International Journal of Biometeorology (2019) 63:1025–1038
https://doi.org/10.1007/s00484-019-01715-z

ORIGINAL PAPER

Effects of weather factors on recreation participation in a humid subtropical region

Ramesh Paudyal[1] · Taylor V. Stein[1] · Birendra KC[2] · Damian C. Adams[1]

Received: 23 April 2018 / Revised: 15 March 2019 / Accepted: 27 March 2019 / Published online: 9 April 2019

Abstract

This study examines effects of weather, temporal factors, and gasoline price on outdoor recreation participation by using a time series model. We obtained more than 5 years of daily outdoor recreation visitation data by using infrared mechanical counters on a section of the Florida National Scenic Trail (FNST). Results showed that days with daily maximum temperatures of 16–22 °C brought the largest number of visitors, which suggests this is the most comfortable range of daily maximum temperatures to recreate on the FNST. Daily maximum temperatures below 6 °C and above 31 °C and heat index values above 38 °C brought significantly lower visitor numbers, suggesting these values are temperature thresholds for this region in a recreation context. A seasonal autoregressive integrated moving average model showed significant negative effects of temperature, relative humidity, cold snaps, and gasoline price and a positive effect of weekends and public holidays on recreational visitations to this trail. Days with heavy rainfall (> 2.54 cm) or a high heat index (≥ 35 °C) were likely to negatively affect recreation participation not only on the same day, but also on the next normal weather day. These findings imply that managers of facilities that need staffing and other resources should expect to receive fewer visitors on days following adverse weather conditions, even if that day has normal weather conditions.

Keywords Nature-based tourism · Weather preferences · Weather thresholds · Tourism climatology · Decision-making · Lag effect

Introduction

Weather and climate[1] are among the key factors that affect outdoor recreation participation and experiences. Change in climate and fluctuation in weather condition and economic factors (e.g., gasoline price) could create unforeseen shifts of demand and supply. Unpredictable shifts in demand are a major problem for outdoor recreation and tourism. These shifts may cause inefficient use of resources, loss of potential profits, difficulties in administrative scheduling, and negative impacts on recreation experience and ecological conditions (Manning and Powers 1984).

Information about how tourists and recreationists respond to climatic conditions and weather fluctuations in diverse geographic and recreation contexts are important for service and facility management and for reducing hazards to visitors (Scott and Lemieux 2010). More specifically, information related to what people consider ideal, suitable, acceptable, or unacceptable conditions, and what specific weather and climate-related criteria people use to make recreation choices are crucial. However, interactions between tourism/outdoor recreation demand and weather/climate are so complex that it is difficult to both predict and manage the consequences of changing weather conditions (Becken and Hay 2007; Denstadli et al. 2011; Dubois et al. 2016). Nevertheless, tourism climatology has now become one of the most widely researched topics that has offered advancement in conceptual theories, models, and research methodologies (Scott and Lemieux 2010; Gössling et al. 2012; Scott et al. 2012; Böcker et al. 2013; de Freitas 2017; Steiger et al. 2017). Researchers have examined the impact of weather and climate on tourism and outdoor recreation participation around the world focusing on different contexts and activities. This body of literature has largely focused on ski tourism (Hamilton et al. 2007; Shih et al. 2009; Beaudin and Huang 2014; Rutty and

[1] Weather refers to an atmospheric condition at any given time or place; whereas, climate refers to an average weather, or more rigorously, as the statistical description in terms of the mean and variability of relevant quantities over a period of time ranging from months to thousands of years (IPCC 2007).

✉ Ramesh Paudyal
rpaudyal@ufl.edu

1 University of Florida, Gainesville, FL, USA

2 University of North Texas, Denton, TX, USA

Andrey 2014; Steiger et al. 2017; Steiger and Abegg 2018) and beach or water-based recreation and tourism (Lin and Matzarakis 2008; Finger and Lehmann 2012; Rutty and Scott 2013; Zhang and Wang 2013; de Freitas 2015; Rutty and Scott 2015). Researchers have also examined weather and climate effects on golfing (Nicholls et al. 2008), hiking, leisure walking, physical activity (Chan et al. 2006; McGinn et al. 2007; Li and Lin 2012), zoo visitations (Aylen et al. 2014; Hewer and Gough 2016; Perkins 2018), and recreation in parks, urban trails, and natural areas (Lindsey et al. 2007; Buckley and Foushee 2012; Becken and Wilson 2013; Aylen et al. 2014; Ndetto and Matzarakis 2017; Lindner-Cendrowska and Błażejczyk 2018). In general, research has shown that people tend to have different expectations and levels of tolerance for weather and climatic conditions as they relate to different activities, recreation settings, and geographic and climate regions (Li and Lin 2012; Böcker et al. 2013; Rutty and Scott 2015; Hewer and Gough 2016; de Freitas 2017).

Effect of weather and climate on outdoor recreation

Weather and climate are found to affect tourism and recreation in various ways, such as travel patterns, planning, choices, experiences, climate policy, infrastructure design, and operation costs (Hamilton and Lau 2005; Yu et al. 2009; Scott and Lemieux 2010; Scott et al. 2012). More specifically, weather and climate affect travel and outdoor recreation decisions, including destination, travel mode, and activity choices, and also affect experience and satisfaction (Smith 1993; Scott and Lemieux 2010; Denstadli et al. 2011; Becken and Wilson 2013; Böcker et al. 2013; De Urioste-Stone et al. 2015; Steiger et al. 2016). In addition, climate is one of the major factors that shape one's perceived images about the destinations (Scott et al. 2012), which in turn determine one's decision about where to go and when to go (Lohmann and Kaim 1999).

Weather condition changes can affect ticket sales (Shih et al. 2009), cause trip and event cancelation (Jones et al. 2006; Tervo 2008; Becken and Wilson 2013; Rutty and Andrey 2014) and closure of recreation areas (Beaudin and Huang 2014), affect time and length of stay (Coghlan and Prideaux 2009; Becken and Wilson 2013), and determine trip and tourism expenditure (Jones et al. 2006; Scott and Lemieux 2010; Wilkins et al. 2017). In addition, poor weather conditions can affect attainment of expected experience for the perceived value of money spent (Coghlan and Prideaux 2009), and may ultimately affect the likelihood of future visits.

Weather and climate are also found to determine and shift seasonality in tourism and outdoor recreation participation (Butler 2001; Yu et al. 2009; Buckley and Foushee 2012). For example, Buckley and Foushee (2012) found a shift in peak park attendance by an average of 4.6 days over the period of three decades across seven parks in USA experiencing shifts in temperature. Research showed that a peak attendance of the Grand Canyon National Park shifted from July 4, 1979, to June 24, 2008, (Buckley and Foushee 2012). Changes in climate patterns may also lead to changes in the populations and the composition of wildlife and vegetation in nature-based recreation areas, and these changes may ultimately affect visitation choices and behaviors (Richardson and Loomis 2004; Paudyal et al. 2015). Depending upon location, activity, and time, the impact of weather and climate could be both positive and negative. For example, an unexpected early snowfall could reduce participation in some outdoor activities such as hiking and camping while increasing participation in other activities like skiing, ice skating, and sledding. Thus, in the tourism and outdoor recreation context, weather and climate are both resources and limiting factor (Scott and Lemieux 2010; Steiger et al. 2016).

Climatic factors affecting tourism and recreation

Researchers have examined the impact of weather and climate by modeling tourism demand and recreation participation with various climatic factors. The major significant climatic factors that are identified as affecting outdoor activity participation are temperature, precipitation, humidity, cloud cover, wind speed, and sunlight hours (Chan et al. 2006; Hamilton et al. 2007; Scott et al. 2008; Li and Lin 2012; Aylen et al. 2014; Steiger et al. 2016; Verbos et al. 2017). Research has shown that temperature has a non-linear effect on recreation participation. Recreation participation increases with rising temperature up to a threshold, and then declines with further temperature increase (Finger and Lehmann 2012; Aylen et al. 2014). But the specific range of thermal comfort and the tolerable threshold level of temperature have been found to vary by specific activity of participation, geographic and climatic region, setting context, and psychological and cultural factors (Finger and Lehmann 2012; Li and Lin 2012; Rutty and Scott 2013; Aylen et al. 2014; Hewer et al. 2015; Hewer and Gough 2016). For example, tolerable threshold temperatures reported in the literature are 21 °C among zoo visitors in Canada (Aylen et al. 2014), 23 °C among visitors to public pools in Switzerland (Finger and Lehmann 2012) and open leisure areas in Portugal (Andrade et al. 2011), 26–28 °C among zoo visitors in England (Hewer and Gough 2016), 29 °C among park visitors in Taiwan (Lin et al. 2011), 34 °C among beach visitors in Caribbean (Rutty and Scott 2013), and 35 °C among campers in Canada (Hewer et al. 2015).

