AN ABSTRACT OF THE THESIS OF

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Title: Wading through Space and Time: Leveraging Geospatial Methods to Better Understand Recreation Behavior, Experience, and Impacts within a Densely Used Lake Destination.

Abstract approved:

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Ashley D'Antonio

In the last decade, many U.S. parks and protected areas (PPA) experienced record breaking visitation levels. Managers of these PPAs face the challenging task of providing a range of quality and accessible outdoor experiences without compromising the integrity and health of surrounding ecosystems. Understanding how PPA visitors move and interact with one another throughout a landscape serves as a foundational tenant toward informing adaptive and effective visitor use management frameworks. Spatial data representing recreationist movement patterns provides critical information on visitor use and flow, and can highlight areas that may be prone to resource degradation, crowding, or user conflicts. More powerfully, spatial data can be leveraged with social, managerial, and biophysical information to provide an inter-disciplinary understanding of the drivers and consequences of recreation use.

Multi-use destinations in PPAs that offer a mix of land and water-based activities represent some of the most sought-after recreation sites, particularly in the

summer months. These sites often contain lakes, rivers, and coastal areas with open shorelines and adjacent trail networks. Despite the prevalence of these mixed-use sites, the majority of integrative spatial research efforts have occurred solely within terrestrial recreation settings. Very few spatial studies have examined mixed-use aquatic recreation locations. This type of research is greatly needed as water-users often produce distinctive impacts to ecological resources and develop unique outdoor experiences and outcomes. Furthermore, to date, there has been no empirical investigation of an emergent, yet highly popular, water-based activity: stand-up paddleboarding.

This Master's thesis employed cross-disciplinary, mixed-method approaches to explore the spatial behaviors, experiences, and impacts of land and water-based recreationists at a popular PPA lake destination in Grand Teton National Park, WY, USA. During the summer of 2018, a random sample of visitors were asked to participate in a pre- and post-survey and carry a handheld GPS unit throughout their day-visit to the recreation site. To obtain biophysical data, this research utilized a high resolution GPS device to identify and map recreation-related resource impacts within study site. In total, 577 GPS tracks were collected with corresponding survey and biophysical information.

The first empirical chapter explored density dependent factors influencing visitor spatiotemporal behavior between two primary user groups: land-based recreationists and water-based recreationists. Results showed that despite having the ability to disperse, behavior became more concentrated at medium and high-use times. Additionally, findings indicated that water-users and land-users utilized the system differently at varying use levels. This chapter serves as one of the first to examine and compare spatiotemporal response to visitor densities across multiple activity types. Furthermore, findings provide insights into the implications of crowding, displacement, and dispersal within a densely populated PPA recreation site.

The second empirical chapter compared the spatial behaviors of non-motorized, paddlesport users: stand-up paddleboarders, canoers, and kayakers. Statistical classification procedures built a typology of water-users based on observed spatiotemporal behaviors. Findings identified distinctions in behavior across paddling activity types, highlighting implications for resource protection and visitor flow. Integrating spatial data with survey and biophysical information revealed numerous drivers and impacts of spatial movement. For example, the motivation to escape and experience natural beauty corresponded to traveling further distances, while higher group sizes and prolonged shoreline exposure aligned with concentrated movement near parking lots and facilities. These findings contribute novel information on paddlesport spatial behavior and experience in PPAs, especially given the emergence of stand-up paddleboarding. Ultimately, the methods and findings from both research chapters responds to a growing call in PPA research to incorporate spatial approaches to research designs, particularly within aquatic recreation settings. Results contribute to theoretical and practical knowledge of recreationist movement and experience across a more representative range of PPAs.

Wading through Space and Time: Leveraging Geospatial Methods to Better Understand Recreation Behavior, Experience, and Impacts within a Densely Used Lake Destination

by
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I understand that my thesis will become part of the permanent collection of Oregon State University libraries. My signature below authorizes release of my thesis to any reader upon request.

Jenna T. Baker, Author

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In recognition of the collaborative nature of this research, I chose to use plural first person pronouns (e.g., 'We' rather than 'I') throughout this thesis.

CONTRIBUTION OF AUTHORS

For this thesis, Dr. Ashley D'Antonio provided feedback and support throughout all phases of the study including conceptual design, methodology, analysis, and revisions of all four chapters. Dr. Chris Monz was essential in the conceptual design and methodology, analysis, and revision process for both empirical chapters. Dr. Ian Munanura was instrumental in providing support during the revision stage of both empirical chapters.

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CHAPTER ONE: INTRODUCTION

Every year, millions of Americans seek opportunities to enjoy the outdoors and experience natural settings (Outdoor Foundation, 2019). A recent report from the U.S. Bureau of Economic Analysis found that the outdoor recreation economy grew by 3.9 percent in 2017, representing a notably faster growth rate than the overall U.S. economy (Bureau of Economic Analysis, 2019). A significant portion of outdoor recreation occurs within federally managed parks and protected areas (PPA) (Interagency Visitor Use Management Council, 2016). Paralleling the recreation economy, PPAs also experienced rising trends in visitation. For instance, National Park Service units had 327 million visits in 2019, representing a 16 percent increase in visitation since 2010 (National Park Service, 2019); similarly, the U.S. Forest Service set a new record with over 150 million annual recreation visits between 2014 and 2018 (U.S. Forest Service, 2016).

Engagement in outdoor recreation can provide numerous health and community benefits: positive outdoor experiences promote mental and physical well-being, and deepen a sense of environmental ethos and connectivity to the natural world (White et al., 2014; Winter, Selin, Cerveny, & Bricker, 2020). However, without proper management, unbridled recreation use can lead to undesirable levels of resource damage, human-wildlife conflicts, and strained visitor experiences (Selin, Cerveny, Blahna, & Miller, 2020). These tensions can be especially pronounced in PPA settings which not only provide space for recreation use, but also serve as locations for maintaining biodiversity and cultural resources (Winter et al., 2020).

Managing for outdoor recreation in PPAs can be an inherently difficult task. Managers must strive to maximize the benefits of outdoor use while simultaneously maintaining desired conservation goals (Interagency Visitor Use Management Council, 2017). To effectively achieve these often conflicting objectives, managers require an empirical understanding of many interrelated aspects of visitor experience and behavior, including: (1) knowledge of how visitors move and interact with a landscape; (2) identification of the economic, social, and ecological factors that drive behavior; and (3) anticipation of the real and potential social and environmental impacts rendered from recreation use (Graefe, Cahill, & Bacon, 2011; Hammitt, Cole, & Monz, 2015; R. E. Manning, 2011). These features of recreation occur at multiple geographic and temporal scales and can be mediated by a host of factors, such as the unique attributes of a landscape, visitor motivations and preferences, and available managerial resources.

Given the complexity of visitor use management (VUM), managers and researchers increasingly conceptualize PPAs as complex social-ecological systems (SES) (Morse, 2020). Prior to this conceptualization, experts often addressed recreation use from either a social or ecological perspective. However, these siloed approaches contained notable disadvantages, including the risk of oversimplifying understandings of recreation use, and creating unnecessary competition for funding and managerial resources (Mccool & Kline, 2020). By contrast, a SES framework emphasizes the recursive, interrelated nature of recreation in PPAs. In essence, this approach positions that outdoor recreation affects, and is affected by, an interconnected web of social, resource, and managerial conditions. By embracing a holistic view of recreation in PPA, and considering inputs across all disciplines, managers can more effectively identify, monitor, and achieve sustainable recreation outcomes (Morse, 2020).

Incorporating spatial approaches into mixed-method study designs

Spatiotemporal data that measures recreationist movement and behavior can serve as a powerful platform for combining multidisciplinary data types and incorporating many tenets of SES frameworks (J. Beeco, 2013). At its core, outdoor recreation is rooted in space and time; visitors arrive to destinations at specific times and make decisions about where to go and how long to recreate. Numerous studies indicate that these spatial decisions contain vital implications for resource protection and experiential outcomes (Riungu, Peterson, Beeco, Brown, et al., 2019). For example, visitor spatial behavior influences, and is influenced by, the amount, level, and extent of resource impacts and wildlife disturbance (D'Antonio et al., 2010; Hammitt et al., 2015). And concentrations or proliferations of use in a recreation system can affect experiential outcomes such as perceptions of crowding and conflict (R. E. Manning, 2011).

Advancements in geospatial tracking technology have greatly contributed to our understanding of the factors that influence and result from visitor spatial patterns (J. Beeco & Hallo, 2014; Riungu, Peterson, Beeco, Brown, et al., 2019). For example, researchers can use GPS-enabled devices to track and record visitor movement patterns. This method procures detailed and accurate information of recreationist behavior, including distance traveled, velocity, and time spent within a recreation area (J. Beeco & Brown, 2013; D'Antonio et al., 2010). In aggregate, GPS point data can also produce maps of total visitor distributions across a landscape, thereby revealing sensitive or congested locations that may warrant increased management attention (Riungu, Peterson, Beeco, Brown, et al., 2019). Perhaps most powerfully, spatial data can be leveraged with relevant social, managerial, and ecological variables. Integrating multiple data types in this way allows the field of recreation science to transition from descriptions of behavior to more robust and holistic explanations of behavior, experience, and impacts (J. Beeco & Brown, 2013; Riungu, Peterson, Beeco, Brown, et al., 2019). This transition promotes adaptive and targeted management strategies that more effectively achieve and maintain desired conditions for a recreation site.

In response to the growing call for spatially integrated study designs, recent research efforts have advanced understandings of VUM in PPAs. For instance, several studies successfully paired GPS-based tracking data with visitor motivations, activity types, skill levels, group characteristics, and site conditions (J. A. Beeco et al., 2013; Kidd et al., 2018; Korpilo, Virtanen, Saukkonen, & Lehvävirta, 2018; Pouwels, van Eupen, Walvoort, & Jochem, 2020). From these combined data sets, researchers produced typologies of recreation behavior and experience (J. A. Beeco et al., 2013; Kidd et al., 2018) and generated predictive models of visitor use and experience across the landscape (Pouwels et al., 2020). These findings informed and updated management frameworks, while also challenged and complicated many long standing assumptions about recreation behavior in PPA. For example, the connections between visitor motivations and spatial behavior produced varied results across recreation systems, highlighting opportunities to refine survey items and incorporate additional variables (J. A. Beeco et al., 2013; Korpilo et al., 2018). Similarly, the influence of visitor density on spatial behavior revealed inconsistencies across study sites, suggesting that use levels may not always predict levels of dispersion or concentration (D’Antonio & Monz, 2016; Irizarry, 2014). These mixed and inconclusive findings underscore the complexity of recreation behavior and decision making in PPA, reaffirming the need to continue to incorporate interdisciplinary, spatially explicit study designs into VUM research (Blahna et al., 2019).

The canon of existing spatial research also highlights notable gaps and areas for much needed future work. For one, the vast majority of existing empirical studies were executed in terrestrial recreation settings and investigated land-based activity types such as hiking, equestrian use, biking, and scenic driving. However, many heavily used recreation sites, particularly in the summer months, occur near water features such as lakes, rivers, and coastal areas (Kakoyannis & Stankey, 2002). As a result, many highly sought-after recreational activities in the United States include fishing, paddlesports, and swimming (Outdoor Foundation, 2019). A recent review of spatial research in PPA remarked on the unfortunate lack of spatial analysis in aquatic PPA systems (Riungu, Peterson, Beeco, Brown, et al., 2019). The review emphasized the necessity of this type of research given the unique managerial implications and ecological consequences of water-based use (Riungu, Peterson, Beeco, Brown, et al., 2019). For example, many water-users can access areas unreachable by trail or roadway, engendering potential complications for resource protection and human-wildlife interactions.

Thesis Purpose and Organization

This Master’s thesis contains two standalone articles that employed mixed-method approaches to explore the behaviors, experiences, and impacts of water and land-based recreationists within a popular lake destination in Grand Teton National Park, Wyoming, USA. Both chapters aimed to fill notable research gaps and develop novel approaches for combining spatiotemporal behavior metrics (distance, time, and velocity) with corresponding social and ecological data. This integration seeks to enhance understandings of the drivers and consequences of visitor use and behavior in multi-use, water-based PPA destinations.

First empirical chapter: Examining responses to visitor densities within a multi-use recreation site

Many water-based activities occur in conjunction with terrestrial use; such as a trail surrounding a lake or running adjacent to a river. When settings contain a variety of user groups, all of whom engage with the landscape in unique ways, managers must consider a broader and more complicated matrix of visitor demands, motivations, and socio-ecological outcomes (e.g., crowding, conflict and proliferations of resource impacts) (R. Manning et al., 2011; Wolf, Brown, & Wohlfart, 2018). Understanding how these user groups respond to changes in visitor use levels is central to sustainable VUM strategies (Interagency Visitor Use Management Council (IVUMC), 2019). To date, minimal research efforts have investigated relationships between visitor use and behavior among both terrestrial and aquatic activity types, particularly within dispersive, multi-use settings (Garber-Yonts, 2005; Riungu, Peterson, Beeco, Brown, et al., 2019).

One reason for this noticeable lack of research may be due to the inherently difficult task of accurately capturing use in open settings. For example, managers often rely on infrared trail counters to measure the amount of people in a recreation system at a given time (Pettebone, Newman, & Lawson, 2010). However, when visitors have opportunities to travel beyond the predictable confines of a trail network, such as along an open shoreline or waterway, the dispersive nature of their behavior can make it challenging to accurately capture use (Garber-Yonts, 2005). Developing study designs that overcome these challenges and assesses behavior across a range of water- and land-based activity types will provide new and foundational information for future VUM frameworks.

The first empirical chapter of this thesis aimed to address these complications and gaps in the literature. This chapter paired spatial and visitor use data to examine the relationships between spatiotemporal behaviors and changing visitor density levels across multiple activity types: land-based recreationists and water-based recreationists. The analytical methods developed for this research chapter sought to demonstrate novel approaches for obtaining hourly estimates of visitor use and density in a disperse use settings. Moreover, this chapter provided one of the comparative investigations of behavior response to visitor use levels in a water-based setting, and between two distinctive user types. Findings broaden theoretical and practical understandings of visitor use and behavior, and reveal multiple managerial, experiential, and resource implications for popular, dispersed use recreation sites.

Second empirical chapter: Exploring non-motorized, aquatic recreation use in a PPA lake setting

Successful visitor use management in PPAs requires a multi-disciplinary understanding of visitor use levels, patterns, trends, and impacts (Graefe et al., 2011; Selin et al., 2020). Incorporating spatial approaches into research designs can expand these understandings and provide avenues for integrating social, environmental, and managerial data. However, to date, the majority of mixed-method spatial research has been conducted in terrestrial recreation settings (Riungu, Peterson, Beeco, & Brown, 2019). The review of literature for this thesis did not locate any study that explored the behaviors, experiences, and impacts of water-based recreation in PPAs. Filling this research gap would provide much needed information on water-based use, experience, and behavior within a multi-use PPA. Furthermore, new and popular water-based activity types, such as stand-up paddleboarding, have yet to be empirically examined within any PPA research efforts. Visitors engaging in these emergent yet highly prevalent activity types may move throughout the system in distinctive ways compared to other recreational activities, thereby triggering a host of new implications for experiential outcomes and resource conservation (Blahna et al., 2019; Garber-Yonts, 2005).

Due to the emergence of novel activity types combined with the paucity of water-based spatial research in PPAs, the second empirical chapter focused on the features of aquatic recreation. More specifically, this chapter sought to explore the behaviors of non-motorized, paddlesport users: stand-up paddleboarders, canoers, and kayakers. This work employed statistical classification procedures to build a typology of water-users based on observed spatiotemporal behaviors. Additionally, this chapter combined the spatial data with survey and biophysical information to investigate potential drivers and impacts of behavior and decision making across paddling activity types. Findings aim to contribute novel information on paddlesport spatial behavior and experience in PPAs, especially given the introduction of an emergent, yet highly sought-after activity type in outdoor recreation: stand-up paddleboarding.

Exploratory research approach

Given the exploratory nature of this work, this thesis did not use theory or have specific hypotheses for research questions. Rather, to generate appropriate and beneficial research objectives, this research relied on the identification of notable gaps and/or inconclusive findings in the literature. Research designs and analytical workflows were informed from prior studies and adapted to adequately answer each research question. Additionally, while this work was motivated by the emerging conceptualization of recreation as a complex SES, it did not formally utilize the theory to ground the methods and analysis. However, the integrated nature of the methods, analyses, and findings hopefully can contribute helpful stepping stones towards moving recreation research in that direction.

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CHAPTER TWO: VISITOR USE AND SPATIAL BEHAVIOR

Examining the relationship between visitor use and spatial behavior across multiple activity types within a densely populated, disperse use lake setting

Introduction

In recent years, U.S. parks and protected areas (PPA) experienced unprecedented levels of visitation (Outdoor Foundation, 2019). These trends can trigger managerial concerns about the effects of high visitation levels on the integrity and health of surrounding ecosystems and visitor experiences (Winter, Selin, Cerveny, & Bricker, 2020). Central to adequately addressing these concerns is understanding the spatial distribution and movement patterns of recreationists (J. Beeco & Brown, 2013; D'Antonio et al., 2010). Obtaining knowledge of where, when, and how people recreate across a landscape enables managers to better anticipate the level and degree of undesirable physical resource disturbance and identify situations where crowding or conflict may occur (Hammitt, Cole, & Monz, 2015; R. E. Manning, 2011). In this sense, research examining the relationships between visitor use levels and spatiotemporal behavior provides foundational information for effective and pro-active PPA management (Interagency Visitor Use Management Council (IVUMC), 2019).

Despite the managerial relevance of understanding these relationships, very few studies have employed in situ spatial methods to measure visitor response to changing recreation densities. Moreover, the research that does exist has only examined terrestrial recreation use (e.g., hiking) (D'Antonio & Monz, 2016; Irizarry, 2014). Yet many densely populated recreation sites contain water-features such as lakes, rivers, or coastal beaches (Kakoyannis & Stankey, 2002). As a result, some of the most highly sought-after recreational activities in the United States include fishing, paddlesports, and swimming (Outdoor Foundation, 2019). Outdoor recreation research indicates that these varying activity types exhibit distinctive spatial movement patterns, and thus, tend to engender unique impacts to vegetation and social experiences (J. Beeco, Hallo, English, & Giumetti, 2013; Hammitt et al., 2015; Korpilo, Virtanen, Saukkonen, & Lehvävirta, 2018). Given the unique social and ecological implications rendered by differing activities, additional research needs to examine the interplay between visitor use and behavior amongst a more representative range of recreational activities and landscapes (Blahna et al., 2019; Riungu, Peterson, Beeco, & Brown, 2019).

In conjunction with obtaining information on the spatial distribution of visitors, managers also require information on how many people recreate in a system. This knowledge is required at multiple geographic and temporal scales (e.g., landscape versus site level; hourly versus yearly, etc.) and informs policy, decision making, and evaluation of outcomes (Garber-Yonts, 2005; R. E. Manning, 2011). At the site level, automated technology, such as trail counters and vehicle tube counters, can provide highly detailed estimates of use (Pettebone, Newman, & Lawson, 2010). However, landscape features often dictate the accuracy and reliability of these estimates. For instance, trail counters tend to only provide accurate estimates of visitor use in terrestrial recreation settings promoting constrained and predictable behavior patterns, such as trails leading to a mountain summit or those existing within dense vegetation (Pettebone, Newman, Beaton, Stack, & Gibson, 2008). Many recreation sites offer opportunities for much more dispersive behaviors, including lakeshores, meadows, and deserts (Fisher et al., 2018). Trail counters in these settings, where visitors have a greater array of movement options, may not obtain visitor use estimates accurately. Human observations, video recording, and manual counting could serve as alternative approaches for measuring use in these locations; however, these efforts typically require extensive time and resources to facilitate and process. This constraint is unfortunate as disperse-use recreation sites often present high potential for visitor dispersion and unanticipated resource impacts (Cole, 2019).

This empirical chapter addresses these research gaps and opportunities by integrating spatial and visitor use data to understand behavioral responses to changes in visitor density levels at a heavily used, lake-based recreation site in a U.S. National Park. The methods employed demonstrate novel approaches for measuring visitor density within an area where isolated trail counter data may not provide accurate information relating to visitor use. Furthermore, this research presents one of the first comparative investigations of behavior response to visitor use levels in a water-based setting, and between two distinctive user types: land-based recreationists and water-based recreationists. Findings from this effort aim to broaden theoretical and practical understandings of visitor use and behavior, highlighting multiple managerial, experiential, and resource implications for popular, dispersed use recreation sites.

Conceptual Foundation

Successful visitor use management (VUM) in PPAs requires a clear understanding of visitor use levels, patterns, trends, and impacts (Graefe, Cahill, & Bacon, 2011; Selin, Cerveny, Blahna, & Miller, 2020). A central, albeit controversial, tool within many VUM frameworks is the determination of visitor capacity within a given recreation area. Visitor capacity is a number, and VUM frameworks define this number as the maximum amount and type of visitor use in an area that achieves and maintains desired resource and experiential conditions (Interagency Visitor Use Management Council (IVUMC), 2019). Critics of visitor capacity point to the subjectivity and variability in determining maximum thresholds for visitor use levels. In other words, determining a single number for visitor use would not adequately capture the dynamic and interactive nature of the recreation system (R. E. Manning, 2007; Mccool & Dawson, 2012). Proponents of visitor capacity claim that the tool enables managers to more effectively and pro-actively identify, monitor, and achieve desired conditions within a recreation site (Graefe et al., 2011; Interagency Visitor Use Management Council (IVUMC), 2019).

Ultimately, the debate around visitor capacity underscores the complicated nature inherent in our understandings of visitor use levels and corresponding social and environmental impacts. Research examining these relationships tend to operate from either a social perspective (e.g. crowding and conflict) or ecological perspective (e.g. resource disturbance) (Mccool & Kline, 2020). A common assumption underlying both approaches claims that fluctuating visitor use levels can alter visitor spatial behavior, thereby catalyzing impacts to social and ecological experiences. However, very few studies have tested these assumptions using explicit spatial approaches (D'Antonio & Monz, 2016). The remaining sections below review existing research on our understanding of the social, ecological, and spatial dimensions of fluctuating visitor use levels in PPA settings, as well as briefly summarizes approaches for measuring visitor use and behavior. These reviews set the framework and justifications for the current study.

