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A temporal and spatial analysis of climate change, weather events, and tourism businesses

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HIGHLIGHTS

- Outdoor tourism businesses face opportunities and threats related to climate change and weather conditions.
- Time-series forecasting demonstrated the impact of temperature and precipitation on 13 outdoor tourism locations.
- Adverse weather conditions impacted sales within two weeks in the future.
- The construal level theory is used to demonstrate the temporal and spatial impact of climate and weather.
- The influence of temperature, precipitation, and extreme events on tourism sales is discussed.

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ABSTRACT

The study explores how precipitation and temperature have changed across the United States at multiple outdoor tourism locations within six unique climate zones from 1990 to 2015 compared to long-term averages from 1901. A multiple-location case-study design is then used to analyze the impact of long-term weather conditions and weather events – both favorable and unfavorable – on daily sales for 13 outdoor tourism locations within the six climate zones. The study is the first to draw on the construal level theory to quantitatively and longitudinally explore the geographic and temporal proximity of climate change and extreme events on business outcomes. The methodologies used, including time-series forecasting, provide a blue-print for at-risk businesses to analyze the impact of climatic factors and weather conditions no matter location.

1. Introduction

Climate change is commonly drawn upon to validate involvement in sustainability initiatives. Specific to climate change, the narrative evoked by many businesses involved in sustainability is to measurably act (e.g., reduce waste, energy consumption, carbon emission) as to not perpetuate macro-level effects (Allen, 2016; Cox, 2009). The macro-level effects of climate change have been documented and clearly articulated globally through indices including air temperature, sea-ice area, sea-surface temperature, carbon emissions, and trends in extreme weather disasters (IPCC, 2014; Melillo, , Richmond, , & Yohe, 2014; NOAA, 2017). Local communities, businesses large and small, and progressive states have demonstrated leadership in mitigating efforts to combat the effects of climate change (Allen, 2016; Asensio & Delmas, 2015; Cox, 2009; Craig, Petrun-Sayers, & Feng, 2018; Gilleo et al., 2014). The need for continued active leadership by these groups in climate mitigating efforts is accentuated in the United States by recent administrative actions to halt international and domestic carbon reducing measures.

Despite continued climate mitigating efforts globally, recent resultant extreme weather events in the United States including hurricanes, wildfire, drought, and flooding (NOAA, 2017) demonstrate heightened economic, safety, and health risks for businesses

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and individuals. This study proposes a new way of seeing, where businesses in the at-risk outdoor tourism industry explore how climate change, extreme or adverse weather events, and favorable weather events influence their own economic viability. This in turn can provide a better understanding of the risks that surrounding communities face, and position businesses to become the voice of mitigation and adaptation prior to extreme weather disasters.

This study will longitudinally explore climatic variability and weather events for outdoor tourism businesses across the United States to address the knowledge gap of the lack of integration of climate and business outcomes. The weather and climatic variables are derived from temperature and precipitation, and the focal business outcome is sales. A multiple-location case-study design is used that will provide a blue-print for businesses to analyze the impact of climatic factors on their own salient economic outcomes (Craig et al., 2018). Building on previous methodological perspectives for analyzing the impact of climate and weather on tourism (Rossello-Nadal, 2014), a retrospective time-series forecasting approach is used that assesses both historical sales performance and the impact of adverse and favorable weather events on current sales. This methodology will allow for future temporal and spatial shifts in the tourism industry (Amelung & Nicholls, 2014) to be addressed. The historical climatic and weather benchmark provided can inform business and community response to persistent change and localized extreme events or favorable conditions within a similar climate zone.

The study begins by characterizing the focal outdoor tourism business group. Next, relevant literature is reviewed starting with historic relationships between businesses, climate, and weather. The construal level theory (Trope & Liberman, 2010) is then presented as a theoretical taxonomy for exploring adaption by businesses, and by extension, communities. The construal level theory contends that close spatial, temporal, and social proximity to climate change are more influential on individual perceptions and behaviors than distal proximities, and that a more concrete construal of climate change is more actionable. The study is the first to quantitatively and longitudinally draw on the construal level theory to explore the geographic, temporal, and social proximity of climate change and extreme events on business outcomes in the outdoor tourism industry. The remainder of the study will include a methods section, a results and analysis section, and a theory section followed by a discussion complete with implications, limitations, and future research.

1.1. *Business overview*

The focal outdoor tourism business group operates campgrounds in the United States and Canada that offer cabin, RV, and tent camping. The business owns and operates 28 corporate-owned locations in six climate zones as defined by Karl and Koss (1984) and adopted by the National Oceanic and Atmospheric Administration (NOAA, 2017). At each of the locations a range of amenities are offered including groceries, camping merchandise, general merchandise, and various outdoor recreation activities. The majority of the business locations are within close proximity to attractions such as state or national parks, beaches, mountains, or entertainment districts. Overall sales for the privately owned business group are estimated to exceed $100 million. No additional information is provided to protect the identity of the business. Daily sales data was retrieved from each of the 28 locations from January 1, 2007 through November 11th, 2016 and was matched with the climatic variables that are discussed in greater detail in the methods section and Appendix A. High resolution climatic data was collected from January 1990 through December 2015 and compared to the long-term averages from 1901 to assess longer-term change at locations within climate zones. Based on the wide geographic dispersion of locations, the business group regularly experiences natural disaster events and/or extreme weather. The leadership team was supportive of the study to provide guidance on how to take advantage of favorable conditions and to adapt to unfavorable conditions across the entirety of the United States.

1.2. *Business, climate, and weather*

Businesses are increasingly facing challenges related to weather conditions and extremes. The focal business group is in the outdoor tourism industry, providing an opportunity to explore how localized conditions impact a range of sales categories with varying vulnerabilities to potentially hazardous conditions. Like other business categories, the tourism industry has experienced changing climatic conditions that effect when and how sales occur, and continued climatic and weather trends will influence the vulnerability and viability of many businesses throughout the world (Craig et al., 2018; Monahan et al., 2016; Yu, Schwartz, & Walsh, 2009). Yet, within the industry the impacts of climate change are often misunderstood (Weir, 2017). Adaptive efforts are needed within the tourism to maintain economically viability in the future (Schliephack & Dickinson, 2017). Seasonality, timing of an event, persistence of an event, and severity of an event can all impact business economic outcomes (Craig et al., 2018; Monahan et al., 2016). Likewise, favorability of conditions, such as cloud cover, precipitation levels, and temperature, can either have positive or negative impacts on business economic outcomes (Craig et al., 2018; Rutty & Scott, 2016).

Businesses across industries are actively adapting to changing conditions. A common challenge for businesses is in creating a roadmap to address long-term climate mitigation and also to adapt to localized conditions (Allen, 2016; Craig et al., 2018). Linnenluecke and Griffiths (2012) noted that one such challenge for businesses is the perception that climate change or weather events are outside of the organization's coping capabilities. This study will provide a benchmark of historic conditions and a methodological blueprint for studying climatic interactions that will enhance business and community coping capacity to climate change and weather events, both favorable and unfavorable.

Businesses in the past have successfully demonstrated adaptive capacity. For instance, businesses have exhibited adaptive capacities to overcome climate challenges related to public health, sales and sales cycles, and carbon emissions (Allen, 2016; Craig et al., 2018; Scott & McBoyle, 2007). Likewise, many large corporations are now utilizing weather data services for sales forecasting, to inform marketing budgets, and to make distribution decisions with companies such as Planalytics (www.planalytics.com) and Weather Analytics (www.weatheranalytics.com). Yet, the majority of small businesses, particularly those in the outdoor tourism industry, have not planned for adverse weather events and in many cases, are unable to stay in business after experiencing an extreme weather event such as a hurricane or flood (FEMA, 2015; Nationwide, 2015). To understand historical trends across the United States for the business group, temperature and precipitation (including long-term trends and short-term events) are used to assess the impact of weather and climatic variability. Specific to the focal 28 business locations and the regional climate zones represented, the following research question is posed:

Research Question 1. What are the weather and climatic trends for the focal locations and climate zones?

