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Using Social Media to Assess the Impact of Weather and Climate on Visitation to Outdoor Recreation Settings

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USING SOCIAL MEDIA TO ASSESS THE IMPACT OF WEATHER AND CLIMATE

ON VISITATION TO OUTDOOR RECREATION SETTINGS

by

Emily J. Wilkins

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ABSTRACT

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Emily J. Wilkins, Doctor of Philosophy

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Department: Environment and Society

Social media has been increasingly used to understand visitor use in parks and protected areas. This dissertation begins with a systematic quantitative literature review summarizing the state of the science on using social media in a park or protected area setting to understand visitation, the spatial patterns of visitors, or aspects of the visitor experience. I identify gaps, limitations, opportunities, and best practices for future research using social media. In the second study, I use geotagged social media from Flickr to understand how weather has impacted where visitors go within 110 U.S. National Park Service units. Specifically, I investigate how visitors' spatial behavior changes during the summer in response to temperature and precipitation. Daily temperature and precipitation influence visitors' elevation and distance to roads, parking areas, buildings, and bodies of water. However, the effect of weather varies substantially by ecoregion. Visitors in parks that contain more microclimates may be more able to adapt to adverse weather conditions by visiting park areas with preferable weather. In the final paper, I examine how the demand for cultural ecosystem services across public lands in the conterminous U.S. varies by season and climate. The demand for cultural ecosystem service, via visits to public lands, was higher in places that had warmer average temperatures in the fall, spring, and winter. However, visitation was higher in places with relatively cooler average temperatures in the summer. Climate has a larger effect on visitation in the summer and winter, and in the Western U.S. Collectively, this dissertation provides a greater understanding of how visitation and visitor use across a variety of outdoor recreation settings may be altered due to weather conditions and climate change.

(191 pages)

PUBLIC ABSTRACT

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When people post photos on social media, these photos often contain information on the location, time, and date the photo was taken; all of this information is stored as metadata and is often never seen or used by the individuals posting the photos. This information can be used by researchers however, to understand the total number of visitors to parks and protected areas, as well as specific places people visit within those parks and protected areas. The first study in this dissertation reviews all the ways social media has been used to understand visitation and visitors' experiences in parks. Researchers can connect the photo locations from social media to other datasets to understand how different factors, such as the weather or climate, influence park visitation. Weather refers to the conditions, such as temperature or precipitation, at any given place and time; climate refers to the long-term weather averages at a location, often over a period of 30 years or more. The second paper explores how weather affects where visitors go within 110 U.S. National Parks. Daily temperature and precipitation influence visitors' elevation and distance to roads, parking areas, buildings, and bodies of water. However, the effect of weather varies in parks with different climates and landscapes. Visitors in some parks may be more able to adapt to adverse weather conditions by visiting park areas with preferable weather. In the third study, I examine how the climate

of federal and state-managed public lands impact visitation by season. Across the conterminous U.S., visitation was higher in places with warmer average temperatures in the fall, spring, and winter. However, visitation was higher in places with relatively cooler average temperatures in the summer. Climate has a larger effect on visitation to public lands in the summer and winter, and in the Western U.S. Collectively, these studies provide insight into how visitation to and within parks, protected areas, and public lands in the U.S. may change due to weather conditions and climate change.

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CHAPTER I

INTRODUCTION

Each year, millions of people recreate outdoors in U.S. parks and protected areas. About half of the U.S. public recreated outside at least once in 2018 (Outdoor Foundation, 2020). The climate of an area impacts the decisions of outdoor recreationists. For example, national parks in the northern U.S. see the most visitors in the summer, and the fewest in the winter when it is cold. However, in the southern U.S., park visitation is typically lowest in the hot summer months, likely because the average temperature is often above comfortable thresholds (National Park Service, 2020a). Park managers expect certain visitation trends based on the climate of the park and the visitation they have seen in recent years.

However, the climate is changing. Average temperatures are increasing across all seasons, and there is increased variability, meaning more extreme weather events are likely (IPCC, 2018). This is expected to impact visitation to the vast majority of U.S. national parks (Fisichelli, Schuurman, Monahan, & Ziesler, 2015). This research provides insight into how weather impacts visitors' spatial patterns within national parks, and how climate impacts the demand for cultural ecosystem services across all public lands in the U.S. Understanding possible changes in visitation due to weather and climate may help managers proactively prepare for changing visitation patterns.

1. Background

1.1 Public lands in the United States

The United States federal government manages 640 million acres of land, which is about 28% of the U.S. (Vincent, Bermejo, & Hanson, 2020). The federal agencies that manage the most land include the Bureau of Land Management (BLM), U.S.D.A. Forest Service (USFS), National Park Service (NPS), and Fish and Wildlife Service (FWS). Although each agency has a different mission and purpose, they all involve providing enjoyment to the public (Vincent et al., 2020). Collectively, these four agencies had 592 million visits in 2016 (Leggett, Horsch, Smith, & Unsworth, 2017).

State park systems manage 18.6 million acres of lands and had 807 million visits in 2017 (Leung, Cheung, & Smith, 2019; Smith & Leung, 2018). This represents a 26% increase in visitation at state park units from 1984 - 2017 (Smith & Leung, 2018). In that same time period, the NPS saw a 33% increase in visitation, with 331 million visitors in 2017 (National Park Service, 2020b). These increases in visitation create management challenges in many parks and protected areas. For instance, increased visitation often causes additional environmental disturbances in parks; it also makes it harder to manage visitor flows to maintain visitor safety and enjoyment (Hammitt, Cole, & Monz, 2015). Consequently, it is helpful for park managers to understand and prepare for possible changes to future visitation patterns.

Visitors are usually counted through traffic counters, trail counters, visitor surveys, observation, and/or administrative data (e.g., registration, fees, permits). Federal agencies collect and release data at monthly (NPS), annual (BLM, USFWS), or 5-year temporal resolutions (USFS) (Leggett et al., 2017). Additionally, most agencies and parks release visitation numbers at the whole park level, and do not release visitation data at individual places within parks. Recently, researchers have been using social media as an indicator of visitation to parks and protected areas (e.g., Sessions, Wood, Rabotyagov, & Fiser, 2016; Tenkanen et al., 2017; Wood, Guerry, Silver, & Lacayo, 2013). Geolocated social media is advantageous because it allows researchers and managers to see the exact time and location of visits. Social media are also comparable across units, whereas visitation data from different agencies are not necessarily comparable because their methods for counting differ (Leggett et al., 2017).

1.2 Climate change in parks

Visitors to parks are highly impacted by both the weather and climate. Weather is defined as the current conditions at any given time and place, whereas climate represents the long-term averages of weather, usually across 30 or more years (NASA, 2020). Visitors often consider climate when choosing their destination and when to visit, but the weather impacts visitors once on-site (Scott & Lemieux, 2010). For instance, daily weather may make park visitors decide to change the length of their stay or change recreational activities (Becken & Wilson, 2013). Therefore, changes to the climate and changes in weather variability are likely to impact park visitors.

Climate change is defined as a “long-term change in the average weather patterns that have come to define Earth’s local, regional and global climates” (NASA, 2020). Globally, the world has warmed by 1.0ºC compared to pre-industrial levels, and it is likely to reach 1.5 ºC by 2030-2052 if emissions continue at the current rate (IPCC, 2018). In the U.S., NPS lands are warming at a faster rate, likely due to the fact that a lot of parklands are at higher elevations and more northerly latitudes (Gonzalez, Wang, Notaro, Vimont, & Williams, 2018). Additionally, U.S. National Parks are already at the extreme warm end of their historical temperature distributions (Monahan & Fisichelli, 2014). There is natural climate variability, because on any given day or year, the weather is not the exact same as the long-term average; deviations from the average represent natural variability. However, climate change is causing both a shift in the mean temperature and an increase in variability, which indicates there will likely be more extreme weather events in the future (IPCC, 2018).

Climate change has created many new risks for national parks and public lands, including increased wildfire probability (Abatzoglou & Williams, 2016), increased drought (Gonzalez et al., 2018), loss of species (Burns, Johnston, & Schmitz, 2003), loss of glaciers (Hall & Fagre, 2003), and changing visitation patterns (Fisichelli et al., 2015). Specifically, warming temperatures alone are expected to alter visitation patterns at 95% of U.S. NPS units (Fisichelli et al., 2015). Park visitors themselves see climate change as a risk, and many believe it is likely to impact their future travel behavior to parks (de Urioste-Stone, Le, Scaccia, & Wilkins, 2016).

2. Research Objectives

Climate change is expected to impact many sectors of the global economy, including outdoor recreation and nature-based tourism (Gössling, Scott, Hall, Ceron, & Dubois, 2012; Hewer & Gough, 2018). Many towns and communities are dependent on revenue from nature-based tourism, so it is beneficial to plan and prepare for any changes to the demand for outdoor recreation and tourism. Climate change may alter when visitors travel to parks, where they travel, the activities visitors participate in, and their overall satisfaction (Askew & Bowker, 2018; Hewer & Gough, 2018). Longer peak visitation seasons (Monahan et al., 2016) may require local businesses to open earlier and close later. Changes to visitation may also impact the quality of the resources (Hammitt et al., 2015). As the climate warms and extreme weather events become more common and variable, it is helpful for park managers to understand if and how visitation patterns may change in parks and protected areas.

This dissertation has three main objectives, each corresponding to its own manuscript. The objectives are to: (1) Review the state of the literature and better understand the uses and limitations of social media data in parks and protected areas; (2) Understand how daily temperature and precipitation affect visitors' spatial behavior within U.S. NPS units; and (3) Understand how climate affects the demand for cultural ecosystem services across public lands in the U.S.

3. Overview of the Dissertation

This dissertation is formatted as three manuscripts to submit to scientific journals (chapters two, three, and four). Each manuscript addresses one of the objectives mentioned above. The fifth chapter of this dissertation provides a broad discussion of the findings, including research contributions, limitations, and future directions.

The first manuscript uses a systematic quantitative literature review to review the state of the scientific literature using social media data in parks and protected areas. I grouped studies based on whether they are using social media to estimate visitation, spatial patterns of visitors, or understand other aspects of the visitor experience. I address specific questions that managers have regarding social media, such as how correlated these data are with traditional measures of visitation. This manuscript was prepared for an audience that includes park managers and researchers who study and inform park management; it has been submitted to *Environmental Management*.

The second manuscript investigates how daily temperature and precipitation impact the spatial behavior of visitors within 110 U.S. NPS units. Specifically, I use 13-years of geotagged photos from Flickr to map visitation patterns at fine spatial and temporal resolutions. I connect each point to the daily weather using data from Daymet (Thornton et al., 2018), and explore how weather conditions impact visitors' elevations and distances to roads, buildings, parking areas, and bodies of water. I also examine how the weather impacts visitors differently in various U.S. ecoregions. This manuscript has been submitted to *Scientific Reports*.

The third manuscript explores how the demand for ecosystem services across public lands in the U.S. varies by season and climate. I use all geotagged Flickr posts within state and federally managed public lands to quantify the demand for cultural ecosystem services. I find both the daily maximum temperature and climatological average maximum temperature at each location and use these climate metrics to understand how weather and climate affect visitation on public lands throughout the whole country. This paper is intended to be published in a climate-centric journal.

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CHAPTER II

USES AND LIMITATIONS OF SOCIAL MEDIA TO INFORM VISITOR USE MANAGEMENT IN PARKS AND PROTECTED AREAS: A SYSTEMATIC REVIEW

Abstract

Social media are being increasingly used to inform visitor use management in parks and protected areas. We review the state of the scientific literature to understand the ways social media has been, and can be, used to measure visitation, spatial patterns of use, and visitors' experiences in parks and protected areas. Geotagged social media are a good proxy for actual visitation; however, the correlations observed by previous studies between social media use and other sources of visitation data vary substantially. Most studies using social media to measure visitation aggregate data across many years, with very few testing the use of social media as a visitation proxy at smaller temporal scales. No studies have tested the use of social media to estimate visitation in near real-time. Studies have used geotags and GPS tracks to understand spatial patterns of where visitors travel within parks, and how that may relate to other variables (e.g., infrastructure), or differ by visitor type. Researchers have also found the text content, photograph content, and geotags from social media posts useful to understand aspects of visitors' experiences, such as sentiment, behavior, and preference. The most cited concern with using social media is that this data may not be representative of all park users. Collectively, this body of research demonstrates a broad range of applications for social media. We synthesize our findings by identifying gaps and opportunities for future research and presenting a set of best practices for using social media in parks and protected areas.

1. Introduction

Park and protected area managers often aim to both conserve natural and cultural resources while also providing enjoyment to visitors. Any changes to visitation patterns, either in space or time, has the potential to degrade the natural environment and cause environmental disturbances (Hammitt, Cole, & Monz, 2015). However, land managers can mitigate disturbances by proactively managing visitor flows. Estimating visitor use and understanding the visitor experience is a critical component to sustainably managing natural environments (Leung et al., 2018). Traditionally, researchers and mangers have gleaned insights into visitors' characteristics, preferences, behaviors, and experiences in parks and protected areas by using visitor surveys, semi-structured interviews, administrative data, as well as vehicle and trail counters (Leggett, Horsch, Smith, & Unsworth, 2017). However, these methods require substantial time and financial costs; they also often limit data collection to relatively small geographic scales such as individual parks (Cessford & Muhar, 2003). Over the last decade, researchers have begun exploring the potential use of large volunteered geographic datasets to overcome the limitations of more traditional methodologies, while still providing insights into visitors' experiences.

One data source that is increasingly being used to inform park and protected area management is social media. Social media generally refers to online content that is user-generated, and hosted by a service (e.g., Facebook, Twitter, etc.) that facilitates connections between individuals or groups (Obar & Wildman, 2015). Social media can include photos, text, and metadata such as the time stamps or geotagged coordinates of posts from parks and protected areas (Toivonen et al., 2019). All of these pieces of information can provide a wealth of knowledge about visitors' behaviors, experiences, and preferences. Some social media platforms make all or some of their users' information publicly available for free and often on a global scale. This provides a unique opportunity to understand many facets of outdoor recreationists' behaviors and preferences across large geographic areas.

Researchers have begun using social media to better understand a variety of topics pertinent to environmental and visitor management. In parks and protected areas, social media were first used to estimate visitation rates and home location of visitors (Wood, Guerry, Silver, & Lacayo, 2013) and have since been used to understand other aspects of visitors' characteristics and experiences. Many studies using social media to estimate visitation to parks and protected areas have found it can be a reliable proxy (e.g., Sessions, Wood, Rabotyagov, & Fisher, 2016; Wood et al., 2013). These investigations have evaluated the social media-visitation relationship over many spatial and temporal scales (Teles da Mota & Pickering, 2020). Additionally, these investigations report a wide range of correlations with other visitation measures (e.g., Fisher et al., 2018; Sonter, Watson, Wood, & Ricketts, 2016; Tenkanen et al., 2017; Walden-Schreiner, Rossi, Barros, Pickering, & Leung, 2018). Given the variety of ways in which social media have been compared to other visitation measures, it would be beneficial to systematically review the methods used in previous research. Doing so could provide the research community and land managers with insight into the spatial and temporal scales where social media can serve as a reliable measure of visitation to parks and protected areas. Additionally, summarizing how social media are correlated with other measures of visitation in various settings may help reveal if there is potential to use social media to predict future visitation.

In addition to the growing body of literature using social media to estimate visitation in parks and protected areas, there is also a rapidly expanding body of literature using social media to understand spatial patterns of visitation or park use (e.g., Campelo & Mendes, 2016; Sinclair, Ghermandi, & Sheela, 2018; Walden-Schreiner, Rossi, Barros, Pickering, & Leung, 2018). When a photograph is taken on a GPS-enabled device (e.g., a smartphone), the exact date and time the photo was taken, as well as the latitude and longitude of the photo location, are automatically stored in the photo's metadata. If the photo is uploaded to a social media platform, researchers can access the time stamp and coordinates through the metadata. Users of fitness applications, such as Strava, can choose to record and upload the GPS track of the route they took during their visit. This information can help researchers map where visitors to parks and protected areas go in space and time. However, it would be useful to understand and synthesize how researchers have used this information, and the spatial resolutions researchers have used to answer different types of questions.

Recent studies have used social media to understand visitors' preferences, sentiment, and experiences (e.g., Barry, 2014; Huang & Sun, 2019; Plunz et al., 2019). Studies have also used social media to explore cultural ecosystem services (CES; e.g., Clemente et al., 2019; Retka et al., 2019), which include the "nonmaterial benefits people obtain from ecosystems" through recreation, spritual, and other experiences with nature (Millennium Ecosystem Assessment, 2005, pg 40). CES can help describe the types of experiences visitors have on landscapes and the benefits they receive. Traditionally, researchers would most often investigate visitors' experiences through direct contact with visitors (e.g., visitor surveys, focus groups) (Leggett et al., 2017). However, social media may provide a lower-cost alternative. Summarizing the types of topics previous studies have explored through social media may help identify the ways social media can be used quantify and track visitor preferences, sentiment, and experiences across space and time.

The overall goal of this study is to review the state of the scientific literature and better understand the ways social media has been, and can be, used to inform visitor use management in parks and protected areas. By synthesizing prior applications, approaches, and limitations for managers and researchers, we aim to clarify the realm of questions that social media may be able to answer. Since this line of literature is still relatively new, and will grow in the future, understanding the collective successes and limitations uncovered by prior research can help inform future research directions. This study follows previous research and reviews of the potential for social media to inform environmental management and conservation (Di Minin, Tenkanen, & Toivonen, 2015; Ghermandi & Sinclair, 2019; Toivonen et al., 2019) with a targeted review of the scientific literature on ways social media has been, and can be, used to inform visitor use management in parks and protected areas. Our review also compliments the recent review by Teles da Mota and Pickering (2020) by focusing on three specific research questions which are guided by the needs of park and protected area managers.

The three questions that we address in this manuscript begin with *what spatial and temporal resolutions have been used to estimate visitation from social media, and how correlated are these estimates with other measures of visitation?* Knowing how much visitation is occurring within a park or protected area is critical to all visitor use monitoring and management efforts (Leung et al., 2018). Understanding the spatial and temporal resolutions at which social media can be used to reliably quantify visitation is currently an open question. Second, *how has previous research used social media to understand spatial patterns of visitation in park and protected areas, and at what spatial scales?* Understanding the spatial distribution of visitation across a park or protected area can help guide the effective allocation of managerial resources to outdoor recreation settings that are heavily used; it is also an area where the qualities of social media provide notable advantages over traditional methods of visitor use monitoring. Third, *how have social media been used to understand visitors' experiences in park and protected areas?* Park and protected area managers often strive to provide an array of recreational experiences for visitors, often using little more than anecdotal evidence to guide their decisions regarding how and where opportunities for these experiences are provided. Social media may be able to provide novel insights into visitors' experiences, however research into this realm is in its infancy. Our review can help provide guidance for where future investigations may be most effective. We synthesize our findings into these three research questions by identifying gaps and opportunities for future research and presenting a set of best practices for using social media in parks and protected areas.

2. Methods

We followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) protocol for searching databases and reporting information (Moher, Liberati, Tetzlaff, & Altman, 2009). This protocol requires us to report specific measures, such as how the literature was searched and what information was recorded, so the systematic review could be replicated in the future.

2.1 Paper Selection

We attempted to find all academic papers that have used social media in a park or protected area to quantify visitation, explore spatial patterns, or understand the visitor experience. We searched for relevant articles in the scientific literature using the Scopus database and ProQuest Agriculture and Environmental Science database. We used broad search criteria to have high sensitivity and low specificity (Petticrew & Roberts, 2006). In other words, we collected all studies that might be relevant, and later removed papers that did not fit our inclusion criteria.

We searched for all research articles that contained at least one of the following terms in the title, abstract, or keywords: social media, Flickr, Twitter, Instagram, Facebook, Panoramio, Strava, MapMyFitness, or Wikiloc. Papers must also have included one of the following terms in the title, abstract, or keywords to be included: park(s), protected area(s), or public land(s). This search was conducted on January 14, 2020; it yielded 582 papers before removing duplicates. We conducted another search on May 1, 2020 which returned 16 new papers. Given that automated searches can sometimes miss pertinent papers, we also added additional relevant papers that we were aware of, which were not captured in the searches.

2.2 Article Screening

We used a two-tier approach to screen articles. First, we evaluated article inclusion based on the title, given the low specificity of the search. At this phase, all papers were kept that alluded to a park or protected area being the study site and mentioned the use of social media. If it was unclear whether or not the paper reported on research within a park or protected area or used social media, the paper was retained at this stage of screening. Second, we read the abstracts of all papers that had potentially relevant titles to determine their suitability. If it was still unclear from the abstract, we read the full text. We retained all papers globally that referenced a park or protected area setting and also reported on the use of social media. All types of parks and protected areas were included (e.g., urban parks, state parks, national parks). If the setting may have referenced a park or protected area, but that was not an explicit focus of the paper, it was not included (e.g., Fisher, Wood, Roh, & Kim, 2019).

Papers that investigated the use of social media to communicate with visitors or market destinations (e.g., Wilkins, Keane, & Smith, 2020; McCreary, Seekamp, Davenport, & Smith, 2019) were not included in this analysis, as they were studying perceptions of social media, rather than using social media to study visitation and/or the visitor experience. Additionally, papers that were explicitly related to protests, political uprisings, or clinical health studies were not included, even if they took place in a park. We also excluded studies that analyzed review site data (e.g., *TripAdvisor*, *Yelp*). These bodies of literature are all outside the scope of this paper. Appendix Figure A.1 shows the number of studies that were identified, screened, eligible, and included.

2.3 Categorizing Papers

We reviewed the full text of each of the 58 relevant papers (Table A.1). For each paper, we recorded the information about the study objective, location, and many other attributes listed in Table 2.1. After recording information on each paper, we categorized papers into non-discrete categories based upon whether the paper used social media to: (1) estimate visitation, (2) understand spatial patterns of visitation, and (3) understand aspects of the visitor experience.

Any paper that explicitly compared social media posts or user-days to another data source was included in the estimating visitation category (even if this was not the main focus of the paper). Any paper that mentioned analyzing or mapping patterns in space was included in the spatial patterns category. These papers either mentioned mapping/understanding spatial patterns in their research questions, or mentioned investigating what factors impact visitation. Papers that asked a research question involving visitors' perceptions, feelings, values, actions, or experiences, were included in the visitor experience category. However, this category does not include papers that were exploring what factors impact visitation. Although this could be considered an aspect of the visitor experience, these papers all had a spatial component to them, and were thus only included in the spatial patterns category. We used these specific categories to help answer our research questions; they do not fully capture every type of question researchers have explored (e.g., comparisons of results from different social media platforms).

Table 2.1

The attributes recorded for each paper and their general purpose.

Broad category	Specific pieces of information	Purpose
Citation information	- Study authors - Article title - Journal title - Year of publication	To cite articles and understand how the number of publications has changed over time.
Objective(s)	- Explicitly stated research objectives, research, questions, or study purpose	To classify papers based on if they were estimating visitation, spatial patterns of visitation, or aspects of the visitor experience. Also used to classify the specific focus of the paper.
Location and setting	- Continent - Country - Specific study site name(s) - Setting (i.e., type of park and/or protected area)	To understand the distribution of studies across continents and countries and see which types of settings are most often studied. Any setting with 2+ mentions was included as a category.
Methods	- Social media platform(s) - What attributes of social media were used (e.g., metadata, photo content, text content) - The extent of social media used (e.g., number of years) - The temporal resolution of the analysis (e.g., annual, monthly, weekly) - The spatial resolution of the analysis (e.g., whole park, grid, trails) - If the authors used user-days or total posts (if applicable)	To understand how researchers have used social media and the spatial and temporal resolutions of the data used.
Social media acquisition and analysis	- How data were acquired (e.g., API vs scrape) - Software used for data collection/analysis - If code to reproduce results is available	To understand technical details about how others have conducted this research.
Other datasets used	- Other types of secondary datasets used, if applicable - Other types of primary data collected, if applicable	To understand if and how researchers use this data source in conjunction with other data.
Limitations	- Any explicitly stated biases, limitations, or ethical concerns of using social media	To understand how researchers perceive the limitations of this data source. This was later summarized into categories, with anything that was mentioned 3+ times being a category.

For papers that used social media to estimate visitation, we also recorded the given correlations with other visitation measures, as well as the sample sizes of the correlations. For papers that looked at spatial patterns of visitation, we noted categories of other variables (i.e., social, environmental, infrastructure, and managerial) authors included in models regarding spatial patterns. For papers that looked at the visitor experience, we recorded what aspect of the visitor experience the authors were studying.

3. Results

3.1 Characteristics of the Current Literature

The first papers using social media in a park or protected area were published in 2013, with mostly increasing numbers of publications each year since then (Figure 2.1). As of April 2020, there were 58 known papers in the scientific literature that used social media to measure visitation and visitors' experiences in parks and protected areas. These papers have been published in journals representing a variety of disciplines, including: tourism, geography, ecology, environmental science, environmental management, remote sensing, and urban planning. The full table with the attributes recorded for each of the 58 papers is available online[1].

[1] Available at: github.com/emilywilkins/Literature-Review

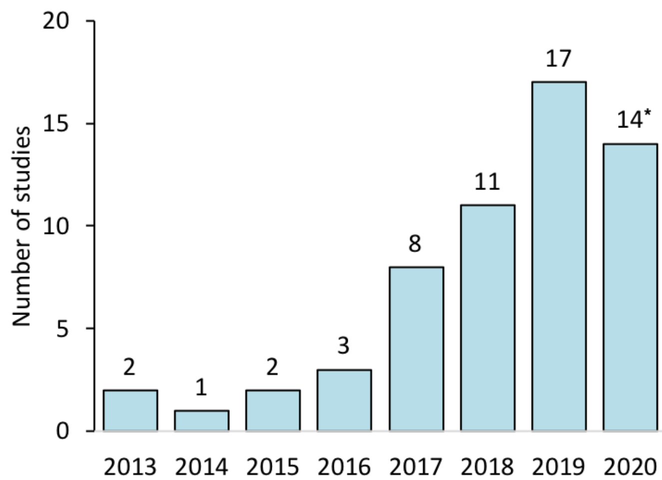

Figure 2.1. Papers published by year (*n* = 58). Note: These are papers published through April 2020, so the number of papers in 2020 only represents four months.

3.2 Locations and Settings

The highest proportion of papers studied sites in Europe and North America, although there were at least five papers from each continent (Figure 2.2a). This body of literature represents 23 countries, with the most papers having study sites in the United States (*n* = 13), Australia (*n* = 6), and Portugal (*n* = 4). The most common setting was national parks, followed by urban parks (Figure 2.2b). The "other" category represents public rangelands, national forests and grasslands, conservation parks, a UNESCO World Heritage site, and an archaeological park. The "variety of settings" category represents papers that either had three or more setting types or stated their study sites contained a variety of protected area types.

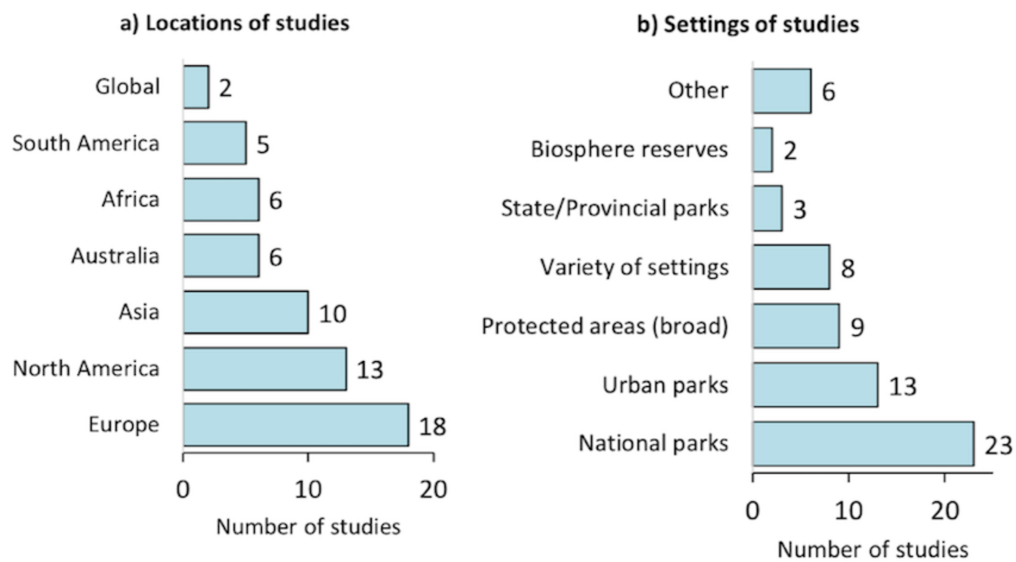

Figure 2.2. The locations of the study sites (a) and the settings of the studies (b).

3.3 Characteristics of Data Collection and Analysis

The majority of studies (79%) used a single social media platform. Flickr was by far the most used social media platform, followed by Twitter and Instagram (Table 2.2). Most studies analyzed the locations of social media content according to the geotagged coordinates of the post or the routes of the users' track. About half of studies relied on the time the social media content was created (Table 2.3). Of the studies that analyzed image content, 21 manually viewed the content, while three used automated tools (e.g., Google Vision) to classify the subject of the photographs. In some of these cases, the authors viewed photograph content to validate geotagged locations assigned by users, but the photograph content was not necessarily the focus of their analysis. Relatively few (14%) of the papers that we reviewed used social media to study visitors' origins for the purpose of understanding visitors' characteristics or their travel routes. Some studies incorporated identifying information about the user, such as their username, into calculating user-days, for instance; this is not included in Table 3 since user identifiers were never a focus of the authors' analyses.

Table 2.2

The number of studies that used each social media platform, and the general use of each platform. Twelve studies used multiple platforms (n = 58). We searched for articles referencing Flickr, Twitter, Instagram, Facebook, Panoramio, Strava, MapMyFitness, and Wikiloc.

Platform	**General use**	**Number of studies**
Flickr	Photo-sharing	35
Twitter	Micro-blogging	10
Instagram	Photo-sharing	8
Wikiloc	Fitness / GPS tracking	6
MapMyFitness	Fitness / GPS tracking	3
Weibo	Micro-blogging	3
Strava	Fitness / GPS tracking	2
Panoramio	Photo-sharing	2
Facebook	General media	1
Vkontakte	General media	1
GPSies	Fitness / GPS tracking	1

Table 2.3

The attributes of social media that were analyzed or used to aggregate data (n = 58).

Attribute of data	**Number of studies**
Geotagged coordinates or routes	47
Time stamp	28
Photograph content	24
Text content	8
Stated home locations (according to user's profile)	8
Photograph title, tags, or hashtags	5
Comments on posts	2
Number of check-ins (*Weibo*)	2
Video content	1
Likes	1
Gender	1

The majority of papers (78%) reported downloading social media directly through Application Programming Interfaces (APIs). Nine studies downloaded data directly from websites, while four used InVEST (Sharp et al., 2016), one used Google Earth, and one used SAS[2]. Three studies did not state how they acquired the data. Three studies used multiple means of data acquisition for different platforms. The authors of these papers used a variety of software to download, organize, and analyze data. Of the studies that mentioned using software, the most popular were R (51% of studies), ArcGIS (47%), Python (25%), SPSS (10%), Excel (10%), and QGIS (10%). Seven studies did not mention any software they used for data processing or analysis. These counts only included software the authors explicitly mentioned using; in some cases, other software was likely used but not directly mentioned. Only five papers made the code they wrote to produce their data and/or analysis publicly available. Of the five papers with available code, four made code available to reproduce parts of their analyses, while two made code available to download social media. The code that was provided was written in either R or Python.

