K-W test is rejected, i.e., there is evidence for seasonality in the time series, pairwise comparisons in terms of post hoc analysis will be helpful in detecting significant differences among quarters. Table 4 presents the results of the post hoc comparisons. Q1 to Q4 stands for the quarters 1 to 4. Each row of Table 4 tests the null hypothesis that the Sample 1 and Sample 2 distributions are the same, i.e., there is not a seasonal difference between the compared quarterly arrivals for detrended data.

Table 3: Results of Kruskal-Wallis test for total quarterly inbound tourist arrivals, 1990-2019

Description	TTA[1]	LDTTA[2]
Number of observations	120	116
Null hypothesis tested	The median of TTA is the same across quarters	The median of LDTTA is the same across quarters
Test Statistic	4.354	80.689
Degrees of freedom	3	3
P-value	0.226	0.0000
Decision	Retain the null hypothesis	Reject the null hypothesis

Notes: 1. Total Tourist Arrivals, 2. Logged Detrended Tourist Arrivals
Source: Author's computations based on sample data

Table 4: Results of the post-hoc comparisons in the Kruskal-Wallis test

		Mean Difference	SE	t	p_{tukey}	$p_{scheffe}$	p_{bonf}	p_{holm}	p_{sidak}
Q1	Q2	0.372	0.025	15.117	< .001	< .001	< .001	< .001	< .001
	Q3	0.166	0.025	6.752	< .001	< .001	< .001	< .001	< .001
	Q4	0.085	0.025	3.452	0.004	0.010	0.005	0.002	0.005
Q2	Q3	-0.206	0.025	-8.365	< .001	< .001	< .001	< .001	< .001
	Q4	-0.287	0.025	-11.665	< .001	< .001	< .001	< .001	< .001
Q3	Q4	-0.081	0.025	-3.300	0.007	0.015	0.008	0.002	0.008

Note. P-value adjusted for comparing a family of 4
Source: Author's computations based on sample data

As Table 4 reveals, all the comparisons are statistically significant at 5% level of significance under several types of post hoc tests conducted. Therefore, the K-W test proves that seasonality is existing in quarterly total inbound tourist arrivals in Sri Lanka for the period from 1999 to 2019. The findings of Table 4 are highly compatible with the graphical evidence provided in Figures 2, 3, and 4. Therefore, it can be concluded that the K-W tests are useful in detecting seasonality in a time series after adjusting the data to be compatible to the K-W test. Although the K-W test is useful in detecting seasonal dynamics and its statistical significance, it does not supply the seasonal indices. A practitioner can accommodate both Trend-Seasonal decomposition and the K-W test for a prolific analysis of seasonal dynamics in a time series. Table 5 provides additional information to confirm the results of the K-W test and graphical illustrations.

Table 5: Seasonal indices for quarterly inbound total tourist arrivals 1990-2019

Variable	Seasonal Indices			
	First quarter	Second quarter	Third quarter	Fourth quarter
TTA	1.16	0.79	0.98	1.07

Table 5 provides the seasonal indices computed via Trend-Seasonal decomposition. The method supplies just the seasonal indices and there is no information given for the statistical inferences of seasonal indices. According to the information available in Table 5, the first and the fourth quarters show a positive seasonal impact while the second and third quarters show negative impact. These seasonal dynamics are statistically significant according to the results of the K-W test and all these results can be confirmed with the graphical illustrations in figures 2, 3, and 4.

