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Climate Resources for Camping: A Resource-Based Theory Perspective

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Climate Resources for Camping: A Resource-Based Theory Perspective

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Abstract

Camping is a salient economic contributor to nature-based tourism that is also beholden to the natural environment. Climate resources are the combination of naturally occurring meteorological variables of empirically observable importance to firm performance. Tourism climatologist are at the forefront of climate resource research, where investigations have been primarily empirically derived rather than guided by theory. Accordingly, we introduce climate resources to the management discipline's resource-based theory, operationalizing climate resources as public goods in addition to other public goods like open access innovation. We investigate the value, rareness, and inimitability of climate resources at 36 managed United States National Park Service campgrounds from 1984 to 2019. Results spatially and temporally demonstrate (1) the value of climate resources to firm performance, (2) that climate resource value varies geographically, and (3) that climate resources are becoming rarer at lower latitude and altitude geographies. Implications, limitations, and future research directions are provided.

Keywords: resource-based theory; climate change; weather; camping; nature-based tourism

Introduction

Nature-based tourism is among the fastest growing segments of tourism (Kunezi & McNeely, 2008; Margaryan et al., 2017). According to Valentine (1992, p. 108), “nature-based tourism is primarily concerned with the direct enjoyment of some relatively undisturbed phenomenon in nature.” A key contributor to nature-based tourism in the United States are National Parks Service (NPS) national parks, a network of 63 preserved natural lands that provide a variety of tourism and recreational activities including camping (NPS, 2022a). In 2019, the last full year uninterrupted by the global COVID-19 pandemic, there were a total of 4.1 million recreational tent and recreational vehicle (RV) overnight camping stays throughout the 63-unit system (NPS, 2022b). According to Craig et al. (2021, p. 354), “camping provides a useful context to study travel decisions because it is susceptible to factors in the natural environment (e.g., weather, climate) [and] has a high participation rate among United States households.” Tourism climatologist refer to these natural environmental factors as *climate resources*, or the combinations of naturally occurring meteorological variables (e.g., temperature, precipitation) that affect the value of goods or services dependent on time and space (de Freitas, 2003; Martin, 2005; Scott et al., 2004).

However, tourism climatologists have yet to theoretically explore contributions of climate resources to performance and competitive advantage (e.g., Perch-Nielson et al., 2010). We address this research gap by introducing climate resources as a natural resource-type to resource-based theory (RBT; Barney, 1991). RBT contends that firm access or control of valuable, rare, and inimitable resources, capabilities, and competencies contributes to firm performance (Barney, 1991). To investigate the value, rareness, and imitability of climate resources, we present a case study of NPS managed campgrounds from 1984 to 2019. NPS campgrounds are conceptualized as nature-based tourism firms, an operationalization that allows us to contribute climate resources to RBT as public goods. Khan and Munira (2021) highlight that weather and climate are public goods ranging from local to national geographic scale, while climate change is of a global scale. Extending RBT, we empirically investigate the contribution of climate resources to explanations of NPS campground performance from 1984 to 2019.

Below, we review the literature on climate resources. We develop three hypotheses and a proposition based on RBT. Next, we provide methods, results and analysis, discussion, and conclusion sections.

Climate Resources

As a discipline, tourism climatology is at the forefront of climate resource research (e.g., de Freitas, 2003; Martin, 2005; Scott et al., 2004). We formally define climate resources as observable meteorological variables of consequence to firm performance that vary across time and space. Climate resources establish favorability of business conditions, and firms with "climate resources of better quality than others enjoy a competitive advantage (Perch-Nielson et al. 2010, p. 364). In the most basic form, weather and climate are nonexcludable and nonrival resources (i.e., public goods) that (1) can be used by more than one person and (2) anyone can use once produced (Turner, 2002). This operationalization allows us to introduce climate resources to RBT alongside other types of public goods (e.g., knowledge, open access innovation) (Alexy et al., 2018; Grant, 1996) as well as other tangible (e.g., cash, equipment, plant) and non-tangible (e.g., corporate diversification, third-party certifications) resources (Barney et al., 2010; Marshall & Standifird 2005; Wheelen et al., 2018).

Climate resources capture the integrated effects of varied meteorological variables that interact with humans and firms in different ways. There are three categories within which climate resources reside including thermal (e.g., temperature, dew point temperature, relative humidity), physical (e.g., precipitation, wind), and aesthetic (e.g., sunshine hours) (de Freitas, 2003; Martin, 2005). Travelers respond differently to the variables within the three resource categories depending on tourism sub-sector (e.g., Ma et al., 2021a; Scott et al., 2016). For instance, beach tourists have higher thresholds for maximum temperature and precipitation than urban tourists (Scott et al., 2016). These differences are captured by the two equation variations for the Holiday Climate Index (i.e., HCI-beach, HCI-urban; Scott et al., 2016). Here, we calculate climate resources for camping using the Camping Climate Index (CCI; Ma, Craig, & Feng, 2020a), an index formulated for camping. The CCI is unique because it includes thresholds levels for extreme hot temperature, extreme low temperature, high winds, and heavy precipitation that force the index to "unfavorable." The CCI has proven more predictive than other indices for non-profit (Ma et al., 2021b) and for-profit (Ma et al., 2020a) campgrounds. Additional information about the CCI is provided in the methods section.

Resource-Based Theory and Hypotheses

Resource-based theory (RBT) posits that firm performance (e.g., profits, revenues, sales) stems from access to valuable, rare, and inimitable resources (Barney, 1991; Kraaijenbrink et al., 2010). Possessing and utilizing valuable, rare, and inimitable resources supported by firm capabilities and competencies contributes to superior performance relative to others that lack those assets (Barney, 2018). Natural resource types like climate resources remain largely absent from RBT (Barney, 2018; George et al., 2015). Here, we explicitly recognize climate resources as a natural resource type that contributes to firm performance. Based on RBT application and researched-based evidence, we establish the value, rareness, and inimitability of climate resources geographically over time. We offer three hypotheses for value and rareness and a proposition for imitability. We refrain from hypothesizing about inimitability because our operationalization precludes empirical testing.

