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Impacts of seasonal patterns of climate on recurrent fluctuations in tourism demand: Evidence from Aruba

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HIGHLIGHTS

- Climate is a significant push and pull factor affecting tourism demand.
- Tourism demand and climate are bounded by intertemporal climate constraints.
- Seasonality matters for short-term tourism demand movements.
- A continued stream of general information on current and average climate conditions during the year is needed.

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ABSTRACT

This study estimates the effect of seasonal patterns of pull and push climate elements (rainfall, temperature, wind, and cloud coverage) on recurrent fluctuations in tourism demand from the United States (USA) and Venezuela to Aruba. The seasonal patterns were first isolated from the series using the Census X-12 decomposition method, after which the analysis included panel data unit root testing, panel data regression, and Euclidean distance calculation. The results show that both pull and push seasonal factors of climate were relevant in determining the seasonal variations in tourism demand from both countries. The study derives two theoretical propositions: (1) climate is a significant push and pull factor affecting tourism demand; and (2) tourism demand and climate are bounded by intertemporal climate constraints.

1. Introduction

The purpose of the study is to investigate how seasonal patterns of climate influences tourism demand seasonality in small island destinations. ‘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 (Belén Gómez Martín, 2005). Climate and weather are notable and influential factors in tourists’ consumer behavior (Amelung, Nicholls, & Viner, 2007; Hamilton & Tol, 2007; Hamilton, Maddison, & Tol, 2005; Kulendran & Dwyer, 2010; Scott, McBoyle, & Schwartzentruber, 2004). The effects of the interaction between climate/weather and tourism are substantial and require close scrutiny in so far as climate and weather may strongly contribute to the determination of the tourist’s destination choice. Small island destinations, for example, are cognizant of the importance of weather and climate. In fact, the Caribbean and the Mediterranean are the two largest global geographical densities propagating climate and weather as crucial attributes of their tourism product (i.e. Sun, Sand, Sea (SSS)). In addition, the combination of favorable weather and an SSS product results in image building. For example, Barbados uses “good weather” as a selling point with a money back guarantee in the event that the weather fails (Scott & Lemieux, 2009).

There is considerable research with regards to the impact of weather and climate on tourism and the environmental resources that are critical attractions for tourism: for example, snow conditions, wildlife productivity and biodiversity, as well as quality water

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and its levels (UNWTO & UNEP, 2008). Past researchers (Belén Gómez Martín, 2005; Kulendran & Dwyer, 2010; Scott, McBoyle, & Schwartzentruber, 2004) reveal that climate attracts visitors who expect favorable weather conditions at the destination. However, climate may also encourage people to stay in their own country rather than travel abroad (Hamilton & Tol, 2007). Hence, climate acts as both a pull and a push factor that affects the motivations of tourists in their decision first to travel and in their destination selection (Amelung, Nicholls, & Viner, 2007; Hamilton, Maddison, & Tol, 2005).

Climate and weather have, however, not been integrated in the mainstream tourism demand literature. This omission is surprising because seasonality triggered by climatic conditions has been recognized in the literature as a major challenge for tourism destinations; and, seasonality is closely associated with climate and weather. Seasonality is a concept that is well studied and documented in the literature. It is defined here as a pattern that repeats itself over fixed intervals of time (Makridakis, Wheelwright, & McGee, 1983), and is revealed in recurring variations in natural phenomena, such as, climate (Butler, 2001). Typical seasonal variables include cycles or patterns of differences in temperature, rainfall, snowfall, sunlight, and daylight. Such variables influence a destination's seasonal demand where swings in demand may produce situations of overcapacity, reduced utilization of infrastructure, decrease in the workforce, and absence of investments during low seasons (Pegg, Patterson, & Vila Gariddo, 2012), causing reduced profitability and productivity (Karamustafa & Ulama, 2010). On the other hand, peak seasons may be characterized by overuse of public utilities (e.g. water supply, waste management, and road use), causing dissatisfaction for residents and tourists alike, while the environment may suffer irreversible damage because of tourism pressures (Cuccia & Rizzo, 2011). Thus, the relationship between climate/weather and seasonal demand patterns becomes clear.

Most studies on the determinants of tourism demand have concentrated on 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). For example, Song, Witt, & Li (2009) and Song et al. (2012), in reviewing the determinants of tourism demand models, do not consider climate as a relevant factor. Shareef, Hoti, & McAleer (2008) examined 53 papers published about tourism demand in small islands, which omitted climate as a determinant of tourism demand. On the other hand, studies by Kulendran & Dwyer (2010), Yu, Schwartz, & Walsh (2010), Buckley & Foushee (2011), Hadwen et al., (2011), and Goh (2012) have shown that climate exerts an influence on the seasonal pattern of tourism. Only a handful of studies, however, have considered climate and weather thus far as important factors affecting tourism demand (Lohmann & Kaim, 1999; Scott & Lemieux, 2009).

Understanding seasonal patterns which impact tourism consumption and production is crucial for tourism enterprises and regions (Chan & Lim, 2011; Cuccia & Rizzo, 2011; Dritsakis, 2008; Hadwen et al., 2011; Yu, Schwartz, & Walsh, 2009). A large number of tourism demand studies are based on annual data (Bicak, Altinay, & Jenkins, 2005; Croes, 2010; Croes & Vanegas, 2005; Lim, 1997; Petrevska, 2012; Song & Li, 2008; Sookram, 2011; Vanegas & Croes, 2000). It is not possible to study seasonal influences when only considering annual time series data. Rather, more frequent observed time series data than annual time series are required for the understanding of the complete effects of seasonality that would include climate and weather (Dritsakis, 2008).

Studies that have resonated with the interaction of climate and tourism demand share some common core assumptions. First, climate is articulated as a pull factor but does not take into account the possible push of climate as a factor of seasonality in tourism. Second, seasonal climatic patterns are assumed to be similar in overall effect (i.e. seasonal, cyclical, trend, and irregular components), to the logic of income and price that exhibit trend effects rather than seasonality effects. Yu, Schwartz, & Walsh (2010) make the case, however, to define the focus of their investigation on seasonal patterns of climate variables because weather impacts are often contained in the seasonal components. And, third, climate seasonality studies have been based mainly on investigating tourism demand in large destinations (e.g. Australia and the USA).

In view of the dearth of studies that investigate how climate influences seasonal patterns of tourism demand in small island destinations, there is a case to better understand the drivers of tourism demand in small island economies. This study investigates whether seasonal patterns of pull and push climate elements (including rainfall, wind, temperature and cloud coverage) affect the seasonal deviations of tourism demand for a small island destination. The study accesses Aruba as the case of interest. According to Yin (2009), individual case studies may contribute to scientific generalizations through the replication effect, where the mode of generalization is analytic (i.e. analytical generalization). The goal then is to expand and generalize theories, and not to enumerate frequencies (statistical generalizations). According to Eisenhardt and Graebner (2007), building theory from case studies is a research strategy that requires at least one case to create theoretical constructs, propositions, and/or midrange theory from case-based empirical evidence.