Precipitation has been found as another important factor to affect outdoor recreation participation. Although light and short-period rains are not generally considered as detrimental as temperature, precipitation in the form of snow, showers, and thunderstorm has the potential to greatly affect travel and outdoor recreation participation (Morgan and Williams 1999; Hamilton et al. 2007; Nicholls et al. 2008; Yu et al.

2009; Finger and Lehmann 2012; Steiger et al. 2016). Activity or recreation context, amount and duration of rain, and the time of day at which rainfall events occur can pose variable effects. For example, Steiger et al. (2016) found rain to be the most important factor affecting recreation participation among summer tourists to mountain environments in Germany. Nicholls et al. (2008) found precipitation and temperature to be the major factors affecting daily numbers of rounds of golf played in Michigan, USA. Clouds and sunshine hours are less likely to determine whether outdoor recreation activity will take place or not; however, they might negatively affect esthetics of the destination and lessen recreation satisfaction (Morgan and Williams 1999; Yu et al. 2009). Even though mild wind gusts could be favorable for outdoor recreation, strong winds could affect outdoor activity participation more severely than temperature (Yu et al. 2009; Hewer et al. 2015).

Each climatic factor affects tourism and outdoor recreation participation to a different extent, but what people perceive and experience when outdoors is the combined effect of multiple factors (Scott et al. 2008; Böcker et al. 2013). Research has also shown that tourists and outdoor recreationists consider more than one climatic factor when planning a trip. For instance, Hamilton and Lau (2005) found that 91% of tourists consider more than one climate attribute when they collect climate information about the destination. In line with this finding, researchers have suggested including combined experiential climatic factors when developing predictive models (Spagnolo and de Dear 2003; de Freitas et al. 2008; Yu et al. 2009; Bafaluy et al. 2014). For example, Yu et al. (2009) examined tourism-related climatic variations and trends over the past 50 years in central Florida by using the heat index as one of the predictors. A heat index is a measure of the combined effects of temperature and relative humidity on human physiological responses to and perceptions of temperature (Rothfusz 1990). In addition, several climate indices related to tourism have been developed that combine various climate variables, such as tourism climate index (Mieczkowski 1985), climate index for tourism (de Freitas et al. 2008), holiday climate index (Scott et al. 2016), and spatial synoptic classification (Perkins 2018).

Effect of temporal and economic factors on tourism and outdoor recreation

In addition to weather and climate, economic factors (e.g., traveling costs) and temporal factors (e.g., seasons, holidays) can significantly affect outdoor recreation participation. People tend to travel more during holidays and when expected travel expenses are low. In models examining weather and climate effects on recreation participation, it is common to include temporal and economic factors as control variables to explain additional variance (Shih et al. 2009; Finger and Lehmann 2012; Aylen et al. 2014). For example, Finger and Lehmann (2012) found temperature and precipitation as the significant determinants of daily visits to public pools in Zurich, Switzerland, by controlling the effect of non-weather factors (e.g., weekends and holidays) in the regression model. Temporal variables (e.g., seasons, months, day of the week, public holidays) also affect tourism and outdoor recreation industry by determining short-term seasonality of demands (Dwyer 1988; Cools et al. 2009; Hewer and Gough 2016). For instance, people are more likely to plan their trips during weekends and public holidays than on weekdays.

Change in market price of goods and services can also affect tourism and outdoor recreation participation. When gasoline prices are high, the price of other goods might also increase, and people could minimize their travel expenses to compensate for the additional expenses (Napier and Bryant 1980; Pergams and Zaradic 2006). For example, Pergams and Zaradic (2006) found increasing oil price as one of the major factors responsible for the decline in per-capita national park visitation in the USA from 1993 to 2003. Thus, gasoline price is likely a relevant control variable on the model examining effect of whether factors on recreation participation and is used, as such, in this study.

Purpose of this study

Although climate and weather impacts on tourism and recreation are a widely researched topic, humid sub-tropical regions in the Southeastern USA remain under-researched; even though, Smith et al. (2013) recorded increased trend of heat waves between 1979 and 2011. Extreme weather conditions (e.g., heat waves) are associated with human health as exposure to excessive heat can cause heat stroke and cardiovascular and respiratory deaths (Sheridan and Allen 2015). However, research has found that change in behaviors to mitigate the effect of heat were less common among urban residents of North America even when warned of dangerous heat conditions (Sheridan 2007). Also, research has found a declining trend of ideal climatic conditions for tourism and outdoor recreation over the past 50 years in Central Florida, mostly due to the occurrence of more frequent heat indices above 35 °C (Yu et al. 2009). However, knowledge is limited regarding how and to what extent these extremes are affecting recreation participation. Thus, it is important to know how weather and changing climate in this region are affecting outdoor recreation participation in various recreation settings and activity contexts.

Research suggests that participation rates in tourism and outdoor recreation are generally higher in summer than winter (McGinn et al. 2007). In locations where the winter season is fairly long and summers are not extremely hot, an increase in temperature in comparison with the long term average tends to increase recreation participation (Dwyer 1988; Aikoh et al. 2012). However, these findings may not be generalizable to a humid subtropical climate region (e.g., Florida), where summers are extremely hot and humid, and winters are mild.

Florida's climate is mainly "cfa" under Köppen climate classification (Kottek et al. 2006; Climate-Data.org 2018), where tourism and outdoor recreation season differs from that of most of the continental USA. For example, summer is the best season for hiking and other trail-based recreation activities in the USA, such that American Hiking Society celebrates National Trails Day every year on the first Saturday of June. However, unlike northern regions of the nation, participation in activities like hiking, biking, camping, and OHV riding is typically low in Florida during the summer and are typically higher during the winter. Thus, Florida has a different tourism and recreation season than most of the other states. Researchers have emphasized that tourists' and recreationists' perceptions and expectations of weather and climatic conditions, bioclimatic comfort, and tolerance thresholds depend upon engaged activity or recreation settings and geographic and climate regions of both origins and destinations (Lin and Matzarakis 2008; Li and Lin 2012; Böcker et al. 2013; Rutty and Scott 2015; Hewer and Gough 2016; de Freitas 2017). As a result, thermal comfort indices and threshold values are not validly transferable to other geographic and climatic regions, activity and setting context, and populations (Perkins 2018). Thus, thermal comfort indices and thresholds identified from other geographic and climatic region and recreation setting context may not accurately relate to the region considered in this study. Also, research on this topic from the recreation setting context of national scenic trails are limited. Therefore, it was worthwhile to examine how weather and other factors affect recreation participation in this region in the context of scenic trail visitation.

In addition to the gap in knowledge discussed above, literature has thus far neglected to examine the consequences of extreme weather conditions on recreation participation on days following extreme weather. To understand short-term impacts of extreme weather, this study uses time series modeling to examine effects of weather factors, including temporal (weekends, public holidays) and economic factor (gasoline price), on daily outdoor recreation participation in a recreational setting context of a national scenic trail. Specifically, this research aims to answer the following research questions.

1. How do weather factors (i.e., temperature, precipitation, and humidity, heat index), temporal factors (i.e., weekend and, public holidays), and economic factors (i.e., gasoline price) affect daily outdoor recreation participation in a humid subtropical region?
2. Does an unfavorable weather condition a day affect recreation participation the following day with normal weather condition?

To answer these questions, we developed a conceptual model as:

$$Y = f(\mathrm{T}, \mathrm{PPT}, \mathrm{RH}, \mathrm{HI}, \mathrm{TF}, \mathrm{GP})$$

Where, Y, daily recreation participation; T, temperature; PPT, precipitation; RH, relative humidity; HI, heat index; TF, temporal factors (e.g., weekend and public holidays); and GP, gasoline price.

Methodology

Study site

We conducted this study in the Ocala National Forest (ONF) section of the Florida National Scenic Trail (FNST). As one of 11 national scenic trails in the USA, the FNST is a federally designated non-motorized recreation trail, which extends more than 1600 km through the most beautiful, unique landscapes in Florida (Fig. 1). An assessment of visitation from 2003 to 2014 has shown that FNST, as a whole, receives about 350,500 visits per year (Wan et al. 2014). Visitors to this trail are motivated to experience quality nature and scenery, fitness and relaxation, social interaction, and solitude (Paudyal 2017). Hiking/walking, jogging/running, camping, biking, and viewing scenery and wildlife are the major recreation activities in this trail. As the trail passes through hundreds of recreation areas, visitors have the opportunity to experience other activities, such as hunting, fishing, canoeing/kayaking, swimming, and OHV riding along or near the trail (Wan et al. 2014; Paudyal 2017). ONF is the second largest national forest in Florida and encompasses about 160 km length of the FNST.