Many studies used other data in addition to social media. The majority of studies (64%) used secondary GIS data, visitation or survey data from agencies, or satellite imagery, for example. A total of 11 studies (19%) collected other primary data on visitor use. This included using trail cameras and counters, surveys, semi-structured interviews with visitors or park experts, focus groups with park experts, and qualitative interviews with people who post on social media. Many of the studies (73%) which did collect

[2] SAS was used to download Panoramio data and has since been depreciated. Google Earth was used to download Wikiloc data; this feature was removed from Google Earth in 2019 (Wikiloc, 2020).

primary data used it to validate or compare to social media. Only thirteen studies relied on social media alone and did not use other datasets (other than for obtaining park boundaries).

3.4 Using Social Media to Estimate Visitation

A total of 20 papers in this review investigated the use of social media to measure visitation (Appendix Table A.2). These studies all compared the user-days of social media posts (e.g., photo-user-days (PUDs) or tweet-user-days) to another data source, such as surveys, trail counters, or agency-reported data. However, not every study reported a measure of association between the datasets. User-days are an aggregate count of individuals who make a post within an area such as a park by day (Wood et al., 2013). For image-sharing platforms, PUDs are often aggregated across multiple years as described below. PUDs are used to eliminate possible measurement bias that may arise due to users who post substantially more content from a place and time compared to other users.

The majority of papers (80%) aggregated social media over entire parks and protected areas. These studies predominately looked at differences in visitation between multiple parks and protected areas and were often not interested in temporal patterns of visitation. Of 16 papers that aggregated data by entire parks or protected areas, 10 papers aggregated data across multiple months and years (i.e., aggregating all data they collected by unit), while four papers looked at monthly or seasonal trends, one analyzed weekly trends, and one paper did not state their temporal scale. Five papers analyzed visitation patterns on smaller spatial scales (e.g., trail, grid, or park subregion); three of these papers aggregated data across all months and years, while two papers aggregated data by month (i.e., summing user-days for all Januarys across multiple years). Thus far, the smallest temporal scale researchers have tested to estimate visitation is the monthly scale, and these papers aggregate between 6 to 13 years of social media by month.

Of the 20 papers which used social media to measure visitation, 17 reported a measure of association between social media and visitation measured by another data source, such as on-site visitor counts. Measures of association included: Pearson's correlation (r), Spearman's rank correlation (R_s), or the coefficient of determination (R^2) from a regression where social media was the only predictor in the model. The other three studies did use social media to estimate visitation compared to visitation measured by another data source, but included other variables in the model (e.g., year, month), so the R^2 values are not comparable. Overall, the measures of correlation reported from each study are powerful, but difficult to meaningfully compare because they use different platforms, different spatial scales, different temporal scales, different measures of association, and some use user-days while others use total images or total users (photographers). Figure 2.3 summarizes the correlations found in the literature when comparing social media to visitation measured by another data source.

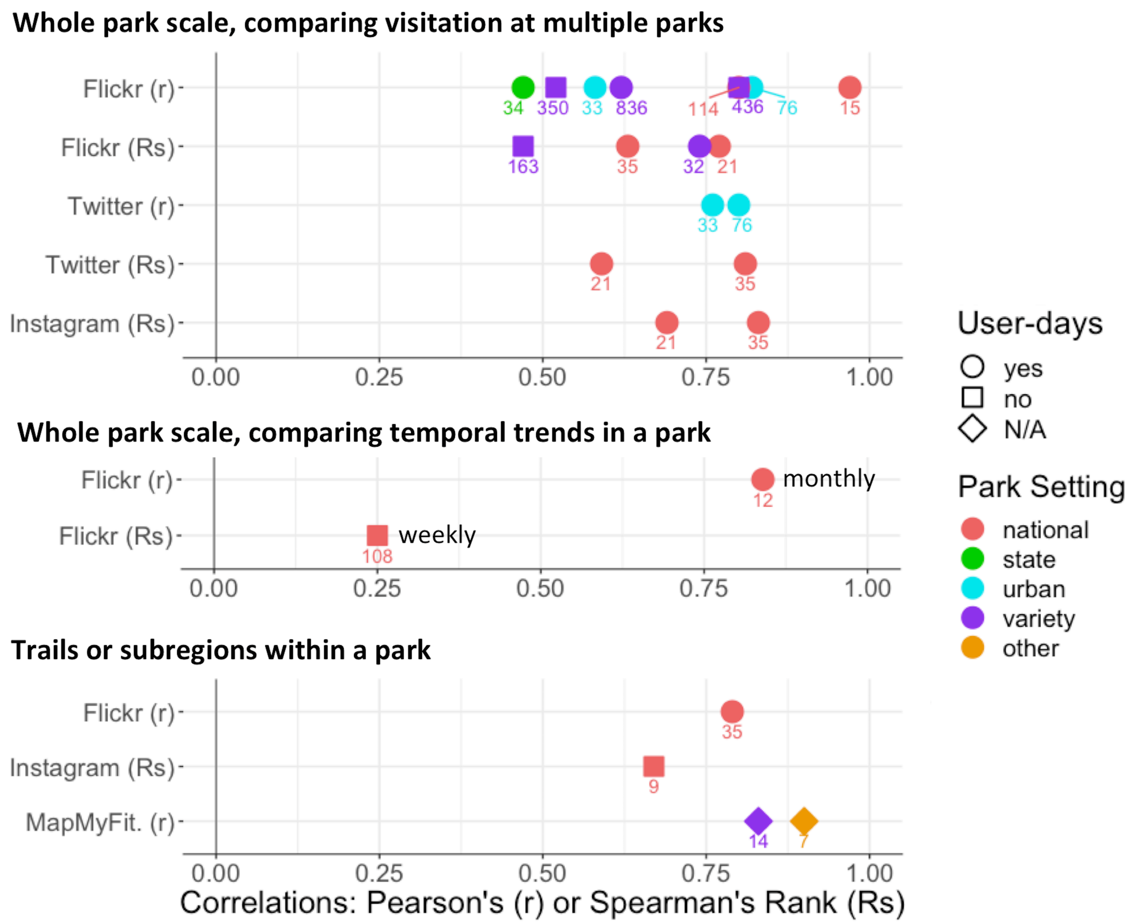

Figure 2.3. Correlation coefficients reported from previous studies measuring the correlation between social media and other measures of visitation. Numbers near the points are sample sizes for correlations. Any studies that reported a R^2 value from a linear regression with social media as the only predictor in the model were converted to r coefficients by taking the square root. Park setting represents what level of government is managing the park(s).

The papers comparing visitation across multiple parks used between one and 14 years of data to estimate correlations. The majority of these papers were not interested in a temporal scale, and thus aggregated all data by park. However, one paper did look at visitation across parks and summers (the point with n = 350 analyzed 75 parks). Papers looking at temporal trends in a single park used five and seven years of data. Notably, the paper analyzing monthly trends aggregated seven years of data by month, while the paper analyzing weekly trends did not aggregate the five years of data. At the trail/subregion scale, these papers aggregated between 2.4 and 13 years of data. Three of these papers aggregated data from all years by trail or subregion, while one aggregated data by month (the point with n = 35). The citations associated with each point, as well as the location of the study, and the number of years of data the authors used can be found in Appendix A, Table A.2.

3.5 Exploring Spatial Distributions of Visitors

Over half of papers (62%) used social media to study spatial distributions of visitors. Many papers were interested in understanding the spatial distribution of visitors (e.g., by producing maps of where people visit), but that was not their main research question. Some papers explored what attributes may affect visitation, while others focused on the distribution of cultural ecosystem services (CES), and some investigated spatial patterns by user group or photo content (Figure 2.4). Of the 15 papers exploring what landscape attributes may affect visitation, 13 included environmental variables (e.g., elevation, waterbodies), 11 included infrastructure variables (e.g., roads, trails), seven included social variables (e.g., GDP, population density), and five included managerial variables (e.g., management type, presence of a fee).

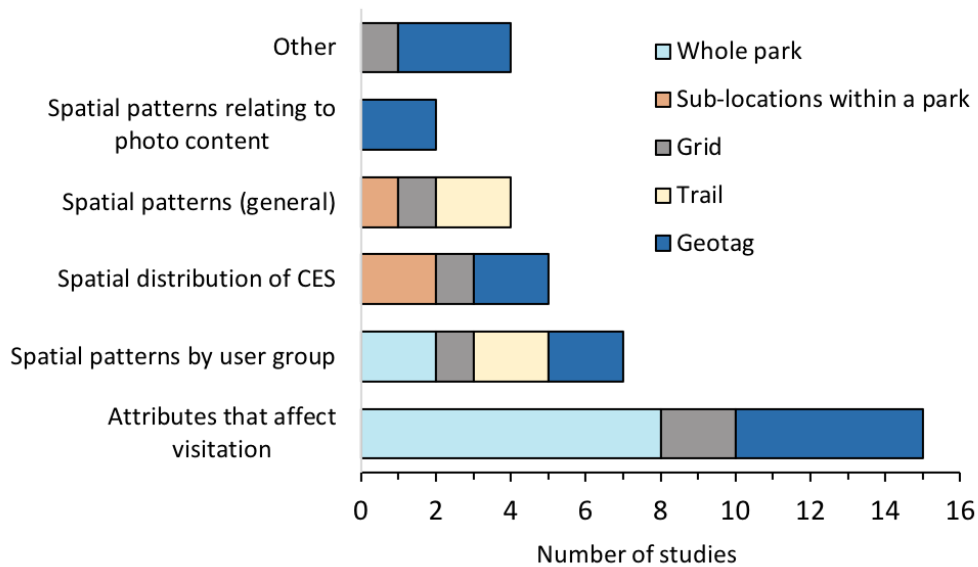

Figure 2.4. Papers that used social media to investigate spatial distributions, along with the spatial scale used in each paper (n = 36). Papers in the spatial patterns (general) category are only those that did not fit into a more specific category. One paper is represented in two categories (spatial distribution of CES and attributes that affect visitation).

The spatial scale used to answer these questions varied. Some studies analyzed distributions at the whole park scale, while others used specific geotags, trails, or grids (Figure 2.4). For grids, a 1 km grid was most common. The majority of these studies (79%) were not interested in a specific temporal scale; the authors analyzed spatial patterns after aggregating all the data they had collected, usually over multiple years. Five studies analyzed spatial patterns at the seasonal level, while one paper mapped patterns on weekends versus weekdays and across years, and another paper looked at patterns based on the time of day, weekend versus weekday, and seasonal scales. Three papers did not state the temporal scale of analysis. Citations and additional details on each paper can be found in Appendix Table A.3.

3.6 Understanding Aspects of the Visitor Experience

Some studies have used social media to understand various aspects of the visitor experience. Of the 29 studies which did investigate the visitor experience, the highest proportion were studying CES, with fewer papers investigating sentiment, behavior, or preferences and perceptions (Figure 2.5). Some social media platforms are more commonly used to study certain aspects of the visitor experience; for example, all studies on sentiment used Twitter as their data source. While the papers using social media to investigate visitation or spatial distributions tended to focus on geotagged coordinates and time stamps, the majority of studies (72%) of visitor experience used photo content to explore their research questions.

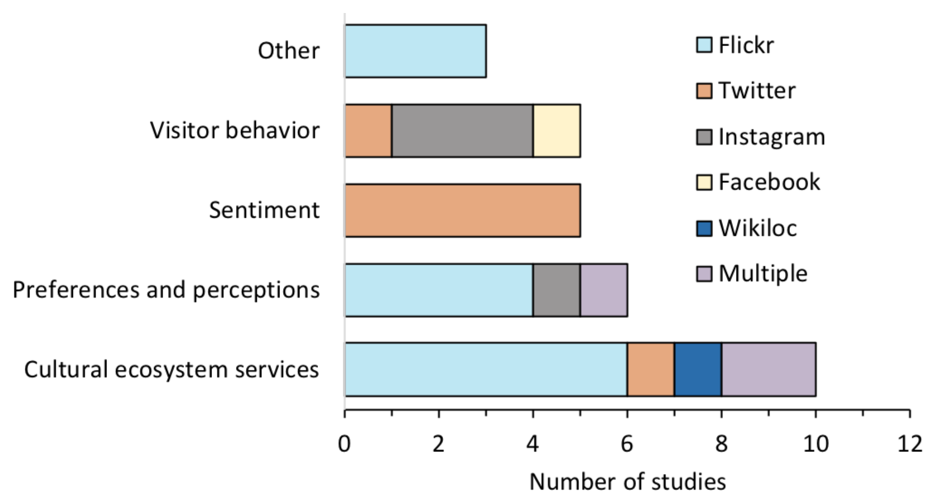

Figure 2.5. Categories of what aspect of the visitor experience each paper was studying, as well as the social media platform the authors used (n = 29).

In most papers, the CES studies were broadly looking at multiple CESs, although a couple studies focused on a specific aspect (e.g., wildlife-viewing as a CES). The majority of the CES studies (90%) analyzed photo content; most of these used the photos to identify different types of CES (e.g., aesthetic value, recreational value, educational value). All of the five studies analyzing sentiment used the text of tweets to gauge sentiment of park users, with four of these studies being situated in urban parks. Of the five studies analyzing visitor behavior, two were looking at unwanted visitor behavior, and three were analyzing visitors' activities. Papers in the "preferences and perceptions" category were looking at perceptions of grazing, preferences for biodiversity, how tourists view the destination, differences between what domestic and international visitors photograph, and experience values. The "other" category includes papers on per-trip benefits and travel cost, the seasonality mismatch between visitors and wildflowers, and the aesthetic value of the parks based on image content and colors. Citations and additional details for each paper can be found in Appendix Table A.4.

3.7 Limitations, Biases, and Ethical Concerns

Although this body of work has displayed many ways social media can be used to ask questions of park and protected area visitation, the authors of papers included in our systematic review do caution this data source should be used appropriately. The majority of papers (86%) explicitly noted limitations, biases, or concerns with using social media. The most commonly cited limitation is that social media may not be representative of all park users (Table 2.4). Some limitations in the "other" category included: noise from bots/spam accounts, accessible areas having more photos, social media use varying due to environmental conditions, and that these data require technical skills and infrastructure to store and analyze. Ethical concerns mentioned were related to the privacy of social media users, and that even though these data are public, users may not know how their data are being used for research purposes.

Table 2.4

Limitations, biases, and concerns explicitly mentioned by authors of each study (n = 58).

Limitations, biases, and concerns	Number of studies	Percentage of studies
Social media is not representative of park users	42	72.4
Users only share select content	16	27.6
Inaccuracies in geotags/GPS	14	24.1
Unknown demographics of social media users	12	20.7
Social media use varies by country or year	10	17.2
Users share different content on different platforms	9	15.5
There is a changing popularity of platforms over time	8	13.8
There is a low amount of social media in some areas	8	13.8
Ethical concerns/ privacy of users	7	12.1
Changes in data accessibility	6	10.3
Some things are hard to photograph	4	6.9
Character limit of *Twitter* may limit descriptions	3	5.2
Other	15	25.9
None	8	13.8

4. Discussion

Collectively, this body of literature demonstrates a broad range of ways in which social media can be used to inform visitor use management in parks and protected areas. In recent years, some parks and protected areas have seen substantial increases in visitors (Smith, Wilkins, & Leung, 2019; National Park Service, 2020). Increased visitation can strain biophysical resources and result in increased environmental disturbances (Hammitt, Cole, & Monz, 2015). Understanding visitor behavior and patterns of visitation is crucial to managing natural environments for future generations. However, collecting data on visitors is often costly and time-consuming; social media provides a new way to understand how visitors are interacting with the environment.

4.1 Characteristics of the Current Literature

Prior applications of social media include estimating visitation, understanding spatial patterns of visitation, and revealing visitors' behaviors, preferences, and sentiment. There has been a notable increase in the number of published papers using social media to inform visitor use management in parks and protected areas from 2013 – 2020, and researchers are likely to continue using social media as an information source. The majority of papers are focused on national parks and urban parks, and the literature is not necessarily representative of all types of park settings. Further research into social media use in peri-urban green spaces or national forests, for example, would provide additional insights into understanding a diversity of visitors and types of visitor use. Additionally, most papers use geotagged coordinates or GPS tracks, time stamps, and photo content of posts, with fewer papers analyzing text content, home location of users, and comments on posts.

Flickr and Twitter are the main platforms researchers have used, with each platform being used in ways that reflect its purpose and functionality. For example, Twitter is used to measure visitor sentiment, while Instagram and Flickr are often used for questions that can be understood by analyzing image content. Social media that are geotagged with precise locations – such as Flickr and GPS tracking platforms (e.g., Wikiloc, MapMyFitness, Strava) – are amenable to mapping the spatial patterns of visitation. However, researchers highlight a number of important limitations and considerations that should be taken. Principle among them is the changing popularity of different social media platforms over time; platforms used in the past may not be the same platforms researchers use in the future. For instance, Instagram started rising in popularity around 2013, while Flickr's popularity began decreasing, and then Panoramio was discontinued in 2016. Additionally, these are private companies that can choose to stop sharing data at any point. For example, Instagram stopped sharing the geolocations of users' images in 2018 (Toivonen et al., 2019). Although Flickr is declining in popularity, this platform contains over a decade of publicly available information, hence its high use by researchers, especially for questions regarding visitor preference. Few papers (22%) used multiple social media platforms, and future studies may be able to minimize the effects of user bias by integrating data from multiple platforms (e.g., Hamstead et al., 2018; Norman & Pickering, 2017; Tenkanen et al., 2017).

Although most studies combined social media with other secondary data (e.g., GIS data), few studies (19%) collected primary data about visitors. The collection of primary data (e.g., via on-site visitor intercept counts or surveys) may overcome some of the limitations of social media (Crampton et al., 2013; Lopez, Magliocca, & Crooks, 2019; Xu, Nash, & Whitmarsh, 2019). The studies which did collect other primary data were largely to validate the results from social media. There is a lot of potential for researchers to leverage social media in conjunction with more traditional means of data collection. For example, interviews or focus groups could be used to inform what information to mine from social media. Conversely, visitor surveys could be used to understand the patterns in social media, such as why spatial or temporal trends exist in social media, or why visitors exhibit certain behaviors. Spatial and temporal patterns found in social media would also be useful to choose sampling times and locations for visitor surveys.

4.2 Using Social Media to Estimate Visitation

Many studies have shown geotagged social media are a good proxy for actual visitation to parks and protected areas. However, the correlations between social media and other sources of visitation data vary substantially. Most of the correlations found in previous studies we reviewed were between 0.50 and 0.80 for visitation data at the entire park scale. However, most of these studies aggregated data across many years, with fewer studies testing the use of social media as a visitation proxy at smaller temporal scales. The smallest amount of data used to estimate visitation was a full year (i.e., using one year of data to estimate monthly visitation), and no studies attempted to estimate visitation in near real-time or forecast future visitation from social media posts. A few recent studies used social media to estimate visitation to trails or other areas within a park (e.g., Fisher et al., 2018), but more research is needed to determine the applicability of using smaller spatial or temporal scales to estimate visitation across different locations, platforms, and settings. Environmental managers may be able to use social media to understand the relative popularity of different parks (or regions within parks) and the temporal distributions of visitors' sub-annual scales (e.g., quarterly or monthly) if there are enough data to yield reliable estimates.

4.3 Exploring Spatial Distributions of Visitors

Not only is social media useful to estimate visitation, but it's very high spatial and temporal resolution makes it possible to map distributions of visitors in time or space. Often the exact hour and minute a photograph was taken is captured in the metadata, and smartphones currently have GPS units that are accurate within 5 meters (National

Coordination Office for Space-Based Positioning, 2020). Although this high resolution is available for the posts that visitors share on some social media platforms, few studies of park visitors have taken advantage of both the high spatial and temporal resolution of social media. Future studies could explore whether spatial patterns differ in time – between weekends and weekdays, for example. They could also integrate daily weather data to better understand the spatial substitution patterns of visitors encountering inclement weather. In these future efforts, researchers will likely need to analyze long time series of social media from multiple platforms in order to have sample sizes big enough to quantify and understand patterns at small spatial or temporal scales. Ultimately, the appropriate scales for using social media to understand spatial patterns will depend on the appropriateness of the data for the research question and setting.

4.4 Understanding Aspects of the Visitor Experience

Relatively few studies in this review used social media to understand aspects such as sentiment, visitor behavior, or perceptions of visitors in parks and protected areas. However, this review only included papers in parks or protected area settings, and these topics have also been studied in other settings (e.g., Arkema et al., 2015; Dunkel, 2015; Mitchell, Frank, Harris, Dodds, & Danforth, 2013; Tieskens, Van Zanten, Schulp, & Verburg, 2018). Previous research in this review found text and photo content of social media useful to understand and analyze these aspects of the visitor experience. Additionally, the majority of studies that analyzed photo content did so manually, but future work may be able to take advantage of automated tools (e.g., Google Vision). Although some research questions do require manually viewing photos (e.g., identifying unwanted behavior), other questions may benefit from using automated tools to quickly process large datasets (e.g., identifying landscape features). This may make analyzing photo content more accessible for studies that span large geographic areas.

4.5 Best Practices

After reviewing the current state of the science, we would like to highlight five recommendations and best practices. These are based on the methods and results of previous studies that use social media to inform visitor use management in parks and protected areas. Broadly, these best practices are aimed at addressing a lack of consistency in the methods employed in previous research. Inconsistency is expected from such a relatively new field of study, yet it suggests to us that it would help to establish common reporting standards for researchers working in this area that would facilitate further meta-analyses and allow the field to mature. Our suggested best practices include:

(1) *Explicitly state the spatial and temporal extent and resolution of all analyses.* The scale of analysis used patently affects the results of a study and also informs the scales utilized in future investigations. Researchers should state if they are using different resolutions for different pieces of analyses within their investigation. They should also detail why they chose those resolutions.

(2) *Use user-days of social media to estimate visitation.* We found the majority of previous studies analyzed user-day metrics such as PUD, which count one photo or post per visitor, per day. Studies that analyze user-days rather than all

social media posts tend to report higher correlations with visitation measured by other data sources.

(3) *When possible, report measures of association between social media and other sources of visitation data; include the temporal resolution and number of observations.* It is useful to compare social media use to other estimates of visitation across different locations and settings. To meaningfully compare results across sites, studies must present similar metrics. Depending on the analysis, Pearson's or Spearman's rank correlation, or the coefficient of determination (R^2), should be provided to help future comparative efforts.

(4) *If analyzing data using grids or multiple sites, report the sensitivity to spatial scale.* Using arbitrary spatial units introduces statistical bias and can potentially impact results (i.e., the modifiable areal unit problem) (Fotheringham & Wong, 1991). Reporting results at multiple spatial scales can reveal whether the results are consistent regardless of the chosen areal unit.

(5) *Make coded workflows for collecting and analyzing data publicly available.* Making code available would make analysis more transparent, increase reproducibility, and lower the barrier for other researchers and practitioners to use social media as a data source.

5. Conclusions

Social media have been used in a variety of ways to inform visitor use management in parks and protected areas. Previous research has used social media to estimate visitation, explore spatial or temporal patterns of visitation, and understand aspects of the visitor experience. The high spatial and temporal resolutions of social media allow researchers to investigate novel questions at small and large geographic scales. Land managers can use the exact geotagged coordinates or GPS tracks to see where visitors go within parks and protected areas, and time stamps to understand when they go places. However, often it is necessary to aggregate multiple years of data to have adequate sample sizes for estimating visitation or mapping spatial patterns – particularly at less visited sites. Although research has shown that social media can be used in many ways to inform park and protected area management, there are also many ways that it could be misapplied – especially if it does not account for the fact that social media users may not be representative of all park visitors. Future research may be able to minimize many biases by leveraging data from multiple platforms or using mixed-method approaches. Additionally, with the use of social media becoming more and more common in the scientific literature, common methodological practices and reporting standards can lead to a more coherent, reliable, and transparent body of knowledge.

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CHAPTER III

SOCIAL MEDIA REVEAL ECOREGIONAL VARIATION IN HOW WEATHER INFLUENCES VISITOR BEHAVIOR IN U.S. NATIONAL PARK SERVICE UNITS

Abstract

Daily weather affects total visitation to parks and protected areas, as well as visitors' experiences. However, it is unknown if and how visitors change their spatial behavior within a park due to daily weather conditions. We investigated the impact of daily maximum temperature and precipitation on summer visitation patterns within 110 U.S. National Park Service units. We connected 489,061 geotagged Flickr photos to daily weather, as well as visitors' elevation and distance to amenities (i.e., roads, waterbodies, parking areas, and buildings). We compared visitor behavior on cold, average, and hot days, and on days with precipitation compared to days without precipitation, across fourteen ecoregions within the continental U.S. Our results suggest daily weather impacts where visitors go within parks, and the effect of weather differs substantially by ecoregion. In most ecoregions, visitors stayed closer to infrastructure and bodies of water on rainy days. Temperature also affects visitors' spatial behavior within parks, but there was not a consistent trend across ecoregions. Importantly, parks in some ecoregions contain more microclimates than others, which may allow visitors to adapt to unfavorable conditions by visiting a park area with preferable weather. These findings suggest visitors' spatial behavior in parks may change in the future due to the increasing frequency of hot summer days.

1. Introduction

Climate change poses risks to ecosystems within parks and protected areas as well as the outdoor recreation opportunities they provide (Hand, Smith, Peterson, Brunswick, & Brown, 2018; Hewer & Gough, 2018). Previous research suggests visitation will likely change at most parks across North America as temperatures continue to rise, extreme heat events become more common, and precipitation becomes more variable (Fisichelli, Schuurman, Monahan, & Ziesler, 2015; Hewer & Gough, 2018). To date, projected impacts to visitation in response to warming temperatures and extreme heat events have only been studied at the scale of whole park units (e.g., Fisichelli et al., 2015; Smith, Wilkins, Gayle, & Lamborn, 2018); we are unaware of any research examining how the spatial patterns of visitation may change *within* parks. Understanding how visitation patterns may change within a park due to weather can help park managers plan and prepare for managing visitor flows, both on a daily scale and when thinking about future climate change. For example, managers could anticipate and proactively manage weather-altered visitation patterns by providing additional information to visitors and increasing signage in certain areas. Managers could also expand recreation infrastructure (e.g., trails, campgrounds, restroom facilities, etc.) in those areas which are more likely to see increased use as the climate continues to warm. In addition, managers can plan to mitigate health risks to visitors posed by extreme weather events through proactive risk communication, infrastructure, and enhanced search-and-rescue resources.

The overall objective of this study is to explore how the spatial behavior of visitors to U.S. parks changes during the summer in response to temperature and precipitation. Visitors' spatial behavior captures *where* individuals choose to go during their park visit. Outdoor recreationists in U.S. national parks make sovereign decisions about which trails to hike, which rivers to float, and which scenic overlooks to stop at, among many other decisions affecting the location of where outdoor recreation occurs. All of these decisions are influenced, to varying degrees, by the weather. This research is the first attempt to quantify how, and to what extent, the weather influences park visitors' spatial behavior. We focus on summer because the influence of weather on the spatial patterns of visitation likely differ by season, and because visitation-related management challenges are most often experienced in the summer, when visitation tends to be highest (National Park Service, 2020a).

We focus on two measures of visitors' spatial behavior: the elevation of an outdoor recreation trip and the distances of that trip from roads, waterbodies, parking areas, and buildings. We test the hypotheses that visitors may be more likely to visit higher locations and stay closer to roads, waterbodies, parking areas, and buildings on extremely hot days, particularly in the warmest ecoregions. We hypothesize this because previous research shows there is a threshold that visitors consider too hot in parks, which may make visitors more likely to stay near infrastructure or seek cooler temperatures at higher elevations (Paudyal, Stein, Birendra, & Adams, 2019; Smith et al., 2018). On days with high precipitation, we expect that visitors will stay at lower elevations and be closer to roads, parking areas, and buildings.

To test these hypotheses, we used geotagged social media to understand exact dates and locations of visits within 110 U.S. National Park Service (NPS) units. NPS units include national parks, national recreation areas, national monuments, and national seashores, among others; these are all considered different designations of parks

(National Park Service, 2020b). Because of the geographic diversity of U.S. NPS units, the influence of weather on visitor behavior is likely to be highly variable. Previous research has found that the effect of weather on tourists and park visitors varies based on the setting and climate of the destination (e.g., Hadwen, Arthington, Boon, Taylor, & Fellows, 2011; Scott, Gössling, & de Freitas, 2008). For example, warmer than average temperatures may cause visitors to travel farther from roads in relatively cool climates, but may cause visitors to stay closer to roads in hot climates. To account for this variability, we examine the proposition that the impact of weather on visitors' spatial patterns within parks varies by ecoregion. Ecoregions represent areas in North America where the ecosystems (i.e., biotic, abiotic, terrestrial, and aquatic components) are generally similar. They were designed as a spatial framework to understand and manage ecosystems across administrative or political boundaries (U.S. Environmental Protection Agency, 2016). Although there is still some variation within an ecoregion with regards to climate and topography, we believe analyzing the affect of weather on visitor behavior by ecoregion is a useful first step in understanding if and how weather impacts visitors' behavior differently across diverse regions.

We used geotagged social media from Flickr to understand spatial patterns of visitation given the fine spatial and temporal resolution of these data. Flickr is a photo-sharing application that has been previously used to understand park visitation and spatial patterns of visitors in parks [11]. Our work is informed by both the growing body of research examining the influence of weather on outdoor recreation, as well as the literature on using social media data to understand park visitors (e.g., da Mota &

Pickering, 2020; Fisichelli et al., 2015; Hewer, Scott, & Fenech, 2016; Smith et al., 2018.)

1.1 The Impact of Weather on Outdoor Recreation

Outdoor recreationists often select their destination and timing of their trip based on the climate (Scott & Lemieux, 2010). Once on-site, weather influences the types of activities chosen, the length of stays, and the amount of satisfaction obtained (Becken & Wilson, 2013). Studies have looked at a variety of ways in which weather influences outdoor recreation; temperature and precipitation are the two most commonly studied weather metrics related to the behavior of outdoor recreationists (Verbos, Altschuler, & Brownlee, 2018). For example, Hewer, Scott, and Fenech (2016) found that visitation to a Canadian park was affected by both daily maximum temperature and daily precipitation. During the summer, the authors found that precipitation was negatively correlated with visitation, and temperature positively correlated with visitation, up to a threshold of 33°C, after which visitation declined (Hewer et al., 2016). Although daily or monthly mean temperature is most commonly studied, recent research indicates maximum temperatures may be even more important in predicting visitation to parks, particularly in the summer (Smith et al., 2018).

Tourists' sensitivities to and preferences for weather differ depending on the climate of their destination (Scott et al., 2008). For instance, tourists in mountain areas or urban areas have been found to believe the "ideal" temperature is lower than the ideal temperature desired by beach tourists, likely because beach tourists expect warmer temperatures (Rutty & Scott, 2010; Steiger, Abegg, & Jänicke, 2016). There is substantial variation found in the literature for optimal temperatures and thresholds for outdoor recreation, largely because outdoor recreation settings (e.g., beach, mountain, forest) and the activities they support vary widely, and many studies tend to be focused on one or two specific settings (Dubois, Ceron, Gössling, & Hall, 2016; Hewer, Scott, & Gough, 2015). Additionally, it can be challenging to compare the effects of weather on outdoor recreation across different settings because studies use different methodologies, data sources, questionnaires, and temporal scales. In this study, we utilize nationwide data to analyze the impact of daily weather on the spatial behavior of visitors across multiple settings.

Changing temperature and precipitation patterns are likely to directly impact both the supply of and demand for outdoor recreation opportunities, although the impacts will also differ by activity and geographic region (Gössling, Scott, Hall, Ceron, & Dubois, 2012; Hewer & Gough, 2018). For example, Hadwen and colleagues (2011) found the impact of monthly weather averages on visitation to Australian parks varied by climate region. Increased temperatures due to climate change have already expanded the length of the peak season in U.S. national parks (Monahan et al., 2016). Warmer than average temperatures generally equate to longer seasons in which individuals can participate in warm-weather recreation activities (e.g., hiking, camping, biking) (Hand et al., 2018). However, the ways in which weather impacts park visitation is likely to be dependent upon the geographic features of particular parks. Some outdoor recreation destinations may see visitation actually decline after reaching a certain temperature threshold (e.g., 25-33°C), while parks with a greater number of different microclimates accessible to visitors (e.g., mountain parks or those with deep canyons) may continue to experience visitation increases above the threshold (Smith et al., 2018).