The methodology involves data decomposition using the Census X-12 technique with subsequent transformation of time series data into panel data, followed by panel unit root testing, panel regression, and Euclidean distance calculation. The analysis strategy employed here is novel when considering studies on the effect of climate on short-term tourism demand. The novelty is in the solving of the issue of seasonal unit roots that may cause permanent changes in seasonal patterns.

The investigation makes three key contributions to the tourism literature. First, it contributes to the further understanding of the specific role of seasonal patterns of climate variables on the seasonality of tourism demand. Second, this investigation simultaneously analyzes the impact of both pull and push climate factors on tourism demand seasonality, which departs from mainstream time series-/panel-based studies on this relationship. Third, the study postulates a novel research strategy calibrating the effects of both pull and push seasonal factors on tourism demand seasonality.

The rest of this paper is organized as follows. Section 2 presents an overview of the literature covering the empirical relationship 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. Finally, Section 6 concludes and indicates some 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 adopts either a micro- or a macro-approach. Pivotal for the micro-approach is the measurement of people's responses to a set of questions, where they report their own subjective state and values (Stiglitz, Sen, & Fitoussi, 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, Buerki, & Fuhrer (2000) interviewed 1000 skiers and snowboarders in five resorts in Central Switzerland, and their findings suggest climate change leading to less snow would have serious implications as a result of 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 at the top of their list of destination attributes. More specifically, absence of rain, a comfortable temperature, and a good number of hours of sunlight scored the highest in terms of their importance to beach tourism. Coombes & 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 on the East Coast of the U.K. They found that warmer weather condition had a positive effect on visitor numbers.

A 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. Berrittella et al., 2006; Hamilton et al., 2005; Hamilton & Tol, 2007; Scott et al., 2004; 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 that climate change will have an impact on future tourism demand.

Another group of researchers within this strand analyzed the relationship between climate change and tourism on the basis of past conditions. For example, Yu et al. (2010) investigated the relationship 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, lightening, hail, and snow) in a climate index in order to generate 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 which have been 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 visitor statistics from 23 protected areas, spread across Australia's six climate zones. The statistics on visitors varied per region, and included data on, for example, the number of campers per month, number of vehicles at one or more campsites, and number of visits. The data also varied 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 which explained 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 Australia's six climate zones.

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 tourism in Aruba

3.1. 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 m 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 28.1 °C, varying from 20.6 °C to 36.5 °C. 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 with the rest of the Tropics. There were on average only 17.9 days per year when thunderstorms passed over the observation site in Aruba (1981–2010). The average relative humidity for that period was 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 highest in the morning hours and lowest in the late evening.

3.2. Tourism

Aruba has more than 50 years of experience with tourism. The island increased its focus on further developing tourism activities, following the closure of its main economic pillar, the Lago oil refinery in 1985 (Ridderstaat, 2007). The number of hotel rooms more than tripled, from 2524 in 1986 to 7975 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$ 1340.8 million in 2011.

The USA is by far the largest market for Aruba, accounting for on average 63.3% of all stay-over visitors between 1986 and 2011. Tourists mainly come from the North-Eastern part of the States. The Venezuelan market is the second largest market for Aruba (average 12.0% between 1986 and 2011). Together, these two countries accounted on average for about 75.3% of all stay-over visitors to Aruba between 1986 and 2011.

4. Data and methods

The basis for this study is the conceptual scheme depicted in Fig. 1, where pull and push 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 radiation 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 speed) as pull factors (i.e. the weather conditions in Aruba that attract visitors), and three weather elements (rainfall, temperature, and wind speed) as push factors (i.e. weather conditions in both the USA and Venezuela that cause residents to travel to destinations like Aruba). Data on cloud coverage in the USA and Venezuela were not available for the complete period of analysis, which is why they were not included in the study.

The variables used in this investigation are shown in Table 1. Climate data for Aruba are from the Meteorological Department of Aruba. The related data for the USA are from the North-Eastern part of that country, given that most US visitors to Aruba are from that region. The climate data for this country come from several sources, including the Global Precipitation Climatology Centre and the European Centre for Medium-Range Weather Forecasts. Climate data for Venezuela (Caracas) are from the same sources as those of the USA.

Tourism demand is proxied by the number of visitors from (particularly the North-Eastern part of) the USA and Venezuela, and the data were collected from the Central Bank of Aruba. All series have been transformed to logarithms, in order to stabilize their variance (Farooque, 2003). The descriptive statistics of the transformed data in Table 1 show limited volatility, which facilitates a valid further analysis of the selected variables.

As a first step, the study applied the Census X-12 decomposition procedure to dissect the series into a seasonally-adjusted series (SA) (which consists of a trend-cycle (TC) and irregular elements (IR)) and a seasonal factor (SF). The Census X-12 decomposition procedure is a widely-used application, based on a software developed and maintained by the US Bureau of Census. Basically, the method applies a series of sophisticated moving averages to estimate the SF, with additional calculations of the TC and IR elements. The International Monetary Fund (2000) describes the TC as a combination of the long-term trend and the (business) cycle movements in the data. Furthermore, the IR captures effects that are unpredictable, including outliers and other irregular effects such as unseasonable weather, natural disasters, strikes, etc. Prior to applying the Census X-12 technique, the data were analyzed according to the type of model (additive or multiplicative) to which they belong. For this purpose, the study applied a model taken from den Butter & Fase (1988):

$$|Y_t - YT_t| = \alpha + \beta YT_t + \varepsilon_t \tag{1}$$

where:

Y = the original value of the time series;
YT = the centralized moving average of Y over a period of a year;
α, β = coefficients;
t = time;
ε = residual.

If Y and YT are uncorrelated, which means that the coefficient β is not significantly different from zero, the model type is then considered additive. If β is significantly different from zero, the model is multiplicative. The question here basically boils down to whether movements away from the moving trend (the absolute difference between Y and YT, or $|Y - YT|$), be it C, SF or IR, are related to YT or not. If they are (i.e. β is significantly different from zero), then the T, C, SF and IR elements are related to each other in a multiplicative way. Otherwise (i.e. β is not significantly different from zero), they have an additive relation with each other.

Testing for the relative importance of seasonal factors in the overall short-term volatility of the applied variables is done using the following regression:

$$\Delta\text{Series}_t = \alpha_1 \Delta\text{Series}_{\text{El},t} + \varepsilon_{1,t}, \tag{2}$$

where:

Δ = first difference;
El = series' element (TC, SF or IR);
t = time;
ε = residual.