Value

Climate resources demonstrate value that varies across space and time. Resources are valuable if firms can charge more than competition or have lower cost structures than competitors (Barney, 1991). Superior value propositions support premium pricing and low-cost structures (Wheelen et al., 2018). The temporal and geographic distribution of climate resources has unequal and disproportionate value dependent on organizational characteristics (Reidmiller et al., 2018) that influence customer willingness to pay. For instance, Craig and Feng (2018) found that climatic variability (operationalized using daily weather) from 2007 to 2016 (i.e., over time) accounted for up to 3.9% of sales dependent on for-profit campground location (i.e., geography) and camping type (i.e., firm characteristic). Resource and performance relationships are positive where improved climate resources are associated with improved firm performance and vice versa, demonstrating resource value across space and time. We offer two hypotheses:

Hypothesis 1 (H1): *Climate resources are valuable.*

Hypothesis 2 (H2): *Climate resource value varies geographically.*

Rareness

The rareness of climate resources also varies across space and time. Resource rareness occurs when the number of firms with access to or control of a resource is smaller than the number of firms needed to create perfectively competitive markets (Barney, 2001). Rareness exists when competitors do not or cannot possess resources at the same level (e.g., Wheelen et al., 2018). Distribution and redistribution of climate resources as a process of climate change are directly related to the rareness of resources. For example, tourism climatologists have empirically established the redistribution of favorable climate resources over the span of decades (i.e., climate change) towards higher latitudes and altitudes, demonstrating that resources influence sub-sectors (e.g., alpine skiing, beach) and geographic locations differently (e.g., Dannevig et al. 2020; Ma et al. 2020b; Fisichelli et al. 2015; Scott et al. 2004; Rivera & Clement, 2019). The redistribution makes favorable climate resources at some locations even more rare (e.g., fewer alpine ski resorts with reliably snowy seasons) allowing firms that possess or can access resources to improve performance (e.g., increased lift ticket sales and/or premium pricing). Therefore, the current distribution of climate resources and redistribution of resources over time as a global process of climate change will determine local and regional geographic locations where resources are rare and where they are not. We offer our third hypothesis:

Hypothesis 3 (H3): *Climate resource rareness varies geographically.*

Imitability

Imitability is the rate at which others can duplicate resources and/or capabilities (Wheelen et al. 2018, p. 136). A capability is a firm's "ability to exploit its resources" (Wheelen et al. 2018, p. 134); the ability to exploit climate resources that result in improved performance (e.g., campsite occupancy) is an example of a climate resource capability. A salient factor influencing imitability is a competitor's financial ability to duplicate resources or capabilities. Inimitable—or nonreplicable—resources, capabilities, and integration of capabilities throughout a firm positively contribute to performance and competitive advantage (Barney, 2001).

An example of an increasingly inimitable resource for alpine skiing firms is snow. Snow is dependent on two climate resources: low temperatures and precipitation (Rutty et al., 2021). Climate change reduces the prevalence of low temperature resources needed to convert precipitation into snow (Feng & Hu, 2004). Firms with lower latitude and altitude locations are increasingly relying on artificial snowmaking (Reidmiller et al., 2018; Scott & McBoyle, 2007). As temperature and precipitation resources needed for alpine skiing decline with climate change, snowmaking will become more difficult, providing high-altitude locations with an advantage over low-altitude locations where outdoor snowmaking may not be viable (Dennevig et al., 2020; Reidmiller et al., 2018).

The imitability of capabilities is also important when considering climate resources. For instance, favorable climate resources for camping are improving at higher altitude and latitude locations in the Rocky Mountains in the Western United States (Ma et al., 2020b). Many of the campgrounds are surrounded by federally preserved and managed lands (NPS, 2022c), limiting competitors' capabilities to access and exploit the climate resources. However, there are locations throughout the NPS system where the access to favorable climate resources is more imitable as evidenced by the presence of for-profit campgrounds. For instance, Jellystone Park (2022) operates an over 300 site campground near Mammoth Caves National Park in Kentucky, United States on privately owned land. The presence of this campground provides evidence of a for-profit firm with the capabilities to access and exploit comparable climate resources to the NPS campground, making the geography's climate resources more imitable. Accordingly, we propose:

Proposition 1 (P1): *The imitability of climate resources and/or capabilities vary geographically.*

Methods

Data

We analyzed 432 months of tent camping occupancy, recreational vehicle (RV) camping occupancy, and climate data from 1984 to December 2019. Tent and RV occupancy are the dependent variables and climate resources are the independent variables. Monthly tent and RV camping occupancy data were obtained from the NPS (NPS, 2020a). Unlike for-profit campsites, NPS campsites are not variably priced making occupancy a synonymous park-level performance indicator with sales. We include both tent and RV camping because each responds differently to weather and climate (Craig & Feng, 2018). As shown in Figure 1, the sample consists of campgrounds at 36 United States National Parks representative of the five NPS management regions (NPS, 2020b). The sample was restricted to parks in the contiguous United States that offered tent or RV camping for the duration of the study period.

[Insert Figure 1 about here]

Climate data were used to compute the generalized Camping Climate Index (CCI; Ma et al., 2020a). Tourism climatologist routinely use indices to quantify bundles of climate resources because different activities (e.g., beach, camping) are influenced by different combinations of meteorological variables (Perch-Nielson et al. 2010). Also, the CCI has been validated at both for-profit and non-profit campgrounds (Ma et al., 2021a). Calculating the CCI requires seven meteorological variables: mean temperature (°C), maximum temperature (°C), minimum temperature (°C), dew point temperature (°C), precipitation (millimeters), windspeed (kilometers/hour), and sunshine hours were calculated based on daily shortwave radiation (Watts/meter^2) as prescribed by Allen et al. (1998).

The sunshine hour is one of the frequently used meteorological variables. For example, the CCI and several other climate related indexes use sunshine and other meteorological variables to estimate the impact of climate on tourism. The sunshine can also be used to estimate the solar radiation as indicated by FAO 56 book (Allen et al., 1998):

$$R_s = (a_s + b_s \frac{n}{N}) R_a$$

Where Rs is the solar (or shortwave radiation), while Ra is the extraterrestrial radiation, n is the actual sunshine, and N is maximum possible duration of sunshine. The a_s and b_s are regression constants, respectively. For a given location, the Ra and N can be calculated based on the latitude and the day of year (i.e., doy=1 for January 1st, and doy=365 or 366 for December 31). Reorder the above equation we get:

$$\frac{R_s}{R_a} = a_s + b_s \frac{n}{N}$$

Therefore, the above equation shows the linear relationship between Rs/Ra and sunshine.

In our study region, the sunshine observations are short and scarce, but the solar radiation can be retrieved from satellite or climate reanalysis (e.g., NASA, 2020). Since the sunshine and Rs/Ra are linearly related, and the a_s and b_s are regression constant, we believe it is reasonable, though certainly not perfect, to estimate sunshine using the Rs:

$$n = N \times (\frac{R_s}{R_a} - a_s)/b_s$$

Our notion is also supported by Kubokawa et al (2014), who firstly estimate the sunshine based on the model simulated solar radiation, and then use the estimated sunshine and other climate variables to evaluate the future changes in tourism climate resources. The method we used is similar to Eq (4) of Kubokawa et al (2014). Furthermore, others have established a very strong correlation between the linear relationship shared by shortwave radiation and sunshine hours (e.g., Yang & Tsukamoto, 2009).