Most studies to date have not taken into account different microclimates within a single destination. For example, Rutty and Scott (2014) found that coastal tourism areas contained varying microclimates, with thermal conditions differing up to 4°C at various areas of a particular resort. This indicates that if conditions are uncomfortable at one area of the resort, visitors can adapt by moving to a different area (Rutty & Scott, 2014). Although some outdoor recreation destinations may appear “too hot” under altered climatic conditions (Fisichelli et al., 2015), it is unknown whether visitors may adapt by visiting different areas within a park (e.g., higher altitudes or near bodies of water). By joining the location and date of social media posts with historical weather data, this research is the first study to understand how temperature and precipitation impact the spatial behaviors of outdoor recreationists within parks at a high spatial and temporal resolution.

1.2 Using Social Media Data in Parks

Social media data has been increasingly used over the last few years to understand a wide array of environmental problems (Ghermandi & Sinclair, 2019; Toivonen et al., 2019). The most commonly used social media platforms in environmental research include Twitter, a microblogging website, and Flickr, a photo sharing website (Ghermandi & Sinclair, 2019). Researchers have used many aspects of social media data to glean insights, including text content, photo content, video content, and metadata (e.g., geographic information and timestamps) (Ghermandi & Sinclair, 2019; Toivonen et al., 2019).

Over the last decade, researchers have found social media data to be helpful to inform outdoor recreation management in parks and protected areas (da Mota & Pickering, 2020). Social media can be used as a relatively accurate estimation of visitation to parks and protected areas at annual and monthly scales (Keeler et al., 2015; Sessions, Wood, Rabotyagov, & Fisher, 2016; Wood, Guerry, Silver, & Lacayo, 2013). Recent research indicates social media data are useful to estimate visitation to individual trails within National Forests (Fisher et al., 2018). Although many land management agencies estimate visitation through surveys, administrative data, and traffic counters (Leggett, Horsch, Smith, & Unsworth, 2017), social media data are unique in that they allow for visitation estimates at fine spatial and temporal resolutions and are comparable across sites. For instance, the NPS only produces visitation estimates at the monthly scale (Leggett et al., 2017), whereas social media data can show temporal trends in visitation at the hourly resolution (Barros, Moya-Gómez, & Gutiérrez, 2019). This is because the timestamp that the photo was taken, and the geographical coordinates of the photo, are recorded in metadata automatically recorded by and stored on individuals' smartphones (Toivonen et al., 2019). For instance, one study used multiple years of geotagged Flickr data to understand trends in what time of day, and what day of the week, people tend to visit a national park in Spain (Barros et al., 2019). More relevant to this work is the high spatial resolution of social media data. The geographic locations of posts are acquired through metadata which accompany posts, but are often not readily seen by users. This metadata includes date and time the photo was taken, as well as the geographic coordinates where the photo was taken. The geographic coordinates are typically accurate within five meters if they are taken with a GPS-enabled device (National Coordination Office for Space-Based Positioning Navigation and Timing, 2017), making the spatial resolution higher than other sources of visitation data.

Researchers have also leveraged this spatial specificity of geotags to show trends in where visitors go within parks and protected areas (Barros et al., 2019; Hale, 2018; Schirpke, Meisch, Marsoner, & Tappeiner, 2018; Walden-Schreiner, Leung, & Tateosian, 2018a). By mapping social media data along with other geospatial data, researchers can better understand what factors relate to visitor demand within a park (Donahue et al., 2018; Walden-Schreiner et al., 2018a; Walden-Schreiner, Rossi, Barros, Pickering, & Leung, 2018b). For example, Walden-Schreiner et al. (2018a) concluded that distance to a road was the most important variable for predicting the presence of Flickr photos within Hawaii Volcanoes National Park, followed by elevation. Spatial patterns of Flickr posts in parks differ by season, and the presence of trails was the most important factor predicting Flickr photos in the summer for national parks in Australia and Argentina (Walden-Schreiner et al., 2018b). Collectively, these studies show the resolution of geotagged social media data is useful to understand how visitation patterns relate to environmental factors and infrastructure. However, none of these studies have investigated how an exogenous factor, like weather, influences the spatial patterns of visitors.

2. Methods

2.1 Study Sites

Study sites include all U.S. NPS units in the continental U.S. that manage more than 10,000 acres of land (4,047 hectares). We imposed this size restriction since we are interested in the spatial behavior of visitors within park units; visitors to parks under 10,000 acres (4,047 hectares) may not have the option to vary their spatial behaviors due to weather conditions. NPS units include national parks, national monuments, national battlefields, national recreation areas, and national seashores, among others. However, national parkways were not included in the sample because of their very different spatial characteristics (i.e., they are roads that span multiple states). The sample includes a total of 110 NPS units.

Each park unit was assigned both a level I and a level II ecoregion based on the location of the centroid of the unit. Level I ecoregions represent the most general category, while level II ecoregions are more detailed. For nearly all ecoregions we used the level I ecoregions. However, two level I ecoregions (North American Deserts and Eastern Temperate Forests) were split into their level II ecoregions due to their vast size and the number of study sites contained within them. Figure 3.1 shows the study sites along with the ecoregion categories used in this paper, and Appendix B, Table B.1

provides a list of all NPS units included in this study and their ecoregion classifications.

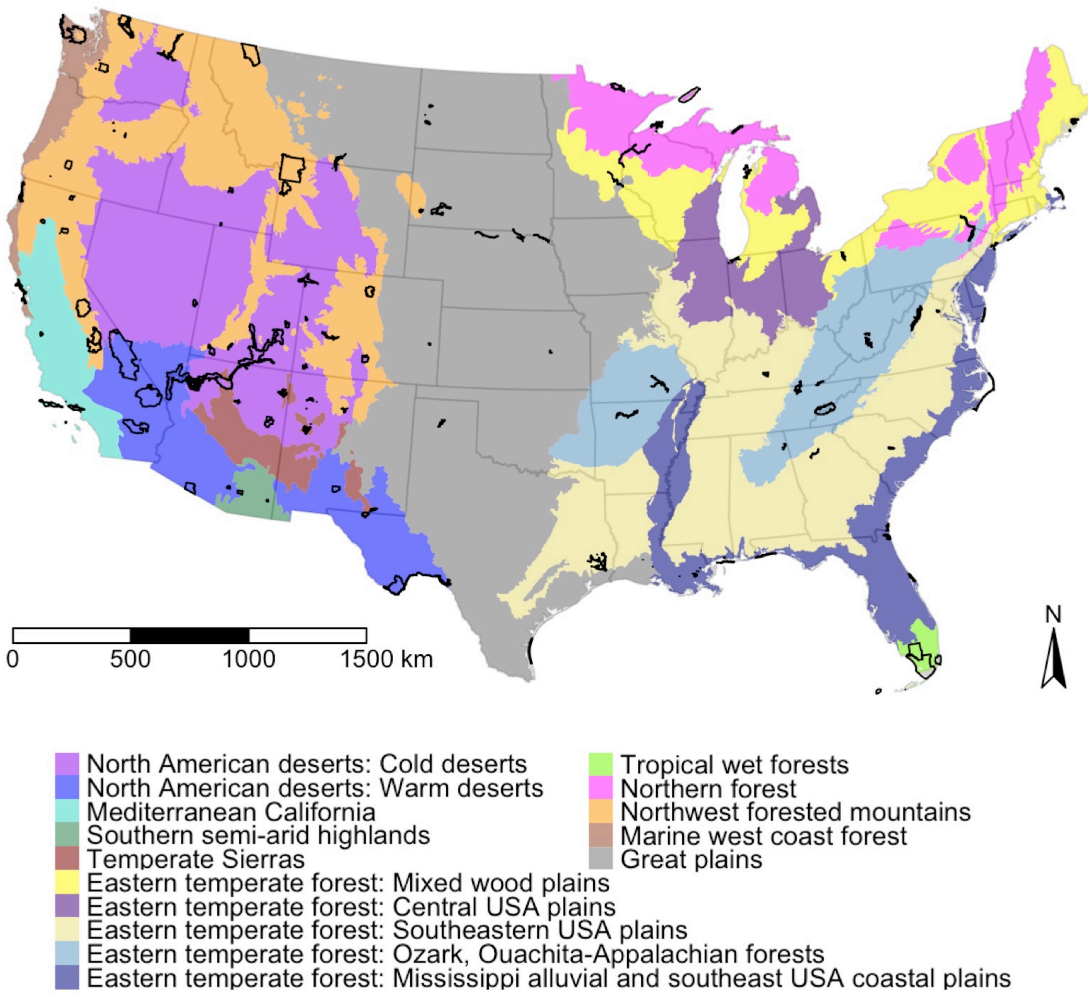

Figure 3.1. Locations of the 110 NPS units used in this study and continental U.S. ecoregions used to categorize parks.

2.2 Data Collection and Processing

All data used in this paper are publicly available. Table 3.1 lists all datasets used along with their sources. In cases where an R package is listed as a source, we downloaded the data directly through R, using the specified packages to interact with the Application Programming Interfaces (APIs). All code written for data collection, processing, and analysis is available at https://dx.doi.org/10.3886/E119191V1.

Table 3.1

Datasets and sources used in this paper.

Data	Type of data	Source	Citation
NPS spatial boundaries	Polygons	NPS	(National Park Service, 2019a)
NPS unit centroids	Table (turned into points from lat/long)	NPS	(National Park Service, 2017)
Main visitor center for each NPS unit	Table (turned into points from lat/long)	Manually compiled via Google Maps and NPS unit websites	Dataset made available at: https://dx.doi.org/10.3886/E119191V1
Acreage of NPS units	Table	NPS	(National Park Service, 2019c)
Visitation at NPS units	Table	NPS	(National Park Service, 2019b)
Ecoregions levels I & II	Polygons	EPA	(U.S. Environmental Protection Agency, 2016)
Geotagged Flickr posts (2006 – 2018)	Points	Flickr API (via Python code)	(Flickr, n.d.)
Daily temperature & precipitation (2006 – 2018)	Raster (1 km resolution)	Daymet R package: daymetr	(Thornton et al., 2018) R: (Hufkens, 2019)
Elevation	Raster (1/3 arcsec resolution)	USGS R package: elevatr	(U.S. Geological Survey, 2017) R: (Hollister and Shah, 2018)
Roads	Lines[1]	OpenStreetMap R package: osmdata	(OpenStreetMap Contributors, 2019) R: (Padgham et al., 2017)
Parking areas	Polygons & multipolygons		
Bodies of water	Polygons, multipolygons, & lines		
Buildings	Polygons & multipolygons		

[1] These data also include raw polygon files (representing loop roads) that were converted to line features

2.3.1 Flickr Data Processing

We downloaded Flickr data from 2006 to 2018 directly from the Flickr API using Python. We downloaded these data in October 2019. Flick*r* points were turned into a spatial object by using their latitude and longitude. We only used Flickr points that were within park unit boundaries, and only retained the points that represented pictures taken between the months of May and September. We added additional attributes to the Flickr data corresponding to individual NPS units and ecoregion.

We deleted any photos by the same user, on the same day, within 10 meters of another photo posted by the same user; therefore, we only retained one photo per user, per location. This is similar to the concept of Photo User Days (PUD) (e.g., Sessions et al., 2016; Wood et al., 2013), except we only deleted duplicates in close proximity rather than duplicates anywhere within the unit. We did this believing it was important to retain posts by the same user if they were in different locations within the park. If a user had multiple posts on the same day within 10 m, we randomly selected one point to retain. Table 3.2 shows the sample sizes for the number of Flickr points in each ecoregion. Appendix B, Table B.2 contains the sample size of Flickr points for each individual unit.

Table 3.2

Ecoregions in this study, along with the number of units and number of data points in each between May – September, 2006 – 2018. Total Flickr points = 489,061.

Ecoregion	**Number of units**	**Number of Flickr points[1]**	**Example units**
Northern forest	6	6,035	Isle Royale, Voyageurs
Northwest forested mountains	20	209,173	Rocky Mountain, Yosemite
Marine west coast forest	1	3,858	Redwood
Eastern temperate forest: Mixed wood plains	4	14,228	Acadia, Cuyahoga Valley
Eastern temperate forest: Southeastern USA plains	5	1,391	Congaree, Mammoth Cave
Eastern temperate forest: Ozark, Ouachita-Appalachian forests	10	17,830	Shenandoah, Great Smoky Mountains
Eastern temperate forest: Mississippi Alluvial and Southeast USA coastal plains	11	18,337	Gateway, Cape Cod National Seashore
Great plains	10	24,901	Badlands, Tallgrass Prairie
North American deserts: cold deserts	21	86,804	Zion, Grand Canyon
North American deserts: warm deserts	9	25,784	Joshua Tree, Lake Mead
Mediterranean California	5	76,508	Channel Islands, Point Reyes
Southern semi-arid highlands	2	1,258	Saguaro, Chiricahua
Temperate Sierras	2	797	Guadalupe Mountains, Carlsbad Caverns
Tropical wet forests	4	2,157	Everglades, Big Cypress

[1] Represents only one post per user, per day, within a 10-meter radius

2.3.2 Joining Flickr Data with Weather and Geospatial Data

We joined each Flickr point to the daily weather on that day at that location using spatially continuous modeled weather data from Daymet; these data were acquired using the R package daymetr (Thornton et al., 2018). These data are at a 1 km resolution and cover the entire continental U.S. However, Daymet does not provide weather estimates over oceans. Therefore, our analysis does not include any Flickr points tagged in an ocean (e.g., off the coast of a national park). Dry Tortugas National Park only had Flickr points in the ocean; although this park was initially included as a study site, it did not contain any observations.

We obtained elevation data for each point from the R package elevatr, which uses data from the U.S. Geological Survey for the continental U.S. We downloaded this data at the 1/3 arcsec resolution, which is a ground resolution of 6.8 m at 45° latitude (joerd respository, 2017).

We also downloaded data on roads, waterbodies, buildings, and parking areas from OpenStreetMap directly from R using the osmdata R package. Table B.3 shows the key-value pairs used to download OpenStreetMap data for each feature category. All OpenStreetMap data were downloaded in December 2019. For each Flickr point, we calculated the straight-line distance to the nearest road, waterbody, parking area, and building.

2.3 Analysis

2.3.1 Social Media Data Validation

We compared the number of Flickr PUDs within each unit between the months of May and September from 2006 to 2018 to the NPS-reported visitation for each unit during the same time period to ensure the Flickr data are a reliable and representative indicator of visitation. PUD indicates that only one photo per visitor was counted each day; duplicate posts by the same visitor on the same day were removed even if they were in different areas of the park. Subsequent analyses used the full dataset filtered to include just one photo per user, per location. The NPS did not have visitation estimates for two units during this time period (Mississippi National River and Recreation Area and Sand

Creek Massacre National Historic Site), so they were not included in the correlations. We ran a Shapiro-Wilk test to see if the distributions of Flickr PUDs and NPS visitation were normal. If the distributions were normal, Pearson's correlation is appropriate; Spearman's correlation was used if the distributions were not normal.

2.3.2 Understanding How Weather Impacts Visitors' Spatial Behavior

We first explored if and how individual parks have different microclimates (i.e., the park offers different areas where visitors can go that may have slightly different climates). We recorded the differences between the daily maximum temperature and precipitation at the Flickr points compared to the main visitor center on that day. We plotted distributions of differences by ecoregion to see if visitors were going to places within parks that have substantially different weather than at the visitor centers.

We then investigated the effect of maximum temperature and precipitation on visitors' spatial behavior by grouping visitors by the weather during the day they visited. For maximum temperature, visitors were grouped into three categories: cold day, average day, or hot day, based on the temperature at the visitor center on the day of the visit. Average days were defined as those within one standard deviation from the unit-specific seasonal mean maximum temperature. Cold days were defined as days with a maximum temperature lower than one standard deviation below the unit-specific seasonal mean maximum temperature. Hot days were classified as days with a maximum temperature greater than one standard deviation above the unit-specific seasonal mean maximum temperature. We grouped these observations by unit rather than ecoregion to reduce bias. For instance, one park within an ecoregion could be warmer than the others; grouping by unit avoids having all data from one park classified in the same temperature category. Precipitation was split into two groups based on whether or not there was precipitation at the visitor center on the day of the visit.

We tested if maximum temperature or precipitation affected: 1) the elevations visitors were traveling to within a park; 2) their distance to roads; 3) their distance to waterbodies; 4) their distance to designated parking areas, and 5) their distance to buildings. We ran Welch's ANOVA tests to determine if there were differences in visitors' elevations and distances to features between cold, average, and hot groups. If the results were significant at the 0.05 level, we ran Games-Howell post-hoc tests to determine where the significant differences were (i.e., if differences were between the cold and average group, hot and average, hot and cold, or all three). We used Games-Howell tests because they do not require the assumptions of equal variances or equal sample sizes to be met (Hilton & Armstrong, 2006). Additionally, if there were significant differences between groups, we reported Cohen's d to measure how large the effect size was. For precipitation, we ran Welch's t-tests with Cohen's d effect sizes. Welch's tests were used rather than Student's t-tests and standard ANOVAs because much of the data violated the assumption of equal variances. Furthermore, Welch's tests often do not lose robustness even if the assumption of equal variances is met (Delacre, Lakens, & Leys, 2017). We ran separate tests for each ecoregion, given that weather may impact visitors differently by ecoregion. Therefore, we ran 70 Welch's ANOVAs to test the effects of maximum temperature on each of the five variables (elevation and distance to roads, waterbodies, parking areas, and buildings) across the 14 ecoregions, and 70 Welch's t-tests to explore the effects of precipitation. We did not adjust for multiple comparisons because each ecoregion represents a different dataset, and we are interested in how weather impacts visitors' elevations and distances to roads, waterbodies, parking areas, and buildings independently. To visually compare how distributions may differ, we mapped spatial distributions in parks on cold days compared to hot days.

3. Results

3.1 Correlations Between Flickr Data and NPS-reported Visitation

Results indicated the distributions of both the Flickr data and the NPS visitation data were non-normal. We therefore ran Spearman's correlation rather than Pearson's correlation tests. When aggregating all data for each unit from 2006 to 2018 for the months of May through September, the correlation between Flickr PUDs and NPS-reported visitation was $R_s = 0.707$ ($n = 108$, $p < 0.001$). At the monthly scale, aggregating monthly data from 2006 - 2018, the correlation was $R_s = 0.709$ ($n = 540$, $p < 0.001$). These results suggest geotagged Flickr data are a useful proxy for summer visitation in U.S. NPS units.

3.2 Descriptive Statistics

Table 3.3 shows all the means and standard deviations by ecoregion for daily maximum temperature at the visitor centers and Flickr points, daily precipitation at the visitor centers and Flickr points, and elevation at the visitor centers and Flickr points. Mean maximum daily temperature at visitor centers was highest in the warm desert ecoregion (37.1 °C) and lowest in the Marine west coast forest ecoregion (22.5 °C). Maximum daily temperature at Flickr points was also highest in the warm desert ecoregion (35.2 °C), but lowest in the northwest forested mountains ecoregion (21.0 °C). Mean daily precipitation at visitor centers was highest in the tropical wet forest ecoregion (6.3 mm) and lowest in the Mediterranean California ecoregion (0.1 mm). Overall, there was not much variation in the amount of daily precipitation at visitor centers compared to Flickr points.

Table 3.3

Means and standard deviations (in parenthesis) for all weather data and elevation by ecoregion. Values represent data from May – September. n represents one Flickr post per person per day, within a 10 m radius.

Ecoregion	***n***	**Max. temp at visitor centers (˚C)**	**Max. temp at Flickr post (˚C)**	**Precip. At visitor centers (mm)**	**Precip. at Flickr post (mm)**	**Elevation at visitor centers (m)**	**Elevation at Flickr post (m)**
Warm deserts	25,784	37.1 (6.6)	35.2 (7.2)	0.3 (2.0)	0.3 (2.3)	478.3 (403.1)	722.2 (560.0)
Southern semi-arid highlands	1,258	33.5 (4.6)	33.1 (5.7)	1.2 (3.5)	1.2 (3.7)	1088.9 (284.1)	1100.6 (479.3)
Tropical wet forests	2,157	32.3 (1.6)	32.4 (1.6)	6.3 (10.3)	6.9 (12.7)	1.2 (0.4)	1.1 (0.9)
Southeastern USA plains	1,391	29.6 (3.8)	29.5 (3.8)	3.9 (9.2)	3.9 (9.1)	210.4 (88.4)	197.9 (89.7)
Temperate Sierras	797	29.5 (4.9)	29.3 (5.5)	1.3 (4.8)	1.3 (4.7)	1506.5 (197.5)	1521.3 (350.2)
Mississippi alluvial and southeast USA coastal plains	18,337	27.6 (4.2)	27.8 (4.3)	3.5 (10.8)	3.2 (9.9)	5.1 (3.8)	3.7 (7.0)
Cold deserts	86,804	27.3 (6.1)	27.4 (6.0)	1.1 (3.1)	1.0 (3.1)	1829.0 (467.1)	1830.8 (501.7)
Ozark, Ouachita-Appalachian forests	17,830	27.1 (3.9)	25.3 (4.6)	4.1 (8.3)	4.6 (8.9)	387.0 (106.2)	770.3 (492.3)
Great plains	24,901	26.3 (5.0)	26.3 (5.0)	2.6 (6.9)	2.8 (7.4)	375.3 (241.0)	385.2 (258.0)
Mixed wood plains	14,228	24.1 (4.2)	23.8 (4.3)	3.1 (7.6)	3.3 (7.9)	99.0 (86.8)	172.5 (128.8)
Northern forest	6,035	24.0 (4.2)	24.0 (4.2)	3.1 (7.7)	3.0 (7.9)	265.6 (93.3)	211.1 (47.0)
Northwest forested mountains	209,173	23.7 (6.7)	21.0 (6.0)	0.9 (2.8)	1.0 (3.0)	1606.8 (685.1)	1999.2 (770.6)
Mediterranean California	76,508	23.0 (4.3)	22.5 (4.2)	0.1 (1.2)	0.1 (1.3)	77.7 (63.3)	82.9 (137.6)
Marine west coast forest	3,858	22.5 (3.2)	21.7 (3.4)	0.7 (2.8)	0.7 (2.7)	47.5 (0.0)	97.1 (126.1)

Elevation at visitor centers was highest for the cold deserts ecoregion (1829.0 m), and highest for Flickr points in the northwest forested mountains ecoregion (1999.2 m).

Flickr points in the northwest forested mountains ecoregion had the largest standard deviation for elevation, indicating this ecoregion has the largest range of elevations visitors frequent. Elevation was lowest in the tropical wet forests ecoregion (1.2 m at the visitor centers, and 1.1 m at Flickr points).

Table 3.4 shows the means and standard deviations by ecoregion for the distance from each Flickr point to the nearest road, waterbody, parking area, and building. We did not use road or parking data for three units (Channel Islands, Isle Royale, and Apostle Islands) because these parks are islands that do not have publicly accessible roads or parking.

Table 3.4

Means and standard deviations (in parenthesis) for all distance measures by ecoregion. Values represent data from May – September. n represents one Flickr post per person per day, within a 10 m radius.

Ecoregion	***n***	**Dist. to road (m)**	**Dist. to water (m)**	**Dist. to parking (m)**	**Dist. to building (m)**
Warm deserts	25,784	83.9 (279.6)	3697.9 (9165.7)	1181.9 (4547.2)	462.9 (1131.6)
Southern semi-arid highlands	1,258	26.0 (66.2)	355.4 (587.0)	347.0 (944.7)	402.7 (828.2)
Tropical wet forests	2,157	120.4 (401.7)	319.9 (643.9)	666.4 (1216.9)	452.0 (1134.9)
Southeastern USA plains	1,391	9.3 (17.2)	145.5 (268.7)	552.3 (1331.9)	174.2 (447.1)
Temperate Sierras	797	165.2 (287.4)	5829.1 (2924.4)	626.9 (1557.3)	612.4 (1586.6)
Mississippi alluvial and southeast USA coastal plains	18,337	161.7 (787.5)	73.1 (108.7)	594.2 (1377.0)	102.2 (222.1)
Cold deserts	86,804	72.3 (351.4)	941.8 (1918.5)	549.2 (1465.6)	574.0 (1201.2)
Ozark, Ouachita-Appalachian forests	17,830	17.3 (32.5)	213.6 (352.8)	505.5 (1329.1)	197.2 (537.2)
Great plains	24,901	9.3 (95.9)	881.6 (1975.9)	309.2 (3307.9)	262.2 (793.2)
Mixed wood plains	14,228	57.6 (348.0)	87.1 (128.3)	430.0 (2109.3)	265.2 (679.5)
Northern forest	6,035	77.0 (425.1)	56.5 (92.1)	752.1 (1431.1)	599.9 (1530.6)
Northwest forested mountains	209,173	72.2 (258.5)	119.9 (213.4)	417.6 (1078.5)	297.9 (546.6)
Mediterranean California	76,508	25.9 (110.3)	80.5 (164.7)	100.6 (252.2)	548.1 (847.9)
Marine west coast forest	3,858	15.1 (20.8)	222.3 (262.8)	259.9 (412.8)	497.4 (543.2)

Mean distance to roads ranged from 9.3 m (Southeastern USA plains) to 165.2 m (Temperate Sierras). Across all ecoregions, the mean distance to roads was 63.0 m, and the median distance to a road was 10.9 m. This indicates many visitors to NPS units stay very close to roads in the summer. In most ecoregions, visitors were farther from buildings and designated parking areas compared to roads. These results suggest many visitors may take photos from their cars, or from pullout areas on the side of roads. Distance to waterbodies varied, with visitors in the Temperate Sierras ecoregion being the farthest from water, and visitors in the Northern forest ecoregion being closest to waterbodies.

3.3 Microclimates Within Parks

Some parks have more microclimates than others. Figure 3.2 shows the distributions for the difference in daily maximum temperature between the visitor center and individual Flickr point locations. Wider distributions (e.g., Northwest forested mountains ecoregion) indicate more microclimates within the parks, while narrower distributions (e.g., Southeastern USA plains) indicate daily temperatures are similar across the whole park unit, in places that receive visitation. These microclimates represent the differences in temperature between where people visit compared to the visitor center; they do not necessarily represent differences in daily temperature across all park areas. Since some places may be inaccessible, we felt it was important to explore temperature differences, and thus microclimates, in park areas that receive visitation.

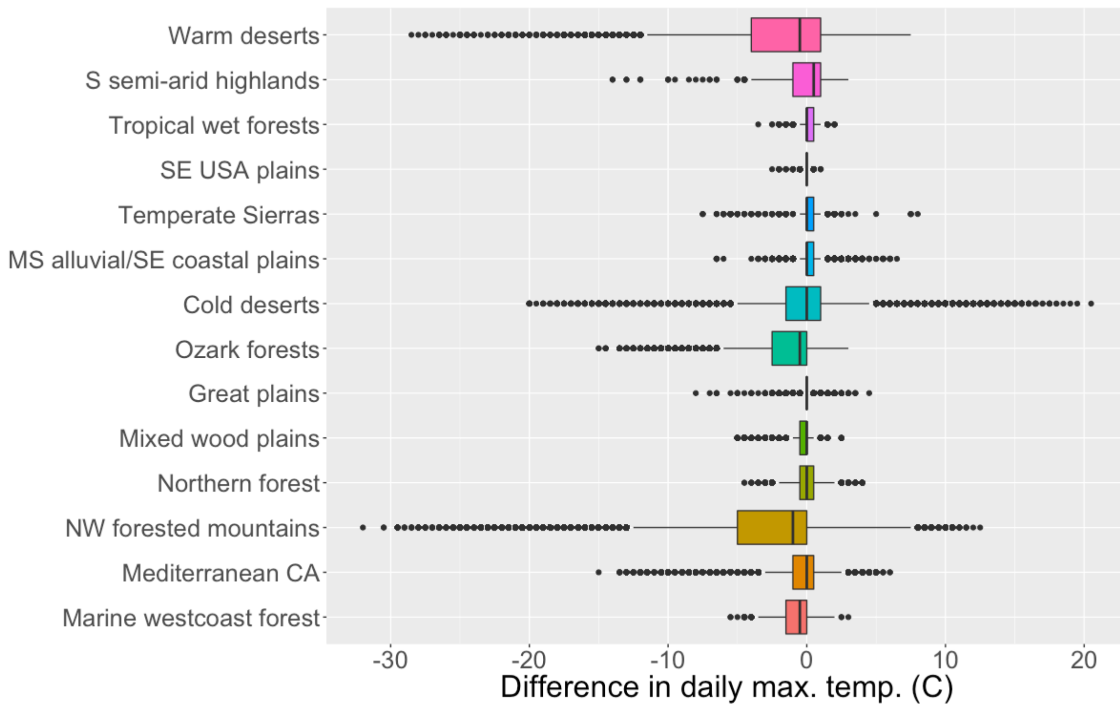

Figure 3.2. Boxplots of the distributions by ecoregion for the difference in daily maximum temperature (°C) between visitor centers and individual Flickr points within each park. Boxes represent the interquartile range, with black lines representing the medians; black dots represent outliers. Negative values indicate visitors are going to places within the park that are colder than the temperature at the visitor center.

Overall, there is less variation in the difference in daily precipitation between the visitor centers and Flickr point locations. For all ecoregions, the interquartile range for the precipitation difference is 0.0 mm to 0.0 mm., indicating at least 50% of the Flickr points in each ecoregion have the same daily precipitation as the visitor centers in every ecoregion. However, there are still some differences in precipitation between Flickr points and visitor centers, with the Mississippi alluvial/southeastern coastal plains ecoregion having the largest differences.

3.4 Differences in Visitation Patterns between Hot and Cold Days

The cutoff points for what was defined as a cold day, average day, and hot day differ by park unit and can be found in Appendix B, Table B.4. The effect of maximum temperature on visitors' elevation and distance to roads, waterbodies, parking areas, and buildings varied by ecoregion (Figure 3.3). There is not a consistent trend in how temperature impacts patterns of visitation across ecoregions for any variable. In some ecoregions (e.g., tropical wet forests, mixed wood plains), visitors stay closer to parking areas and buildings on cold days, but in other regions (e.g., cold deserts, warm deserts), visitors travel farther from infrastructure on cold days. Visitors tend to frequent lower elevations on cold days in most ecoregions, but there is not a consistent trend in elevation on hot days. Although temperature does affect visitors' spatial distributions within parks, the effect sizes were all very small or small.

Boxes without values in Figure 3.3 indicate there was no statistical differences across the three temperature classifications for that particular ecoregion; this does not necessarily mean no difference exists. Some ecoregions had smaller sample sizes (e.g., temperate sierras at n = 797), while some had very large sample sizes (e.g., northwest forested mountains at n = 209,173). Statistical power is higher when sample sizes are larger, so we were inherently more likely to detect significant differences in ecoregions with larger sample sizes. Appendix Table B.5 shows the sample sizes for each ecoregion based on temperature and precipitation grouping. Additionally, Appendix Table B.6 shows the full statistical results associated with Figure 3.3, including p-values and effect sizes. Within each ecoregion, different units contain different sample sizes; therefore, the results are likely driven by the parks with the largest samples in each ecoregion.