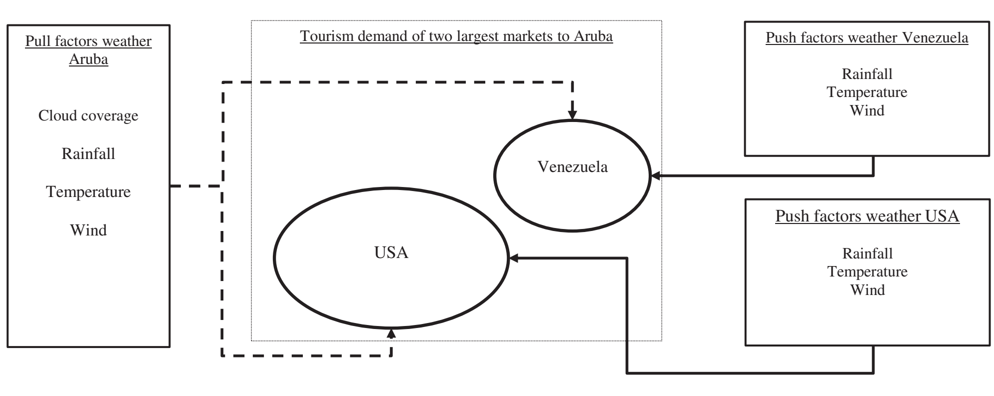

Fig. 1. Conceptual framework of the relation between the seasonal patterns of (pull/push) weather and tourism demand for the largest market of Aruba's tourism.

Table 1
Variables used in the analysis.

Variable	Description	Mean	Median	Maximum	Minimum	Standard deviation	Coefficient of variation (in %)
Pull factors							
LAUA_CLOUD	Cloud coverage in Aruba[a]	3.8559	3.8918	4.3399	3.0007	0.2134	5.5
LAUA_RAIN	Rainfall in Aruba[a]	4.8925	4.7858	6.0215	4.6052	0.3008	6.1
LAUA_TEMP	Temperature in Aruba[a]	3.3368	3.3393	3.4177	3.2465	0.0371	1.1
LAUA_WIND	Wind in Aruba[a]	1.9703	2.0149	2.2925	1.0986	0.1872	9.5
Push factors							
United States							
LUSA_RAIN	Rainfall in the USA[b]	4.3773	4.4035	5.3232	3.1088	0.3526	8.1
LUSA_TEMP	Temperature in the USA[c]	4.6909	4.6944	4.8065	4.5330	0.0779	1.7
LUSA_WIND	Wind in the USA[d]	1.5948	1.6192	1.9184	1.1132	0.1742	10.9
Venezuela							
LVEN_RAIN	Rainfall in in Venezuela[b]	5.1472	5.1789	6.0580	4.6052	0.3378	6.6
LVEN_TEMP	Temperature in Venezuela[c]	3.2391	3.2269	3.3789	3.1575	0.0455	1.4
LVEN_WIND	Wind in Venezuela[d]	1.6652	1.6890	1.9334	1.2876	0.1384	8.3
Tourism demand							
LUSA_TOUR	Tourism demand from the USA[e]	10.2998	10.3889	10.9381	8.9149	0.4221	4.1
LVEN_TOUR	Tourism demand from Venezuela[e]	8.5275	8.6201	9.9317	6.1903	0.7025	8.2

Sources of data.
[a] Meteorological Department Aruba.
[b] Global Precipitation Climatology Centre operated by Deutscher Wetterdienst.
[c] National Centers for Environmental Prediction–National Center for Atmospheric Research (NCEP–NCAR) re-analysis (NCEP1) data.
[d] The European Centre for Medium-Range Weather Forecasts (ECMWF) Re-Analysis (ERA-Interim).
[e] Central Bank of Aruba.

The aim here is to determine the coefficient of determination (adjusted R^2) in order to assess the contribution of each of these three elements to the variability of the overall series. Given that the differencing occurs over a short-time range (i.e. month versus the next month), it is expected that the effects of the monthly differences would be likely dominated by a combination of both SF and IR elements.

Working with seasonal factors implies the possibility of the presence of seasonal unit roots, whereby seasonal patterns may change permanently due to shocks (Hylleberg et al., 1990). The existing seasonal tests (e.g. Beaulieu & Miron, 1993; Franses, 1990; Hylleberg et al., 1990) are more complex than the simple unit root tests, because seasonal time series tend to have different roots (e.g. quarterly and semi-annual) than the conventional long-run frequency (Song, Witt, & Li, 2009). Furthermore, according to Rodrigues & Franses (2005), the power of seasonal unit roots deteriorates the more unit roots one has to examine. To circumvent the problem of seasonal unit root testing, the structure of the data was amended from time-series-based to panel-oriented:

$$V_t \rightarrow V_{i,t} \tag{3}$$

where:

V = variable;
t = time;
i = group or unit.

Each variable now contains 12 units (January–December), and each unit has 26 years of data (1986–2011). Subsequently, we proceeded to test for stationarity in panel data by applying a simpler unit root test (than the seasonal unit root test) provided by Im, Pesaran, & Shin (2003). The model behind this test is as follows (Asteriou, 2006):

$$\Delta Y_{i,t} = a_i + \rho_i Y_{i,t-1} + \sum_{k=1}^{n} \varnothing_k \Delta Y_{i,t-k} + \delta_i t + \theta_t + u_{i,t}, \tag{4}$$

where:

Y = variable to be tested;
a = intercept of unit element of panel;
i = unit element of panel;
t = time element of panel;
ρ = coefficient to be tested for unit root;
θ = intercept of time element of panel;
u = residual.

The null hypothesis of this test is that all units are non-stationary, versus the alternative hypothesis that a fraction of the series in the panel are assumed to be stationary (Asteriou, 2006). The outcome of the unit root test determines whether data differencing is needed, and the eventual order of differencing. With the data requirements known, the study can then proceed to analyze whether the climate seasons are important in determining short-term tourism demand. For this purpose, we tested three types of panel models, i.e. (1) a pooled OLS regression model; (2) a fixed effects model (FEM); and (3) a random effects model (REM). The following equations and methodological analyses were based on Gujarati (2012). The pooled OLS model in this case consists of the following equations:

$$\begin{aligned} \mathrm{TDCO}_{i,t} = {} & \alpha_{i,t} + \alpha_2 \mathrm{CAUA}_{i,t} + \alpha_3 \mathrm{RAUA}_{i,t} + \alpha_4 \mathrm{TAUA}_{i,t} + \alpha_5 \mathrm{WAUA}_{i,t} \\ & + \alpha_6 \mathrm{RCO}_{i,t} + \alpha_7 \mathrm{TCO}_{i,t} + \alpha_8 \mathrm{WCO}_{i,t} + u_{i,t} \\ & i = 1, \ldots, 12; \quad t = 1986, \ldots, 2011, \end{aligned} \tag{5}$$

where:

TDCO = tourism demand to Aruba from country of origin (USA or Venezuela);
α's = coefficients;
CAUA = cloud coverage in Aruba;
RAUA = rainfall in Aruba;
TAUA = temperature in Aruba;
WAUA = wind in Aruba;
RCO = rainfall in country of origin (USA or Venezuela);
TCO = temperature in country of origin (USA or Venezuela);
WCO = wind in country of origin (USA or Venezuela);
u = residual.