Data and variables

We obtained counts of daily recreation visits by installing and operating infrared mechanical counters at three trailheads in ONF (Fig. 1) from January 1, 2010, to May 31, 2015. The dependent variable represents the sum of the counts from these three locations. The regressor variables included in the model were various climatic, temporal, and gasoline price factors (Table 1).

We obtained daily weather data from Daytona Beach International Airport weather station (National Centers for Environmental Information 2016). This station was about 35–55 km away from the study sites. There were a few other weather stations closer to the study area than this station, but the data from those stations were not complete for the study time period. The climatic regressor variables included in the model were temperature, precipitation, relative humidity, and cold snaps. Deviation of temperature from the long-term average (e.g., cold snap) can affect recreation participation both positively and negatively depending upon the direction of deviation and season (Dwyer 1988). In the context of weather in Florida, we defined a cold snap as a dummy variable if daily average temperature during the winter season was > 6 °C below the long-term normal, 0 otherwise.

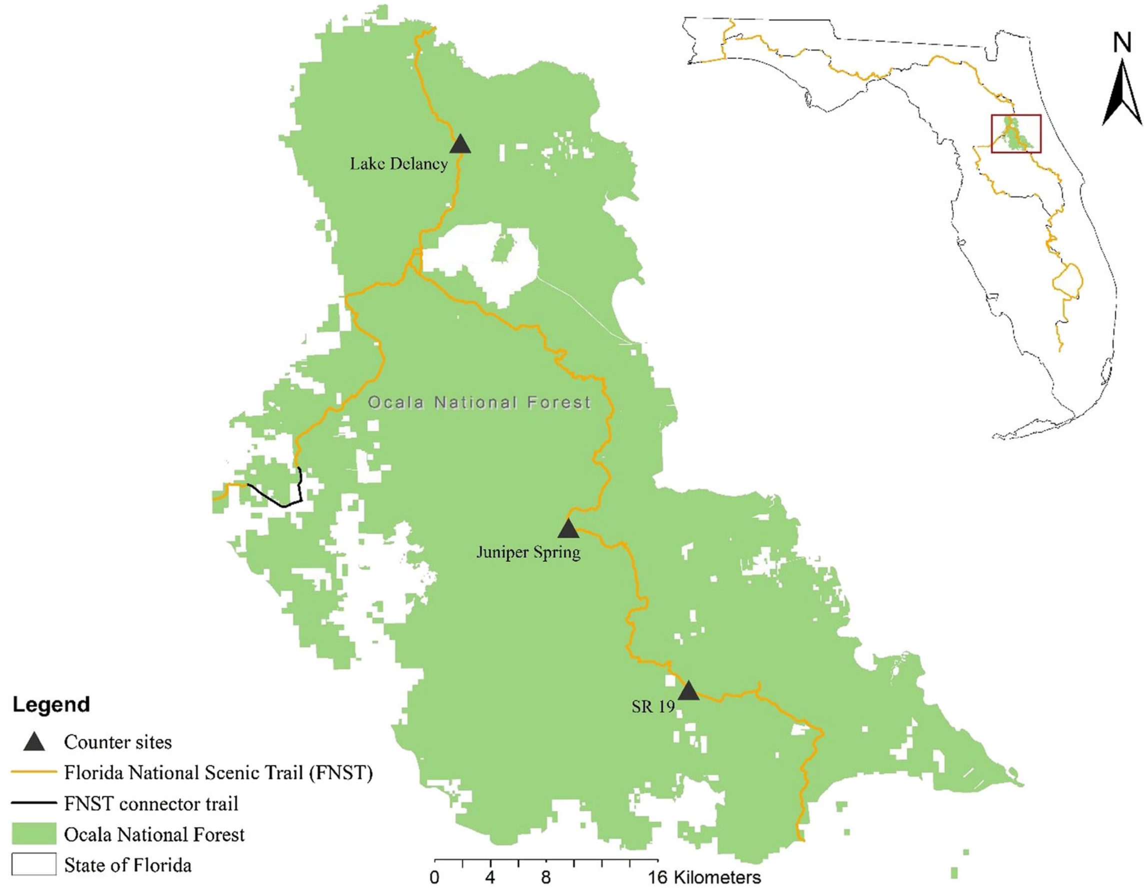

Fig. 1 Study area with sampling locations at Ocala National Forest Section of Florida National Scenic Trail, in Florida, USA

We included two additional dummy variables representing suitability of a day for recreation in terms of weather factors. First, we created a variable, "unfavorable day," as 1, if maximum heat index was ≥ 35 °C or precipitation was ≥ 2.54 cm; and 0 otherwise. Second, we created a variable, "day following an unfavorable day," as 1, if a day next to an unfavorable day had normal weather conditions, 0 otherwise to test whether a bad weather conditions on a day would affect recreation participations on the following day. We calculated heat index from daily maximum temperature and relative humidity by following the equations developed by Rothfusz (1990) and used by the National Weather Service.

Table 1 Descriptive characteristics of independent variables in the time series model examining daily recreation visits (dependent variable) to Ocala National Forest, USA

Variables	Definition	Mean	Std. dev.
Climatic			
Temperature	Average temperature (°C)	21.81	5.80
Precipitation	Daily precipitation (cm)	0.33	1.05
Relative humidity	Relative humidity in %	71.56	9.53
Cold snap	1, if average temperature is ≥ 6 °C below the normal in winter; 0 otherwise	0.04	0.19
Unfavorable day	1 if a day had heat index > 35 °C or precipitation > 2.54 cm, 0 otherwise	0.38	0.47
Day following an unfavorable day	1, if next day of an unfavorable day had normal weather; 0 otherwise	0.05	0.23
Economic			
Gas price	Daily avg. price for regular gas in Florida ($/liter)	0.85	0.11
Temporal			
Weekend and public holidays	1, if weekend or US public holidays; 0 otherwise	0.31	0.46
March	1, if month is March; 0 otherwise	0.09	0.29

In addition to the climatic variables, we included temporal factors (e.g., weekends and US public holidays) and fuel price, which improved the variance explained by the model without causing any multi-collinearity issue. A recent survey has shown that 70% of drivers in the USA own gasoline-operated vehicles (American Automobile Association 2016). Thus, we included state average price/l data of regular gasoline in the model (U.S. Energy Information Administration 2016).

Model selection

The dependent variable (daily recreation visits) was a time series count data, i.e., the data had properties of both count data (non-negative integer) and time series (temporal dependence). In time series data, an observation at a certain time usually correlates with the observation(s) from a previous time. As a result, the multiple linear regression models and count data models exhibit serial dependence, thus resulting in inefficient or biased estimates (Cameron and Trivedi 2013), although using these models are common in the recreation demand literature related to weather and climate (Dwyer 1988; Nicholls et al. 2008; Finger and Lehmann 2012; Li and Lin 2012; Hewer and Gough 2016). One potential option to work with this kind of data would be to include lag(s) of dependent variable as the explanatory variable(s) in the model. Including a lag(s) of the dependent variable in the model infers that the observations are dependent across time. However, the count data model assumes that the observations are independent (King 1989). Brandt and colleagues (Brandt et al. 2000; Brandt and Williams 2001) have argued that if a count regression model includes a lagged dependent variable, the exponentiated coefficient of the lag represents the linear exponential growth rate not the autocorrelation component. Thus, lagged dependent Poisson or negative binomial models were not suitable for this data.

One of the most common approaches to take account of the temporal dependence in the data is to use a time series model. Researchers have used time series models to predict effects of weather and climate on recreation participation in various activity and setting contexts (Hamilton et al. 2007; Cools et al. 2009). Time series model assumes stationarity of the data, which we tested using a Dickey-Fuller unit root test. Autoregressive (AR) and moving average (MA) are two fundamental roots of time series models. Although some time series data are best explained by either AR or MA models, some data require combined AR and MA model, e.g., autoregressive integrated moving average (ARIMA). Autocorrelation function (ACF) and partial-autocorrelation function (PACF) determine the selection of appropriate time series model.

ACF is defined as the correlation between a time series value at time $t(Y_t)$ and its value at time $t-k(Y_{t-k})$, where $k = 1, 2, 3\ldots$etc. (Montgomery et al. 2008). Likewise, a PACF is defined as the autocorrelation between a time series value at time $t(Y_t)$ and its value at time $t-k(Y_{t-k})$ after adjusting for $Y_{t-1}, Y_{t-2}, \ldots \ldots, Y_{t-k+1}$ (Montgomery et al. 2008).