	Cold vs average days					Hot vs average days				
	Elev. (m)	Dist. to roads (m)	Dist. to water (m)	Dist. to parking (m)	Dist. to building (m)	Elev. (m)	Dist. to roads (m)	Dist. to water (m)	Dist. to parking (m)	Dist. to building (m)
Warm deserts		20.4		536.4	135.3	-30.1	-12.1		246.0	
S semi-arid highlands		-10.8		-116.0	-126.0	192.4				
Tropical wet forests	-0.1	-60.1		-321.9	-224.9					253.7
SE USA plains		-3.1								-72.2
Temperate Sierras					719.8			1082.8		
S alluvial/SE coastal plains		224.3		227.6	37.9					
Cold deserts	-82.1	9.6	-63.8	170.6	71.1	33.7	-9.5		-95.9	-44.3
Ozark forests	-112.4	-1.6				-40.8		-22.7		
Great plains										43.1
Mixed wood plains	-11.8	-26.5	-11.8	-254.8	-66.1		-41.4		-228.5	-43.3
Northern forest				-158.3						
NW forested mountains	-146.3	-19.6		-90.5	-30.9	21.1		-9.5	-17.1	13.1
Mediterranean CA	16.5		19.1	15.0	84.4		6.3	-4.1		
Marine west coast forest					87.0	-14.1			66.3	

Cells with no value are not significantly different at $\alpha = 0.05$. Cells with lighter shading represent Cohen's *d* effect sizes from 0.0 – 0.2; darker shading represents effect sizes from 0.2 – 0.5.

Figure 3.3. Differences in means on cold days, compared to average days (left side), and differences in means on hot days, compared to average days (right side). All numbers are differences in meters. Positive values represent higher elevations and farther distance from features on cold or hot days (compared to average); negative values represent lower elevations and closer distance to features on hot or cold days.

Figure 3.4 shows examples of how spatial distributions differ during cold and hot days for two parks: Yosemite National Park (Northwest forested mountains ecoregion) and Death Valley National Park (warm deserts ecoregion). These maps suggest some trails or regions are more popular on hot days, while others are more popular on cold days. In Yosemite, the map shows that visitors are more likely to stay closer to roads on cold days. This is consistent with findings from the results in Figure 3 from the Northwest forested mountains ecoregion, that visitors stay 19.6 m closer to roads on cold days compared to average days. In Death Valley, visitors appear more likely to stay near roads on hot days, consistent with results from the warm deserts ecoregion that shows visitors stay 12.1 m closer to roads on hot days, and 20.4 m farther from roads on cold days, compared to average days. Maps showing general spatial distributions of visitors in each study site, as well as spatial distributions on cold versus hot days, are available online (https://dx.doi.org/10.3886/E119191V1).

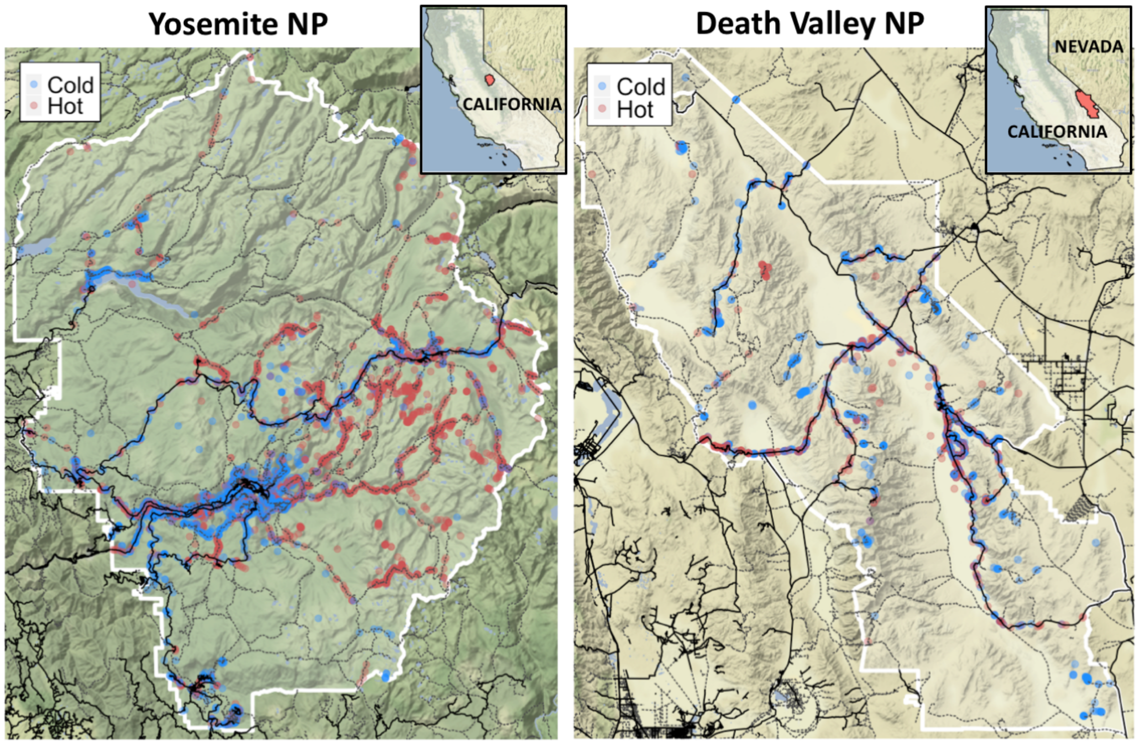

Figure 3.4. Spatial distribution of visitors in Yosemite National Park and Death Valley National Park on cold days (blue dots) compared to hot days (red dots). Solid black lines represent roads, and dotted black lines represent trails downloaded from OpenStreetMap. Figures created in R with ggmap.

3.5 Differences in Visitation Patterns Between Wet and Dry Days

The effect of daily precipitation on visitors' elevation and distance to roads, waterbodies, parking areas, and buildings also varied by ecoregion, although there are some trends across ecoregions (Figure 3.5). Overall, on rainy days, visitors were more likely to stay near roads, waterbodies, parking areas, and buildings. However, this trend does not hold for some of the warmest ecoregions (e.g., warm deserts), where visitors were farther from infrastructure on rainy days. In the warmer ecoregions, visitors went to higher elevations on rainy days, but in the cooler ecoregions, visitors stayed at lower elevations on rainy days. Although rain does impact visitors spatial behavior in all ecoregions, the effect sizes are mostly very small, with a few effects being small or medium. Appendix B, Table B.7 contains the full statistical results associated with Figure 3.5, including p-values and effect sizes.

	Days with precipitation vs days with no precipitation				
	Elev. (m)	Dist. to roads (m)	Dist. to water (m)	Dist. to parking (m)	Dist. to buildings (m)
Warm deserts	110.2	40.1	4600.6	973.2	78.7
S semi-arid highlands	90.5		140.4		
Tropical wet forests	0.1		65.6	155.7	
SE USA plains	19.1				
Temperate Sierras	205.5	69.9	-837.3		
MS alluvial/SE coastal plains		-45.2	-5.0	-150.0	-7.1
Cold deserts	37.1	-12.7	-111.1		-39.0
Ozark forests	46.5		-19.4	-59.5	-39.4
Great plains	-37.4	-3.1	-292.9	-208.2	-130.1
Mixed wood plains	-9.3	-26.1	-17.5	-188.5	-106.5
Northern forest		37.3		-92.1	
NW forested mountains	-12.7	-22.4		-43.7	-65.3
Mediterranean CA	-18.7	5.8	-10.4		189.3
Marine westcoast forest	-21.6		38.0	-91.4	

Cells with no value are not significantly different at $\alpha = 0.05$. Cells with light shading represent very Cohen's *d* effect sizes 0.0 – 0.2; medium shading represents effect sizes 0.2 – 0.5, and the darkest shading represents effect sizes 0.5 – 0.7.

Figure 3.5. Differences in means on days with precipitation, compared to days with no precipitation. All numbers are differences in meters. Positive values represent higher elevations and farther distance from features on days with precipitation; negative values represent lower elevations and closer distance to features on days with precipitation.

4. Discussion

Our results suggest visitors in some ecoregins do change their elevations and/or distances to roads, waterbodies, parking areas, or buildings based on daily temperature and precipitation. The effect of temperature on elevation and distance to a road, distance to a waterbody, distance to a parking area, and distance to a building varied by ecoregion, with no consistent trends across all ecoregions. Overall, visitors were more likely to stay near infrastructure and waterbodies on days with precipitation, although this is not true in every ecoregion. It is not clear why visitors would be staying closer to bodies of water on days with precipitation; further research is needed to determine what the reasoning is for this or if there are confounding effects. However, the effect sizes of the differences are mostly very small, indicating that maybe only a subset of visitors are impacted by weather. Weather impacts visitors differently depending on their activity type and demographic characteristics, so some visitors may be more or less impacted by the weather (Verbos et al., 2018). We found that the majority of visitors stay very close to roads (i.e., over half are within 11 meters from a road); it is possible that weather may have less of an impact on visitors who plan to stay near roads, most likely very close to (if not in) a vehicle. More research would be needed to determine if and why only certain groups of visitors alter their spatial behavior within parks based on the weather.

Climate change is expected to alter the total number of visitors to parks, with the majority of parks in the U.S. expected to see an increase in visitation (Fisichelli et al., 2015). This could strain park resources and cause overcrowding in some parks. Since most visitors stay close to roads, it is important to maintain the roads and infrastructure that are already present. Accommodating visitation demand may not require substantial increases in some types of outdoor recreation infrastructure (e.g., trails), but rather a rethinking of what the typical park experience is for most visitors. With most visitors choosing to stay extremely close to existing park infrastructure, capital investments should be focused on infrastructure upgrades and developments (e.g., remodeling and expanding visitor centers) that are better able to serve the needs and desires of more visitors in the future. However, it is important to note that climate change is not the only factor that is likely to change patterns of park visitation; other factors that impact visitation patterns include the economy, advertising, population growth, and shifting demographics (Jones & Scott, 2006; Poudyal, Paudel, & Tarrant, 2013; Stevens, More, Markowski-Lindsay, 2014; Weber & Sultana, 2013).

Previous work has found total visitation to parks is influenced by daily and monthly weather conditions (e.g., Paudyal et al., 2019; Smith et al., 2018). Our findings suggest that some visitors will respond to warmer than average temperatures by adapting where they go within a park. For example, some visitors may go to higher elevations on warm days, while other parks may see more visitors at lower elevations, possibly in cooler canyons or near the ocean. In some ecoregions, visitors may also choose to stay closer to roads or bodies of water on exceptionally hot days. Once a visitor is already at a park unit, they can respond to adverse weather by not visiting (i.e., staying in nearby towns), visiting a different location in the park, or changing activities (Verbos et al., 2018). More research is needed to understand how visitors decide to respond in different ways, and how that varies by user group. Park managers can help visitors adapt to extreme temperatures by providing information on which areas of the park, that are accessible by road, are comparatively cooler. However, not all parks contain microclimates that may allow for adaptation.

Parks in some ecoregions have more microclimates than others. For example, our analyses showed that parks in the warm deserts, cold deserts, and the Northwest forested mountains ecoregions had wide distributions in the difference in temperature between visitors' locations in the park and the temperature at the visitor center. In other ecoregions, such as the Southeast USA plains, visitors were almost always at a location in the park that had the same temperature as the visitor center. Visitors may therefore have a greater ability to adapt and spatially substitute outdoor recreation settings within park boundaries at some parks compared to others. In parks that do not have varying microclimates, visitors may be less likely to visit on days with unfavorable temperatures rather than change their spatial behavior within the park. This is consistent with findings from Smith and colleagues (2018), which found that visitation declined in some Utah national parks once temperatures were above 25 °C, but visitation continued to increase above this threshold in parks that seemingly had more microclimates. However, we only investigated microclimates with regards to where people currently visit; it is possible that some parks in this study do have microclimates within their boundaries that are not currently visited, but may see visitation in the future.

Although this analysis only covered the summer season (defined as May – September), it is likely that some trends may be attributed to within-season variability. For instance, it is more likely to be cold in May and September, and hot in July and August. In some mountainous parks, certain roads or trails may be closed at the beginning of the summer season until snow melts. Therefore, visitors may not have had the option to visit some park areas on colder than average days. Visitor patterns may be driven by managerial factors (i.e., closed roads or trails) rather than solely visitors' decisions in some parks. Parks in the Northwest forested mountains ecoregion are the most likely to have certain areas closed due to snow in the summer, so these managerial factors are likely to have the biggest influence in this ecoregion. Additionally, the impact of weather of visitors' behavior is likely to be different in other seasons.

As with any data source, social media data has its limitations. Social media data may not be representative of the spatial patterns of all park visitors, since only a small portion of total visitors post photos to Flickr. During the time period of this study (May – September, 2006 – 2018), the NPS recorded 1.17 billion visits across 108 parks in this study for which they had visitation data. Our Flickr dataset for these 108 parks represents 470,894 points, indicating that only 0.04% of visits to these parks during our period of analysis are captured on Flickr. We also cannot obtain visitor demographics from social media, so it is unknown if weather alters spatial behavior of some visitor demographics more than others. Additionally, some parks (e.g., Yellowstone, Yosemite) tend to have substantially more social media posts than other parks, indicating the most popular parks were overrepresented in this analysis. OpenStreetMap was an excellent resource for large-scale volunteered geographic information, but the accuracy of this data source does vary by location and feature (Parr, 2015; Zhang & Malczewski, 2017). While the road and water features appeared to be complete in all NPS units, the parking and building datasets were likely not entirely complete. In other words, some buildings and parking areas were missing, but all of the parking areas and buildings documented on OpenStreetMap did exist in that location. Therefore, the estimates for distance to parking and buildings likely represent high estimates. In addition, distances to features do not necessarily indicate how far a visitor hikes or ventures; a visitor could hike for over 500 m and still be within 10 m of a road.

Our investigation began with an effort to understand how weather may impact visitors' spatial behavior within U.S. NPS units. Further studies could explore if weather changes spatial patterns of visitors outside park boundaries, such as to gateway towns and surrounding parklands. Additionally, a visitor survey would be a useful complement to understand stated preferences, and if weather impacts the behavior of some visitors but not others. Future research should also consider that the effect of weather on park visitation is not homogenous across a country. Our results indicated large differences across ecoregions, so results from one ecoregion cannot necessarily be extrapolated onto parks with differing climates or topography. We would expect parks in other countries may exhibit comparable results to the ecoregion that has the most similar climate and topography; however, this needs additional research. In addition, this analysis demonstrates the utility of social media data for revealing visitation patterns within parks at high spatial and temporal resolutions, which can be useful to understand visitor behavior beyond the context of weather-dependencies.

5. Conclusions

In certain ecoregions, visitors alter the locations they go to within NPS units based on daily weather conditions. The effect of temperature and precipitation on visitors' spatial behavior varies by ecoregion, likely because the climates, topography, and availability of microclimates within parks differ by these ecoregions. Some parks may see an increase in visitors to higher elevations on hot days, while other parks may see more visitors at lower elevations on hot days. Visitors are overall more likely to stay near infrastructure, such as roads and parking areas, on rainy days. Park managers should expect spatial distributions of summer visitors within parks to change somewhat in the future due to increasing numbers of hot days. In parks that contain more microclimates, visitors may have a greater ability to adapt to adverse temperature conditions by spatially substituting one outdoor recreation setting for another.

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CHAPTER IV

CLIMATE AND THE DEMAND FOR RECREATIONAL ECOSYSTEM SERVICES ON PUBLIC LANDS IN THE UNITED STATES

Abstract

Cultural ecosystem services (CES) represent nonmaterial benefits people derive from the environment, such as recreational or aesthetic enjoyment. However, a warming climate may shift the demand for CES spatially or temporally. Here, we explore how the average seasonal maximum temperature affects the demand for recreational CES across public lands in the continental United States. We use 14 years of geotagged data from Flickr to understand how the climate of an area affects the demand for recreational CES by season. We use geographically weighted negative binomial regression models to explore if the effect of average seasonal maximum temperature on the demand for recreational CES may vary in different regions of the U.S. Results indicate that in the spring, fall, and winter, the demand for recreational CES on U.S. public lands is higher in places with warmer climates; in the summer, the demand is higher in cooler climates. The effect of average temperature on visitation is not spatially stationary in the winter and summer, with a greater impact on the Western U.S. These results suggest that under climate change, there may be an increased demand for recreational CES in the spring, fall, and winter, but a lower demand in the summer. People may choose to visit in different seasons, choose different location, or visit on days that are comparatively warmer or cooler depending on their preferences. In hotter locations, in the fall, spring, and summer, people were more likely to visit on days that were colder than seasonal averages.

1. Introduction

Ecosystem services represent all direct and indirect benefits humans receive from the environment. These include provisioning services (e.g., food), regulating services (e.g., water purification), supporting services (e.g., nutrient cycling), and cultural services. Cultural ecosystem services (CES) are defined as "the nonmaterial benefits people obtain from ecosystems through spiritual enrichment, cognitive development, reflection, recreation, and aesthetic experiences" (Millennium Ecosystem Assessment, 2005). CES reflect the social and psychological values ascribed to an environment. As such, they have been mapped using a variety of different methods which allow individuals to provide input on what those values are, and where they are provided on a landscape (Lee et al., 2019). Mapping CES helps landowners, land managers, and policymakers understand the trade-offs associated with different policies and decisions (Plieninger et al., 2015, Ruckelshaus et al., 2015). Public land management decisions may also be seen as more acceptable and legitimate if the non-material benefits, such as CES, that individuals receive from the landscape are included in decision-making processes (McKenzie et al., 2014; Milcu, Hanspach, Abson, & Fischer, 2013).

Mapping CES can be costly; the process often requires individuals who use a landscape to provide input on how they value that landscape through surveys or participatory exercises. Consequently, maps of CES are often limited to small geographic scales such as municipalities (Van Berkel & Verburg, 2014) and regions (Martínez-Harms & Balvanera, 2012). Outdoor recreation and tourism opportunities are CES that are relatively easy to quantify when compared to other types of CES such as spiritual value (Crossman et al., 2013; Egoh, Drakou, Dunbar, Maes, & Willemen, 2012). For example, researchers can use data on park visitation or hotel and campsite occupancy to map outdoor recreation and tourism opportunities (e.g., Arkema et al., 2015). Outdoor recreation and tourism opportunities are also intertwined with other CES like spiritual, educational, and aesthetic values, making them a good indicator of these broader CES (Hermes et al., 2018).

Many factors affect the demand for recreational CES across landscapes and drive changes in the production of CES (Milcu et al., 2013). Previous research shows the overall climate of an area, as well as the daily weather, impact the demand for outdoor recreational opportunities (Finger & Lehmann, 2012; Smith, Wilkins, Gayle, & Lamborn, 2018). Thus, warmer than average temperatures, and increasing variability in weather due to climate change, are likely to shift the demand for recreational CES spatially and/or temporally. Additionally, climate change may affect the demand for CES indirectly. For example, there may be spatial or temporal shifts due to changing ecosystems and species distributions (Moreno & Amelung, 2009). Climate change may threaten CES in some locations or seasons but increase the demand for CES in other areas or seasons. In this research, we identify how climate affects the demand for recreational CES on public lands across the continental United States. We use geotagged social media posts as a measure of visitation to public lands; direct use, or visitation, is one measure that has been used to represent the demand for CES (Wolff, Schulp, & Verburg, 2015). Understanding potential future shifts in the demand for recreational CES can help public land managers plan and prepare for changing demand.

1.1 Mapping Cultural Ecosystem Services

Studies that map CES have used a wide variety of data as indicators (Egoh et al., 2012; Kopperoinen, Luque, Tenerelli, Zulian, & Viinikka, 2017). Recently, researchers have used social media to map CES within public lands (e.g., Clemente et al., 2019; Rossi, Barros, Walden-Schreiner, & Pickering, 2019; Vaz et al., 2020). Social media often have a fine spatial resolution and have been shown to be correlated with visitation to public lands across many locations around the globe (Tenkanen et al., 2017; Wilkins, Wood, & Smith, 2020; Wood, Guerry, Silver, & Lacayo, 2013). The majority of studies mapping CES with social media tend to use data from Flickr, a photo-sharing application.

Researchers studying CES using social media data have predominately analyzed photo content and geotags to understand spatial distributions of what visitors photograph (Wilkins, Wood, & Smith, 2020). For example, studies have manually viewed and classified Flickr photos in public lands based on the specific CES depicted (e.g., aesthetic landscapes, recreation, cultural heritage, spiritual, research/education) (e.g., Clemente et al., 2019; Retka et al., 2019). The most common CES present in Flickr photos include aesthetic and recreational values, both of which are ascribed to landscapes and their characteristics (Clemente et al., 2019; Retka et al., 2019; Rossi et al., 2019). Other CES (e.g., spiritual values) may also be present in Flickr photos, however they are often underrepresented because they are harder to photograph and identify through photos (Clemente et al., 2019). Other studies have analyzed Flickr photographs to understand a specific CES, such as wildlife viewing (Runge, Hausner, Daigle, & Monz, 2020; Willemen, Cottam, Drakou, & Burgess, 2015).

Previous research has also used other aspects of social media, beyond photo content, to analyze CES. Johnson et al. (2019) found all categories of CES mentioned in the Millennium Ecosystem Assessment were present in geotagged tweets within an urban park. Other studies have used geotagged Flickr photos and viewsheds to map the demand for and the production of CES across a landscape (Van Berkel et al., 2018; Yoshimura & Hiura, 2017). Previous research has used social media to quantify recreational and aesthetic CES at large geographic scales (van Zanten et al., 2016). Collectively, this growing body of literature has demonstrated the potential utility of using geotagged social media to map CES across landscapes.

Most of the studies using social media analyze the demand for CES. 'Demand', in an economic sense, refers to the desire of an individual to use a CES as well as a willingness to pay the costs associated with doing so. For recreational CES, if an individual travels to a destination from one's home, the travel cost indicates the individual's willingness to pay to participate in outdoor recreation (Khan, 2006). Related to demand, is the supply of CES; this is the total potential for a landscape to produce a CES (Tallis et al., 2012). While the term "demand" in the CES literature has been used to indicate preferences and values as well as direct use, we adopt the stricter definition and use demand to refer specifically to direct use (Wolff et al., 2015).

Many factors influence visitation to public lands, and by inference the demand for CES, including the daily weather and long-term climatological averages (Hewer, Scott, & Fenech, 2016; Smith et al., 2018). There is a need to better understand how the demand for CES provided by public lands changes in response to climate.

1.2 The Effect of Weather and Climate Change on Visitors to Public Lands

Individuals often consider the climate of a destination when choosing where and when to visit an outdoor recreation or tourism destination (Scott & Lemieux, 2010). Once on-site, the daily weather impacts where visitors go within parks, what activities they choose, and how long they stay (Hewer, Scott, & Gough, 2017; Wilkins, Howe, & Smith, in review). For example, visitors to some U.S. national parks venture farther from roads, but stay closer to bodies of water, on hot days (Wilkins et al., in review). Visitors' sensitivity to weather conditions, as well as their behavioral responses, varies based on the location, climate, and topographic features of the area (Scott, Gössling, & de Freitas, 2008; Verbos, Altschuler, & Brownlee, 2018).

Visitation to public lands generally increases with increasing temperatures, but there is a threshold that visitors consider too hot, and visitation declines (Fisichelli et al., 2015). Previous research has found this threshold to be between 25 - 33°C, although this varies based on the climate and topography of the park, as well as the season, and the recreational activity of interest (Fisichelli et al., 2015; Hewer, Scott, & Gough, 2018; Hewer et al., 2016; Smith et al., 2018). Recent research suggests maximum daily temperature affects park visitors more than mean or minimum daily temperature, likely because visitors tend to be outside in the afternoons, when temperatures tend to be the hottest (Jones & Scott, 2006; Smith et al., 2018).

Climate change has already expanded the length of the peak visitation season for some parks (Buckley & Foushee, 2012; Monahan et al., 2016), and is expected to change total visitation at 95% of U.S. National Park Service units (Fisichelli et al., 2015). However, the effects of climate change on visitation to public lands may vary by season, location, and activity (Hewer & Gough, 2018). Some places may see an increase in visitation in the shoulder seasons, but a decrease in summer visitation (Scott, Jones, & Konopek, 2007). Warmer winters may decrease outdoor recreation opportunities in places that traditionally provided snow-dependent recreation (e.g., skiing, snowmobiling), but may increase opportunities for warm-weather activities (Askew & Bowker, 2018; Hand, Smith, Peterson, Brunswick, & Brown, 2018).

Climate may also indirectly impact the demand for CES. For instance, people may have less desire to recreate on landscapes with melted glaciers (Stewart et al., 2016), or in places that recently experienced wildfire (Kim & Jakus, 2019; Duffield, Neher, Patterson, & Deskins, 2013). The demand for CES may also shift spatially or temporally depending on changing distributions of plants, fish, and wildlife (Lamborn & Smith, 2019; Moreno & Amelung, 2009). For example, snow melting earlier than usual may change the timing of wildflower blooms in parks, which in turn may decrease visitor satisfaction, or change the timing of trips (Breckheimer et al., 2020). However, most studies that investigate the impacts of climate change on visitors to public lands tend to focus on one agency and often one park; there is a need for research across multiple agencies and public lands (Brice et al., 2017).

Given this need to understand how climate may impact visitors to public lands across multiple sites, our research is guided by two related research questions: (1) *How does average maximum temperature influence the seasonal demand for recreational CES across U.S. public lands?* And (2) *Are there seasonally- and geographically-dependent temperature preferences that may influence the seasonal demand for recreational CES across U.S. public lands?*

2. Methods

2.1 Study Sites

Study sites include public lands managed by state or federal agencies within the continental U.S. Specifically, this includes lands managed by state agencies, and lands managed by the National Park Service, USDA Forest Service, Fish and Wildlife Service, Bureau of Land Management, and Army Corps of Engineers. We did not include easements in this study. Table 4.1 shows the types of lands managed by each of these agencies, and Figure 4.1 shows the distribution of these lands across the U.S. We downloaded the boundaries for all public lands in 2019 from the Protected Areas Database of the United States; this database was last updated in September 2018 (U.S. Geological Survey Gap Analysis Project, 2018).

Table 4.1

Land management agencies included in this study, as well as the types of lands they manage.

Land management agency	**Type(s) of lands**
Federal agencies:	
Bureau of Land Management (BLM)	BLM lands
Fish and Wildlife Service (FWS)	National wildlife refuges Resource management areas Conservation areas
National Park Service (NPS)	National parks National monuments National recreation areas National seashores National historic sites Wild & scenic rivers
Army Corps of Engineers (USACE)	Recreation management areas State recreation areas
USDA Forest Service (USFS)	National forests National grasslands
State Agencies:	
State Department of Conservation (SDC) State Department of Natural Resources (SDNR) State Department of Land (SDOL) State Fish and Wildlife (SFW) State Land Board (SLB) State Park and Recreation (SPR) Other state agency (OTHS)	State parks State recreation areas State conservation areas State resource management areas State cultural or historic areas

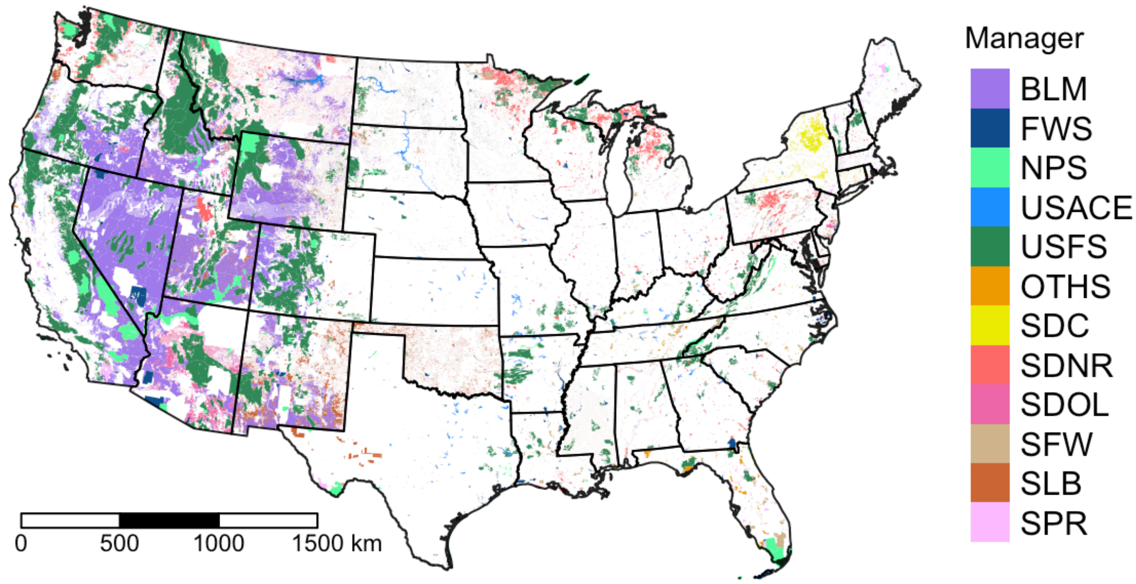

Figure 4.1. Public lands managed by select federal and state agencies in the U.S.

2.2 Data Collection and Processing

We downloaded all Flickr data within the study sites from 2006 – 2019 directly from the Flickr Application Programing Interface (API) using a Python script. These data were downloaded in March 2020 and included geotagged coordinates, time stamps, user IDs, photo IDs, URLs to photographs, and spatial precisions. We only retained posts that had a spatial precision of 15 - 16 (on a scale from 1 – 16, with 16 being the highest spatial precision). We only retained one post per user, per day, within the same grid cell (described below). This represents the concept of a Photo-User-Day (PUD), which has been previously used to avoid oversampling users who post many pictures (Wood et al., 2013; Wilkins et al., 2020). We used Flickr PUD as an indicator of visitation to public lands, and thus the demand for recreational CES. Each geotagged point indicated a person was at a specific place on the landscape for the purposes of obtaining CES.

We aggregated PUD across all years, by season, at a 30 km hexagonal grid[3]. Given that weather impacts visitors differently in different seasons, we separated PUD based on the season the photos were taken during: Summer (June, July, August); Fall (September, October, November); Winter (December, January, February); or Spring (March, April, May).

For each photo location, we found the average daily maximum temperature from 1990 - 2019, for the specific season the photo was taken, using data from Daymet. Daymet provides spatially continuous modeled weather data at a 1-km scale; we used 30-years of monthly climate summary rasters (Thornton et al., 2016a). For instance, if a photo was taken on July 1, 2018, we found the average daily temperature across June, July, and August, from 1990 – 2019, at that location. We then calculated the average temperature by grid cell, for each season, by taking the mean of the temperature at all Flickr points within the grid cell. We analyzed temperature at the Flickr points rather than the average across entire grid cells to account for the fact that some areas may not be easily accessible (e.g., steep slopes, road-less areas) or have much demand for CES. If a grid cell had 0 PUD, we found the average seasonal maximum temperature from 1990 – 2019 at the cell centroid.

We calculated the population residing within 500 km of each grid cell using 2010 population data from the NASA Socioeconomic Data and Applications Center (Center for International Earth Science Information Network, 2017). We used population within 500 km to control for local population and potential local visitors, but do not assume that the population within 500 km is the only source of demand for recreational CES. We also

[3] 30 km grid size was chosen after analyzing the proportion of cells with 0 PUD at different scales (see Appendix C, Figure C.1.)

calculated the area of each grid cell that was public lands, as well as the area that was managed by the NPS. Lands managed by the NPS have substantially more visitation than the BLM, FWS, and USFS, yet the NPS manages less land (Leggett, Horsch, Smith, & Unsworth, 2017); therefore, this is likely an important predictor of the demand for CES. Additionally, we found the area of each cell that is designated wilderness (U.S. Geological Survey, n.d.); wilderness areas tend to be harder to access and may have lower visitation; again, a useful piece of information to include in a model estimating the demand for CES. In Appendix C, Figure C.2 provides a visual example of what the Flickr, public lands, and population data look like for one cell.

We also found the daily maximum temperature at each point on the date the Flickr photo was taken using weather data from Daymet (Thornton et al., 2016b). We used maximum temperature because this has been shown to be a more influential predictor of visitation to parks than minimum or mean temperature (Smith et al., 2018). Maximum temperature often occurs in the afternoon, which is when public lands visitation is the highest, and visitors are more likely to see forecasts for maximum temperature than mean temperature. We downloaded maximum temperature data directly using the R package daymetr (Hufkens, 2019). We subtracted this value from the average 30-year seasonal daily maximum temperature at the same location, to see whether the visitor was at the location on a hotter or colder than average day. We used this data to understand how temperature at the date of visit may deviate from seasonal climatological averages.

