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Impacts of Seasonal Patterns of Climate on Recurrent Fluctuations in Tourism Demand

Evidence from Aruba

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Abstract

This study estimates the effect of seasonal patterns of pull/push weather elements (rainfall, temperature, wind, and cloud coverage) on recurrent fluctuations in tourism demand for Aruba, originating from the USA and Venezuela. The estimation is based on an econometric methodology consisting of decomposing time series of weather elements and tourism demand, using a Census X-12 decomposition procedure, and subsequently applying a unit root test, an Engle & Granger cointegration test, a Granger causality test, and a Euclidean distance measure. The results show no influence of weather (pull and push) on the seasonal patterns of tourism demand from Venezuela. On the other hand, the study showed a clear causal relationship between (pull and push) seasonal weather variability and tourism demand from the USA.

Keywords: seasonality, tourism demand, climate, cointegration, Granger causality, small island, Aruba.

1. Introduction

Over the last century, tourism has become the world's largest business, surpassing defense, manufacturing, oil and agriculture industries (Lundberg et al., 1995; Goeldner & Brent Ritchie, 2012). Tourism is one of the fastest growing sectors (Vanhove, 2005; Salish & Rodrigues, 2011; Schubert & Brida, 2011), an unprecedented feature since World War II (Apostolopoulos, 1996). Between 1950 and 2010, international tourist arrivals grew at an annual average of 6.2%, from 25 million to 940 million travelers (UNWTO, 2011). The number of destinations has also increased over time. While in 1950, the 15 foremost destinations absorbed 88% of the international arrivals, by 2010

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the top 15 destinations accounted for only 55% of the total international arrivals (UNWTO, 2011).

To keep abreast with the rapidly growing tourism phenomenon, destinations need adequate forecasts of tourism demand for planning and managerial decisions (Goh, 2012). This calls firstly for adequate insight into the factors that influence tourism demand (Vanegas Sr. & Croes, 2000). Secondly, it requires detailed understanding of the patterns of development of tourism demand over time.

Many studies on the determinants of tourism demand have been concentrated around economic factors (e.g., income and price) (Goh, 2012), while remaining particularly silent on the potential impact of climate on the choice of destinations (Kulendran & Dwyer, 2010). According to Belén Gómez Martín (2005), climate is the prevailing condition of the atmosphere drawn from long periods of observation, contrary to the term weather which is the state of the atmosphere at a given time and in a given place. Climate, in other words, is the average weather for a specific location, impacting a wide array of environmental resources that are critical attractions for tourism, for example, snow conditions, wildlife productivity and biodiversity, water levels and their quality (UNWTO & UNEP, 2008). Climate also is important, because it attracts visitors who expect favorable weather conditions at the destination (Scott et al., 2004; Belén Gómez Martín, 2005; Kulendran & Dwyer, 2010). On the other hand, climate in the originating country can affect the decisions of people to stay in their own country or to travel abroad (Hamilton & Tol, 2007). Hence, climate acts both as pull and push factors affecting the motivations of tourists to go on a holiday and their choice of the destination (Hamilton et al., 2005; Amelung et al., 2007).

Swings in demand produce situations of over-capacity, non-utilization of infrastructure, decrease in the work force and absence of investments during low seasons (Pegg et al., 2012), causing reduced profitability and productivity (Karamustafa & Ulama, 2010). On the other hand, peak seasons can be characterized by over-use of public utilities (e.g., water supply, waste management, and road use), causing dissatisfaction with residents and tourists alike, while the environment can irreversibly suffer from damages because of tourism pressures (Cuccia & Rizzo, 2011). Understanding the effects of seasonality is critical for the tourism industry because of its important influence on the seasonal variation of tourism flows for any destination (Kulendran & Dwyer, 2010), affecting destination image, destination choice, and tourists' decisions on spending (Goh, 2012). The study of seasonal influences cannot be done when only considering annual time series data. Rather, time series data of less than a year are required for the understanding of the effects of seasonality (Dritsakis, 2008).

A large number of tourism demand studies, however, is based on annual data (Lim, 1997; Vanegas Sr. & Croes, 2000; Croes & Vanegas Sr., 2005; Bicak et al., 2005; Song & Li, 2008; Croes, 2010; Sookram, 2011; Petrevska, 2012), missing vital developments in tourism demand during the year. Understanding seasonality patterns which impact tourism consumption and production is crucial for tourism enterprises and regions (Dritsakis, 2008; Yu et al., 2009; Chan & Lim, 2011; Cuccia & Rizzo, 2011; Hadwen et al., 2011).

Seasonality is a concept well studied and documented in the literature. For example, Butler (2001) defines seasonality as "…a temporal imbalance in the phenomenon of tourism, which may be expressed in terms of dimensions of such elements as numbers of visitors, expenditure of visitors, traffic in highways and other forms of transportation, employment and admissions to attractions." (p. 5). There are two main dimensions of seasonality for tourism. First, there is the institutional seasonality, resulting from religious, cultural, ethnic and social behavior of humans. Often inconsistent in pattern, they are primarily linked to factors such as holidays (e.g., school, industrial or religious holidays), social pressure or fashion (e.g., privileged elite spending a specific time at recurring events, such as regattas, racing, and classical music festivals), and sporting events (e.g., skiing or snowboarding). And second, there is natural seasonality, which has to do with regular temporal and recurring variations in natural phenomena, for example, climate. Typical variables here include cycles or patterns of differences in temperature, rainfall, snowfall, sunlight, and daylight (Butler, 2001).

Studies by Kulendran & Dwyer (2010), Yu et al. (2010), Buckley and Foushee (2011), and Hadwen et al. (2011) all showed that climate exerts an influence on the seasonal pattern of tourism. Despite looking at the relation between climate factors and seasonal tourism demand, these studies bring forward a number of focal points. First, these studies have mostly considered weather as a pull factor, without accentuating the effect of possible push weather factors on the seasonality of tourism. The previous discussion has shown the possibility of climate acting as both a pull and a push factor. Second, it is not clear whether climate as an influencing factor should be considered in terms of only its seasonal pattern, or its overall effect (i.e., seasonal, cyclical, trend, and irregular components). According to Yu et al. (2010), it makes more sense to concentrate only on the seasonal pattern of climate variables, because weather impacts are often contained in the seasonal components, contrary to other factors (for example, income and price) that often do not exhibit seasonality, but have their effects concentrated in the trend component. And third, weather seasonality studies have been based mainly on tourism demand in large destinations (e.g., Australia and the USA).

There is a dearth of studies investigating how weather influences seasonal patterns of tourism demand in small island destinations. There is a case in point for better understanding the drivers of tourism demand in small island economies. According to Croes (2006), many small islands use tourism development as a growth strategy for greater economic and development performance. Thacker et al. (2012) found that the positive contribution from specializing in tourism has helped to more than offset the negative impact of being a small island economy, and according to the authors tourism has been a significant contributor to lower output volatility in many countries. The latter presents an argument for learning more on the development of tourism demand during a period, let's say a year.

This study investigates whether seasonal patterns of pull and push climate elements (rainfall, wind, temperature, and cloud coverage) affect the seasonal deviations of tourism demand for a small destination like Aruba. The methodology involves decomposing time series on both tourism demand and climate using a Census X-12 procedure, and subsequently applying a unit root test, an Engle & Granger cointegration test, Granger causality test, and a Euclidean distance calculation. The investigation allows for a triad of contributions to the tourism literature. First, it contributes to further understanding the specific role of seasonal patterns of climate variables on the seasonality of tourism demand. Second, this investigation analyzes the impact of both pull and push weather factors on tourism demand seasonality, which as far as we can see is a primer when it comes to time series-based studies on mentioned relation. And third, the methodology employed in this study is novel in terms of assessing the causality, strength, and timing of the relationship between tourism demand and weather patterns.

The rest of this paper is organized as follows. Section 2 presents an overview of the literature covering the empirical relation between climate and tourism seasonal movements. Section 3 discusses climate and tourism conditions in Aruba, while section 4 reviews the data and the applied methodology. Section 5 presents the empirical results, while section 6 concludes and offers policy implications and lines for future research.

2. Tourism and climate seasonality in the literature

The literature on the impact of climate on tourism demand generally departs from either a micro or a macro approach. Pivotal for the micro approach is the measurement of people's response to a set of questions, where they report their own subjective state and values (Stiglitz et al., 2009). People's perceptions of climate conditions are likely to play a central role in their decision-making process as tourists (UNWTO & UNEP, 2008). For example, Behringer et al. (2000) interviewed 1,000 skiers and snowboarders in five resorts in Central Switzerland, and their findings suggest climate change would have serious implications through a lower demand. Moreno Sánchez (2010) found, in a survey of tourists waiting for departure flights to European coastal destinations, at Dutch and Belgian airports, that climate was on top of their list of destination attributes. More specifically, absence of rain, comfortable temperature, and hours of sunlight scored the highest in terms of importance to beach tourism. Coombes and Jones (2010) examined the behavior of visitors participating in different activities (e.g., dog walking, recreational walking, relaxing and sunbathing) through bi-weekly surveys undertaken at two beaches at the east coast of the U.K. They found that warmer weather condition had a positive effect on visitor numbers.