Conclusions

The K-W test has been used in seasonality analyses without confirming the assumptions of the test when it applies to time series data (Kurukulasooriya & Lelwala, 2014; Marcos et al., 2016; Gnanapragasam et al., 2016). This study is a complete demonstration of the right application of the nonparametric Kruskal-Wallis test to detect the seasonality of a time series with special reference to tourist arrivals data. The steps of the test procedure have been presented, and the empirical application was based on total quarterly tourist arrivals from all countries to Sri Lanka. ADF was conducted before the seasonality analysis, and it has shown that inbound tourist arrivals are nonstationary in their level form. Detrended values of the tourist arrivals are also tested for unit roots and have shown that the detrended time series is stationary and fulfills the requirement of assumptions of Kruskal-Wallis test. This empirical study presented the evidence to use Kruskal-Wallis test for detecting seasonality in a time series on detrended data. The use of detrended data for seasonal analysis was assured in the literature (Nwogu, Iwueze, & Nlebedim, 2016). The test results were also strengthened by adding graphical illustrations that are powerful tools for statistical analyses. The post hoc comparison procedure, which is highly neglected in literature, is helpful in investigating the statistically significance differences between different seasons of a time series of interest. Therefore, the conclusion of the study is that the Kruskal-Wallis test is a proper method for detecting seasonality in a time series with necessary treatments to the original assumptions of the test and adjusting the data accordingly. Furthermore, the post hoc procedure will also help in analyzing the seasonality between different seasons. One of the major disadvantages of the Kruskal-Wallis tests is that it does not provide any information about the seasonal factors related to each season. Therefore, researchers can use the Kruskal-Wallis test to confirm the existence of seasonality with statistical significance and need another method such as time series decomposition for computation of the seasonal indices. However, time series decomposition does not provide statistical significance for the seasonal indices. Therefore, the use of a combination of both methods is recommended. It is recommended to repeat the same research in different disciplines where the seasonality prevails in time series to confirm the results and evidence presented in this research.

References

Alzboun, N. (2018). Measuring seasonality of tourism demand in Petra, Jordan (2006-2017). *Modern Applied Science, 12*(9), 131-139. doi:10.5539/mas.v12n9p131

Bar-On, R. l. (1999). The measurement of seasonality and its economic impacts. *Tourism Economics, 5*(4), 437-458. doi:10.1177/135481669900500409

Bender, O., Schumacher, K. P., & Stein, D. (2005). Measuring seasonality in central Europe's tourism – how and for what? *10th International conference on information & communication technologies (ICT) in urban planning and spatial development and impacts of ICT on physical space* (pp. 303-309). Wien: Technische Universität.

Bigović, M. (2011). Quantifying seasonality in tourism: a case study of Montenegro. *Academica Turistica, 4*(2), 15-32.

Bigovic, M. (2012). The strength and dynamics of the seasonal concentration in Montenegrin tourism. *Turizam, 16*(3), 102-112. doi:10.5937/Turizam1203102B

Butler, R. (1998). Seasonality in tourism: issues and implications. *The Tourist Review, 53*(3), 18-24. doi:10.1108/eb058278

Cleveland, R. B., Cleveland, W. S., Mcrae, J. E., & Terpenning, I. J. (1990). A seasonal trend decomposition procedure based on loess. *Journal of Official Statistics, 6*, 3-73.

Commons, J., & Page, S. (2001). Managing seasonality in peripheral tourism regions: the case of Northland, New Zealand. In T. Buam, & S. Lundtrops, *Seasonality in tourism* (pp. 154-173). New York: Pergamon. doi:10.1016/B978-0-08-043674-6.50013-1

Corluka, G. (2019). Tourism Seasonality: an overview. *Journal of Business Paradigms, 4*(1), 21-43.

Corluka, G., Mikinac, K., & Milenkovska, A. (2016). Classification of tourist season in costal tourism. *UTMS Journal of Economics*, 71-83.

Ćorluka, G., Vukušić, A., & Kelić, I. (2018). Measuring tourism seasonality: application and comparison of different methods . *Tourism & Hospitality Industry*, 55-63.

Crum, W. L. (1925). Statistical methods, applied to economics and business by Frederick Cecil Mills. *The Quarterly Journal of Economics*, 469-472.