We retrieved daily values from NASA (2020) for each variable from January 1, 1984 to December 31, 2019 (n = 13,149) using latitude and longitude coordinates for each of the 36 parks. The CCI equally weights (i.e., 50%) thermal comfort (i.e., mean daily temperature, mean daily dew point temperature) and sunshine hours based on a four-tiered rating system:

unfavorable (0-3), acceptable (3-5), good (5-7), and optimal (7-10; see Table 1). Our measure of thermal comfort is known as the Humidex. The CCI also considers daily thresholds for thermal (maximum and minimum temperature) and physical (precipitation and windspeed) variables. Exceeding a threshold forces the CCI to 3 (categorized as “unfavorable”) or the average for thermal comfort and sunshine hours, whichever is the lowest (Ma et al. 2020b).

[Insert Table 1 about here**]**

Statistical Methods

SARIMA models

We used Autoregressive Integrated Moving Average (ARIMA) models to test **H1** and **H2**. ARIMA-based models are retrospective time series models fitted to time series data to predict future points in the series. Rice et al. (2019) established SARIMA (i.e., seasonal ARIMA) models as the best-fit forecasting models for camping using historical monthly NPS camping reservation data. To test the first two hypotheses, SARIMA models were formed using the *auto.arima* function from the *forecast* package in R. The *auto.arima* function applies the Akaike information criterion (AIC) to optimize each model to reduce risks of over- (i.e., goodness of fit) and underfit (i.e., model simplicity).

We ran two models for each location and camping type, one with no regressor and one with CCI as the regressor. The model without the regressor provides a retrospective timeseries forecast based on historical occupancy alone. The model with CCI as the regressor provides a retrospective timeseries forecast based on climate resources and historical occupancy. The root mean square errors (*RMSE*) difference between the two models indicates if the regressor (i.e., CCI) improves explanatory power of the model or not.

For the two models, we used the first 35-years of data (1984 – 2018, *n* = 420 months) as the training dataset, and the last one year (2019, *n* = 12 months) as the testing dataset. We compare accuracy of both models by using *RMSE*. Unlike R^2 which is a relative measure of fit, the *RMSE* is an absolute measure of fit thus is reported in the same units as the dependent variable (i.e., camping occupancy). The difference in *RMSE* demonstrates the comparative value (i.e., occupancy) of climate resources at each park location.

SARIMA (p, d, q)(P, D, Q)[s] models include integers greater than or equal to zero and refer to the order of the following terms: (p) non-seasonal autoregressive, (d) non-seasonal integrated, (q) non-seasonal moving average, (P) seasonal autoregressive terms, (D) seasonal integrated, (Q) seasonal moving average, and (s) periodic. For example, a SARIMA notation (1,0,1)(2,0,1)[12] is interpreted: (p) one lag of stationarized series (e.g., April's occupancy is related to March's); (d) zero differencing to stationarized series (e.g., the 35 year training data are stable); (q) one lag of moving averages (e.g., April's forecast error is related to March's); (P) two lags of stationarized series (e.g., April 2019 occupancy is related to April 2018 and 2017 occupancy); (D) one seasonal differencing is needed to stationarized (i.e., stabilize) data; (Q) one lag of the seasonal moving average (e.g., the April 2019 forecast error is related to the April 2018 forecast error); and (s) the periodic term for monthly data is 12.

Fitted Linear Trend

H3 contends that climate resource rareness varies geographically throughout the study period. Consistent with climatology studies (e.g., Feng and Hu 2004, IPCC 2021, Stewart et al. 2005), we used fitted linear lines via the *stats* package in R to test the hypothesis**.** Including all observations throughout the study period reduces internal variability of the data (IPCC, 2021). The fitted linear lines provide the long-term trends for daily CCI (i.e., climate resources) from

1984 to 2019 for the 36 parks. The number of optimal camping days with CCI ≥ 7 were aggregated both annually and seasonally at each location to form a 36-year time series from 1984 to 2019. The slope of the fitted linear line multiplied by the years of observation is the total number of optimal days change from 1984 to 2019 (see Figure 2), and the comparison of the last period (i.e., 2019) with the first period (i.e., 1984) on the fitted line is the total percentage change (see Table 3).

Results and Analysis

H1 and H2*:* Value

To test **H1** and **H2**, that climate resources are of value and vary geographically, we compared changes in *RMSE* for SARIMA models with and without climate resources (i.e., CCI) as the regressor (Table 2). Findings indicate positive changes in *RMSE* for all locations and both camping types, an indication of the widespread value of climate resources to firm explanation of performance. Overall, *RMSE* changes indicate the inclusion of climate resources as a regressor improves the prediction accuracy for both tent and RV camping performance over the test periods, 9.23% for tent occupancy (n = 36) and 8.61% for RV occupancy (n = 33). This equates to 4,795 tent camping occupancy nights and 5,864 RV occupancy nights in 2019 alone (see Table 2). Results provide robust support for **H1**.

[Insert Table 2 about here]

Results indicate value varied from inconsequential to substantial. For instance, at the lower altitude Big Bend NP in Texas, model improvement with climate sources was only .01% and .16% for tent and RV occupancy, respectively. The greatest improvement for tent occupancy (i.e., where climate resources were of most value) occurred at Great Sand Dunes NP in Colorado (52.40%) and for RV occupancy at Bryce Canyon NP in Utah (69.60%). On average, the

Northeast region demonstrates the largest improvement in model accuracy (13.01%; not shown) whereas the Southeast demonstrates the smallest improvement (2.91%; not shown), suggesting the influence of climate resources is of greater significance to value and performance in the Northeast. The variable nature of SARIMA model improvement in Table 2 supports **H2**, that value of climate resources varies geographically.

H3: Rareness

H3 posits that climate resource rareness varies geographically throughout the study period. To test **H3**, linear fitted lines were produced to observe trends for the 36 NPS campgrounds from 1984 to 2019 (see Figure 2 and Table 3). During this span, optimal climate resources (i.e., optimal CCI days) became rarer at five of the 36 locations (13.9%) in lower-latitude Intermountain (i.e., Big Bend and Guadalupe Mountains National Parks in Texas), Southeast (i.e., Dry Tortugas and Everglades National Parks in Florida), and Pacific West (i.e., Joshua Tree National Park in California) regions. For the other 31 locations, optimal climate resources became more abundant. In general, summer experienced the bulk of the climate resource improvement, shoulder seasons—the spring and fall meteorological seasons—experienced a moderate improvement, and resource favorability became rarer in the winter. Based on results reported by Figure 2 and Table 3, we observed that climate resources are becoming rarer below around 35°N latitude during the summer months. The findings support **H3.** This finding is consistent with Fisichelli et al. (2015) who estimated parks visitation will improve into the 2050's with exception of lower latitudes due to unacceptably warm temperatures.