The FEM is indicated as follows:

$$\left(\mathrm{TDCO}_{i,t}-\overline{\mathrm{TDCO}_i}\right) = \alpha_2\left(\mathrm{CAUA}_{i,t}-\overline{\mathrm{CAUA}_i}\right)+\alpha_3\left(\mathrm{RAUA}_{i,t}-\overline{\mathrm{RAUA}_i}\right)+\alpha_4\left(\mathrm{TAUA}_{i,t}-\overline{\mathrm{TAUA}_i}\right)+\alpha_5\left(\mathrm{WAUA}_{i,t}-\overline{\mathrm{WAUA}_i}\right)+\alpha_6\left(\mathrm{RCO}_{i,t}-\overline{\mathrm{RCO}_i}\right)+\alpha_7\left(\mathrm{TCO}_{i,t}-\overline{\mathrm{TCO}_i}\right)+\alpha_8\left(\mathrm{WCO}_{i,t}-\overline{\mathrm{WCO}_i}\right)+u_{i,t}. \tag{6}$$

To determine whether the FEM is superior to the pooled OLS model, we calculated a restricted F-test, which compares the coefficients of determination of both pooled OLS and FEM (see Gujarati, 2012).

The REM model is expressed as follows:

$$\mathrm{TDCO}_{i,t}=\alpha_{i,t}+\alpha_2\mathrm{CAUA}_{i,t}+\alpha_3\mathrm{RAUA}_{i,t}+\alpha_4\mathrm{TAUA}_{i,t}+\alpha_5\mathrm{WAUA}_{i,t}+\alpha_6\mathrm{RCO}_{i,t}+\alpha_7\mathrm{TCO}_{i,t}+\alpha_8\mathrm{WCO}_{i,t}+w_{i,t}, \tag{7}$$

where:

$$w_{i,t} = \varepsilon_i + u_{i,t}. \tag{8}$$

Basically, the error term $w_{i,t}$ is composed of an individual-specific error (ε_i, with mean of zero and variance of σ_ε^2) and a combined time-series and cross-section error component. Furthermore, the REM assumes that the intercept of any cross-section unit is not fixed, but a random variable with a mean value of α_1, and can, thus, be expressed as:

$$\alpha_{1,i} = \alpha_1 + \varepsilon_i. \tag{9}$$

To test for the adequacy of the REM against the FEM, we apply what is called the Hausman test, where the null hypothesis is that both the FEM and the REM do not differ significantly. The test involves the comparison of a calculated χ^2 against a critical χ^2. If the calculated χ^2 is larger than the critical χ^2, we can then conclude that the REM is not the appropriate model, and that the FEM is to be preferred over the REM.

As a further step, we added a dummy variable to the equations, capturing the effect of vacation and holiday periods on tourism demand seasonality (1 = holiday or vacation period; 0 = no holiday or vacation period). In the case of the USA, the selected holiday months were March, April, May, June, July, August, November and December. For Venezuela, the months of February, March, April, June, July, August, September and December were selected. The selected months in both cases were based on national school vacation and official holidays. The vacation and holiday periods in the USA and Venezuela vary somewhat, but both countries have several holiday and vacation months in common (i.e. March, April, June, July, August, December).

Lastly, based on the results of the model which incorporates the vacation and holiday dummy, we calculated the monthly differences between the statistically significant seasonal factor of climate and the seasonal factors of tourism demand. This provides an indication of the strength of association during several periods of the year. For this purpose, we used the Euclidean distance measure formula, based on Kulendran & Dwyer (2010):

$$\mathrm{EDM}_m = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\text{climate series}_m-\text{tourism demand series}_m\right)^2}, \tag{10}$$

where:

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

The smaller the EDM, the stronger the seasonal association between the climate factor and the tourism demand factor.

5. Empirical results

All estimates were obtained from Eviews version 7 and Excel 2010. The regression results show that those variables with the additive form dominated slightly over those with the multiplicative form, implying that in most cases the elements of the cycle, seasonal, and irregular factors were unrelated to the moving trend (Table 2).

The series were subsequently decomposed using the Census X-12 technique, taking into consideration their model form. The regression results from the analysis of short-term explanatory power indicate that both seasonal and irregular factors did indeed explain most of the short-range variability of the series, with the seasonal factors explaining more than 50% of the variability in: temperature in Aruba; temperature and wind in both the USA and Venezuela; and tourism demand from both the USA and Venezuela (Table 3). This suggests that the causation of the short-term volatility of the indicated variables is largely due to repeating factors over time. Given the important influence of seasonality in tourism demand of both countries of origin, and the nature of the irregular factors (i.e. they are unpredictable, with possible outliers and other irregular effects that are normally not expected to permanently affect seasonality), we omitted the effects of irregular factors from the rest of the analysis.

Charts 1.1–1.12 (Fig. 2) provide an overview of the standardized seasonal factors of the variables. Standardization makes the seasonal factors comparable to each other, and practically eliminates the distinction whether the seasonal factors were derived from an additive or a multiplicative model. The charts show that the seasonal patterns are dynamic over time, with changing amplitudes (maximum and minimum points).

With the time series transformed to panel data, the next analysis involves assessing the data for stationarity, using the Im, Pesaran, & Shin (2003) unit root test. The results are included in Table 4, and show that most variables were either integrated of zero or first order. Only the variables representing rainfall in Aruba and wind in Venezuela showed clear signs of being $I(1)$. All variables were subsequently transformed to first difference for calculating the relationships between the seasonal factors of weather and those of tourism demand from both the USA and Venezuela.