Social Dimension of Visitor Use

The social dimension of high visitor use levels describes the notion that at some point in time, the density of visitors within a recreation area will become too high and decrease the quality of recreational experiences; stated simply, visitors will begin to feel crowded (Shelby & Vaske, 1989). Given that managers of PPAs strive to provide quality outdoor opportunities, extensive research has investigated components of crowding in PPAs (R. Manning, Valliere, Minteer, Wang, & Jacobi, 2000). Findings from these efforts suggest that most visitors report high levels of satisfaction with their experiences despite instances of feeling crowded. These positive outcomes occur because visitors employ a range of coping strategies in response to the undesirable situation (Gramann & Burdge, 1984; Hammitt & Patterson, 1991; R. E. Manning & Valliere, 2001).

Outdoor recreation literature divides visitor coping responses into three categories: product shift, cognitive rationalization, and behavior change. Product shift and rationalization represent cognitive forms of coping, which usually transpires as visitors altering their thinking about recreation sites or experiences to reconcile their expectations with reality (Cole & Hall, 2012; Schuster & Hammitt, 2000). Behavioral responses to crowding manifest as spatial and/or temporal displacements. Displacement occurs when visitors alter their behavior to avoid undesirable stimuli (R. E. Manning & Valliere, 2001). Many research efforts have devoted considerable attention to the drivers and consequences of displacement in PPAs, mainly because this type of coping response can engender the most explicit socio-ecological consequences (Cole, 2019). For example, visitors may displace to less-frequented regions within a recreation site, increasing potential for first time contact with sensitive vegetation or wildlife.

Given the many consequences of behavioral displacement, researchers have examined the phenomenon across a wide range of uses and settings: lake users in highly used wilderness areas (Cole & Hall, 2012), boaters at a reservoir (Hall & Shelby, 2000), and walkers and bikers within an urban-proximate park (Arnberger & Haider, 2007). In many cases, findings showed that visitors altered their behavior due to crowded conditions (Cole & Hall, 2012; Hall & Shelby, 2000). However, findings from these efforts also noted several variable and inconsistent relationships between the number of visitors in an area and decisions to displace, remarking on other mediating factors such as preexisting resource conditions, activity types, and available facilities (Arnberger & Haider, 2007; Cole & Hall, 2012). These findings further emphasize that the relationship between the amount of visitor use and behavioral response to use is not straightforward. Additionally, the methods for measuring behavioral response in the aforementioned studies relied on surveys, observations, and human-recall. Adding on-the-ground spatial approaches to these examinations would greatly contribute to our understanding of these complex relationships (Irizarry, 2014).

Ecological Dimension of Visitor Use

In conjunction with the social consequences of high visitor use levels, managers and researchers must also understand how rising use levels correspond to ecological resource conditions. Research has found that the relationship between visitor use and resource disturbance typically follows a curvilinear trajectory, with first time contact causing the most severe levels of impact (Hammitt et al., 2015). In general, the spatial distribution of resource impacts mimics visitor movement trends, with concentrated impacts occurring near highly used locations such as trail heads, facilities, and scenic view-sites; thus, surrounding areas with infrequent use remain largely undisturbed (Monz, Cole, Leung, & Marion, 2010). Managers anticipate these patterns and build appropriate infrastructure to support visitor demands while minimizing the proliferation of impacts into less-frequented locations. However, when visitors disperse away from these highly used areas in unpredictable ways (e.g. to avoid crowds), then their behaviors can trigger unmanaged disturbances to the surrounding vegetation (Hammitt et al., 2015).

Given the negative ecological consequences stemming from unanticipated dispersive behavior, many recreation ecologists have investigated the influence of visitor recreation use on the level, extent, and type of resource impacts (Monz et al., 2010). In general, these efforts show that visitor spatial behavior and activity style can often play a more significant role in determining the severity of impact than changes in the amount of use (D'Antonio, Monz, Newman, Lawson, & Taff, 2013; Hammitt et al., 2015). However, while these previous studies greatly contributed to our understanding of visitor use and the magnitude of anticipated impacts, they did not explicitly examine how the *areal extent* of impact changes in response to increasing visitation (Cole, 2019). Similar to research on displacement, a long-standing assumption in recreation ecology posits that increases in visitor use can engender increases in dispersion. These tendencies are more likely to occur in areas with flat, accessible terrain containing an attractive feature such as water access or scenic views (Cole, 2019). Arguably, with increased dispersion, visitors may expand the areal extent of impacts in ways that may be undesirable for managers.

Given this relevant management implication, additional research is greatly needed to empirically test these assumptions and better understand the relationship between visitor use levels and areal extent of resource impacts.

Spatial Dimension of Visitor Use

The common denominator undergirding both the social and ecological dimensions is that visitor use levels influence spatial behavior; in turn, changes in visitor spatial behavior can induce a cascade of social and ecological consequences. Despite the inherently spatial nature of these relationships, this review of literature uncovered only two studies that examined the interplay between visitor use levels and spatial behaviors using in situ geospatial approaches (D’Antonio & Monz, 2016; Irizarry, 2014). In both efforts, researchers utilized GPS-based tracking methods to measure differences in visitor dispersion at varying use levels. Findings proved to be mixed and inconclusive. For example, one study used Euclidean distance metrics to measure dispersion around aggregated visitor GPS points across a range of PPA settings (D’Antonio & Monz, 2016). Results indicated that in most cases, levels of dispersion did *not* vary as a function of changing use (D’Antonio & Monz, 2016). The other study used clustering algorithms to identify the relationship between use levels and changes in spatial clustering within multiple recreation sites in Yosemite National Park (Irizarry, 2014). By contrast, this research found that during high use times, visitors tended to spread out within the analysis area, particularly in disperse-use settings (Irizarry, 2014).

These results highlight mixed, and somewhat counterintuitive, management implications for visitor use and the extent of spatial behavior, indicating a need for additional explorations.

Furthermore, the methods employed in both studies point to several opportunities for refinement. For example, D'Antonio et al. (2016) utilized trail counter estimations as proxies for determining visitor use levels within each PPA. The counter estimates for each PPA varied by temporal resolution (e.g., some use estimates were collected at hourly intervals while others were binned into full- or multi-day time intervals). Additional site-level research should aim to measure visitor use changes across finer and more consistent temporal scales to represent actual average daily use fluctuations within a recreation site (Irizarry, 2014). Secondly, both studies measured visitor dispersion by aggregating GPS point data. While this approach successfully illustrated the overall spatial extent of visitor behavior, it did not capture some of the more discriminant features of individual behavior response. Examining the effects of visitor use levels on individual spatiotemporal behaviors such as maximum distance traveled, velocity, and time spent would provide a more nuanced understanding of the relationships between visitor use and behavior. Finally, these studies solely examined hiker response to visitor densities. Other activity types may respond to visitor use levels differently. Thus, additional research needs to incorporate a wider range of visitor uses, including aquatic-based recreation, into these investigations.

Measuring Visitor Use and Behavior

Ultimately, to know how people utilize a recreation area, managers must obtain information on the spatiotemporal distributions of visitors (D'Antonio et al., 2010; Walden-Schreiner & Leung, 2013). Many traditional methods for estimating visitor behavior relied on mail-in surveys, on-site questionnaires, and visitor observations (Hallo et al., 2012). While these approaches expanded our theoretical understanding of reported behaviors, they fell short in capturing in situ visitor movement patterns across a range of spatial and temporal scales. Increasingly, researchers have begun to rely on GPS-enabled tracking methods to estimate visitor spatiotemporal behavior in PPAs (J. Beeco & Hallo, 2014; D’Antonio et al., 2010; Riungu et al., 2019)(J. A. Beeco & Hallo, 2014; D’Antonio et al., 2010). GPS-based approaches can procure largely accurate and detailed information on the movement of visitors across a diversity of settings with minimal burden to participants (D’Antonio et al., 2010; Riungu et al., 2019).

The aforementioned literature on crowding, resource disturbance, and spatial behavior stress the importance of obtaining accurate estimations of visitor use in a recreation setting. Advances in visitor use monitoring and tracking technologies have contributed significantly to these research endeavors. For example, in many trail-based recreation areas, automated trail counters serve as an efficient and cost-effective tool for estimating visitor use levels (Pettebone et al., 2010). Researchers and managers mount the counters in discrete locations along a recreation area. The counters contain an infrared beam that records whenever a moving object interrupts the beam. Counter data precision may be limited because most counters do not distinguish between the directionality of movement. Additionally, some counters may experience more errors depending on the physical and climatic attributes of the landscape (e.g., steep slopes, wide trails, heavy snow, etc.). Many counters require manual calibration via human observation to correct for these errors (Pettebone et al., 2010). Unfortunately, many densely used recreation sites contain open shorelines, vistas, and meadows. Counters in this type of terrain may not be able to accurately capture use levels because visitors have options for freer and more dynamic movement patterns. Thus, capturing high resolution estimates of visitor use in these settings can be much more challenging. However, these locations often pose the most significant risk for potential crowding, off-trail use, and undesirable proliferation of resource impacts due to the more diverse array of movement scenarios (Cole, 2019).

Research Objective

To effectively manage for quality visitor experiences and resource protection, managers must understand the relationships between visitor use levels and the associated effects on recreational experiences and biophysical environments (Interagency Visitor Use Management Council (IVUMC), 2019). The canon of existing research contributes to the knowledge of these relationships, yet also reveals noticeable gaps and areas for methodological improvement, including: the need for more spatially integrated approaches, the lack of examinations of multi-use aquatic settings, and the need to overcome challenges of measuring use in dispersive recreation areas. This research aims to address these research gaps by comparing visitor spatial behavior across both terrestrial and aquatic activity types as a function of changing visitor use levels. Moreover, this research provides a method for obtaining site-level visitor use estimates within a densely populated, disperse-use recreation setting. Findings from these efforts will greatly contribute to our theoretical and practical understanding of visitor use and spatial behavior, to better inform effective VUM planning

1. How can visitor use and density levels be captured within a complex, mixed-use recreation system?

2. What relationships exist between the density of visitors in a dispersed use area and the spatiotemporal behaviors of visitors?

3. Do behavioral responses to visitor density levels vary between water-based recreationists and land-based recreationists?

Methods

Study Area

Grand Teton National Park (GRTE), located in Wyoming, U.S.A., spans 485 square miles (National Park Service, 2019a). In 2019, GRTE had nearly 3.4 million recreation visits, representing a 30% increase in visitation from 2010 (National Park Service, 2019b). GRTE contains a mixed-use destination called the String and Leigh Lakes (SLL) recreation area. SLL provides ample summer recreation opportunities for non-motorized, water-based uses, such as canoeing, kayaking, and stand-up paddleboarding, and a wide range of terrestrial activity-types, including hiking, climbing, and picnicking (Figure 1).

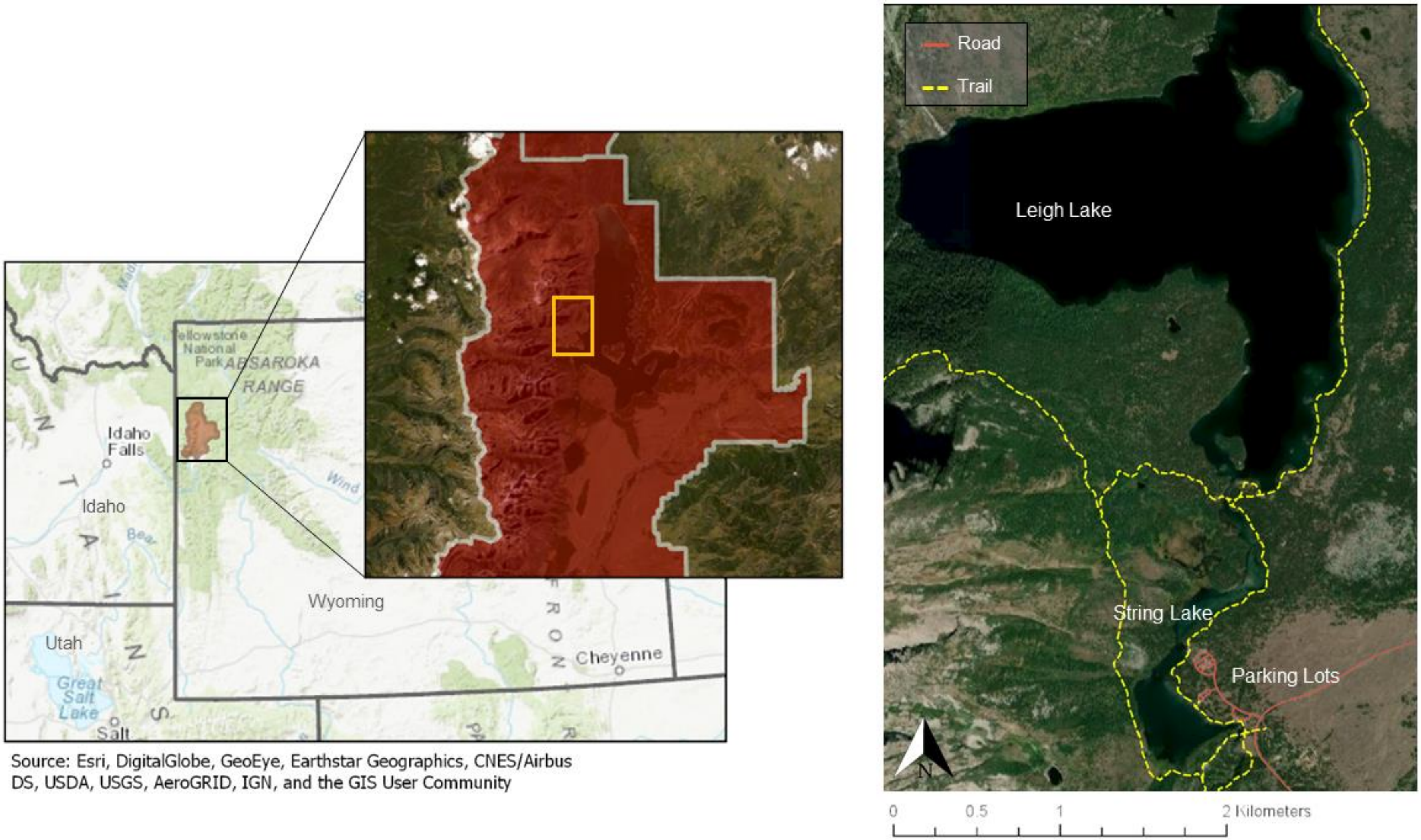


Figure 1. Map of Grand Teton National Park in Wyoming USA (left) and String and Leigh Lakes recreation area (right)

Three parking lots provide access to the southeast shoreline of String Lake. During the summer months, the section of shoreline connecting to these parking lots fills with recreationists seeking water and land-based activities. Leigh Lake lies directly north of String Lake; visitors can access Leigh Lake by portaging their boat or by hiking one mile from the String Lake trailhead. Leigh Lake contains multiple backcountry campsites. In contrast to String Lake, Leigh Lake offers a more remote visitor experience with many western sections of the lake only accessible by watercraft.

In recent years, GRTE management noticed a rise in visitation to SLL (National Park Service, 2017). More specifically, management reported an increasingly congested shoreline along the trail connecting to the three parking lots. A Visitor Use and Experience study at SLL found that this half-mile section of shoreline contained the highest levels of visitor densities within the entire SLL recreation system (D’Antonio et al., 2017). Moreover, this study indicated that 50% of all visitors to SLL did not travel beyond the southeast shoreline. This percentage is remarkable given the large and proliferating extent of the SLL trail system. For example, this section of shoreline only accounts for 2% of the total area of the immediate SLL trail system (see Figure 1 for visual of study system). Furthermore, up to 85% of all visitors to SLL reported feeling crowded while recreating in this location (D’Antonio et al., 2018). Recreation related resource impacts follow similar trends: findings indicate that within the entire extent of the SLL recreation area, 80% of impacts existed along this small swath of shoreline (D’Antonio et al., 2017).

The findings from the technical report paint a picture of a highly used recreation area containing disproportionate amounts of visitor densities within a small geographic footprint. The lake features of the system present an additional layer of complexity to the management of SLL, as water-users can access several shoreline locations not reachable by trail. Therefore, obtaining accurate visitor use estimates within SLL proves difficult. For example, trail counters would not register the many visitors who launched watercraft into String Lake, nor those who remained stationary while picnicking along sections of shoreline. Due to the inherent complexity of this multi-use recreation system, SLL offered an appropriate location to test a method for measuring visitor use and density in a dispersed use recreation area and to continue testing theoretical assumptions about changing visitor use levels and spatiotemporal behavior across a range of activity types.

Sampling Frame

We deemed the southeast shoreline of String Lake as the Analysis Area (AA) (Figure 2). We labeled String and Leigh Lake and the adjacent trail system as the Study System (SS). In essence, we wanted to understand how changing visitor densities within the AA impacted behavior throughout the SS.

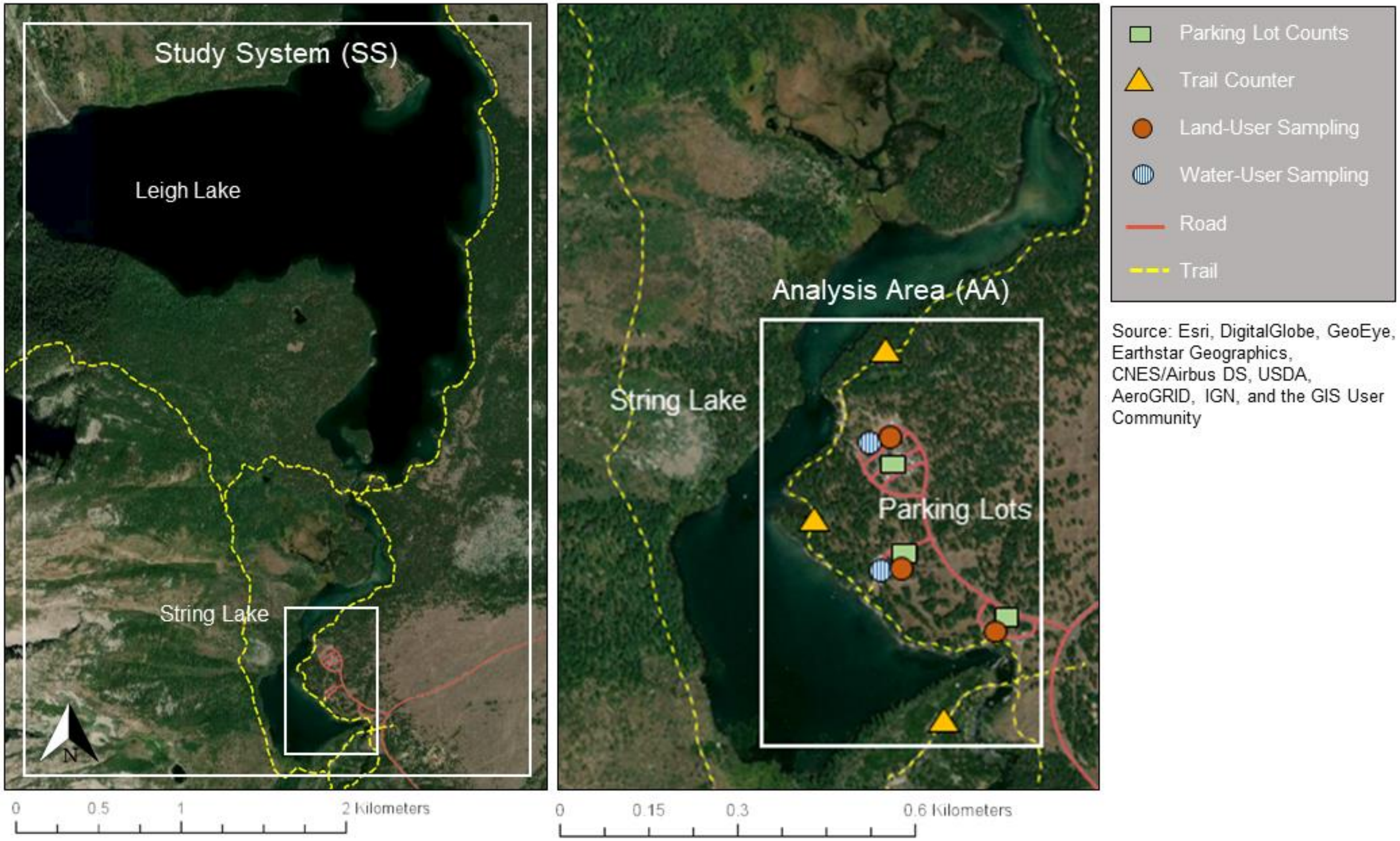


Figure 2. Maps delineating the boundaries of the Study System (left) and Analysis Area (right)

Data Collection

The primary data types used in this study included GPS tracking data, hourly trail counter data, and hourly parking lot data.

GPS Tracking Data

GPS-based data collection occurred across 28 days in the summer of 2018: June 28 through August 12, from 8 am to 5 pm. We randomly stratified sampling days across weekdays and weekends, mornings, and afternoons to ensure an accurate representation of summertime day-use visitation. To intercept visitors, study technicians positioned themselves by the three main parking lots that provide recreational access to the SLL system (Figure 1). Study eligibility guidelines restricted participants to individuals over the age of 18 who participated in day-use activities in the SLL area. Two categories represented visitor use: water-users and land-users. Water-users encompassed individuals whose primary activity included: canoeing, kayaking, and stand-up paddleboarding. Land-users included visitors whose primary activity involved hiking, wildlife viewing, and photography, beach-going, swimming, and picnicking.

This research employed a census sampling method to intercept water-users as they entered the SLL area (Singh & Mangat, 2013). A systematic random sampling approach was employed for land users. These sampling approaches forged representative and comparable sample sizes among the two user types. For example, most water-users recreated in larger groups compared to land-users; therefore, we expected a disproportionate number of land-user GPS tracks. To account for these differences and to build roughly equal sample sizes for subsequent analyses, we used the two different sampling approaches.

We employed D'Antonio et al. (2010) GPS-based tracking protocols to collect spatial and temporal movement data. Before deploying GPS units, technicians asked respondents about their group size and their intended locations of travel. Then, participants received a hand-held, recreation-grade, Garmin eTrex 10 GPS unit. We asked recreationists to carry a GPS unit during their day-trip to the SLL area. For example, water-users secured a water-proof GPS unit to their watercraft to record movement information. While the visitors engaged in various activities, the GPS units collected coordinate and timestamp point data at 15-second intervals. After their recreation visit, participants returned the GPS units to a researcher or a GPS drop-box.