De Cantis, S., Ferrante, M., & Vaccina, F. (2011). Seasonal pattern and amplitude – a logical framework to analyse seasonality in tourism: an application to bed occupancy in Sicilian hotels. *Tourism Economics, 17*(3), 655-675. doi:10.5367/te.2011.0055

DeLurgio, S. A. (1988). *Forecasting principles and applications* (1st ed.). New York: McGraw-Hill.

Dickey, D. A., & Fuller, W. A. (1979). Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American Statistical Association, 74*(366), 427-431. doi:10.2307/2286348

Falkner, H. D. (1924). The measurement of seasonal variation. *Journal of the American Statistical Association, 19*(146), 167-179.

Franses, P. H. (2008). Forecating seasonal time series. In R. S. Mariano, & Y. -K. Tse, *Econometric forecasting and high frequency data analysis* (pp. 93-130). London: World Scientific Publishing Co. Pte. Ltd.

Gnanapragasam, S. R., Cooray, T. M., & Dissanayake, R. A. (2016). Prediction of international tourist arrivals to Sri Lanka using state space modelling method: an empirical study after the civil war. *Proceedings in Medical, Allied Health, Basic and Applied Sciences, 9th International Research Conference* (pp. 50-55). Colombo: Kothalawala Defence University.

Granger, C. W. (1978). Seasonality: causation, interpretation, and implications. In A. Zellner, *Seasonal Analysis of economic time series* (pp. 33-56). National Bureau of Economic Research.

Granger, C. W., & Newbold, P. (1986). *Forecasting econometric time series.* New York: Academic Press.

Halpern, N. (2012). Measurement and decomposition of seasonal demand for tourism in Norway. *11th Global forum on tourism statistics*, (pp. 1-11). Reykjavik, Iceland. Retrieved July 8, 2022, from https://docs.wixstatic.com/ugd/c9b399_7da9ddfbc10e45408967630946af40ea.pdf

Hinch, T. D., & Jackson, E. L. (2000). Leisure constraints research: its value as a framework for understanding tourism seasonality. *Current Issues in Tourism, 3*(2), 87-106. doi:10.1080/13683500008667868

Hopken, W., Eberle, T., Fuchs, M., & Lexhagen, M. (2020). Improving tourist arrival prediction: a big data and artificial nueral network approach. *Travel research, 60*(5), 1-20. doi:10.1177/0047287520921244

Hylleberg, S. (1986). *Seasonality in regression.* New York: Academic Press Inc.

Jeffrey, D., & Bardon, R. R. (1999). An analysis of the nature, causes and marketing implications of the seasonality in the occupancy performance of English hotels. *Tourism Economics, 5*(1), 69-91. doi:10.1177/135481669900500105

Karamustafa, K., & Ulama, S. (2010). Measuring the seasonality in tourism with the comparison of different methods. *EuroMed Journal of Business, 5*(2), 191-214. doi:10.1108/14502191011065509

Koenig, N., & Bischoff, E. (2003). Seasonality of tourism in Wales: a comparative analysis. *Tourism economics, 9*(3), 2244-259.

Koenig, N., & Bischoff, E. E. (2005). Seasonality research: the state of the art. *International Journal of Tourism Research, 7*, 201–219. doi: 10.1002/jtr.531

Kruskal, W. H., & Wallis, W. A. (1952). Use of ranks in one-criterion variance analysis. *Journal of the American Statistical Association, 47*(260), 583-621. doi:10.1080/01621459.1952.10483441

Kurukulasooriya, N., & Lelwala, E. (2014). Time series behavior of burgeoning international tourist arrivals in Sri Lanka: the post-war experience. *South Asian Journal of Business Insights, 1*(1), 1-14.

Kurukulasooriya, N., & Lelwala, E. I. (2011). Short-term forecasting of international tourist arrivals to Sri Lanka : comparative evidence using exponential smoothers. *6th International conference on economics and finance.* Colombo: University of Colombo.