Table 5 provides the results of the tested equations. In the estimation models without the holiday dummy, the results of the restricted F-test show that, in both cases, the FEM is superior to the pooled OLS model for the purpose of estimating the impact of seasonal factors of weather on the tourism demand variables (USA: $F(11,292) = 5.3361$ ($p = 0.000$); Venezuela: $F(11,292) = 5.6498$ ($p = 0.000$)). The Hausman test in the case of the USA as the dependent variable was 10.1237 (d.f. = 7 and $p = 0.1817$), indicating that the unit-specific effects were not correlated with any of the explanatory variables included in the model, and that the REM was the appropriate model to use. In the case of Venezuela, the Hausman test was

Table 2
Model type selection based on significance of coefficient of independent variable.

Variable type	Model type selection	
	Regression result of β	Model type
Pull factors		
LAUA_CLOUD	−0.2159***	Multiplicative
LAUA_RAIN	−1.0768***	Multiplicative
LAUA_TEMP	0.0627	Additive
LAUA_WIND	−0.2546***	Multiplicative
Push factors		
United States		
LUSA_RAIN	−0.0464	Additive
LUSA_TEMP	−0.5034	Additive
LUSA_WIND	−0.0072	Additive
Venezuela		
LVEN_RAIN	−0.0023	Additive
LVEN_TEMP	0.0304	Additive
LVEN_WIND	−0.4898*	Multiplicative
Venezuela		
LVEN_RAIN	−0.0023	Multiplicative
Tourism demand		
LUSA_TOUR	−0.0396***	Multiplicative
LVEN_TOUR	0.0413	Additive

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

13.5571 (d.f. = 7 and $p = 0.0596$), revealing that the unit-specific effects were correlated with the explanatory variables in the model, meaning that the FEM was the most suitable model to use in this case.

For the model with no inclusion of a holiday dummy variable, in the case of the USA the results showed that, when it comes to seasonal pull factors, only the variable wind in Aruba was significant in determining the short-term seasonal factor of US tourism demand. An increase in the seasonal factor of wind in Aruba would result in an increase in the seasonal factor of tourism demand from the USA, most likely reflecting the attractiveness of the cooling effect of wind in a warm environment (Scott & McBoyle, 2001). In the same setting, the coefficients of the seasonal push factors, rainfall and wind speed in the USA, were also positive, indicating that increases in the seasonal factors of rainfall and wind speed in the USA would have a positive effect on the seasonal factor of US tourism demand for Aruba. The positive effect of the increase in the seasonal factor of wind speed on that of tourism demand from the USA can be explained by the thermal effect it has on people, particularly when it comes to wind chills in cold climates (Scott & McBoyle, 2001). On the other hand, the seasonal factor of temperature in the USA has a negative impact on the seasonal factor of tourism demand from that country to Aruba. In other words, short-term increases in the seasonal factors of temperature in the USA would have a negative impact on the short-term seasonal factor of tourism demand from that country, given that the push effect of this seasonal factor becomes smaller as temperatures increase in the USA.

In the case of Venezuela, initial estimates showed that the seasonal factors of temperature and wind in that country did not show the expected signs, while both factors were statistically significant. For this reason, both variables were excluded from the regression and the re-estimated coefficients showed that the seasonal factors of both rainfall and temperature in Aruba were significant pull influences at, respectively, the 1% and the 10% level of significance. Furthermore, the seasonal factor of rainfall in

Table 3
Explanatory power of time-series elements.

Dependent variable type	Adj. R^2 trend-cycle	Adj. R^2 seasonal factor	Adj. R^2 irregular factor
ΔLAUA_CLOUD	0.0117	0.3527	0.5484
ΔLAUA_RAIN	0.0126	0.1814	0.7855
ΔLAUA_TEMP	0.0388	0.6989	0.2369
ΔLAUA_WIND	0.0091	0.3389	0.6257
ΔLUSA_RAIN	0.0043	0.1792	0.8098
ΔLUSA_TEMP	0.0012	0.8667	0.1419
ΔLUSA_WIND	0.0014	0.5348	0.4529
ΔLVEN_RAIN	0.0088	0.3688	0.6324
ΔLVEN_TEMP	0.0532	0.5932	0.3416
ΔLVEN_WIND	0.0014	0.8122	0.2125
ΔLUSA_TOUR	0.0274	0.8159	0.1957
ΔLVEN_TOUR	0.0083	0.6898	0.2821

Note: Δ = first difference of variable. Adj. R^2 = adjusted coefficient of determination. The higher the adj. R^2, the more explanatory power an element of the variable has.

Table 4
Panel unit root test results.

Variable $\bar{t}$	$\bar{t}$ values (intercept only)		$\bar{t}$ values (intercept and trend)		Degree of integration
	Lag = 0	Lag = 1	Lag = 0	Lag = 1	
P_LAUA_CLOUD	−2.0905***	−2.9245***	−3.8988***	−3.2984***	$I(0)$ or $I(1)$
P_LAUA_RAIN	−1.5044	−2.6609***	−2.0791	−3.0067***	$I(1)$
P_LAUA_TEMP	−1.6816	−3.2900***	−2.8722***	−3.6325***	$I(0)$ or $I(1)$
P_LAUA_WIND	−2.1708***	−3.0187***	−3.6821***	−3.4085***	$I(0)$ or $I(1)$
P_LUSA_RAIN	−1.5164	−3.8855***	−4.1346***	−4.1138***	$I(0)$ or $I(1)$
P_LUSA_TEMP	−2.0527***	−2.4903***	−2.4615*	−2.8929***	$I(0)$ or $I(1)$
P_LUSA_WIND	−1.0875	−4.0201***	−3.6307***	−4.1427***	$I(0)$ or $I(1)$
P_LVEN_RAIN	−2.0342**	−3.1155***	−3.3355***	−4.3447***	$I(0)$ or $I(1)$
P_LVEN_TEMP	−1.5601	−3.5292***	−3.4304***	−4.0127***	$I(0)$ or $I(1)$
P_LVEN_WIND	−1.2922	−3.1416***	−2.3105	−3.7425***	$I(1)$
P_LUSA_TOUR	−1.8584*	−4.5055***	−4.4369***	−4.7402***	$I(0)$ or $I(1)$
P_LVEN_TOUR	−1.9736**	−3.9191***	−3.7415***	−4.1578***	$I(0)$ or $I(1)$
Critical values	Intercept		Intercept and trend		
1%	−2.05		−2.68		
5%	−1.90		−2.53		
10%	−1.82		−2.45		

Note: test is based on panel unit root test proposed by Im, Pesaran, & Shin (2003). ***, ** and * indicate significance at, respectively, the 1%, 5% and 10% level. H_0 = series is non-stationary. A series is considered stationary if $\bar{t} < t_{\text{critical value}}$.

Table 5
Panel regression results.