At the end of every field day, technicians saved the tracks from each GPS device as point features for future analysis in ArcGIS Pro (v. 10.3-5, Environmental Systems Research Institute, Redlands, CA, USA). We used high accuracy Trimble GPS units to calibrate the Garmin eTrex units and correct for positional errors (D'Antonio & Monz, 2016; Kidd et al., 2015). Before analysis, we removed outlier GPS points that fell outside of the SLL area, e.g., wayward and removed points that occurred at the GPS drop-box sites. We analyzed all GPS data using R and ArcGIS Pro software.

Visitor Use Data

To estimate hourly visitor trail use, we used data from two TRAFx and one Diamond Traffic trail counters (Diamond Traffic Products, 2016; TRAFx, 2017). Study technicians installed the counters in camouflaged locations along the shoreline trail of String Lake (Figure 2). Technicians calibrated counter accuracy and direction by visually observing and recording visitor numbers and direction of travel (Pettebone et al., 2010). These observations occurred at randomly selected two-hour time intervals between 8 a.m. and 5 p.m. across the study period and totaled 8-10 hours of manual calibrations per counter. The manual counts served as inputs into a regression analysis, which determined a correction factor for the automated trail counts (Pettebone, Newman, & Lawson, 2010). We used the corrected automated trail counts for subsequent analysis.

Technicians also counted the number of vehicles in each parking lot every hour between 8 a.m. and 5 p.m. to measure day-time parking lot use. The parking lot counts for this study included vehicles parked in designated, undesignated, or illegal parking spaces (e.g., parking spots demarcated with red striping or cones), and overflow vehicles parked along the roadside.

Preparing Variables for Analysis

Table 1 represents the variables measured in this study. We discuss the processes for measuring each variable below.

Table 1. Description of variables used in the study.

	Variable	Metric	Data Source
Explanatory/Independent	Visitor Density	Total area of HDL1	All GPS Tracks[1]
		Maximum expected counts in HDL	All GPS Tracks
		Hourly trail counts	Infrared trail counter
		Hourly parking lot counts	Technician recorded counts
	User type	Land	Study participant
		Water	Study participant
Response/Dependent	Spatial Behavioral Response	Maximum distance traveled in SS	GPS track in SS
		Average velocity within the AA	GPS track in AA
		Proportion time stopped within AA	GPS track in AA
		Proportion time in AA	GPS track in SS
		Total recreation time in SS	GPS track in SS

[1] HDL = High Density Locations
[2] All GPS Tracks = the original sample of visitors, i.e. all visitors who arrived at the SLL study area.

Independent Variables

The independent variables in this study were user type and visitor use level within the AA. However, given the dispersive nature of the AA, isolated estimates of visitor use may not have accurately represented visitation. Therefore, we integrated GPS tracking data, trail counter data, and parking lot data to build a composite categorical index that represented the extent, degree, and magnitude of visitor use levels within the AA. To achieve this we extracted the following metrics from each data source: (1) spatial extent of high-density locations (GPS tracks); (2) relative densities of visitors (GPS tracks); (3) trail use estimates (trail counters); (4)

parking lot use estimates (parking lot counts). We summarize the extraction of these metrics below.

(1) Spatial extent of high-density locations

We relied on information from the GPS data to quantify the spatial extent of visitor densities within the AA. To achieve this, we used the original sample of GPS tracks (i.e., all water and land users, including those traveling outside of the SS). Then, we created hourly subsets of the GPS data points. For example, we extracted all GPS data points collected from 9:00 to 9:59a.m., and then those collected between 10:00 a.m. to 10:59 a.m., and so forth. We ended with points collected between 5:00 and 5:59 p.m. This process produced nine point-based shapefiles representing hourly resolution 'snapshots' of visitor behavior across the day. To standardize the data set, we extracted a random subset of 100 tracks from each time bin.

For each shapefile, we conducted a Kernel Density Estimation (KDE) analysis in ArcGIS Pro. The KDE procedure created a smoothed raster surface over each GPS point; the value of each cell on the surface grid was highest at the collection point and then decreased with increasing distance from that point. A pre-defined search radius determined when the cell value eventually reached zero. For the KDE in this analysis, we pre-selected output cell sizes of 10 meters and search radii of 30 meters. The selection of a 30-meter search radius was consistent with previous outdoor recreation KDEs and adequately captured visitor density patterns in our system (Walden-Schreiner & Leung, 2013). Finally, we weighted the GPS points by the reported group size of the person carrying the unit. This form of weighting instructed the KDE procedure on how many times to 'count' each point. Thus, larger group sizes would be considered to have more points, thereby increasing the density estimate for that cell. This decision assumed similar spatial behavior within groups.

The KDE procedure produced raster surfaces for each time bin. We classified the raster cells into three categories: high, medium, and low density. Our goal at this point was to calculate the area of medium and high-density locations to provide an understanding of the spatial spread of high-density visitor use. To achieve this in ArcGIS Pro, we converted the rasters into polygons via the ‘Reclassify’ tool and ‘Raster to Polygon’ tools in the ArcGIS Pro Conversion Toolbox. These tools produced a layer of polygons for each time bin density categorization. We removed the low-density polygon from the final product because the Raster to Polygon tool produced a simplified version of the original raster by smoothing over the more detailed cell edges. Consequently, the low-use polygon layer subsumed most of the analysis area (Figure 3). Since we were primarily interested in the medium- and high-density locations, the decision to remove low-density polygons did not disrupt our analytical workflow. Within this final format, we calculated the total area of each high and medium density polygon across each time bin.

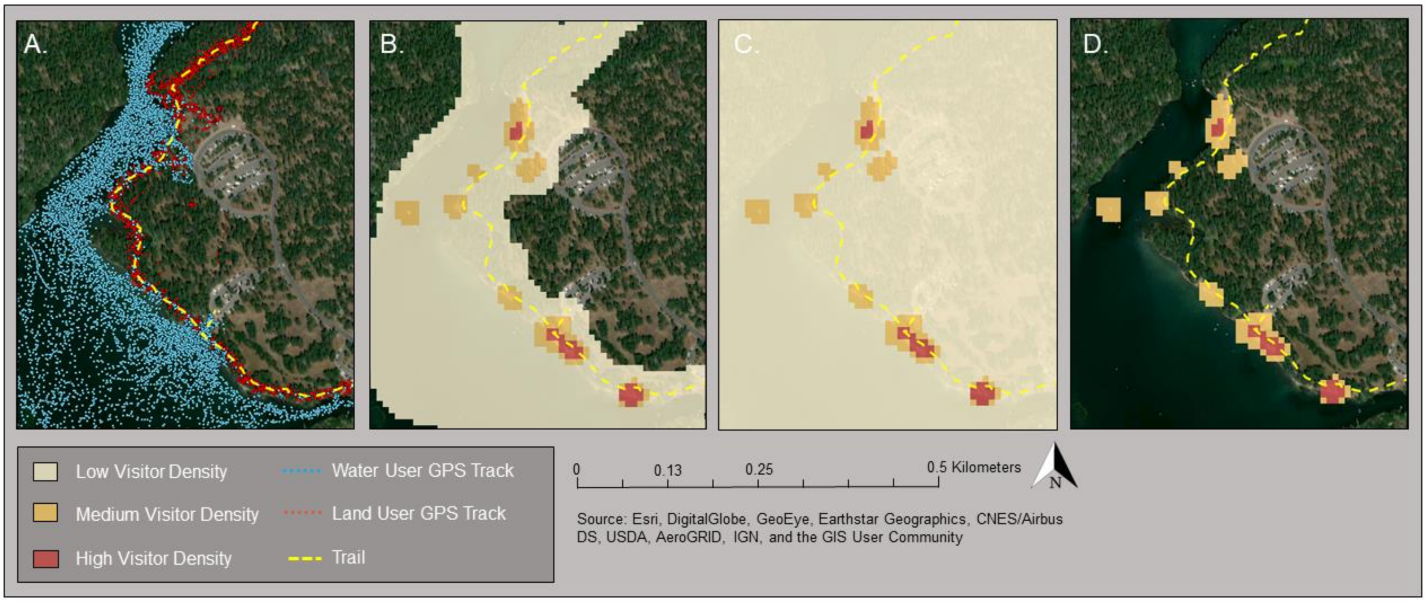


Figure 3. Example of analytical workflow and output to determine spatial extent of visitor densities.

(2) Create relative densities of visitor use in AA

We used the expected counts rendered from the KDE procedure to measure the density of recreation use within the AA. The expected counts indicated how many GPS points were expected within each 10m x 10m cell. Thus, the expected counts rendered from the KDE did not illustrate how many unique visitors moved within each unit of space, but how many movement-points to expect within each unit of space. Given this distinction, we conceptualized the expected counts as relative proxies of visitor density (i.e., on average, areas with higher expected counts contained higher densities of visitation). For this analysis, we extracted the maximum expected count from each KDE raster time bin to determine the maximum concentration or density of visitor use across each hour of the day. We chose to use the maximum expected count to demonstrate changes in average peak densities across each time bin.

(3) Trail use estimates

We used data from automatic trail counters to estimate total visitor use numbers on the trail system. We assumed that trail counts would underestimate actual visitor use levels, particularly given the dispersive nature of the trail and lake system. For instance, many water-users and shoreline visitors may not have traveled past a counter during their visit. To obtain trail counter estimates, we summed the hourly counts from each of the trail counters for every sampling day. This method allowed us to obtain hourly estimates of the total visitor numbers. Then, we aggregated the counts by each hour of the day and calculated the average trail estimate, which produced an array of average hourly estimates of trail use within the analysis area across the sampling season.

(4) Parking lot use estimates

By including parking lot counts, we hoped to add to our understanding of the changes in overall visitor use levels across the day. We employed the same approach from trail counter estimates to determine the average total parking lot counts for each hour of the day across the sampling season.

Creating composite density index

We created a composite index of visitor density in the AA that captured the extent, degree, and magnitude of use. To achieve this, we standardized the units within each use estimation variable to z-scores and summed the scores for each hourly time bin. By using z-scores, the resulting index produced a weighted spectrum of low to high use with low use as anything below zero and high use as anything above zero. Informed by these values, we created categorical variables of the low, medium, and high visitor densities. Finally, we paired this visitor density category to correspond to the start time of each response variable GPS track (i.e., all GPS tracks within the SS).

Dependent Variables

The dependent variables in this study were the spatiotemporal behaviors of visitors. From the GPS tracks, we calculated five spatiotemporal metrics (STM): (1) Maximum distance traveled from the starting point, (2) average velocity within the AA, (3) proportion time stopped within the AA, (4) proportion time spent in the AA, and (5) total time spent in the SS. All STM were generated using R-studio and Python software. To determine stopping time, we plotted histograms of the velocities of all recreationists in the sample. Natural breaks in the histograms identified the threshold for stopped versus moving velocities. These thresholds identified stopped points as anything less than 0.2 meters per second, and any velocity above that threshold as a moving point.

A preliminary analysis of results revealed that 80% of participating visitors to SLL traveled to their intended locations (D'Antonio et al., 2018). Informed by these findings, the sample of GPS tracks used for our response variables included all visitors who intended to travel within the pre-defined SS. We excluded visitors with intentions to travel to the outer reaches of the SS, such as Paintbrush Canyon and Cascade Canyon because: (1) these recreationists intended to visit the peripheral regions of the system; thus, their behaviors may not have been influenced by visitor density at the lakeshore and could skew the results of those who remained within the SLL area; and (2) examining String and Leigh Lake recreationists allowed us to standardize the geographic extent of movement between water and land-based visitors.

Data Analysis

Using R-software, we visually examined the data to understand overall distributions of each visitor behavior metric. We removed outliers within our response variables, which we identified visually via box plots and histograms, and quantitatively as responses with z-scores higher than |3| (Kannan, Manoj, & Arumugam, 2015).

Two-way multivariate analysis of variance

We conducted a two-way, Type III (for unbalanced sample sizes) multivariate analysis of variance (MANOVA) using the 'car' package in R (Fox & Weisberg, 2019). The MANOVA identified differences among the five mean behavioral responses (maximum distance traveled in SS, average velocity in AA, proportion time stopped in AA, proportion time in AA, total time recreating in SS) depending on user type and visitor density levels.

Before running the MANOVA, we noticed that the dataset violated the homogeneity of covariance matrix assumption (Box's M: $F = 84.1$, $p < .0001$). Despite this violation, we continued to proceed with the test because MANOVAs often stand against violations of homogeneity of covariance when group sample sizes exceed 30 (Allen & Bennett, 2008). However, to further account for this violation, we used the Wilks lambda test-statistic, which offers the most robust results in situations with unbalanced group samples and responses that exhibit heterogeneous variance (Ateş, Kaymaz, Kale, & Tekindal, 2019).

Two-way univariate analysis of variance

We followed the two-way MANOVA with four two-way univariate ANOVAs to investigate whether the five spatiotemporal behavior responses varied across user types and density levels. Before running the two-way ANOVA, we executed model diagnostics with QQ-Plots in R to identify violations of normality and equal variance. Maximum distances traveled and proportion time stopped contained skewed, right-tailed distributions, which we corrected via log10 transformations.

Additionally, we used the Levene's F-test to test for homogeneity of variance within each spatiotemporal behavior response. The results from Levene's F-test indicated that all five spatiotemporal responses violated equal variance assumptions. Upon this finding, we examined the standard deviations. We found that none of the largest standard deviations from each response variable exceeded four times the size of their smallest standard deviation (Howell, 1992). Therefore, a univariate ANOVA could offer a robust approach. However, in consideration of the heightened risk of Type I error violations (i.e., falsely rejecting the null hypothesis), we pre-established a more rigorous alpha level of .01 as our criterion for statistical significance (Sakoda, Cohen, & Beall, 1954). We conducted post-hoc analyses of all significant relationships using the more conservative Bonferroni's pairwise comparison method (Song E., Lin P., Ward P., & Fine P., 2013).

Results

Summary statistics

We collected 577 visitor movement trajectory GPS tracks. Within this sample, 281 tracks corresponded to land users (85% response rate), and 296 tracks corresponded to water users (83% response rate) (Figure 4). Table 2 represents a breakdown of the tracks within each visitor density class and their corresponding response rates.

Table 2. Sample size and response rate for GPS tracks at each visitor density level.

User Type	Density Index	Unique Tracks (N)	Response Rate (%)
Land	Low Density	46	90%
	Medium Density	103	89%
	High Density	132	80%
	Total	281	85%
Water	Low Density	60	87%
	Medium Density	94	83%
	High Density	142	80%
	Total	296	85%
All Users	Grand Total	577	83%

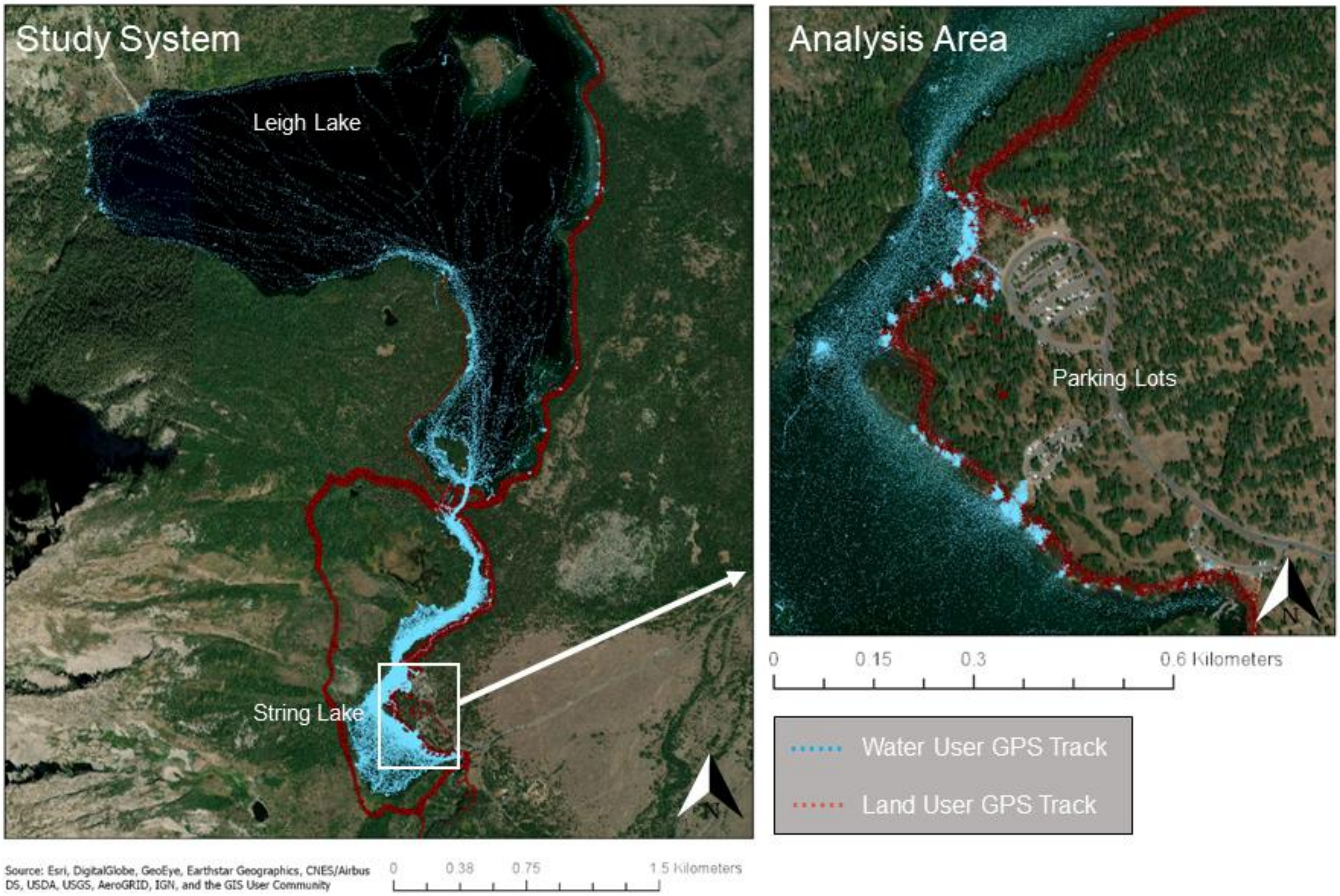
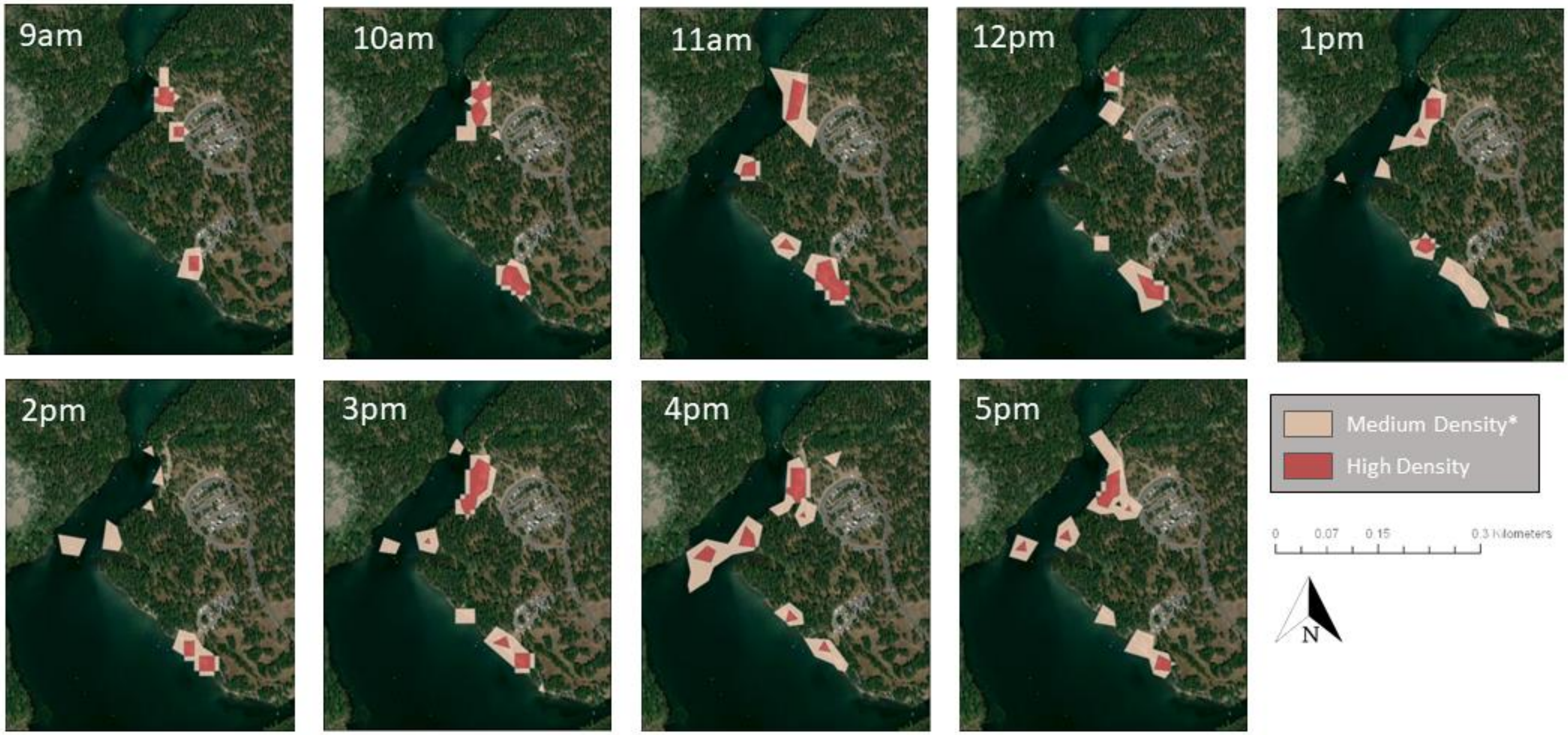


Figure 4. Map representing total GPS tracks collected for this study.

Figure 5 displays a spatial time-series of the medium and high visitor density polygons within the AA. The figure reveals concentrated use, represented as smaller polygons, between 11a.m. and 2 p.m., with more diffuse spread before 11a.m. and after 2p.m. Table 3 shows the values and z-scores for each variable. This table reveals a noticeable dip in the total area of high-density locations at 11a.m. and again at 2p.m.; however, the expected counts follow opposite directions. These contrasting trends suggest that visitor use may be more geographically concentrated at high-density periods. In other words, more people are recreating within a small geographic space, particularly at high use times. Interestingly, we found that the areas with high-density locations did not follow similar parabolic distributions as expected counts, parking lot counts, and trail counts. Essentially, the areal extent of high density locations did not diminish with decreasing use levels, but in some cases, followed opposite trends.