1.3. Construal level theory

The construal level theory is used here as a guiding theory to assess the proximity of outdoor tourism business locations to climate change and weather events. The construal level theory has been used to understand psychological responses of individuals in a variety of context including advertising, organizational behavior, and climate studies (Brugger, Dessai, Devine-Wright, Morton, & Pidgeon, 2015a; McDonald, Chai, & Newell, 2015; Oreg, Bartunek, Lee, & Do, 2016). By exploring the geographic and temporal impact of climate and weather on sales, this study will provide a local lens through which businesses can look to understand both when and how adverse and favorable relationships occur. By making these relationships proximate to decision makers within businesses, the likelihood of adaptive and mitigating action increases.

The construal level theory (Trope & Liberman, 2010) contends that an individual's response to an event, object, or issue is influenced by both individual understanding (i.e., construal) and psychological distance (i.e., proximity). Construals range from high to low, where high construals are characterized by an abstract yet enduring understanding (Trope & Liberman, 2010). For instance, a leadership team may equate sustainability to organizational efforts that reduce global warming. This understanding, or construal, of sustainability is high. For the employees tasked with functionally implementing sustainability initiatives, however, the understanding of sustainability is more likely to be tied to specific tasks such as efficiency improvements or recycling than to global warming. Construals are perceptions about events, objects, or issues, and while related to psychological distance the two are not synonymous (Trope & Liberman, 2010).

Psychological distance is the proximity of an individual to an event, object, or issue in terms of time, space, and social inclusion (Trope & Liberman, 2010). There is also a hypothetical element, where individuals can explore the likelihood of occurrence. Temporal proximity assesses recency, spatial proximity assesses geography, social proximity assesses inclusion, and hypothetical proximity assesses perceptions of occurrence (Craig & Feng, 2018; Trope & Liberman, 2003, 2010). Considering the example above, the employees tasked with implementing sustainability initiatives are temporally proximate, geographically proximate, socially proximate, and the sustainability actions are actively (not hypothetically) occurring. For all four of these elements, the leadership team would be more proximally distant than the employees tasked with enacting the initiatives. Furthermore, the construals of the employees are likely to be more concrete (i.e., low) yet less persistent in that additional sustainability initiatives at the functional level could be easily enacted but not necessarily tied to the abstract, higher level concept of climate change. Again, high construals are associated with higher psychological distance but are not interchangeable with proximity (Trope & Liberman, 2003).

There is a need among business decision makers in outdoor tourism to address the proximate temporal and spatial changes in weather and climate (Amelung & Nicholls, 2014). Studies have drawn on the construal level theory to better understand how individuals construe climate change based on proximity to actual and hypothetical events. However, there is a salient gap in the literature where climate change and weather have not been longitudinal and/or broadly spatially dispersed. Generally speaking, climate change as a topic has been highly construed and perceived as geographically, temporally, and socially distant, as well as hypothetical (Brugger et al., 2015a; Craig & Feng, 2018; Schill & Shaw, 2016; Trope & Liberman, 2010). With regards to unlikely or adverse events, such as extreme weather disasters, individuals tend to perceive that events will occur in the future, and will not be personally impactful (Gifford, Scannell, Kormos, & Uzzell, 2009; Milfont, Abrahamse, & McCarthy, 2011; Wakslak & Trope, 2009). The challenge remains how to engage individuals, particularly business leadership, to take actions prior to events to either mitigate or adapt to adverse impacts. Consequently, with a knowledge of the adverse impacts that occur, businesses can also take action to adapt through taking advantage of favorable conditions.

Accordingly, to address the research gap related to proximity, the study will extend the construal level theory by integrating actual climatic and weather conditions within definable climate zones at outdoor tourism business locations throughout the United States.

Research Question 2. What temporal and geographic relationships exist between sales for focal business locations and weather?

2. Materials and methods

2.1. Procedure, measures, and statistical analysis

This section outlines the methodological blueprint that can be used to (1) assess past weather and climatic conditions, and (2) analyze the impact of weather variables on important business outcomes. To address Research Question 1, daily climatic data was collected for the 28 locations across the United States from January 1, 1990 through December 31, 2015 for minimum temperature, maximum temperature, and precipitation. The data was collected from the high resolution PRISM dataset, providing approximately a 4 km resolution (DiLuzio, Johnson, Daly, Eischeid, & Arnold, 2008). Please note that the % changes represented in Fig. 1 and Table 1 are the trend over the past 25 years (i.e., 1990–2015) compared to the long-term average (i.e., 1901–2015).

To address Research Question 2, daily data was collected for cabin, RV, and tent sales for 28 business locations throughout the United States between January 1, 2007 and November 11, 2016. The same procedures described above were used to obtain the matched daily weather data. Descriptives are provided for the weather variables aggregated to the climate zone in Table 1 from January 1, 2007 through November 11, 2016, and the aggregate changes for the climate zone between 1990 and 2015 are also included. Once data were obtained, the climatic variables were nominally recoded to capture desirable/undesirable weather conditions and extreme weather events. Two categories were used: (1) days that exceeded an extreme or were within the desirable/undesirable range, and (2) days that were not.

Previous research has described extreme events (e.g., frost days, precipitation over 10 mm) and desirable temperatures for the tourism industry (e.g., Fisichelli, Schuurman, Monahan, & Ziesler, 2015; Frich et al., 2002; Rutty & Scott, 2016). According, we included the additional variables to provide a higher resolution of conditions and how they are specifically related to key business outcomes rather than consumer opinions, positively and negatively. Please see Appendix A for the full list of climatic variables used in the study, and the abbreviation for the term used in tables.

Only 13 locations were included in the analysis of Research Question 2. Locations that did not have all three categories of sales or that had experienced a strategic change that altered sales (e.g., significantly altering the mix of occupancy options) during the study period were removed. For the 13 locations, with at least two representative locations from each climate zone, retrospective time series forecasting was used to explore the relationships between historical daily sales, long-term weather, desirable/undesirable conditions, and extreme weather events. This method allowed for the analysis to move beyond correlational or hierarchical regression analysis by exploring predictors – both previous sales and weather conditions – on current sales.