Kuznets, S. (1933). The economic problem. In S. Kuznets, *Seasonal variations in industry and trade* (pp. 7-22). NBER.

Lim, C., & McAleer, M. J. (2008). Analysing seasonal changes in New Zealand's largest inbound market. *Tourism Recreation Research, 33*(1), 83-91. doi:10.1080/02508281.2008.11081292 ·

Lind, D. A., Marchal, W. G., & Wathen, S. A. (2018). *Statistical techniques in business and economics* (17th ed.). New York: McGraw-Hill.

Lundtorp, S. (2001). Measuring tourism seasonality . In T. Baum, & S. Lundtorp, *Seasonality in tourism* (pp. 23-50). Oxford: Elsevier Science Ltd.

MacKinnon, J. G. (1996). Numerical distribution functions for unit root and cointegration tests. *Journal of Applied Econometrics, 11*(6), 601–618. doi:doi:10.2307/2285154

Manning, R. E., & Powers, L. A. (1984). Peak and off-peak use: redistributing the outdoor recreation/tourism load. *Journal of Travel Research, 23*(2), 25–31. doi:10.1177/004728758402300204

Marcos, S., Viegas, V. D., De Costa, D. F., Freitas, R. M., & Russo, B. B. (2016). Demand seasonality analysis of hgigh valued-added items: a Kruskal-Wallis test applicationin an oil and gas multinational company. *International Journal of Basic and Applied Sciences, 16*(5), 10-15.

Miron, J. A. (1990, November). The economics of seasonal cycles. *NBER working paper series*. Retrieved July 28, 2022, from https://www.nber.org/system/files/working_papers/w3522/w3522.pdf

Miron, J. A. (1994). The economics of seasonal cycles. In C. A. Sims, *Advances in Econometrics (Sixth World Congress)* || *The economics of seasonal cycles* (pp. 213-255). Cambridge: Cambridge University Press.

Molinaro, A., & DeFalco, F. (2022). Empirical assessment of alternative methods for identifying seasonality in observational healthcare data. *BMC Medical Research Methodology, 22*(182), 1-11. doi:10.1186/s12874-022-01652-3

Nwogu, E. C., Iwueze, I. S., & Nlebedim, V. U. (2016). Some tests for seasonality in time series data. *Journal of Modern Applied Statistical methods, 15*(2), 382-399. doi:10.22237/jmasm/1478002920

Ollech, D., & Webel, K. (2020). *A random forest-based approach to identifying the most informative seasonality tests.* Frankfurt: Deutsche Bundesbank. Retrieved from https://www.bundesbank.de/resource/blob/847066/91b632c7d380e084c1cd34bd957664e7/mL/2020-10-07-dkp-55-data.pdf

Petrevska, B. (2013). Empirical analysis of seasonality patterns in tourism. *Journal of Process Management, 1*(2), 87-95.

Shiskin, J., Young, A. H., & Musgrave, J. C. (1967). The X_II variant of the census method II:Seasonal adjustment programme. *Working papers*. Retrieved August 25, 2022, from https://www.census.gov/content/dam/Census/library/working-papers/1967/adrm/shiskinyoungmusgrave1967.pdf

Suits, D. B. (1957). Use of dummy variables in regression equations. *Journal of the American Statistical Association, 48*(280), 548-551.

Swarbrooke, J., & Horner, S. (2007). *Consumer behaviour in tourism* (2nd ed.). New York: Elsevier Ltd.

Theobald, M., & Price, V. (1984). Seasonality estimation in thin markets. *The Journal of Finance, 39*(2), 377-392. Retrieved July 10, 2023, from www.jstor.org/stable/2327866

Thomas, J., & Wallis, K. (1971). Seasonal variation in regression analysis. *Journal of Royal Statistical Society, 134*(1), 57-72. doi:10.2307/2343974

Yacoumis, J. (1980). Tackling seasonality: The case of Sri Lanka. *Tourism Management, 1*(2), 84-98.