In our data set, the ACF plot showed exponential decay after the second lag, and the PACF plot showed damped sinusoid after the first lag, thus suggesting for the possibility of a first- or second-order ARIMA model (Table 2 and Fig. 2). In addition, both the ACF and PACF plots indicated consistent higher values at the seventh cycle, thus suggesting for a seasonal (weekly) ARIMA (SARIMA7) model (Brockwell and Davis 2002; Hamilton et al. 2007). Following Montgomery et al. (2008), a seasonal ARIMA model of orders (p, d, q) × (P, D, Q) with a seasonal cycle is given as:

$$\Phi(B^s)\Phi(B)(1-B)^d(1-B^s)^D y_t = \delta + \Theta(B^s)\Theta(B)\epsilon_t \tag{2}$$

Based on the ACF and PACF plots of dependent variable (Fig. 2), we tested and compared 15 possible SARIMA7 models with various combinations of AR(p) and MA(q). We used Akaike information criterion (AIC) and Bayesian information criterion (BIC) to assess the model fit. SARIMA models $(2,0,1) \times (1,0,1)_7$, $(1,0,1) \times (1,0,1)_7$, and $(1,0,0) \times (1,0,1)_7$ were the best three models based on low values of both AIC and BIC (Montgomery et al. 2008; Cameron and Trivedi 2013).

Once we identified the best three $SARIMA_7$ models, we introduced the exogenous regressors (see Table 1) in each model and compared the results. This time the comparison of the models was based on the errors (mean error (ME)), root mean square error (RMSE), and mean absolute error (MAE)) in addition to AIC and BIC. Similar to AIC and BIC, the lowest value of each error term indicates the best fit model (Nau 2017). Among the three competing $SARIMA_7X$ models,

Table 2 Theoretical characteristics of ACF and PACF for stationary data (Montgomery et al. 2008)

Model	Autocorrelation function (ACF)	Partial autocorrelation function (PACF)
$AR_{(P)}$	Exponential decay and/or damped sinusoid	Cuts off after lag *p*
$MA_{(q)}$	Cuts off after lag q	Exponential decay and/or damped sinusoid
$ARMA_{(p,q)}$	Exponential decay and/or damped sinusoid	Exponential decay and/or damped sinusoid

AR autoregressive, *MA* moving average

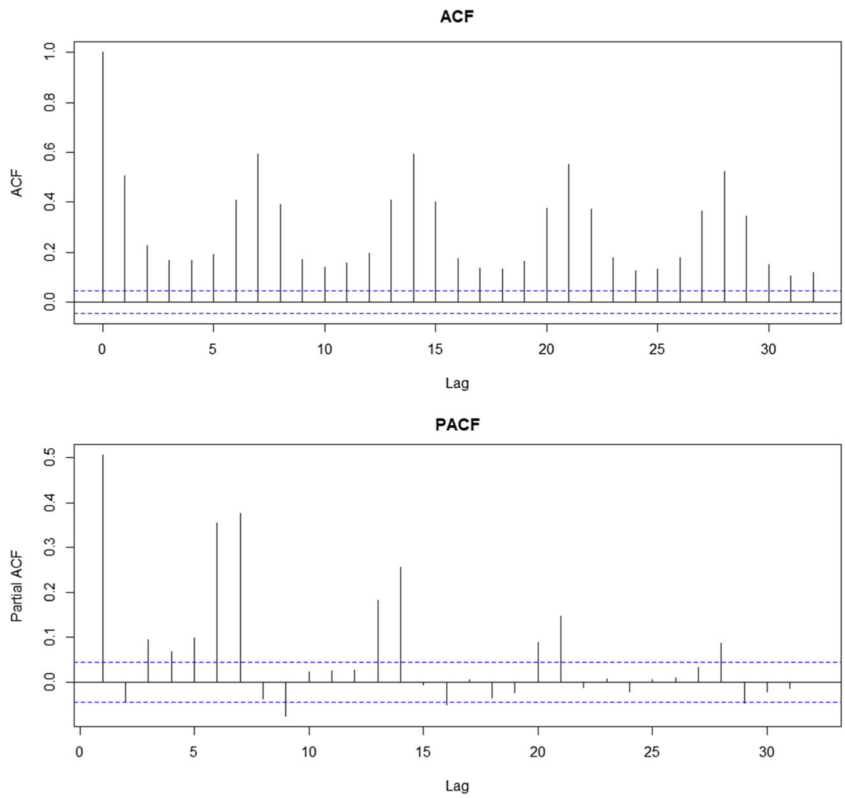

Fig. 2 Autocorrelation function (ACF) and partial autocorrelation function (PACF) of dependent variable

information criteria and errors from SARIMA ((1, 0, 0) (1, 0, 1)$_7$) X) were lowest (Table 3), thus suggesting this model as the best fitting time series model. We used Ljung-Box goodness-of-fit test to examine whether the time series observations were white noise, i.e., uncorrelated and random with constant variance (Montgomery et al. 2008). Finally, we used squared correlation between actual and fitted values (R^2CORR), which is equivalent to the multiple R^2 in linear models (Cameron and Trivedi 2013; Fogarty and Monogan 2014), to examine the percentage of variance in dependent variable that was explained by the model.

We used an Excel Spreadsheet (version 2016) to combine and manage data for daily visits, daily observations of climatic factors, and daily gasoline price. Then we computed analyses and graphs in *R* statistical software (version 3.4.4).

Results

Descriptive characteristics of the variables

During the study period, cumulative daily visits to the study area ranged from 0 to 120, with an average of 20 (± 21) visits per day. The average daily visits in 2011 was higher ($\overline{X}$ =24 ± 19.4) than in other years. Among months, March received the highest number of average daily visits ($\overline{X}$ =39 ± 24), followed by February ($\overline{X}$ =34 ± 25), and January ($\overline{X}$ =32 ± 25), whereas time between June and September received average daily visits of 10 or fewer. The average daily visits were highest on Saturday ($\overline{X}$ =39 ± 29), followed by Sunday ($\overline{X}$ =31 ± 25), while the average daily visits during the weekdays ranged from 13 to 18 visits.

Table 3 AIC, BIC, and errors of best three time-series models with exogenous regressors

S.N.	Model	Information criteria*		Errors*		
		AIC	BIC	ME	RMSE	MAE
1	SARIMA ((1, 0, 0) (1, 0, 1)$_7$) X)	15,926.80	16,005.05	0.04	13.47	9.52
2	SARIMA ((1, 0, 1) (1, 0, 1)$_7$) X)	15,928.08	16,011.92	0.07	13.48	9.51
3	SARIMA ((2, 0, 1) (1, 0, 1)$_7$) X)	15,928.59	16,018.02	0.07	13.47	9.50

AIC Akaike information criterion, *BIC* Bayesian information criterion, *ME* mean error, *RMSEA* root mean square error, *MAE* mean absolute error

Regressors(X) are as listed in Table 1. *Lowest value indicates the best fit model

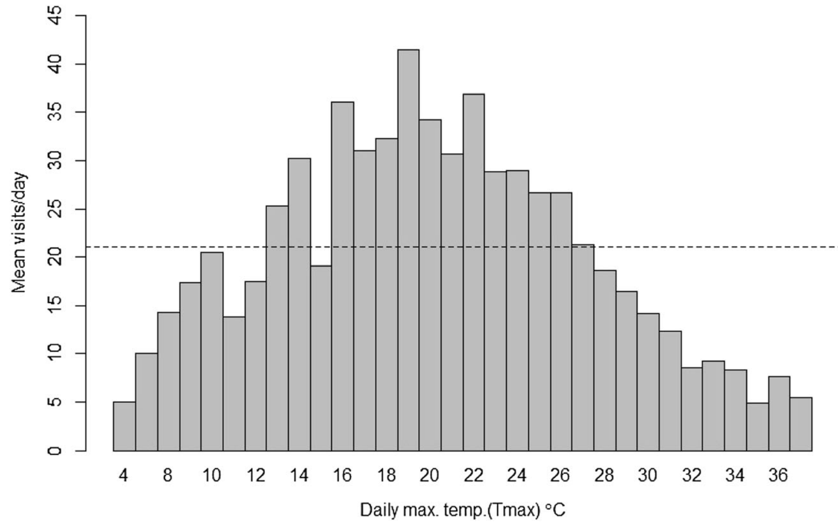

Fig. 3 Average daily visits to Ocala National Forest section of Florida National Scenic Trail by daily maximum temperature (°C) during the period of January 1, 2010, to May 31, 2015. Horizontal line indicates total average

There was a significant negative correlation between daily visits and average daily temperature ($r = -0.44$, $p \leq 0.01$), indicating decreased recreation visits with increased temperature. Analysis showed an increasing trend of average daily visits with increase in daily maximum temperature up to 19 °C (Fig. 3). When temperature went above 19 °C, visitation decreased gradually, with significant drops for temperature above 31 °C. Days with maximum temperature range of 13–27 °C consistently received at least the mean number of visits (21 visits day^{-1}) and 16–22 °C received the highest daily visits (35 visits day^{-1}), thus indicating the former as favorable and later as the most preferable range of maximum daily temperature for scenic trail use in Florida. Likewise, days with maximum temperature below 6 °C and above 31 °C received less than 10 visits indicating these range of maximum temperatures as thresholds for trail-based recreation activities. Given Florida's high humidity, a heat index variable provides a more holistic explanation of how people react to weather conditions. A trend of mean visitation with heat index (Fig. 4) showed that recreation participation on the scenic trail significantly declined below half of average (i.e., 10 visits/day) when the heat index was above 38 °C, thus suggesting this value as a threshold of tolerable thermal comfort to recreate in FNST.