	Model 1 (without holiday dummy)		Model 2 (with holiday dummy)	
	Random effects model	Fixed effects model	Random effects model	Random effects model
	USA	Venezuela	USA	Venezuela
Intercept	−0.0002	0.0000	−0.0349***	0.0024
LAUA_CLOUD	−0.1179	0.0220	−0.1641***	0.0206
LAUA_RAIN	−0.0095	−0.1766***	0.0011	−0.1764***
LAUA_TEMP	0.1224	−0.1865*	0.1753	−0.1909**
LAUA_WIND	0.3384***	−0.1327	0.3427***	−0.1240
LUSA_RAIN	0.0518**		0.0523**	
LUSA_TEMP	−1.0572**		−0.9491*	
LUSA_WIND	0.2754**		0.2907**	
LVEN_RAIN		0.1047**		0.1056**
LVEN_TEMP				0.0102
LVEN_WIND				
Dummy holiday USA			0.0520***	
Dummy holiday Venezuela				−0.0037
Adj. R^2	0.0511	0.0740	0.0854	0.0684
F-test	3.3010***	5.7776***	4.4914***	4.1385***

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

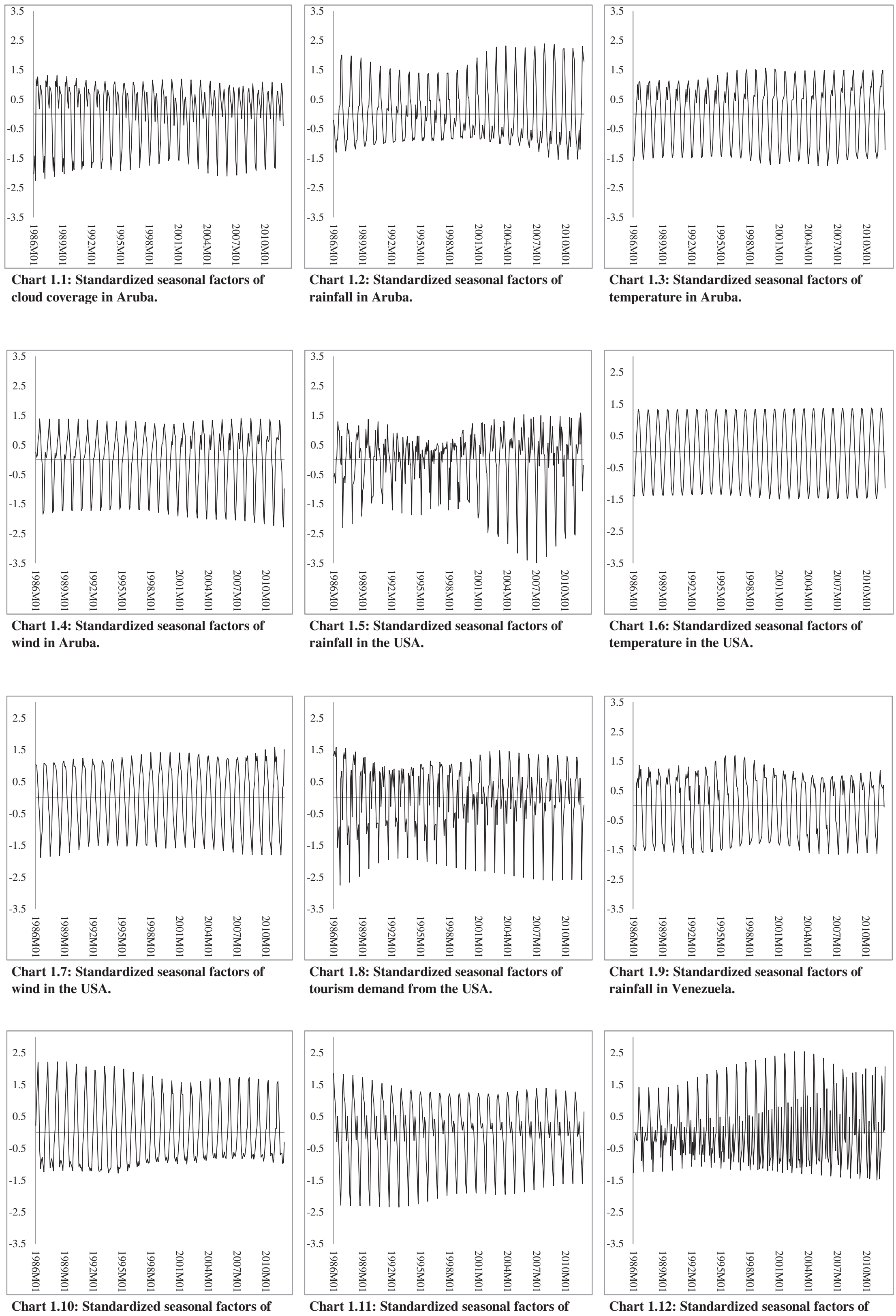

Fig. 2. Chart 1.1: standardized seasonal factors of cloud coverage in Aruba. Chart 1.2: standardized seasonal factors of rainfall in Aruba. Chart 1.3: standardized seasonal factors of temperature in Aruba. Chart 1.4: standardized seasonal factors of wind in Aruba. Chart 1.5: standardized seasonal factors of rainfall in the USA. Chart 1.6: standardized seasonal factors of temperature in the USA. Chart 1.7: standardized seasonal factors of wind in the USA. Chart 1.8: standardized seasonal factors of tourism demand from the USA. Chart 1.9: standardized seasonal factors of rainfall in Venezuela. Chart 1.10: standardized seasonal factors of temperature in Venezuela. Chart 1.11: standardized seasonal factors of wind in Venezuela. Chart 1.12: standardized seasonal factors of tourism demand from Venezuela.

Venezuela has a positive impact on the seasonal factor of tourism demand of that country. In other words, increased effects of seasonal rainfall in Venezuela will likely have a positive effect on the seasonal factor of tourism demand from that country.

Next, we added the holiday dummies in both regressions, and the first notable effect of doing this is that of what is called dummy trap in the case of the fixed effect model, where there is most likely interaction between the added dummy and the fixed effect dummies. Therefore, the fixed effect model cannot be used under the new condition. Hence, we resorted to the REM for estimating the model which includes the holiday dummy variable. The results are also included in Table 5. In the case of the USA, the holiday dummy variable was significant, meaning that the seasonality of vacations and holidays was a determining factor in the tourism demand seasonality of US visitors. This significance may be explained by the relatively low number of paid vacation days that Americans have compared with other nations (on average 10 paid vacation days and 6 paid holidays in the private sector, according to a study by the Center for Economic and Policy Research (Ray, Sanes, & Schmitt, 2013)). Furthermore, the pull seasonal factors of cloud coverage and wind speed in Aruba were important determinants of the seasonal factor of US tourism demand both at the 1% level of significance. In the case of push seasonal factors, rainfall, temperature, and wind speed were statistically significant (at, respectively, the 5%, 10% and 5% level of significance) in influencing the seasonal pattern of tourism demand from the USA.