[Insert Figure 2 and Table 3 about here]

Discussion

The primary contribution of the study is the theoretical introduction and operationalization of climate resources to RBT. The tourism discipline's study of climate resources has been primarily empirically derived without application of management theory to inform the performance implications of the resources (e.g., Ma et al., 2021a,b; Perch-Neilson et al., 2010). We overcome this research gap contributing climate resources as public goods for camping, extending the RBT's capacity to explain nature-based tourism firm performance as a function of resource value, rareness, and inimitability. We empirically demonstrate that the (1) resource bundles of weather and climate captured by the CCI significantly influence value creation and campground performance (i.e., occupancy), and (2) heterogeneity of climate resources as a process of climate change impacts rareness geographically (e.g., latitude) and temporally (e.g., meteorological season). We also provide interdisciplinary findings to support the proposition that imitability of climate resources and capabilities vary geographically.

The introduction of climate resources to RBT contributes to the expansion of RBT beyond its original scope to include public resources alongside private resources (Kraaijenbrink et al., 2010). Knowledge (Grant, 1996; Spender & Grant, 1996) and open-access innovation (Aelxy et al., 2018) are two previously documented RBT examples where firms are organized to exploit public resources. Nature-based tourism provides a necessary pathway to introduce climate resources as a public good to RBT because its representative firms (e.g., camping, alpine skiing) are organized to leverage natural resources (e.g., climate resources) in pursuit of competitive advantage. Because climate resources help explain firm performance, identifying and operationalizing climate resources expands RBT's power to explain performance heterogeneity.

Despite being an over $150 billion industry in the United States, camping remains an understudied segment of tourism (Rice et al., 2019; Rogerson & Rogerson, 2020). Accordingly, the application of RBT to camping—here operationalized as a nature-based segment of tourism—is another study contribution. In terms of value, results highlight the financial value that campgrounds can capture from climate resources, even when campground operators are not actively working to exploit the resources. This is consistent with Craig and Feng (2018), who found that campgrounds can gain up to 3.9% in additional value (i.e., sales) when favorable daily climate resources are observed. The documented value of climate resources for camping point to an opportunity for non-profit and for-profit campgrounds alike to utilize CCI forecasts to inform value-chain activities (e.g., marketing favorable camping conditions, variable pricing) to capture additional value, particular for desirable climate resources that are becoming rarer. Comparably, campground operators can utilize historical CCI conditions in the United States (Ma et al., 2021b) and globally (Ma et al., 2021b) in addition to forward looking CCI projections with future climate change scenarios to establish where favorable climate resources for camping will become rarer, unchanged, or more abundant. Climate resource capabilities (e.g., CCI forecasts or projections) that other firms to cannot replicate indicates inimitability, another potential source for competitive advantage.

Looking forward, the remainder of the study provides climate resource implications, limitations and future research, and conclusion sections.

Climate Resource Implications

Climate resources have powerful impacts on human activities and firm behaviors, and climate change complexities are projected to accelerate in the coming decades (IPCC, 2021; Riedmiller et al., 2018). It is imperative to explore how tourism firms are impacted by climate resources—and how these resources are changing due to climate change—to inform response. This study makes a significant contribution to the tourism and management literatures by translating climatology knowledge (i.e., climate resources) into practical information for managerial decision-making based on management theory (i.e., RBT; Barney, 1991). Climate resources are supply-side resources for the firm, and the use of variably weighted composite climate indices (or bundles) can be used to integrate climatic elements into a standard measure that reflects the quality and quantity of the resources relevant to firm performance. The CCI used in this study is able to quantify the climate resources for camping and comparable nature-based firms that seek to explore climatic impact-based development associated with opportunities and risks across space and time (Ma et al., 2021a). Considering that the CCI has proven to be more predictive of camping behaviors at for-profit and non-profit campsites than other indices (Ma et al., 2021a), campground operators may consider using the index for short-term forecasts to inform value-chain activities (e.g., marketing, staffing) that either (1) exploit favorable climate resources or (2) minimize disruptions from unfavorable conditions.

The business environment enjoyed by firms for most of human economic history is becoming increasingly destabilized, where climatic conditions can quickly challenge resource boundaries (Grasso, 2007; McKercher, 1999). The potential for rapid and potentially disruptive changes to climate resources highlights a need to actively manage the resources throughout the value chain to maximize opportunities and minimize threats to firm performance (Bergmann et al., 2016; Reidmiller et al. 2018). Climate resource thresholds (e.g., maximum and minimum temperature, extreme precipitation, high wind) are particularly susceptible to the increased frequency and intensity of disruptive extreme weather events (e.g., Becken & Wilson 2013; Hewer, 2020). Thresholds within climate resource bundles should also be actively managed since extremes may or may not influence value chain activities depending on industry and firm characteristics (Bergmann et al., 2016). The CCI can serve as a useful index for campground operators—non-profit and for-profit—to project the short-term (un)favorability of camping conditions, and to identify potentially dangerous upcoming weather events to help manage the safety of staff and travelers.

As our findings demonstrate (Figure 2, Table 3), the redistribution of climate resources occurs unequally and can inequivalently impact geographies. The same holds true for other tourism subsectors such as coastal tourism (Bestard & Nadal, 2020) and alpine skiing (Dannevig et al., 2020). For camping, our results generally demonstrate that higher latitudes and altitudes benefit the most from the redistribution of climate resources as a result of climate change than lower latitudes, where the improvement is significantly and positively related to our measure of firm performance (i.e., camping occupancy). For campground operators, the redistribution of favorable conditions suggests two potentially adaptive responses: (1) camping accommodations that better respond to adverse conditions at existing locations (e.g., air-conditioned cabin camping) and/or (2) identification and acquisition of locations with increasingly rare, favorable climate resources. Furthermore, globally (Ma et al., 2021a) and in the United States (Ma et al., 2021b) favorable climate resources for camping are extending into the spring and fall shoulder meteorological seasons, providing existing campgrounds with an opportunity to expand camping season overlapping with the improved conditions.

Limitations and Future Research

Though novel, this study is not without limitations. The primary limitation is the use of monthly rather than daily data for our outcomes of interest, tent and RV camping occupancy. This is a common limitation for camping (Craig & Feng, 2018) where high temporal resolution data is not readily available. We partially overcome the use of monthly camping data by first calculating the CCI daily then aggregating the scores to monthly. The CCI was validated using daily camping data at for-profit campgrounds, and has a mechanism force the score to the "unfavorable" when daily thresholds (e.g., maximum temperature, extreme precipitation) are exceeded. From a tourism climatology perspective, the use of daily data aggregated to monthly is superior to using monthly means because it better captures within month weather variations that are more relevant in influencing tourists' decisions on short-term basis (Ma et al., 2020a; Wilkins et al., 2021). For researchers and managers who only have access to monthly performance data, we recommend capturing within month thresholds (e.g., frequency of days with high temperatures or heavy precipitation). Ideally, researchers can match daily climate resource data with higher resolution tourism behaviors to gain a clearer perspective about within-month travel decisions.