During the study period, average daily price for regular gasoline in Florida was significantly lower in 2010 ($\overline{X}$ =\$0.73 ± 0.03/l) in comparison to other years ($p \leq 0.01$). Although annual averages for the rest of the years were almost equal, average daily price fluctuated among the months for each year (Fig. 5). For instance, the price ranged from \$0.70/lit during summer of 2010 to \$1.03/lit in April 2012 and dropped to \$0.57/lit in January 2015. As the data indicated, most of the peaks in gasoline price occurred in the summer each year, when recreation visits were low, thus indicating a negative correlation between gasoline price and recreation participation, and relevance of this variable in the regression model (Fig. 5).

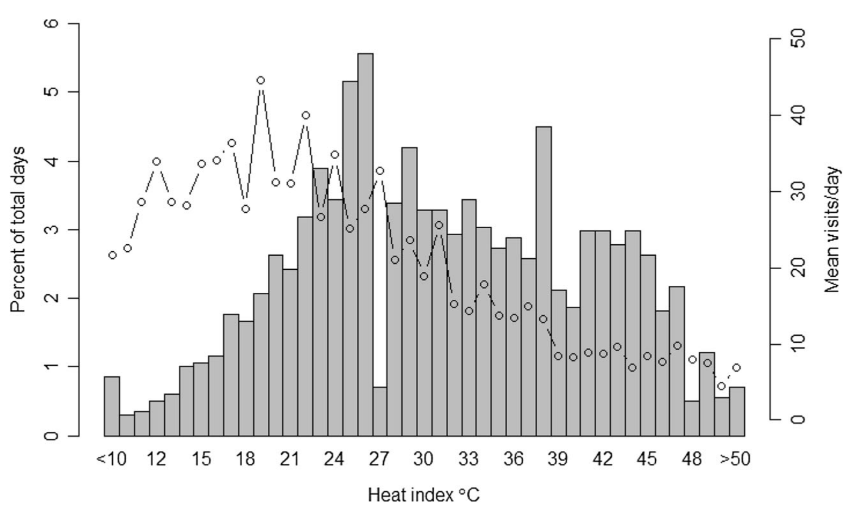

Fig. 4 Occurrence of various heat index values (bar graph and left axis) and mean recreational visits (line and right axis) in Ocala National Forest section of Florida National Scenic Trail during the time-period of January 1, 2010, to May 31, 2015

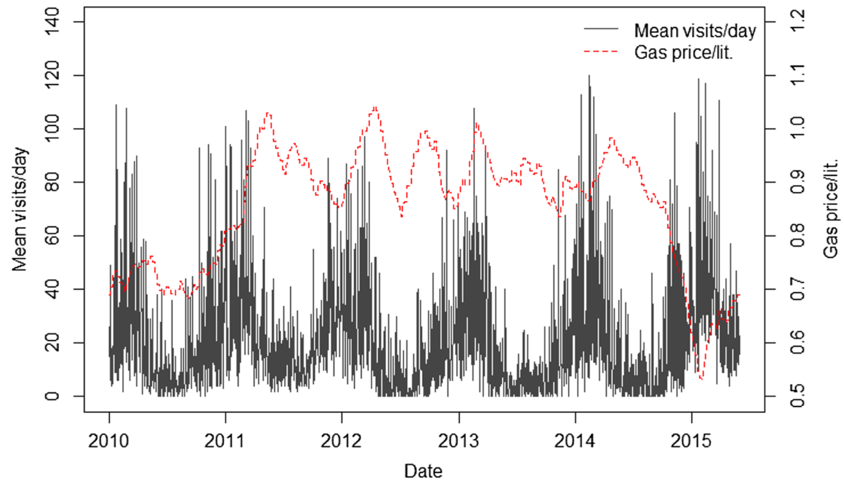

Fig. 5 Average daily visits to Ocala National Forest section of Florida National Scenic Trail and average daily price for regular gas in Florida during the study period of January 1, 2010, to May 31, 2015

Regression results from final time series model

As indicated by the Ljung-Box test (X squared = 10.03, df = 10, p value = 0.44), there was no serial correlation among residuals from the final model. Also, ACF and PACF values of residuals were almost equal to zero up to the 30th lag, and the histogram of residuals closely resembled normality (Fig. 6). In addition, all the time series lag factors, first-order auto-regression (AR (1)), seasonal first-order auto-regression (AR (1)7), and seasonal first-order moving average (MA (1)7) were statistically significant (Table 4), thus indicating the suitability of time series model (SARIMA (1, 0, 0) (1, 0, 1)7) X) to fit the data.

Among the climatic factors, temperature ($\beta = -1.01$, $p < 0.001$) and relative humidity ($\beta = -0.15$, $p < 0.001$) had significant negative effects on visitation numbers. A sudden fall in temperature (cold snap) also had a negative effect. Specifically, a day in the winter season received about 16 fewer visits than other days ($p < 0.001$) if the average temperature was below the long-term daily average by 6 °C or more.

Rainfall as a continuous variable was not a significant predictor of recreation visits, but high rainfall had a significantly negative effect. Specifically, an unfavorable day with 2.54 cm or higher rainfall (24-h) or maximum heat index of 35 °C or higher received about three fewer visits than other days ($p < 0.05$), keeping everything else constant (Table 4). In addition, unfavorable weather conditions negatively affected recreation visits of not only the same day, but also the visits of the next day, even if weather conditions returned to normal. In other words, a day with normal weather following an unfavorable weather day also received about five fewer visits than other days ($p < 0.001$), all other factors remaining constant. An analysis of frequency distribution of heat index during the study period has shown that about 44% of the total days ($n = 1977$) had a heat index above 35 °C. This indicates that annual seasonality of land-based recreation in Florida is mostly driven by heat index.

Weekends or public holidays and the month of March (a month with highest average daily visits) were positively associated and gasoline price was negatively associated with the recreation visits, thus suggesting the relevance of these control variables on the model. Particularly, everything remained constant, weekend or public holidays received about eight more visitors, and a day in March received about 11 more visitors than other days ($p < 0.001$). Likewise, the number of recreation visits was likely to decrease by about 25 visits per day ($p < 0.001$) for every one-dollar (per liter) increase in gasoline price, keeping all other factors constant (Table 4).

Discussion and conclusion

The aim of this research was to examine how weather factors affect outdoor recreation participation in Florida while controlling for temporal factors and gasoline price. This research adds to the body of knowledge in two ways. First, it identifies the best approach of modeling long-term data of daily recreation use with weather factors and other relevant temporal (e.g., weekend/public holidays) and market factors (e.g., gasoline price). Second, it improves our knowledge about the dependence of outdoor recreation participation on weather. Specifically, it identified specific weather conditions that affect Florida outdoor recreation, which had not been previously examined.