The results for Venezuela show that holiday vacations were not statistically significant, which might be explained by the number of paid vacation days that Venezuelans have (a minimum of 15 days, and one additional day each year of service, up to a maximum of 30 days (http://www.lottt.gob.ve)). Additionally, Venezuelans have a maximum of 12 public holidays, provided that they fall on a weekday. Theoretically, a Venezuelan worker could have up to 42 days of paid vacation and holiday, making it easier than for the US visitors to come to Aruba, even more than once a year. The available data suggest that 78% of Venezuelans who patronize Aruba are repeat visitors, and 37% of the Venezuelan repeat tourists have visited the island more than six times (Croes et al., 2011), indicating that Venezuelan travelers are likely to have experience with the possible climate patterns on the island. Further results show that particularly rainfall and temperature in Aruba (with respective significance statistics of 1% and 5%) were important pull factors for the seasonal travel behavior of Venezuelan visitors to the island. Additionally, the seasonality of rainfall in Venezuela itself was an important influence on the seasonal factor of tourism demand from that country.

The EDMs were subsequently calculated for the statistically significant seasonal factors of climate and the seasonal tourism demand patterns. The results are reported in Charts 2.1–2.8 (Fig. 3), showing different degrees of sensitivity of seasonal patterns of tourism demand to seasonal climate factors. To complement the charts, we also included in Table 6 the months where the EDM outcomes were smaller than the average, as a proxy for when the sensitivity of the seasonal factors of tourism demand to those of climate were the highest. In the case of the USA, sensitivity to the pull and push seasonal factors of climate was most pertinent in the months of February, August, September, and November, with both the respective pull and push seasonal factors being implicated most of the time as influencing factors on the sensitivity. This may suggest that vacation patterns may be more dominant in determining movements in the seasonal factors of tourism demand in the remaining months of the year. It may also suggest the effect of a possible third factor, which is the seasonality of the timeshare component, where tourists come in a certain month of the year to make use of their timeshare ownership. According to the Aruba Timeshare Association, almost 40% of the overall hotel inventory in Aruba consists of timeshare units, and approximately 300,000 timeshare members (and exchangers) – or nearly 50% of all guests to Aruba – visit the island on an annual basis (http://www.arubatimeshare.net). This may explain why the sensitivity of the seasonal factor of US tourism demand was low with respect to both pull and push climate patterns.

In the case of Venezuela, the seasonal factor of tourism demand was more influenced by climate patterns in the first half of the year, with the exception of May, where the sensitivity was low in all climate circumstances. Further low sensitivities were found particularly in the second half of the year, possibly explained by the dominating role of what is known as the 'lock-in effect' in these months. The 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). The fact that the previously-mentioned characteristics of a large majority of Venezuelan visitors (i.e. more than $^3/_4$ being repeat visitors, with slightly more than $^1/_3$ of them having multiple-visit experience) may corroborate the possibility of the lock-in effect existing for this market.

The previous analysis reveals that short-term mutations in tourism demand from both the USA and Venezuela are impacted by both pull and push seasonal climate factors. However, these impacting effects are not homogeneous, meaning that they can vary in intensity, depending on the type of climate variable and the time of year. This heterogeneity of climate impacts on tourism demand presents opportunities for improving the management of short-run tourism development.

6. Conclusion

Climate is possibly the third-most important attribute in tourists' decision-making process, next to the aquatic and natural attributes of a destination (Hamilton & Lau, 2004). This study has investigated the influence of seasonal patterns of pull and push climate on the seasonal fluctuations of tourism demand for Aruba. According to Yu et al. (2010), working only with seasonal factors facilitates a more efficient examination of the impacts of the specific weather influences on tourism demand variability, i.e. by filtering out 'noise', and so a better understanding of the nature of the relationships. The applied data showed that seasonal factors significantly influenced the overall short-term behavior of tourism demand from both the USA and Venezuela, thus legitimizing the seasonal approach followed in this study. The results show that both pull and push seasonal factors of climate were relevant in determining the seasonal variations in tourism demand from both countries. In the case of the USA, the seasonal factors of cloud coverage and wind speed in Aruba were important pull factors, while rainfall, temperature, and wind speed in the USA were key push factors. For Venezuela, the two essential climate pull factors were rainfall and temperature in Aruba, while rainfall in Venezuela was a paramount push factor.

Moreover, short-term movements in tourism demand from the USA were also impacted by vacations and holidays (probably influenced by the limited number of paid leave days that many Americans have), while the timeshare factor could be a third impacting element in the seasonal behavior of US tourists. In the case of Venezuela, the findings do not suggest a significant role for vacations and holidays, but the fact that many Venezuelans have multi-time experience with Aruba as a tourist destination may suggest the impact of the lock-in effect as a secondary factor that influences the short-term variations in tourism demand from this country.

While this study suggests climate in Aruba is an imperative factor determining short-term movements in tourism demand, climate conditions on the island are also important in determining long-term tourism demand. For example, a study by Sookram (2011), based on annual data, found that temperature and rainfall in Aruba

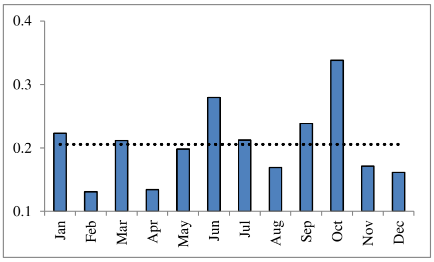

Chart 2.1: Euclidean distance of cloud coverage in Aruba and tourism demand from the USA. Dotted line = average.

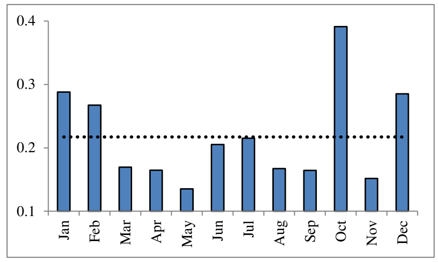

Chart 2.2: Euclidean distance of wind speed in Aruba and tourism demand from the USA. Dotted line = average.

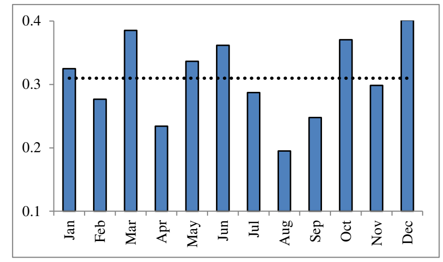

Chart 2.3: Euclidean distance of rainfall in the USA and tourism demand from the USA. Dotted line = average.