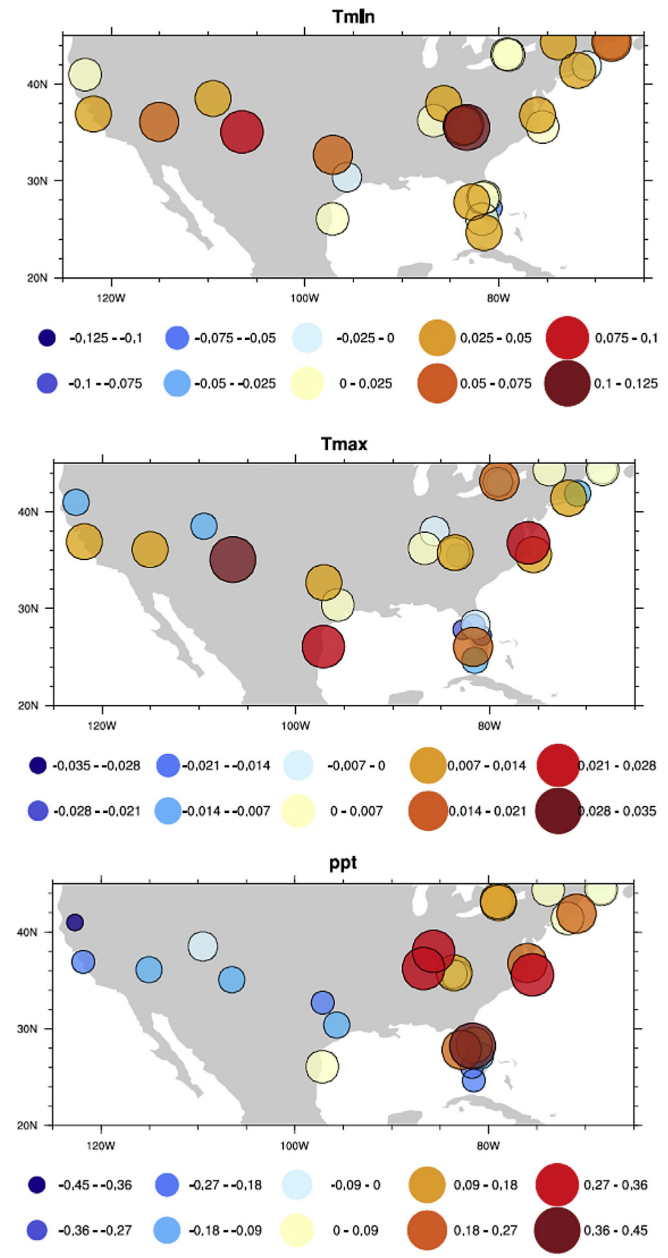

Fig. 1. Annual percentage change in precipitation, minimum temperature, and maximum temperature from January 1, 1990 to December 31, 2015.

The time series modeler function and expert modeler method via the IBM SPSS version 24 software suite were used. This method explores autoregressive integrated weighted average (ARIMA) models (Craig & Feng, 2016), which is appropriate for differencing as well as determining the lags/delays, the autoregressive and moving average components, and seasonality (Clement, 2014; Craig & Feng, 2016; van Heck, 2010). Detailed explanation of ARIMA modeling in the section below. The goodness-of-fit statistics of stationary r^2 is provided for each category. Stationary r^2 is the primary goodness-of-fit statistic and is more appropriate than r^2 when there is seasonality in a dataset. The model type (i.e., ARIMA, Simple Seasonal, Exponentially Smoothed) is presented in addition to the number of climatic predictors observed. Two time series forecasts were run to assess % improvement, one that retroactively forecasted sales only and a second that included sales and the climatic variables. Percentage change in forecast accuracy is reported.

Table 1
Descriptives and change statistics for climate zones.

Item	Min	Max	Mean	SD	% Δ
Southeast Climate Zone (9 locations, N = 32427)					
ppt	0	295.73	3.56	9.77	7.76%
tmin	−23.15	29.67	15.86	8.48	2.18%
tmax	−8.09	38.00	25.64	7.43	-.53%
Northeast Climate Zone (6 locations, N = 17993)					
ppt	0	138.92	3.18	8.00	5.64%
tmin	−32.12	25.44	3.87	10.22	2.67%
tmax	−20.38	37.43	14.05	14.05	-.31%
West Climate Zone (3 locations, N = 10787)					
ppt	0	132.51	1.59	6.64	−25.95%
tmin	−12.83	32.79	9.57	7.58	3.61%
tmax	−2.11	47.39	22.47	9.62	.20%
Southwest Climate Zone (2 locations, N = 7195)					
ppt	0	42.09	.73	2.60	−6.03%
tmin	−23.29	25.43	6.13	9.13	5.78%
tmax	−12.71	41.86	20.76	10.74	1.08%
South Climate Zone (3 locations, N = 10798)					
ppt	0	229.56	2.66	9.73	−10.88%
tmin	−10.22	29.11	16.00	8.62	1.83%
tmax	−6.51	42.93	26.10	7.86	1.40%
Central Climate Zone (4 locations, N = 14392)					
ppt	0	182.62	3.72	9.11	16.72%
tmin	−21.18	25.43	8.41	8.35	4.39%
tmax	−14.65	41.74	20.73	9.82	.36%

Note. Date range for ppt, tmin, and tmax January 1, 2007–November 11, 2016; Date range for percentage annual change January 1, 1990–December 31, 2015.

2.2. ARIMA modeling

AR is the autoregressive term, and the MA is the moving average, or error, term. In the first set of parentheses in Table 2, the first number represents the number of lags for the autoregressive term, the second numbers represents the number the order of differencing, and the third number represents the number of lags for the moving average term. For the second set of parentheses, the first number represents the number of lags in seasonality for the autoregressive term, the second number represents seasonality differences, and the third number represents the number of lags in seasonality for the moving average term. For example, an ARIMA model reported as (3, 1, 2) (1, 1, 0) would indicate three days lag for the autoregressive term, one degree of differencing, and two days lag for the moving average term. The second set of numbers demonstrates there is one season lag for the autoregressive term, there is a one seasonality difference, and the there is no seasonal lag for the moving average term.

For weather predictors, the AR term is also called the numerator and the MA term the denominator. Differencing and seasonality can also occur for predictors, and there is the possibility for delays. The numerator, differencing, and denominator are reported similar to the first set of parentheses described above. Seasonality and the delays are reported as subscripts. For example, a predictor reported as $(1, 1, 3)_{1,\,4}$ would indicate a one day lag for the numerator (the AR term), one degree of differencing, and three days lag for the denominator (the MA term). The subscripts would demonstrate there is a one seasonality difference, and the relationship with sales exhibited a four day delay. Please note that the negative sign in Fig. 1 for predictors indicates a negative relationship.

3. Results and analysis

The following can be used as a benchmark for the focal climate zones. The results and analysis contained within this section are

Table 2
Retrospective time series forecasting outputs for focal locations within climate zones.