The model developed in this study would be useful to agencies and other nature-based recreation organizations in predicting daily use volume with the information of weather condition and past use volume. Information on recreation demand response to weather conditions will be useful for staffing and other resource management (Manning and Powers 1984), which will be beneficial to prepare for daily recreation use during times of variable weather conditions. Managers should expect a higher use volume on Florida hiking trails when the daily maximum temperature is 13–27 °C,

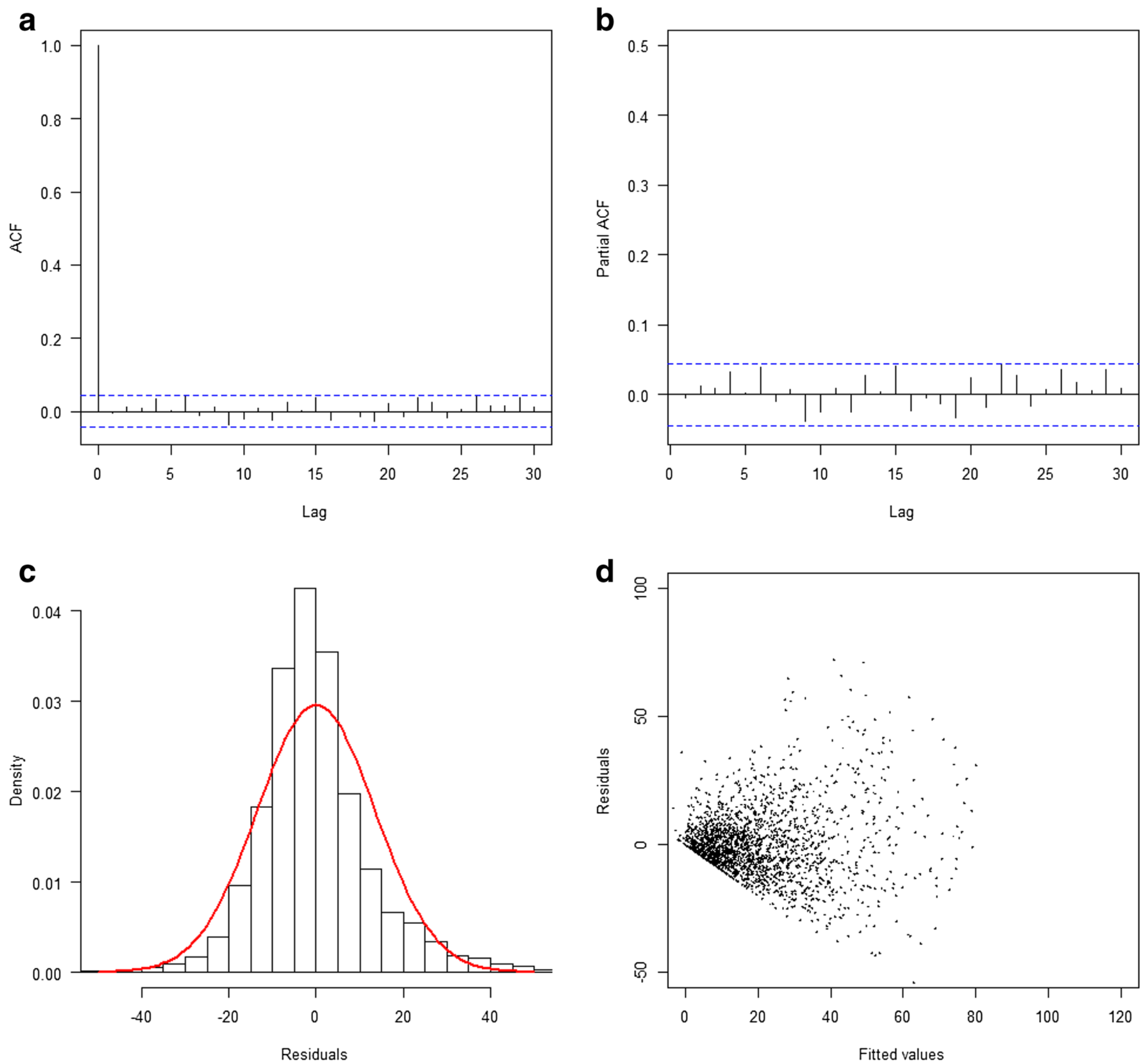

Fig. 6 Autocorrelation function (**a**), partial autocorrelation function (**b**), histogram of residuals (**c**), and plot of residuals versus fitted (**d**) of time series SARIMAX ((1,0,0) $(1,0,1)_7$ with regressors) model

with the highest use on days with a maximum temperature of 16–22 °C.

Previous studies conducted elsewhere (Taiwan and Tanzania) have found 21–31 °C to be the comfortable range of temperatures for visitors to urban parks and beaches in humid climatic regions (Lin 2009; Ndetto and Matzarakis 2017). Thus, the comfortable range of temperature identified in this study was slightly lower than those reported for similar climatic regions. There are several possible reasons for this discrepancy. First, the range of favorable and preferable temperature identified in this study was daily maximum temperature, not the physiologically equivalent temperature as reported by Lin (2009) and Ndetto and Matzarakis (2017). The perceived or experienced temperature might have been much higher than the measured temperature because of high humidity in Florida, and outdoor physical activity depends on perceived temperature rather than objective measures (McGinn et al. 2007). Second, outdoor recreationists' preferable thermal condition varies by activities, recreation settings, geographic and climatic regions, and expectations of visitors (Li and Lin 2012; Böcker et al. 2013; Rutty and Scott 2015; Hewer and Gough 2016; de Freitas 2017; Lindner-Cendrowska and Błażejczyk 2018). Although the preferable range of temperature was lower than that identified in the past studies, the threshold values of 31 °C in terms of daily maximum temperature and 38 °C in terms of heat index were slightly higher than the threshold values identified for similar recreation settings from other regions (Lin 2009; Andrade et al. 2011; Lin et al. 2011; Aylen et al. 2014; Hewer et al. 2015; Hewer and Gough 2016). This finding suggests that visitors would prefer cool weather conditions to recreate on the FNST but can tolerate a higher temperature, perhaps because they are accustomed to heat in this region. The finding regarding significance of heat index and heavy rainfall was as expected and is consistent with other studies (Yu et al. 2009). The likelihood of suffering from a heat-

Table 4 Regression results from SARIMA (100,101)$_7$ with regressors model examining daily recreation visits (dependent variable)

Variables	Coefficient	Std. error	Z value	$P > \|Z\|$
Climatic				
Average temperature (°C)	− 1.01	0.12	− 8.70	< 0.001
Precipitation (cm)	− 0.49	0.30	− 1.65	0.10
Relative humidity	− 0.15	0.04	− 3.67	< 0.001
Cold snap (average temperature > 6 °C below long-term normal in winter)	− 15.98	2.15	− 7.43	< 0.001
Unfavorable day (heat index > 35 °C or precipitation > 2.54 cm)	− 2.80	1.16	− 2.40	0.02
Normal day following an unfavorable day	− 4.81	1.37	− 3.51	< 0.001
Economic				
Gas price ($/liter)	− 24.93	8.84	− 2.82	0.01
Temporal				
Weekend and public holidays	8.45	2.24	3.77	< 0.001
March	10.60	1.54	6.87	< 0.001
AR(1)	0.24	0.02	10.64	< 0.001
AR(1)$_7$	0.94	0.02	58.37	< 0.001
MA(1)$_7$	− 0.77	0.03	− 30.65	< 0.001
Intercept	72.34	8.21	8.81	< 0.001

R^2 Corr, 0.58; AR(1), 1st-order auto-regression; AR(1)7, seasonal (weekly) 1st-order auto-regression; MA(1)7, seasonal (weekly) 1st-order moving average; unfavorable day, (heat index > 35 °C or precipitation > 2.54 cm)

related sickness and physical danger associated with strong thunderstorms could be major reasons for the significant negative effect of high heat index and heavy rainfall on hiking participation in forest land–based recreation settings (Nicholls et al. 2008). Global climate change is predicted to increase higher maximum temperatures, frequency and duration of heat waves, and intensity and frequency of precipitation extremes throughout the twenty-first century (IPCC 2014). An analysis of the past 50 years of central Florida's weather data has shown an increasing trend in frequency of heat indices above 35 °C (Yu et al. 2009). If these trends continue, this study can help managers better predict visitation changes, as they relate to these new weather conditions, and improve efficient allocation of resources for high and low use days.

The finding of delayed response to bad weather conditions has important implications for management and future research. Specifically, if the weather condition of a day is not favorable, recreation visitation numbers on the following day will be significantly lower even if the weather conditions improve. With this finding, managers will more likely predict use on a day that might seem favorable but experience less use because of previous bad weather conditions. Lag effects of weather on recreation participation have been detected elsewhere in different recreation contexts. For example, Hamilton et al. (2007) found that the amount of snow seen in town was significantly associated with the number of skiers visiting nearby ski areas the next day. While snow might impact regional areas for a longer term, periodic episodes of rainfall or dramatic temperature change might not affect recreation conditions the following day, so it is unclear why this lag in visitation exists. Perhaps immediate conditions have a larger effect on recreation decision-making than previously known.