2.3 Data Analysis

2.3.1. *Global and Local Regression Models to Estimate the Influence of Climate on the Demand for CES*

We first examined the spatial autocorrelation of Flickr PUDs using Moran's I. We then used geographically weighted negative binomial regression (GWNBR) models to understand how the effect of average seasonal maximum temperature on Flickr PUDs varies spatially across the country. We used a Gaussian weighting scheme and found the bandwidth that minimized the root mean square prediction error using cross-validation. GWNBR is useful to model spatial non-stationarity while more accurately representing count data that is overdispersed (da Silva & Rodrigues, 2014). We ran separate models by season and plotted the spatial heterogeneity of the coefficients for the effect of average maximum temperature on PUD counts. We also ran season-specific negative binomial regression models to understand the global coefficients and global model fit. Global model fit was assessed using Nagelkerke R^2, a pseudo-R^2 measure that is appropriate for regression models using count data (Nagelkerke, 1991).

We ran both season-specific GWNBRs and global negative binomial regressions to understand how the recent climate of an area affects the demand for CES in that area. The global negative binomial regression model for each season can be generally expressed as:

$$Y_i = NB[B_0\, exp(B_1 x_{1i} + B_2 x_{2i} + B_3 x_{3i} + B_4 x_{4i} + B_5 x_{5i}), \alpha] + e_i$$

Where the subscript *i* refers to each cell, NB represents negative binomial, and α refers to the overdispersion parameter. B_0 refers to the intercept, and x_1 refers to the cell-specific historical maximum temperatures. x_2 refers to the cell-specific population within 500 km,

x_3 refers to the area of public lands included in this study per grid cell, x_4 refers to the area of NPS lands per cell, and x_5 refers to the area of designated wilderness per grid cell.

We tested the spatial non-stationarity of each independent variable by conducting a Monte Carlo significance test (Brunsdon, Fotheringham, & Charlton, 1996). The null hypothesis of this test is that coefficients do not vary spatially across the study area.

2.3.2. *Spatial Correlation to Identify Seasonally- and Geographically-dependent Temperature Preferences*

For each cell, we found the difference between the temperature at the date of visit and the 30-year temperature averages at that location and season; these differences were averaged across all Flickr PUDs by cell. We plotted these values by season to visually explore how temperature preferences deviate across the U.S. by season. We also calculated Spearman's rank correlations between temperature deviation and average climate, by season, to understand if temperature preferences may be related to average seasonal temperatures.

3. Results

3.1. Descriptive Statistics and Autocorrelation

Across public lands in the continental U.S., the demand for recreational CES was highest in the summer and lowest in the winter (Table 4.2). Flickr PUDs by season, aggregated from 2006 – 2019 at a 30 km grid, ranged from 159,620 to 326,810 posts. Between 31 – 45% of cells had public lands but no Flickr posts over this time period. The spatial distributions of PUD on public lands can be found in Appendix C, Figure C.3.

Additionally, PUDs per cell are spatially correlated (Moran's I = 0.245 – 0.276, $p <$ 0.001; Queen's case to define neighbors and symmetric binary weights).

Table 4.2

Descriptive statistics of the total posts and PUDs by cell and by season (data aggregated from 2006 – 2019). Numbers only represent Flickr posts within study sites shown in Figure 4.1. There were 9,096 cells that had federal or state public lands (1,488 cells had no federal or state public lands included in this study). Moran's I values are from a Monte-Carlo simulation using 999 simulations.

Season	Total posts	PUD (30 km grid)	Cells with 0 PUD (%)	Mean PUD per cell* (SD)	Median PUD per cell*	Moran's I	Moran's I: p-value
Summer	2,187,355	326,810	2,832 (31.1%)	52.2 (257.7)	9	0.276	0.001
Fall	1,645,887	258,869	3,274 (36.0%)	44.5 (228.9)	7	0.266	0.001
Winter	879,950	159,620	4,064 (44.7%)	31.7 (185.7)	5	0.252	0.001
Spring	1,618,287	249,441	3,245 (35.7%)	42.6 (264.3)	7	0.245	0.001

* Does not include cells that have 0 PUD

3.2. Global and Local Models of the Demand for Recreational CES

Results from the global negative binomial regression models indicate average maximum temperature has a positive relationship with the demand for recreational CES on public lands in the fall, winter, and spring, but a negative relationship in the summer (Table 4.3). The global coefficient is the largest in the summer, indicating the relationship between average temperature and the demand for recreational CES is the strongest in the summer. The population within 500km, area of public lands included in this study, and area of NPS land all have positive and significant relationships with the demand for recreational CES in every season. The area of wilderness is positively and significantly related to the demand for recreational CES in all seasons excluding summer. The Nagelkerke R^2 values from the models are: 0.145 (spring), 0.155 (fall), 0.159 (winter), and 0.234 (summer). Figures showing the spatial distribution of average seasonal maximum temperature can be found in Appendix C, Figure C.4.

Table 4.3

Results by season for global negative binomial regression models and GWNBR models. Coefficients are not standardized and represent the change in the log PUD for every one-unit change in the predictor variables. Average maximum temperature is in ºC, population within 500 km is in millions, and area variables represent 100 km^2.

		Global regression		Geographically weighted negative binomial regression					
		Coef	S.E.	Min.	First Qu.	Med-ian	Third Qu.	Max.	p-value*
Summer	**Intercept**	5.166	0.155	4.658	4.896	5.034	5.178	5.322	0.00
	Average max temp.	-0.117	0.005	-0.120	-0.117	-0.114	-0.111	-0.106	0.00
	Population 500 km	0.035	0.001	0.034	0.035	0.035	0.036	0.037	0.00
	Area PPAs	0.160	0.009	0.154	0.167	0.167	0.171	0.176	0.01
	Area NPS	0.798	0.031	0.732	0.782	0.832	0.889	1.044	0.11
	Area wilderness	0.014	0.027	0.012	0.016	0.020	0.023	0.032	0.53
Fall	**Intercept**	1.482	0.094	1.336	1.404	1.431	1.460	1.513	0.00
	Average max temp.	0.012	0.005	0.008	0.010	0.012	0.014	0.017	0.24
	Population 500 km	0.036	0.001	0.035	0.035	0.036	0.037	0.038	0.03
	Area PPAs	0.130	0.010	0.120	0.129	0.137	0.143	0.153	0.01
	Area NPS	0.872	0.033	0.815	0.856	0.896	0.939	1.035	0.50
	Area wilderness	0.173	0.029	0.165	0.172	0.176	0.179	0.185	0.31
Winter	**Intercept**	0.684	0.054	0.623	0.652	0.669	0.688	0.707	0.00
	Average max temp.	0.084	0.004	0.079	0.081	0.083	0.085	0.088	0.00
	Population 500 km	0.035	0.001	0.034	0.034	0.035	0.035	0.036	0.02
	Area PPAs	0.096	0.010	0.091	0.095	0.099	0.102	0.106	0.00
	Area NPS	0.689	0.036	0.661	0.684	0.701	0.726	0.770	0.89
	Area wilderness	0.366	0.031	0.363	0.366	0.369	0.370	0.374	0.90
Spring	**Intercept**	1.195	0.086	0.969	1.083	1.139	1.197	1.273	0.01
	Average max temp.	0.033	0.004	0.031	0.033	0.034	0.034	0.036	0.08
	Population 500 km	0.035	0.001	0.034	0.035	0.036	0.036	0.038	0.26
	Area PPAs	0.102	0.010	0.092	0.101	0.109	0.116	0.125	0.01
	Area NPS	0.844	0.033	0.805	0.837	0.868	0.899	0.969	0.89
	Area wilderness	0.147	0.029	0.141	0.147	0.149	0.151	0.156	0.61

Note: Bold variables are statistically significant at $p < 0.01$.
* Represents p-values from Monte Carlo significance tests for spatial non-stationarity.

Summer and winter show statistically significant spatial non-stationarity of average maximum temperature, but we do not detect spatial non-stationarity in fall and spring at the 0.05 level (Table 4.3). Spatial non-stationarity indicates that the regression coefficient varies across the study period. Figure 4.2 displays the spatial patterns of GWNBR coefficients for the relationship between average maximum temperature and PUD, by season. In both the summer and winter, the coefficients are largest on the West coast, and smallest on the East coast. This suggests average maximum temperature has a stronger effect on the demand for recreational CES on the West coast.

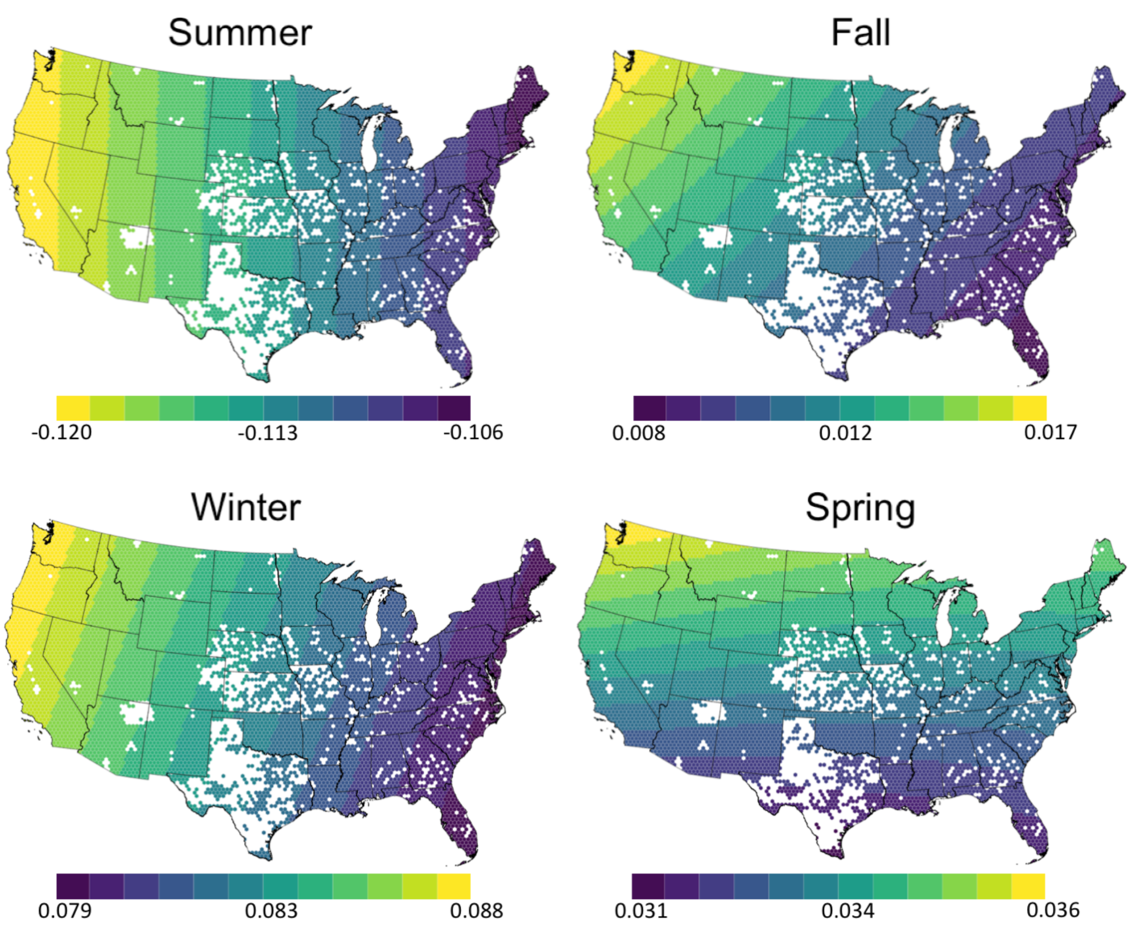

Figure 4.2. Spatial patterns of the GWNBR model coefficients for only the average maximum temperature variable. Positive coefficients represent the increase in log PUDs by cell, for every 1ºC temperature increase, holding all the other independent variables constant. White cells represent areas that have no public lands included in this study. Spatial non-stationarity is only statistically significant for summer and winter.

3.3. Temperature Preferences by Season

The previous analysis explored how average maximum temperature is related to the demand for recreational CES on public lands. However, as the climate continues to warm, the demand for reacreational CES may be more variable in certain regions and seasons due to temperature preferences of visitors. Figure 4.3 shows if visitors tend to visit public lands on days that are hotter or cooler than seasonal 30-year averages across the U.S. Overall, there are not strong visual trends in preferences in the summer and winter. In both the fall and the spring, people tended to visit on warmer days in Northern and mid-latitudes; however, in the Southern U.S., people visited on days with temperatures that were colder than seasonal climatological averages.

Temperature preferences are correlated with the climatological averages. In the fall and spring, in hotter areas, people were more likely to visit on colder days (fall: $r_s = -0.439$, $p < 0.001$; spring: $r_s = -0.317$, $p < 0.001$). This trend was the same in the summer, but the correlation is lower ($r_s = -0.116$, $p < 0.001$). In the winter, the correlation is smaller, but positive, indicating in hotter areas, people were slightly more likely to visit on hotter days ($r_s = 0.029$; $p = 0.037$). The larger correlations in the fall and spring may be somewhat attributable to ecosystem characteristics rather than just temperature preferences. For instance, fall visitation may be substantially influenced by peak foliage colors and spring visitation may be influenced by wildflower blooms in some regions.

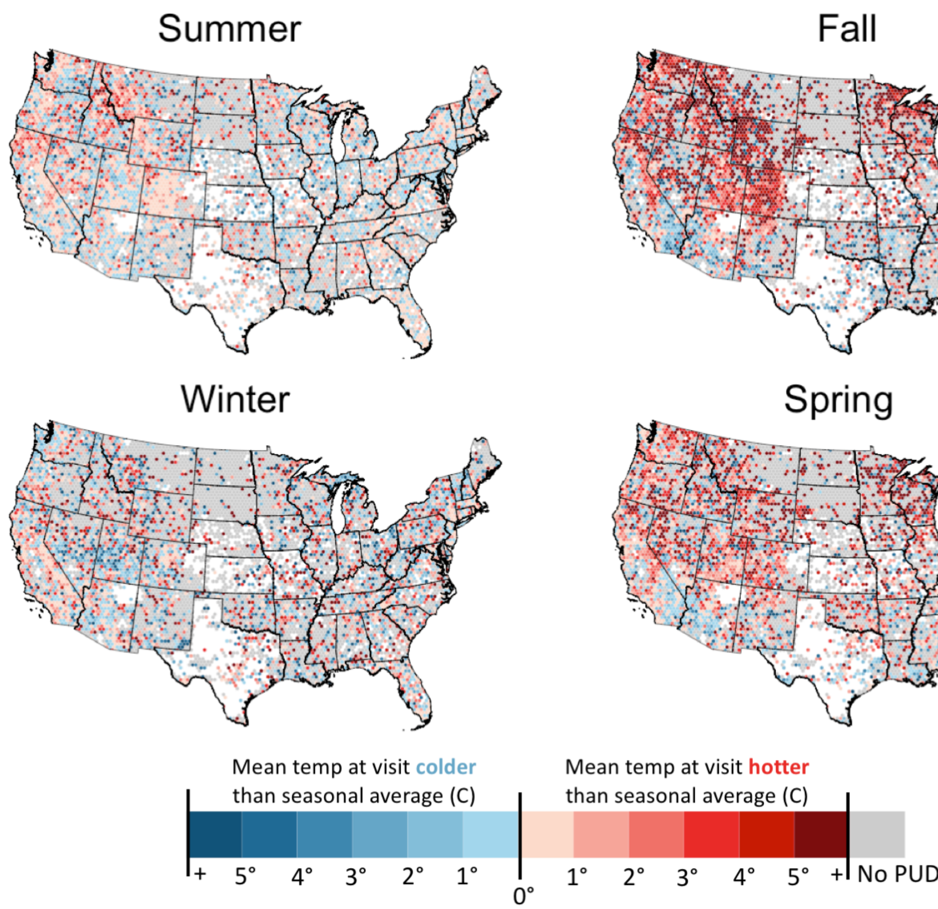

Figure 4.3. Distribution of the difference in maximum temperature at the day of visit compared to seasonal climate averages. Numbers are averaged for all Flickr PUD within public lands in each 30 km grid cell. White cells represent areas that have no state or federal public lands included in this study.

4. Discussion

Overall, the demand for recreational CES on U.S. public lands was the highest in the summer and lowest in the winter. The demand for recreational CES on public lands between 2006 – 2019 was twice as high in the summer compared to the winter. In the spring, fall, and winter, the demand for recreational CES on public lands was higher in places with warmer climates, with the largest effect in the winter. However, in the summer, demand was higher in places with cooler climates. The effect of average temperature on PUD was not stationary in the summer and winter, with the greatest impact of temperature being in the Western U.S.

As the climate continues to warm, our results suggest there will likely be a greater demand for recreational CES on public lands in the spring, winter, and fall, and a lower demand for recreational CES in the summer compared to past seasonal visitation patterns. Our findings support the idea of the expanding peak season of visitation others have found (Buckley & Foushee, 2012; Monahan et al., 2016). Rather than have high demand for CES during only a few months (often in the summer), the demand may be either spread out more or be elevated for a longer period of time (i.e., expanding shoulder seasons).

As temperatures rise across the U.S., visitors may choose to shift the timing, location, and frequency of their trips to public lands. Visitors may shift the timing of their trips to a different season entirely, or they may choose to visit on a day that has preferable weather. For example, the temperature preference maps in Figure 4.3 indicate that in hot locations, visitors may be more apt to visit on comparatively cooler days. This supports what others have found, that although warmer temperatures are generally preferred, there is likely a threshold that people consider too hot (Fisichelli et al., 2015; Hewer et al., 2018). However, non-local visitors may have less ability to adapt by visiting on comparatively cooler days, since trips are often planned weeks or months in advance. Future research is needed to better understand how different groups of visitors, such as local versus non-local visitors, may shift their demand for CES spatially or temporally due to increasing temperatures.

Our study does have limitations that need to be considered when interpreting the findings. Overall, the pseudo-R^2 values from the global models were relatively low, indicating there are other variables that impact the demand for recreational CES on public lands which we did not account for. We were not aiming to create the best possible model to explain PUD counts; rather, our models show the impact of average temperature on PUD, while holding other known important predictors constant. Additionally, the coefficients from the global models represent the change in log PUD per change in one degree Celsius. It is unknown how Flickr PUDs relates to actual visitation numbers across all of our study sites. For instance, one study found that one Flickr PUD in a U.S. National Park may indicate an estimated 1,000 visitors, but there is variation by park (Wood et al., 2013). Another study in a national forest found one monthly PUD corresponded to roughly 1,000 visitors counted via trail counters, with variation by trail (Fisher et al., 2018). And another study found that in western U.S. National Parks, a 1% increase in PUD translated to a 0.65% increase in visitation, but that the exact relationship varies by season (Sessions, Wood, Rabotyagov, & Fisher, 2016). With only a portion of visitors posting to the Flickr platform, these data are not likely representative of all the users of public lands and may be biased towards some user groups.

Future research could aim to investigate how PUDs relates to actual visitation numbers at different types of settings (e.g., state parks, BLM lands, wilderness areas), in order to better understand how factors such as climate change may impact total visitation (e.g., Zhang & Smith, 2020). Additionally, future studies could explore the direct versus indirect impact of climate on the demand for CES. For example, some of the temperature preferences found in this study may be due to indirect factors such as seasonal blooms or foliage changes, rather than temperature alone. Finally, visitor surveys would be useful to determine if and how warming temperatures would affect the amount, location, and timing of visits to public lands. Our study found the demand for recreational CES is higher in warmer climates in the fall, spring, and winter, but it is unknown if visitors would predominately change locations, timing of trips, or total demand due to increased warming.

5. Conclusion

This study is an exploration into how climate may impact the demand for recreational CES across U.S. public lands across different seasons. We found the demand for recreational CES was positively related to average temperatures in the fall, spring, and winter, but negatively related in the summer. This suggests that as the climate continues to warm, demand for CES on public lands may increase in the fall, spring, and winter, but decrease in the summer. In many locations, managers may want to consider preparing for an increased peak season length, and more visitation in the winter than usual. Some visitors may be able to adapt to warmer temperatures by visiting on comparatively cooler days. Although this study shows climate does have an impact on the demand for recreational CES across public lands, further research is needed to determine if visitors will adapt to a changing climate by altering the frequency, location, and timing of their visits to public lands.

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CHAPTER V

CONCLUSIONS

1. Summary of Findings

The three studies presented in this dissertation provide a better understanding of visitor use management in parks and protected areas. In the first study (Chapter II), I examine how social media has been used to inform visitor use management in parks and protected areas and the limitations of using these data. The second study (Chapter III) investigates how daily temperature and precipitation affect the summer spatial behavior of visitors within U.S. NPS units. Lastly, the third study (Chapter IV) looks at how the climate of an area affects the demand for cultural ecosystem services (CES) on public lands by season. The second and third studies investigate public lands throughout the entire conterminous U.S. and provide insight on how the influences of weather and climate vary in different regions of the country.

Study 1 (Chapter II). Social media are being increasingly used to understand the spatial patterns of visitation to parks and protected areas; they are also beginning to be used to understand the on-site experiences of visitors. Geotagged social media are a good indicator for observed or reported visitation; however, the correlations reported in previous studies between social media use and other sources of visitation data vary substantially. Most studies using social media to measure visitation aggregate data across many years, with very few testing the use of social media as an indicator of visitation at smaller temporal scales. No studies have tested the use of social media to estimate visitation in near real-time. Additionally, text and photo content can be useful to understand visitors' experiences, such as sentiment, behavior, and preferences. Researchers have found the geotags and GPS tracks provided via social media are useful for understanding the specific locations of where visitors travel in parks and protected areas, and the timestamps on posts can be used to glean the exact day or time of visit. We leveraged this high spatial and temporal resolution to understand how daily weather impacts visitors in parks and protected areas.

Study 2 (Chapter III). By combining weather data at the exact location and date that images on Flickr were taken, I showed both daily temperature and precipitation impact where visitors travel within National Parks in the conterminous U.S. In most ecoregions, visitors stayed closer to infrastructure (e.g., roads, buildings, parking areas) on rainy days. However, in some ecoregions we did not detect a difference in visitors' spatial patterns on days with precipitation versus no precipitation. The effects of temperature also differed across the country, with no consistent trends across all ecoregions. For instance, in some ecoregions, exceptionally hot days correlated with visitors going to higher elevations, and in some ecoregions, visitors went to lower elevations on cold days. This could be due to both the climate of an area as well as the topography of individual parks. Importantly, parks in some ecoregions contain more microclimates than others, which may allow visitors to adapt to unfavorable conditions by visiting a park area with preferable weather. These results indicate visitors' spatial behavior within parks may change in the future due to the increasing frequency of hot summer days. However, all parks may not see changes in future visitation patterns due to changing weather, and the changes are likely to vary by ecoregion.

Study 3 (Chapter IV). CES represent nonmaterial benefits people derive from the environment, such as recreational or aesthetic enjoyment. In the spring, fall, and winter, the demand for CES on public lands was higher in places with warmer climates. However, in the summer, demand was higher in places with cooler climates. Average temperature has the greatest effect on the demand for CES in the summer and winter, and the effect also varies across the U.S. in these seasons. Average temperature has the greatest impact on the demand for CES on public lands in the Western U.S. These results indicate the peak season to visit public lands (often in the summer for most parks) may expand to include additional weeks or months under climate change. Demand for CES on public lands may decline in the summer in some locations but increase in the shoulder seasons. Together, studies 2 and 3 utilized social media to understand how both the daily weather and the long-term climatological averages affect visits to and within public lands.

2. Research Contributions

Collectively, these three studies aim to advance the state of the science while also providing information that may be useful for park and protected area management. Chapter II provides a synthesis of how social media has been used to answer visitor use management questions in parks and protected areas. This paper addresses specific, common questions both managers and researchers have with regards to using social media data. For instance, although many papers have concluded that social media is a good indicator of observed or reported visitation in parks, there is substantial variation in the literature in the spatial and temporal resolution and extent of the data used, as well as the correlations reported. Having information from all previous studies summarized in one location can save future researchers time and reveal the current state of the literature. Although there has been one previous study summarizing the use of social media in nature-based tourism research (da Mota & Pickering, 2020), my study is unique in that it focuses on specific questions helpful for park and protected area managers. Additionally, I summarize best practices for researchers using social media data; these are recommendations that have been used in previous studies, but more consistency in the literature would aid in the comparability of future research.

Chapter III is the first study I am aware of that investigates how weather impacts where visitors travel within parks and protected areas. Previous studies have shown that weather impacts total visitation to parks (e.g., Hewer, Scott, & Fenech, 2016; Smith, Wilkins, Gayle, & Lamborn, 2018), but no known studies have looked at weather-altered visitation patterns *within* parks. This is important because changing visitation patterns within parks could create unexpected crowding or increase the strain on resources in some locations. Understanding potential changes to visitation patterns can help park managers plan and prepare for managing visitor flows, both on a daily scale and when thinking about future climate change. For example, managers could anticipate and proactively manage weather-altered visitation patterns by providing additional information to visitors and increasing signage in certain areas. In parks with more microclimates, park staff could provide information on the coolest areas of the park on exceptionally hot summer days. Managers could also expand recreation infrastructure (e.g., trails, campgrounds, restroom facilities, etc.) in areas that are more likely to see increased use as the climate continues to warm.

Chapter IV is the first study I am aware of that explores how climate may affect the demand for CES across all state and federal public lands in the conterminous U.S. Previous studies have looked at how climate impacts visitation to public lands (e.g., Hewer & Gough, 2018; Smith et al., 2018), but these studies tend to focus on a single park or agency, and it can be difficult to compare or extrapolate results to other locations (Brice et al., 2017). Understanding the impact of climate on the demand for CES across U.S. public lands can help public land managers plan and prepare for changing demand in the future as a result of climate change.

3. Research Limitations

As with any data source, social media does have its limitations. Social media users are likely not representative of all park users. Social media users tend to be younger than the average population, and are more likely to live in urban areas (Greenwood, Perrin, & Duggan, 2016; Perrin & Anderson, 2019). Additionally, some people may be less likely to take photos and post them online during adverse weather conditions. This may have somewhat biased the total number of posts and PUD on rainy days or in colder seasons. However, this was deemed to be the most suitable dataset to answer the questions posed in this dissertation due to the data's fine spatial and temporal resolutions, as well as its broad geographic extent. Using social media data for research also presents possible ethical and privacy concerns (Thatcher, 2014). Although no personally identifying information was presented in this research, Flickr users may not be aware how their data is used for research. In social science research, we often explain the purpose of the study and get consent from all our participants; however, this is unfortunately not possible when using data scraped from the web. Researchers using social media data need to be extra cautious with how these data are used, shared, and interpreted.

There are also limitations associated with other geospatial datasets. For instance, Daymet provides gridded weather data that is interpolated and extrapolated from weather stations. Although the interpolations are overall fairly accurate, there is some error. The mean absolute error and mean bias are higher for precipitation than temperature, and the extent of the bias varies by ecoregion (Behnke et al., 2016). Additionally, Daymet is more accurate at interpolating weather data that is close to climate averages rather than extreme weather events (Behnke et al., 2016).

Data from OpenStreetMap also has limitations. This content is user-generated, and thus completeness, accuracy, and consistency likely vary by location (Kaur, Singh, Sehra, & Rai, 2017). From visual inspection of OSM data in U.S. National Parks, it was clear that the accuracy of different layers varied (e.g., roads layers were complete and accurate, while building layers were not). However, the geographic scope of these data sources makes them useful for doing analyses across the U.S.

4. Future Research Directions

Future research could aim to better understand the magnitude of the limitations and biases of using social media data that researchers mentioned in Chapter II. For instance, no known research to date has actually looked at the differences between visitors to parks who post on social media, and visitors who do not post. A visitor survey would be useful to both understand how social media users differ from other visitors, and if the content they share is biased (e.g., only taking photos or sharing content on sunny days, or when they are traveling away from home). Understanding how park visitors choose to take and share content could help researchers better understand the extent of these different biases. Additionally, more research is needed to determine the applicability of using social media data in remote or low-use locations.

Regarding the impact of weather on visitation, future research could aim to better understand the separate impacts of the seasonal cycle and extreme weather events on visitors' spatial patterns. For instance, future studies could look at how spatial patterns differ by month or season to understand how the seasonal cycle may affect where visitors go within parks. To understand extreme weather events without the seasonal cycle, we could see if the weather on any given day was in the 90th percentile or greater, when compared to 30-year historical data for the weather on that day or week. Additionally, a visitor survey would be useful to understand if only a subset of visitors change the locations they visit within parks, and if so, the characteristics of those who change their visitation (e.g., activities, motivations, demographics). The social media analysis and maps presented in Chapter III could be used to choose sampling locations or the timing of surveys.

Additionally, the results presented in Chapter IV could be used to more precisely understand how the demand for CES across U.S. public lands may change in the future under differing climate change scenarios. Although this analysis did not extrapolate results out into the future, this could be accomplished by obtaining the temperature projections from RCP scenarios out until 2100. In addition, more analysis could be done to understand the relationship between Flickr PUDs and total visitation to different settings, in order to better interpret what an increase in one PUD means in a practical sense. Furthermore, additional variables could be added to the models to understand what factors affect the demand for CES beyond climate. Factors such as distance to roads, distance to a major airport, presence of amenities, miles of trails, land cover, and species distributions may all affect the demand for CES, but these variables were not included in my analysis.

5. Concluding Remarks

This dissertation contributes to our knowledge on how weather and climate impact visitation to parks, protected areas, and public lands. Using geotagged social media data, I was able to explore the impacts of weather and climate at a nationwide scale, and at fine resolutions. Although the focus of this dissertation was on how weather and climate impact visitation to parks, protected areas, and public lands, these studies also provide further evidence of how social media can be used to understand spatial patterns of visitors. The first study shows that social media can inform visitor use management in a variety of ways, but there are limitations. The subsequent two studies provide examples of how social media can be used to answer research questions in parks, protected areas, and on public lands which may not have been possible to answer with traditional methods of data collection. Collectively, these studies advance the literature of how weather and climate affect park visitors, while also increasing our understanding of methodologies that can be used to answer research questions in parks, protected areas, and on public lands.