Item	Sales St.r^2	Climatic St.r^2	% Change	Model	Weather Predictors
Southeast Climate Zone					
Coastal Florida (Mean St. r^2 = .395)					
Cabin	**.463**	.463	0.0%	Simple Seasonal	0
RV	.262	.266	1.5%	(0, 1, 5) (1, 0, 1)	3
Tent	**.457**	.455	−0.4%	(0, 0, 2) (2, 0, 1)	0
RV Predictors: ppt0 (0, 1, 0)$_{0,5}$; ppt1 (0, 1, 0)$_{0,2}$; - tmin4555 (0, 1, 0)$_{0,10}$					
Coastal Virginia (Mean St. r^2 = .580)					
Cabin	.529	.537	1.5%	(0, 0, 4) (1, 0, 1)	6
RV	**.511**	.474	−7.2%	Exponentially Smoothed	0
Tent	.682	.693	1.6%	(1, 0, 5) (1, 1, 1)	5
Cabin Predictors: tminC (0, 0, 0)$_{1,4}$; ppt7 (0, 0, 2)$_{1,6}$; ppt10 (0, 0, 0)$_{1,7}$; - ppt>20 (0, 0, 1)$_{1,0}$; tmin6575 (0, 0, 1)$_{1,2}$; tmax9095 (0, 0, 0)$_{1,9}$					
Tent Predictors: ppt1 (0, 0, 2)$_{1,4}$; - ppt3 (6, 0, 0)$_{1,3}$; - ppt10 (1, 0, 0)$_{1,3}$; - ppt20 (0, 0, 0)$_{1,3}$; - tmin7585 (0, 0, 2)$_{1,6}$					
Mountainous North Carolina (Mean St. r^2 = .664)					
Cabin	.637	.646	1.4%	(2, 0, 6) (1, 1, 1)	7
RV	**.788**	.785	-.03%	(4, 0, 5) (0, 1, 1)	0
Tent	.558	.565	1.2%	(1, 0, 3) (0, 1, 1)	5
Cabin Predictors: tmax (0, 0, 0)$_{1,0}$; ppt2 (0, 0, 2)$_{1,2}$; ppt4 (0, 0, 0)$_{1,1}$; pp7 (0, 0, 2)$_{1,4}$; ppt10 (0, 0, 2)$_{1,4}$; - tmin5565 (0, 0, 0)$_{1,4}$; tmax6575 (0, 0, 0)$_{1,6}$					
Tents Predictors: ppt (0, 0, 0)$_{1,0}$; ppt2 (0, 0, 1)$_{1,2}$; -ppt3 (0, 0, 1)$_{1,2}$; ppt>10 (0, 0, 0)$_{1,5}$; - tmin4555 (0, 0, 0)$_{1,8}$					
Northeast Climate Zone					
Connecticut (Mean St. r^2 = .607)					
Cabin	**.548**	.546	-.04%	(4, 0, 4) (0, 1, 1)	0
RV	.690	.694	.06%	(4, 0, 3) (0, 1, 1)	4
Tent	.560	.575	2.6%	(0, 0, 6) (0, 1, 1)	14
RV Predictors: tmin (0, 0, 2)$_{1,1}$; - ppt3 (0, 0, 0)$_{1,1}$; ppt4 (1, 0, 0)$_{1,1}$; - ppt5 (0, 0, 0)$_{1,2}$					
Tent Predictors: tmin (0, 0, 0)$_{1,1}$; ppt1 (0, 0, 2)$_{1,3}$; ppt2 (0, 0, 0)$_{1,10}$; - ppt4 (0, 0, 0)$_{1,8}$; ppt>10 (0, 0, 2); ppt20 (0, 0, 0)$_{1,3}$; - ppt>1inch (0, 0, 2)$_{1,2}$; - tmin<32 (0, 0, 2)$_{1,3}$; - tmin3245 (0, 0, 0)$_{1,3}$; tmin4555 (0, 0, 1)$_{1,2}$; - tmin6575 (0, 0, 0)$_{1,3}$; tmax3245 (0, 0, 0)$_{1,0}$; tmax4555 (0, 0, 0)$_{1,0}$; tmax8590 (0, 0, 0)$_{1,8}$					
Niagara Falls, Canada (Mean St. r^2 = .667)					
Cabin	.502	.511	1.8%	(3, 0, 5) (1, 0, 1)	6
RV	.761	.774	1.7%	(1, 0, 3) (0, 1, 1)	5
Tent	.694	.717	3.2%	(1, 0, 3) (0, 1, 1)	4
Cabin Predictors: ppt>20 (0, 0, 2)$_{1,1}$; - ptt>1inch (0, 0, 2)$_{1,1}$; tmin4555 (0, 0, 0)$_{1,6}$; tmin6575 (0, 0, 0)$_{1,3}$; - tmax<32 (0, 0, 0)$_{1,0}$; tmax9095 (0, 0, 0)$_{1,3}$					
RV Predictors: ppt3 (2, 0, 2)$_{1,8}$; -ppt10 (2, 0, 2)$_{1,1}$; ppt>10 (0, 0, 2)$_{1,4}$; ppt>20 (0, 0, 1)$_{1,4}$; - tmin6575 (0, 0, 0)$_{1,8}$					
Tent Predictors: ppt10 (2, 0, 2)$_{1,2}$; ppt>20 (0, 0, 0)$_{1,4}$; -tmin3245 (0, 0, 2)$_{1,4}$; tmin6575 (0, 0, 0)$_{1,1}$					
Western Climate Zone					
Coastal California (Mean St. r^2 = .567)					
Cabin	.501	.520	3.6%	(4, 0, 5) (0, 1, 1)	3
RV	.677	.681	.06%	(4, 0, 4) (0, 1, 1)	5
Tent	.482	.500	.04%	(0, 0, 6) (0, 1, 1)	6
Cabin Predictors: ppt1 (0, 0, 0)$_{1,10}$; -tmin3245 (0, 0, 0)$_{1,3}$; -tmin7585 (0, 0, 0)$_{1,3}$					
RV Predictors: ppt2 (0, 0, 2)$_{1,4}$; - ppt>10 (0, 0, 1)$_{1,5}$; - tmin3245 (0, 0, 2)$_{1,3}$; tmin4555 (0, 0, 0)$_{1,6}$; tmax>95 (0, 0, 2)$_{1,0}$					
Tent Predictors: ppt (1, 0, 2)$_{1,0}$; - tmin (9, 0, 0)$_{1,0}$; - tmax (0, 0, 0)$_{1,8}$; tmin4555 (0, 0, 0)$_{1,8}$; - tmax5565 (6, 0 0)$_{1,4}$; tmax7585 (0, 0, 0)$_{1,4}$					
Mountainous California (Mean St. r^2 = .668)					
Cabin	.636	.650	2.2%	(4, 0, 5) (1, 1, 1)	4
RV	.544	.555	2.0%	(0, 1, 6) (0, 1, 1)	6
Tent	.796	.799	.04%	(2, 0, 4) (0, 1, 1)	5
Cabin Predictors: tmin (0, 0, 0)$_{1,0}$; - ppt10 (2, 0, 1)$_{1,4}$; tmin<32 (1, 0, 1)$_{1,6}$; - tmax3245 (1, 0, 0)$_{1,0}$					
RV Predictors: tmin (0, 1, 0)$_{1,10}$; - ppt10 (0, 1, 0)$_{1,2}$; ppt>20 (0, 1, 0)$_{1,4}$; - tmin3245 (0, 1, 0)$_{1,9}$; tmin4555 (0, 1, 0)$_{1,6}$; - tmax3245 (1, 1, 0)$_{1,0}$					
Tent Predictors: tmin (0, 0, 2)$_{1,1}$; ppt7 (0, 0, 2)$_{1,2}$; ppt10 (0, 0, 0)$_{1}$; ppt>20 (0, 0, 0)$_{1,4}$; tmin6575 (0, 0, 0)$_{1,6}$					
Southern Climate Zone					
Urban Texas (Mean St. r^2 = .630)					
Cabin	.609	.619	1.6%	(0, 0, 4) (1, 0, 1)	2
RV	**.761**	.337	55.7%	(5, 0, 5) (1, 0, 1)	0
Tent	.502	.510	1.6%	(1, 0, 5) (1, 1, 1)	5
Cabin Predictors: ppt2 (0, 0, 1)$_{0,1}$; - tmin (0, 0, 0)$_{0,10}$					
Tent Predictors: ppt7 (0, 0, 0)$_{1,2}$; - tmin6575 (0, 0, 0)$_{1,3}$; -tmin7585 (0, 0, 0)$_{1,8}$; - tmax5565 (0, 0, 0)$_{1,8}$; - tmax8590 (0, 0, 0)$_{1,10}$					

Table 2 (*continued*)