Another limitation to the study is that firm data (i.e., camping occupancy) was not available at all national parks, so some regions are underrepresented (e.g., the Southeast and Northeast). Future researchers should consider extending the application of climate resources to other outdoor outcomes like visitation, another important measure of parks performance that is more widely available than camping data. For instance, Wilkins et al. (2021) recently published a study that utilized geotagged social media posts to establish daily temperature thresholds at 110 parks in the United States. Consistent with our methods, Wilkins et al. (2021) aggregated daily threshold data to monthly, which correlated well with matched monthly parks visitation data. Future researchers and practitioners should continue to utilize mobile applications to establish high resolution climate resource and organizational performance relationships, regardless of industry. For example, Liu et al. (2020) utilized GPS data from a mobile fitness application to establish the relationship between hiking and daily climate resources (i.e., temperature, relative humidity, and sunshine duration) across 100 cities in China. Firms from a multitude of industries (e.g., automotive, media, retail, tourism) are increasingly utilizing GPS-enabled mobile applications like Liu et al. (2020), collecting vast amounts of "big" consumer data. This data holds great potential to establish unique climate resource bundles for specific customers and geographic locations.

Further, some of the regions used in the study include multiple climate zones, meaning that the climate characteristics within NPS megaregions can vary widely. Future researchers and managers should consider sorting by climate regions in addition to management designated regions. As the NRF (2017) demonstrates, consumers respond differently to climatic conditions in different geographic regions and at different times. While specific customer data (e.g., from a mobile application) can inform the management of some value chain activities (e.g., marking and sales), a broader geographic understanding of relationships between organizational outcomes and climate resources can inform the management of a wider array of activities such as operations, logistics, and human resource management.

Lastly, the study is representative of camping as form of nature-based tourism, but there are other instances when camping is not nature-based (e.g., urban tourism). It may be necessary for future researchers to explore the fit of the CCI compared to other potentially more predictive indices (e.g., HCI-urban; Scott et al., 2016) dependent on the which type of tourism camping is most closely aligned.

Conclusion

This study introduces climate resources within the resource-based theory (RBT), drawing from the case study of NPS managed campgrounds throughout the contiguous United States.

Climate resources are combinations, or bundles, of meteorological variables that are of empirical significance to firm performance. Using a composite climate index (i.e., the camping climate index) to operationalize climate resources, we empirically demonstrate the value and variability of climate resources dependent on location, meteorological season, and occupancy type (i.e., tent or RV). Study results also demonstrate that climate resources are being redistributed as a process of climate change. Further, results demonstrate that favorable climate resources for camping are becoming rarer in certain regions of the United States (i.e., lower latitudes); however, the majority of the locations (i.e., middle and upper latitudes) in the study benefited from improved climate resources as a process of climate change over time. Though the context of climate resources operationalization is tourism, study methods, findings, and implications are applicable in practice for any firm regardless of size or industry.

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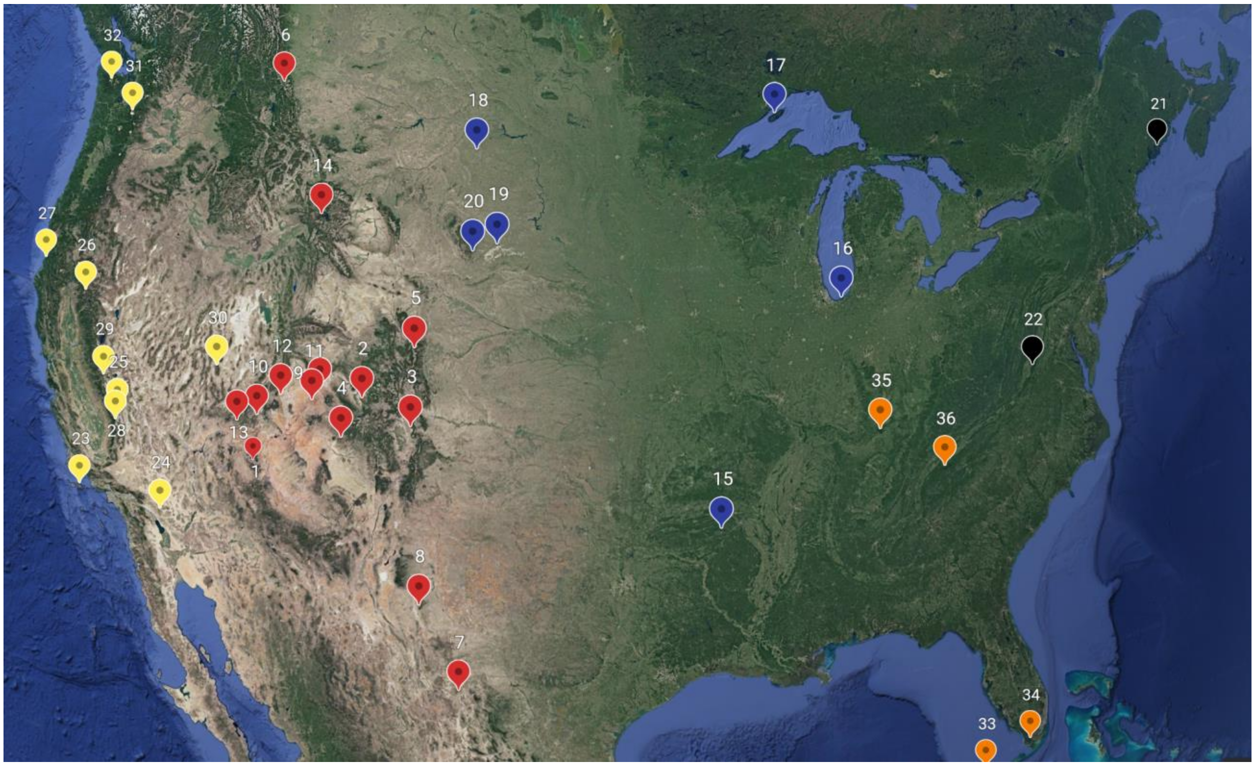
Figure 1. Camping Locations Sorted by National Park System Megaregion