The second strand in the tourism literature has explored the impact of climate on tourism from a macro perspective, whereby variables representing climate are assessed against those of tourism demand. Within this literature, there is a first group of researchers who gauge the future impact of climate on tourism through simulation models (e.g., Scott, et al., 2004; Hamilton et al., 2005; Berrittella et al., 2006; Hamilton & Tol, 2007; Soboll & Dingeldey, 2012). These forward-looking studies incorporated multiple destinations as units of analysis, making scenarios for up to the year 2100. All these investigations found an impacting influence of climate change on future tourism demand.

Another group of researchers within this strand analyzed the relation based on past conditions. For example, Yu et al. (2010) investigated the relation between climate and tourism in terms of seasonality for the Denali National Park in Alaska and the Everglades in Florida. Their data consisted of hourly weather observations and monthly statistics both ranging from 1979 to 2006. They further integrated the multiple weather elements (e.g., rain, lightning, hail, and snow) in a climate index to allow for unidimensional weather data. The applied methodology consisted of three stages. First they decomposed the data into a stochastic trend and a seasonal component, given their specific interest in the seasonal patterns of both statistics. Next, they standardized the seasonal patterns to compare their shapes using a Euclidean distance measure, and last, the authors applied univariate regression analysis to estimate the relationship between climate and seasonal tourism demand. The results showed that climate plays a dominant role in shaping the seasonal patterns of tourism demand in both Denali and the Everglades.

Kulendran & Dwyer (2010) measured the influence of changes in temperature, humidity and sunshine on tourist arrivals from the USA, UK, Japan and New Zealand for the case of Australia. They collected data from the third quarter of 1975 to the third quarter of 2009, subsequently extracting their seasonal patterns using the Basic Structural Model approach. The authors applied the Euclidean distance method to investigate the link between the (standardized) variations of climate indicators and seasonal tourism demand. Next, they used the Autoregressive Conditional Heteroskedasticity (ARCH) modeling approach to estimate the direct impact of temperature, humidity and sunshine on the seasonal pattern of tourism demand. The results showed links between the climate variability and seasonal pattern of tourism demand from all four origin markets, although the results tended to vary by season and country of origin. The results from the ARCH modeling approach showed that the impact of the climate variables on the seasonal patterns of tourism demand varied by country of origin.

Buckley & Foushee (2011) showed that peak attendance in US national parks experiencing climate change has shifted 4 days earlier since 1979. They gathered monthly visitors' and temperature data between 1979 and 2008. The authors applied a direct Fourier transformation method to determine the seasonal patterns, and their analysis focused on the shifts in the seasonal distribution of visits rather than the changes in the shape of the distribution. Moreover, their results showed that humans tend to shift their behavior in response to climate change.

Hadwen et al., (2011) assessed the relative importance of natural versus institutional factors in driving tourism demand seasonality. For this purpose, the authors collected visitors statistics from 23 protected areas, spread across the six climate zones governing Australia. The statistics on visitors varied per region, and included data on, e.g., number of campers per month, number of vehicles at one or more campsites, and number of visits. Data varied as well in terms of frequency (monthly or daily) and period (1995-2000; 2000-2006; 2001-2002; 2004-2006). Climate data included temperatures and rainfall on a monthly basis. The timing of holiday periods was used as an institutional factor explaining the seasonality in visitation. The monthly visitation statistics were subsequently transformed to monthly percentage changes, and regressed against the climate and holiday variables. The results showed climate was the principal force driving seasonal patterns of visitation in most of the six climate zones in Australia.

The results of the previously presented investigations show several distinct features in the analysis of the relationship between climate and tourism demand. First, the studies were all characterized by a high level of heterogeneity in terms of methodological approach, a feature also signalled by Bigano et al. (2005). This makes these studies not readily comparable. Second, only a few studies have assessed the impact of climate on the seasonal patterns of tourism demand, which, given the importance of seasonality for tourism demand, is a weakness in the literature. Third, whether it is a micro or a macro perspective, past conditions or simulations, climate does seem to impact the demand of tourists.

3. Climate conditions and the tourism industry in Aruba

Climate conditions

The island of Aruba is located in the tropics, and has a tropical steppe, semiarid hot climate. The wind over Aruba blows for more than 95 % of the time from the northeast and the southeast direction, at an average speed of 7.3 m/s at 10 meter distance (1981-2010). The minimum wind-speed is observed in October and November and the strongest winds are recorded in May-July (Departamento Meteorologico Aruba, 2012). The average temperature in Aruba is 27.9 degrees Centigrade, varying from 19.0 degrees Centigrade to 36.5 degrees Centigrade. The coolest months are January and February and the warmest months are August and September. The average yearly rainfall in Aruba for the period (1981-2010) was 471.7 mm. The wettest months are from October through December, and the driest months are March through May. The potential for thunderstorms on Aruba is relatively low, as compared to the rest of the tropics. There are on average only 17.9 days per year where thunderstorms pass over the observation site in Aruba (1981-2010). The average relative humidity for the mentioned period is 77.4%, while the average cloud coverage on the island was 47.3%, with the lowest average in January and the highest in May. On a daily basis, the average cloudiness of the sky was the highest in the morning hours and the lowest in the late evening.

The tourism industry

Aruba has more than fifty years of experience with the tourism industry. Starting from 1959, the island built its first 100-room hotel, modeled after similar ones in Florida and Puerto Rico (Cole & Razak, 2009). However, the tourism industry played only a small role in the overall economic development of the island, given the dominant position of an oil refinery, the Lago Oil & Transport Company, Ltd. (Vanegas & Croes, 2000). Between 1981 and 1985, Aruba welcomed between 195,000 and 222,000 stay-over visitors each year, carried by 8,700 and 11,300 annual commercial landings, respectively. The number of hotel rooms varied between 1,900 and 2,300 in that period. The situation changed drastically in 1985, when the oil refinery closed its doors, considerably shocking the Aruban economy. At that time, the refinery contributed to about 25% of Aruba's gross domestic product (GDP), and directly and indirectly employed between 30%-40% of Aruba's population (Ridderstaat, 2007). Moreover, it provided about 50% of the foreign exchange earnings of the island and contributed to about 40% of all tax earnings.

The detrimental situation made finding a new source of economic activity a top priority. The most obvious way to increase income and foreign exchange receipts was to expand the tourism industry (Ridderstaat, 2007). Soon, new hotels, shopping malls and other commercial buildings were rising from the ground. The number of hotel rooms more than tripled, from 2,524 in 1986 to 7,975 in 2011. The majority of visitors came by airplane, and the number of aircraft landings grew from 7,768 in 1986 to 14,732 in 2011. The efforts paid off: the number of stay-over visitors grew from 181,211 in 1986 to 871,316 in 2011. The stimulus also included cruise tourism, where the number of cruise passengers grew from 73,338 in 1986 to 599,893 in 2011. Tourism receipts grew from US$ 157.2 million in 1986 to US$ 1,340.8 million in 2011.

Off all countries of origin of the tourists, the United States is by far the largest market for Aruba, accounting for on average 63.5% of all stay-over visitors between 1981 and 2011. Tourists come from particularly the North-Eastern part of that country.

The Venezuelan market is the second largest market for Aruba (average 12.4% between 1986 and 2011). Together, these two countries accounted on average for about 75.9% of all stay-over visitors to Aruba between 1981 and 2011.

4. Data and Methods

The basis for this study is the conceptual scheme depicted in Figure 1, where pull and push seasonal factors of weather elements are set against those of tourism demand. According to Matzarakis (2006), the most relevant meteorological parameters include air temperature, air humidity, wind speed, wind direction, cloud coverage, sunshine duration, or radiations fluxes, rain and precipitation, snow coverage, and water temperature. For the purpose of this research, we use four weather fundamentals (cloud coverage, rainfall, temperature, and wind) as pull (weather conditions in Aruba that attract visitors) and push factors (weather conditions in respectively the USA and Venezuela that cause residents to travel to destinations like Aruba).

[INSERT FIG. 1 HERE]

The variables used in this study are shown in Table 1. Weather data for Aruba, consisting of cloud coverage (AUA_CLOUD), rainfall (AUA_RAIN), temperature (AUA_TEMP), and wind (AUA_WIND) are available for 1981-2011, from the Meteorological Department of Aruba. Weather data for the United States (USA_CLOUD, USA_RAIN, USA_TEMP, and USA_WIND) are from the North-eastern part of that country, given that most US visitors to Aruba are from this region. The weather data for this country come from several sources, including the Climatic Research Unit at the University of East Anglia and the European Centre for Medium-Range Weather Forecasts. The variables USA_CLOUD and USA_RAIN have a shorter data range period (1986-2011), given the availability of data at the consulted sources. Weather data for Venezuela are from the same sources as those of the U.S.A., and generally range from 1981 to 2011.