Research has shown that recreationists and day visitors usually plan their trip at short notice and adjust their plan according to short-term weather predictions (McEvoy et al. 2006). Visitors may respond to unexpected weather conditions by changing their travel route, timing of travel, and choice of activity (Becken and Wilson 2013). Visitors to this recreation trail drive an average one-way distance of about 90 km to reach their recreation destination (Paudyal 2017). Potential visitors may have experienced different weather conditions in their residence location than that recorded around this recreation area, which may have made them change their destination and/or activity participation. There are several weather forecast sources visitors may use, and the reliability of these information sources may vary. More accurate weather forecast for recreation destinations and trustworthy sources to disseminate such information could potentially help address the lag effect of bad weather conditions on recreation participation.

Results also indicate that recreation participation is likely to decline with higher gasoline prices, which was expected and consistent with the existing literature (Napier and Bryant 1980; Pergams and Zaradic 2006). As mentioned above, the average distance traveled by the visitors to reach their destination in FNST was fairly high (i.e., 90 km). Thus, an increase in gasoline price logically decreases trail use volume, and including the variable improved the model performance.

Research has suggested that time spent per visit is a better indicator of recreation demand than attendance alone (de Freitas 2015), and weather preferences are not only affected by physical condition but also by psychological factors, such as attitude and expectations (Lindner-Cendrowska and Błażejczyk 2018). Given that the dependent variable considered in this study was a daily count of recreational visits recorded over a period of five and a half years, information about duration of each visit was impossible to record. Recording psychological responses of visitors and time spent per visit could be too costly to afford for long-term data. However, balancing the trade-off between duration and details of data and integrating counter data with survey data could improve models predicting weather and climate effects on recreation participation.

The dependent variable was the total count of daily visits from three trailheads of a section of FNST in ONF collected using infrared counters. Infrared counters are low cost and easy to operate relative to other monitoring techniques used to monitor visitation volume of trail and recreation areas (e.g., observation, visitor logs). However, there are a number of disadvantages of using infrared counters on open trails. For example, visitors may be miscounted when more than one person crosses the counter side-by-side; counts can be triggered by vegetation, wildlife, or other environmental factors; and the recorded data do not indicate whether the same person passed the counter multiple times. Therefore, counter-recorded data may not represent the recreation use volume of the sites accurately. Also, the data used in this study do not represent the entire use volume of ONF or the entire section of the FNST within the ONF. There are more than ten official trailheads of the FNST within the ONF, of which only three trailheads were selected to install and operate infrared counter to collect visitation data. Thus, caution should be taken to interpret the overall use volume of both the ONF and FNST.

The best-fit time series model explained about 60% of the variance in the dependent variable. Within 1 day, weather conditions can fluctuate considerably in terms of temperature or precipitation. Including hourly data of both weather and visitation is one change that could improve the model.

To conclude, this research showed a preference for cool weather conditions (16–22 °C of daily maximum temperature) for recreation on the FNST, and that temperatures above 31 °C or heat indices above 38 °C significantly decrease recreation participation. A time series model showed significant negative effects of temperature, relative humidity, cold snaps, and gasoline price and a positive effect of weekend and public holidays on recreational visitations to FNST. Trends of visitation and weather factors suggest that recreation season in Florida is largely determined by temperature and related variables (e.g., heat index). A lag effect observed via the model suggests that bad weather conditions also affect recreation participation on the subsequent day even if weather condition is normal.

References

Aikoh T, Abe R, Kohsaka R, Iwata M, Shoji Y (2012) Factors influencing visitors to suburban open space areas near a northern Japanese city. Forests 3(2):155–165

American Automobile Association (2016) Premium fuel research: proprietary research into the use of premium octane gasoline when not required by the manufacturer. American Automobile Association, Inc, Heathrow

Andrade H, Alcoforado M-J, Oliveira S (2011) Perception of temperature and wind by users of public outdoor spaces: relationships with weather parameters and personal characteristics. Int J Biometeorol 55(5):665–680

Aylen J, Albertson K, Cavan G (2014) The impact of weather and climate on tourist demand: the case of Chester zoo. Clim Chang 127(2): 183–197

Bafaluy D, Amengual A, Romero R, Homar V (2014) Present and future climate resources for various types of tourism in the bay of Palma, Spain. Reg Environ Chang 14(5):1995–2006

Beaudin L, Huang J-C (2014) Weather conditions and outdoor recreation: a study of New England ski areas. Ecol Econ 106:56–68

Becken S, Hay JE (2007) Tourism and climate change: risks and opportunities, climate change, economics, and society: leadership and innovation. Channel View Publication, Victoria Road

Becken S, Wilson J (2013) The impacts of weather on tourist travel. Tour Geogr 15(4):620–639

Böcker L, Dijst M, Prillwitz J (2013) Impact of everyday weather on individual daily travel behaviours in perspective: a literature review. Transp Rev 33(1):71–91

Brandt PT, Williams JT (2001) A linear Poisson autoregressive model: the Poisson AR (p) model. Polit Anal 9(2):164–184

Brandt PT, Williams JT, Fordham BO, Pollins B (2000) Dynamic modeling for persistent event-count time series. Am J Polit Sci 44(4):823–843

Brockwell PJ, Davis RA (2002) Introduction to time series and forecasting. Springer, New York

Buckley LB, Foushee MS (2012) Footprints of climate change in US national park visitation. Int J Biometeorol 56(6):1173–1177

Butler RW (2001) Seasonality in tourism: issues and implications. In: Baum T, Lundtorp S (eds) Seasonality in tourism. Routledge, New York, pp 5–22

Cameron AC, Trivedi PK (2013) Regression analysis of count data. Cambridge University Press, New York

Chan CB, Ryan DA, Tudor-Locke C (2006) Relationship between objective measures of physical activity and weather: a longitudinal study. Int J Behav Nutr Phys Act 3(1):21

Climate-Data.org (2018) Climate: Florida. https://en.climate-data.org/north-america/united-states-of-america/florida-1000/. Accessed 10/23 2018

Coghlan A, Prideaux B (2009) Welcome to the wet tropics: the importance of weather in reef tourism resilience. Curr Issue Tour 12(2): 89–104

Cools M, Moons E, Wets G (2009) Investigating the variability in daily traffic counts through use of ARIMAX and SARIMAX models: assessing the effect of holidays on two site locations. Transp Res Rec 2136:57–66

de Freitas CR (2015) Weather and place-based human behavior: recreational preferences and sensitivity. Int J Biometeorol 59(1):55–63

de Freitas CR (2017) Tourism climatology past and present: a review of the role of the ISB commission on climate, tourism and recreation. Int J Biometeorol 61(1):107–114

de Freitas CR, Scott D, McBoyle G (2008) A second generation climate index for tourism (CIT): specification and verification. Int J Biometeorol 52(5):399–407