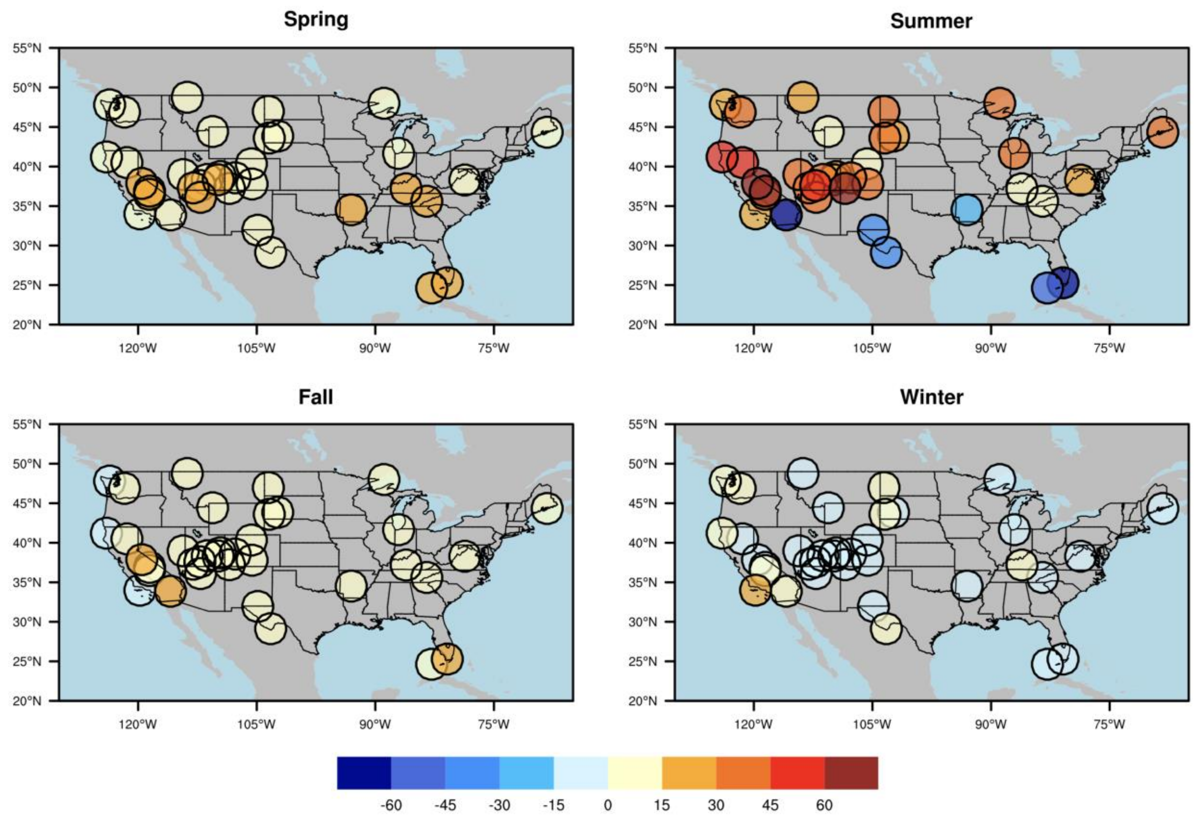
- Pacific West
- Intermountain
- Midwest
- Southeast
- Northeast

† Image and locations generated by www.googleearth.com

Table 1. CCI Rating System (adopted from Ma et al., 2020b)

Thermal Comfort (°C)	*Rating*	*Sunshine (hours)*	*Rating*	*Thresholds*	*Rating*
28-34	10	≥ 14	10	Maximum Temperature > 34°C	CCI ≤ 3
23-28	9	12-14	9	Minimum Temperature < 8°C	CCI ≤ 3
20-24	8	9-12	8	Precipitation > 10mm	CCI ≤ 3
16-20, 34-42	7	6-9	4	Windspeed > 23 m/s	CCI ≤ 3
12-16	6	4-6	2		
8-12	5	< 4	0		
4-8	4				
2-4	3				
≥42, < 4	0				

Figure 2. Total Number of Optimal CCI Camping Days Change by Season from 1984 to 2019



† CCI calculated daily from 1984 to 2019 (n = 13,149 days per park location)

Table 3. Change in Total Number of Optimal CCI days from 1984 to 2019

	Park	*State*	*Lat*	*Long*	*NP Region*	*Total Days Δ*	*Total %Δ*	*Spring*	*Summer*	*Fall*	*Winter*
1	Grand Canyon NP	AZ	36.11	-112.11	Intermountain	56	62%	18	37	6	-5
2	Black Canyon of the Gunnison NP	CO	38.58	-107.74	Intermountain	43	53%	12	40	3	-12
3	Great Sand Dunes NP & PRES	CO	37.79	-105.59	Intermountain	45	55%	10	40	2	-6
4	Mesa Verde NP	CO	37.23	-108.46	Intermountain	69	71%	10	64	6	-11
5	Rocky Mountain NP	CO	40.34	-105.68	Intermountain	5	5%	10	8	2	-15
6	Glacier NP	MT	48.76	-113.79	Intermountain	26	35%	9	23	2	-8
7	Big Bend NP	TX	29.13	-103.24	Intermountain	-21	-33%	7	-34	2	5
8	Guadalupe Mountains NP	TX	31.95	-104.87	Intermountain	-35	-41%	12	-36	0	-11
9	Arches NP	UT	38.73	-109.59	Intermountain	26	31%	13	17	6	-11
10	Bryce Canyon NP	UT	37.59	-112.19	Intermountain	71	86%	15	59	8	-11
11	Canyonlands NP	UT	38.33	-109.88	Intermountain	39	48%	16	28	6	-11
12	Capitol Reef NP	UT	38.37	-111.26	Intermountain	42	50%	12	35	8	-13
13	Zion NP	UT	37.3	-113.03	Intermountain	53	54%	16	34	11	-8
14	Yellowstone NP	WY	44.43	-110.59	Intermountain	21	29%	10	14	2	-5
15	Hot Springs NP	AR	34.52	-93.04	Midwest	2	2%	16	-16	5	-3
16	Indiana Dunes NP	IN	41.65	-87.05	Midwest	50	53%	13	32	14	-9
17	Isle Royale NP	MI	48	-88.91	Midwest	41	51%	9	34	6	-8
18	Theodore Roosevelt NP	ND	46.98	-103.54	Midwest	41	42%	6	34	0	2
19	Badlands NP	SD	43.86	-102.34	Midwest	38	38%	12	23	5	-2
20	Wind Cave NP	SD	43.6	-103.42	Midwest	55	53%	13	32	3	7
21	Acadia NP	ME	44.34	-68.27	Northeast	52	66%	10	43	5	-5
22	Shenandoah NP	VA	38.29	-78.68	Northeast	29	24%	15	16	3	-5
23	Channel Islands NP	CA	34.01	-119.78	Pacific West	41	46%	12	20	-6	15
24	Joshua Tree NP	CA	33.87	-115.9	Pacific West	-26	-29%	8	-60	16	10
25	Kings Canyon NP	CA	36.89	-118.56	Pacific West	81	93%	16	64	12	-11
26	Lassen Volcanic NP	CA	40.5	-121.42	Pacific West	71	77%	13	55	14	-11
27	Redwood NP	CA	41.21	-124	Pacific West	59	45%	7	50	-9	11
28	Sequoia NP	CA	36.49	-118.57	Pacific West	62	54%	18	34	9	2
29	Yosemite NP	CA	37.87	-119.54	Pacific West	87	87%	16	68	15	-12
30	Great Basin NP	NV	38.98	-114.3	Pacific West	62	59%	15	44	5	-2
31	Mount Rainier NP	WA	46.88	-121.73	Pacific West	46	43%	9	35	0	2
32	Olympic NP	WA	47.8	-123.6	Pacific West	37	32%	9	28	-2	2
33	Dry Tortugas NP	FL	24.63	-82.87	Southeast	-36	-17%	16	-46	5	-10
34	Everglades NP	FL	25.29	-80.9	Southeast	-35	-13%	18	-65	16	-4
35	Mammoth Cave NP	KY	37.19	-86.1	Southeast	35	40%	18	11	5	2
36	Great Smoky Mountains NP	TN	35.61	-83.49	Southeast	27	20%	16	13	0	-2