[INSERT TABLE 1 HERE]

Tourism demand is proxied by the number of visitors from (particularly) the North-eastern part of the USA (USA_TOUR) and Venezuela (VEN_TOUR) for 1981-2011. The data are from the Central Bank of Aruba. All series have been transformed to logarithm, in order to stabilize their variance (Farooque, 2003).

Following Yu et al (2010), this study is based on the notion that the series can be decomposed into four different time varying components (i.e., trend, cycle, incidental, and seasonal components). The point of reference here is the seasonal component, and concentrating solely on this component has several advantages (Yu et al., 2010). Firstly, it allows for the examination of weather elements and tourism demand in different seasons of the year. Secondly, weather impacts are often contained in the seasonal components, contrary to other factors (e.g., income and price) that often do not exhibit seasonality, but have their effects concentrated in the trend component. Thirdly, by using the seasonal components alone, we can determine how similar the seasonal patterns of weather elements are from those of tourism demand: the more similar they are, the more significant the impact of weather seasonality on tourism demand seasonality.

Prior to applying the Census X-12 technique, the data were analyzed for the type of model (additive or multiplicative) they belong to. We apply the following regression, adapted from den Butter & Fase (1988), to assess the model type:

$$|Y - Y_T| = \alpha + \beta Y_T + \varepsilon_t \tag{1}$$

where:

Y = the original value of the time series;

Y_T = the centralized moving average of Y over a period of a year;

α, β = coefficients;

ε = error term.

If Y and Y_T are uncorrelated, meaning that the coefficient β is not significantly different from zero, the model type is additive. If β is significantly different from zero, the model is multiplicative.

Simultaneously, when applying the Census X-12 methodology, we tested the variables for the presence of seasonality using the following tests included in this decomposition approach: (1) a test for the presence of seasonality assuming stability (an

F-test assessing the presence of seasonality at the 0.1% level); (2) a nonparametric test for the presence of seasonality assuming stability (a Kruskal-Wallis test assessing seasonality at the 1% level); (3) a moving seasonality test (an F-test assessing moving seasonality at the 5% level). These tests will allow us to decide whether seasonality has a key role in the climate and tourism demand variables.

The next step is to assess whether the selected series are stationary. This study applied both the Augmented Dickey-Fuller test (ADF) and the Kwiatkowski-Phillips-Schmidt-Shin test (KPSS). According to authors such as Pao at al. (2012) and Jafari et al. (2012), the KPSS is often used to complement the widely used ADF and Phillips-Perron tests to obtain robust results. Following Gujarati et al. (2009a), the basic ADF test is based on the succeeding equation:

$$\Delta Y_t = \beta_1 + \beta_2 TR + \delta_1 Y_{t-1} + \sum_{i=1}^{m} \alpha_i \Delta Y_{t-1} + \varepsilon_t \tag{2}$$

where:

Y = relevant series;

TR = linear deterministic trend;

α, β, δ = coefficients;

ε = pure white noise error term, with a zero mean and constant variance.

Depending on the type of model (random walk, random walk with a drift, or random walk with a drift around a deterministic trend), the equation may be shortened to exclude the trend or both intercept and trend. The null hypothesis here is that $\delta = 0$, meaning that the time series is nonstationary, with the alternative hypothesis ($\delta = 1$) suggesting the time series is stationary. The idea with the ADF is to include enough lagged dependent variables in the equation to get rid of serial correlation in the residuals (Mahadeva & Robinson, 2004).

The KPSS test is a test where the null hypothesis is the other way around, meaning that we are actually testing whether we can reject the null hypothesis of stationarity against the alternative of nonstationarity (Kwiatkowski et al., 1992; Mahadeva & Robinson, 2004; Enders, 2010). The KPSS test involves the following equation (Greene, 2012):

$$Y_t = \alpha + \beta TR + \gamma \sum_{i=1}^{t} z_i + \varepsilon_t \quad (3)$$

where

z = an independent and identically distributed stationary series with mean zero and variance one;

ε = stationary series.

The null hypothesis here ($\gamma = 0$) implies a stationary process if $\beta = 0$ and trend stationary if $\beta \neq 0$.

The tests for stationarity are performed on both the levels and the first differences of the variables. Commonly, the assumption of stationary economic variables can be presumed to hold after differencing these series (Engle & Granger, 1987).

Following the test for stationarity, the next step is to assess whether the series are cointegrated. According to Engle & Granger (1987), if two variables (say y and x) are I(d), with *d* denoting the order of integration, then the linear combination ($z_t = y_t - ax_t$, with *a* being a constant suggesting some possible scaling needs to be done before achieving stationarity) will also be I(d). Thus, if both y_t and x_t are I(1), then one would normally expect $y_t - ax_t$ to be I(1), regardless of the value of *a*, not I(0) (i.e., not stationary) (Greene, 2012). *However*, there *may* be an *a* value where the linear combination between y_t and x_t ($y_t - ax_t$) is I(0), meaning that the series are drifting together at roughly the same rate, indicating that they are cointegrated (Greene, 2012). With this in mind, we test whether the residuals of regressions between pairs of standardized weather and tourism demand series exhibit stationary characteristics to ensure that there is a long-term relation between them. Following Enders (2010), this entails first estimating the long-run equilibrium relationship from the following regression:

$$Y_t = \beta_1 X_t + e_t \quad (4)$$

where

e = residual.

In this equation, the dependent variable is tourism demand, given that we are looking only to determine the effect of climate on tourism demand and not vice versa. Moreover, the equation does not include an intercept in a situation where the variables are first standardized, because the intercept term is always zero in such a situation (Gujarati et al., 2009b).

Next, we apply an ADF test on the following autoregression (Enders, 2010):

$$\Delta\hat{e}_t = a_1\hat{e}_{t-1} + \sum_{i=1}^{n} a_{i+1}\,\hat{e}_{t-i} + \varepsilon_t \qquad (5)$$

where e is the residual of the regressions under (4).

The Granger causality test allows us to statistically determine the direction of causality between two variables. Following in part Gujarati et al. (2009a), the test here involves only one of the two bivariate regressions for the purpose of our research:

$$Y_t = \sum_{i=1}^{n} \alpha_i\, Y_{t-i} + \sum_{j=1}^{n} \beta_j X_{t-j} + u_t \qquad (6)$$

where u_t is an uncorrelated disturbance, and α_i and β_j are coeffcients. The null hypothesis (Y does not Granger cause X) cannot be rejected if:

$\beta_1 = \beta_2 = \beta_3 = \ldots \beta_j = 0$

The hypothesis testing occurs through a standard F-test, using a number of lagged terms to test for the stability of the results

The Granger causality test presented above provides information about whether climate seasonality causes the seasonal variations in tourism demand, but it does not provide us with knowledge about how strong the relation is, when the relation is the strongest, or what is the time lag from weather-related impulse to the actual arrival of the U.S. visitor. Calculating the so-called Euclidean distance measure provides an answer to these questions. This measure calculates the deviation between one variable and another. In formula, based on Kulendran & Dwyer (2010):

$$\mathrm{EDM} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\mathrm{series1} - \mathrm{series2})^2} \qquad (7)$$

where

EDM = Euclidean distance measure;
n = number of values.

The smaller the EDM, the stronger the influence of climate is on tourism demand.

By combining all these calculations, we are able to determine the possible causality, strength, timing and lag of the relation between the series being analyzed. The results are included in the following section.

5. Empirical results

All estimates were obtained from Eviews version 7 and Excel 2010. Regression results show most of the variables have the multiplicative form, with the exception of the variables AUA_TEMP, USA_RAIN, VEN_RAIN, and VEN_WIND, which were found to be additive (Table 2). Seasonality test results show little evidence of stable seasonality at the 0.1% level, with the exception of the variable VEN_TEMP and both tourism demand variables (Table 3). The Kruskal-Wallis test also shows little evidence of seasonality at the 1% level, again for the same variables as in the previous test. Moving seasonality appeared to be present in almost all variables, with the exception of USA_RAIN, USA_WIND, VEN_RAIN, VEN_WIND, and VEN_TOUR. Based on these results, the variables USA_RAIN, USA_WIND, VEN_RAIN, and VEN_WIND were dropped from further analysis in this study.

Prior to testing for stationarity, we first selected the type of model, based on ordinary least squares. Of the three possible model types (random walk without a drift, random walk with a drift, and random walk with a drift around a deterministic trend), the second type (model including an intercept) proved to be the one most frequently found. Only the variables AUA_RAIN and VEN_TOUR were found to be of model type one (no intercept and no trend).

Subsequently, we determined the maximum number of lags, following the method proposed by (Schwert, 1989):

$$P_{\max} = \mathrm{int}\left[12\mathrm{x}\left(\frac{\mathrm{T}}{100}\right)^{\frac{1}{4}}\right] \tag{7}$$

P_{max} indicates the maximum number of lags and T indicates the maximum number of observations. In our case, T = 360 for most of the variables, and the maximum lag length was therefore established at 16. Next, we determined the optimal lag within that maximum, based on the minimum of the AIC, SIC and HQIC. For almost all the applied variables, the optimal lag length was between 1 and 6. The optimal lag lengths were subsequently applied in the ADF test. The KPSS test does not require setting an optimal lag length, and could be immediately calculated. The results for the stationarity test are shown in Table 4, where the ADF test shows in several cases significance at I(0), but the KPSS test shows that most of the variables were I(1). Given these results, we conclude that the series were stationary at the first difference form, and thus integrated of the order one (I(1)).