De Urioste-Stone SM, Scaccia MD, Howe-Poteet D (2015) Exploring visitor perceptions of the influence of climate change on tourism at Acadia National Park, Maine. J Outdoor Recreat Tour 11:34–43
Denstadli JM, Jacobsen JKS, Lohmann M (2011) Tourist perceptions of summer weather in Scandinavia. Ann Tour Res 38(3):920–940
Dubois G, Ceron J-P, Gössling S, Hall CM (2016) Weather preferences of French tourists: lessons for climate change impact assessment. Clim Chang 136(2):339–351
Dwyer JF (1988) Predicting daily use of urban forest recreation sites. Landsc Urban Plan 15:127–138
Finger R, Lehmann N (2012) Modeling the sensitivity of outdoor recreation activities to climate change. Clim Res 51(3):229–236
Fogarty BJ, Monogan JE (2014) Modeling time-series count data: the unique challenges facing political communication studies. Soc Sci Res 45:73–88
Gössling S, Scott D, Hall CM, Ceron J, Dubois G (2012) Consumer behaviour and demand response of tourists to climate change. Ann Tour Res 39(1):36–58
Hamilton JM, Lau MA (2005) The role of climate information in tourist destination choice decision making. In: Gössling S, Hall CM (eds) Tourism and global environmental change: ecological, economic, social and political interrelationships. Routledge, London, p 229
Hamilton LC, Brown C, Keim BD (2007) Ski areas, weather and climate: time series models for New England case studies. Int J Climatol 27(15):2113–2124
Hewer MJ, Gough WA (2016) Weather sensitivity for zoo visitation in Toronto, Canada: a quantitative analysis of historical data. Int J Biometeorol 60(11):1645–1660
Hewer MJ, Scott D, Gough WA (2015) Tourism climatology for camping: a case study of two Ontario parks (Canada). Theor Appl Climatol 121(3–4):401–411
IPCC (2007) Climate change 2007: the physical science basis. Working group I contribution to the fourth assessment of the intergovernmental panel on climate change. Cambridge University Press, New York
IPCC (2014) Climate change 2014: synthesis report. contribution of working groups I, II and III to the fifth assessment report of the intergovernmental panel on climate change. Geneva, Switzerland
Jones B, Scott D, Khaled HA (2006) Implications of climate change for outdoor event planning: a case study of three special events in Canada's National Capital region. Event Manag 10(1):63–76
King G (1989) Event count models for international relations: generalizations and applications. Int Stud Q 33(2):123–147
Kottek M, Grieser J, Beck C, Rudolf B, Rubel F (2006) World map of the Köppen-Geiger climate classification updated. Meteorol Z 15(3): 259–263
Li C, Lin S-H (2012) Influence of weather conditions on hiking behavior. Int J Biometeorol 56(4):777–781
Lin T-P (2009) Thermal perception, adaptation and attendance in a public square in hot and humid regions. Build Environ 44(10):2017–2026
Lin T-P, Matzarakis A (2008) Tourism climate and thermal comfort in sun moon Lake, Taiwan. Int J Biometeorol 52(4):281–290
Lin TP, de Dear R, Hwang RL (2011) Effect of thermal adaptation on seasonal outdoor thermal comfort. Int J Climatol 31(2):302–312
Lindner-Cendrowska K, Błażejczyk K (2018) Impact of selected personal factors on seasonal variability of recreationist weather perceptions and preferences in Warsaw (Poland). Int J Biometeorol 62(1):113–125
Lindsey G, Wilson J, Rubchinskaya E, Yang J, Han Y (2007) Estimating urban trail traffic: methods for existing and proposed trails. Landsc Urban Plan 81(4):299–315
Lohmann M, Kaim E (1999) Weather and holiday destination preferences image, attitude and experience. Tour Rev 54(2):54–64
Manning RE, Powers LA (1984) Peak and off-peak use: redistributing the outdoor recreation/tourism load. J Travel Res 23(2):25–31
McEvoy D, Handley J, Cavan G, Aylen J, Lindley S, McMorrow J, Glynn S (2006) Climate change and the visitor economy: the challenges and opportunities for England's northwest. Sustainability Northwest (Manchester) and UKCIP (Oxford)
McGinn AP, Evenson KR, Herring AH, Huston SL (2007) The relationship between leisure, walking, and transportation activity with the natural environment. Health Place 13(3):588–602
Mieczkowski Z (1985) The tourism climatic index: a method of evaluating world climates for tourism. Can Geogr/Le Géographe Canadien 29(3):220–233
Montgomery DC, Jennings CL, Kulahci M (2008) Introduction to time series analysis and forecasting. Wiley, Hoboken
Morgan R, Williams A (1999) Video panorama assessment of beach landscape aesthetics on the coast of Wales. J Coast Conserv 5(1): 13–22
Napier TL, Bryant EG (1980) The impact of increasing fuel costs on future outdoor recreation participation. The Ohio State University. https://kb.osu.edu/bitstream/handle/1811/67373/CFAES_ESO_770.pdf?sequence=1&isAllowed=y. Accessed 25 Jan 2016
National Centers for Environmental Information (2016) Climate data online. National Ocenic and atmospheric administration. https://www.ncdc.noaa.gov/cdo-web/. Accessed 25 Jan 2016
Nau R (2017) What's the bottom line? How to compare models. https://people.duke.edu/~rnau/compare.htm. Accessed 27 June 2017
Ndetto EL, Matzarakis A (2017) Assessment of human thermal perception in the hot-humid climate of Dar Es Salaam, Tanzania. Int J Biometeorol 61(1):69–85
Nicholls S, Holecek DF, Noh J (2008) Impact of weather variability on golfing activity and implications of climate change. Tour Anal 13(2):117–130
Paudyal R (2017) Motivational, forest management, and climatic factors affecting outdoor recreation participation and experience in Florida. Dissertation, University of Florida, Gainesville, Florida
Paudyal R, Poudyal NC, Bowker JM, Dorison AM, Zarnoch SJ, Green GT (2015) A value orientation approach to assess and compare climate change risk perception among trout anglers in Georgia, USA. J Outdoor Recreat Tour 11:22–33
Pergams OR, Zaradic PA (2006) Is love of nature in the US becoming love of electronic media? 16-year downtrend in national park visits explained by watching movies, playing video games, internet use, and oil prices. J Environ Manag 80(4):387–393
Perkins DR (2018) Using synoptic weather types to predict visitor attendance at Atlanta and Indianapolis zoological parks. Int J Biometeorol 62(1):127–137
Richardson RB, Loomis JB (2004) Adaptive recreation planning and climate change: a contingent visitation approach. Ecol Econ 50(1–2):83–99
Rothfusz LP (1990) The heat index equation (or, more than you ever wanted to know about heat index). Scientific Services Division, National Weather Service - Southern Region Headquarters, Fort Worth
Rutty M, Andrey J (2014) Weather forecast use for winter recreation. Weather Clim Soc 6(3):293–306
Rutty M, Scott D (2013) Differential climate preferences of international beach tourists. Clim Res 57(3):259–269
Rutty M, Scott D (2015) Bioclimatic comfort and the thermal perceptions and preferences of beach tourists. Int J Biometeorol 59(1):37–45
Scott D, Lemieux C (2010) Weather and climate information for tourism. Procedia Environ Sci 1:146–183
Scott D, Gössling S, de Freitas CR (2008) Preferred climates for tourism: case studies from Canada, New Zealand and Sweden. Clim Res 38(1):61–73
Scott D, Gössling S, Hall CM (2012) International tourism and climate change. Wiley Interdiscip Rev Clim Chang 3(3):213–232
Scott D, Rutty M, Amelung B, Tang M (2016) An inter-comparison of the holiday climate index (HCI) and the tourism climate index (TCI) in Europe. Atmosphere 7(6):80

Sheridan SC (2007) A survey of public perception and response to heat warnings across four north American cities: an evaluation of municipal effectiveness. Int J Biometeorol 52(1):3–15

Sheridan SC, Allen MJ (2015) Changes in the frequency and intensity of extreme temperature events and human health concerns. Curr Clim Chang Rep 1(3):155–162

Shih C, Nicholls S, Holecek DF (2009) Impact of weather on downhill ski lift ticket sales. J Travel Res 47(3):359–372

Smith K (1993) The influence of weather and climate on recreation and tourism. Weather 48(12):398–404

Smith TT, Zaitchik BF, Gohlke JM (2013) Heat waves in the United States: definitions, patterns and trends. Clim Chang 118(3–4):811–825

Spagnolo J, de Dear R (2003) A human thermal climatology of subtropical Sydney. Int J Climatol 23(11):1383–1395

Steiger R, Abegg B (2018) Ski areas' competitiveness in the light of climate change: comparative analysis in the eastern Alps. In: Müller D, Więckowski M (eds) Tourism in transitions. Geographies of tourism and global change. Springer, Cham, pp 187–199

Steiger R, Abegg B, Jänicke L (2016) Rain, rain, go away, come again another day. Weather preferences of summer tourists in mountain environments. Atmosphere 7(5):63

Steiger R, Scott D, Abegg B, Pons M, Aall C (2017) A critical review of climate change risk for ski tourism. Curr Issue Tour:1–37

Tervo K (2008) The operational and regional vulnerability of winter tourism to climate variability and change: the case of the Finnish nature-based tourism entrepreneurs. Scand J Hosp Tour 8(4):317–332

U.S. Energy Information Administration (2016) Weekly retail gasoline and diesel prices. https://www.eia.gov/dnav/pet/pet_pri_gnd_dcus_sfl_w.htm. Accessed 01/25 2016

Verbos RI, Altschuler B, Brownlee MT (2018) Weather studies in outdoor recreation and nature-based tourism: a research synthesis and gap analysis. Leis Sci 40(6):533–556

Wan B, Paudyal R, Huntley C, Stein T (2014) Florida National Scenic Trail Visitor Assessment. School of Forest Resources and Conservation, University of Florida, Gainesville

Wilkins E, De Urioste-Stone SM, Weiskittel A, Gabe T (2017) Effects of weather conditions on tourism spending: implications for future trends under climate change. J Travel Res 57(8):1042–1053

Yu G, Schwartz Z, Walsh JE (2009) A weather-resolving index for assessing the impact of climate change on tourism related climate resources. Clim Chang 95(3):551–573

Zhang F, Wang XH (2013) Assessing preferences of beach users for certain aspects of weather and ocean conditions: case studies from Australia. Int J Biometeorol 57(3):337–347