Source: Esri, DigitalGlobe, GeoEye, Earthstar Geographics, CNES/Airbus DS, USDA, AeroGRID, IGN, and the GIS User Community

Figure 5. Time series representing the spatial extent of medium and high density locations. *Low density polygons were removed from map due to the wide spatial extent of low-density use.

Table 3. Summary statistics representing average visitor use and visitor density estimates and corresponding z-scores between 9 a.m. and 5 p.m.

Time	Combined Area of High and Medium Density Locations (m^2)	Maximum Expected Point Count	Average Hourly Trail Count	Average Hourly Parking Lot Count	Composite Density Index (*Sum of Z-Scores*)	Visitor Density Status
9 a.m.	7,470	180	311	95	-4.67	Low
	(-1.31)	(-1.40)	(-0.13)	(-1.83)		
10 a.m.	12,062	457	389	141	-1.22	Low
	(0.01)	(-0.81)	(0.59)	(-1.01)		
11 a.m.	8,179	759	422	190	-0.49	Medium
	(-1.11)	(-0.16)	(0.90)	(-0.12)		
12 p.m.	15,445	674	405	224	1.87	High
	(0.98)	(-0.34)	(0.74)	(0.49)		
1 p.m.	14,994	852	422	256	2.86	High
	(0.85)	(0.05)	(0.89)	(1.07)		
2 p.m.	9,537	1725	375	254	2.71	High
	(-0.72)	(1.93)	(0.47)	(1.04)		
3 p.m.	9,384	1381	293	242	0.94	Medium
	(-0.76)	(1.18)	(-0.30)	(0.82)		
4 p.m.	16,441	785	189	207	0.10	Medium
	(1.26)	(-0.10)	(-1.26)	(0.20)		
5 p.m.	14,878	666	121	160	-2.09	Low
	(0.81)	(-0.36)	(-1.89)	(-0.66)		

Two-way multivariate analysis of variance (MANOVA)

The MANOVA test identified differences among the mean responses for each spatiotemporal variable as a function of visitor density levels and user type. The two-factor MANOVA produced a statistically significant effect for both independent variables (visitor density and user type): visitor density contained Wilks lambda = .95, F = 2.76, p <.01 with a 'small' overall effect size of .04; user type resulted in Wilks lambda = .21, F = 456.36, p = <.0001 with a 'large' overall effect size of .79 (Cohen, 2013). A significant interaction effect was also obtained between user type and visitor density among at least one or more spatiotemporal responses (Wilks lambda = .96, F= 2.42, p <.01). However, the interaction had a very 'small' effect size of .04 (Cohen, 2013).

Two-way univariate analysis of variance (ANOVA)

Visitor density levels may contribute to the spatiotemporal behavior patterns of outdoor recreationists, but that effect may differ depending on user type. Therefore, next, we conducted four univariate two-way ANOVAs to identify differences in the spatiotemporal behaviors of recreationists who started their trips at different visitor density levels and who engaged in either land-based or water-based use.

All four spatiotemporal responses contained statistically significant differences in mean responses depending on visitor density levels and user type (Table 5). For the maximum distance travelled response, both user type and visitor density levels had statistically significant effects; however, the effect size in both cases was 'small' (user type: F = 7.89, p <.001, η^2 = .03; visitor density level: F = 8.17, p <.01, n^2= .03). Similarly, average velocity revealed significant results for both user type ($F = 9.61$, $p < .01$, $n^2 = .03$) and visitor density levels ($F = 8.83$, $p <.001$, $\eta^2 = .03$), yet these results also yielded ‘small’ overall effect sizes. Proportion time stopped in AA revealed statistically significant differences in mean responses for both visitor density levels and user type with user type notably exhibiting a ‘large’ effect size ($F = 621.87$, $p <.0001$, $\eta^2 = .72$) (Cohen, 2013). Proportion time in the AA contained statistically significant differences in mean responses for visitor density levels ($F = 7.83$, $p < .0001$, $\eta^2 = .02$). Meanwhile, total time recreating only contained significant results for user types ($F = 40.04$, $p <.0001$, $\eta^2 = .18$). Using a critical value threshold of .01, the interaction effects between visitor density level and user type were not significant among any of the response variables.

Table 4. Output of two-way univariate ANOVA testing relationship between visitor density levels and activity type on spatial behavior[1]

	Independent Variables								
	Visitor Density Level			User type			Visitor Density Level × User type		
Response Variables	F-value	p-value	Effect Size η 2	F-value	p-value	Effect Size η 2	F-value	p-value	Effect Size η 2
Maximum Distance Traveled (m)	8.17	<.0001*	.03	7.87	<.01*	.03	2.05	.13	.01
Average Velocity in AA (mps)	8.83	<.001*	.03	9.61	<.01*	.03	2.73	.07	.1
Proportion Time Stopped in AA	7.09	<.001*	.002	621.87	<.0001*	.72	3.48	.03	.004
Proportion Time Spent in AA	5.67	<.001*	.02	1.18	.29	-	2.49	.08	-
Total Time Recreating (Hours)	.54	.58	.004	40.04	<.0001*	.178	3.36	.04	.01

[1] To minimize the risk of Type I error violation due to unequal variances, critical p-value threshold is <.01, denoted as an * (Sakoda et al., 1954).

Posthoc tests

We conducted pairwise comparisons with Bonferroni posthoc tests. Posthoc tests showed that land-user recreationists demonstrated the most distinctions in travel patterns as a result of changing density levels. For instance, land-user recreationists who arrived at low visitor density times travelled significantly further (M = 1,038 meters) than those who arrived at medium- and high-density times (M = 663 meters and M = 706 meters, respectively; Figure 6 and Table 5). Moreover, land users arriving at low-density times travelled nearly 40% faster than those who arrived during medium- and high-density times (M = .7 meters per second). Similarly, low-density land users spent only 10% of their time stopped along the shoreline, compared to 14% among medium and high-density land users. Despite differences in speed and distance travelled, land users spent similar amounts of time in the study system across all density levels. In contrast to land users, water user behavior did not significantly vary across the three density levels. However, significant differences did emerge between water-user and land-user behaviour. For instance, compared to land-users, water-users travelled significantly further distances, particularly during medium- and high-density levels. Additionally, water users spent significantly more time recreating in the system compared to land users, averaging nearly three hours in the system. Furthermore, water-users spent over 50% of this time within the AA and 'stopped' along the shoreline. These differences are significantly different from land-users who spent between 10% and 14% of their time stopped. However, land-users arriving at medium and high density times spent similar amounts of time within the AA as water-users (over 50%).

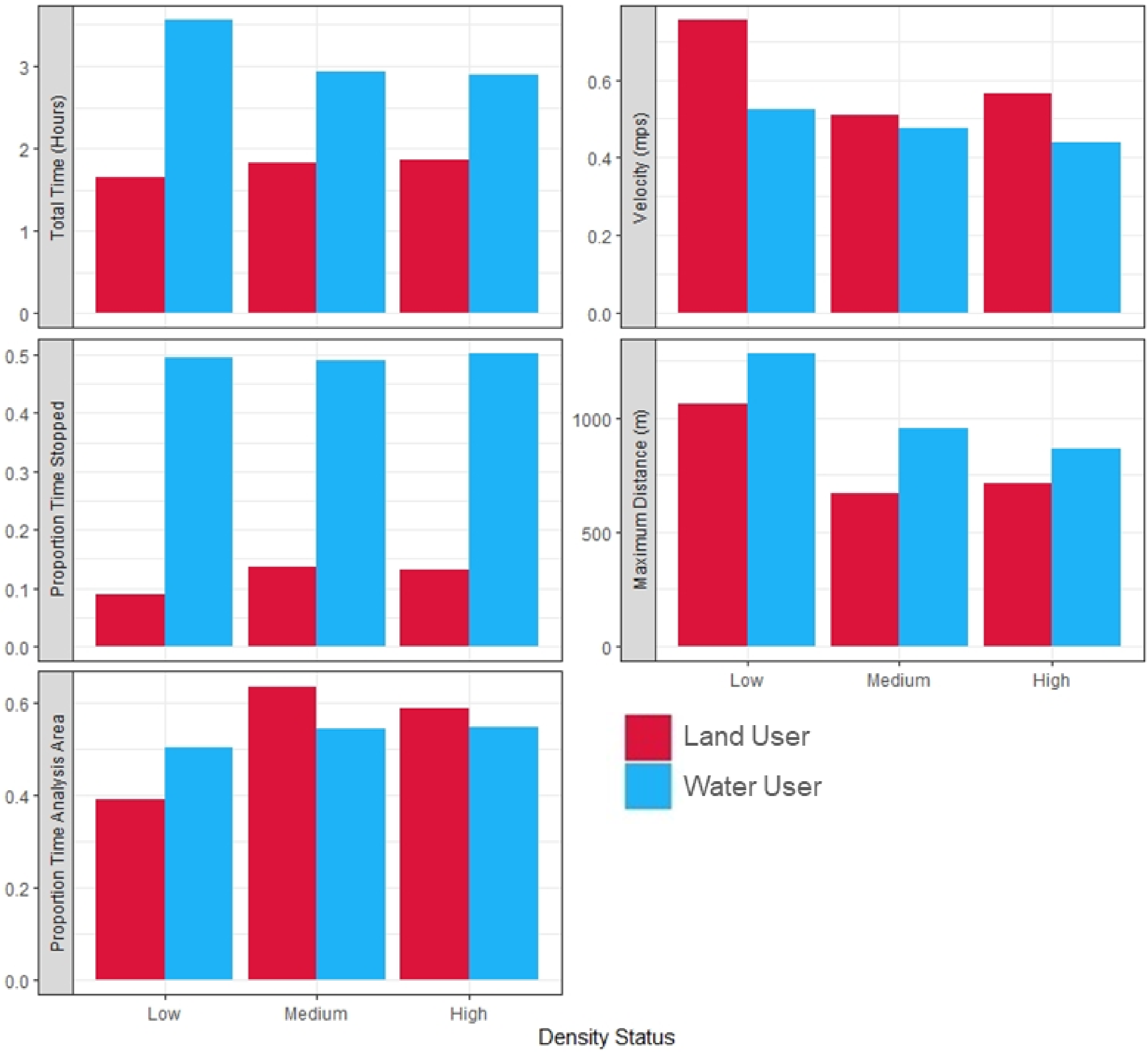


Figure 6. Bar plots representing average values for each response variable among land and water users at varying visitor densities.

Table 5. Means and posthoc tests from two-way ANOVA

	Land User			Water User		
	Density Index			Density Index		
Spatiotemporal Response[1]	Low	Medium	High	Low	Medium	High
Maximum Distance Traveled in System[2] (m)	1038[a] (±720)	663[b] (±722)	706[b] (±645)	1252[a] (±970)	943[a] (±980)	863[a] (±869)
Velocity in Analysis Area (mps)	0.73[a] (±.33)	0.51[b] (±.36)	0.56[b] (±.38)	0.55[b] (±.27)	0.45[b] (±.24)	0.46[b] (±.22)
Proportion Time Stopped in Analysis Area	0.10[b] (±.08)	0.14[a] (±.10)	0.14[a] (±10)	0.50[bc] (±.11)	0.48[bc] (±.09)	0.49[bc] (±.09)
Proportion Time Spent in Analysis Area	0.38[a] (±.34)	0.63[b] (±.39)	0.59[b] (±.38)	0.50[b] (±.32)	0.54[ab] (±30)	0.54[ab] (±.29)
Total Time Recreating in System (Hours)	1.61[a] (±1.17)	1.80[a] (±1.25)	1.85[a] (±1.12)	3.48[b] (±1.73)	2.91[b] (±1.53)	2.89[b] (±1.17)

[1] Values are means ± 1 standard deviation. Means with different superscripts are significant at $p < .01$ based on Bonferroni's posthoc test of pairwise comparison.

[2]Means represent values from un-transformed data.

Discussion

Managers of PPAs require knowledge on the relationships between visitor use and visitor behavior. This knowledge informs targeted decision making to more effectively balance the provisioning of quality recreational experiences with adequate resource protection (Interagency Visitor Use Management Council (IVUMC), 2019). This research aimed to examine differences in visitor spatial behavior at varying visitor use levels within a densely populated, mixed-use, lake-based recreation setting. Findings from these efforts contribute to a small and mixed body of work examining the relationships between visitor use and visitor spatial behavior. This research also contributes one of the first comparative investigation visitor use and spatial behavior between multiple activity types within a disperse use PPA setting.

Key findings

Several key takeaways emerged from this study: (1) despite having the ability to disperse, behavior became more concentrated at medium and high-use times; (2) water-users and land-users utilized the system differently at varying use levels, highlighting implications for resource protection and visitor experience; (3) visitor density levels on their own may not serve as adequate predictors of visitor spatial behavior; (4) integrating GPS data into visitor use estimations can enrich understandings of visitor density, particularly within disperse use settings; (5) limitations including spatial and temporal autocorrelation and analytical circularity present opportunities for future research. We address the interpretations and implications from these takeaways in the discussion below.

Concentrated behaviors at high use times

Understanding how visitor spatiotemporal behavior relates to visitor use levels provides managers with foundational information to monitor and mitigate issues such as crowding, conflict, and undesirable resource disturbance (Interagency Visitor Use Management Council (IVUMC), 2019). Results from this work indicated that visitors, particularly land-users, behaved differently at varying visitor density levels: land-users arriving at low density times traveled further distances, spent less time in the analysis area, and traveled at faster speeds than land-users arriving at medium and high density times. These findings contribute to a small body of mixed and inconclusive research examining these relationships in disperse use settings. For example, in some cases the spatial extent of visitation at the recreation site expanded with higher use levels (Irizarry, 2014). However, in other instances, similar to the findings presented in this research, at high use levels, visitor behavior became more concentrated (D'Antonio & Monz, 2016). These mixed findings add evidence to suggest that in some recreation locations visitors will tend to follow consistent and concentrated use patterns, even during high use times. However, the mixed findings simultaneously confirm that other variables besides use levels may drive visitor movement patterns.

This work also provided new levels of detail to our understanding of specific behavior responses to visitor densities. For example, by extracting a suite of individual spatiotemporal behavior metrics, including several temporal features of movement, we found that land-users arriving at low-density times spent slightly *less* time recreating in the entire system than those arriving at medium and high-density times. These distinctions contain specific implications for visitor flow, parking lot turnover, and visitor experiences across the day. For instance, to mitigate congestion at peak use times, managers can use this type of information to notify visitors of alternative times or locations for recreating. However, by providing a new approach for measuring visitor behavior response, this study also complicated generalizable understandings of the relationships between visitor use and spatial behavior in PPAs. In other words, the unique operationalization of visitor behavior can make it difficult to compare responses to previously applied methods. Thus, subsequent efforts should aim to standardize measurements of behavior response and examine those relationships throughout a diversity of PPA locations.

Comparing across activity types

Different activity types engender distinctive movement patterns, ecological impacts, and social experiences (J. A. Beeco et al., 2013; Hammitt et al., 2015; Korpilo et al., 2018). The second component of this research aimed to compare spatiotemporal responses to visitor use levels across two recreational activity types: water-based users and land-based users. Our findings indicated notable differences and similarities in water-user and land-user behavior across the varying visitor use levels. Compared to land-users, water-users did not exhibit changes in their spatiotemporal behavior as a function of visitor densities; however, the magnitude of water-user behavior differed significantly compared to land-users. For example, water-users spent significantly more time recreating in the system, traveled further distances, and spent more time stopped while recreating within the analysis area across all use levels.

Furthermore, water-users spent significantly longer amounts of time within the analysis area, and over half of this time was considered as stopped. These behaviors have notable social and ecological implications. For instance, when visitors remain within a small geographic footprint for an extended period of time, these behaviors often trigger consequences such as increases in crowding and conflict perception, ecological damage, and issues with visitor congestion (Fennell, 1996). Yet, as previously noted, when water users did leave the analysis area, they traveled significantly further than land-users across all use levels. Longer traveling distances into less-visited areas also contain unique ecological consequences including wildlife disturbance and trampled vegetation; these implications are particularly relevant among water users as many can access sections of shoreline not reachable by trail. These observed patterns and implications suggest that visitor behavior and activity type may be more accurate indicators of the areal extent of use than visitor use levels.

Visitor density as predictor of behavior

Ultimately, the mixed outcomes from this research continues to challenge and complicate many long-standing assumptions about visitor use and behavior within recreation management frameworks. For instance, managers and researchers tend to posit that increases in visitor use can trigger increases in visitor intra-site dispersion, especially in disperse use settings (David N Cole, 2019a). However, the contrary results from this study suggest that other factors likely influence behavioral responses beyond visitor use numbers.

For example, from a social perspective, a recent study examined displacement at a highly used wilderness lake; results from this work indicated that visitors tended to favor using cognitive coping strategies, rather than behavioral coping strategies, when confronted with high visitor densities (Cole & Hall, 2012). Perhaps more strikingly, if visitors did change their behavior, the scale at which they modified their distance to other visitors was small (e.g., moved 10 meters away rather than 100 meters away) (Cole & Hall, 2012). In light of these findings, future research should not only consider the cognitive aspects of coping, but also consider modifying the scale for measuring behavioral differences to more accurately correspond to actual on-the-ground behaviors (Irizarry, 2014).

Furthermore, in addition to considering scale and the experiential aspects of high density settings, our observed trends highlight other potential ecological and managerial drivers of spatial behavior, such as pre-existing resource conditions and proximity to parking lots. For instance, prior research in the study area found that 80% of resource impacts existed within the analysis area (D'Antonio et al., 2017). Many of these impacts included swaths of denuded shoreline conducive for lounging, picnicking, and nature viewing. Thus, the resource impacts, engendered by frequent shoreline use in the analysis area, may have served as a desirable recreational amenity. Additionally, these impact sites existed within a short walking distance to the parking lots; therefore, visitors hoping to engage in a more leisurely lake-side outing may have prioritized quick access to the parking lot and shoreline rather than escaping crowds of people. A recent study adds support to these conjectures, which found that proximity to parking lot served as the most salient predictor of visitor behavior and densities (Pouwels, van Eupen, Walvoort, & Jochem, 2020).

The range of potential factors contributing to visitor density and spatial behavior underscore the interconnected and complex nature of the drivers and consequences of spatial behavior in PPA (Selin et al., 2020). Thus, this research adds evidence to suggest that visitor density levels on their own may not serve as adequate predictors of visitor spatial behavior. Moreover, this research highlights the need for additional research to continue examining these relationships while additionally incorporating cross-disciplinary data into study designs.

Measuring visitor density in dispersive settings

Due to the dispersive nature the study site, we found that isolated estimates of visitor use (e.g., trail counters) could not adequately capture visitor use levels and visitor distributions along the analysis area's densely populated shoreline. By integrating GPS data with counter-based visitor use estimations (e.g., parking lot counts and trail counts), we successfully achieved a much more nuanced, and spatially explicit understanding of visitor use over time. Moreover, by combining the multiple measures of visitor use into a composite index, we successfully produced a succinct, yet comprehensive, estimate of visitation across the day. Managers can adapt this methodological approach within a wide range of recreation settings where isolated estimates of visitor use may not procure accurate estimations, or where manual counts may not be feasible due to time and resource constraints.

Limitations and future research

While this work contributed to our theoretical understandings of visitor use and spatial behavior in multi-activity, disperse-use recreation settings, our efforts also revealed notable limitations and opportunities for future research.

The first limitation we experienced centered on issues of accounting for spatial and temporal autocorrelation. This study utilized high resolution GPS tracking data to measure visitor movement. However, GPS tracking point data are inherently auto-correlated; i.e., the position and timing of one GPS point depends on, and informs, the position and timing of the previous and subsequent GPS point. The auto-correlated structure of GPS data precludes the use of traditional parametric statistics which rely on independence between observations (Boyce et al., 2010). To mitigate this issue and maintain independence, we calculated total measures of behavior within each individual track (e.g., total distance traveled, average velocity, etc.) and grouped tracks by arrival time and its corresponding density class. Unfortunately, these mitigating efforts consequently reduced highly relevant details about changes in visitor behavior throughout all phases of an individual's trip in the study system. The literature emphasizes that visitor experience, decision making, and behavior is not a static phenomenon, but rather is mediated by a continuous stream of internal and external stimuli. Thus, by reducing the data to meet statistical assumptions, we missed out on the opportunity to capture much more detailed information about visitor behavior across time.

These analytical challenge suggest that parametric statistical tests may not serve as adequate approaches for understanding and assessing differences in human behavior in outdoor recreation settings (J. Beeco et al., 2013). Thus, we argue that future GPS tracking studies should aim to leverage the inherently auto-correlated structure of movement data to more accurately and finely capture differences in visitor behavior across space and time. These efforts could be obtained by employing more sophisticated spatial modeling approaches that account for autocorrelation, such as agent-based modeling or path segmentation (Edelhoff, Signer, & Balkenhol, 2016), or, perhaps more controversially, future efforts could forego statistical inference and rely instead on observable and descriptive patterns.

A secondary limitation that emerged from this research involved the circularity within data analysis. For this study, we utilized the GPS tracking data to derive the independent variable (visitor density estimates) and dependent variables (behavior response). Similar to the issues stated previously regarding autocorrelation, we found that, once again, setting up the data to meet parametric statistical assumptions hindered us from capturing actual setting conditions and behavior responses of the visitors. For example, to maintain independence between variables, we could not simply use density estimates from a prior year, as those conditions would not align with the actual conditions experienced by those carrying the GPS units. In essence, we needed to examine how the visitor simultaneously contributed to and responded to the density of visitors; thus, the visitor acted as both our independent and dependent variable. This issue represents a classic chicken-or-egg problem: visitor behavior both influences, and is influenced by, the density of other visitors. Given the circularity of these variables, future work should continue to acknowledge the interconnectedness of these relationships and carefully consider making any causal interpretations of the drivers and consequences of visitor use, experience, and behavior (Mccool & Kline, 2020).

Conclusion

This research examined the relationships between visitor use levels and spatiotemporal behaviors within a dispersive, highly-used, mixed-activity recreation site. Overall, our findings revealed distinctions in spatial behaviors among both land and water-based users; land-users tended to disperse more at low-use times, while water-users exhibited similar behaviors across all use levels. These findings suggest that activity type may play a role in behavior response at varying visitor densities. These results also contrasted previous work examining similar relationships, suggesting that visitor densities on their own may not be accurate predictors of visitor behavior patterns. By including a comparative component to the study design, this research found that land and water-based users utilized the system in distinctive ways across all visitor use levels, highlighting numerous implications for resource protection and visitor flow management. Finally, this study demonstrated a novel approach for understanding visitor densities within a disperse use recreation setting. Integrating multiple measures of use into a composite density index provided a comprehensive and managerially relevant method for conceptualizing the amount and spatial extent of visitor use in a disperse-use system. Results both broaden and complicate our understanding of the relationship between visitor spatial behavior and visitor use levels. Therefore, future efforts should continue to examine these relationships under a wider range of landscapes and visitor use conditions.