Before testing for causality of the seasonal patterns of weather against those of tourism demand, we tested if the residuals in these relations were stationary to determine whether the relation is a long-run one. First, we standardized each series by subtracting the mean value of the series from its individual value, subsequently dividing the outcome by the series' standard deviation. The relevant series were then regressed on each other, and the results are shown in Table 5. The t-test showed the seasonal pattern of AUA_TEMP, USA_CLOUD, USA_TEMP were statistically significant in a regression with the seasonal pattern of USA_TOUR. No significant results were found in the case of the seasonal patterns of weather elements in both Aruba and Venezuela and that of tourism demand from that country. The residuals of the significant results were further tested for stationarity, where the ADF results for the residuals of these regressions were all found to be significant at the 1% level. This indicates the presence of a long-term causality relation between these variables. Further analysis of the causality was done on these selected variables using a Granger causality test, whereby the sample period was also split into the period before tourism became the most important sector of the economy (1981-1985) and the period thereafter (1986-2011) (Table 5a-c). For stability purposes, we tested the results against different lag selections, and the F-statistics for the null hypothesis of no causality for all three relations. The results indicated a causality relation departing from, respectively, the seasonal patterns of temperature in Aruba, cloud coverage in the USA, and temperature in the USA to the seasonal variability of tourism demand from that country for Aruba. These indicate that both pull and push weather seasonality appear to exert an influence on the seasonal variations of tourism demand from the USA.

The Euclidean distances were subsequently calculated for these three relations, where we first determined the optimal lag length, based on the lowest value of the EDMs. In our case, the lagged series was the seasonal pattern of tourism demand from the USA, which may be explained by the fact that it takes tourists some time from the impulse to start planning (for example, the weather) up to actually arrive at the destination. According to Kozak and Karadag (2012), the decision process does not just involve making a decision to go somewhere at a specific time, but involves, among others, other decisions such as the selection of the accommodation facilities, travel agencies, etc. Factors such as room or seat availability, budget and pricing can also influence the tourists' decision on the time of traveling, and so do differences in type of visitor. On the latter, a study by Croes et al. (2011a), for example, showed about 30% of *waning influentials* (Generation X) making a reservation between 1-3 month before their traveling to Aruba, while between 25-30% did this between 3-6 months and slightly more than 20% were making this more than 6 months ahead of their visit to the island. The other two groups, *waxing influential* (Generation Y) and *Aruban classics* (Baby Boomers), had different patterns of reservation than the first group. Yet, the majority of the tourists within these groups were making reservations at least 1 month prior to coming to Aruba, advancing to more than 6 months before their visit.

The results of the optimal lag calculations are shown in Charts 1a-3c, again indicated for different periods. In the case of EDM between temperature in Aruba and tourism demand from the USA, the optimal lag was 5 months for all three periods (1981-2011; 1981-1985; and 1986-2011). For the EDM between cloud coverage in the USA and tourism demand from that country, the optimal lag was 6 months for the period 1981-2011, and, respectively, 2 months and 6 months for the periods 1981-1985 and 1986-2011. In the case of the EDM between temperature in the USA and tourism demand from that country, the lags were 7 months (1981-2011), 10 months (1981-1985), and 7 months (1986-2011), respectively. While the lag for the period 1986-2011 coincided in all three weather cases with that of the overall period (1981-2011), those of the period 1981-1985 were visibly different than the overall, which can be explained by the relatively shorter timeframe (5 years compared to 26 years for 1986-2011). Given these differences and the fact that the period 1981-1985 reflects the period prior to the structural change in Aruba's tourism, the ensuing analysis will only emphasize the period 1986-2011. With the results above, we proceeded to determine the strength of the monthly EDMs based on these lags, with the outcome included in Charts 4a-6c. The general pattern of the monthly EDMs in the case of temperature in Aruba and tourism demand from the USA is generally one of slowly increasing in the first months of the year, and subsequently decreasing somewhat afterwards, with some exceptional cases in March, August and December. With our understanding that a small EDM value is associated with a strong relation between the seasonal factors of weather and tourism demand, the results suggest a decreasing sensitivity of North-eastern US tourism demand for the temperature factor in Aruba up to somewhere during the middle months of the year. The latter probably has to do with weather conditions in the North-eastern USA itself, in the sense that periods of warmer weather in that area make Aruba less attractive as a pull factor than at the beginning and the end of the year, where it is cloudier and colder in that particular region of the USA. In the latter course of the year, the sensitivity increases slightly again, congruent with weather developments in the US region of review. The unexpectedly high EDMs in March, August, and December could indicate that there are other factors (such as Easter holidays, school vacation, and Christmas holidays) that have a more pronounced impulse effect on tourism demand from the USA than temperature conditions on the island.

The general pattern of the monthly EDMs in the case of cloud coverage and tourism demand is one of starting low in the early months of the year, slowly increasing up to a maximum somewhere in the middle of the year, and subsequently decreasing by the end of the year. This coincides to some extent with the pattern found in the case of temperature in Aruba. A somewhat resembling pattern is also visible in the case of the monthly EDMs between temperature and tourism demand from the USA, with some exceptional cases. These movements generally coincide with the weather seasons in the North-eastern USA (winter = Dec.-Feb.; spring = Mar.-May; summer = Jan.-Aug.; and Fall = Sep.-Nov.), where the beginning and ending months are cloudier with relatively lower temperatures than the middle months. Overall, the EDMs seem to indicate a more or less structured movement in terms of the strength of the relation between weather and tourism demand seasonality.

In the previous exercise, the lag time was kept fixed in order to determine the monthly strength of the relation under the fixed lag of month. We now move to more specifically analyze the time lag from a weather-related impulse to the actual arrival of the US visitor in order to see the concentration of response time after a weather-related impulse. For this purpose, we calculated for each month the optimal lag between the seasonal factors of the weather series and tourism demand, based on the minimum EDM calculations within the maximum lag period of 16 month. Subsequently, we coded as much as possible the results according to the timeline criteria applied by Croes et al. (2011) in order to have a more aggregated time structure of the data. The results are incorporated in Charts 7a-9c. In all three cases (temperature in Aruba, cloud coverage in USA, and temperature in USA), the difference between the weather-related impulse and the actual arrival in Aruba is largely concentrated in the period longer than 6 months. This possibly indicates that the impulse of the selected weather-related factors, both pull and push, in a majority of cases does not cause hurried visits to Aruba. The North-eastern US traveler is not likely to be an impulsive buyer of tourism services offered by the destination Aruba when it comes to weather-related influences: adequate planning is still seems essential for them.

6. Conclusion

Climate is seen as a possible third most important attribute in tourists' decision making process, next to aquatic (sea/lakes) and natural (nature/landscape) attributes of a destination (Hamilton & Lau, 2004). This study investigated the influence of seasonal patterns of pull/push weather on tourism demand for Aruba. Working with seasonal factors only facilitates a more efficient examination of the impacts of the specific weather influences on tourism demand variability, by filtering out "noise" and so better understand the nature of the relations (Yu et al., 2010). The results show no influence of the seasonal patterns of weather elements whatsoever (neither pull nor push) on the seasonality of tourism demand from Venezuela.

The lack of seasonal effects provoked by weather may initially reflect a high level of similarity between weather patterns between Aruba and Venezuela, but may also indicate the presence of the so-called lock-in effect in the case of this country. Lock-in effect refers to tourists' preference for spending their holidays in conventional well-known destinations even when there are changes in the climate (Faulkner, 2000; Moreno Sánchez, 2010). As a matter of fact, 78% of Venezuelans patronizing Aruba are repeat visitors, and 37% of Venezuelan repeat visitors have visited the island more than six times. The lack of natural seasonality also indicates that there are other factors that may influence the seasonal patterns of tourism demand from Venezuela, for example Easter, School and Christmas holidays. Finding no relation between seasonal weather-related factors and tourism demand does not mean that tourism demand is not affected at all by weather as a pull factor. It means that the timing of coming to Aruba is not affected by weather conditions in both Aruba and the country of origin of the tourists. Weather conditions on the island still remain important in determining tourism demand, as indicated in a study by Sookram (2011) who found, based on annual data, that temperature and rainfall in Aruba influenced tourism demand for this destination. In this regard, for example, the favorable weather in Aruba could still influence the decision of Venezuelans to spend their holidays on the island.

In the case of tourism demand from the USA, both pull and push weather seasonal factors appeared to exert an influence on the seasonal patterns of tourism demand. Temperature in Aruba was a significant pull factor, driving demand from the USA. On the other hand, push weather factors, temperature and cloud coverage in the North-eastern USA, were relevant stimulants. The results further showed that the strength of the impulse of the seasonal patterns of, respectively, temperature in Aruba, cloud coverage and temperature in the North-Eastern part of the USA, determines the seasonal patterns of tourism demand from the USA to Aruba. The influence generally starts strong at the beginning of the year, grows weaker by the middle of the year, and subsequently grows stronger again at the end of the year, indicating fluctuating but structured effects during the year.