Item	Sales St.r^2	Climatic St.r^2	% Change	Model	Weather Predictors
Coastal Texas (Mean St. r^2 = .736)					
Cabin	.705	.706	.01%	(0, 0, 6) (0, 1, 1)	1
RV	.839	.849	1.2%	(2, 0, 4) (0, 1, 1)	1
Tent	.651	.651	.02%	(1, 0, 3) (0, 1, 1)	4
Cabin Predictors: tmin>85 (0, 0, 2)$_{1,0}$					
RV Predictors: tmax3245 (0, 0, 0)$_{1,10}$					
Tent Predictors: ppt10 (0, 0, 1)$_{1,5}$; - tmin<32 (0, 0, 0)$_{1,6}$; tmin>85 (0, 0, 0)$_{1,6}$; - tmax3245 (0, 0, 0)$_{1,7}$					
Southwest Climate Zone					
Mountainous Utah (Mean St. r^2 = .588)					
Cabin	.651	.665	2.1%	(2, 0, 6) (1, 1, 1)	3
RV	.450	.460	2.2%	(3, 1, 5) (1, 1, 1)	1
Tent	.633	.639	.01%	(2, 0, 6) (0, 1, 1)	8
Cabin Predictors: ppt (0, 0, 0)$_{1,9}$; tmax (0, 0, 0)$_{1,3}$; tmin>85 (0, 0, 1)$_{1,0}$					
RV Predictors: tmin>85 (0, 1, 2)$_{1,0}$					
Tent Predictors: ppt10 (0, 0, 0)$_{1,3}$; - tmin<32 (0, 0, 1)$_{1,0}$; - tmin3245 (0, 0, 1)$_{1,0}$; -tmin4555 (0, 0, 1)$_{1,0}$; - tmin5565 (0, 0, 1)$_{1,0}$; - tmin6575 (0, 0, 1)$_{1,0}$; tmax7585 (0, 0, 0)$_{1,10}$					
Urban New Mexico (Mean St. r^2 = .554)					
Cabin	.582	.600	3.0%	(4, 0, 3) (1, 0, 1)	2
RV	**.538**	.086	84.0%	Exponentially Smoothed	0
Tent	.508	.524	3.1%	(1, 0, 6) (1, 0, 0)	5
Cabin Predictors: ppt (0, 0, 0)$_{0,2}$; - tmax (7, 0, 0)$_{0,0}$					
Tent Predictors: tmax (0, 0, 0)$_{0,9}$; -ppt10 (0, 0, 1)$_{0,3}$; ppt>20 (0, 0, 1)$_{0,1}$; - ppt>1inch (0, 0, 1)$_{0,1}$; tmax>95 (0, 0, 0)$_{0,10}$					
Central Climate Zone					
Mountainous Kentucky (Mean St. r^2 = .606)					
Cabin	.580	.596	2.7%	(0, 0, 2) (0, 1, 1)	7
RV	.754	.764	1.3%	(0, 0, 5) (0, 1, 1)	4
Tent	.441	.459	3.9%	(0, 0, 2) (2, 0, 1)	4
Cabin Predictors: ppt0 (0, 0, 2)$_{1,5}$; -ppt4 (0, 0, 1)$_{1,3}$; ppt7 (0, 0, 1)$_{1,4}$; - ppt>20 (0, 0, 1)$_{1,1}$; - tmin4555 (0, 0, 2)$_{1,5}$; - tmin5565 (2, 0, 2)$_{1,1}$; tmin6575 (0, 0, 0)$_{1,7}$					
RV Predictors: tmax (0, 0, 0)$_{1,5}$; - ppt7 (2, 0, 2)$_{1,4}$; - ppt10 (0, 0, 2)$_{1,3}$; timn3245 (0, 0, 0)$_{1,5}$					
Tent Predictors: tmax (0, 0, 0)$_{0,5}$; ppt2 (0, 0, 0)$_{0,9}$; - ppt4 (0, 0, 1)$_{0,7}$; tmax<32 (0, 0, 0)$_{0,9}$					
Urban Tennessee (Mean St. r^2 = .538)					
Cabin	.697	.701	.06%	(1, 0, 5) (0, 1, 1)	2
RV	**.513**	.512	-.02%	Exponentially Smoothed	0
Tent	.395	.401	1.5%	(0, 1, 6) (1, 0, 1)	4
Cabin Predictors: tmax (0, 0, 2)$_{1,0}$; tmax3245 (0, 0, 0)$_{1,10}$					
Tent Predictors: ppt10 (0, 1, 0)$_{0,6}$; - tmin<32 (0, 1, 0)$_{0,0}$; tmin7585 (0, 1, 0)$_{0,0}$; tmax3245 (0, 1, 0)$_{0,0}$					

Note. St. r^2 = stationary r-squared; all models significant at a $p < .01$ level or below; all predictors significant at $p < .05$ or below.

accompanied by findings from Melillo et al. (2014) that were published in the 3rd National Climate Assessment for each climate zone to provide historical and temporal relevance. Research Question 1 asked about climate and weather trends across the United States and in the focal climate zones. Please note that the analysis for longer term change (an indication of climate change) for precipitation, minimum temperature, and maximum temperature were run between 1990 and 2015 as compared to the long-term average from 1901 to provide the most robust context possible using the highest resolution daily data that was available. See Table 1 and Fig. 1 for all results for Research Question 1.

3.1. Research question 1

In the northeast climate zone, between 1990 and 2015 the vast majority of locations experienced an increase in minimum temperature, maximum temperature, and increased precipitation. For the nine locations explored, Table 1 shows the average change compared to the long-term average from 1901 was 2.67% for minimum temperature, −.31% for maximum temperature, and 5.64% for precipitation. Our results are consistent with the 3rd National

Climate Assessment for this region (Melillo et al., 2014).

For the southeast and central climate zones, between 1990 and 2015 the dominant trend throughout the two zones was an increase in minimum temperatures, where results for maximum temperature changes are mixed. Also, most locations in these regions saw an increase in precipitation with the exception of those in southern Florida. For the nine locations explored in the southeast climate zone, Table 1 shows the average change from 1990 to 2015 compared to the long-term average from 1901 was 2.18% for minimum temperature, −.53% for maximum temperature, and 7.76% for precipitation. For the four locations in the central zone the average change was 4.39% for minimum temperature, .36% for maximum temperature, and 16.72% for precipitation. Our results are consistent with the 3rd National Climate Assessment for this region (Melillo et al., 2014).

All five locations in the west and southwest climate zones experienced an increase in minimum temperature and a decrease in precipitation between 1990 and 2015. For the three locations in the west climate zone, Table 1 shows average change was 3.61% for minimum temperature, .20% for maximum temperature, and −25.95% for precipitation. Similarly, for the two locations in the southwest climate zone, the average change was 5.78% for minimum temperature, 1.08% for maximum temperature, and −6.03% for precipitation. Our results are consistent with Melillo et al. (2014).

For the southern climate zone, between 1990 and 2015 two of the three locations observed an increase in minimum temperature and all three locations observed in increase in maximum temperatures compared to the long-term average from 1901. Also, two of the three locations saw a decrease in precipitation. When considering aggregate change for the locations in the southern climate zone, the average was 1.83% for minimum temperature, 1.40% for maximum temperature, and −10.88% for precipitation. With projected increases in 100 °F and drought (Melillo et al., 2014), the trends observed are expected to continue.

3.2. Research question 2

Research Question 2 explored the impact of these conditions on sales spatially and temporally. Due to the volume of weather predictors in the study, results for Research Question 2 (see Table 2) will only be reported analyzed where weather predictors improved the sales forecast by 1% of greater. The % figures reported indicate the improvement of forecast with the addition of weather predictors. The stationary r^2 values reported for each location are the overall model fit that take into consideration both sales and weather predictors. The retrospective time series analysis used for this study can be used as a blueprint for assessing the impact of previous sales and weather events on current sales.

3.2.1. Northeast

There were two locations in the northwest climate zone included in the study: Connecticut and Niagara Falls. For the Connecticut location, weather predictors enhanced the models for RV camping (.06%) and tent camping (2.6%), and the historical sales model for cabin camping was the best fit (overall model fit stationary $r^2 = .607$). There were four weather predictors for RV camping, and 14 for tent camping. For precipitation events of 3.00–3.99 mm, there was a negative impact on tent sales with an eight day delay. It may be that the higher likelihood of rain negatively impacted decisions to camp just over a week in advance. In terms of heavy precipitation that exceeded 10 mm, 20 mm, and 25.6 mm (or 1 inch), the delay was either two or three days. That is, the impact of the more severe or extreme conditions occurred only a few days prior to deciding to tent camp. Low minimum temperatures were among the predictors influencing decisions to tent camp with a maximum of three days in advance, where temperatures between 85 and 90 °F were positively related to sales eight days in advance.