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CHAPTER THREE: WHAT'S 'SUP' WITH PADDLERS?

Integrating spatial, social, and ecological data to understand behavior among paddlesport users at a popular lake destination

Introduction

Every year, millions of people in the United States recreate in public parks and protected areas (PPAs)(Outdoor Foundation, 2019a). Managers of PPAs aim to provide opportunities for high quality outdoor experiences without compromising the desired social and ecological conditions and objectives for the area. To effectively balance these goals, managers require an understanding of the amount, type, timing, and distribution of recreational behavior and activities (Interagency Visitor Use Management Council (IVUMC), 2019).

Within PPA settings, water sources often serve as central and defining features, and provide a variety of highly desired outdoor opportunities (Kakoyannis & Stankey, 2002). Identifying the spatial and temporal dimensions of water-based recreation engenders distinctive resource and experiential consequences. Unlike in a trail or road system where spatial movement is often constrained by linear features, water-movement can be much more open; in a lake or coastal system, for instance, recreational boaters are able to move freely within the bounds of the water while simultaneously having access to a continuous edge shoreline. As a result, a water-user may have access to locations that are more difficult to reach by foot or vehicle (J. Beeco & Brown, 2013). This type of behavior presents unique monitoring challenges for resource protection and safety, including wildlife disturbance, shoreline congestion, erosion, vegetation loss, and increased levels of water turbidity (Hammitt, Cole, & Monz, 2015). Despite these distinctions, spatiotemporal examinations of water-based recreation remain notably lacking in

PPA research (Riungu, Peterson, Beeco, & Brown, 2019); the vast majority of spatial research to date centers on terrestrial recreation use, such as trail-based use, skiing, and vehicle behavior.

Paddlesports, defined as kayaking, rafting, canoeing, and, most recently, stand-up paddleboarding (abbreviated and pronounced as 'SUP'), are among the most common water-based activities in PPAs (Outdoor Foundation, 2019b). In 2018, an estimated 22.9 million people, nearly 8% of the U.S. population, participated in a paddlesport activity of some kind (Outdoor Foundation, 2019b). Even with its newfound relevance to water-based recreation, stand-up paddleboarding has yet to be investigated within the context of paddlesport recreation. An investigation of this kind is warranted as the emerging activity may be changing both the management and experience of aquatic recreation.

The relevance of paddlesport recreation in PPAs, combined with the introduction of a novel activity type – stand-up paddleboarding – indicates a substantial need for empirical examinations of the experiences, travel patterns, and impacts of paddlesport use (Riungu, Peterson, Beeco, Brown, et al., 2019; Sidman & Fik, 2005). With advances in spatial tracking technology, it is possible to pair high resolution GPS spatial data with corresponding social (motivations, preferences, personal characteristics) and ecological (resource exposure, landscape interactions, vegetation types) factors to build a comprehensive understanding of water-based recreation in PPAs (J. Beeco & Hallo, 2014; Riungu, Peterson, Beeco, Brown, et al., 2019). In response to these gaps and opportunities, the purpose of this research was twofold. First, we used GPS-based tracking methods to execute a comparative study investigating the spatial behaviors of stand-up paddleboarders, canoers, and kayakers. Secondly, we performed a statistical classification procedure as a method for interpreting behavior patterns and integrating spatial and non-spatial information. Findings contribute to our understanding of paddlesport use in PPAs and inform the theory and practice of managing water-based recreation.

Conceptual Foundation

Water-based Recreation Research in PPAs

Within the canon of recreation and tourism social science, numerous studies explored the motivations and experiences of traditional paddlesports (i.e. paddlesport activities prior to stand-up paddleboarding), revealing differences in the experiences and motivations among activity types. For example, prior research suggests that the level of paddler specialization, or experience level, plays a role in motivations and site preferences (Lee, Graefe, & Li, 2007; Lepp & Herpy, 2015). Lee et al. found that more specialized paddlers preferred new sites, wilderness, and challenge compared to novice paddlers who favored convenience and access to facilities (2007). However, a more recent study examined river recreationists in New Zealand, discovering that the nature of the activity itself had a stronger effect on motivations and site preferences than the level of specialization (Galloway, 2012). Ultimately these mixed results highlight the variation in motivations and preferences among paddling activity types in PPAs, and emphasize the need to update our understanding of these relationships given the arrival of stand-up paddleboarding to water-based recreation.

While in situ spatiotemporal examinations of water-recreation in PPAs are lacking, previous work in other water-based environments demonstrate how spatial research promotes effective management strategies for mitigating undesirable social and environmental impacts (Cui & Mahoney, 2015). For instance, prior to advanced spatial tracking technology, managers of water-based systems used aerial surveys and questionnaires to estimate behavior and inform zoning recommendations (Heatwole & West, 1982; Lentnek, Van Doren, & Trail, 1969). Subsequent research recognized the value of combining spatial data with other situational variables (e.g. launching locations, vessel type, and shoreline morphology) to more accurately model boating patterns in coastal, open water settings (Cui & Mahoney, 2015; Sidman & Fik, 2005). However, these former studies operationalized behavior based on survey responses rather than actual travel trajectories. To date, we found only one published study that used GPS-based tracking methods to derive behavior metrics such as distance traveled, speed, and turning angle to characterize and compare recreational boating travel patterns in Canadian waterways (Pelot & Wu, 2007). Findings from this work showed significant differences in movement depending on activity type, which consequently informed coast guard safety and zoning protocols.

Measuring Visitor Movement Patterns

To balance the conflicting social and ecological pressures of recreation, managers rely on monitoring strategies that indicate how people behave across space and time. This information reveals locations, or times of day, where resource degradation, crowding, or conflict may be likely to occur (D'Antonio & Monz, 2016; Walden-Schreiner & Leung, 2013). Advancements in geospatial technologies, such as GPS-based tracking, have greatly contributed to these efforts by capturing accurate, detailed information on the movement patterns of visitors, across a diversity of settings, with minimal participatory burden (J. Beeco & Brown, 2013; D'Antonio et al., 2010; Riungu, Peterson, Beeco, & Brown, 2019).

Throughout the literature, the majority of GPS studies in PPAs researched land-based recreation activities, including hiking and off-trail behavior in trail systems (e.g. Kidd et al., 2015; Korpilo, Virtanen, Saukkonen, & Lehvävirta, 2018), ecological impacts from hikers (e.g.

D'Antonio, Monz, Newman, Lawson, & Taff, 2013), behaviors in dispersed use settings (e.g., Stamberger, van Riper, Keller, Brownlee, & Rose, 2018), vehicle movement and flow (e.g., Kidd et al., 2018; Newton, Newman, Taff, D'Antonio, & Monz, 2017)(Kidd et al., 2018; Newton et al., 2017), and human and wildlife interactions (e.g., Pouwels, van Eupen, Walvoort, & Jochem, 2020). The travel trajectories of visitors are often represented visually with density maps and overlays of visitor use across the landscape, or descriptively with aggregate summaries of behavior (e.g. where people go, total duration, speed, and directionality). Results successfully informed a range of management decisions, including infrastructure design, communication strategies, zoning, and visitor services.

Increasingly, however, researchers emphasize the need to transition from descriptions of spatial behavior, to explanations of spatial behavior in PPAs (J. Beeco, Hallo, English, & Giumetti, 2013; Riungu, Peterson, Beeco, Brown, et al., 2019). One method for achieving this goal is to combine spatial data with corresponding social and environmental variables. By doing so, we begin to identify the underlying mechanisms that drive visitor movement and decision making. An example of this application includes a study which paired survey data with GPS-tracked trail users (mountain bikers, runners, horseback riders, and hikers) to identify variables that may be influencing movement (J. Beeco & Hallo, 2014). Motivations and personal characteristics had a modest effect on the movement patterns of runners and mountain bikers, but activity type emerged as the strongest predictor of spatial behavior. Findings from an integrated research approach enables managers to develop customizable monitoring and outreach strategies to more effectively meet their objectives for the area. Applying similar methods to water-based

PPA settings would contribute to our knowledge of paddler behavior and build on the small, but growing, body of mixed method, integrative spatial research.

Classifying Visitor Behavior

Classifying visitors based on specific social or behavioral attributes has long served as an approach for interpreting visitor use patterns (J. A. Beeco et al., 2013; Elands & Lengkeek, 2000; Kloek, Buijs, Boersema, & Schouten, 2015). Traditionally, the classification of visitor types in outdoor recreation settings was rooted in socio-psychological disciplines (E. Cohen, 1972; Plog, 1974), and evolved into a complex set of visitor ‘typologies’ that factored in travel style, reported behaviors, and motivations (McKercher & Lau, 2008; Park, Tussyadiah, Mazanec, & Fesenmaier, 2010). Beeco et al., recognized the implicit spatial component of visitor classifications and executed a study using GPS-based tracking methods to compare the actual movement patterns of a four-category typology of ‘Wanderer and Planners’ in a PPA setting (2013). Interestingly, results showed no significant differences in the actual spatial behavior among the four categories, despite reported differences in travel styles. A more recent study only classified visitors by activity type (e.g. runners, cyclers, mountain bikers, and walkers) and found significant differences in their spatial behavior (Korpilo et al., 2018). The contrasting results emphasize the inherent complexity of classifying recreationists, and present the need for more comparative spatial studies in PPA settings, particularly those that compare among activity types and travel styles (Andkjær & Arvidsen, 2015; J. A. Beeco et al., 2013; Korpilo et al., 2018).

With the development of spatial tracking technology, an increasing number of studies classified visitors using measured spatial and temporal behaviors via GPS-based tracking methods (J. Beeco, 2013; Kidd et al., 2018)(J. A. Beeco et al., 2013; Kidd et al., 2018;

Ligtenberg, Marwijk, Moelans, & Kuijpers, n.d.; Meijles, de Bakker, Groote, & Barske, 2014; Shoval & Isaacson, 2009). For example, Kidd et al. extracted behavior metrics from GPS tracked vehicles along a popular recreation corridor and used a clustering algorithm to produce three distinct vehicle typologies: ‘Opportunistic’, ‘Wildlife/Scenery Viewers’, and ‘Hikers’ (2018). This form of classification can support management efforts to communicate with visitors in ways that enhance desired experiences and behaviors, while also revealing situations where increased monitoring may be appropriate. Importantly, however, the collection of prior classification studies demonstrate effective methods for distilling and deriving meaning from visitor spatial behavior solely in land-based settings, where use is typically dictated by linear features such as roads and trails. Classification procedures in water-based settings, where movement can be less constrained, would contribute to our knowledge of recreation behavior across a more representative range of PPA landscapes.

Research Objective

Despite the advancements in spatial applications and the use of classification tools in PPAs, we continue to know little about the actual behavior patterns and corresponding experiences of water-based recreationists, particularly in light of the introduction of stand-up paddleboarding. This work aims to address this gap by integrating spatial, social, and environmental data to examine the behaviors and experiences of paddlesport users at a popular lake destination. Findings serve to not only enhance our theoretical interpretations of spatial behavior in PPAs, but allow for more predictive and adaptive decision making that tailors to a diversity of visitor demands without compromising recreation experiences and resources.

1. To what extent are there differences in the spatial and temporal behaviors among stand-up paddle boarders, canoers, and kayakers?

2. To what extent are there classifications, or typologies, of paddlers based on spatial and temporal behavior patterns?

3. How do activity types, social characteristics, and exposure to resource conditions vary among paddlesport users?

Methods

Study Site

Grand Teton National Park (GRTE), located in Wyoming U.S.A. spans across 485 square miles (National Park Service, 2019). In recent years, visitation to the park steadily increased; in 2019, GRTE experienced nearly 3.4 million recreation visits, representing a 30% increase in visitation from 2010 (National Park Service, 2019). GRTE contains a mixed-use destination called the String and Leigh Lakes (SLL) recreation area. SLL provides ample summer recreation opportunities for non-motorized, water-based activities such as canoeing, kayaking, and stand-up paddleboarding, and land-based activities including hiking, climbing, and picnicking (Figure 1).

String Lake connects to three parking lots that run adjacent to its southeast shoreline (Figure 1). During the summer months, the section of shoreline connecting to the String Lake parking lots fills with recreationists seeking water and land-based activities. Leigh Lake lies directly north of String Lake; visitors can access Leigh Lake by portaging or by hiking one mile from the String Lake trailhead. Leigh Lake contains multiple back-country campsites. In contrast to String Lake, Leigh Lake offers a more remote visitor experience with many western sections of lake only accessible by water-craft.

In the past five years, GRTE management noticed a rise in visitation to SLL (National Park Service, 2017). Furthermore, SLL managers recognized the emergence of an increasingly prevalent water-based recreation activity: stand-up paddleboarding. In 2017, stand-up paddleboarders accounted for over 40% of all water-based users in the SLL area (D'Antonio et al., 2017). Given SLL's central access point to a lake-based water system, combined with its popularity as a location for paddlesport recreation, the area served as an appropriate location to execute a study exploring the behaviors, experiences, and impacts of paddlesport use in a PPA.

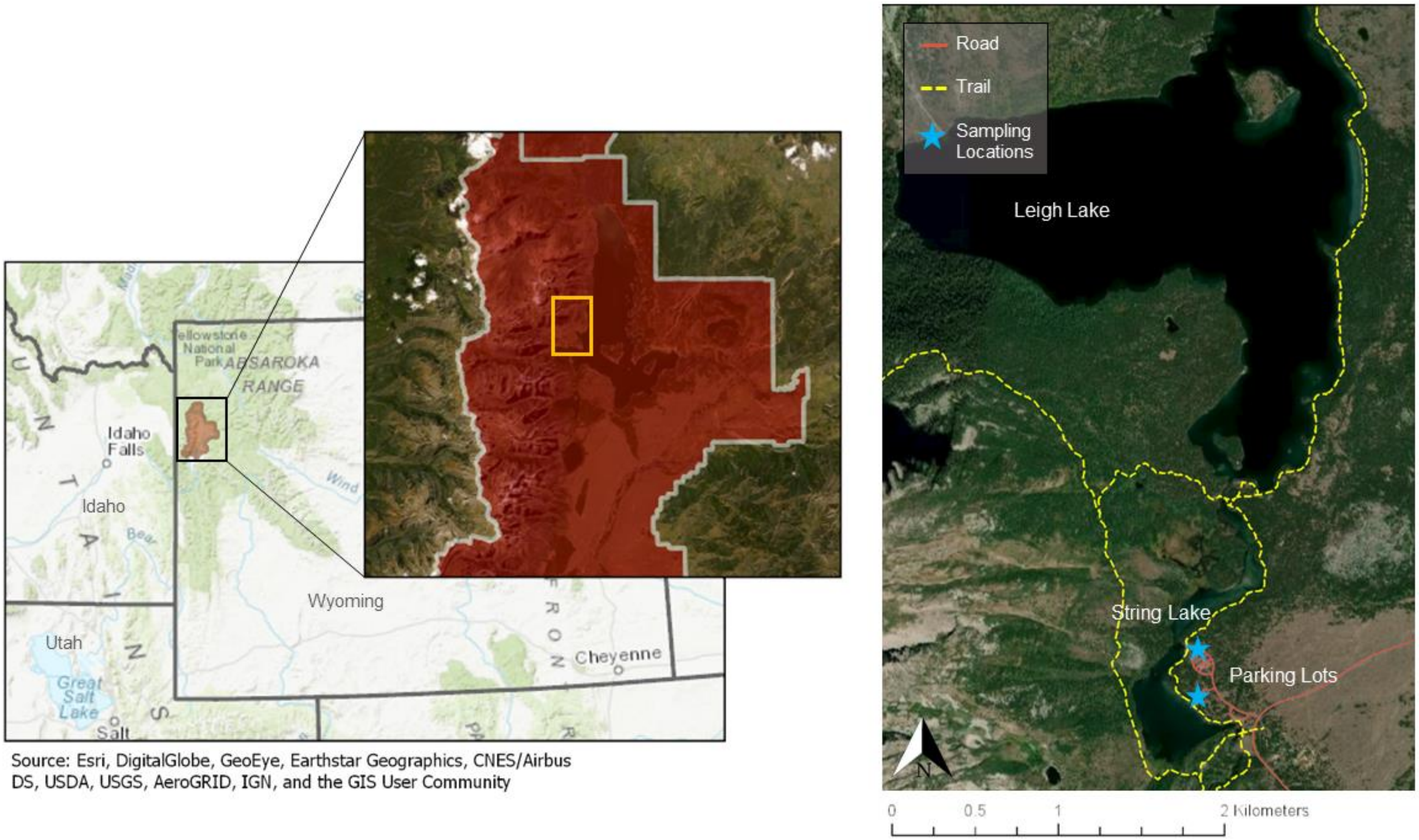

Figure 7. Map of Grand Teton National Park in Wyoming, USA (left) and the String and Leigh Lake (SLL) study area (right).

Data Collection

Data collection at SLL occurred across 14 days in the summer of 2018: June 28 through August 12, from 8 am to 5 pm. We randomly stratified sampling across weekdays and weekends, mornings and afternoons to ensure a representation of summertime, day-use visitation. Respondents were asked to participate in three phases of data collection: complete a pre-trip questionnaire at the beginning of their visit to SLL, carry a GPS unit on their water vessel while recreating at SLL for the day, and complete a post-trip questionnaire at the conclusion of their day-visit (see Figure 8 for order of participation). To link the data types, each respondent received a unique identifying code corresponding to their GPS track and survey responses.

To intercept visitors, technicians positioned themselves along the two primary parking lots providing water-based access into the SLL system (see Figure 7). Technicians used the census sampling method to intercept all paddlesport groups as they entered the SLL area for the day (Singh & Mangat, 2013). One randomly selected individual per group was asked to complete the pre-and post- survey and carry the GPS unit on their water vessel. Eligible participants included recreationists over the age of 18 participating in day-use, water-based activities such as kayaking, canoeing, and stand-up paddleboarding.

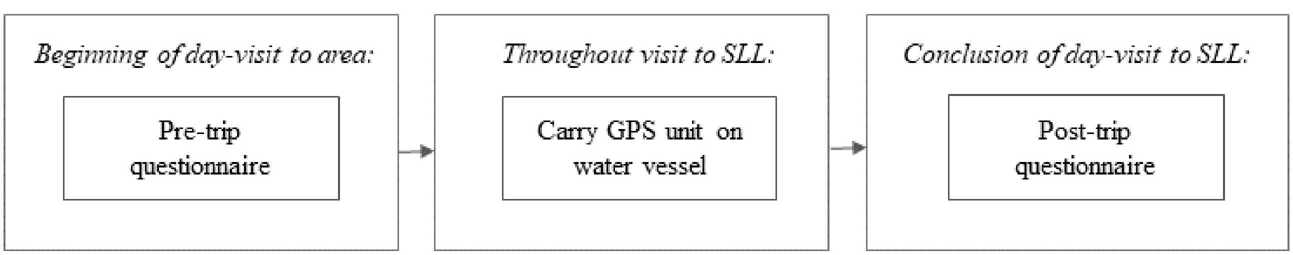

Figure 8. Order of survey participation and types of data collected from each respondent

Description of Data Collected

This study combined spatial, social, and environmental data to explore the behaviors, experiences, and impacts of paddlesport use in a PPA setting. Table 6 outlines the data types and specific variables extracted from each data source.

Table 6. Data collected and variables measured from each participant

Data Type	Source	Variables
Spatial	GPS track of water user	Maximum distance traveled from the parking lot Average distance traveled from the shoreline Total time spent in SLL area Average velocity on the water
Surveys	Pre-Trip Questionnaire	Primary activity type Start Time Total number of vessels Motivations Group size Frequency of visitation Age
	Post-Trip Questionnaire	Experienced crowding
Ecological	GPS mapping of visitor created resource impacts	Proportion of time water-user spent on user-created *sites* Proportion of time water-users spent on user-created *trails*
	World Imagery basemap of SLL	Proportion of time water-user spent on land

Spatial Data

We used GPS-based tracking methods from protocols developed by D'Antonio et al. (2010) to collect spatial and temporal movement data. Participants received a hand-held, recreation-grade, Garmin eTrex 10 GPS unit at the beginning of their visit to SLL and asked to keep the unit on their water vessel throughout the duration of their trip to the SLL area. GPS units collected coordinate and timestamp point data at 15-second intervals and were secured to the participant's water vessels. At the conclusion of their recreation activities, participants returned the GPS units to a researcher or to a GPS drop box if a researcher was unavailable. Those that returned GPS units to the GPS drop box did not participate in the post-trip questionnaire. Throughout the field season, the GPS units were calibrated to measure and correct for any positional errors (D'Antonio & Monz, 2016; Kidd et al., 2015). Prior to analysis, we removed outlier GPS points that fell outside of the study area, and points that accrued at the GPS collection sites.

Four spatiotemporal metrics (STM) were calculated from each GPS track to provide a quantitative assessment of behaviors: (1) maximum distance traveled from the starting point, (2) average distance traveled from the shoreline, (3) total time spent in the SLL recreation area, and (4) average velocity on the water.

Survey Data

Technicians administered surveys to participants on-site using iPads equipped with Qualtrics software. The pre-trip questionnaire contained twelve items measuring visitor demographics and motivations for recreating at SLL. The post-trip questionnaire contained sixteen items measuring recreational outcomes, and any factors that may have hindered the acquisition of outcomes (e.g. crowding, conflict, exposure to resource impacts).

The following variables were utilized for this study: Primary activity type was measured as the paddling activity that respondents claimed to be their primary activity for the day. Start time was measured as the time the respondent arrived at the SLL and took the pre-survey. Open-ended questions on the questionnaire determined frequency of visitation, age, group size, and total vessels.