The results also showed that in the majority of cases the lag response time after a weather-related impulse was at least half a year, implying that tourists from the North-eastern USA do not respond impulsively to weather-related catalysts. The tourist from the North-eastern region of the USA seems to take time to adjust to weather conditions, suggesting that the tourist is likely to take at least 6 months for planning a trip to Aruba. Actually, the recent report of the Ministry of Tourism, “Winning the Future” (Croes, et al., 2011) suggests that 31% of tourists visiting Aruba from the USA plan their journey to Aruba at least six months ahead, corroborating the results of this study.

The previously alluded findings are important, because they shed light into the influence of seasonal variations of push and pull weather elements on the seasonal deviations of tourism demand. Moreover, in the case of the USA, the results show that monitoring economic factors alone is not enough when it comes to analyzing the determinants of tourism demand for Aruba. Weather patterns, in this case temperature in Aruba, cloud coverage and temperature in the North-eastern USA, matter for travel from the USA to Aruba. Knowledge about the structure of the variations in strength of the impact of weather on tourism demand over the course of the year, as well as the time lag from a weather-related impulse to the actual visit to Aruba, could assist managers in the tourism industry and government representatives to (better) cope with weather elements in their planning, forecasting and marketing efforts.

In addition, distinguishing between markets that are sensitive to weather and those that are not, could assist people involved in the tourism industry to build a complementary relation between these two types of markets to minimize the fluctuation in tourism demand over the year. For example, one possible strategy to follow by policy makers and tourism industry leaders could be to keep an eye on longer-term weather forecasts, such as that of the National Oceanic Atmospheric Administration Climate Prediction Center (http://www.cpc.ncep.noaa.gov) to get a lead onto expected seasonal weather conditions in the North-eastern USA. For instance, if temperature during the winter season is projected to be higher than normal, then the likelihood for lower demand from the North-eastern USA increases. Policy makers and industry chiefs could react to this information by making more special offers available for this period to counter expected low demand. Alternatively, they could increase marketing efforts from other markets that are not affected by pull and push seasonal weather factors (e.g., Venezuela) to stimulate demand from these markets, compensating for this expected fall-down in demand from the North-eastern USA. The current marketing plan of the Aruba Tourism Authority does not account for a strategy on the interactions between markets in terms of mitigating the negative demand effects of push weather factors.

Given that temperature conditions in Aruba are important in pulling demand from the North-eastern USA, continuously providing wide-spread information on current and average weather conditions during the year is needed, nodding an additional economic benefit of public weather and climate services. The Aruba Tourism Authority has an excellent page (http://www.aruba.com/weather.aspx) with current and average monthly temperature for Aruba, as well as detailed general weather description. Visitors to this website can also find a link with the Meteorological Department of Aruba, which provides short-term and long-term forecasts that could be used for planning purposes. However, many hotels themselves do not provide information on (average) weather conditions on the island, which could be an important complement to the visitor in the planning process. It is recommended that all hotels should incorporate local weather information on their websites, derived from the official meteorological sources.

Future research should focus on extending this investigation to include other destination markets for Aruba, such as European countries to get a more complete picture of the influence of seasonal pull and push weather on recurrent tourism demand for the island. Moreover, this study could be expanded to include other destinations in the Caribbean, so to compare weather effects in terms of impacts and timing on the demand from similar tourism markets in other Caribbean destinations. It makes much sense to have a thorough understanding of the development of tourism demand during the course of the year, including the factors that mark its pattern.

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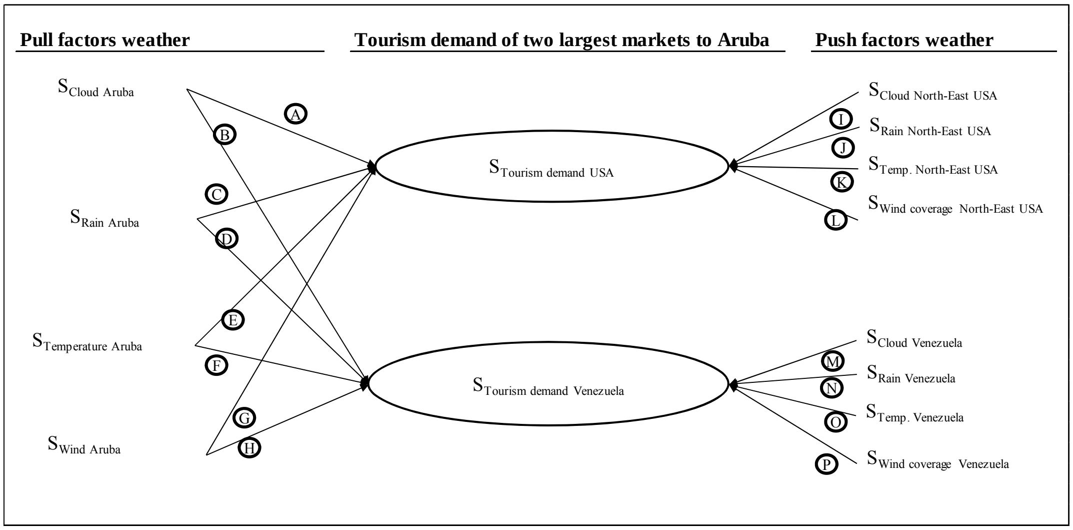

Fig. 1: Conceptual framework of the relation between the seasonal patterns of (pull/push) weather and tourism demand for the largest market of Aruba's tourism

Table 1: Variables used in the analysis

Variable type	Data description	Data period	Source
Pull factors			
AUA_CLOUD	Cloud coverage Aruba	1981-2011	Meteorological Department Aruba
AUA_RAIN	Rainfall in Aruba	1981-2011	Meteorological Department Aruba
AUA_TEMP	Temperature in Aruba	1981-2011	Meteorological Department Aruba
AUA_WIND	Wind in Aruba	1981-2011	Meteorological Department Aruba
Push factors			
United States			
USA_CLOUD	Cloud coverage USA	1981-2009	Climatic Research Unit (CRU) at the University of East Anglia
USA_RAIN	Rainfall in USA	1986-2011	Global Precipitation Climatology Centre operated by Deutscher Wetterdienst
USA_TEMP	Temperature in USA	1981-2011	National Centers for Environmental Prediction–National Center for Atmospheric Research (NCEP–NCAR) reanalysis (NCEP1) data
USA_WIND	Wind in USA	1981-2011	The European Centre for Medium-Range Weather Forecasts (ECMWF) Re-Analysis (ERA-Interim)
Venezuela			
VEN_CLOUD	Cloud coverage Venezuela	1981-2009	Climatic Research Unit (CRU) at the University of East Anglia
VEN_RAIN	Rainfall in Venezuela	1986-2011	Global Precipitation Climatology Centre operated by Deutscher Wetterdienst
VEN_TEMP	Temperature in Venezuela	1981-2011	National Centers for Environmental Prediction–National Center for Atmospheric Research (NCEP–NCAR) reanalysis (NCEP1) data
VEN_WIND	Wind in Venezuela	1981-2010	The European Centre for Medium-Range Weather Forecasts (ECMWF) Re-Analysis (ERA-Interim)
Tourism demand			
USA_TOUR	Tourism demand from the USA	1981-2011	Central Bank of Aruba
VEN_TOUR	Tourism demand from Venezuela	1981-2011	Central Bank of Aruba

Table 2: Model type

Variable type	Regression result of β		Model type
Pull factors			
L_AUA_CLOUD	-0.119343	*	multiplicative
L_AUA_RAIN	0.400119	*	multiplicative
L_AUA_TEMP	-0.014648		additive
L_AUA_WIND	-0.193562	*	multiplicative
Push factors			
United States			
L_USA_CLOUD	-0.104059	*	multiplicative
L_USA_RAIN	-0.028264		additive
L_USA_TEMP	-0.049015	*	multiplicative
L_USA_WIND	0.046297	*	multiplicative
Venezuela			
L_VEN_CLOUD	-0.024255	*	multiplicative
L_VEN_RAIN	0.034241		additive
L_VEN_TEMP	0.10465	*	multiplicative
L_VEN_WIND	0.008474		additive
Tourism demand			
L_USA_TOUR	0.38974	*	multiplicative
L_VEN_TOUR	-0.030153	*	multiplicative

Note: The symbols *, ** and *** indicate, respectively, the 1%, 5% and 10% significance levels.