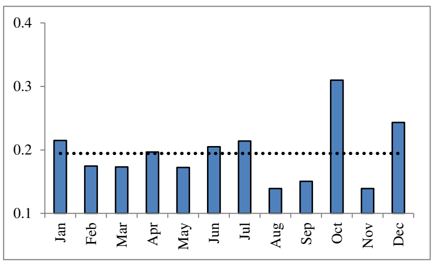

Chart 2.4: Euclidean distance of temperature in the USA and tourism demand from the USA. Dotted line = average.

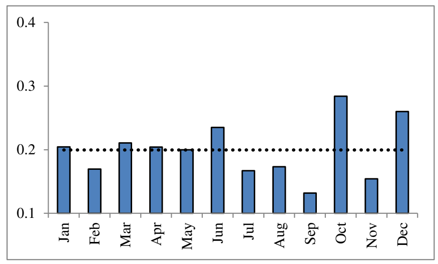

Chart 2.5: Euclidean distance of wind speed in the USA and tourism demand from the USA. Dotted line = average.

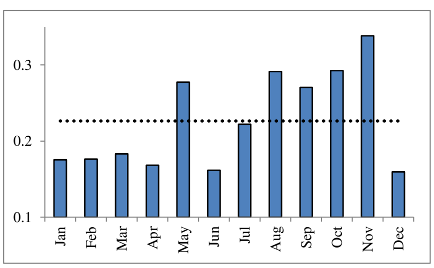

Chart 2.6: Euclidean distance of rainfall in Aruba and tourism demand from Venezuela. Dotted line = average.

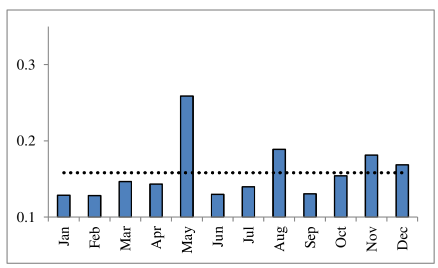

Chart 2.7: Euclidean distance of temperature in Aruba and tourism demand from Venezuela. Dotted line = average.

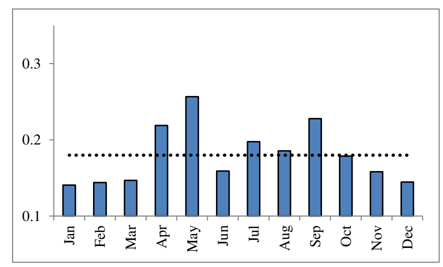

Chart 2.8: Euclidean distance of rainfall in Venezuela and tourism demand from Venezuela. Dotted line = average.

Fig. 3. Chart 2.1: Euclidean distance of cloud coverage in Aruba and tourism demand from the USA. Chart 2.2: Euclidean distance of wind speed in Aruba and tourism demand from the USA. Chart 2.3: Euclidean distance of rainfall in the USA and tourism demand from the USA. Chart 2.4: Euclidean distance of temperature in the USA and tourism demand from the USA. Chart 2.5: Euclidean distance of wind speed in the USA and tourism demand from the USA. Chart 2.6: Euclidean distance of rainfall in Aruba and tourism demand from Venezuela. Chart 2.7: Euclidean distance of temperature in Aruba and tourism demand from Venezuela. Chart 2.8: Euclidean distance of rainfall in Venezuela and tourism demand from Venezuela.

influenced US tourism demand for this destination, in addition to per capita income, and the gross domestic product in the USA.

The findings of this study are important, because they shed light on the combined influence of seasonal variations of push and pull weather elements on the seasonal deviations of tourism demand. Moreover, the results show that monitoring economic factors alone is not enough when it comes to analyzing the short-term determinants of tourism demand for Aruba. Climate patterns matter for travelers from both the USA and Venezuela to Aruba. Knowledge about the structure of the climate variations over the course of the year could assist tourism managers and government representatives to (better) cope with short-term demand fluctuations in their planning, forecasting, and marketing efforts.

Table 6
Months where the EDM is below average.

Month of the year	United States					Venezuela		
	Cloud coverage AUA	Wind speed AUA	Rainfall USA	Temperature USA	Wind speed USA	Rainfall AUA	Temperature AUA	Rainfall Venezuela
January						●	●	●
February	●		●	●	●	●	●	●
March		●		●		●	●	●
April	●	●	●			●	●	
May	●	●		●				
June		●				●	●	●
July			●		●		●	
August	●	●	●	●	●			
September		●	●	●	●		●	
October							●	
November	●	●	●	●	●			●
December	●					●		●

Note: ● indicates that the EDM outcome is below its average.

Furthermore, distinguishing between the climate sensitivities of the markets could assist people involved with tourism development to build a complementary relationship between these two types of markets in order to minimize the fluctuation in tourism demand over the year. For example, one possible strategy that policy makers and tourism leaders could follow would 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) in order to get a lead on 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 of lower demand from the North-Eastern USA increases. This could be the case in, for example, February, where the intensity of the seasonal factor of temperature in the North-Eastern USA is the highest in the winter season. Policy makers and tourism chiefs in Aruba could react to this information by first comparing bookings for this month against a year earlier. If these do indeed point to lower demand, policy makers could then react by making more special offers available for this period to counter the expected low demand. Alternatively, they could increase marketing efforts from other markets (e.g. Venezuela) to stimulate demand, thereby compensating for the expected fall-down in demand from the North-Eastern USA. It is important to mention is that the current marketing plan of the Aruba Tourism Authority (Croes et al., 2011) does not include a strategy on the interactions between markets in terms of mitigating the negative demand effects of push climate factors.

Given that climate conditions in Aruba are important in pulling demand from both the USA and Venezuela, a continuous stream of general information on current and average climate conditions during the year is needed, thus providing an additional economic benefit from public weather and climate services. Visitors can 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 do not themselves provide information on (average) weather conditions on the island, which could be important complementary information for the visitor in the planning process. It is recommended that all hotels should incorporate up to date local weather information on their websites, derived from the official meteorological sources.

The theoretical implications are twofold. First, climate is a significant push and pull factor affecting tourism demand. Second, tourism demand and climate are bounded by intertemporal climate constraints. Future research should focus on extending this investigation to include other destination markets for Aruba, such as the European countries, in order to obtain 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 as to compare weather effects in terms of impacts and timing on the demand from similar tourism markets in other Caribbean destinations. It makes good sense to have a thorough understanding of the development of tourism demand during the course of the year, including the factors that determine its pattern.

Appendix A. Supplementary data

Supplementary data related to this article can be found at http://dx.doi.org/10.1016/j.tourman.2013.09.005.

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