Motivations for recreating at SLL were adapted from the Recreation Experience Preference (REP) scale (Manfredo, Driver, & Tarrant, 1996; Manning et al., 2011). Respondents were provided with a list of 26 possible motivations with each response measured on a five-point scale with 1 corresponding to 'not at all true', 3 as 'moderately true' and 5 as 'completely true'. An Exploratory Factor Analysis in SPSS categorized the 26 possible experiences into 6 motivation domains: (1) escape, (2) socialization, (3) enjoy nature, (4) adventure, (5) sharing, (6) family and friends, (D'Antonio et al., 2018; Rice et al., 2020). Reliability analysis using Cronbach alpha in SPSS assessed the internal consistency of the multiple items measuring the eight motivation domains. Perceptions of crowding were measured in the post-trip questionnaire. Respondents were asked to rate on a scale of 1 to 5 how crowded they felt at specific locations in the SLL study area (1 – 'not at all crowded,' 3 – 'moderately crowded,' 5 – 'extremely crowded').

Ecological Data

We identified and classified user-created resource impacts to understand the landscape and resource conditions associated with the SLL study area (D'Antonio, Monz, Newman, Lawson, & Taff, 2013). Technicians used a sub-meter accuracy Trimble GPS unit to map and classify recreation-related resource impacts. For this study, resource impacts were defined as a user-created site (mapped as a polygon) or as a user-created trail (mapped as a line feature).

The proportion of time spent on a user-created resource impact was calculated in ArcGIS. All water user GPS tracks were overlayed and intersected with a polygon shapefile representing user-created sites and a line-based shapefile indicating user-created trails. A 2.5-meter buffer was added to both layers to account for GPS errors. For each track, we calculated the proportion of total time spent on any user-created site and the proportion of total time traveling on any user-created trail. To measure the proportion of total time spent on land, we used the 0.5-meter resolution world imagery basemap of the SLL area (Esri, DigitalGlobe, GeoEye, i-cubed, USDA, USGS, AEX, Getmapping, Aerogrid, IGN, IGP, swisstopo, and the GIS User Community). We created a new layer that represented the boundaries of the water and land features by tracing and digitizing the perimeter of String Lake and Leigh Lake. We overlaid the GPS tracks onto the land and water layers to calculate the proportion of total time spent on land.

Analysis Methods

Given the diversity of data types and analytical approaches, this section is organized by research question. All quantitative analyses were achieved in R (R Core Team, 2014). Spatial visualization and map making were created using ArcGIS® software by Esri®. Workflow diagrams of each analytical workflow are located in supplementary material.

Examining differences in the behaviors between paddlesport users

A combination of qualitative and quantitative analytical approaches examined differences in the behaviors of paddlesport user groups. Paddlesport users were separated into two categories, including traditional users (canoers and kayakers) and stand-up paddleboarders.

The kernel density procedure allowed for visual comparisons of the spatial behaviors of traditional paddlesport users and stand-up paddleboarders. The kernel density tool used the points within each GPS track to generate a raster surface of expected counts. We rescaled the expected counts for both user group rasters to 0 -1 and then used the raster calculator tool to subtract the traditional user raster from the stand-up paddleboarder raster. The resulting raster revealed spatially explicit areas dominated by each user group, and areas that were shared equally. Welch's two-sample t-test provided a quantitative assessment of differences in the behaviors of paddlesport user groups. The t-test compared the averages of the four STM's generated from each group.

Identifying typologies of paddlers based on spatial and temporal behavior

This research question aimed to identify any underlying patterns or distinct groupings of behavior within the sample of paddlesport users. To achieve this, we ran a k-means cluster test on the four STMs derived from each GPS track. The emerging clusters were labeled into typologies of behavior and used as independent variables to reveal socio-ecological drivers and impacts of paddlesport use.

The input data for the k-means cluster test included the four STM's. The data were rescaled and standardized using z-scores. Before running the k-means cluster test, we assessed the dataset for its 'clusterability' by using the Hopkins statistic. This statistics tests the spatial randomness of the data, or its clustering tendency, and validates the subsequent use of a clustering tool (Adolfsson, Ackerman, & Brownstein, 2019; Banerjee & Davé, 2004). The Hopkins statistic generated for these data was 0.178, providing strong evidence that the dataset contained clusterable data (Banerjee & Davé, 2004). We used the ‘NbClust’ function in R to calculate and aggregate 30 indices commonly used for determining the number of cluster designations (Charrad, Ghazzali, Boiteau, & Niknafs, 2014). Additionally, we used the qualitative ‘elbow method’ to visualize the variation within each cluster (Everitt & Hothorn, 2006). From these two validation tools, we pre-selected a three cluster solution as this quantity could be interpreted meaningfully, while also maintaining sufficient sample sizes within each cluster grouping.

The ‘kmeans’ function from the ‘cluster’ package in R generated a three cluster solution for the data (Maechler, Rousseeuw, Struyf, Hubert, & Hornik, 2019). The cluster attributions for each track (e.g. cluster one, two, and three) were appended to the original attribute table of behavior metrics for visualization and further analysis. Descriptive behavioral summaries informed the labeling of typologies.

Exploring how activity types, social characteristics, and exposure to resource conditions vary among paddler types

The cluster groupings that emerged from the k-means cluster test provided categorical typologies of behavior among paddlers. The goal of this research phase was to identify how various social and ecological variables differed among the groupings – or typologies – of paddlers. A chi-square test examined differences in the proportion of users who engaged in specific paddlesport activity types and proportion of users who were first time visitors across the three behavior typologies. A one-way Analysis of Variance (ANOVA) test determined if the mean responses for the social and environmental variables varied across the cluster groups. Posthoc analyses of all significant relationships were conducted using Bonferroni's pair-wise comparison method.

Results

Summary statistics

We collected 285 GPS tracks. Of this sample, 277 tracks contained corresponding survey information: 141 represented stand-up paddleboarders, 104 represented kayakers, and 32 represented canoers. The response rate for carrying a GPS unit and participating in the pre and post-survey was 82% (Table 7). For subsequent analysis, stand-up paddleboarders were labeled as one primary group, and, given the low sample size among canoers, the canoe tracks were concatenated with the kayak tracks and labeled 'traditional' users. Average GPS error in this study was calculated as 2.5 meters (D'Antonio et al., 2018) (Figure 9).

Table 7. Summary of sample sizes and response rates among water-users at SLL.

Primary Activity	# of GPS tracks (response rate)	# of GPS tracks with both pre and post-survey (response rate for post-survey)	# of GPS tracks who only took the pre-survey (response rate for pre-survey)
Stand-up paddleboard	149 (81%)	106 (72%)	35 (81%)
Kayak	104 (87%)	95 (78%)	21 (86%)
Canoe[1]	32 (92%)	29 (89%)	19 (92%)

[1] Due to the low sample size among canoers, kayakers and canoers were concatenated into one group labeled 'traditional' users.

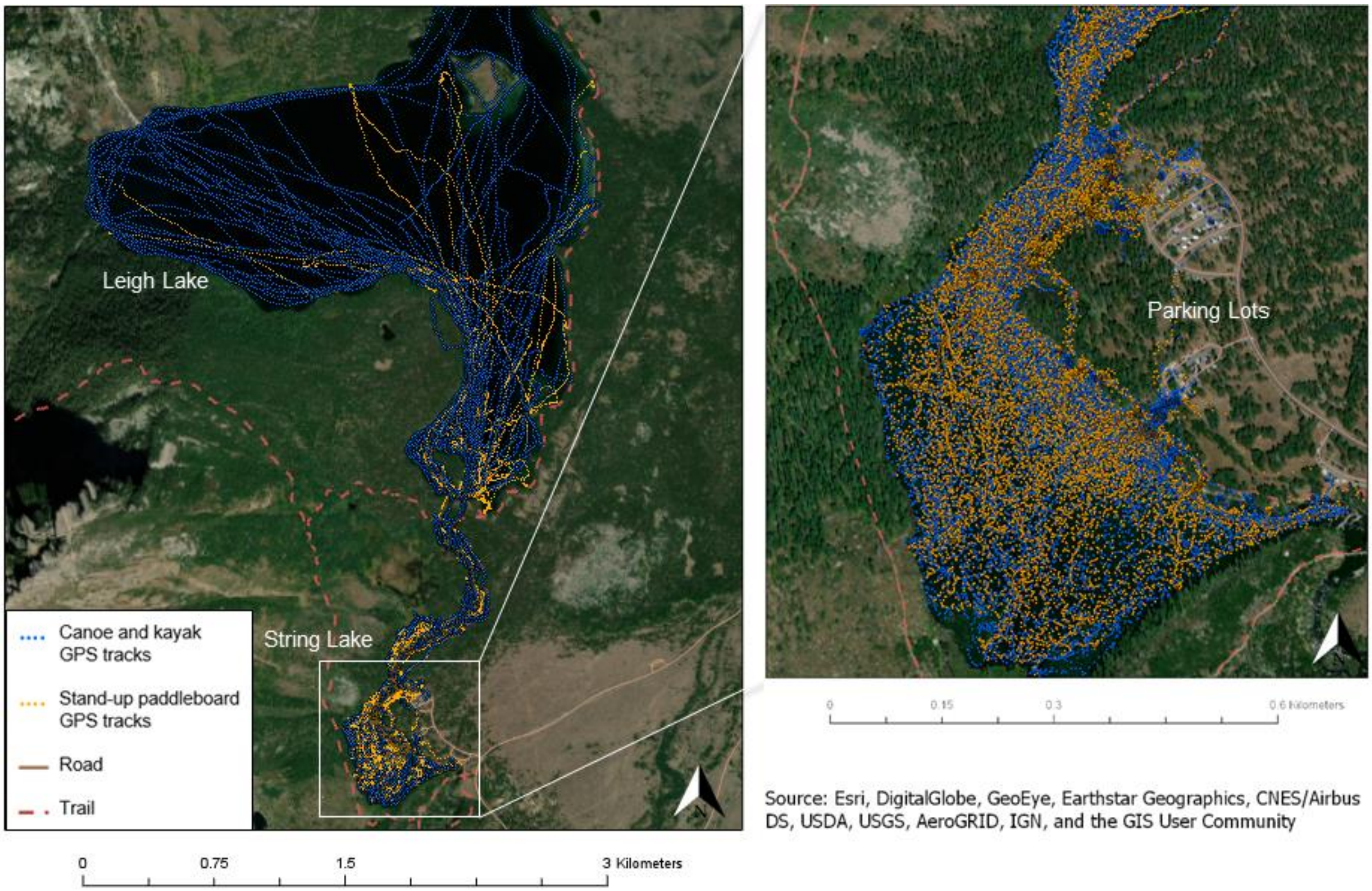

Figure 9. Map of all water-user GPS tracks collected for this study.

Examining differences in the behaviors

Stand-up paddleboarders and traditional users exhibited concentrated use levels near the three parking lot locations. These high-density areas were expected as the parking lots served as the primary access points to the system. Overall, traditional users utilized larger portions of the Leigh Lake system compared to stand-up paddleboarders (Figure 10). The raster calculator produced a continuous surface indicating locations in SLL that were either disproportionally dominated by an activity type, or locations where spaces were utilized equally (Figure 11). In general, paddleboarders occupied areas associated with the northern parking lot and mostly remained in the southern section of the system. By contrast, traditional users traveled further north towards Leigh Lake. Among the traditional users, several pockets of use emerged along numerous locations that traced the western shoreline of Leigh Lake; these locations can only be accessed via watercraft (i.e. there are no designated trails on the western shoreline of Leigh Lake).

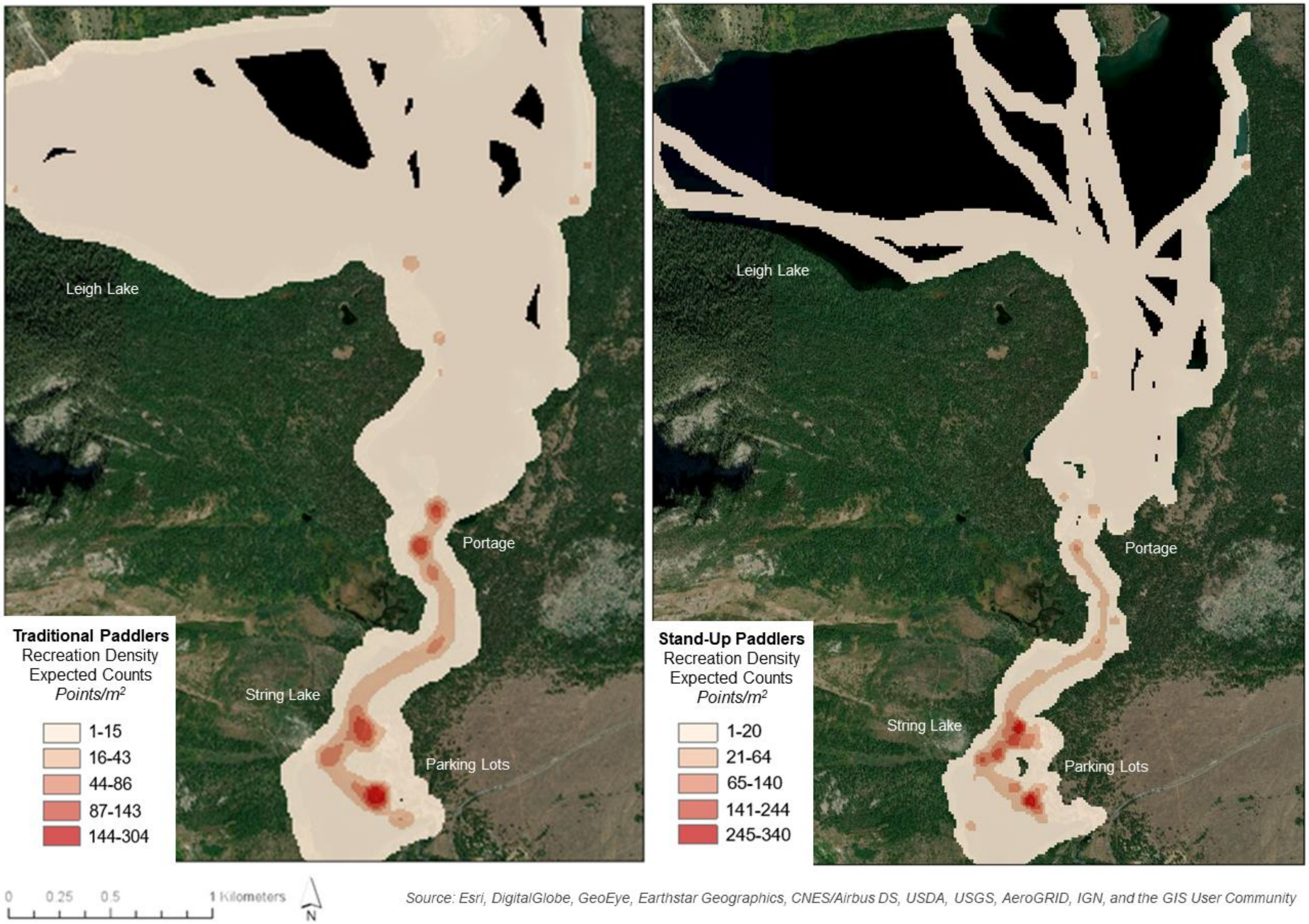

Figure 10. Kernel Density Estimation representing the spatial distribution of traditional users (kayakers and canoers) (left) and stand-up paddleboarders (right) at String and Leigh Lakes. Expected counts are rounded to the nearest whole number and represent the estimated number of points per square meter.

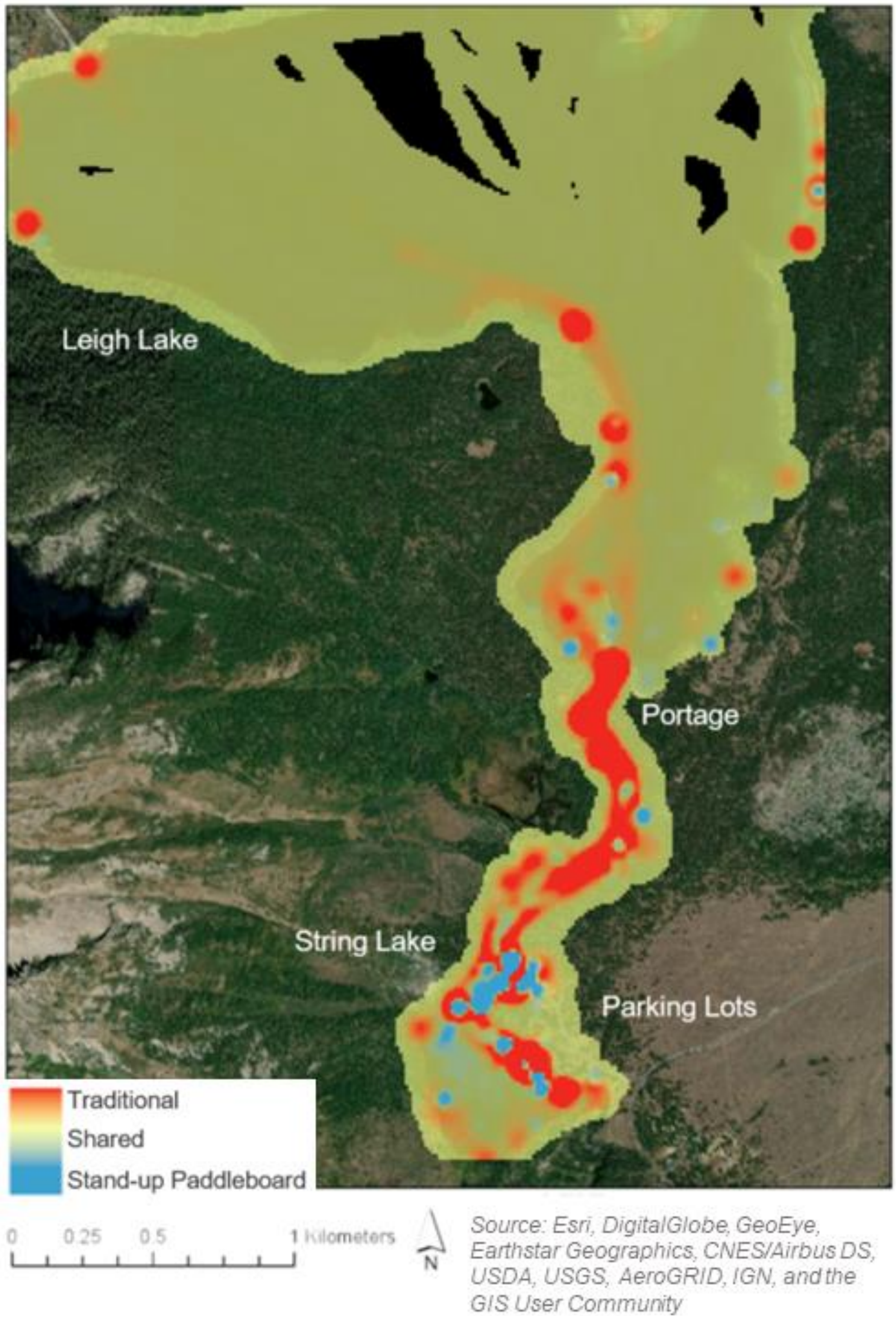

Figure 11. Calculated raster representing areas where stand-up paddleboarders dominated the system (blue) compared to traditional users (red). Shared spaces are characterized by the color yellow.

Welch’s two-sample t-tests for unequal variances identified significant differences in spatial and temporal behavior between traditional users and stand-up paddleboarders. Results indicated differences across all four STMs (Table 8). For maximum distance traveled, traditional users traveled an average of 712.71 meters further from their starting point than stand-up paddleboarders ($t = -5.34$, $p = < .001$) (Table 8). Similarly, with average distance traveled from shoreline traditional users traveled an average of 5.75 meters further from the shoreline than stand-up paddleboarders ($t = -2.08$, $p < .05$). For time spent recreating within the study area, traditional users spent an average of 40 minutes longer in the SLL area than stand-up paddleboarders ($t = -3.03$, $p < .05$) (Table 3). Lastly, on average, traditional users traveled .06 m/sec faster than stand-up paddleboard users ($t = -2.14$, $p < .05$).

Table 8. Differences in behaviors between stand-up paddleboarders and traditional paddlesport users.

	User Group			
Spatiotemporal Behavior	Traditional	Stand-up paddleboard	*t*-value	*p*-value
Max distance from starting point (m)	1463.48 (± 737.54)	750.77 (±1248.43)	-5.34	<.001
Distance from shoreline (m)	29.26 (±24.20)	23.51 (±17.05)	-2.08	.04
Time spent recreating (hh:mm)	3:50 (±3:40)	3:10 (±1:35)	-3.03	<.01
Average velocity on water (m/sec)	.47 (±.20)	.41 (±.18)	-2.14	.03

Identifying typologies of paddlers based on spatial and temporal behavior

The k-means cluster test revealed underlying patterns and distinct groupings of behavior within the full sample of paddlesport users. A three cluster solution for the data produced behavioral typologies of paddlesport use in the SLL recreation area.

Cluster one users traveled the furthest from the parking lot and spent an average of 4 hours and 50 minutes recreating in the system. Cluster two contained the highest number of tracks with 159 users. In contrast to those in Cluster one, users in Cluster two did not travel far from the parking lot, only paddling an average of 708 meters from their starting point. These users also traveled at slower speeds and remained closer to the shoreline (17 meters on average). The defining difference among those in Cluster three was they spent half the amount of time recreating in the system compared to the other users (2 hours and 2 minutes). Table 4 summarizes the means and standard deviations of the four behavioral metrics for each cluster category. The cluster categories were re-labeled as three typologies aiming to succinctly characterize the behaviors of each group: Cluster one as ‘Adventurers,’ Cluster two as ‘Beachers,’ and Cluster three as ‘Passing Through.’

Table 9. Summary of clusters and their corresponding means and standard deviations for each behavioral parameter.

Cluster Category & Descriptive Label	Average Maximum Distance from Parking (± SD) (m)	Average Distance from Shoreline (± SD) (m)	Average Time Spent in Area (± SD) (hh:mm)	Average Velocity on Water (± SD) (m/sec)
1. (N = 41) *Adventurers* Travel furthest from the parking lot, spend the most time in the area, travel furthest from the shoreline, and travel at quicker speeds.	3,260 (±590)	60 (± 32)	04:50 (± 01:46)	0.66 (±0.16)
2. (N = 159) *Beachers* Do not travel very far from the parking lot, stay for a long time, stay closer to the shoreline, and travel slowly.	708 (±561)	17 (±10)	04:11 (± 01:29)	0.31 (±0.12)
3. (N = 101) *Passing Through* Do not travel far from the parking lot, spend half the amount of time in the area compared to Beachers and Adventurers, and travel moderately fast.	702 (±492)	25 (± 11)	02:02 (±02:30)	0.52 (±0.15)

The kernel density tool allowed us to visualize and compare the movement trajectories of the three clusters (Figure 12). The rasters demonstrated spatial similarities between the Beachers and Passing Through groups: both groups tended to remain along the southern portions of the study system, closer to the parking lots. However, the Passing Through group was more diffuse throughout String Lake, with concentrated use along the northern portion String Lake. By contrast, the Beachers had the highest density near the parking lot location and in the southern section of String Lake. The Adventurers used much of String Lake and Leigh Lake, with dense areas of use around the portage; the concentrated use levels near the portage are understandable as it takes increased time to carry a vessel from String Lake to Leigh Lake.