For the Niagara Falls location, weather enhanced all models including cabin (1.8%), RV (1.7%), and tent (3.2%; overall model fit stationary $r^2 = .667$). There were six weather predictors for cabin sales, five for RV sales, and four for tent sales. The results demonstrate that cabin campers have a higher threshold for extreme precipitation, where only precipitation over 1 inch with a one day delay was negatively related to sales. Five of the six precipitation factors for RV were related to precipitation. Like the Connecticut location, the chance of rain − 2–2.99 mm − eight days out seemed to negatively impact sales, while the relationship with extreme precipitation events occurred between one and four days prior. The positive relationship with extreme precipitation for tent campers suggest either (1) they are waiting two to four days after heavy rain to camp, (2) that heavy rain occurs in a busy season, or (3) they may not be able to cancel stays within a short temporal proximity. If tent campers are in fact enduring the extreme events, this is an area for concern for this location. Freezing or near freezing temperatures are negatively related to same day sales for cabins, and sales four days prior for tents. The findings highlight favorable temperatures for both cabin and tent campers. For RVs, a higher minimum temperature between 65 and 75 °F is adversely related to sales eight days prior, suggesting warmer nights are not favorable conditions for RV campers. All weather models exhibited seasonality.

3.2.2. Southeast and central

There were three locations examined within the southeast climate zone and two in the central climate zone. For the coastal Florida location, only the RV model (1.5%) included significant weather predictors (overall model fit stationary $r^2 = .395$). This was the worst fit and least climate predictors for any location. There were no seasonal differences for the three weather predictors for RV sales. No rain was negatively related to sales with a five day delay, and low levels of rain below 1 mm were positively related to sales with a two day delay. These results are trivial and may have been influenced by the differencing/smoothing that took place. The significant negative relationship between lower minimum temperatures between 45 and 55 °F and sales delayed 10 days is clearer to interpret. RV sales are adversely influenced over a week prior to arrival when low temperatures occur in winter months.

Unlike the coastal Florida location, for the Virginia location weather predictors enhanced the forecast cabin sales (1.5%) and tent sales (1.6%) but not for RV sales (overall model fit stationary $r^2 = .395$). The cabin model had six predictors and the tent model had five predictors. For cabins, sales were negative related to minimum temperature with a four day delay, meaning that sales and minimum temperature rose and fell together. Higher minimum temperatures 65 and 75 °F were significant with a two day delay, and higher maximum temperatures between 90 and 95 °F were significant with a 10 day delay. For tents, the only significant predictor for temperature was a negative relationship with high minimum temperatures between 75 and 85 °F with a six day delay. Tent campers appear to be avoiding hot nights approximately a week in advance. Tent campers are more risk averse in terms of precipitation than cabin campers. Cabin sales was positively related to higher levels of precipitation − 6–6.99 mm and 9–9.99 mm − with six and seven day delays, however, for extreme precipitation over 20 mm the day of sales were adversely impacted. Tent campers had negative relationships with precipitation with a three day delay for moderate − 2–2.99 mm − and extreme precipitation over 10 mm and over 20 mm.

Like the Virginia location, the mountainous North Carolina location model improved with the addition of the cabin (1.4%) and tent (1.2%) sales but not RV sales (overall model fit stationary $r^2 = .664$). Cabin sales included seven weather predictors and tent sales five. Maximum temperature the day of was a positive predictor of cabin sales. There was a positive relationship with moderate high temperatures between 65 and 75 °F with a six day delay, and negative relationship with minimum temperatures between 55 and 65 °F with a four day delay. For tent campers, only cooler minimum temperatures between 45 and 55 °F were a significant (and negative) predictor with an eight day delay. All four of the precipitation predictors were positively related to cabin sales. There was a positive relationship with precipitation in general with tent sales the day of, meaning sales decreased with day-of rain. As precipitation levels increased, the relationship became negative with a two day delay for both predictors. Extreme precipitation above 10 mm was positively related to sales with a five day delay. This suggest that tent camping at this location impacting sales for almost a week after the event.

Central climate zone locations were in mountainous Kentucky and urban Tennessee. The location in Kentucky saw model improvement in categories including cabin (2.7%), RV (1.3%), and tent (3.9%; overall model fit stationary $r^2 = .606$). There were seven weather predictors for cabin sales, four predictors for RV sales, and four predictors for tent sales. Seasonality was present for all weather predictors for cabins and RVs but there was no seasonality for tent sales. There were negative relationships between no precipitation with a five day delay, between moderate precipitation – 3–3.99 mm – with a three day delay, and between extreme precipitation over 20 mm with a one day delay for cabin sales. There was a positive relationship as precipitation approached extreme levels – 6–6.99 mm – with a five day delay. For RV sales, higher levels of precipitation – 6–6.99 mm and 9–9.99 mm – were negatively related six and three day delays. The higher levels of precipitation are keeping RV campers away three days in advance of a stay. Like other tent locations, it appears as though the chance of moderate precipitation – 3–3.99 mm – is adversely impacting sales with a seven day delay.

For cabins, lower minimum temperatures – 45–55 °F and 55–65 °F – are adversely impacting sales with five and three day delays, and higher minimum temperatures between 65 and 75 °F are positively related with a seven day delay. RV sales are positively related to maximum temperature and lower temperature between 32 and 45 °F with five day delays, and maximum temperature and below freezing maximum temperatures with five and nine day delays. Warmer temperatures are preferred for all categories of sales at the Kentucky location.

The urban Tennessee location saw improvement in sales forecasts with addition of weather predictors for cabin (.06%) and tent (1.9%) sales, but not for RV sales (overall model fit stationary $r^2 = .538$). There were four significant weather predictors for tent sales that all exhibited seasonality. Tent sales were adversely impacted by precipitation that approached extreme – between 9 and 9.99 mm – with a six day delay and minimum temperatures below freezing in real-time. Positive relationships between lower maximum temperatures between 32 and 45 °F and high minimum temperature between 75 and 85 °F were positively related in real-time. Trends include cabin camping in warmer and colder temperatures, as well as tent camping being adversely impacted by intense precipitation approximately a week in advance of the weather event.

3.2.3. West and southwest

For the western climate zone, locations from coastal and mountainous California were included. The coastal location saw the largest model improvement from adding weather predictors for cabin sales (3.6%) followed by RV (.06%) and tent (.04%; overall model fit stationary $r^2 = .567$). There were three significant weather predictors for cabin sales that all exhibited seasonality. Negative relationships with low precipitation below 1 mm, lower minimums between 32 and 45 °F, and higher minimums between 75 and 85 °F emerged with delays of 10 days, three days, and three days, respectively.

The mountainous California location saw improvement for models with weather predictors for cabin sales (2.2%), RV sales (2.0%), and tent sales (.04%; overall model fit stationary $r^2 = .668$). There were four weather predictors for cabin sales, and six for RV sales. Higher levels of precipitation exhibited significant relationships for both cabin and RV sales. There was a negative relationship with precipitation levels approaching extreme – 9–9.99 mm – for cabins and RVs with six and two day delays, and there was a positive relationship between extreme precipitation over 20 mm for RVs with a four day delay. Cabin campers were adverse to lower maximum temperature between 32 and 45 °F the day of, and there was a positive relationship with below freezing minimum temperatures with a seven day delay. For RV sales, minimum temperature with a 10 day delay and cool minimum temperatures between 45 and 55 °F with a six day delay were positively related. Negative relationships emerged between lower minimum and maximum temperatures between 32 and 45 °F with delays of nine days and the day of, respectively. Planning appears to play a role for lower minimum temperatures, where lower maximum temperatures are influencing immediate RV camping decisions.