Table 3: Seasonality test results based on Census X-12

Series	Stable seasonality F-test	Stable seasonality p-value *(0.1% level)*	Kruskal_Wallis test χ^2	Kruskal_Wallis test p-value *(1% level)*	Moving seasonality F-test	Moving seasonality p-value *(5% level)*
Pull factors						
L_AUA_CLOUD	1.2800	0.2339	14.4640	0.2084	1.8570	0.0057 *
L_AUA_RAIN	1.3010	0.2220	22.1140	0.0235	2.3320	0.0002 *
L_AUA_TEMP	0.6660	0.7704	6.9790	0.8008	1.6660	0.0192 *
L_AUA_WIND	1.9390	0.0338	24.8020	0.0097 *	2.1710	0.0006 *
Push factors						
United States						
L_USA_CLOUD	1.6470	0.0844	18.5000	0.0707	2.0330	0.0020 *
L_USA_RAIN	0.8990	0.5418	13.7120	0.2493	1.3780	0.1164
L_USA_TEMP	1.2260	0.2679	11.5450	0.3988	3.4430	0.0000 *
L_USA_WIND	0.6640	0.7724	10.3010	0.5035	1.2630	0.1700
Venezuela						
L_VEN_CLOUD	1.4550	0.1470	23.3970	0.0155	2.5530	0.0000 *
L_VEN_RAIN	0.6240	0.8084	7.0510	0.7949	0.6030	0.9304
L_VEN_TEMP	3.5750	0.0000 *	44.4460	0.0000 *	2.8340	0.0000 *
L_VEN_WIND	1.2170	0.2737	16.0090	0.1408	0.8070	0.7512
Tourism demand						
L_USA_TOUR	58.4180	0.0000 *	216.8120	0.0000 *	2.5500	0.0000 *
L_VEN_TOUR	49.5340	0.0000 *	213.6280	0.0000 *	1.3740	0.0994

Note: * indicates significance at the level of testing.

Table 4: Unit root results

		ADF	KPSS
L_AUA_CLOUD	Level	-3.7243 *	0.9257
	First diff.	-16.9264 *	0.0324 ***
Order of integration		I(0)	I(1)
L_AUA_RAIN	Level	-5.8672 *	1.0202
	First diff.	-9.5737 *	0.0045 ***
Order of integration		I(0)	I(1)
L_AUA_TEMP	Level	-2.8999 **	1.0719
	First diff.	-8.9524 *	0.0611 ***
Order of integration		I(0)	I(1)
L_AUA_WIND	Level	-2.8632 ***	1.1776
	First diff.	-12.8030 *	0.1413 ***
Order of integration		I(0)	I(1)
L_USA_CLOUD	Level	-2.5823 ***	0.4990 *
	First diff.	-16.0887 *	0.1579 ***
Order of integration		I(1)	I(1)
L_USA_TEMP	Level	-1.5194	0.8752
	First diff.	-20.5249 *	0.5530 *
Order of integration		I(1)	I(1)
L_VEN_CLOUD	Level	-0.8489	0.6983 *
	First diff.	-13.1376 *	0.5008 *
Order of integration		I(1)	I(0)
L_VEN_TEMP	Level	-3.9031 *	1.5393
	First diff.	-16.5989 *	0.0099 ***
Order of integration		I(0)	I(1)
L_USA_TOUR	Level	-11.1185 *	2.2654
	First diff.	-11.6287 *	0.1401 ***
Order of integration		I(0)	I(1)
L_VEN_TOUR	Level	-15.6583 *	1.4720
	First diff.	-13.2505 *	0.0880 ***
Order of integration		I(0)	I(1)

Note: The symbols *, ** and *** indicate, respectively the 1%, 5% and 10% significance levels.

Table 5: Test for long-run relation (standardized series)

Variable structure in regression equation	β_1	Adj. R^2	DW	ADF
L_AUA_CLOUD (independent), L_USA_TOUR (dependent)	-0.0327	0.0007	2.4845	
L_AUA_RAIN (independent), L_USA_TOUR (dependent)	0.0299	0.0009	2.4891	
L_AUA_TEMP (independent), L_USA_TOUR (dependent)	-0.1016 *	0.0198	2.4590	-24.4075 *
L_AUA_WIND (independent), L_USA_TOUR (dependent)	0.0288	0.0004	2.4858	
L_AUA_CLOUD (independent), L_VEN_TOUR (dependent)	-0.0144	0.0001	2.4829	
L_AUA_RAIN (independent), L_VEN_TOUR (dependent)	0.0844	0.0056	2.4783	
L_AUA_TEMP (independent), L_VEN_TOUR (dependent)	0.0452	0.0024	2.4980	
L_AUA_WIND (independent), L_VEN_TOUR (dependent)	0.0129	0.0000	2.4839	
L_USA_CLOUD (independent), L_USA_TOUR (dependent)	0.1312 *	0.0274	2.4272	-11.7772 *
L_USA_TEMP (independent), L_USA_TOUR (dependent)	-0.0850 **	0.0159	2.4575	-12.3998 *
L_VEN_CLOUD (independent), L_VEN_TOUR (dependent)	-0.0054	0.0000	2.4929	
L_VEN_TEMP (independent), L_VEN_TOUR (dependent)	-0.0415	0.0033	2.4676	

Note: The symbols *, ** and *** indicate, respectively the 1%, 5% and 10% significance levels. Critical values for ADF test are based on Enders (2010).

Table 6: Partial granger causality test results (standardized series, 1981-2011)

Variables	L=1		L=2		L=3		l=4		L=5		L=6		L=7		L=8	
	F-test	Prob.	F-test	Prob.	F-test	Prob.	F-test	Prob.	F-test	Prob.	F-test	Prob.	F-test	Prob.	F-test	Prob.
L_AUA_TEMP does not GC L_USA_TOUR	2.4315	0.1198	1.5447	0.2148	1.2692	0.2847	0.4337	0.7843	6.0400	0.0000	14.2823	0.0000	11.8621	0.0000	9.9781	0.0000
L_USA_CLOUD does not GC L_USA_TOUR	5.5693	0.0188	13.1951	0.0000	12.8258	0.0000	10.5036	0.0000	12.0615	0.0000	18.9094	0.0000	9.4217	0.0000	10.4249	0.0000
L_USA_TEMP does not GC L_USA_TOUR	6.0154	0.0146	5.1741	0.0061	4.1654	0.0064	3.2699	0.0119	3.9290	0.0018	10.7129	0.0000	13.0551	0.0000	15.3683	0.0000

Variables	L=9		L=10		L=11		L=12		L=13		L=14		L=15		L=16	
	F-test	Prob.	F-test	Prob.	F-test	Prob.	F-test	Prob.	F-test	Prob.	F-test	Prob.	F-test	Prob.	F-test	Prob
L_AUA_TEMP does not GC L_USA_TOUR	9.8711	0.0000	13.3877	0.0000	3.4625	0.0001	5.2273	0.0000	8.9446	0.0000	7.2190	0.0000	7.6388	0.0000	7.2049	0.000
L_USA_CLOUD does not GC L_USA_TOUR	12.7933	0.0000	17.1109	0.0000	2.3270	0.0093	2.8967	0.0008	3.8426	0.0000	3.3459	0.0001	4.5716	0.0000	4.2685	0.000
L_USA_TEMP does not GC L_USA_TOUR	13.9375	0.0000	10.6395	0.0000	2.9464	0.0010	3.3392	0.0001	3.0923	0.0002	4.1928	0.0000	4.0748	0.0000	3.7655	0.000

Table 6b: Partial granger causality test results (standardized series, 1981-1985)

Variables	L=1		L=2		L=3		l=4		L=5		L=6		L=7		L=8	
	F-test	Prob.	F-test	Prob.	F-test	Prob.	F-test	Prob.	F-test	Prob.	F-test	Prob.	F-test	Prob.	F-test	Prob.
L_AUA_TEMP does not GC L_USA_TOUR	0.1608	0.6900	0.5588	0.5753	2.1338	0.1077	3.3728	0.0166	5.5324	0.0005	7.8279	0.0000	11.4414	0.0000	11.7572	0.0000
L_USA_CLOUD does not GC L_USA_TOUR	2.5565	0.1156	16.9282	0.0000	15.7944	0.0000	14.6725	0.0000	30.0512	0.0000	59.5474	0.0000	228.3070	0.0000	173.8460	0.0000
L_USA_TEMP does not GC L_USA_TOUR	1.4460	0.2343	0.6660	0.5181	1.6142	0.1981	1.6949	0.1674	3.0329	0.0197	9.0431	0.0000	17.6267	0.0000	17.7596	0.0000

Variables	L=9		L=10		L=11		L=12		L=13		L=14		L=15		L=16	
	F-test	Prob.	F-test	Prob.	F-test	Prob.	F-test	Prob.	F-test	Prob.	F-test	Prob.	F-test	Prob.	F-test	Prob
L_AUA_TEMP does not GC L_USA_TOUR	18.1034	0.0000	16.6693	0.0000	7.0390	0.0000	10.8773	0.0000	15.4129	0.0000	12.7356	0.0000	8.6613	0.0001	6.8055	0.001
L_USA_CLOUD does not GC L_USA_TOUR	139.5070	0.0000	204.7520	0.0000	3.9958	0.0020	5.9059	0.0002	6.3659	0.0002	5.9756	0.0005	3.9542	0.0086	2.2627	0.096
L_USA_TEMP does not GC L_USA_TOUR	13.5849	0.0000	48.9842	0.0000	15.2903	0.0000	15.9540	0.0000	13.0991	0.0000	12.7733	0.0000	13.7438	0.0000	10.8334	0.000