† CCI calculated daily from 1984 to 2019 (n=13,149 days, 36 years)

Table 2. Root Mean Square Error (*RMSE*) Change with CCI

Tent	*Park*	*SARIMA Tent*	*SARIMA w/CCI*	*RMSE Tent*	*RMSE w/CCI*	*%Δ*	*# Δ*
1	Grand Canyon NP	(2,0,0)(0,1,1)[12]	(5,1,0)(2,0,0)[12]	1812	1072	40.84%	739.90
2	Black Canyon of the Gunnison NP	(3,0,2)(1,1,1)[12]	(4,1,2)(1,0,0)[12]	495	374	24.55%	121.61
3	Great Sand Dunes NP & PRES	(1,0,1)(0,1,2)[12]	(1,0,0)(0,0,2)[12]	848	404	52.40%	444.44
4	Mesa Verde NP	(1,0,2)(0,1,1)[12]	(1,0,2)(0,1,1)[12]	1376	1376	0.03%	0.46
5	Rocky Mountain NP	(1,0,0)(1,1,1)[12]	(1,0,0)(1,1,1)[12]	4453	4114	7.62%	339.26
6	Glacier NP	(0,0,1)(2,1,2)[12]	(0,0,2)(2,1,2)[12]	1555	1428	8.15%	126.75
7	Big Bend NP	(1,0,1)(2,1,2)[12]	(1,0,1)(2,1,2)[12]	1651	1651	0.01%	0.13
8	Guadalupe Mountains NP	(1,0,2)(2,1,2)[12]	(1,0,2)(2,1,2)[12]	169	169	0.11%	0.19
9	Arches NP	(3,0,1)(2,1,2)[12]	(3,0,1)(2,1,2)[12]	578	545	5.72%	33.07
10	Bryce Canyon NP	(0,0,2)(0,1,2)[12]	(1,0,1)(0,1,2)[12]	567	504	11.10%	62.88
11	Canyonlands NP	(2,0,2)(0,1,1)[12]	(2,0,3)(0,1,2)[12]	478	466	2.66%	12.72
12	Capitol Reef NP	(1,0,1)(0,1,2)[12]	(0,0,3)(0,0,2)[12]	856	585	31.63%	270.71
13	Zion NP	(1,0,1)(1,1,2)[12]	(0,1,0)(0,0,2)[12]	2922	2299	21.34%	623.69
14	Yellowstone NP	(1,0,2)(1,1,1)[12]	(1,0,2)(1,1,1)[12]	1543	1496	3.05%	47.02
15	Hot Springs NP	(1,0,1)(2,1,2)[12]	(1,0,1)(2,1,2)[12]	651	649	0.24%	1.57
16	Indiana Dunes NP	(3,0,2)(1,1,1)[12]	(1,1,1)(1,0,0)[12]	429	374	12.87%	55.23
17	Isle Royale NP	(0,0,2)(0,1,2)[12]	(1,1,0)(1,0,0)[12]	567	565	0.27%	1.53
18	Theodore Roosevelt NP	(2,0,2)(0,1,1)[12]	(2,0,3)(0,1,2)[12]	249	248	0.37%	0.93
19	Badlands NP	(3,0,1)(2,1,2)[12]	(3,0,1)(2,1,2)[12]	182	181	0.42%	0.77
20	Wind Cave NP	(1,0,1)(0,1,2)[12]	(1,0,1)(0,0,2)[12]	153	151	1.30%	1.98
21	Acadia NP	(1,0,0)(2,1,1)[12]	(1,0,0)(2,1,1)[12]	954	915	4.11%	39.20
22	Shenandoah NP	(0,0,3)(2,1,2)[12]	(1,0,1)(2,1,2)[12]	1476	1359	7.93%	116.99
23	Channel Islands NP	(1,0,1)(0,1,1)[12]	(1,0,1)(0,1,1)[12]	2390	2362	1.17%	27.91
24	Joshua Tree NP	(1,0,2)(0,1,1)[12]	(1,0,2)(0,1,1)[12]	2487	2346	5.67%	140.94
25	Kings Canyon NP	(1,0,1)(2,1,2)[12]	(1,0,0)(2,1,2)[12]	2666	2586	3.01%	80.28

26	Lassen Volcanic NP	(0,0,2)(0,1,1)[12]	(0,0,2)(0,1,1)[12]	394	364	7.57%	29.82
27	Redwood NP	(2,0,1)(0,1,1)[12]	(1,1,1)(1,0,1)[12]	165	164	0.15%	0.25
28	Sequoia NP	(0,0,3)(1,1,1)[12]	(1,0,0)(1,1,1)[12]	2046	1085	46.97%	960.84
29	Yosemite NP	(0,0,2)(2,1,0)[12]	(0,0,2)(2,1,0)[12]	2130	1939	8.95%	190.56
30	Great Basin NP	(1,0,0)(0,1,1)[12]	(1,0,0)(0,1,1)[12]	1627	1580	2.85%	46.43
31	Mount Rainier NP	(0,0,2)(1,1,0)[12]	(1,0,0)(1,1,0)[12]	1277	1227	3.93%	50.21
32	Olympic NP	(0,0,1)(0,1,1)[12]	(0,0,1)(0,1,1)[12]	393	284	27.72%	108.91
33	Dry Tortugas NP	(2,1,0)(1,0,0)[12]	(2,1,0)(1,0,0)[12]	409	402	1.68%	6.86
34	Everglades NP	(1,0,1)(1,1,1)[12]	(1,0,1)(0,1,1)[12]	532	500	6.04%	32.13
35	Mammoth Cave NP	(1,0,0)(0,1,1)[12]	(1,0,0)(0,1,1)[12]	521	468	10.21%	53.22
36	Great Smoky Mountains NP	(1,0,1)(1,1,1)[12]	(1,0,1)(1,1,1)[12]	1930	1904	1.35%	26.05
					Total	9.23%	4,795.33