Southwestern locations came from mountainous Utah and urban New Mexico. For Utah, sales for cabins (2.1%), RVs (2.2%), and tents (.01%) all saw improvement with the addition of weather predictors. There were three weather predictors significantly related to cabin sales and just one for RV sales. Precipitation in general was positively related to sales with a nine day delay for cabins, and there was a positive relationship with maximum temperature and minimum temperatures greater than 85 °F with delays of three and zero days. Higher temperatures in general were positively related to cabin sales as were extremely high minimum temperatures in real-time. High minimum temperatures above 85 °F were positively related to day of RV sales.

For the urban New Mexico location, cabin (3.0%) and tent (3.1%) sales models saw improvement with weather predictors, but RV sales did not (overall model fit stationary $r^2 = .554$). There were two weather predictors for cabins and five for tents, and there was no seasonality for any weather predictor. Cabin sales were positively related to precipitation with a two day delay and negatively related to maximum temperature with a seven day lag. For tent sales, maximum temperature in general was positively related to sales with a nine day delay, and maximum temperatures greater than 95 °F were positive with a 10 day delay. The chance of high precipitation – 9–9.99 mm – appears to contribute to negative sales with a three day delay, and precipitation over an inch is negatively related with a one day delay. Another extreme precipitation measure, greater than 20 mm, is positively related to tent sales with a one day delay, however. More refined research is needed to understand how the two extremes that are close in volumes differ in impact on sales.

3.2.4. South

The southern climate zone included urban and coastal locations in Texas. For the urban Texas location, weather predictors enhanced the models for cabin camping (1.6%) and tent camping (1.6%), and the historical sales model for cabin camping was the best fit (overall model fit stationary $r^2 = .630$). There were two weather predictors for cabin sales, and five for tent sales. There was no seasonality present in weather predictors for cabins, where there was a one season difference for each of the significant factors for tent sales. Minimum temperature was negatively related to sales 10 days prior, suggesting that sales fell and rose with minimum temperature. Warmer minimums – 75–85 °F – and maximums – 85–90 °F – were negatively related to tent sales with an eight to 10 day delay. Lower high temperatures between 55 and 65 °F were negatively related to tent sales with an eight day delay. For tent sales, precipitation that approach extreme levels – 6–6.99 mm – was positively related to tent sales with a two day delay, and lower levels of precipitation – 1–1.99 mm – had a one day delay for cabin sales.

For the coastal southern location in Texas, cabin (.01%) and tent (.02%) models only improved slightly with the addition of weather predictors, where RV sales improved by 1.2% (overall model fit stationary $r^2 = .736$). Maximum temperature of 32 °F through 45 °F was the only significant weather predictor for RV sales, where there was a positive relationship with a 10 day delay. Considering that historical findings for this region have shown extreme heat and extreme weather events such as hurricanes and severe thunderstorms, the lack of strong relationships suggest that occupants may be vulnerable based on the destination nature of the location.

4. Theory

Previous research drawing from the construal level theory has demonstrated that individuals who have experienced a negative weather or climatic interaction were more willing or likely to adopt adaptive and mitigating actions (Craig & Feng, 2018; Haden, Niles, Lubell, Periman, & Jackson, 2012; Rudman, McLean, & Bunzl, 2013). For individuals located within environmentally at-risk areas, actual climatic conditions have acted as the most salient determinant of individual perceptions, beliefs, and support for mitigating efforts (Craig & Feng, 2018). Regarding climate change and the adverse effects, however, in hypothetical situations individuals tend to have higher levels of construal and perceive the impacts as being geographically, temporally, and socially distant (Brugger et al., 2015a; Trope & Liberman, 2010). However, Brugger, Morton, and Dessai (2015) found that it is not enough to message adverse effects of climate change and proximate. As such, this study addressed this gap in the construal level theory by operationalizing localized impacts that can be linked to higher level construals such as climate change and the resultant extreme weather events. The study overcomes barriers to action to address weather and climate change challenges by allowing decision makers to draw on historical, local, and recent relationships rather than attitudes or political ideologies. This is important for outdoor tourism businesses located in at-risk areas including individuals throughout the communities and climate zones studied here. With a new understanding of local conditions, business leaders have more of a capacity to adapt to changes both before and after occurrences of events.

5. Discussion

This study analyzed longer-term climatic trends at 28 business locations within six distinct climate zones across the United States. Using a multiple location case-study, the construal level theory was operationalized at 13 business locations to assess the proximal geographic and temporal interaction between weather and categorical sales. Accordingly, the study addressed the salient gap in the management literature by integrating actual climate change with business outcomes in local communities throughout the United States. In doing so, the study provides a robust benchmarking tool for other businesses located within the respective climate zones, and also a methodological blue print that businesses and communities can use to assess the local impact of climate change, adverse weather events, and favorable weather events (Craig et al., 2018). By drawing on retrospective time-series forecasting rather than traditional correlation or hierarchical regression methodologies, the study provided a temporal mechanism that includes both weather and historical sales performance, thus taking into account current business adaptive capacities at each location. A new way of seeing climate change is presented where a high construal item, climate change, can be linked to geographic and temporally weather events.

5.1. Climate and weather conditions

Adverse weather and climatic conditions vary widely throughout the United States, where the salience of specific threats varies as well. The findings of this study provide support for previous regional analysis of climate change and extreme weather events (e.g., Melillo et al., 2014; Preston, 2013). A commonality across the United States is that extreme weather events are increasing (NOAA, 2017) placing businesses and individuals at risk whether that be in terms of health, safety, or economics (Allen, 2016; Craig et al., 2018; Preston, 2013). To better understand these risks, and the potentially adverse impacts of weather events and longer term change, the study provides insights within climate zones about how people respond to specific weather conditions, and also how those weather conditions can improve the financial understanding of businesses. In the Results and Analysis section above, a robust description of climatic conditions, weather events, and the interactions with business outcomes is provided specific to long-term trends, adverse events, favorable events, and seasonality.

Consistent with the 3rd National Climate Assessment and global trajectories (IPCC, 2014; Melillo et al., 2014), the 28 locations and six climate zones exhibited changing climate and increased intensity of weather events. For instance, in the central, southeast, and northeast regions there was an increase in precipitation from 1990 to 2015 of 16.72%, 7.76%, and 5.64%, respectively. With an understanding the changing climate has led to more extreme intense events across these regions (Melillo et al., 2014), the percentage increases point to heightened risks related to extreme precipitation. The findings for the study show that sales throughout all regions exhibited a significant relationship with extreme precipitation – most with multiple locations and sales categories – where extreme precipitation is that above 10 mm per day (Frich et al., 2002). Maximum daily total precipitation ranged from 42.09 mm to 295.73 mm in the sites analyzed across the six climate zones from 2007 through November 11, 2016, demonstrating that all locations are at-risks of severe precipitation and flooding. For coastal regions that have experienced rising sea levels, and for arid regions that have experienced drought such as the west and southwest, intense rains also increases the risks of dangerous flash floods (Melillo et al., 2014).

The most salient temperature change variable for all regions was increased minimum temperature (see Fig. 1 and Table 1) with the highest increase between 1990 and 2015 in the southwest (5.78%) and central (4.39%) climate zones compared to the long-term average from 1901. There was a slight percentage increase in maximum temperature for four of the six represented climate zones, with the southeast (–.53%) and northeast (–.31%) experiencing a slight decrease. However, of all the higher maximum temperatures represented in the retrospective analysis in Table 2, ***only one*** location (i.e., urban Texas) exhibited a significant relationship with high maximum temperatures –between 85 and 90 °F – and only for the tent sales category. This finding is contrary to previous survey where tourists have indicated that temperatures moving into the 90s °F is adversely related to travel (Fischelli et al., 2015; Rutty & Scott, 2016). That is, while visitors may indicate that they will not travel, when it comes to sales across the United States at the focal business locations, this is not the case. This is a major contribution of the study, in that stated preferences of consumers related to temperature are not confirmed in actual sales behaviors.