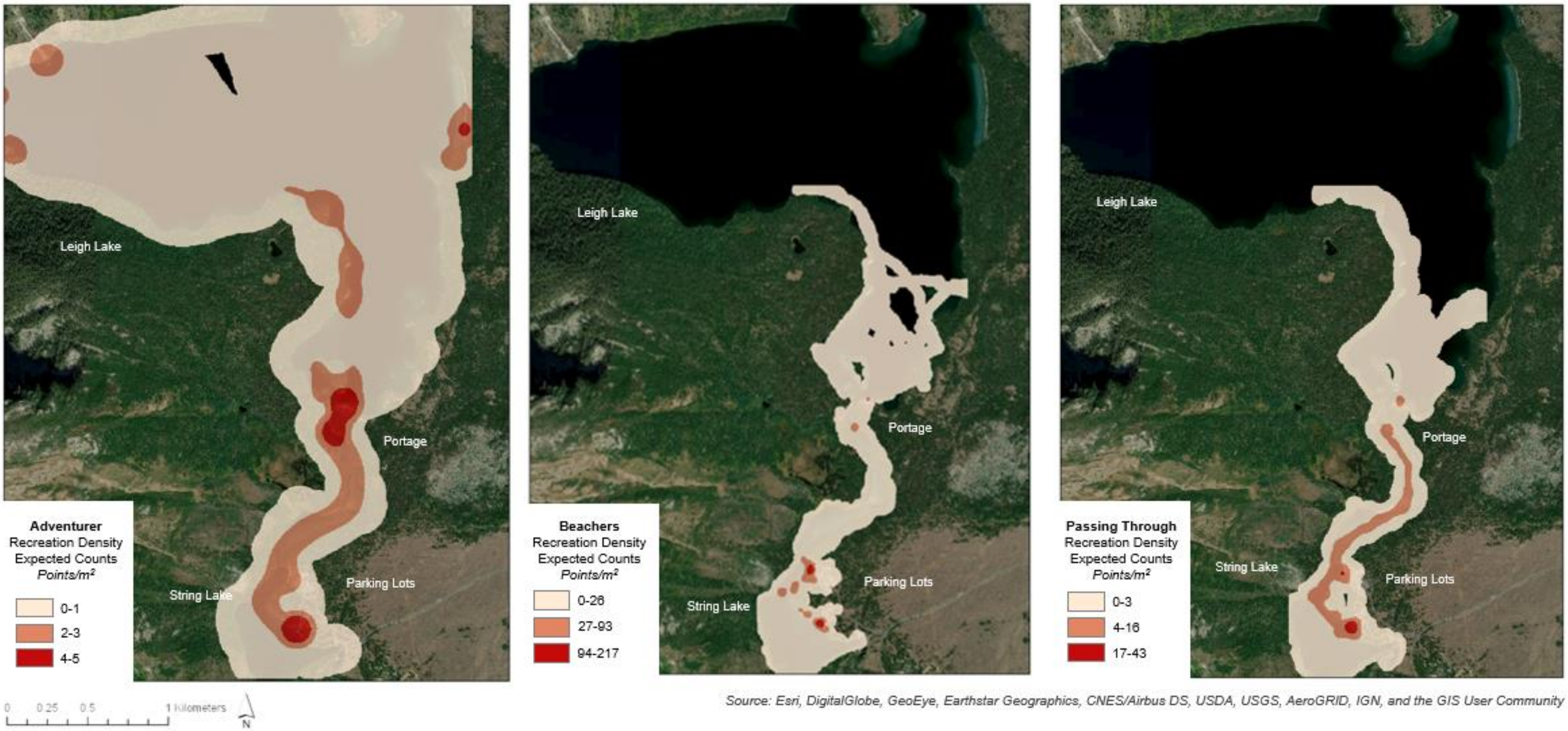

Figure 12. Kernel density plots of the three paddler typologies in the String and Leigh Lake recreation system. Expected counts are rounded to the nearest whole number and represent estimated number of points per square meter.

Exploring how activity types, social characteristics, and exposure to resource conditions vary among paddler types

Pearson’s Chi-Square (χ^2) test examined differences in activity type and visitation among the three paddler typologies (Table 10). Overall, 96% of stand-up paddleboarders belonged to the Beacher group and the Passing Through group, suggesting stand-up paddleboarders at SLL do not travel far from their starting point and stay closer to the shore. This result is further validated by the t-tests comparing the differences in behavior between stand-up paddleboarders and traditional users (see Research Question 1 section of the results).

Among the Adventurer group, 80% were comprised of traditional paddlesport users, while only 20% was stand-up paddleboarders. Stand-up paddleboarders made up the majority, 64%, of the users in the Passing Through group. The Beacher group, the largest of the three groups, contained roughly half stand-up paddleboard and half traditional use. These distributions significantly differed across the cluster categories ($\chi^2 = 22.04$, $p < .001$). The Cramer’s V effect size was ‘Medium’ suggesting activity types do play a role in how people behave at SLL (J. Cohen, 2013). There were no significant differences in visitation; nearly 75% of all paddlers were repeat visitors (Table 10).

Table 10. Chi-Square of activity type and visitation by cluster

	Cluster Category						
	Adventurers (1)	Beachers (2)	Passing Through (3)	Total	χ2	p-value	Cramer's V effect size
Stand-up Paddleboard	20% (9)	53% (79)	64% (62)	149			
Traditional Users	80% (32)	47% (69)	36% (35)	136	22.04	<.001	.29
First Time Visitors	29% (10)	25% (29)	31% (28)	67			
Repeat Visitors	71% (24)	75% (85)	69% (62)	144	.83	.66	-

A one-way ANOVA test identified differences in the means of several social and environmental variables among the three typologies (Table 11). Results from the ANOVA revealed variables that may drive and impact different types of paddlesport use. Among variables with significant differences, the Bonferroni method identified pairwise differences. Results from the test indicated that the start time differed among the three typologies ($F = 24.51$, $p < .001$). This was also the case for group size ($F = 13.34$, $p < .001$) and the total number of vessels ($F = 6.39$, $p = .01$). For the start time, all three typologies differed with the Adventurers arriving the earliest, around 11:00 am, and the Passing Through group arriving at the latest, with an average arrival time of 13:30. For the visitation variable, the Beachers visited the SLL area the most frequently (m = 19 visits) followed by the Passing Through (m = 13) group and the Adventurers (m = 10). Beachers also had significantly larger average group sizes than the other two groups, averaging six people per group compared to about four people per group among Adventurers and Passing Through users. Further, Beachers had more vessels on average, with nearly three vessels per user compared to two for the other groups.

Among the motivation indices, the motivation to escape ($F = 5.48$, $p = .02$), and the motivation to enjoy nature ($F = 5.44$, p-value = .02) significantly differed among the three typologies. Adventurers were more motivated to visit SLL to escape (m = 4.12) and to enjoy nature (m = 4.46) compared to Beachers and Passing Through groups (Table 11).

The proportion of time spent in user-created sites and trails showed significant results (user-created sites: $F = 80.03$, $p < .001$; user-created trails: $F = 14.02$, $p < .001$) (Table 11). Similarly, the proportion of time spent on land had significant results ($F = 28.43$, $p<.001$). For the proportion of time spent on a visitor-created site, Beachers spent more time (40% of their time on average) on a resource impact area. The Passing Through group and Adventurer group spent only 22% and 18% of their time on a visitor-created site, respectively. We also tested the proportion of time each group spent on the land compared to the water. Interestingly, the Adventurer group spent 32% of their time on land; this behavior is likely because of the time it took to portage from String Lake to Leigh Lake. This assumption is supported by the kernel density outputs that illustrated dense pockets of visitor use at the portage between String Lake and Leigh Lake (see Kernel Density Comparisons in the Research Question 2 section). Beachers spent 42% of their time on the land and those Passing Through spent only 24% of their time on land.

The eta effect sizes for start time, group size, total vessels, and motivation variables were ‘small’ with values under .3 for each variable (J. Cohen, 2013). This suggests that, although there were statistically significant differences between the average responses among the groups, the strength of these relationship was small.

Table 11. Differences in social and environmental characteristics among the three cluster categories1

	Cluster Category					
	Adventurers (1)	Beachers (2)	Passing Through (3)	F-value	p-value	Effect size (ŋ)
Start time (hour)	11:06 (±01:44)	12:36 (±01:50)	13:30 (±01:57)	24.51	<.001*	.14
Age (years)	45 (±16)	41 (±13)	39 (±12)	1.18	.278	-
Group Size	3.5 [b] (±3.33)	6.38 [a] (±5.84)	4.21 [b] (±5.31)	13.34	<.001*	.05
Total Vessels	2.21 [a b] (±2.21)	2.95 [a] (±2.13)	2.11 [b] (±1.36)	6.39	.01*	.02
Experience Level	2.94 (±0.98)	2.81 (±1.19)	2.92 (±1.12)	.035	.85	-
Motivated to Escape	4.12 [b] (±.77)	3.72 [a] (±.99)	3.74 [a] (±.91)	5.48	.02*	.02
Motivated to Share	2.50 (±1.20)	2.59 (±1.30)	2.62 (±1.29)	.06	.814	-
Motivated to Enjoy Nature	4.46 [b] (±.676)	4.12 [a] (±.849)	4.20 [a b] (±.964)	5.44	.02*	.02
Motivated for Adventure	3.36 (±.974)	3.01 (±1.10)	3.16 (±1.09)	3.52	.06	-

Table 11. Continued

	Adventurers (1)	Beachers (2)	Passing Through (3)	F-value	p-value	Effect size (ŋ)
Perception of crowding (SL Shoreline)	2.91 (±1.20)	3.12 (±.91)	3.19 (±1.09)	1.55	.22	-
Perception of crowding (SL Open Water)	2.82 (±1.16)	2.68 (±1.08)	2.15 (±.94)	.46	.50	-
Proportion of total time spent on user-created *site*	.18 [b] (±.10)	.42 [a] (±.23)	.22 [b] (±.16)	80.03	<.001*	.21
Proportion of total time spent on user-created *trail*	.06 [b] (±.04)	.14[a] (±.18)	.04[b] (±.06)	14.02	<.001*	.09
Proportion of total time spent on land	.32 [c] (±.11)	.42 [a] (±.22)	.24 [b] (±.16)	28.43	<.001*	.09

[1] For experience level, means are on a 5-point scale of 1 "Beginner", 3 "Intermediate" and 5 "Expert". For motivations, means are from a 5-point scale of 1 "not at all true" to 5 "extremely true." For perceived crowding, means are on a 5-point scale of 1 "not at all crowded" to 5 "extremely crowded." Means with different superscripts in are significant at p < .05 based on Bonferroni's post-hoc test of pairwise comparison.

Discussion

Key findings

Managers of PPAs strive to provide a range of quality recreational experiences while minimizing undesirable impacts to resources. In the face of high levels of visitation and the expansion of novel recreational uses – such as stand-up paddleboarding – managers increasingly require interdisciplinary, mixed-method approaches that reveal the ways in which visitors navigate and experience outdoor spaces (Riungu, Peterson, Beeco, Brown, et al., 2019). Driven by the lack of spatial investigations of water-based recreation and the emergence of a new activity type to water-sports, this research coupled in situ GPS-data with social and environmental variables to understand the behaviors, preferences, and impacts of paddlesport use in a PPA setting.

Several key findings emerged from our exploration: (1) Stand-up paddleboarders utilized the lake system in unique ways compared to traditional users; (2) Despite having the option to travel longer distances, the majority of paddler movement concentrated along the southern portion of the lake system; (3) The temporal use of space varied across user groups highlighting distinctions in space-time budgets; (4) Paddlers, regardless of behavior, had high social motivations which may explain tendencies to concentrate close to the parking lots. The Adventurer paddlers were the most motivated to escape, which corresponded to their more dispersive behavior; (5) The level of contact with shoreline impacts differed across paddler types, highlighting management implications for crowding, conflict, and resource damage.

Identifying patterns in paddler spatial behavior

Assessing and comparing visitor spatial distributions among recreational activity types aids in the identification and evaluation of social and environmental impacts (J. Beeco & Hallo, 2014; Korpilo et al., 2018). Our findings corroborate with Pelot and Wu's GPS tracking study of recreational boaters which identified differences among the spatial trajectories of sailboats, kayaks, canoes, and motorboats (Pelot & Wu, 2007). However, unlike Pelot and Wu, this work compared water-based travel trajectories in a strictly non-motorized lake setting. The distinctions among stand-up paddleboarders and traditional users render both social and ecological consequences. For instance, given that stand-up paddlers are more prone to make contact with the shoreline, their behavior may manifest in undesirable levels of impacts, particularly in sensitive ecological areas that may not be accessible by trail. From a social perspective, concentrated use levels along sections of the lake may give rise to heightened perceptions of crowding and trigger coping responses such as traveling to less frequented areas of the system (intra-site displacement), changing the timing of a visit (temporal displacement), or visiting an alternative location in the park (inter-site displacement) (Hall & Shelby, 2000). Over time, these responses could encourage the proliferation of use into less visitor-dense areas, further catalyzing potentially undesirable resource changes.

Statistical classification tools allowed us to build a typology of water-users based on observed spatiotemporal behaviors. From this procedure we revealed overarching paddler movement trends at SLL and accounted for interactions and overlaps among activity types. Our findings showed that the vast majority of paddlers, and nearly all stand-up paddleboarders, did not travel beyond the southern portion of the system. Traditional paddlers encompassed the majority of users in the Adventurer group, however their noticeably small sample size indicates that despite having the option to travel further distances, most paddlers, regardless of activity type, did not exhibit this behavior. Previous research found that trail-use densities tend to be highest around the parking lot areas (Meijles et al., 2014; Pouwels et al., 2020; Zhai, Korça Baran, & Wu, 2018). On the one hand, we would expect higher frequencies of GPS points in the parking lots given that all paddlers needed to start and end their trip in this location. However, we aimed to control for naturally higher point densities by extracting specific measures of dispersive behavior, such as maximum distance traveled from starting point. These findings contribute to recent work suggesting that even in dispersed, spatially-unconstrained settings, such as a lake system, the majority of day-use visitors will still tend to concentrate close to designated roads, facilities, and parking lots (Bielański et al., 2018; Jurado, Dantas, & Da Silva, 2009; Stamberger et al., 2018).

Notably, if not for the temporal factor, the Beachers and Passing Through groups appeared to use the space similarly: both groups concentrated their movement along the southern portions of the lake and traveled moderately close to the shoreline. However, paddlers in the Passing Through group spent half the amount of time in the area compared to the Beacher group. The distinctions in temporal use of space sheds light on the concept of space-time budgets in PPAs (J. Beeco & Brown, 2013). Space-time budgets posit that the amount of time a visitor chooses to spend in a recreation area determines the amount of space they can travel through (Ruingu, 2019). Typically, one would anticipate a positive relationship between time spent in the recreation area and distance traveled (Barros & Machado, 2010; Fennell, 1996). For example, we witnessed this trend with the Adventurers who remained in the area the longest and traveled the furthest distances. The Beachers, however, challenge this assumption because they did not travel far from the parking lots despite spending a significant amount of time in the area. From a methodological standpoint, these results emphasize the need to conceptualize travel patterns as multi-dimensional constructs that incorporate multiple measures of behavior (Beeco, 2014). Managerially, these distinctions have numerous implications for the timing and intensity of visitor use across the day. For one, the system may experience a surge of late afternoon paddlers which could influence levels of congestion in the parking lot or boat launch areas. Secondly, with visitors spending long portions of time within a confined geographic area, this poses greater risks for crowding, ecological damage, and restricted visitor flows (Fennell, 1996).

Relating spatial behavior to social and ecological factors

Comparing the social and ecological attributes of paddler groups lends insights into why water-users exhibited distinctive behavior trends. Findings from these efforts equip managers with information to customize decision making in ways that align with the observed preferences and behaviors of visitors. Moreover, this type of integration expands our understandings of how motivations and experiences relate to spatial behavior in PPAs, and demonstrates how landscape characteristics, such as user-created impact areas, can exist as both a driver and consequence of visitor movement.

Interestingly, regardless of spatial behavior, all paddler groups ranked high in their social motivations. These findings shed light on previous work that explored perceptions of crowding and motivations along coastal beaches in South Africa (De Ruyck, Soares, & McLachlan, 1997). Results from De Ruyck et al. (1997) indicate that those who ranked high in social motivations preferred developed shorelines with dense visitor usage, while those motivated to engage in a nature-based experiences preferred quieter and less populated areas. Along similar lines, a recent study examined recreationists at SLL and found that those who were motivated to socialize were less likely to attain the goal of experiencing an adventure, characterized by taking risks, having thrills, and experiencing a sense of exploration (anonymous). Given that the majority of paddlers did not venture far from the parking lot, with Beachers in particular spending long periods of time on hardened impact areas and exhibiting significantly larger group sizes, our findings correspond to Rice et al. (2020) and DeRuyck et al. (1997), suggesting that social factors may play some role in the concentrated behavior patterns (i.e., most visitors did not venture to the more distant section of the lake system). Additionally, the Adventurers contribute a more nuanced interpretation of these patterns. For example, while Adventurers ranked high in their social motivations, they stood out from the other typologies by reporting significantly higher motivations to escape and experience the natural beauty of the area. These additional motivations may explain their more dispersive behavioral tendencies. Overall, these results suggest that the relationships between motivations and behavior are multi-faceted; motivations for having a social experience, for instance, may be a factor in spatial behavior (e.g., preferring close access to parking lots and denser locations), but must be considered in conjunction with other characteristics including group dynamics, time budgets, and accompanying motivations for recreating. In practice, managers can utilize this information to effectively communicate to water-users about times and locations where they can obtain a range of desired experiences.

Ecologically, the Beacher typology demonstrates how visitor use both influences, and is influenced by, setting and landscape characteristics. For instance, the denuded sections of shoreline offer convenient areas for staging water vessels, picnic blankets, and moving in and out of the water at leisure. In this way, the impact areas influence behavior by providing a hard-packed location conducive for a more ‘beach-like’ paddling experience. On the other hand, these impacts are the direct consequence of visitor behavior, with frequent exposure resulting in erosion, soil compaction, and vegetation loss (Hammitt et al., 2015). Managerially, recognizing how visitors interact with the shoreline in this way can proactively alert managers to vulnerable locations that may benefit from reduced or restricted visitor use access, or conversely, select areas where hardening surfaces, or adding infrastructural supports, could better support visitor demands.

Limitations and future research

Most paddlers at SLL recreated in groups. To maintain independence between samples, we made the assumption that the individual who completed the survey and carried the GPS unit represented group behavior. This assumption underscores the need for future research that examines the effect of group dynamics on recreationist movement and decision making (Hallo et al., 2012; Lew & McKercher, 2006; Meijles et al., 2014; Riungu, Peterson, Beeco, Brown, et al., 2019). The SLL area also offers abundant opportunities for land-users, with a complex trail network running adjacent to the lake. This work did not investigate the interactions between land and water-users, which could play an important role in visitor behavior and the overall user experience. Along similar lines, our findings highlight opportunities to research the effect of visitor use levels on behavior, as well as some of the more discriminant features of several of the survey variables, such as identifying specific dimensions of crowding or conflict and their resulting behavior patterns, or expanding on the motivation battery to better tailor them to the experiences of paddlers. By doing so, we could enrich our interpretation of the underlying drivers of paddler behavior.

Conclusion

This research paired GPS-tracking data with corresponding social and environmental information to build a robust understanding of paddlesport behavior and experience in a PPA setting. Overall, our findings revealed distinctions in behavior across paddling activity types, highlighting implications for resource protection and visitor flow management. Factoring in temporal dimensions of behavior uncovered differences in the timing and intensity of use among paddlers that would not be evident from a purely spatial examination. Lastly, integrating spatial and non-spatial data identified numerous drivers and impacts of paddlesport use: the motivation to escape and experience natural beauty, for example, corresponded to traveling further distances, while higher group sizes and prolonged shoreline exposure aligned with concentrated use levels near parking lots and facilities. These results serve to broaden our knowledge of recreationist movement and experience, and add to a growing body of PPA research that incorporates mixed method spatial approaches to research designs. Furthermore, these findings contribute novel information on paddlesport spatial behavior in PPAs, especially given the introduction of a new, yet highly sought after activity type: stand-up paddleboarding.

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CHAPTER FOUR: CONCLUSION

Managers of parks and protected areas (PPA) strive to provide a variety of quality and safe recreational experiences without compromising the integrity and health of ecosystems and natural resources (Interagency Visitor Use Management Council (IVUMC), 2019). In the face of changing technologies, emergent activity types, and increasing visitor demands, managers must continue to monitor and adapt visitor use management (VUM) strategies (Selin, Cerveny, Blahna, & Miller, 2020). By doing so, managers can effectively maintain and achieve desired outcomes within a recreation area. Understanding how visitors move and interact with one another throughout a landscape serves as a foundational tenant in guiding successful VUM frameworks (J. Beeco & Brown, 2013; Riungu, Peterson, Beeco, & Brown, 2019). Spatial data representing these movement patterns provides critical information on visitor use and flow, and can highlight areas that may be prone to resource degradation, crowding, or user conflicts (D'Antonio et al., 2010; Rupf et al., 2011). More powerfully, spatial data can often be leveraged with social, managerial, and biophysical information to provide a cross-disciplinary understanding of the drivers and consequences of recreation use (Riungu et al., 2019).

To date, the majority of integrated spatial research efforts have occurred in terrestrial recreation systems. Very few spatial studies have examined water-based recreation (i.e. kayakers, standup paddleboarders, etc.), particularly within multi-activity, dispersive recreation settings (e.g., along open coastlines, riverfronts, and lakeshores) (Riungu et al., 2019). This type of research is greatly needed as water-users often produce distinctive impacts to ecological resources and develop unique outdoor experiences and outcomes (Hammitt, Cole, & Monz, 2015; Manning, 2011). Moreover, water-based use comprises a large portion of outdoor recreation activities. For instance, in 2019, over half the U.S. population engaged in a water-based activity of some kind (Outdoor Foundation, 2019). For these reasons, spatially integrated work examining aquatic recreation systems must be added to canon of research in PPAs to build a more thorough understanding of visitor use and behavior across a representative range of recreational uses and settings.