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APPENDICES

APPENDIX A

SUPPLEMENTARY MATERIAL ASSOCIATED WITH CHAPTER II

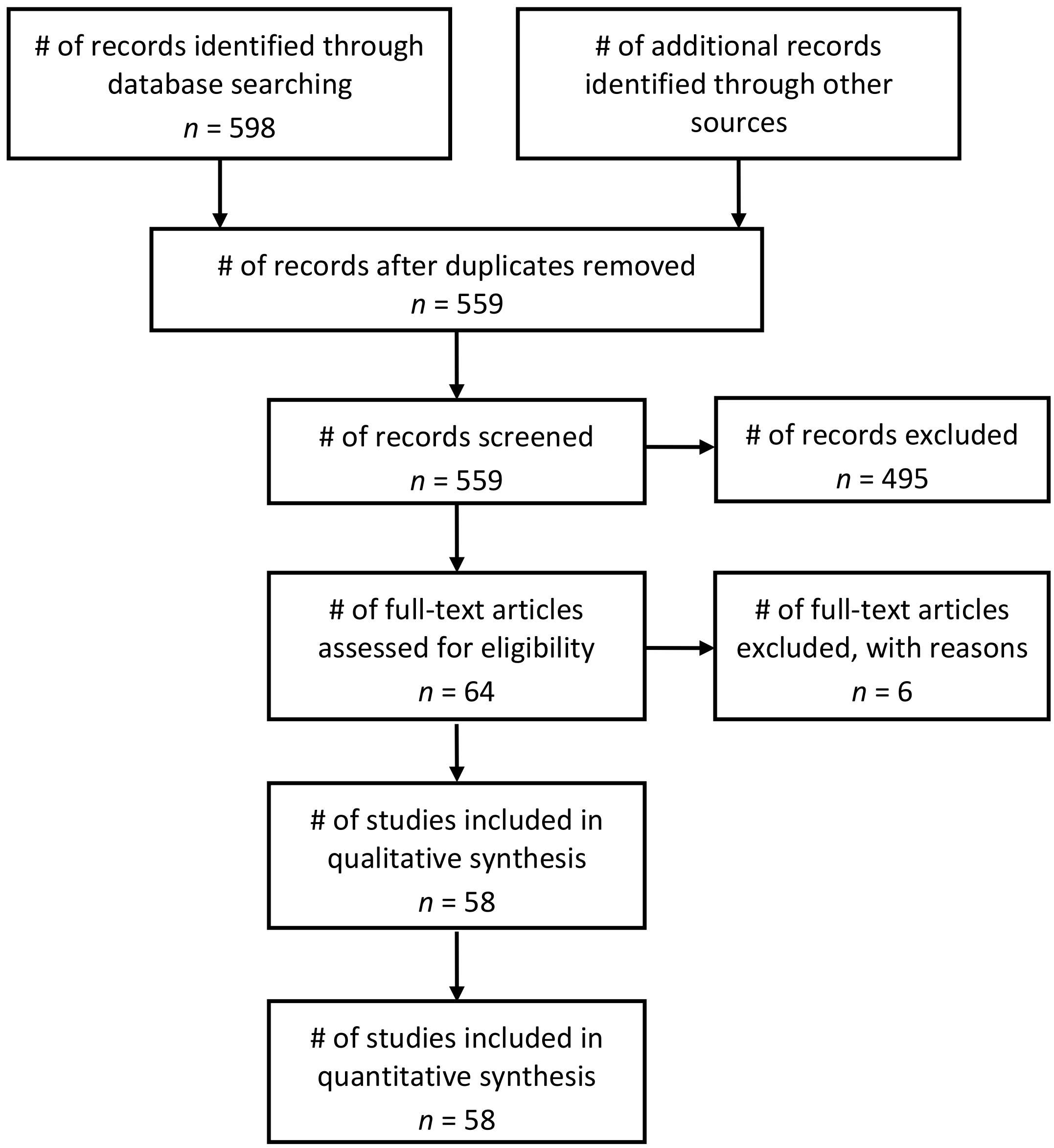

Figure A.1. Diagram of how many studies were identified, screened, and included in Chapter II. Figure template from Moher, Liberati, Tetzlaff, & Altman (2009).

Table A.1

The 58 papers included in the Chapter II analysis after article screening.

Authors	Title	Year	Journal title	Source
Barros, C., Moya-Gómez, B., Gutiérrez, J.	Using geotagged photographs and GPS tracks from social networks to analyse visitor behaviour in national parks	2019	Current Issues in Tourism	Scopus
Barry, S.J.	Using social media to discover public values, interests, and perceptions about cattle grazing on park lands	2014	Environmental Management	Scopus, ProQuest
Breckheimer, I.K., Theobald, E.J., Cristea, N.C., Wilson, A.K., Lundquist, J.D., Rochefort, R.M., HilleRisLambers, J.	Crowd-sourced data reveal social ecological mismatches in phenology driven by climate	2020	Frontiers in Ecology and the Environment	Scopus
Callau, A.À., Albert, M.Y.P., Rota, J.J., Giné, D.S.	Landscape characterization using photographs from crowdsourced platforms: Content analysis of social media photographs	2019	Open Geosciences	Scopus
Campelo, M.B., Mendes, R.M.N.	Comparing webshare services to assess mountain bike use in protected areas	2016	Journal of Outdoor Recreation and Tourism	Scopus
Clemente, P., Calvache, M., Antunes, P., Santos, R., Cerdeira, J.O., Martins, M.J.	Combining social media photographs and species distribution models to map cultural ecosystem services: The case of a Natural Park in Portugal	2019	Ecological Indicators	Scopus, ProQuest
Conti, E., Lexhagen, M.	Instagramming nature-based tourism experiences: a netnographic study of online photography and value creation	2020	Tourism Management Perspectives	Scopus
Do, Y. & Kim, J.Y.	An assessment of the aesthetic value of protected wetlands based on a photo content and its metadata	2020	Ecological Engineering	Scopus
Donahue, M.L., Keeler, B.L., Wood, S.A., Fisher, D.M., Hamstead, Z.A., McPhearson, T.	Using social media to understand drivers of urban park visitation in the Twin Cities, MN	2018	Landscape and Urban Planning	Scopus, ProQuest
Fisher, D.M., Wood, S.A., White, E.M., Blahna, D.J., Lange, S., Weinberg, A., Tomco, M., Lia, E.	Recreational use in dispersed public lands measured using social media data and on-site counts	2018	Journal of Environmental Management	ProQuest
Garzia, F., Borghini, F., Bruni, A., Lombardi, M., Mighetto, P., Ramalingam, S., Russo, S. B.	Emotional reactions to the perception of risk in the Pompeii Archaeological Park	2020	International Journal of Safety and Security Engineering	Scopus

Gosal, A.S., Geijzendorffer, I.R., Václavík, T., Poulin, B., Ziv, G.	Using social media, machine learning and natural language processing to map multiple recreational beneficiaries	2019	Ecosystem Services	Scopus, ProQuest
Hamstead, Z.A., Fisher, D., Ilieva, R.T., Wood, S.A., McPhearson, T., Kremer, P.	Geolocated social media as a rapid indicator of park visitation and equitable park access	2018	Computers, Environment and Urban Systems	Scopus
Hausmann, A., Toivonen, T., Heikinheimo, V., Tenkanen, H., Slotow, R., & Di Minin, E.	Social media reveal that charismatic species are not the main attractor of ecotourists to sub-Saharan protected areas	2017	Scientific Reports	Scopus
Hausmann, A., Toivonen, T., Slotow, R., Tenkanen, H., Moilanen, A., Heikinheimo, V., Di Minin, E.	Social media data can be used to understand tourists' preferences for nature-based experiences in protected areas	2017	Conservation Letters	Authors
Heikinheimo, V., Di Minin, E., Tenkanen, H., Hausmann, A., Erkkonen, J., Toivonen, T.	User-generated geographic information for visitor monitoring in a national park: A comparison of social media data and visitor survey	2017	ISPRS International Journal of Geo-Information	Scopus, ProQuest
Huang, S.-C.L., Sun, W.-E.	Exploration of social media for observing improper tourist behaviors in a National Park	2019	Sustainability (Switzerland)	Scopus
Johnson, M.L., Campbell, L.K., Svendsen, E.S., McMillen, H.L.	Mapping urban park cultural ecosystem services: A comparison of twitter and semi-structured interview methods	2019	Sustainability (Switzerland)	Scopus
Karasov, O., Vieira, A.A.B., Külvik, M., Chervanyov, I.	Landscape coherence revisited: GIS-based mapping in relation to scenic values and preferences estimated with geolocated social media data	2020	Ecological Indicators	Scopus
Kim, Y., Kim, C.-K., Lee, D.K., Lee, H.-W., Andrada, R.I.T.	Quantifying nature-based tourism in protected areas in developing countries by using social big data	2019	Tourism Management	Scopus
Kovacs-Györi, A., Ristea, A., Kolcsar, R., Resch, B., Crivellari, A., Blaschke, T.	Beyond spatial proximity-classifying parks and their visitors in London based on spatiotemporal and sentiment analysis of twitter data	2018	ISPRS International Journal of Geo-Information	Scopus
Kuehn, D., Gibbs, J., Goldspiel, H., Barr, B., Sampson, A., Moutenot, M., Badding, J., Stradtman, L.	Using social media data and park characteristics to understand park visitation	2020	Journal of Park and Recreation Administration	Authors
Levin, N., Kark, S., Crandall, D.	Where have all the people gone? Enhancing global conservation using night lights and social media	2015	Ecological Applications	Scopus, ProQuest

Levin, N., Lechner, A.M., Brown, G.	An evaluation of crowdsourced information for assessing the visitation and perceived importance of protected areas	2017	Applied Geography	Scopus, ProQuest
Li, F., Li, F., Li, S., Long, Y.	Deciphering the recreational use of urban parks: Experiments using multi-source big data for all Chinese cities	2020	Science of the Total Environment	Scopus
Liang, Y., Kirilenko, A.P., Stepchenkova, S.O., Ma, S.	Using social media to discover unwanted behaviours displayed by visitors to nature parks: comparisons of nationally and privately owned parks in the Greater Kruger National Park, South Africa	2019	Tourism Recreation Research	Scopus
Mancini, F., Coghill, G.M., Lusseau, D.	Using social media to quantify spatial and temporal dynamics of nature-based recreational activities	2018	PLoS ONE	Scopus, ProQuest
Martinez-Harms, M.J., Bryan, B.A., Wood, S.A., Fisher, D.M., Law, E., Rhodes, J.R., Dobbs, C., Biggs, D., Wilson, K.A.	Inequality in access to cultural ecosystem services from protected areas in the Chilean biodiversity hotspot	2018	Science of the Total Environment	ProQuest
Muñoz, L., Hausner, V.H., Runge, C., Brown, G., Daigle, R.	Using crowdsourced spatial data from Flickr vs. PPGIS for understanding nature's contribution to people in Southern Norway	2020	People and Nature	Authors
Norman, P., Pickering, C.M.	Factors influencing park popularity for mountain bikers, walkers and runners as indicated by social media route data	2019	Journal of Environmental Management	Scopus, ProQuest
Norman, P., Pickering, C.M.	Using volunteered geographic information to assess park visitation: Comparing three on-line platforms	2017	Applied Geography	Authors
Norman, P., Pickering, C.M., Castley, G.	What can volunteered geographic information tell us about the different ways mountain bikers, runners and walkers use urban reserves?	2019	Landscape and Urban Planning	Scopus, ProQuest
Orsi, P., Geneletti, D.	Using geotagged photographs and GIS analysis to estimate visitor flows in natural areas	2013	Journal for Nature Conservation	Authors
Pickering, C., Walden-Schreiner, C., Barros, A., Rossi, S.D.	Using social media images and text to examine how tourists view and value the highest mountain in Australia	2020	Journal of Outdoor Recreation and Tourism	Scopus
Plunz, R.A., Zhou, Y., Vintimilla M.I.C., Mckeown, K., Yu, T., Uguccioni, L., Sutto, M.P.	Twitter sentiment in New York City parks as measure of well-being	2019	Landscape and Urban Planning	Scopus, ProQuest

Retka, J., Jepson, P., Ladle, R.J., Malhado, A.C.M., Vieira, F.A.S., Normande, I.C., Souza, C.N., Bragagnolo, C., Correia, R.A.	Assessing cultural ecosystem services of a large marine protected area through social media photographs	2019	Ocean and Coastal Management	Scopus, ProQuest
Rice, W.L., Mueller, J.T., Graefe, A.R., Taff, B.D.	Detailing an approach for cost-effective visitor-use monitoring using crowdsourced activity data	2019	Journal of Park and Recreation Administration	ProQuest
Roberts, H., Sadler, J., Chapman, L.	The value of Twitter data for determining the emotional responses of people to urban green spaces: A case study and critical evaluation	2019	Urban Studies	Scopus, ProQuest
Roberts, H., Sadler, J., Chapman, L.	Using Twitter to investigate seasonal variation in physical activity in urban green space	2017	Geo: Geography and Environment	Scopus
Rossi, S.D., Barros, A., Walden-Schreiner, C., Pickering, C.	Using social media images to assess ecosystem services in a remote protected area in the Argentinean Andes	2019	Ambio	Scopus
Sessions, C., Wood, S.A., Rabotyagov, S., Fisher, D.M.	Measuring recreational visitation at U.S. National Parks with crowd-sourced photographs	2016	Journal of Environmental Management	Scopus, ProQuest
Sim, J., Miller, P.	Understanding an Urban Park through Big Data	2019	International Journal of Environmental Research and Public Health	Scopus, ProQuest
Sinclair, M., Ghermandi, A., Sheela, A.M.	A crowdsourced valuation of recreational ecosystem services using social media data: An application to a tropical wetland in India	2018	Science of the Total Environment	Scopus
Sinclair, M., Mayer, M., Woltering, M., Ghermandi, A.	Using social media data to estimate visitor provenance and patterns of recreation in Germany's national parks	2020	Journal of Environmental Management	Scopus
Song, X. P., Richards, D. R., & Tan, P. Y.	Using social media user attributes to understand human–environment interactions at urban parks	2020	Scientific Reports	Authors
Song, Y., Zhang, B.	Using social media data in understanding site-scale landscape architecture design: taking Seattle Freeway Park as an example	2020	Landscape Research	Scopus
Sonter, L.J., Watson, K.B., Wood, S.A., Ricketts, T.H.	Spatial and Temporal Dynamics and Value of Nature-Based Recreation, Estimated via Social Media	2016	PLoS ONE	Authors

Tenkanen, H., Di Minin, E., Heikinheimo, V., Hausmann, A., Herbst, M., Kajala, L., Toivonen, T.	Instagram, Flickr, or Twitter: Assessing the usability of social media data for visitor monitoring in protected areas	2017	Scientific Reports	Scopus
Ullah H., Wan W., Haidery S. A., Khan N. U., Ebrahimpour Z., Muzahid A. A. M.	Spatiotemporal patterns of visitors in urban green parks by mining social media big data based upon WHO reports	2020	IEEE Access	Scopus
Vaz A.S., Gonçalves J.F., Pereira P., Santarém F., Vicente J.R., Honrado J.P.	Earth observation and social media: Evaluating the spatiotemporal contribution of non-native trees to cultural ecosystem services	2019	Remote Sensing of Environment	Scopus, ProQuest
Vaz, A.S. et al.	Digital conservation in biosphere reserves: Earth observations, social media, and nature's cultural contributions to people	2020	Conservation Letters	Scopus
Vieira, F.A.S., Bragagnolo, C., Correia, R.A., Malhado, A.C.M., Ladle, R.J.	A salience index for integrating multiple user perspectives in cultural ecosystem service assessments	2018	Ecosystem Services	Scopus
Walden-Schreiner, C., Leung, Y.-F., Tateosian, L.	Digital footprints: Incorporating crowdsourced geographic information for protected area management	2018	Applied Geography	ProQuest
Walden-Schreiner, C., Rossi, S.D., Barros, A., Pickering, C., Leung, Y.-F.	Using crowd-sourced photos to assess seasonal patterns of visitor use in mountain-protected areas	2018	Ambio	Scopus, ProQuest
Willemen, L., Cottam, A.J., Drakou, E.G., Burgess, N.D.	Using social media to measure the contribution of red list species to the nature-based tourism potential of African protected areas	2015	PLoS ONE	Scopus, ProQuest
Wood, S.A., Guerry, A.D., Silver, J.M., Lacayo, M.	Using social media to quantify nature-based tourism and recreation	2013	Scientific Reports	Scopus
Yoshimura, N., Hiura, T.	Demand and supply of cultural ecosystem services: Use of geotagged photos to map the aesthetic value of landscapes in Hokkaido	2017	Ecosystem Services	Scopus, ProQuest
Zhang, S., Zhou, W.	Recreational visits to urban parks and factors affecting park visits: Evidence from geotagged social media data	2018	Landscape and Urban Planning	Scopus, ProQuest

Table A.2

A full list of papers that correlate social media posts with other measures of visitation. Note: some papers are included as multiple rows if they used different platforms or scales.

Corr.	Platform	Setting	Full setting	Spatial scale for correlation	Temporal scale for correlation	Amount of data	PUD	Citation	In fig 2.3?
0.62	Flickr (r)	variety	Over 800 tourism sites globally	Whole unit	Mean annual	7 years	yes	(Wood, Guerry, Silver, & Lacayo, 2013)	yes
0.47	Flickr (r)	state	State parks in Vermont (U.S.)	Whole park	8-year sum, only summer months	8 years	yes	(Sonter, Watson, Wood, & Ricketts, 2016)	yes
0.58	Flickr (r)	urban	Urban parks in New York City (U.S.)	Whole park; excluded parks with < 3 daily observations	2-year sum, only summer months	Flickr: 10 years	yes	(Hamstead et al., 2018)	yes
0.82	Flickr (r)	urban	Urban parks in Twin Cities, MN (U.S.)	Whole park	Mean annual	Flickr: 10 years	yes	(Donahue et al., 2018)	yes
0.80	Flickr (r)	national	All U.S. National Forests	Whole forest	Mean annual	11 years	yes	(Fischer et al., 2018)	yes
0.84	Flickr (r)	national	A National Park in Spain	Whole park	Monthly, but aggregated 7 years	7 years	yes	(Barros, Moya-Gomez, & Gutierrez, 2019)	yes
0.52	Flickr (r)	variety	National and State Parks in the northern forest region (U.S.)	Whole park	Summers	5 years	no	(Kuehn et al., 2019)	yes
0.80	Flickr (r)	variety	436 protected areas globally	Whole park	Mean annual	9 years	yes	(Levin & Crandall, 2015)	yes
0.97	Flickr (r)	national	16 national parks across Germany	Whole park	Mean annual	14 years	yes	(Sinclair, Mayer, Woltering, & Ghermandi, 2020)	yes
0.77	Flickr (Rs)	national	National Parks in	Whole park	Annual	1 year	yes	(Tenkanen et al., 2017)	yes

			South Africa						
0.63	Flickr (Rs)	national	National Parks in Finland	Whole park	Annual	1 year	yes	(Tenkanen et al., 2017)	yes
0.36	Flickr (Rs)	variety	All protected areas in Victoria (Australia)	Whole park	Mean annual	9 years	no	(Levin, Lechner, & Brown 2017)	yes
0.25	Flickr (Rs)	national	A National Park in Argentina	Whole unit	Not given	5 years, only peak season (5 months)	no	(Walden-Schreiner, Rossi, Barros, Pickering, & Leung, 2018)	yes
0.74	Flickr (Rs)	variety	Protected areas in a Chilean biodiversity hotspot	Whole unit	Mean annual	8 years	yes	(Martinez-Harms et al., 2018)	yes
0.76	Twitter (r)	urban	Urban parks in New York City (U.S.)	Whole park; excluded parks with < 3 daily observations	2-year sum, only summer months	Twitter: 3 years	yes	(Hamstead et al., 2018)	yes
0.8	Twitter (r)	urban	Urban parks in Twin Cities, MN (U.S.)	Whole park	Mean annual	Twitter: 3 years	yes	(Donahue et al., 2018)	yes
0.59	Twitter (Rs)	national	National Parks in South Africa	Whole park	Annual	1 year	yes	(Tenkanen et al., 2017)	yes
0.81	Twitter (Rs)	national	National Parks in Finland	Whole park	Annual	1 year	yes	(Tenkanen et al., 2017)	yes
0.69	Instagram (Rs)	national	National Parks in South Africa	Whole park	Annual	1 year	yes	(Tenkanen et al., 2017)	yes
0.83	Instagram (Rs)	national	National Parks in Finland	Whole park	Annual	1 year	yes	(Tenkanen et al., 2017)	yes
NA	Flickr	national	National Parks in the Western U.S.	Whole park	Monthly	6 years	yes	(Sessions, Wood, Rabotyagov, & Fisher, 2016)	no
NA	Flickr	national	A national park in Scotland	5 km, 10 km, 20 km	6-year sum	6 years	yes	(Mancini, Coghill, & Lusseau, 2018)	no

NA	Flickr	national	Mount Rainier National Park in Washington, USA	Whole park	Mean monthly	7 years	Not sure	(Breckheimer et al., 2019)	no
0.67	Instagram (Rs)	national	A National Park in Finland	Subregions within a park	2.4-year sum	2.4 years	no	(Heikinheimo et al., 2017)	no
0.79	Flickr (r)	national	A National Forest in Washington State (U.S.)	Trailshed	Monthly, but aggregated 11 years	11 years	yes	(Fischer et al, 2018)	no
0.83	MapMyFitness (r)	variety	Three parks in Queensland, Australia	Trails	3-year sum	3 years	NA	(Norman, Pickering, & Castley, 2019)	no
0.9	MapMyFitenss (r)	other	A conservation park in Queensland, Australia	Trails	Mean monthly	13 years for Flickr, unsure about trail counters	NA	(Norman & Pickering, 2017)	no
NA	Weibo (r)	urban	Urban parks in 4 Chinese cities	Whole unit	Not given	Not given	NA	(Li, Li, Li, & Long, 2020)	no

Table A.3

A full list of papers in Figure 2.4 that analyze spatial distributions.

Category of spatial paper	Additional details	Spatial scale for analyzing distributions	Temporal scale for analyzing distributions	Attributes	Platform (s)	Citation
What attributes affect park use; spatial patterns of CES	spatial patterns for CES; how variables impact CES spatial distribution	geotag	Multiple years	envi., infra., manag.. (distribution of CES)	Flickr	(Clemente et al., 2019)
What attributes affect park use	NA	whole park	Multiple years	social, envi., infra.	Flickr; Twitter	(Donahue et al., 2018)
What attributes affect park use	NA	whole park	Multiple years	social, envi., infra.	Flickr, Twitter	(Hamstead et al., 2018)
What attributes affect park use	NA	0.01 degree grid	Multiple years	social, infra.	Flickr	(Levin, Kark, & Crandall, 2015)
What attributes affect park use	NA	whole park	Not given	social, envi., infra., manag.	Weibo	(Li, Li, Li, & Long, 2020)
What attributes affect park use	NA	whole park	Multiple years	social, envi.	Flickr	(Martinez-Harms et al., 2018)
What attributes affect park use	NA	whole park	Multiple years	social, envi., infra., manag.	Flickr	(Sonter, Watson, Wood, & Ricketts, 2016)
What attributes affect park use	NA	geotag	Seasonal, multiple years of data	envi., infra.	Flickr	(Walden-Schreiner, Rossi, Barros, Pickering, & Leung, 2018)
What attributes affect park use	NA	whole park	Multiple years	envi., infra., manag.	MapMyFitness, Strava, Wikiloc	(Norman & Pickering, 2019)
What attributes affect park use	NA	1 km grid	Multiple years	envi., infra.	Flickr	(Kim, Kim, Lee, Lee, & Andrada, 2019)
What attributes affect park use	NA	geotag	Seasonal, multiple years of data	envi., infra.	Flickr	(Walden-Schreiner, Leung, & Tateosian, 2018)
What attributes affect park use	NA	geotag	Multiple years	envi.	Flickr	(Yoshimura & Hiura, 2017)
What attributes affect park use	NA	whole park	Multiple years	social, envi., infra., manag.	Weibo	(Zhang & Zhou, 2018)
What attributes affect park use	specifically looking at what factors affect social media posts	whole park	One year	social, envi.	Instagram	(Hausmann et al., 2017)
What attributes affect park use	NA	geotag	Multiple years	envi., infra.	Flickr	(Muñoz, Hausner, Runge, Brown, & Daigle, 2020)

spatial patterns relating to photo content	spatial patterns of bird, seal, dolphin, and whale watching by year	geotag	Multiple years	NA	Flickr	(Mancini, Coghill, & Lusseau, 2018)
spatial patterns relating to photo content	spatial patterns by type of photograph	geotag	Multiple years	NA	Wikiloc	(Callau, Albert, Rota, Giné, 2019)
spatial patterns by user group	differences between runners and walkers and off trail use	trail	Multiple years	NA	MapMyFitness, GPSies, Wikiloc	(Norman & Pickering, 2017)
spatial patterns by user group	differences between runners, walkers, and bikers	trail	Multiple years	NA	MapMyFitness	(Norman, Pickering, & Castley, 2019)
spatial patterns by user group	spatial patterns by season and type of visitor	1 km grid	Seasonal, multiple years of data	NA	Flickr	(Gosal, Geijzendorffer, Václavík, Poulin, & Ziv, 2019)
spatial patterns by user group	spatial patterns by type of visitor (local, domestic, international)	geotag	Multiple years	NA	Flickr	(Sinclair, Ghermandi, & Sheela, 2018)
spatial patterns by user group	spatial patterns of different groups of visitors	whole park	Multiple years	NA	Flickr	(Song, Richards, & Tan, 2020)
spatial patterns by user group	Spatial patterns by type of visitor (local, domestic, international)	geotag	Seasonal, multiple years of data	NA	Flickr	(Sinclair, Mayer, Woltering, & Ghermandi, 2020)
spatial patterns by user group	Spatial patterns by gender	whole park	Annual, weekend vs weekday	NA	Weibo	(Ullah et al., 2020)
spatial patterns (general)	NA	subregions of a park	Multiple years	NA	Instagram	(Heikinheimo et al., 2017)
spatial patterns (general)	NA	trail	Multiple years	NA	Wikiloc; GPSies	(Campelo & Mendes, 2016)
spatial patterns (general)	spatial patterns and off-trail use	trail	Multiple years	NA	Strava	(Rice, Mueller, Graefe, & Taff, 2019)
spatial patterns (general)	Estimate popular destinations within the study site	Grid (210 m)	Multiple years	NA	Panoramio	(Orsi & Geneletti, 2013)
spatial distribution of CES	NA	zones within the park	2 weeks (all data collected)	NA	Twitter	(Johnson, Campbell, Svendsen, & McMillen, 2019)

spatial distribution of CES	NA	geotag	Multiple years	NA	Flickr	(Retka et al., 2019)
spatial distribution of CES	spatial patterns (of trees for CES, by season)	1 km grid	Seasonal, multiple years of data	NA	Flickr; Wikiloc	(Vaz et al., 2019)
spatial distribution of CES	NA	specific locations	Multiple years	NA	Flickr, Instagra m	(Vieira, Bragagnolo, Correia, Malhado, & Ladle, 2018)
other	places to put information stands	200 m hexagon grid	Multiple years	NA	Flickr; Wikiloc	(Barros, Moya-Gómez, & Gutiérrez, 2019)
other	how spatial patterns are affected by snow	geotag	Not given	NA	Flickr	(Breckheimer et al., 2019)
other	viewsheds	geotag	Not given	NA	Flickr, Panorami o	(Karasov, Vieira, Külvik, & Chervanyov, 2020)
other	find main center of activity, and find distance to given parks	geotag	Time of day, weekend/we ekday, and seasonal	NA	Twitter	(Kovacs-Györi et al., 2018)

Table A.4

A full list of papers included in Figure 2.5 that analyze aspects of the visitor experience.

Topic analyzed	Topic category	Aspect of social media	Platform(s)	Citation
Sentiment	Sentiment	text	Twitter	(Kovacs-Györi et al., 2018)
Sentiment	Sentiment	text	Twitter	(Plunz et al., 2019)
Sentiment	Sentiment	text	Twitter	(Roberts, Sadler, & Chapman, 2019)
Sentiment	Sentiment	text	Twitter	(Sim & Miller, 2019)
Sentiment	Sentiment	text	Twitter	(Garzia et al., 2020)
Cultural ecosystem services	CES	photo content, geotag	Flickr	(Clemente et al., 2019)
Cultural ecosystem services	CES	photo content, geotag	Flickr	(Retka et al., 2019)
Cultural ecosystem services	CES	photo content, geotag	Flickr	(Rossi, Barros, Walden-Schreiner, & Pickering, 2019)
Cultural ecosystem services	CES	photo content, geotag	Flickr, Instagram	(Vieira, Bragagnolo, Correia, Malhado, & Ladle, 2018)
Cultural ecosystem services	CES	photo content, geotag	Wikiloc	(Callau, Albert, Rota, & Giné, 2019)
Cultural ecosystem services	CES	text, photo content (if applicable), geotag	Twitter	(Johnson, Campbell, Svendsen, & McMillen, 2019)
Cultural ecosystem services	CES	photo content, geotag	Flickr	(Vaz et al., 2020)
Cultural ecosystem services (demand for)	CES	geotag	Flickr	(Yoshimura & Hiura, 2017)
Cultural ecosystem services: non-native trees	CES	photo content, geotag	Flickr, Wikiloc	(Vaz et al., 2019)
Cultural ecosystem services: wildlife-viewing	CES	photo tags and content	Flickr	(Willemen, Cottam, Drakou, & Burgess, 2015)
Monitor unwanted behavior	Behavior	photo, video, text, and comments	Facebook	(Huang & Sun, 2019)
Monitor unwanted behavior	Behavior	photo content	Instagram	(Liang, Kirilenko, Stepchenkova, & Ma, 2019)
Visitors' activities	Behavior	photo content	Instagram	(Heikinheimo et al., 2017)
Visitors’ activities and use of the park	Behavior	Photo content, hashtags	Instagram	(Song & Zhang, 2020)
Seasonal differences in physical activity	Behavior	text	Twitter	(Roberts, Sadler, & Chapman, 2017)
Cluster visitors and understand differences in what they photograph	Preferences	photo content, geotag	Flickr	(Song, Richards, & Tan, 2020)
Public perceptions of grazing	Preferences	photo content, title, and comments	Flickr	(Barry, 2014)
Preferences for biodiversity	Preferences	photo content	Flickr, Instagram	(Hausmann et al., 2017)

How tourists view and value the destination in different seasons	Preferences	photo content, title, and tags	Flickr	(Pickering, Walden-Schreiner, Barros, & Rossi, 2020)
Experience values from the destination	Preferences	photo content	Instagram	(Conti & Lexhagen, 2020)
How photo content differs between international and domestic visitors	Preferences	photo content, home location	Flickr	(Muñoz, Hausner, Runge, Brown, & Daigle, 2020)
Understand aesthetic value and colors of photographs	Other	photo content	Flickr	(Do & Kim, 2020)
Per-trip benefits and travel cost	Other	geotags, home location	Flickr	(Sinclair, Ghermandi, & Sheela, 2018)
Mismatch between visitors & wildflowers	Other	photo content, geotag	Flickr	(Breckheimer et al., 2019)

APPENDIX B

SUPPLEMENTARY MATERIAL ASSOCIATED WITH CHAPTER III

Table B.1

The NPS units included in Chapter III, by ecoregion.

Ecoregion	# units	NPS Units
Northern forest	6	Apostle Islands NL, Isle Royale NP, Pictured Rocks NL, Saint Croix NSR, Upper Delaware S&RR, Voyageurs NP
Northwest forested mountains	20	Bandelier NM, Crater Lake NP, Curecanti NRA, Glacier NP, Grand Teton NP, John Day Fossil Beds NM, Kings Canyon NP, Lava Beds NM, Lake Chelan NRA, Lassen Volcanic NP, Mount Rainier NP, North Cascades NP, Olympic NP, Ross Lake NRA, Rocky Mountain NP, Sequoia NP, Whiskeytown NRA, Wind Cave NP, Yellowstone NP, Yosemite NP
Marine west coast forest	1	Redwood NP
Eastern temperate forest: Mixed wood plains	4	Acadia NP, Cuyahoga Valley NP, Indiana Dunes NP, Sleeping Bear Dunes NL
Eastern temperate forest: Southeastern USA plains	5	Big Thicket NPRES, Chattahoochee River NRA, Congaree NP, Mammoth Cave NP, Prince William Forest Park
Eastern temperate forest: Ozark, Ouachita-Appalachian forests	10	Big South Fork NRRA, Buffalo NR, Cumberland Cap NHP, Delaware Water Gap NRA, Gauley River NRA, Great Smoky Mountains NP, Little River Canyon NPRES, New River Gorge NR, Ozark NSR, Shenandoah NP
Eastern temperate forest: Mississippi Alluvial and Southeast USA coastal plains	11	Assateague Island NS, Cape Cod NS, Cape Hatteras NS, Cape Lookout NS, Canaveral NS, Cumberland Island NS, Fire Island NS, Gateway NRA, Gulf Island NS, Jean Lafitte NHP & PRES, Timucuan EHP
Great plains	10	Badlands NP, Bighorn Canyon NRA, Lake Meredith NRA, Mississippi NRRA, Missouri NRR, Niobrara NSR, Padre Island NS, Sand Creek Massacre NHS, Tallgrass Prairie NPRES, Theodore Roosevelt NP
North American deserts: cold deserts	21	Arches NP, Black Canyon of the Gunnison NP, Bryce Canyon NP, Canyon de Chelly NM, Canyonlands NP, Capitol Reef NP, Chaco Culture NHP, City of Rocks NRES, Colorado NM, Craters of the Moon NM & PRES, Dinosaur NM, El Malpais NM, Glen Canyon NRA, Great Basin NP, Grand Canyon NP, Great Sand Dunes NP & PRES, Lake Roosevelt NRA, Mesa Verde NP, Petrified Forest NP, Wupatki NM, Zion NP
North American deserts: warm deserts	9	Amistad NRA, Big Bend NP, Death Valley NP, Joshua Tree NP, Lake Mead NRA, Mojave NPRES, Organ Pipe Cactus NM, Rio Grande W&SR, White Sands NM
Mediterranean California	5	Channel Islands NP, Golden Gate NRA, Pinnacles NP, Point Reyes NS, Santa Monica Mountains NRA
Southern semi-arid	2	Chiricahua NM, Saguaro NP

highlands		
Temperate Sierras	2	Carlsbad Caverns NP, Guadalupe Mountains NP
Tropical wet forests	4	Big Cypress NPRES, Biscayne NP, Dry Tortugas NP, Everglades NP

NP = National Park, NM = National Monument, NRA = National Recreation Area, NS = National Seashore, NHP = National Historical Park, NL = National Lakeshore, NSR = National Scenic River, S&RR = Scenic & Recreational River, NPRES = National Preservation, NR = National River, NRRA = National River & Recreation Area, EHP = Ecological & Historic Preserve, NHS = National Historic Site, W&SR = Wild & Scenic River

Table B.2

The number of Flickr data points in each study site between May – September, 2006 – 2018. Numbers represent only one post per user, per day, within a 10-meter radius.