While higher temperatures have been attributed to an increase in intense precipitation events (Melillo et al., 2014) that are negatively related to sales, the same is not true higher maximum temperatures. Low temperatures that approach or exceed freezing temperatures below 32 °F generally have a negative impact on sales around the United States, and with rising minimums and maximums, sales tend to share a positive relationships. With the knowledge that minimum temperatures are raising across the country, and that seasonality is shifting across the majority of the United States (Monahan et al., 2016), this is an area of opportunity for businesses throughout the country, especially considering the enhanced accuracy of forecasting technologies.

5.2. Business outcomes

As shown in the strength of the retrospective forecasting models, the most powerful predictor of future sales is historical sales. Weather predictors were significantly related to sales in the vast majority of models for sales categories, with the greatest enhancement to forecasting accuracy of 3.6% for cabin sales in coastal California followed by 3.1% for tent sales in urban New Mexico. These findings are very encouraging, as the predictability of weather variables enhanced the forecasts despite no formalized action by the business unit to address adverse or favorable conditions per the organization's leadership. With a focus on seasonality of the relationships that were shown to be significant, and by exploring temporal relationships exhibited, the study provides a blueprint for how business locations can address both adverse and favorable conditions. This in turn would presumably increase the predictive strength of the weather variables when businesses are actively addressing local conditions.

Businesses have adaptive capacity to counteract climate change and extreme weather events by planning beforehand and responding after an adverse event. This may not be as apparent. As shown in the ARIMA models, the auto-regressive term demonstrates for the majority of models that previous sales are positively related to future sales. For popular locations, it is likely that strong seasonal sales and cancellation policies protect sales from interacting with weather variables. Also, the moving average term demonstrates that there are unexplainable “errors” in the model. That is, there are unaccounted for external or internal factors that cannot be determined from the models. Scott and McBoyle (2007) demonstrated that organizations can make local changes to mitigate the adverse effects of changes, and many large businesses are using analytic tools to shift marketing and distribution budgets to counteract adverse weather conditions. For instance, if the ARIMA portion of the models reads (2, 0, 4) this would indicate that sales up to two days previously impact the current day sales, and that an error term from up to four days previous impact the current day's sales. However, the model does not tell what the business and/or market is doing for previous days to account for future lost sales. Additionally, the Results and Analysis section above provides a detailed discussion about the weather predictor models, and the temporal impact they have on sales throughout the United States within climate zones. As eluded to above, with a seasonal focus and a clearer understanding of the local impact of specific events, businesses can make better informed decisions to adapt to adverse and favorable conditions with a knowledge of climatic projections in the respective climate zone. With this focus, it could be expected that explained variability in the forecast would increase and the error terms would weaken.

5.3. Community engagement

For some areas, business-as-usual overrides the impacts of weather on the forecast. This could be viewed positively and also with caution. In terms of the businesses themselves and the financial outcomes, this demonstrates the adaptive capacity to cope, and even thrive, in the face of adverse conditions. For instance, for the coastal Florida location in the southeast the increased frequency and intensity of storms and floods is well documented (Melillo et al., 2014). However, retrospective time series forecasts for this location are largely immune to weather predictors. When this is the case, it is important for businesses to be vigilant of approaching systems and have warning systems in place for unpredicted and adverse weather events to protect the health and safety of customers and employees. This adaptive capacity could extend into surrounding communities, where businesses could draw from their social inclusivity to engage residents to respond to environmental hazards before, during, and after extreme events (Craig et al., 2018). As trusted members of the community, and with a more robust knowledge of the time it takes for individuals to respond to approaching weather events, businesses can communicate both internally and externally to enhance mitigating and adaptive response efforts to severe events.

5.4. Limitations and future research

The study was not without limitation. As shown in Table 2, the majority of the models demonstrated seasonality. With the analysis focusing on long-term daily data for almost 10 years, the study was able to provide an overall assessment of the relationships between weather, climatic variability, and sales. However, a higher resolution time series forecast for each location that focused on time periods where adverse or favorable conditions occurred with higher frequency would have likely enhanced the predictability of the weather variables. Future research should examine the seasonal shifts and impact of specific events when they are more likely to occur.

For the time series forecasting portion of the study, there were only 13 locations included. The inclusion of 28 locations within six climate zones were included to provide a historical benchmark. Future research should include more businesses throughout the focal climate zones to create a more accurate benchmark for local businesses and communities. The study did provide a methodological blue-print for studying the relationships between sales and weather predictors. Future studies should be conducted around the world using a similar methodology, and results should be used to enhance the adaptive capacity of businesses and communities in practice. Also, the inclusion of error terms in the models could potentially counter-act weather impacts. Future studies should include additional variables to help decrease the amount of error, including marketing efforts, response strategies, and other quantifiable variables that could counteract the impacts of localized weather events.

Understand of events and willingness among local business location leadership is not captured in this study. Consistent with the previous pro-environmental research (Allen, 2016), even when there is a knowledge of an environmental risks, there are still salient barriers that keep individuals from acting. As such, future studies should explore the leader understanding and behaviors enacted in order to use the information at hand to adapt and mitigate the adverse effects of climate change, adverse weather events, and favorable conditions.

6. Conclusion

This study was the first to operationalize the construal level theory in order to assess the impact of climate change and weather events – both adverse and favorable – on businesses located throughout six climate zones in the United States. The study provided a historical benchmark of changing climatic conditions, where climate zones in the central and eastern United States experienced increased precipitation and increased minimum temperatures. Conversely, locations within the west, southwest, and south climate zones experienced a decrease in precipitation, while also experiencing both warmer maximum and minimum temperatures. The study addressed the salient gap in the management literature by integrated climatic and business outcomes, finding that weather events – both adverse and favorable – significantly enhanced overall sales forecasts by up to 3.6%. The retrospective time series forecasting method is discussed as a blueprint for how all businesses can analyze weather and business outcomes. With the integration of weather forecasting into sales forecasting, and by examining at-risks seasons with a higher resolution, businesses have the capacity to use this methodology to greatly enhance their adaptive response to persistent climate change and localized weather events.

Appendix A. Weather and Extreme Weather Variables

Minimum temperature (tmin) and maximum temperature (tmax) values were observed in degrees Celsius (°C) as reported in Table 1. Minimum temperature is the lowest observed temperature during a given day, and maximum temperature the highest. There are several variations for both measures used to capture specific and extreme events. For comparison sake, the temperatures were reported in °F. Minimum temperature below 32 °F (tmin<32), from 32 °F to 45 °F (tmin3245), from 45 °F to 55 °F (tmin4555), from 55 °F to 65 °F (tmin5565), from 65 °F to 75 °F (tmin6575), from 75 °F to 85 °F (tmin7585), and over 85 °F (tmin>85) are included. Temperature maximums were reported for all of the same values as minimum temperature other than over 85 °F, and included the root tmax for abbreviations. The additional high temperature variables include from 85 °F to 90 °F (tmax8590), from 90 °F to 95 °F (tmax9095), and over 95 °F (tmax>95).

Precipitation (ppt) was the observed rain level in millimeters for a given day. There are several variations of precipitation used to analyze the impact of specific and extreme precipitation events. No precipitation (ppt0), precipitation from .01 to .99 mm (ppt1), from 1 to 1.99 mm (ppt2), from 2 to 2.99 (ppt3), from 3 to 3.99 mm (ppt4), from 4 to 4.99 (ppt5), from 5 to 5.99 mm (ppt6), from 6 to 6.99 (ppt7), from 7 to 7.99 (ppt8), from 8 to 8.99 mm (ppt9), and from 9 to 9.99 mm (ppt10) are included. There are four extreme precipitation variables included: precipitation over 10 mm (ppt>10), over 20 mm (ppt>20), over one inch (ppt1inch), and over two inches (ppt2inch).

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