This thesis addresses this gap in the literature by examining visitor use and behavior among both terrestrial and aquatic activity types within a densely populated, disperse-use PPA lake setting: String and Leigh Lakes Recreation Area in Grand Teton National Park, Wyoming. The first empirical chapter investigates behavioral responses to visitor densities between land and water-based users. The second empirical chapter explores spatiotemporal features of paddlesport use and offers approaches for integrating spatial, social, and ecological data. The methods and findings from both chapters provide novel tools and approaches for conceptualizing visitor use and behavior in PPAs and contributes to theoretical and practical understandings of aquatic-based outdoor recreation.

Key findings

Key findings from the first empirical chapter include: (1) Visitors to String Lake tended to concentrate more, rather than disperse, during moderate and high-use times; (2) Water-users and land-users moved throughout the system differently at varying use levels, suggesting that activity type plays a role visitor response to user densities; (3) Visitor use levels on their own may not serve as adequate predictors of visitor spatial behavior; (4) Integrating GPS data into visitor use estimations can enrich understandings of visitor density, particularly within disperse use settings; (5) Spatial and temporal autocorrelation within GPS data highlight opportunities to transition to more sophisticated spatial modeling approaches, and (6) analytical circularity amongst variables underscores the notion that examining outdoor recreation is inherently recursive and interrelated.

Key findings from the second empirical chapter include: (1) Stand-up paddleboarders at String and Leigh Lakes utilized the lake system in unique ways compared to canoers and kayakers; (2) Despite having the option to travel longer distances, the majority of paddlers concentrated along the southern portion of the lake system; (3) The temporal use of space varied across user groups highlighting distinctions in space-time budgets; (4) Paddlers had high social motivations which may explain tendencies to concentrate close to the parking lots. The paddlers most motivated to escape corresponded to dispersive behavior; (5) The level of contact with shoreline impacts differed across paddler types, highlighting implications for crowding, conflict, and resource damage.

Broad contributions to the literature

Broadly, these results add to a growing body of evidence suggesting that visitor use, regardless of activity type, landscape features, and high visitor use levels, tends to concentrate near parking lots, facilities, and hardened surfaces (Pouwels, van Eupen, Walvoort, & Jochem, 2020; Stamberger, van Riper, Keller, Brownlee, & Rose, 2018). These trends emerged among both water- and land-based users in each empirical chapter. However, findings from this thesis also revealed notable nuances and exceptions to these concentrated behavior patterns. For example, motivations to escape aligned with traveling further distances; and land-based recreationists arriving at low-use times tended to travel further than those arriving at medium and high-use times. Additionally, this thesis showed striking differences in behaviors within water-based activity types: for instance, compared to canoers and kayakers, stand-up paddleboarders exhibited the highest potential for prolonged, concentrated use near the parking lot and on denuded sections of shoreline.

Ultimately, these similarities and distinctions in spatiotemporal behaviors add support for the need to examine multiple dimensions of movement in any given recreation setting (Mccool & Kline, 2020). Furthermore, these findings demonstrate the necessity and utility of comparative examinations of visitor use and behavior among multiple and emerging activity types (Korpilo, Virtanen, Saukkonen, & Lehvävirta, 2018). Additionally, this study reveals how incorporating social, ecological, and managerial variables into spatial analyses offers potential reasons for *why* visitors exhibited specific movement patterns (e.g., motivations to escape, or activity types and tendencies to spend long portions of time along the shoreline) (J. A. Beeco & Hallo, 2014; Riungu et al., 2019).

This thesis also provides methodological and analytical contributions that better support VUM frameworks. For instance, this thesis demonstrates a novel approach for combining GPS-data of visitor movement patterns with visitor use estimations. This approach produces a more comprehensive understanding of changes in use levels across the day, particularly within a complex and disperse use recreation setting. More specifically, this approach can be leveraged in settings where isolated estimations of visitor use (e.g. trail counter or parking lot data) may not be able to adequately capture use due to a complex array of movement options.

Furthermore, this thesis shows how extracting spatiotemporal metrics (e.g., distance, time, velocity) from GPS data allows for a variety of integrative analytical applications with aspatial attributes (e.g., ecological, managerial, social data). For example, this thesis used these behavior metrics to create typologies of recreationist behavior patterns. These typologies were related to relevant socio-ecological information and informed site-specific management strategies to effectively target and mitigate recreation demands and consequences.

Finally, this thesis demonstrates the importance of including temporal aspects of visitor use into spatial research designs. By doing so, findings identified notable distinctions in space-time budgets among visitor activity types that would not be revealed from solely examining the spatial component of movement.

Management implications

The findings from this thesis contain numerous implications for managing visitor flow, experience, and ecological conditions. For example, within the study site system, most visitors concentrated near parking lots and facilities, particularly at high use times. If managers of the recreation area desire less congested shorelines, they can use this information to: (a) notify visitors of alternative times for recreating along the shoreline and/or; (b) inform visitors of additional locations adjacent to the shoreline where they can achieve similar recreational outcomes. These approaches can also promote opportunities that align with visitor expectations and desires. For example, since stand-up paddleboarders dominated many hardened sections along the shoreline, managers of the recreation site can use this information to build more appropriate infrastructural supports to meet these spatial demands and discourage undesirable proliferations of use into other sections of the shoreline. Moreover, managers of the system can use the findings from this thesis to identify vulnerable sections of shoreline that may only be accessible by water-craft, and hone in on locations that may warrant increased attention and monitoring. Ultimately, utilizing spatially integrated research approaches informs more effective decision making for recreational zoning, educational initiatives, and outreach strategies. These informed strategies can better cater to the unique set of activity types, landscape conditions, and desired visitor experiences that exist within a recreation site.

Future research

Overall, this thesis explores original research questions that contribute to VUM frameworks, advance theoretical understandings of aquatic and terrestrial visitor spatial behavior, and offer novel approaches for research methodology and analysis. Future research can build on these contributions in a number of ways. First, this study only examined a single recreation setting, thus results cannot be generalized beyond the String and Leigh Lakes recreation area. Future efforts should examine the features and implications of recreation in PPAs across a diversity of landscapes. By doing so, we can build a more representative understanding of the drivers and consequences of visitor spatial behavior in PPAs.

Moreover, future spatial research efforts should build study designs that explore behavior across finer and broader spatial scales. More fine scale work could take advantage of the high temporal resolution of GPS tracking data and examine changes in individual behavior across the day. This approach would expand understandings of how visitors alter behavior within a site depending on real-time stimuli and experiential inputs. To achieve this, researchers would need to harness the inherently auto correlated nature of GPS data and consider transitioning away from traditional parametric statistics in favor of more sophisticated spatial modeling approaches.

At the other end of the spectrum, future work should also aim to broaden the scale of analysis and examine the drivers and effects of recreation at the landscape level. These efforts will greatly advance understandings of the long term and long range consequences of recreation and better inform sustainable and holistic VUM strategies (Perry et al., 2020).

Lastly, future work should continue to develop multi-disciplinary, mixed-method study designs that effectively capture the interconnected, feedback elements of outdoor recreation use (Morse, 2020). In other words, research should work towards examining how visitor use influences, and is influenced by, a range of inputs and setting conditions. This approach will honor the inherently complex structure of VUM management by cultivating research designs that adequately capture these integrative and dynamic systems.

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APPENDIX

Pre-Trip Questionnaire

OMB Control Number 1024:0224

Grand Teton Pre-trip Survey: String and Leigh Lakes

PAPERWORK REDUCTION and PRIVACY ACT STATEMENT: The Paperwork Reduction Act requires us to tell you why we are collecting this information, how we will use it, and whether or not you have to respond. We are authorized by the National Park Service Protection Interpretation and research in System (54 USC §100702) to collect this information. The routine uses of this information will be for the benefit of NPS Managers and Planning staff Grand Teton National Park (GRTE) in future initiatives related to the visitor use and resource management within the String and Leigh Lakes area. The data collected will

be summarized to evaluate visitor uses and expectations during their visit at GRTE. Your responses to this collection are completely voluntary and will remain anonymous. You can end the process at any time and will not be penalized in any way for choosing to do so. Data collected will only be reported in aggregates and no individually identifiable responses will be reported. A Federal agency may not conduct or sponsor, and you are not required to respond to, a collection of information unless it displays a currently valid OMB Control Number (1024-0224). We estimate that it will take about 5 minutes to complete and return this on-site questionnaire. You may send comments concerning the burden estimates or any aspect of this information collection to: Dr. Peter Newman, Department Head & Professor, Recreation, Park and Tourism Management, 801 Ford Building, University Park, PA 16802, Penn State University (address) or pbn3@psu.edu (email); or Phadrea Ponds NPS Information Collection Coordinator at pponds@nps.gov (email).

String and Leigh Lakes Water-User Pre-Survey - 2018

1) Including this visit, how many times have you visited the String and Leigh Lakes area? (Please insert your number of visits)
   ________Number of Visits

2) How would you describe your planning for this visit to the String and Leigh Lakes area? (Please select only one response)
   ☐ Spontaneous; no planning ☐ Very little pre-planning ☐ Some pre-planning ☐ Carefully planned

3) Which of these activities do you plan on participating in at the String and Leigh Lakes area today? (Please select all that apply)
   ☐ Canoeing
   ☐ Kayaking
   ☐ Stand-up Paddle boarding
   ☐ Hiking
   ☐ Wildlife Viewing
   ☐ Photography
   ☐ Swimming
   ☐ Beach Using
   ☐ Picnicking
   ☐ Scenic Driving
   ☐ Other (Please Specify) ____________________

4) From the activities you have selected, please indicate the **primary activity** you plan on participating in during today's visit. (Please select only one response)

   ☐ Canoeing
   ☐ Kayaking
   ☐ Stand-up Paddle boarding
   ☐ Hiking
   ☐ Wildlife Viewing
   ☐ Photography
   ☐ Swimming
   ☐ Beach Using
   ☐ Picnicking
   ☐ Other (Please Specify) ____________________

5) Please rate your current experience level in the **primary activity** you selected above? (Please select only one response)

Beginner	Novice	Intermediate	Advanced	Expert
1	2	3	4	5

6) Please indicate your level of agreement or disagreement with each of the statements. (Please select only one response for each item)

	Strongly Disagree	Disagree	Neither	Agree	Strongly Agree
I wouldn't substitute any other place for doing the type of things I do at the String and Leigh Lakes area	1	2	3	4	5
The String and Leigh Lakes area is the best place for the things I like to do	1	2	3	4	5
What I do at the String and Leigh lakes area is more important to me than doing it at any other place	1	2	3	4	5

7) Below is a list of statements related to your primary activity at the String and Leigh Lakes area. Please rate how true the following statements are according to your visit today.

During my primary activity at the String and Leigh Lake area, I am motivated to…	Not at all True	Slightly True	Moderately True	Very True	Completely True	Not Applicable
…view scenic beauty.	1	2	3	4	5	0
…be close to nature.	1	2	3	4	5	0
…view wildlife.	1	2	3	4	5	0
...experience tranquility.	1	2	3	4	5	0
...feel independent from rest of society.	1	2	3	4	5	0
...be away from crowds of people.	1	2	3	4	5	0
…physically relax.	1	2	3	4	5	0
...have my mind move at a slower pace.	1	2	3	4	5	0
...get away from the noise back home.	1	2	3	4	5	0
...enjoy the sounds of nature.	1	2	3	4	5	0
...experience natural quiet.	1	2	3	4	5	0
...take risks.	1	2	3	4	5	0
...have thrills.	1	2	3	4	5	0
...experience a sense of exploration.	1	2	3	4	5	0
...bring my family closer together.	1	2	3	4	5	0
...have fun with my family.	1	2	3	4	5	0
...share the outdoors with my children.	1	2	3	4	5	0
...be with friends.	1	2	3	4	5	0
...be with people who share similar values.	1	2	3	4	5	0
...be with others who enjoy the same things I do.	1	2	3	4	5	0
...gain a sense of self-confidence.	1	2	3	4	5	0
...learn what I am capable of.	1	2	3	4	5	0

...show others my abilities.	1	2	3	4	5	0
...share photos on social media.	1	2	3	4	5	0
...tell others about my trip.	1	2	3	4	5	0
...have others know that I have been here.	1	2	3	4	5	0

8) When you entered the String and Leigh Lakes area, did you notice a sign indicating that the parking lots were full?

☐ No ☐ Yes

9) On this trip to the String and Leigh Lakes area, how difficult did you did you **<u>expect it</u>** to be to find parking when you arrived? (Please select only one response)

Not at all difficult	Slightly difficult	Moderately difficult	Very difficult	Extremely difficult
1	2	3	4	5

10) How difficult **<u>was it</u>** to find parking at String and Leigh Lakes when you arrived? (Please select only one response)

Not at all difficult	Slightly difficult	Moderately difficult	Very difficult	Extremely difficult
1	2	3	4	5

11) During this trip to Grand Teton National Park, were there any places you intended to visit, but did not? (Please respond "yes" or "no")

☐ No ☐ Yes- please describe the places you avoided and why
____

12) During this trip to String and Leigh Lakes, were there any visitation times you avoided? (Please respond "yes" or "no")

☐ No ☐ Yes- please describe the times you avoided and why
____

13) If Grand Teton National Park offered a voluntary shuttle bus system to popular park locations during peak periods with parking outside the park, how likely would you be to ride the shuttle?

Not at all likely	Slightly likely	Very likely	Extremely likely	Completely likely
1	2	3	4	5

14) Why did you choose the String and Leigh Lakes area as the setting to do your primary activity today?
____

15) Are you a permanent resident or citizen of the United States? (Please respond “yes” or “no”)

☐ NO - What is your country of origin? ________________________

☐ YES - What is your primary zip code

Zip code _______________

16) In what year were you born? (Please respond in the blank below)

____

Post-Trip Questionnaire

OMB Control Number 1024:0224

Grand Teton Post-trip Survey: String and Leigh Lakes

String and Leigh Lakes Recreational User Post-Survey – 2018

1) Below is a list of benefits you may have attained while visiting the String and Leigh Lakes area. For each statement, please indicate how true you find each statement to be for your primary activity during your trip to String and Leigh Lakes area today.

During my primary activity at the String and Leigh Lake area, I have…	Not at all true	Slightly true	Somewhat true	Very true	Completely true
…improved my connection with nature.	1	2	3	4	5
…improved my appreciation of natural beauty.	1	2	3	4	5
…stimulated my senses through experiencing nature.	1	2	3	4	5
…increased my sense of absorption in nature.	1	2	3	4	5
…reduced my anxiety.	1	2	3	4	5
…restored my mind from unwanted stress.	1	2	3	4	5
…reduced my physical stress.	1	2	3	4	5
...improved my mood.	1	2	3	4	5
…gained a greater acceptance of myself.	1	2	3	4	5
…gained higher self-esteem.	1	2	3	4	5
…improved confidence in my abilities.	1	2	3	4	5
…increased my sense of adventure.	1	2	3	4	5
…enhanced my satisfaction through challenge.	1	2	3	4	5
…improved my sense of freedom.	1	2	3	4	5
…increased my sense of independence.	1	2	3	4	5
…increased my family bonds.	1	2	3	4	5
…enhanced my family life.	1	2	3	4	5
…kept the children of our group engaged in the outdoors.	1	2	3	4	5
…enhanced my socialization.	1	2	3	4	5
…improved my social bonds.	1	2	3	4	5
…enhanced my social identity.	1	2	3	4	5

2) Did you plan to visit the String and Leigh Lakes area **earlier** in the day than you would have liked to avoid crowds? (Please respond “yes” or “no”)

☐ NO ☐ YES

3) Did you plan to visit the String and Leigh Lakes area **later** in the day than you would have liked to avoid crowds? (Please respond "yes" or "no")
☐NO ☐YES

4) How crowded did you feel while recreating at the following sites in the String and Leigh Lakes area today? (Please select only one response per item)

Location	Not at all crowded	Slightly Crowded	Moderately crowded	Very Crowded	Extremely crowded
String Lake Picnic Area	1	2	3	4	5
String Lake Canoe Launch	1	2	3	4	5
String Lake Shoreline	1	2	3	4	5
Leigh Lake Trail	1	2	3	4	5
String Lake Open Water	1	2	3	4	5
Leigh Lake Open Water	1	2	3	4	5
Paintbrush Canyon Trail	1	2	3	4	5
Laurel Lake	1	2	3	4	5
Trapper Lake	1	2	3	4	5
Holly Lake	1	2	3	4	5
Hidden Falls	1	2	3	4	5
Inspiration Point	1	2	3	4	5
Jenny Lake Loop Trail	1	2	3	4	5

5) Did you do any of the following in response to the density of visitors at the String and Leigh Lakes area today? (Please respond "yes" or "no")

Went to a different area of the lake that has less people	☐ **NO**	☐ **YES**
Went to Leigh Lake to avoid crowds at String Lake	☐ NO	☐ YES
Continued with my planned activity and location	☐ NO	☐ YES
Changed my primary activity to adjust to the number of people (if yes, please specify) ____	☐ NO	☐ YES

6) Did you do any of the following in the String and Leigh Lakes area today: Canoeing, Kayaking, Stand-up Paddle boarding, or other water based recreation?
☐NO ☐YES

7) Below is a list of possible user groups you may have encountered in the String and Leigh Lakes area. For each item please indicate how true you find the following statements about the groups you may have encountered.

The behaviors of the following user group detracted from my experience today:	**Not at all True**	**Slightly True**	**Moderately True**	**Very True**	**Completely True**
Stand-up Paddle boarders	1	2	3	4	5
Canoeists	1	2	3	4	5
Kayakers	1	2	3	4	5
Shoreline Visitors	1	2	3	4	5
Other (please specify) ___________________________________	1	2	3	4	5

8) You indicated that the behavior of other visitors detracted from your experience today. How did you respond to other users' behaviors that detracted from your experience today? (circle one) (**SKIP LOGIC WILL BE USED FOR THIS QUESTION. ALL RESPONDENTS WHO ANSWER 2 OR HIGHER FOR ANY CATEGORY OF QUESTION 5 WILL BE SHOWN THIS QUESTION)**

	I **DID NOT** do this	I **DID NOT** do this, but I **thought** about doing this	I **DID** do this
Changed your direction of travel	1	2	3
Created more distance between yourself and other user group(s)	1	2	3
Traveled to a different area on String or Leigh Lake	1	2	3
Verbally engaged with other user group(s)	1	2	3
Ended activity on String and Leigh Lakes earlier than planned	1	2	3
Switched activity type	1	2	3
Other (please specify___________________________	1	2	3

9) On this visit to the String and Leigh Lakes area, did you or your group do any of the following things in response to crowded conditions? (Please respond "yes" or "no")

Parallel parked along a curb	☐ **NO**	☐ **YES**
Parked along the Jenny Lake Road	☐ NO	☐ YES
Parked in a lot other than your preferred parking lot	☐ NO	☐ YES
Waited until a parking spot opened up in my preferred parking lot	☐ NO	☐ YES

Left and came back at an alternative time	☐ NO	☐ YES
Came to String and Leigh Lakes because you were unable to visit another area of the park (please specify)	☐ NO	☐ YES
Other (please specify ________________________________	☐ NO	☐ YES

10) How did the following conditions you may have experienced **ADD** or **DETRACT** from your experience in the String and Leigh Lakes area today? (Please select only one response per item)

Conditions	Detracted greatly	Detracted somewhat	Had no effect	Added somewhat	Added greatly	Did not experience
Bare soil	1	2	3	4	5	☐
Trampled vegetation	1	2	3	4	5	☐
Eroded soil	1	2	3	4	5	☐
Tree damage	1	2	3	4	5	☐
Number of undesignated trails	1	2	3	4	5	☐
Vegetation loss on lakeshores	1	2	3	4	5	☐
Litter	1	2	3	4	5	☐
Presence of park personnel	1	2	3	4	5	☐
Water quality	1	2	3	4	5	☐
Condition of the restrooms	1	2	3	4	5	☐
Other (please specify): ____________________	1	2	3	4	5	☐

11) How many people were in your personal group today, including you? (Please respond below)
____ Number of people

12) When planning your trip to Grand Teton National Park, which information source did you use **most** to find information about visiting the String and Leigh Lakes area? (Please select only one response)

☐ Brochure/map
☐ Ranger/employee
☐ Other visitors
☐ Newspaper
☐ Interpretive program
☐ Social media
☐ NPS Website
☐ Other website
☐ Educational groups
☐ I did not use any of these

Factor and Reliability Analysis for Pre-Survey Motivation Battery

		Statistics		
Motivation[1]	Indicator	λ	*Mean*	SD
Enjoy Nature			**4.23**	
	…view wildlife	.763	3.89	1.131
	…be close to nature	.692	4.61	0.663
	…experience tranquility.	.675	4.04	1.172
	…enjoy the sounds of nature	.644	4.05	1.102
	Cronbach's Alpha (α)	*.733*		
Socialization			**4.32**	
	...be with people who share similar values.	.891	4.16	1.155
	...be with others who enjoy the same things I do.	.875	4.21	1.066
	…to be with friends	.622	4.41	1.062
	Cronbach's Alpha (α)	*.894*		
Escape			**3.77**	
	…physically relax	*.820*	4.13	0.921
	...get away from the noise back home	*.793*	3.88	1.186
	...have my mind move at a slower pace	*.709*	3.95	1.071
	…feel independent from the rest of society	*.702*	3.44	1.290
	…be away from crowds of people	*.678*	3.11	1.401
	…experience natural quiet	*.568*	3.83	1.234
	Cronbach's Alpha (α)	*.822*		
Adventure			**3.05**	
	...take risks.	.840	2.36	1.224
	...have thrills.	.821	2.79	1.396
	...experience a sense of exploration.	.598	3.74	1.115
	…learn what I am capable of	.543	3.15	1.447
	…gain a sense of self confidence	.476	3.39	1.447
	Cronbach's Alpha (α)	*.829*		
Sharing			**2.59**	
	...have others know that I have been here.	.888	2.64	1.528
	...tell others about my trip.	.846	2.99	1.480
	...share photos on social media	.841	2.64	1.527
	...show others my abilities	.566	2.40	1.382

Motivation[1]	Indicator	Statistics		
		λ	*Mean*	SD
	Cronbach's Alpha (α)	*.875*		

[1]For all motivations, means are from a 5-point scale of 1 "not at all true" to 5 "extremely true."