Code	Park Name	*n*	Code	Park Name	*n*
ACAD	Acadia National Park	8,101	GUMO	Guadalupe Mountains National Park	322
AMIS	Amistad National Recreation Area	32	INDU	Indiana Dunes National Lakeshore	1,372
APIS	Apostle Islands National Lakeshore	355	ISRO	Isle Royale National Park	1,183
ARCH	Arches National Park	9,020	JELA	Jean Lafitte National Historical Park and Preserve	313
ASIS	Assateague Island National Seashore	1,532	JODA	John Day Fossil Beds National Monument	1,151
BADL	Badlands National Park	4,416	JOTR	Joshua Tree National Park	4,552
BAND	Bandelier National Monument	974	KICA	Kings Canyon National Park	7,770
BIBE	Big Bend National Park	1,688	LABE	Lava Beds National Monument	684
BICA	Bighorn Canyon National Recreation Area	153	LACH	Lake Chelan National Recreation Area	313
BICY	Big Cypress National Preserve	492	LAKE	Lake Mead National Recreation Area	8,725
BISC	Biscayne National Park	52	LAMR	Lake Meredith National Recreation Area	20
BISO	Big South Fork National River and Recreation Area	768	LARO	Lake Roosevelt National Recreation Area	303
BITH	Big Thicket National Preserve	32	LAVO	Lassen Volcanic National Park	4,340
BLCA	Black Canyon of the Gunnison National Park	1,289	LIRI	Little River Canyon National Preserve	134
BRCA	Bryce Canyon National Park	10,581	MACA	Mammoth Cave National Park	498
BUFF	Buffalo National River	490	MEVE	Mesa Verde National Park	3,272
CACH	Canyon de Chelly National Monument	992	MISS	Mississippi National River and Recreation Area	18,130
CACO	Cape Cod National Seashore	3,429	MNRR	Missouri National Recreation River	132
CAHA	Cape Hatteras National Seashore	2,352	MOJA	Mojave National Preserve	1,526
CALO	Cape Lookout National Seashore	201	MORA	Mount Rainier National Park	17,415
CANA	Canaveral National Seashore	341	NERI	New River Gorge National River	1,385
CANY	Canyonlands National Park	4,540	NIOB	Niobrara National Scenic River	72
CARE	Capitol Reef National Park	3,394	NOCA	North Cascades National Park	1,880
CAVE	Carlsbad Caverns National Park	475	OLYM	Olympic National Park	12,365
CHAT	Chattahoochee River National Recreation Area	597	ORPI	Organ Pipe Cactus National Monument	216
CHCU	Chaco Culture National Historical Park	963	OZAR	Ozark National Scenic Riverway	316
CHIR	Chiricahua National Monument	266	PAIS	Padre Island National Seashore	141
CHIS	Channel Islands National Park	1,331	PEFO	Petrified Forest National Park	2,836

CIRO	City of Rocks National Reserve	265	PINN	Pinnacles National Park	986
COLM	Colorado National Monument	1,184	PIRO	Pictured Rocks National Lakeshore	1,836
CONG	Congaree National Park	154	PORE	Point Reyes National Seashore	6,259
CRLA	Crater Lake National Park	4,558	PRWI	Prince William Forest Park	110
CRMO	Craters of the Moon National Monument	1,110	REDW	Redwood National Park	3,858
CUGA	Cumberland Gap National Historical Park	231	RIGR	Rio Grande Wild and Scenic River	240
CUIS	Cumberland Island National Seashore	309	ROLA	Ross Lake National Recreation Area	1,951
CURE	Curecanti National Recreation Area	618	ROMO	Rocky Mountain National Park	15,152
CUVA	Cuyahoga Valley National Park	2,523	SACN	Saint Croix National Scenic Riverway	335
DEVA	Death Valley National Park	7,671	SAGU	Saguaro National Park	992
DEWA	Delaware Water Gap National Recreation Area	1,721	SAMO	Santa Monica Mountains National Recreation Area	15,385
DINO	Dinosaur National Monument	1,258	SAND	Sand Creek Massacre National Historic Site	37
DRTO	Dry Tortugas National Park	0	SEQU	Sequoia National Park	8,724
ELMA	El Malpais National Monument	198	SHEN	Shenandoah National Park	4,423
EVER	Everglades National Park	1,613	SLBE	Sleeping Bear Dunes National Lakeshore	2,232
FIIS	Fire Island National Seashore	2,447	TAPR	Tallgrass Prairie National Preserve	276
GARI	Gauley River National Recreation Area	21	THRO	Theodore Roosevelt National Park	1,524
GATE	Gateway National Recreation Area	3,899	TIMU	Timucuan Ecological and Historic Preserve	457
GLAC	Glacier National Park	16,459	UPDE	Upper Delaware Scenic and Recreational River	2,189
GLCA	Glen Canyon National Recreation Area	5,721	VOYA	Voyageurs National Park	137
GOGA	Golden Gate National Recreation Area	52,547	WHIS	Whiskeytown-Shasta-Trinity National Recreation Area	248
GRBA	Great Basin National Park	674	WHSA	White Sands National Monument	1,134
GRCA	Grand Canyon National Park	26,192	WICA	Wind Cave National Park	497
GRSA	Great Sand Dunes National Park and Preserve	1,918	WUPA	Wupatki National Monument	472
GRSM	Great Smoky Mountains National Park	8,341	YELL	Yellowstone National Park	56,850
GRTE	Grand Teton National Park	15,928	YOSE	Yosemite National Park	41,296
GUIS	Gulf Islands National Seashore	3,057	ZION	Zion National Park	10,622

Table B.3

Key-value pairs used to download OpenStreetMap data for each category of data used in this analysis.

Category	Key	Value(s)	Types of data used
Roads	highway	motorway, trunk, primary, secondary, tertiary, motorway_link, trunk_link, primary_link, tertiary_link, unclassified, residential, service	lines, polygons
Water	natural	water, bay, strait, coastline	lines, polygons, multipolygons
	waterway	river	
Parking	amenity	parking	polygons, multipolygons
Buildings	building	(all)	polygons, multipolygons

Table B.4

Maximum daily temperature ranges for what is considered a cold, average, or hot day, by park unit. Average days are within one standard deviation of the mean, while cold days are greater than one standard deviation colder, and hot days are greater than one standard deviation warmer.

Unit	Ecoregion	Cold range (ºC)	Average range (ºC)	Hot range (ºC)
ACAD	Mixed wood plains	9 - 19	19.5 - 27	27.5 - 33.5
CUVA	Mixed wood plains	11 - 21.5	22 - 30	30.5 - 36
INDU	Mixed wood plains	10.5 - 20.5	21 - 29.5	30 - 38
SLBE	Mixed wood plains	9 - 20	20.5 - 28.5	29 - 33.5
AMIS	Warm deserts	27.5 - 31	31.5 - 37.5	39 - 41
BIBE	Warm deserts	16 - 28.5	29 - 36	36.5 - 40.5
DEVA	Warm deserts	25.5 - 36.5	37 - 47.5	48 - 50
JOTR	Warm deserts	18 - 26	26.5 - 37.5	38 - 43.5
LAKE	Warm deserts	20.5 - 32	32.5 - 42.5	43 - 48
MOJA	Warm deserts	21 - 30	30.5 - 41	41.5 - 45.5
ORPI	Warm deserts	NA (no obs.)	25 - 35.5	36 - 42
RIGR	Warm deserts	25 - 34	34.5 - 40.5	41 - 43
WHSA	Warm deserts	18.5 - 27.5	28 - 35	35.5 - 41
APIS	Northern forest	11.5 - 19.5	20 - 27.5	28 - 32
ISRO	Northern forest	9 - 19	19.5 - 26	26.5 - 30.5
PIRO	Northern forest	4.5 - 18.5	19 - 26.5	27 - 32.5
SACN	Northern forest	11 - 21.5	22 - 29.5	30 - 35
UPDE	Northern forest	11 - 21.5	22 - 29.5	30 - 35.5
VOYA	Northern forest	10.5 - 19	20 - 27.5	28 - 30.5
ARCH	Cold deserts	13.5 - 26	26.5 - 36.5	37 - 42.5
BLCA	Cold deserts	4.5 - 18	18.5 - 30	30.5 - 32.5
BRCA	Cold deserts	4.5 - 17.5	18 - 27.5	28 - 32.5
CACH	Cold deserts	16 - 26	26.5 - 33.5	34 - 37
CANY	Cold deserts	9.5 - 21	21.5 - 32.5	33 - 37.5
CARE	Cold deserts	11.5 - 23	23.5 - 33	33.5 - 37.5
CHCU	Cold deserts	13.5 - 24	25 - 32	32.5 - 36
CIRO	Cold deserts	8 - 18	19 - 29.5	30 - 33.5
COLM	Cold deserts	11.5 - 24	24.5 - 33	33.5 - 37.5
CRMO	Cold deserts	7 - 20	20.5 - 31.5	32 - 36
DINO	Cold deserts	13 - 23.5	24 - 34	34.5 - 37.5
ELMA	Cold deserts	12 - 23	24 - 32	32.5 - 34.5
GLCA	Cold deserts	14 - 27.5	28 - 37.5	38 - 43
GRBA	Cold deserts	10.5 - 26	26.5 - 34.5	35 - 38.5
GRCA	Cold deserts	5.5 - 19.5	20 - 29	29.5 - 35.5
GRSA	Cold deserts	9 - 20	20.5 - 28	28.5 - 32
LARO	Cold deserts	13.5 - 23	23.5 - 33.5	34 - 40.5
MEVE	Cold deserts	7 - 20.5	21 - 30.5	31 - 34
PEFO	Cold deserts	14 - 25	25.5 - 33.5	34 - 38.5
WUPA	Cold deserts	13 - 25.5	26 - 35.5	36 - 40.5
ZION	Cold deserts	14 - 26	26.5 - 37	37.5 - 42.5
ASIS	MS alluvial/SE coastal plains	11.5 - 23.5	24 - 31.5	32 - 37.5

CACO	MS alluvial/SE coastal plains	8.5 - 19.5	20 - 27	27.5 - 33.5
CAHA	MS alluvial/SE coastal plains	17 - 25.5	26 - 30.5	31 - 34
CALO	MS alluvial/SE coastal plains	21.5 - 27	27.5 - 31.5	32 - 36.5
CANA	MS alluvial/SE coastal plains	25.5 - 28.5	29 - 32.5	33 - 36
CUIS	MS alluvial/SE coastal plains	24.5 - 28	28.5 - 33	33.5 - 37.5
FIIS	MS alluvial/SE coastal plains	9.5 - 22.5	23 - 29.5	30 - 40
GATE	MS alluvial/SE coastal plains	11 - 22.5	23 - 31	31.5 - 39
GUIS	MS alluvial/SE coastal plains	22.5 - 29	29.5 - 33.5	34 - 38
JELA	MS alluvial/SE coastal plains	25 - 28.5	29 - 33.5	34 - 38
TIMU	MS alluvial/SE coastal plains	24 - 28.5	29 - 33.5	34 - 36.5
BADL	Great plains	7.5 - 23.5	24 - 34	34.5 - 42.5
BICA	Great plains	10.5 - 19	20 - 32.5	33 - 37.5
LAMR	Great plains	23.5 - 26.5	30.5 - 36	38 - 39
MISS	Great plains	5 - 20.5	21 - 30	30.5 - 37
MNRR	Great plains	15 - 24.5	25 - 32	32.5 - 38.5
NIOB	Great plains	17 - 27.5	28 - 35	36 - 37.5
PAIS	Great plains	25 - 29.5	30 - 33	33.5 - 35.5
SAND	Great plains	18 - 24	26 - 34	NA (no obs.)
TAPR	Great plains	18.5 - 25	25.5 - 34	34.5 - 39.5
THRO	Great plains	6.5 - 21.5	22 - 32	32.5 - 38.5
BAND	NW forested mountains	15.5 - 22	22.5 - 32	32.5 - 36
CRLA	NW forested mountains	-2 - 13	13.5 - 23.5	24 - 29
CURE	NW forested mountains	9 - 21.5	22 - 29.5	30 - 33
GLAC	NW forested mountains	6.5 - 21	21.5 - 31	31.5 - 37.5
GRTE	NW forested mountains	2 - 18	18.5 - 28.5	29 - 34
JODA	NW forested mountains	13 - 24	24.5 - 36.5	37 - 40
KICA	NW forested mountains	1.5 - 19.5	20 - 29	29.5 - 32.5
LABE	NW forested mountains	9 - 21	21.5 - 32	33 - 36.5
LACH	NW forested mountains	16 - 21	21.5 - 29	29.5 - 36.5
LAVO	NW forested mountains	1 - 19	19.5 - 27	27.5 - 31.5
MORA	NW forested mountains	1 - 11.5	12 - 21.5	22 - 29
NOCA	NW forested mountains	11 - 19.5	20 - 30.5	31 - 37
OLYM	NW forested mountains	10.5 - 16.5	17 - 24	24.5 - 34
ROLA	NW forested mountains	11.5 - 18	18.5 - 29	29.5 - 38
ROMO	NW forested mountains	1 - 19	19.5 - 27.5	28 - 32
SEQU	NW forested mountains	14.5 - 29.5	30 - 38.5	39 - 46
WHIS	NW forested mountains	15.5 - 24.5	25.5 - 38	38.5 - 41
WICA	NW forested mountains	9.5 - 21.5	22 - 32.5	33 - 39.5
YELL	NW forested mountains	2 - 15	15.5 - 25.5	26 - 31.5
YOSE	NW forested mountains	7.5 - 23.5	24 - 34	34.5 - 39.5
BICY	Tropical wet forests	27.5 - 31.5	32 - 34.5	35 - 36.5
BISC	Tropical wet forests	27.5 - 28.5	29 - 32.5	33 - 33.5
EVER	Tropical wet forests	27.5 - 30.5	31 - 33.5	34 - 35
BISO	Ozark forests	10.5 - 19.5	20 - 29.5	30 - 33
BUFF	Ozark forests	6.5 - 24.5	25 - 34	34.5 - 39.5
CUGA	Ozark forests	18 - 23.5	24 - 32	32.5 - 36
DEWA	Ozark forests	11 - 21	21.5 - 29	29.5 - 35
GARI	Ozark forests	21 - 22	24.5 - 28	30.5 - 32
GRSM	Ozark forests	11 - 24	24.5 - 30.5	31 - 38

LIRI	Ozark forests	13.5 - 22.5	23.5 - 31.5	32 - 35.5
NERI	Ozark forests	10.5 - 22	22.5 - 29	29.5 - 35.5
OZAR	Ozark forests	19.5 - 27.5	28 - 35	36 - 40
SHEN	Ozark forests	12.5 - 22.5	23 - 30.5	31 - 37.5
BITH	SE USA plains	24.5 - 24.5	29.5 - 36	36.5 - 36.5
CHAT	SE USA plains	16 - 25.5	26 - 33	33.5 - 38.5
CONG	SE USA plains	18.5 - 27	27.5 - 34.5	35 - 37.5
MACA	SE USA plains	16 - 26	26.5 - 32.5	33 - 38
PRWI	SE USA plains	19 - 23	23.5 - 30	30.5 - 35
CAVE	Temperate Sierras	17 - 25.5	26 - 35.5	36 - 41
GUMO	Temperate Sierras	14.5 - 23	24 - 31.5	32 - 37
CHIR	S semi-arid highlands	20 - 24	24.5 - 31.5	32 - 36
SAGU	S semi-arid highlands	23 - 31	31.5 - 38	38.5 - 43.5
CHIS	Mediterranean CA	16.5 - 22	22.5 - 28	28.5 - 35.5
GOGA	Mediterranean CA	13.5 - 18	18.5 - 25	25.5 - 39
PINN	Mediterranean CA	16 - 23.5	24 - 33.5	34 - 39.5
PORE	Mediterranean CA	13.5 - 18.5	19 - 26.5	27 - 39.5
SAMO	Mediterranean CA	14.5 - 22	22.5 - 31	31.5 - 41.5
REDW	Marine west coast forest	12 - 19	19.5 - 25.5	26 - 34.5

Table B.5

Sample sizes for each group based on daily temperature and precipitation at the visitor center, by ecoregion.

Ecoregion	Total *n*	Cold days	Average days	Hot days	No precip.	Precip.
Warm deserts	25,784	4,543	17,623	3,618	24,623	1,161
Southern semi-arid highlands	1,258	234	823	201	1,024	234
Tropical wet forests	2,157	448	1,485	224	1,077	1,080
Southeastern USA plains	1,391	201	985	205	957	434
Temperate Sierras	797	110	573	114	697	100
Mississippi alluvial and southeast USA coastal plains	18,337	2,832	12,969	2,536	13,237	5,100
Cold deserts	86,804	13,871	59,961	12,972	72,301	14,503
Ozark, Ouachita-Appalachian forests	17,830	2,506	12,638	2,686	11,017	6,813
Great plains	24,901	3,708	17,550	3,643	18,221	6,680
Mixed wood plains	14,228	2,334	9,838	2,056	9,589	4,639
Northern forest	6,035	905	4,369	761	4,196	1,839
Northwest forested mountains	209,173	32,764	148,875	27,534	175,730	33,443
Mediterranean California	76,508	11,564	53,691	11,253	74,483	2,025
Marine west coast forest	3,858	577	2,728	553	3,273	585

Table B.6

Full statistical results associated with Figure 3.3. Welch's ANOVA tests comparing distributions on hot, cold, and average days by ecoregion.

	Mean: Cold days	Mean: Avg. days	Mean: Hot days	Welch's ANOVA p-value	Cold-Avg Games-Howell p-value	Hot-Avg Games-Howell p-value	Cold-Avg Cohen's d	Hot-Avg Cohen's d
ELEVATION								
Warm deserts	733.3	725.0	694.8	**0.003**	0.614	**0.007**	0.015	-0.053
S semi-arid highlands	1035.5	1077.7	1270.2	**0.000**	0.386	**0.000**	-0.094	0.398
Tropical wet forests	1.0	1.1	1.1	**0.012**	**0.008**	0.888	-0.150	-0.034
SE USA plains	203.0	196.3	200.1	0.581	0.596	0.851	0.075	0.042
Temperate Sierras	1581.1	1498.5	1577.7	**0.032**	0.098	0.152	0.248	0.232
MS alluvial/SE coastal plains	4.0	3.7	3.5	0.074	0.177	0.507	0.038	-0.024
Cold deserts	1785.2	1833.5	1867.2	**0.000**	**0.000**	**0.000**	-0.095	0.068
Ozark forests	679.8	792.2	751.4	**0.000**	**0.000**	**0.000**	-0.229	-0.081
Great plains	384.4	384.4	389.6	0.537	1.000	0.516	0.000	0.020
Mixed wood plains	162.3	174.2	175.8	**0.000**	**0.000**	0.864	-0.092	0.012
Northern forest	208.3	211.9	210.1	0.063	0.060	0.543	-0.076	-0.039
NW forested mountains	1873.1	2019.4	2040.5	**0.000**	**0.000**	**0.000**	-0.191	0.027
Mediterranean CA	97.3	80.9	78.0	**0.000**	**0.000**	0.082	0.119	-0.021
Marine westcoast forest	96.1	99.6	85.5	**0.039**	0.826	**0.030**	-0.028	-0.113
DISTANCE TO ROADS								
Warm deserts	102.4	82.0	69.9	**0.000**	**0.000**	**0.034**	0.072	-0.045
S semi-arid highlands	16.5	27.3	31.8	**0.002**	**0.003**	0.802	-0.182	0.063
Tropical wet forests	66.4	126.5	188.0	**0.000**	**0.002**	0.147	-0.153	0.145
SE USA plains	7.0	10.1	7.3	**0.004**	**0.011**	0.056	-0.178	-0.158
Temperate Sierras	175.9	157.2	195.4	0.438	0.820	0.447	0.066	0.134
MS alluvial/SE coastal plains	351.9	127.6	124.0	**0.000**	**0.000**	0.947	0.273	-0.006
Cold deserts	81.7	72.2	62.7	**0.000**	**0.010**	**0.010**	0.027	-0.027
Ozark forests	16.0	17.6	17.0	**0.035**	**0.028**	0.650	-0.048	-0.017
Great plains	9.4	9.4	8.6	0.523	1.000	0.683	0.000	-0.008
Mixed wood plains	41.5	68.0	26.6	**0.000**	**0.001**	**0.000**	-0.071	-0.116
Northern forest	90.4	75.8	67.2	0.550	0.734	0.809	0.033	-0.021
NW forested mountains	55.2	74.8	78.4	**0.000**	**0.000**	0.055	-0.075	0.013
Mediterranean CA	25.5	24.8	31.2	**0.000**	0.809	**0.000**	0.006	0.057
Marine westcoast forest	15.8	15.2	13.9	0.184	0.840	0.245	0.026	-0.065

DISTANCE TO WATERBODIES								
Warm deserts	3995.6	3646.9	3572.5	0.068	0.079	0.890	0.038	-0.008
S semi-arid highlands	353.7	349.8	380.1	0.876	0.995	0.864	0.007	0.051
Tropical wet forests	295.8	324.9	335.4	0.645	0.669	0.973	-0.045	0.016
SE USA plains	137.6	151.7	123.6	0.267	0.819	0.248	-0.051	-0.107
Temperate Sierras	6333.9	5568.6	6651.4	**0.000**	**0.061**	**0.000**	0.260	0.382
MS alluvial/SE coastal plains	76.4	72.4	72.5	0.199	0.178	0.999	0.036	0.001
Cold deserts	887.0	950.8	958.6	**0.000**	**0.000**	0.910	-0.033	0.004
Ozark forests	203.3	219.2	196.6	**0.002**	0.095	**0.004**	-0.045	-0.064
Great plains	945.9	865.2	894.7	0.102	0.096	0.669	0.040	0.015
Mixed wood plains	78.1	89.9	84.4	**0.000**	**0.000**	0.163	-0.091	-0.042
Northern forest	57.5	57.3	51.2	0.079	0.997	0.077	0.002	-0.065
NW forested mountains	122.7	120.8	111.3	**0.000**	0.291	**0.000**	0.009	-0.044
Mediterranean CA	97.3	78.2	74.1	**0.000**	**0.000**	**0.021**	0.114	-0.026
Marine westcoast forest	216.7	223.6	221.8	0.826	0.811	0.988	-0.026	-0.007
DISTANCE TO PARKING								
Warm deserts	1589.3	1052.9	1298.9	**0.000**	0.066	**0.000**	0.122	0.061
S semi-arid highlands	237.0	353.0	450.7	**0.004**	0.148	**0.007**	-0.151	0.095
Tropical wet forests	409.1	731.0	753.3	**0.000**	**0.000**	**0.000**	-0.263	0.017
SE USA plains	469.6	597.5	416.4	0.090	0.891	0.386	-0.094	-0.134
Temperate Sierras	1160.3	515.3	672.9	**0.038**	0.233	0.065	0.401	0.134
MS alluvial/SE coastal plains	788.1	560.5	550.0	**0.000**	**0.000**	**0.000**	0.160	-0.009
Cold deserts	706.9	536.3	440.3	**0.000**	**0.000**	**0.000**	0.113	-0.071
Ozark forests	551.7	497.7	499.4	0.199	0.338	0.176	0.040	0.001
Great plains	321.1	282.1	427.3	0.148	0.490	0.809	0.013	0.045
Mixed wood plains	250.0	504.8	276.3	**0.000**	0.819	**0.000**	-0.116	-0.103
Northern forest	619.2	777.5	761.9	**0.046**	0.257	**0.035**	-0.112	-0.011
NW forested mountains	343.5	434.0	416.9	**0.000**	**0.000**	**0.000**	-0.082	-0.015
Mediterranean CA	112.9	97.9	101.2	**0.000**	**0.002**	**0.000**	0.060	0.013
Marine westcoast forest	237.6	252.6	318.9	**0.003**	**0.011**	0.772	-0.037	0.168
DISTANCE TO BUILDINGS								
Warm deserts	570.0	434.5	466.9	**0.000**	**0.000**	0.286	0.121	0.030
S semi-arid highlands	292.7	418.7	465.3	**0.001**	**0.001**	0.883	-0.183	0.052
Tropical wet forests	247.4	472.3	726.0	**0.000**	**0.000**	**0.035**	-0.207	0.212
SE USA plains	171.3	187.2	115.0	**0.022**	0.902	**0.016**	-0.034	-0.163
Temperate Sierras	1210.2	490.4	648.6	**0.023**	**0.037**	0.326	0.439	0.132
MS alluvial/SE coastal plains	133.1	95.2	103.2	**0.000**	**0.000**	0.125	0.167	0.041

Cold deserts	640.4	569.3	525.0	**0.000**	**0.000**	**0.000**	0.058	-0.038
Ozark forests	213.0	192.8	203.6	0.181	0.192	0.635	0.038	0.020
Great plains	270.0	253.4	296.5	**0.020**	0.476	**0.019**	0.021	0.054
Mixed wood plains	216.2	282.3	239.0	**0.000**	**0.000**	**0.012**	-0.096	-0.063
Northern forest	582.5	617.5	519.8	0.093	0.855	0.076	-0.022	-0.067
NW forested mountains	273.5	304.4	291.3	**0.000**	**0.000**	**0.000**	-0.056	-0.024
Mediterranean CA	623.5	539.1	512.8	**0.001**	**0.004**	0.522	0.098	-0.031
Marine westcoast forest	576.5	489.6	453.5	**0.001**	**0.008**	0.257	0.158	-0.069

Table B.7

Full statistical results associated with Figure 3.5. Welch's t-tests comparing distributions on days with no precipitation to days with precipitation, by ecoregion.

	Mean: no precipitation	Mean: precipitation	p-value	Cohen's d
ELEVATION				
Warm deserts	717.235	827.427	**0.000**	-0.197
S semi-arid highlands	1083.800	1174.308	**0.018**	-0.189
Tropical wet forests	1.053	1.160	**0.007**	-0.117
SE USA plains	191.913	211.008	**0.000**	-0.214
Temperate Sierras	1495.471	1700.929	**0.000**	-0.598
MS alluvial/SE coastal plains	3.733	3.636	0.409	0.014
Cold deserts	1824.627	1861.756	**0.000**	-0.074
Ozark forests	752.506	798.958	**0.000**	-0.094
Great plains	395.204	357.775	**0.000**	0.145
Mixed wood plains	175.480	166.193	**0.000**	0.072
Northern forest	210.761	211.990	0.352	-0.026
NW forested mountains	2001.266	1988.599	**0.004**	0.016
Mediterranean CA	83.423	64.694	**0.000**	0.136
Marine westcoast forest	100.349	78.758	**0.000**	0.172
DISTANCE TO ROADS				
Warm deserts	82.099	122.218	**0.003**	-0.144
S semi-arid highlands	23.728	36.009	0.061	-0.186
Tropical wet forests	124.465	116.369	0.640	0.020
SE USA plains	9.391	9.025	0.709	0.021
Temperate Sierras	156.452	226.336	**0.038**	-0.244
MS alluvial/SE coastal plains	174.310	129.067	**0.000**	0.057
Cold deserts	74.406	61.743	**0.000**	0.036
Ozark forests	17.037	17.650	0.213	-0.019
Great plains	10.158	7.022	**0.000**	0.033
Mixed wood plains	66.157	40.028	**0.000**	0.075
Northern forest	64.878	102.224	**0.019**	-0.088
NW forested mountains	75.782	53.416	**0.000**	0.087
Mediterranean CA	25.698	31.469	**0.038**	-0.052
Marine westcoast forest	15.274	14.288	0.261	0.047
DISTANCE TO WATERBODIES				
Warm deserts	3490.725	8091.293	**0.000**	-0.505
S semi-arid highlands	329.268	469.620	**0.013**	-0.240
Tropical wet forests	287.111	352.694	**0.018**	-0.102
SE USA plains	139.511	158.703	0.231	-0.071

Temperate Sierras	5934.186	5096.904	**0.002**	0.287
MS alluvial/SE coastal plains	74.442	69.441	**0.004**	0.046
Cold deserts	960.319	849.269	**0.000**	0.058
Ozark forests	220.968	201.604	**0.000**	0.055
Great plains	960.132	667.203	**0.000**	0.149
Mixed wood plains	92.831	75.372	**0.000**	0.136
Northern forest	55.680	58.462	0.275	-0.030
NW forested mountains	120.075	118.821	0.309	0.006
Mediterranean CA	80.783	70.344	**0.010**	0.063
Marine westcoast forest	216.552	254.583	**0.001**	-0.145
DISTANCE TO PARKING				
Warm deserts	1138.106	2111.281	**0.000**	-0.214
S semi-arid highlands	314.737	488.248	0.121	-0.184
Tropical wet forests	588.471	744.166	**0.003**	-0.128
SE USA plains	544.165	570.388	0.736	-0.020
Temperate Sierras	604.803	780.709	0.191	-0.113
MS alluvial/SE coastal plains	635.943	485.954	**0.000**	0.109
Cold deserts	552.066	534.838	0.159	0.012
Ozark forests	528.246	468.773	**0.003**	0.045
Great plains	365.037	156.851	**0.000**	0.063
Mixed wood plains	491.480	302.948	**0.000**	0.089
Northern forest	781.969	689.876	**0.041**	0.064
NW forested mountains	424.566	380.824	**0.000**	0.041
Mediterranean CA	100.455	107.517	0.257	-0.028
Marine westcoast forest	273.715	182.306	**0.000**	0.222
DISTANCE TO BUILDINGS				
Warm deserts	459.378	538.059	**0.030**	-0.070
S semi-arid highlands	370.259	544.649	0.065	-0.211
Tropical wet forests	408.153	495.657	0.073	-0.077
SE USA plains	175.735	170.957	0.857	0.011
Temperate Sierras	582.249	822.247	0.095	-0.151
MS alluvial/SE coastal plains	104.157	97.039	**0.042**	0.032
Cold deserts	580.556	541.520	**0.000**	0.032
Ozark forests	212.291	172.898	**0.000**	0.073
Great plains	297.094	167.027	**0.000**	0.164
Mixed wood plains	299.900	193.417	**0.000**	0.157
Northern forest	624.292	544.391	0.063	0.052
NW forested mountains	308.311	242.990	**0.000**	0.120
Mediterranean CA	542.751	732.033	**0.008**	-0.223
Marine westcoast forest	494.896	511.353	0.492	-0.030

APPENDIX C

SUPPLEMENTARY MATERIAL ASSOCIATED WITH CHAPTER IV

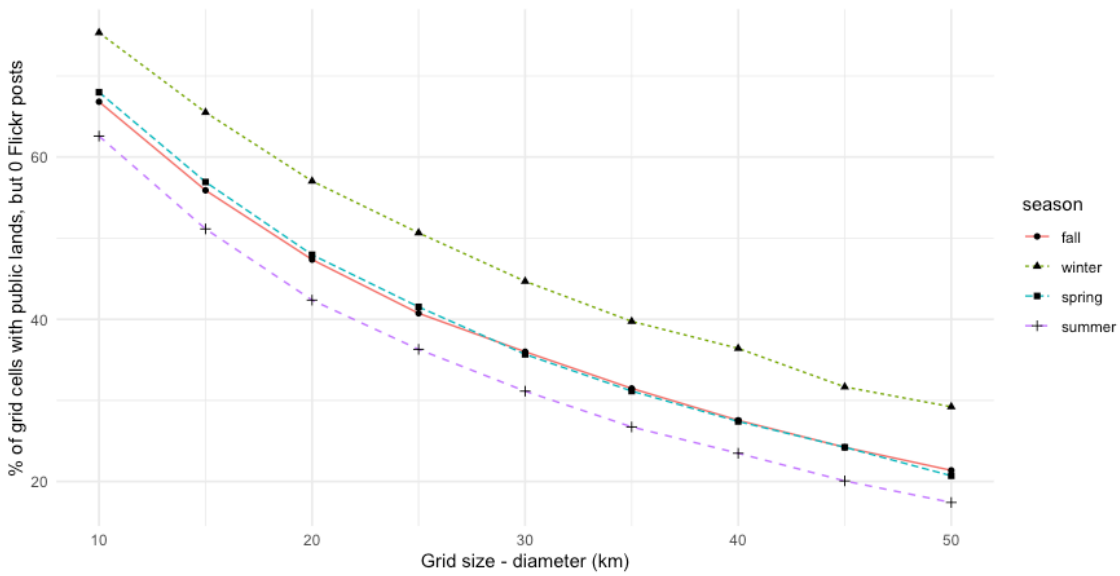

Figure C.1. Percent of grid cells that have federal and/or state public lands, but 0 Flickr posts between 2006 - 2019, by season, across varying grid sizes.