Table 6c: Partial granger causality test results (standardized series, 1986-2011)

Variables	L=1		L=2		L=3		l=4		L=5		L=6		L=7		L=8	
	F-test	Prob.	F-test	Prob.	F-test	Prob.	F-test	Prob.	F-test	Prob.	F-test	Prob.	F-test	Prob.	F-test	Prob.
L_AUA_TEMP does not GC L_USA_TOUR	3.8353	0.0511	2.7707	0.0642	1.9657	0.1191	0.7757	0.5417	3.5420	0.0040	13.7895	0.0000	10.0673	0.0000	10.2562	0.0000
L_USA_CLOUD does not GC L_USA_TOUR	12.0386	0.0006	12.0271	0.0000	12.8632	0.0000	13.8885	0.0000	13.0632	0.0000	19.4207	0.0000	13.7178	0.0000	19.3393	0.0000
L_USA_TEMP does not GC L_USA_TOUR	4.4726	0.0352	6.6545	0.0015	6.5752	0.0003	6.0286	0.0001	6.0447	0.0000	10.0044	0.0000	9.0613	0.0000	12.9910	0.0000

Variables	L=9		L=10		L=11		L=12		L=13		L=14		L=15		L=16	
	F-test	Prob.	F-test	Prob.	F-test	Prob.	F-test	Prob.	F-test	Prob.	F-test	Prob.	F-test	Prob.	F-test	Prob
L_AUA_TEMP does not GC L_USA_TOUR	10.7761	0.0000	20.0868	0.0000	3.5881	0.0001	3.6772	0.0000	5.9827	0.0000	4.9942	0.0000	5.5322	0.0000	7.2789	0.000
L_USA_CLOUD does not GC L_USA_TOUR	29.1033	0.0000	22.8527	0.0000	3.4131	0.0002	3.9524	0.0000	5.1521	0.0000	4.6414	0.0000	5.0740	0.0000	4.8395	0.000
L_USA_TEMP does not GC L_USA_TOUR	12.5166	0.0000	10.3767	0.0000	2.7353	0.0022	2.5991	0.0027	2.2413	0.0083	3.1976	0.0001	3.1881	0.0001	3.1767	0.000

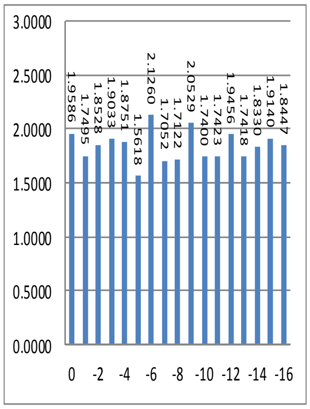

Chart 1a: Euclidean distance temperature in Aruba and tourism demand USA (1981-2011), lags 1-16

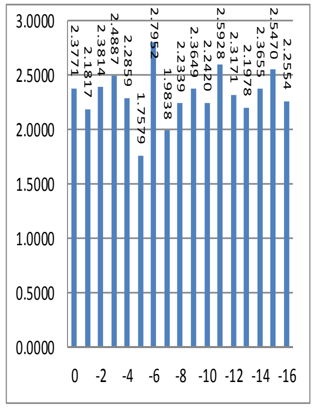

Chart 1b: Exlidean distance temperature in Aruba and tourism demand USA (1981-1985), lags 1-16

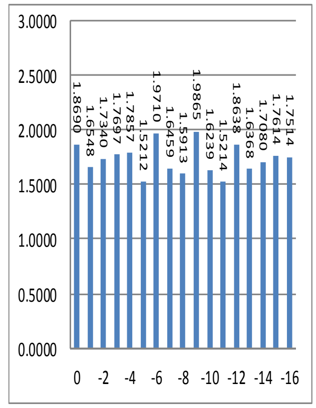

Chart 1c: Exlidean distance temperature in Aruba and tourism demand USA (1986-2011), lags 1-16

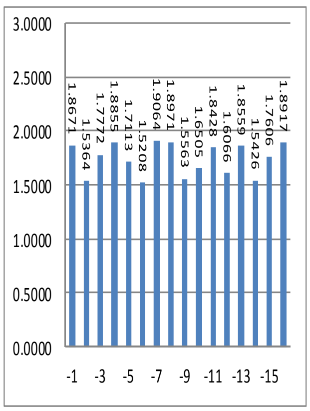

Chart 2a: Euclidean distance cloud coverage in the USA and tourism demand USA (1981-2011), lags 1-16

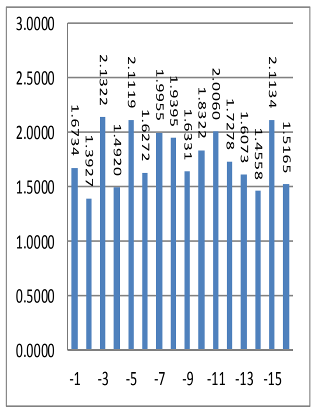

Chart 2b: Euclidean distance cloud coverage in the USA and tourism demand USA (1981-1985), lags 1-16

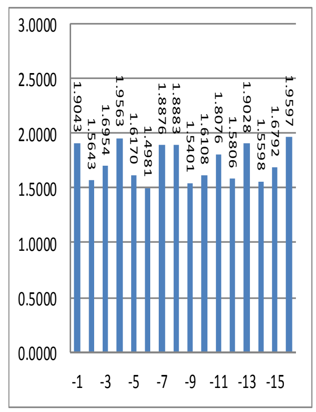

Chart 2c: Euclidean distance cloud coverage in the USA and tourism demand USA (1986-2011), lags 1-16

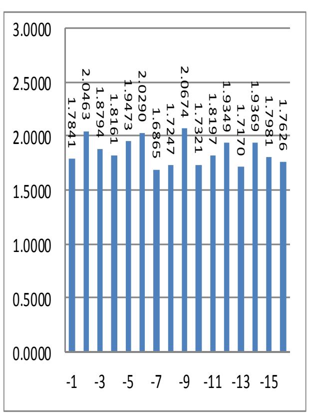

Chart 3a: Euclidean distance temperature in the USA and tourism demand USA (1981-2011), lags 1-16

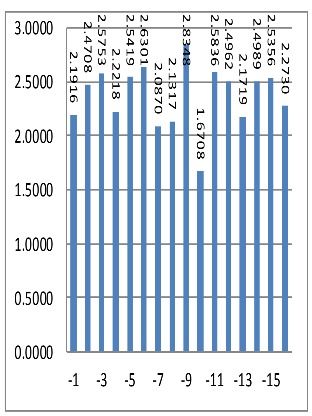

Chart 3b: Euclidean distance temperature in the USA and tourism demand USA (1981-1985), lags 1-16

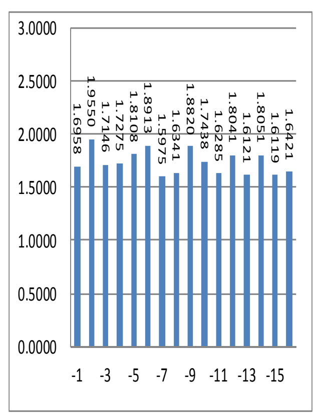

Chart 3c: Euclidean distance temperature in the USA and tourism demand USA (1986-2011), lags 1-16

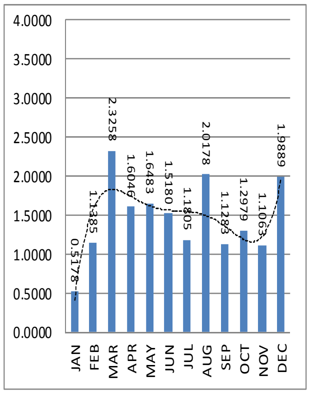

Chart 4a: Euclidean distance temperature in Aruba and tourism demand USA (1981-2011), 5 month lag (dotted line = polynomial trend line)

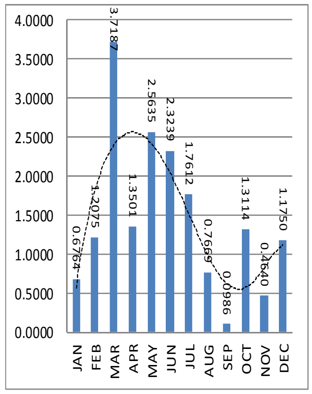

Chart 4b: Euclidean distance cloud coverage in the USA and tourism demand USA (1981-1985), 5 month lag (dotted line = polynomial trend line)

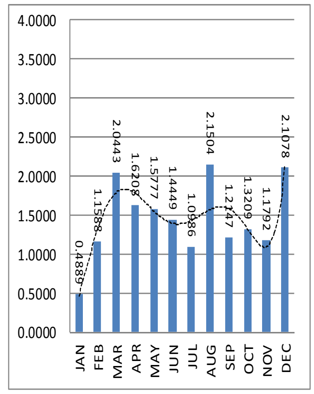

Chart 3c: Euclidean distance cloud coverage in the USA and tourism demand USA (1986-2011), 5 month lag (dotted line = polynomial trend line)