RV	*Park*	*SARIMA RV*	*SARIMA w/CCI*	*RMSE RV*	*RMSE w/CCI*	*%Δ*	*# Δ*
1	Grand Canyon NP	(1,0,1)(0,1,1)[12]	(1,1,2)(0,0,2)[12]	1933	1679	13.17%	254.61
2	Black Canyon of the Gunnison NP	(3,0,3)(1,1,1)[12]	(5,1,2)(2,0,0)[12]	342	261	23.66%	81.01
3	Great Sand Dunes NP & PRES	(1,0,0)(0,1,1)[12]	(0,1,0)(1,0,0)[12]	600	584	2.61%	15.66
4	Mesa Verde NP	(1,0,2)(0,1,1)[12]	(1,0,2)(0,1,1)[12]	1020	1017	0.24%	2.45
5	Rocky Mountain NP	(1,0,0)(0,1,1)[12]	(1,0,0)(0,1,2)[12]	2297	2123	7.58%	174.11
6	Glacier NP	(0,0,2)(2,1,0)[12]	(0,0,2)(2,1,0)[12]	2081	1992	4.25%	88.39
7	Big Bend NP	(2,0,2)(0,1,1)[12]	(2,0,2)(0,1,1)[12]	1578	1576	0.16%	2.49
8	Guadalupe Mountains NP	(1,0,0)(0,1,1)[12]	(1,0,0)(0,1,1)[12]	167	166	0.25%	0.41
9	Arches NP	(1,0,1)(2,1,0)[12]	(1,0,1)(2,1,0)[12]	641	637	0.62%	3.94
10	Bryce Canyon NP	(1,0,0)(0,1,1)[12]	(1,0,0)(1,0,0)[12]	2803	852	69.60%	1950.68
11	Canyonlands NP	(1,0,2)(0,1,2)[12]	(1,0,2)(0,1,2)[12]	221	221	0.01%	0.01
12	Capitol Reef NP	(2,0,1)(0,1,1)[12]	(1,0,1)(1,1,2)[12]	440	403	8.31%	36.53
13	Zion NP	(1,0,2)(2,1,0)[12]	(1,0,2)(2,1,0)[12]	1169	1136	2.75%	32.08
14	Yellowstone NP	(0,0,3)(2,1,0)[12]	(0,0,3)(2,1,0)[12]	2395	1877	21.64%	518.25

15	Hot Springs NP	(2,0,2)(0,1,1)[12]	(2,0,2)(0,1,1)[12]	1578	1551	1.75%	27.62
16	Indiana Dunes NP	(3,0,3)(1,1,1)[12]	(3,1,2)(1,0,0)[12]	345	261	24.18%	83.36
17	Isle Royale NP	(1,0,0)(0,1,1)[12]	(1,1,0)(1,0,0)[12]	-	-	-	-
18	Theodore Roosevelt NP	(1,0,2)(0,1,2)[12]	(5,0,0)(0,1,2)[12]	221	185	16.21%	35.76
19	Badlands NP	(1,0,1)(2,1,0)[12]	(2,0,2)(2,1,0)[12]	641	635	0.90%	5.79
20	Wind Cave NP	(2,0,1)(0,1,1)[12]	(2,0,1)(0,1,1)[12]	440	434	1.25%	5.50
21	Acadia NP	(1,0,1)(2,1,2)[12]	(1,0,0)(2,1,0)[12]	764	534	30.16%	230.41
22	Shenandoah NP	(1,0,0)(2,1,1)[12]	(1,0,0)(2,1,2)[12]	1360	1228	9.67%	131.50
23	Channel Islands NP	(0,0,2)(0,1,1)[12]	(1,0,0)(0,1,1)[12]	3621	3620	0.04%	1.29
24	Joshua Tree NP	(1,0,0)(1,1,1)[12]	(2,0,1)(1,1,1)[12]	1446	1436	0.70%	10.11
25	Kings Canyon NP	(1,0,1)(2,1,2)[12]	(1,0,1)(2,1,2)[12]	1280	1248	2.49%	31.91
26	Lassen Volcanic NP	(0,0,2)(0,1,1)[12]	(1,0,0)(0,1,1)[12]	420	417	0.69%	2.91
27	Redwood NP	(0,1,1)(1,0,1)[12]	(0,1,1)(0,0,2)[12]	-	-	-	-
28	Sequoia NP	(0,0,2)(1,1,1)[12]	(4,1,1)(1,0,0)[12]	2674	2211	17.31%	462.81
29	Yosemite NP	(1,0,3)(2,1,2)[12]	(0,1,0)(2,0,0)[12]	12286	10674	13.12%	1611.41
30	Great Basin NP	(1,0,2)(0,1,1)[12]	(0,1,4)(1,0,0)[12]	320	318	0.80%	2.55
31	Mount Rainier NP	(1,0,0)(2,1,2)[12]	(0,0,1)(2,1,2)[12]	589	548	7.00%	41.22
32	Olympic NP	(1,0,0)(0,1,2)[12]	(1,0,0)(0,1,2)[12]	1823	1817	0.37%	6.82
33	Dry Tortugas NP	(0,0,0)(0,0,0)[12]	(0,0,0)(0,0,0)[12]	-	-	-	-
34	Everglades NP	(0,0,3)(0,1,1)[12]	(0,0,3)(0,1,1)[12]	491	490	0.19%	0.93
35	Mammoth Cave NP	(1,0,0)(1,1,1)[12]	(1,0,0)(1,1,1)[12]	247	241	2.08%	5.12
36	Great Smoky Mountains NP	(0,0,2)(2,1,2)[12]	(0,0,2)(2,1,2)[12]	1225	1218	0.53%	6.47
					Total	8.61%	5,864.11

† *RMSE* values represent monthly occupancy; See *SARIMA models* section for definition of SARIMA integers (i.e., (p, d, q)(P, D, Q)[s]) and interpretations
‡ *SARIMA w/ CCI* indicate models with CCI as the regressor; *RMSE w/ CCI* indicates improvement in occupancy forecasts with addition of CCI as the regressor
§ Isle Royale NP and Dry Tortugas NP are omitted because there was no RV data
¶ Redwood NP is omitted because there is no RV data after 2004

APPENDIX A. Abbreviations and symbols.

Abbreviation	**Name**
AIC	Akaike information criterion
ARIMA	Autoregressive integrated moving average
°C	Degrees Celsius
CCI	Camping Climate Index
HCI	Holiday Climate Index
IPCC	Intergovernmental Panel on Climate Change
mm	Millimeters
m/s	Meters per second
NASA	National Aeronautics and Space Administration
NP	National Park
NPS	National Park System
RBT	Resource-based theory
RMSE	Root mean square errors
RV	Recreational vehicle
SARIMA	Seasonal autoregressive integrated moving average