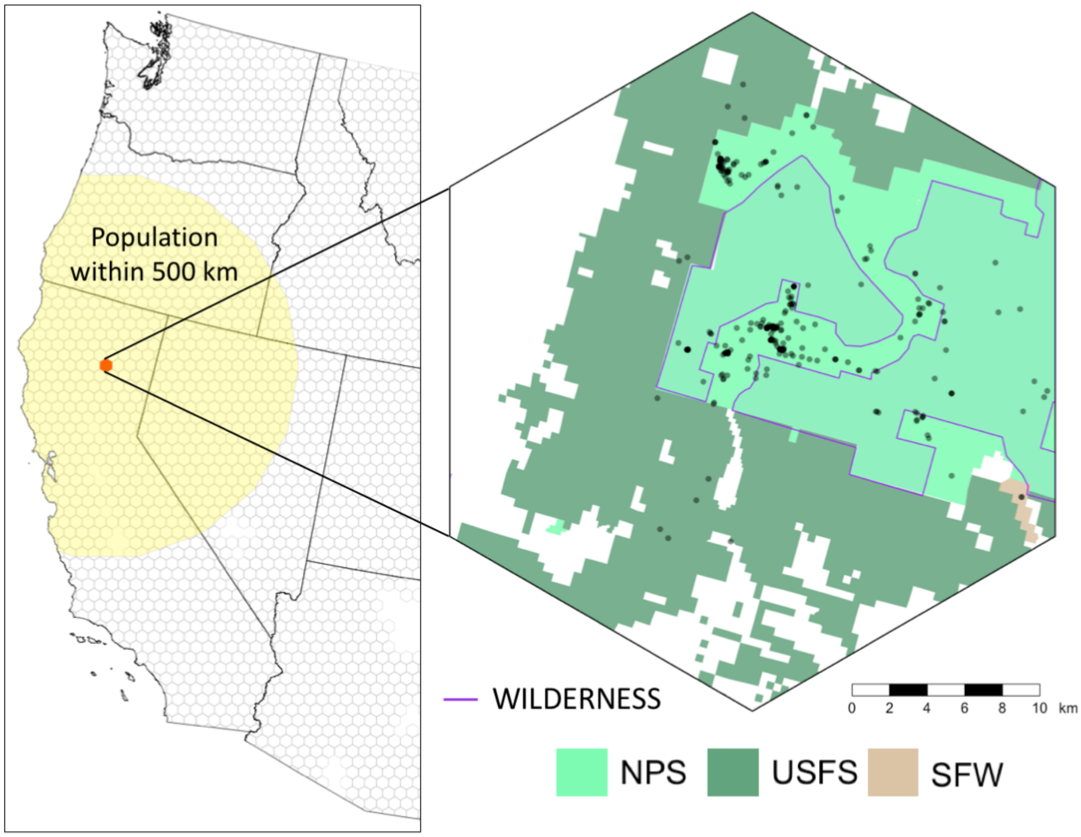

Figure C.2. An example of what these data look like for one grid cell. Black dots represent Flickr PUD in the fall (n = 314). This cell has 689.7 km^2 of total public lands, 309.7 km^2 of NPS lands, 206.8 km^2 of designated wilderness, and 16.5 million people within 500 km. NPS = National Park Service; USFS = U.S.D.A. Forest Service; SFW = State Fish and Wildlife.

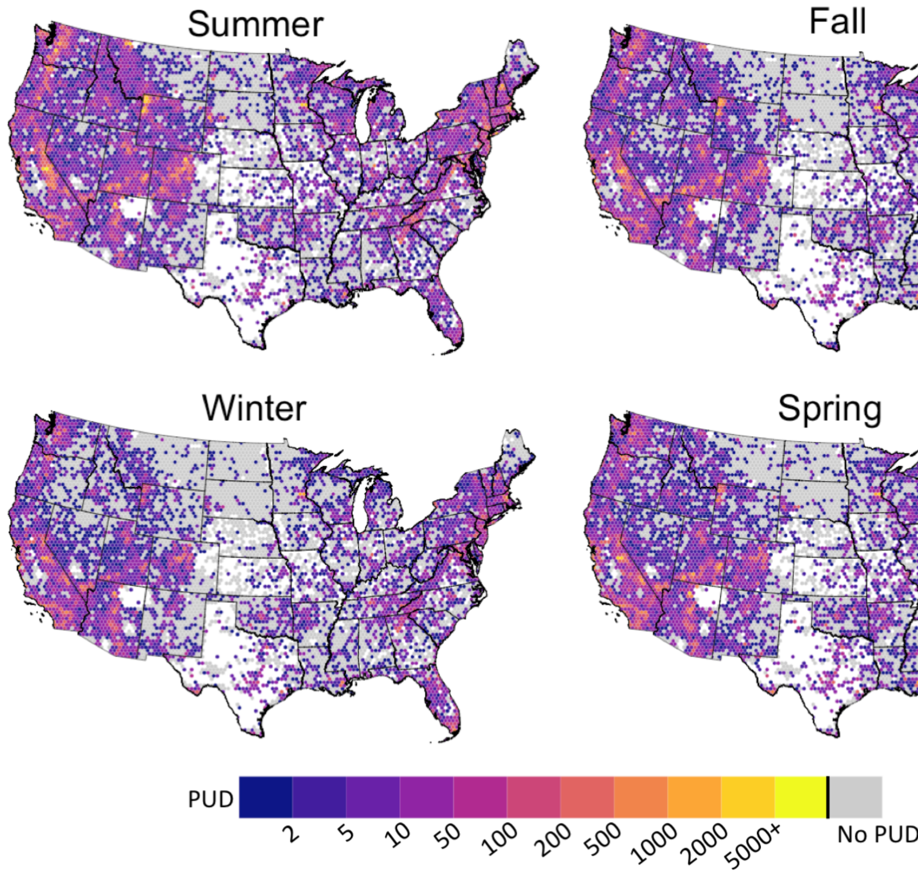

Figure C.3. Spatial distribution of Flickr PUDs by season across U.S. public lands in this study. White cells represent areas that have no state or federal public lands included in this study.

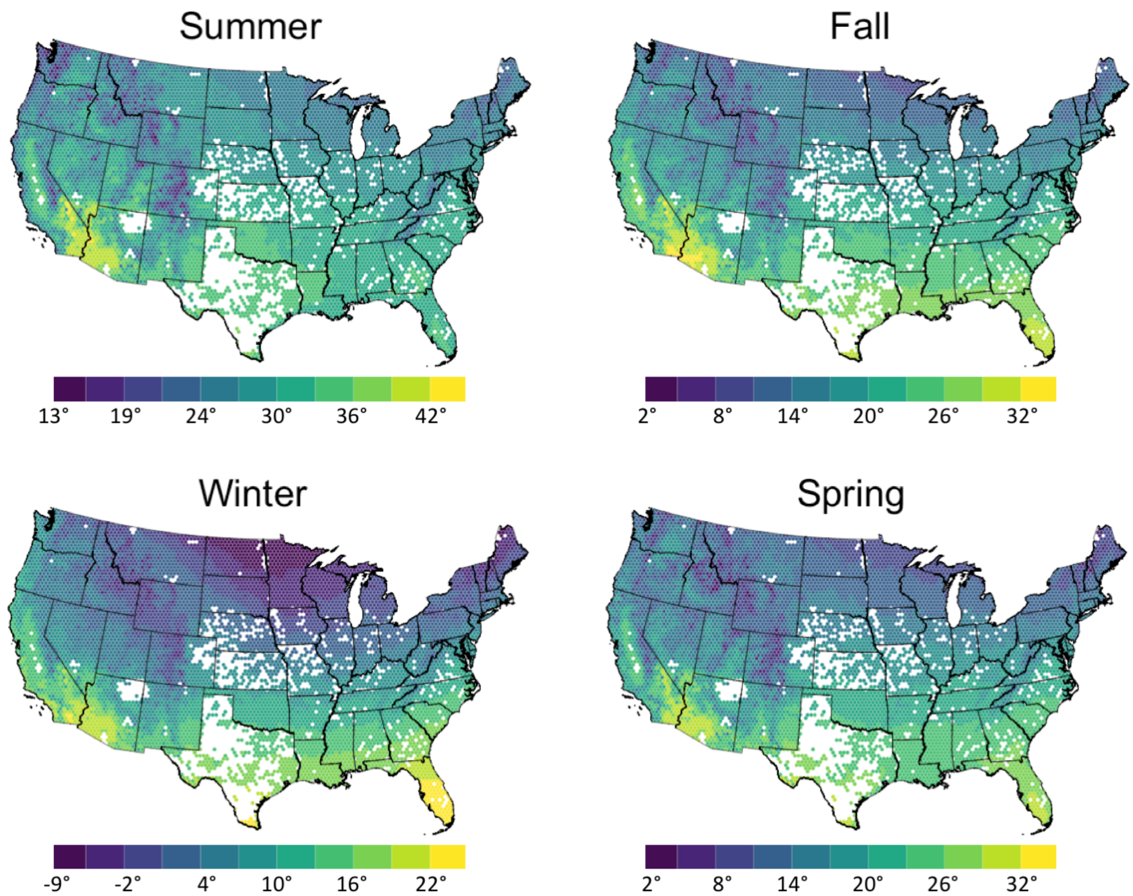

Figure C.4. Spatial distribution of average seasonal maximum temperature (ºC; 1990 – 2019), based on where people currently visit. Average seasonal maximum temperature was averaged over all Flickr PUD in each 30-km cell; if a cell had 0 PUD, the average seasonal maximum temperature was found at the centroid. White cells represent areas that have no state or federal public lands included in this study.

CURRICULUM VITAE

Emily J. Wilkins

Utah State University
Department of Environment and Society
emily.wilkins@aggiemail.usu.edu

EDUCATION

Utah State University, Logan, Utah **August 2020**
PhD in Environment and Society, GPA: 3.9
Specialization: Climate Adaptation Science
Dissertation: Using social media to assess the impact of weather and climate on visitation to outdoor recreation settings

University of Maine, Orono, Maine **May 2016**
M.S. in Forest Resources, GPA: 4.0
Thesis: Tourism in Maine: Visitation and Economic Impacts of Weather

Drake University, Des Moines, Iowa **May 2014**
B.S. in Environmental Science and Environmental Policy, GPA: 3.7
Minor: Biology

RESEARCH INTERESTS

- Outdoor recreation
- Public lands management
- Climate change adaptation
- Human dimensions of natural resources

METHODS INTERESTS

- Geospatial analysis
- Survey methodology
- Social media data analytics
- Statistical learning
- Big data analytics

PEER-REVIEWED PUBLICATIONS

2020 **Wilkins, E. J.**, Wood, S. A., & Smith, J. W. Uses and limitations of social media data to inform visitor use management in parks and protected areas: A systematic review. *Environmental Management.* doi: 10.1007/s00267-020-01373-7

2020 Dagan, D. T., Sharp, R. L., Brownlee, M. T. J., & **Wilkins, E. J**. Social media data in remote and low-use wilderness areas: Applications and limitations. *International Journal of Wilderness, 26*(1).

2020 **Wilkins, E. J.**, Smith, J. W., & Keane, R. Social media communication preferences of national park visitors. *Applied Environmental Education & Communication, 19*(1), 4-18. doi: 10.1080/1533015X.2018.1486247

2019 **Wilkins, E. J.,** Cole, N., Miller, H. M., Schuster, R. M., Dayer, A. A., Duberstein, J. N., Fulton, D. C., Harshaw, H. W., Raedeke, A. H., Rural-urban differences in hunting and birdwatching intent. *Human Dimensions of Wildlife, 24*(6), 530-547. doi: 10.1080/10871209.2019.1661046

2019 Smith, J. W., **Wilkins, E. J**., Leung, Y.-F. Attendance trends threaten future operations of America's state park systems. *Proceedings of the National Academy of Sciences, 116*(26), 12775-12780. doi: 10.1073/pnas.1902314116

2019 Clark, M., **Wilkins, E. J.,** Dagan, D. T., Powell, R., Sharp, R. L., & Hillis, V. Bringing forecasting into the future: Using Google to model national park visitation. *Journal of Environmental Management, 243,* 88-94*.* doi: 10.1016/j.jenvman.2019.05.006

2019 **Wilkins, E. J.**, Sinclair, W., Miller, H., & Schuster, R. Does proximity to wetlands matter? A landscape-level analysis of the influence of local wetlands on the public's concern for ecosystem services and conservation involvement. *Wetlands, 39*(6), 1271 - 1280. doi: 10.1007/s13157-018-1076-8

2018 **Wilkins, E. J.**, Miller, H., Tilak, E., & Schuster, R. Communicating information on nature-related topics: Preferred information channels and trust in sources. *PLOS ONE*, *13*(12), e0209013. doi: 10.1371/journal.pone.0209013

2018 Smith, J. W., **Wilkins, E. J.**, Gayle, R., & Lamborn, C. Climate and visitation to Utah's 'Mighty 5' national parks. *Tourism Geographies*, *20*(2), 250-272. doi: 10.1080/14616688.2018.1437767

2018 **Wilkins, E.,** De Urioste-Stone, S., Weiskittel, A., & Gabe, T. Effects of weather conditions on tourism spending: Implications for future trends under climate change. *Journal of Travel Research*. 57(8), 1042 – 1053. doi: 10.1177/0047287517728591

2018 **Wilkins, E. J.,** & De Urioste-Stone, S. Place attachment, recreational activities, and travel intent under changing climate conditions. *Journal of Sustainable Tourism*, *26*(5), 798-811. doi: 10.1080/09669582.2017.1417416

2018 **Wilkins, E. J.,** De Urioste-Stone, S., Weiskittel, A., & Gabe, T. Weather sensitivity and climate change perceptions of tourists: A segmentation analysis. *Tourism Geographies, 20*(2), 273-289. doi: 10.1080/14616688.2017.1399437

2016 De Urioste-Stone, S., Le, L., Scaccia, M., & **Wilkins, E.** Nature-based tourism and climate change risk: Visitors' perceptions in Mount Desert Island, Maine. *Journal of Outdoor Recreation and Tourism, 13*, 57-65. doi: 10.1016/j.jort.2016.01.003

TECHNICAL REPORTS AND OTHER PUBLICATIONS

2020 Johnson, D., Brune, S., Dagan, D. T., Meier, E., **Wilkins, E. J.,** & Zhang, H. A holistic strategy for carbon reduction programs in parks and protected areas: Leveraging three "fixes." *Parks Stewardship Forum, 36*(3). doi: 10.5070/P536349858

2020 Smith, J. W., **Wilkins, E. J.,** & Miller, A. B. Bears Ears and outdoor recreation in San Juan County: The impact of Bears Ears National Monument on outdoor recreation and industries related to outdoor recreation in San Juan County, Utah. Research report for Utah Outdoor Partners.

2018 Dorning, M. A., van Berkel, D., Beck, S. M., **Wilkins, E. J.**, Zhang, H., Smith, J. W. Aesthetic characteristics of the front range: An analysis of viewsheds provided by Boulder OSMP lands. Research report to Boulder Open Space and Mountain Parks. Available from: https://digitalcommons.usu.edu/extension_curall/1975/

2018 **Wilkins, E. J.**, Zhang, H., van Berkel, D., Dorning, M. A., Beck, S. M., & Smith, J. W. Landscape values and aesthetic preferences across the front range. Research report to Boulder Open Space and Mountain Parks. Available from: https://digitalcommons.usu.edu/extension_curall/1898/

2018 Dagan, D., Wheeler, I., Beck, L, Benedetti, A., Blacketer, M., Clark, M., McHugh, K., Noss, C., Sizek, J., **Wilkins, E.,** Powell, R., & Sharp, R. 2018 Park break report: Developing a visitation forecasting tool and management recommendations for the Mojave Desert Region NPS Units. Research report to the National Park Service.

2018 **Wilkins, E. J.** & Miller, H. M. Public views of wetlands and waterfowl conservation in the United States – Results of a survey to inform the 2018 revision of the North American Waterfowl Management Plan. U.S. Geological Survey Open-File Report 2017–1148. https://doi.org/10.3133/ofr20171148.

2016 **Wilkins, E** & Reagan, S. Implementing and maintaining recreational fees on federal lands: Lessons from Sam D. Hamilton Noxubee National Wildlife Refuge. Report for the U.S. Fish and Wildlife Service.

2016 **Wilkins, E**. Morgan, A., & De Urioste-Stone, S. Visitor characteristics, travel behavior, and perceptions of tourism. Research report to Maine Bureau of Parks and Lands.

2016 **Wilkins, E**. Morgan, A., & De Urioste-Stone, S. Visitor characteristics, travel behavior, and perceptions of tourism. Research report to the Maine Office of Tourism and Maine visitor's centers.

2016 **Wilkins, E**. Morgan, A., & De Urioste-Stone, S. Visitor perceptions of climate change and weather on outdoor recreation and travel behavior. Research report to Acadia National Park.

2015 **Wilkins, E**. Morgan, A., & De Urioste-Stone, S. Visitor perceptions of tourism and climate change and its effects on spending. Research report to Baxter State Park.

TEACHING EXPERIENCE

2019 **Utah State University.** ENVS 4500: Wildland Recreation Behavior. Co-instructor of record. *Evaluations available upon request.*

PROFESSIONAL EXPERIENCE

2017-2020 **Utah State University,** Presidential Doctoral Research Fellow
Logan, Utah

2016-2018 **U.S. Geological Survey (Contractor),** Social Scientist
Fort Collins, Colorado

2016 **U.S. Fish and Wildlife Service**, Directorate Resource Assistant Fellow
Brooksville, Mississippi

2014-2016. **University of Maine,** Research Assistant
Orono, Maine

2014 **Rocky Mountain Conservancy**, Conservation Corps Assistant Leader
Estes Park, Colorado

2012- **Drake University,** Service-Learning Ambassador

2014 Des Moines, Iowa

2013 **Rocky Mountain Conservancy**, Conservation Corps Crew Member
Estes Park, Colorado

AWARDS AND FELLOWSHIPS

2019 **Doctoral Researcher of the Year**, S.J. & Jessie E. Quinney College of Natural Resources, Utah State University
2017-20 **Presidential Doctoral Research Fellowship,** Utah State University
2018-19 **Climate Adaptation Science Fellowship,** National Science Foundation
2018 **Park Break Fellowship,** George Wright Society & The National Park Service
2018 **Student Scholarship**, Society of Outdoor Recreation Professionals
2017 **Emerging Leader Award,** American Trails
2016 **International Travel Award**, University of Maine School of Forest Resources
2015 **Best Student Poster**, International Congress on Coastal and Marine Tourism
2015 **Student Scholarship**, Society of Outdoor Recreation Professionals
2014 **Houston Award,** University of Maine School of Forest Resources
2014 **Drake Service Award,** Drake University
2014 **Environmental Policy Scholar and Citizen**, Drake University
2013 **Top Sophomore of the Year**, Drake University
2013 **Safety Award.** U.S. Forest Service, Sulfur-Ranger District.
2011-14 **Presidential Scholarship**, Drake University

FUNDING ACQUIRED

PROFESSIONAL DEVELOPMENT

2018 Sustainable Climate Risk Management (SCRiM); $2,500 to attend summer school at Penn State
2018 The George Wright Society and NPS; $2,000 to participate in Park Break in Death Valley and Joshua Tree National Parks
2018 Society of Outdoor Recreation Professionals; $300 to attend the National Outdoor Recreation Conference in Vermont

2018	National Science Foundation; $34,000 + tuition as a Climate Adaptation Science National Research Traineeship Fellow
2017	American Trails; $1,500 to attend the International Trails Symposium in Ohio
2016	UMaine Graduate Student Government; $850 to present at MMV in Serbia
2016	UMaine School of Forest Resources; $1,500 to present at Tourism Naturally in Italy
2016	UMaine Graduate Student Government; $638 to present at ISSRM in Michigan
2015	UMaine Graduate Student Government; $425 to present at the International Congress on Coastal and Marine Tourism in Hawaii
2015	Society of Outdoor Recreation Professionals; $800 to attend the National Outdoor Recreation Conference in Maryland

NON-PROFITS

2014	**Wilkins, E.,** Berry, R., Pries, J & Courard-Hauri, D. (2014-2016). Amount: $67,595. *Environmental Learning Center Ecological Restoration.* State Farm Youth Advisory Board Grant.
2014	**Wilkins, E.** & McReynolds, M. Amount: $1,500. (2014). *Sprout: The Des Moines Urban Youth Learning Garden.* Midwest Gardening Grant.
2014	**Wilkins, E.** & Johansen, M. (2014). Amount: $3,100. *Sprout: The Des Moines Urban Youth Learning Garden.* Drake University Student Senate.
2014	**Wilkins, E.** Amount: $500. (2014). *Sprout: The Des Moines Urban Youth Learning Garden.* Sodexo Grant.

CONFERENCE PRESENTATIONS

2020	**Wilkins, E. J.**, & Smith, J.W., Temperature, extreme heat events, and the spatial behavior of national park visitors. American Association of Geographers Annual Meeting, April. Virtual due to COVID-19. (Oral presentation).
2019	**Wilkins, E. J.**, Smith, J.W., Wood, S., & Milnor, A. Using social media to estimate park visitation. National Outdoor Recreation Conference. May. Rapid City, SD (Oral presentation).
2019	**Wilkins, E. J.**, Saley, T., Akbar, H. & Hager, R. Climate change at Utah ski resorts: Impacts, perceptions, and adaptation strategies. Utah

State University Research Symposium. April. Logan, UT (Oral presentation).

2018 **Wilkins, E. J.** & Smith, J. W. Using Twitter to understand the impact of weather on skiers and snowboarders across Utah. International Symposium on Society and Resource Management. June. Salt Lake City, UT (Oral presentation).

2018 Schuster, R., **Wilkins, E.,** Miller, H., Fulton, D., Harshaw, H.W., Duberstein, J., Dayer, A., & Raedeke, A. Communicating information on nature-related topics: Information channels and trust in sources preferred by the American public. International Symposium on Society and Resource Management. June. Salt Lake City, UT (Oral presentation).

2018 Dayer, A., **Wilkins, E.,** Miller, H., Schuster, R., Duberstein, J., Fulton, D., Harshaw, H.W., & Raedeke, A. Wetland conservation behaviors of hunters, wildlife viewers, anglers, and non-wildlife recreationists. International Symposium on Society and Resource Management. June. Salt Lake City, UT (Oral presentation).

2018 Dagan, D., **Wilkins, E**., Blacketer, M., Beck, L., Benedetti, A., Clark, M., Wheeler, I., McHugh, K., Noss, C., Sizek, J., Sharp, R., & Powell, R. Using Google Trends data to forecast visitation & proactively manage visitors at three NPS units: Park Break 2018 final products. International Symposium on Society and Resource Management. June. Salt Lake City, UT (Poster presentation).

2018 **Wilkins, E.** & Smith, J. W. Using social media data to understand the impact of weather on skiing and snowboarding in Utah. National Outdoor Recreation Conference. April. Burlington, VT (Oral presentation).

2017 **Wilkins, E.** & Miller, H. Human dimensions of waterfowl conservation: Results from the general public survey. Future of Waterfowl Management 2. September. Shepherdstown, WV (Oral presentation).

2017 **Wilkins, E.** & Miller, H. Effects of residence on hunting and birdwatching participation. Pathways: Human Dimensions of Wildlife. September. Estes Park, CO. (Oral presentation).

2017 Miller, H. & **Wilkins, E.** Wetlands and waterfowl views among the general public. Pathways: Human Dimensions of Wildlife. September. Estes Park, CO. (Oral presentation).

2017 **Wilkins, E.** & De Urioste-Stone, S. Willingness to take action on climate change: A cluster analysis of Maine, USA, tourists. International Symposium for Society and Resource Management. June. Umeå, Sweden (Oral presentation).

2017 **Wilkins, E.** et al. Twenty-something visions: The future of trails. International Trails Symposium. May. Dayton, OH. (Oral presentation).

2016 De Urioste-Stone, S., Le, L., **Wilkins, E.**, & Scaccia, M. Tourists' perceptions about climate change: A segmentation analysis of visitors to Maine. Society of American Foresters National Convention. November. Madison, WI. (Oral presentation).

2016 **Wilkins, E.,** De Urioste-Stone, S., Weiskittel, A., & Gabe, T. The impact of climate change on tourism: A segmentation analysis of tourist groups to Maine, USA. Tourism Naturally. October. Alghero, Italy. (Oral presentation).

2016 **Wilkins, E.,** & De Urioste-Stone, S. Recreational activities, place attachment, and intended future visitation under climate change conditions. Monitoring and Management of Visitors in Recreational and Protected Areas. September. Novi Sad, Serbia. (Oral presentation).

2016 **Wilkins, E.,** De Urioste-Stone, S., Weiskittel, A., & Gabe, T. The effects of changing weather on Maine's nature-based tourism industry. International Symposium on Society and Resource Management. June. Houghton, MI. (Oral presentation).

2016 **Wilkins, E.,** De Urioste-Stone, S., Weiskittel, A., & Gabe, T. The impact of weather and climate change on nature-based tourism: A segmentation analysis of tourist groups to Maine, USA. International Symposium on Society and Resource Management. June. Houghton, MI. (Poster).

2016 **Wilkins, E.** & De Urioste-Stone, S. Economic impacts of weather and climate change on tourism in Maine. University of Maine Research Symposium, April. Bangor, ME. (Oral presentation).

2016 **Wilkins, E.** & De Urioste-Stone, S. The impact of weather and climate change on tourism: A segmentation analysis of tourist groups to Maine. University of Maine Research Symposium, April. Bangor, ME. (Pecha Kucha presentation).

2015 **Wilkins, E.,** De Urioste-Stone, S., Weiskittel, A., & Gabe, T. The effects of changing climate and weather on Mount Desert Island's nature-based tourism industry. International Congress on Coastal and Marine Tourism. November. Kailua-Kona, HI. (Poster; Best Student Poster award).

2015 De Urioste-Stone, S., Le, L., **Wilkins, E**. & Scaccia, M. Climate change risk: Perceptions of visitors to Acadia National Park, Maine. International Congress on Coastal and Marine Tourism. November. Kailua-Kona, HI. (Oral presentation).

2015	De Urioste-Stone, S., **Wilkins, E.** & Scaccia, M. Climate change vulnerability and risk perceptions: Views from visitors to Acadia National Park. SAF National Convention. November. Baton Rouge, LA. (Oral presentation).
2015	**Wilkins, E.,** De Urioste-Stone, S., Weiskittel, A., Horne, L., Cooper, A., Scaccia, M. & Gabe, T. The effects of changing weather: Impacts on tourism-related spending on Mount Desert Island, Maine. Acadia Science Symposium. October. Winter Harbor, ME. (Poster).
2015	Scaccia, M., De Urioste-Stone, S. & **Wilkins, E.** The future of destination selection in a changing seasonal climate: Implications for visitation to Acadia National Park and Mount Desert Island, Maine. Acadia Science Symposium. October. Winter Harbor, ME. (Poster).
2015	**Wilkins, E.,** De Urioste-Stone, S., Weiskittel, A., & Gabe, T. The effects of changing weather on nature-based tourism: Visitation and economic impacts on Mount Desert Island, Maine. International Symposium on Society and Resource Management. June. Charleston, SC. (Poster).
2015	Scaccia, M., De Urioste-Stone, S. & **Wilkins, E.** The future of destination selection in a changing seasonal climate: implications for visitation to Acadia National Park and Mount Desert Island, Maine. National Outdoor Recreation Conference. April. Annapolis, MD. (Poster).
2014	**Wilkins, E.,** & Courard-Hauri, D. Agent-based modeling of the role of selective expert opinion in the dissemination of scientific ideas under uncertainty. Drake University Conference on Undergraduate Research in the Sciences. April. Des Moines, IA. (Poster).

COMPUTER SKILLS

Statistical software: R; SPSS; SAS (preference for R)
Spatial analysis software: R, QGIS, ArcGIS (preference for R)
Other data analysis software: Python for social media data streaming and NetLogo for agent-based modeling
Survey programs: SurveyGizmo; SurveyMonkey; Qualtrics
Other programs: Microsoft Word, Excel, and Powerpoint

WORKSHOPS ATTENDED

2018	**Sustainable Climate Risk Management Summer School.** State College, PA. July.
2017	**Software Carpentry.** Logan, UT. September.
2017	**Future of Waterfowl 2 Workshop**. Shepherdstown, WV. September.
2017	**Data Carpentry**. Logan, UT. September.

PROFESSIONAL SOCIETIES

Present	Society of Outdoor Recreation Professionals (SORP)
Present	American Association for the Advancement of Science (AAAS)
Present	The George Wright Society (GWS)
Present	American Association of Geographers (AAG)
Present	International Association for Society and Natural Resources (IASNR) Founder of the University of Maine's student chapter

SERVICE

Present	**Peer reviewer for:** *Advances in Meteorology* *Applied Environmental Education & Communication* *Annals of Tourism Research* *Atmosphere* *Human Dimensions of Wildlife* *Journal of Leisure Research* *Journal of Parks and Recreation Administration* *Journal of Sustainable Tourism* *Sage Open* *Tourism Geographies* *Wetlands* *Wildlife Society Bulletin*
2017-20	Reviewer for undergraduate research grants at Utah State
2019	Utah State University undergraduate student mentor
2018-19	Judge for undergraduate poster presentations at Utah State University
2018-19	Letters to a Pre-Scientist - scientist pen pal to a middle school student
2018	Student representative on Utah State University faculty search committee

2018	Reviewer for the Society of Outdoor Recreation Professionals (SORP) individual service awards
2015-16	Reviewer for graduate travel grants at University of Maine
2015-16	Treasurer of the Forestry Club at University of Maine
2015-16	Founder and Vice President of the Student Organization for Society and Natural Resources at University of Maine