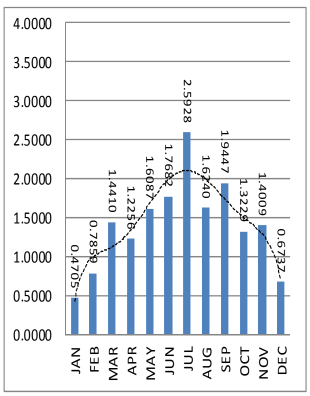

Chart 5a: Euclidean distance cloud coverage in the USA and tourism demand USA (1981-2011), 6 month lag (dotted line = polynomial trend line)

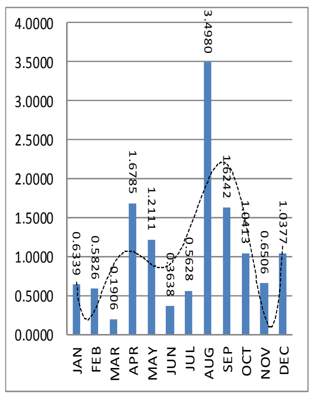

Chart 5b: Euclidean distance cloud coverage in the USA and tourism demand USA (1981-1985), 2 month lag (dotted line = polynomial trend line)

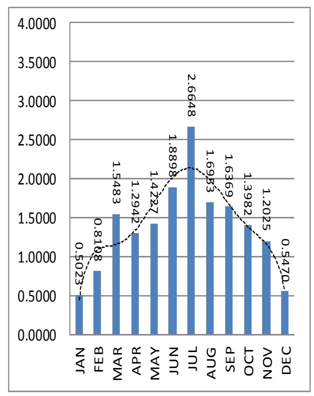

Chart 5c: Euclidean distance cloud coverage in the USA and tourism demand USA (1986-2011), 6 month lag (dotted line = polynomial trend line)

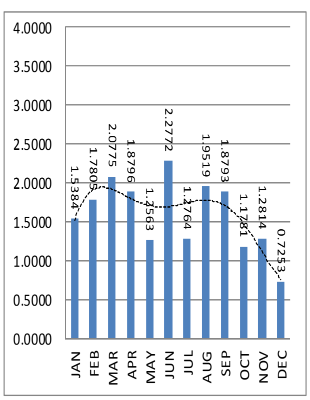

Chart 6a: Euclidean distance temperature in the USA and tourism demand USA (1981-2011), 7 month lag (dotted line = polynomial trend line)

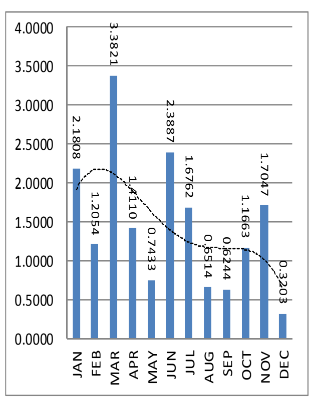

Chart 6b: Euclidean distance temperature in the USA and tourism demand USA (1981-1985), 10 month lag (dotted line = polynomial trend line)

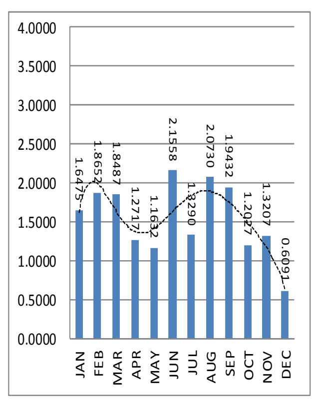

Chart 6c: Euclidean distance temperature in the USA and tourism demand USA (1986-2011), 7 month lag (dotted line = polynomial trend line)

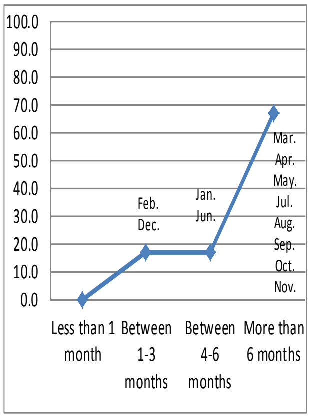

Chart 7a: Euclidean distance temperature in Aruba and tourism demand USA (1981-2011), lag frequency in %

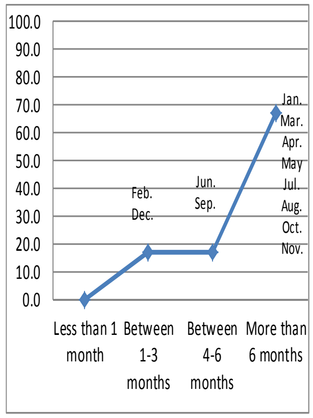

Chart 7b: Euclidean distance temperature in Aruba and tourism demand USA (1981-1985), lag frequency in %

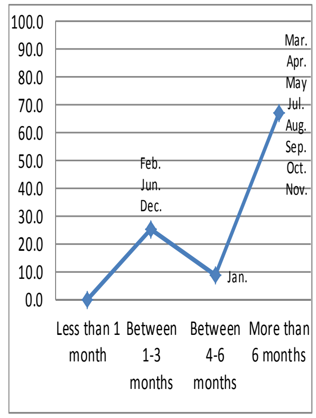

Chart 7c: Euclidean distance temperature in Aruba and tourism demand USA (1986-2011), lag frequency in %

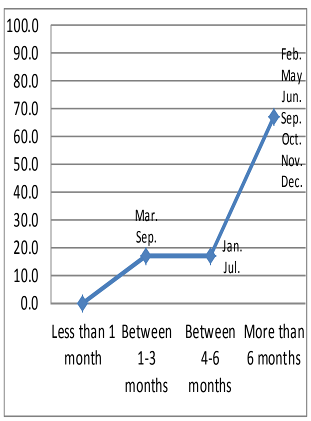

Chart 8a: Euclidean distance cloud coverage in USA and tourism demand USA (1981-2011), lag frequency in %

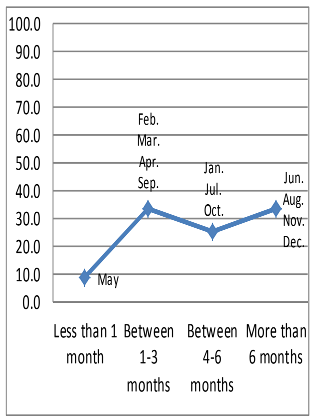

Chart 8b: Euclidean distance cloud coverage in USA and tourism demand USA (1981-2011), lag frequency in %

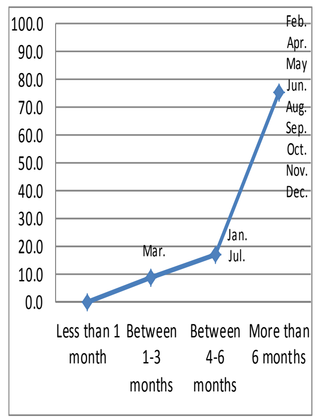

Chart 8c: Euclidean distance cloud coverage in USA and tourism demand USA (1981-2011), lag frequency in %

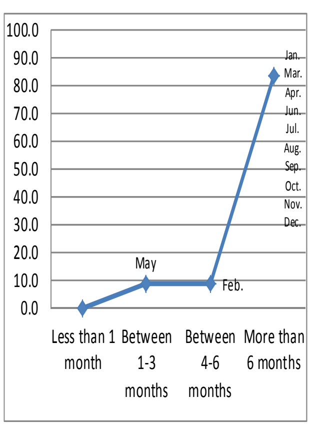

Chart 9a: Euclidean distance temperature in USA and tourism demand USA (1981-2011), lag frequency in %

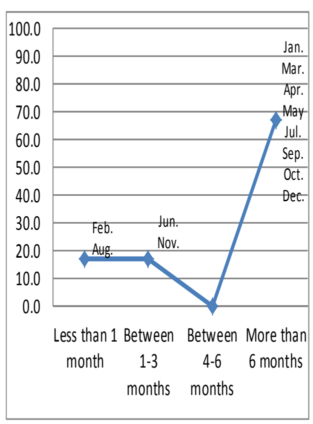

Chart 9b: Euclidean distance temperature in USA and tourism demand USA (1981-2011), lag frequency in %

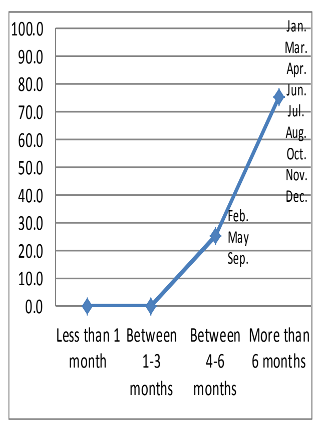

Chart 9c: Euclidean distance temperature in USA and tourism demand USA (1981-2011), lag frequency in %

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